

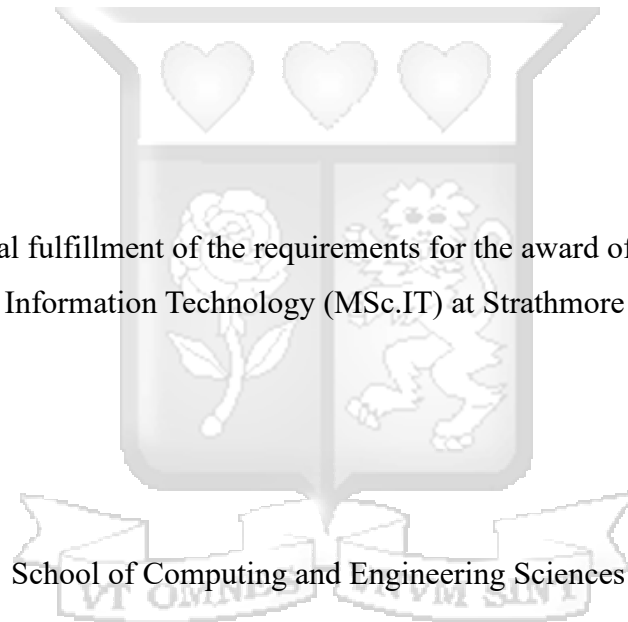
An Intelligent Chatbot Implementation for Early Detection and Intervention for Anorexia  
Nervosa

By

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Degree in Information Technology (MSc.IT) at Strathmore University



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## Declaration and Approval

This thesis is entirely my original work, and it has not been submitted elsewhere to any degree. I have ensured that all information used is properly cited, and to my knowledge, no part of this work constitutes plagiarism.

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## Abstract

Anorexia nervosa (AN), an exhausting and potentially fatal eating disorder, has long been a significant public health concern. Characterized by extreme eating habits and an intense fear of gaining weight, this disorder may lead to other mental illnesses such as depression, obsessive compulsive disorder (OCD), borderline personality disorder (BPD) and sometimes self-harm. Notwithstanding its devastating consequences and prevalence amongst adolescence and youths especially women, its early detection and intervention remains challenging. This research presents a novel approach in addressing anorexia through utilization of random forest, a machine learning algorithm and natural language processing to create an intelligent chatbot for detection and provision of personalized intervention for anorexia patients. The chatbot is built based on RASA framework and it is deployed on Telegram, a social media platform where it can engage users in supportive dialogues to detect potential risk factors and deliver timely intervention for anorexia nervosa. The implications of this research underscore the value of machine learning in mental health detection and treatment. Besides provision of a toolkit that could be used by medical practitioners, it introduces an accessible means of reaching individuals who may not seek help through the conventional means. Additionally, it connects individuals to health care professionals and support networks enhancing early detection and reducing further complications. To assess the feasibility of the proposed concept, a functional chatbot prototype was developed using a Rapid Application Development (RAD) approach. The training and testing data were split in an 80/20 ratio, and the Telegram messaging platform was utilized for user interaction testing. While the study presents promising results, some of the limitations included constraints of limited data set and the need for ongoing refinement of the chatbot's algorithm. There is also limited research regarding anorexia. Future studies could investigate refining the technology, expanding the dataset, and addressing ethical concerns around mental health with an aim to contribute to more effective and accessible mental health support.

**Keywords:** *Anorexia, Chatbot, Machine Learning, Natural Language Processing, Eating Disorder, Sentimental Analysis*

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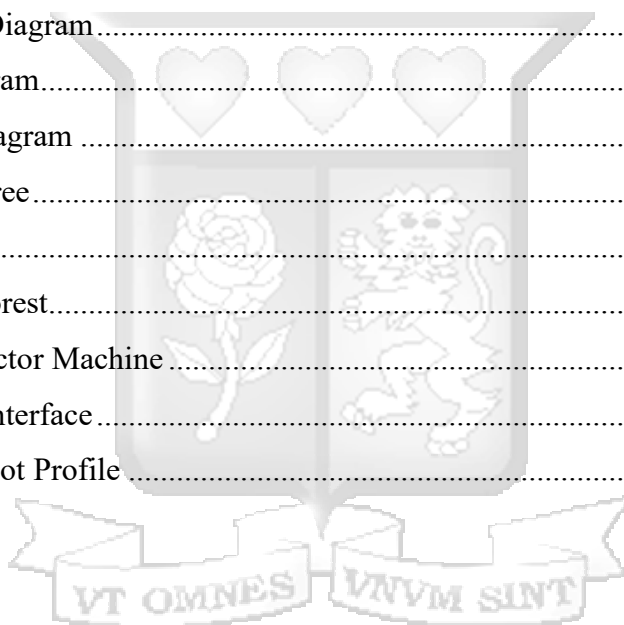
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## Abbreviation and Terms

- AI – Artificial Intelligence
- ML – Machine Learning
- NLP – Natural Language Processing
- NLU – Natural Language Understanding
- DSM – Diagnostic and Statistical Manual of Mental Disorder
- OCD – Obsessive Compulsive Disorder
- BPD – Borderline Personality Disorder
- APA – American Psychiatric Association
- SDG – Sustainable Development Goals
- WHO – World Health Organization
- ED – Eating Disorder
- CBT – Cognitive Based Therapy
- FBT – Family Based Therapy



## Definition of Terms

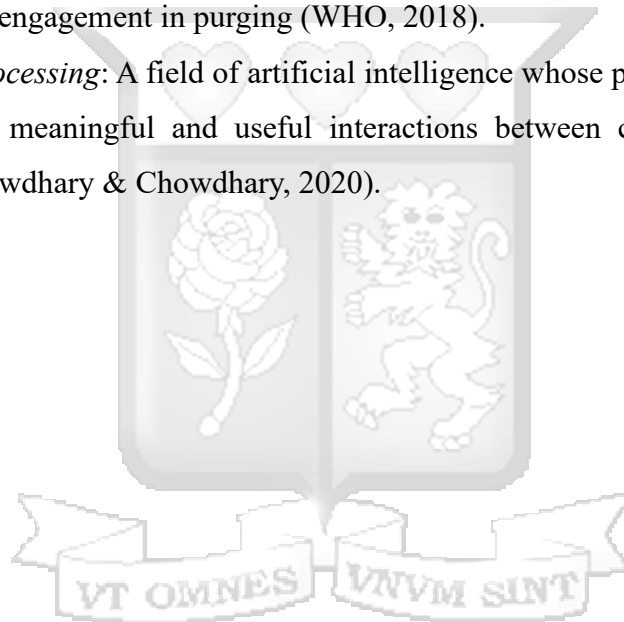
*Artificial Intelligence (AI)*: Artificial intelligence involves the creation of computer systems, computer-controlled robots or software that can mimic human intelligence (PwC., 2023).

*Machine Learning (ML)*: Machine learning is a branch of artificial intelligence which develops algorithms and models that enables computers to learn from experience and improve their capabilities without the need for explicit programming (Naqa & Murphy, 2015).

*Chatbot*: Computer program capable of engaging in a conversation with an individual, typically via the internet.

*Anorexia*: A mental health condition dominated by significantly low body weight caused by diet alongside engagement in purging (WHO, 2018).

*Natural Language Processing*: A field of artificial intelligence whose primary focus is around facilitation of meaningful and useful interactions between computers and human language (Chowdhary & Chowdhary, 2020).



# Chapter 1: Introduction

## 1.1 Background

The Sustainable Development Goals (SDG) of the United Nations incorporated mental health in 2015 under SDG goal 3 target 3.4. This was a momentous step towards acknowledging the burden of mental health illnesses as a hinderance to global development (Votruba & Thornicroft, 2016). A step that saw the rise of global initiatives such as FundaMentalSDG, World Health Organization Special Initiative for Mental Health, International Initiative for Mental Health Leadership (IIMHL), African Mental Health Research and Training Foundation (AMHRTF), Sentebale and StrongMinds. Mental health remains a pressing concern with a significant impact on individuals and society.

Eating disorders have become recognized as a worrisome and intricate subset of mental health problems in the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) published by the American Psychiatric Association (APA). Eating disorders (EDs) are identified by abnormal attitudes towards food and unconventional eating patterns (American Psychiatric Association 2013). A report by Harvard reported that every 52 minutes in the US someone dies from an eating disorder (2020). In the recent years the number of people with eating disorders have increased significantly with women being the mostly affected (Matkovic, 2023).

The widespread of eating disorders were fuelled by the COVID-19 pandemic attributed to social distancing policies which made it mandatory to stay at home with little access to health care. This restriction led to changes in dietary habits such as frequent eating of snacks, change in mealtimes, uncontrolled eating and eating of less healthy foods (Ammar et. al., 2020). Lockdowns and fear of infection led to reduced satisfaction with relationships between family and friends which are factors that contribute to unusual life routines that are an indicator of eating disorders (Monteleone, 2021).

The most popular and well-experienced disorders on the list of eight in the most recent edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) are binge eating disorder, bulimia nervosa, and anorexia nervosa. In the past research has been done in understanding eating disorders by identifying genes, examination of environmental risk factors and developing treatments (Culbert et. al., 2015). However there has been less effort in predicting these disorders

with most studies focusing on binge eating and ignoring other eating disorders such as anorexia and bulimia.

Anorexia, often known as anorexia nervosa, is an eating illness marked by abnormally low body weight, a crippling dread of gaining weight, and a misguided understanding of weight. People with anorexia prioritize weight control, often through extreme measures that disrupt their lives. They directly relate their self-worth to being thin and sometimes they continue to see themselves fat even when they are thin.

Ashley Schiros & Kevin Antshel identified the relationship between eating disorders and they identify that they could be comorbid given that their symptoms and psychological identifiers overlap (2023). If not treated in time anorexia can result to further Axis II and III diseases in the DSM-5 i.e., Depression, Obsessive Compulsive Disorder (OCD), Borderline Personality Disorder (BPD), substance use, and self-harm (Ashley & Kevin, 2023).

Machine learning has emerged as an advanced computational model with the ability to advance eating disorder prediction and treatment. While they have not been able to attain accuracy, these researches form the foundation for promising results in detection of eating disorders such as anorexia in dealing with this mental health issues (Cyr et al., 2018; Haynos et al., 2020; Sadeh-Sharvit et al., 2020). Machine learning together with chatbots provide an avenue for a natural, real-time, and convenient conversations within the gadget that we use for our daily communication amidst the present digital revolution.

## 1.2 Problem Statement

Supported by a recent study conducted by the McPin Foundation, Keele University, University of Exeter, and University of Manchester (2023); Kostro, Lerman, and Attia (2014) establish the relationship between eating disorders such as anorexia with self-harm to the extent of suicide especially amongst teenage girls. Anorexia not only affect the individual's physical health but also, it has severe psychological implications, leading to feelings of shame, guilt, and low self-esteem. The mortality rates associated with anorexia are alarmingly high, making early intervention and support crucial to improving patient outcomes. Despite advancements in mental health awareness, detecting this disorder in their early stages remains challenging thus resulting to late intervention.

As demonstrated by the accurate predictions made for depression (Chekroud et al., 2016), schizophrenia (Koutsouleris et al., 2016), anxiety (Boeke et al., 2020), self-harm and suicide (Fox et al., 2019; Wang et al., 2021), and obsessive-compulsive disorder (Lenhard et al., 2018), machine learning has proven its capacity to analyze and learn from large and complex datasets. This research leverages on this technology in contributing to the field of mental health by developing an intelligent chatbot which utilizes machine learning for early detection and intervention for anorexia nervosa.

## **1.3 Objectives**

### **1.3.1 General Objective**

The main purpose of this research is to develop an intelligent chatbot implementation for early detection and intervention for anorexia nervosa.

### **1.3.2 Specific Objectives**

- i. To determine the risk factors and challenges associated with anorexia nervosa.
- ii. To review the current methods for detection and intervention for anorexia and their limitations.
- iii. To develop an anorexia detection model using machine learning and natural language processing and integrate it into a chatbot using the RASA framework.
- iv. To implement intervention strategies for anorexia patients within the chatbot framework, based on detected risk factors and user interactions.
- v. To perform validation and testing of the chatbot model and application in detection and delivery of intervention strategies.

## **1.4 Research Questions**

- i. What are the risk factors and challenges linked to anorexia nervosa?
- ii. What are the current methods used to detect anorexia nervosa and their limitations?
- iii. Which machine learning algorithms that can be used for building a prediction model?
- iv. How will the model be developed?
- v. How will the model be tested?

