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Amharic Text to Ethiopian Sign Language Translation Model using Factored Phrase-Based Statistical Machine Translation Approach

Yoseph Belay Tesfaye

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Yoseph Belay Tesfaye

Advisor: *Solomon Gizaw (PhD)*

This is to certify that the thesis prepared by *Yoseph Belay,* titled: *Amharic Text to Ethiopian Sign Language Translation Model using Factored Phrase-Based Statistical Machine Translation Approach* and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Computer Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

	Name	Signature	Date
Advisor:	Solomon Gizaw (PhD)		
Examiner:	Yaregal Assabie (PhD)		
Examiner:	Solomon Atnafu (PhD)		

Abstract

Machine translation is a process of natural language translation automation to translate text from one natural language to another natural language. Machine translation is the fastest way to process a vast amount of data and produce usable translations in any language in the world. In this paper, we deal with the design of an Amharic to Ethiopian Sign Language machine translator. Amharic is the official language of Ethiopia. Ethiopian Sign Language is a visual-gestural language used to communicate and interacting by the Ethiopian Deaf community.

This study presents a factored Amharic to Ethiopian Sign Language statistical machine translation system composed of three main components. The first component is a neural network-based Amharic part of speech tagger that is used as a preprocessor to factorize the words in the parallel corpora. The second component is a factored statistical machine translator that is used to translate text from Amharic to Ethiopian Sign Language grammatical structure. The third component is a word to Ethiopian Sign Language video clip mapper which takes the translated text as an input and finds matches from the video corpus.

We conducted experiments using three different machine translation approaches and compared with the evaluation result of the proposed system. The first experiment is performed using a standard phrased based statistical approach as a baseline model. The second experiment conducted using a factored phrased-based approach. The third experiment carried out by using a neural machine translation approach.

Our evaluation's findings demonstrate that the use of factored phrase-based statistical translation approach effectively improves Amharic to EthSL machine translation. Our proposed factored statistical translation achieves a 35.28 BLEU score which outperforms both the baseline standard phrase-based statical machine translation model and the neural machine translation model.

Keywords: Machine Translation, Statistical Machine Translation, Factored Machine Translation, Amharic to Ethiopian Sign Language Machine Translation

Dedication

I would like to dedicate this thesis to my mom, Shege Tulu. At every stage of my life, she has been an inspiration of strength for me. This would not have been possible without her relentless love, encouragement, and strong support. I am grateful for my mom today, and every day. She is the reason I am the man I am today, and for that, I am so grateful. I LOVE YOU, MY HEROINE!

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Acronyms and Abbreviations

ANN	Artificial Neural Network
ASCII	American Standard Code for Information Interchange
ASL	American Sign Language
BiLSTM	Bi-Directional Long Short-Term Memory
BLEU	Bilingual Evaluation Understudy
CBOW	Continuous Bag-of-Words
CNN	Convolutional Neural Networks
DDMT	Data-Driven Machine Translation
DMT	Direct Machine Translation
DoH	Deaf or Hard-of-Hearing
EBMT	Example-Based Machine Translation
ELRC	Ethiopian Languages Research Center
ENAD	Ethiopian National Association of the Deaf
EthSL	Ethiopian Sign Language
GRU	Gated Recurrent Units
HMM	Hidden Markov Model
IDE	Integrated Development Environment
IRSTLM	The IRST Language Modeling
LM	Language Model
LSTM	Long Short-Term Memory
METEOR	Metric for Evaluation of Translation with Explicit Ordering
MLE	Maximum Likelihood Estimate
MT	Machine Translation
NER	Named Entity Recognition
NIST	National Institute of Standards and Technology
NLP	Natural Language Processing
NMT	Neural Machine Translation
PER	Position Independent Word Error Rate
PoS	Part of Speech
RBMT	Rule-Based Machine Translation
RNN	Recurrent Neural Networks

Seq2Seq	Sequence to Sequence
SiGML	Signing Gesture Markup Language
SL	Source Language
SMT	Statistical Machine Translation
SOV	Subject Object Verb
SRILM	The SRI Language Modeling
TER	Translation Error Rate
TL	Target Language
WER	Word Error Rate

Chapter 1

Introduction

1.1 Background

Sign language is a nonverbal language that is used for communication primarily among the Deaf and hard-of-hearing. People who are Deaf or hard-of-hearing depend on sign language in which a combination of hand signs, facial expressions, head movements or body language are used to communicate and interact with those around them. Deaf and hard-of-hearing people from different countries with different sign languages have a unique skill in communicating with each other easily compared to hearing people with different spoken languages [1]. Like spoken languages, sign language has its own linguistic structure [2].

With roughly one percent of the Ethiopian population classified as Deaf or hard-of-hearing, a significant portion of Deaf people in the country faces communications barriers in the workplace, in schools, markets, religious sites, public service provision areas and others. The Deaf community faces barriers to education, social services, and employment opportunities because the written form, as well as the voiced form of spoken languages, is inaccessible [3]. Given the prevalent lack of access to education, employment opportunities, information or services, and a widespread exclusion from engaging with their communities in general, life for the Deaf in Ethiopia is an uphill struggle.

Ethiopian Sign Language (EthSL) is the sign language of the Deaf in Ethiopia [4]. While the very existence of the EthSL is a welcome news for the Deaf in Ethiopia, they are still challenged due to EthSL's differences with Amharic - the official working language in Ethiopia. Amharic and the EthSL belong to different language groups and have different syntactic and morphophonological structures. For instance, In the EthSL, the noun comes before the adjective instead of after, where the opposite applies in Amharic.

For instance, when translating the Amharic sentence "ባህላዊ ቅርሶቻችንን መንከባከብ የሁላችንም ግዴታ ነው" into its equivalent in the EthSL, one will have "ቅርስ ባህል መንከባከብ ሁሉም ግድ". Because of grammatical structural difference, a great deal of difficulties arises when Deaf and hearing people try to communicate through written text. It is usually quite difficult for most hearing people to interpret sign language and similarly on the other side, it is problematic to read and understand the meaning of written Amharic text for most Deaf or hard-of-hearing people [6].

Consequently, due to the communications barriers in education, employment opportunities and overall social interactions, Deaf and hard-of-hearing people in Ethiopia are in no small extent economically, politically, culturally, and socially marginalised and excluded. This is not an isolated case, as the fate of Deaf people across developing countries has a mirror-like resemblance of marginalisation and discrimination. Luckily though, the overall communications gaps faced by people with hearing impairments can be significantly bridged using technology.

Advancement in technology during recent years have allowed many applications such as real-time transcription systems, real-time captioning and text or speech to sign language machine translator in helping the social integration and easing the communication between Deaf and hearing people. There is still an untapped potential through technological advancements to assist the Deaf to communicate effortlessly in the society by building robust systems that can translate spoken languages into sign languages and vice versa [2].

Machine translation (MT) is a process of language translation automation to translate content from one natural (human) language to another natural language. It is an area of research that combines ideas and techniques from Linguistics, Computer Science, Artificial Intelligence, Translation theory and Statistics for automating the process of translation from one language to another [47]. Machine translation is the fastest way to process a vast amount of data and produce usable translations in any natural language in the world.

The exponential advancement of the computing power has made data-driven machine translation approaches such as statistical machine translation and neural machine translation more dependable and effective. The application of statistical machine translation to text to sign language machine translation has been demonstrated by Achraf Othman, et al [104]; and it has shown a promising result. In spite of the successful outcome of this approach for this kind of translation models, research in Amharic Text to Ethiopian Sign Language translation within the field of statistical machine translation gets less attention of researchers as the previous studies were conducted by making use of techniques like rule-based machine translation [4, 5], example-based machine translation [1] or direct word to word translation [9].

There is not enough in the way of using data-driven machine translation strategy and associated artificial intelligence capabilities to help the Deaf effectively engage in society, considering the promising outcome of statistical machine translation approach for this kind of translation models. There is limited access to hearing aids and other technology, especially in developing countries, that can enable the Deaf to learn and communicate with others effectively [7]. To this end, technological interventions based on substantial evidence from research and practice would significantly alleviate many of the political, academic, economic, cultural and social inequalities faced by the Deaf. Developing powerful translation applications also hold huge potential in assisting the Deaf in understanding written languages [8].

The relevance of Amharic Text to Ethiopian Sign Language Translation model is to facilitate inclusion of the Ethiopian Deaf community into society regardless of their hearing disability. It is particularly important, given the limited number of professional human sign language interpreters in the country. A machine translation system is helpful in the absence of a human translator, which can be an assistant for the Deaf to communicate. Ultimately, it could even be used as a replacement for a human sign language interpreter so that privacy and the cost issues of human interpreters would be alleviated.

This research is conducted to bridge the communication gap between the Deaf and hearing communities in Ethiopia by deploying a factored statistical phrase-based machine translation, capabilities in natural language machine translation. Primarily, the thesis aims to make use of a data driven method to develop a model that can automatically translate Amharic text into Ethiopian sign language. The deployment of automatic translation of Amharic text to Ethiopian sign language translation using factored phrase-based statistical machine translation approach would potentially boost the inclusion of and significantly ease communication of the Deaf or hard-of-hearing people in Ethiopia.

1.2 Motivation

EthSL has its own grammatical structure that is independent of a set of syntactic that regulate the Amharic language. The grammar and syntax of EthSL vary from that of Amharic, and this may therefore influence the ability of the individual to effectively interpret written text. The Deaf must have the capacity to read and comprehend Amharic written text or the hearing person must have knowledge of EthSL in order to communicate, or human interpreters of sign language must facilitate communication. The first two modes of communication are difficult as it is difficulty understanding the meaning of the written text for most Deaf or hard of hearing and, on the other hand, most of hearing people do not know EthSL [6]. In the latter case, there are human sign language interpreters who translate EthSL to Amharic and vice versa to help to bridge the communication gaps between Deaf and hearing people, but it has disadvantages in terms of availability of professional interpreters, cost of interpreter services and privacy. Although in Ethiopia using translator person is a current solution for filling the gap between hearing and non-hearing people, it has its own drawback according to privacy and economic factors [5]. It is not always possible to find interpreters when needed; in addition to cost and losing privacy [4].

As the amount of electronic Amharic text exchanged in the workplace, in schools, public service provision areas and other places increasingly growing, language translation automation can solve many of the communication challenges for the Deaf and Hard of Hearing while making the written form of spoken language more accessible to them. Although a considerable amount of text contents has been created in digital format, there is no robust and effective language-translation tool. Therefore, this leads to a growing need for effective and powerful automatic translation of Amharic text to EthSL. This has motivated us to develop Amharic text to Ethiopian Sign Language model to ensure social integration and ease the communication between Deaf and hearing people.

1.3 Statement of the Problem

It is believed information that is communicated between individuals enhances their activity and thereby enables them to fulfil their interest. The literature indicates that communication between individuals takes place when they are understood and understand the other [4]. However, individuals may have a different personality, i.e. some of them may have a disability such as hearing impairment. This can be a barrier to communication and may lead to misunderstanding. Deafness is not merely a barrier of sound, but also a barrier of verbal language [3]. Moreover, language differences have a negative influence on communication, such as a communication gap between the Deaf and non-Deaf people.

While substantial progress has already been made in the text to sign languages translation systems of other countries, Amharic text to Ethiopian Sign language machine translation gets less attention of researchers. Classical approaches like rule-based [4, 5], direct word to word translation [10] and example-based [1] machine translation have been deployed by previous studies. Data-driven machine translation approaches such as statistical machine translation and neural machine translation have become more dependable and efficient as computing power has increased exponentially. In spite of the successful outcome of these approaches for this kind of translation systems, research in Amharic Text to Ethiopian Sign Language translation within the field of statistical machine translation gets less attention of researchers.

Due to the problems mentioned earlier with the existing Amharic text to EthSl machine translation models, it is desirable to look for a different method of machine translation. In the last decades, statistical based have been producing superior results on various NLP tasks. Research in Amharic Text to Ethiopian Sign Language translation within the field of data driven machine translation gets less attention of researchers.

To address this research gap, this work makes use of factored phrase-based statistical machine translation approach to develop a model that will automatically translate from Amharic text to Ethiopian Sign Language (EthSL). Building a translation system that can generate real-time statements via a signing avatar is helpful for the Deaf [9].

This study addresses the following research questions:

- Is Factored Phrase-based statistical machine translation approach applicable for translating Amharic text to EthSL?
- How a neural network based PoS tagger can be adapted to learn from a small amount of data?

1.4 Objectives

The general and specific objectives of the research are outlined below.

General Objective

The main objective of conducting this research is to design a model that enables the automatic translation of Amharic text to Ethiopian sign language using factored phrase-based statistical machine translation.

Specific Objectives

In order to achieve the above general objective, the following are specific objectives of this research.

- Review previous works on text to sign language translation and the general architecture of statistical machine translation models.
- Prepare a corpus containing Amharic and Ethiopian Sign Language sentence pairs.
- Train a neural network based part-of-speech tagger and annotate the Amharic - EthSl sentence pairs.
- Design a model for the translation of Amharic text into Ethiopian Sign Language.
- Develop a prototype.
- Evaluate the performance of the model.

1.5 Methods

In this research, a combination of methodologies will be used in order to meet the above-stated research objectives.

Literature Review

An in-depth literature review will be performed to uncover and understand new insights and knowledge gaps that demand further investigation and research. Journals articles, books, conference papers and websites, which will be helpful to accomplish the objective of this research will be reviewed.

Data Collection

Training statistical machine translation systems usually require bilingual and monolingual corpora. We will collect the Amharic - EthSL parallel corpus in two different ways: i) Simple Amharic - EthSL sentence paires translated by expert of the language, and ii) by collecting Amharic - EthSL language pair from previous Example-based machine translation research by Lily Abebe [1]. In addition to the machine translation monolingual and bilingual text corpora, we will also use Ethiopian Sign Language video corpus prepared by Lily Abebe [1]. The video corpus contains 280 EthSL signs and 245 EthSL fingerspellings.

To train our Amharic PoS tagger models, we will use two publicly available corpora: i) the first corpus, amWaC16 contains around 20 million tokens that were crawled and annotated by the "Annotated Amharic Corpora" project. The second corpus contain 210,000 annotated tokens prepared by the Ethiopian Languages Research Center (ELRC) of Addis Ababa University using around 1065 news articles from Walta Information Center.

In order to investigate the research gaps, Secondary data will be collected from documents, reports and files.

Develop a Prototype

A prototype will be developed for the purpose of testing concepts of the research. Different individual components/models will be developed as part of the machine translation system. Model for PoS tagging, and for mapping words into sign language video will be developed. And lastly, components will be integrated in order to obtain the full functionality of the prototype.

Experiment and Evaluation

In order to measure the translation accuracy, comparison will be made between the system outputs with the original translation of the input text. We will use BLEU and NIST score metrics to evaluate the performance of the system, which are automatic evaluation methods.

1.6 Scope and Limitations

The scope of this research is restricted to the development of a machine translation system that illustrates the support of translations between Amharic text and Ethiopian sign Language using factored phrase based statistical machine translation.

This research is limited to address the objectives mentioned owing to time and financial resource availability. The following are considered as the limitation of this research work:

- This study includes only simple Amharic sentences without considering the tense.
- Amharic Words (homonyms) spelled the same as another word but has a different sign such as 'መተኮስ' ('to shoot' or 'to iron') are not incorporated.
- This study only considers plural words formed by adding the sign to mean ብዙ (many).
- This study does not take into account Amharic compound words consisting of up two or three words with a single EthSL sign and Amharic words that have two or more signs when converted to EthSL.
- Since human evaluation method is time consuming & resource intensive, we used automatic evaluation score metrics to evaluate the performance of the system.
- Although effective two-way communication process involves the transmission of a message from one person to another person and vice-versa, this research work does not provide recognition of sign language to establish two-way communication.

1.7 Application of Results

The automatic translation from Amharic text to Ethiopian sign language have several applications, mainly assist the communication with Deaf people, education system for sign language students, and among others. The result of this research could also be used as an input for future studies in the effort of improving Ethiopian sign language and Amharic bilingual machine translation.

1.8 Organisation of the Rest of the Thesis

This thesis is divided into six chapters.

- Chapter 2 discusses the background of the study, providing an insight into Amharic language, sign language, machine translation and the different approaches to machine translation.
- Chapter 3 reviews different literatures regarding spoken to sign language Machine Translation together with its different approaches with a special focus on Amharic and EthSL.
- Chapter 4 presents general architecture of the proposed part of speech tagger (PoS) based factored statistical machine translation system and detail description of its components.
- Chapter 5 describes the experimental setup used to evaluate the effectiveness of factored language model and presents and explains experimental results.
- Chapter 6 is the last chapter which gives conclusions and recommendations.

Chapter 2

Literature Review

2.1 Introduction

This chapter discusses the background of the study, providing an insight into Amharic language, sign language, machine translation and the different approaches to machine translation such as rule-based machine translation, data-driven machine translation, and hybrid machine translation. Special emphasis is put on the description of the statistical machine translation, which is applied in this work. In addition, this chapter also briefly introduce Ethiopian Sign Language, and the numerous sign language elements.

2.2 Overview of Amharic Language

Amharic, the official language of the federal government of Ethiopia, is an Afroasiatic language belonging to the Semitic language family which includes Arabic and Hebrew as well. Amharic is somewhat different from any of these and together with the other Ethiopian Semitic languages, such as Tigrinya, form a very distinct branch within the family. Amharic is the second most widely spoken Semitic language next to Arabic [11]. Amharic is related to Geʿez, or Ethiopic, the Ethiopian Orthodox Church's liturgical language; it is also related to Tigré, Tigrinya, and South Arabic dialects [12].

The Amharic manuscripts are known from the 14th century, and since the 19th century the language has been used as a general medium for literature, journalism, education, and communication [13]. Despite its long history, only from the second half of the nineteenth century onward did Amharic become Ethiopia's written language, when Emperor Tewodros II actively promoted its use in government bureaucracy [14].

Ethiopia is a multiethnic country with multiple individual languages. According to the 2007 Ethiopian census, there are over 80 individual languages indigenous to Ethiopia. The Amharic and Affan Oromo languages are spoken mostly across the country. Amharic has more than twenty-one million native speakers, according to the 2007 Ethiopian Census, and about four million second-language speakers live primarily in Ethiopia, which is about one-third of Ethiopia 's population. Widely spoken in Ethiopia, Amharic is used by many groups as a first language, and by others as a lingua franca to serve as the official Ethiopian language for business and administrative duties in most part of the country [15]. Moreover, Millions of emigrants outside Ethiopia, such as the Ethiopian Jewish communities in Israel and Ethiopians migrated to North America and European countries, also speak the language.

2.2.1 Amharic Writing System

Amharic is written using the Ge'ez script called Fidel (ፊደል), which evolved out of the Ge'ez method of writing [1]. The Amharic alphabet consists of seven major orders or a family of symbols, each with distinct characteristics of shape and tone. It consists of 33 base character from which six additional characters are derived, each with a mixture of vowels and consonants. Thus, these 33 basic characters would then give 7 * 33 syllable patterns based on which vowel to pronounce in the syllable. Some of the basic characters represent similar sounds, even if all of them have their own usage. The sets {ሀ, ሐ, ኀ}, {ሠ, ሰ}, {አ, ዐ} and {ጸ, ፀ} represent similar sounds [16]. There are also four (incomplete, five characters) orders of labialised velars and 24 additional labialised consonants in the writing system [17].

Table 2.1: Ge'ez script (ፊደል) example

First Order	Second Order	Third Order	Fourth Order	Fifth Order	Sixth Order	Seventh Order
ሀ hä	ሁ hu	ሂ hi	ሃ ha	ሄ he	ህ hə	ho
ለ lä	ሉ lu	ሊ li	ላ la	ሌ le	ል lə	ሎ lo
ሰ sä	ሱ su	ሲ si	ሳ sa	ሴ se	ስ sə	ሶ so

The full Ge'ez alphabet is shown in Annex A.

