Addis Ababa University

College of Natural Sciences

Chatbot based customer service model using Deep Learning: the case of Ethiopian Airlines

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This is to certify that the thesis project prepared by Natnael, titled: "Chatbot based customer service model using Deep Learning: the case of Ethiopian Airlines." and submitted in partial fulfillment of the requirements for the Degree of Master of Science in Computer Science complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

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Abstract

Chatbot systems implemented for different purposes and plays significant role in terms of accessibility, reliability, and offers cost efficient auto services. The usage of chatbots grown rapidly in various fields in recent years, including Marketing, Supporting Systems, Education, Health Care, Cultural Heritage, and Entertainment. Therefore, we are motivated to design, develop, and implement automated Deep Learning based chatbots for Ethiopian airlines customer services. The reason to select Ethiopian airlines is even though it has a best customer service currently, the chatbot service will enhance improving its services more. This study aimed on designing and implementing a chatbot based model using deep learning methods which can facilitate customer service for enhancing Ethiopian airlines services. For this study, 30,000 question and answer pair statements has been collected from Ethiopian Airlines FAQ and from Kaggle websites. The collected documents have been passed through the appropriate data preparation. The dataset has split into 80% for training and 20% for testing sets. The researcher applied two different neural network techniques. The two neural network techniques experimented in this research are Long Short-Term Memory (LSTM) techniques and Convolutional Neural Network (CNN). To evaluate the performance of each technique, the researcher used various performance evaluation metrics such as Precession, Recall, F-score, Accuracy. The feature extraction techniques used for neural network techniques are word embedding, bag of words and word2vec methods. The evaluated Neural network techniques accomplished accuracy for LSTM 83.25% and CNN 85.20%. According to the performance result from the techniques applied, the CNN technique achieved better accuracy compared to LSTM and we applied CNN to deploy our model.

Keywords: Chatbot, Deep Learning, Neural network, Feature extraction, Word2Vec

Dedication

This work is dedicated to my mother Genet Negash and my father Mekuanent Agumasie.

Acknowledgment

First and foremost, I would like to praise and thank the Almighty God for his abundant grace and giving me the strength from the beginning to the end of this research work.

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Acronyms and Abbreviations

AI	Artificial Intelligence
AIML	Artificial Intelligence Markup Language
ALICE	Artificial Linguistic Internet Computer Entity
ANN	Artificial Neural Networks
BOW	Bag-of-Words
CBOW	Continuous Bag-of-Words
F1	F1-score
BLEU	Bilingual Evaluation Understudy
CNN	Convolutional Neural Network
ELIZA	Elisabeth
FAQ	Frequently Asked Questions
GUI	Graphical User Interface
LSTM	Long short-term memory
NLTK	Natural Language Toolkit
RNN	Recurrent Neural Network
Word2Vec	Word to vector
NLP	Natural Language Processing
TF-IDF	Term Frequency-Inverse Document Frequency
XML	eXtensible Markup Language

CHAPTER ONE

1.INTRODUCTION

Nowadays, the way we communicate with digital devices is mostly constrained, based on what features and accessibility each device offers [1]. However simple it may be, there is a learning curve associated with different new device we communicate with. Currently, Chatbots are the simplest method we have for software to be native to humans because they offer an experience of talking to another person. Since chatbots imitate a real person, Artificial Intelligence (AI) techniques are applied to build them [2].

Tasks previously performed by secretaries are now getting digitized by virtual assistants. To increase and improve the ease of user interaction with any system, human and artifact collaboration is essential. The assistants also called as chatbots can interact with humans through text, voice, or images [3]. A chatbot is a program designed to simulate an intelligent conversation with a human partner. Virtual assistants can quickly change into capable, responsible, and valuable assets to the public. A deep learning software is a set of algorithms which typically uses artificial neural networks to learn in multiple levels corresponding to different level of abstraction data such as images, sound, text. This type of software is Present in some of these devices to deliver high-end speech recognition and clarity [4].

Conversational agent or Chatbot is a program that produces response based on given input to imitate human conversations in text or voice mode. These applications are created to imitate human-human interactions. Chatbots are mainly used in business and corporate organizations including government, non-profit and private ones. Chatbot operations can range from customer service, product suggestion, product inquiry to personal assistant [5]. Lots of these chat agents are developed using rule-based techniques, retrieval techniques or simple machine learning algorithms. Rule-based chatbots are also described to as decision-tree bots. As the name indicates, they apply a series of defined rules. These rules are the foundation for the types of challenges the chatbot is familiar with and can deliver solutions for. As a flowchart, rule-based chatbots map out the conversations. In retrieval-based techniques, chat agents search for keywords within the input phrase and retrieves relevant answers according to the query string. They depend on keyword similarity and retrieve text is pulled from internal or external data sources including world wide web or organizational database [6]. Some other advanced chatbots are designed with natural language processing (NLP) techniques and machine learning algorithms. Also, there are several commercial chat engines available, which help build chatbots as per the client data input.

Recently, there have been major increase of need in use and deployment of dialogue generation systems. A chatbot can be taken as a question-answer system where professionals offer knowledge for act of asking of the user. These chatbots are mostly supported by Artificial Intelligence. Several main technology enterprises are utilizing virtual aid or chat agent to fill the demands of customers. Some commonly available chatbots are Amazon Alexa, Apple Siri, Google Assistant, Microsoft Cortana, and many more [7]. Although they are primarily question answering systems, their implementation by major corporations has picked interest in clients and appears encouraging for more improved conversational agent system for research and development. The dialogue between users and customer service agents on different applications platform can be taken as representing one sequence of words as a query and the next sequence of words an answer [8].

1.2 Motivation

Various organizations are looking to integrate automated AI-based solutions such as chatbots into their customer service to offer quicker and low-cost assistance to their customers who are becoming increasingly comfortable with technology. Chatbots can effectively operate a dialogue, usually replacing additional communication tools such as email, telephone, or SMS. Numerous studies have been conducted studying user preferences concerning customer service [9]. The first motivation of the work is chatbot systems are very helpful as they permit users to submit a question based on some truths or stories and the system attempts to use the context in the assisting truths and stories to answer the questions successfully. The Second motivational work seen as customers experience problems with traditional online communication channels: websites are hard to navigate; Users cannot get answers to simple questions through the communication vectors. The customers' needs, and expectations are not being fulfilled by traditional channels such as communicating with customers thru phone call, email, company websites or customer going on person to company offices. This serves as motivation to analyze chatbot services and resolve those problems to develop a system that be able to mainly use to solve most of traditional channel problems. The other motivational work is customers get potential benefits in chatbot services: Such as 24-hour service; instant replies, answers to simple questions. Generally, the motivation of this research project is, achieving customer satisfaction by providing chatbot service to the customer through identifying the customer needs and based on the customer queries.

1.3 Statement of the Problem

Most companies attempt to deliver highest quality customer experiences, but few evaluate if they are actually meeting customer expectations [10]. In technologically changing era, a service sector like airline Company must adopt set of tools to build robust and competitive service business. Chatbots are virtual assistants that can engage customers 24×7 as well as improve customer experience. Someone may want information, which airline services are available and needs to receive assistance for pre-flight-related queries, related to baggage, check-in, online booking, as well as travelling with infants and children. However, the user may not get better information due to different reasons like, the user may not be aware of FAQ on websites or Information may not be available on websites. It might be boring to get information about all the services provided by the airline by checking and navigating each of the company websites, there are many contents on the company websites, which will lead the user for information overload. Besides, the user may not know how to navigate through sites to extract useful information.

Ethiopian Airlines communicate with customers via phone call, email, company websites or customer going in person to company offices. Passenger or User may ask customer service support staff by phone call or going in person but imagine user chats with smart bots to get information about airline services information like, booking, check-in, on board services, depart or arrival time and any other services based on user preferences. Customer may require additional information how to manage a booking, update cabin and it will handle multiple customers at a time. Therefore, the aim of this research is to design chatbot based customer service model using deep learning for Ethiopian Airlines. The system can answer customer question regarding Ethiopian airline services, analyze user queries, frequently asked questions and provide guidance for users about airline specific queries and to show the capability of deep learning to implement and enhance chatbots.

Research Question

- How to design and develop deep learning model for supporting Customer service by using Natural language understanding?
- Which deep learning algorithms are better for developing chatbot based customer service model using deep learning approach?

1.4 Objectives

General objective

The general objective of this research is to model a chatbot based customer service using deep learning for enhancing customer services of Ethiopian airlines.

Specific objective

- Conduct literature review and related works to conversational chatbot system.
- Identify and analyze the requirements for the Company.
- Identify the data source that is used as an input to the chatbot based customer service system.
- Identify and design deep learning model suitable for chatbot system.
- Develop chatbot based customer service model that can learn, answer questions based on the user request.
- Evaluate the performance of the model using a proper functionality with different scenarios.

1.5 Methods

The methods that are going to be undertaken to achieve the objectives of this work are described as follows.

Literature review – Literature review is conducted to study and analyze the chatbot technology, explore the current development chatbot requirements, and related work assessment will be done focusing on related developed chatbot systems.

Data Collection – All the data that are related to chatbot will be identified and analyzed from different perspective of relevance to the airline customer service. These data sources will be collected, managed, processed, and used to enhance the customer experience. Analyzing the existing data can be a data source to understand the customers` needs based on internal and external factors.

Development Tools – the chatbot customer service model for Ethiopian airlines will be design, implement, and evaluate using python which have many scientific libraries by different datasets. We use deep learning algorithm to analyze natural language understanding processes.

Evaluations – the final stage of the research is evaluating the model to get convinced and ensuring the applicability of the research. Accordingly, the evaluation is done using the metrics such as accuracy, precision, Recall and F-measure to evaluate the model.

Additionally, to test objectively, how the chatbot system offer a service in quality manner with respect to the customer need, an evaluation test will be conducted by gathering data using questionnaire from the customers.

1.6 Scope and Limitation

This study focused on the design, develop, and implement chatbot based customer service model using deep learning for Ethiopian airlines. The scope of the work is user query understanding and analysis, response to user query and provide relevant services. Information about Airline Company can be documents in different languages, scripts/encodings and there may be various kinds of information about airline such as texts, image, animations, audio, and video etc. However, the system designed with dataset of text documents written in English languages and will provide respond in English scripts.

The limitation of this work is that the system will not support speech conversation. The users interact with system using written query in English language.

1.7 Application of Result

The major significance of this study is design and develop chatbot based customer service model using deep learning for Ethiopian airlines. It provides services based on user question. Chatbot systems help companies to focus on increasing sales, enhance customer service experience [12]. It helps users to search contents easily, and optimally and customer will get interactive experiences, modifying the search by providing additional information. The other major benefits chatbots offer when it comes to dealing with customers is that chatbots are all the time there and always running, 24 hours a day, seven days a week, 365 days a year. This is an enormous operational benefit, specifically for call centers [13]. Chatbots can significantly alleviate the burden and query number for call centers by managing fundamental questions and issues on their own or seamlessly forwarding clients to active agents who can address the more important, complicated customer service issues that still need a human intervention. This, in turn, can significantly minimize call wait times and enhance the efficiency and quality of these activities [14].

1.8 Organization of the Thesis

The whole thesis is organized into six chapters. Chapter one presented introduction of the study, motivation, statement of problems, proposed solutions, scope and limitation, objective of the study, methodology and application results of the study. Chapter Two discussed literature review, which includes an overview of different chatbot system approaches. Chapter Three states different related works which are done by other researchers about chatbot systems tools and methodologies used with their respective finding. Chapter Four presents design of Chatbot based customer service system. The implementation and evaluation of Chatbot based customer service system are discussed in Chapter Five. Chapter Six deals with conclusions and future works.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this chapter the different types of the chatbots and evolution of the chatbots with their approaches of implementation has discussed. The chatbot status through considering the problems they suffer, and challenges are also observed. The state of the art in chatbot systems is explained, similarly neural network based chatbot models and techniques also discussed. Finally, the chatbots evaluation metrics has stated.

2.1.1 Definition of a chatbot

A chatbot is a conversational software system that is developed to imitate communication experiences of a human being that communicates automatically with a user. It signifies a new, modern form of customer assistance operated by artificial intelligence through a chat interface. Chatbots are based on AI techniques that recognize natural language, detect meaning, feeling, and design for expressive responses. For example, it creates simple for customers to acquire responses to their queries in a convenient way without spending their time waiting in phone queues or send repetitive emails. Chatbots can decrease the number of customer calls, average handling time and budget of customer care. However, it is not easy to attain these functionalities as it needs various complex interactions between systems [14].

2.1.2 Classification of Chatbot

The current need in chatbots can be provided to two key developments. Firstly, messaging service development has blowout quickly over the past few years. It includes features such as payments, ordering and booking, which would necessitate a separate application or website. So rather than downloading a sequence of individual applications, users can achieve tasks such as buy goods, book restaurant, and request questions all through their favorite messaging apps. Example of some of the famous applications are Facebook Messenger, WhatsApp, WeChat, and Line. Secondly, advanced AI techniques in connection with machine learning and deep learning techniques have prepared understandable progress to improve the quality of understanding and decision making on low-cost processing power. It can process the huge amount of data and process it to acquire results that surpass human capability [15].

Chatbot applications can be classified into four different groups, namely service, commercial, entertainment and advisory chatbot [16]. Service chatbots are developed to deliver facilities to customers. For example, logistics firm to reply to questions about deliveries and provide copies of communication documents through prompt messaging channel rather than emails or phone calls. Commercial chatbots are implemented to streamline purchases for customers. For example, a pizza company can facilitate delivery orders or inform promotions via messaging interface. Entertainment chatbots are intended to keep customers involved with sports, favorite band, movies, or other events. It gives the option of placing bets, detail on upcoming events and ticket deals. Advisory chatbots are aimed to provide suggestions, provide recommendations on service, offer maintenance or overhaul goods. This kind of chatbot be able to contact people, provide support and advice tips when it is required.

According to [17], chatbot application can be categorized into two groups such as task-oriented and non-task-oriented. Task-oriented chatbots objective is to help the customers to accomplish certain tasks and have short conversations. For example, Siri, Google Now, Alexa dialogue agents can give travel directions, discover restaurants, and assist to make phone calls or texts. On the other hand, non-task-oriented chatbots emphasis on speaking with customers to answer questions and entertainment.

According to the literature [18], they categorized chatbot applications into four groups such as goal-based, knowledge-based, service-based and response generated-based as shown in Figure.1.

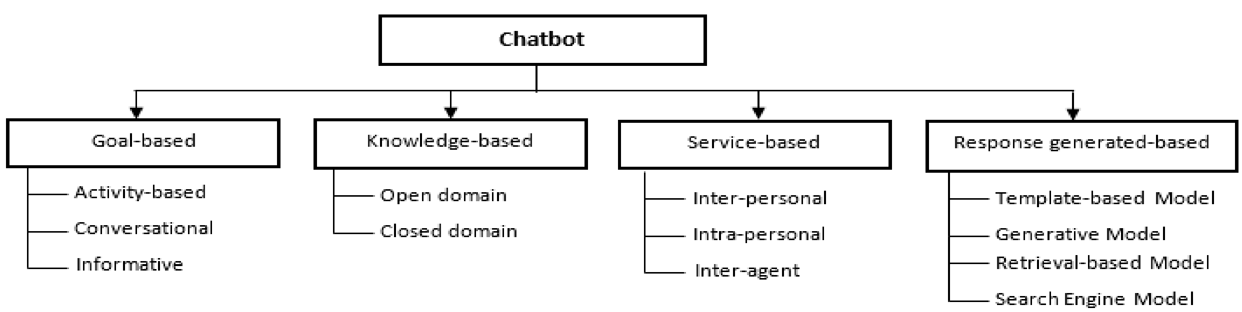

Figure 2.1 *Taxonomy of Chatbot Application [05]*

2.1.2.1 Goal-based Chatbot

Goal-based chatbots are categorized as per the primary goal aim to achieve. They are intended for a specific task and setup to have small talks to get information from the user to finish the task. For example, a company set up chatbot on their websites to assist the customer to answer their question or to solve their problems.

2.1.2.2 Knowledge-based Chatbot

Knowledge-based chatbots are categorized according to the knowledge they retrieve from the underlying data sources or the volume of data they are trained on. The two key data sources are open-domain and closed-domain. Open-domain data sources response depends on general topics and respond applicably. For example, open domain are Allen AI Science and Quiz Bowl. Closed-domain data sources emphasis on a specific knowledge domain. All information needed for answering the question is provided in the dataset itself.

2.1.2.3 Service-based Chatbot

Service-based chatbots are categorized according to facilities delivers to the customer. It might be personal or commercial purpose. For example, logistics company could deliver copies of message documents through chatbot rather than phone calls or customer can make a meal order from MacDonald.

