Prediction of childhood Depression using machine learning Technique

A Thesis Presented

By

Samrawit Abera Bogale

To

The Faculty of Informatics

Of

St. Mary's University

In Partial Fulfillment of the Requirements

For the Degree of Master of Science

In

Computer Science

February 3, 2025

ACCEPTANCE

PREDICTION OF CHILDHOOD DEPRESSION USING MACHINE LEARNING TECHNIQUE

By

Samrawit Abera Bogale

Accepted by the Faculty of Informatics, St. Mary's University, in partial fulfillment of the requirements for the degree of Master of Science in Computer Science

Thesis Examination Committee:

Dr. Mulugeta Adibaru

Internal Examiner

Dr. MESFIN ABEBE 26/02/25

External Examiner

Dean, Faculty of Informatics

February 3, 2025

DECLARATION

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

____

Samrawit Abera Bogale

____

Signature

Addis Ababa

Ethiopia

This thesis has been submitted for examination with my approval as advisor.

Alembante Mulu (PhD)

____

Signature

Addis Ababa, Ethiopia

February 3, 2025

ACKNOWLEDGEMENT

First and foremost, I would like to express my deepest and most heartfelt gratitude to Almighty God, whose constant guidance and blessings have been a source of strength and inspiration throughout this journey.

I am sincerely grateful to my advisor, Dr. Alembante Mulu, for his exceptional guidance, patience, and invaluable expertise. His thoughtful insights, constructive feedback, and continuous encouragement have played a crucial role in shaping this research and enhancing my academic experience. I truly appreciate the time and effort he invested in helping me.

To my beloved parents, I owe a debt of gratitude that words can hardly express. Their unwavering love, boundless support, and countless sacrifices have been the foundation of my success. They have always believed in me, even in times when I doubted myself, and their encouragement has been a constant source of motivation. Thank you for your unconditional faith and for providing me with everything I need to pursue my dreams.

TABLE OF CONTENTS

LIST OF ACRONOMY

ACEs: Adverse childhood experiences

ACT: Acceptance and commitment therapy

ADHD: Attention Deficit Hyperactivity Disorder

ANOVA: Analysis of Variance

ASD: Autism Spectrum Disorder

Bi-LSTM: Bidirectional Long Short-Term Memory

BRIEF: Behavior Rating Inventory of Executive Function

CBCL: Achenbach Child Behavior Checklist

CBT: Cognitive behavioral therapy

CD: Conduct disorder

CNNs: Convolutional neural networks

CSV: Comma-separated value

DT: Decision Tree

ERP: Exposure and response prevention

EF: Executive function

FP: False positive

FN: False negative

GWAS: Derived from large-scale genome-wide association studies

GEE: Generalized estimating equation

GLM: General linear models

GRU: Gated Recurrent Units

HTML: Hypertext Markup Language

HTTP: Hypertext transfer protocol

IQR: Interquartile range

KNN: K-Nearest Neighbors

LSTM: Long Short-Term Memory

LR: Logistic Regression

MLP: Multi-Layer Perceptron’s

MST: Mean sum of squares due to treatment

MSE: Mean sum of squares due to error

MDD: Major depressive disorder

NB: Naïve Bayes

NSSI: Non-suicidal self-injury

OCD: Obsessive-compulsive disorder

PRS: Polygenic risk scores

PDD: Persistent Depressive Disorder

QoL: Quality of life

RFECV: Recursive feature elimination with cross-validation

RNN: Recurrent neural network

RF: Random Forest

SD: Standard deviation

SVM: Support Vector Machine

SSRIs: Selective serotonin reuptake inhibitors

T-CNN: Time-Distributed Convolutional Neural Networks

TCAs: Tricyclic antidepressants

TP: True positive

TN: True negative

UFS: University feature selection

LIST OF FIGURES

LIST OF TABLES

ABSTRACT

Childhood depression is a critical public health issue that often goes undiagnosed due to subtle symptoms and limited awareness. This research proposes a machine learning and deep learning based system to predict childhood depression using supervised learning algorithms and neural network architectures such as Multi-Layer Perceptron’s (MLP), Gated Recurrent Units (GRU), and Long Short-Term Memory (LSTM) networks. The study addresses challenges such as the lack of organized datasets and the time-consuming process of digitizing paper-based records. Feature selection techniques were utilized to identify the most predictive attributes, while comparative analysis of models ensured the selection of the most effective approach. Blockchain technology is suggested as an enhancement to improve data security and transparency, enabling professionals and guardians to monitor mental health status seamlessly. The study stresses the importance of incorporating real-time datasets to advance the model's accuracy and responsiveness. The results show that, while promising accuracy was achieved, future research should explore additional features and larger, more diverse datasets to further improve performance. This system aims to assist mental health professionals in making timely, data-driven decisions and contribute to the early identification and management of childhood depression.

Keywords: Multi-Layer Perceptron’s, Gated Recurrent Units, Long Short-Term Memory, Blockchain technology.

CHAPTER ONE

1. INTRODUCTION

1.1. Background

A severe psychological condition that are currently affecting mental and physical health of children and adult is referred as depression [4], it is considered as the main reason of disability.as per the study of [5] indicates almost three out of four people that is affected by chronic depression said to be suffered from childhood disturbance, that is the they have experienced a serious childhood abuse and this factor is considered to be the leading cause of depression. This abuse includes emotional abuse, verbal attacks, disgrace, blames, bullying and criticism which the kids experienced from family, friends and communities. Due to the abuse of children in their early age, mental health, physical and growth is harshly and permanently impacted and will lead to problem like anxiety, depression, and low self-esteem [4].

Over 280 million individuals globally are thought to suffer from depression [6]. Out of the million individuals Approximately 3.2% of people between the ages of 3 and 17 who have received a clinical diagnosis of depression are classified as children with depression. By 2020, that percentage is expected to increase to about 4.0%. These figures demonstrate the rising awareness of children's mental health. As discussed in the journal referenced [7], depression is affected by various risk factors, including gender, hereditary influences, and environmental conditions. As the research of [8] explains early identification of indicators of mental illness in children and youths has a significant importance in avoiding and treating the serious long-term consequences.

Studies on child and adult mental health have shown that both positive and negative experiences during childhood significantly impact physical, cognitive, and psychological development [9]. Positive childhood experiences tend to have a beneficial effect on adulthood, whereas the lack of such experiences may contribute to mental health issues throughout life [9]. The work of [10] explains emotional abuse by itself drives different negative feeling such as anger, sadness, fear, and shame in children. to resolve this issue children always try to understand the cause and try to prevent the same issue happens again [11]. But because of their mental immaturity and lack of skill in reasoning they don’t exactly address or get the right answer. Thus, the feeling continuous and leads to frustration and this will lead the development of the negative emotions inside the child [11].

There are many factors that make one child feel down, disgrace, annoyed, and distress [12]. The very first reason or factor for all this is emotional abuse. To scape this all emotional abuse they have faced, they try to find reasoning and countless struggle for why they face such issue. But for their mind is not mature they will not able to reason out so this experience will persist. Eventually they will face emotional experience cycle leading to serious adulthood mental illness. The long outstanding unresolved emotional abuse can have significant contribution to the youngster's mental instability in the later life [12] [13].

Symptoms like irritability, ongoing sadness and loss of faith about the future, isolation, feeling to be rejected, changes in need to eat (either overeating or loss of appetite), sleep problems (insomnia or excessive sleeping), frequent crying or emotional instability, and difficulty focusing or concentrating is basic indicators of compromised children mental health [12].

As outlined in "depressive disorders are categorized into several types: Major Depressive Disorder (MDD), Persistent Depressive Disorder, Disruptive Mood Dysregulation Disorder, Premenstrual Dysphoric Disorder, Substance/Medication-Induced Depressive Disorder, Depressive Disorder Related to Another Medical Condition, Other Specified Depressive Disorder, and Unspecified Depressive Disorder" [14]. In children, depression is commonly classified under MDD or PDD [14]. Major Depressive Disorder is a critical form of depression, requiring the presence of at least five depressive symptoms and is further divided into mild, moderate, or severe levels. Persistent Depressive Disorder means sadness and long emotional reasoning circle that last at least a year.