Amharic has two other vowels /ä, ə / than the five vowels / a, e, i, o, u/ common in most languages [1]. In contrast to most Semitic languages, Amharic is written from left to right. There are no capital and small letter distinctions of the Amharic script.

Compared to English, the Amharic language has unique punctuation marks except for certain punctuation such as a question, quotation, and exclamation marks. In the Amharic language,

- Two words are separated by ፡ symbol (ሁለት ነጥብ) punctuation. It is not rare to see the punctuation mark ' : ' used to demarcate words in Amharic electronic or paper-based writings instead of white spaces [18].
- ። symbol (አራት ነጥብ) is used to denote the end of a sentence.
- Items in a list separated by ፣ or ፥ (ነጠላ ሰረዝ) punctuation mark and
- ፤ (ድርብ ሰረዝ) is used to connect two closely related independent clauses.

2.2.2 Amharic Word Classes

Amharic word classes most used are nouns, verbs, adjectives, adverbs, prepositions, and conjunctions.

Nouns

Amharic nouns can be derived or primitive. Nouns can be derived from other nouns, adjectives, roots, stems, and the infinitive form of a verb by affixation and intercalation [18]. For instance, እግረኛ(pedestrian) is a derived noun which is derived from the primitive noun እግር(leg). The morphemes'-ነት, '-ኧኛ', '-ኧት', '-አዊ', '-ተኛ', '-ኛ' and the prefix 'ባለ- 'are used to derive nouns [18].

Table 2.2: Derived and primitive nouns

Base noun	affix	Derived noun
ልጅ / ləjə (Child)	-ነት	ልጅነት / ləjə - nätə (childhood)
መንገድ / mänəgädə (Road)	-ኧኛ	መንገደኛ / mänəgädə - nga (traveler)
ደግ / dägə (Kind)	-ነት	ደግነት / dägə - nätə (kindness)
ፀጋ / tsäga (wealth)	ባለ	ባለፀጋ / balä - tsäga (wealthy)

For masculine and feminine nouns, the definite determiner 'the' is the suffix -u for male and -itu for female after consonants, and-w for male and -wa for female after vowels [19]. For example: ፈረሱ 'the horse (m)', ውሻው 'the dog (m)', ውሻዋ 'the dog (f)', and ድመቲቱ 'the cat (f)'. Some nouns are distinct in gender lexically.

Most plural nouns are formed by adding a suffix of plural markers to the singular nouns. The '-ኦች'(-očč) or '-ዎች'(-wočč) suffix usually mark plurality. መንገዶች / mänəgädə-očč (rods), ወንዞች / wänəzo-očč (rivers), ገበሬዎች / gäbäre-wočč (farmers). Some plural nouns are formed by the singular noun replication such as ቁሳቁስ / qusaqusə (materials), ጥራጥሬ /

tərаtəre (grain). There are also nouns inherited from Geez ending with -at or -an suffix, for example ሰማዕታት / sämaeətatə (martyrs), ጻድቃን / tsadəqanə (righteous).

Table 2.3: Forming plural nouns by adding a suffix of plural markers

Singular Noun	Suffix	Plural Noun
ተማሪ / tämari (student)	-ዎች	ተማሪዎች / tämari-wočč (students)
ንጉስ / nəgusə (king)	-ኦች	ንጉሶች / nəgusə-očč (kings)
ሰው / säwə (human)	-ዎች	ሰዎች / säwə-wočč (humans)
መኪና / mäkina (car)	-ኦች	መኪኖች / mäkina-očč (cars)
ሀገር / hägärə (country)	-ኦች / -ኦት	ሀገሮች (hägärə-očč) / ሀገራት(hägärə-at) (countries)
በቅሎ bäqəlo (mule)	-ዎች	በቅሎዎች bäqəlo- wočč (mules)

Pronouns

Amharic has three pronoun sets, namely independent pronouns, noun-possessive pronouns, and verb-object pronoun suffixes [19]. As the name indicates, independent pronouns are used independently, in place of nouns that refer to persons, places, or objects. The pronouns of the noun-possessive suffixes are suffixed with the noun possessed. These pronouns distinguish singular and plural and, in the singular, masculine, and feminine.

Table 2.4: Amharic pronoun examples

	Independent pronouns	Noun-possessive pronouns	Verb-object pronoun suffixes
Singular			
1	እኔ	መኪናዬ	ሰጠኝ
2	አንተ	መኪናህ	ሰጠህ
3	አንቺ	መኪናሽ	ሰጠሽ
4	እሱ	መኪናው	ሰጡት
5	እሷ	መኪናዋ	ሰጣት
Plural			
6	እኛ	መኪናችን	ሰጠን
7	እናንተ	መኪናችሁ	ሰጣችሁ
8	እነሱ	መኪናቸው	ሰጣቸው

Verbs

In Amharic, verbs are the most complex class of words morphologically, with a stem and none or more prefixes and suffixes. Several verbs in surface forms are generated from a single verbal root, verbal stems, and compound words [20]. Amharic verbs are marked for any combination of person, gender, number, case, tense, and mood resulting in thousands of words coming from a single verbal root [21]. For instance, we can derive verbal stems from the verbal root ngr:

Table 2.5: Deriving verbal stems from the verbal root.

ነገረሽ	nägäräshə	He told you
ነገራት	nägäratə	He told her
ነገረህ	nägärähə	He told you
ነገራቸው	nägärachäwə	He told them
ነገራችሁ	nägärachəhu	He told you
ነገሩት	nägärutə	They told him
ነገረችው	nägärächəwə	She told him
ነገረው	nägäräwə	He told him
ነገረኝ	nägärägnə	He told me
አልነገረም	alnägärämə	He did not tell
etc		

The subject and object of the sentence can be conveyed by a single Amharic verb [15]. For example: the word 'ከፈለቺኝ / käfälächignə' (she paid me), includes root kfl ('to pay'), stem: kefl ('pay'), subject: ቺኝ (she) and object: nə (me). The verbal root is, in most cases, tri-consonantal, although it may be bi-consonantal or tetra-consonantal [22]. For instance, ngr 'tell' (3 consonants), qr 'remain' (2 consonants), and mskr 'testify' (4 consonants) [19].

Adjectives

Amharic adjectives always precede the nouns or pronouns which they describe or modify. In the term "ሰላማዊ ህዝብ" for example, the word "ሰላማዊ" is used to describe the noun (ህዝብ) behavior. Most of the Amharic adjectives are derived from nouns and verbs; however, there are also some primitive adjectives such as ባዶ, ብልህ and ቢጫ. The ones derived from nouns are accomplished by the addition of suffix -gififa (-እኛ), -awi (-አዊ), -amma (-አማ)

and -am (-አም) [23, 24]. The suffix -awi derives an adjective of quality or characteristics while -amma derives an adjective of similar, perhaps slightly intensified meaning. Adjectives may also be formed by adding prefix 'የ' to a noun.

Adverbs

Amharic adverbs modify the verb right next to them. Between the adverb and the verb, there may be other words, but the modified verb appears next to the modifier before any other verb in the sentence [23]. For example, the word "ዛሬ" (today) is used in the expression "እህቴ ዛሬ መጣች" (My sister came today) to describe when the activity occurs. The Amharic adverbs are few in number and can be found in the primary word, as a separate word which arises on its own and in a compound form, as a combination of two words appearing as a word or detached words [1]. The adverbs that most frequently appear are ቶሎ, አሁን(now), በኋላ(later), ትናንት(yesterday), ገና (Yet) and ዛሬ(today).

Prepositions and Conjunctions

Amharic demonstrates positional relations through prepositions or postpositions, together called adpositions. Adpositions usually pair with a noun or a pronoun, or more commonly a noun phrase, which is referred to as its complement [18]. Preposition precedes its complement; thus, it is pre-positioned. A postposition comes next to its complement. Amharic appears to have more postpositions than prepositions. Amharic prepositions include ለ, በ, እ, ከ, ስለ, ያለ, ወደ, እስከ, በስተ and እንደ while postpositions include ኋላ, ላይ, ማዶ, መጠን, ውስጥ, ውጪ, ዳር, ጀምሮ, ጋር, ጎን, ገደማ, ፊት etc. Single letter prepositions are prefixes, written as part of the preceding word; prepositions written with two or more letters are normally written as separate prepositions [19, 25].

Conjunctions and prepositions in Amharic have similar behaviors and they are categorised in the same class of words, known as mestewadid [23]. The most widely used Amharic coordinate conjunctures are: "እና (and)", "ግን (but)", and "ወይም (or)".

2.2.3 Amharic Phrasal Categories

The Amharic phrases are grouped into five groups, including the noun phrase, verb phrase, adjective sentence, adverbial phrase, and preposition term [26, 27]. The headword in a phrase is considered the keyword or the expression that is what the phrase is about. Each phrase category can be further categorised into 'simple' where only one-word class is represented and 'complex' where more than one-word class is represented [27].

Noun Phrases

A noun phrase is a set of words that is headed by a noun or pronoun. Amharic noun phrase can be simple or complex. The simplest noun phrase consists of one single head word, a noun, or a pronoun usually. A complex noun phrase consists of a noun and other constituents such as complements, specifiers, adverbial and adjectival modifiers that modify the head from various aspects [26]. In the following complex phrase: 'የዓመቱ ምርጥ ተዋናይ' (yeametu mirte tewanay/Best Actor of the Year): የዓመቱ is an adverbial modifier, ምርጥ is an adjectival modifier, and ተዋናይ is the headword or a noun.

Verb Phrases

Verb phrase is a set of words composed of a verb as head word and its complements, adverb, or other modifiers that serves the same grammatical function as a verb. Verb phrases also have simple and complex form as noun phrases [15]. Take the example: "በባቡር ወደ ቤት መጣች (she came home by train)". The adverb በባቡር /by train" and prepositional phrase "ወደ ቤት /to home" have modified the verb "መጣች/came".

Adjectival phrases

An adjective phrase is a set of words with an adjective as a head describing a noun or a pronoun, thereby serving the same function as an adjective. In the adjectival phrase: ያ በጣም ረጅሙ (ya betam rejimu / That very long), ያ 'that' is a specifier, በጣም' very' is a modifier modifying the head of the adjectival phrase "ረጅሙ".

Adverbial phrases

Amharic adverbial phrases are made up of an adverb as headword and one or more other lexical categories including adverbs themselves as modifiers. Adverbial phrases modify other words by describing whether, how, where, or when an event occurs, thus serving the same function as an adverb. The adverbial phrases modifiers are mostly prepositional phrases which often come before adverbs [18]. Contrary to other phrases, adverbial phrases take no complements. Adverbial phrases are formed by the rule: AdvP➔Adv or AdvP ➔Adv Adv [20]. For example, "በዝግታ ተራመደ/he walked slowly", "በዝግታ" (slowly) is the only adverb whereas in "ቶሎ ቶሎ ተራመድ", composed of two adverbs "ቶሎ ቶሎ".

Prepositional Phrases

A prepositional phrase is constructed from a preposition (head) and other constituents such as nouns, noun phrases, verbs, verb phrases [15, 17, 27]. Contrary to most phrase constructions, prepositions cannot be used as a phrase, but should be paired with other constituents, and the constituents may come either previous to or next to the preposition [20]. In the prepositional phrase እስከ መጨረሻ 'until the end', for instance, እስከ 'until' is preposition that is combined with the nouns መጨረሻ' end' and form their prepositional phrase.

2.2.4 Amharic Sentence

In Amharic sentences, the most common word order is Subject-Object-Verb (SOV) where the subject comes first, the verb comes last, and if the verb takes an object, it comes in the middle. Example: ዮናስ መስኮቱን ሰበረው "ዮናስ" is the subject, "መስኮቱን" is the object and, "ሰበረው" is the verb. However, when the referent of the direct object is old, backgrounded, or topicalised information, or if the subject is new, foregrounded, or focused information, the direct object may precede the subject, and a resumptive pronoun, which repeats reference to the direct object, is suffixed to the verb [19]. Most of the sentence elements, such as words, objects, adjectives, or even adverbs, always come before the verbs in Amharic. Subject and verb are the main constituents of Amharic phrases [15]. Based on their composition, Amharic sentences can be classified mainly into two simple, and complex sentences.

A simple Amharic sentence consists of a noun phrase, which is the subject, preceded by a verb phrase that consists of the predicate [18]. It comprises only one independent clause. An independent clause is a set of words comprising a subject and a verb and representing a full thought. Examples of different structures of simple sentences are shown below.

- አብረሃም ተመለሰ / Abraham returned
- ቴዎድሮስ ስራ ሄደ / Tewodros went to work
- መቼ ስራ ትጀምራለህ? / When do you start work?
- ሀላፊዎቹ በትልቅ መኪና ወደ አዳማ ሄዱ / The officers drove to Adama in a large car

A complex sentence is a sentence containing an independent clause as well as one or more dependent(subordinate) clauses. In Amharic, complex sentences are those sentences that consist of complex phrases such as noun phrase, verb phrase, or adjective phrase [27].

"ሰብለ **[ልጇ ፈተና ስላለፈ]** ተደሰተች "

Seble is happy that her son passed the test

2.3 Deafness

Deafness is an inability to hear sound that could occur when one or both ears are affected, either totally or partially. People who cannot hear and those with average hearing – 25 dB or better sound levels in both ears-are said to have hearing loss [28]. Deafness can result from heredity, age, exposure to excessive noise, disease or infection, ototoxic drugs, or physical injuries but is not limited to them. Deafness can be either congenital or acquired. Deafness that is present at birth is considered Congenital deafness (Born-Deaf), whereas deafness that occurs after birth, likely due to sickness or accident, is considered acquired deafness (Late-Deaf) [1]. Deafness can also be conductive or sensorineural. Conductive loss of hearing is caused by damage to the outer or middle ear and sensorineural loss of hearing is attributed to damage to the inner ear [29].

Deaf refers to those with profound hearing loss. They primarily use sign language as a medium of communication. Hard of Hearing refers to people with hearing loss ranging from mild to severe. People who are Hard of Hearing usually communicate through spoken language and can benefit from hearing aids, cochlear implants, and other assistive devices as well as captioning [1, 28, 30]. In compliance with the convention, the word "deaf" applies to individuals with a hearing deficiency and have less strong feelings of identity and ownership within the Deaf community, and the term "Deaf" for individuals who are part of a Deaf society and share Deaf Culture and sign language [1, 4]. The term "hearing impaired" is used to describe people with any degree of hearing loss, including those who are Deaf and hard of hearing.

Hearing deficiency before a person learns language abilities is referred to as pre-lingual deafness. People who are born into Deaf parents, and whose first native language is a signed language, not a spoken one, are "culturally deaf" [5, 30]. A hearing deficiency that occurs after a person learns language abilities is known as post-lingual deafness. Post-lingual Deafs are "physically deaf", but "culturally hearing" [5, 30]. Deaf children to deaf parents are usually introduced to sign language at birth. At least 90% of deaf children, though, are born to hearing parents who use a spoken language [31].

According to the World Health Organization (WHO), a substantial 5% of the world's population are individuals with hearing loss and with roughly one percent of the Ethiopian population classified as Deaf.

2.4 Sign Language

Sign languages are natural languages that are mainly used by Deaf people and which visually transmits meaning by making use of shape, placement, and movement of the hands, facial expressions, and body movements instead of sound. Sign languages are produced by the hands, face, and body and perceived primarily visually, in contrast to spoken languages, which are produced by the mouth and vocal tract and perceived primarily auditorily [32]. People who are Deaf mainly depend on sign language in order to communicate with those around them. Sign languages are Deaf peoples' natural languages which have phonological structures, morphological structures, and function in specific grammatical systems [1, 33]. By using the hands, upper body parts and facial expressions, they create meaningful signals [34].

Deaf people around the world use Sign Languages as a way of communication in their day-to-day-life. Signing is not only used by the deaf; it is also used by people who can hear but cannot physically speak [35]. Like spoken language, Sign languages are not universal language as they differ across countries. There are more than 200 distinct sign languages in the world [30]. Each country has one or sometimes two or more sign languages, although different sign languages can share the same linguistic roots in the same way as spoken languages do [35]. Compared to people with different spoken languages, Deaf people from different countries and different sign languages have a unique skill to communicate with each other easily.

Sign languages are distinct because they use "corporal-visual," formed by the body and perceived through the eyes. Just like spoken languages, Sign languages have their own grammatical and linguistic structure. [37]. Fingers, hands, and arms are the primary articulators of sign languages, compared to spoken languages where the predominant articulators are the throat, nose and mouth [1].

Sign languages are generally composed of three main components, namely manual signs that are gestures made by hand or fingers movements, nonmanual signs such as facial expressions or body postures, and fingerspelling where words are spelt out using gestures by the signers to convey the meaning [38]. Manual parameters include the shape of the hand (configuration), direction of the hand (orientation), placement of the hand (joint direction) and gestures of the hand (hand movement), while nonmanual parameters include parameters include head and body posture, facial expression, gaze, mouth movements and structured gesture [1].

2.4.1 Parameters of Sign Language

Handshape

Handshapes are the base element of sign languages which are the shape of the hand to form a single sign. The basic handshapes used for fingerspelling are also used to make words when combined with other movements or signs [5, 30]. A specific handshape is used in each sign. In the same way that in spoken language, a change in sound in one-word results in a different meaning, a change of handshape may result in a different meaning. Figure 1 shows, for the days in EthSL sign language shown below every parameter is the same except the shape of the hands, [100].

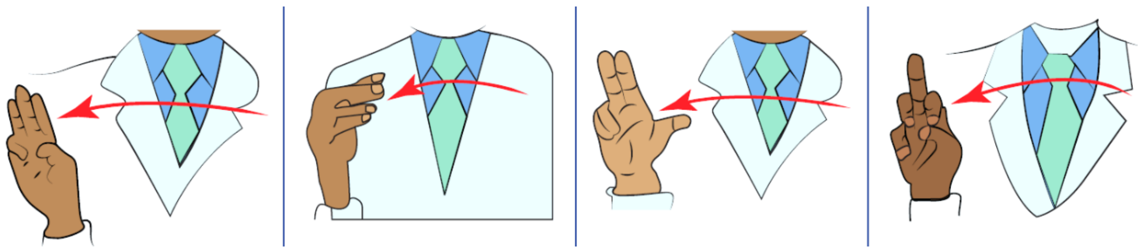

Figure 2.1:Handshape and movement of days of the week (from left to right Friday, Sunday, Thursday, Saturday)

Location

The location parameter is where the hands are placed close or on some parts of the body. It may begin in one part of the body and finish in another part of it. The signing space is an imaginary rectangle, shoulder width, from head to just below waist [5, 30]. The location of a sign also relates to its meaning. For instance, many signs that denote feelings are formed near to the heart, whereas signs related to cognitive concepts are formed near to head [39]. Figure 2.2 shows location of the primary hand is at left wrist [100]

Figure 2.2: The location of the primary hand

Palm Orientation

Orientation refers to the direction in which the fingers and palm of the hand are pointing during the production of a sign [1]. It shows the rotation of the entire hand, regardless of its shape and the individual positions of the fingers [40]. The fingers and palm may be oriented into seven basic directions upwards, downwards, right, left, facing each other, towards or away from the signer's body [1]. Changing the orientation of the hands can reverse the meaning of the sign. Figure 2.3 shows palm orientations [5].

