



ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

ENHANCED AMHARIC SPEECH RECOGNITION SYSTEMS

BY

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A THESIS SUBMITTED TO
THE SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY
IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF
MASTER OF SCINECE IN COMPUTER SCIENCE

JUNE 2011

ADDIS ABABA UNIVERSITY
SCHOOL OF GRADUATE STUDIES
FACULTY OF COMPUTER AND MATHEMATICAL SCIENCES
DEPARTMENT OF COMPUTER SCIENCE

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Acknowledgments

First and foremost, I would like to thank the Almighty God for His support and being with me in all directions of my life.

Next, I would like to express my sincere gratitude to my advisor Dr. Sebsbie Hailemariam for his support, encouragement and guidance throughout this work.

My sister Samri, Eshetie Derb and Adina Berie merit my heartfelt gratitude for their inexhaustible help in recording the training and evaluation test sentences.

I also thank my family for their love and support. My parents have always given me their encouragement and support in a non-intrusive way I appreciate deeply.

Finally, I am grateful to my girl friend, Lety, for her love, support and unwavering confidence in me. Her contribution in the research is greatly appreciated, but most important is her contributions in all the matters that are beyond a thesis.

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Acronyms

ASR- Automatic Speech Recognition

ASRS- Automatic Speech Recognition Systems

CSR-Continuous Speech Recognition

HMM- Hidden Markov Model

HMMs- Hidden Markov Models

HTK- Hidden Markov Model Toolkit

LM- Language Model

MFCC- Mel Frequency Cepstral Coefficient

SER- Sentence Error Rate

WER- Word Error Rate

Abstract

Pronunciation variation is one of the main factors that degrade the performance of Amharic ASRS. It is caused either by intra-speaker or inter-speaker variability. This paper describes how the performance of a speaker dependent continuous Amharic speech recognizer is enhanced by modeling pronunciation variation. It uses three methods to design Amharic pronunciation dictionaries.

The first method is a grapheme based canonical pronunciation dictionary that contains a single pronunciation for each word in the lexicon. The second method is a grapheme based multiple pronunciation dictionary that contains alternate pronunciations for some of the words in the lexicon. The pronunciation variants in the second method are generated using knowledge based approach. The third method is a grapheme based multiple pronunciation dictionary where the pronunciation variants are generated using data-derived approach.

Using the second and third methods has led to a larger improvement in SER compared to the benchmark first method. The SER rates measured for the first method are 39%, 41%, 42% and 44% for speaker1, speaker2, speaker3 and speaker4 respectively. The SER rates measured for the second method are 31%, 33%, 35% and 38% for speaker1, speaker2, speaker3 and speaker4 respectively. Compared to the first method, a statistically significant decrement of 8%, 8%, 7% and 6% SER is measured in the second method for speaker1, speaker2, speaker3 and speaker4 respectively. Using the third method for only one of the four speakers has led to a 6% SER which is a further decrement of 25% SER compared to the second method. Using the acoustic evidence transcription of this speaker to the other three speakers has led to 12%, 17% and 19% SER for speaker2, speaker3 and speaker4 respectively. Compared to the second method, a statistically significant decrement of 21%, 18% and 19% SER is measured in the third method for speaker2, speaker3 and speaker4 respectively.

Key words: Automatic Speech Recognition Systems, Pronunciation Dictionary, Pronunciation Variation, Pronunciation Variation Modeling.

CHAPTER ONE

INTRODUCTION

1.1 General Background

Speech is the physical production of sound units. These sound units are produced to represent letters, words and sentences of a given language. Automatic Speech Recognition (ASR) is the decoding of information conveyed by a speech signal into a set of characters (words). ASR is a complex task and as a result, different constraints may need to be imposed during the development of speech recognition systems. Based on the constraints, ASR systems may be categorized as speaker dependent or independent, isolated or continuous speech, small, medium or large vocabulary system, read or spontaneous speech and noisy or noise free speech (Deller *et al.*, 2000).

Using a lot of speakers during the training phase of the Acoustic Models will result in speaker-independent systems. They are capable of recognizing speech from any speaker enrolled or not during the training phase. The opposite is to tailor the system to one speaker using only speech data from this particular speaker during training resulting in speaker-dependent systems. Such speech recognition systems recognize speech of a speaker whose speech is used during the development of the recognizer. While they usually perform better for this speaker, the performance for other speakers will be worse.

If only single words are to be recognized, i.e. the words in a sentence are spoken with long pauses in between so that each word can easily be isolated from each other; they are called isolated word recognition systems. This mode of operation is often used in command and control systems where devices are controlled by speech and in high quality dictation systems. In this case, all the words in the dictionary are equally probable to be spoken at any time. Systems that do not require pauses between the words and that allow complete sentences to be spoken are called continuous speech recognition (CSR) systems. Here, all words are not equally probable, but a Language Model is employed to predict the likelihood of word sequences.

Small vocabulary recognition systems are those which have a vocabulary size of 1 to 99 words whereas medium and large vocabulary systems have a vocabulary size of 100 – 999 and 1000 or more words, respectively.

Broadly speaking, there are three approaches to speech recognition namely acoustic phonetic approach, pattern recognition approach and artificial intelligence approach (Rabiner and Juang, 1993). The Acoustic-Phonetic approach is based on the theory of acoustic phonetics that postulates that there exists finite, distinctive phonetic units in spoken language and that the phonetic units are broadly categorized by a set of properties that are manifested in the speech signal, or its spectrum, over time. The Pattern-Recognition approach is basically the one in which the speech patterns are used directly without explicit features. It consists of two steps- namely, training of speech patterns and pattern recognition via pattern comparison. Artificial Intelligence approach is a hybrid of acoustic phonetic approach and pattern recognition approach in that it exploits ideas and concepts from both methods.

The typical ASR system mainly consists of the acoustic model, pronunciation model, language model and decoder components. The acoustic model provides the probability that when the speaker utters a word sequence, the acoustic processor produces the representation of the word sequence. The pronunciation model specifies the words that may be output by the speech recognizer. The language model provides an estimate of the probability of a word sequence W for a given recognition task. The decoder takes the acoustic model, the pronunciation model and the language model and output the most likely sequence of words.

1.2 Statement of the Problem

Amharic, which belongs to the Semitic language family, is the official language of Ethiopia. In this family, Amharic stands second in its number of speakers after Arabic (Ethnologue, 2004). Amharic has five dialectical variations (Addis Ababa, Gojjam, Gonder, Wollo, and Menz) spoken in different regions of the country (Bender *et al.*, 1976). For various reasons, words in Amharic are pronounced differently and varied from one speaker to another and from one situation to another. This is termed as pronunciation variation and is one of the major factors that degrade the performance of Amharic ASR systems.

The objective of ASR is to derive the correct string of spoken words from an acoustic signal. However, pronunciation variation makes it more difficult to achieve this objective, as the variation can result in recognition errors. The goal of pronunciation modeling is to minimize the recognition errors due to pronunciation variation and thus improve the performance of the ASR system. The recognition errors can be a direct result of variants that are pronounced but not included in the lexicon.

A canonical pronunciation dictionary contains a single pronunciation for each word. However, some Amharic words have more than one pronunciation. Table 1.1 shows some examples of Amharic words that have multiple pronunciations.

Table 1.1: Sample Amharic words that have more than one pronunciation

Word	Pronunciation 1	Pronunciation 2
Yours father	የአባትህ/yeabath/	ያባትህ/yabath/
Aloes	እሬት/ixriet/	ሬት/riet/
Merciful	ሩህሩህ/ruhruh/	ርህሩህ/rhruh/
After growing	ከአደገ/keadege/	ካደገ/kadege/
Refuse	እምቢ/ixmbii/	እምቢይ/ixmbiiy/
Country	አገር/ager/	ሀገር/hager/
Idea	ሀሳብ/asab/	አሳብ/asab/
Forever	ዘላለም/zelalem/	ዘለአለም/zelealem/
Vow	ስዕለት/sixilet/	ስለት/sixlet/
Minister	ሚንስትር/miinsixtixr/	ሚኒስትር/miiniistixr/
Salary	ደሞዝ/demoz/	ደመወዝ/demewez/

These pronunciation variations can be the result of either intra-speaker variability or inter-speaker variability. Intra-speaker variability is the variation in pronunciation for one and the same speaker where as inter-speaker variability is the variation among different speakers. Inter-speaker variability can be due to factors such as vocal tract differences, age, gender, regional accent, voice quality etc. (Biemans, 2000).

There are also cases where contaminations of phone models caused by a mismatch between the acoustic signal and the corresponding transcription during training due to phone insertion, phone deletion or phone substitution degrade the performance of Amharic ASR. Some Amharic words as shown in Table 1.2 may have a different transcription acquired from acoustic evidence in contrary to language grapheme transcription. While acoustic evidence transcription is

acquired from acoustic data, language grapheme transcription is acquired from transliteration scheme.

Table 1.2: Sample Amharic word transcriptions from transliteration scheme and acoustic evidence

Amharic Word	Language grapheme transcription	Acoustic evidence transcription
ትምህርት(education)	/tmhrt/	/tixmhixrt/
ግል(private)	/gl/	/gixl/
ምርምር(research)	/mrmr/	/mixrmixr/
ስታዲየም(stadium)	/stadiiyom/	/sixtadiiyom/
ብር(Ethiopian currency)	/brr/	/bixrr/
ምክር(advice)	/mkr/	/mixkr/
ትዕግስት(patience)	/tixgst/	/tixgsixt/
ግልጽ(clear)	/glxx/	/gixlxx/
ምክትል(vice)	/mktl/	/mixktixl/

These epitomize how pronunciation variation causes problems for ASR and consequently why it should be modeled. Although there are many factors that affect the performance of ASR system, the existence of pronunciation variation is one of the main factors that degrade the performance of Amharic Speech recognition systems. Pronunciation variation is not modeled for Amharic ASR systems so far and the performance of Amharic Speech Recognition System has not reached its maximum possible performance when compared to technologically favored languages. Hence, this research focuses on pronunciation variation modeling to enhance the performance of Amharic Speech Recognition Systems.

1.3 Motivation

One of the major difficulties in speech recognition systems is the variability in speech data, due, among other reasons to alternate pronunciation of words, even within the same speaker (Wooters and Stolke, 1996). The lexicon is usually composed of a set of words and a single pronunciation for each of them. This pronunciation is considered to be the standard or correct one, but it usually doesn't have to do very much with the actual pronunciation of the word in a real environment (Westendorf and Jelitto, 1996).

Words are pronounced differently by different people, a phenomenon called pronunciation variation. Pronunciation variation has been studied in the speech recognition field and reports

show that pronunciation variation can cause the performance of automatic speech recognition systems deteriorate if it is not well accounted for. This is due to the fact that variants of a pronunciation are not included in the lexicon. This failure to capture an important source of variability is potentially a significant cause for the relatively poor performance of Amharic ASR.

Studies by McAllaster *et al.* (1998) and Saraclar *et al.* (2000) have shown that large improvements are feasible, if there is match between the acoustic models used during recognition and the transcription in the lexicon. In other words, these experiments show that substantial improvements are possible through pronunciation variation modeling.

No research has been done to the best of our knowledge to enhance the performance of Amharic ASR through pronunciation variation modeling. Hence, this research work focuses on solving the pronunciation variation problem by adding multiple pronunciations to words that have more than one pronunciation in the corpus and acquiring the actual pronunciation for each word in the lexicon from acoustic evidence in order to fit the acoustic data better.

1.4 Objectives

The general and specific objectives of this research are described below.

1.4.1 General Objectives

The general objective of this research work is to enhance the performance of Amharic ASR system.

1.4.2 Specific Objectives

The specific objectives of this research work are:

- Selecting appropriate speech recognition model.
- Designing enhanced Amharic ASR system.
- Incorporating multiple pronunciations into Amharic lexicon.
- Incorporating acoustic and linguistic evidence into the multiple pronunciation Amharic lexicon.
- Integrating the pronunciation dictionary with the ASR.
- Training the ASR model using Amharic parallel corpus.

- Testing and analyzing the performance of enhanced ASR model.

1.5 Scope of the Study

The scope of this study is limited to modeling the pronunciation variation of Amharic to minimize the recognition errors due to pronunciation variation and thus enhance the performance of large vocabulary, continuous, speaker dependent Amharic speech recognition system.

1.6 Methodology

In order to achieve the objectives of the study, the following methods are employed.

1.6.1 Literature Review

Extensive literature review is conducted to get a deeper understanding of pronunciation variation modeling to improve the performance ASR systems for other languages and review works done on Amharic ASR.

1.6.2 Data Collection

A speech corpus is one of the fundamental requirements for any speech recognition research. The speech corpus is collection of speech recordings which is accessible in computer readable form, and which has an annotation and documentation sufficient to allow re-use of data.

The speech corpus is designed according to best-practice guidelines established for other languages. Standard speech corpora consist of a training set and evaluation test sets. The training set is intended to collect speech data for training the recognizer and the evaluation test set is for the purpose of final evaluation of the recognizer.

The selection of sentences aims at both a phonetically rich and balanced collection of sentences. To accomplish phonetic richness, we select 800 training and 100 evaluation test sentences. The training sentences consist of 3309 distinct Amharic words of which 190 of them have pronunciation variants. They are selected from 8 different Amharic sources (political news, economy news, sport news, health news, fiction, Bible, penal code and 100 Federal Negarit Gazzeta) which contribute to the inclusion of all Amharic phones. The text corpus is shown in

Appendix K. Phonetic balance of the corpus is achieved by selecting those sentences which contribute to the preservation of the distribution of phones in the Amharic language.

Having obtained the text, some problems that are encountered are solved. These include abbreviations are expanded and numbers are textually transcribed. To avoid elongated sentences that create difficulty for the readers, sentences with a maximum of twenty words in length are chosen from the available sources.

Having the text corpus, a sample of 800 training sentences are selected for recording. Hence, a parallel Amharic speech corpus is prepared. The corpus is recorded by four speakers (two male and two female). The evaluation test sets consist of 100 distinct sentences. The training and evaluation test sets are recorded by speakers in the age range of 22 to 30. Though the scope of the research is limited to speaker dependent ASR, the recording of the four speakers is used to perform various analysis as per the design of the pronunciation variation stated in section 1.6.4

The prepared sets of training and evaluation test sentences are recorded using Audacity software with the sample frequency of 48 kHz, sample size of 16 bits and Mono channel. The training and evaluation sentences are saved in the Resource Interchange File Format (RIFF). Both the training and test data are carried in a quite resident environment using microphone. Since the training and test data are recorded in the same environment, the effect of noise is not significant.

1.6.3 Modeling

HMM-based systems are currently the most commonly used and most successful approach for ASR. The research uses phoneme based HMM model with three emitting states and without skip arcs as it is the state of art number of states and topology for phoneme based ASR systems.

1.6.4 Design of Pronunciation Variation Methodology

The research has designed three pronunciation dictionaries for the Amharic ASR. They are described as follows:

The first pronunciation dictionary has a single pronunciation for each word in the corpus collected for training and testing purpose where the pronunciation of each word is blindly defined as the transliteration of the language grapheme. It has distinct 3009 Amharic words. For

example, the Amharic words “ትምህርት” and “ተማሪ” are pronounced as “t m h r t” and “t e m a r ii” respectively. We call this as *grapheme based method with single pronunciation*.

The second pronunciation dictionary has multiple pronunciations for words that have more than one pronunciation in the first pronunciation dictionary. The multiple pronunciations in the second pronunciation dictionary are collected from Amharic linguistic literature and dictionaries. It has distinct 3499 Amharic words. For example, the Amharic words “ትዕግስት” (patience) and “ደሞዝ” (salary) can also be pronounced as “ትግስት” and “ደመዝ” respectively. Hence, the Amharic words “ትዕግስት” and “ደሞዝ” will have two pronunciations. Each pronunciation is represented as the transliteration of the grapheme sequence of the alternate pronunciation word. We call this as *grapheme based multiple pronunciation method without acoustic evidence*.

The third pronunciation dictionary has multiple pronunciations for some of the words in the lexicon where the pronunciation of each word is manually transcribed from acoustic evidence in addition to the alternate pronunciations obtained above. Acoustic evidence is collected from the speech corpus for one of the speaker and it is used for the other speakers to see the effect of the acoustic evidence transcription of one speaker on the other. We call this as *grapheme based multiple pronunciation method with acoustic evidence*.

The three pronunciation dictionaries are tested by building ASR model for each of the four speakers independently.

1.6.5 Tools and Techniques

The research uses the Hidden Markov Model Toolkit (HTK) that is a portable toolkit for building and manipulating HMM. HTK is primarily used for research in speech recognition. It consists of a set of library modules and tools available in C source code. The tools provide sophisticated facilities for speech analysis, HMM training, testing and results analysis. The HTK tools are prepared for all the processing steps involved in speech recognition system. The main phases or steps are: data preparation, training, recognition and performance analysis. In data preparation, all of the speech data needed both for training and testing are recorded. The training phase defines the topology required for each HMM. The recognition phase outputs a

transcription file against which the recognizer's performance is analyzed. The performance analysis phase enables to evaluate the performance of the ASR system. The research uses Audacity software for recording and editing sounds, Cygwin software for executing HTK commands on Windows operating system and praat software for transliterating words manually from acoustic evidence.

1.6.6 Evaluation and Analysis

The research evaluates the performance of the developed ASR system using the Sentence Error Rate (SER) and Word Error Rate (WER) criterion. The SER tells us the rate of wrongly recognized sentences. The WER metric is the ratio of the number of word recognition errors to the number of words in the reference.

1.7 Application of the Results

Speech recognition systems are applied in different application domains. Some of the most common application areas of speech recognition systems include dictation systems, command and control systems, telephony systems, as an assistive technology for disabled people like the handicapped that cannot use keyboard or any pointing devices, audio based information retrieval systems etc. Dictation system includes medical transcriptions, legal and business dictation, and general word processing. Command and control systems use speech input to perform functions and actions. Telephony systems allow callers to speak commands instead of pressing buttons to dial a number.

In general, apart from being a natural way of interfacing with machines (like PCs, Telephones, Television etc), ASR renders the following advantages: it helps to speed up inputting information (much faster than using the ubiquitous, keyboard even for the fastest possible typists); it avoids pains related to typing (like repetitive stress injury); using ones voice, the hands and the eyes are free and movement is unconstrained.

1.8 Organization of the Thesis

The rest of the thesis is organized as follows. Chapter 2 discusses about the major components of ASRs, errors made by speech recognizers, the Amharic language, types of ASR, HMMS, approaches to the development ASR, types of HMMs, pronunciation variation, pronunciation variation modeling for ASR and issues in pronunciation variation modeling. Chapter 3 discusses

about related works done on pronunciation variation modeling to improve the performance of speech recognition systems for other languages and review works done so far on Amharic ASRs. Chapter 4 discusses about the design and implementation of the research. It describes about the description of the system design, major components, data preparation, training, recognition and analysis. Chapter 5 discusses about the experimental result and analysis. Chapter 6 concludes the thesis by outlining achievements, drawbacks and possible future works to improve the work carried out by this research.

CHAPTER TWO

LITERATURE REVIEW

The statistical approach for speech recognition (Huang *et al.*, 1993) has virtually dominated Automatic Speech Recognition (ASR) research over the last few decades, leading to a number of successes (Rabiner and Juang, 1993). The problem of speech recognition is defined as the conversion of spoken utterances into textual sentences by a machine. An utterance that is given as input to an Automatic Speech Recognition (ASR) system is digitized and processed using signal processing algorithms to extract representational vectors $X = x_1, x_2 \dots x_t$. The problem of speech recognition can be formally stated as (Young *et al.*, 2006):

$$\hat{W} = \underset{W \in \mathcal{W}}{\operatorname{argmax}} P(W|X) \quad (2.1)$$

with W being the set of possible word sequences. Thus, the problem is to maximize the conditional probability over all possible word sequences W given the acoustics X .

Because of the extremely large number of possible word sequences in natural language and the enormous range of variation in the acoustic signals that is produced when different speakers pronounce the “same” sequence of words, $P(W|X)$ cannot be computed directly. In order to deal with this problem, Bayes’ rule is used to break up this probability into components:

$$\hat{W} = \underset{W}{\operatorname{argmax}} \frac{P(X|W)P(W)}{P(X)} \quad (2.2)$$

As the prior probability $P(X)$ in the denominator of equation 2.2 is constant over all W , equation. 2.2 may be simplified to:

$$\hat{W} = \underset{W}{\operatorname{argmax}} P(X|W)P(W) \quad (2.3)$$

Thus, the ASR system must model two probability distributions: $P(X|W)$ which is the posterior probability of the acoustics given a string of words, and is modeled by the acoustic models; and $P(W)$, the prior probability of a string of words, which is modeled by the language model.

Since hypothesis W is a sequence of words $W = w_1, w_2 \dots w_N$,

$$\max_W P(X/W)P(W) = \max_W P(X/w_1, w_2 \dots w_N) * P(w_1, w_2 \dots w_N) \quad (2.4)$$

The statistical approach is itself dominated by the powerful statistical technique called Hidden Markov Model (HMM). Words in utterances are represented by sub-word units called phones. If w_i is a word model, then $P_i = p_1, p_2 \dots p_n$ is corresponding sequence of phonemes. Each phoneme may further be realized as a sequence of states, $Q = q_1, q_2 \dots q_s$. Thus models of utterances are deconstructed into a phoneme state sequence Q_i .

An HMM consists of N hidden states, M distinct types of observations, state transition probability matrix A , probability distribution of the observations B and the initial state distribution π parameters. Together, these parameters are denoted by $\lambda = (A, B, \pi)$.

The operation of an HMM is characterized by the hidden state sequence $Q = \{q_1, q_2, \dots, q_n\}$ and the observation sequence $O = \{o_1, o_2, \dots, o_n\}$.

$$P(Q|\lambda) = \pi_{q_1} \cdot \prod_{n=1}^{N-1} a_{q_n, q_{n+1}} = \pi_{q_1} \cdot a_{q_1, q_2} \cdot a_{q_2, q_3} \cdot \dots \cdot a_{q_{N-1}, q_N}$$

The probability of a state sequence $Q = \{q_1, q_2, \dots, q_n\}$ coming from an HMM parameters λ corresponds to the product of the transition probabilities from one state to the following.

To decode the best state sequence, a Viterbi approximation is often employed. The Viterbi algorithm tries to find the state sequence which has the highest posterior probability on the observations.

2.1 Components of ASR

Although there are different kinds of speech recognition systems, most have similar major components (Rabiner and Juang, 1993). Figure 2.1 shows the general architecture of ASR system. It is described as follows:

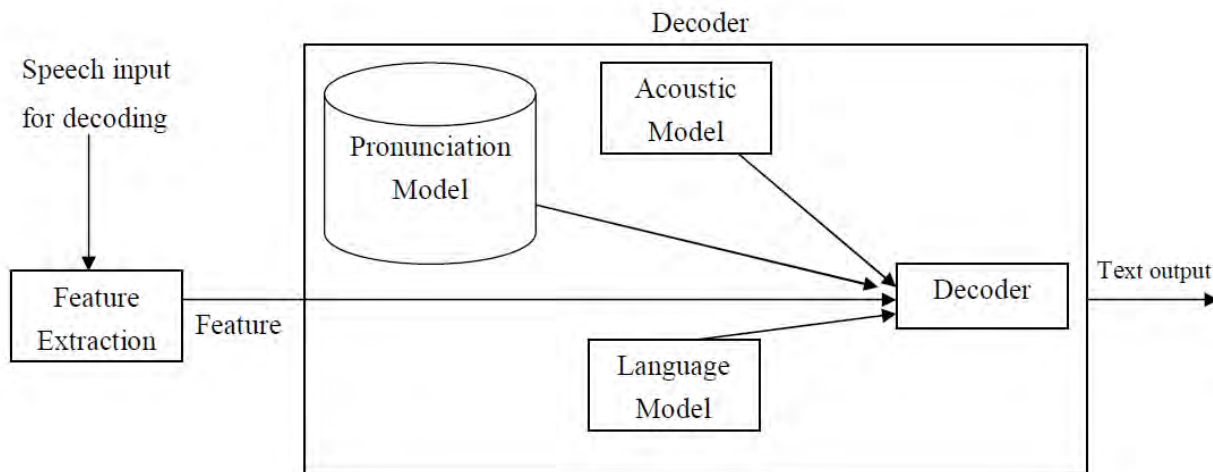


Figure 2.1: The general architecture of ASR systems (Rabiner and Juang, 1993)

Feature Extraction: It converts the speech signal into a sequence of acoustic feature vectors. The goal is to extract a number of features from the signal that have a maximum of information relevant for classification. That means features that are robust to acoustic variation but sensitive to linguistic content are extracted. Put in other words, features that are discriminant and allow distinguishing between different linguistic units (e.g., phones) are required. On the other hand, the features should also be robust against noise and factors that are irrelevant for the recognition process. The number of features extracted from the waveform signal is commonly much lower than the number of signal samples, thus reducing the amount of data.

Acoustic model: The acoustic models are statistical models which capture the correspondence between a short sequence of acoustic vectors and an elementary unit of speech. The elementary units of speech that are most often used in ASR are phones. Phones are the minimal units of speech that are part of the sound system of a language, which serve to distinguish one word from another.

The predominant approach to acoustic modeling in speech recognition is to use Hidden Markov Models (HMMs). An alternative to the standard HMM approach is a hybrid approach in which

Artificial Neural Networks (ANN) and HMMs are employed. In order to recognize speech, the acoustic models must first be trained. During training, the parameters for the models are estimated from recorded speech material which has been orthographically transcribed (i.e., at word level). Additionally, a phonetic transcription of the words is needed. Transforming a word sequence to a phone sequence is accomplished by looking up the phonetic transcription for a word in the lexicon (Rabiner and Juang, 1993).

An HMM is a stochastic automaton, consisting of a collection of states connected by transitions. Two sets of probabilities are associated with each state: a transition probability, which gives the probability of taking the transition from one state to another, and an output or emission probability density function, which specifies the probability of emitting each output symbol at each state. An HMM is trained for each recognition unit (e.g. phones) defined in the system.

Pronunciation Model: It consists of the orthography of words that occur in the training material and their corresponding phonetic transcriptions. It specifies the finite set of words that may be output by the speech recognizer. The transcriptions can be obtained either manually or through grapheme-to-phoneme conversion.

A pronunciation dictionary can be classified as a canonical or alternative on the basis of the pronunciations it includes. For each word, a canonical pronunciation dictionary includes only the most probable pronunciation that is assumed to be pronounced in read speech. It does not consider pronunciation variations such as speaker variability, dialect, or co-articulation in conversational speech. On the other hand, an alternative pronunciation dictionary is a pronunciation dictionary that includes all the alternate pronunciations that are assumed to be pronounced in speech (Fukada *et al.*, 1999).

Language Model: The language model contains rudimentary syntactic information. Its aim is to predict the likelihood of specific words occurring one after another in a given language. Typical recognizers use n-gram language models. An n-gram contains the prior probability of the occurrence of a word (unigram), or of a sequence of words (bigram, trigram etc.):

unigram probability $P(w_i)$
bigram probability $P(w_i|w_{i-1})$
ngram probability $P(w_n|w_{n-1}, w_{n-2}, \dots, w_1)$.

Decoder: The decoder is the speech engine that takes the acoustic model, the pronunciation model, the language model, and observation sequence and outputs the most likely sequence of words.

2.2 Errors Made by Speech Recognizers

Though ASR research has come a long way, today's systems are far from being perfect. Speech recognizers are brittle and make errors due to various causes. L. L. Chase (1997) attempts a detailed characterization of errors made by speech recognizers. Accordingly, most errors made by ASRs fall into one of the following categories:

1. Out of Vocabulary errors: Current state of the art speech recognizers are closed vocabularies. So, they are incapable of recognizing words outside the system's vocabulary. Besides misrecognition, the presence of an Out of Vocabulary in an input utterance causes errors to its neighboring words.
2. Homophone Substitution: These errors are caused if more than one lexical entry has the same pronunciation (phone sequence). While decoding, they may be confused with one another causing errors. In general, the language model disambiguates in the event of such confusion.
3. Language model bias: Because of an undue bias (effected by high language weight) towards the language model, the decoder may be forced to reject the true hypothesis in favor of a spurious candidate. These errors may occur along with analogous acoustic model bias.
4. Multiple acoustic problems: This is a broad category of errors comprising those due to bad pronunciation entries; disfluency, mispronunciation by the speaker himself/herself or confused acoustic models (possibly due to noise etc.)

2.3 The Amharic Language

Amharic, the official language of Ethiopia, is a Semitic language that has the greatest number of speakers after Arabic. It is believed that Amharic has 17.4 million speakers as a mother tongue language and 5.1 million speakers as a second language (Ethnologue, 2004).

2.3.1 Consonants

A set of 38 phones, seven vowels and 31 consonants, makes up the complete inventory of sounds for the Amharic language (Baye, 2010). Consonants are generally classified as stops, fricatives, nasals, liquids and semi-vowels. Table 2.1 shows the phonetic representation of Amharic consonants as to their manner of articulation, voicing and place of articulation.

Some of the Amharic consonants have similar phonetic transcriptions like English. These include ብ [b], ደ [d], ፍ [f], ግ [g], ሀ [h], ክ [k], ለ [l], ሞ [m], ን [n], ጥ [p], ር [r], ሰ [s], ተ [t], ሸ [w], ረ [y] and ገ [z]. They correspond to English consonants b,d,f,g,h,k,l,m,n,p,r,s,t,v,w,y, and z.

There are also sounds that have similar sound as English sounds, but are represented using different symbols. These include ሻ [ch], ሻ [nx], ሻ [sx] and ሻ [zx]. Sounds that are the characteristics of Amharic but not found in English are ጵ [px], ጥ [tx], ፅ [xx], ጭ [cx] and ቅ [q] (Solomon, 2006).

In Amharic, all consonants except ሀ /h/ and ፅ /ax/ may occur in either a geminated or a non-geminated form. The gemination of Amharic is not shown in the orthography. Gemination is the lengthening in time of the consonants.