## 1.5 Justification

The United Nations Sustainable Development Goal 3 (SDG3) titled ‘Good Health and WellBeing’, emphasizes the need for comprehensive mental health care, including early detection and intervention, to reduce the burden of mental health disorders and their subsequent societal impact. However, eating disorders which are a subset of mental health disorders are affecting millions of individuals impacting not only their physical but also their psychological and social well-being, yet little effort has gone into detection and treatment of eating disorder such as anorexia nervosa which affects all ages, genders and background.

Additionally, rural areas and low-income communities often face barriers to accessing professional care for anorexia due to limited resources and social stigmas. Utilization of machine learning provides a platform for addressing these issues in comparison to the traditional methods, due to several advantages such as personalized predictions, scalability, ability to analyze vast amounts of data, extracting intricate patterns and risk factors that might be overlooked by traditional diagnostic methods.

Chatbots are already being used in customer engagements across various industries. For most websites especially e-commerce chatbots enable customer engagement a phenomenon that other researchers have termed a disaster due to lack of human touch resulting to poor customer satisfaction (Luo et al., 2019). Maina (2022) however notes that a good chatbot can be four times better than an inexperienced worker.

Through integrating chatbot with machine learning, this research will seek to make chatbots that are indistinguishable from a human agent for detecting and recommending possible treatment for individuals with anorexia. This research thus contributes towards the SDG agenda of universal mental health through proposal of a novel approach ‘an intelligent chatbot for detection and intervention for anorexia nervosa’. through utilization of the power of machine learning specifically natural language processing.

## 1.6 Scope and Limitation

This study is focused on developing an intelligent chatbot that utilizes natural language processing (NLP) in identifying signs of anorexia and providing initial support for anorexia patients. With a specific focus on anorexia, it doesn't replace professional help thus real-world implementation to institutions will depend on other factors such as policies which could be beyond the scope of this study.



## Chapter 2: Literature Review

### 2.1 Introduction

Anorexia nervosa is often primarily regarded as a physical disorder with the patients submitting themselves to the pressure of western model of beauty which emphasizes slenderness as the ideal body image. This chapter explores research, applications and interventions around this mental disorder in indicating the severity of the anorexia beyond being just a body image disorder. The chapter ends by conceptual framework preceded by an examination of the research gap which necessitated this research.

### 2.2 Anorexia

Anorexia is defined by the World Health Organization (WHO) as a mental illness marked by significantly low body weight brought about by diet alongside engagement in purging which entail misuse of laxatives, excessive exercise and self-induced vomiting (2018). The patient often called sufferer is motivated by the fear of gaining weight therefore they deny or underestimate the seriousness of the emancipation (APA, 2013).

Richard Morton in 1694 presented one of the earliest documented accounts of anorexia nervosa. In his work titled 'Treaties of Consumptions', anorexia is a 'nervous atrophy or consumption' which signified a gradual decline of the body without any signs of cough, fever or breathlessness. He attributed the cause of this disease to intense emotional turmoil which he described as 'violent passions of the mind'. He noted that like other nervous conditions, it is chronic and challenging to cure unless a physician is consulted at the beginning of the disease.

It was initially referred to as "anorexie hysterique" by Lasegue in France in 1874. William Gull in the UK then gave it the name anorexia nervosa, which it still has today. Giordano notes that treating anorexics can be challenging since, despite their persistent resistance to hunger, they frequently claim that "they are not hungry." Notwithstanding the unpleasant side effects of hunger, such as amenorrhea, sleeplessness, hypothermia, low blood pressure, cramps, and digestive issues, they continue to diet (2021).

Anorexia is a very puzzling condition, difficult to understand and poses challenges in terms of effective intervention (Zipfel et al. 2015). This condition exhibits the highest mortality rates

compared to other mental disorders (Fichter and Quadflieg 2016). Moreover, even when it doesn't lead to death, anorexia is linked to severe health complications.

## **2.3 Anorexia Risk Factors**

In order to effectively prevent and cure anorexia, it is important to understand the circumstances that expose and make individuals vulnerable to this disease. Several risk factors have been identified for anorexia nervosa, however there is limited understanding on how much each factor contributed and whether these factors are specific to anorexia or they apply to other eating disorders or psychiatric conditions in general (Fairburn et al., 1999). Risk factors for anorexia entail a range of biological, psychological and sociocultural issues. Their occurrence may be different for every individual hence people from different regions and backgrounds with diverse experiences are still at risk of anorexia. In this study we discuss these risk factors in 3 categories: biological, psychological and social risk factors.

### **2.3.1 Biological Risk Factors**

According to studies, an individual's chance of getting an eating disorder is increased by having close relatives with eating disorders and mental health issues such depression, anxiety, and addictions, with anorexia nervosa having the highest heritability (Thornton et al, 2015). Genetic elements constitute a huge role in the development of eating disorders with ladies being at a greater risk compared to men (Bould et al., 2015). When looking at genetic variations contributing to the risk of anorexia, there have been associations between EDs and other psychiatric comorbidities. Based on the eating disorder diagnosis, these comorbidities change. For people suffering from binge-type eating disorders, such as binge eating disorder (BED) and bulimia nervosa (BN), the highest correlations are noted for ADHD while those with anorexia nervosa show strong correlation for obsessive compulsive disorder (OCD), depression (MDD), suicidality, schizophrenia and neurotics (Thornton et al, 2015).

Furthermore, studies have been conducted on the proteins that gut bacteria generate, which have a role in the dysregulation of appetite and safety in anorexics. The number of E. coli bacteria in the gastrointestinal (GI) tract can significantly rise because of intestinal infections and persistent inflammation. This increase may elevate levels of peptide YY, potentially influencing ED risk

Notably, the CIPB protein produced by *E. Coli* prompts an immune response, resulting in the creation of autoantibodies. The position of these autoantibodies on receptors has been shown to differentiate the risk factors for BN, BED, or AN. Thus, autoimmune and autoinflammatory diseases such as diabetes 1 and 2, Crohn's disease and inflammatory bowel increases once chance at AN and to a larger extent eating disorder risk (Reinehr et al., 2019).

### **2.3.2 Psychological Risk Factors**

There are several psychological factors associated with an increased risk of anorexia nervosa. To begin with, perfectionism, particularly self-oriented perfectionism involving setting exceedingly high personal standards, is a prominent risk factor. Individuals who develop eating disorders often experience heightened levels of body image dissatisfaction and internalize societal ideals of appearance, leading to a negative self-perception (Sarah et al., 2023).

Furthermore, there are indications of pre-existing anxiety problems in anorexics, including obsessive-compulsive disorder (OCD), mood disorders, social phobia, post-traumatic stress disorder (PTSD), and generalized anxiety prior to the onset of their eating disorder. In addition, behavioral inflexibility, where individuals tend to rigidly adhere to rules and a singular "right way" of doing things, is a characteristic reported by many individuals with anorexia, particularly during their childhood (Sarah et al., 2023).

Evidence has shown a relationship between one's early experience from utero environment through to their adolescence as a contribution to ED risk (Bould et al., 2015). From high birth weight associated with BN and low birth weight associated with AN, the quality of parental relationship contributes to ED risk where individuals with low rating of parental care and warmth being at a high risk of AN compared to their counterparts. Experiences in childhood events such as trauma whether sexual or emotional contribute to binge type eating disorder such as AN binge type (AN-BP) (Larsen et al., 2015).

### **2.3.3 Social Risk Factors**

Social and cultural factors have been extensively researched as some of the common risk factors for anorexia given their role in shaping a person's self-perception in determining their ideal weight and physical appearance (Stice et al., 2017). Sarah et al., (2023) notes that majority of this research

has been focused on women and girls whose definition of ideal body is centered around low weight and thinness.

Weight stigma, characterized by the pervasive message that thinner equates to better, exposes individuals to heightened body dissatisfaction, a precursor to eating disorders. Weight stigma, which involves discriminatory or stereotypical treatment based on a person's weight, is prevalent in our society and can have profound negative effects (Stice et al., 2017). Studies have found that teasing or bullying, particularly when it targets an individual's weight, has emerged as a significant risk factor for various eating disorders including anorexia nervosa. In the recent years the harmful consequences of bullying, especially in regards to weight, has gained national attention. Individuals affected by eating disorders have identified bullying as a contributor to their condition, emphasizing the need to address weight shaming in anti-bullying discussions, amidst increase of anti-obesity messaging (Thornton et al, 2015).

The National Eating Disorders Association (NEDA) has found that a persistent internalization of the socially defined "ideal body" increases the chance of dieting and restricting one's diet, which in turn increases the risk of developing an eating disorder. Furthermore, the intricate interaction of stress, acculturation, and body image that results from acculturation, especially among rapidly westernizing racial and ethnic minority groups, increases the likelihood of eating disorders.

For example, the introduction of western television to Fiji led to significant shifts in body image perceptions and eating behaviours where 74% of women felt that they were too fat, 69% started dieting to lose weight, 29% were found at clinical risk of EDs whereas 11% engaged in self-induced vomiting (2022). The study also discovered that social isolation and small social networks are typical features of anorexia. Many people who suffer from the illness claim to have fewer friends, engage in fewer social activities, and receive less social support. It is still up for debate whether this is a stand-alone risk factor or linked to other possible reasons, such social anxiety (NEDA, 2022).

In summary, a study by Sarah et. al., (2023) which studied risk factors for EDs through examining over 12 years literature list the following risk factors in their study:

- i. Genetics: endocrines and neurotransmitters
- ii. Gastrointestinal and autoimmune reactions
- iii. Childhood and early adolescence experiences
- iv. Personality traits and comorbid conditions

- v. Gender differences
- vi. Body image and social influence
- vii. Elite Sports and excessive exercises

Below is a figure of these risk factor and associated EDs

Risk factor category	Features of risk factor	Associated ED
Genetic	See Sect. Introduction and Table 2 for details	AN, BN, BED
Gut microbial dysbiosis	<i>Escherichia Coli</i> (ClpB)	AN
Autoimmune disease	Diabetes, inflammatory gastrointestinal disease	AN, BN, EDNOS
Childhood weight status	Low BMI	AN
	High BMI	BN, BED
Relationship with parents	Parent perception that the child is overweight	AN-BP, BN, BED, PD
	Parental teasing about weight	AN-BP, BN, BED
	Perceived pressure from parents to eat	ARFID
Neglect/abuse/trauma		AN, BN, BED, PD
	Post-traumatic stress disorder	BED
Personality traits	Perfectionism	AN-R, A-AN
	Obsession	AN-R, A-AN
	Impulsiveness	AN-BP, BN, BED, PD
Comorbid conditions	Obsessive compulsive disorder	AN
	Social anxiety disorder	BN, AN
	Borderline personality disorder	BN, BED, PD
	Bipolar disorder	BN, BED
	Depression	All EDs
Social/environmental	Exposure to 'thin ideal'	All ED
	Body dissatisfaction	BN, BED, PD
	Early puberty development	BN, AN
	Food insecurity	Binge eating behaviours
	High educational attainment	Restricting type ED behaviours
	Involvement in elite sports	All ED

*ED* eating disorder; *AN* anorexia nervosa; *BN* bulimia nervosa; *BED* binge eating disorder; *EDNOS* eating disorder not otherwise specified; *BMI* body mass index; *AN-BP* anorexia nervosa (binge-purge subtype); *PD* personality disorder; *ARFID* avoidant restrictive food intake disorder; *AN-R* anorexia nervosa (restrictive subtype); *A-AN* atypical AN

Figure 1: Anorexia Risk Factors

## 2.4 Types of Anorexia

Chronic disruption of eating and eating-related behaviours, which results in changes in food consumption or absorption and adverse effects on physical and psychological health, is a hallmark of feeding and eating disorders. These conditions include binge eating disorder, bulimia, and anorexia as listed in the DSM (IV). Researchers have gone ahead to classify anorexia into two major categories restricting type and binge eating/purging type.

### **2.4.1 Restricting Type**

People who suffer from this kind of anorexia severely restrict the amount and kind of food they eat. They are likely to engage in activities such as skipping meals, counting calories for every substance, following strict food rules, avoiding certain foods and only eating foods of specific colors. Many combine restrictive dieting with other activities such as fasting and excessive exercises.