2.1.2.4 Response Generated-based Chatbot.

Response Generated-based chatbots are categorized based on what tasks they accomplish in response generation. The answer models take input and output in natural language text. The dialogue manager is responsible for joining response models together. To produce a response, dialogue manager follows three steps. First, it practices all response models to generate a set of responses. Second, get back a response based on priority. Third, if no priority response, the response is chosen by the model selection policy. The emphasis of the literature is on response generated-based chatbot. In this category, there are numerous response models that are based on four groups as shown in Figure 2.

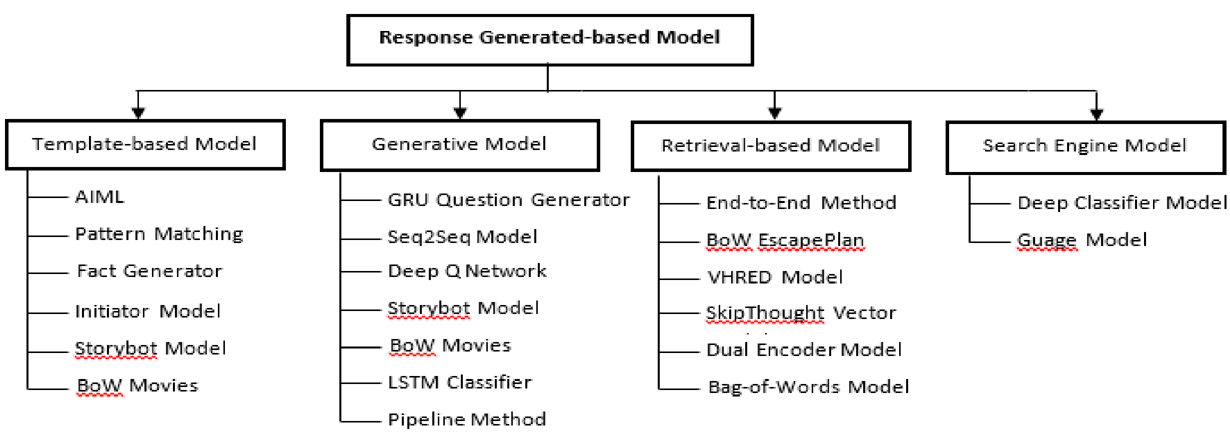

Figure 2.2 Classification of Generated-based Models [08]

2.1.3 Evolution of the Chatbots

In this section, we see different types of chatbots developed for different purposes based on the research done by [18] as discussed below.

2.1.3.1 Elizabot

Elizabot is one of the earliest popular chatbots in its long history. It was created at MIT Lab in 1966 [16] and was planned to exhibit natural language conversation between humans and machines to offer responses for the patients. Elizabot answers are personal questions that are meant to involve the patient to carry on the conversation. It applies rule-based techniques and a script to respond to patient's questions with keyword matching from a set of templates and context identification. The model notices the appropriate template and choose the equivalent answers. If there are multiple templates, a template is chosen arbitrarily. which the model runs it through a set of reflections to better format the string for a response. ELIZA uses keyword matching, which means that after a certain input, the program will look for similar keywords. If similar keywords are found, the system will construct an answer according to the rules noted for this specific keyword, and if not, a linked remark is recalled. Therefore, ELIZA does not essentially understand the problems of the users, she only matches the users' answers with her standard responses. In order not to abruptly end the conversation and to stay as human-like as possible, ELIZA tries to keep the chat going by using certain phrases when no keyword match can be found, such as "Very interesting. Please go on.", or "Can you elaborate on that?" and others.

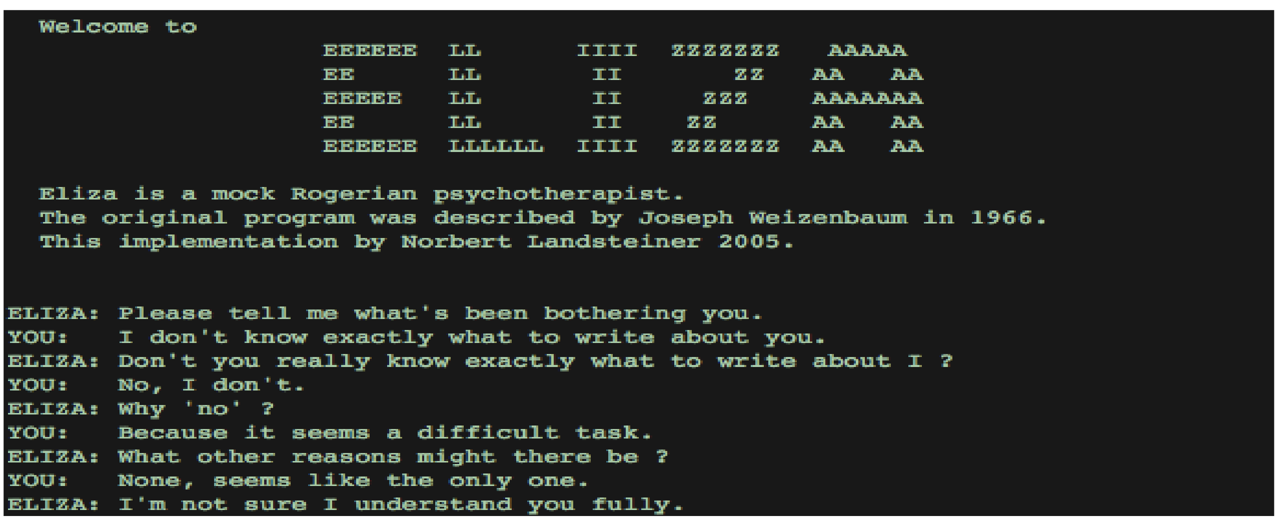

Figure 2.3 *Screenshot of a conversation with ELIZA [18]*

Figure 1 well describes the function of ELIZA. As described above, in this conversation, ELIZA uses the input, re-phrases it and simply exchanges the personal pronouns for matching ones. The shortcoming of Elizabot is to hold onto a conversation going. Moreover, Eliza is incapable of learning new patterns of speech or words, find out context through interaction and logical reasoning abilities [23].

2.1.3.2 Alicebot

The Artificial Linguistic Internet Computer Entity (ALICE) was designed and first applied by Richard Wallace in 1995. Alicebot is based on the modernized version of Eliza's architecture. Nevertheless, Alicebot is still only based on pattern matching and depth-first search method to user's entry. It is a type of XML phrase that encodes rules for questions and answers. It performs a set of artificial intelligence markup language (AIML) templates to produce answers given to the dialogue history and user utterance [21]. At first, AIML accepts the user sentence as input and stored in known as a category. Each category consists of a reply template and set of conditions that provide connotation to the template know as context. Then the model prepossesses it and matched against nodes of the decision tree. When user input is matched, the chatbot will answer or execute an action. The AIML templates replicate the user's input utterance using recursive techniques and it is not always meaningful answers. Therefore, string-based rules are required to decide if the response creates an accurate or meaningful.

Different to the simple keyword matching ELIZA uses, ALICE stores its knowledge about English conversation patterns in AIML files, Artificial Intelligence Mark-up Language [19]. These AIML files are contained of data objects called AIML objects, which again, consist of units called topics and categories. The topics have a name attribute and a set of categories related to this specific topic, while categories refer to the basic unit of knowledge in AIML. Each single category serves as a rule for aligning the user's input to the desired output, while also consisting of a pattern and a template. The shortcoming of Alicebot is modelling of personality to define the chatbot behavior such as traits, attitudes, mood, emotions, and physical states [23]. The botmaster must be included personality elements within the AIML. However, this is not a simple task. Alicebot is also unable of generating appropriate answers, no reasoning capabilities and unable to generate human-like responses (Turing test). It requires several categories to create a robust bot and may lead to unfeasible, difficult to maintain or time-consuming application. Alicebot does not have intelligence features like

NLU, sentiment analysis and grammatical analysis to structure a sentence. In addition, if the same input repeats during the conversation, Alicebot provides similar answers based on the user questions based on predefined patterns.

2.1.3.3 Mitsuku

Mitsuku is a most broadly used standalone human-like chatbot created by [24] using AIML. It was developed for general typed conversation based on rules written in AIML [25] and a combination in a bot network such as twitter, telegram, and firebase to serve as a personality layer. Mitsuku bot applies NLP using heuristic patterns and hosted at Pandorabot. Bot modules abstract a lot of the work that goes into creating a robust chatbot system. To integrate its module, need to include some AIML categories to direct inputs from users. Whenever bot fails to find a better match for an input, it will automatically redirect to the default category. Mitsuku can grasp a long conversation, learns from the conversation, remembers personal details about the user (age, location, gender, etc.). Its feature includes the capability to reason with specific objects. Mitsuku is a multi-lingual bot and uses directed machine learning. As it learns something different, the data is sent to the human manager for verification. Mitsuku is not operational without a large amount of training data, fail to provide dialogue management components.

2.1.3.4 IBM Watson

Watson is rule-based AI chatbot implemented by IBM's DeepQA project [26]. It is aimed for information retrieval and question-answering system that includes natural language processing and hierarchical machine-learning method. Watson uses a wide range of mechanisms to recognize and assign feature values such as names, dates, geographic locations, or other entities to generated response. The machine learning system then learns how to associate the values of these features into a final score for each response. Based on that score, it scores all possible answers and chooses one as its top response. Watson has a shortcoming such as it does not process structure data directly, no relational databases, higher maintenance cost, targeting towards bigger organizations and yield longer time and effort to teach Watson to use its full potential.

2.1.3.5 Google Dialogflow

Dialogflow known as Api.ai and it was developed by Google [27] and part of Google Cloud Platform. It gives app programmers provide their users to communicate with interfaces via voice and text exchanges powered by machine learning and natural language processing technologies. This lets them focus on other integral parts of app creation rather than on defining in-depth grammar rules. Dialogflow recognizes the intent and context of what user says. Then match user input to specific intents and uses entities to extract relevant data from them. And finally, permit the conversational interface to provide responses. The shortcoming of Dialogflow is no handheld device version, not interactive user interface and poor documentation.

2.1.3.6 Amazon Lex

Amazon Lex is an AWS service for producing conversational interfaces into applications using voice and text. It was implemented by Amazon [28]. It offers deep learning functionality and flexibility of natural language understanding (NLU) and automatic speech recognition (ASR) to form highly engaging user experiences with lifelike, conversational interactions. Amazon Lex integrates with AWS Lambda that user can easily start functions for execution of back-end business logic for data retrieval and updates. The shortcoming of Amazon Lex is not supporting many languages, currently, it supports only English. Unlike Watson, Lex has a serious process to follow for web integration. In addition to that, preparation of dataset is complex; the utterances and entities mapping are somewhat critical.

2.2. Techniques applied in chatbots

In this section the theory of deep learning techniques for NLP specifically, recurrent neural networks; word embedding, LSTM and sequence to sequence model will be discussed.

2.2.1 Word Embedding

Word embedding is a description of text where words that have similar meaning have similar representation in the document. In other explanation it is a technique of representing text in which each word in the vocabulary is represented by a real-valued vector in a high-dimensional space. These vectors are educated in such a way that words that have similar meanings will have similar representations in the vector space. TensorFlow, Keras frameworks of the deep learning part is usually facilitated by an embedding layer which stores a lookup table to map the words acted by numeric indexes to their condensed vector representations [29].

Word2vec is one of the words embedding feature extraction technique. Word2vec is a technique that was presented by Mikolov [30], it uses a shallow neural network to train word embedding. It is broadly applied in training word embedding from raw text. The concept of word2vec (word embedding) implemented from the concept of distributed representation of words, it uses a shallow neural network to train word embedding and predicts between every word and its context words to words occurring in similar contexts are related.

Word vector is a process of changing the words into vectors or some sort of real numbers which can be preprocessed by the natural language modeling [31]. After all the last output is word embedding. Word embedding (output of vectorized word) can be able to store the meaning of the word using low-dimensional vector (representation of words that incorporates context.), and it can be used in multi aspect of NLP research. The word embedding approach is holding word co-occurrence statistical information with certain sequence to determine phrases, words, or paraphrases. Naturally, every feed-forward neural network that takes words from a dictionary or word gallery as input and embeds them as vectors into a lower dimensional space, after that made adjustment via back-propagation, certainly produces word embedding, which is usually referred to as Embedding Layer [32].

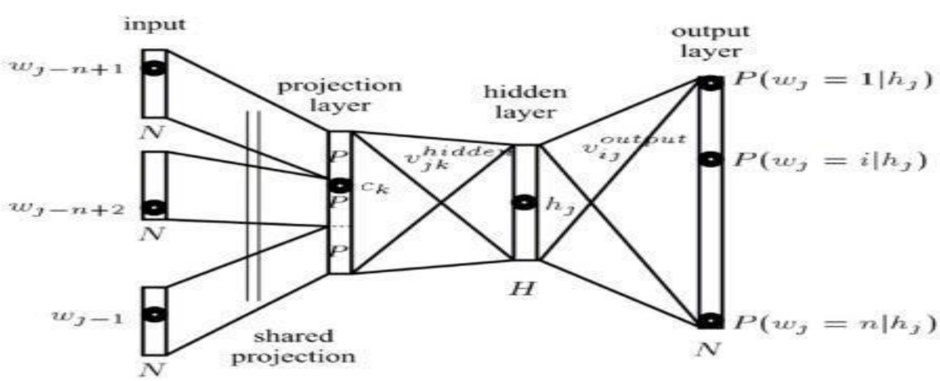

Figure 2.4 *A neural language model, which embed the input to the output [29]*

The basic difference between a neural language model network and Word2Vec is, its computational complexity that embedding becoming popular in the NLP space. The recent and rapid expansion and affordability in computational power has certainly aided its emergence [32].

The training goals in GloVe and Word2Vec are the other comparison for selecting successful word embedding, with both equipment towards producing word embeddings that encode general semantic relationships and can provide advantage in many deep learning tasks.

Common neural networks, in comparison, mostly creates task-oriented embedding with constraint in connection to their usage all over the place.
Bengio et al. [29] firstly introduce word embedding with a real-valued word feature vector in R. Foundation of their model still be applied in many neural language and word embedding models. The author formally set three major layers of their network.
1. Embedding Layer: the function of this layer is generating word embedding by reproducing an index vector with a word embedding matrix.
2. Intermediate Layer(s): this layer is based on one or more layers that creates an intermediate representation of the input, for example a fully connected layer that implements a non-linearity to the jointing of word embedding of **n** previous words.
3. Softmax Layer: this layer implements a probability distribution in vector space V.

In general, word embedding is basically the act of mapping words into vectors. This vector representation can then be directly getting into a machine learning algorithm as features. There are different methods of implementing this operation, which broads from a simple count vector to deep learning approaches such as word to vector [30] and GloVe [31]. According to this there is specific focus for this research as they evident to work effectively about chatbots. Specially, the skip-gram model is showed broadly since it is the approach used in the python library, Keras for embedding layers.

Word2Vec is not deep learning neural network, but it runs with deep neural network approaches to create an embedding layer. It can be produced by using the two methods (both using Neural Networks as their training approaches): skip gram and CBOW [30].
a) Skip Gram: This method requires the context of each word as the input and try to forecast the word equivalent to the context. It is applicable for small volume of data and is established to represent infrequent words well.
b) Common Bag of Words (CBOW): This looks like several context CBOW model just got reversed to some extent. It has improved representations for more repeated words and fast.