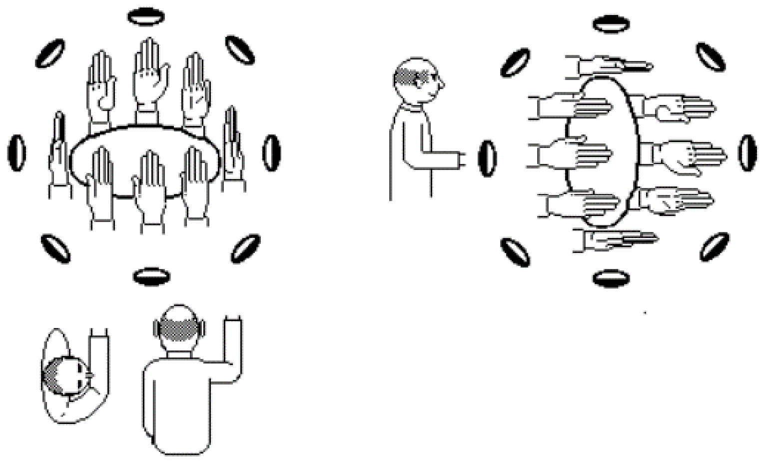

Figure 2.3: Palm Orientation

Movement (signation)

Movement refers to the unique hand gestures that make up words. In addition to the shape and location of the hand, each sign has its own unique movement. A sign may show various kinds of movement such as circular, wiggling, tapping, twisting, forward, backward, back and forth, up and down or a combination of any of these movements. It is possible to convey much of the meaning of signs by movement. For instance, the direction the sign moves can show the subject or object of an action, the repetition of the movement may indicate several things: - the frequency of the location, if the noun is plural or singular, or the distinction between a noun or verb. Or the size of the movement may indicate the relative extent of something [4, 39]. Figure 2.4 shows hand movement to form the sing book (መፀሀፍ) [100]

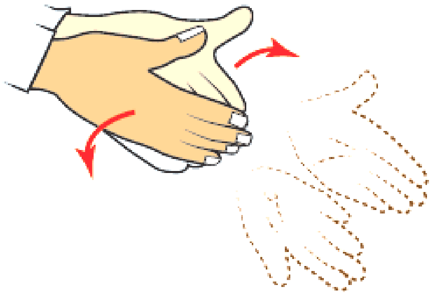

Figure 2.4: Hand movement (signation)

Nonmanual Features

The nonmanual means of articulation in signed languages include movements of the eyes, head and body, various kinds of facial expression, mouthing and mouth gestures [41]. Nonmanual elements are an essential part of sign languages that are necessary to add grammar, emotions, and other information in sign languages. The presence of a nonmanual feature with a manual feature in a discourse can change the meaning of a sign, and its omission can make a sign meaningless [1]. Figure 2.5 shows Facial expression when signing grief [100].

Figure 2.5: Facial expression

The sign for the word "Police / ፖሊስ" shown [100] and described below is an ideal example to demonstrate the parameters of sign language since it contains all the five criteria for the sign language.

- **Hand Shape:** Bent index finger
- **Location:** The left shoulder
- **Palm Orientation:** Downward
- **Hand Movement:** From out to in
- **Nonemanual** feature: Expanded shoulder

Figure 2.6: Using all the parameters of sign language.

Fingerspelling

Fingerspelling is a way of expressing words using each letter that the word incorporates. Fingerspelling is the use of hand configurations to represent the letters of a writing system [1]. It is not in itself a sign language; it is a method that uses only the hands to represent the letters of a writing script, and numeral systems [4]. It is used to representing proper nouns, technical phrases, acronyms, initialized signs, loan signs and foreign language words [4]. It can also be used to represent words that do not have direct signs, or the signer do not know.

Different hand positions are used in fingerspelling to represent the various letters of the alphabet [41]. Some sign languages use a one-handed fingerspelling alphabet, such as the Ethiopian Sign Language and the American sign Language, while some other sign languages use a Two-handed fingerspelling alphabet, such as the British Sign Language. Various countries have created sign language fingerspelling manual alphabets of their own. In various parts of the world, with different system used when one fingerspell fully, one more or less 'writes in the air' manually, letter by letter, spelling words out [1].

2.4.2 Ethiopian Sign Language

Ethiopian Sign language (EthSL) is one of the visual gestural natural languages used to communicate, interacting, sharing emotions and feelings by the Deaf community in Ethiopia. EthSL is an autonomous language which fulfils the features of sign languages [1]. It has its own fingerspelling and sign vocabulary and generally acquired by Deaf children as their native language. EthSL, a national standard which is used in primary, secondary, and tertiary Deaf education, as well as in national television. With ASL is deemed to have a significant effect, EthSL has its own linguistic structure and has many signs entirely unique to the language.

EthSL has a historical association with American sign language. The exact beginnings of EthSL are not clear, but some researchers suggest that its development is closely related to the establishment of the first school for deaf students in Addis Ababa by American and Nordic missionaries in 1963 [43, 4, 5]. Since then, EthSL has been adapted to suit the Ethiopian culture and broadly extended to schools and the communities of the Deaf. It is understood that the American Sign Language (ASL) has a strong influence on the EthSL, with some influence from the Nordic countries' sign languages such as Swedish Sign Language. Today, more than a million Ethiopian Deaf people use EthSL, but it is still a language that has not been researched well enough [43].

There are two primary dialects of EthSL, one of which is in Addis Ababa where several Deaf clubs and organizations concentrated, and the other of Hosaena School for the Deaf in Hosaena. The dialect in Addis Ababa is more heavily influenced by Amharic than is the Hosaena dialect, as evidenced by greater use of initialized signs, fingerspelling, and general grammatical influences [44]

EthSL gestures are shown with one hand or both hands, as most sign languages. The Primary hand (right hand for a right-handed person and left hand for left-handed person) which is the dominant hand is used to convey almost all signs. Single hand signs are therefore articulated always by primary hand. For two-handed signals, if both hands move, both hands can have the same handshape, or if the hands have opposite forms, only the primary hand moves. [1, 4].

Nouns

In Ethiopian Sign language, certain nouns and verbs use the same handshape. Proper nouns and nouns that do not have any sign are fingerspelled. EthSL does not alter the noun form to express plurality, thus, plurality can be represented either with repeating the noun or by adding a number or sign that indicates quantity. For instance, the plural form of the noun መፅሃፍ/book is denoted by adding the sign additional sign "ብዙ/many" whereas the plural form of ዛፍ/tree is denoted by repeating the singular noun. Figure 2.8 shows plural forms formed by adding the word ብዙ and figure 2.7 shows the plural form formed by repetition [100].

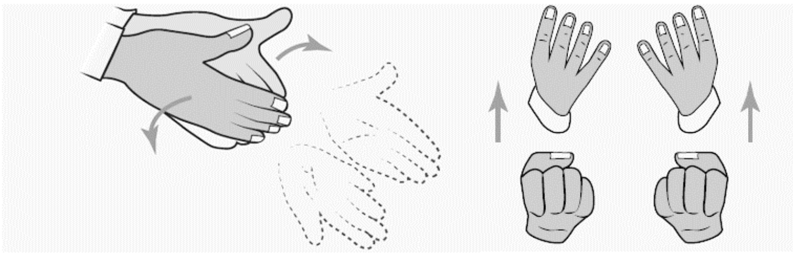

Figure 2.7: Plural form of book/መፅሃፍ

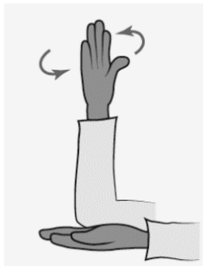

Figure 2.8: Plural form of ዛፍ/tree

Pronouns and Possessives

In EthSL, the use of pronouns is the same as the use of pronouns in spoken languages in a manner that you need to refer to a noun before you use a pronoun. Pointing signs are used for pronoun reference in EthSL. If an individual or object is not available to the signer physically, identify the person first by fingerspelling the name of the person or the object, then you can index the person or object to a certain point in the space [5].

Verbs

In comparison to Amharic, EthSL verbs are not morphologically complex class of words. The EthSL does not use suffixes or prefixes so verbs are represented without any affixes. Person, gender, number, tense, and mood markers are expressed with either additional signs or facial expression.

Adjectives and Adverbs

Unlike the Amharic language, EthSL Adjectives and Adverbs are placed after the noun and verb, respectively. EthSL places an adjective after the noun it modifies, but for stylistic reasons, one may place the adjective before the noun [5]. Example, an Amharic phrase ቀይ ውሻ (red dog) is signed as ውሻ + ቀይ (dog red).

Prepositions

Prepositions in EthSL may be found in some contexts sometimes, but not in most cases. All most all prepositions are mostly avoided in EthSL because they are mostly shown in context [5]. EthSL does not use these prepositions such as "ከ", "ለ", "የ"," በ", etc as much as Amharic does. Prepositions such as "ወደ", "ታች", and "ስር" have signs.

Negation

In Ethiopian Sign Language, you make a sign or a statement negative either by shaking head back and forth or by adding the sign "Not (አይደለም)". For example, for the statement "እኔ አልመጣም" (I will not come) is the expressed using three signs "እኔ መምጣት አይደለም" (I-come-not) as the sign language representation shown in the figure below.

Fingerspelling and Numbers

Ethiopian Sign Language includes a fingerspelling system that represents the Amharic orthography [45]. The Ethiopian sign language fingerspelling consists of 34 base handshapes which from each six additional fingerspellings are derived using hand movements. The 34 base handshapes have an iconic similarity with the Amharic Fidel [43]. As a consonant-vowel sound pair is encoded by each character of the Amharic Fidel, each symbol in the EthSL fingerspelling system uses handshapes to denote a base consonant, and a movement, location and orientation combination to represent a paired vowel[45]. Like American Sign Language, EthSL uses the one-handed manual alphabet. Most EthSL manual alphabets are denoted by movement and handshapes. Figure 2.9 shows EthSL manual alphabets

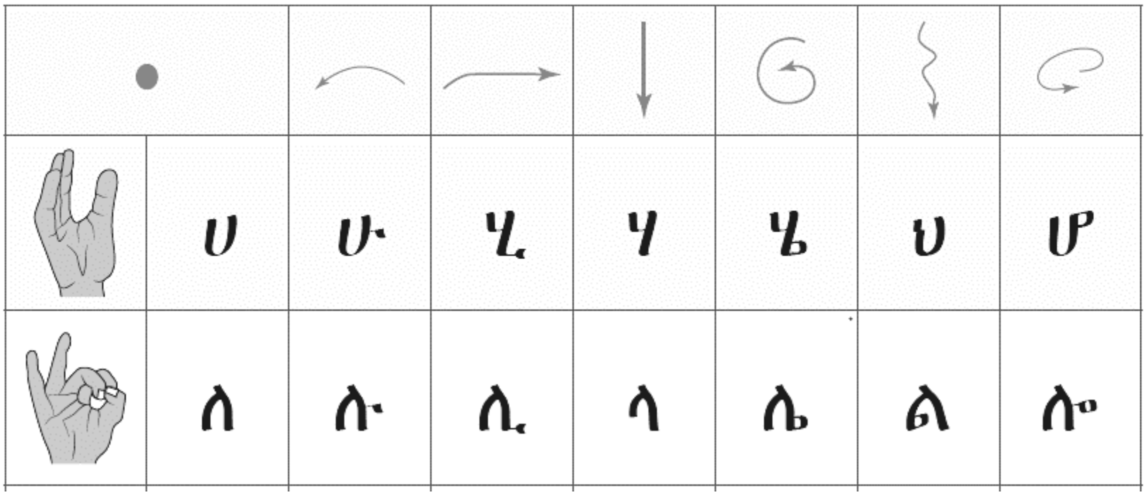

Figure 2.9: EthSL manual alphabets

In EthSL, all numbers below 1,000 are signed with one hand, and the second hand is used only to show that a number is in the thousands or millions [5]. The Fingerspelling and Numbers are shown in Annex B and Annex C.

2.5 Overview of Machine Translation

Machine translation (MT) is a process of language translation automation to translate content from one natural (human) language to another natural language. MT is a multidisciplinary field of research [46]. It is an area of research that combines ideas and techniques from Linguistics, Computer Science, Artificial Intelligence, Translation theory and Statistics for automating the process of translation from one language to another [47]. The aim machine translations are to translate from the source language (SL) whose content is to be translated to a target language (TL) in which the source content is to be translated through a computerized system. Machine translation is the fastest way to process a vast amount of data and produce accurate, usable translations in any natural language in the world.

In a more than ever-connected world where the primary form of communication is a natural language, the demand for translations is only rising [48]. In recent years, in the modern digital world, with the rapidly growing amount of information available in different languages made the need for robust and effective machine language translation increased. The need for a machine translation system is higher in this era, resolving culture and nation boundary [49]. Manual translation of a text can both be very time consuming and expensive, providing another reason to improve automatic machine translation and evaluation [48].

Machine translation continues to improve day by day. Significant progress has been witnessed since its inception, but to date, a long way to go in terms of matching human fluency, exactness, and understanding of nuance, ambiguity, sarcasm, and humour.

Machine translation systems are designed for either bilingual or multilingual machine translation. In bilingual translation, the system involves two languages (the source and target) and if the translation is from the source language to target language only then, it is referred to as unidirectional otherwise bidirectional. Multilingual involves more than two languages and by default are supposed to be bidirectional [50, 46].

2.6.1 Rule-Based Machine Translation (RBMT) Approach

Rule-based machine translation (RBMT) is a classical machine translation approach that uses a large set of manually developed linguistic rules of source and target languages to analyses and generate text in the target language. Rule-based techniques are linguistically driven methods of MT in the sense that they require dictionary and grammar to understand the syntactic, semantic, and morphological aspects of both languages [51]. Basically, RBMT contains a source language morphological analyser, a source language parser, translator, target language morphological analyser, target language parser and several lexicon dictionaries [52]. The rules which are defined in such a system are extensively used in the various processes which analyse an input text, such as during morphological, syntactic, and semantic analysis [53]

RBMT requires human experts with extensive knowledge of the source and target sentences. The approach depends heavily on language theory hence resource-intensive in terms human labour and hours spend when building the rules but easy to maintain, easy to extend to other languages and can deal with varieties of linguistic phenomena's [50].

The rule-based approach further is categorised into three (as shown in Vauquois Triangle below, [54] : Direct, transfer and interlingua approach. They differ in the depth of analysis of the source language and the level to form language-independent representation of meaning between the source language and target language [54].

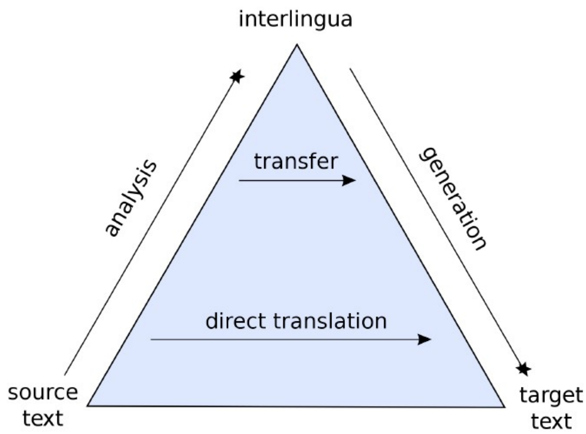

Figure 2.10: Vauquois Triangle

Direct Machine Translation (DMT) Approach

Direct Machine Translation is the oldest and the most straightforward machine translation approach that uses a sizeable bilingual dictionary where words are looked up after some simple morphological analysis to generate the target sentence. Direct MT involves only word-level analysis without considering structure and the grammatical correlation between words. The source language is morphologically analysed to derive the target language without an analysis of its internal structure or grammatical correlation [55].

Direct MT systems are easy to develop, but they cannot be adapted for different language pairs since they are developed for a specific language pair. The Direct approach of machine translation unable to resolve ambiguities and only bilingual and unidirectional machine translations are suitable for this approach [56]. Figure 2.11 shows architecture of direct machine translation [56].

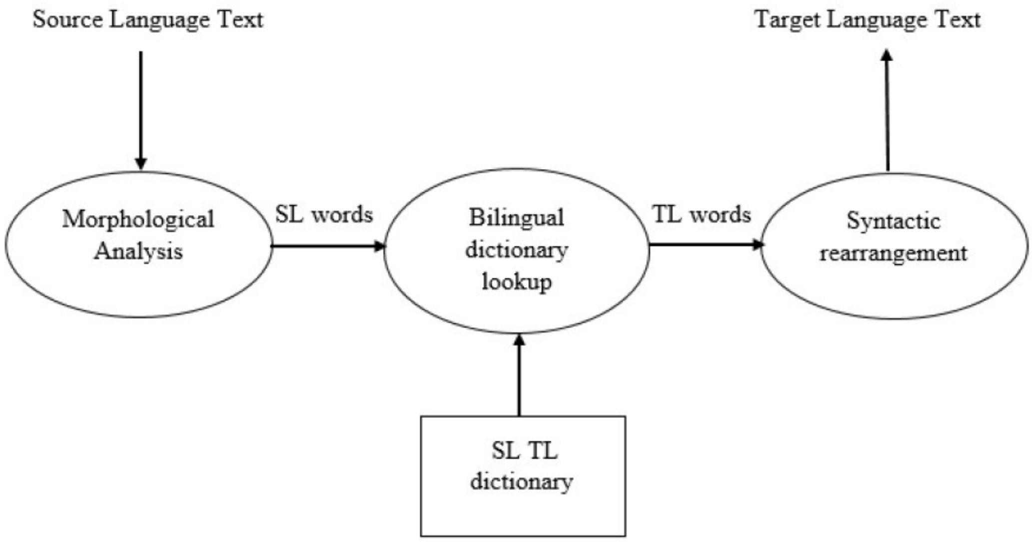

Figure 2.11: Direct Machine Translation

Interlingual Machine Translation Approach

In Interlingua MT system, the source language is analysed and translated intermediate abstract language-independent representation known as an Interlingua. Then, the target sentence is generated from language independent representation with the help of target language dictionaries [57]. The Interlingua approach assumes that it is possible to convert source texts into representations common to more than one language [46]. Thus, this approach is applicable to multilingual machine translation systems. The prime reason to go for interlingua is that if there are n languages, we need only 2n translation models instead of n2 [51]. The main disadvantage of this approach is that it is challenging to define an independent universal abstract language representation and convert languages to it. It is even difficult to do so for similar systems. Figure 2.12 shows architecture of interlingual machine translation [56].

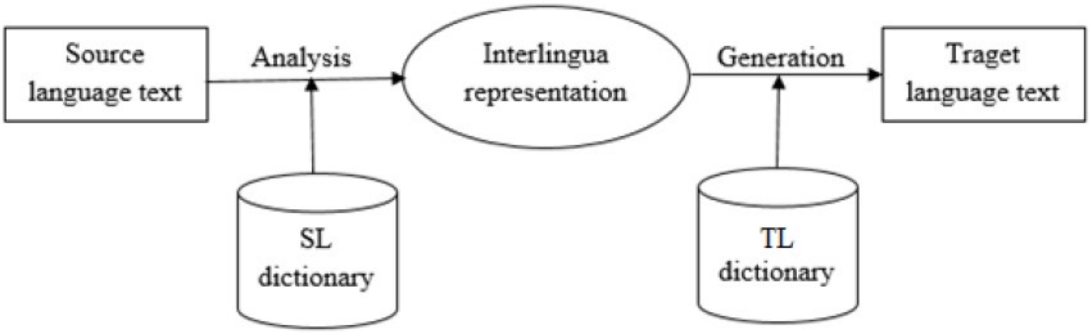

Figure 2.12: Interlingual Machine Translation

Transfer-based Machine Translation Approach

Transfer-based Machine Translation is a rule-based approach where the source language is analysed into an SL-dependent representation which is then transferred into a TL-dependent representation, from which a TL sentence is generated via some generation procedure [58]. Transfer-based MT is similar to Interlingua MT in that it creates a translation from an intermediate representation that simulates the meaning of the original sentence [1]. Unlike Interlingua MT, it depends partially on the language pair involved in the translation. The transfer approach can be broken down into three stages:

1. *Analysis*: this the first stage where a source language analysed to its morphological, syntactic, and semantic structure and converted into abstract source language-oriented representations (e.g. a parse tree.)
2. *Transfer*: in this stage, the transfer module maps the representations resulted from the first stage to target language representations using bilingual dictionaries and grammar rules.
3. *Generation*: the third stage generates the target language text. Figure 2.13 shows architecture of transferred-based machine translation [56].