[15] [16] Artificial intelligence has a subset called machine learning where different research area is conducted. From this area healthcare is one of them. From these area machine learning plays a vital role in predicting diseases and timely medical treatment care could be the leading. This all is done by learning the machine patient history data that the machine could help the medical experts for decision making whether the diseases available or not. Different type of machine learning techniques is there that includes supervised, non-supervised and semi supervised [16]. This study focuses on predicting childhood depression using a publicly available dataset and data set provided from St. Paul Hospital which classifies

the condition into categories such as mild, moderate, and severe. The study employs machine learning models combined with data preprocessing and feature selection methods, considering factors like age,

gender, sleep patterns, weight fluctuations, history of mental illness, family history of depression, chronic medical conditions, physical activity levels, and social relationships. Based on the prediction outcomes, healthcare experts will recommend suitable treatment and prevention strategies [16].

1.2. Statement of the Problem

Mental disorders are a major cause of death and disability worldwide [17], regardless of geographic location, population size, or socio-economic status, impacting millions of individuals in all countries. Until recently, depression was not considered a significant issue in m any low-income nations, such as Ethiopia. Depression is a mental health illness that frequently manifests with no apparent reason and causes enduring feelings of melancholy, emptiness, or an inability to enjoy life.

In underdeveloped nations like Ethiopia, patients often receive treatment only after their condition becomes critical. This delay is due to a lack of medical resources, expert doctors, low income for treatment, and limited awareness, especially in rural areas, where 85% of Ethiopia's population resides. Including Ethiopia most of the countries in the east or sub-Saharan Africa cannot afford getting the proper treatment for the childhood depression. Additionally, due to the absence of established prevention policies and strategies, depression has become one of the main reasons of death in Ethiopia [18].

[19] In Ethiopia, there is a shortage of specialists and medical professionals, particularly psychologists. Additionally, many people are unaware that children can experience depression due to various factors. When unhealthy behaviors are observed in children, the issue is often perceived as a spiritual matter rather than a medical one, leading to a delay in seeking professional help. Most of the time parents of the affected children think that such a case is very normal which happens most of the time and treated by different medicines. This mindset is detrimental, and several underlying factors contribute to this misconception.

Due to the complexity of clinical data, modern healthcare systems face the challenge of gathering, evaluating, and applying the vast amounts of knowledge necessary to address complicated clinical issues.

Providing high-quality services at reasonable prices is a significant challenge for healthcare organizations (such as hospitals, clinics, etc.), as this type of service requires prompt patient diagnosis and the timely administration of efficient and effective therapies. However, there is a lack of studies on predicting depression in children in Ethiopia. Therefore, the main contribution of this paper is to develop a dataset with relevant factors for predicting depression severity levels. By using feature selection techniques and machine learning classification algorithms, this approach assists practitioners in making recommendations based on expected values. As a result, this technique may help doctors and other healthcare professionals identify the illness and provide timely treatment to patients. To address this issue, this works planned to answer the following question:

- What are the key variables to consider when designing effective datasets for children mental illness?
- What is the best machine-learning model for childhood depression disorder?
- What are the ways to assess the performance of the model?

1.3. Objective of the study

1.3.1. General Objective

Developing a childhood depression prediction system using machine learning technique to support the healthcare professional in diagnosing patients more effectively and accurately is the general objective of this work.

1.3.2. Specific objective

- To conduct a study of advanced literature review.
- To prepare required dataset using depressed child disorder patient history data.
- To identify the best model for childhood depression prediction.
- To build the model of childhood depression prediction.
- To assess the functionality of the proposed model.

1.4. Implication of the Work

Mental illness in children is now a days rapidly growing concern. If not treated on time its lefts a lifelong significance. In order to prevent a lifelong consequences timely intervention and treatment is essential. Most of the time because of the issue is complicated for the child performing checkups is not enough [8]. This work tries to use machine language called neural network to predict mental illness availability in a child and if available then to predict the severity level of the problem. To do this the machine will learn the data that include behavioral, psychological, family mental illness history, school performance, socio economic status from medical data. So, making this work will help accurate result for deciding whether the child has menta illness or not.

The benefit of using neural network is it’s capable of handling large amount of data any the complexity between features that can’t be handled by traditional diagnosed method [15]. It can potentially assist healthcare professionals by identifying whether one child has mental illness or not by analyzing large dataset and the relationship between features. Timely intervention for treatment could save one child’s life to the adulthood. In addition to this huge benefit it could be also used where limited healthcare professionals where psychiatrist not available.

The significance of this research extends beyond the prediction of childhood depression. It contributes to the growing field of personalized medicine, where interventions are tailored to individual needs based on predictive analytics. The outcome of this work could influence the growth of scalable, non-invasive, and cost-effective tools that could be implemented in schools, pediatric clinics, and mental health centers, thus revolutionizing the approach to childhood mental health care and intervention, especially in underserved regions.

1.5. Scope and Limitation

1.5.1. Scope

The childhood depression prediction system can be developed in several ways. This work emphases on using machine learning classification algorithms [16] to predict the occurrence of childhood depression and its risk level, which allows professionals to provide the right treatment.

1.5.2. Limitation

The research identifies several limitations related to the availability of datasets. In Ethiopia, particularly in the medical field, it is challenging to discover organized data in electronic format, and many hospitals are reluctant to share data due to concerns about patient privacy [17]. The data employed in this work were gathered from a public dataset and St. Paul Hospital. Nevertheless, constructing the work with data from various medical centers and performing external justification could have improved its performance and reliability.

1.6. Organization of the Study

This study is prearranged into the following chapters:

Chapter 1

Chapter 1 introduces the study of childhood depression, focusing on its increasing prevalence and the importance of early detection. It highlights sleep disturbance, financial issue and family history of depression, child abuse as a key factor for childhood depression. The chapter emphasizes the need for improved diagnostic methods, particularly through machine learning techniques like neural networks. It also addresses the challenges of diagnosing childhood depression in resource-limited settings, such as Ethiopia. The chapter concludes with the study's aim to develop a predictive model for early detection and better treatment.

Chapter 2

Chapter 2 discuss about different research related to childhood depression and the wide occurrence of and danger aspects of children mental illness. And it highlighting it impact on mental health, especially among adolescents. It highlights and try to explain the sign and indicators od mental health illness, history of mental health inside the family and feeling of ending oneself life. Key studies are reviewed, focusing on genetic, environmental, and social factors influencing childhood depression. In this chapter it is also discussed about how machine learning technique could help identifying childhood mental illness and the benefit of timely intervention.

Chapter 3

In this section of the study it is discussed that how the dataset is sourced, what type of machine learning technique is employed in this work [16]. And, how neural network model [15] could be employed to predict whether a child has mental illness or not is explained. In addition, every dataset preparation including data preprocessing, feature variety, and how model could be trained is discussed.

Chapter 4

In this part of the research, the outcome of the model after training is discussed briefly. Also, the assessment of the model with different Metrix including exactness, correctness, and recall evaluate the trained model whether it performs as it's expected to with higher accuracy or not [18] [19].

Chapter 5

In this section of the work it did briefly explains the clarification of the evaluation result and the selection of the excellent performing model among the three. Also, comparing the highest performing model is discussed deeply.

Chapter 6

In this chapter, the study elaborates the major finding of the study output, and the potential contribution for the area of children mental illness and the influence of this result is discussed.

Chapter 7

This is the final chapter of study and it will discuss about conclusion of the study, recommendation and future works.