### **2.4.2 Binge eating/ purging type**

Like individuals with restricting anorexia, people with this kind of anorexia likewise restrict their food intake, but on occasion they also indulge in binge eating followed by purging. During binge eating an individual will engage in eating large amounts of food after which they will have a feeling of lost control leading them to ‘compensate’ for this eating by engaging in extreme purging conditions through self-induced vomiting, misuse of laxatives, diuretics or enemas.

## **2.5 Chatbot**

A key aspect of our everyday life are chatbots, also known as chatter robots, smart bots, conversational AI, digital assistants, or intellectual agents. The Oxford Dictionary define chatbots as ‘a computer program capable of engaging in a conversation with an individual, typically via the internet.’ These entities which may assume a physical form generate pre-determined responses through analysis of user input whether in text or spoken form then accessing the relevant knowledge (Xu et al., 2021).

The benefits of chatbots have seen them implemented in various areas which include travel, entertainment, gaming, robotics, security and healthcare. Harnessing their capacity for intricate conversation control and adaptability, incorporating chatbot technology into clinical settings has the potential to lower expenses, enhance workflow efficiency, and enhance patient results (Laranjo et al., 2018).

### **2.5.1 Chatbot History**

The concept of a chatbot was first introduced in 1950 when Alan Turing posed the question, "Can machines think?" Early versions of chatbots were designed to pass the Turing test, with an aim to mimic human conversations as closely as possible. The first chatbot ever created was called ELIZA, and it was created at the Artificial Intelligence Laboratory at MIT in 1966. Its purpose was to

serve as a psychotherapist. ELIZA conducted question-based discussions using template-based responses and pattern matching (Weizenbaum, 1966).

Enhancements to create more personalized and human-like chatbots resulted in Kenneth Colby's creation of PARRY, a personality simulator for paranoid patients. Alice, the medical industry's most well-known chatbot, was first presented by Richard Wallace in 1995. In order to retrieve example sentences from output templates and prevent incorrect answers, ALICE employed pattern-matching algorithms (AbuShawar & Atwell, 2015).

A renewed interest in Artificial Intelligence (AI) and advancements in Machine Learning (ML) has resulted to an increased use and accessibility of chatbots across various domains fields. One early such development was SmarterChild, developed by ActiveBuddy, Inc., which became widely available through messenger applications, paving the way for webbased assistants that use voice-activated systems such as Apple Siri, Amazon Alexa, Google Assistant, and Microsoft Cortana. Xu et al. (2021) highlights that chatbots have found substantial use in healthcare, with major applications in diagnostics, patient support (such as mental health counseling), and health promotion.

Several studies have explored the use of chatbot in healthcare industry. Amato et al., (2017) explored enhancing medical interactions with chatbots, specifically highlighting HMOLeS (Health On-Line Medical Suggestions), a modular system capable of adapting to various medical scenarios, making it a comprehensive medical chatbot. Comendador et al., (2015) introduced Pharmabot, designed for parents to determine proper generic medicine dosages for children, using pictorial representations and parsing algorithms. Divya et al., (2018) discussed a chatbot that enables text-to-text communication, allowing users to access disease details and their chat history stored in a database, while also performing symptom mapping for disease classification.

### **2.5.2 Types of Chatbot in healthcare industry**

Chatbots used in the healthcare industry can be divided into the following types:

#### *Conversational or AI Chatbots*

These chatbots use machine learning (ML) and natural language processing (NLP) algorithms to comprehend human language and intent, enabling them to deliver thorough automated answers to patient inquiries They are commonly utilized for tasks such as scheduling appointments, handling insurance inquiries, and delivering medical information.

### *Rule-based Chatbots*

Rule-based chatbots respond to user selections by following established decision paths, which are frequently shown as flowcharts. The chatbot then provides appropriate responses. These bots are employed by healthcare providers for tasks like managing appointments, engaging with patients, handling registration, conducting initial screenings, and maintaining health records. Patients and payers can also use them to address queries, check claim statuses, and receive notifications about specific treatments.

### *Informative Chatbots*

These automated support bots deliver valuable information to users through push notifications and pop-ups. They are typically employed by health news websites and mental wellness platforms to provide detailed insights into specific medical topics.

### **2.5.3 Limitations of chatbot**

Chatbots have rapidly evolved and they are able to understand human language better than ever. This presents an opportunity for their utilization in several sectors as has been witnessed, however they also have limitations. Some of these as observed by Ying (2021) include:

Finite set of answers and responses: Chatbots can only respond from a particular predefined set of answers. Thus, they may lack the ability to ask extra questions for clarity which can be a challenge when dealing with complex user queries.

Artificial Intelligence and Machine Learning

Need for human intervention: Though data analytics can be automated for efficiency, chatbots still require human intervention to act upon the insights that are derived from its interactions.

Data dependency: Chatbots require a huge amount of data to be trained in order for them to perform well. Without sufficient data to train the model, its performance could fall short.

Data protection challenge: Chatbots require user data in order to personalize their experience. However, strict regulations and policy on data may hinder acquisition of data to train and test chatbot models.

## **2.6 Artificial Intelligence Concepts**

Artificial Intelligence (AI) is currently one of the most prominent and widely discussed topics in the technology field and this attention is well deserved. There have been numerous groundbreaking developments over the past few years which were once considered only possible in science fiction.

According to an article by PwC, AI could potentially contribute to \$15.7 trillion to the global economy by the year 2035 with China and USA benefitting the most from this AI surge by 70% (PwC., 2023).

The development of software, computer-controlled robotics, and computer systems that can simulate human intelligence is known as artificial intelligence. This can be accomplished by looking at human brain patterns and analyzing cognitive functions. Thus, the outcomes may contribute to the creation of intelligent systems and software.

AI entails a range of technologies which empower computers to perform advanced tasks, such as recognizing and interpreting spoken and written language, analyzing data and providing recommendations. Artificial intelligence can broadly be categorized into two, that is strong AI and weak AI. Weak AI represents systems that are specialized in carrying out specific tasks, excelling in their specific domain but lacking broad intelligence example Siri and Alexa. Strong AI on the other hand possess human level or superior intelligence across various tasks enabling them to understand, reason, learn and solve complex problems in a similar manner to human cognition.

## **2.7 Machine Learning**

Machine learning is a subset of artificial intelligence which creates algorithms and models that enable computers to learn and enhance their performance through experience without the need for explicit programming (El Naqa & Murphy, 2015). These algorithms analyze extensive datasets to detect patterns and then utilizes these patterns in making decisions. Machine learning can be categorized into three types supervised, unsupervised and reinforcement learning.

Supervised learning involves learning from labelled data with known outcomes, unsupervised learning entails learning from unlabeled data through discovery of patterns and structure in unsupervised data. Reinforcement learning using an agent to accomplish a task in a series of iterative trial and error until the outcome is within desirable bounds. The agent is rewarded for successful task execution and penalized for poor performance.

Within machine learning, several algorithms could potentially be used for our chatbot-based anorexia detection system. Here we discuss some of the most approaches and their potential relevance to the project.

### **2.7.1 Decision trees**

Decision trees are a fundamental supervised learning approach that works by creating a tree-like structure with branching decisions based on features in the data. Each branch leads to a leaf node representing a class prediction. In our case, the class would be either "anorexia" or "not anorexia." Decision trees are intuitive and relatively easy to interpret, making them valuable for understanding which conversation features contribute most to the model's predictions. This interpretability can be helpful in refining the model and ensuring alignment with our understanding of anorexia (Mahesh, 2020).

Additionally, decision trees can handle complex and non-linear relationships between features, which might be present in conversational data. However, Decision trees can be susceptible to overfitting, especially when dealing with large datasets. This means the model might perform well on the training data but not generalize well to unseen conversations. Pruning techniques can be applied to mitigate this risk.

### **2.7.2 Feedforward Neural Network (FNN)**

FNNs are a type of artificial neural network inspired by the structure of the brain. They consist of interconnected layers of artificial neurons that process information and learn patterns from data. In our case, the network would learn to identify patterns in conversation data that indicate the presence or absence of anorexia (Mahesh, 2020).

FNNs are powerful tools for capturing complex relationships in data, which could be beneficial for analyzing the nuances of human conversation. They can potentially achieve high accuracy, especially with large amounts of training data. FNNs can be computationally expensive to train, especially for large datasets. Additionally, they can be like "black boxes," making it difficult to understand how they arrive at their predictions. This lack of interpretability can be a challenge in healthcare settings where understanding the decision-making process is crucial (Mahesh, 2020).

### **2.7.3 Support Vector Machines (SVMs)**

SVMs are powerful algorithms that aim to create a clear separation hyperplane between different classes in the data. In our case, the classes would be "anorexia" and "not anorexia." SVMs excel at handling high-dimensional data, which might be relevant if we incorporate additional features

beyond just text from the conversations. However, SVMs can be computationally expensive for very large datasets and may not be as interpretable as other options.

#### **2.7.4 Naive Bayes**

This probabilistic approach assumes independence between features, making it efficient for classifying data. It calculates the probability of a data point belonging to a particular class based on the individual probabilities of its features. For our project, Naive Bayes could be suitable if we identify specific keywords or conversation patterns strongly associated with anorexia. However, the assumption of feature independence might not always hold true in real-world chat conversations.

#### **2.7.5 Random Forest as the Right Machine Learning Approach**

Within machine learning, selecting the most suitable algorithm for a particular task is crucial for optimal performance. Different algorithms have varying strengths and weaknesses, making them effective depending on the problem at hand. Some factors to consider when choosing an algorithm include the size and complexity of the data, the desired level of accuracy, and the interpretability of the results.

This study aims to develop a chatbot for anorexia detection through conversation analysis. To achieve this, a random forest algorithm has been chosen, a supervised learning approach that combines the predictions of multiple decision trees. This combination results in a more robust and accurate model, making it ideal for our specific needs.

Random Forests excel in handling large datasets, a crucial factor considering the potentially significant amount of conversation data involved in anorexia detection. They are also robust to noise, meaning inconsistencies, typos, or informal language commonly found in chat conversations, will have less impact on the model's performance. This is essential for dealing with the messiness of real-world chat interactions.

While some machine learning models can be opaque, random forests offer a level of interpretability. By analyzing the contributions of individual decision trees, we can gain valuable insights into which conversational features hold the most weight in the model's predictions. This interpretability allows us to both improve the model's accuracy and ensure it aligns with our understanding of anorexia.

Finally, random forests have a strong track record of achieving high accuracy in classification tasks. This characteristic is paramount for our project, where the accurate detection of anorexia is of the utmost importance. Considering all these factors and the strengths of random forests, we believe this algorithm is the best choice for anorexia detection through chatbot conversations.

## 2.8 Deep Learning

Deep learning is a branch of machine learning which employs neural networks to model and understand complex patterns and relationship within data. These networks, which are made up of interconnected layers of neurons and are modelled after the structure of the human brain, are able to extract high-level information from data by learning complicated patterns and relationships. Significant advancements in natural language processing, picture and speech recognition, predictive modelling, and other fields have been made possible by this technique.

Some of the most common types of artificial neural networks include:

Feedforward neural network (FF)

Recurrent neural network (RNN)

Long/short term memory (LSTM)

Convolutional Neural Networks (CNN)

Generative adversarial networks (GAN)

## 2.9 Natural Language Processing

NLP is a subset within AI whose primary focus is around facilitation of meaningful and useful interactions between computers and human language. It entails a wide range of activities such as text classification sentimental analysis, language translation, question-answering and speech recognition. NLP can achieve this through several technologies from linguistics, machine learning and deep learning allowing it to process and analyze textual data (Chowdhary & Chowdhary, 2020).

Professionals in this domain concentrates on development of algorithms and systems designed to comprehend and generate human language. Activities in this domain involve speech recognition, enabling language translation and refining text classification.

## 2.10 Deep Learning vs Natural Language Processing in Chatbot Creation

Though they are closely linked AI paradigms, natural language processing (NLP) and deep learning have different features. As seen in the images below, this link has been studied by several academics, including Kasera (2022), Ponteves et al. (2021), Sigmoidal (2020), and Banerjee (2020). Figure A by Ponteves et al. (2021) shows that deep learning, which includes artificial neural networks (ANN), is represented by the right side, whereas NLP is represented by the left nonoverlapping section. There is no overlap between these two sections.