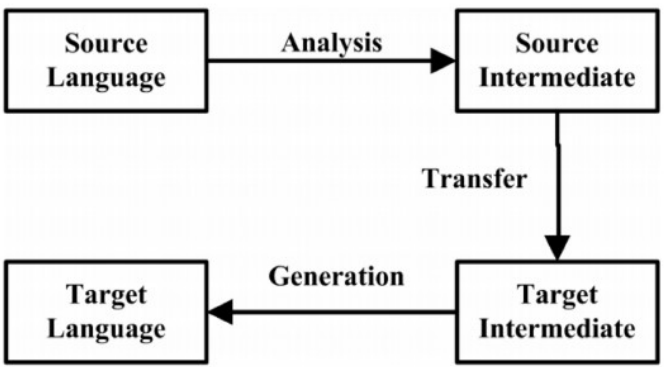

Figure 2.13: Transfer-based Machine Translation

One of the limitations with transfer Based MT approach is that rules must be applied at every step of translation. There are rules for source language analysis (syntactic/semantic), rules for source-to-target transfer and rules for target language generation [1].

2.6.2 Data-driven Machine Translation (DDMT) Approach

Data-driven machine translation (MT) has outstripped rule-based approaches as the predominant means of analysing bilingual aligned corpora and automatically learn how to translate without the need for explicit linguistic information. Data-driven machine translation is an alternative approach for machine translation to overcome the knowledge acquisition problem of rule-based machine translation [18]. Data-driven MT systems base their knowledge on bilingually aligned corpora, and the accuracy of their output depends strongly on the quality and the size of these corpora [59].

Data-driven approaches are robust and provide a simple procedure for building a machine translator when a good training bilingual corpus are available. The reliance on domain-specific data is one of the significant bottlenecks of data-driven approaches [60]. Especially, they do not perform well in data-scarce languages such as with under-resourced languages like Amharic.

The data-driven approach further classified into three: Example-Based Machine Translation (EBMT) approach, Statistical Machine Translation (SMT), and Neural Machine Translation (NMT).

Example-based Machine Translation Approach

Example-based Machine Translation is a data-driven machine translation which generates translations by adapting similar linguistic patterns from a large parallel aligned database consisting of translation examples. EBMT implements the idea of machine translation by the analogy principle and is based on the intuition that humans construct translations for new unseen input by making use of previously seen translation examples, rather than performing "deep linguistic analysis" [61]. It can be viewed as an implementation of a case-based reasoning approach to machine learning, which means solving newer problems based on the solution of similar past problems [57].

The production of the translations in EBMT involves three stages:

i. *Matching*: involves breaking down the new input and looking for close matches from the translation examples and extracting their translations.

ii. *Adaption*: If the match is exactly, the fragments are recombined to form TL output, else find the TL portion of the relevant match correspond to a specific portion in SL and align them [50].

iii. *Recombination*: Once relevant matches have been extracted, the target language fragments are recombined to form target language translation.

EBMT is an attractive approach to translation because it avoids the need for manually derived rules [1, 18]. However, it requires analysis and generation modules to produce the dependency trees needed for the examples database and for analysing the sentence. Another problem with EBMT is computational efficiency, especially for large databases, although parallel computation techniques can be applied [39, 1, 18]. Furthermore, as the system is example-based, gathering examples, the number of examples, suitability of them and lastly storage of examples builds up the main problems and divergence point of example-based MT systems [62, 1, 18].

Statistical Machine Translation (SMT) Approach

SMT is an approach to machine translation that deals with automatic translation of natural languages using statistical models that are generated through analysis of a large monolingual or bilingual corpus. The first ideas of SMT were introduced in 1947; however, it gained interest only in the late 1980s and early 1990s when the IBM Watson Research Center started using it.

A statistical model of the translation process can be approximated by analysing the co-occurrence and relative ordering of words in vast amount of texts [63]. SMT belongs data-driven approach as it is based on models that are automatically induced from a large parallel corpus [63]. The key idea is to use statistical probabilistic models, given a sentence in the source language, to find the translation to the target language with the highest probability match. If the probability is higher, so is the translation more accurate and vice versa [18]. SMT can easily be applied to any language domain if adequate bilingual and/or monolingual corpora is available. Compared to rule-based machine translations, SMT approach overcomes the need for a time-consuming and costly manual production of linguistic rules.

SMT approaches require the processing of a large quantity of training data that are compute-intensive to process. The accuracy of the translation of SMT depends primarily on the corpus in terms of its domain, quantity, and quality [64]. A good parallel corpora should include naturally occurring language data, which is representative of its domain, the alignment process should be conducted with high precision and should have a fair length per sentence pair [65].

Given a sentence S in the source language, the SMT aims to find that Ť in the target language from all possible T (target language sentences) for which P(T|S) is the highest probability match. This can be defined using the Bayesian noisy-channel model [76]:

$$P(T|S) = \frac{P(T).P(S|T)}{P(S)}$$

$$\check{T} = \boldsymbol{argmax_T\, P(T|S) = argmax_T\, P(T)\, .P(S|T)} \qquad (1)$$

The terms P(T) and P (S|T) can be considered respectively as the probability of the language model which calculates the fluency of T in the target language and the probability of the translation model which calculates the faithfulness of T as a translation of S. $argmax_T$ is a function that maximises the product of fluency and faithfulness.

Therefore, the noisy channel model based SMT architecture (shown in the figure below) consists of three components, namely: language model, translation model and decoder.

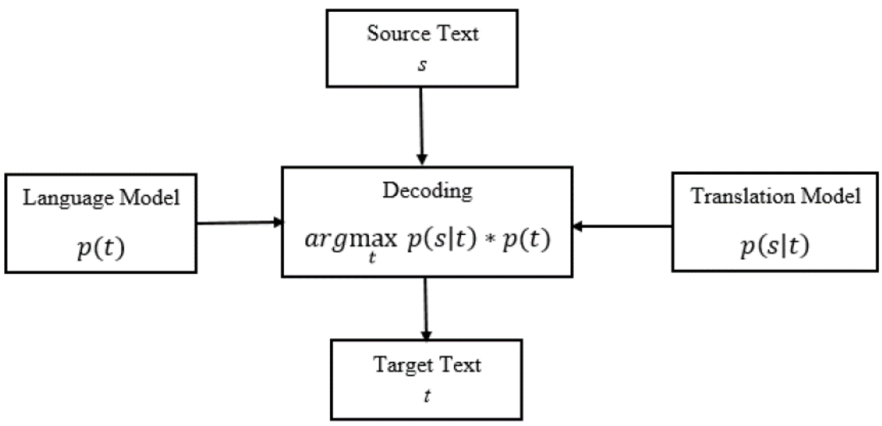

Figure 2.14: Statistical Machine Translation (SMT) Approach

The Language Model

The language model is one of the main components of the SMT that measures the fluency in the translated target language sentences. It is a statistical model that provides a distribution of probability over possible word sequences [66]. Statistical techniques like HMM, maximum entropy language model and N-grams are used to measure the probability distribution of words in a sentence. N-gram model is a straightforward and most widely used statistical language model technique. The n-gram models estimate the probability of a sequence of n words appearing in a given order [67].

Let T be a sentence with a sequence of words $w_1, w_2, w_3 \ldots, w_n$. The goal of a language model is to model $P(T) = P(w_1, \ldots, w_n)$ such that P(T) predicts the probabilities of each word pair appearing next to each other. In an n-gram language model, the probability P (T) of observing the sentence $w_1, \ldots, w_n$ can be calculated as [76]:

$$\mathrm{P(T)} = \mathrm{P}\ (w_1, \ldots, w_n)$$

$$\boldsymbol{P(T) = P(w_1)\,.\,P(w_2\,|w_1)\,.\,P(w_3|w_1w_2)\,.\,P(w_n\,|w_1w_2w_3 \ldots w_{n-1})}$$

$$\boldsymbol{P(T)} = \sum_{i=1}^{n} P(w_i\,|w_{i-(n-1)} \ldots w_{i-1}) \tag{2}$$

These probabilities can now be computed through counting to get a Maximum Likelihood Estimate (MLE). Smoothing techniques are used so that not frequent translations are not discarded beforehand.

The Translation Model

The translation model measures the probability of the translation P(T|S) given the source language; that is, the faithfulness of T as a translation of S. It captures the correspondence between words and phrases in the source language and target language [68]. Statistical translation models estimate the conditional probability of a target sentence given a source sentence, using word alignments [69].

Statistical translation models originally were word-based, focusing on translation probabilities for an individual word, but a substantial development is made in introducing machine translation models based on phrases and syntax.

Word-based Statistical Translation Models

Word-based statistical translation models use words as their basic translation units. Alignment of words between the target sentence and source sentence with maximum probability extracted through analysing a large parallel corpus employing statistical techniques. IBM Models (IBM-1 to IBM-6) are word-based models that constitute the first SMT model generation.

IBM Model 1 includes modelling the lexical correspondences at the word level without considering word reordering or word adding and dropping. All alignment decisions are independent. IBM Model 2 further enhanced IBM Model 1 by modelling the absolute word position by means of the alignment probability distribution. IBM Model 3 introduced the concept of fertility probabilities that enables a word in the source language to translate to many words in the target language. As opposed to IBM Model 2, Model 4 does relative reordering, which allows reordering of the whole sentence. It also implements word classes for better prediction of probability. IBM Model 5 fixes deficiency of the previous models by keeping track of free word positions, allowing placement only in these positions. IBM Model 6 integrates the IBM Model 4 with the HMM alignment model in a log-linear way.

One of the significant drawbacks of word-based SMT is that it only learns the translation of individual words. Neighbouring contexts are not well captured as the translation unit of this model are the individual words [70]. Moreover, substitution and reordering choices are taken separately for individual terms in word-based translation models. This adds to a higher likelihood of error that typically leads to the "word salad" – a translation where certain words are accurate, but their order is entirely incorrect [71].

Phrase-based Translation Models

Phrase-based translation models are the most widely used models where the basic unit of translation is an ad hoc phrase (sequences of words). The translation of word sequences rather than one word at a time results in better translations as more contexts can be considered. The word sequences are called phrases or blocks, but they are not normally linguistic phrases but corporate mathematical phrases [72]. Phrase-level alignment starts by segmenting the source sentence into phrases with arbitrary boundaries [70]. Then they are translated into the target language phrases and phrases are reordered according to a distortion probability.

There are two main extensions of phrase-based translation models and they are described by the literature [73] as follows:

- **Hierarchical phrase-based models**: Hierarchical phrase-based translation combines the strengths of phrase-based and syntax-based translation. It uses phrases (segments or blocks of words) as units for translation and uses synchronous context-free grammars as rules (syntax-based translation).
- **Factored phrase-based models**: Phrase-based models are a special case of factored models. The key concept behind factored phrase-based translation models is to represent phrases not merely as sequences of surface form of words, but rather as sequences of surface form of words along with additional linguistic information. Elements of these sequences are called factors. Factors can be anything, including stems, roots, part of speech tags, and other linguistic information.

Syntax-based Translation Models

The syntax-based translation models are based on the idea of translating syntactic units, rather than single words or strings of words as in phrase-based MT [72]. They rely on parsing the sentence in the source or the target language, or in some cases in both languages [74]. These models incorporate an explicit representation of the syntax of a sentence such as parse trees, POS tags, etc. into the statistical machine translation systems.

Decoding

Given an input, the decoder is responsible for finding the best translation with the highest score of all alternative translation hypotheses that are generated during the translation process. Decoding or finding the sentence that maximises the translation and language model probabilities is a search problem [75]. The process of decoding involves exhaustively finding possible translations, scoring, and choosing the best possible translations [76]. Heuristic search techniques, such as beam search, are used to minimise search errors and concentrate on the most interesting translation hypotheses when adding reordering constraints. Decoding is a compute-intensive and challenging task since there is an exponential number of alternative translations for a given single input sentence and picking the best possible translation that maximises the P(T) * P(T|S).

Neural Machine Translation

Neural Machine Translation is a recent approach to machine translation that uses deep learning techniques to model the entire machine translation process through a single artificial neural network. An artificial neural network (ANN), commonly called a neural network (NN), is a mathematical model or computational model inspired by biological neural network structure and/or functional aspects [77]. Nodes in neural machine translation networks function like neurons in the brain, interacting and working together to generate a final output [78].

Neural Machine Translation models typically comprise two components: an encoder module to read and encode the input text into a hidden vector representation and a decoder to decode hidden representations and generate a sequence of words in a target language. The whole encoder-decoder system, which consists of the encoder and the decoder for a language pair, is jointly trained to maximise the probability of a correct translation given a source sentence [79]. The basic encoder-decoder model is generally equipped with an attention model, which repetitively re-accesses the source sequence during the decoding process [80]. Before Attention mechanism, neural machine translation relies on reading a complete sentence and compress all information into a fixed-length vector which leads to information loss and inadequate translation [81].

The current neural machine translation models include the use of recurrent neural networks (RNN) [82], convolutional neural networks (CNN) [83, 80, 84], and the Transformers [85] neural machine translation architectures. RNNs are the incumbent technology for text applications and have been the top choice for language translation because of their high accuracy [84]. The main idea is that the encoder encodes the source sentence with the RNN encoder and uses the last hidden state as input for the RNN decoder; this represents the output in the target sentence [18]. LSTM are a popular choice for this type of RNN based NMT architectures.

CNN models can process parallel information to allow them to search for non-linear relation in data. They are more common in image processing and less common in sequence-to-sequence modelling. They are computationally more effective by allowing all input elements to be calculated at the same time, taking full advantage of hardware parallelism.

The transformer is a fully attentional sequence to sequence architecture, which has obtained state-of-the-art results for several NMT shared tasks. It replaces the use of sequential cell units (such as LSTM) by Multi-Head Attention operations, which make the architecture considerably faster [86].

NMT is capable of generalising better to unseen text by exploiting word similarities in embeddings and capturing long-distance reordering by conditioning on broader contexts in a continuous way [87]. Unlike traditional methods of machine translation that involve separately engineered components, NMT works cohesively to maximise its performance [88]. In NMT networks, the systems can understand full sequences of words (sentences), while SMT networks only understand up to the phrase-level [78].

Recurrent Neural Network

Recurrent Neural Networks (RNN) are a variant of neural networks that has an internal memory. RNNs can use their internal memory (state) to process sequential data as they allow previous layer outputs to be fed as inputs to the current layer. RNN can recall key facts because of its internal memory about the input they received and can anticipate what's coming very precisely. RNN were created on top of feed-forward neural network to alleviate the issue memorizing the previous steps.

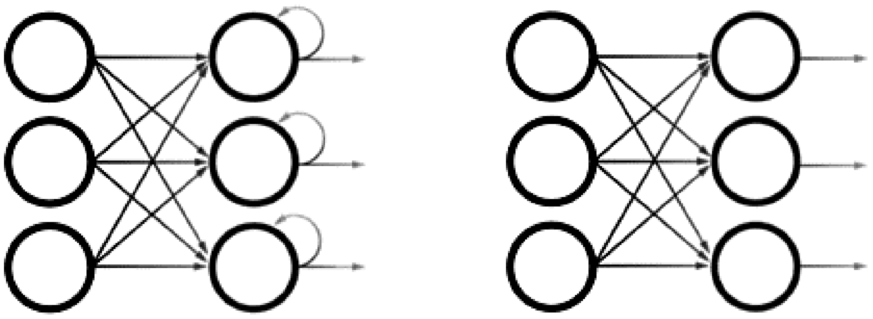

Figure 2.15: RNN (on the left) and Feedforward Neural Networks (on the right)

RNNs come in a variety of extension such as Long short-term memory (LSTM), Gated recurrent units (GRU) and Bidirectional Long short-term memory (BI-LSTM)

LSTM: is an RNN extension which is created to solve learn long term dependency problem of the standard RNNs. LSTMs enable RNNs to maintain inputs for a long period. LSTM has three gates that can regulate the flow of information: input gate decides whether new values to let through or not, forget gate discovers what values to be deleted, and the output gate uses the input and the memory of the block to decide the output. This enables the LSTM to read, write, and delete information from its memory which enables it to learn what information is and what is not relevant over time.

BiLSTM: is an improvement to the LSTM architecture consisting of two LSTMs, one process input in forward direction and another process input in reverse direction. BiLSTM uses both the past and future information by processing the input sequence in two directions. Thus, it captures both the past and future context by using two LSTM networks for precise prediction.

GRU: is an RNN extension which is similar the LSTMs as they also work to address solve learn long term dependency problem of standard RNNs models. Unlike LSTM, Instead of GRU has only two gates to regulate the flow of information: the reset gate decides whether the previous cell state is important or not. and the update gate decides whether the cell state should be updated with the current activation value or not.

2.6.3 Hybrid Machine Translation Approach

The integration of two or more translation mechanisms is known as Hybrid Machine Translations. Such integration involves the incorporation of different Rule-based approaches into data-driven MT approaches, the hybridisation of data-driven components into rule-based approaches, or data driven and rule-based pre-processing and post-processing for both types of MT approaches. The aim is to blend the best characteristics and take advantage of multiple MT paradigms. Hybrid MT is a MT approach that has been found to provide improved benefits in MT systems using multiple MT methods in a single MT system [1].

2.6.4 Evaluation of Machine Translation Systems

The evaluation of the quality of machine translation output is a research task of its own, since there is not one correct translation for every sentence, but natural language provides many ways of conveying the same meaning [99]. It can be broadly categorized into two: manual evaluation and automatic evaluation. In Manual evaluation, human evaluators who are familiar with the at least with the target language, preferably with both the source and the target language, conduct evaluation of machine translation quality. A standard procedure for manual evaluation is to provide adequacy and fluency scales from 1 to 5 to judge translation adequacy and fluency in the target language separately [99]. Automatic evaluation techniques for machine translation require the availability of a reference translation against which the machine translation output is compared. Manual assessment is too costly and time-consuming, as opposed to automated evaluation.

The most widely automatic used are Word Error Rate (WER), Position independent word Error Rate (PER), Translation Error Rate (TER), the BLEU score, Metric for Evaluation of Translation with Explicit Ordering (METEOR) and the NIST score.

Bilingual Evaluation Understudy (BLEU)

BLEU is an algorithm for evaluating a machine translation system by comparing the candidate translation to one or more translations of reference. BLEU introduced by Paninani et al. in 2001 [89], remains a benchmark for the measurement of any new assessment metric. It is a standard algorithm to calculate the degree of similarity between candidate machine translation against the human translations based on the n-gram precision [90]. BLEU measures how many word sequences in the sentence under evaluation match the word sequences of some reference sentence [18]. BLEU measures the precision with the brevity penalty (BP) coefficient for n-grams of scale 1-to-4. The BLEU score is defined by the following formula, [89]:

$$\mathrm{BLEU} = \mathrm{BP} \times \exp\left(\sum_{n=1}^{N} w_n \log p_n\right) \tag{3}$$

Where:

- $BP = \begin{cases} 1, & if\ c > r \\ e^{1-\frac{r}{c}}, & if\ c < r \end{cases}$ Where c be the length of the candidate translation and r be the effective reference corpus length.

- p_n: the number of n-grams of machine translation is also present in one or more reference translation, divided by the number of total n-grams of machine translation.
- w_n : positive weights.

The BLEU metric ranges from 0 to 1 of which only a few translations will attain a score of 1 unless they are identical to a reference translation [89]. BLEU stated to be well-connected with human judgment [91]. While BLEU has considerable benefits, it was argued that there is no assurance that a rise in the score in BLEU will mean higher quality translation [92].

Word Error Rate (WER)

The WER metric, introduced by Popovic and Ney in 2007 [93], measures up the quality of a candidate translation to a reference translation based on Levenshtein distance. The word error rate (WER) is based on the Levenshtein distance, which is the minimum number of edits that have to be performed to convert the generated text into the reference text [93]. The key idea is to measure the minimum quantity of words to be added, omitted, or substituted in the hypothesis translation to make it equivalent to the translation of the reference. This metric takes word order into account. The WER score is defined by the following formula, [93]:

$$WER = \frac{S + D + I}{N} \tag{4}$$

Where:

- S is the number of substitutions,
- D is the number of deletions,
- I is the number of insertions,
- N is the number of words in the reference text.