Table 2.1: Categories of Amharic Consonants

		Labials		Alveolar		Palatals		Velars		Labio-Velar		Glottals	
Stops	Voiceless	p	ፕ	t	ት			k	ክ	kwa	ካ	ax	ዕ
	Voiced	b	ብ	d	ድ			g	ግ	gwa	ገ		
	Glottalized	px	ጽ	tx	ፕ			q	ቅ	qwa	ቋ		
Fricatives	Voiceless	f	ፍ	s	ሰ	sx	ሸ					h	ህ
	Voiced			z	ዝ	zx	ሻ						
	Glottalized			xx	ጽ							hwa	ሕ
Affricatives	Voiceless					c	ች						
	Voiced					j	ጅ						
	Glottalized					cx	ጭ						
Nasals	Voiced	m	ጠ	n	ን	nx	ኝ						
Liquids	Voiced			l	ሊ								
	Voiced			r	ር								
Glides		w	ወ			y	ይ						

2.3.2 Vowels

The seven vowels, along with their representation in Ge'ez characters, are shown in terms of their place of articulation in Table 2.2. In addition to the five vowels common among many languages, Amharic has two central vowels, /e/ and /ix/, the latter with a mainly epenthetic function. The epenthetic vowel /ix/ plays a key role in syllabification.

Table 2.2: Categories of Amharic Vowels

	Front	Central	Back
High	ከ [ii]	ኧ [ix]	ኡ [u]
Mid	ኮ [ie]	ኩ [e]	ኰ [o]
Low		ኣ [a]	

The vowel /ኧ/ is pronounced like /e/ in „vowel“: the word ደሐየ [deheye] „become poorer“ can be transcribed as ደኧህኧይኧ. The vowel ኡ /u/ is pronounced approximately like the English /o/ in „to“. For example, ሙያ [muya] „profession“. The vowel [ii] is pronounced like the /ee/ in English „feet“. For example, ኢትዮጵያ [iityopxya] „Ethiopia“. The vowel ኣ [a] is pronounced

like the /a/ in English „man“. For example, ሳር [sar] „Grass“. The vowel ኤ/ie/ has a pronunciation approximately like that the vowel /a/ in the English „gemination“. For example, ሴቲ[siet]“Female“. The vowel ኦ [ix] is pronounced like the /e/ in English „code“. For example, ግብ[bixb] „goal. The vowel ኦ [o] is pronounced like the /o/ in English „or“. For example, ዶሮ [doro] „“.

2.3.3 Amharic Writing System

Amharic uses the Ge‘ez (or Ethiopic) writing system which is originated with the ancient Ge‘ez language. In the writing system, even if the symbols are consonant-based, they also contain an obligatory vowel marking. Most of the symbols represent consonant vowel combinations. Each Amharic consonant is associated with seven characters (referred to as “orders”) for the seven vowels of the language. It is the sixth-order character that is the special symbol, representing the plain consonant. The basic pattern for each consonant is shown in Fig. 4.1, where C is consonant and [] shows vowels.

Table 2.3: Amharic syllabic structure with example for consonant

1st order	2nd order	3rd order	4th order	5th order	6th order	7th order
m[e]	m[u]	m[ii]	m[a]	m[ie]	m	m[o]
መ	ሙ	ሚ	ማ	ሚ	ም	ሞ

Gemination and Epenthetic vowel insertion are the two main ambiguities in Amharic orthography. Gemination in Amharic is one of the most distinctive characteristics of the rhythm of the speech, and also carries a very heavy semantic and syntactic functional weight. If we take Amharic word „ገና“, it may have two meanings. The first meaning is [gena] „still/yet“ and the second meaning is [genna] „Christmas“.

Epenthesis is the process of inserting a vowel to break up consonant clusters. Epenthesis, unlike gemination, is not contrastive. Although it carries no meaning, the Amharic epenthetic vowel /ix/ (in Amharic „ሳርኅ ገብ“ Baye, 2010) plays a key role for proper pronunciation of speech and in syllabification.

2.4 Types of ASR

Speech recognition systems can be classified on the basis of the constraints under which they are developed and which they consequently impose on their users. These constraints include: speaker dependence, type of utterance, size of the vocabulary, linguistic constraints, type of speech and environment of use. We will describe each constraint as follows:

Speaker Dependence: Speaker dependent speech recognition system requires the user to be involved in its development whereas speaker independent systems do not. Speaker independent systems can be used by anybody. Speaker dependent systems usually perform much better than speaker independent systems. This is due to the fact that the acoustic variations among different speakers are very difficult to describe and model. There are approaches to make a system speaker independent. The first one is the use of multiple representations for each reference to capture the speaker variation and the second one is the speaker adaptation approach.

Speaker adaptation is the modification of speaker independent model parameters using a small number of adaptation sentences from the new speaker so that the parameters are adjusted to the new speaker. Speaker adaptation techniques examine the speech from the new speaker and determine the difference between his/her way of speaking and the „average“ way of speaking which is reflected by the speaker independent models. Once these differences are known, either the speaker-independent models or the incoming features are modified so that they better match the new speaker’s acoustics.

Type of Utterance: A speech recognizer may recognize every word independently. It may require its user to speak each word in a sentence separating them by artificial pause or it may allow the user to speak in a natural way. The first type of system is categorized as an isolated word recognition system. It is the simplest form of a recognition strategy. It can be developed using word-based acoustic models without any language model. If, however, the vocabulary increases sentences composed of isolated words to be recognized, the use of sub-word acoustic models and language models become important. The second one is the continuous speech recognition systems. It allows the users to utter the message in a relatively or completely unconstrained manner. Such recognizers must be capable of performing well in the presence of

all the co-articulatory effects. Developing continuous speech recognition systems is, therefore, the most difficult task. This is due to the following properties of continuous speech:

1. word boundaries are unclear in continuous speech; and
2. co-articulatory effects are much stronger in continuous speech

Vocabulary Size: The number of words in the vocabulary is a constraint that makes a speech recognition system small, medium or large. As a rule of thumb, small vocabulary systems are those which have a vocabulary size in the range of 1-99 words; medium, 100-999 words; and large, 1000 words or more (Deller *et al.*, 1993).

Large vocabulary speech recognition systems perform much worse compared to small vocabulary systems due to different factors such as word confusion that increases with the number of words in the vocabulary. For small vocabulary recognizers, each word can be modeled. However, it is not possible to train acoustic models for thousands of words separately because we cannot have enough training speech and storage for parameters of the speech that is needed. The development of large vocabulary recognizers, therefore, requires the use of sub-word units. On the other hand, the use of sub-word units results in performance degradation since they cannot capture co-articulatory effects as words do. The search process in large vocabulary recognizers also uses pruning instead of performing a complete search. Pruning, however, increases recognition errors.

Linguistic Constraints: Most, if not all, of the present speech recognition systems are unable to reliably determine the identity of a speech unit (a phone or a word) based on the speech signal alone. To improve reliability, linguistic constraints are put on a recognizer by using a language model and a pronunciation dictionary. They capture syntactical and lexical constraints, respectively.

The pronunciation dictionary determines how the smallest units of recognition form words. For example, it contains the sequence of recognition units for every word of the vocabulary. Small vocabulary speech recognition systems generally do not rely heavily on language models to accomplish their tasks. A large vocabulary speech recognition system, however, is dependent on linguistic knowledge included in the input speech.

Type of Speech: A speech recognizer can be developed to recognize only read speech or to allow the user speak spontaneously. The latter is more difficult to build than the former due to the fact that spontaneous speech is characterized by false starts, incomplete sentences, unlimited vocabulary and reduced pronunciation quality.

The primary difference in recognition error rates between read and spontaneous speech are due to disfluencies in spontaneous speech (Junqua and Haton, 1996). Disfluencies in spontaneous speech can be characterized by long pauses and mispronunciations. Spontaneous is, therefore, both acoustically and grammatically difficult to recognize.

Environment: Speech recognizers may require the speech to be clean from environmental noises, acoustic distortions, microphones and transmission channel distortions or they may ideally handle any of these problems.

While current speech recognizers give acceptable performance in carefully controlled environments, their performance degrades rapidly when they are applied in noisy environments. This noise can take the form of speech from other speakers; equipment sounds, air conditioners or others. The noise might also be created by the speaker himself in a form of lip smacks, coughs or sneezes.

2.5 Approaches to the development of Speech Recognition

Broadly speaking, there are three approaches to speech recognition namely acoustic-phonetic approach, pattern recognition approach and artificial intelligence approach (Rabiner and Juang, 1993).

2.5.1 Acoustic-Phonetic Approach

It is based on the theory of acoustic phonetics that postulates that there exists finite, distinctive phonetic units in spoken language and that the phonetic units are broadly categorized by a set of properties that are manifested in the speech signal, or its spectrum, over time. Even though the acoustic properties of phonetics units are highly variable, both with speakers and neighboring phonetic units (the so called articulation of sounds), it is assumed that the rules governing the variability are straightforward and can readily be learned and applied in practical situations.

The Acoustic-Phonetic approach assumes that the phonetic units are broadly characterized by a set of features such as voiced/unvoiced and pitch. These features are extracted from speech signal and are used to segment and label the speech.

The process of recognition in this approach involves three steps (Rabiner and Juang, 1993):

The first step is a spectral analysis of the speech combined with a feature detection that converts the spectral measurements to a set of features that describe the broad acoustic properties of the different phonetic units.

The next phase is segmentation and labeling phase in which the speech signal is segmented into stable acoustic regions, followed by attaching one or more phonetic labels to each segmented region, resulting in a phone lattice characterization of the speech.

The last step attempts to identify a valid word (or string of words) from the sequence of phonetic labels produced by segmentation and labeling.

The Acoustic-Phonetic approach has not been widely used in most of the ASR systems. Rabiner and Juang (1993) mentioned four major problems that account for the lack of success of this approach in speech recognition systems. These are:

1. It requires extensive knowledge of acoustic properties of phonetic units.
2. The choice of features is mostly based on adhoc considerations.
3. The design of sound classifiers is also not optimal.
4. No well defined, automatic procedure exists for tuning the method on real, labeled speech.

2.5.2 Artificial Intelligence Approach

It is a hybrid of acoustic phonetic approach and pattern recognition approach in that it exploits ideas and concepts from both methods. The AI approach tries to mechanize the recognition procedure according to the way a person applies his/her intelligence in visualizing, analyzing, and finally making a decision on the measured acoustic features. The basic idea of AI approach is to compile and incorporate information drawn from a variety of knowledge sources into the system. Thus, for example the AI approach to segmentation and labeling would be to augment the generally used acoustic knowledge with the other high level information sources, like

phonemic, lexical, syntactic, semantic and even pragmatic knowledge. That is, the Artificial Intelligence approach incorporates knowledge about the world and the background of the speech into the ASR system.

According to Rabiner and Juang (1993), among the techniques used within this class of methods are:

1. The use of an expert system for segmentation and labeling such that this crucial and most difficult step can be performed taking more and other knowledge into account rather than just the acoustic information used by pure Acoustic-Phonetic methods;
2. Learning and adapting over a period of time;
3. The use of neural networks for learning the relationship between phonetic events and all known input, as well as to discriminate between similar sound classes.

2.5.3 Pattern-Recognition Approach

The most known and well performing method for speech recognition is the pattern recognition approach. In the pattern recognition approach, the speech patterns are used directly without explicit determination of phonetic feature and segmentation. It requires no explicit knowledge of speech. This approach has two steps, namely, training of speech patterns based on some generic spectral parameters and recognition of patterns via pattern comparison. Speech knowledge is brought into the system via the training procedure.

In the pattern-recognition approach, all acoustic realizations of units, words and sentences are considered as patterns consisting of sequences of feature vectors. Sentence recognition is, therefore, accomplished by performing pattern matching at unit, word and sentence levels in an integrated manner. This approach is the most common one for three basic reasons:

1. Simplicity of use: The method is easy to understand, and it is rich in mathematical and communication theory justification for individual procedures used in training and decoding, and it is widely used and understood.
2. Robustness and invariance to different speech vocabularies, users, feature sets, pattern comparison algorithms and decision rules: This property makes the algorithm

appropriate for a wide range of speech units(ranging from phoneme like units all the way through words, phrases and sentences), word vocabularies, background environments, transmission conditions, etc.

3. Proven high performance: It has already been shown that the pattern recognition approach provides high performance than the other approaches (Rabiner and Juang, 1993).

The most successful and popular method of pattern recognition approach in the area of speech recognition is the Hidden Markov Model (HMM). An HMM is a collection of states connected by transitions. An N-state Markov Model is completely defined by a set of N states forming a finite state machine and an $N \times N$ stochastic matrix defining transitions between states whose elements $a_{ij} = P(\text{state } j \text{ at time } t \mid \text{state } i \text{ at time } t-1)$ are the transition probabilities.

Its output symbols are probabilistic, and all symbols are possible at each state. Therefore, each state or transition is associated with a probability distribution of all possible symbols. An HMM is composed of a non-observable “hidden” process (a Markov chain) and an observation process which links the acoustic vectors extracted from the speech signal to the states or transitions of the “hidden” process. In that sense, an HMM is a doubly stochastic process.

The mathematics framework of the HMM method enables us to combine modeling of stationary stochastic process (for the short time spectra) and the temporal relationship among the processes, (via a Markov chain) together in a well defined probability space.

Another advantage of HMM comes from the fact that it is relatively easy and straight forward to train a model from a given set of labeled training data.

Flexibility is also an attractive feature of the basic HMMs. It is manifested in three aspects of the model, namely: observation distributions, model topology and decoding hierarchy. We can develop either discrete HMMs or continuous HMMs. In discrete HMMs, distributions are defined on finite spaces while in continuous HMMs; distributions are defined as probability densities on continuous observation spaces. We do also have different alternatives of HMM topologies with different number of states. It is also possible to build HMMs that can decode speech in various hierarchies that range from phones to sentences.

These strengths have made HMMs the predominant method in current automatic speech recognition technology and research.

An HMM has the following five basic parameters (Rabiner and Juang, 1993):

1. N , the number of states in the model. We denote the set of all possible states as $S = \{S_1, S_2, \dots, S_N\}$, the state at time t as q_t .
2. M , the number of distinct observation symbols per state, i.e., the discrete alphabet size of the output set. We denote the set of all possible output symbols as $V = \{v_1, v_2, \dots, v_M\}$, the output symbol at time t as O_t . The sequence of observed symbols is denoted as

$$O = O_1 O_2 \dots O_T .$$

3. The state-transition probability distribution $A = \{a_{ij}\}$ where

$$a_{ij} = P[q_{t+1} = j | q_t = i], \quad 1 \leq i, j \leq N$$

4. The observation symbol probability distribution, $B = \{b_j(k)\}$, in which

$$b_j(k) = P[o_t = v_k | q_t = j], \quad 1 \leq k \leq M,$$

defines the symbol distribution in state $j, j=1, 2, \dots, N$.

5. The initial state distribution $\pi = P[q_1 = i], \quad 1 \leq i \leq N$

The HMM model in the Figure 2.2 is a model of five emitting states that are numbered from 2 to 6 and output probability distributions associated with them. States number 1 and 7 are non-emitting states and serve only to join models together.

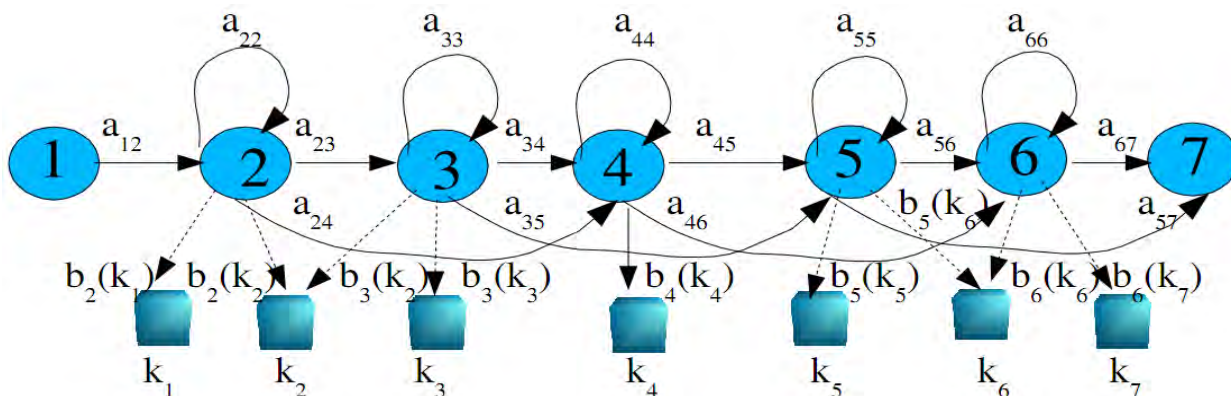


Figure 2.2: Example of HMM (Solomon, 2006)

The arrows from one state to the other and the indexed letter „a“ indicate the transition lines and their probabilities respectively. For example a_{12} means the probability of transition from state 1 to state 2 and a_{22} means the probability of looping in state 2.

In a first order hidden Markov model, there are two assumptions. The first is the Markov assumption. It states “the probability that the Markov chain is in a particular state at time $t + 1$ depends only on the state of the Markov chain at time t and is conditionally independent of the past”. The second is the output-independence assumption according to which the probability that a particular symbol will be emitted at time t depends only on the state at the time and is conditionally independent of the past. Although these assumptions severely limit the memory of the first-order hidden Markov models, they reduce the number of parameters and also make learning and decoding algorithms extremely efficient.

There exist three problems when constructing HMM. For an HMM model to be useful in building speech recognizers, three fundamental problems must be solved (Rabiner and Juang, 1993). These problems are

Problem 1: Given the model parameters, how do we compute the probability of a particular output sequence?

Problem 2: Given the model parameters, how do we find the most likely sequence of hidden states which could have generated a given output sequence?

Problem 3: Given an output sequence, how do we find the most likely set of state transition and output probabilities?

In order to deal with these problems, HMM possesses elegant and efficient algorithms; namely,

1. The forward algorithm
2. The Viterbi algorithm
3. The Baum-Welch algorithm

Problem 1 is a problem of evaluating how well a given model matches a given observation sequence. To solve this problem, the forward algorithm is used. The forward algorithm is an inference algorithm for HMMs which computes the posterior marginal of all hidden state

variables given a sequence of observations/emissions i.e. it computes, for all hidden state variables, the distribution.

To solve problem 2; that is, to find the single best state sequence, $Q = \{q_1 q_2 \dots q_T\}$ for the given observation sequence $O = \{o_1 o_2 \dots o_T\}$, the Viterbi algorithm is used. The Viterbi algorithm chooses the best state sequence that maximizes the likelihood of the state sequence for the given observation sequence.

Problem 3 is solved by using the Baum-Welch re-estimation algorithm. Baum-Welch re-estimation algorithm computes maximum likelihood estimates and posterior mode estimates for the parameters (transition and emission probabilities) of an HMM, when given only emissions as training data.

2. 6 Types of HMMs

HMMs can be classified in a variety of ways:

1. The left-to-right, directional HMM vs. Ergodic Models
2. Continuous Density vs. Discrete Density HMMs

2.6.1 Left-to-right vs. Ergodic Models

The most common HMM architecture found in speech recognition systems is the left-to-right, directional HMM (Markowitz, 1996). The fundamental property of all left-right HMMs is that the state-transition coefficients have the property:

$$a_{ij} = 0, \text{ where } j < i$$

i.e. no transitions are allowed to states whose indices are lower than that of the current state (Rabiner and Juang, 1993).

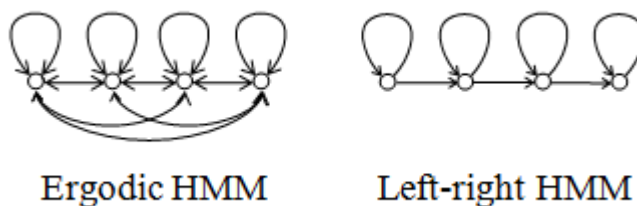


Figure 2.3: Ergodic and Left-to-right HMM (Young *et.al*, 2006)

The ergodic or fully connected HMM is another common HMM architecture in which every state of the model could be reached from every other state of the model. Ergodic models are non-directional and link every state to every other state.

2.6.2 Discrete HMMs vs. Continuous HMMs

HMMs may be based on either:

1. Discrete probability distributions (Discrete HMMs)
2. Continuous output probability density functions (Continuous HMMs)

An HMM consists of states. Each state j has an associated observation probability distribution $b_j(O_t)$ which determines the probability of generating observation O_t at time t and each pair of states i and j has an associated transition probability (Young *et al.*, 2006). The transition parameters in HMM model temporal variabilities while the output distributions model spectral variabilities.

The observation probability distribution may be a discrete output probability distribution, $b_j(O_t)$ for discrete HMMs or continuous output probability density function $b_j(X)$ for continuous HMMs.

HTK is designed primarily for modeling continuous parameters using continuous density multivariate output distributions (Young *et al.*, 2006). It can also handle observation sequences consisting of discrete symbols in which case, the output distributions are discrete probabilities. In continuous density HMMs, each observation probability distribution is represented by a mixture of Gaussian density.

2.7 Pronunciation Variation

Speech is variable. The way in which a sound, word or sequence of words is pronounced can be different every time it is produced (Strik and Cucchiarini, 1999). This pronunciation variation can be the result of either intra-speaker variability or inter-speaker variability. While intra-speaker variability is the variation in pronunciation for one and the same speaker, inter-speaker variability is the variation among different speakers. Inter-speaker variation can be caused due to factors such as vocal tract differences, age, gender, regional accent, dialect, voice quality etc. (Biemans, 2000).

There are numerous factors that influence the degree of intra-speaker pronunciation variation that is encountered in speech. These include speaking style, speaking rate, co-articulation, state of health of the speaker, emotional state of the speaker, external conditions etc.

- Speaking style: this type of variation depends on whether the speech is scripted, planned or spontaneous (Weintraub *et al.*, 1996). For example, an Amharic sentence may be pronounced differently when it is read or spoken spontaneously.
- Speaking rate: it has been shown that speaking rate can have a dramatic impact on the degree of variation in pronunciation (Greenberg and Fosler-Lussier, 2000). For example in the Amharic sentence, “ማንም ሰው ባንድ ወንጀል ሁለት ጊዜ አይቀጣም”, the word ባንድ (only once) can also be pronounced as በአንድ (only once). This variation is normally caused by whether the speaker speaks fast or slow.
- Co-articulation: the overlapping of adjacent articulations affects the way words are pronounced and variation in the degree of co-articulation causes pronunciation variation.
- State of health of the speaker: factors such as whether the speaker has a cold or is fatigued influences how the words are pronounced.
- Emotional state of the speaker: whether the speaker is happy, sad, or excited.
- External conditions: for instance noise, which causes speakers to modify their speech: the Lombard effect (Junqua *et al.*, 1993).

These sources of variation all contribute to the fact that a word is never pronounced in exactly the same way by the same or different speakers. This is referred to as pronunciation variation. The objective of automatic speech recognition (ASR) is to recognize what a person has said, i.e., to derive the string of spoken words from an acoustic signal. Due to the above described variation, this objective becomes more difficult to achieve, as the pronunciation variation may lead to recognition errors. Therefore, avenues are sought to model pronunciation variation.

2.8 Pronunciation Modeling for ASR

The objective of ASR is to derive the correct string of spoken words from an acoustic signal. However, pronunciation variation makes it more difficult to achieve this objective, as the variation can result in recognition errors. The goal of pronunciation variation modeling is to minimize the recognition errors due to pronunciation variation and thus improve the

performance of the ASR system. This section illustrates in what way pronunciation variation can have a negative impact on speech recognition both during training and recognition.

In ASR, the continuous speech signal is described as a sequence of discrete units, which in general are phones. In the studies presented in this thesis, we deal with pronunciation variation that becomes apparent in a careful phonetic transcription of speech, in the form of insertions, deletions or substitutions of phonemes relative to the canonical transcription of the words. This type of pronunciation variation can be said to occur at the segmental level. All of the variation that takes place below the level of the phonetic transcription (for example, the variation due to vocal tract differences) is implicitly left to the HMMs to model.

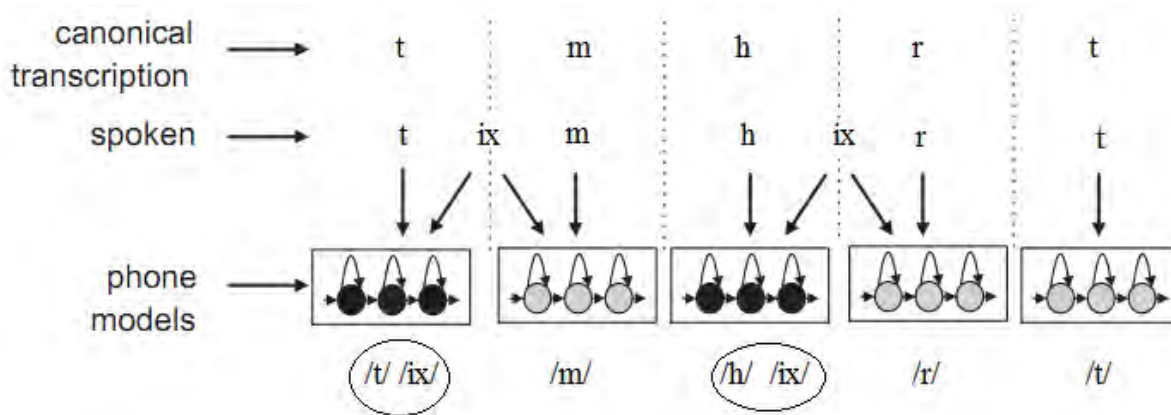


Figure 2.4: Contamination of phone models caused by mismatch due to λ (ix) insertion

Figures 2.4 and 2.5 exemplify the way in which pronunciation variation at the segmental level causes problems for ASR during training, and consequently why it should be modeled. The Figures show how phone models become contaminated when a word's pronunciation differs from the canonically expected pronunciation. The first example illustrates the effect of an insertion, and the second example illustrates a deletion. The resulting phone models are contaminated due to the mismatch between the acoustic signal and the phoneme label assigned to it, indicated by the darker shaded of the phone models.

In the example in Figure 2.4, the word “tmhrt” (education) with its canonical transcription /t m h r t/ is pronounced as /t ix m hix r t/, i.e., ix-insertion has taken place. This means that, during training, parts of the acoustic signal corresponding to /ix/ are used to train models for /t/ and /h/ causing contamination of the models for /t/ and /h/. In the example in Figure 2.5, “keixsat”

(from fire) with its canonical transcription /k e ix s a t/ is pronounced as /k e s a t/, i.e., ix-deletion has taken place. During training this leads to contamination of the /ix/ model.

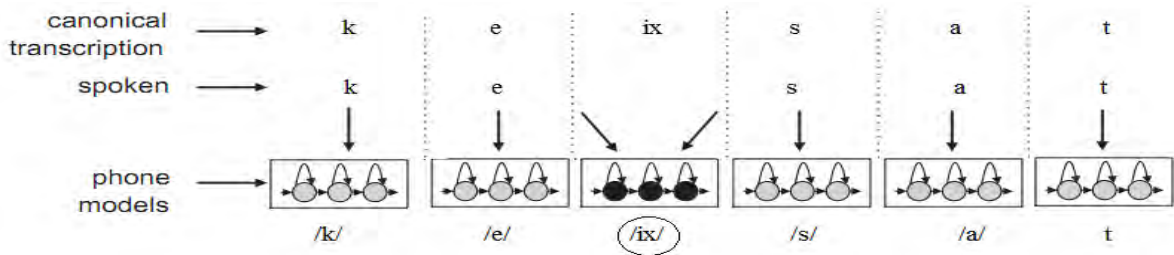


Figure 2.5: Contamination of phone models caused by mismatch due to Δ (ix)-deletion

During recognition, pronunciation variation may also cause errors. The recognition errors can be a direct result of the fact that contaminated models are less effective in distinguishing between different phones. Another reason why errors may occur is that variants can be pronounced which are not included in the lexicon. For instance, if /k e s a t/ is pronounced but the baseline transcription is /k e ix s a t/, the possibility exists that the baseline transcription of another word in the lexicon will match the acoustic signal better, for example, /k e s e a t/ (“keseat” meaning “in the afternoon”).

Taking all of this into account, one may wonder whether modeling pronunciation variation at a segmental level can contribute to the improvement of recognition performance. Studies by McAllaster *et al.* (1998) and Saraçlar *et al.* (2000) have shown that large improvements are feasible, if there is a match between the acoustic models used during recognition and the transcriptions in the lexicon. In other words, these experiments show that substantial improvements are possible in principle through pronunciation variation modeling.

In a nutshell, the reason for carrying out pronunciation modeling is because of the mismatch between the acoustic signal and the transcription of the signal (i.e. phone transcriptions in the lexicon). In our study, an attempt is made to reduce this mismatch by ensuring that the different pronunciations of a word are accounted for during recognition.

2.9 Issues in Pronunciation Variation Modeling

Issues that play a role when performing pronunciation variation modeling for ASR are described. There are two questions which cover most of the issues that must be addressed when modeling pronunciation variation (Strik and Cucchiarini, 1999):

1. How the pronunciation variation knowledge that is required to describe pronunciation variation is obtained?
2. How the knowledge is incorporated into the ASR system?

2.9.1 Approaches to acquire Pronunciation Variation Knowledge

There are two major approaches to acquire pronunciation variation knowledge. These are knowledge based and data-derived approaches.

The knowledge based approach derives the pronunciation variation knowledge from phonological or phonetic knowledge and/or linguistic literature (Cohen, 1989). It also includes existing dictionaries.

The idea behind data-derived approach is that information on pronunciation variation is obtained directly from the acoustic signals. The acoustic signals are analyzed in order to determine all possible ways in which the same word or phoneme is realized.