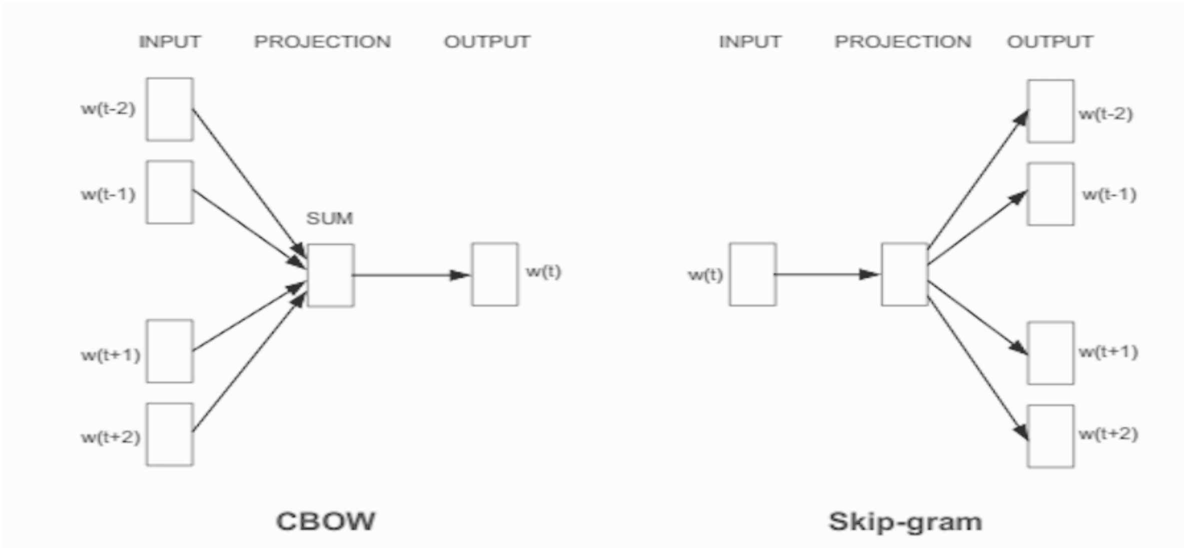

Figure 2.5 *Skip and CBOW Word2Vecmethod [30].*

TF-IDF feature extraction uses to get the word frequency in the dataset by applying the TF and the importance of the word in the dataset represented by measuring IDF of the word in the dataset.

TF: Term Frequency counts the number of times a particular word. Frequency increases when the term has occurred multiple times.TF is calculated by taking the ratio of the frequency to several terms in that particular document.

IDF: TF counts only the frequency of the word. Some words like stop words may found repeatedly but may not be useful. Hence Inverse Document Frequency (IDF) is used to measure term's importance.

2.2.2 Recurrent neural network (RNN):

In Recurrent neural network the input for the present step is the output from previous step. In old-fashioned neural networks, all the inputs and outputs are independent of each other, but in some occurrences when it is needed to forecast the next word of a sentence, the previous words are necessary; hence, there is a necessity to recognize the previous words. Thus, RNN has resolved problem with the use of a hidden layer. The key and most important feature of RNN is hidden state, which reside upon some information about a sequence [35]. The basic building of RNN is presented in Figure 3.13.

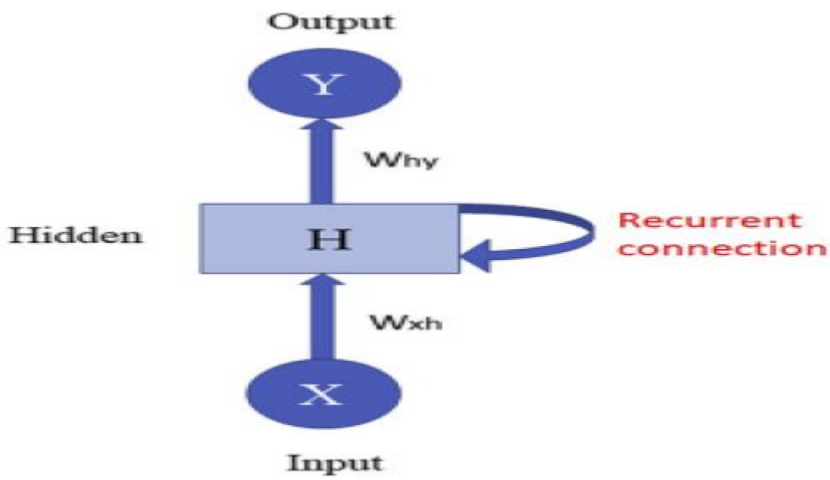

Figure 2.6 *Structure of RNN [32].*

The recurrent neural network works, let as assume a deeper network comprises of one input layer, three hidden layers, and one output layer. Each hidden layer will have its specific set of weights and their biases. The importance for hidden level is 1; then the weights and biases are w1 and b1, w2 and b2 for second hidden level, and w3 and b3 for third hidden level. This means that each of these layers is self-determining of each other, i.e., they do not memorize any other previous outputs [35].

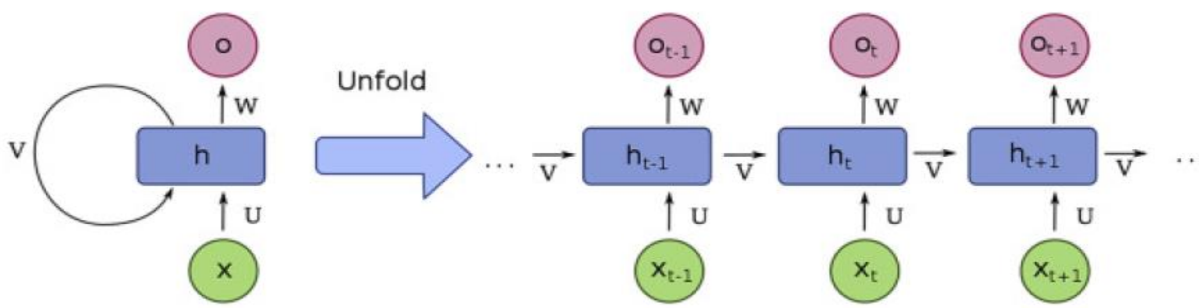

Figure 2.7 *RNN input and output Architecture [32].*

RNN is intended for sequence of data and the current input is decided by the past learnt from previous hidden state [36]. RNNs can obtain one or more input vectors and yield one or more output vectors and the output(s) are specific by the "hidden" state vector on behalf of the context based on previous input(s)/output(s). So, the similar input could produce a different output depending on previous inputs in the series.

RNN is a neural network implemented for assessing streams of data by means of hidden units. Since RNNs deal with sequential data, they are well appropriate for the health informatics domain where huge amounts of sequential data are available to process [37]. Figure 7.4 shows a model of RNN.

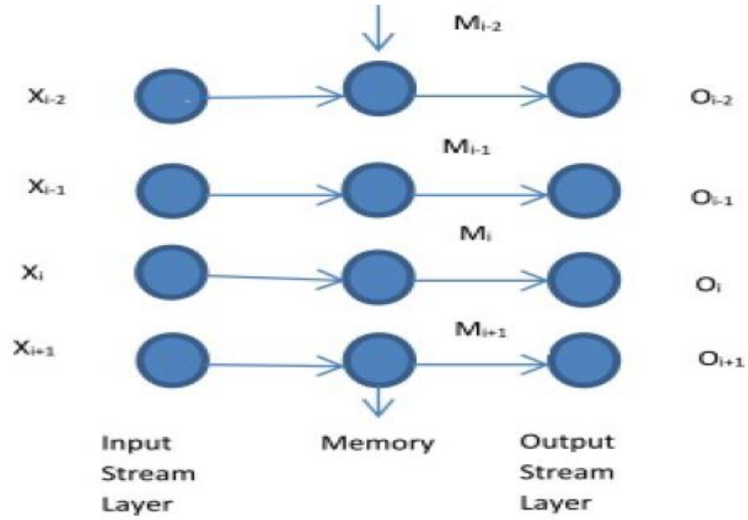

Figure 2.8 *Recurrent neural network*

In general, RNN have a major representation for keeping the information about the past time steps. They have built with the input models which contain more mutuality. RNNs have two kinds of present one and the past recent one input to prepare the output for the new data.

2.2.2.1 Long Short-Term Memory (LSTM):

Long short-term memory networks fundamentally extend the memory and extension for recurrent neural networks Therefore, it is well matched to learn from important experiences that have very long time delays in between. The units of an LSTM are used as building units for the layers of a RNN, often called an LSTM network [38].

LSTMs permit RNNs to recall inputs over a long period of time. This is because LSTMs includes information in a memory, much like the memory of a computer. Information can be read, write and from its memory. This memory can be taken as a gated cell, with gated meaning the cell determine to store or delete information per the importance it allocates to the information. The assigning of importance happens through weights, which are also learnt by the algorithm over time what information is important and what is not.

In an LSTM we have three gates: input, forget and output gate. These gates decide to allow new input in (input gate), remove the information because it is not important (forget gate), or let it impact the output at the current time step (output gate). Below is an illustration of a LSTM with its three gates:

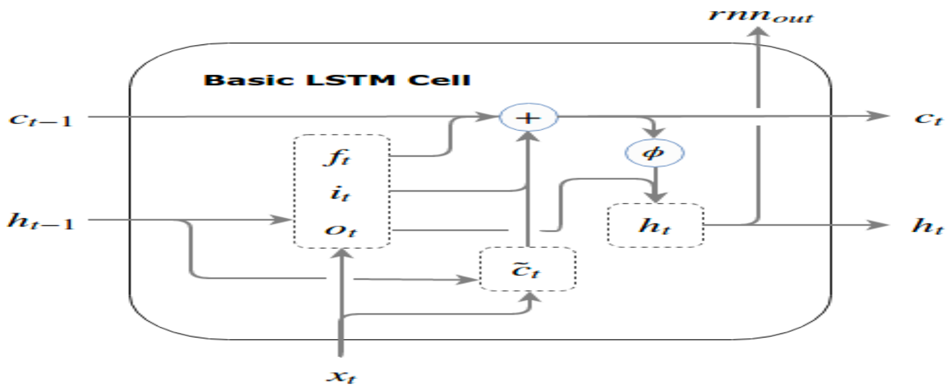

Figure 2.9 *An LSTM cell. The figure demonstrates forget gate (f), input gate (i), output gate (o). [26]*

The gates in an LSTM are analog in the form of sigmoid, that means they range from zero to one and analog enables them to do backpropagation. The issues of vanishing gradients are resolved via LSTM because it retains the gradients vertical enough, which keeps the training relatively short and the accuracy high [39]. LSTM is one of the categorization techniques of artificial recurrent neural network (RNN) architecture widely used in deep learning. A Recurrent Neural Network is one of artificial neural network in which the output of a unique layer is preserved and fed back to the input that used to forecast the result of the layer. The first layer made in the same way as it is in the feedforward network. This can be done in the way that the product of the sum of the weights and features. However, in later layers, the recurrent neural network process starts [40].

Each node will remember some information from each time-step to the next node that it had in the previous time-step. In other expression, each node acts as a memory cell while computing and performing the operations. The front propagation of the neural network remembers the information it may need to use in the future. The system self-learns and works towards making the right prediction, even if the prediction is wrong during the backpropagation. This kind of neural network is very effective in text-to-speech conversion technology. [40]

2.2.2.2 Sequence to Sequence modeling:

Sequence to sequence models is based on RNN architecture and contains of two RNNs: an encoder and a decoder. The encoder’s function is to process the input, and the decoder to process the output. Sequence to sequence models can be taken as one decoder node producing output corresponding to one encoder node. This model has easy application in machine translation as a corresponding word for the output language can be generated by decoder easily by considering only at one word of input language at a time [41]. Figure 2.10 shows a simple sequence to sequence model.

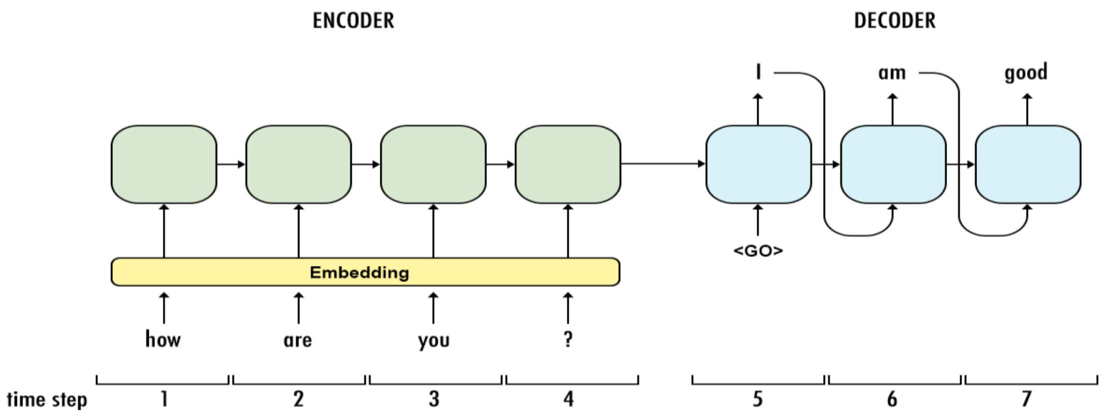

Figure 2.10 *Sequence to sequence model architecture [39]*

2.2.3 Convolutional Neural Network (CNN):

A Convolutional Neural Network (CNN) is a convolutional layer to extract information by a bigger piece of text, has many hierarchical layers, consisting of feature maps layers and classification layers. Typically, CNN start with convolutional layer that accepts data from input layer as shown in Figure 2.3. According to B. Jan et al. in [43] the convolutional layer is responsible for convolution operations having few filter maps of same size. Additionally, output from this layer is forwarded to sampling layer which is responsible for decreasing size of upcoming layers. In CNN, a huge number of deep learning methods are connected locally. The feature maps are allocated based on the blocks of information coming from the previous layer and directly depends on the amount of feature maps that a single block contains of numerous threads and each thread is involved to a single neuron. Similarly, the remaining of the process is held by the convolution of neurons, activation, and summation. Finally, the output from above methods is kept in a global memory. This entire process follows a backward and propagation model for processing data efficiently.

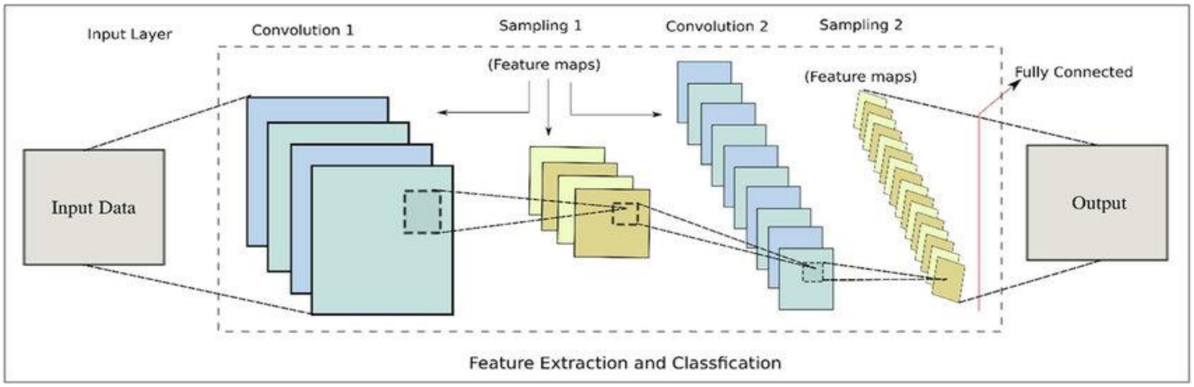

Figure 2.11 *Convolutional Neural Network architecture [43].*

2.3 Neural Network Based Models for Chatbots

2.3.1 Retrieval based Neural Network

Retrieval-based chatbots work on the principle of graphs or directed flows. The chatbot is trained to provide the best possible response from a database of predefined responses. The answers are based on existing information. They use techniques like keywords matching, machine learning or deep learning to identify the most appropriate response. Regardless of the technique, these chatbots deliver only predefined responses and do not produce new output [44].

Retrieval-based models for chatbots have existed traditionally as rule based responding systems. They have a permanent database of responses plotted to questions [45]. Some complex models, as used by Young et al. in [46] store context of the conversation, generating multiple responses as per the context, assessing each response, and outputting the response with the top score. Retrieval based systems are now combined with Deep Learning techniques to deliver more precise responses.

2.3.2 Generation based Neural Network

Chatbots that use generative methods can generate new dialogue based on large amounts of conversational training data [44]. Unlike, retrieval-based systems are restricted to predefined responses, they do not depend on fixed responses. They produce new answers from scratch [45]. Responses are based only on machine learning and the training data. Sequence to sequence model is well fitted for Generation-based Neural Networks. In [46], Young et al. applied a Generation based model in their chatbot for asking follow-up questions to the user, word by word.

2.4 Chatbots evaluation metrics

Currently, there are various performance metrics to evaluate chatbot performance usually being used in different phases. Certain measurement standards are followed across industry for Chatbot [47].

Loss is used to improve a machine learning algorithm and it is calculated on training and validation and its analysis is based on how fine the model is performing in these two sets. It is the addition of mistakes made for each example in training or validation sets. Loss value indicates how poorly or well a model behaves after each iteration of optimization. It is commonly applied in the training process to obtain the "best" parameter values for model [48].

Accuracy is a system measurement that commonly describes how the model performs throughout all classes. It is helpful when all classes are of equal significance and computed as the ratio between the number of correct predictions to the whole number of predictions. we use this system of measurement to assess how accurate our model's prediction is compared to the true data [49].

Precision answers how many are essentially correct from which are categorized as important. It expresses how many times the model predicts are true [50].