CHAPTER TWO

2. LITERATURE REVIEW AND RELATED WORKS

In this chapter, we review the relevant literature related to the main goal of the paper, aiming to thoroughly investigate the research problem. This includes a technical review of children's mental health, particularly focusing on depression, and an examination of existing systems designed to detect levels of mental health issue in young individuals. The paper begins by providing an overview of mental health disorders, followed by a discussion on childhood depression, its stages, and an introduction to machine learning in healthcare. It also covers classification algorithms and reviews previous studies related to the topic.

2.1. Mental health Disorders

A mental disorder is defined by significant disruptions in a person's thought processes, emotional regulation, or behavior [14]. These disturbances frequently lead to suffering or weakening in critical domains of functioning, including academic, professional, and social. There are numerous types of mental disorders and the term "mental health conditions" is often used as a broader category. This study covers mental disorders such as depression, as well as psychosocial disabilities and mental states in childhood and adolescence.

Anxiety disorders affect about 19% of adults and 31% of adolescents at some point in their lives. Prevalence rates of depression are higher among adolescents, with estimates suggesting that 1 in 5 teens experience depression before adulthood. In the United States, “the second most common cause of death for those aged 10 to 34 is suicide. With over 47,500 suicide deaths in 2019” [20], it is evident that suicide is a serious public health concern. The COVID-19 pandemic has had a major impact on mental health, as seen by the rise in cases of depression, anxiety, and other associated disorders [20]. As the study [21]explains about 40% of people reported having mental health or substance use problems during the epidemic, according to surveys.

2.2. Childhood mental health issue and its impacts

A short-tempered child who appears depressed or agitated occasionally is not the same as a child suffering from depression. Emotional swings are common. But those behaviors and sensations could indicate an emotional disorder like depression if they continue for more than fifteen days. It's not just adults who suffer from depression. Mental health issue in children and teenagers is possible and does occur. The inability of parents and caregivers to identify the symptoms of the disorder may result in children going undetected and untreated.

Childhood depression is a severe mental health condition that can be treated if caught early [4]. The main symptoms are as follows “Symptoms of this disorder include difficulty focusing, feelings of overwhelming guilt or low self-worth, despair about the future, suicidal thoughts, disturbed sleep, changes in appetite or weight, and a particularly drained or low energy level” [22]. Individuals who suffer from depression are more likely to commit suicide. Effective psychological treatment is available, nevertheless, and medication may also be taken into consideration based on the patient's age and severity.

When a child exhibits symptoms associated with depression, several life-threatening social issues may arise, including increased social isolation, problematic behavior, discussions about suicide, death, or dying, expressions of hopelessness or helplessness, frequent accidents, substance use, and an interest in weapons or guns [23] [24].

Using UK birth-cohort data, “Menta, Lepinteur, and D'Ambrosio explore the causal relationship between maternal genetic risk for depression and child human capital” [22]. Their findings reveal that for each standard deviation (SD) growth in the mother's polygenic risk score for depression, children's cognitive and non-cognitive skill scores decline by 5% to 7% during adolescence [22]. The authors recommend that policymakers address the inequalities in children's outcomes driven by their mother's genetic propensity [22]. Yet, they note that the feasibility of such public actions hinges on a better understanding of the primary features contributing to the negative effects observed.

Elmore and Crouch aimed to examine” the association between Adverse Childhood Experiences (ACEs) and anxiety and depression in children aged 8 to 17 years [25]”. Based on data from the 2016-2017 National Survey of Children’s Health, their study found that 8% of children experienced four or more ACEs “The two most common types of ACEs were parental divorce (31%) and economic hardship (25%). The researchers concluded that ACEs, which include abuse, neglect, and household trouble before the age of 18, are directly associated with an increased risk of anxiety and depression in children” [26] .

“Claxton et al. [27] conducted a study on metadata to identify the risk factors for depression in trauma-exposed children and adolescents”. They developed a research question focusing on post-trauma depression and analyzed the data accordingly. The outcome for their proposed study shown that several substantial input for mental health problem for children. The main one discussed in their study includes trauma exposed children, low social support and avoidant environment [27] . These children are highly exposed for childhood mental problems.

“Ball et al. [28] examine a study on the relationship between children school performance or intelligence and the mental health problems in later adulthood life”. They have done intelligence score collected from Scottish Mental Survey of 1947 at age eleven. The health records were taken from 1980 to 2020 which has been kept electronically. Depending on these records they have identify the availability of mental illness for children on age eleven. Doing so the researchers were able to discover twenty-seven present of children was dragonized with mental illness. Finally, they have concluded that lower childhood performance in school could be one of a risk factors for mental illness for adulthood.

A research [29] was done on finding and addressing the challenge of mental illness severity prediction from multimodal data which is speed and text. The study proposes two model combination which is Bidirectional long short-term memory and time distributed convolutional neural network [29] . Doing so the they can integrate pitch and intensity from speed of a child which is called semantic feature. Eventually this semantic feature was intended to accurately classify the level of mental illness in childhood.

“Bishal Lamichhane, Joanne Zhou &Akane Sano [30], this work conducted an LSTM based model to identify psychotic revert in schizophrenia patients”. They have used mobile sensing data of similar demographics or baseline mental health score. So, this results the highlight of possible LSTM network in observing and identifying mental health issues.

2.2.1. Prevalence of childhood depression in Ethiopia

In 2024, Woredaw Minichil1, Wondale Getinet1, Habtamu Derajew and Sofia Seid, they conducted a research on “the occurrence of mental illness and its relationship causes among caregiver children” [31]. They have used 416 participants which is randomly sampled and used cross sectional method. The dataset was measured from prepared questionnaires by researchers. Doing so they have found that children who have stayed with caregivers more than five years old, and children having Autism and Attention deficit hyperactivity disorder were having more mental illness problems [31]. The work tries to highlight the importance of screening and treating depression in these caregivers to enhance their well-being and the quality of care they provide.

Demewoz Kefale, Tigabu Munye Aytenew, Yohannes Tesfahun, Amare Simegn, Mahilet Wondim, Shegaw Zeleke, Solomon Demis, Gashaw Kerebeh, Gebrehiwot Berie Mekonnen, Habtamu Shimels Hailemeskel, Muluken Chanie Agimas, Mastewal Endalew, Worku Necho Asferie, Amare Kassaw, Yeshiambaw Eshetie, and Sintayehu Asnakew conducted “a meta-analysis to examine the prevalence, consequences, and contributing factors of child maltreatment in Ethiopia” [32]. Using databases such as PubMed, Cochrane, and SCOPUS, they gathered relevant articles and performed statistical analysis with STATA 17, employing a random effects model to address heterogeneity among studies. The study [32] found a shared occurrence of childhood mistreatment at 57.0% (95% CI: 32.00, 83.00). Key factors associated with an increased risk of maltreatment included being female (AOR = 2.94), being younger (AOR = 1.22), father lack of education (AOR = 2.16), and having open family discussions. These findings underscore that child maltreatment is a significant public health issue in Ethiopia, with various associated risk factors.

2.2.2. Types of childhood depression

Childhood depression is distinct from typical moodiness while emotional fluctuations are normal. The feeling of unhappiness that stayed for more than fifteen days could indicates there is a serious emotional disorder. Unfortunately, families and people around children most of the time doesn’t understand their real indicators, so many cases will stay undetected and untreated for a very long time. Approximately 3% of children and teens aged 3 to 17 are affected by childhood depression with the prevalence rates being higher among adolescents. From five children one is said to be diagnosed with major depression, although this statistic only includes those with an official diagnosis.

There are various types of depression, and recognizing the signs can be challenging for parents and caregivers. Persistent sadness can significantly disrupt daily life, affecting school performance and social interactions.

The figure below shows, the different features for childhood & Adolescent depression.