Although both knowledge based and data-derived approaches are used for generating pronunciation variants, they have their drawbacks too. The linguistic literatures, including pronunciation dictionaries are not complete i.e. all pronunciation variations are not described in the linguistic literature or present in pronunciation dictionaries. Furthermore, a knowledge-based approach is subject to discrepancies between theoretical pronunciations and phonetic reality. The major drawback of data-derived approach is it is labor intensive, and therefore expensive. Moreover, manual transcriptions tend to contain an element of subjectivity. Transcriptions made by different transcribers, and even made by the same transcriber, may differ quite considerably (Cucchiarini, 1993).

This research acquires pronunciation variations of Amharic words using both the knowledge-based approaches and data-derived approaches. The research tries to find the different Amharic pronunciation variants of words from Amharic linguistic literature and Amharic dictionaries for the grapheme based approach with single pronunciation and grapheme based multiple

pronunciation approach without acoustic evidence. The research uses databases of Amharic real speech to find the variations present between words for grapheme based multiple pronunciation approach from acoustic evidence. The research uses data driven methods because some of the transcriptions derived using knowledge based methods do not match with the acoustic signal.

2.9.2 Incorporating the knowledge into the ASR

After the pronunciation variants are obtained, the next question that must be addressed is how the information should be incorporated into the ASR system. One of the major ASR components where the acquired knowledge is incorporated is the lexicon.

2.9.2.1 Adding variants to the Lexicon

As speech recognizers make use of a lexicon, pronunciation variation is often modeled at the level of the lexicon. In this research, variations that occur within a word are dealt with in the lexicon by adding variants of the words into it. A single word may have different phonetic transcriptions.

Although adding variants to the lexicon increases the chance that one of the transcriptions of a word will match the corresponding acoustic signal, adding variants may increase lexical confusability. It has been shown in many studies that simply adding variants to the lexicon does not lead to improvements, and in many cases even causes deteriorations in WER. For instance, in the studies of Kessens *et al.* (2001), it has been shown that when the average number of variants per word in the lexicon exceeds roughly 2.5, the system with variants starts performing worse than the baseline system without variants.

Confusability in data-derived approaches is often introduced by errors in phonetic transcriptions. These phonetic transcriptions are used as the information source from which new variants are derived. Consequently, incorrect variants may be created. One commonly used procedure to alleviate this problem is to smooth the phonetic transcriptions by using decision trees (D-trees) to limit the observed pronunciation variation (Fosler-Lussier, 1999).

Forced recognition is employed in various ways in pronunciation variation modeling. The main objective of using forced alignment in pronunciation modeling is to clean up the transcriptions

in the training material, i.e. to obtain a more precise transcription given multiple transcriptions for the words in the lexicon.

This research models the Amharic pronunciation variation at the level of lexicon by adding the Amharic pronunciation variants and their transcription into it for grapheme based multiple pronunciation dictionary approach.

CHAPTER THREE

RELATED WORKS

In this chapter, we will present related works on pronunciation variation modeling to enhance the performance of ASR systems done in other languages and review the works done in Amharic ASR so far. To the best of our knowledge, there is no research work done for Amharic on pronunciation variation modeling.

3.1 Introducing Multiple Pronunciation in Spanish Speech Recognition Systems

Javier *et al.* (1998) describes variability in speech data as one of the major difficulties in speech recognition systems. The work has described that the lexicon is usually composed of a set of words and a single pronunciation for each of them and therefore suggests that specific techniques must be developed to handle them.

The work has first generated the standard pronunciations from the orthographic forms and applied a set of phonological rules to introduce pronunciation variation for each word in the lexicon. The rules were manually developed according to expert linguistic knowledge. Then an automatic grapheme-to-phoneme system was used to generate alternate pronunciations.

It incorporates the pronunciation alternative for both continuous and isolated word speech recognizers.

The continuous word speech recognizer has a training set size of 600 phrases trained by 4 speakers (2 male and 2 female). It used 100 phrases per speaker, uttered by the same 4 speakers for test set. It had a base dictionary size of 979 words (standard transcriptions only). It then extended the dictionary size to 1211 words (adding multiple pronunciations, resulting in a 23.7% increase in dictionary size).

The isolated word speech recognizer has a base dictionary size of 1175 words. It then extended the dictionary size to 1266 words resulting in a 7.7% increase in dictionary size.

The work has reported improvements of up to 20% decrease in error rate, for the continuous speech task, while for the isolated word recognition task, no significant effect has been found.

The results obtained from the work clearly show that the use of multiple pronunciations has a direct and significant impact on the performance of continuous speech recognition system.

3.2 Improving the Performance of a Dutch CSR by Modeling Within-Word and Cross-Word Pronunciation Variation

J.M. Kessens *et al.* (1999) describes how the performance of a continuous speech recognizer for Dutch has been improved by modeling pronunciation variation. It consists of adding pronunciation variants to the lexicon, retraining phone models and using language models to which the pronunciation variants have been added. First, within-word pronunciation variants were generated by applying a set of five optional phonological rules to the words in the baseline lexicon. Next, a limited number of cross-word processes were modeled, using two different methods. While the first method added cross-word variants to the lexicon, the second method added multi-words. Finally, the combination of the within-word method with the two cross-word methods is tested.

The starting point of the research was to measure the CSR's baseline performance since any improvements or deteriorations in recognition performance due to modeling pronunciation variation are measured compared to the results obtained using the baseline. Their baseline lexicon contained one pronunciation for each word. The lexicon was automatically generated using the Text- to-Speech (TTS) system developed at the University of Nijmegen. Phone transcriptions for the words in the lexicon were obtained by looking up the transcriptions in two lexica with proper names and a lexicon with words from mainly fictional texts. The grapheme-to-phoneme converter was employed whenever a word cannot be found in either of the lexica. There was also the possibility of manually adding words to a user lexicon if the words did not occur in either of the lexica and were not correctly generated by the grapheme-to-phoneme converter. In this way, transcriptions of new words were easily obtained automatically and consistency in transcriptions was achieved.

The general procedure for testing methods of modeling pronunciation variation consisted of three steps: the baseline lexicon was expanded by adding pronunciation variants; the multiple pronunciation lexicon was used to perform a forced recognition.

The method used to model within-word pronunciation variation is described as follows: pronunciation variants were automatically generated by applying a set of optional phonological rules for Dutch to the transcriptions in the baseline lexicon. The rules were applied to all words in the lexicon. All of the variants generated by the script were added to the baseline lexicon, thus creating a multiple pronunciation lexicon. The work modeled within-word variation using five optional phonological rules.

The two different methods used to model cross-word pronunciation variation are explained below:

Method 1 consisted of selecting the 50 most frequently occurring word sequences from the training material. Next, from those 50 word sequences, it chose those words which are sensitive to the cross-word processes: cliticization, contraction and reduction. The variants of these words were added to the lexicon.

The second method the work adopted for modeling cross-word variation was to make use of multi-words which are joined together and added as separate entities to the lexicon. These multi-words were added to the lexicon.

In addition to testing the within-word method and the two cross-word methods in isolation, the work also employed and tested the combination of the within-word method and cross-word method 1, and the combination of the within-word method and cross-word method 2.

The training and test material consisted of 25,104 utterances (81,090 words) and 6267 utterances (21,106 words) respectively for the experiments conducted using methods within word and cross word variation. The training material was used to train the HMMs and the LMs. Then the training corpus was expanded with 49,822 utterances leading to a total of 74,926 utterances (225,775 words).

The single variant training lexicon contained 1412 entries, which are all the words in the training material. Adding pronunciation variants generated by the phonological rules increased the size of the lexicon to 2729 entries (an average of about 2 entries per word). Adding 50 multi-words plus their variants led to a lexicon with 2845 entries. The maximum number of variants that occurs for a single word is 16.

The single variant test lexicon contained 1158 entries, which are all the words in the test corpus, plus a number of words which must be in the lexicon because they are part of the domain of the application. The testing corpus did not contain any out-of-vocabulary (OOV) words. This is because the work did not want the recognition performance to be influenced by words which could never be recognized correctly as they are not present in the lexicon.

The results of the study for modeling within-word variation are described as follows. Adding pronunciation variants to the lexicon leads to an improvement of 0.31% in WER compared to the baseline. When, in addition, retrained phone models are used, a further improvement of 0.22% is found. Finally, incorporating variants into the language model leads to an improvement of 0.15%. In total, a significant improvement of 0.68% was found for modeling within-word pronunciation variation.

The results of the study for modeling cross-word variation are described as follows: in contrast to the within-word method, adding variants to the lexicon leads to deteriorations of 0.25% and 0.33% WER for cross-word methods 1 and 2 respectively. Although for cross-word method 1, part of the deterioration is eliminated when retrained phone models are used, there is still an increase of 0.14% in WER compared to the baseline. Using retrained phone models for cross-word method 2 leads to a further deterioration in WER of 0.25%. Adding pronunciation variants to the language model leads to improvements of 0.30% and 0.54% for cross-word method 1 and 2 respectively. Compared to the baseline, the total improvement is 0.16% WER for cross-word method 1, and 0.30% WER for cross-word method 2.

The results of combining the within-word method with the two cross-word methods is described as follows: adding variants to the lexicon improved the CSR's performance by 0.05% and 0.04% for cross-word methods 1 and 2 respectively. Using retrained phone models improved the WER by another 0.12% for cross-word method 1, and 0.07% for cross-word method 2. Finally, the improvements were largest when the pronunciation variants are used in the language model too. For cross-word method 1, a further improvement of 0.44% is found, and for cross-word method 2, an even larger improvement of 0.67% is found.

For the combination of the within-word method with cross-word method 1, a total improvement of 0.61% is found compared to the baseline (SSS). For the same test condition, the combination of the within-word method with cross-word method 2 leads to a total improvement of 0.78%.

3.3 Review of works done so far on Amharic ASR

Kinfe (2002) developed sub-word based isolated word recognition systems for Amharic using HTK. The sub-word units used in the experiment are phones, triphones and CV-syllables. It considered 20 phones (out of 39) and 104 CV syllables, which are formed using the selected phones. Speech data of 170 words, which are composed of the selected sub-word units, have been recorded by 20 speakers (speech of 15 speakers for training and the remaining for testing). Speaker dependent phone-based and triphone-based systems have an average recognition accuracy of 83.07% and 78% respectively. Phone-based and triphone-based speaker independent systems have an average recognition accuracy of 72% and 68.4% respectively. In addition, a comparison of the different sub-word units revealed that the use of CV syllables has led to relatively poor performance.

Zegaye (2003) investigated the possibility of developing large vocabulary, speaker independent and continuous speech recognizer for Amharic language. The recognizer was developed using both phone-based and tri-phone based recognizers using HTK. For the training and testing of its recognizers, it used the speech data of 8000 sentences read by 80 people. In order to support the acoustic models, a bigram language model was constructed. In addition, pronunciation dictionary was prepared and used as an input. Since the recognizer was meant to recognize large vocabulary and continuous speech, phonemes were opted as the basic unit of recognition. The best recognizer was a tri-phone based recognizer which has 76.2% word recognition accuracy.

Martha (2003) explored the possibility of developing an Amharic speech input interface to command and control Microsoft Word. It required a speech recognizer and a communication interface between the recognizer and the application. 50 command words were selected from different menus (File, View, Insert, Tools, Table, Window, and Help), translated to Amharic and used to develop the prototype system. To develop and test the required Amharic speech recognition system, speech data were recorded from 26 people (10 female and 16 male) in the age range of 20 to 35. 76.9% of the recorded data were used to train the recognizers and the

remaining data were used for testing the performance of recognizers. To test the performance of the system, 18 randomly selected command words were given to 6 people (3 command words for each) and these people were asked to command Microsoft Word orally. The system performed 16 commands accurately and only two command words were wrongly recognized and thus Microsoft Word performed wrong actions.

Hussein and Gamback (2005) developed an Amharic speaker independent continuous speech recognizers based on an HMM/ANN hybrid approach. The model was constructed at a context dependent phone level with the help of the CSLU Toolkit. It used part of the data (5000 sentences) recorded by Solomon *et al.* (2005). The recognizers were tested with a total of 20 sentences read by 10 speakers (2 sentences each) who also read the training data. When the same recognizer was tested for another ten speakers who were not involved in the training, the recognition rate degraded. The best result obtained with this test data was 74.28% word recognition accuracy.

Solomon (2006) developed an Amharic speech corpus that can be used for various kinds of investigations in the development of ASR for Amharic. It explored various possibilities for developing a Large Vocabulary Speaker Independent Continuous Speech Recognition System for Amharic. The work assumed that, due to their highly regular Consonant Vowel (CV) structure, Amharic syllables lend themselves to be used as a basic recognition unit. Indeed, it has been able to show that syllable models can be used as a competitive alternative to the standard architecture that is based on triphone models. The acoustic model of the syllable-based recognizer requires 15MB memory. Together with the language model and use of speaker adaptation, it has a word recognition accuracy of 90.43% on the 5,000 words evaluation test set at a speed of 2.4 minutes per sentence. While the acoustic model of the triphone-based recognizer requires 38MB memory and has a word recognition accuracy of 91.31% on the same test set at a speed of 3.8 minutes per sentence. Although this is the state-of-the-art recognition performance in Amharic, it still sees the room for improvement because the word recognition accuracy of ASR in the technologically favored languages is approaching to 100%.

Solomon (2006) developed a multiple pronunciation model for Amharic speech recognition system based on the five dialects of Amharic language (Gonder, Gojam, Shewa, Menz and

Wello). The research was based on Hidden Markov Model (HMM) and was guided by the assumption that incorporating variations of pronunciation from the Amharic dialects in ASRS can improve performance of Amharic Speech Recognition Systems. The study used 731 and 129 utterances for training and testing respectively. The research found that using Amharic phone-based system with five emitting states multiple pronunciation dictionary together with set of acoustic model and language model obtained a word and sentence recognition accuracy of 85.54 %.

Summary

Although there are many Amharic ASR systems that are done by many researchers, the performance of Amharic ASRS is low compared to the performance of ASRS for technologically favored languages. The major reasons for the poor performance of Amharic ASRS are most of the pronunciation dictionaries are canonical, do not handle the problem of gemination of consonants and irregular realization of the six order vowel.

This research is different from other Amharic ASR researches in that it has an alternate pronunciation for 190 Amharic words that have more than one pronunciation in the corpus and tries to handle the problem of irregular realization of the six order vowels as the transliteration of words is mainly acquired from acoustic evidence.

CHAPTER FOUR

DESIGN AND IMPLEMENTATION

4.1 Description of the System Design

This research is mainly concerned with speaker-dependent continuous Amharic ASR system i.e. it is tailored to one speaker using only speech data from this particular speaker during training. It recognizes speech of a speaker whose speech is used during the development of the recognizer.

Even if we collect similar training and evaluation test sentences from four people (two male and two female), we have trained and tested each speaker's training and evaluation test sentences independently. This is mainly done to understand and analyze the effect of pronunciation variation on the performance of Amharic speech recognition systems and generalize from the results found.

Based on the pronunciation dictionary used for the research, we have designed three different ASR systems for Amharic. These are:

1. Grapheme based ASR with single pronunciation for every word in the lexicon. We refer this ASR system as ASR system with Type I pronunciation dictionary.
2. Grapheme based ASR with multiple pronunciations for some of the words in the lexicon where the multiple pronunciations are derived from Amharic linguistic literature and dictionaries. We refer this ASR system as ASR system with Type II pronunciation dictionary.
3. Grapheme based ASR with multiple pronunciations for some of the words in the lexicon where the multiple pronunciations are derived using Amharic linguistic literature, dictionaries and acoustic evidence. We refer this ASR system as ASR system with Type III pronunciation dictionary.

4.1.1 Description of Type I Pronunciation Dictionary

Type I pronunciation dictionary of this research is a canonical one that has a single pronunciation for each word in the corpus used for training and testing purpose. It transcribes

distinct 3309 Amharic words. The Amharic words in Type I pronunciation dictionary are transcribed blindly as the transliteration of the language grapheme using the transliteration scheme proposed by Sebsbie *et al.* (2004) as shown in Appendix A. Type I pronunciation dictionary does not consider both intra-speaker and inter-speaker variability. It contains only one transcription for each word in the lexicon. It also does not handle the variation of the pronunciation of the sixth order grapheme and the difference between geminated and non-geminated consonants.

4.1.2 Description of Type II Pronunciation Dictionary

Type II pronunciation dictionary of this research is an alternate one that transcribes distinct 3499 Amharic words. The Amharic words in Type II pronunciation dictionary are transcribed blindly as the transliteration of the language grapheme using the transliteration scheme proposed by Sebsbie *et al.* (2004) as shown in Appendix A. Its major difference with Type I pronunciation dictionary is that the former tries to consider both intra-speaker and inter-speaker variability from Amharic linguistic literature and dictionaries i.e. it contains alternate transcriptions for some of the words in the lexicon. But it does not handle the variation of the pronunciation of the sixth order grapheme and the difference between geminated and non-geminated consonants.

4.1.3 Description of Type III Pronunciation Dictionary

Type III pronunciation dictionary of this research is an alternate one that transcribes distinct 3499 Amharic words. Its major difference with Type II pronunciation dictionary is that the Amharic words in the former are transcribed manually from acoustic evidence. Since the words are transcribed from acoustic evidence, Type III pronunciation dictionary tries to handle the variation of the pronunciation of the sixth order grapheme and the difference between some of the geminated and non-geminated consonants. In Type III pronunciation dictionary, acoustic evidence transcription is extracted only from one of the four speakers and the knowledge extracted from this speaker is used to the other three speakers without analyzing whether the obtained acoustic evidence is valid to the other three speakers or not.

For example, if we take the Amharic word “ስታዲየም” (stadium), the transcription acquired using the transliteration scheme shown in Appendix A for Type I and Type II pronunciation

dictionaries is /stadiiyom/. But, the transcription acquired from acoustic evidence for Type III pronunciation dictionary is /sixtadiiyom/. Here, the epenthetic vowel “ኧ”/ix/ is inserted between the phones “ስ”/s/ and “ታ”/t / /a/. If we take another example that has gemination of consonants like “ብር” (Ethiopian currency), the transcription acquired for Type I and Type II pronunciation dictionaries is /br/. But, the transcription acquired from acoustic evidence for Type III pronunciation dictionary is /bixrr/. Here, the epenthetic vowel “ኧ”/ix/ is inserted between the phones “ብ”/b/ and “ር”/r / and the phone “ር”/r/ is geminated.

The main reason why the research implements the research using three different pronunciation dictionaries is that some of the words in Type I pronunciation dictionary do not match with the actual acoustic signal. This is one of the major reasons for the poor performance of Amharic speech recognition systems. Although Type II pronunciation dictionary tries to incorporate some words that have more than one pronunciation in it, there is still a problem of mismatch between the acoustic signal and the words in the lexicon. To solve this mismatch, the research uses acoustic evidence transcription in Type III pronunciation dictionary which has greatly enhanced the performance of the Amharic Speech Recognition Systems.

4.2 Major Components

Although there are different kinds of speech recognition systems, most have similar major components. Figure 1.1 shows the general architecture of ASR system. This research mainly focuses on the pronunciation model of ASR component. The research uses both knowledge based and data driven approaches to model the pronunciation variation. We will describe the major components as follows:

4.2.1 Feature Extraction

The feature extraction component of an ASR system maps the speech waveform into a sequence of feature vectors. This sequence of feature vectors is subsequently used to train acoustic model and decode input speech waveform.

To apply digital signal processing techniques to the speech waveform, the analogue wave form is firstly converted into a digital signal. This is done via sampling and quantization of the waveform. Once the digital signal has been obtained, a variety of techniques can be used to

extract features which are useful for the speech classification task. These speech analysis techniques usually assume that the characteristics of the speech signal are stationary over a short time period, typically of the order of 25 milliseconds. The resulting features are a representation of the speech signal over this short time period. Parameterization is performed not only for size reduction of the original speech signal data but also for pre-processing of that signal that fits into the classification stage. An important property of feature extraction is the suppression of information that is irrelevant for a correct classification such as information about speaker and transmission channel. Currently the most popular features are Mel Frequency Cepstral Coefficients MFCC. We have used MFCC for our experiment in developing our research. The speech signal is divided into frames of size 25ms with a frame rate of 10ms. We have used 12 MFCC coefficients and delta.

4.2.2 Pronunciation Dictionary

The development of a large vocabulary speaker dependent recognition system requires the availability of an appropriate pronunciation dictionary that encompasses a large number of words with their pronunciation. The pronunciation dictionary, which is the lexical model, is one of the most important blocks in the development of large vocabulary speaker dependent recognition systems. A pronunciation dictionary is a machine-readable transcription of words in terms of sub-word units. It specifies the finite set of words that may be output by the speech recognizer and gives, at least, one pronunciation for each.

In pronunciation variation research, one is usually confronted with two types of lexica: a canonical (or baseline) lexicon and a multiple pronunciation lexicon. A canonical lexicon contains the normative or standard transcriptions for the words; this is a single transliteration per word. A multiple pronunciation lexicon contains more than one transliteration variant per word, for some or all of the words in the lexicon.

We have prepared a canonical pronunciation for Type I pronunciation dictionary as shown in Table 4.1.

Table 4.1: Sample Type I pronunciation dictionary

Amharic words	English Equivalent	Transliteration	Canonical Pronunciation
ስታዲየም	Stadium	/stadiiyom/	s t a d i i y o m s p
ባጭር	In short	/bacxr/	b a c x r s p
በአምስት	By five	/beamst/	b e a m s t s p
በጥፍ	By double	/betxf/	b e t x f s p

We have prepared Type II pronunciation dictionary as shown in Table 4.2.

Table 4.2: Sample Type II pronunciation dictionary

Amharic words	English Equivalent	Alternate Transliteration	Alternate Pronunciation
ስታዲየም	Stadium	/stadiiyom/	s t a d i i y o m
ስቴዲየም		/stiediiyom/	s t i e d i i y o m
ባጭር	In short	/bacxr/	b a c x r
በአጭር		/beacxr/	b e a c x r
ባምስት	By five	/bamst/	b a m s t
በአምስት		/beamst/	b e a m s t
በጥፍ	By double	/betxf/	b e t x f
በእጥፍ		/beixtxf/	b e i x t x f

We have prepared Type III pronunciation dictionary from acoustic evidence as shown in Table 4.3.

Table 4.3: Sample Type III pronunciation dictionary

Amharic words	English Equivalent	Alternate Transliterations	Alternate Pronunciation
ስታዲየም	Stadium	/sixtadiiyom/	s i x t a d i i y o m
ስቴዲየም		/sixtiediiyom/	s i x t i e d i i y o m
ባጭር	In short	/bacxixr/	b a c x i x r
በአጭር		/beacxixr/	b e a c x i x r
ባምስት	By five	/bamsixt/	b a m s i x t
በአምስት		/beamsixt/	b e a m s i x t
በጥፍ	By double	/betxixf/	b e t x i x f
በእጥፍ		/beixtxixf/	b e i x t x i x f

4.2.3 Language Model

Language model is one of the most important knowledge sources for large vocabulary speaker dependent recognition systems. It incorporates knowledge of the language, such as its syntactic and semantic information in ASR by providing the probabilities that a word or string of words is/are followed by another word in a given text.

The way the words are connected to form sentences is modeled by the language model with the use of a pronunciation dictionary. The language model of our system is a statistical based language model. By assuming that the next word in the sequence depends only upon one previous word, we have created a bigram (2-gram) language model. Finally using this bigram language model, a network which contains words in the training data is created. The process of language modeling is shown in Figure 4.1.

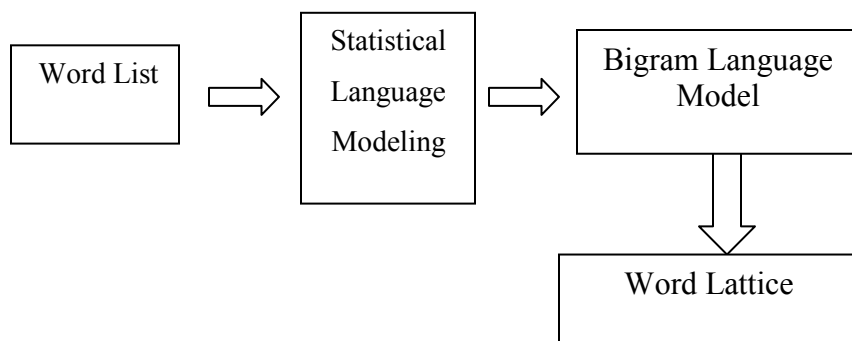


Figure 4.1: Block Diagram of the Language Modeling process.

The Language Model used in this study is a backed-off bigram language model. It is developed using the HTK tools HLstats and HBuild. HLstats is primarily used to generate the bigram probability matrix. It reads in a sorted file and generates a bigram language model. The probability matrix is prepared by using the word level transcriptions and statistics on the number of occurrences of each word and each combination of two words.

These statistics are then used to create backed-off bigram language models for the training and test using the HBuild tool which translates the gathered statistics into HTK Standard Lattice Format that are used for storing word models and multiple hypotheses from the output of a speech recognizer.

4.2.4 Acoustic Model

Acoustic models are statistical models which capture the correspondence between a short sequence of acoustic vectors and an elementary unit of speech. The elementary units of speech that are used in our research are phones. Phones are the minimal units of speech that are part of the sound system of a language.

We use HMM to model the acoustic component in this research. During training, the parameters for the models are estimated from recorded Amharic speech corpus which is transcribed at word level. We have created the acoustic model using audio recordings of speech and their text scripts and compiling them into a statistical representation of sounds which make up words. This is done through modeling the HMMs. The process of acoustic modeling is shown in Figure 4.2.

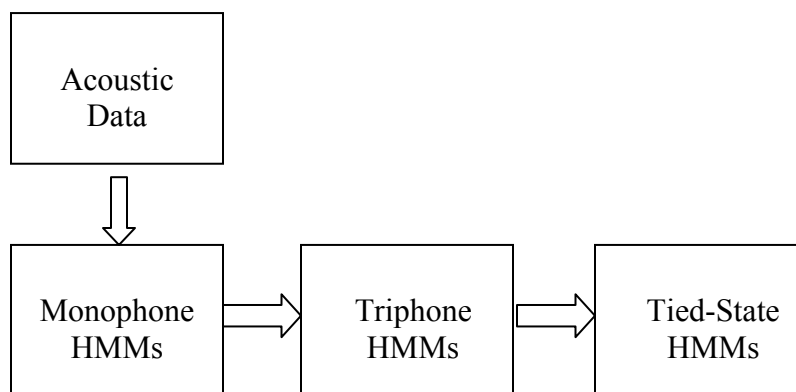


Figure 4.2: Block Diagram of the Acoustic Modeling process

4.3 HMM Topologies and Initialization

There is no general rule for the number of states of HMM model that can be taken as a rule of thumb for modeling syllable HMMs, especially, for Amharic Consonant Vowel (CV) syllables. It needs conducting an experiment to select the optimal model topology to have a good model for Amharic CV syllables as a recognition and the amount of the training speech data (Solomon, 2006).

Designing an HMM topology consists of choosing an appropriate number of states, the allowed initial states and the allowed transitions. This has to be done with proper consideration of the size of the unit of the recognition units. This is due to the fact that as the size of the recognition

unit increases and the size of the model (in terms of the number of states and number of transitions) grows, the model requires more training data.

For phone-based systems, a good topology to use is 3-state left-right with no skips. We initialize the model with the flat start method and use it for all monophones. The monophone models are then retrained, short-pause models are added and the silence model is extended slightly.

4.4 Basic Unit Definitions

Type I and Type II pronunciation dictionaries are transliterated by substituting each Amharic grapheme by the corresponding phoneme sequence as shown in Appendix A. For example, if we take the Amharic word “ምልክት” (symbol), we transliterate the grapheme “ም” by the corresponding phoneme /m/, “ል” by /l/, “ክ” by /k/ and “ት” by /t/ which gives us the phoneme sequence /m/ /l/ /k/ /t/. Type III pronunciation dictionary is on top of the surface form representation and is mainly transliterated using acoustic data evidence from one of the four speakers. We transcribe the above Amharic grapheme “ም” by phoneme /m/ and /ix/, “ል” by /l/, “ክ” by /k/ and /ix/ and “ት” by /t/ which gives us the phoneme sequence /m/ /ix/ /l/ /k/ /ix/ /t/.

4.5 Tied state

Having a set of monophone HMMs, the final stage of model building is to create context dependent triphone HMMs. This is done in two steps. Firstly, we convert the monophone transcriptions into triphone transcriptions and create a set of triphone models by copying the monophones and re-estimating them. Secondly, we tie similar acoustic states of triphones to ensure that all state distributions are robustly estimated.

Context-dependent triphones are made by simply cloning monophones and then re-estimating using triphone transcriptions. Then we tie states within triphone sets in order to share data and thus be able to make robust parameter estimates.

Although adding variants to the lexicon increase the chance that one of the transcriptions of a word will match the corresponding acoustic signal, adding variants may increase lexical confusability. It has been shown in many studies that simply adding variants to the lexicon does not lead to improvements, and in many cases even causes deteriorations in WER (Kessens *et al.*,

2001). Therefore, we limit the average number of variants per word in phase II and phase III of our lexicon to be 2.

We have trained the acoustic models on the basis of the output of forced alignment to obtain more accurate acoustic models and to achieve a better match between the Amharic multiple pronunciation lexicon and the Amharic acoustic models used during recognition. We also try to optimize the acoustic models so that they better match the Amharic transcriptions to reduce the mismatch between the Amharic acoustic models and the Amharic transcriptions.

4.6 Data Preparation

The first stage of the Enhanced Amharic Speech Recognition System research is data preparation. Speech data is needed both for training and testing. In this research, all of the speech data are recorded from scratch by four people (two male and two female) in the age range of 22 to 30. The test data provides the reference transcriptions against which the recognizer's performance can be measured. The training data are used in conjunction with the pronunciation dictionary to provide the initial phone level transcriptions needed to start the HMM training process. Before recording the data, we have defined a phone set, task grammar and constructed a dictionary that covers both training and testing. Since the research requires that arbitrary Amharic words be added to the recognizer, training data with good phonetic balance and coverage is needed. Here for convenience, the prompt scripts needed for training are taken from eight different Amharic sources.