Recall shows the number of proportions that are truly relevant [47]. It measures the completeness of the model.

F-1 score calculated as the weighted average of Precision and Recall. Hence, this score requires both false positives and false negatives into consideration. But F1 is usually more suitable than accuracy, especially if we have an unbalanced class distribution. F-1 score evaluation metrics used as evaluating intents in classification problems [51].

2.5 Summary

According to the literature, to make chatbot the various technology has been used and it is stated that how the numerous chatbot differs from each other's. A chatbot can be considered as a question-answer system where professionals provide knowledge for demand of users. A chatbot is a software devised to imitate a conversation with human partner. They are a program that communicates with humans using natural language. Chatbots are utilized in many organizational domains where it can reinstate humans. However, the broadest application of chatbots is in the field of e-commerce for automating customer service. Chatbots assist to improve customer relations as well as drastically minimize human efforts.

This literature presented an overview of an existing approaches of implementing a chatbot system and review on some of the existing state-of-the-art models. We start from the taxonomy of the chat bots. Then the existing chatbots that compares various chatbot from the first chatbot ELIZA to one of the latest chatbot like ALEXA, IBM Watson, Siri, etc. Then this section discussed how those different chatbots have been implemented and how they actually work. Then we looked at Techniques applied in chatbots, Neural network-based models for Chatbots and finally the metrics that uses to evaluate chatbots.

CHAPTER THREE

RELATED WORK

There are many researchers conducted their research regarding chatbots in various parts of the world for the different cases. Therefore, in this chapter some of the researchers work along with the tools and methodologies used with their respective finding is the target of the review.

Peters, Florian [52] designed and implemented a chatbot in the context of customer support. The author defined the chatbot's goals, a set of user problems and constraints. Then a scalable software solution was designed and developed for training and deploying chatbots. The author extracted ticket data dynamically from an existing Zendesk environment and label them using tags attached to the tickets. The research described the chatbot concept was decomposed into several modules which solve a particular design problem. Among the modules, some of them make use of neural network models. These models' structure and property were analyzed. A way for the chatbot to allow users to clarify themselves was also devised, derived from Bayes' rule. Finally, the results from the chatbot were shown. as stated by the author adequate performance metrics were measured for each neural network generated beforehand and a manual way of testing the chatbot was presented. The research described the developed system, can be ported on virtually any system provided of a Python environment.

Yashvardhan & Sahil [53] presented deep learning approaches for question answering systems. The authors used a generalized dataset called babI, generated by AI of Facebook. The work concentrated on examining, executing, and enhancing the different popular approaches. Basic NLP and Deep learning algorithms-based approach has been conducted. The research described that the assessment of the proposed models was done on twenty activities of babI dataset of Facebook. The author described assessment of all the main deep learning algorithms for question answering has been conducted. In this research, neural network based framework for general question answering tasks have been proposed that are trained using raw input question answer triplets. The frameworks on the research can resolve sequence tagging tasks, classification problems, sequence-to-sequence tasks and question answering tasks that require sequential reasoning.

Vyas [54] Deep Learning for chatbots explored the challenges and techniques used to build chatbots and where enhancements can be made. The author analyzed various architectures to develop chatbots and propose a hybrid model, partly retrieval-based and partly generation-based which gives the best outcomes. The chatbot has learned on the fixed data. Hence, the data does not obtain the latest information available, like current events.

Anjana [55] Intelligent Chatbot using Deep Learning have developed intelligent conversational agent using state of the art techniques proposed in recently published researchs. The author described for developing an intelligent chatbot, they have used Google's Neural Machine Translation (NMT) Model which is based on Sequence to Sequence (Seq2Seq) modeling with encoder-decoder architecture. This encoder-decoder is applying Recurrent Neural Network with bi-directional LSTM (Long-Short-Term-Memory) cells. They utilized Neural Attention Mechanism and Beam Search during training for performance optimization. They have used Python with PyQT as a front end and Python as back end.

Antons et al. [56],) A Systematic Approach to Implementing Chatbots in Organizations RTU is a chatbot that was developed to support potential new students during the admission process. The model has been learned based on a knowledge base of questions and answers. Then each answer can be associated with multiple questions. The system applied a neural network and implemented by python using genism, TensorFlow and Keras. The model has been packaged into Flask web application that displays it as a web service. The authors presented the developed system has ability for conversational log that is used to analyze the statistics on chatbot performance and implement improvements.

Raja et al. [57] A Banking Chat Bot Conversational Bot for Customer Care using Deep Neural Networks presented a conversational bot that answers to user queries on the norms and procedures of a bank using Deep Neural Networks, to achieve higher accuracy in the response. In addition, Natural Language Processing is used to preprocess the text, so that the data fed into the neural network is of appropriate type. User gets the correct answer usually when a higher accuracy rate is attained. Instead of going to the bank or contacting a customer care executive, user can get the information at their location without spending time. The author used Flask Web Framework to deploy the conversational bot in real time. Python needs its own web framework like Django or Flask to link to a website/Frontend/User Interface. As described on this research the Design of User Interface has been developed using HTML-5, CSS-3, and Java Script. The author described the developed project can be hosted and made available for public usage.

Yash [58] developed chatbot based question answering system using deep learning models to build a chatbot for flight booking. The author described the flight booking system has been integrated with One Task, a task manager for intra-project collaborations. The chatbot server has built using Python Flask. The author stated that the training is done on the SQuAD dataset which is a popular machine understanding dataset consisting of 100,000+ questions created by crowd workers on 536 Wikipedia articles. The author presented the multi-attention model for machine comprehension. The model computes the context-to-query attention and query-to-context attention, with respect to the context as well as the query. This helps them to solve complex query sentences up to some extent.

Vinothini [59] AIRA Chatbot for Travel: Case Study of AirAsia is proposed a verbot (Verbal-Robot) to improve the performance, quality, and credibility of customer service for AirAsia (Malaysia) Berhad called AIRA. Author described AIRA is developed as a stand-alone application, with possible extended features provided by web connectivity. AIRA is implemented using C# in Verbot 5.0 and plays an important role as an information gatherer, gathers all the latest and correct information to provide the best service to customers. As stated on the research, the main objective of AIRA is two-fold. The first objective is to reduce customers' waiting time at the airport, from check-in to boarding. With the ability to perform basic services to customer, AIRA able to solve the lack of human resources problem within AirAsia. With consideration to the fact that boarding or waiting time can be unpleasant for most travelers, AIRA is able to recommend good places based on the leisure category that the user prefers within the vicinity of the airport itself. The author described the system works by prompting a website displaying information and floor plans for further exploration by the users. The second objective is to recommend the customers with places, hotels and foods based on customer preferences and requirements. The proposed system will bring the user to a webpage whereby the user can book their respective flights immediately.

Anbang et al. [60] A New Chatbot for Customer Service on social media created a new conversational system to automatically generate responses for user requests on social media. As stated on the research the system is integrated with state-of-the-art deep learning techniques and is trained by nearly one million Twitter conversations between users and agents. The author described the evaluation reveals many of the requests were emotional, and the system shows empathy to help users cope with emotional situations like human beings. The experimental result on the research shows the system outperforms information retrieval system based on both human judgments and an automatic evaluation metric.

Susmit [61] developed Chatbots with Personality Using Deep Learning the chatbots. unidirectional LSTM units are using to create the chatbots, which mean they maintain information of the past since the only inputs it has seen are from the past. The author used the data in an utterance-response pair form for training a chatbot. The dialogue should have a flow, context and should not be arbitrary expressions. The data source they used are from Twitter Chat Log, Cornell Movie-Dialogs Corpus, publicly available Reddit comments. The model has developed using Python tools including TensorFlow, Pandas, NumPy and Jupyter Notebook. The author stated the chatbot model has examined by BLEU metrics including computer calculated scores and assessments by people.

Table 3.1 *Summary of Related work*

Author	Title	Method	Limitations
Peters, Florian	Design and implementation of a chatbot in the context of customer support	- Deep Learning approaches -Word embedding -Recurrent Neural Networks	-The approach taken for generating responses is a retrieval-based.

Yashvardhan Sharmaa , Sahil Guptaa	Deep Learning Approaches for Question Answering System	Deep Learning approaches	- Limited to small question answer, and Unable to work well on large information-based questions, answering which contain reasoning - The babI dataset was used to evaluate all the models. The babI dataset is an artificially produced dataset by Facebook which is very general in nature. - The architectures may give some unusual outcome on the usage of natural dataset
Vyas Ajay Bhagwat	Deep Learning for chatbots	**-**Deep Learning approaches -a hybrid model, partially retrieval-based and partially generation based which gives the best results -Sequence to sequence Models -LSTM (Long Short-Term Memory)	- This chatbot is learned on constant data (i.e., from January 2015) - Therefore, the data does not obtain the latest information available, such as current events. -The training time of the model is high.
Anjana Tiha	Intelligent Chatbot using Deep Learning	-Google's Neural Machine Translation	-Unable to imitate real human conversation

		(NMT) Model which is based on Sequence to Sequence (Seq2Seq) modeling with encoder-decoder architecture.	and not have flexibility in functioning since they are using easy rule-based techniques
Antons Mislevics, Janis Grundspenkis and Raita Rollande	A Systematic Approach to Implementing Chatbots in Organizations – RTU Leo Showcase	-Neural network -Knowledge base of questions and answers	-
Raja Rathina.G, Syed Shenaz.S, Vani.R, Dr.V.Gowri	A Banking Chat Bot - Conversational Bot for Customer Care using Deep Neural Networks	-Used Deep Neural Networks	-The approach experimented on limited set of data -The dataset not extracted from real time conversations
Yash Sinha	Chatbot Based Question Answering System	-Deep learning basics which included CNN, RNN, Word Embeddings, Attention Mechanism, Pointer Networks, Memory Networks, and Reinforcement Learning	-Not efficient capturing of the semantics passages and questions.
Vinothini Kasinathan	AIRA Chatbot for Travel: Case Study of AirAsia	-Knowledge Representation	-Consider only the root of the words that may be results to the same score for different words

Anbang Xu, Zhe Liu, Yufan Guo, Vibha Sinha, Rama Akkiraju	A New Chatbot for Customer Service on social media	-Qualitative analysis -LSTM networks	-The average response consuming time is high
Dinesh Kalla , Vatsalya Samiuddin	Chatbot for Medical Treatment using NLTK Lib	-NLTK (Natural Language toolkit) -thematic analysis on the qualitative data	-The chance of giving unrelated answers is high
Susmit Gaikwad	Chatbots with Personality Using Deep Learning	-Deep Learning approaches	-Limited output sequences to smaller lengths to be efficient

3.1 Summary

In this chapter, several selected researches that have focused specifically on chatbot models and design techniques have described in detail. Selected studies that affect Chatbot design has been presented, and the contribution of each study has been identified. In addition, it discusses about the similarity and differences in the Chatbot design techniques that are used in the selected studies. Their design and methods have been discussed with the limitations of their study.

CHAPTER FOUR

Design of Chatbot Based Customer Services system

4.1 Introduction

This chapter describe the proposed architectural design and components with the tools and techniques used to keep through the research objectives proposed. The first part discusses how the data is acquired and provided to be used by various deep learning models. The second part is dedicated on the actual procedure used in developing and training models, including data preprocessing, feature extraction methods, and model architectures. In the last part, the model evaluation method used in the research is explained.

4.2 Architecture of the Chatbot System

The architecture designed based on the literature. It consists of data preprocessing, feature extraction, Training and Testing phase, compare patterns from Intent's data, Retrieval of Matched Information and continue to chat as shown in Figure 4.1. The preprocessing component includes data extraction and preparation of all the data that is going to be used as an input for the chatbot customer service. The training data model is the main component of the system which processes the data that is prepared in the preprocessing and gives response using Deep learning. The selected techniques for this project are a convolutional neural network (CNN) and Long Short-Term Memory due to their state-of-the-art performance. The final process takes the trained data model and provide the decisive service which includes giving a response based on the user request.

In the first part of this work, the question-and-answer pair conversations dataset is collected and create the different intents file. The dataset is preprocessed to make fit for further processing. The preprocessing tasks involves tokenization, stop word removal, normalization. After that, the text is converted to vectors using word2vec. The next phase of this work is training the model, performed to extract data from the text corpus. The text corpus is a collection of customized airline customer conversations. Then the trained model is performed for handling the user requests. When the user provides the query, the system will retrieve matched information comparing patterns from intents data.

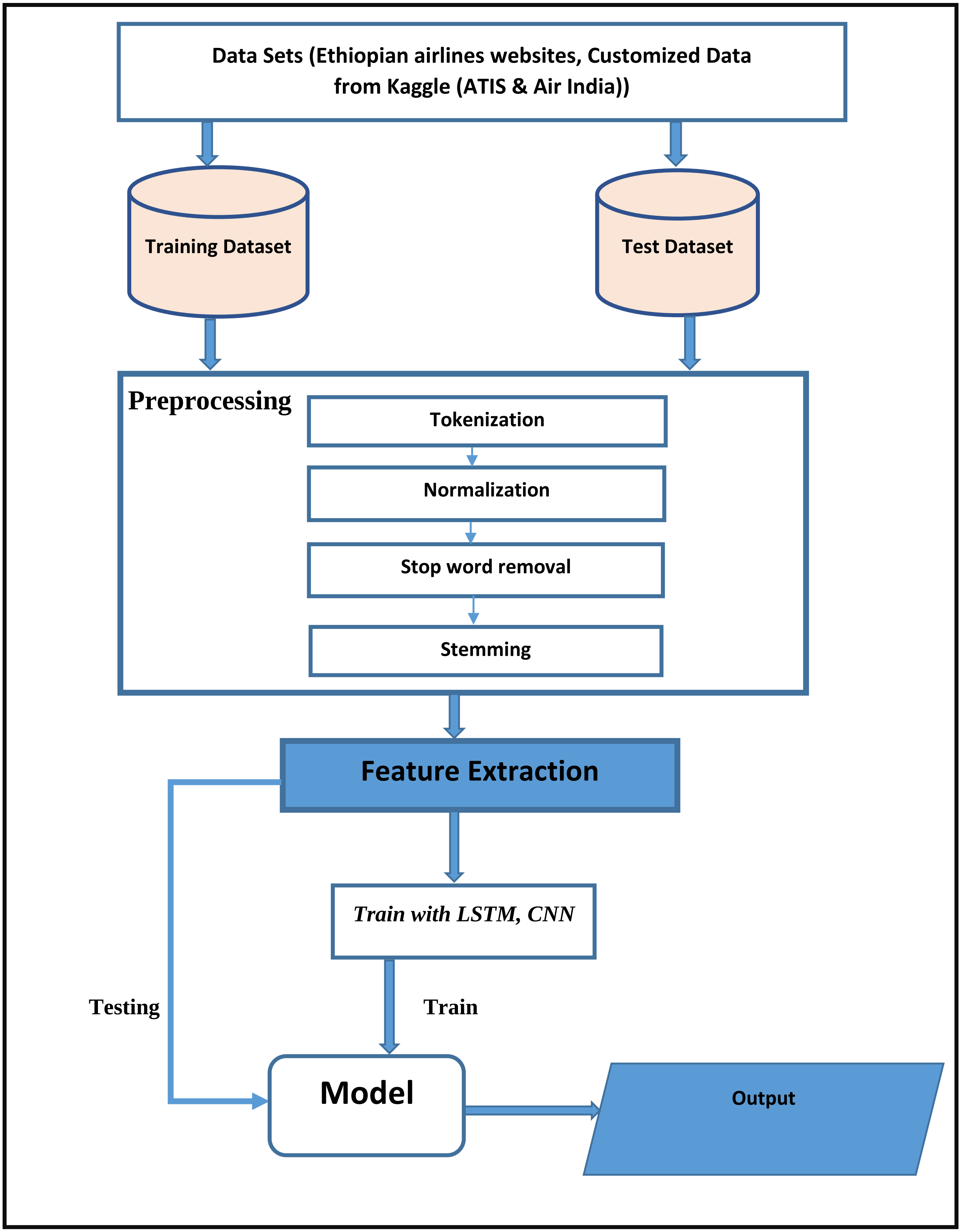

Figure 4.1 *Architecture of Chatbot based Ethiopian airlines customer service system*

4.3 Data Sets

In any task involving Machine Learning, the first step is to prepare data so that it can be correctly interpreted by the machine. In the case of designing a chatbot, the task consists of inputting thousands of existing interactions between customers and customer service representatives to instruct the machine [63].

The data used in this thesis is Ethiopian Airlines FAQ that are available and collected from the web (such as from https://www.ethiopianairlines.com/et/services/help-and-contact/frequently-asked-questions) and from Kaggle (https://www.kaggle.com/datasets). The collected documents pass through data preparation.