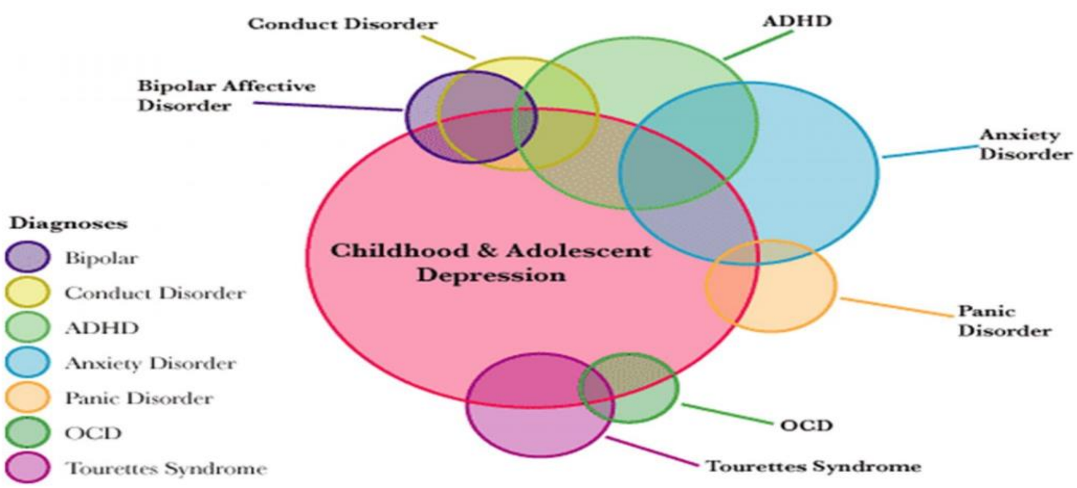


Figure 1 Model for childhood & Adolescence depression

There are various approaches to managing childhood depression, including early detection, preventing progression to severe stages, addressing complications such as social withdrawal and academic decline, managing associated risk factors, and providing appropriate therapeutic interventions.

Table: 1 Stated the different type of Childhood and adolescence depression

Type of depression	Description	Treatment
Anxiety Disorder	Excessive fear, worry, and associated feelings that are out of proportion to the situation are characteristics of a group of mental health illnesses known as anxiety disorders.	Medicine and therapy

ADHD	[33] Attention-Deficit Hyperactivity Disorder (ADHD) is a neurodevelopmental condition characterized by a persistent pattern of inattention, hyperactivity, and impulsivity that interferes with development or daily functioning.	Medication and Cognitive behavioral therapy
Panic Disorder	[34] Panic Disorder is an anxiety condition marked by recurrent, unexpected panic attacks—intense episodes of fear with symptoms like rapid heartbeat, shortness of breath, and dizziness. Fear of future attacks can lead to avoidance behaviors, significantly impacting daily life. Treatment often involves therapy, lifestyle changes, and sometimes medication.	Medicine and therapy
Tourette's Disorder	[35] Tourette Syndrome is a neurodevelopmental disorder characterized by repetitive movements or unwanted sounds (tics) that are difficult to control. Tics can range from mild to severe and may be disabling in some cases. The condition typically appears between ages two and fifteen, with the typical start around 6 years of age.	Behavioral treatments, Medications and Surgical options
Conduct Disorder	[36] **Conduct Disorder (CD)** is a mental health condition diagnosed in childhood or adolescence, characterized by a persistent pattern of disruptive behavior. Key symptoms include aggression, destruction of property, deceitfulness, and violation of rules	Behavioral Therapy: Helps children control their behavior through structured strategies. Talk Therapy: Addresses underlying mental health issues

		by exploring thoughts and feelings.
Bipolar Affective Disorder	Bipolar disorder is a long-term feeling disorder that primes to extreme fluctuations in mood, energy, and behavior. The condition is primarily marked by manic and hypomanic episodes, and most children with bipolar disorder also experience depressive episodes.	Medications, Talk therapy and lifestyle changes
OCD	Obsessive-Compulsive Disorder (OCD) is marked by recurring, unwanted thoughts (obsessions) that drive children to perform repetitive actions (compulsions) [37]. These obsessions and compulsions significantly disrupt everyday activities and cause considerable distress.	Psychotherapy treatments for OCD include Cognitive Behavioral Therapy (CBT), Exposure and Response Prevention (ERP), and Acceptance and Commitment Therapy (ACT) [37].

Identifying depression in kids and youngsters early is very important for determining the type and stage of the disorder. Early recognition allows for timely involvement, which can meaningfully help the outcomes. Treatment is customized to the type and stage of depression diagnosed, with each child's plan tailored to their unique symptoms and circumstances, ensuring the most appropriate care.

2.2.3. Treatment and management of childhood depression

Apart from medication, "the two major treatments for depression in children and adolescents are tricyclic antidepressants (TCAs) and selective serotonin reuptake inhibitors (SSRIs) [38]". SSRIs are generally preferred due to their favorable safety profile and effectiveness. For children tricyclic antidepressants (TCA) could be effective medicine but due to harmfulness it is less favorable. So, it is usually given less dosage for children and adolescence who have mental illness.

Children or adolescence who have therapy resistant response or other mental illness medication will be threaten with combining children tricyclic antidepressants (TCA) with monoamine oxidase inhibitors (MAOIs). If still resistant, then the healthcare will proceed with electroconvulsive therapy (ECT).

Sometimes treating children and adolescence mental illness can be very complex and needs effective interventions because it cannot be sure how the medicine reacts. Studies that focus how this child are in which stage they might be could help for target treatment. This all happens because children have a developing rational thinking development.

Different studies have shown that family dynamics and social influence could directly affect the mental wellness of children or youth. This specific study is called Longitudinal studies and it is a comprehensive approach which make sure the effective treatment is applied as it supposed to be applied.

2.3. Machine Learning

Today most of the population uses a computer-based system which help them to save time and money. Machine language which is a subset of artificial intelligence is capable of working huge data. Which can handle to solve complex issue and difficult problem. Thus, in medicine, law and commerce has a massive research area and machine learning has a numerous advantage. Target patterns are found in the data by using machine learning. Without explicit programming, it focuses on teaching the machine what to do and enabling it to act autonomously based on experience [16]. Different academics have classified machine-learning techniques into three categories: reinforcement learning, supervised, unsupervised, and semi-supervised [15].

2.3.1. Supervised Learning

Supervised learning is a machine learning approach where a model is trained using labeled data [15], with known outputs (target or dependent feature) and inputs (predictor or independent features). The main target is to learn a rule that can forecast the target feature from new, unseen data. “Common tasks in supervised learning include classification and regression. Examples of supervised learning algorithms include Naïve Bayes, Support Vector Machine, Decision Tree, Random Forest, K-Nearest Neighbor, and Logistic Regression [39] [40].”

2.3.2. Unsupervised Learning

“Unsupervised learning is the algorithm used to work with unlabeled data. This algorithm is a very powerful tool for analyzing data and for identifying patterns and trends without the unknown label the instances belong to. It is the learning algorithm applicable to clustering a given dataset into different groups. K-means is the most common examples of unsupervised learning [41].”

2.3.3. Semi-supervised Learning

“Semi-supervised learning combines both supervised and unsupervised machine learning techniques [42].” In this approach, both labeled and unlabeled data are utilized together. The aim of this algorithm is to construct a model that can more precisely predict results for future data by leveraging both the labeled and unlabeled data, compared to a model trained solely with labeled data.

2.3.4. Reinforcement Learning

It is an algorithm that learns from interaction with its environment, continuously improving through trial-and-error and feedback mechanisms. The system builds knowledge from past experiences to make informed decisions. A common example of reinforcement learning is the Markov decision process, where the system receives feedback and adjusts its behavior to optimize its performance and achieve specific goals. Given that this study focuses on classification techniques, which are part of supervised learning, other machine learning approaches like reinforcement learning were excluded from the scope of this research [43].

2.4. Machine learning and Health sector

The healthcare sector plays a key role in safeguarding the well-being of a country's population. “In developing countries like Ethiopia, where most people live in rural areas with limited access to safe water, housing, sanitation, food, and healthcare, good healthcare services are especially important [44].” However, the current healthcare system in Ethiopia lacks customer satisfaction. A key area for improvement is placing more emphasis on disease prevention. While not all diseases are avoidable, early checkup can lead to good health results and reduced medical costs.