The Deep Natural Language Processing (DNLP) model, which integrates sophisticated models like the sequence-to-sequence (Seq2Seq) model, is present in the overlapped region. DNLP makes use of both Deep Learning and NLP. Figure B from Sigmoidal (2020) emphasizes deep learning as a part of the larger discipline of machine learning. Figure C illustrates how Banerjee (2020) highlights the computational linguistics component of NLP that enables smooth communication between computers and people.

Modern software robotics, such as chatbots are notable applications of both NLP and Deep Learning models (Mandelbaum, 2021). This research seeks to employ natural language processing in coming up with a chatbot for detection and provision of intervention for anorexia patients. This approach seeks to enable the machine to comprehend natural language effectively.

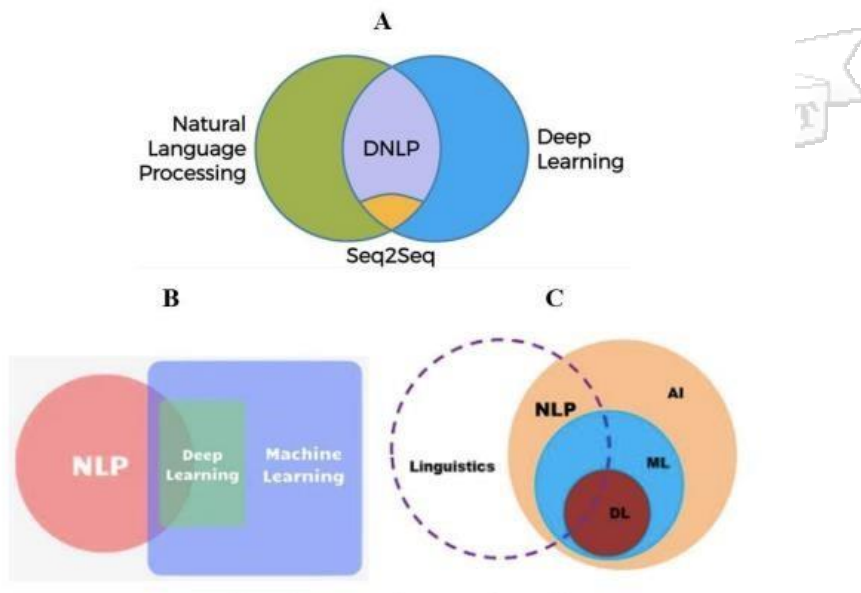


Figure 2: NLP vs Deep Learning For Chatbot

## 2.11 Related Applications

Established anorexia nervosa recovery programs often encompass a comprehensive approach when dealing with the affected patients. Interventions typically range from psychotherapy to supervised strategies for promoting healthy weight gain. For adolescence some of the recommended treatment include family-based therapy (FBT) and cognitive based therapy (CBT). FBTs operate on the premise that the eating disorder is a concern for the family thus emphasizing in the role of parental involvement for effective treatment. CBT on the other hand views eating disorder as primarily affecting the individual, with treatment success dependent on the willingness of the patient and their active participation in the process of change. A few notable applications have been developed in dealing with anorexia, below is their discussion.

### *2.11.1 RiseUp+ Recovery*

This application by Recovery Warriors caters for individuals struggling with eating disorders, with a primary focus on its mood and meal tracking functionality. Once the app is launched the user is prompted to ‘check in’ and assess their daily emotional state from a customizable list. They can also record their meals, including details such as time, food choice, location and mood and if they have any problematic behavior which can be converted to pdf in case of sharing. Additionally, the applications provide tips related to the recovery journey based on themes such as body image, journaling, mindfulness and relationships.

Some of the benefits of the application is that it empowers its users in managing eating habits through development of meal routines. It also avoids incorporating weight and calorie counting features thus maintaining a user-friendly approach. Unfortunately, the application does not allow users to preplan their meals and snacks. Moreover, it doesn’t provide any capability for pictures to be provided when logging in photos of their meals. Lastly some users are unable to use the find support feature in countries such as New Zealand.



Figure 3: Riseup+ Recovery

### 2.11.2 Anorexia Nervosa

This application by Jupiter Apps which was published in January 2023, is a free Android health and fitness application. The application provides details on the symptoms, causes, diagnosis and treatment of anorexia nervosa.

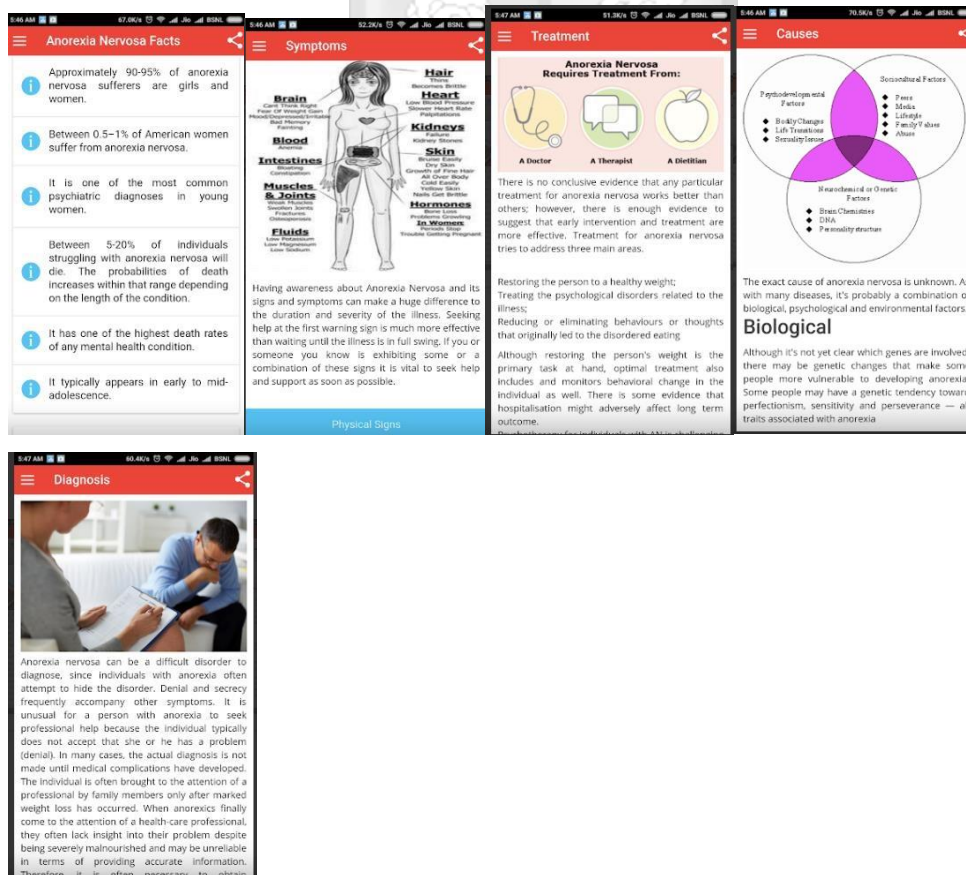


Figure 4: Anorexia Nervosa App

### 2.11.3 Anorexia Recovery Guide

Anorexia Recovery guide currently at version 1.1 was developed by Jackline Moline and published in October 2020. The application is designed for those suffering from anorexia and it contains information on the causes, signs, symptoms and treatment information for anorexia.



Figure 5: Anorexia Recovery Guide App

## 2.12 Research gap

Anorexia nervosa has garnered increased attention by researchers given the growing applications and research in this area for mental health interventions. However, most existing solutions offer generalized support through resources and professional contacts. A specific gap exists in anorexia detection and personalized intervention through chatbots. Current applications lack the ability to identify anorexia and tailor interventions to individual needs. This limited focus on personalized detection and intervention can be attributed to the predominance of research on eating disorders in a broader context, with less emphasis on the specific needs of anorexia patients. This research aims to address this gap by leveraging the power of machine learning, specifically a random forest algorithm, to create a chatbot capable of detecting anorexia and offering personalized interventions.

## 2.13 Conceptual Framework

The figure below provides an overview of the solution that this study proposes. The chatbot is built based on RASA which is an open-source machine learning framework used to build custom AI chatbots using Python and Natural Language Understanding (NLU). RASA has two main

components RASA NLU (Natural Language processing) for intent classification and RASA core for dialogue management and predicting of next steps based on probabilistic models such as LSTM.

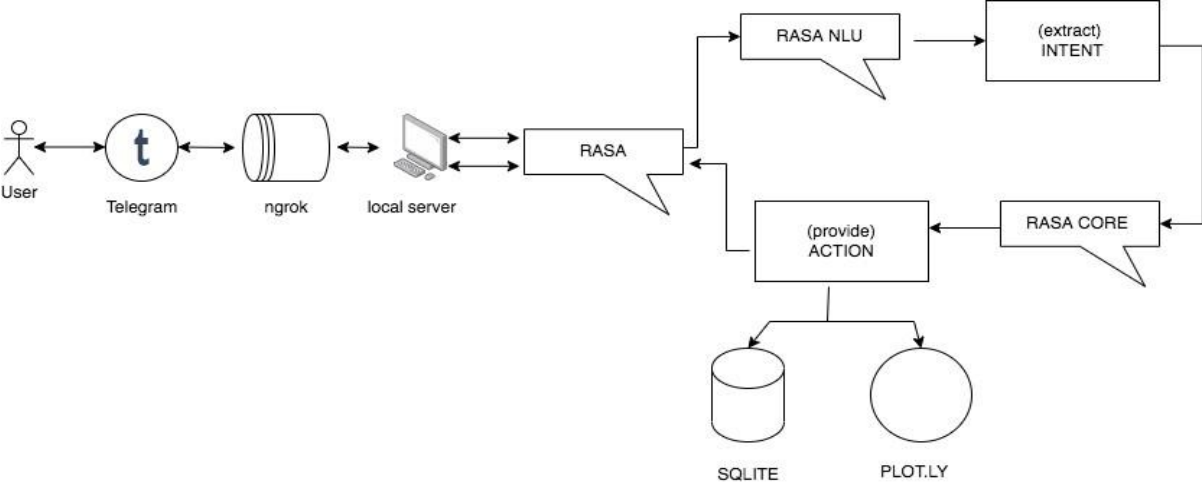


Figure 6: Conceptual Framework



## **Chapter 3: Methodology**

### **3.1 Introduction**

Research methodology is a systematic and structured approach for problem solving. It is the science of studying how research should be conducted encompassing methods and processes that researchers employ to describe, elucidate, and forecast phenomena (Goundar, 2012). The development methodology applied in the construction of the model, ethical considerations and the methods used in data collection, sampling and data analysis are discussed in this chapter.

### **3.2 Research Design**

A research design is the framework of research method chosen by a researcher to carry out research. This framework empowers the researcher to refine methods which are suitable to the subject matter in order to succeed in their research. This research employed a mixed methods approach in undertaking this research whereby quantitative research was employed in quantifying dietary intake necessary in detecting and providing intervention to anorexia while qualitative methods enabled an in depth understanding of the ‘non-mathematical’ factors such as psychological well-being which also contributes to anorexia nervosa.

### **3.3 Model Development**

The development of the chatbot model for detection and provision of intervention for anorexia nervosa followed the following steps:

- i. Data Collection and Data Preprocessing
- ii. Model Development
- iii. Testing and Validation
- iv. Deployment and Maintenance

#### **3.3.1 Data Collection and Pre-processing**

In order to facilitate the training of our chatbot, dataset which consists of data related to eating disorder were compiled. The dataset included conversations, informational content and common phrases which are associated with anorexia. After obtaining the data, the researcher carried out data preprocessing tasks which involved tokenization, stemming and removal of any irrelevant information in enhancing the quality of the training data.

### **3.3.2 Model Development**

The development of the model involved the following steps.

#### *Intent Recognition and Sentimental Analysis*

Intent recognition was a fundamental part of the model, using the framework we employed RASA NLU based on NLP to classify user intents effectively. Through intent classification, the chatbot was able to identify the requests and statement which are related to anorexia, which is crucial for it to engage in the conversation.

Additionally sentimental analysis was used in gauging the emotional state of users. This functionality assists in identification of users who could be in distress or require emergency intervention which prompts for a quick response and support.

#### *Dialogue Management*

In order to ensure meaningful and coherent conversation, effective dialogue management is very crucial. RASA framework utilizes its RASA core to ensure that dialogue management guides user interactions. The core will utilize a combination of rule-based approach and reinforcement learning technique to manage the conversations flow and user engagement.