For this study, 30,000 question and answer pair statements has been collected from Ethiopian Airlines FAQ and from Kaggle websites. The collected documents have been passed through the appropriate data preparation. The dataset has split into 80% for training and 20% for testing sets.

We just used all information and tagging them appropriately with JavaScript Object notation (JSON) format. The data is structured into tags, patterns, responses, and context in an intents file and train a chatbot to suit to our chatbot based customer service for Ethiopian airlines.

Tags: Possible periods of user plan for asking a question.

Patterns: The methods in which users frequently ask questions relating to a specific tag.

Responses: Predefined responses for every tag in the dataset from which the model can select to respond to a specific question.

Context: Contextual words linking to a tag for simple and improved classification of what the user aims with their questions.

4.4 Data Preprocessing

Data preprocessing is needed to transform raw unordered, unusable data to structured usable format. It is done to convert the raw data into a required format. In this research, the datasets are gathered from different resources that have different formats and attributes manually. Therefore, the data can be duplicated, and they may contain some attributes, which are not valuable. So, it is a must to convert the data into the required format with the required attributes that are used to train the model. To do so different duplications and unnecessary tokens such as special characters, prefix, suffix, numbers and symbols should be eliminated. Preprocessing consists of tokenizing, stemming, and lemmatizing the chats and this makes the chats readable for the deep learning chatbot. The training data for a chatbot necessitates it to get a conversational flow. It requires to have a sentence or a question and an answer.

4.4.1 Tokenization

Tokenization is the method of splitting the statements into a separate part of words or tokens by using space between words, tokens, or punctuation mark. In the feature extraction process, tokenization is important because the meaning of a statement can depend on the relationship between word arrangements, this helps to get meaningful data. Tokenization methods help to grasp appropriate feature from the provided dataset. In the tokenization process, input texts are tokenized into a sequence of tokens by detecting word boundaries from the written texts. White space and punctuation marks are used as boundary markers that the punctuation marks are used to demarcate or separate words, sentences, etc. into a stream of characters. Punctuation marks such as period (.), comma (,), and semicolon (;) are also included to demarcate words. For example: - when the sentence “Welcome to Ethiopian Airlines chatbot system” tokenized, the result will be:

['Welcome', 'to', 'Ethiopian', 'Airlines', 'chatbot', 'system'].

4.4.2 Normalization

Normalization is very important task for the languages that use Latin characters. The process of converting case of the characters in the text data might be UPPER CASE, or lower case or Mixed Cases). Hence, it is better to transform all text data into similar case. It is best to convert into lowercase since the users usually use lower case without dealing with the capitalization. This is a process to take place after the tokenization tasks. The dataset gathered have a special character, symbols, numbers, and punctuation. This task removes all inappropriate character as well as special character that the text contains.

```
Input: unprocessed dataset
Output: normalized dataset
1.  Read text data from the given dataset
2.  If text contains Uppercase and Mixed case, then
     change to lower case.
3.  If text contains special character [,'! @#$%*] then
    Remove special character
4.  If text contains symbol [<>‹›« »=:-`~_/] then
    Remove symbol
5.  If text contains numbers= [0-9] then
    Remove number
    Return normalized data
    End while
    close
```

Algorithm 4.1 Normalization

4.4.3 Removal of stop words

Stop word removal is a sub- module used to remove stop words from the input text. Every language has its own list of stop words: words that have no significant discriminating powers in the meaning of ambiguous words. Stop words mainly consist of prepositions, conjunctions, and articles. Stop words, are the high frequency words in a language, which do not contribute much to the topic of the sentence. Commonly, stop word list consists of prepositions, conjunctions, and articles.

```
1. Open corpus and stop word list
2. Read the corpus file and do check
For each term in the corpus
If a term is in the stop word list, then
Remove the term from the corpus and End
Output the list of word without stop word
3. End while
4. Close
```

Algorithm 4.2 Stop word removal

4.4.4 Stemming of words

Stemming is a process of finding the root of the word. It means to remove all the punctuations, plural forms, tenses, and other such elements of a word. The resulting word is the root of that word. For example, the word "that's" stem might be "that" and the word "happening" would have the stem of "happen" [64]. Process of stemming words is used to reduce the vocabulary of our model and attempt to find general meaning or context of the sentences. The stemmed words are stored as a unique list to use in the next step of our data preprocessing.

```
1.  Open corpus for stemming
2.  READ the next word to be stemmed
    If word matches with one of the rules
    Remove the prefix and suffix
    While not end of words
    Output stemmed word
3.  End while
4.  Close
```

Algorithm 4.3 Stemming of words

4.4.5 Vocabulary building

After removing the stop words, the text is becoming cleaner, and at least in the middle prepared for modeling. The next step is to create a vocabulary, which is a set of words in a given dataset after the removal of stop words. This will come in very helpful in the course of data encoding.

4.5 Feature Extraction

A feature refers to the information that could be extracted from any data sample in Machine Learning. After preprocessing data, there are different techniques to extract various noticeable features to convert the text data into a numeric format, text data needs to be encoded. Various encoding techniques are widely being used to extract the features from the text data such techniques are bag of words, TF-IDF, word2vec.

4.5.1 Bag of words

Bag of word is the technique that uses the word's frequency in each text data set that only recognize the frequency of the words in a given data. Neural network algorithms require numerical input whereas, a chatbot essentially takes text or string type input. Therefore, to represent the sentences or string type input as numerical data, we apply the concept of bag of words. We will represent each sentence with a list, the length of the number of words in our model's vocabulary. Each position of the list will represent a word from our vocabulary. If the position in the list is a 1 then that will mean that the word occurs in our sentence, if it is a 0 then the word is not appear. This is called a bag of words since the order in which the words appear is not considered. Rather, only the existence or absence of a word is only concluded.

4.5.2 Word2vec

Word2vec feature extraction is one of the words embedding techniques which is a two-layer neural network that processes text by vectorising words. Its input is text corpus, and its output is a set of vectors: feature vectors that represent words in the corpus. These models are shallow two-layer neural networks having one input layer, one hidden layer and one output layer.

In this study bag of words and word2vec feature extraction techniques are used. The User question and answer of the model should be converted into numeric vectors to be able to apply machine learning on the data. The words will be represented as a vector by using bag of word and the extracted feature can be used to train the model to compare the patterns.

4.6 Create Training and Testing Data

The encoded data can divide it into training and testing sets. The training set will be applied to train the model while the testing set will be used for assessing its efficiency on invisible data. To train the model, we will convert each input pattern into numbers. First, we will lemmatize each word of the pattern and create a list of zeroes of the similar length as the total number of words. We will set value 1 to only those indexes that contain the word in the patterns. Similarly, we will create the output by setting 1 to the class input the pattern where belongs to.

4.7 Model Building

After the training data ready, the proposed deep learning model aims to work with Neural Network Model technique of CNN. This technique applied after feature extraction has been done by bag of words and word2vec and the feature vector known. The process of modeling is to determine patterns in the training set of the dataset that represents the collected data with their features. The model developed to chat with the users by using deep neural network that has three layers. To do this, we used the Keras sequential API.

Convolutional Neural network CNN has a convolutional layer to extract information by a larger piece of text from feature extracted vector. In this model a text as a sequence is passed to the model of CNN. We design a simple convolutional neural network model and evaluate it with the metrics provided for this study.

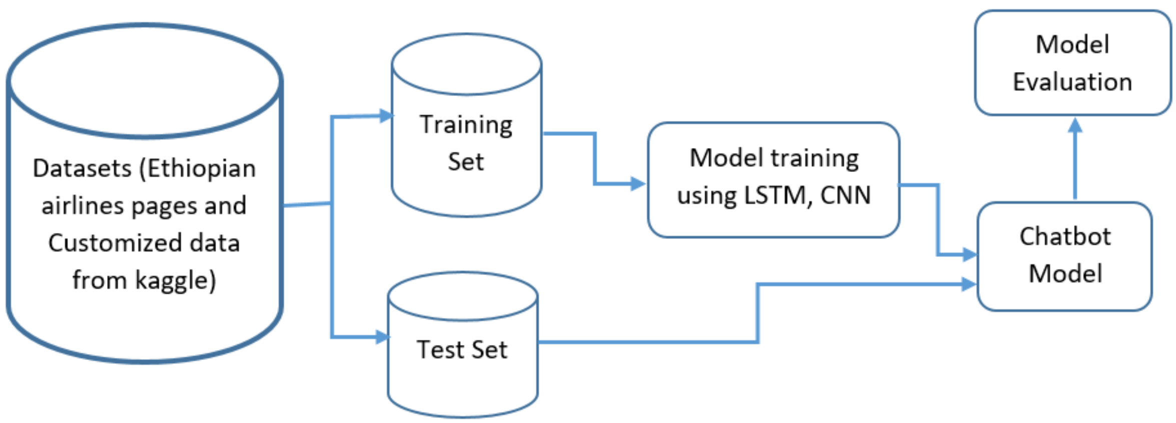

Figure 12 *Model building flow diagram*

4.8 Evaluation Metrics

To accurately measure the performance of Ethiopian airlines chatbot based customer service System, we need metrics that can provide good indication on how the system would perform in real world scenario. The evaluation metrics applied in these systems are accuracy, precision, recall and F-1 measure as presented in chapter three for chatbot evaluation metrics.

CHAPTER FIVE

Implementation of Chatbot based customer service system

5.1 Introduction

This chapter deals with the implementation of the Chatbot based customer service system. Based on the design of the Chatbot based customer service system explained in chapter 4, the implementation of the Chatbot based customer service system is presented in detail in this chapter.

In this chapter, section 5.2 describes about the dataset that used for the implementation and section 5.3 discusses about the intents management of the system. In section 5.4, we discussed the implementation of Chatbot based customer service system. In 5.5 we discussed the performance evaluation of the system. Section 5.6 explained user acceptance testing. Finally, in section 5.6, we summarize about the implementation of this work.

5.2 Data Set collection

In the previous chapter, we discussed about all the data sources that is used, from where it was obtained, how the data extraction was done and how the data was processed and stored. In this section all the results achieved about the data set that is used as an input for the chatbot based customer service for Ethiopian airlines are discussed.

The data used in this thesis is Ethiopian Airlines FAQ that are available and collected from the web (such as from https://www.ethiopianairlines.com/et/services/help-and-contact/frequently-asked-questions) and from Kaggle (https://www.kaggle.com/datasets). The collected documents pass through data preparation. The data is extracted first in Question (Q) and answer (A) pairs to feed the data to the model then via this, the model learns what to be remember and how to extract information. The utterances given to the model is not the only one, those may be varying depend on different user, and the given question or intent is representative to announce the model to remember the fact. The flexible behavior of the question is finally tracked by the sequence-to-sequence modeling techniques by considering the input structure.

The Ethiopian airlines FAQ available on the web and sentences are the main data source for the model of data, and we just used all information and tagging them appropriately with JavaScript Object notation (JSON) format. Each information tag has its own intent with unique ID. Again, each intent finally retrieved to the user utterance. Here, this organization of data creates the basic data core of the designed system. The tagging is done manually which is handcrafted.

5.3 Intents Management

Textual data cannot be fed directly to the neural network due to their design. They require to be transformed into sequences of integers of the same length. The preprocessing steps are listed below in terms of order they are performed:

- Turn all characters to lower case.
- Filter unimportant punctuation characters (e.g., "!?, ...)
- Tokenize the words by using words as tokens. A word in this context is defined as a continuous sequence of characters surrounded by whitespace.
- Building the dictionary of the model via computing the texts' vocabulary (i.e., the set of tokens used).
- Exchanging or swapping each token in the sequences by their corresponding index in the vocabulary.

Based on the above steps we get the final sequences, which are suitable for training the intended neural networks.

5.4 Implementation

We used different tools and developing environment to implement the algorithms and to do necessary experiment on the system. Python was used as the major language to develop the models along with the general deep learning libraries namely Keras and Tensorflow. The aim of the prototype of the system is to demonstrate and test the developed system.

5.4.1 Preparing data

The training data for a chatbot needs it to have a conversational flow. It requires to come up with a pair of question and an answer form. As stated in the previous chapter, The data used in this thesis is Ethiopian Airlines FAQ that are available and collected from the web (such as from https://www.ethiopianairlines.com/et/services/help-and-contact/frequently-asked-questions) and from Kaggle (https://www.kaggle.com/datasets). The collected data prepared as shown on the figure 5.1.

```
{"tag": "book flight",
 "patterns": ["How do I book my flight?"],
 "responses": ["You can make a new booking by any of the following methods Buy a seat Online at www.ethiopianairlines.com",
 "Walk into any of ethiopian airlines ticket offices or city offices or airports to purchase over the counter",
 "Visit one of our approved Travel Agents. You can also book through our 24x7 Call Centre at 0115176665 or 6879"],
 "context": [""]
},
{"tag": "seats",
 "patterns": ["What is the maximum number of seats that I can book at a time?","maximum number of seats",
 "seats that I can book at a time?", "I want to book a maximum seats"],
 "responses": ["You can book up to nine passengers in a single booking including adults and children",
 "For group bookings please contact us, as the specific terms vary from time to time."],
 "context": [""]
},
{"tag": "book a seat for infant",
 "patterns": ["How can I book a seat for my infant?", "book a seat for infant","Show a seat for infant", "Find a seat for infant"],
 "responses": ["Booking an infant seat can be done through our contact centre","ethiopian airlines overseas offices by requesting to make the
 "context": [""]
},
{"tag": "online pay for my ticket",
 "patterns": ["How can I pay for my ticket online?"],
 "responses": ["You can use a credit card, debit card or Net Banking","Once the payment is done successfully, you will receive the itinerary r
 "context": [""]
},
{"tag": "book tickets online with my credit card",
 "patterns": ["Can I book tickets online with my credit card","tickets online with my credit card"],
 "responses": ["If you are making an online booking with your credit card, but you are not travelling","The passenger for whom you booked the
 ,"Please strike out the CVV numbers on the copy of the card"," The photocopy should contain the name of the passenger, the date of journey, a
 "The aforesaid document should be produced at the time of check-in","If a passenger fails to comply with this condition, we reserve the right
 "context": [""]
},
{"tag": "pay booking",
 "patterns": ["How do I pay for my booking?","pay for booking"],
 "responses": ["There are four ways to pay for your ethiopian airlines booking","Online booking we accept Credit or Debit cards","Net Banking
 "Cash,Credit or Debit cards. Booking through our 24x7 Contact center we accept","Credit or Debit cards","Payzapp Booking with ethiopian airli
 "context": [""]
```


Figure 5.1 *Snapshot of corpus for building Word2Ve (JSON file)*

5.4.2 Cleaning the corpus collected – remove stop words

Once the JSON file loaded the first step is cleaning the corpus for eliminating stop words. Stop words are the high frequency words in a language, which do not contribute much to the topic of the sentence. Stop words mainly consist of prepositions, conjunctions, articles. For building Word2Vec stop words, punctuations and special characters are irrelevant. After removing stop words collection of sentences are produced by separating data which removes irrelevant punctuations (!, (,), =,¨, _, +, -, …) and special characters (#,@,%,&,*,~,^,…).

```
#With our intents JSON file loaded, we can now begin to organize our documents, words and classification classes.
words=[]
classes = []
documents = []
ignore_words = ['?', '!','-','[',']','{','}',';',':',',','<','>','.','/','?','@','#','$','%','^','&','*','_','~']
for intent in intents['intents']:
    for pattern in intent['patterns']:

        # take each word and tokenize it
        w = nltk.word_tokenize(pattern)
        words.extend(w)
        # adding documents
        documents.append((w, intent['tag']))

        # adding classes to our class list
        if intent['tag'] not in classes:
            classes.append(intent['tag'])

# stem and lower each word and remove duplicates
words = [lemmatizer.lemmatize(w.lower()) for w in words if w not in ignore_words]
words = sorted(list(set(words)))

# remove duplicates
classes = sorted(list(set(classes)))

print(stopwords.words('english'))
print(len(ENGLISH_STOP_WORDS), "Stop Words", ENGLISH_STOP_WORDS)
```