The WER metric is easily measured and reproducible Due to the diversity of the language expression, the word order is not adequately taken into consideration as some so-called "wrong” order by WER often prove to be successful translations [94]. This is considered the key downside of WER.

Position-independent word Error Rate (PER)

To address this word order problem of WER, Tillmann et al. proposed PER metric. PER counts the number of times that the same words appear in both sentences, without the word sequence being considered. Depending on whether the translated sentence is longer or shorter than the reference translation, the rest of the words are either insertion or deletion ones [94]. PER calculates the difference between the number of words in the hypothesis and reference sentences, and then the corresponding number is divided by the number of words in the reference number [95]. The PER score is defined by the following formula, [94]:

$$PER = 1 - \left(\frac{correc - max\ (0, Output_{lengeth - Reference_{lengeth}})}{Reference_{lengeth}}\right) \quad (5)$$

Translation Error Rate (TER)

TER is defined as the minimum number of edits needed to change a hypothesis so that it exactly matches one of the references, normalised by the average length of the references [96]. Editing may involve adding, removing, and changing words, as well as word sequence changes. The TER score is defined by the following formula, [96]:

$$TER = \frac{\#\ of\ edits}{average\ \#\ of\ reference\ words} \quad (6)$$

Metric for Evaluation of Translation with Explicit Ordering (METEOR)

METEOR is an automatic machine translation evaluation metric based on a generalised concept of unigram matching that compares hypothesis translation with reference translations [98]. The matching of terms is possible in stages, beginning at the surface shape and providing additional matching measures for steps and for WordNet synonyms. It determines a translation on the basis of clear word-to - word correspondence between the translation and a reference translation. “If more than one reference translation is available, the given translation is scored against each reference independently, and the best score is reported. The literature reveals that METEOR has greatly enhanced correlation with human opinions and reveals that recall plays a more important role in achieving high rates of correlation with human opinions than accuracy” [98].

NIST (National Institute of Standards and Technology)

NIST is a BLEU variant that takes into account the information gain from each n-gram. NIST uses the arithmetic mean of weighted n-gram precision values for evaluating the quality of the translated text [97]. NIST also differs from BLEU in brevity penalty calculation, where small differences in translation length do not impact the overall score [18].

Chapter 3

Related Work

3.1 Introduction

In this part, previous works in the text to sign language machine translation are discussed. We reviewed existing research works which have been considered during our thesis on text to Ethiopian sign language machine translation. There are very few researches focused on Amharic text to Ethiopian sign language machine translation. First, the reviews on previous works in the area of Amharic text to Ethiopian sing language presented. Then, neural network methods implemented for non-Ethiopian sign languages are presented.

3.2 Rule-Based Text to Sign Language Machine Translation

A research work by Daniel Zegeye [5] was conducted with the aim of implementing RBMT approach to translate Amharic Text into Ethiopian Sign Language. The translator accepts simple Amharic sentence, letters or numbers as input and translates it into Ethiopian sign language. The output of the system is 3D animation of Ethiopian sign language. The translator consists of three core modules: the Amharic text analysis module which accepts input from the interface and generates Romanized Amharic sentence; the NLP module which is responsible for all Amharic language processing and generating a sentence in EthSL grammar; and the text-to-sign mapping module that maps each Amharic word with the SiGML and generates signing avatars. As part of the translator, the author developed Amharic POS tagger, grammar translator, and preposition remover. The author evaluated the performance of the translator at sentences, letter and number level and achieved accuracy of 58.77%, 75.76% and 84% respectively.

Dagnachew Feleke[10] implemented direct RBMT approach to model the translator that accepts Unicode written Amharic word and convert it into ASCII representation; the morphological analyser applies available linguistic rules to form other possible words. The finally, then it synthesises ESL morphology and presents the output using signing avatar. Dagnachew described a simple morphological level machine translation approach for Amharic to Ethiopian Sign Language machine translation system.

Masresha Tadesse proposed an approach for translating commonly used Amharic words, letters, and numbers into ESL [4]. It uses Web-based user interface to accept inputs from the user and the system search the word in the ESL dictionary which is constructed from 50 Amharic words, 34 letters and 30 numbers. According to the study, if the input exists in the dictionary, then the system retrieves the animation script (SiGML) from file and passed it to the signing avatar and display it in a web browser. If not, morphological analysis is performed in order to find the stem word and It then looks up the stem word in the dictionary. In the evaluation of the AmESL-T, the author took two Deaf and two ESL interpreters. The participants were presented with selected signed words, letters and numbers and asked to write down what they understood. 30 words, 34 letters and 20 numbers were selected randomly for this purpose to check the accuracy of identification of words, letters and numbers across four users. The average accuracy of identification was 51% for words, 76% for letters and 80%for numbers.

Example-based and rule-based interlingua approaches were used to develop a machine translation system that translates Arabic text to the Arabic sign language [102]. The authors pointed that the system must perform a morpho-syntactic analysis of the text in the input and convert it to video sequences phrases playing by a 3D human avatar who expresses the usual signs used by Deaf people. Their system first checks if a sentence exists in the bilingual corpus which contains Arabic sentences and the corresponding translation of Arabic sign language. If a sentence exists in the corpus, the example-based approach is used. If the sentence doesn't exist, the rule-based Interlingua is used.

3.3 Data-driven Text to Sign Language Machine Translation

Lily Abebe [1] used the example-based approach to translate Amharic Text into Ethiopian Sign Language. The system uses example data which is processed to produce morphologically analysed Amharic words, word structures and sentence structures. Besides, it includes Amharic to EthSL dictionary of about 245 EthSL Finger spellings and about 280 words. The model consists of a word feature analysis component for analysing text so that it can get the important features and a component that performs matching, alignment and recombination to translate the text based on the knowledge acquired from example cases. The system accepts Amharic text and produces EthSL as a sequence of video clips.

Achraf Othman and Mohamed Jemni [104] proposed a statistical machine translation model for written English text to ASL. They suggested that artificial corpus should be generated using rules-based methods driven by the use of grammatical dependency graphs due to the lack of sign language tools. During the generation process, the authors integrate more than 52 grammatical relationships which the system for analysis is organized according to three predominant levels: lexical, syntactic, and semantic. Then the machine translation model was trained and a decoder was implemented for translating English text to the ASL using a novel proposed transcription system based on gloss annotation. They conducted automatic evaluation method and achieved BLUE score of 35.17. They also implemented another Jaro–Winkler distance to optimize training process and achieved a BLUE score of 46.35.

The research by Stephanie Stoll et al. exhibited a neural machine translation model for producing sign videos from spoken language sentences [2]. They introduced a three-stage process to convert a sentence into sign language. First, using an encoder-decoder network their system translates spoken language sentences into sign gloss sequences. Second, they use a lookup-table that provides a data-driven mapping between glosses and 2D skeletal pose sequences. Finally, sign language video sequences conditionally generated based on the resulting information of the previous step. They argued that they set a baseline for text-to-gloss translation by reporting a BLEU-4 score of 16.34 on development set and 15.26 on the test set.

Mourad Brour and Abderrahim Benabbou[103] proposed a feedforward back-propagation Artificial Neural Network machine translation system that translates simple sentences to Arabic sign language. The system performs its translation in the three-step process: the first step consists of giving morphological characteristics to each word of the sentence. The second step is encoding sentences with the morphological properties of each word and providing a context vector representing the sentence to be translated. The final step is decoding of the vector produced in a sentence in Arabic Sign Language and animating using the database of signs. They demonstrated that neuron network approaches are outperforming classical approaches by comparing their previous rule-based Interlingua and example-based text to sign language translation model with a neural translation system. They trained the neural network model using a corpus of 9715 sentences pairs, and they achieved an average BLEU score 0.79 which is closer to the ideal score of 1. Their previous rule-based Interlingua and example-based system achieved an average BLEU score of 0.37 which is relatively low.

3.4 Summary

We reviewed previous machine translation researches that are done in Ethiopian Sign Language and non-Ethiopian sign languages using different approaches. This enables us to understand that Amharic text to Ethiopian Sign language translation is relatively less matured research area in the natural language processing field.

The early works, Masresha [4], Daniel [5] and Dagnachew[10], sought to solve the research gap by making use of rule-based machine translation technique. However, Machine translation approaches based on the rules are not effective in addressing problems of obscure languages such as Ethiopian sign language that is not studied well. Moreover, such approaches eventually achieved a relatively low percentage of accuracy in translation of Amharic text to Ethiopian sign language, to differing degrees. Lily [1] tried to solve the same problem by using example-based machine translation technique and achieved an encouraging result. As computational power has increased exponentially, data-driven machine translation approaches such as statistical machine translation and neural machine translation have become more dependable and accurate. One of the fields where a factored phrase-based statistical machine translation method can be very useful is automated text to sign language machine translation.

Although significant progress has already been made in the text to sign languages translation models of other countries, research on Amharic text to Ethiopian Sign language machine translation within the field of statistical machine translation gets less attention of researchers, despite the successful outcome for this kind of machine translation models.

Thus, this study addresses the identified research gap and proposed suggestions to achieve improved machine translation using factored phrase-based statistical machine translation.

Chapter 4

Design of Amharic Text to EthSL Translator

4.1 Introduction

This chapter describes the proposed part of speech tagger (PoS) based factored statistical machine translation system for translating Amharic sentences into Ethiopian Sign Language. The general architecture of the proposed system and detail description of components are discussed in the following sections.

4.2 Architecture of the System

The architecture of the proposed system, shown in Fig. 16, is based on three main modules that were trained on different corpora.

The first module, the Amharic PoS was trained using a relatively huge PoS corpus by making use of state-of-the-art deep learning network, BiLSTM. The Amharic PoS tagger was used to factorize all the words in the corpus of the factored statistical machine translation model. Our BiLSTM based PoS tagger model achieves high accuracy.

The second module is a factored statistical machine translation model. It is composed of three essential components that are translation model, language model and decoder. The translation model assigns a probability translation; that is, the faithfulness of EthSL as a translation of Amharic. The language model component measures the fluency in the translated Ethiopian sign language sentences. The third component is a decoder which searches for the highest scoring sentence in the Ethiopian sign language given the corresponding Amharic sentence.

The proposed system also composed of a video mapping module which takes the translated text as an input and finds matches for each word from the video corpus based on a simple string-matching algorithm between the transformed text and labels of videos. The following parts discuss detailed explanations of each modules.

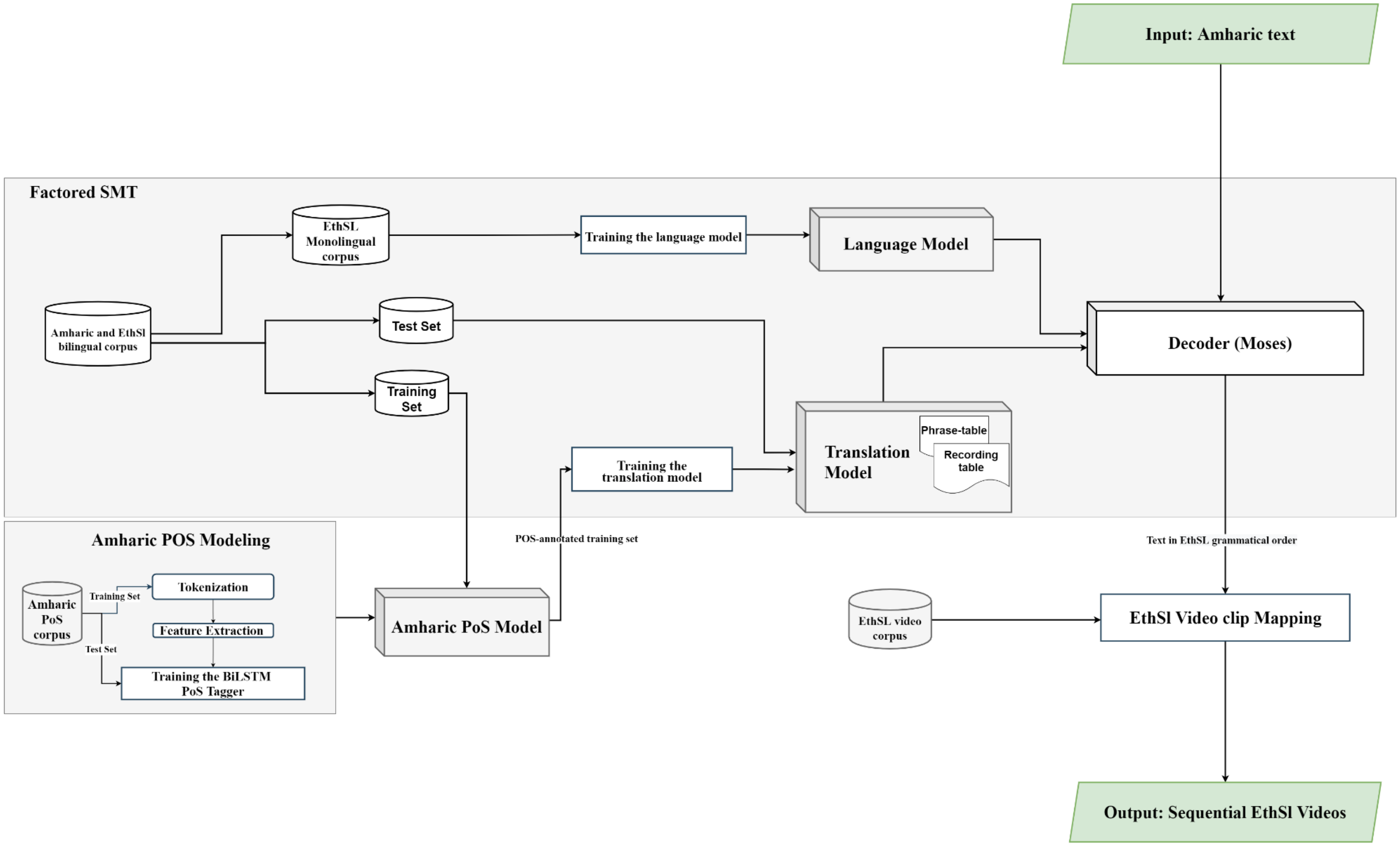

Figure 4.1: Architecture of the Amharic text to EthSL Translator

4.3 Amharic PoS Tagger Modelling

Part-of-speech (PoS) tagging is the process in which words are classified into their lexical categories (also known as word classes or parts of speech), based on their context. A PoS tag can be of a noun, verb, pronoun, conjunction, preposition, adjective, adverb, or their subcategories. PoS tagging is one of the first processes that directly affect the performance of other subsequent text processing tasks in NLP applications [99]. It is crucial for numerous NLP applications, including machine translation, sentiment analysis, question answering, word sense disambiguation and named entity recognition (NER).

In Factored phrase-based machine translation models, the surface form of words is augmented with additional linguistic information such as PoS tags. In this study, we attempted to use PoS information in the corpus as an additional linguistic clue, rather than simply using the surface form of the words. Thus, a word is represented together with a PoS factor as *Surface|POS-Tag*. This requires data preprocessing to factorize all the words in the parallel corpus.

Since there are no publicly available Amharic PoS taggers, we trained and used our own Amharic PoS tagger. We implemented a BiLSTM architecture to accomplish the task of building a PoS tagger and assigning tags to words in the source and target language sentences of the statistical machine translation corpus.

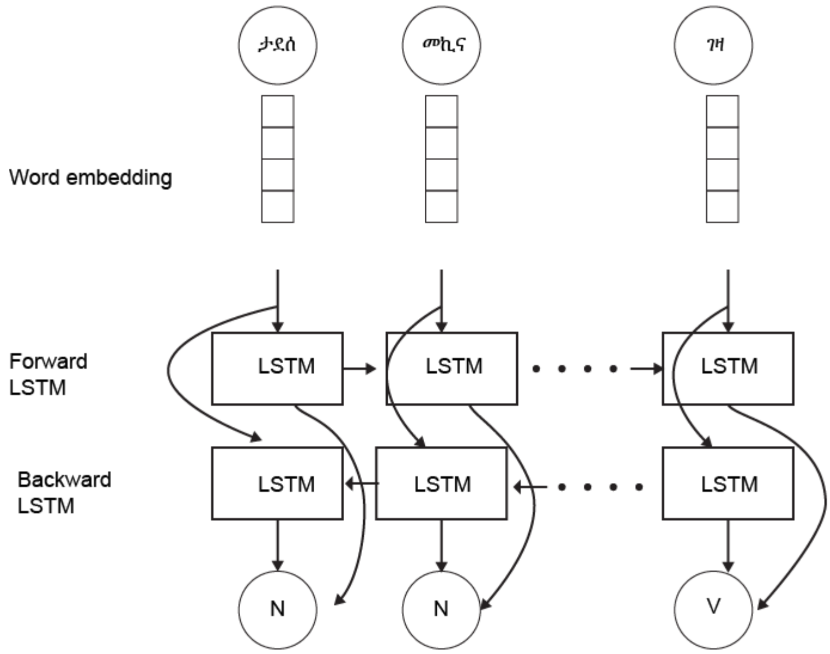

Figure 4.2: The Amharic BiLSTM PoS tagger architecture

The PoS Corpus

To train our Amharic PoS tagger models, we used two publicly available corpora. The first corpus, amWaC16 (Amharic `Web as Corpus' corpus, year 2016) contains around 20 million tokens that were crawled and annotated by the "Annotated Amharic Corpora" project [106]. The corpus consists of three columns: Amharic words written in Geez alphabet (Fidel), the PoS tags and the Amharic words written in the English alphabet. Only the first two columns are relevant for this study. The second corpus contain 210,000 annotated tokens prepared by the Ethiopian Languages Research Center (ELRC) of Addis Ababa University using around 1065 news articles from Walta Information Center [105]. This corpus requires splitting each sentence and words from one another and cleaning of XML tags. Figure 18 shows a screenshot of a single news article in the original corpus.

```
<document>
<filename>mia01a6.htm</filename>
<title>የድህነት <NP> ቅነሳ <N> ሰነድ <N> በሰኔ <NP> ወር <N> ይፋ <N> ይሆናል <AUX> ፡፡ <PUNC></title>
<dateline place="አዲስ አበባ" month="ሚያዝያ" date="1/1994/(WIC)/" />
<body>

በድህነት <NP> ቅነሳ <N> ሰነድ <N> ዝግጅት <N> ላይ <PREP> የቀረቡ <VREL> ሃሳቦችን <N> በማጣጣም <NP> ሰነዱን <N> በሰኔ <NP> ወር <N> ይፋ <N> እንደሚያደርግ <VP> የድህነት <NP> ቅነሳ <N>
ስትራቴጂ <N> ሰነድ <N> ዝግጅት <N> ስህፈት ቤት <N> አስታወቀ <V> ፡፡ <PUNC> የጽህፈት <NP> ቤቱ <N> ሃላፊ <N> አቶ <ADJ> ሲሳይ <N> ወርቁ <N> ለዋልታ <NP> እንፎርሜሽን <N> ማእከል <N> እንደገለጹት <VP>
ስህፈት <N> ቤቱ <N> የተለያዩ <VREL> አካላት <N> ያጠኑትን <VREL> እና <CONJ> በ116 <NUMP> ወረዳዎች <N> የተካሄደውን <VP> የህዝብ <NP> የምክክር <NP> ሀሳብ <N> አጣጥሞ <V> ያቀርባል <V> ፡፡ <PUNC> በመሆኑም <NPC>
በአሁኑ <ADV> ወቅት <N> በምክክሩ <NP> የተገኙትና <VPC> የተለያዩ <VREL> ድርጅቶች <N> ያቀረቧቸው <VREL> ሀሳቦች <N> በአብዛኛው <ADJP> ትቅል <ADJ> በመሆናቸው <NP> በጽህፈት <NP> ቤቱ <N> እየተፈተሹ <V> መሆኑን <VN>
የገለጹት <VP> አቶ <ADJ> ሲሳይ <N> በተለይ <ADV> በፍተኛው <NP> ዙሪያ <PREP> የድህነት <NP> መንሴ <N> ሀሳቦች <N> ቅድሚያ <N> እንደሚሰጣቸው <VP> አስታውቀዋል <V> ፡፡ <PUNC> ለስድስት <ADJP> ወራት <N> በጽህፈት <N>

<copyright>copyright 1998 - 2002 Walta Information Center</copyright>
</body>
</document>
```

Figure 4.3: News article in the original PoS corpus

The data is then converted into a list of tuples having the format: Token_1, PoS_1,…Token_n, PoS_n (see Annex E for the sample PoS corpus). We reduced the final corpus size to 10M tokens due to resource limitation. The corpus split into a training set (60%), a validation set (20%) and a test set (20%).