4.6.1 Task Grammar

The goal of this research is to enhance the performance of Amharic Speech Recognition Systems. Thus, the recognizer must handle the different inputs uttered by a speaker. Examples of inputs might be

```
yeneqentie sixtadiiyom gixnbata sixlsa bemeto tetxenaqeqe  
axxede bedubay maraton ledixl kemiitxebequt atlietoc andwa nec  
txixrunesx beiedenbra ager aqwaracx wixddixr asxenefec
```

HTK provides a grammar definition language for specifying simple task grammars. It consists of a set of variable definitions followed by a regular expression describing the sentences to recognize. The suitable grammar for this research is

```

$word=yeneqemtie sixtadiiyom gixnbata sixlsa bemeto tetxenaqeqe|axxedede bedubay
maraton ledixl kemiitxebequt atletoc andwa nec|txixrunesx beiedenbra ager aqwaracx
wixddixr asxenefec|beiityopxya yenietbol sixport ixndiisfafa ixngixliiz
tixdegfalec|yemeqelie sixtadiiyom yemejemeriiyaw mixraf gixnbata tetxenaqeqe|haylu
betokiiyo maraton asxenefe|.....|txeyba bebosten maraton ledixl
tixtbeqalec ;
(NS_B (<$sentence>) NS_E)

```

where the vertical bars denote alternatives, NS_B and NS_E correspond to the silence that occurs just before the utterance we want to recognize and after, and sentence is the actual sentence to be recognized.

The HTK recognizer requires a sentence network to be defined using a low level notation called HTK Standard Lattice Format (SLF) in which each sentence is listed explicitly. This network is created automatically from the grammar using the HTK tool HParse. The lists of HTK commands with their parameters used in this research are shown in Appendix J.

4.6.2 Dictionary

The first step in building pronunciation dictionary is creating a sorted list of the words contained in the grammar, one per line, with pronunciations (the phonemes that make up a word).

To create the pronunciation dictionary in HTK, we have followed the following steps:

- We create a prompts file which is the list of sentences to be recorded;
- We derive a file from the prompts file which is a sorted list of the unique words that appear in the prompts file;
- We create the pronunciation dictionary by adding pronunciation information to the words in word list.

4.6.2.1 Prompts File

First, we need to create a prompts file that includes the grammar words to create a phonetically balanced corpus. This file basically contains the list of sentences to be recorded and the names of the audio files. The sample prompts file of the research is shown in Appendix H.

The first column of the prompts file contains the name of the audio file to be created, and the next column contains the text transcriptions of what to be recorded in the audio file.

4.6.2.2. Word List File

The HTK Perl script `prompts2wlist` takes the prompts file created, and remove the file name in the first column and print each word on one line into a word list file as shown in Appendix E.

4.6.2.3 Pronunciation Dictionary

We then add pronunciation information (i.e. the phonemes that make up the word) to each of the words in the lexicon, thus creating a pronunciation dictionary. HTK uses the `HDMAN` command to go through the word lists shown in Appendix E, and look up the pronunciation for each word in a separate lexicon file, and output the result in a pronunciation dictionary.

For HTK to compile the acoustic model, we need to make sure that we have at the very least 3 to 5 usage counts for each phone. If there are phones that only have one occurrence, we must add words that use these phones to the prompts file. The sample output of Type III pronunciation dictionary is shown in Appendix F.

4.6.3 Recording the Data

Before we begin, we make sure that the resident we were recording in was as quiet as possible. In addition, we turned off speakers while recording to avoid acoustic feedback in audio files.

The training and test data are recorded from 4 speakers (two male and two female) in the age range of 22-30. It is important to note that no analysis is made in determining the age range. Only availability of speakers was considered. The training and test sentences are recorded by speakers whose first language is Amharic.

The data were recorded using Audacity, which is free, open source software for recording and editing sounds, at a sampling rate of 48 KHz. Audacity is preferred over HSLab (HTK's recording tool) since the quality of speech data recorded by Audacity is better than that of HSLab. The microphone used was headset, close-speaking, noise canceling and monophone.

The recorded data was classified into training and test sets. The research uses 800 training and 100 evaluation test sentences.

4.6.4 Creating Transcription Files

Since HTK toolkit cannot process prompts file directly, we create a Master Label File (MLF) that contains a label entry for each line in the prompts file. We use the HTK script `prompts2mlf` that outputs each word on a single line and each utterance terminated by a single period on its own as shown in Appendix G.

Next we need to execute the `HLEd` command that expands the word level transcriptions to phone level transcriptions as shown in Appendix I.

4.6.5 Coding the Data

The final stage of data preparation is parameterizing the raw speech waveforms into sequences of feature vectors. Since HTK is not as efficient in processing `wav` files as it is with its internal format, we need to convert the audio `wav` files to another format called MFCC (Mel Frequency Cepstral Coefficients) which are more generally referred to as feature vectors.

We use the tool `HCopy` that automatically converts the `wav` files into MFCC vectors. We create a file containing a list of each source audio file and the name of the MFCC file it will be converted to, and use that file as a parameter to the `HCopy` command. To do this, a configuration file (`wav_config`) is needed which specifies all the conversion parameters. The settings of `wav_config` file are shown in Appendix D.

The configuration file specifies that source format is `wav` file, the target parameters are to be MFCC, the output should be saved in compressed format, and a cyclic redundancy check (CRC) checksum should be added.

4.7 Training

The second step of the enhanced Amharic speech recognizer is defining the topology required for each HMM by writing a prototype definition. HTK allows HMMs to be built with any desired topology. The purpose of the prototype definition is only to specify the overall characteristics and topology of the HMM. The actual parameters will be computed later by the training tools.

We will describe the creation of a well-trained set of single-Gaussian monophone HMMs. The starting point will be a set of identical monophone HMMs in which every mean and variance is identical. These are then retrained, short-pause models are added and the silence model is extended slightly. The monophones are then retrained.

4.7.1 Creating Flat Start Monophones

The first step in HMM training is defining a prototype model. The focus here is to create a model structure, the parameters are not important.

The topology of this research model consists of start and end states and three emitting states, using single Gaussian density functions. The states are connected in a left-to-right way, with no skip transitions.

We have chosen a five state topology because it is the state of art number of states for phoneme based ASR systems. The prototype model used in this research is adopted from Young *et al.* (2006) HTK book and is attached as it is in Appendix B.

The HTK tool HCompV scans a set of data files, compute the global mean and variance and set all of the Gaussians in a given HMM to have the same mean and variance. Executing the command HCompV replaces the zero means and unit variances by the global speech means and variances.

We then re-estimate the flat start monophones using the HTK command HERest. HERest loads re-estimate them using the MFCC files.

4.7.2 Fixing the Silence Models

In 4.7.1, we created HMM models that did not include short pause silence model which refers to the types of short pauses that occur between words in normal speech. However, we did create a silence model which are typically of longer duration, and occur at the end of a sentence.

Steve Young *et al.* (2006) mentions that the short pause model needs to have its emitting state tied to the centre state of the silence model i.e. we need to create a new short pause model that uses the centre state of silence, and then they both need to be 'tied' together. This is done by copying the centre state from the silence model and adding it to the short pause model, and then

running a special tool called HHED to tie the short pause model to the silence model so that they share the same centre state. By tying, it is to mean one or more HMMs share the same set of parameters.

4.7.3 Realigning the Training Data

Type II and Type III pronunciation dictionaries contain multiple pronunciations for some words. The phone models created so far can be used to realign the training data and create new transcriptions. This is done with a single invocation of the HTK recognition tool HVite that transform the input word level transcription to the new phone level transcription using the pronunciations stored in the dictionary. The key difference between this operation and the original word to phone mapping performed by HLEd in 4.6.4 is that the recognizer considers all pronunciations for each word and outputs the pronunciation that best matches the acoustic data.

4.7.4 Creating Tied-State Triphones

Given a set of monophone HMMs, the final stage of model building is to create context dependent triphone HMMs. This is done in two steps. Firstly, the monophone transcriptions are converted to triphone transcriptions and a set of triphone models are created by copying the monophones and re-estimating. Secondly, similar acoustic states of these triphones are tied to ensure that all state distributions can be robustly estimated.

4.7.4.1 Making Triphones from Monophones

In the dictionary file we created in 4.6.2, the pronunciation of a word was given by a series of phonemes (also called monophones - i.e. a single phone). To generate a triphone (i.e. a group of 3 phones) declaration from monophones, the "L" phone (i.e. the left-hand phone) precedes "X" phone and the "R" phone (i.e. the right-hand phone) follows it. The triphone is declared in the form "L-X+R".

We are therefore moving to an improved level of recognition accuracy. With such a model, we are not looking at the context of the monophone. The speech recognition engine is trying to match the sound that it has heard to a single phone.

With a triphone acoustic model, we are essentially looking for a monophone in the context of other monophones i.e. the one immediately before and the one immediately after. This greatly

improves recognition accuracy, because the speech recognition engine is looking to match a specific sequence of 3 sounds together (a triphone), rather than only one sound. Triphones reduce the possibility of error caused by confusing one sound with another, because we are now looking for a distinct sequence of 3 sounds.

We execute the HLEd command that converts the monophone transcriptions we created in 4.7.3 to an equivalent set of triphone transcriptions.

4.7.4.2 Making Tied-State Triphones

The phone models described so far were context independent. There was a big assumption that the phonemes are more or less the same in every situation. In reality, this is not the case as two neighboring phonemes may influence each other in Amharic.

To capture these effects, called co-articulations, models are needed that take into account the context of a phone. One way of modeling co-articulation effects is using triphones. Triphones model the context by taking in to consideration the left and right neighboring phones. If two phones have the same identity but different left or right context, they are considered as different triphones. The context-dependent triphones are prepared by simply cloning monophones and then re-estimating using triphones transcriptions.

4.8 Recognition

HTK provides a recognition tool called HVite that allows recognition using pronunciation dictionary, language models, and output a transcription file against which the recognizer's performance is analyzed.

4.9 Analysis

After the enhanced Amharic Speech recognizer is completed, it is necessary to evaluate its performance. The recognition network and dictionary have already been constructed, and test data has been recorded. Thus, all that is necessary is to run the recognizer and then evaluate the results using the HTK analysis tool HResults which uses dynamic programming to align the two transcriptions and then count substitution, deletion and insertion errors. Sample output of the recognizer's performance for speaker 1 for Type III pronunciation dictionary is shown in Figure 4.3.

```
Abraham@SOT-84 /home/voxforge/APhaseIII
$ HResults -I ../test3/testref.mlf monophones1 recout.mlf
===== HTK Results Analysis =====
Date: Tue Jun 14 16:01:37 2011
Ref : ../test3/testref.mlf
Rec : recout.mlf
----- Overall Results -----
SENT: %Correct=94.00 [H=94, S=6, N=100]
WORD: %Corr=99.21, Acc=99.21 [H=756, D=0, S=6, I=0, N=762]
=====
```

Figure 4.3: Recognizer's performance of Type III pronunciation dictionary for speaker1

As shown in Figure 4.3, the line starting with SENT indicates that of the 100 test sentences, 94 (94%) are correctly recognized. The following line starting with WORD gives the word level statistics and indicates of the 762 words in total, 756 (99.21%) were recognized correctly. There is 0 deletion error (D), 6 substitution error (S) and 0 insertion error (I).

CHAPTER FIVE

EXPERIMENTAL RESULT AND ANALYSIS

5.1 Recognizer Evaluation

As mentioned in data collection, 100 distinct Amharic sentences are recorded for the purpose of testing from four speakers for the three different Amharic pronunciation dictionaries. Before starting the test, the acoustic data files and word level transcriptions are generated for the test speech set. Acoustic data files that contain extracted speech features from the test set are generated by executing the HCopy tool.

Next, the acoustic data of the test set is input to the decoder and recognized using the Viterbi decoding algorithm. In HTK, this is done by executing the HVite tool. The inputs to the HVite tool are the acoustic model, acoustic feature of the test set and the pronunciation dictionary.

After generating these files, the performance of the Enhanced Amharic Speech Recognition System is measured by comparing the manually created transcription files that contain the transcriptions of the input utterances and the reference output transcription files that contain transcriptions of the recognized utterances. HResults matches each of the recognized and reference label sequences by performing an optimal string match using dynamic programming.

The designed ASR model is evaluated under the Word Error Rate (WER) and Sentence Error Rate (SER) criterion. The WER metric is the ratio of the number of recognition errors to the number of words in the reference. The number of recognition errors is calculated as the minimum number of insertion, substitution or deletion operations required to obtain the same string as the reference from the recognizer output. The general difficulty of measuring performance lies in the fact that the recognized word sequence can have a different length from the reference word sequence. The error rate is therefore derived at the word level instead of the phoneme level.

$$\text{WER} = \frac{\text{Substitutions} + \text{Deletions} + \text{Insertions}}{\text{\# words in reference}} \times 100$$

Sentence Error Rate (SER) is the number of sentences with at least one word error.

$$\text{SER} = \frac{\text{\# of sentences with at least one word error}}{\text{Total number of sentences}} \times 100$$

The starting point of this research is to measure the performance of Type I pronunciation dictionary for the four different speakers independently. This is done since any improvements or deteriorations in recognition performance due to modeling pronunciation variation are measured compared to the results obtained using this pronunciation dictionary.

The recognition results of the four speakers for Type I pronunciation dictionary are shown in Table 5.1.

Table 5.1: Recognizer's performance of Type I pronunciation dictionary

Speaker Code	% of words accurately recognized	% sentences accurately recognized
Speaker 1	94.23	61
Speaker 2	93.83	59
Speaker 3	93.76	58
Speaker 4	93.18	56
Average	93.75	58.5

As shown in Table 5.1, the percentage of sentences correctly recognized for Type I pronunciation dictionary are 61%, 59%, 58% and 56% for speaker1, speaker2, speaker3 and speaker4 respectively. The percentages of words accurately recognized are 94.23%, 93.83%, 93.73% and 93.18% for speaker1, speaker2, speaker3 and speaker4 respectively. The average percentage of words and sentences accurately recognized are 93.75% and 58.5% respectively.

The main reasons why the performance of the recognizer is low in Type I pronunciation dictionary is the transliteration of words in Type I pronunciation dictionary fail to incorporate cases such as epenthetic vowel insertion and gemination. Moreover, pronunciation variation is not captured in this pronunciation dictionary though the same word may be pronounced differently.

Table 5.2: Recognizer's performance of Type II pronunciation dictionary

Speaker code	% of words accurately recognized	% of sentences correctly recognized
Speaker 1	95.28	69
Speaker 2	94.75	67
Speaker 3	94	65
Speaker 4	93.36	62
Average	94.35	65.75

As shown in Table 5.2, the percentage of sentences correctly recognized for Type II pronunciation dictionary are 69%, 67%, 65% and 62% for speaker1, speaker2, speaker3 and speaker4 respectively. The percentages of words correctly recognized are 95.28%, 94.75%, 94% and 93.36% for speaker1, speaker2, speaker3 and speaker4 respectively. The average percentage of words and sentences accurately recognized are 94.35% and 65.75% respectively.

As shown in Table 5.2, the performance of Type II pronunciation dictionary leads to decrement of 1.05%, 0.92%, 0.24% and 0.18% WER for speaker1, speaker2, speaker3 and speaker4 respectively. It leads to decrement of 8%, 8%, 7% and 6% SER for speaker1, speaker2, speaker3 and speaker4 respectively. The average decrement of WER and SER are 0.6% and 7.25% respectively.

The main reason why the performance of Type I pronunciation dictionary is lower than Type II pronunciation dictionary is that the latter's pronunciation dictionary contains alternate pronunciations for some of the words in it which the former does not. Since different people may pronounce the same Amharic word differently, an alternate Amharic pronunciation dictionary improves the performance of Amharic ASRS.

Although there are both WER and SER reductions in Type II pronunciation dictionary, the decrement can be take is not significant and its performance is negligible compared to the performance of speech recognition systems for technologically favored languages.

An error analysis was done to identify the causes for the incorrect recognitions for the above two pronunciation dictionaries. When the incorrectly identified utterances are manually compared with the correct ones, on most of the utterances, only few phones happened to be

incorrectly identified. This is due to the fact that most of the words in manual utterances miss the epenthetic vowel “ኧ”/ix/. Very few utterances are incorrectly recognized due to gemination problem.

As shown in Table 5.1 and 5.2, there are variations in the percentage of words and sentences accurately recognized for each speaker.

Since Type II pronunciation dictionary has alternate pronunciations for only 190 Amharic words, the decrement in both WER and SER is not significant. Hence, the research uses acoustic evidence transcription for all words that are found in Type II pronunciation dictionary. Transcribing all words manually for speaker1 from acoustic evidence leads to word and sentence accuracy rate of 99.21% and 94% respectively as shown in Table 5.3. It leads to a further decrement of 3.93% WER and 25% SER for speaker1 as shown in Table 5.3.

Table 5.3: Recognizer’s performance of Type III pronunciation dictionary for speaker1

Speaker Code	% of words accurately recognized	% of sentences correctly recognized
Speaker 1	99.21	94

The acoustic evidence transcription of speaker1 is used for the other three speakers. As shown in Table 5.4, the percentages of sentences correctly recognized for Type III pronunciation dictionary are 88%, 83% and 81% for speaker2, speaker3 and speaker4 respectively. The percentages of words correctly recognized are 98.3%, 98.1% and 97.7% for speaker2, speaker3 and speaker4 respectively. It leads to a further decrement of 21%, 18% and 19% SER for speaker2, speaker3 and speaker4 respectively. The percentage of WER reductions are 3.55%, 4.1% and 4.34% for speaker2, speaker3 and speaker4 respectively. The average WER and SER acquired from acoustic evidence is 3.98% and 20.75% respectively.

Table 5.4: Recognizer's performance of Type III pronunciation dictionary

Speaker Code	% of words accurately recognized	% of sentences correctly recognized
Speaker1	99.21	94
Speaker 2	98.3	88
Speaker 3	98.1	83
Speaker 4	97.7	81
Average	98.33	86.5

CHAPTER SIX

CONCLUSION AND RECOMMENDATION

This paper describes a study to enhance the performance of a speaker dependent continuous Amharic ASR system. This section discusses the achievements of the research, drawbacks and possible future works to improve the work carried out by this research.

6.1 Conclusion

The primary objective of this research is to enhance the performance of speaker dependent continuous Amharic ASR system. As this is the first work on pronunciation variation modeling through both knowledge based and data driven approaches to enhance the performance of Amharic ASR, it can be said that the primary goal of the research has been achieved to a considerable and sufficient extent. The test results show that adding pronunciation variants to the lexicon using knowledge based approach has enhanced the performance of the Amharic ASR for the four speakers. The test results also show that the system achieves 94% sentence recognition accuracy and 99% word recognition accuracy for one speaker when the whole words in the lexicon are transcribed from acoustic evidence. Using the acoustic evidence transcription of this speaker to the other three speakers has also decreased both the WER and SER.

Of all 3309 words in Type I pronunciation dictionary, 190 of them have pronunciation variants. Incorporating these 190 pronunciation variants in Type II pronunciation dictionary has led to performance increment. This shows the impact of pronunciation variations on the performance of Amharic ASRS.

According to the error analysis, it shows that most of the incorrectly identified utterances differ from the correct ones only by few phones especially for Type I and Type II pronunciation dictionaries. A better n-gram based language model could potentially help reduce such error further.

Since this research's ASR system is trained only from four speakers (two male and two female), the above results are accurate only for the speakers who were involved in the training. It gives a

very low sentence and word accuracy for speakers who were not involved in training. This can be alleviated by training the system using a variety of human voices of speakers.

6.2 Recommendation

The performance of the continuous, speaker dependent Amharic Speech Recognition System can further be enhanced by adding pronunciation variants to all words that have pronunciation variants in the pronunciation dictionary. This is due to the fact that the research has got performance increment for the four speakers after adding pronunciation variants to words that have pronunciation variants in the pronunciation dictionary.

As mentioned in Experimental Result and Analysis, the speech recognizer's performance reaches to its highest level for one speaker when the words in the lexicon are transcribed from acoustic evidence. Therefore, we recommend that transcribing all the words for the other three speakers from acoustic evidence will enhance the performance of Amharic ASR for them.

In addition to these, the trained ASR model can be improved to build a speaker independent speech recognition system by training the system using a large speech corpus representing voices from various kinds of human voices. To gain this target, the speech corpus should consist of not only many speakers, but also should be representative in respect age group, gender, education levels, and dialects.

Finally, we recommend using Grapheme to Phoneme converter to transcribe all words in the multiple pronunciation dictionary and compare its performance with the acoustic evidence transcription performance of this research.

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Appendices

Appendix A: Transliteration Scheme

(Adopted from Sebsbie *et al.* (2004) work)

Amharic symbol	Etop font	Amharic Word Example	
ፕ	p	/profieser/	'professor'
ት	t	/tixmhixrt/	'education'
ክ	k	/kixb/	'circle'
ዕ	ax	/axda/	'credit'
ብ	b	/bixrr/	'Ethiopian Currency'
ድ	d	/dixmet/	'cat'
ግ	g	/gixl/	'private'
ኦ	px	/pxapxas/	'bishop'
ጥ	tx	/txixtx/	'cotton'
ጭ	cx	/cxixra/	'tail'
ቅ	q	/qixlliet/	'scandal'
ፍ	f	/fixndata/	'explosion'
ስ	s	/sixm/	'name'
ሽ	sx	/sxixnkurt/	'onion'
ሀ	h	/hixnd/	'India'
ጸ	xx	/xxixnu/	'Determined'
ች	c	/cxixgixnx/	'seedling'
ጅ	j	/jixb/	'hyena'
ግ	m	/mixn/	'what'
ን	n	/nixb/	'bee'
ኝ	nx	/monx/	'fool'
ል	l	/lixb/	'heart'
ር	r	/rixhruh/	'merciful'
ይ	y	/ayn /	'eye'
ወ	w	/wixsxa/	'dog'
ቫ	v	/nerv/	'nerve'
ዝ	z	/zixnb/	'fly'
ዥ	zx	/zxereggege/	'stripped off'

ከ	e	/deheye/	'he become poorer'
ከሁ	u	/mulu/	'full '
ከሁ	ii	/ iityopxya/	'Ethiopia'
ከ	a	/arat/	'Four'
ከ	ie	/meriet/	'Land'
ከ	ix	/ixnat/	'Mother'
ከ	o	/bota/	'Land'

Appendix B: The Prototype HMM

```
~o <vecSize> 25 <MFCC_0_D_N_Z>
~h "proto"
<BeginHMM>
  <NumStates> 5
  <State> 2
    <Mean> 25
      0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
    <Variance> 25
      1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0
  <State> 3
    <Mean> 25
      0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
    <Variance> 25
      1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0
  <State> 4
    <Mean> 25
      0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0
    <Variance> 25
      1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0 1.0
  <TransP> 5
    0.0 1.0 0.0 0.0 0.0
    0.0 0.6 0.4 0.0 0.0
    0.0 0.0 0.6 0.4 0.0
    0.0 0.0 0.0 0.7 0.3
    0.0 0.0 0.0 0.0 0.0
<EndHMM>
```

Appendix C: Fragment of the tree.hed script

```
RO 100.0 stats

TR 0

QS "R_NonBoundary" { ** }
QS "L_NonBoundary" { *- }
QS "R_Silence" { *+sil }
QS "R_Silence" { sil-* }
QS "L_Stops" { b-*, d-*, g-*, p-*, t-*, k-*, px-*, tx-*, *+q }
QS "R_Stops" { *+b, *+d, *+g, *+p, *+t, *+k, *+P, *+tx, *+q }
QS "L_Fricatives" { v-*, z-*, Z-*, f-*, s-*, sx-*, h-*, *+x }
QS "R_Fricatives" { *+v, *+z, *+zx, *+f, *+s, *+sx, *+h, *+x }
QS "L_Affricates" { j-*, C-*, *+cx }
QS "R_Nasal" { *+m, *+n, *+nx }
QS "L_Nasal" { m-*, n-*, nx-* }
QS "R_Liquid" { *+l, *+r }
QS "L_Liquid" { l-*, r-* }
QS "R_semivowels" { *+w, *+y }
QS "L_semivowels" { w-*, y-* }
QS "R_Vowel" { *+e, *+ii, *+o, *+u, *+a, *+ie, *+ix }
QS "L_Vowel" { e-*, ii-*, o-*, u-*, a-*, ie-*, ix-* }
QS "L_a" { a-* }
QS "R_a" { *+a }
QS "L_b" { b-* }
QS "R_b" { *+b }
.
.
QS "L_ix" { ix-* }
QS "R_ix" { *+ix }

TR 2

TB 350 "ST_a_2_" { ("a", "*-a+", "a+", "*-a").state[2] }
TB 350 "ST_b_2_" { ("b", "*-b+", "b+", "*-b").state[2] }
.

TB 350 "ST__4_" { ("", "*-+", "+", "*-").state[4] }

TR 1

AU "fulllist"
CO "tiedlist"

ST "trees"
```

Appendix D: The Configuration Parameter

```
SOURCEFORMAT=WAV
TARGETKIND = MFCC_0
TARGETRATE = 100000.0
SAVECOMPRESSED = T
SAVEWITHCRC = T
WINDOWSIZE = 250000.0
USEHAMMING = T
PREEMCOEF = 0.97
NUMCHANS = 26
CEPLIFTER = 22
NUMCEPS = 12
ENORMALISE = F
```

Appendix E: Sample Word List File

```
ab  
aba  
abal  
abalat  
abarii  
abat  
abay  
abeba  
abebe  
abedhu  
abedku  
abeje  
aberetac  
abietuta  
ablixtxa  
  
.  
  
.  
  
.  
  
zixq  
zixryawoc  
zon  
zonal  
zuriya
```

Appendix F: Sample Type III Multiple Pronunciation Dictionary

NS_B	[]	si l
NS_E	[]	si l
ab	[ab]	a b sp
aba	[aba]	a ba sp
aba l	[aba l]	a b a l sp
abalat	[abalat]	a b a l a t sp
abat	[abat]	a b a t sp
abay	[abay]	a b a y sp
abeba	[abeba]	a b e b a sp
abebe	[abebe]	a b e b e sp
abedhu	[abedhu]	a b e d h u sp
abedku	[abedku]	a b e d k u sp
abeje	[abeje]	a b e j e sp
aberetac	[aberetac]	a b e r e t a c sp
abietuta	[abietuta]	a b i e t u t a sp
ablixtxa	[ablixtxa]	a b l i x t x a sp
abnet	[abnet]	a b n e t sp
abrixham	[abrixham]	a b r i x h a m sp
	.	
	.	
zonal	[zonal]	z o n a l sp
zuriya	[zuriya]	z u r i i y a sp

Appendix G: Sample Master Label File

```
#!MLF!  
"/Sentence1.lab"  
yeneqemtie  
sixtadiiyom  
qixnbata  
sixlsa  
bemeto  
tetxenageqe  
.  
"/Sentence2.lab"  
axxede  
bedubay  
maraton  
ledixl  
kemiitxebequ  
atlietoc  
andwa  
nec  
.  
.  
.  
"/Sentence1000.lab"  
tekesasxu  
kixrsixtyan  
hono  
sayfata  
bebietu  
ixqubat  
yasqemetxe  
beixsrar  
yixqetxal  
.
```

Appendix H: Sample Prompts File

```
*/Sentence1 yeneqemtie sixtadiiyom gixnbata sixlsa bemeto tetxenaqeqe
*/Sentence2 axxede bedubay maraton ledixl kemiitxebequt atlietoc andwa nec
*/Sentence3 txixrunesx beledenbra ager aqwaracx wixddixr asxenefec
*/Sentence4 beiiyopxya yenietbol sixport ixndiisfafa ixngixliiz tixdegfalec
*/Sentence5 yemeqelie sixtadiiyom yemejemeriiyaw mixraf gixnbata tetxenaqeqe
*/Sentence6 haylu betokiiyo maraton asxeneffe
*/Sentence7 txeyba bebosten maraton ledixl tixtxebeqalec
*/Sentence8 yefiedieral maremiya bietoc sixport kixleb adiiis yesra askiiyaj komiitie meretxe
*/Sentence9 beqana yehiiyusten maratonn kixbre wesen bemasxasxal asxeneffe
*/Sentence10 haylie bemancester yegodana rucxa ledixl yixtxebeqal
*/Sentence11 bixzunesx bemumbay maraton ledixl tixtxebeqalec
*/Sentence12 fiedieriesxixnu baxxedeqacew memeriiyawoc kebaledrixsxa akalat gar teweyaye
*/Sentence13 haylie beniinyork gixmasx maraton wixddixr yixkafelal
*/Sentence14 hunenxaw bespien yeager aqwaracx wixddixr asxeneffe
*/Sentence15 belaliibela ketema talaqu rucxa tekahiede
*/Sentence16 keafriika haya amixst mixrtx sixportenxoc iityopxyawyan gixnbar qedem sixfra yixzewal
*/Sentence17 genzebie begient yeand sxii amixst meto mietixr rucxa asxenefec
*/Sentence18 siiraj berom yemaraton wixddixrn bebado ixgixru bematxenaqeq tariik asmezegebe
*/Sentence19 iityopxya ledoha wixddixr bemeseret defar yemiimera budixn tixlkalec
*/Sentence20 tawaqii atlietoc bemiigenxubet behawasa ketema yerucxa wixddixr yixkahiedal
*/Sentence21 leweldixya sixtadiiyom gixnbata yemiawl gebii masebaseb tejemere
*/Sentence22 xxegaye kebede belenden maraton asxeneffe
*/Sentence23 haylie yetalaqu mancester rucxa wixddixrn asxeneffe
*/Sentence24 qeneniisa bedohaw yedaymend liig wixddixr aysatefixm
*/Sentence25 iityopxya beolompiik lemesatef zixgjixt ixyadieregec new
*/Sentence26 beager aqef dereja beteleyayu yesport aynetoc sixltxena ixyetesetxe new
*/Sentence27 sixpien yealem wancxan yasxenefecbat qwas becixereta seba arat sxiih dolar awetac
*/Sentence28 lealem wancxa bekokebnet asixr teccawacoc tacxu
*/Sentence29 iityopxya be asixra sostenxaw yealem wetxatoc sxampiiyona yeamsixtenxa derejan agenxec
*/Sentence30 iitvooxva bemosko betekahiedu verucxa wixddixroc asxenefu
```

Appendix I: Sample Phone Level Transcription

```
"*/Sentence6.1ab"  
sil  
h  
a  
y  
l  
u  
sp  
b  
e  
t  
o  
k  
ii  
y  
o  
sp  
m  
a  
r  
a  
t  
o  
n  
sp  
a  
sx  
e  
n  
e  
f  
e  
sp  
sil  
.
```

Appendix J: List of HTK commands used

HTK command	Function
HParse	It generates a word level lattice file from a text file
HDMan	It prepares a pronunciation dictionary from one or more sources.
HLEd	It reads in a list of editing commands from an edit script file and then makes an edited copy of one or more label files.
HCopy	It automatically converts wav files into MFCC vectors
HCompV	It calculates the global mean and covariance of a set of training data.
HHed	It is mainly used for applying tyings across selected HMM parameters.
HERest	It is used to perform a single re-estimation of the parameters of a set of HMMs
HVite	It is a general-purpose Viterbi word recognizer. It s match a speech file against a network of HMMs and output a transcription for each.
HResults	It is the HTK performance analysis tool. It reads in a set of label files from a recognition tool and compares them with the corresponding reference transcription files.