One approach to enhancing preventive healthcare is the early forecast of diseases. This allows for quicker diagnoses and enables healthcare practitioners to begin treatment sooner. After identifying a disease, healthcare providers can use predictive tools to identify individuals at high risk and recommend tests or interventions [45]. Machine learning in healthcare can be applied in various areas, such as disease diagnosis, drug discovery, medical imaging, personalized medicine, behavioral modifications, smart health records, clinical trials, and outbreak prediction [46].

2.4.1. Disease Prediction Using Machine Learning

Machine learning have an essential role in disease prediction by analyzing patient history data [47]. It is proved that successful in predicting and diagnosing various critical diseases within the healthcare system. By enabling practitioners to process large and complex medical datasets, machine learning helps convert these datasets into valuable clinical insights [48]. As a result, the implementation of machine learning in healthcare significantly enhances rapid disease prediction, improves treatment outcomes, and increases patient satisfaction. In childhood depression prediction, the most commonly used approach is supervised machine learning. This type of algorithm is applied to labeled data and encompasses both classification and regression tasks. Classification is particularly prevalent in disease prediction and diagnosis, as it allows for categorizing data into specific disease types. Many studies on depression prediction utilize multiple classifier algorithms for computational comparison, ultimately identifying the model that offers the highest performance and accuracy in predicting depression outcomes [47] [49].

Table: 2 Frequently used classifier algorithms for childhood depression prediction.

Classifiers	Advantage	Disadvantage
Support Vector Machine (SVM)	[47] Generate exact classification outcomes, optimize memory usage, manage high-dimensional data, address class imbalance, and solve non-linear problems.	It requires significant training time when dealing with large datasets and can be challenging to interpret.

Decision Tree (DT)	[49] It is easy to understand and generate rules, and complex decision tree models can be greatly simplified through visualizations.	Suffer from over fitting, low prediction accuracy, the calculation is complex for many class labels,
Random Forest (RF)	Used for feature engineering, work with a large dataset, high accuracy, avoid over fitting. RF works well on both categorical and numerical features [49].	It is complex, needs many computational resources, needs much training time.
Naïve Bayes (NB)	It is easy to understand and implement, not affected by irrelevant features, fast, works with both continuous and discrete data, and performs well on small datasets.	Strong assumption of independence of every feature.
K-Nearest Neighbors (KNN)	It is easy to understand and implement, requires minimal training time, and demonstrates strong predictive power [47].	Computationally expensive, Sensitive to an unbalanced sample set
Logistic Regression (LR)	It can handle various types of relationships, no multi collinearity easy to implement, and very efficient to train.	Unable to solve non-linear problems; only predict a categorical outcome. It is vulnerable to over fitting.
Gated Recurrent Unit (GRU):	[2] Simpler architecture than LSTM, with fewer gates (only two). Faster to train and more computationally efficient than LSTM.	- Less flexibility compared to LSTM in certain complex tasks. - The simpler architecture may not perform as well for tasks requiring fine-grained control over memory.
long-short-term memory (LSTM)	[3] Better for taking continuing dependencies in sequential data.	- Computationally expensive and slower to train due to a larger number of

	Effectively addresses tasks such as language modeling and time series forecasting.	parameters. - Requires more memory for storing parameters.
Multilayer Perceptron (MLP):	Simple and easy to implement. Effective for non-sequential tasks (e.g., classification, regression). Fast training and inference time [3].	Does not handle sequential or time-dependent data. - Cannot capture temporal dependencies in data.

2.4.2. Deep learning for Mental Illness Identification

Deep learning plays an important role in the healthcare system by uncovering hidden patterns and opportunities in clinical data, assisting doctors in faster diagnoses and treatment [47]. It applies neural network techniques to vast amounts of patient-related data, including medical reports, to deliver improved outcomes. Unlike traditional machine learning algorithms, deep learning excels in solving complex problems that are beyond the scope of machine learning [15]. By utilizing advanced neural network methods, deep learning provides more accurate results in healthcare.

Deep learning algorithms support doctors in identifying diseases, assessing their severity, and making informed medical decisions. These techniques analyze patient history data with high accuracy, aiding in disease detection and optimizing treatment plans. In various applications, deep learning helps physicians analyze critical data such as blood samples, glucose levels in diabetic patients, image analysis for tumor detection, identifying cancerous cells, diagnosing cancer, and even detecting early signs of osteoarthritis through MRI scans before significant damage occurs [47].

2.5. Feature selection methods

In machine learning, feature selection is very important for choosing pertinent features to build the model. In order to obtain an accurate and efficient result, feature selection aims to decrease the dataset's dimensions and eliminate noisy and inconsistent data. Moreover, feature extraction and selection can be used to simplify the data [50].

Feature extraction: it a method of choosing significant variables from the row dataset. The benefit of feature selection is to get accurate prediction. This study did not apply feature selection method by the direction of health care professionals. All the features that are in the dataset are equally valuable to identify the mental illness in children [50].

Feature selection: it is the method of selecting significant variable for the target output from the dataset [51]. This method is performed during data preprocessing, it removes all redundant features and identifies the most relevant features [50]. In predicting mental illness in children identifying which feature is main feature from the patient history data is a very important task. In this study this part is also provided from health care professionals.

Algorithms like Correlation-based Feature Selection (CFS) and the chi-squared test are known to perform well in selecting features for medical datasets [52]. Feature selection methods are typically divided into four main categories: filter approaches, wrapper approaches, and embedded approaches. These methods increase the correctness and effectiveness of predictive models by ensuring that only the most relevant features are used for classification tasks [52] [53].

Filter methods: is the process of choosing and sifting features prior to putting any machine-learning model into practice. Modeling algorithms can only employ the best features once they have been identified. In order to filter the most pertinent features, filter techniques assess the relationship between input features and target class using statistical measures [54]. When working with a dataset that has a big number of features, this method is quick and effective at filtering features. This method's drawback is that it fails to recognize the relationship and interaction between the independent and dependent properties. The two main categories of filter methods are multivariate filter methods and university filter methods. Multivariate filters assess a full feature, whereas university filter feature selection typically assesses and ranks a single variable subset [54].

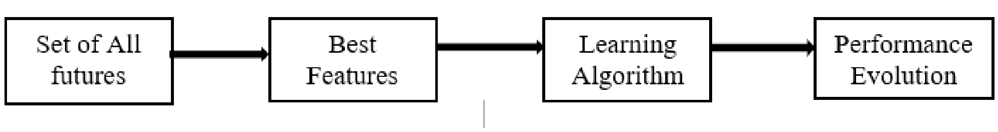


Figure 2 Filter Mode [54]

Wrapper methods: To assess the model's accuracy on the dataset, the approach uses a machine-learning model to randomly choose a pertinent feature and train the model using this feature subset This method mainly imitates the model selection with feature nature, and relationship between every individual feature. Comparing with filter method approach wrapper model is more vulnerable for overfitting and high cost. [55].

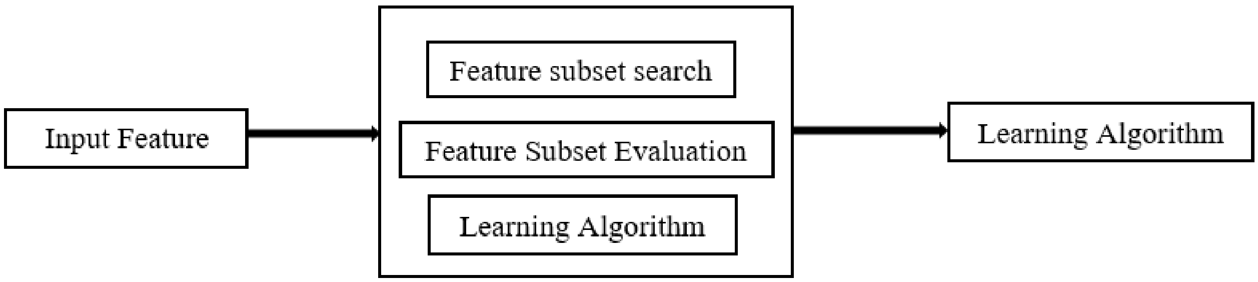


Figure 3 Wrapper model [56]

Embedded methods: it is a process of selecting feature during training process. It allows the model to select feature by its self so because of this functionality it more capable than wrapper method. Additionally, it allows the algorithm for local search thus the algorithm will find time to distinguish the main features for prediction.