Pre-trained Word Embedding

Word embeddings are a type of word representation that maps every word into dense vector space. Each word is mapped to a vector, whereas related words may have the same vector. Word vectors are capable of improving the performance of some NLP tasks such as sentiment analysis, PoS tagging, machine translation, etc. Fasttext, proposed by Facebook's AI Research lab provides pre-trained word embeddings of dimension 300 for Amharic built on the Continuous Bag-of-Words (CBOW) model. For training the BiLSTM PoS tagger, we used FastText pretrained embedding to learn vector representation of words.

PoS Tagger Model Training

Our BiLSTM PoS tagger model uses two layers for the forward and backward LSTMs whose dimensions are set to 300. Our vocabulary contains unique 542,085 tokens, and the embedding vector has 300 dimensions. These vector representations are fed into a BiLSTM model. We set the dropout rate to 0.25. The model trained for 10 epochs (Training and validation result of each epoch shown in Annex F) on the entire training corpus. Experimental results show that our model reached 91% of accuracy.

Algorithm 4.1: PoS tagging algorithm

```
Input: TS= parallel corpus
BiLSTM_PoSTagger= Amharic BiLSTM PoS Tagger Model
Output: TTS: PoS Tagged training Set Document
Begin:
1. PoSTagger = load (BiLSTM_PoSTagger)
2. WHILE NOT EOF(TS)
3.      SET tagged_sentence = “”
4.      sentence = Input Line
5.      tokens = Tokenizer(sentence)
7.      FOR EACH token in tokens
8.          SET tag= PoSTagger(token)
9.          APPEND tagged_sentence = “token|tag “
10.     END FOR
11.     WRITE tagged_sentence to TTS
12. END WHILE
13. CLOSE TS
14. CLOSE TTS
End
```

4.4 Language Modelling

The language model, as described in Chapter 2, is used to ensure fluent output, so is built with the target language (i.e the EthSL in this case). The KenLM language modeling tool, included in the Moses SMT toolkit, was used for the training of 3-gram LM across the entire EthSl monolingual corpus. After estimating the probability distribution and smoothing, the n-grams with probabilities and back-off weights are stored in ARPA file format. The diagram below summarizes the language model training process:

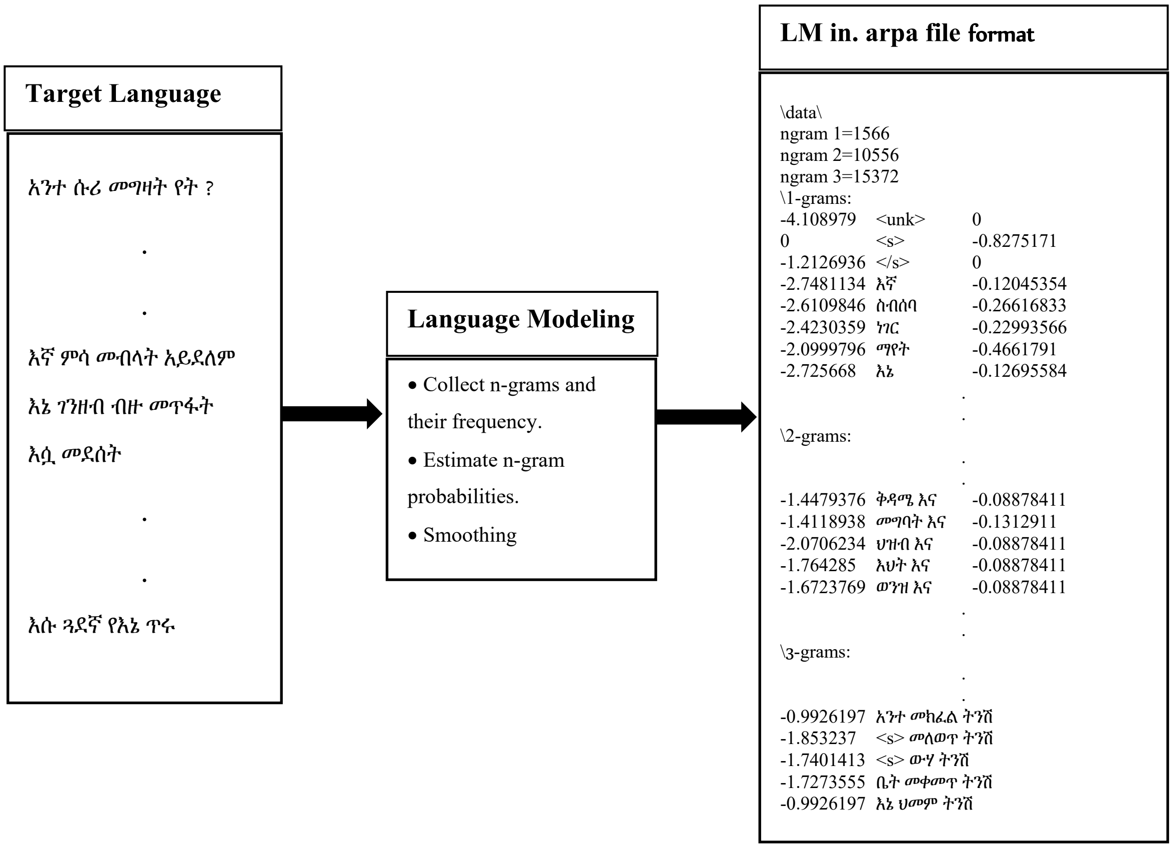

Figure 4.4: Language model training

We converted the ARPA file to binary file format in order to reduce loading time. The language model is then used to estimate how probable a sequence of EthSl strings is in a given order. For example: it gives high probability for the the EthSL word order "ዘመድ የእኔ መምጣት" over "የእኔ ዘመድ መምጣት" for the Amharic sentence "የእኔ ዘመድ መጣ/ች".

4.5 Translation Model

In this research, we trained a factored phrase-based statistical translation model. A two-factor translation model is trained using Moses [1]toolkit where the first factor is the surface

[1] http://www.statmt.org/moses/

word itself and the second factor is its part-of-speech tag. Training translation model includes word alignment, phrase extraction and scoring and creating phrase-table and lexicalized reordering tables. The Moses toolkit is used to train the statistical machine translation model in this research, along with GIZA++ for word alignment. Since Amharic and EthSl belong to different language families, identifying word alignments is the first step in the SMT model training process. The figure 4.3 shows an example of Amharic and EthSL word alignment.

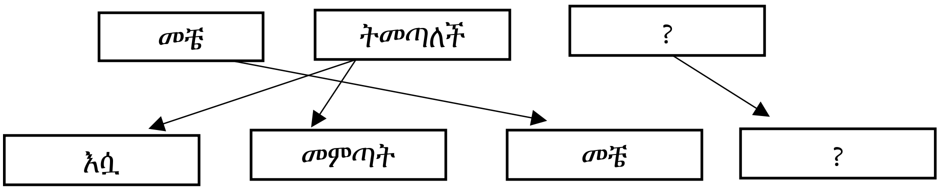

Figure 4.5: Amharic and EthSl word alignment.

Based on the alignment of words, phrase pairs are extracted from the Amharic-EthSL parallel corpus and their translation probability estimated and stored in a phrase-table. Here is an example for a phrase translation entry in phrase-table:

```
ለዘመናት ||| ዘመን|N ብዙ|ADJ ||| 1 0.0938161 0.5 0.222222 ||| 0-0 0-1 ||| 1 2 1 ||| |||

ለዘመናት አብሮ የኖረ ሕዝብ ነው ||| ዘመን|N ብዙ|ADJ መኖር|V አንድነት|ADV ህዝብ|N ||| 1 8.44856e-06 1 0.0013457 ||| 0-0 0-1 1-2 2-3 3-3 4-3
3-4 ||| 1 1 1 ||| |||

ባህላችን የተለያየ ||| እኛ|PRON ባህል|N ልዩ|ADJ ልዩ|ADJ ||| 1 0.0139751 1 0.0868056 ||| 0-0 0-1 1-2 1-3 ||| 1 1 1 ||| |||

ባህላችን የተለያየ ሊን    ||| እኛ|PRON ባህል|N ልዩ|ADJ ልዩ|ADJ መን  |V ||| 1 0.00028716 1 0.0651042 ||| 0-0 0-1 1-2 1-3 2-4 ||| 1 1 1 ||| |||

ባህላችን የተለያየ ሊን    ይችላል ||| እኛ|PRON ባህል|N ልዩ|ADJ ልዩ|ADJ መን  |V መቻል|V ||| 1 2.84573e-05 1 0.0651042 ||| 0-0 0-1 1-2 1-3 2-4
3-5 ||| 1 1 1 ||| |||
```

Figure 4.6: Sample phrase-table

4.6 Decoder

In this research, the Moses decoder used to find the maximum translation likelihood of from the Amharic text to the respective EthSL text. Given a trained language model and translation model, the Moses decoder translates the Amharic text into the EthSL language. It searches for all translations of every Amharic language phrases in the phrase-table and recombines the EthSL phrases that maximizes the translation model probability multiplied by the language model probability.

We run the decoder as a server process using the Moses server and thereby enables us to send Amharic text to be translated via XML-RPC. Then the decoder search and return the highest scoring text in the EthSl grammatical order.

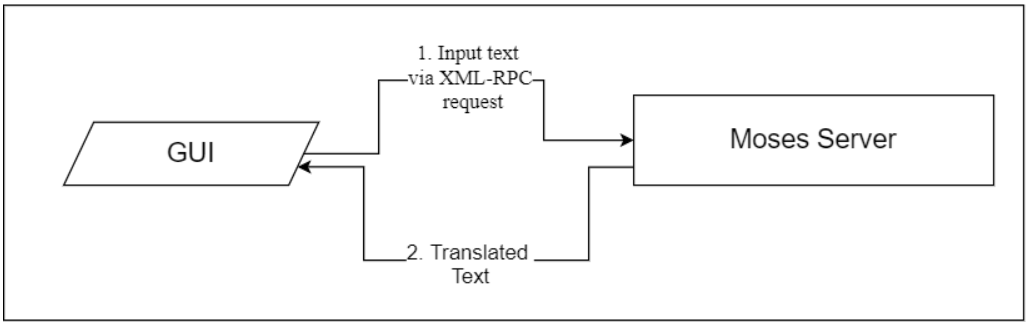

Figure 4.7: Accessing the Decoder via XML-RPC request

4.7 EthSL Video Mapping

Upon completing the above steps, we obtain the EthSL transformed text, which is equivalent to the input text. The system can find matches for each word from the video corpus based on a simple string-matching algorithm between the transformed text and labels of videos. Nouns and words that do not have signs are represented using fingerspelling. Finally, a series of video clips can be viewed on the screen one after the other.

Algorithm 4.2: Sign Video Clips Mapping

```
Input: sentence = Text in EthSL Grammatical Order
Output: EthSL Video Sequence path
Begin:
tokens = Tokenizer(sentence)
SET VideoSequence = []
FOR EACH token in tokens
     IF file(token)EXIST
         APPEND VideoSequence = filepath
     ELSE
         FOR EACH char in token
            IF file(char)EXIST
               APPEND VideoSequence = filepath
            END IF
         END FOR
     END IF
END FOR EACH
RETURN VideoSequence
End
```

Chapter 5

Experiment and Discussion

5.1 Introduction

In this chapter, we discuss the experiments conducted and results obtained. This chapter discusses the results of the experiments by conducting automatic evaluations. Three different types of models trained and tested using Amahric-EthSL parallel corpus. We compared the two versions of our factored phrased-based machine translation models against the standard phrase-based model and neural machine translation model for evaluation. The experiments involve several steps. Data preprocessing, including factoring, tokenization, cleaning, and splitting has been performed. We described the tools and procedures used in setting up and evaluating the experiments for this study.

5.2 Data Acquisition and Preprocessing

5.2.1 Data Acquisition

Training statistical machine translation systems usually require bilingual and monolingual corpora. The monolingual corpus used to train the target language model, and the bilingual corpora is used to train the translation model. The bilingual corpus needs to be aligned at the sentence level. Since the proposed machine translation system is between spoken and sign language, it also requires a sign language video corpus to represent words to their equivalent signs and fingerspellings.

For this research work, we used two different corpora: 160 Amharic-EthSL language pair from previous Example-based machine translation research [1] and relatively large parallel corpus that was prepared manually with the help of EthSL expert. Overall, for this study a total of 5,181 sentences are used. The bilingual corpus randomly split 90% of the corpus for training and 10% for testing.

Table 5.1: Amharic - EthSL corpus split

	Amharic		EthSL	
Set	**Sentences**	**Tokens**	**Sentences**	**Tokens**
Training Set	4205	14362	4205	16293
Validation Set	476	1608	476	1860
Test Set	519	1687	519	1971
Total	5181	17657	5181	20124

Since there are no publicly available large EthSL text corpora, we used the bilingual corpus's target language sentences for the language model training.

In addition to the machine translation monolingual and bilingual text corpora, we also used Ethiopian Sign Language video corpus prepared by Lily Abebe [1]. The video corpus contain 280 EthSL signs and 245 EthSL fingerspellings,

Table 5.2: Amharic PoS corpus split

	Number of Tokens
Training Set	6,511,383
Validation Set	1,627,855
Test Set	2,034,814
Total	10,174,052

5.2.2 Data Preprocessing

Factored Corpus Preparation

Factored Statistical machine translation models require linguistic clue in addition to the surface form of the words in the sentence pair. This requires us to preprocess the Amharic and the EthSL sentences by factorizing all words. We used an Amharic PoS tagger model (described in Section 4.3) to get a factored representation of each word.

First, to conduct our experiment, Amharic tagger trained using Google Colab cloud server from Google Research. Google Colab allows us to train a sizeable deep learning-based PoS tagger on a free GPU. After training the tagger, both the source language and the target language files separately fed into the PoS tagger. The tagger read the sentences line by line to factorize each word as *Surface|PoS-Tag* format. After that, our factored statistical machine translation corpus is now ready to experiment with the results. The table below shows examples of the factored representation of the Amharic and EthSL sentences.

Table 5.3: Factorized sentence example

<table>
<tr><th></th><th>Sentence 1</th><th>Sentence 2</th></tr>
<tr><td>Amharic Sentence</td><td>እሷ ጥሩ ተማሪ ናት</td><td>ልጆች የአምላክ ስጦታ ናቸው</td></tr>
<tr><td>EthSL Sentence</td><td>እሷ ተማሪ ጥሩ</td><td>ልጅ አምላክ መስጠት</td></tr>
<tr><td>Tagged Amharic sentence</td><td>እሷ|PRON ጥሩ|ADJ ተማሪ|N ናት|AUX</td><td>ልጆች|N የአምላክ|NP ስጦታ|N ናቸው|AUX</td></tr>
<tr><td>Tagged EthSL Sentence</td><td>እሷ|PRON ተማሪ|N ጥሩ|ADJ</td><td>ልጅ|N ልጅ|N አምላክ|N መስጠት|V</td></tr>
</table>

Cleaning

To prepare the data for training the translation model, the parallel corpus is cleaned by eliminating empty lines, deleting unnecessary space characters, misaligned sentences and eliminating sentence pairs that are too short or too long (less than one or greater than 20 words). Data cleaning was performed using the Moses Toolkit scripts.

Tokenization

The corpus for training the translation model and language model tokenized using standard Moses scripts with default settings.

5.3 Packages and Tools

We used different packages and tools that are appropriate to develop and evaluate the machine translation system. Python programming with different libraries packages and libraries. The following table summarizes the package and tools used.

Table 5.4: Packages and Tools

Package	Version	Description
Moses	4.0	Moses is an opensource toolkit to develop statistical machine translation system.
GIZA++	-	GIZA++ is a word alignment tool that can be used as part of the statistical machine translation. It is used to train IBM model 1 to 5.
KenLM	-	KenLM is a language modeling library that features algorithms and data structures for efficient estimate, store, and access large n-gram language models.
PyTorch	1.7.0	PyTorch is an open-source machine learning library that is used for applications such as natural language processing.
Flask	1.1.2	Flask is a Python web framework used for developing web applications.
Torchtext	0.8.0	The torchtext package consists of data processing utilities for natural language.
OpenNMT (-py)		OpenNMT is an open-source neural machine translation and neural sequence learning framework.
mteval-v14	14	Mteval is an automatic machine translation evaluation tool.
Colab Notebook	-	Google Colab Notebook is a Jupyter notebook environment that runs entirely in the cloud.

PyCharm Community Edition	2020.3	PyCharm is a cross platform integrated development environment (IDE) used for Python language programming.

5.4 User Interface

We developed a prototype using Flask Python web application framework. The user interface of the prototype is developed using HTM and CSS. The prototype accepts Amharic text from the user, sends API request to the machine translation server and displays the equivalent EthSL signs.

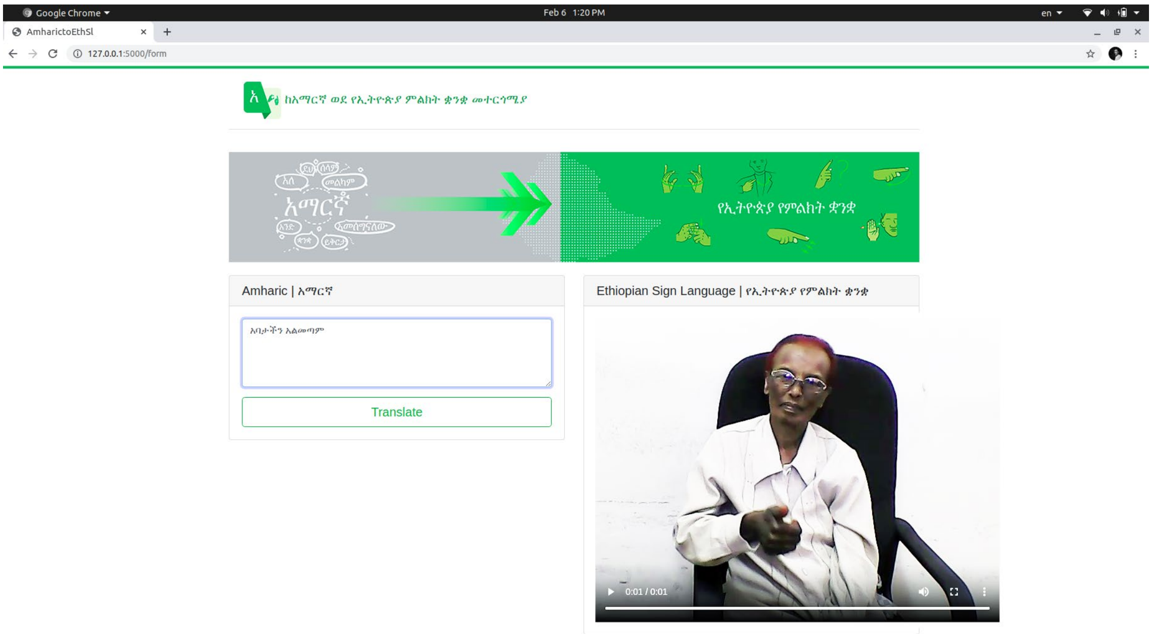

Figure 5.1: Amharic to EthSL machine translator user interface.