#### *Anorexia Detection*

The model is developed to be able to analyze signs, symptoms of anorexia based on user conversations. It utilizes relevant keywords, patterns and sentiments which are associated with anorexia enabling the chatbot to provide a timely and sensitive response.

#### *Provision of Intervention and Support*

Based on the severity of the anorexia detected, the chatbot has several levels of interventions and support. In case of less severe diagnosis, it will provide general information about anorexia coupled with empathetic response. When the situation is very severe, the chatbot should provide critical crisis intervention resources, actively encouraging users to seek professional help.

### **3.3.4 Testing and Validation**

The model was tested through interaction with real users, accessing its accuracy in detecting anorexia and providing intervention.

### 3.3.5 Deployment and Maintenance

Once the model is constructed, it will be deployed in in Telegram where it can reach and assist several users who are our target audience. There will be continuous maintenance and updates based on the user's feedback.

### 3.4 System Development Methodology

Rapid Application Development (RAD) was utilized in the development of the suggested chatbot. RAD is an agile software development methodology that prioritizes rapid feedback and prototyping over extensive planning. This agile method of developing software lays less focus on adhering to a rigid plan and more on ongoing software projects and user input.

An illustration of Singh's 2019 RAD development methodology procedures can be found below.

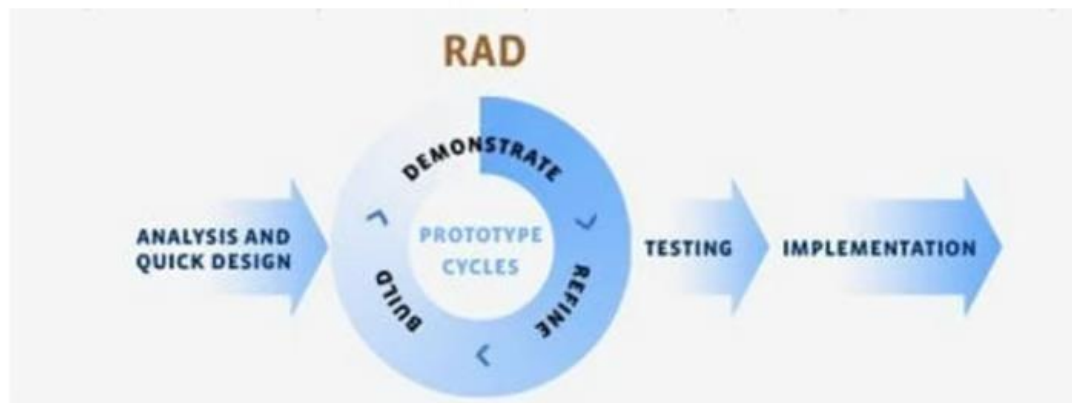


Figure 7: Rapid Application Development

#### 3.4.1 Analysis and quick design

This stage involved gathering project requirements such as project timelines, expectations, objectives and goals. Obtaining and refining project requirements entailed going through secondary research and engaging in consultations in order to determine the scope of the project.

#### 3.4.2 Prototype Cycles

This step involved the development of prototypes given that the project requirements were already defined. The researcher carried out design to ensure the user interface was appealing after which they engaged in development of the prototype. Several users were also involved in order to obtain feedback which is useful in refining the model.

### **3.4.3 Testing**

This crucial step involved testing the software product in ensuring that it achieved its objective and that the end users were able to work with it. Given the nature of RAD methodology user feedback were used to improve the model after which tests were carried out.

### **3.4.4 Implementation**

After several satisfactory tests, this last step involved deployment of the model on Telegram as the finished product. Users will be notified to access the bot on Telegram in order to test whether they have anorexia and if they do to leverage on the bot as an intervention avenue.

## **3.5 Target Population and Sampling**

### **3.5.1 Target Population**

Muriithi (2022) defines the target population as an interest group from whom the study sample is to be drawn. The study's target demographic consists of those with anorexia who may not be aware that they have the disorder as well as those who have it but don't have any treatments.

### **3.5.2 Sampling**

The research utilized a non-probabilistic method for selecting the sample participants in this research. This technique relies on sampling techniques other than random selection such as accessibility, physical proximity or the expertise of the individual under investigation in addressing the research questions.

### **3.6 Data Collection**

In meeting our objective of utilizing an intelligent chatbot for detecting and providing intervention for anorexia, we employed various data collection methods in gathering insights from individuals who have experienced or working with anorexia. These data collection methods are discussed below.

### **3.6.1 Interviews**

Semi structured interviews were conducted in order to capture subjective experience, emotions and perceptions related to anorexia and intervention methods. The researcher utilized open ended questions in encouraging in depth responses.

### **3.6.2 Observation**

The researcher also utilized both direct and indirect observation as a data collection method in order to understand the challenges of anorexia. Direct observation involved interaction with anorexia patients while indirect observation involved gathering of insights from secondary sources such as academic literature and reports.

### **3.7 Data Analysis**

The data obtained from data collection underwent analysis in an attempt to extract valuable insights for evaluation of the chatbot. A hybrid approach combining content analysis and thematic analysis allowed for a comprehensive exploration of the experiences and the perspectives shared by the interviewees. Analysis helped the researcher to uncover critical themes, patterns and insights related to anorexia and the potential role of an intelligent chatbot in providing interventions to anorexia.

### **3.8 Research Quality**

The chatbot model's effectiveness was measured based on two well established metrics namely the Root Mean square error (RMSE) and the Mean absolute error (MAE). Also called the root mean square deviation, RMSE utilizes Euclidean distance to measure the difference between the predicted value and the actual value.

### **3.9 Ethical issues**

This research sought ethical approval from the university ethical approval committee (Strathmore Ethical Approval Committee). In addition, the researcher will ensure that participant's data is treated with utmost confidentiality and only used for scholarly purposes.

This research has cited works used within this study in ensuring that there is no plagiarism.

## Chapter 4: System Analysis, Design and Architecture

### 4.1 Introduction

This chapter presents the overall architecture and the detailed design of the proposed model by incorporating a variety of user requirements. The functional and non-functional requirements are discussed, and the design of the proposed system utilizes UML diagrams. These diagrams which include use case diagrams, class diagram and sequence diagrams in describing the systems architecture provide a through description of the various components of the system and explains the interactions between users and the system components.

### 4.2 Requirement Analysis

This research seeks to develop an intelligent chatbot implementation for early detection and intervention for anorexia nervosa. Aligned with the earlier defined objectives, the system must meet certain criteria for it to be deemed successful. These requirements are discussed below.

#### 4.2.1 Functional Requirements

- i. The system should enable the chatbot to engage users in supportive dialogues on the Telegram platform.
- ii. The chatbot should be capable of interactive conversations to detect potential risk factors related to anorexia nervosa.
- iii. The system should incorporate a robust anorexia detection model based on natural language processing.
- iv. The detection model should analyze user input to identify signs of anorexia, including extreme eating habits and expressions of fear of weight gain.
- v. The chatbot should integrate intervention strategies tailored to address the specific needs of anorexia patients.
- vi. The system should implement machine learning algorithms that demonstrate accuracy and reliability in identifying potential cases of anorexia based on user interactions.

## 4.2.2 Non-Functional Requirements

- i. **Security and Confidentiality:** The system should prioritize the security and confidentiality of user data thereby ensuring that sensitive information in relation to individuals' health is protected.
- ii. **Scalability:** The system should be scalable to be able to accommodate a growing user base amongst various individuals seeking help.
- iii. **Usability:** The chatbot interface should be user-friendly, making it easy to use by users of varying levels of technological literacy.
- iv. **Performance:** The chatbot response time should be optimized to not more than 30 seconds in providing responses and timely interventions thus enhancing the effectiveness of early detection and support.
- v. **Maintainability:** The system should allow for continuous improvement and refinement of the chatbot's algorithm, addressing the limitations and incorporating advancement in machine learning and mental health research.

## 4.3 System Design and Architecture

### 4.3.1 System Architecture

The figure below depicts the system architecture for anorexia nervosa detection and intervention accessed via Telegram and implemented using the RASA framework with ngrok integration. Users engage with the chatbot through Telegram application and ngrok exposes the RASA powered chatbot to the internet for accessibility. RASA's NLU and Core components enable the chatbot to understand user intent, manage dialogue and predict next steps based on RASA policy. The system leverages a database to store user interactions and training data, while monitoring tools such as logs and metrics ensure continuous performance optimization.

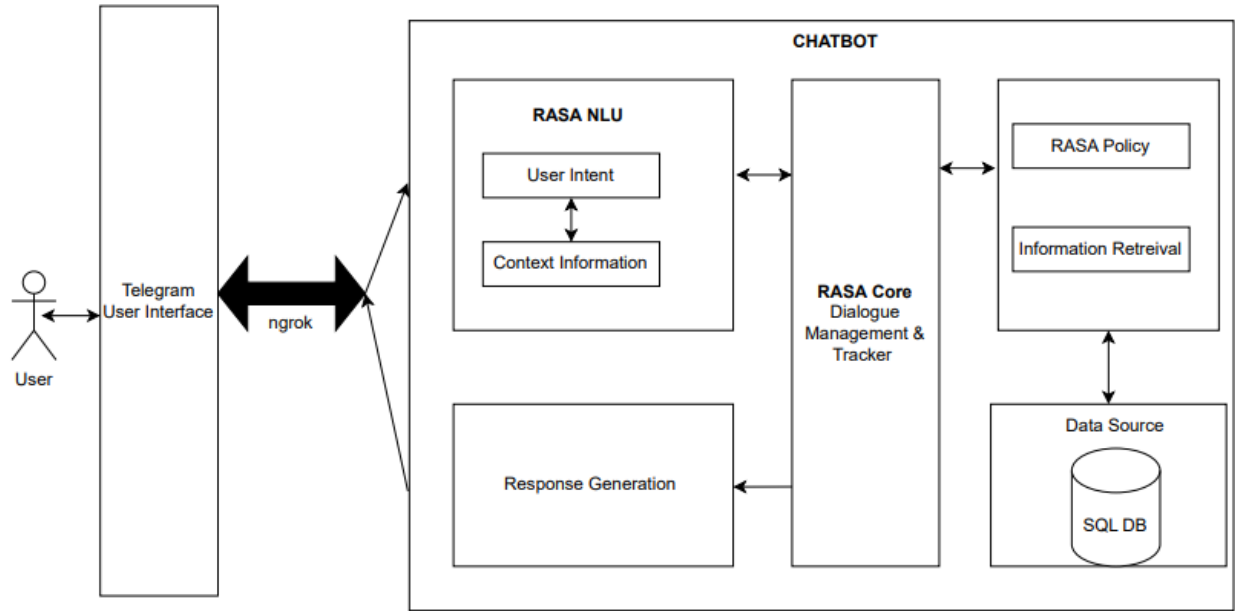


Figure 8: System architecture

## 4.3.2 System Design

### 4.3.2.1 Use Case Diagram

The diagram below serves as a comprehensive use case representation outlining the diverse interactions between users (actors) and the system. The primary actors include the user (telegram user), administrator, and external intervention. The Telegram user engages with the bot by sending messages, while the administrator oversees user management, configures alerts, monitors system health, and updates training data. In cases of emergencies, external intervention becomes imperative. The external intervention actor is equipped to receive alerts, access relevant data, and trigger emergency responses as needed.