HDMan Parameters

- -m: It merges pronunciations from all source dictionaries.
- -n monophones1: It outputs a list of all distinct phones encountered to file monophones1.
- -l dlog: It writes a log file to dlog. The log file will include dictionary statistics and a list of the number of occurrences of each phone.
- -w wordlist: It loads the word list stored in file wordlist.

HLEd Parameters

- -l '*': It causes a label file named xxx to be prefixed by the pattern"/xxx" in the output MLF file.

- -d dict: It reads a dictionary from file dict and use this for expanding labels when the EX command is used.
- -i mlf: It specifies that the output transcriptions are written to the master label file mlf.

HCopy Parameters

- -C wav_config: It specifies a configuration file wav_config

HCompV

- -C config: It calculates cluster-based mean/variance estimate.
- -f f: It creates variance floor macros with values equal to f times the global variance.
- -m: It updates the means and variances.
- -M hmm0: It outputs HMM macro model files in the directory hmm0.

HHed

- -H filename: It loads the file filename.
- -M dir: It outputs the files in the directory dir.

HVite

- -l dir: It specifies the directory to store the output label files.
- -b silence: It uses silence as the sentence boundary during alignment.
- -H file: It load HMM file.
- -i aligned.mlf: It outputs transcriptions to MLF aligned.
- -y lab: It sets the extension for output label files to lab.
- -I words.mlf: It loads the master label file words.mlf.

HResults:

- -I mlf: It loads the master label file mlf.

Appendix K: Amharic Text Corpus

1. የነቀምቴ ስታዲዮም ግንባታ 60 በመቶ ተጠናቀቀ
2. አፀደ በዱባይ ማራቶን ለድል ከሚጠበቁት አትሌቶች አንዱ ነች
3. ጥሩነሽ በኤደንብራ አገር አቋራጭ ውድድር አሸነፈች
4. በኢትዮጵያ የኔትቦል ስፖርት እንዲስፋፋ እንግሊዝ ትደግፋለች
5. የመቀሌ ስታዲዮም የመጀመሪያው ምዕራፍ ግንባታ ተጠናቀቀ
6. ኃይሉ በቶኪዮ ማራቶን አሸነፈ.
7. ጠይባ በቦስተን ማራቶን ለድል ትጠበቃለች
8. የፌዴራል ማረሚያ ቤቶች ስፖርት ክለብ አዲስ የሥራ አስኪያጅ ኮሚቴ መረጠ
9. ቢቃና የሂዩስተን ማራቶንን ክብረ ወሰን በማሻሻል አሸነፈ.
10. ኃይሌ በማንቸስተር የጎዳና ሩጫ ለድል ይጠበቃል
11. ብዙነሽ በሙምባይ ማራቶን ለድል ትጠበቃለች
12. ፌዴሬሽኑ ባጸደቃቸው መመሪያዎች ከባለድርሻ አካላት ጋር ተወያየ
13. ኃይሌ በኒው ዮርክ ግማሽ ማራቶን ውድድር ይካፈላል
14. ሁነኛው በስፔን የአገር አቋራጭ ውድድር አሸነፈ.
15. በላሊበላ ከተማ ታላቁ ሩጫ ተካሔደ
16. ከአፍሪካ 25 ምርጥ ስፖርተኞች ኢትዮጵያውያን ግንባር ቀደም ሥፍራ ይዘዋል
17. ገንዘቤ በጌንት የ1500 ሜትር ሩጫ አሸነፈች
18. ሲራጅ በሮም የማራቶን ውድድርን በባዶ እግሩ በማጠናቀቅ ታሪክ አስመዘገበ
19. ኢትዮጵያ ለዶሃ ውድድር በመሠረት ደፋር የሚመራ ቡድን ትልካለች
20. ታዋቂ አትሌቶች በሚገኙበት በሃዋሳ ከተማ የሩጫ ውድድር ይካሄዳል
21. ለወልድያ ስታዲዮም ግንባታ የሚውል ገቢ ማሰባሰብ ተጀመረ
22. ጸጋዬ ከበደ በለንደን ማራቶን አሸነፈ.
23. ኃይሌ የታላቁ ማንቸስተር ሩጫ ውድድርን አሸነፈ.
24. ቀነኒሳ በዶሃው የዳይመንድ ሊግ ውድድር አይሳተፍም
25. ኢትዮጵያ በአሎምፒክ ለመሳተፍ ዝግጅት እያደረገች ነው

26. በአገር አቀፍ ደረጃ በተለያዩ የስፖርት ዓይነቶች ሥልጠና እየተሰጠ ነው
27. ስፔን የዓለም ዋንጫን ያሸነፈችባት ኳስ በጨረታ 74ሺህ ዶላር አወጣች
28. ለዓለም ዋንጫ በኮከብነት 10 ተጫዋቾች ታጩ
29. ኢትዮጵያ በ13ኛው የዓለም ወጣቶች ሻምፒዮና የአምስተኛ ደረጃን አገኘች
30. ኢትዮጵያውያን በሞስኮ በተካሄዱ የሩጫ ውድድሮች አሸነፉ
31. የኢትዮጵያ ብሄራዊ የእግር ኳስ ቡድን አሰልጣኝ አንግሊዛዊ ነው
32. አመታዊ የአዲስ አበባ የክለቦች ብስክሌት ሻምፒዮና የፍፃሜ ውድድር ተካሄደ
33. የአዲስ አበባ የዱላ ቅብብል ውድድር ሰኔ ላይ ይካሄዳል
34. የአዳማ ዩኒቨርሲቲ ለታዳጊ ወጣቶች የስፖርት ስልጠና እየሰጠ ነው
35. የዓለም የወጣቶች አሎምፒክ ሻምፒዮና በሲንጋፖር እየተካሄደ ነው
36. ታሪኩ በበርሊን የሦስት ሺህ ሜትር አሸነፈ
37. ታዲሰ በሊዝበን ግማሽ ማራቶን አሸነፈ
38. ደቡብ አፍሪካ ያስተናገደችው የዓለም ዋንጫ ታላቅ ውጤት የተመዘገበበት እንደነበር ፊፋ ገለጸ
39. የመቀሌ ስታዲየም እድሳት እየተደረገለት ነው
40. መሠረት የዓመቱ ምርጥ አትሌትነት ምርጫን በመምራት ላይ ነች
41. የኢትዮጵያ እግር ኳስ ፌዴሬሽን ጠቅላላ ጉባኤ ተጀመረ
42. የጋራ ብልፅግና አገሮች የስፖርት ሻምፒዮና ተጀመረ
43. የዘንድሮው የታላቁ ሩጫ ውድድር ምዝገባ ተጠናቀቀ
44. መንግስቱ ወርቁ ከዚህ አለም በሞት ተለየ
45. አዝመራውና ሱሌ የታላቁ ሩጫ ውድድርን አሸነፉ
46. ኃይሌ ሩጫ የሚያቆምበትን ትክክለኛ ጊዜ እንደሚያውቀው ተናገረ
47. ፌዴሬሽኑ ብጥብጥ ባስነሱ ወገኖች ላይ ተገቢውን እርምጃ እንደሚወስድ ገለጸ
48. ኃይሌ የዓለማችን የምንጊዜም ምርጥ ወንድ አትሌትነትን ምርጫ በድምፅ ብልጫ እየመራ ነው
49. አቡትሪካ የአፍሪካ የዓመቱ ኮከብ ተጫዋቾች ተብሎ ተሸለመ
50. ሀገር አቀፍ የከፍተኛ ትምህርት ተቋማት የስፖርት ፌስቲቫል በጎንደር ተጀመረ
51. የክልሎች የስፖርት ውድድር ምርጥ ስፖርተኞችን ለማፍራት ያስችላል
52. ሀገር አቀፍ የከፍተኛ ትምህርት ተቋማት የስፖርት ፌስቲቫል ተጠናቀቀ

- 53. የኢትዮጵያ እግር ኳስ ፌዴሬሽን አስመራጭ ኮሚቴ ከፊፋ ይሁንታን አገኘ
- 54. ኢቫንደር ሆሊፊልድና ሳሚ ረታ አዲስ አበባ ገቡ
- 55. ጥሩነሽ ለዓለም ላውረስ ስፖርት አካዳሚ ሽልማት ታጩኙ
- 56. ሜሲ የዓለም የዓመቱ ኮከብ ተጫዋች ተብሎ ተሸለመ
- 57. ፌዴሬሽን እግር ኳስን ለማሳደግ ልዩ ትኩረት መስጠቱን አስታወቀ
- 58. አትሌት ጥሩነሽ በበስተን ሩጫ ትሳተፋለች
- 59. በፕሪሚየር ሊጉ ውድድር 27 ቡድኖች እንደሚካፈሉ ፌዴሬሽን አስታወቀ
- 60. አዲሱ የኢትዮጵያ እግር ኳስ ፌዴሬሽን ሥራውን በይፋ ጀመረ
- 61. የኢትዮጵያ እግር ኳስ ፌዴሬሽን ጠቅላይ ጉባዔ የአቋም መግለጫ አወጣ
- 62. በአፍሪካ ዋንጫ የጋና ቡድን ሶስተኛ ሆነ
- 63. አትሌት መሰረት ደፋር በ3 ሺህ ሜትር የቤት ውስጥ ውድድር አሸነፈች
- 64. የኦሮሚያ ክልል ስፖርት ሻምፒዮና በጅም ከተማ ተጀመረ
- 65. አትሌት ኃይሌ ከሊድስ ዩኒቨርሲቲ የክብር ዲግሪ ተሸለመ
- 66. የአማራ ክልልን ወክለው ላሸነፉ አትሌቶች የማበረታቻ ሽልማት ተሰጠ
- 67. አትሌት ጸጋዬ ከበደ በፓሪስ ማራቶን ውድድር ፈጣን ሰዓት በማስመዘገብ አሸነፈ
- 68. ቤጂንግ ለሚካሄደው ኦሎምፒክ ኢትዮጵያ አስፈላጊውን ዝግጅት በማድረግ ላይ ናት
- 69. በማይጨው ከተማ የተገነባው የአትሌቲክስ ማሰልጠኛ ማዕከል ተመረቀ
- 70. መብራት ኃይል ሐረር ቢራን ሁለት ለአንድ አሸነፈ
- 71. ኢትዮጵያ በ10ሺህ ሜትር የወንዶች ውድድር አሸነፈች
- 72. 16ኛው የአፍሪካ አትሌቲክስ ሻምፒዮና ደማቅ እንደነበር ተገለጸ
- 73. የኢትዮጵያ ብሔራዊ ቡድን ግማሽ ደርዘን ጎል አስቆጥሮ አሸነፈ
- 74. የአዲስ አበባ ቮሊ ቦል ፌዴሬሽን ያዘጋጀው ዓመታዊ ስፖርት ውድድር ተጠናቀቀ
- 75. ኢዛንባዬቫ የምርኩዝ ዝላይ ክብረወሰን ሰበረች
- 76. በደብረ ብርሃን ከተማ ሁለገብ ዘመናዊ ስታዲዮም እየተገነባ ነው
- 77. ፊፋ ኢትዮጵያን ከዓለም አቀፍ ወደድሮች አገደ
- 78. ጥሩነሽ የምሩፅን ታሪክ ተጋራች
- 79. ቶጎ በታሪኳ ለመጀመሪያ ጊዜ የኦሎምፒክ ሜዳልያ አገኘች

- 80. እግር ኳስ ፌዴሬሽን ለአስልጣኞች የሙያ ማሻሻያ ስልጠና ይሰጣል
- 81. የአልመዳ ጨርቃ ጨርቃ ፋብሪካ የእግር ኳስ ክለብ አባላት ተሸላሙ
- 82. ገለጽ ቡርቃ አሸነፈች
- 83. መሰረት በስቴትጋርት በተካሄደው ሦስት ሺህ ሜትር ሩጫ አሸነፈች
- 84. የአትሌት ጥሩነሽ ዲባባና ስለሽ ስህን የጋብቻ ስነ ስርዓት ተካሄደ
- 85. በኢትዮጵያ እግር ኳስ ፌዴሬሽን እና በፊፋ መካከል የነበረው አለመግባባት መፍትሄ አገኘ
- 86. በቤጂንግ አሎምፒክ ለተሳተፉ ሽልማት ተሰጠ
- 87. የታላቁ ሩጫ ውድድር ለስምንተኛ ጊዜ በአዲስ አበባ ከተማ ተካሄደ
- 88. ደረሰ በአሜሪካ የተካሄደውን የግጥም ማዘጋጀት ወደድር አሸነፈ
- 89. ጥሩነሽ ዲባባ እና ቀነኒሳ በቀለ ለዓለም ምርጥ አትሌትነት ታጩ
- 90. ቅዱስ ጊዮርጊስ የአሸናፊዎች አሸናፊ ዋንጫን ለኢትዮጵያ ቡና እንዲመልስ ተወስነበት::
- 91. አበበ ድንቁሳ በናይጄሪያ የማውንቴን ሬስ ውድድር አሸነፈ
- 92. የእግር ኳስ ሊግ ኮሚቴን ለማቋቋም በሚያስችል ረቂቅ ደንብ ላይ ውይይት እየተካሄደ ነው
- 93. በኢትዮጵያ እግር ኳስ ፌዴሬሽን እና በፊፋ መካከል የተካሄደው ውይይት ያለ ውጤት ተጠናቀቀ
- 94. አትሌት ጥሩነሽ በበርሚንግሃም የቤት ውስጥ ውድድር ትካፈላለች
- 95. የባህራይን አትሌቶች በኢትዮጵያ ልምምድ ያካሂዳሉ
- 96. አትሌት ብርሃኔ በዱባይ ማራቶን ያገኘችውን የወርቅ ሜዳሊያ ለእንጦጦ ማሪያም ሰጠች
- 97. የኢትዮጵያ ብሄራዊ ቡድን በናይጄሪያው አቻው ተሸነፈ
- 98. ኢትዮጵያ ቡና ደደቢትን አሸነፈ
- 99. ተስፋየ ታፈሰ ኮከብ ጎል አግቧ ሆነ
- 100. የአዲስ አበባ ስታዲየም እየታደሰ ነው
- 101. በኢትዮጵያና በዓለም ባንክ መካከል የብድር ስምምነቶች ተፈረሙ
- 102. የአዲስ ንግድ ለእድገት ባዘር ተከፈተ
- 103. ማህበሩ ከ1ሺህ 500ለሚበልጡ ሰዎች የሰራ እድል አስገኝቷል ተባለ
- 104. የኩታበር ወረዳ አርሶ አደሮች በምግብ እህል ራሳቸውን ቻሉ
- 105. በጎንደር ከተማ ጥሬ ዕቃ ማምረቻ ሊቋቋም ነው
- 106. ከ17 ሺህ ኩንታል በላይ የጓሮ አትክልት ምርት ተሰበሰበ

- 107. በአርሲ ዞን ከ145 ሺህ ኩንታል ምርጥ ዘር ተገኝቷል
- 108. በቦንኬ ወረዳ 400 ሄክታር መሬት በአፕል ተክል ተሸፍኗል
- 109. የቤቶች ልማት ፕሮጀክት ለ170 ሺህ ዜጎች ሥራ መፍጠሩን ሚኒስቴሩ አስታወቀ
- 110. በኢትዮጵያና ሱዳን መካከል ያለው የንግድ ግንኙነት ተጠናክሮ ቀጥሏል
- 111. የአንግሊዝ ባለሀብቶች በኢትዮጵያ ኢንቨስት ለማድረግ ፍላጎት እንዳላቸው ገለጹ
- 112. ሰባት የልማት ድርጅቶችን ወደ ግል ይዞታ ለማዘዋወር ታቅዷል
- 113. ከደቡብ ክልል ከ43 ሺህ ቶን የሚበልጥ ቡና ለማእከላዊ ገበያ ቀረበ
- 114. የአዲስ አበባ መሪ ፕላን እየተከለሰ ነው
- 115. ኢትዮ ቴሌኮም አዲስ ስምና ሎጎ ይፋ አደረገ
- 116. መቀሌ ዩኒቨርሲቲ ከጃፓን መንግስት ድጋፍ አገኘ
- 117. የኢትዮጵያ አየር መንገድ ወደ ሐንግዝሁ አዲስ በረራ ጀመረ
- 118. ዓባይ ባንክ በደሴ ከተማ አራተኛ ቅርንጫፍ ከፈተ
- 119. የደቡብ ወሎ ነዋሪዎች የቁጠባ ባህል እያደገ ነው ተባለ
- 120. በነቀምቱ ከተማ ለባለሀብቶች ፈቃድ ተሰጠ
- 121. በአፋር ክልል 968 ሺህ ኩንታል ምርት ተገኘ
- 122. የአሮሚያ ኢንተርናሽናል ባንክ በፍቼ ከተማ ቅርንጫፍ ከፈተ
- 123. በድሬደዋ የጨርቃጨርቅ ፋብሪካ ግንባታ ተጀመረ
- 124. ወርቅ ከቡና ቀጥሎ ለአገሪቱ የውጭ ምንዛሪ ከፍተኛ ገቢን እያስገኘ ነው
- 125. ሸራተን 15 ቢሊዮን ብር የማስፋፊያ ግንባታ ሊያካሄድ ነው
- 126. ሕንድ የዜጎችን የምግብ ዋስትና ለማረጋገጥ የሚያስችል ሕግ ለፓርላማ ታቀርባለች
- 127. የጎንደር ግብርና ምርምር ማዕከል የበግ ማድለብ ቴክኖሎጂ እያስፋፋ ነው
- 128. ደደቢት ማይክሮ ፋይናንስ ተቋም አንድ ቢሊዮን ብር ብድር ሰጠ
- 129. ዓለም አቀፍ የንግድ ትርኢት ተከፈተ
- 130. በአሮሚያ ለግንባር ቀደም አርሶ አደሮች ሽልማት ተሰጠ
- 131. በአዳማ በልማት ግቦች ላይ ያተኮረ የምክክር ኮንፍራንስ ተካሄደ
- 132. የአፋር ክልል የእድገትና ትራንስፎርሜሽን እቅድ ለውይይት ቀረበ
- 133. መንግስት ባወጣው ፖሊሲ የአርብቶ አደሩ ህይወት እየተለወጠ ነው

134. የኢትዮጵያ ንግድ ባንክ በሰሜን ጎንደር በደልጊ ከተማ ቅርንጫፍ ከፈተ
135. በጅንካ ከተማ የአርብቶ አደሮች ቀን ተከበረ
136. ሰፋሪ አርሶ አደሮች ከ500ሺህ ኩንታል የሚበልጥ ምርት ሰበሰቡ
137. በምስራቅ ጎጃም በግ ሚዳቋ ወለደች
138. መንግሥት ሲሚንቶ ከውጭ ማስገባቱን ሊያቆም ነው
139. የጎንደር ገጠር መንገድ ጥገና ጽህፈት ቤት የመንገዶች ጥገና አከናወነ
140. የኢትዮጵያ አየር መንገድ የአውሮፓ በረራውን በማስፋፋት ላይ ነው
141. የጃፓን አምባሳደር በጋምቤላ ክልል ጉብኝት አደረጉ
142. ኢትዮጵያ የሻይ ቅጠል ምርቷን ልታሳድግ ነው
143. በትግራይ ደቡባዊ ዞን የአፈርና ውሃ ጥበቃ ሥራ እተከናወነ ነው
144. በትግራይ ምስራቃዊ ዞን ለልማት ስራ ገንዘብና የምግብ እህል ተመደበ
145. በሰሜን ጎንደር የሰፈራ ፕሮግራም ውጤታማ መሆኑ ተገለጸ
146. በንብ ማኑብ የተሰማሩ አርሶ አደሮች ትርፍ አገኙ
147. ብሄራዊ ሎተሪ 20 ሚሊዮን ብር የተጣራ ትርፍ አገኘ
148. በደቡብ ክልል በግብርናው ዘርፍ ከፍተኛ ውጤት ተመዘገበ
149. አዲስ የአዲት ሕግ በመዘጋጀት ላይ ነው
150. በደባርቅ ከተማ የውሃ ግንባታ ጥናት እየተካሄደ ነው
151. በደቡብ ክልል አዲስ ስምራትና የታሪፍ መመሪያ እየተዘጋጀ ነው
152. የኢትዮጵያ አየር መንገድ የስታር አሊያንስ ሕብረት አባል ሆነ
153. በትግራይ ክልል የተካሄደው የወጣቶች የስራ ዘመቻ ውጤታማ ሆነ
154. ቻይና ዓሣን በማምረት ቀዳሚ አገር ሆነች
155. በሰሜን ወሎ ዞን የእንስሳት መኖ ልማት በመካሄድ ላይ ነው
156. በቤንች ማጂ ዞን ከ7 ሚሊዮን በላይ የዛፍ ችግኝ ተተክለ
157. የአንፍራንዝ ወንዝ ድልድይ ተጠግኖ ለትራፊክ ክፍት ሆነ
158. ብሄራዊ የቤተ-ሙከራ ማህበር ተመሰረተ
159. መንግስት ለውሃ ሴክተር ከፍተኛ ትኩረት ሰጥቶ እየሰራ ነው
160. የዶላርና የሌሎች አለም አቀፍ ገንዘቦች የምንዛሪ ዋጋ አደገ

- 161. በአማራ ክልል የሰፈሩ አርሶአደሮች በምግብ ራሳቸውን ቻሉ
- 162. በሰሜን ጎንደር ዞን በርካታ ኩንታል የጥጥ ምርት ተሰበሰበ
- 163. የነቀምት ዘላቂ የውሃ ፕሮጀክት ዘንድሮ ይጠናቀቃል
- 164. በጎንደር ከተማ የሚገኘው ጸሐይ ዩኒቨርሲቲ የትርፍ ክፍፍል አካሄደ
- 165. በተያዘው የበጀት ዓመት 42 የመንገድ ፕሮጀክቶች ግንባታ ስራ ይጀመራል
- 166. በጎንደር ከተማ የተቋቋመው የፈሳሽ ናይትሮጂን ማምረቻ 4-ብሪካ ስራውን ጀመረ
- 167. በጋምቤላ ክልልበርካታ የውሃ ተቋማት ሊገነቡ ነው
- 168. በድሬደዋ ለ112 ፕሮጀክቶች የኢንቨስትመንት ፈቃድ ተሰጠ
- 169. በሰሜን ጎንደር ዘመናዊ የሰሊጥ ግብይት ስርዓት ተጀመረ
- 170. የኢትዮጵያ ንግድ ባንክ 229ኛ ቅርንጫፉን በካማሽ ከተማ ከፈተ
- 171. ማህበሩ በ140 ሚሊዮን ብር የመስኖ ልማት ሊያካሂድ ነው
- 172. በመቀሌ ከተማ የተቋቋመው የፕላስቲክ ቱቦ ማምረቻ 4-ብሪካ ስራ ጀመረ
- 173. የአዲስ አበባ ቴክኖሎጂ ኢንስቲትዩት በይፋ ተመረቀ
- 174. በኢትዮጵያ የዓለም ምግብ ቀን ጥቅምት 6 ይከበራል
- 175. በአፋር በማህበር የተደራጁ ወጣቶች አሳ ማስገር ጀመሩ
- 176. በቡሬ ከተማ የአስፓልት መንገድ ስራ ተጀመረ
- 177. ዓለም አቀፍ የውተት ቀን በጎንደር ከተማ ተከበረ
- 178. በኢትዮጵያ ለምግብነት የሚውሉ 120 የዱር ተክል ዝርያዎች ተመዘገቡ
- 179. የኢትዮጵያ አየር መንገድ ወደ ቶሮንቶ በረራ ጀመረ
- 180. በአዲስ አበባ 18 ሺ ቤቶች በግንባታ ላይ ናቸው
- 181. በአክሱም በማር ምርት ላይ ያተኮረ አውደ ጥናት ተካሄደ
- 182. የደቡብ ወሎ አርሶ አደሮች የግብርና ፍላጎት እየጨመረ ነው
- 183. በአፍሪካ በገቢዎችና ጉምሩክ አሰራሮች ላይ የሚወያይ ዐውደ ጥናት ተጀመረ
- 184. በወሊጋ ከማር ምርት ከ21 ሚሊዮን ብር የሚበልጥ ገቢ ተገኘ
- 185. የሬዲዮ 4ና የምስረታ በዓል በጎንደር ከተማ ተከበረ
- 186. በትግራይ ክልል የአካባቢ ጥበቃ ስራ ክፍተኛ ውጤት እያሰገኘ ነው
- 187. የያቤሎ ሜጋ መንገድ ከ770 ሚሊዮን ብር በሚበልጥ ወጪ ሊገነባ ነው

188. ከወላይታ ዞን ቡና ቆዳና ሌጦ ለማእከላዊ ገበያ ቀረበ
189. የአዲስ አበባ ቦሌ ዓለም አቀፍ ኤርፖርት የዓመቱን ምርጥ ሽልማት አገኘ
190. መንግሥት ለውሃ ሃብት ልማት ዘርፍ ትኩረት ሰጥቶ እየንቀሳቀሰ ነው
191. ምስራቅ ወለጋ ዞን ከ13 ሚሊዮን የሚበልጥ ኩንታል ምርት ይጠበቃል
192. ከጅማ ዞን 35 ሺህ ቶን ቡና ለማእከላዊ ገበያ ይቀርባል
193. በግብርና ኢንዱስትሪ ልማት ላይ ያተኮረ አውደ ጥናት በአሰላ ከተማ ተካሄደ
194. የአማራ ብድርና ቁጠባ ተቋም ሁለት ህንፃ እያስገነባ ነው
195. ከደቡብ ክልል በሩብ ዓመቱ ከ234 ሚሊዮን ብር ገቢ ተሰበሰበ
196. በሰሜን ሸዋ ዞን ከ53 ሺ ሄክታር የሚበልጥ መሬት በመሰኖ ሊለማ ነው
197. በሱማሌ ክልል የዝናብ ውሃ ለማጠራቀም ሁለት ግድብ እየተሰራ ነው
198. በዲላ ከተማ ዘመናዊ የገበያ ማእከል ሊገነባ ነው
199. በዓፋር ክልል የሶስት አስፋልት መንገዶች ግንባታ ተጀመረ
200. በሃዋሳ ክልል የሶስት አስፋልት መንገዶች ግንባታ ተጀመረ
201. ኢህአዴግ የ2002ቱን ምርጫ አሸነፈ
202. ያልተመጣጠነ የሕዝብ ቁጥር መጨመር በአገር እድገት ላይ ተጽእኖ ያስከትላል
203. ለህጻናትና ወጣቶች የእእምሮ ጤንነት ትኩረት መስጠት ያስፈልጋል ተባለ
204. የደብረ ብርሀን መምህራን ማሰልጠኛ ተቋም ወደ ኮሌጅ አደገ።
205. የኢትዮጵያ መምህራን ከማህበራቸው ጋር ያላቸውን ግንኙነት ማጠናከር ይጠበቅባቸዋል
206. ወርልድ ቪዥን ኢትዮጵያ ያሰራቸውን የጤና ተቋማት ለተጠሚዎች አስረከበ ።
207. ፋርሚድ የመድኃኒትና የሕክምና መገልገያ አቅርቦቱን አሻሻለ
208. ባህሪን በኢትዮጵያ ኤምባሲዋን መክፈት ትሻለች
209. ፕሬዚዳንት ግርማ ወልደጊዮርጊስ ከሩዋንዳ ተመለሱ
210. በጠቅላይ ሚኒስትር መለስ ዜናዊ የተመራ የልዑካን ቡድን ጅቡቲ ሄደ
211. ወልማ ያሰራቸው አራት ፕሮጀክቶች ለአገልግሎት በቁ
212. ሴቶች ከድህነት ካልወጡ ለእድገት የሚደረገው ጥረት ፈተና ይገጥመዋል ተባለ
213. የሐረር ከተማን የሚጎበኙ የውጪ ሃገር ቱሪስቶች እየተበራከቱ ነው
214. በዲላ ኮሌጅ ቦምብ ፍንዳታ እጃቸው አለበት ተብለው የተጠረጠሩ ተያዙ
215. ኢትዮጵያውያን አገርና ሕዝብን ከድህነት እንዲያላቅቁ ጥሪ ቀረበ