Figure 5.1 *Snapshot code for cleaning the corpus and removing stop words*

5.4.3 Creating training and testing data

After the appropriate preprocessing have completed, we created the training data in which we provided the input and the output. Our input is the set of the patterns, and the output is the class of our input pattern associated which are the responses. Since the computer does not recognize text, we converted text into numerical forms.

```
# create our training data
training = []
# create an empty array for our output
output_empty = [0] * len(classes)
# training set, bag of words for each sentence
for doc in documents:
    # initialize our bag of words
    bag = []
    # list of tokenized words for the pattern
    pattern_words = doc[0]
    # lemmatize each word - create base word, in attempt to represent related words
    pattern_words = [lemmatizer.lemmatize(word.lower()) for word in pattern_words]
    # create our bag of words array with 1, if word match found in current pattern
    for w in words:
        bag.append(1) if w in pattern_words else bag.append(0)
    # output is a '0' for each tag and '1' for current tag (for each pattern)
    output_row = list(output_empty)
    output_row[classes.index(doc[1])] = 1
    training.append([bag, output_row])
# shuffle our features and turn into np.array
random.shuffle(training)
training = np.array(training)
# create train and test lists. X - patterns, Y - intents
train_x = list(training[:,0])
train_y = list(training[:,1])
#print(train_x) applied the 80/20 train-test splitting ratio, which means, 80% of the dataset used for training the model
#and the remaining 20% of the dataset used for testing the model.
X_train, X_test, y_train, y_test = train_test_split(train_x, train_y, test_size=0.20, random_state=1)
print("Training data created")
```

Figure 5.3 *Snapshot of code for creating training and testing data*

5.4.4 Develop the model

After our training data ready, then we will build a deep neural network that has 3 model layers. Which First layer 128 neurons, second layer 64 neurons and 3rd output layer contain number of neurons which is equal to number of intents to predict output intent with Softmax activator. We apply the Keras sequential API for this. After training the model for different epochs, we achieved better accuracy on our model.

```python
# Create model - 3 layers. First layer 128 neurons, second layer 64 neurons and 3rd output layer contains number of neurons
# equal to number of intents to predict output intent with softmax
model = Sequential()
model.add(Dense(128, input_shape=(len(train_x[0]),), activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(len(train_y[0]), activation='softmax'))

# Compile model. Stochastic gradient descent with Nesterov accelerated gradient gives good results for this model
sgd = SGD(lr=0.01, decay=1e-6, momentum=0.9, nesterov=True)
model.compile(loss='categorical_crossentropy', optimizer=sgd, metrics=['accuracy'])

#fitting and saving the model
hist = model.fit(np.array(train_x), np.array(train_y), epochs=200, batch_size=5, verbose=1)
model.save('chatbot_model.h5', hist)

print("Model created")
```

Figure 5.4 *Snapshot of code for developing the model*

5.4.5 Prototype of the System

We have prepared a prototype for chatbot which can respond based on the user request. The algorithm developed are implemented using python PyCharm IDE and Flask web framework. The system is developed on a system with Intel®core™ i5-6200U CPU of 2.40GHz, a 4GB RAM, a 1000GB Hard Disk and a windows 10 operating system.

Table 5.1 *Tools and packages*

No	Tools and packages	Description
1	Python	An interpreted, high-level, and general-purpose programming languages that are used to develop machine learning models easily.
2	Jupyter notebook	Is an open –source application that allows creating and sharing documents that contain live code, equations, visualizations, and texts.
3	Pycharm	It is Python Integrated Development Environment (IDE). It provides an essential tool for Python developers, to create a suitable environment for productive Python, web, and data science implementation.
4	Sckit learn	It is a free and the most useful and robust machine learning library. Provides efficient tools for machine learning.
5	NLTK	It is a platform used for constructing python programs that work with human language data for applying statistical natural language processing (NLP).
6	NumPy	Library for python that adds support for multi-dimensional, large, array and matrices, along with a large collection array.

7	Matplotlib	It is a plotting library for the python programming language and provides object-oriented API for embedding plots into applications using general-purpose GUI toolkits.
8	Tensorflow	It is a symbolic math library based on dataflow and differentiable programming. We used it for CNN and LSTM neural Networking.
9	Keras	is one of python libraries which high-level neural network that runs on top of **TensorFlow.**
10	Microsoft Excel	Used for data preparation tasks in cleaning filtering and sorting the gathered data.

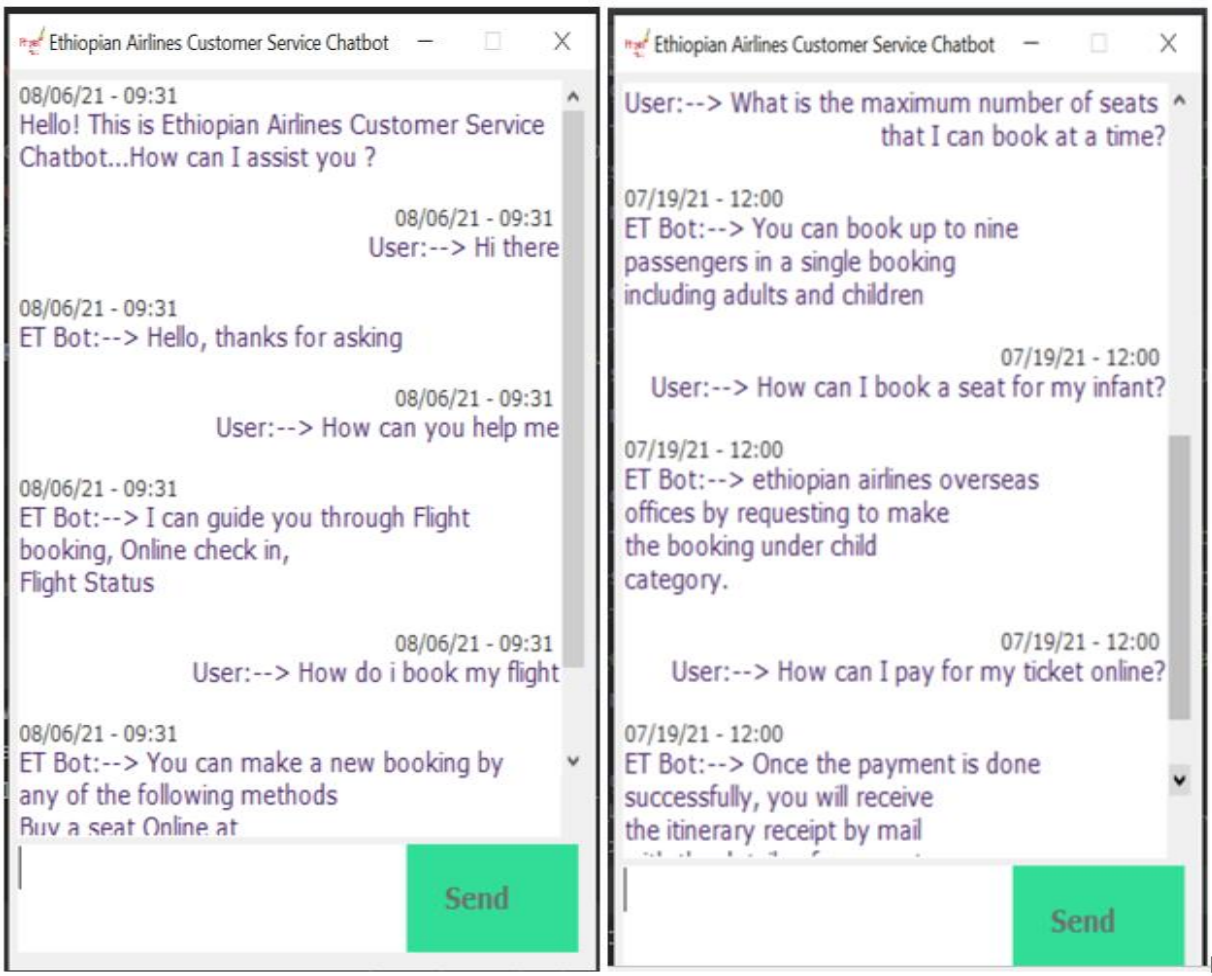

Figure 5.5 *Snapshot of Ethiopian airlines chatbot based customer service system Conversation Interface*

5.5 Evaluation of the model

We applied the 80/20 train-test splitting ratio, which means, 80% of the dataset used for training the model and the remaining 20% of the dataset used for testing the model. According to the literature, it is more appropriate for most research works especially for deep learning algorithms that require more training data and it is better to improve the model performance [64].

LSTM and CNN techniques have applied on this model, Keras and Sklearn python module used for neural network implementations. To implement we used the following libraries.

```
import nltk
import matplotlib.pyplot as plt
import json
import pickle
# things we need for Tensorflow
import numpy as np
import random
from keras.models import Sequential
from keras.layers import Dense, Activation, Dropout
from keras.optimizers import SGD
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
# things we need for NLP
import nltk
from nltk.stem.lancaster import LancasterStemmer
stemmer = LancasterStemmer()
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
lemmatizer = WordNetLemmatizer()
nltk.download('punkt')
nltk.download('wordnet')
```

Figure 5.6 *Snapshots of Libraries for neural network*

5.5.1 Long Short-Term Memory**:** LSTM is one of the model techniques we used in this research work. It is one of the classification techniques of artificial recurrent neural network (RNN) architecture broadly applied in deep learning. A Recurrent Neural Network is one of artificial neural network in which the output of a distinctive layer is preserved and fed back to the input. This helps to forecast the effect of the layer. The first layer prepared in the same way as it is in the feedforward network. In LSTM strategies a memory cell which preserves its state for a long period of time and non-linear providing components adaptable information flow into and out of the cell. By using this memory cell, LSTM has the capacity to catch competently long-distance dependencies of sequential data without disappearing gradient challenges of recurrent neural network.

Table 5.2 *LSTM architecture parameter configuration*

Trained parameters name	**Parameter's size**
Dropout	0.5
Epoch	20
Activation	Relu, Softmax
Batch-size	64
Embedding dimension	100
Optimizer	SGD, Adam
Learning rate	0.01

LSTM model accomplished the accuracy of 83.25% according to the architecture configuration depicted on the table 5.2 and the loss value of this model is 0.41. Table 5.3 describes the accuracy and loss of both train and test value of LSTM model. The evaluation metrics applied for performance evaluation of this models are as follows:

Table 5.3 *LSTM performance evaluation of overall dataset*

Evaluation Metrics	**Percentage (%)**
Precision	83.31
Recall	83.43
F-score	83.36
Accuracy	83.25

5.5.2 Convolutional Neural Network**:** The other neural network techniques we applied for this study is CNN. CNN classification technique is one of the artificial neural networks, which has strong adaptability and good at mining data local features. Convolutional neural networks are qualified to feed-forward neural systems. Where the neurons are accomplished of learning enhanced point (weights) and tendencies. In CNN, the statement model of each word in the input data is connected to a vector representation, which comprises in a dimensional vector. The means of its distribution network structure make it more alike to the biological neural networks, decrease the complication of the network model, a decrease in the number of weights, makes the CNN be useful in various fields of pattern recognition, and accomplished very good results.

Table 5.4 *CNN architecture parameter configuration*

Trained parameters name	**Parameter's size**
Dropout	0.5
Epoch	20
Activation	Relu, Softmax
Batch-size	64
Embedding dimension	100
Optimizer	SGD, Adam
Learning rate	0.01

CNN model accomplished the accuracy of 85.20% according to the architecture configuration presented on table 5.4. Table 5.5 describes precision, recall, F-score and accuracy of both train and test value of CNN model. The accuracy value of this model is 0.852 and the loss model is 0.41 as shown on Fig. 2 and Fig. 3 respectively.

Table 5.5 *CNN performance evaluation of overall dataset*

Evaluation Metrics	**Percentage (%)**
Precision	85.60
Recall	84.92
F-score	85.25
Accuracy	85.20

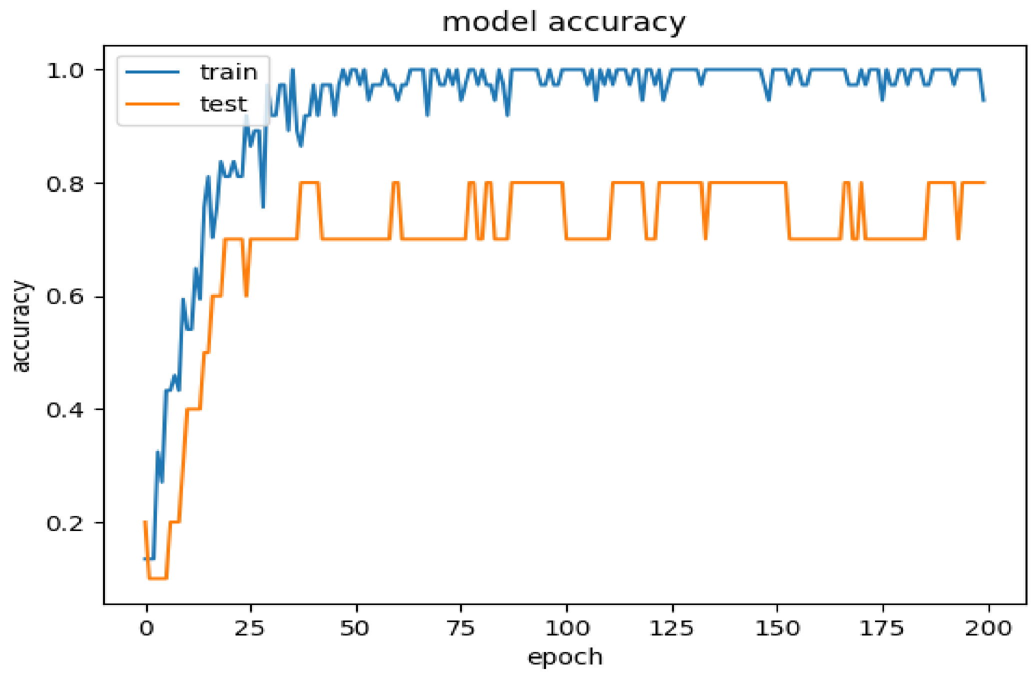

Figure 5.7 *Accuracy value diagram of CNN*

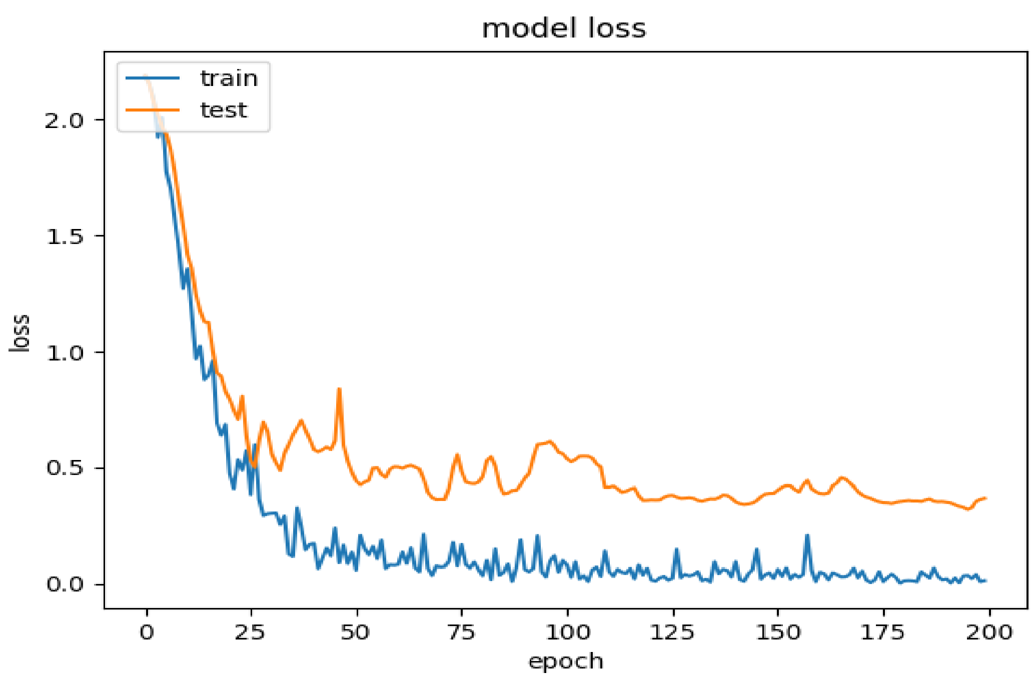

Figure 5.8 *Loss value diagram of CNN*

5.6 Discussion

To come across the objective for this thesis work, we have done several tasks. First, we gather data from Ethiopian airlines FAQ page and airline question and answer pairs from Kaggle. Then the extracted data has further processed which includes normalization and data preparation to make the data suitable for the next process. The next step is preprocessing the data to filter out less useful data and to come up with quality data. During preprocessing, we applied several tasks like removing stop words such as prepositions, conjunctions, articles. Stop words, are the high frequency words in a language, which do not contribute much to the topic of the sentence. After preprocessing of data, we applied several feature extraction techniques to vectorising our datasets. For feature extraction, we used techniques word embedding of word2vec. After our dataset vectorized we applied several algorithms. We used CNN and LSTM neural network technique. To evaluate the performance of the model, we used different performance evaluation metrics such as Accuracy, F-score, recall and Precession. Therefore, the neural network technique, LSTM achieved accuracy of 83.25 and CNN achieved accuracy of 85.20 % by using word2vec feature extraction techniques.