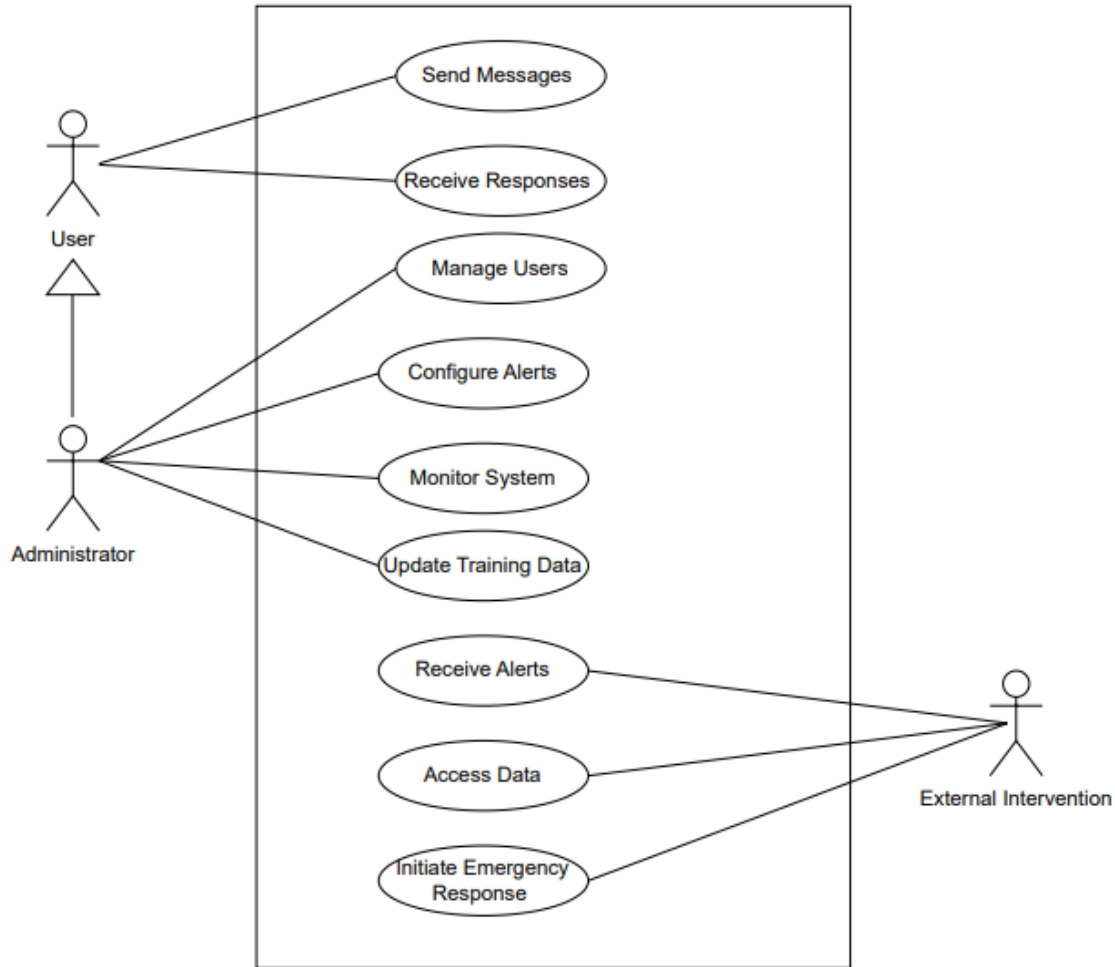


Figure 9: Use Case Diagram



Below are use case descriptions for the user and the administrator.

Use Case: Send Message

Description	Telegram user initiate communication with the chatbot by sending messages through the telegram app, serving as the starting point for engagement.
Actors	Telegram User
Preconditions	- The Telegram app is installed and operational on the user's device. - The user has a valid and active account on Telegram.
Main Flow	1. The Telegram User opens the Telegram app on their device. 2. The user navigates to the chat interface with the chatbot. 3. The user types a message expressing their inquiry, concern, or request.

	4. The user sends the message.
Postconditions	- The message is successfully sent to the chatbot. - The system processes the user's message for further interaction.
Alternative Flows	- If there are connectivity issues or errors in message transmission, the user may receive a notification indicating the problem.

#### Use Case: Receive Response

Description	Telegram User receives responses from the chatbot based on their previously sent messages, including information, guidance, or interventions.
Actors	Telegram User
Preconditions	- The Telegram User has sent a message to the chatbot. - The chatbot is operational and capable of processing user messages.
Main Flow	1. The Telegram User awaits a response from the chatbot after sending a message. 2. The chatbot processes the user's message, extracting intent and generating a relevant response. 3. The chatbot sends the response to the user.
Postconditions	- The Telegram User receives a response from the chatbot. - The response may include information, guidance, or interventions related to Anorexia Nervosa.
Alternative Flows	- If the chatbot encounters difficulties in generating a response or if there are system errors, the user may receive a notification about the issue.

#### Use Case: Manage Users

Description	Administrators have the capability to manage users, overseeing user-related functionalities within the chatbot system.
Actors	Administrator
Preconditions	- The administrator is authenticated and has the necessary privileges.
Main Flow	1. The administrator accesses the user management interface. 2. The administrator views and manages user profiles, including adding, modifying, or deactivating user accounts.

Postconditions	- User management operations are successfully executed by the administrator.
Alternative Flows	- If there are errors in the user management process or if the system encounters issues, the administrator may receive notifications for resolution.

#### Use Case: Configure Alerts

Description	Administrators can configure alerts, defining conditions under which specific notifications are triggered within the chatbot system.
Actors	Administrator
Preconditions	- The administrator is authenticated and has the necessary privileges.
Main Flow	1. The administrator accesses the alert configuration interface. 2. The administrator defines alert conditions, including severity levels and triggering events.
Postconditions	- Alert configurations are successfully set by the administrator.
Alternative Flows	- If there are issues in the alert configuration process, the administrator may receive notifications or feedback for adjustments.

#### Use Case: Monitor System

Description	Administrators monitor the overall health and performance of the chatbot system, ensuring its smooth operation and identifying any anomalies or issues promptly.
Actors	Administrator
Preconditions	- The administrator is authenticated and has the necessary privileges.
Main Flow	1. The administrator accesses the system monitoring interface. 2. The administrator reviews system metrics, including resource utilization, response times, and user engagement.
Postconditions	- The administrator gains insights into the system's health and performance.
Alternative Flows	- If there are abnormalities or issues detected during monitoring, the administrator may receive alerts or notifications for further investigation and resolution.

#### Use Case: Update Training Data

Description	Administrators have the responsibility to update the chatbot's training data, incorporating new insights, patterns, or information relevant to the detection of Anorexia Nervosa.
Actors	Administrator

Preconditions	- The administrator is authenticated and has the necessary privileges.
Main Flow	1. The administrator accesses the training data management interface. 2. The administrator reviews existing data and incorporates new insights, patterns, or information into the training data.
Postconditions	- The chatbot's training data is successfully updated by the administrator.
Alternative Flows	- If there are errors in the update process or if the system encounters issues, the administrator may receive notifications for resolution.

4.3.2.2 Sequence Diagram

The figure below, a sequence diagram, depicts the interaction between the user and the bot. The interaction begins as the Telegram User takes the initiative to engage with the chatbot by sending a message, such as "Hello." The Telegram Bot then receives this message and transfers it to the RASA Server for processing. Within the RASA Server, the processUserMessage method is invoked, delving into the natural language understanding (NLU) and dialogue management components to decipher the user's intent. Following this comprehension, the generateBotResponse method is activated to formulate a tailored response. Finally, the Telegram Bot, now armed with the generated response, forwards it back to the Telegram User, thereby completing the interaction loop with a meaningful reply, for instance, responding with "Hi!".

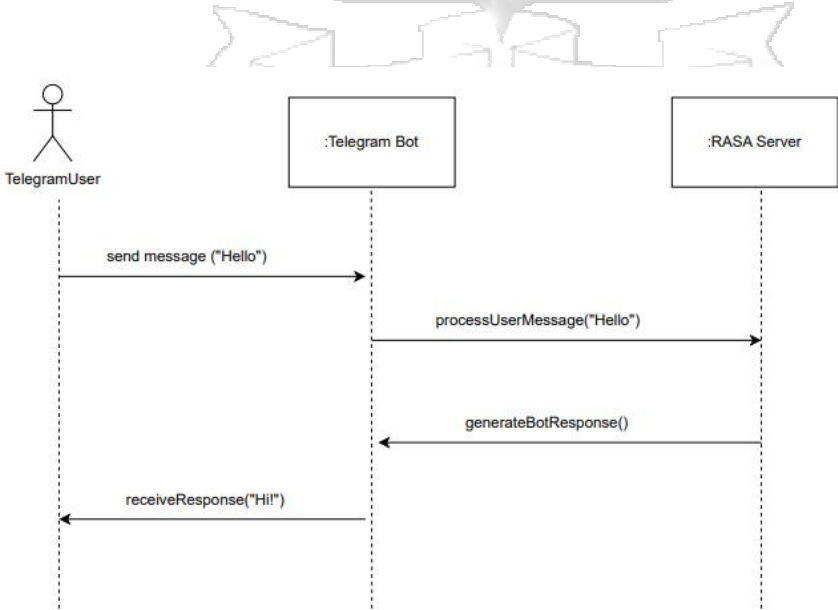


Figure 10: Sequence Diagram

### 4.3.2.2 Class Diagram

Class diagrams serve as a valuable tool in system design, by enabling seamless transformation of classes into various object-oriented programming languages. They effectively outline the characteristics and functions of a class while also establishing the interactions between objects. Below is a class diagram of the anorexia detection and intervention system.

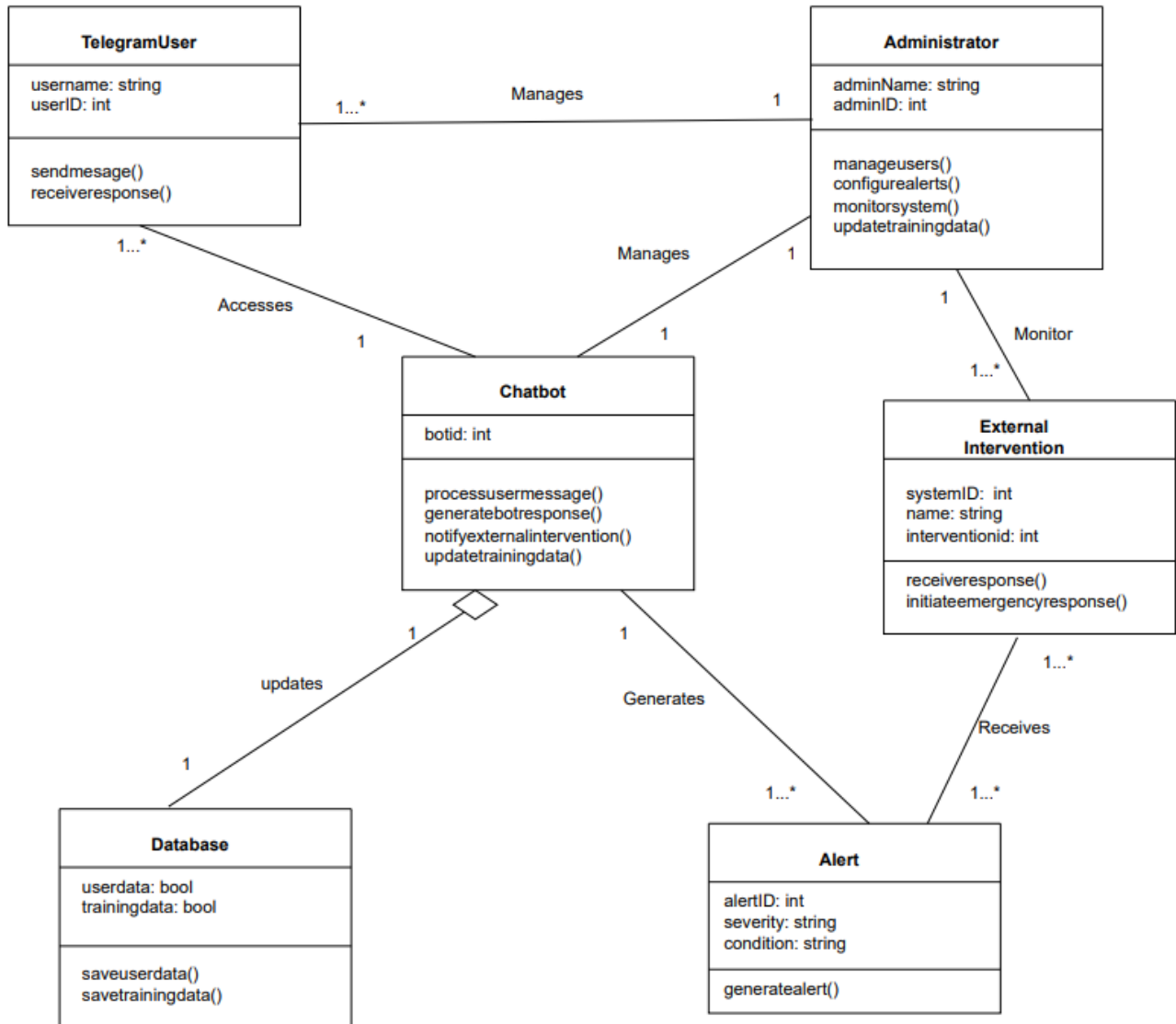


Figure 11: Class Diagram

### 4.3.2.3 Context Diagram

The diagram below represents a context diagram which provides a concise visual representation, focusing on the key external entities and their relationships with the intelligent chatbot system. It omits internal details and complexities to offer a clear overview of the system's interactions with external elements.