- 216. የአርብቶ አደሩን የልማት ራዕይ ለማሳካት የሚያግዙ ሥራዎች መከናወናቸው ተገለፀ
- 217. በምስራቅ ወለጋ ለሠፋሪዎች የእርሻ በሬ እየተከፋፈለ ነው
- 218. የሰማዕታት አጽም በክብር አረፈ
- 219. በመስኖ ልማት ከፍተኛ አስተዋጽኦ ያደረጉ ገበሬዎች ተሸለሙ
- 220. ጠቅላይ ሚኒስትር መለስ ከፕሬዚዳንት አራፋት የተላከ መልዕክት ተቀበሉ
- 221. በራያ አዘቦ ወረዳ ከፍተኛ የምርት መቀነስ ደርሷል ተባለ
- 222. የ35 ማህበራዊ አገልግሎት መስጫ ተቋማት ፕሮጀክቶች ግንባታ ተጠናቅቋል
- 223. በሻዕቢያ ጦርነት ለተፈናቀሉ ወገኖች ከ14 ሚሊዮን ብር በላይ ተሰጠ
- 224. ለድርቅ ተጎጂዎች የሚሰጠው እርዳታ ቀጥሏል
- 225. የኢትዮጵያ ምርጥ ዘር ድርጅት ሠራተኞች ከደመወዛቸው 10 በመቶ ለመስጠት ተስማሙ
- 226. በአምባላጌ ወረዳ ለሚገኙ ተረጂዎች የአንድ ወር ቀለብ እየተከፋፈለ ነው
- 227. ስፔን በኢትዮጵያ ለተከሰተው ድርቅ ተጨማሪ እርዳታ ትሰጣለች
- 228. የኮንስትራክሽን ኤግዚቢሽን ተከፈተ
- 229. የሱዳን የእርስ በርስ ግጭት በሰላም የሚፈታበት ጊዜ መቃረቡ ተገለጸ
- 230. የአፍሪካ ኅብረት ሁለተኛው የሚነስትሮች ምክር ቤት ስብሰባ ተጀመረ።
- 231. የትምህርት ተቋማትን የኢንፎርሜሽን ቴክኖሎጂ ተጠሚ የሚያደርግ ስራ እየተከናወነ ነው።
- 232. በውርጃ ምክንያት በእናቶች ላይ የሚደርሰው ሞት በልማት ላይ ተፅእኖ ያሳድራል
- 233. የአድዋ 107ኛው በዓል በነገው እለት በመላው ኢትዮጵያ ተከብሮ ይወላል
- 234. ከአውሮፓ መምጠቱን የሚገልጥ ቀለበት በአግሩ ላይ ያሰረ ወፍ ሞቶ ተገኘ
- 235. የኢትዮጵያ ቀን በአሜሪካ አህዮ እስቴት ተከበረ
- 236. የፕሬስ ነፃነት እንዲጠናከር አስፈላጊው ርብርብ ሁሉ ይደረጋል
- 237. የኢትዮጵያ ሰማዕታት 66ኛ ዓመት በመላው ኢትዮጵያ ታስቦ ዋለ
- 238. ያለእድሜያቸው በስራ የተሰማሩ ህፃናትን ሁኔታ የሚሳይ መረጃ ይፋ ሆነ
- 239. የአፍሪካ ልማት ባንክ ለኢትዮጵያ የሚያደርገው ድጋፍ እየጨመረ መጥቷል
- 240. በመላ ኢትዮጵያ ስለሴቶች ልጆች ትምህርት አስፈላጊነት ትምህርት ሊሰጥ ነው
- 241. ዩክሬን በኢትዮጵያ ኤምባሲ ለመክፈት ወሰነች

- 242. በሳይንስና ቴክኖሎጂ ዘርፍ የላቀ አስተዋጽኦ ያበረከቱ ሶስት ተማራማሪዎች ተሸለሙ
- 243. ያለእድሜአቸው ሊዳሩ የታጩት ሴቶች ጋብቻቸው እንዲቀር ተደረገ
- 244. የኢህአዴግ ምክር ቤት ስብሰባ ተጠናቀቀ
- 245. 93 ኢትዮጵያውያን ከሊቢያ ወጡ
- 246. የአዲስ አበባ መሪ ፕላን እየተከለሰ ነው
- 247. የኮንሶ የባህል ማዕከል አገልግሎት ጀመረ
- 248. የኢትዮጵያ የባህል ምሽት ለንደን ውስጥ ተከበረ
- 249. በጋምቤላ ክልል የሴቶች የትምህርት ተሳትፎ እያደገ ነው ተባለ
- 250. የውጭ ጉዳይ ሚኒስቴር ኢትዮጵያውያንን ከቤንጋሊ ማስወጣት ጀመረ
- 251. የቤኒሻንጉል ጉሙዝ ክልል ምክር ቤት ጉባኤ ተጠናቀቀ
- 252. በዓለም ትልቁ የመጻሕፍት ትርጉሚያት በበርሊን ተከፈተ
- 253. ዓባይ ባንክ በደሴ ከተማ አራተኛ ቅርንጫፍ ከፈተ
- 254. የጎንደር ዩኒቨርሲቲ 61 ጥናትና ምርምር እያካሄደ ነው
- 255. የጅንካ ዞና ሀሰፒታል ለአይን ህመማን ነጻ ሕክምና አደረገ
- 256. በመቀሌ ከተማ የተንቀሳሽ ስልክ አገልገሎት ጀመረ
- 257. የኢትዮጵያ ህንድ የባህል ግንኙነት ተጠናክሯል ተባለ
- 258. የሙስና ወንጀል ፈጽመዋል የተባሉ አስር ሰዎች ታሰሩ
- 259. ኅብረተሰቡ ለአዕምሮ ሕመማን እንክብካቤ ማድረግ እንዳለበት ተገለጸ
- 260. የማጅራት ገትር በሽታ ከቁጥጥር ውጭ አልሆነም
- 261. ብድር ያገኙ ግለሰቦች ኑሯቸው እየተሻሻለ መሆኑ ተገለጠ
- 261. የኢትዮጵያ ሴት አትሌቶች ድል ተቀዳጁ
- 262. በምእራብ ሀረርጌ 320 ሺህ ሕዝብ የመጠጥ ውሃ ተጠምሏ ሆነ
- 263. ኢትዮጵያና የመን ስምምነት ተፈራረሙ
- 264. ከውጭ ንግድ የውጭ ምንዛሪ ይገኛል
- 265. ፕሬዚዳንት ነጋሶ ጊዳዳ ለቀጣይ ህክምና ወደሪየያ ወደ ሄዱ
- 266. የምክር ቤቱ ጉባኤ በጀት በማጽደቅ ተጠናቀቀ
- 267. የምርምር ስርጭት መደበኛ ስብሰባ ተጀመረ
- 268. ለ60 አባወራ ገበሬዎች የመስኖ ግድብ ተሰራ
- 269. የፓናል ውይይት ተካሂዶ

- 270. ለአዲስ አበባ ዩኒቨርሲቲ ሁለት ምክትል ፕሬዚዳንቶች ተሾሙ
- 271. የኤድስ ስርጭትን ለመከላከል የ1 ሚሊዮን ብር ስምምነት ተፈረመ
- 272. የሱማሌ ክልል ምክር ቤት በጀት አጸደቀ
- 273. የሀዲያ ዞን መምህራን ውይይት ተጠናቀቀ
- 274. በጋምቤላ አዲስ የምርምር ማእከል እየተገነባ ነው
- 275. በደቡብ ክልል 19 ልዩ መድሀኒት ቤቶች ተከፈቱ
- 276. የሕዝብ ሀብትን ለመጠበቅ ከአዲት ባለሙያዎች ብዙ ይጠበቃል ተባለ
- 277. የኮሪያ የፊልም ሣምንት አዲስ አበባ ውስጥ ይከበራል
- 278. የሰማታት ቀን ተከበረ
- 279. ኢትዮጵያና ጅቡቲ ስምምነቶችን ተፈራረሙ
- 280. የኢትዮጵያ ብሔራዊ ምርጫ ቦርድ የሥነ ምግባርና የአሰራር መመሪያ አዘጋጀ
- 281. ሜዲትራኒያን ባህር ላይ የተከሰከሰው የኢትዮጵያ አየር መንገድ አውሮፕላን ፍላጎት ደጋጋሚ ሪከርደር ተገኘ
- 282. ጠቅላይ ሚኒስትር መለስ ዜናዊ የሰማሊያ የሽግግር መንግሥት ፕሬዚዳንትን ተቀብለው አነጋገሩ
- 283. የአርብቶ አደሮች ቀን በጅጅጋ ከተማ ተከበረ
- 284. በልማት ወደ ኋላ ለቀሩ ክልሎች በተደረገው ድጋፍና እገዛ አመርቂ ውጤት ነገኘ
- 285. ጠቅላይ ሚኒስትር መለስ ዜናዊ በኢትዮጵያ አየር መንገድ አውሮፕላን ላይ በደረሰው አደጋ የተሰማቸውን ሃዘን ገለጹ።
- 286. በሱማሌ ክልል በትምህርት ዘርፍ አበረታች ውጤት ተመዘገበ
- 287. መንግስት በአርብቶ አደሮች አካባቢ ሰፋፊ የመሰረተ ልማት ስራዎችን አስናወነ
- 288. የትምህርትን ሽፋን ለማሻሻል መንግስታዊ ያልሆኑ ድርጅቶች ድርሻቸውን እየተወጡ ነው
- 289. ኢትዮጵያ ፀጥታ የሚገኝባት መሆና ተገለፀ
- 290. ኢትዮጵያ ለነዳጅ የምታወጣው ወጪ በአጥፍ ጨመረ
- 291. የአዋሽ ባንክ የቀድሞ አመራሮች ክስ ተመሰረተባቸው
- 292. የንግድ ባንክ ኤቲኤም ማሸናፊ ግዢ ጥያቄ አስነሳ
- 293. የጋዜጣ አሳታሚዎች ለሦስት ወራት የዋጋ ጭማሪ እንዳይደረግባቸው ጠየቁ
- 294. ወረቀት ቢወደድም እንኳን የፕሬስ ጉዳይ ከንግድ አንጻር መታየት የለበትም ተባለ
- 295. ዘጠና ሦስት ኢትዮጵያውያን ከሊቢያ ወደ ቱኒዚያ ተጓዥተዋል
- 296. አሜሪካዊው መሀንዲስ በሚስታቸው የድረ ገፅ አስተያየት ከሀገር እንዲወጡ ተደረገ
- 297. እንዲወረስ ጥያቄ የቀረበበት የዶ/ር ብርሃኑ ንብረት አወዛገበ
- 298. ነጋሶ እና ሰዬ የአንድነት የብሔራዊ ምክር ቤት አባል ሆነው ተመረጡ

- 299. በታላቁ ቤተ መንግሥት እየተገነባ ያለው ቤት ለኢትዮጵያ ጠቅላይ ሚኒስትሮች መሆኑ ተገለጸ
- 300. ኢትዮጵያ ሰላማዊ አገር ነች ተባለ
- 301. ጎንደር ዩኒቨርሲቲ ያስገነባው ዘመናዊ የዓይን ህክምና ሆስፒታል ተመረቀ
- 302. የአድዋ አፀደ ጤና ጣቢያ ዘመናዊ አምቡላንስ በእርዳታ አገኘ
- 303. የሳንባ ምች በሽታን ለመከላከል ክትባት እየተሰጠ ነው
- 304. ቡና የስኳር በሽታን ለመከላከል እንደሚያስችል ተመለከተ
- 305. በዲላ ከተማ አንድ ወይዘሮ አራት ሴት ህጻናትን በሰላም ተገላገሉ
- 306. በአፋር የእንስሳት ሀብት ቁጥር በሶስት ሚሊዮን ጨመረ
- 307. ለክልሎች አምቡላንሶችን ማከፋፈሉን የጤና ጥበቃ ሚኒስቴር አሰታወቀ
- 308. ሕብረተሰቡ ጥራት ባለው የጤና ተቋም አገልግሎት ማግኘት ይገባዋል
- 309. በጋምቤላ ክልል የኩፍኝና የፖሊዮ ክትባት ዘመቻ ተጀመረ
- 310. የጎንደር ዩኒቨርሲቲ ሆስፒታል የህጻናት የዓይን ህክምና ማዕከል ሊከፍት ነው
- 311. በአፋር ክልል 12 ጤና ተቋማት እየተገነቡ ነው
- 312. በሰሜን ሸዋ በጤናው ዘርፍ የተቀመጡ ግቦችን ለማሳካት የሕዝብ ንቅናቄ ተፈጠረ
- 313. የደብረብርሃን ሪፈራል ሆስፒታል የተሻሻለ የህክምና አገልግሎት እየሰጠ ነው
- 314. የጅንካ ዞናል ሆስፒታል ለአይን ህመማን ነጻ ሕክምና አደረገ
- 315. ማህበረሰብ አቀፍ የጤና መድሃኒት ተግባራዊ ለማድረግ ጥረት መደረግ አለበት
- 316. የአዳማ ሆስፒታል የራዲዮሎጂ ህክምና መሳሪያዎች ተከለ
- 317. ብሔራዊ የሥነ ምግብ ስትራቴጂና ፕሮግራም ውጤት እያስመዘገበ ነው
- 318. የጥሩነሽ ቤጂንግ ሆስፒታል ግንባታ 25 ከመቶ ያህል ተከናውኗል
- 319. የዓለም የካንሰር ቀንን በማስመልከት በአዲስ አበባ የእግር ጉዞ ተካሄደ
- 320. ዓለም አቀፍ የኒውሮኢንፌክሽን ስብሰባ በአዲስ አበባ ተከፈተ
- 321. የአክሱም ቅድስት ማርያም ሪፈራል ሆስፒታል ማሻሻያ ግንባታ 95 በመቶ ተከናወነ
- 322. በኤች አይ ቪ አድስ የሚሞቱ ሰዎች ቁጥር እየቀነሰ ነው
- 323. የሰመራ የጤና ሳይንስ ኮሌጅ ከ80 በላይ ነርሶችን አስመረቀ
- 324. በምዕራብ አርማጭሆ ወረዳ ለሚገነባው ሆስፒታል የመሰረት ድንጋይ ተጣለ
- 325. በጉጂ ዞን ከ38 ሺህ በላይ ሰዎች የኤች አይቪ. የደም ምርመራ አደረጉ

- 326. በኢትዮጵያ የሕጻናት ጤና እንክብካቤና ትምህርት ፖሊሲ ማዕቀፍ ይፋ ሆነ
- 327. በሰሜን ጎንደር የመተማ ሆስፒታል ህንጻ ዕድገትና ማስፋፊያ ተጠናቀቀ
- 328. የደብረ ማርቆስ ሪፈራል ሆስፒታል የህክምና መሳሪያዎች በእርዳታ አገኘ
- 329. በጋምቤላ ክልል አስር ጤና ጣቢያዎች ተገነቡ
- 330. በጋምቤላ ክልል የኤድስ ስርጭትን ለመግታት ጥረት እንዲደረግ ተጠየቀ
- 331. በምስራቅ ወለጋ የተገነባ ሆስፒታል ተመረቀ
- 332. አዲስ አበባ ውስጥ የሕጻናት ሆስፒታል ሊገነባ ነው
- 333. ዓለም አቀፉ የግላኮማ ቀን አዲስ አበባ ውስጥ ታስቦ ዋለ
- 334. የጤና ተቋማትን ፍላጎት መሠረት ያደረገ የመድሃኒት ግዥና አቅርቦት ሊዘረጋ ነው
- 335. በሰዌና ወረዳ ከ7 ሚሊዮን ብር በላይ የተገነቡ የጤና ተቋማት ስራ ጀመሩ
- 336. የዓለም የኩላሊት ቀን አዲስ አበባ ውስጥ በሕዝባዊ ስብሰባ ታስቦ ዋለ
- 337. በአድዋ 4 ሚሊዮን ብር በሚጠጋ የጤና ጣቢያ ተገነባ
- 338. የመድሐኒት ፈንድና አቅርቦት ኤጀንሲ የአልጋ አገበር እያከፋፈለ ነው
- 339. በሲዳማ ዞን ከሚገነቡት ጤና ጣቢያዎች መካከል 62ቱ ተጠናቀቁ
- 340. በባሌ ዞን በ100 ሚሊዮን ብር ጤና ተቋማት ግንባታ እየተካሄደ ነው
- 341. በአማራ ክልል በባቲ ወረዳ የሁለት ጤና ጣቢያዎች ግንባታ ተጠናቀቀ
- 342. በመላ ሀገሪቱ የ953 ጤና ጣቢያዎች ግንባታ በመፋጠን ላይ ነው
- 343. የዓለም የጤና ቀን የከተሞች እድገትና ጤና በሚል መሪ ቃል ነገ ይከበራል
- 344. በ3 ነጥብ 6 ሚሊዮን ብር የተገነቡ ጤና ጣቢያዎች ስራ ጀመሩ
- 345. አለም አቀፍ ሲጋራ የማይጨስበት ቀን በኢትዮጵያ ይከበራል
- 346. የሥራ ጫናና ውጥረት ለአስም በሽታ የማጋለጥ ዕድሉ ከፍተኛ ነው
- 347. በምዕራብ ሐረርጌ ዞን የጤና ተቋማት ግንባታ እየተካሄደ ነው
- 348. በምእራብ ወለጋ ዞን የተገነቡ 19 ጤና ጣቢያዎች ተመረቁ
- 349. ኢትዮጵያ 13ኛውን ዓለም ዓቀፍ የጤና አጠባበቅ ጉባዔ ታስተናግዳለች
- 350. የሆስፒታሎች አገልግሎት ሪፎርም ይፋ ተደረገ
- 351. የጤናማ እናትነት ዘመቻ ሊካሄድ ነው
- 352. ቡና መጠጣት የአጥንትና የአንገት ካንሰርን ለመከላከል ይረዳል

- 353. በሞያሌ ወረዳ የተገነቡ ጤና ተቋማት አገልግሎት ጀመሩ።
- 354. ከአርግዘናና ወሊድ ጋር በተያያዘ እናቶች መሞት የለባቸውም ተባለ
- 355. በሰሜን ጎንደር የ15 ጤና ጣቢያዎች ግንባታ እየተካሄደ ነው።
- 356. በኢትዮጵያ የኤች.ዋን.ኤን ዋን መከላከያ ክትባት ሊሰጥ ነው።
- 357. ኢትዮጵያ ውስጥ የወፍ ጉንፋን የመከላከያ ክትባት መሰጠት ተጀመረ
- 358. በኢትዮጵያ የጤና መድሃኒ ስርዓት ተግባራዊ ሊሆን ነው።
- 359. በኢትዮጵያ በርካታ ሴቶች ላልተፈለገ አርግዘና ይጋለጣሉ
- 360. በደቡብ ወሎ የጤና አገልግሎት ሽፋን 95 በመቶ ደረሰ
- 361. በጋምቤላ ክልል ወባን ለመከላከል የሚደረገው ጥረት ውጤታማ እየሆነ ነው።
- 362. የአዶላ ከተማ ሆስፒታል ግንባታ ተጠናቀቀ
- 363. የመቱ ከተማ ሆስፒታል ግንባታ ተጠናቀቀ
- 364. መንግስታዊ ያልሆነ ድርጅት በሶስት ክልሎች በጤናና ልማት ላይ እየሰራ ነው።
- 365. ዓለም አቀፍ የጡት ማጥባት ቀን በአዲስ አበባ ተከበረ
- 366. ኢትዮጵያና ግብጽ በጤናው ዘርፍ በጋራ በሚሰሩበት ሁኔታ ላይ ውይይት አካሄዱ።
- 367. ኢትዮጵያ ከፖሊዮ ነጻ ሆነች
- 368. የኮረም ሪፈራል ሆስፒታል ግንባታ በመፋጠን ላይ ነው።
- 369. በምዕራብ ሐረርጌ ዞን ከ227 ሺህ በላይ የአልጋ አጎበር ተሰራጨ
- 370. በካማሽ ከተማ በ73 ነጥብ 1 ሚሊዮን ብር ሆስፒታል ሊገነባ ነው።
- 371. በመላው ሃገሪቱ የእናቶች ሞት ዝቅ ብሏል።
- 372. በሰሜን ሸዋ ዞን የኩፍኝ ክትባት ይሰጣል
- 373. በደቡብ ሕዝቦች ክልል የኩፍኝ መከላከያ ክትባት ተጀመረ
- 374. የቆላ ዝንቦችን የማጥፋት ዘመቻ ተካሄደ
- 375. የቤኒሻንጉል ጉሙዝ ክልል የጤና ሽፋን 78 በመቶ ደረሰ
- 376. የዓለም አቀፍ የአዕምሮ ጤና ቀን በአዲስ አበባ ተከበረ
- 377. የእጅ መታጠብ ቀን ጥቅምት 5 ይከበራል
- 378. የካንሰር በሽታ በአፍሪካ እየተስፋፋ ነው።
- 379. በኤች አይ ቪ ኤድስ የሚያዙ ሰዎች ቁጥር እየቀነሰ ነው።

- 380. በኮንሶ ልዩ ወረዳ ከተገነቡ ጤና ጣቢያዎች አራቱ አገልግሎት ጀመሩ።
- 381. በአጋሮ ከተማ ሆስፒታል ሊገነባ ነው።
- 382. ሥርዓተ ጾታን በመጠጥና ወሃ ሳኒቲሽን ፕሮግራም ላይ ማካተት ይገባል።
- 383. ዘመናዊ የላብራቶሪ መረጃ አያያዝ ሥርዓት ተግባራዊ መሆን ጀመረ።
- 384. የፊልቱ ሆስፒታል በሪፈራል ደረጃ የህክምና አገልግሎት መስጠት ጀመረ።
- 385. የአፍዴራ ጨው አምራቾች ማህበር ምርቱን ለውጭ ገበያ ሊያቀርብ ነው።
- 386. በሶማሊያ የፖሊዮ ስርጭት በቁጥጥር ስር ዋለ።
- 387. የዓለም የቲቢ ቀን ተከበረ።
- 388. የዓለም የኩላሊት ቀን ተከበረ።
- 389. ዓለም አቀፍ ሲጋራ የማይጨሰብት ቀን ተከበረ።
- 390. የኤቸ አ ይ ቪ መረጃ መለዋወጫ መረብ ዛሬ ይፋ ሆነ።
- 391. በሰሜን ሸዋ ዞን የፀረ-ኤድስ ኤቸ አ ይ ቪ አበረታች ውጤት እያሳየ ነው።
- 392. የሚሊኒየሙ የጤና ፌስቲቫል በአማራ ክልል በሀገር አቀፍ ደረጃ ይከበራል።
- 393. የአማራ ክልል የጤና አገልግሎት ሽፋን ከ94 በመቶ በላይ ደረሰ።
- 394. በሐረር በ5 ሚሊዮን ብር የተገነባው የፌስቲላ ህክምና መስጫ ማዕከል ተመረቀ።
- 395. መለስተኛ የጤና ጣቢያዎችን ደረጃ የማሰደግ ሥራ እየተካሄደ ነው።
- 396. በምዕራብ ሸዋ ወባን ለመቆጣጠር የተከናወኑ ሥራዎች ውጤታማ ሆኑ።
- 397. በሸርካ የተገነባው ጤና ጣቢያ ለአገልግሎት በቃ።
- 398. በምዕራብ በለሳ ወረዳ የጤና ተቋማት አገልግሎት እየሰጡ ነው።
- 399. በአፍሪካ በወባ ምክንያት በዓመት ከ12 ቢሊዮን በላይ ዶላር እንደሚወጣ ተገለጸ።
- 400. በምእራብ አርሲ የ ጤና ተቋማት ግንባታ በመፋጠን ላይ ነው።
- 401.ልጅ ሆይ የአባትህን ምክር አድምጥ፤
- 402.ጥበብ በየአደባባዩ ድምጽዎን ከፍ ታደርጋለች፤
- 403.ልጅ ሆይ ትምህርቱን አትርሳ ትእዛዛቱን በልብህ ጠብቅ
- 404.ፍቅርና ታማኝነት ከቶ አይለዩህ
- 405.ጥበብን የማያገኛት ማስተዋልንም ገንዘብ የሚያደርጋት ሰው ብሩክ ነው።
- 406.ልጅ ሆይ የእግዚአብሔርን ተግሣጽ አትናቅ በዘለፋም አትመረር
- 407.የአመንገራ ሴት ከንፈር በመጨረሻ እንደ እሬት ትመለች
- 408.በልጅነት ሚስትህ ደስ ይበልህ ጡቶቿ ዘወትር ያርኩህ

- 409.እግዚአብሔር የጻድቃንን መንገድ ይጠብቃል
- 410.ጻድቃን ሆን በእግዚአብሔር ደስ ይበላችሁ
- 411.ጠቢብ ሴት ቤቷን ትሠራለች ተላላ ሴት ግን በገዛ እጇ ታፈርሰዋለች
- 412.ጠቢባን ብልጥግና ዘውዳቸው ነው
- 413.እግዚአብሔር ለአብርሃም ተገለጠለት
- 414.እግዚአብሔር “በሰዶም ከተማ አምሳ ጻድቃን ባገኝ ለእነርሱ ስል አገራቱን እምራለሁ” አለ።
- 415.ያዕቆብን “ተነሥና ወደ ቤቴል ውጣ፤ አለው
- 416.ሙሴ ካደገ በኋላ ወገኖቹ ወደሚገኙበት ስፍራ ወጣ
- 417.እግዚአብሔር አልያስን በዐውሎ ነፋስ ወደ ሰማይ ወሰደው
- 418.እግዚአብሔር በዚህ ተራራ ቆዩ አለ
- 419.አምላክህን እግዚአብሔርን ውደድ ሕጉን ሁልጊዜ ጠብቅ
- 420.ጉድለት ያለበትን በሬ ወይም በግ በእርሱ ዘንድ አስ ጸያፊ ነውና ለአምላክህ ለእግዚአብሔር አትሠዋ
- 421.በእግዚአብሔር ፊት መሐላ ከፈፀምክ አክብር
- 422.ልጆቹ ሆይ የአባትን ምክር አድምጡ፤ ልብ ብላችሁ ስሙ፤ ማስትዋንም ገንዘብ አድርጉ
- 423.ቃሌን በሙሉ በልብህ ያዝ፤ ትእዛዜንም ጠብቅ በሕይወት ትኖራለህ
- 424.እግዚአብሔርን መፍራት ክፍትን መጥላት ነው
- 425.ሰነፍ እጆች ሰውን ያደኸያሉ ትጉ እጆች ግን ብሕጽግናን ይመጣሉ
- 426.የእግዚአብሔር መንገድ ለጻድቃን መጠጊያ ነው
- 427.ርኅሩኅ ሴት ክትር ታገኛለች
- 428.እግዚአብሔር ልብ ጠማሞችን ይጸየፋል
- 429.ተላላ ሰው ቁጣው ወዲያውኑ ይታወቅበታል
- 430.ትዕቢት ጠብን ብቻ ያስፋፋል ጥበብ ግን ምክርን በሚቀበሉ ዘንድ ትገኛለች
- 431.ለነገ የሚባል ተስፋ ልብን ያሳምማል
- 432.በጉ ሰባተኛውን ማኅተም በፈታ ጊዜ ግማሽ ሰዓት ያህል በሰማይ ዝምታ ሆነ
- 433. በእግዚአብሔር ፊት በዙፋኖቻቸው ላይ የተቀመጡት ሃያ አራቱ ሽማግሌዎችም በግምባራቸው ተደፍተው ለእግዚአብሔር ሰገዱ
- 434. ሕግን የምትፈጽም ከሆነ ግዝረት ዋጋ አለው
- 435.በእምነቱ ደካማ የሆነውን ሰው፤ አከራካሪ በሆኑ ጉዳዮች ላይ በእ ቋሙ ሳትፈርዱበት ተቀበሉት።
- 436.እኛ ብርቱዎች የሆንን፤ የደካሞችን ጉድለት መሸከም እንጂ ራሳችንን ማስደሰት የለብንም።
- 437.ወደ እግዚአብሔር በመጸለይ የተጋድሎ አጋር ሁን
- 438.እናንተን ባስታወስሁ ቁጥር አምላኬን አመሰግናለሁ
- 439.ከእግዚአብሔር ከአባታችን፤ ከጌታም ከኢየሱስ ክርስቶስ ጸጋና ሰላም ለእናንተ ይሁን
- 440.ቃሉ የሚናገረውን አድርጎ እንጂ ሰሚዎች ብቻ ሆናችሁ ራሳችሁን አታታልሉ
- 441.ወንድሞት ሆይ ጌታ እስከሚወጣ ድረስ ታገሡ
- 442.ገበሬ መሬቱ መልካምን ፍሬ እስከሚሰጥ ድረስ እንዴት እንደሚታገስ አስተውሉ
- 443.ወንድሞች ሆይ በጌታ ስም የተናገሩትን ነቢያት የመከራና የትዕግሥት ምሳሌ አድርጋችሁ ተመልከቱ