CHAPTER SIX

Conclusion and Recommendation

The last chapter of this thesis report summarizes the work of the thesis and recommendations are discussed to show further research that can be incorporated in our system and enhance the quality of the chatbot system by further analyzing the demands of the users.

6.1 Conclusion

In this work, we proposed to develop chatbot based customer service for Ethiopian airlines using deep learning approaches. To achieve the successful execution of the research it was first necessary to understand about chatbot. In this research we collected data from Ethiopian airlines FAQ page and airline question and answer pairs from Kaggle. Then vital pre-processing steps were performed based on the requirement of the language to get cleaned corpus. The dataset has a format of patterns and responses. In this thesis, we have used our trained Word2vec word embedding model to generate word vectors that able to capture syntactic and semantic relations of words. We experimented using state of the art deep learning algorithms such as CNN and LSTM, Word2Vec embedding, neural word embedding and bag of words. CNN achieved better performance with an accuracy of 85.20% and an f1-score of 85.25%. Finally, this study showed promising results, however, more comprehensive future works make this finding more improved.

6.2 Contribution of the work

The main contribution of this thesis work is:

- The study has Propose, design, develop, implement model of chatbot based customer service system for Ethiopian airlines and based on that prototype has developed with deep learning approaches.
- A dataset for the system is customized and prepared.
- Design and split train and test set to train and test the model simultaneously.
- Identify the main components for developing chatbot related Airline customer services.
- Identify different feature extraction techniques which is related with the chatbots developments.

6.3 Recommendation

Additional research is needed as a future works based on limitations of the current study. The researcher would like to recommend this research work can further be enhanced by adding the following functionalities.

- Using big dataset to implement the system. To conduct the experiment, we have used a small amount of corpus for word embedding and to train the models. By increasing the dataset quality and quantity improve the performance of the model.
- The deep neural network we used can be further tested by changing the architecture and by integrating different deep learning algorithms to get a better result.

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Annexes

Annex A: Sample Patterns

"Patterns": ["How can you help me?", "What you can do?", "What help you provide?", "How you can be helpful?", "What support is offered"],

"Patterns": ["How do I book my flight?"],

"Patterns": ["What is the maximum number of seats that I book at a time?"],

"Patterns": ["How can I book a seat for my infant?", “Show a seat for infant", "Find a seat for infant"],

"Patterns": ["How can I check my flight status?"],

"Patterns": ["How do I check-in?"],

"Patterns": ["How can I pay for my ticket online?"],

"Patterns": ["Can I book tickets online with my credit card"],

"Patterns": ["How do I pay for my booking?"],

"Patterns": ["Can I reserve a seat and pay later?", "reserve a seat", "Looking up seat and pay details”],

"Patterns": ["give me a flight from Addis Ababa to Dubai"],

"Patterns": ["My ticket was purchased from a travel agent Can I change my itinerary on Ethiopian airlines.com?”],

"Patterns": ["Do I receive a ticket when I book a seat on an Ethiopian airlines flight?"],

"Patterns": ["Can I purchase an open dated Ethiopian airlines ticket?"],

"Patterns": ["What will I do if I have to fly Ethiopian airlines within the next 24 hours?"],

"Patterns": ["How do I check whether my payment was successful?”, “check payment"],

"Patterns": ["What should I do if I have not received my booking confirmation?"],

"Patterns": ["Can I change my reservation date and time?"],

"Patterns": ["How can I cancel my ticket and get a refund if there is a sudden change in travel plan?"],
"Patterns": ["Can I pre-select a seat of my choice?"],
"Patterns": ["Can I get a refund for a seat that has not been used"],
"Patterns": ["Is an Ethiopian airlines booking valid for travel on other airlines?"],
"Patterns": ["Does a return Ticket mandatory for travel to the UAE on a tourist Visa?"],
"Patterns": ["Does Ethiopian airlines have any promotional fares?"],
"Patterns": ["How much baggage can I check-in on Ethiopian airlines flights?"],
"Patterns": ["What is the baggage acceptance policy at Addis Ababa Airports?"],
"Patterns": ["May I carry excess baggage?"],
"Patterns": ["How much hand luggage can I carry onboard Ethiopian airlines flights?"],
"Patterns": ["What is the cabin baggage acceptance criteria?"],
"Patterns": ["Can I through check my baggage to another airline up to final destination?"],
"Patterns": ["What can’t I carry on board an Ethiopian airlines flight?"],
"Patterns": ["What should I do if I lost my baggage when I travelled with Ethiopian airlines? Am I entitled to compensation?"],
"Patterns": ["What is Ethiopian airlines' procedure for delayed flights?"],
"Patterns": ["What is Ethiopian airlines policy if a flight is cancelled?"],
"Patterns": ["Am I entitled to a refund if I cancel my flight?"],
"Patterns": ["In the event that I miss my onward flight as a result of my first flight being delayed will Ethiopian airlines put me on the next available flight or refund my ticket?"],
"Patterns": ["How does Ethiopian airlines classify an infant a child and an adult?"],
"Patterns": ["How do I book for an infant?"],

"Patterns": ["What should I do if I need special assistance?"],
"Patterns": ["What is Ethiopian airlines policy regarding unaccompanied young passengers?"],
"Patterns": ["What is the procedure for Children below 12 years traveling international without their parent?"],
"Patterns": ["What is the procedure for children and minors 18 years or below travelling to UAE without their parent?"],
"Patterns": ["What are the regulations for expectant mothers travelling on Ethiopian airlines?"],
"Patterns": ["Does Ethiopian airlines provide any food or drinks onboard?"],
"Patterns": ["Can I Pre-book my on-board meal before my departure?"],
"Patterns": ["What type of aircraft does Ethiopian airlines fly?"],
"Patterns": ["Does Ethiopian airlines offer any frequent flyer programs?"],
"Patterns": ["I want to fly from Addis Ababa at 838 am and arrive in Lalibela at 1110 in the morning"],
"Patterns": ["what flights are available from Addis Ababa to Bahirdar on Thursday morning", "what flights are available from Addis Ababa"],
"Patterns": ["what is the arrival time in Addis Ababa for the 755 AM flight leaving Gondar", "what is the arrival time in Addis Ababa"],
"Patterns": ["cheapest airfare from Addis Ababa to Bahirdar","cheapest airfare from Addis Ababa"],
"Patterns": ["round trip fares from Addis Ababa to Lalibela under 5000ETB","round trip fares from Addis Ababa"],
"Patterns": ["I need a flight tomorrow from Addis Ababa to Mekele","I need a flight tomorrow from Addis Ababa", "I need a flight tomorrow"],
"Patterns": ["what kind of aircraft is used on a flight from Addis Ababa to Dubai", "what kind of aircraft is used on a flight from Addis Ababa", "What kind of aircraft is used on a flight"],
"Patterns": ["show me the flights from Addis Ababa to Bahirdar on Thursday", "show me the flights from Addis Ababa"],

"Patterns": ["all flights from Addis Ababa to Bahirdar","all flights from Addis Ababa"],
"Patterns": ["what kind of ground transportation is available in Addis Ababa", "what kind of ground transportation"],
"Patterns": ["show me the flights from Addis Ababa to Paris", "show me the flights from Addis Ababa", "show me the flights"],
"Patterns": ["show me the flights from Addis Ababa to Toronto by way of Dublin", "show me the flights from Addis Ababa"],
"Patterns": ["what is the cheapest flight from Addis Ababa to Dubai", "what is the cheap flight from Addis"],
"Patterns": ["show me the first class fares from Boston to Denver", "show me the first class fares"],
"Patterns": ["show me the ground transportation in Denver", "show me the ground transportation"],
"Patterns": ["all flights from Addis Ababa to Beijing leaving after 6 pm and before 7 PM", "All flights from Addis Ababa to Beijing"],
"Patterns": ["I need information on flights for Tuesday leaving Addis Ababa for Toronto to Dublin and Dublin to Toronto", "I need information on flights for Tuesday"],
"Patterns": ["please give me the flights from Addis Ababa to Frankfurt on Thursday of next week", "please give me the flights from Addis Ababa"],
"Patterns": ["I would like to fly from Addis Ababa to Nairobi on Ethiopian airlines", "I would like to fly from Addis Ababa"],
"Patterns": ["show me the flights from Dubai to Addis Ababa", "show me the flights from Dubai"],
"Patterns": ["please list all flights on Ethiopian from Dubai to Addis Ababa", "please list all flights on Ethiopian"],
"Patterns": ["what kinds of planes are used by American airlines", "what kinds of planes are used"],
"Patterns": ["I would like to book a flight from Dubai to Addis Ababa", "I would like to book a flight"],
"Patterns": ["show me all flights from Addis Ababa to Dubai on Wednesday of next week which leave Addis Ababa after 2 o'clock PM", "show me all flights from Addis Ababa to Dubai"],

"Patterns": ["please find a flight on Ethiopian from Addis Ababa to Lagos and give me the flight numbers"
"Patterns": ["I need a flight from Toronto to Addis Ababa"],
"Patterns": ["what are the flights from Lalibela to Addis Ababa on Sunday "],
"Patterns": ["I'd like to arrange a flight from Bahirdar to Addis Ababa"],
"Patterns": ["show flights from Addis Ababa to Awassa between 6 pm and 8 pm on Friday"],
"Patterns": ["I would like a list of round trip flights between Rome and Frankfurt for the twenty seventh and the twenty eighth of December"],
"Patterns": ["show me all flights from Addis Ababa to Dallas both direct and connecting that arrive before noon"],
"Patterns": ["I need a flight from Lalibela to Gondar leaving today morning"],
"Patterns": ["what are the times that you have planes leaving from Los Angeles going to Moscow on July seventh"],
"Patterns": ["what flights go from Addis Ababa to Dubai after 6 o'clock next Tuesday"],
"Patterns": ["Does Ethiopian airlines have any flights out of Washington DC to Addis Ababa"],
"Patterns": ["I'd like to know the shortest trip between Istanbul and Addis Ababa"],
"Patterns": ["I would like to see information for flights from Addis Ababa leaving after 12 pm to Bangkok on Monday"],
"Patterns": ["what is the least cost flight from Addis Ababa to Mumbai"],
"Patterns": ["I need to know information for flights leaving Addis Ababa on Tuesday evening and returning to Paris"],
"Patterns": ["what flight goes from Dubai to Addis Ababa business class on Ethiopian airlines arriving on may seventh"],
"Patterns": ["what flights do you have from Washington to Addis Ababa on Tuesday"],
"Patterns": ["what is the ground transportation from Addis Ababa airport to the city "],

"Patterns": ["which airlines have first class flights today"],
"Patterns": ["find the latest flight from Addis Ababa to Atlanta that serves a meal"],
"Patterns": ["I would like to make a reservation for a flight to Atlanta from Addis Ababa on this coming Sunday"],
"Patterns": ["Show me flights from Nairobi to Addis Ababa on Wednesday"],
"Patterns": ["Show me the flights from Addis Ababa to Kigali"],
"Patterns": ["Please give me the flights from Addis Ababa to Washington DC"],
"Patterns": ["Please advise the flight from Seattle to Addis Ababa"],
"Patterns": ["what is the earliest flight from Washington DC to Addis Ababa that serves a snack"],
"Patterns": ["what types of aircraft does Ethiopian airlines fly"],
"Patterns": ["what is the cost of a round trip flight from Addis Ababa to Paris beginning on April twenty fifth and returning on may sixth"],
"Patterns": ["give me the flights leaving Denver august ninth coming back to Addis Ababa"],
"Patterns": ["list all the flights that fly into Paris"],
"Patterns": ["what flights fly from Rome to Addis Ababa on Monday, Wednesday, Thursday and Friday"],
"Patterns": ["I want to find the first flight from Addis Ababa to Lusaka that serves a meal"],
"Patterns": ["Display all flights from Addis Ababa to Lusaka on July twenty ninth"],
"Patterns": ["I want to travel from Atlanta to Addis Ababa early in the morning first flight"],
"Patterns": ["what are the flights available after 6 pm between Addis Ababa to Mombasa"],
"Patterns": ["what flights depart Addis Ababa on Friday and arrive in Addis Ababa by 8 pm"],
"Patterns": ["what nonstop flights between Addis Ababa and Washington arrive after 4 o'clock pm"],
"Patterns": ["please tell me how many nonstop flights there are from Addis Ababa to Atlanta"],

"Patterns": ["where does Ethiopian airlines international fly"],
"Patterns": ["what flights from Denver to Dubai arrive before 8 in the morning"],
"Patterns": ["find me the earliest flight from Addis Ababa to Atlanta"],
"Patterns": ["list nonstop flights from Addis Ababa to Dallas which arrive before midnight"],
"Patterns": ["show me the flights from Addis Ababa to Lusaka that stop in Atlanta"],
"Patterns": ["On the earliest flight from Addis Ababa to Atlanta on Ethiopia is a meal being served"],

Annex B: Sample Responses

"Responses": ["Hello, thanks for asking", "Good to see you again", "Hi there, how can I help?"],
"Responses": ["I have had fun chatting with you! Until next time! See you"],
"Responses": ["Happy to help!", "Any time!", "My pleasure"],
"Responses": ["Sorry, I am not sure what you are saying. To help me to understand you better, you may want to rephrase your question by asking one question at a time.", "Sorry, can't understand you", "Please give me more info", "Not sure I understand"],
"Responses": ["Hello, my name is ET Chatbot. We can chat about flight bookings, check-in, and baggage. Please ask me one question at a time."],
"Responses": ["I am still learning so I may not be able to answer all your questions just yet -- But i am getting there. For now, we can chat about community asked preflight questions and you can ask me about Flight booking, Online check in, Flight Status"],
"Responses": ["You can make a new booking by any of the following methods Buy a seat Online at www.ethiopianairlines.com.Walk into any of Ethiopian airlines ticket offices or city offices or airports to purchase over the counter. Visit one of our approved Travel Agents. You can also book through our 24x7 Call Centre at 0115176665 or 6879"],
"Responses": ["You can book up to nine passengers in a single booking including adults and children. For group bookings please contact us, as the specific terms vary from time to time."],
"Responses": ["Booking an infant seat can be done through our contact Centre", "Ethiopian airlines overseas offices by requesting to make the booking under child category."],
"Responses": ["You can check the status of Ethiopian airlines operated flights by flight number or by route. Here is a tip: For multi sector flight, my recommendation is to check your flight status by the flight number."],
"Responses": ["Please enter your flight reservation code PNR, it contains 6 English alphabets or eTicket number which contains 13 Arabic numbers only"],

"Responses": ["You can use a credit card, debit card or Net Banking. Once the payment is done successfully, you will receive the itinerary receipt by mail with the details of payment made."],

"Responses": ["If you are making an online booking with your credit card, but you are not travelling. The passenger for whom you booked the ticket must carry A photocopy of both sides of the card. Please strike out the CVV numbers on the copy of the card. The photocopy should contain the name of the passenger, the date of journey, and the sector on which the journey is made. The aforesaid document should be produced at the time of check-in. If a passenger fails to comply with this condition, we reserve the right to deny boarding and cancel his/her tickets"],

"Responses": ["There are four ways to pay for your Ethiopian airlines booking.1/Online booking we accept Credit or Debit cards.2/Net Banking Booking at Ethiopian Airlines City or Airport offices we accept.3/Cash or Credit or Debit cards. Booking through our 24x7 Contact center.4/we accept. Credit or Debit cards. Payzapp Booking with Ethiopian airlines approved travel agents. Kindly refer to the individual agent for details"],

"Responses": ["Please provide booking type for example Economy or Business, one way or Round trip"," you can Book Now & Pay Later for travelling from any origin destination"],

"Responses": ["I can search for available flights operated by Ethiopian airlines and our codeshare partners. May I have your departure date? For example, 25 AUG"],

"Responses": ["Yes, you can modify your booking under Manage my Booking section on our website www.ethiopianairlines.com."],

"Responses": ["Ethiopian airlines issues Itinerary Receipts (ITRs) with payment details instead of conventional tickets. The itinerary receipt is available online for web-based bookings. Customers can get their ITRs mailed to their registered e-mail id."],

"Responses": ["Should you need to travel within the next 24 hours then - Bookings can be made up to 3 hours prior to flight departure through Travel Agent. Contact Centre or website www.ethiopianairlines.com It may be noted that Check-in counters close 60 minutes prior to flight departure."],

"Responses": ["If your payment was successful you would have received a copy of the Itinerary receipt with the payment details based on the mode of booking done. If you have not received the itinerary receipt, it is recommended that you access your booking record using the confirmation number displayed in the confirmation page through Manage my Booking on www.ethiopianairlines.com."],

"Responses": ["For bookings made on our website, you should have received a copy of the receipt with the payment details at the email address you entered during booking."],

"Responses": ["Yes, reservations can be changed or modified through Manage my Booking option on our website."],

"Responses": ["Cancellation and refund is permissible. It will be based on the cancellation and refund policy."],

"Responses": ["Seat selection is offered on most flights. You can select a seat of your choice while making your booking or purchase it later from call centers."],

"Responses": ["All seat charges are nonrefundable on cancellations and nontransferable on modifications. Please refer to Ethiopian airlines cancellation and refund policy for more details."],

"Responses": ["No, all the bookings are solely for travel on Ethiopian airlines. The ITR is non-endorsable to any other Airline."],

"Responses": ["Passenger should be holding a RETURN TICKET on any carrier, valid for travel within the window of VISA validity."],

"Responses": ["From time to time Ethiopian airlines may have promotional fares with different conditions for cancellations/ Re-booking/ refunds etc.",

"Responses": ["Each passenger, including infants can carry free baggage depending on the destination subject to Airline regulations. From time to time, Ethiopian airlines may offer tiered fares with 20 or 30 or 40 Kgs free baggage allowance on selected destinations based on seasonal trends"],

"Responses": ["Effective, 1st April, 2018, a fee of 45 AED will be charged at the Addis Ababa Airport for all Out of Gauge (OOG) baggage."],

"Responses": ["Based on the payload available, excess baggage may be accepted at the time of check in."],

"Responses": ["Only 1 cabin baggage of maximum 7 Kgs including duty free shopping bags with overall dimensions not exceeding 115 cms (L+W+H) is allowed to be carried onboard per passenger, free of cost

"Responses": ["Contours are available at all airports to check the dimensions of your carry-on baggage."