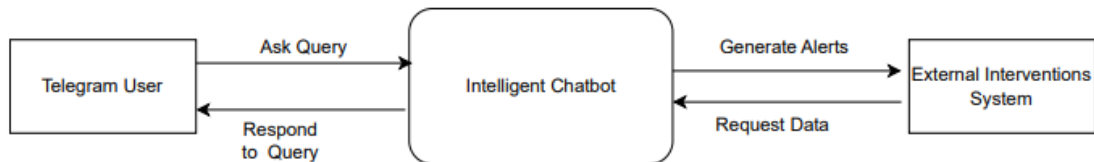


Figure 12: Context Diagram



## Chapter 5: System Implementation and Testing

### 5.1 Introduction

This chapter explores the development, testing, and validation of the chatbot model. It illustrates the methodology used to construct the model, illustrating the results observed on the trained dataset. It outlines the procedures for data preprocessing and explains the model evaluation approach. The implementation section explores the system's structure and components, while testing ensures alignment with the predefined requirements and objectives.

### 5.2 Hardware and Software Environment

The model leveraged a combination of classification and Natural Language Understanding (NLU) techniques, a powerful approach within machine learning. The development environment of choice was Visual Studio Code (VS Code), utilizing Python as the primary programming language for the RASA framework actions. The Python ecosystem provided valuable libraries for data manipulation and analysis, including pandas and scikit-learn (sklearn).

Python's vast selection of libraries and its clear, readable syntax made it a perfect fit for building the model. Furthermore, pandas, provided a comprehensive toolkit for manipulating and analyzing the dataset. This data manipulation was crucial for training and testing the model effectively. Finally, scikit-learn (sklearn) offered specialized data structures and operations specifically designed to work with the numerical data that formed the foundation of the machine learning models.

#### 5.2.1 Hardware Environment

The hardware specifications of the machine hosting the chatbot system included:

- Operating System: Windows 10 Pro 64-bit, Build 19045
- Manufacturer: Lenovo
- Processor: Intel Core i5 @ 2.20GHz
- RAM: 8GB

#### 5.2.2 Software Environment

The software components included:

- Integrated Development Environment (IDE): Visual Studio Code (VS Code) and Sublime Text

- Chatbot Framework: RASA
- Programming Language: Python 3.9.13
- Libraries and Dependencies: pandas and TensorFlow:
- Messaging Platform: Telegram app for integration and accessibility of the chatbot via Telegram

## **5.3 Data Source, Cleaning and Preprocessing**

### **5.3.1 Data Source**

The study utilized a dataset drawn from research exploring the link between weight status and food-related obsessions and compulsions. Two participant groups were involved: a healthy group ( $n = 27$ ) and an unhealthy group ( $n = 33$ ). Both groups completed self-report questionnaires to assess food preoccupations, compulsive eating behaviors, and emotional responses to intrusive thoughts about food. This research aimed to investigate the relationship between weight status and food-related obsessive-compulsive traits, ultimately contributing valuable insights into the factors influencing overeating, undereating, and weight management.

The selection of this dataset aligned with the project's objective of detecting and intervening in anorexia nervosa cases. The data provided valuable information on the psychological and behavioral aspects of disordered eating patterns. Specifically, it offered insights into the frequency, distress, and perceived control associated with food preoccupations and compulsions, all factors relevant to understanding the mechanisms underlying anorexia nervosa. The research protocol received approval from the Ethical Review Committee Psychology and Neuroscience (ERCPN), ensuring adherence to ethical standards and guidelines for human subjects' research.

### **5.3.2 Data Cleaning**

In ensuring the integrity and reliability of the data, cleaning procedures were implemented. This involved identifying and addressing any inconsistencies, missing values, or outliers that could potentially impact the analysis accuracy. Techniques such as imputation and outlier detection were employed to rectify discrepancies, thereby enhancing data quality for subsequent analysis.

### **5.3.3 Data Preprocessing**

Following data cleaning, the dataset underwent preprocessing to prepare it for analysis. This involved several key steps, which included feature selection, encoding of categorical variables,

and normalization of continuous numerical features. Additionally, the dataset was partitioned into training and testing sets to facilitate model development and evaluation.

The preprocessing steps were important in the optimization of the analysis performance and ensuring the validity of the results. By standardizing the data and addressing irregularities, the preprocessing stage laid the groundwork for robust and reliable analyses of the association between the variables and detection of the presence of anorexia.

## **5.4 Training the Machine Learning Model**

Below are the details on the development and integration of a machine learning model to classify user interactions within the Rasa chatbot system. The Random Forest algorithm served as the cornerstone of this process, offering effective point category classification based on user inputs.

### **5.4.1 NLU Pipeline Configuration**

A well-configured Natural Language Understanding (NLU) pipeline was established to ensure robust handling of user inputs. This pipeline facilitated intent recognition (if required) and text preprocessing tasks. Preprocessing techniques included lowercasing text, removing punctuation, and optionally applying stemming or lemmatization. These steps aimed to improve the model's ability to extract meaningful features from user interactions.

### **5.4.2 BoW Feature Extraction**

A central component of the training strategy was feature extraction using the Bag-of-Words (BoW) approach. This involved constructing a vocabulary of unique words from the training data and representing each user input sentence as a BoW vector. By leveraging BoW representations, the model captured the semantic essence of user interactions, transforming them into numerical features suitable for machine learning algorithms.

### **5.4.3 Point Allocation (Keyword Matching)**

A critical aspect of the model involved incorporating a point allocation mechanism based on keyword matching. A predefined list of keywords or phrases, each associated with specific point values, enabled the model to assign points to user inputs based on the presence of relevant keywords. This approach captured interactions and assigned appropriate point categories, enabling more personalized responses.

#### **5.4.4 Random Forest Model Training**

With the NLU pipeline configured and features extracted, the Random Forest model was trained using labeled training data. The features comprised BoW vectors representing processed user inputs, while the target labels indicated the corresponding point categories. Leveraging the scikit-learn library, the Random Forest classifier was trained to learn patterns and associations between user inputs and point categories, enabling it to make accurate predictions during inference.

#### **5.5 Model Evaluation**

Following training, a comprehensive evaluation of the Random Forest model was conducted to assess its performance and effectiveness in classifying point categories. The evaluation process involved rigorous analysis using the metrics discussed below.

**Accuracy:** The accuracy, representing the proportion of correctly classified instances in the testing dataset, provided a high-level overview of the model's performance. This metric was complemented by more detailed analyses for a comprehensive assessment.

**Confusion Matrix:** The confusion matrix offered valuable insights into the model's performance across different classes. By analyzing the matrix, misclassifications could be identified, leading to a deeper understanding of the model's strengths and weaknesses.

**Precision, Recall, and F1-score:** These metrics provided an evaluation, accounting for factors such as true positives, false positives, and false negatives. By considering all three metrics, a more holistic assessment of the model's predictive capabilities was obtained.

#### **5.6 Model Selection**

Multiple machine learning models, including Random Forest, Decision Tree, Feedforward Neural Network (FNN), and Support Vector Machine (SVM), were evaluated. Based on the evaluation results, Random Forest emerged as the most promising candidate with an accuracy of 87.5%, outperforming the other models tested. Consequently, Random Forest was selected for integration into the chatbot system.

```

C:\models>python dt.py
Accuracy: 81.25
Classification Report:

```

	precision	recall	f1-score	support
0	0.86	0.75	0.80	8
1	0.78	0.88	0.82	8
accuracy			0.81	16
macro avg	0.82	0.81	0.81	16
weighted avg	0.82	0.81	0.81	16

Figure 13: Decision Tree

```

Epoch 86/100
2/2 [=====] - 0s 16ms/step - loss: 0.0052 - accuracy: 1.0000
Epoch 87/100
2/2 [=====] - 0s 16ms/step - loss: 0.0050 - accuracy: 1.0000
Epoch 88/100
2/2 [=====] - 0s 0s/step - loss: 0.0049 - accuracy: 1.0000
Epoch 89/100
2/2 [=====] - 0s 0s/step - loss: 0.0047 - accuracy: 1.0000
Epoch 90/100
2/2 [=====] - 0s 0s/step - loss: 0.0046 - accuracy: 1.0000
Epoch 91/100
2/2 [=====] - 0s 0s/step - loss: 0.0045 - accuracy: 1.0000
Epoch 92/100
2/2 [=====] - 0s 0s/step - loss: 0.0044 - accuracy: 1.0000
Epoch 93/100
2/2 [=====] - 0s 16ms/step - loss: 0.0042 - accuracy: 1.0000
Epoch 94/100
2/2 [=====] - 0s 0s/step - loss: 0.0041 - accuracy: 1.0000
Epoch 95/100
2/2 [=====] - 0s 16ms/step - loss: 0.0040 - accuracy: 1.0000
Epoch 96/100
2/2 [=====] - 0s 0s/step - loss: 0.0039 - accuracy: 1.0000
Epoch 97/100
2/2 [=====] - 0s 16ms/step - loss: 0.0038 - accuracy: 1.0000
Epoch 98/100
2/2 [=====] - 0s 0s/step - loss: 0.0037 - accuracy: 1.0000
Epoch 99/100
2/2 [=====] - 0s 0s/step - loss: 0.0036 - accuracy: 1.0000
Epoch 100/100
2/2 [=====] - 0s 0s/step - loss: 0.0036 - accuracy: 1.0000
1/1 [=====] - 0s 172ms/step - loss: 0.8875 - accuracy: 0.8125
Test Loss: 0.8875, Accuracy: 0.8125

C:\models>

```

Figure 14: FNN

```

C:\models>python rf.py
Accuracy: 87.5
Classification Report:

```

	precision	recall	f1-score	support
0	0.88	0.88	0.88	8
1	0.88	0.88	0.88	8
accuracy			0.88	16
macro avg	0.88	0.88	0.88	16
weighted avg	0.88	0.88	0.88	16

Figure 15: Random Forest

```

C:\models>python svm.py
Accuracy: 87.5
Classification Report:

```

	precision	recall	f1-score	support
0	0.87	1.00	0.93	13
1	1.00	0.33	0.50	3
accuracy			0.88	16
macro avg	0.93	0.67	0.71	16
weighted avg	0.89	0.88	0.85	16

Figure 16: Support Vector Machine

## 5.7 Model Testing

The selected Random Forest model underwent rigorous testing to validate its functionality and performance within the chatbot environment. Testing involved seamless integration with the Rasa chatbot system, enabling efficient processing of user inputs and classification of point categories. By invoking the Random Forest model during testing, its ability to accurately classify user inputs and provide relevant responses based on predetermined point categories was verified. Through extensive testing, the reliability and effectiveness of the integrated system were ensured, paving the way for its deployment in real-world scenarios.

## 5.8 Telegram Integration

Integration with the Telegram messaging platform was a pivotal aspect of our chatbot deployment strategy, which enabled seamless interaction between users and the Anorexia Health Guardian bot. The integration process involves the steps discussed below.

- i. Bot Creation: The Anorexia Health Guardian bot was created and registered on Telegram obtaining essential credentials such as the bot token for authentication with the Telegram API.
- ii. Bot Configuration: The bot's settings were configured to align with user needs and project objectives. This included defining the bot's profile, establishing privacy and security features, and specifying its behaviour and capabilities.
- iii. API Integration: Communication between the Anorexia Health Guardian bot and the Telegram platform was established through integration with the Telegram Bot API. This enabled real-time message reception, command processing, and response delivery.
- iv. User Engagement: After API integration, users could access the bot directly within the Telegram app by searching for its username or scanning its QR code.