- 444.ሙሴ ካደገ በኋላ የፈርኦን የልጅ ልጅ መባልን በእምነት እምቢ አለ
- 445.ሕዝቡ በደረቅ መሬት እንደሚኬድ ቀይ ባሕርን በእምነት ተሻገሩ
- 446.እርስ በርሳችሁ እንደ ወንድማማች ተዋደዱ
- 447.ከክፉ ባሕርያችሁ የተነሣ ቀድሞ ከእግዚአብሔር የተለያችሁ በአሳባችሁም ጠላቶች ነበራችሁ
- 448.ስለ እናንተ በተቀበልሁት መከራ አሁንም ደስ ይለኛል
- 449.አንዳንዶች እምነትን ክደው አታላይ መናፍስትንና የእናጋንንትን ትምህርት እንደሚከተሉ መንፈስ በግልጥ ይናገራል
- 450.የእግዚአብሔር ፈቃድ ከዝሙት ርቃችሁ እንድትቀደሱ ነው
- 451.ከዝሙት ሸሹ
- 452.ፍቅር ታጋሽ ነው ደግሞም ቸር ነው
- 453.ጴጥሮስና ዮሐንስ ከተፈቱ በኋላ ወደ ወገኖቻቸው ተመልሰው የካህናት አለቆችና ሽማግሌዎች ያሏቸውን ሁሉ ነገሯቸው
- 454.ሐዋርያት በሕዝቡ መካከል ብዙ ታምራዊ ምልክቶችንና ድንቅ ሥራዎችን አደረጉ
- 455.የዮሐንስ ልብስ የግመል ጠጉር ሲሆን ወገቡንም በጠፍር ይታጠቅ ነበር
- 456.ሰዎች በእኔ ምክንያት ቢሰድቧችሁ ቢያሳድዷችሁና ክፉውን ሁሉ በሐሰት ቢያስወሩባችሁ ብዙዎን ናችሁ
- 457.ለቀደሙት ሰዎች፣ በሐሰት አትማል፣ በእግዚአብሔር ፊት የማልኸውንም ጠብቅ እንደ ተባለ ሰምታችኋል
- 458.የሚለምን ሁሉ ይሰጠዋል፣ የሚፈልግም ያገኛል ለሚያንኳኳም በሩ ይከፈትለታል
- 459.በሰማይ ያለውን ያባቴን ፈቃድ ፈጽሙ
- 460.ሰንበት ካለፈ በኋላ ማርያም መግደላዊትና ሌላዋ ማርያም መቃሩን ሊያዩ ሄዱ
- 461.ሐዋርያት በኢየሱስ ዙሪያ ተሰብስበው የሠሩትንና ያስተማሩትን ሁሉ ነገሩት
- 462.ኢየሱስና ደቀ መዛሙርቱ መንገድ ሲሄዱ ኢየሱስ ወደ አንድ መንደር ገባ
- 463.አንድ ቀን ኢየሱስ ድዳ ጋኔን የወጣ ነበር፣ ጋኔኑም ከወጣለት በኋላ ድዳው ሰው ተናገረ ሕዝቡም ተገረመ
- 464.ከእግዚአብሔር ከአባታችን ጸጋና ሰላም ለእናንተ ይሁን
- 465.ወንድሞች ሆይ በመካከላችሁ መለየት እርስ በርሳችሁም እንድትስማሙ አሳስባችሁለሁ
- 466.ወንድሞች ሆይ በተጠራችሁ ጊዜ ምን እንደ ነበራችሁ እስቲ አስቡ
- 467.ባየሁት ጊዜ እንደ ሞተ ሰው ሆኜ በእግሩ ሥር ወደቅሁ
- 468.ሺሁም ዓመት ሲፈጸም ሰይጣን ከእስቱ ይፈታል
- 469.ሁሉን ቻይ ጌታ አምላክና በጉ መቅደስ ስለ ሆኑ በከተማይቱ ውስጥ ቤተ መቅደስ አላየሁም
- 470.እነሆ ቶሎ እመጣለሁ ዋጋዬ በእኔ ዘንድ አለ ለእያንዳንዱም እንደ ሥራው መጠን እከፍለዋለሁ
- 471.አብ እንደ ወደደኝ ሁሉ እኔም ወደድኋችሁ፣ በፍቅሬ ኑሩ፡፡
- 472.ከእግዚአብሔር አብ ከአዳኛችንም ከክርስቶስ ኢየሱስ ጸጋና ሰላም ይሁን
- 473.ሰዎች ለገዢዎችና ለባለስልጣናት እንዲገዙ አሳስቧቸው
- 474.ለአምላካችንና ለአባታችን ከዘላለም እስከ ዘላለም ክብር ይሁን አሜን
- 475.አብርሃም በእምነት የልጅ አባት ለመሆን በቃ
- 476.አንድ ቀን መላእክት በእግዚአብሔር ፊት ሊቆሙ በመጡ ጊዜ፣ ሰይጣንም መጥቶ በመካከላቸው ቆመ
- 477.በመጀመሪያ እግዚአብሔር ሰማይና በምድር ፈጠረ
- 478.እባብ እግዚአብሔር አምላክ ከፈጠራቸው የዱር አራዊት ሁሉ ተንኮለኛ ነበረ

- 479. ሰዎች በምድር ላይ እየበዙ ሲሄዱ ሴቶች ልጆች ተወለዱላቸው
- 480. ቃየን ሚስቱን ተገናኛት እርሷም ፀንሳ ሄኖክን ተወለደ
- 481. የጥፋት ውሃ በምድር ላይ በወረደ ጊዜ ኖኅ የ600 ዓመት ሰው ነበር
- 482. ሰዎች ሁሉ የሚናገሩትና የሚግባቡበት ቋንቋ አንድ ብቻ ነበር
- 483. በሰዶም እግዚአብሔር በተናገረው መሠረት ሣራን አሰባት ይግብዋቸውም ተስፋ ፈፀመላት
- 484. በመጀመሪያ ቃል ነበረ፤ ቃልም ከእግዚአብሔር ጋር ነበረ፤ ቃልም ከእግዚአብሔር ጋር ነበረ፤ ቃልም እግዚአብሔር ነበረ።
- 485. በእግዚአብሔር የተላከ የሐንስ የተባለ አንድ ሰው ነበረ
- 486. እርሱ በዓለም ውስጥ ነበረ ዓለም የተፈጠረው በእርሱ ቢሆንም እንኳ ዓለም አላወቀውም
- 487. ያለውና የነበረው የሚመጣውም ሁሉን ቻይ ጌታ አምላክ አልፋና የሜጋ እኔ ነኝ ይላል።
- 488. የጌታ የኢየሱስ ጸጋ ከእግዚአብሔር ሕዝብ ጋር ይሁን አሜን
- 489. ወንድሞች ሆይ የሰበክሁላችሁ ወንጌል ሰው-ሠራሽ አለመሆኑን እንድታውቁ እፈልጋለሁ
- 490. ሁላችሁም በክርስቶስ ኢየሱስ በማመን የእግዚአብሔር ልጆች ናችሁ
- 491. ስለ እናንተ በምንጸልይበት ጊዜ የጌታችንን የኢየሱስ ክርስቶስን አባት እግዚአብሔርን ሁልጊዜ እናመሰግናለን
- 492. ወዳጅ ሆይ መልካም የሆነውን እንጂ ክፉውን አትምሰል።
- 493. ጸጋ ምሕረትና ሰላም ከእግዚአብሔር አብ ከጌትችንም ከክርስቶስ ኢየሱስ ይሁን
- 494. እግዚአብሔር ጌታችን ኢየሱስ በማወቅ ጸጋና ሰላም ይብዛላችሁ
- 495. በክርስቶስ ትምህርት የማይኖር ከትምህርቱ የሚወጣ ሁሉ አምላክ የለውም
- 496. ኢየሱስ ክርስቶስ በሥጋ እንደ ሞተ የማያምኑ ብዙ አሳዥች ወደ ዓለም ወጥተዋል
- 497. በክርስቶስ ላላችሁ ለሁላችሁ ሰላም ይሁን
- 498. ኢየሱስ የማታየው አምላክ አምሳል ነው
- 499. የክርስቶስ የሆኑት ስጋን ከክፉ ምኞቱና መሻቱ ጋር ሰቅለውታል
- 500. በቃላት ሊገለጥ ስለማይቻል ስጦታው እግዚአብሔር ይመስገን
- 501. ጎጃም ውስጥ በጋለ መብራቱ የሚባሉ ሰው ነበሩ
- 502. በጋለ መብራቱ ከድሃ ቤተሰብ የተውልዱ ነበሩ
- 503. ቁስ ታምሩ ከዛሬ በፊት ባሎችዎን ሲያገቡ ላንዳቸውም አማላጅ ሆኜ እንዳልመጣሁ እስከ ያውቃሉ አሉ
- 504. እግዚአብሔር ይየው አንጂ አሉ እመት ውድነሽ
- 505. እሱስ እውነት ነው ብቻ የሰው መላስ ከላት የበለጠ ያቃጥላል አሉ እመት ውድነሽ
- 506. ያይን ጅማቱን መከፋት አላልቶት እንባ አላቆም ብሎ ነውንጂ ለማልቀስ ፈልጌ አይምሰልም አሉ እመት ውድነሽ
- 507. በዛብህ በልጅነቱ ጉዋደኞቹ የስዕለት ልጅ እያሉ ሲቀልዱበት ወደናቱ እያለቀሰ ይሄዳል
- 508. ካህን በካህን አፍ ተመስግኖ የማይውቀውን ያንለት ካህናቱ በዛብህን አመሰገኑት
- 509. ከግብር በሁዋላ ካህናቱ ማህሌተ ገንባቸውን ይወርሱ ጀመር
- 510. ሰብለውንጌል በአስራ አራት አመት ለመኩዋንንት ልጆች ወግ መልክ ኢየሱስና መልክ ጊዮርጊስ አወቀች
- 511. ፈታውራሪ አሰጌ ወጣት ሳሉ ሁለት ልጃገረዶች በተራ እየተሰረጉ አግብተው ፈትተዋል
- 512. የድሜ ልዩነት ይህን ያክል ቁምነገር የለውም አሉ ወ/ሮ ጥሩዓይነት
- 513. ፈታውራሪ መሸሻ ምሽታቸው የፈሩትን ቁስላቸውን ስለነኩባቸው በጣም አመቸቸው ተቆጡ
- 514. ጉዱ ካላ መጀመርያ ሰብለውንጌል ባል እንዳታገባ ጋኔን ተቆራኝቱዋል ሲል እውነት መስሎቸው ደንግጠው ነበር
- 515. ሰብለውንጌል ከዘመዶች ሁሉ ካባት ከናት ሳይቀር አብልጣ ጉዱ ካላን ትወድ ነበር

- 516. ፈታውራሪ መሸሻ ተመትቶ ካሱኝ ከሚል መትቶ ካሳ የሚክሰውን የሚያክብሩ ናቸው
- 517. ፈታውራሪ አሰጌ ከመንፈሳቸው ታላቅነትና ክልባቸው ለጋሰነት አንዳንድ ሰባዊ ድካሞች ነበርዋቸው
- 518. ስተት ላይ የጣልቀቸውን ሰዎች ላጭር ጊዜ ይቀየሩባቸውና ወዲያው መልሰው ሁሉንም ይረሱታል
- 519. ፈታውራሪአሰጌ ☐ፈታውራሪ መሸሻ ደብዳቤ ሲነበብ በቅገርት እንጂ በውን የነበሩ አልመሰላቸውም
- 520. ፈታውራሪ መሸሻ ከፈረስ ቤት ሲወጡ ዘመድ ወዳጆቻቸው ውጭ ይጠብቁባቸው ነበር
- 521. በሰው ቁስል እንጨት ቢሰዱ አያምም ህመሙ የሚሰማው ባለቁስሉን ብቻ ነው
- 522. ያ አገር ምድር አልብሶ ቀስ እያለ የሚገባዋዘና ባሞራ ያጀበ ህዝብ እየቀረበ መጣ
- 523. ፈታውራሪ አሰጌ የፈታውራሪ መሸሻ ደብዳቤ ሲነበብ በቅገርት እንጂ በውን የነበሩ አልመሰላቸውም
- 524. በዛብህ ዲማ በቆየበት አንድ አመት ካለቃ ክንፉ የቅኔ መምህርነት ተመርቆ ወጣ
- 525. ደመቀች ለታምራት ተገኘ ስትዳር አምስት አግብቶ የፈታ ያምሳ አመት ሰው ነበር
- 526. ታምራት ተገኘ አገሩ ኤልያስ እረኛ ነበር
- 527. ታምራት ጥሩ ተኩዋሽ ስለነበረ በነጋዴዎች መሀከል እንደ ጉዋደኛ እንጂ እንዳሽከር አይታይም ነበር
- 528. ደመቀችን ወደ ባሰቡትዋ እንድትሄድ ቢያባብሉዋትም ቢያስፈራሩዋትም እሺ የማትል ሆነች
- 529. ደመቀች ያክስትዋ ቤት ውስጥ በርከት ያሉ የድሜ ጉዋደኞችዋ ስለነበሩ አዘውትራ ትሄድ ነበር
- 530. ደመቀች ልጅዋን በጣም ትወድ ነበር
- 531. እስቲ ልቅሶሽን ተይና የኛን ምክር ስሚ ልጄ አሉ እማሆይ ወለተ እየሱስ
- 532. ደመቀችና ልጅዋ ካራት ሰዓት በፊት ገብተው አያውቁም
- 533. የደመቀች ውበት እስዋ ለሌሎች ማጥመጃ ልታውለው ባትሻም ሰላም አሳጣት
- 534. ደጄኔ መክርዋቸው ከስዋ ጋር አምባገብር ሲያነሱ ያገኛቸው እንደሆነ ልክ ያገባቸዋል
- 535. ደጄኔ አምስት ብር ካምስት ሰዎች ተበደረ
- 536. እህትና ወንድም መሆናችንን የሚያስትውስሽ ጌጥ እንድትገኝበት ብዬ ነው አለ ደጄኔ
- 537. ደመቀች ከወላጆቿዋ ጠፍታ ወደ አዲስአበባ ስትሸሽ ከናታችንና ካቶ መላኩ ብር የተቀበለችው ግዴታ ሆኖባት ነው
- 538. ግራ ጌታና ደጄኔ ከዝምድናቸው ሌላ ምስጢር የማይደባበቁ የምስጢር ጉዋደኞች ናቸው
- 539. አንድ ቀን ጥዋት ደመቀች ለልጅዋ ቁርሱን ወስዳለት ስትመለስ ደጄኔ አገኛት
- 540. አንድ ድሀ ጎበዝ አንድ ልጅ ይወድና አበድሁ ይላል አለ ግራ ጌታ
- 541. አንድ ድሀ ጎበዝ አንድ ልጅ ይወድና አበድሁ ይላል አለ ግራ ጌታ
- 542. ልጅቷ ዳግመኛ ፊቴን እንዳታይ ስትለው ተናዶ ሄዶ ካበው ደብተራ የመስተፋቅር አልማዝ ☐
- 543. የምትወደውን እርሜኛዋን ትታ በልምዋም በውንዋም የሚታያት ያባረረችው ሆነ
- 544. ምስጢሩ ሁሉ ይለጸጽና አስማት አድራጊው በፖሊስ ተይዘው ፍዳቸውን አዩ
- 545. ተክስተ ትምህርት አጥብቆ ይወዳል
- 546. እህል የራብ አብነት መሆኑን ሰው ስላወቀ አብነቱ አይቀርም
- 547. የሴት ልቧ ከንፈርዋ ነው
- 548. የደመቀች ቤት ከልፍኙ አቁዋራጭ አጥር ራቅ ብሎ ነው
- 549. ደመቀች ባጭር ጊዜ ውስጥ ተወደደች
- 550. መቸም ሊያዘዙትና ሊገዙት የማይቻል አመል ሆኖባቸው ነው እንጂ ወደው አይለም
- 551. ደመቀች ወ/ሮ ጽጌ ሳያስደበድብዋት እንደማይቀሩ እርግጠኛ ነበረች
- 552. የተክስተ ጽዳት ስልጡን ሞግዚት ተጠንቅቃ የምትጠብቀው ይመስል ነበር
- 553. ወደ ፈታውራሪ መሸሻ የተላኩት የባላገር መልክተኞች ባማላጅ ተለቀው ወደያገራቸው ተመለሱ
- 554. የእንጨት ልጅ እሳት የሳት ልጅ አመድ አሉ ብላታ ንጉሴ
- 555. እንደኔ በድሜ የታደላችሁ እንደምታውቁባቸው ፈታውራሪ በሪሁን ታላቅ ሰው ነበሩ አሉ ብላታ ንጉሴ
- 556. ያገኘውን ሁሉ የሚፈጅ በቦታቸው ተተካ አሉ ብላታ ንጉሴ

- 557. ፈታውራሪ መሸሻ አዲስ አሳብ ይጠላሉ
- 558. ባላገር ከጉልቴ እየበላ ባደባባይ የሰደበኝን ተናገሩ አሉ ፈታውራሪ መሸሻ
- 559. በጎልማስነትም ጊዜ የነበረው ጀግንነትም በስህተት መነገድ መርቶታል አሉ ቀኛዝማች አካሉ
- 560. ዘማችች ሮብና አርብ ከቤታቸው የተነሱ እንደሆነ አይቀናቸውም የሚባለውን ፈታውራሪ ያምኑበታል
- 561. ፈታውራሪ መሸሻን ከተከተሉት ሰላሳው ባለጠመንጃ ነበሩ
- 562. የናሞራ ህዝብ ባበጀ በለው መሪነት እንዋጋ ባይ ሆነ
- 563. ሀብትሽ ባሎችን ለማስታወስ አይኖችን እጣራው ላይ ሰቀለች
- 564. ድሮኮ የኔ የምትይው ምስጢር አልነበረሽም አለ ጉዱ ካሳ
- 565. ግራ ጌታ ቀለመ ወርቅ እቤቱ ጥግ ተቀምጦ ታምረ ጊዮርጊስ ይጽፍ ነበር
- 566. ሲኖዳ ዩሃንስ በግራ ጌታ ቀለመ ወርቅ አማካይነት በዛብህ መሪ ጌትነት የተቀጠረበት አገር ነው
- 567. በዛብህ እቤቱ እንደገባ ጡዋፉን አብርቶ ብሩን ቆጠረ
- 568. ሰብለ መጽሀፉን ሳትገልጥ በጉልበትዋ ላይ ይዛ እናታ መጡ
- 569. እመቤትዋ አጥሩን እንደወጡ ሀብትሽም እንደድሮዋ ሳትቀልድ ወደ ማድቤትዋ ሄደች
- 570. የኮርቻ በቅሎየን ስድሳ አጋሰሱን አምሳ ብር ሽጫለሁ አለ ጉዱ ካሳ
- 571. ፈታውራሪ መሸሻ ስቀው በቅጽበት የተቆጠቡትን ምክንያት ፈልጎ አገኘው
- 572. የጭዋ ልጅ ምንም ቢሆን ጭዋነቱን አይረሳም አሉ ፈታውራሪ መሸሻ
- 573. ሰብለ አንድ ነገር ብትሆን ደም መላሽዋ እኔ ነኝ አለ ጉዱ ካሳ
- 574. ከራት በሁዋላ በዛብህ ወደ ቅኔ ቤቱ ለመሄድ ተሰናብቶ ወጣ
- 575. ቅኔ ቤቱ በራፍ ሲደርሱ ግራ ጌታ ተመለሰ
- 576. ቁዋንጣው ከተዘለዘለ ሶስት ቀኑ ስለሆነ ማምሻውን ይደርቃል አለች እንቆጳ
- 577. ርዳታ እንደሚፈልግ እያወቅህ ርዳታህን ነፍገህዋል አለ በዛብህ
- 578. በዛብህ የሄኖክን አሳብ ተቀበለ
- 579. ውጭ እበሩ ላይ ጠብቀኝ አለ በዛብህ
- 580. ባደግሁበት አደባባይ ዋስ አጣሁ አሉ ፈታውራሪ መሸሻ
- 581. ለስምዎ መጣራቱ ይሻላል ብየኮ ነው አሉ ቁስ ሞገሴ
- 582. የሰብለን መፈታት ጉዱ ካሳም በዛብህም አያውቁም ነበር
- 583. በዛብህ እምባው እየወረደ ተነስቶ የጉዱ ካሳን ጉልበት ሳመ
- 584. በጎጃም ያሳገባች ልጃገረድ ቆንጆ ትባላለች
- 585. አባ አለም ለምኔ ሁለት ሌሊትና አንድ ቀን ጦማቸውን አደሩ
- 586. እንቅልፍና ድካም አባ አለም ለምኔን ያንገላትዋቸው ጀመሩ
- 587. አምስት አመት እስሊሞላው ድረስ ሙሉ ጤና አልነበረውም
- 588. በልጅነቱ ጨዋታ በጣም ይወድ ነበር
- 589. አቶ ቦጋለ አንደበታቸው ተይዞ ሳይናገሩ ሰባት ቀን ቆዩ
- 590. አቶ ቦጋለ የተቀበሩ እለት እመት ውድነሽ ታመው አደሩ
- 591. በዛብህ በራስ ምክንያር አመካኝቶ ምንም ሳይበላ ተነሳ
- 592. በዛብህ ሌሊቱን ሙሉ ሳይተኛ አደረ
- 593. በዛብህ ዲማን ከወሬው በቀር ረግጦት አያውቅም ነበር
- 594. በዛብህ በበአሉ ሳምንት ለፈታውራሪ መሸሻ ባለመዋል ሆኖ ሰነበተ
- 595. ፈታውራሪ መሸሻ በባላባትነታቸው እጅግ የሚኮሩ ሰው ነበሩ

- 596. አባ ሞገሴ ቅን ሰው ነበሩ
- 597. ካሳ ዳምጤ በሁለት እጅ የማይነሳ ከባድ የጌታ ዘር ነበር
- 598. ፈታውራሪ አሰጌ ቆንጆ ሴት ከመጠን ያለፈ ይወዳ ነበር
- 599. የጎንቻ ህዝብ አበጀ በለውን ይወደው ነበር
- 600. ጉዳ ካሳ የሰብለን ጤንነት ተጠራጠረ
- 601. የወንጀለኛ መቅጫ ሕግ ግብ የመንግስትንና የዜጎችን ጸጥታ መጠበቅ ነው።
- 602. አንድ ወንጀል በህብረት በተሠራ ጊዜ የወንጀሉ ተካፋይ አለመሆኑ የታወቀለት ሰው አይቀጣም።
- 603. ሆነ ብሎ ለሚሠራው ወንጀል አባሪ መሆን ለሁል ጊዜ የሚያስቀጣ ነው።
- 604. በሕግ የታዘዙ ተግባሮች እንደ ወንጀል የማይቆጠሩ ናቸው
- 605. በመደቡ ማንም ሰው ከጥፋቱ ነጻ ለመውጣት ሕግን አለማወቁን ምክንያት ለማድረግ አይችልም።
- 606. በወንጀል ምክንያት መቀጮ የሚከፈለው በገንዘብ ነው።
- 607. የጽኑ እስራት ቅጣት የሚወሰነው ከባድ ወንጀል በሠሩ ጥፋተኞች ላይ ነው።
- 608. ጾታቸው የተለያዩ ወንጀለኞች ቅጣታቸውን የሚፈጽሙት በተለያዩ እስር ቤት ውስጥ ነው።
- 609. ያልተፈረደባቸው እስረኞች ከተፈረደባቸው እስረኞች ጋር አይቀላቀሉም።
- 610. የሞት ፍርድ ርዕሰ ብሔሩ ካላጸኑት በቀር ሊፈጸም አይችልም።
- 611. በፍርድ የተገደለው ሰው ፊሳ በቤተሰቦቹ ጠያቂነት ተሰጥቷቸው በሚገባ ይቀበራል።
- 612. ሞት የተፈረደበት ሰው ቅጣቱ እስኪጸናና እስኪፈጸም ድረስ በጽኑ እስራት ታስሮ ይቆያል።
- 613. ፍርድ ካልተሰጠ በቀር ክስን መተው ይቻላል።
- 614. ፍርድ ከመወሰኑ በፊት ወንጀለኛው የሞተ እንደሆነ ክሱ አይከፈትም
- 615. አስቦ በሰው ላይ አንድ ተላላፊ በሽታ ያስተላለፈ ሰው በእስራት ይቀጣል።
- 616. በማናቸውም አይነት ሰውን የገደለ ማንም ሰው ነፍስ ገዳይ ነው።
- 617. ጥፋት በሆነ ችልተኝነት ሰውን የገደለ ሰው በእስራት ይቀጣል።
- 618. ባለመጠንቀቅ የሚደርስ የፅንሰ መቋረጥ በወንጀል ሕግ የሚያስቀጣ አይደለም።
- 619. የማስወረድ ተግባርን የምትፈጽም እርጉዝ ሴት ከሦስት ወር በማያስ እስራት ትቀጣለች።
- 620. አስቦ የሌላ ሰው አካል የጎዳ ይቀጣል።
- 621. ማንኛውም ሰው የግብረ ሥጋን ተግባር በእንስሳት ላይ የፈጸመ እንደሆነ በእስራት ይቀጣል።
- 622. የመንግስትም ሆነ የግል የሆነው ንብረት ሁሉ የወንጀል ተግባር እንዳይደርስበት የተጠበቀ ነው።
- 623. የደንብ መተላለፍ ነገር የሚወሰነው በጠቅላላው በአገሩ ሕግ የመዳኘት ደንብ መሠረት ነው።
- 624. በደንብ መተላለፍ ረገድ አላፈነትና ተቀጭነት የግል ናቸው።
- 625. ማንም ሰው ባንድ የወንጀል ሥራ ሁለት ጊዜ አይቀጣም።
- 626. የወንጀለኛ መቅጫ ሕግ በሁሉም ሰው ላይ በትክክል ይፈጸማል
- 627. ጠቅላይ አቃቤ ሕግ የክስ ጥያቄ የሚያቀርበው ከፍርድ ሚኒስትር ጋር ከተስማማበት በኋላ ነው።
- 628. ያስቀጣል ተብሎ በሕግ የተደነገገውን መሥራት ወንጀል ነው።
- 629. ወንጀልን ለመሥራት የተደረጉት የሙከራ ተግባሮች ቅጣት ይፈጸምባቸዋል።
- 630. የተፈጸመውን ወንጀል አለማስታወቅ ወንጀለኛን መርዳት ነው።

- 631. ፍርድ ቤት ተገቢ የሆነን ሕጋዊ ውሳኔ ይሰጣል።
- 632. የሕግ ድንጋጌዎች ዕድሜያቸው ዘጠኝ ዓመት ባልሞላ ሕፃናት ላይ አይፈጸሙም።
- 633. በሕጉ አሳብ አጥፊነቱ ተገልጾ ካልታወቀ በቀር ማንም ሰው ሊቀጣ አይችልም።
- 634. ከወንጀል ሥራ አላፊነት የተነሣ የሚሰጠው ውሳኔ የኪሳራ ጉዳዮችን አያስቀራቸውም።
- 635. ሊታገድ የሚችል ሆኖ ለማሸነፍ ችሎታ እያለው ጥፋት ያደረገ በመደቡ ይቀጣል።
- 636. ምክንያት በሆነ ነገር ላይ የተደረገ መሳሳት ወንጀል መሆኑን አያስቀርም።
- 637. ፍርድ ቤት ቅጣትን የሚወሰነው ከስሕተት የደረሰበትን ምክንያት በመገመት ነው።
- 638. ወንጀለኛው በፈጸመው ጥፋት ምክንያት ላደረሰው ጉዳት ከሳ በአላፊነት ይጠየቃል።
- 639. ለሰው ተፈጥሮ የሚገባውን ክብር ሁሉ አክብሮ መጠበቅ ተገቢ ነው።
- 640. በወንጀል ምክንያት የሚከፈለው መቀጮ ገቢነቱ ለመንግሥት ነው።
- 641. ሙስና ወንጀል ነው
- 642. የገንዘብ መቀጮ አድራጊው በወንጀሉ ተግባር ምክንያት ካገኘው ጥቅም ጋራ ግንኙነት የለውም።
- 643. የመቀጮ ገንዘብ መክፈያ ጊዜ ከሁለት ዓመት ሊበልጥ አይችልም።
- 644. የተፈረደበት ሰው ሳይፈጽም የቀረውን የቅጣት ሥራ በዳነ ጊዜ እንዲፈጽም ይደረጋል።
- 645. የጽኑ እስራት ቅጣት የሚፈጸመው ወህኒ ቤቶች ውስጥ ብቻ ነው።
- 646. እስር ቤት ውስጥ ሴቶችና ወንዶች እንዳይገናኙ በጥብቅ ማነጣጠል ያስፈልጋል።
- 647. ለመጠበቂያ ተቀጨው እጁ ተይዞ የቆየበትን ጊዜ ፍርድ ቤቱ ከዋናው ቅጣት ጋር ይቆጠርለታል።
- 648. የሞት ፍርድ የሚፈጸመው በመሰቀል ነው።
- 649. 18 ዓመት ባልሞላቸው ወንጀለኞች ላይ የሞት ፍርድ አይፈረድባቸውም።
- 650. የሞት ፍርድ በምሕረት ሊለወጥ ይችላል።
- 651. ሞት የተፈረደበት ሰው ልዩ የጥንቃቄ ጥበቃ ሊደረግበት ይችላል።
- 652. ሞት የተፈረደበት ሰው ለማረጋገጫው የገባበት ቃል በፍርዱ ላይ ይፃፋል
- 653. የፍርድ ለሕዝብ መገለጽ የሚጠቅም መሆኑ በተገመተ ጊዜ ይገለጻል።
- 654. የአለንጋ ቅጣት የሚፈጸምባቸው ወንዶች ላይ ብቻ ናቸው።
- 655. አካለ መጠን ያልደረሱትን የሚመለከት ነገር የፍርድ ውሳኔ ምን ጊዜም በግልጽ በማስታወቂያ አይወጣም።
- 656. ቅጣትን የመተው ሥልጣንን ፍርድ ቤት የሚያገኘው ሕጉ በትክክል ያዘዘለት ከሆነ ነው።
- 657. ወንጀለኛው ደጋጋሚና ቅጣት የማይመልሰው ሲሆን ወደ ጽኑ ግዞት ይላካል።
- 658. ፍርድ ቤቱ ተገቢ መስለው የሚታዩትን ደንቦች በፍርዱ ላይ ይወስናል።
- 659. የእድሜ ልክ ጽኑ እስራት የተወሰነበት ወንጀለኛ የአመክሮው ጊዜ ከአምስት ዓመት አይወርድም።
- 660. በአመክሮ የመለቀቅ ትዕዛዝ ሲሻር ተለቃቂው ወደ ነበረበት ተመልሶ እንዲገባ ይደረጋል።
- 661. የክስ አቀራረብ ደንብ ፎርም በወንጀል ሥነ ሥርዐት ሕግ ላይ ይገለጻል።
- 662. የክስ አቤቱታ ደንብ ፎርም በወንጀል ሥነ ሥርዐት ሕግ ላይ ይገለጻል።
- 663. ክስን ለመተው ግልጽ የሆነ ማስተወቂያ ከሳሹ ማቅረብ አለበት።
- 664. የይርጋ ዘመን በተቋረጠ ቁጥር እንደገና መቆጠር ይጀምራል።
- 665. ማንም ሰው አንዱን የበላይ አለቃ የመታው እንደሆነ በእስራት ይቀጣል።