5.5 Experimental Setup

The factored statistical machine translation system was trained, tested, and evaluated using a local machine. The experimental setting, such as the specification of computer hardware and operating system we used to build the prototype application as well as to carry out the experiment is shown in the table below:

Table 5.5: Hardware and OS experimental setup

Processor	Intel(R) Core (TM) i7-8550U CPU @ 1.80GHz, 1992 Mhz, 4 Core(s), 8 Logical Processor(s)
RAM	Installed Physical Memory (RAM) 16.0 GB
Hard Disk	500 GB SSD
OS	Ubuntu 20

5.6 Experiments

5.6.1 Experiment I:

As a baseline model, we first trained a phrase-based statistical machine translation model on a plain corpus. This experiment aims to compare the result of this baseline model with the proposed factored phrase-based machine translation model. We trained our baseline model using Moses toolkit along with Giza++ for word alignment, and KenLM for building a 3-gram language model.

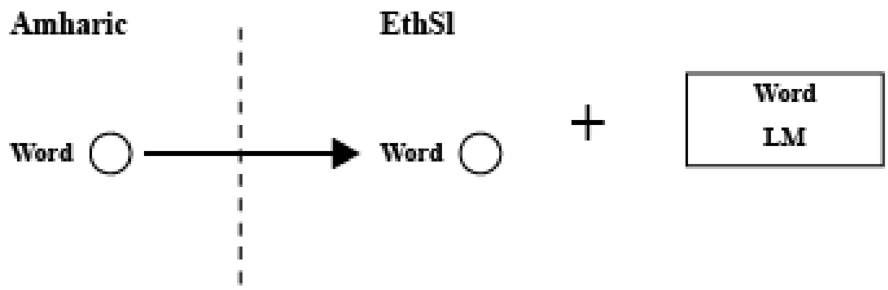

Figure 5.2: The baseline model

The translation model trained using 4196 sentence pairs. Each word in the sentence pairs is represented by its surface form only. The language model is also trained using only EthSL plain monolingual corpus. We used the bilingual corpus's target language sentences for the language model training. In order to find optimal weights, we tuned the translation systems on a set of 466 sentence pairs.

Experiment Result

After training and tuning machine translation model, testing is conducted to measure the performance of the model. We evaluated the translation systems on a set of 519 sentence pairs. BLEU and NIST automatic evaluation methodologies, which were discussed in

Chapter 2, are used to evaluate translation quality. Based on our experiment, our baseline model obtained BLEU score of 35.2 and NIST score of 6.13 (See Annex G).

5.6.2 Experiment II:

Our second experiment with the factored corpus was to train two versions of factored phrased-based machine translation models. The aim of the second experiment is to evaluate the proposed model using the factored corpus. The language models respectively trained on surface EthSL sentences and EthSL sentence PoS sequences. We trained our proposed model using Moses toolkit along with Giza++ for word alignment, and KenLM for building a 3-gram language model.

The translation model trained using 4196 factorized sentence pairs. Each word in the sentence pairs is represented by its surface form along with their lexical category. The first language model is trained using only EthSL plain monolingual copra. The second language model trained on PoS tag sequence of the EthSL sentences. We conducted two experiments: using the surface language model with and without the PoS sequence language model.

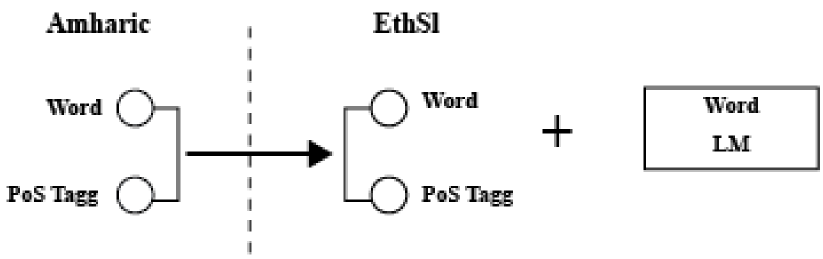

Figure 5.3: The factored model with single language model

The second factored model is identical to the previous factored experiment model except that we used additional PoS tag sequence language model.

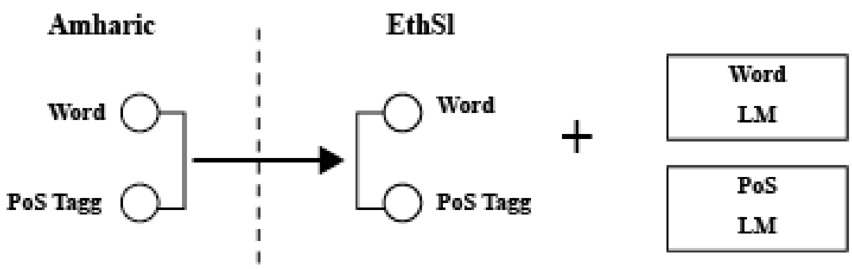

Figure 5.4: The factored model with two language models

Experiment Result

After training and tuning machine translation model, testing is conducted to measure the performance of the models. We tested the translation systems on a set of 519 sentence pairs. Based on our experiment's result, our first factored model (with the surface LM only) obtained BLEU score of 35.28 and NIST score of 6.16. The second factored model (with additional PoS LM) obtained BLEU score of 35.09 and NIST score of 6.14 (See Annex H and I).

5.6.3 Experiment III:

Our third experiment carried out on Neural machine translation with an attention mechanism. This experiment aims to compare our proposed factored SMT model with the neural machine translation model. The model is based on the seq2seq architecture where the encoder converts a sequence of words into a context vector, and the decoder predicts the target sentence based on the encoded source sentence. The encoder and the decoder are recurrent neural networks (RNNs). The model is implemented with the OpenNMT [2]toolkit, an opensource neural machine translation library.

The NMT model was also trained on the plain of the corpus where each word in the sentence pairs is represented by its surface form only. It is trained, validated, and tested using the same corpus split as the factored models. The attention-based NMT model consists of a 2-layer LSTM with 512 hidden states. The NMT training was conducted on Google Colab cloud server that allows a large deep learning-based NMT model on a free GPU.

Experiment Result

After training and evaluating the attention-based NMT model, testing is conducted on a set of 519 Amharic-EthSL sentence pairs. Like the factored SMTs models, BLEU score methodology is used in order to evaluate translation quality. Based on our experiment's result, the third NMT model obtained BLEU score of 26.38 and NIST score of 5.64 (See Annex J).

[2] https://opennmt.net/

The evaluation results of the SMT models and the NMT model summarized in the below table.

Table 5.6: Evaluation result

Model	BLEU	NIST
Baseline – Phrase-based SMT model	35.2	6.13
Factored (Surface LM) SMT Model	35.28	6.16
Factored (Surface and PoS LMs) SMT Model	35.09	6.14
Neural Machine Translation	26.38	5.64

5.7 Discussion

This chapter described experimental results obtained which are used to measure the effectiveness of Amharic to EthSL factored phrase-based machine translation system. The experimental results obtained from the three different machine translation methods are discussed.

The proposed factored machine translation model that the language model was trained on the surface form of the word sequences achieved higher BLEU than the NMT model and the baseline standard phrase-based SMT. Moreover, the factored translation model with two language models performs less than the proposed factor model on the same evaluation test-set. The NIST evaluation findings also demonstrate that our proposed model outperforms both the baseline standard phrase based SMT model and the NMT model.

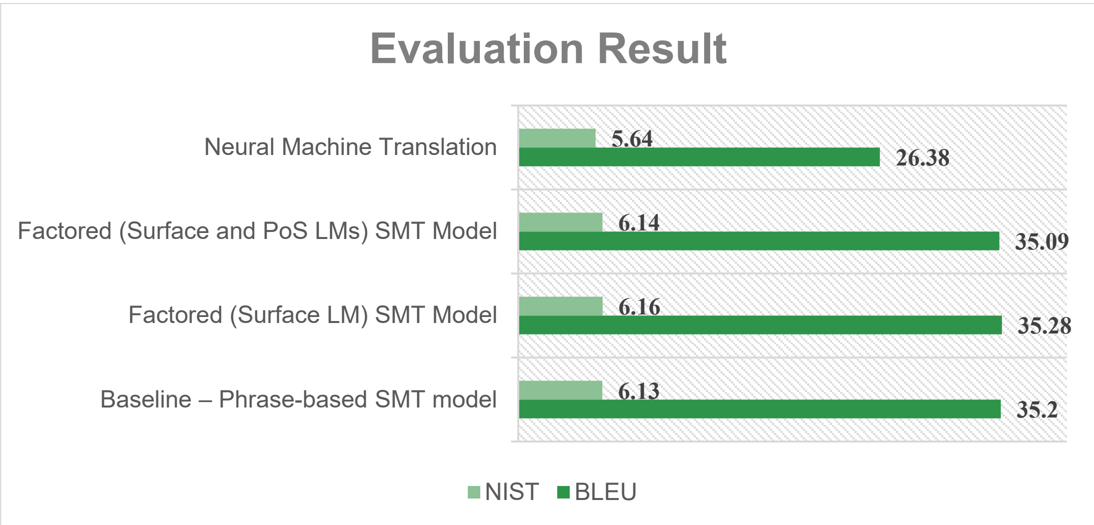

Figure 5.5: Evaluation result

Chapter 6

Conclusions and Recommendations

6.1 Introduction

This chapter presents conclusions that discuss the activities done in this research work with how the problems are addressed and achieved the intended objectives. In addition, Section 6.4 addresses suggestions which go beyond the reach and results of this study from various perspectives.

6.2 Conclusions

In this study, we propose a factored Amharic to Ethiopian Sign Language statistical machine translation system. The machine translation system is composed of a neural network-based Amharic PoS tagger used as preprocessor, a machine translator built using a factored statistical machine translation approach, and word to EthSL video mapper. The Amharic to EthSL machine translation development involves the collection of Amharic and EthSL parallel corpus, Amharic PoS tagger development, machine translation corpus preparation which involves PoS tagging, tokenization and cleaning, language modeling using KenLM, translation modeling by using GIZA++ (for word alimenting) and Moses.

We conducted three experiments using the collected parallel corpus to evaluate and compare the result of the system using three different approaches. The first experiment is conducted using a standard phrased based statistical approach as a baseline model and achieved a BLEU score of 35.2 and a NIST score of 6.13. The second experiment is carried out using a factored phrased based approach and achieved a BLEU score of 35.28 and a NIST score of 6.16. The third experiment is carried out using a neural machine translation approach and achieved a BLEU score of 26.38 and a NIST score of 5.64. All the developed models are evaluated with the same test-set, which contains 519 sentences.

The evaluation scores clearly demonstrate that the use of factored statistical translation for Amharic to EthSL MT achieves improvement over the standard phrased-based statistical machine translation and the neural machine translation trained on a plain corpus. It can also be observed the preprocessing methodology built in this study helped improve the quality of machine translation between Amharic and EthSL with very limited data for machine translation task. Our study concludes that the proposed pre-processing technique for incorporating linguistic information is vital for training machine translation models with small corpus.

6.3 Contribution

The main contributions of the study are the following:

- We implemented a novel neural network-based preprocessing system that is used to preprocess the Amharic-EthSL corpus.
- We developed Amharic to Ethiopian Sign Language factored phrase-based statistical machine translation system.
- We collected a larger size parallel corpus of Amharic to EthSL sentence pares.

6.4 Recommendations

This study addresses the technique to improve the quality of Amharic to EthSL machine translation by implementing a neural network-based preprocessing technique for adding PoS information to surface words in the Amharic and EthSL sentences. Based on the findings of this study, different potential areas could be explored further. Some of the recommendations are given below.

- Incorporating more linguistic clues such as the lemma form of the words to the Amharic - EthSL sentence pairs would improve the proposed factored machine translation system's performance.
- Including a feature to handle Amharic compound words which consisting of up two or three words with a single EthSL sign, and Amharic words that have two or more signs when converted to EthSL.
- The inclusion of more Amharic-EthSL sentence pairs in the corpus would improve the performance of the proposed system.
- This study proposed a novel approach that can be used to translate Amharic sentence to Ethiopian sign language. In addition, Amharic Automatic Speech recognition system can be built and integrated.
- Incorporating EthSL recognition component will benefit to establish a two-way communication.
- Apart from the proposed approach, finetuning large deep learning pre-trained language models like XLM-R (Amharic) using the collected corpus might improve the performance of Amharic to EthSL machine translation.

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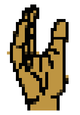
Annexes

Annex A: Amharic Alphabets

First Order		Second Order		Third Order		Fourth Order		Fifth Order		Sixth Order		Seventh Order				
ሀ	hä	ሁ	hu	ሂ	hi	ሃ	ha	ሄ	he	ህ	h	ሆ	ho			
ለ	lä	ሉ	lu	ሊ	li	ላ	la	ሌ	le	ል	l	ሎ	lo		ሏ	lWa
ሐ	Hä	ሑ	Hu	ሒ	Hi	ሓ	Ha	ሔ	He	ሕ	H	ሖ	Ho		ሗ	HWa
መ	mä	ሙ	mu	ሚ	mi	ማ	ma	ሜ	me	ም	m	ሞ	mo		ሟ	mWa
ሠ	Sä	ሡ	Su	ሢ	Si	ሣ	Sa	ሤ	Se	ሥ	S	ሦ	So		ሧ	SWa
ረ	rä	ሩ	ru	ሪ	ri	ራ	ra	ሬ	re	ር	r	ሮ	ro		ሯ	rWa
ሰ	sä	ሱ	su	ሲ	si	ሳ	sa	ሴ	se	ስ	s	ሶ	so		ሷ	sWa
ሸ	śä	ሹ	śu	ሺ	śi	ሻ	śa	ሼ	śe	ሽ	ś	ሾ	śo		ሿ	śWa
ቀ	qä	ቁ	qu	ቂ	qi	ቃ	qa	ቄ	qe	ቅ	q	ቆ	qo		ቋ	qWa
በ	bä	ቡ	bu	ቢ	bi	ባ	ba	ቤ	be	ብ	b	ቦ	bo		ቧ	bWa
ቨ	vä	ቩ	vu	ቪ	vi	ቫ	va	ቬ	ve	ቭ	v	ቮ	vo		ቯ	vWa
ተ	tä	ቱ	tu	ቲ	ti	ታ	ta	ቴ	te	ት	t	ቶ	to		ቷ	tWa
ቸ	cä	ቹ	cu	ቺ	ci	ቻ	ca	ቼ	ce	ች	c	ቾ	co		ቿ	cWa
ኀ	Ĥä	ኁ	Ĥu	ኂ	Ĥi	ኃ	Ĥa	ኄ	Ĥe	ኅ	Ĥ	ኆ	Ĥo		ኋ	ĤWa
ነ	nä	ኑ	nu	ኒ	ni	ና	na	ኔ	ne	ን	n	ኖ	no		ኗ	nWa
ኘ	Nä	ኙ	Nu	ኚ	Ni	ኛ	Na	ኜ	Ne	ኝ	N	ኞ	No		ኟ	NWa
አ	xä	ኡ	xu	ኢ	xi	ኣ	xa	ኤ	xe	እ	x	ኦ	xo		ኧ	xWa
ከ	kä	ኩ	ku	ኪ	ki	ካ	ka	ኬ	ke	ክ	k	ኮ	ko		ኳ	kWa
ኸ	Kä	ኹ	Ku	ኺ	Ki	ኻ	Ka	ኼ	Ke	ኽ	K	ኾ	Ko		ዃ	KWa
ወ	wä	ዉ	wu	ዊ	wi	ዋ	wa	ዌ	we	ው	w	ዎ	wo			
ዐ	Xä	ዑ	Xu	ዒ	Xi	ዓ	Xa	ዔ	Xe	ዕ	X	ዖ	Xo			
ዘ	zä	ዙ	zu	ዚ	zi	ዛ	za	ዜ	ze	ዝ	z	ዞ	zo		ዟ	zWa
ዠ	Zä	ዡ	Zu	ዢ	Zi	ዣ	Za	ዤ	Ze	ዥ	Z	ዦ	Zo		ዧ	ZWa
የ	yä	ዩ	yu	ዪ	yi	ያ	ya	ዬ	ye	ይ	y	ዮ	yo			
ደ	dä	ዱ	du	ዲ	di	ዳ	da	ዴ	de	ድ	d	ዶ	do		ዷ	dWa
ጀ	jä	ጁ	ju	ጂ	ji	ጃ	ja	ጄ	je	ጅ	j	ጆ	jo		ጇ	jWa
ገ	gä	ጉ	gu	ጊ	gi	ጋ	ga	ጌ	ge	ግ	g	ጎ	go		ጓ	gWa
ጠ	Tä	ጡ	Tu	ጢ	Ti	ጣ	Ta	ጤ	Te	ጥ	T	ጦ	To		ጧ	TWa
ጨ	Cä	ጩ	Cu	ጪ	Ci	ጫ	Ca	ጬ	Ce	ጭ	C	ጮ	Co		ጯ	CWa
ጰ	Pä	ጱ	Pu	ጲ	Pi	ጳ	Pa	ጴ	Pe	ጵ	P	ጶ	Po		ጷ	PWa
ጸ	ťä	ጹ	ťu	ጺ	ťi	ጻ	ťa	ጼ	ťe	ጽ	ť	ጾ	ťo		ጿ	ťWa
ፀ	Ťä	ፁ	Ťu	ፂ	Ťi	ፃ	Ťa	ፄ	Ťe	ፅ	Ť	ፆ	Ťo			
ፈ	fä	ፉ	fu	ፊ	fi	ፋ	fa	ፌ	fe	ፍ	f	ፎ	fo		ፏ	fWa
ፐ	pä	ፑ	pu	ፒ	pi	ፓ	pa	ፔ	pe	ፕ	p	ፖ	po		ፗ	pWa

Annex B: EthSL Fingerspelling for Amharic Alphabets

							
	ሀ	ሁ	ሂ	ሃ	ሄ	ህ	ሆ
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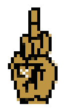
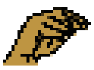
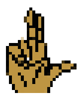
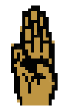
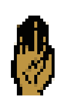
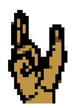
	ሐ	ሑ	ሒ	ሓ	ሔ	ሕ	ሖ
	መ	ሙ	ሚ	ማ	ሜ	ም	ሞ
	ሠ	ሡ	ሢ	ሣ	ሤ	ሥ	ሦ
	ረ	ሩ	ሪ	ራ	ሬ	ር	ሮ
	ሰ	ሱ	ሲ	ሳ	ሴ	ስ	ሶ
	ሸ	ሹ	ሺ	ሻ	ሼ	ሽ	ሾ
	ቀ	ቁ	ቂ	ቃ	ቄ	ቅ	ቆ
	በ	ቡ	ቢ	ባ	ቤ	ብ	ቦ
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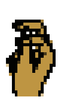
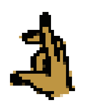
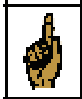
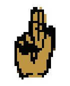
	ቸ	ቹ	ቺ	ቻ	ቼ	ች	ቾ
	ኀ	ኁ	ኂ	ኃ	ኄ	ኅ	ኆ

	ነ	ኑ	ኒ	ና	ኔ	ን	ኖ
	ኘ	ኙ	ኚ	ኛ	ኜ	ኝ	ኞ
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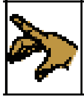
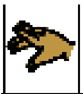
	ከ	ኩ	ኪ	ካ	ኬ	ክ	ኮ
	ኸ	ኹ	ኺ	ኻ	ኼ	ኽ	ኾ
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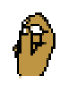
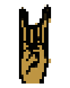
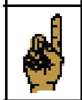
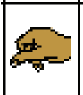
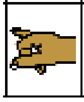
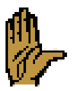
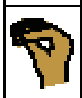
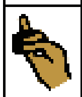
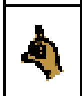
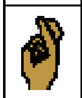
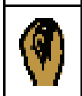
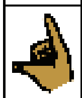
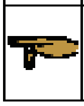
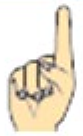
	ዐ	ዑ	ዒ	ዓ	ዔ	ዕ	ዖ
	ዘ	ዙ	ዚ	ዛ	ዜ	ዝ	ዞ
	ዠ	ዡ	ዢ	ዣ	ዤ	ዥ	ዦ
	የ	ዩ	ዪ	ያ	ዬ	ይ	ዮ
	ደ	ዱ	ዲ	ዳ	ዴ	ድ	ዶ
	ጀ	ጁ	ጂ	ጃ	ጄ	ጅ	ጆ
	ገ	ጉ	ጊ	ጋ	ጌ	ግ	ጎ
	ጠ	ጡ	ጢ	ጣ	ጤ	ጥ	ጦ
	ጨ	ጩ	ጪ	ጫ	ጬ	ጭ	ጮ
	ጰ	ጱ	ጲ	ጳ	ጴ	ጵ	ጶ
	ጸ	ጹ	ጺ	ጻ	ጼ	ጽ	ጾ
	ፀ	ፁ	ፂ	ፃ	ፄ	ፅ	ፆ
	ፈ	ፉ	ፊ	ፋ	ፌ	ፍ	ፎ
	ፐ	ፑ	ፒ	ፓ	ፔ	ፕ	ፖ