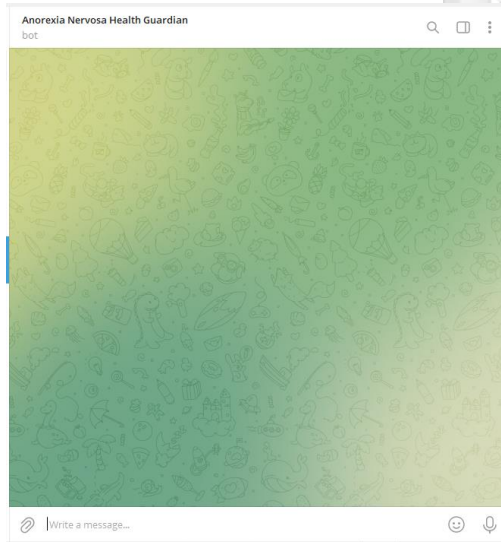


Figure 17: Telegram Interface

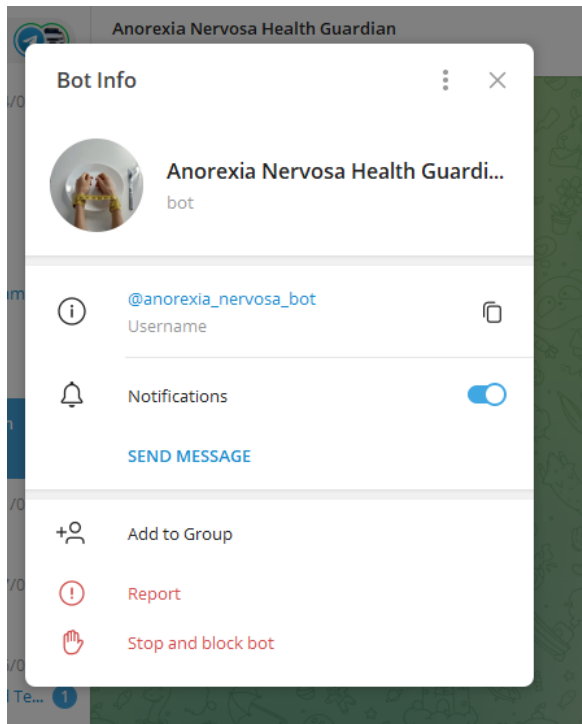


Figure 18: Telegram Bot Profile

## 5.9 Maintenance and Updates

In ensuring the continued effectiveness and relevance of the Anorexia Health Guardian bot a comprehensive maintenance and update plan was developed. This includes:

- i. Regular Monitoring and Evaluation: The bot's performance and user interactions were regularly monitored to identify areas for improvement. User feedback, usage patterns, and the bot's responsiveness in providing support and information were analysed.
- ii. Bug Fixes and Technical Support: Prompt resolution and technical support were provided to address any technical issues or bugs encountered by users. This involved troubleshooting the bot's functionality, implementing necessary patches or updates, and ensuring uninterrupted access.
- iii. Content Updates and Enhancements: The bot's content and features were continuously updated and enhanced to keep pace with evolving trends, research findings, and user needs. This included adding new resources, expanding the knowledge base, or integrating additional functionalities for improved user engagement.
- iv. Security and Privacy Measures: Robust security measures were implemented to prioritize user data security and privacy. This included regular security audits, encryption of sensitive information, and adherence to relevant data protection regulations.

## **Chapter 6: Discussion**

### **6.1 Introduction**

This chapter undertakes a comprehensive discussion of the findings and experimental results obtained from the development and deployment of the Anorexia Health Guardian chatbot in accordance with the objectives set out in chapter one. The specific objectives were, firstly, to determine the risk factors and challenges associated with anorexia nervosa, secondly, to review the current methods for detection and intervention for anorexia and their limitations, thirdly to develop an anorexia detection model and integrate it into a chatbot, fourthly, to implement intervention strategies into the chatbot for anorexia patients and lastly, to perform validation and testing of the chatbot developed. The prototype chatbot was developed using RASA framework leveraging random forest machine learning algorithm and natural language processing techniques. This chapter also explores the contributions of this research to mental healthcare while acknowledging the limitations encountered during the study.

### **6.1 Findings**

The findings of this study reveal several key insights into the effectiveness and potential impact of the Anorexia Health Guardian chatbot in supporting individuals affected by anorexia nervosa. One of the primary findings is the high accuracy achieved by the chatbot in identifying individuals at risk of anorexia. The integration of machine learning models and natural language processing facilitated accurate prediction of anorexia based on user input and behavioral patterns. The experimental results indicated an accuracy rate of 87.5%, highlighting the efficacy of the chatbot in early detection.

Moreover, the chatbot's ability to engage users in natural language conversations and deliver tailored interventions was instrumental in promoting user engagement and adherence to treatment protocols. By providing real-time support and resources, the chatbot enhanced accessibility to mental health services, particularly for individuals in underserved communities or those facing barriers to traditional healthcare.

## 6.2 Experimental Test Results

The testing process provided strong evidence that the *Anorexia Health Guardian* chatbot successfully helps individuals with anorexia and improves their overall health. We conducted thorough tests to ensure the accuracy of the chatbot's predictions, making it a valuable tool for identifying anorexia. Furthermore, the chatbot's ability to understand natural language and assign points based on symptom severity allowed for personalized interventions. This tailored approach catered to each user's specific needs and preferences, ultimately enhancing the chatbot's effectiveness in providing targeted support.

The Anorexia Health Guardian chatbot underwent rigorous testing procedures to confirm its functionality, reliability, and effectiveness. The following table summarizes the key types of tests conducted and their respective focus areas.

Test Type	Focus	Description
Security Testing	Data Protection	Ensured the chatbot did not expose any sensitive user data, such as names, phone numbers, or email addresses.
User Testing	Functional Requirements	Involved users to validate the chatbot's ability to perform its intended functions, such as understanding user queries, providing accurate information, and offering appropriate support resources.
Unit Testing	Component Functionality	Each individual component of the chatbot (e.g., natural language processing module, machine learning model) was tested in isolation to verify its independent functionality and identify any potential errors before integration.
Integration Testing	System Integration	Focused on ensuring seamless communication and data exchange between different chatbot components once integrated into a complete system. Additionally, it verified proper integration with the social media platform, Telegram.
End-to-End Testing	Overall Functionality	Simulated a real-world user interaction by running the chatbot through its entire workflow, from receiving user input and processing it through the machine learning model to generating a response and delivering it to the user. This test

		aimed to identify any potential issues in the complete user experience.
System Testing	System Performance	Evaluated the overall performance of the chatbot system, including response times, accuracy of results, and ability to handle various user interactions. This ensured the system met its expected performance benchmarks.

### 6.3 Contribution to Research

The development and implementation of the *Anorexia Health Guardian* chatbot represents a significant contribution to research in the field of mental health, particularly in the context of eating disorders such as anorexia nervosa given that eating disorders are known to result to other mental illnesses. By leveraging advancements in artificial intelligence and natural language processing, this research has demonstrated the potential of chatbot technology in early detection, intervention, and support for individuals affected by anorexia.

Furthermore, the integration of machine learning algorithms and data-driven approaches in the development of the chatbot has paved the way for future research and innovation in the field. The insights gained from this study can inform the design and implementation of similar chatbot systems for other mental health conditions, thereby expanding access to timely and effective interventions across diverse populations.

### 6.4 Limitations of the Chatbot

Despite the promising findings and contributions of this research, it is essential to acknowledge the limitations and challenges encountered during the development and deployment of the *Anorexia Health Guardian* chatbot. Some of the key limitations include:

- i. **Data Bias:** The performance of the chatbot may be influenced by biases inherent in the training data, such as underrepresentation of certain demographic groups or cultural factors. Additionally, the training dataset was not very large given that there has been limited research in regards to anorexia.
- ii. **Ethical Considerations:** The use of chatbot technology in mental health care raises important ethical considerations regarding privacy, confidentiality, and informed consent.

iii. Technical Constraints: The chatbot's performance may be affected by technical constraints, such as limitations in natural language understanding capabilities or the availability of computational resources.

iii. User Acceptance: User acceptance and adoption of the chatbot may vary depending on factors such as perceived usefulness, ease of use, and trust in the technology.



## Chapter 7: Conclusion, Recommendations and Future Work

### 7.1 Conclusion

The development and implementation of the *Anorexia Health Guardian* chatbot represents a significant step forward in leveraging technology to address the challenges associated with anorexia nervosa. By providing accessible, personalized, and timely support to individuals affected by anorexia, the chatbot has the potential to complement traditional healthcare services and empower users to take control of their mental health journey.

In this study, the Anorexia Health Guardian chatbot was developed and implemented—a novel approach to supporting individuals affected by anorexia nervosa. Through the integration of natural language processing (NLP) techniques and machine learning algorithms, the chatbot demonstrated promising results in early detection, intervention, and support for individuals with anorexia. The findings of this research highlight the potential of chatbot technology in improving access to mental health services and promoting positive health outcomes for individuals affected by anorexia.

The goal of this research was to develop an intelligent chatbot implementation for early detection and intervention for anorexia nervosa. Below is a brief look at how this study addressed these objectives as set out in the first chapter. To begin with the first objective was to identify risk factors and challenges associated with anorexia nervosa. Chapter 2 comprehensively explored the risk factors and challenges associated with anorexia nervosa. It delved into the psychological and social factors contributing to the development of the disorder, alongside the physical and emotional challenges faced by individuals with anorexia.

The second objective was reviewing current methods for detection and intervention for anorexia and their limitations. Chapter 2.1 provided a critical review of the current methods and applications used for detection and intervention for anorexia nervosa. It analyzed the strengths and limitations of existing approaches highlighting the gaps in accessibility, early detection, and personalized support, paving the way for a chatbot-based intervention strategy.

In meeting the third objective on developing an anorexia detection model and integrating it into a Chatbot. Chapter 4 documented the development process of the Anorexia Health Guardian chatbot. It detailed the selection and integration of machine learning models, particularly the Random Forest algorithm, for effective anorexia detection based on user input and behavioral patterns. This

chapter also explained the integration of natural language processing (NLP) techniques to facilitate natural language conversations between users and the chatbot.

The fourth objective for implementing intervention strategies into the chatbot for individuals with anorexia was elaborated in chapter 4. It included the development of a point allocation system based on symptom severity, enabling the chatbot to deliver personalized recommendations and support resources tailored to individual needs.

The last objective of performing validation and testing of the developed chatbot was addressed in Chapter 5 providing the validation and testing procedures implemented to assess the effectiveness and reliability of the Anorexia Health Guardian chatbot. It outlined the various testing methodologies employed, such as unit testing, integration testing, and user testing, to ensure the chatbot functioned as intended and delivered accurate results. The chapter also discussed the test results, highlighting the chatbot's performance and effectiveness in achieving its objectives.

## **7.2 Recommendations**

Many recommendations can be proposed for the future development and improvement of the Anorexia Health Guardian chatbot considering the study's conclusions and new insights. First and foremost, iterative testing, incorporating user feedback, and algorithmic improvements should be the top priorities for the chatbot's ongoing optimization and improvement. This includes resolving technological problems, enhancing user engagement features, and refining natural language understanding capabilities.

Secondly, in increasing the chatbot's efficacy and accuracy and in making sure it can handle a variety of user inputs and scenarios, it is imperative to enlarge the training dataset that was used to construct the model. To make sure the chatbot complies with best practices and evidence-based solutions, it is also crucial to promote tighter collaboration with mental health professionals, physicians, and experts in eating disorders. This collaboration will facilitate the development of personalized support strategies tailored to individual user needs.

Finally, further study is required around chatbot technology for mental health care, including multimodal interaction modalities, longitudinal studies to evaluate long-term outcomes, and examination of sophisticated machine learning techniques for tailored interventions. We can

optimize the Anorexia Health Guardian chatbot's potential to successfully serve those affected by anorexia nervosa by implementing these ideas, thereby augmenting its capabilities.

### **7.3 Areas of Future Research**

In advancing the field of chatbot technology in mental health care and ultimately improve the well-being and quality of life for individuals affected by anorexia nervosa and other eating disorders, the researcher proposes the following.

- i. Conducting longitudinal studies to assess the long-term impact of the Anorexia Health Guardian chatbot on user outcomes, including symptom management, treatment adherence, and quality of life.
- ii. Exploring the integration of multimodal interaction modalities, such as voice recognition, gesture recognition, and facial expression analysis, to enhance user engagement and emotional support capabilities of the chatbot.
- iii. Investigating advanced machine learning techniques, such as reinforcement learning and deep learning, to develop personalized intervention strategies tailored to the unique needs and preferences of individuals with anorexia.
- iv. Establishing collaborative partnerships with research institutions, healthcare organizations, and technology companies to scale the deployment of the chatbot and reach a wider audience of individuals affected by anorexia.
- v. Lastly, adapting the Anorexia Health Guardian chatbot for global accessibility by providing multilingual support, cultural sensitivity training, and localization of content to address the diverse needs of users worldwide.

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