- 666. ያደጋ ምልክት በሆነ ጊዜ ግርግር የማነጣጠል ሙከራ ያስቀጣል።
- 667. አንድ ወታደር ያገልግሎት ተግባሩን ያላገባብ እንዲፈጽም የሚያስገድድ ሰው በእስራት ይቀጣል።
- 668. ማንኛውም ሰው በሕግ የተደነገገው ግብር እንዳይከፈል ያነሳሳ በገንዘብ መቀጮ ይቀጣል።
- 669. ፈቃዱ ባልሆነ ሰው ስም ሰነድ የሰጠ ሰው ይቀጣል።
- 670. ሌሎችን ሰዎች ለማታለል ዋጋ የመረመረ ሰው ይቀጣል።
- 671. የነገር መንዛት እንደ ተሠራ በደል ሆኖ ይቆጠራል
- 672. ወንጀሉን የሠራው አንድ የሰውነት መብት የተሰጠው ማህበር ሲሆን በማህበሩ ላይ መቀጮ ይጣልበታል።
- 673. በሀይል ለግብረ ስጋ ተግባር የሚያስገድድ ሰው በእስራት ይቀጣል።
- 674. ከ 15 እስ 18 ዓመት የሆነ ሰው የግብረ ሥጋ ግንኙነት ከፈጸመ በእስራት ይቀጣል።
- 675. የጋብቻ ሥርዓት ካልፈረሰ በቀር ክስ ማቅረብ አይቻልም።
- 676. በሕግ የተከለከለውን ያስፈጸመ ሰው በእስራት ይቀጣል።
- 677. በጋብቻ ሥርዓት ግዴታ ታስራ የምትገኝ ሴት ያገባ በእስራት ይቀጣል።
- 678. የሴቶችን ሥራ የሠራ ሰው ተበዳዩ የክስ አቤቱታ ባቀረበ ጊዜ መቀጮ ይቀጣል።
- 679. ተከላሹ ክርስቲያን ሆኖ ሳይፈታ በቤቱ ዕቁባት ያስቀመጠ በእስራት ይቀጣል።
- 680. አካለ መጠን ያልደረሱ ልጆች የወንጀሉን ሥራ የፈጸሙት ከሆነ ቅጣቱ አይፈጸምባቸውም።
- 681. የሌላውን ሰው የክብር መዝገብ ያጠፋ በህግ ይቀጣል
- 682. የሌላውን ሰው ዕቃ የሰረቀ ሰው በህግ ይጠየቃል
- 683. የጦር መሣሪያ ይዞ የወንበዴነት ወንጀል መሥራት የሞት ፍርድን ያስከትላል።
- 684. ሆን ብሎ የሌላ ሰው ሀብትን ያፈረሰ በእስራት ወይም በገንዘብ መቀጮ ይቀጣል።
- 685. የክስ አቤቱታ ሲቀርብበት በእስራት ወይም በገንዘብ መቀጮ ይቀጣል።
- 686. በአበዳሪ ላይ ጉዳት እንዲደርስ በማሰብ ተንኮል ማቀድ ቅጣት ያስከትላል።
- 687. የደንብ መተላለፍ ነገር የሚወሰነው በጠቅላላው በአገሩ ሕግ የመዳኞት ደንብ መሠረት ነው።
- 688. በውጭ አገር የሚደረጉት የደንብ መተላለፍ ሥራዎች በኢትዮጵያ አገር አያስቀጡም።
- 689. በደንብ መተላለፍ ረገድ አላፊነትና ተቀጭነት የግል ናቸው።
- 690. የደንብ መተላለፍ ጥፋተኛ ሕግ መኖሩን አላወቅውም በማለት ከቅጣት ለመዳን መከላከያ ሊቀርብ አይችልም።
- 691. አስቀድሞ ለአመክሮ መፈታት ለማረፊያ ቤት እስራት ጉዳይ ተፈጻሚ አይሆንም።
- 692. የማረፊያ ቤት እስራት የተፈረደበት ሰው እንዲሰራ አይገደድም።
- 693. ሆነ ብለው በሚሠራ ወንጀል አባሪ መሆን ሁል ጊዜ የሚያስቀጣ ነው።
- 694. በወንጀል ምክኒያት መቀጮ የሚከፈለው በገንዘብ ነው።
- 695. የማስወረድ ተግባርን የምትፈጽም ርጉዝ ሴት ከሦት ወር በማያስ እስራት ትቀጣለች።
- 696. በወንጀል ምክንያት መቀጮ የሚከፈለው በገንዘብ ነው።
- 697. አስቦ በሰው ላይ አንድ ተላላፊ በሽታ ያስተላለፈ ሰው በስራት ይቀጣል።
- 698. ባለመጠንቀቅ የሚደርስ የፅንሰ መቁዋረጥ በወንጀል ሕግ የሚያስቀጣ አይደለም።
- 699. በደንብ መተላለፍ ረገድ ሀላፊነትና ተቀጭነት የግል ናቸው።
- 700. በወንጀል ምክኒያት የሚከፈለው መቀጮ ገቢነቱ ለመንግሥት ነው።

- 701. የግብርና ምርት ማለት ሚኒስትሩ የሚሰይሙት ምርት ማለት ነው
- 702. ሚኒስቴር ማለት የኢትዮጵያ ፌዴራላዊ ዲሞክራሲያዊ ሪፐብሊክ ማለት ነው
- 703. ሰው ማለት የተፈጥሮ ሰው ወይም በሕግ የሰውነት መብት የተሰጠው አካል ማለት ነው።
- 704. አንድ ሰው በዕቃ ማከማቻ ቤቱ ውስጥ ለማከማቻት የሚረከባቸው ዕቃዎችን በአግባቡ የመጠበቅ ኃላፊነት አለበት
- 705. አንድ የዕቃ ማከማቻ ደረሰኝ የሚተላለፍ ወይም የማይተላለፈ ሊሆን ይችላል።
- 706. የንግድ ማህበራትን የንግድ ምዝገባ ሶስተኛ ወገኖች እንዲያውቁት መዝገቡ ክፍት ይደረጋል።
- 707. በሕግ በተለየ አኳኋን ካልተደነገገ በቀር የሥራ ውል የተለየ ፎርም አይኖረውም።
- 708. አንድ ሰው ለታቀደው ቦታ ተስማሚ መሆኑን ለመመዘን ለሙከራ ጊዜ መቅጠር ይቻላል።
- 709. በሙከራ ላይ ያለ ሰራተኛ ያለማስጠንቀቂያ ስራውን ሊለቅ ይችላል
- 710. አንድ ሰራተኛ የስራ ስንብት ክፍያ ከማግኘቱ በፊት ቢሞት ለጥገኞቹ ይከፈላቸዋል
- 711. ደመወዝ ማለት አንድ ሰራተኛ የሚከፈለው መደበኛ ክፍያ ነው
- 712. የማንኛውም ሰራተኛ የስራ ሰዓት በቀን ከስምንት ሰዓት አይበልጥም
- 713. በወር ደመወዝ የሚከፈለው ሰራተኛ በህዝብ በዓላት ባለመስራቱ ምክንያት ከደመወዙ አይቀነስበትም
- 714. የዓመት ፈቃድ ሊተላለፍ ይችላል
- 715. ሴቶች በጾታቸው ምክንያት በስራ ቅጥር ልዩነት አይደረግባቸውም
- 716. ነፍስ ጡር የሆነች ሰራተኛ ከደመወዟ ጋር ፍቃድ ይሰጣታል
- 717. ኮንፌዴሬሽን ማለት ከአንድ በላይ የሆኑ አሠሪዎች የሚያቋቁሙት ማኅበር ነው።
- 718. ወላጆቹ ወይም ከወላጆቹ አንዱ ኢትዮጵያዊ የሆነ ሰው በትውልድ የኢትዮጵያ ዜጋ ነው።
- 719. ፖሊስ ማለት የፌዴራል ወይም የክልል ፖሊስ ነው።
- 720. ኮሚሽን ማለት የፌዴራል ማረሚያ ቤቶች ኮሚሽን ማለት ነው።
- 721. ማንኛውም ፖሊስ አደገኛ ቦዜ መሆኑን በሚገባ የሚጠረጥረውን ሰው ያለፍርድ ቤት ትዕዛዝ መያዝ ይችላል።
- 722. እርዳታ ማለት የአደጋ ሰለባዎችን ፍላጎት ማሟላት ነው።
- 723. መንግሥታዊ የማሰልጠኛ ተቋም ማለት በመንግሥት ባለቤትነት የተያዘ የማሰልጠኛ ተቋም ነው።
- 724. የመጀመሪያ ደረጃ ትምህርት ማለት በስምንተኛ ክፍል የሚጠናቀቅ የቀለም ትምህርት እርከን ነው።
- 725. የአጠቃላይ ሁለተኛ ደረጃ ትምህርት ማለት በ10ኛ ክፍል የሚጠናቀቅ የአጠቃላይ ሁለት ደረጃ የትምህርት እርከን ነው።
- 726 መንግስት ማለት የፌዴራል ወይም የክልል መስተዳድር ነው።
- 727. ጽህፈት ቤት ማለት በትምህርት ሚኒስቴር ትምህርት ሥልጠና ዘርፍ ነው።
- 728. በመሠረታዊ ሙያ ሥልጠና የሚታቀፉ ሠልጣኞች ማንበብና መጻፍ የሚችሉ መሆን አለባቸው።
- 729. የመሠረታዊ ሙያ ሥልጠና መደበኛ ባልሆነ ዘዴ ሊካሄድ ይችላል።
- 730. የመሠረታዊ ሙያ ሥልጠና የሚሰጥበት ቋንቋ በክልል መንግሥት ይወሰናል።
- 731. የመለስተኛ ቴክኒክና ሙያ ሥልጠና በተግባርና በንድፈ ሃሳብ የተደገፈ ይሆናል።
- 732. ማንኛውም ሠልጣኝ ክሂሎቱን በበለጠ ለማዳበር የሥራ ላይ ልምምድ ማድረግ አለበት።
- 733. ማንኛውም መንግሥታዊ የማሰልጠኛ ተቋም ውስጣዊ የፋይናንስ ነፃነት አለው
- 734. ብሮድካስቲንግ ማለት ድምፅ ምስልንና ሽቦ አልባ በሆነ መንገድ ለህዝብ ማሰራጨት ነው።
- 735. የብሮድካስቲንግ ድርጅት ማለት ሬድዮ ወይም ቴሌቪዥን ነው።

- 736. የድሬደዋ አስተዳደር የሥራ ቋንቋ አማርኛ ነው።
- 737. የድሬደዋ ምክር ቤት አባላት በየአምስት ዓመቱ በከተማው ነዋሪ ይመረጣሉ።
- 738. የድሬደዋ ምክር ቤት ተጠሪነት ለፌዴራሉ መንግስትና ለከተማው ነዋሪዎች ይሆናል።
- 739. የገንዘብ እና የኢኮኖሚ ልማት ሚኒስቴር ለክልሎች የሚሰጠውን የድጎማ በጀት ይቆጣጠራል።
- 740. አካሚክ መኮንን ማለት የምርምርና ህትመት መኮንን፣ ማለት ነው።
- 741. የትምህርት ክፍል ማለት ኮሌጅ ፋካልቲ ወይም ዲፓርትመንት ነው።
- 742. በፌዴራል መንግስት በጀት የሚተዳደር ተቋም በሚኒስትሮች ምክር ቤት ደንብ መሠረት ይቋቋማል።
- 743. ማንኛውም ተቋም በዩኒቨርሲቲ መቋቋም ይችላል።
- 744. ማንኛውም ተቋም በተቋሙ ተልዕኮ አካዳሚያዊ ነፃነት ይኖረዋል።
- 745. ማንኛውም ተቋም ግልፅነት ያለው የምርምር ፈንድ አስተዳደር አስተዳደር ሥርዓት ይኖረዋል።
- 746. የመንግሥት ተቋማት የበጀት ዓመት የመንግሥት በጀት ዓመት ይሆናል።
- 747. የሴኔት የአባልነት ሁኔታና የአባልነት ቁጥር በተቋሙ ማቋቋሚያ ህግ ይወስናል
- 748. ሴኔት የአባላቱን ዲስፕሊን በሚያወጣው የውስጥ ደንብ ይወስናል።
- 749. በማንኛውም የመንግስት ተቋም ውስጥ ተባባሪ ምክትል ንግድነት የሚባል አይኖርም።
- 750. ምክትል ንግድነት አብዛኛው የሥራ ጊዜያቸውን ለቢሮ ስራዎች ያውላሉ
- 751. የዩኒቨርሲቲ ካውንስል መደበኛ የሰብሰባ ቀን ቢያንስ በስድስት ወር አንድ ጊዜ ይሰበሰባል።
- 752. የመንግሥት ተቋም መዘጋት በተገቢው ሚዲያ ይፋ መደረግ አለበት።
- 753. በማንኛውም የመንግስት ተቋም ውስጥ ለንግድነት ተጠሪ የሆነ የውስጥ ኦዲት ይቋቋማል።
- 754. የመንግሥት ተቋም የውስጥ ኦዲት ክፍል ኃላፊ በንግድነት አቅራቢነት በቦርድ ይሾማል።
- 755. መንግስት ለመንግስት ተቋማት ጥቅል በጀት የሚመድብበትን መሥፈርት ይወስናል።
- 756. አሠሪ ማለት ቀጥሮ የሚያሠራ ግለሰብ ወይም ድርጅት ነው።
- 757. ድርጅት ማለት ለህጋዊ ዓላማ የተቋቋመ በአንድ አመራር የሚካሄድ ተቋም ነው።
- 758. የሥራ ውል ሕግን ተቃራኒ ለሆነ ሥራ አይደረግም።
- 759. ለሴት ሠራተኞች በጾታቸው ምክንያት የክፍያ ልዩነት ማድረግ አይቻልም።
- 760. ሠራተኛን በሕይወቱ ላይ አደጋ ሊያደርስበት በሚችል አካላት እንዲሰራ ማድረግ ህገ ወጥ ነው
- 761. አሠሪው በግልጽ ሳይፈቅድ ከሥራ ቦታ ንብረት መውሰድ ህገ ወጥ ነው።
- 762. በሥራ ላይ ሰክሮ መገኘት ክልክል ነው
- 763. ያለበቂ ምክንያት የሥራ ሰዓት አለማክበር ከሥራ ያስወግዳል
- 764. የራሱን በመሻት በማንኛውም የአሠሪው ንብረት አላግባብ መጠቀም ከሥራ ያስወግዳል
- 765. የትርፍ ሰዓት ሥራ ክፍያ እንደ ደሞዝ አይቆጠርም።
- 766. የተለየ ስምምነት ካልተደረገ በቀር ደመወዝ በሥራ ቀንና በሥራው ቦታ ይከፈላል።
- 767. በአንድ ጊዜ ከሠራተኛ ደመወዝ ላይ ሊቆረጥ የሚችለው የገንዘብ መጠን ከወር ደመወዙ አንድ ሶስተኛ መሰለጥ የለበትም።
- 768. አሠሪው ሠራተኛው ሲጠይቅ የክፍያ መዝገቡን እንዲያይ የመፍቀድ ግዴታ አለበት።
- 769. የሥራ ሰዓቶች ለሃምሳቱ የድርጅቱ የሥራ ቀኖች እኩል ይደለደላሉ።
- 770 ማንኛውም ሠራተኛ የትርፍ ሰዓት ሥራ እንዲሠራ አይገደድም

- 771. የትርፍ ሰዓት ክፍያ ለደመወዝ መክፈያ በተወሰነው ቀን ይከፈላል።
- 772. ማንኛውም ሠራተኛ በሰዓት ቀናት ጊዜ ውስጥ ከሃያ አራት ሰዓት የማያንስ የሣምንት ዕረፍት ያገኛል።
- 773. አግባብ ባለው ሕግ መሠረት የሚከበሩ የሕዝብ በዓላት ደመወዝ የሚከፈልባቸው ይሆናሉ።
- 774. የሥራ ውሉ የተቋረጠ ሠራተኛ ያልወሰደው የዓመት ፈቃድ ታስቦ በገንዘብ ይከፈለዋል።
- 775. አሠሪው የሥራ ሁኔታ ሲያስገድደው የሠራተኛውን የፈቃድ ጊዜ ሊያስተላልፍ ይችላል።
- 776. ነፍሰ ጡር የሆነች ሴት ሠራተኛን ከምሽቱ 4 ሰዓት እስከ ንጋቱ 12 ሰዓት ባለው ጊዜ ማሠራት አይቻልም።
- 777. ነፍሰ ጡር የሆነች ሴት ሠራተኛን በሥራ ውሏ ከተመለከተው የሥራ ቦታዋ ውጭ ማሠራት አይቻልም።
- 778. ነፍሰጡር የሆነች ሠራተኛ ከመውለዷ በፊት ሐኪም እንድታርፍ ካዘዘ ከክፍያ ጋር እረፍት ይሰጣታል።
- 779. እድሜያቸው ከ14 ዓመት በታች የሆኑትን መቅጠር ክልክል ነው።
- 780. የወጣት ሠራተኞች መደበኛ የሥራ ሰዓት ቀን ከሰዓት ሰዓት መብለጥ የበለጠም።
- 781. ማንኛውንም ወጣት ሠራተኛ በሕዝብ በዓላት ቀን ማሠራት ክልክል ነው
- 782. የአካል ጉዳት ማለት የመሥራት ችሎታ ማጣትን በሚያስከትል ሥራ ላይ የሚደርስ ጉዳት ነው።
- 783. ጉዳት ለደረሰበት ሠራተኛ የመጀመሪያ ሕክምና ማንኛውም አሠሪ ዕርዳታ በጊዜው መሰጠት አለበት
- 784. በመንግሥት የጡረታ ሕግ ላልተሸፈኑ ሠራተኞች የሚሰጠው የጉዳት ካሳ በአንድ ጊዜ በአሠሪው ይከፈላል።
- 785. መደበኛ መኖሪያ ቦታ ማለት የአንድ ሰው መኖሪያ ቦታ ነው።
- 786. የኢትዮጵያ ዜግነት በሕግ እንዲሰጥ የቀረበ ማመልከቻ በዜግነት ጉዳይ ኮሚቴ ይጣራል።
- 787. ማንኛውም ከአካለ መጠን የደረሰ የኢትዮጵያ ዜጋ የዜግነት መታወቂያ ወረቀት ይሰጠዋል።
- 788. ማንኛውም ከአካለ መጠን የደረሰ የኢትዮጵያ ዜጋ ፓስፖርት መጠየቅ ይችላል።
- 789. ለአካለ መጠን ያልደረሱ ልጆች በወላጅ መታወቂያ ወረቀት ላይ መመዝገብ አለባቸው።
- 790. መንግስት ለዜጎች መብቶችና ሕጋዊ ጥቅሞች ጥበቃ ያደርጋል።
- 791. ማንኛውም ኢትዮጵያዊ ዜጋ ለሌላ መግሥት ተላልፎ እንዲሰጥ አይደረግም።
- 792. ማንኛውም ኢትዮጵያዊ ዜግነቱን የመለወጥ መብት ይኖረዋል።
- 793. የመሠረታዊ ሙያ ሥልጠና ኘሮግራም ዓላማ በጀማሪ ባለሙያነት ማሰልጠን ነው።
- 794. ከንቲባ ማለት የከተማውን አስተዳደር የሚመራ ዋና ሥራ አስፈጻሚ ነው።
- 795. የድሬደዋ ፓሊስ ኮሚሽነርና ምክትል ኮሚሽነር በፌዴራል ጉዳዮች ሚኒስትር ይሾማሉ።
- 796. ኘራይቪታይዜሽን ማለት የመንግሥት የልማት ድርጅቶችን ማዛወር ነው
- 797. ማንኛውም የኅብረት ሥራ ማኅበር የማምረት ተግባራት ሊኖሩት ይችላሉ።
- 798. የተለያዩ የህብረት ሥራ ዓይነቶች ሀገሪቱ በሚኖራት የሥራ ዘርፎች ውስጥ ሊደራጁ ይችላሉ።
- 799. ማንኛውም ማኅበር ከተመዘገበበት ቀን ጀምሮ ሕጋዊ ሰውነት ያገኛል።
- 800. የቅጅ መብት ማለት ከአንድ ስራ የሚመነጭ የኢኮኖሚ መብት ነው።

Evaluation Test Sentences

1. የመቀሌ ስቴዲዮም ግንባታ ተጠናቀቀ
2. ሀይሌ የአገር አቋራጭ ውድድር አሸነፈ
3. ሁነኛው በሰፔን ሩጫ ለድል ይጠበቃል
4. ብዙነሽ በሙምባይ ማራቶን ለድል ትጠበቃለች
5. ፌዴሬሽኑ ከባለድርሻ አካላት ጋር ተወያየ
6. በመቀሌ ከተማ ሩጫ ተካሔደ
7. ከአፍሪካ ምርጥ ስፖርተኞች ኢትዮጵያውያን ሥፍራ ይዘዋል
8. ቀነኒሳ በለንደን ማራቶን አሸነፈ
9. ለወልድያ ስታዲዮም ገቢ ማሰባሰብ ተጀመረ
10. ኢትዮጵያውያን በሞስኮ የሩጫ ውድድሮች አሸነፉ
11. የጋራ ብልፅግና አገሮች የስፖርት ሻምፒዎች ተጀመረ
12. የኢትዮጵያ እግር ኳስ ፌዴሬሽን ብጥብጥ ባስነሱ ወገኖች ላይ እርምጃ እንደሚወስድ ገለጸ
13. የከፍተኛ ትምህርት ተቋማት የስፖርት ፌስቲቫል በሀዋሳ ተጀመረ
14. በጅም ከተማ የአትሌቲክስ ማሰልጠኛ ማዕከል ተመረቀ
15. በደብረ ብርሃን ከተማ ሁለገብ ዘመናዊ ስቴዲዮም እየተገነባ ነው
16. በኢትዮጵያና ባለም ባንክ መካከል የብድር ስምምነቶች ተፈረሙ
17. ዓባይ ባንክ ቅርንጫፍ ከፈተ
18. የአዲስ አበባ መሪ ፕላን እየተከለሰ ነው
19. የቁጠባ ባህል እያደገ ነው ተባለ
20. የኢትዮጵያ ንግድ ባንክ በምስራቅ ጎጃም ቅርንጫፍ ከፈተ
21. በአፋር የአርብቶ አደሮች ቀን ተከበረ
22. ቻይና ዓሣን በማምረት ቀዳሚ ሀገር ሆነች
23. የኢትዮጵያ አየር መንገድ የዓመቱን ምርጥ ሽልማት አገኘ
23. ብሔራዊ ሎተሪ 10 ሚሊዮን ብር ትርፍ አገኘ
24. የኢትዮጵያ ንግድ ባንክ ቅርንጫፍ ከፈተ
25. በጋምቤላ የውሃ ተቋማት ሊገነቡ ነው
26. የራዲዮ ፋና የምስረታ በዓል ተከበረ
27. በሰማሌ ውሃ ለማጠራቀም ግድብ እየተሰራ ነው
28. የሕዝብ ቁጥር መጨመር በሀገር እድገት ላይ ተጽእኖ ያስከትላል
29. ለህጻናትና ወጣቶች የእይምሮ ጤንነት ትኩረት መስጠት ያስፈልጋል
30. ባህሬን በኢትዮጵያ ኤምባሰ ከፈተች
31. በዲላ ኮሌጅ ቦንብ ፍንዳታ እጃቸው አለበት ተብለው የተጠረጠሩ ተያዙ
32. ፕሬዚዳንት ግርማ ከየመን ተመለሱ
33. የሰማታት አጽም በክብር አረፈ
34. በምስራቅ ወለጋ ለሠፋሪዎች የርሻ በሬ እየተከፋፈለ ነው
35. በመስኖ ልማት አስተዋጋ ያደረጉ ገበሬዎች ተሸለሙ
36. ጠቅላይ ሚኒስትር መለስ መልዕክት ተቀበሉ
37. በሻዕቢያ ጦርነት ለተፈናቀሉ ወገኖች የሚሰጠው እርዳታ ቀጥሏል
38. የኮንስትራክሽን ኤግዛቢሽን ተከፈተ
39. ስፔን በኢትዮጵያ ለተከሰተው ድርቅ ርዳታ ትሰጣለች
40. የሱዳን የርስ በርስ ግጭት በሰላም የሚፈታበት ጊዜ መቃረቡ ተገለጸ
41. ጎንደር ዩኒቨርሲቲ ዘመናዊ አምቡላንስ በእርዳታ አገኘ
42. ጎንደር ዩኒቨርሲቲ ሆስፒታል ያይን ህክምና ማዕከል ሊከፍት ነው
43. የካንሰር ቀንን በማስመልከት በአዲስ አበባ የግር ጉዞ ተካሄደ
44. ዓለም አቀፍ የኤች አይቪ ስብሰባ በአዲስ አበባ ተከፈተ
45. በኤች አይ ቪ አድስ የሚሞቱ ሰዎች ቁጥር እየቀነሰ ነው
46. በአድዋ የተገነባ ሆስፒታል ተመረቀ
47. በመላ አገሪቱ የጤና ጣቢያዎች ግንባታ በመፋጠን ላይ ነው
48. የዓለም የኩላሊት ቀን አዲስ አበባ ውስጥ ታስቦ ዋለ
49. በአድዋ የጤና ጣቢያ ተገነባ
50. ከርግዝናና ወሊድ ጋር በተያያዘ እናቶች መሞት የለባቸውም ተባለ
51. ጎጃም ውስጥ ፈታውራሪ አሰጌ የሚባሉ ሰው ነበሩ

52. ቦጋለ መብራቱ ከደሃ ቤተሰብ የተወለዱ ነበሩ
53. የሰው ምላስ ከእሳት የበለጠ ያቃጥላል አሉ እመት ወድነሽ
54. ሰብለወንጌል ጉዳ ካሳን ትወድ ነበር
55. የእድሜ ልዩነት ቁምነገር የለውም አሉ ቁስ ታምሩ
56. ከግብር በሁዋላ ካህናቱ በዛብህን አመሰገኑት
57. ፈታውራሪ መሸሻ በጣም ተቆጡ
58. በዛብህ ካለቃ ክንፉ ቅኔ ተማረ
59. ደመቀች በአጭር ጊዜ ውስጥ ተወደደች
60. ታምራት ጥሩ ተኩዋሽ ነበር
61. ፈታውራሪ አሰጌ ሁለት አግብተው ፈትተዋል
62. ደጅኔ አምስት ብር ከአምስት ሰዎች ተበደረ
63. ልጄ ሆይ ያባትህን ምክር አድምጥ
64. ጥበብ በያደባባዩ ድምጽዎን ከፍ ታደርጋለች
65. በእግዚአብሔር ደስ ይበላችሁ
66. ተላላ ሴት ቤቷን ታፈርሰዋለች
67. ለአምላክህ እግዚአብሔር ሕጉን ሁልጊዜ ጠብቅ
68. ፍቅርና ታማኝነት ከቶ አይለዩህ
69. ወደ እግዚአብሔር በመጸለይ አምላኬን አመሰግናለሁ
70. ከኢየሱስ ክርስቶስ ሰላም ለእናንተ ይሁን
71. ፍቅር ቸር ነው
72. በሰማይ ያለውን የአባቴን ፈቃድ ፈጽሙ
73. ሐዋርያት በኢየሱስ ዙሪያ ተሰብስበው ያስተማሩትን ነገሩት
74. ከዝሙት ርቃችሁ ሸሹ
75. በአየሁት ጊዜ እንደ ሞተ ሰው ሆኜ በእግሩ ሥር ወደቅኩ
76. የወንጀለኛ መቅጫ ሕግ ግብ የዜጎችን ጸጥታ መጠበቅ ነው
77. በፍርድ የተገደለ ሰው ሬሳ በሚገባ ይቀበራል
78. ከጥፋት ነጻ ለመውጣት ሕግን አለማወቅ ምክንያት ማድረግ አይቻልም
79. ፍርድ ከመወሰኑ በፊት ክስን መተው ይቻላል
80. ሆነ ብሎ ተላላፊ በሽታ ያስተላለፈ ሰው በስራት ይቀጣል
81. ሰውን የገደለ ነፍሰ ገዳይ ነው
82. በእንስሳት ላይ የግብረ ሥጋን የፈጸመ በእስራት ይቀጣል
83. ሕግ በሁሉም ሰው ላይ ይፈጸማል
84. ወንጀልን አለማስታወቅ ወንጀለኛን መርዳት ነው
85. ፍርድ ቤት ሕጋዊ ውሳኔን በትክክል ይሰጣል
86. ሙስና በእስራት ያስቀጣል
87. ወላጆቹ ኢትዮጵያዊ የሆነ የኢትዮጵያ ዜጋ ነው
88. የስራ ሰዓት በቀን ከስምንት ሰዓት አይበልጥም
89. ደሞዝ ማለት መደበኛ ክፍያ ነው
90. ሴቶች በስራ ቅጥር ልዩነት አይደረግባቸውም
91. ያዓመት ፈቃድ ሊተላለፍ ይችላል
92. የኢትዮጵያ የሥራ ቋንቋ አማርኛ ነው
93. በመሠረታዊ ሙያ ሥልጠና የሚታቀፉ ሠልጣኞች በንድፈ ሃሳብ የተደገፈ ይሆናል
94. ርዳታ ማለት የአደጋ ሰለባዎችን ፍላጎት ማሟላት ነው
95. ዲፓርትመንት ማለት የትምህርት ክፍል ማለት ነው
96. የትርፍ ሥራ ክፍያ እንደ ደመወዝ አይቆጠርም
97. መንግስት ለዜጎች ጥበቃ ያደርጋል
98. አንድ ኢትዮጵያዊ ዜግነቱን የመለወጥ መብት አለው
99. በሕዝብ በዓላት ቀን ሰራተኛን ማሠራት ክልክል ነው
100. ነፍስ ጡር የሆነች ሴት ከመውለዷ በፊት ዕረፍት ይሰጣታል

Declaration

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

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Place and date of submission: Addis Ababa, June, 2011.