Annex C: EthSL Numbers

	0 ዜሮ
	1 አንድ
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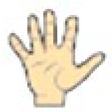
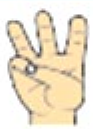
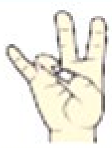
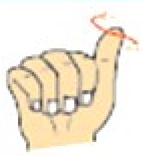
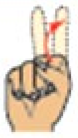
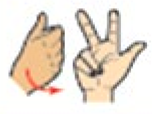
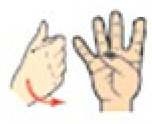
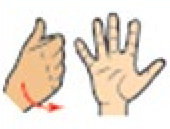
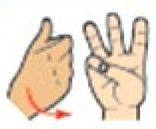
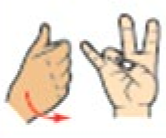
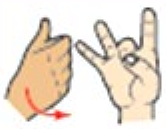
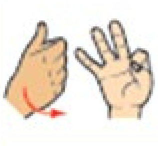
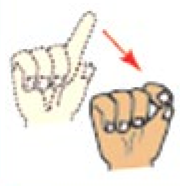
	3 ሦስት
	4 አራት
	5 አምስት
	6 ስድስት
	7 ሰባት
	8 ስምንት
	9 ዘጠኝ
	10 አሥር

	11 አስራ አንድ
	12 አስራ ሁለት
	13 አስራ ሦስት
	14 አስራ አራት
	15 አስራ አምስት
	16 አስራ ስድስት
	17 አስራ ሰባት
	18 አስራ ስምንት
	19 አስራ ዘጠኝ
	20 ሃያ

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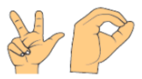
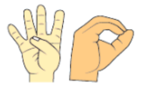
	20	ሃያ
	30	ሰላሳ
	40	አርባ
	50	ሃምሳ

Annex D: Sample Amharic EthSL Dataset

Amharic	Ethiopian Sign Language
ወሰን|N በወታደር|NP ይጠበቃል|V	ድንበር|N ወታደር|N መጠበቅ|V
ሱሪ|N የት|ADV ገዛህ|V	አንተ|PRON ሱሪ|N መግዛት|V የት|ADV ?|PUNC
ወላጆቻችንን|N እናመስግን|V	እኛ|PRON ወላጅ|N ማመስገን|V
እሱ|PRON ጥሩ|ADJ ጓደኛዬ|N ነው|AUX	እሱ|PRON ጓደኛ|N የእኔ|PRON ጥሩ|ADJ
እኔ|PRON ትንሽ|ADV ፈራሁ|V	እኔ|PRON መፍራት|V ትንሽ|ADV
እርሱ|PRON እየሳቀ|V ነው|AUX	እሱ|PRON መሳቅ|V
መወዳደር|V አይፈልግም|V	እሱ|PRON መወዳደር|V መፈለግ|V አይደለም|ADV
የቀረሽው|VP በምን|ADV ምክንያት|N ነው|AUX	አንቺ|PRON መቅረት|V ምክንያት|N ምን|PRON ?|PUNC
ለምንድነው|AUX የምትከታተለኝ|V ?	አንተ|PRON እኔ|PRON መከተል|V ለምን ?|PUNC
እኔ|PRON ደስተኛ|V ነኝ|AUX	እኔ|PRON መደሰት|V
2012|NUCR ከባድ|ADJ አመት|N ነው|AUX	2012|NUMCR አመት|N ከባድ|ADJ
ምሳ|N አልበላንም|V	እኛ|PRON ምሳ|N መብላት|V አይደለም|ADV
ብዙ|ADJ ገንዘብ|N ጠፋብኛ|V	እኔ|PRON ገንዘብ|N ብዙ|ADJ መጥፋት|V
እቤት|N መቀመጥ|V አልወድም|V	እኔ|PRON ቤት|N መቀመጥ|V መውደድ|V አይደለም|ADV
ቀኝ|ADJ እጅህ|N ቆሽሿል|V	አንተ|PRON እጅ|N ቀኛ|ADJ መቆሸሽ|V
የድሮ|ADJ ሰዎች|N ብር|N መሬት|N ይቀብራሉ|V	ሰው|N ድሮ|ADJ መሬት|N ብር|N መቅበር|V
መንግስት|N አልወሰነም|V	መንግስት|N መወሰን|V አይደለም|ADV
ወንዶች|N ጠንካራ|ADJ ናቸው|AUX	ወንድ|NC መጠንከር|ADJ
የስራ|NP ማስታወቂያ|N ወጣ|V	ስራ|N ማስተዋወቅ|N መውጣት|V
ከጦርነት|NP የምናተርፈው|V ነገር|N የለም|V	እኛ|PRON ጦርነት|N ማትረፍ|V ነገር|N የለም|V
መቼ|ADV ትመጣለች|?|PUNC	እሷ|PRON መምጣት|V መቼ|ADV ?|PUNC
ወደ|PREP ቤት|N ሄዱ|V	እነሱ|PRON መሄድ|N ቤት|V
ውሾቹ|NP ወዴት|ADV ሄዱ|V	ውሻ|N ብዙ|ADJ መሄድ|V የት|ADV ?|PUNC
እስከ|PREP ሶስት|NUMCR ሰአት|N እቆያለሁ|V	እኔ|PRON እስከ|PREP ሶስት|NUMCR ሰአት|N መቆየት|V
በመመለሴ|VP ተደስቻለው|V	እኔ|PRON መመለስ|V መደሰት|V
ህክምናዬን|N ጨርሼ|V እቤት|N ገባሁ|V	እኔ|PRON ህክምና|N መጨረስ|V ቤት|N መግባት|V

የምግብ|NP ዋጋ|N ጨምሯል|V	ምግብ|N ዋጋ|N መጨመር|V
የእሱ|PRON እናት|N	እናት|N የእሱ|PRON
የተለያዩ|ADJ አማራጮች|N ተሰጡ|V	መምረጥ|N ልዩ|ADJ ልዩ|ADJ መሰጠት|V
እንዴት|ADV አሸነፍክ|V	አንተ|PRON ማሸነፍ|V እንዴት|ADV ?|PUNC
የዝናብ|NP ጃኬት|N ለብሻለሁ|V	እኔ|PRON ዝናብ|N ጃኬት|N መልበስ|V
ድራማው|N ታይቶ|V አልቋል|V	ድራማ|N ማየት|V ማለቅ|V
የአስር|NUMP አመታት|N እቅድ|N	አስር|NUMCR አመት|N እቅድ|N
ሰዎች|N የሞቱበት|N ቦታ|N ነው|V	ሰው|N ብዙ|ADJ መሞት|V ቦታ|N
ብዙ|ADV መሄድ|V አልችልም|V	እኔ|PRON መሄድ|V ብዙ|ADV መቻል|V አይደለም|ADV
ለበርካታ|ADJP አመታት|N አስጨንቀውት|V ነበር|AUX	ዓመት|N ብዙ|ADJ መጨነቅ|V
ዜጎች|N አማራጮችን|N መጠቀም|V ያስፈልጋቸዋል|V	ዜጋ|N መምረጥ|N መጠቀም|V አስፈላጊ|V
እኔ|PRON ስራ|N ስለሌለኝ|V ብዙ|ADV ተኛሁ|V	እኔ|PRON ስራ|N የለም|V መተኛት|N ብዙ|ADV
ጥሩ|ADJ ዘመን|N አይደለም|V	ዘመን|N ጥሩ|ADJ አይደለም|V
ፊትለፊታችን|PREP መኪና|N ቆምዋል|V	ፊት|PREP መኪና|N መቆም|V
ትልቅ|ADJ ዛፍ|N ተቆረጠ|V	ዛፍ|N ትልቅ|ADJ መቁረጥ|V
ድመት|N ምቾት|N ትፈልጋለች|V	ድመት|N መመቸት|N መፈለግ|V
ተራራው|N ትልቅ|ADJ ነው|AUX	ተራራ|N ትልቅ|ADJ
ረጃጅም|ADJ ዛፎች|N ተቆረጡ|V	ዛፍ|N ረጅም|ADJ ብዙ|ADJ መቆረጥ|V
አልፎ|ADJ አልፎ|ADJ ፊልም|N አያለሁ|V	እኔ|PRON ፊልም|N አልፎ|ADJ አልፎ|ADJ ማየት|V
ቁርስ|N አልተዘጋጀም|V	ቁርስ|N መዘጋጀት|V አይደለም|ADV
ስልክ|N ቁጥርህን|N ንገረኝ|V	አንተ|N ስልክ|N ቁጥር|N መንገር|V
የንፋስ|NP አቅጣጫ|N መቀያየር|V	ንፋስ|N አቅጣጫ|N መለወጥ|V
የኢትዩጵያ|NP ፖለቲካ|N ወዴት|ADV እያመራ|V ነው|AUX	ኢትዮጵያ|N ፓለቲካ|N መምራት|V የት|ADV ?|PUNC

Annex E: Sample Amharic PoS Dataset

ታሪክ,N
የምስክሮችንና,NPC
ባልታጠቁ,VP
ካደረጋችሁ,N
የእግዚአብሔርን,NP
እንደማያምን,N
የሚችልበት,VREL
የአስተሳሰብ,NP
ግንቦት,N
ኃይሎች,N
አብነት,N
ለጋሽ,N
አንድ,NUMCR
ጦሩን,N
ያህል,UNC
መንፈስ,N
ያለኝ,V
ዘጋቢ,N
ጉዞ,N
የሰረቅን,NP
አለዚያም,N
የት,ADV
የኑት ,VREL
ነው,AUX
በጻፉት,VP
በደሌን,NP
እንገታለን,VP
ላይ,PREP
ይኖራል,VP
ፓርቲ,N
ህልውና,N
አቶ,ADJ
እሾምሃለሁ,N
አዲስ,ADJ
ላይ,PREP
ሲባልም,VP
ተናግረዋል,V
ቃል,N
በማስተዋል,VP
ለነገረ,VP
አይስማው,N
ወንጀል,N

Annex F: The PoS Tagset Used in this Work

	Tag category	Tag	Description
1	Noun	N	Noun
2		NP	Noun + Preposition
3		NC	Noun + Conjunction
4		NPC	Noun + Preposition + Conjunction
5	Pronoun	PRON	Pronoun
6		PRONP	Possessive pronoun
7		PRONC	Pronoun + conjunction
8		PRONPC	Possessive pronoun + conjunction
9	Verb	V	Verb
10		VP	Verb + Preposition
11		VREL	Relative verb
12		VN	Verbal Noun
13		AUX	Auxiliary
14		VC	Verb + conjunction
15		VPC	Verb + Preposition + Conjunction
16	Adjective	ADJ	Adjective
17		ADJC	Adjective + conjunction
18		ADJP	Adjective attached with Preposition
19		ADJPC	Numeral (cardinal or ordinal) + preposition and conjunction
20	Adverb	ADV	adverb
21		ADVP	adverb attached preposition
22		ADVC	Adverb attached with conjunction
23	Prepositions	PREP	Preposition
24		PREPC	Preposition attached with conjunction
25	Conjunction	CONJ	conjunction
26	Numerals	NUMCR	Cardinal Number
27		NUMOR	Ordinal number
28		NUMC	Number (cardinal or ordinal) + conjunction
29		NUMP	Numeral (cardinal or ordinal) + preposition
30		NUMPC	Numeral (cardinal or ordinal) + preposition and conjunction
31	Punctuation	PUNC	Punctuation
32	Interjection	INT	Interjection

Annex G: Amharic PoS Tagger Training and Validation

```
Epoch: 01 | Epoch Time: 22m 42s
        Train Loss: 0.358 | Train Acc: 88.18%
         Val. Loss: 0.273 |  Val. Acc: 90.66%
Epoch: 02 | Epoch Time: 22m 34s
        Train Loss: 0.179 | Train Acc: 94.02%
         Val. Loss: 0.282 |  Val. Acc: 90.57%
Epoch: 03 | Epoch Time: 22m 34s
        Train Loss: 0.178 | Train Acc: 93.85%
         Val. Loss: 0.303 |  Val. Acc: 90.62%
Epoch: 04 | Epoch Time: 22m 34s
        Train Loss: 0.172 | Train Acc: 93.96%
         Val. Loss: 0.313 |  Val. Acc: 90.64%
Epoch: 05 | Epoch Time: 22m 33s
        Train Loss: 0.168 | Train Acc: 94.07%
         Val. Loss: 0.333 |  Val. Acc: 90.68%
Epoch: 06 | Epoch Time: 22m 36s
        Train Loss: 0.166 | Train Acc: 94.11%
         Val. Loss: 0.341 |  Val. Acc: 90.71%
Epoch: 07 | Epoch Time: 22m 40s
        Train Loss: 0.165 | Train Acc: 94.14%
         Val. Loss: 0.332 |  Val. Acc: 90.65%
Epoch: 08 | Epoch Time: 22m 39s
        Train Loss: 0.165 | Train Acc: 94.14%
         Val. Loss: 0.326 |  Val. Acc: 90.71%
Epoch: 09 | Epoch Time: 22m 40s
        Train Loss: 0.164 | Train Acc: 94.15%
         Val. Loss: 0.344 |  Val. Acc: 90.73%
Epoch: 10 | Epoch Time: 22m 39s
        Train Loss: 0.164 | Train Acc: 94.15%
         Val. Loss: 0.368 |  Val. Acc: 90.70%
```

Annex H: Evaluation result of the baseline model

```
MT evaluation scorer began on 2021 Jan 30 at 14:33:10

command line:  mteval-v14c.pl -r /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/xml_data/test_ref.xml -s /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/xml_dat
a/test_src.xml -t /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/xml_data/test_tst.xml

Evaluation of Amharic-to-Amharic translation using:
    src set "xml_data/test" (1 docs, 519 segs)
    ref set "xml_data/test" (1 refs)
    tst set "xml_data/test" (1 systems)

NIST score = 6.1277  BLEU score = 0.3520 for system "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Individual N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.0981   0.9520   0.0670   0.0026   0.0081   0.0000   0.0000   0.0000   0.0000   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/corpus.translated.ethsl"

 BLEU:  0.6404   0.4207   0.3153   0.2533   0.2083   0.2333   0.2500   1.0000   1.0000   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Cumulative N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.0981   6.0500   6.1170   6.1196   6.1277   6.1277   6.1277   6.1277   6.1277   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/corpus.translated.ethsl"

 BLEU:  0.5885   0.4770   0.4040   0.3520   0.3116   0.2928   0.2828   0.3277   0.3675   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline/corpus.translated.ethsl"

root@joss-Inspiron-7573:/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/baseline#
```

Annex I: Evaluation result of the proposed model

```
MT evaluation scorer began on 2021 Jan 30 at 13:51:56

command line:  mteval-v14c.pl -r /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/xml_data/test_ref.xml -s /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSi
mple/xml_data/test_src.xml -t /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/xml_data/test_tst.xml

Evaluation of Amharic-to-Amharic translation using:
    src set "xml_data/test" (1 docs, 519 segs)
    ref set "xml_data/test" (1 refs)
    tst set "xml_data/test" (1 systems)

NIST score = 6.1583  BLEU score = 0.3528 for system "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Individual N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.1098   0.9554   0.0714   0.0053   0.0164   0.0000   0.0000   0.0000   0.0000  "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/corpus.translated.ethsl"

 BLEU:  0.6425   0.4243   0.3176   0.2561   0.2203   0.2759   0.2500   1.0000   1.0000  "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Cumulative N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.1098   6.0651   6.1366   6.1418   6.1583   6.1583   6.1583   6.1583   6.1583  "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/corpus.translated.ethsl"

 BLEU:  0.5873   0.4773   0.4044   0.3528   0.3154   0.3038   0.2917   0.3365   0.3760  "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple/corpus.translated.ethsl"

MT evaluation scorer ended on 2021 Jan 30 at 13:51:57
root@joss-Inspiron-7573:/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factoredSimple#
```

Annex J: Evaluation Result of The Factored Model (surface LM and PoS LM)

```
MT evaluation scorer began on 2021 Jan 30 at 14:38:57

command line:  mteval-v14c.pl -r /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/xml_data/test_ref.xml -s /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/xml_dat
a/test_src.xml -t /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/xml_data/test_tst.xml

Evaluation of Amharic-to-Amharic translation using:
    src set "xml_data/test" (1 docs, 519 segs)
    ref set "xml_data/test" (1 refs)
    tst set "xml_data/test" (1 systems)

NIST score = 6.1409  BLEU score = 0.3509 for system "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Individual N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.0937   0.9528   0.0738   0.0051   0.0154   0.0000   0.0000   0.0000   0.0000   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/corpus.translated.ethsl"

 BLEU:  0.6390   0.4204   0.3174   0.2487   0.2143   0.2500   0.1667   1.0000   1.0000   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Cumulative N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  5.0937   6.0465   6.1204   6.1255   6.1409   6.1409   6.1409   6.1409   6.1409   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/corpus.translated.ethsl"

 BLEU:  0.5876   0.4766   0.4047   0.3509   0.3126   0.2970   0.2702   0.3149   0.3547   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored/corpus.translated.ethsl"

root@joss-Inspiron-7573:/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/factored#
```

Annex K: Evaluation Result of the NMT Model

```
MT evaluation scorer began on 2021 Jan 30 at 14:46:41

command line:  mteval-v14c.pl -r /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/xml_data/test_ref.xml -s /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/xml_data/
test_src.xml -t /media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/xml_data/test_tst.xml

Evaluation of Amharic-to-Amharic translation using:
    src set "xml_data/test" (1 docs, 519 segs)
    ref set "xml_data/test" (1 refs)
    tst set "xml_data/test" (1 systems)

NIST score = 5.6417  BLEU score = 0.2638 for system "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Individual N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  4.7345   0.8479   0.0485   0.0026   0.0082   0.0000   0.0000   0.0000   0.0000   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/corpus.translated.ethsl"

 BLEU:  0.6149   0.3437   0.2153   0.1482   0.1092   0.0250   0.0192   0.0109   0.0057   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/corpus.translated.ethsl"

# ------------------------------------------------------------------------

Cumulative N-gram scoring
        1-gram   2-gram   3-gram   4-gram   5-gram   6-gram   7-gram   8-gram   9-gram
        ------   ------   ------   ------   ------   ------   ------   ------   ------
 NIST:  4.7345   5.5824   5.6309   5.6335   5.6417   5.6417   5.6417   5.6417   5.6417   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/corpus.translated.ethsl"

 BLEU:  0.5660   0.4232   0.3286   0.2638   0.2175   0.1496   0.1103   0.0817   0.0602   "/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT/corpus.translated.ethsl"

MT evaluation scorer ended on 2021 Jan 30 at 14:46:42
root@joss-Inspiron-7573:/media/joss/b65be960-9616-4e9f-81a5-1b39cec52e1c/Evaluation/openNMT#
```

Declaration

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

Declared by:

Name: Yoseph Belay Tesfaye ________________.

Signature:________________________________.

Date:____________________________________.

Confirmed by advisor:

Name: Solomon Gizaw (PhD) ________________.

Signature:________________________________.

Date:____________________________________.