Independent measures are employed in this method to classify the optimal feature subset, considering the best subset among potential candidates. This will help for better selection of variables that subsidize most to the model performance, resulting in more precise and effective model [57].

2.6. Related Works

This section presents a review of research papers on mental illness identification. This help the study to a clear understanding of the systems, approaches, and results of existing studies. Some studies have focused on developing systems that predict the diseases patients are suffering from. However, there are still important gaps in the healthcare sector that require further exploration, particularly in the use of machine learning and deep learning for disease classification and prediction [58]. Various related works, both locally and globally, have been conducted in the healthcare domain using machine learning techniques, and these have been reviewed in this context.

Lin Wang, Li Chen [59], created a risk-prediction nomogram to offer a methodical way to measure and display risk profiles. An online survey was used in this nationwide multicenter study to collect information on children's and teenagers' behavioral and psychological functioning. A popular technique for detecting behavioral and emotional issues in young people, the Achenbach Child Behavior Checklist (CBCL), was used to evaluate the functioning of the participants [60]. The collected data were analyzed using STATA software and R, enabling robust statistical analysis and modeling. The creation of the risk-prediction nomogram indicates that the study aimed to quantify the identified risks, making it easier for practitioners to assess and address the needs of affected children and adolescents.

Rachel M. Latham and Christian Kieling [61] conducted their study on children and adolescence who are exposed for air pollution could possibly develop a mental illness called Major Depressive Disorder (MDD). They have prepared their dataset from UK birth cohort of 2232 children. They have prepared a mental illness which is MDD predictive model based on sociodemographic factor. Thy have selected the main prediction feature as sex, skin color, drug habit, academic frailer, social loneliness, history of running away from home, participation of fights, childhood abuse. E-Risk is used for evaluation of the selected model. They have come with the conclusion of children and adolescence mental illness prediction has a complex relationship between environmental factors and mental health.

Tove Wichstrøm and Lars Wichstrøm [62] they studied about the “identification of children and adolescence mental illness for non-suicidal self-injury (NSSI).” They have prepared their data through questionnaires from 2003-2004 birth in Trondheim. Logistic regression is used to employ for identifying mental illness through parental factors, child factor and external events. The parent factor is evaluated as parenting stress and negative thought toward the child at age 6. This result a successful mental health identification of NSSI during adolescence.

Fang Li, Frederike Jorg, Maarten J.M. Merkx, and Talitha Feenstra [63], they studied cognitive behavioral therapy (CBT) result after early system treatment and in future life outcome. So, the researcher applied machine learning in order to identify the continuous treatment effect and determines the result variance compared with traditional regression approach. They have used naturalistic dataset that has 1975 patient record with mental illness. The study found that early symptom changes and baseline symptom scores were the only significant predictors of treatment outcomes. To identify the 10th gathering the researcher uses sociodemographic data, pre-treatment predictor, and early signs change. Various machine learning models, including random forest, support vector machine (SVM), extreme gradient boosting (XGBoost), and neural network, were compared to linear regression techniques.

Lawrence M. Chen, BSc, and Irina Pokhvisneva [64] investigated "the influence of prenatal maternal depression and anxiety on child socioemotional and behavioral challenges" while accounting for the potential confounding effects of specific genomic risk factors. Th participant of thin study work were 15,454 pregnant women and children who are at age one and count totally 14901. Polygenic risk scores (PRS), ADHD, and schizophrenia, were used as indicators of genetic susceptibility to internalizing and externalizing symptoms in the context of prenatal adversity exposure. Linear regression models assessed whether maternal health issue during the third period of pregnancy predicted child mental health status scores across various stages of development. The analysis revealed significant associations between maternal health issue and child or adolescent symptoms. Prenatal maternal depression emerged as a notable predictor, with a generalized estimating equation (GEE) estimate of 0.093 (95% CI: 0.065-0.121, $p < 0.0001$). Similarly, motherly anxiety forecast child and young symptoms, with a GEE estimate of 0.065 (95% CI: 0.037-0.093, $p < 0.0001$). These relations sustained substantial after controlling for the child's genomic risk, underscoring the substantial effect of maternal health issue on child mental health outcomes.

Hui-Nien Yang, Yueh-Ming Tai, Li-Kuang Yang, and Susan Shur-Fen Gau [65] conducted research to explore "the long-term effects of childhood attention-deficit/hyperactivity disorder (ADHD) symptoms on quality of life (QoL) in adulthood." In this study questionaries assessing ADHD symptoms experienced during childhood (ages 6–12) using the SNAP-IV Chinese version, as well as current ADHD and anxiety/depression (ANX/DEP) symptoms are filled by 1382 young men with the age gap of 18 to 30 basing in Taiwan. Then after participant are categorized into four different groups: ADHD-C (Combined Type), ADHD-I (Inattentive Type), ADHD-HI (Hyperactive-Impulsive Type), and Non-ADHD. For continuous outcome the model is analyzed by QoL and adult ADHD. And researched the relationship between them by Univariate and multivariate regression analyses outcome for the study emphasizes that ADHD, adult symptoms of mental illness and QoL has a strong relationship.

Mehmet Emin Şanlı, İlhan Çiçek, Murat Yıldırım, and Veysi [66], they have studied the outcome of positive childhood experience on mental illness and severity level in adults. They have gathered their data from social media and the recorded 3090 participants where 2059 were women's. The association between positive childhood experience and mental health with demographic feature is evaluated using regression analysis. ANOVA and Independent T-test was used to select and evaluate main features form the dataset. The finding of their research is there is association of mental illness and anxiety for a children or adolescence who has positive childhood experience. The regression results exposed that positive childhood experiences describes10% of the variance in depression and 8% in anxiety levels. The findings highlight the critical role of fostering positive experiences during childhood to reduce mental health challenges in adulthood.

Elizabeth J. Hawkey, Rebecca Tillman, Joan L. Luby, and Deanna M. Barch [67] examined "the role of executive function (EF) in predicting the onset or worsening of ADHD and depression" as well as its association with brain network functional connectivity during school age. Executive function was evaluated using the Behavior Rating Inventory of Executive Function (BRIEF), which has been shown to distinguish children with ADHD from control groups. However, the study specifically addressed the limited research linking early EF to later depression and brain network organization. The study followed 247 children between the age of three and six years, who were enrolled in a longitudinal investigation of emotional development. Results demonstrated that early EF deficits significantly projected new start and worsening of ADHD and mental health symptoms as children transitioned into school age. Multivariate linear regression analyses, conducted using R Studio, addressed that the major cause for increasing Major Depressive Disorder (MDD) and ADHD can be the shortages of EF in early childhood.

even after controlling for preschool symptom levels. The findings suggest that early deficits in EF may act as a shared cause for the advancement of ADHD and MDD, highlighting the importance of early intervention to address EF challenges.

Yara J. Toenders, Laura S. van Velzen, Ivonne Z. Heideman, Ben J. Harrison, Christopher G. Davey, and Lianne Schmaal [68] conducted "a systematic review to investigate neuroimaging markers associated with pediatric major depressive disorder (MDD)". Recognizing that MDD most of the time occurs during teenage years, significantly influencing developmental trajectories and long-term outcomes, the review analyzed 68 longitudinal neuroimaging studies published up to February 1, 2019.