"Responses": ["No. As Ethiopian airlines is a point to point carrier, baggage is booked only for IX sector and not beyond."],

"Responses": ["For safety and security reasons, you are prohibited from carrying the following items in your cabin baggage: Dry cell batteries Knives Scissors Sharp instruments Tools Compressed gases: deeply refrigerated, flammable, non-flammable and poisonous such as butane oxygen, liquid nitrogen, aqualung cylinders and compressed gas cylinders Corrosives such as acids, alkalis, mercury and wet cell batteries and apparatus containing mercury Explosives, munitions, fireworks and flares, ammunition including blank cartridges handguns, fireworks, pistol caps, and their toy replicates Flammable liquids and solids such as lighter refills, lighter fuel, matches, paints, thinners, fire-lighters, lighters that need inverting before ignition, radioactive material, briefcases and attach case with installed alarm devices. Oxidizing materials such as bleaching powder and peroxides. "],

"Responses": ["In the event of loss or damage to baggage, the Airline's liability is limited to SDR 17 (or equivalent local currency) per kilo of checked-in baggage, provided, loss of baggage has been reported to the Airline, prior to leaving the customs enclosure and if not traced after 21 days. Delays and Cancellation of Flights"],

"Responses": ["In the event of a delayed flight, every effort is made to contact passengers in advance to inform them of the rescheduled departure. "],

"Responses": ["Ethiopian airlines has 2 options available to passengers in the event that a flight is cancelled."],

"Responses": ["Please refer to Ethiopian airlines' cancellation and refund policy."],

"Responses": ["No, Ethiopian airlines operates on a point-to-point basis and will not be held responsible for the miss-connection of the onward journey."],

"Responses": ["An infant is one who is below 2 years of age on the day of departure, a passenger is classified as child if she/he is between 2 and 12 years of age on the day of departure and an adult is anyone over the age of 12 years."],

"Responses": ["The same procedure has to be applied as is applicable for booking an adult. Infant must be booked with the accompanying adult. The date of birth has to be filled in while making the booking."], "Responses": ["Should you require any special services while you travel with Ethiopian airlines, please call our reservation offices or contact Centre and inform our staff of your requirements. They will guide you on the procedure."],

"Responses": ["Ethiopian airlines will accept unaccompanied minor between 5 years and 16 years of age. Kindly contact the nearest Ethiopian Airlines City/ Airport Office to make a reservation for an unaccompanied Minor as there are certain formalities to be completed."],

"Responses": ["Children below age of 12 years traveling with anyone other than their parents will have to submit an Ethiopian Embassy (Destination Point) attested letter stating so. This is a requirement of the Ethiopian Emigration authorities when travelling international from Ethiopia."],

"Responses": ["without their parent(s). All minors (18 years and below) would need to have an authorization form filled from their parents with relevant details of their address abroad and in the UAE and information about who would be receiving them in the UAE (in case they are not travelling with a parent."],

"Responses": ["Passengers who are completely immobile and unable to sit may request for an onboard stretcher"],

"Responses": ["Ethiopian airlines offers pre-set meals varying from hot meals to wholesome snacks to fresh cut fruits (in addition to soft beverages/ tea/ coffee) which can be purchased in advance. We also provide free complimentary snack box with tea/ coffee"],

"Responses": ["You can pre-book your on-board meal 24 hours prior to the departure of your flight." ,"Ethiopian airlines operates B737-800 new generation aircrafts in an all economy version"],

"Responses": ["Yes, Ethiopian airlines offer a frequent flyer program"],

"Responses": ["Ethiopian passport holders holding passport with ECR status and is travelling on Tourist Visa/ paper visas must get OK to Board message updated in their PNRs."],

"Responses": ["We found cheapest fares for round trip 4500ETB"],

"Responses": ["Travel, Track and Go30 minutes before the pick-up, Passengers receive an SMS with a GPS Tracking link. In case of a flight delay, we update the driver. After you book, we take care of everything."], "Responses": ["ET 704 Airbus A350 Changes on check-in time for flight ET705.Due to CDG airport congestion and actions taken by airport authorities, Ethiopian Airlines check-in time for ET705 will start at 5:15 p.m. and the check-in counter will be closed at 7:45 p.m. Passengers arriving late after 7:45 p.m. will not be accepted and date / flight penalties will apply."],

"Responses": ["Economy class starting from 17,768ETB Dear Esteemed customer, due to the COVID-19 pandemic and social distancing requirement, at Dubai Airport, security limits the number of passengers that can enter into the Terminal at a time. In order to be on time for your flight, we strongly recommend you to show up at the airport at least 3 hours before your departure time. Thank you."],

"Responses": ["here is the flights ET 602 08:40 PM, ET606 10:40 PM, ET608 ,11:20 PM. I can search for available flights operated by Ethiopian airlines and our codeshare partners. May I have your departure date? For example, 25 AUG"],

"Responses": ["Here is the flight number ET 600 /Saturday, Dear Esteemed customer, due to the COVID-19 pandemic and social distancing requirement, at Dubai Airport, security limits the number of passengers that can enter into the Terminal at a time. In order to be on time for your flight, we strongly recommend you to show up at the airport at least 3 hours before your departure time. Thank you."],

"Responses": ["Travel, Track and Go minutes before the pick-up, Passengers receive an SMS with a GPS Tracking link. In case of a flight delay, we update the driver. After you book, we take care of everything."],

"Responses": ["Here is the flight number ET 600 /Saturday. Dear Esteemed customer, due to the COVID-19 pandemic and social distancing requirement, at Dubai Airport, security limits the number of passengers that can enter into the Terminal at a time. In order to be on time for your flight, we strongly recommend you to show up at the airport at least 3 hours before your departure time. Thank you."],

"Responses": ["I can search for available flights operated by Ethiopian airlines and our codeshare

"Responses": ["Convenient train travel to the airport Enjoy a carefree start to your journey with Lufthansa Express Rail. Train and plane are optimally synchronized. However, if there are any delays, we will automatically rebook you onto the next train or flight – at no charge to you, naturally. One ticket for the train and the plane Guaranteed connection and optimal coordination of train and flight Advance seat reservation included"],

"Responses": ["Services to :Africa Abidjan, Abuja, Addis Ababa, Accra, Antananarivo, Asmara, Bahir Dar, Bamako, Beira, Blantyre, Bosaso, Brazzaville, Bujumbura, Cairo, Cape Town, Comoros Moroni, Conakry, Cotonou, Dakar, Dar-es-Salaam, Dire Dawa, Djibouti, Douala, Durban, Entebbe, Enugu, Gaborone, Garowe, Goma, Harare, Hargeisa , Johannesburg, Juba, Kaduna, Kano, Khartoum, Kigali, Kilimanjaro, Kinshasa, Kisangani, Lagos, Libreville, Lilongwe, Lomé, Luanda, Lubumbashi, Lusaka, Malabo, Maputo, Mbuji-Mayi, Mombasa, Moroni, Nairobi, Ndola, Niamey, Nosy Be, N'djamena, Ouagadougou, Pointe Noire, Seychelles, Victoria Falls, Windhoek, Yaoundé, Zanzibar Ethiopia & Canada Buenos Aires, Chicago, Addis Ababa, Newark, Sao-Paulo, Toronto, Washington DC Europe Athens, Brussels, Frankfurt, Geneva, Istanbul, Liege, London, Manchester, Marseille, Milan, Moscow, Oslo, Paris, Rome, Stockholm, Vienna, Zaragoza Asia Ahmedabad, Bangkok, Bangalore, Beijing, Delhi, Chennai /Madras, Chengdu, Guangzhou, Hanoi, Hong Kong, Jakarta, Kuala Lumpur, Manila, Mumbai, Narita- Tokyo, Seoul, Shanghai, Singapore Middle East Bahrain , Beirut, Dammam, Dubai, Dubai Al-Maktoum, Doha, Jeddah, Kuwait, Madinah, Muscat, Riyadh, Sharjah, Tel Aviv Freighter Destinations Accra, Ahmedabad, Bamako, Bangalore, Beirut, Brazzaville, Brussels Bujumbura, Chennai, Dakar, Duala, Dubai, Entebbe, Enugu, Guangzhou, Harare, Hong Kong, Istanbul Jeddah, Johannesburg, Juba, Kano, Khartoum, Kigali, Kinshasa, Lagos, Liege , Lomé, Lusaka, Milan, Mumbai, Nairobi, N'Djamena, New Delhi, Ouagadougou, Riyadh, Shanghai, Sharjah, Zaragoza."],

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"Responses": ["Convenient train travel to the airport Enjoy a carefree start to your journey with Lufthansa Express Rail. Train and plane are optimally synchronized. However, if there are any delays, we will automatically rebook you onto the next train or flight – at no charge to you, naturally. One ticket for the train and the plane Guaranteed connection and optimal coordination of train and flight Advance seat reservation included"],

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"Responses": ["Overbooked Flight means a flight where the number of passengers holding confirmed reservation and presented themselves for check-in within the required time limit exceeds the number of available seats on that flight/compartment."],

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"Responses": ["Denied Boarding means refusal to accommodate passengers on a flight although they have valid ticket, a confirmed reservation on that flight and presented themselves for check-in within the required time limit due to an overbooking."],

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"Responses": ["Yes, you can hold your reservation and pay later with credit card at our call center or at any local Ethiopian ticket office."],

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"Responses": ["Before finalizing the booking or making payment, you can modify your cities, travel dates & times along with your connection preference."], "Responses”: ["You can book one-way, return trips or multiple cities in Economy and Business class. Bookings can be made only for adults, children and infants."],

"Responses”: ["To obtain only our flight schedules, select Flight Schedules at the home page, insert the sector and date of travel and click on the \"Find Schedule\" Button."],

"Responses”: ["To enter the airport and for check-in, you must present the itinerary receipt along with valid photo identification: Passport (for international passengers)."],

"Responses”: ["E-tickets will be issued for all bookings made online at www.ethiopianairlines.com On a successful purchase the system will generate an Electronic Ticket and a printable itinerary receipt will be displayed. The itinerary receipt is your confirmation of travel. You will also receive an email with the status of your booking. You can print the confirmation shown on your screen or print the email. Then all you have to do is walk in to the airport and check-in with valid photo identification and printed itinerary receipt. Your boarding pass will be issued against the itinerary receipt."],

"Responses”: ["Ethiopian airlines is committed to the safety and security of the online transactions. Customer’s credit card is as safe as possible when booked on www.ethiopianairlines.com Information exchanged with us online is treated securely and protected by using the internationally accepted and industry standard powerful encryption technology (secure socket layer, SSL). This software encrypts customer's personal data as it is sent between the browser and our systems. The web booking engine is directly connected to Sabre Reservation System & payment gateway(s) for credit card processing."],

"Responses”: ["Debit card is also accepted if it is branded with Master, visa and American Express Note: Local debit cards are acceptable from few African countries"],

"Responses”: ["Payment for online booking can be made through credit card/debit card, mobile or in cash at Ethiopian airlines offices. Ethiopian accepts VISA, MASTER, AMERICAN EXPRESS, DINERS CLUB, union pay & UATP cards and PayPal. Please note: The credit card used to pay for tickets is required at check-in or during refund processing for verification."],

"Responses”: ["Once you have confirmed your booking online, we will immediately debit your credit. This applies even if you decide to change your travel plans right after. Please contact the nearest Ethiopian office should you like to rearrange your travel plans or would like to seek a refund. Please note that refund and/or cancellation charges may apply according to applicable fare conditions."], "Responses": ["All revenue tickets booked online will earn miles. Please ensure that the frequent flier number is provided in the form while booking."],

"Responses": ["Yes, you will see a confirmation page after making a successful booking. If you do not see one, please contact us at onlinebooking@ethiopianairlines.com."],

"Responses": ["Currently, we can only handle new bookings made directly online. If you already have a ticket, please contact your travel agent or Ethiopian airlines ticket/reservations office to confirm your travel dates."],

"Responses": ["You can book a maximum of 9 seats at a time (adults and children included)."],

"Responses": ["The facility to waitlist bookings is not currently available while booking online on www.ethiopianairlines.com.However, you can contact our reservations office, and we will be glad to help you."],

"Responses": ["After you issue ticket online (https://www.ethiopianairlines.com), it is possible to refund (cancel) and rebook your ticket using "Manage Your Booking" option."],

"Responses": ["If you meet the date, time and eligibility criteria, you can book the advance purchase fares online."],

"Responses": ["Currently you can book only Ethiopian airlines flights."],

"Responses": ["You can make booking for up to three infants (ages 0-23 months) without seat. However, each infant must be accompanied by an adult passenger."],

"Responses": ["Currently, online booking service is available for all Ethiopian destinations. Please contact Reservation@ethiopianairlines.com for your travel plan on destinations which are not available online."],

"Responses": ["Although you do not receive a conventional paper ticket, you will receive an itinerary/receipt confirming your booking on your screen. This itinerary/receipt will also be sent to you by email either of which can be printer and used to enter the airport and also for check-in."],

"Responses": ["E-Ticket is a convenient, fast and safe option to the regular physical paper ticket. Now no more worries about losing or having the ticket stolen. You can book a confirmed ticket on www.ethiopianairlines.com up to 48 hours prior to departure. It's convenient: you can buy and print your Electronic Ticket online in your home / office. It's safe: The Electronic Ticket cannot be lost or stolen. It's fast: you no longer have to collect the ticket from our office or rush to the airport to meet ticketing deadlines."],

"Responses": ["Electronic Ticket is ticket less travel service. It is a way of issuing air tickets electronically which eliminates traditional paper tickets and creates an electronically held record (ticket) of the transaction. This electronic image of the ticket is stored in the Ethiopian Airlines reservation system."],
"Responses": ["Ethiopian airlines web sales engine allows booking one way and return in 5 simple steps with features such as interactive calendar, low fare option, flexible schedule options etc. The reservation has to be made online at www.ethiopainairlines.com at least 48 hours before departure. You will need to pay online through your credit card or can pay in cash at Ethiopian ticket offices. non purchase, the system will generate your itinerary receipt which is confirmation for your confirmed reservation and e-ticket issuance and display the same on the screen. On it, you will find the key information about your reservation and flights. You will need to print the page and produce it along with valid photo identification in order to enter the airport and for check-in. Also, an email will be sent to the passenger’s email address which can also be printed and used to enter the airport and for check-in. Go directly to the check-in counter. Your boarding pass will be issued against this itinerary receipt and the valid identification"],

Declaration

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

Declared by:

Name: ___Natnael Mekuanent___

Signature: ____________________

Date: _July 19, 2021

Confirmed by advisor:

Name: ____Ayalew Belay (PhD)____

Signature: ______________________

Date: July 19, 2021