The review underscores the importance of further research into neurobiological markers of MDD in youth, advocating for larger, well-controlled studies that account for demographic and developmental variables.

Table: 3 Summary of related work

Authors	Study Focus	Dataset	Methodology	Key Findings	Impact of Study
Lin Wang, Li Chen	Risk-prediction nomogram for children's mental health	Nationwide multicenter study, online survey	Achenbach Child Behavior Checklist (CBCL), STATA & R for statistical analysis	Created a risk-prediction nomogram to assess behavioral and emotional issues in children and adolescents	Provides a systematic way to quantify mental health risks, aiding clinicians in early diagnosis and intervention.
Rachel M. Latham, Christian Kieling	Air pollution and Major Depressive Disorder (MDD) in children	UK birth cohort (2232 children)	E-Risk model, sociodemographic factors	Environmental factors have a complex relationship with mental health	Highlights the role of environmental factors in childhood depression, emphasizing the need for policy changes to reduce pollution exposure.
Tove Wichstrøm, Lars Wichstrøm	Identification of non-suicidal self-injury (NSSI) in adolescents	2003-2004 birth cohort in Trondheim	Logistic regression	Parenting stress and negative parental thoughts at age 6 predict NSSI in adolescence	Reinforces the importance of parental mental health and early childhood interventions in preventing self-harm in adolescents.
Fang Li, Frederike Jorg, Maarten J.M. Merkx, Talitha Feenstra	Cognitive behavioral therapy (CBT) outcome analysis	1975 patient records with mental illness	Machine learning (RF, SVM, XGBoost, NN) vs. Linear Regression	Early symptom changes and baseline scores were the only significant predictors of treatment outcomes	Demonstrates how machine learning can improve mental health treatment personalization and effectiveness.

Lawrence M. Chen, Irina Pokhvisneva	Prenatal maternal depression and child socioemotional health	15,454 pregnant women, 14,901 children	Polygenic risk scores (PRS), Linear regression, GEE model	Prenatal maternal depression significantly predicts child/adolescent mental health outcomes	Strengthens the case for prenatal mental health care to prevent long-term psychological issues in children.
Hui-Nien Yang, Yueh-Ming Tai, Li-Kuang Yang, Susan Shur-Fen Gau	ADHD symptoms and quality of life in adulthood	1382 young men (18-30, Taiwan)	SNAP-IV Chinese version, Univariate & Multivariate regression	Strong relationship between childhood ADHD symptoms and adult mental health outcomes	Highlights the long-term consequences of ADHD, supporting early diagnosis and intervention.
Mehmet Emin Şanlı, İlhan Çiçek, Murat Yıldırım, Veysi	Positive childhood experiences and mental illness in adults	3090 participants from social media	Regression analysis, ANOVA, Independent T-test	Positive childhood experiences influence depression (10% variance) and anxiety (8% variance)	Emphasizes the role of childhood experiences in shaping long-term mental health, advocating for supportive environments.
Elizabeth J. Hawkey, Rebecca Tillman, Joan L. Luby, Deanna M. Barch	Executive Function (EF) and ADHD/Depression	247 children (3-6 years)	Behavior Rating Inventory of Executive Function (BRIEF), Multivariate regression	Early EF deficits predict the onset and worsening of ADHD and depression	Suggests that improving executive function in early childhood may prevent mental health disorders later in life.
Yara J. Toenders, Laura S. van Velzen, Ivonne Z. Heideman, Ben J. Harrison, Christopher G. Davey, Lianne Schmaal	Neuroimaging markers in pediatric MDD	68 longitudinal neuroimaging studies	Systematic review	Advocates for larger studies on neurobiological markers in youth	Calls for further research on neurobiological predictors of MDD, improving precision in diagnosis and treatment.

CHAPTER THREE

3. METHODOLOGY

This section outlines the methodology and process involved in building a childhood depression prediction system using machine-learning techniques. The practice of machine learning is rapidly expanding across various sectors [69], with healthcare being one of the primary fields that heavily relies on this technology to meet customer needs. The healthcare sector handles vast amounts of complex data that are challenging for humans to analyze, but machine learning simplifies the process by identifying patterns and providing insights. The research follows a structured approach, incorporating various approaches, measures, and techniques to construct machine-learning models. Each phase is justified and explained in detail. First, the methods and techniques for data collection are described. The second phase focuses on the very important preprocessing steps and feature selection methods, which play a important role in building effective model. The third phase discusses and validates the use of supervised machine learning algorithms in building the childhood depression prediction system.

3.1. Data Source

To investigate the causes of childhood depression, the work used past patient data from St. Paul Hospital in Addis Ababa, Ethiopia. Where the study population starts from 2020 to 2024. The participant is randomly selected using proportion-based study where sample size to estimate a population proportion with a specified confidence level and margin of error. Key variables included in the dataset include sociodemographic (gender, age), health and medical history (physical health conditions, medication history), life events and stressors (trauma or abuse, major life changes (family divorce), family history (family history of depression, parental mental health), and risk factors (length of sleep, financial stress, academic pressure). Confidentiality was ensured by anonymizing the data and gathering it without speaking with patients directly. Developing predictive models and identifying risk factors for childhood depression could be the main goals of this study.

Formula for Sample Size (n):

n = (Z^2 * p * (1 - p)) / E^2

Where:

- n = Required sample size

- Z = Z-score for confidence level (1.96 for 95%)

- p = Estimated proportion (0.5 for maximum variability)

- E = Margin of error

Step-by-Step Calculation:

n = (1.96^2 * 0.5 * (1 - 0.5)) / (0.0437^2)

n = (3.8416 * 0.25) / 0.001911

n = 0.9604 / 0.001911

n ≈ 502

Conclusion: A sample size of 502 is required for a 95% confidence level with a 4.37% margin of error when estimating a proportion of 0.5.

3.2. Preprocessing

In the building of a prediction model for our investigation, preprocessing is essential. In this process, noisy and massive datasets are transformed into clean, meaningful data. Since the gathered data contains categorical variables and missing values, the suggested system needs to handle these problems in order to make ready the data in the way the model can use. Machine learning requires preprocessing because data which are not correct can affect the correctness of the model. In order to achieve accurate and dependable illness prediction, preprocessing makes sure that the dataset is cleaned after it has been gathered and prepared. Getting the prediction model finished requires careful preprocessing. Preprocessing procedures are carried out after the dataset is prepared to produce a clean dataset.

Cleaning noisy data: One of the very necessary preprocessing phases for developing the best prediction model is cleaning noisy, outlier data. Outliers are values in the dataset that fall outside of the range of the other values. Consequently, controlling them is essential to develop a prediction model that is more accurate. Because clinical data is inherently volatile, outliers may appear. Most often, researchers utilize boxplots as a quick way to find outliers. In boxplots, outliers are identified using the median, which is the center value of an ordered set of values, and the interquartile range, which is the variance between the first and third quartiles [70]. In particular, data points that are below Q1−1.5 (IQR), where IQR=Q3−Q1, and above Q3+1.5 (IQR), Q1 is the 1st quartile, and Q3 is the 3rd quartile. The mean value is used to replace the values of the outliers in this study [70].

Handling Missing Values: Due to mistakes made during data collection and the fact that some fields were left empty, some results contained missing numbers. Diagnostic test findings, which are very important for forecasting the probability of diagnoses or the efficacy of treatment, are commonly absent from patient data [71]. The prediction model's accuracy may be considerably impacted by these missing values. Missing values can be treated in a number of ways, including filling them in or eliminating them. Sometimes, mislaid values are disregarded if they are minor less than 10% for a single instance but this is not the best course of action because the missing data may be a very important component that aids in the development of the model. Although it usually has little effect on the model, another technique is to substitute zeros for the missing variables. In this study, the mean of the observed values was used to handle mislaid values, as the mislaid variable were numerical, and mean imputation is generally more effective for numerical missing data.

How to handle categorical data: This stage involves converting actual data into the necessary format.

The data gathered are different type, Real data, decimal values, and insignificant data are all included in the gathered data. Consequently, insignificant data was transformed into numerical data of the forms 0 and 1 in this step. The nominal value of "Gender," for example, can be designated as 0-for females and 1-for males. All of the integer and float values for the various features are included in the final CSV file once the data has been preprocessed.

3.2.1. Feature Selection Methods

In this study, feature selection was not applied because all features were deemed essential for accurately assessing childhood depression. Childhood depression is a very complex condition where parents and healthcare professional may not able to identify easily. Because of the difficulty of the issues selecting proper feature needs a serious research and discussion with the healthcare professional. By doing so, feature’s like academic pressure, sleep period, family history, and suicidal ideation, lack of focus on education and other features is carefully selected. Excluding any one of the features may impact the result since they have a high interdependency.

Medical experts stress that including all features is important for the model to handle the complex nature of the issues. Having the proper data or futures helps the model to minimize the data loss, maintain reliable prediction quality and make sure easiness to use by the professionals and different educators. Additionally, the interconnected nature of the aspects involved and the advice provided by healthcare experts will help to examine the issues holistically.

3.2.2. Machine Learning Models

The main goal of this work is, based on categorized or labelled data to develop a machine learning classification algorithm which performs prediction of childhood depression. Measures like how good it achieves on sequence related tasks, time series prediction, and how accurately predict childhood mental health issue is the base for selecting the proper algorithm. From the well-known classification algorithm Long short-term memory (LSTM), gated recurrent unit (GRU) and multilayer perceptron (MLP) is used in this work [1] [2] [3].

Multilayer Perceptron (MLP) is a one of artificial neural network which is capable of handling structured data as well as sequential data [15]. It is used widely for data classification and prediction. In the proposed system we have both functionality which is a binary classification and severity level prediction. Starting from data analysis which includes behavioral assessment, family history of mental illness, evaluation of child emotional well beingness to the prediction level it performs accurately [1] [72].

Long- short-term memory is a type of recurrent neural network [15]. Unlike multi-layer perceptron it could handle less structured data and performs well for sequential data types [2]. Depending on personal behavior, emotional status, mental illness symptoms it's capable of forecasting the availability of mental illness in children. It can potentially provide real time mental health monitoring and identify the indicator for mental illness occurrences by using continuous data from daily surveys [2] [73].

Gated recurrent unit is also a one of recurrent neural network [15]. It is originated to handle continuous type of data through gating mechanisms. This architecture is capable of handling sequential mental illness episodes that include mood swing or physiological state happening time to time. Prediction in gated recurrent unit take place by analyzing pattern in a given data so depending on that it will predict the future mental illness episode. This model accurately predicts with analyzing historical data to the future mental health issue. [74].

3.3. Evaluation

3.3.1. Prediction model evaluation

After preprocessing the required data and initializing the model the next step will be evaluating the performance and regulating whether the model really fits the given data or not. And also making sure the model is performing as it is supposed to will be taking place. Primary the model has to give a new value from observed data. Mainly there are two type of evaluation method holdout and cross validation [75].

Holdout method is one of model evaluation method which is known by this simplicity, flexibility and quicker execution. This method evaluates the model by dividing the dataset into three parts as training, validation, and testing set [75]. This results for unbiased estimation of model performance. However, it counters some limitation like high variability influence the performance result from the executions. Moreover, when the split of training and test data set splits, the might be data redundancy which makes the evaluation result less acceptable.

The second model evaluation is cross validation. It’s known to be more accurate than holdout method. It works by dividing data into multiple parts for evaluating the model [75]. For this study we have used the k-fold cross validation technique [76]. This is taking place to evaluated the model is learned well in each training data. The advantage of this evaluation method is it minimizes the risk of overfitting.

k-fold cross validation is one of the most known type of cross validation [76]. It works by splitting the dataset into k equal sizes which is called folds. The model is expected to train all the folds which is k times. And remaining k-1 are used for test set. This ensures all data are data evaluated equally. So practically this study uses 10-fold cross validation which the test is equally divided 10 folds [75].

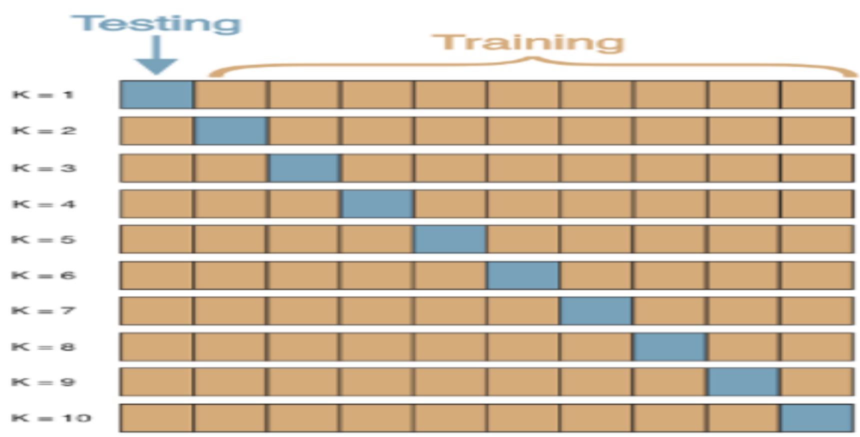


Figure 3 10-fold cross-validation [76] [75]

3.3.2. Prediction model performance evaluation metrics

Various performance evaluation metrics, including precision, recall, confusion matrix, f1-score, sensitivity, and specificity [18] [19], are used in this study with cross-validation to assess prediction model performance because classifier algorithms do not produce identical results.

Key Terms in Performance Measurement:

- True Positive (TP): Actual value and the predicted value are true.
- True Negative (TN): Actual value and the predicted value are false.
- False Positive (FP): Actual value is false, but the model predicts it as true.

- False Negative (FN): Actual value is true, but the model predicts it as false.

These metrics collectively help evaluate the prediction model's correctness, robustness, and capability to specify to new data [18] [19].

3.3.2.1. Accuracy

Accuracy refers to the capability of a classification algorithm to correctly identify the classes within a dataset. It measures how close the predicted values are to the actual or expected values [77]. In general, accuracy is explained as the ratio of right predictions to the total number of occurrences in the dataset [77]. It can be calculated using the following equation:

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

3.3.2.2. Precision

Precision is a measure of how many true values were accurately predicted out of all the expected values in the real class [78]. Precision measures how well classifiers can avoid classifying a bad case as positive. The following formula can be used to determine precision [78] [79]:

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

The macro average is utilized in this study for multiclass classification since it assigns each class an equal amount of weight. To determine the macro average precision, use [78] [79]:

$$Precision\_macro = \frac{1}{|C|}\sum_{i=1}^{|C|}\frac{TPi}{TPi + FPi}$$

3.3.2.3. Sensitivity

Another name for sensitivity is True Positive Rate. The average percentage of real true positives that are accurately identified is known as sensitivity [78] [79].

$$Sensitivity = \frac{TP}{TP + FN}$$

3.3.2.4. Specificity

True Negative Rate is an alternative term for specificity. The percentage of negative values that are accurately categorized is measured using this method [78] [79].

$$Specificity = \frac{TN}{TN + FP}$$

3.3.2.5. Recall

This measures the amount of positive occurrence that is properly classified and it gives replies for the question of what ratio is actual positive [18] [78].

Below is formula to calculate recall [18]:

$$Recall = \frac{True\ Posotive}{True\ Posotive + False\ Negative}$$

To calculate the macro average, we will be using the below using the below formula [18]:

$$Recall\_macro = \frac{1}{|C|}\sum_{i=1}^{|C|}\frac{TPi}{TPi + FNi}$$

Where: C = class

CHAPTER FOUR

4. PROJECTED SOLUTION FOR CHILDHOOD DEPRESSION PREDICTION

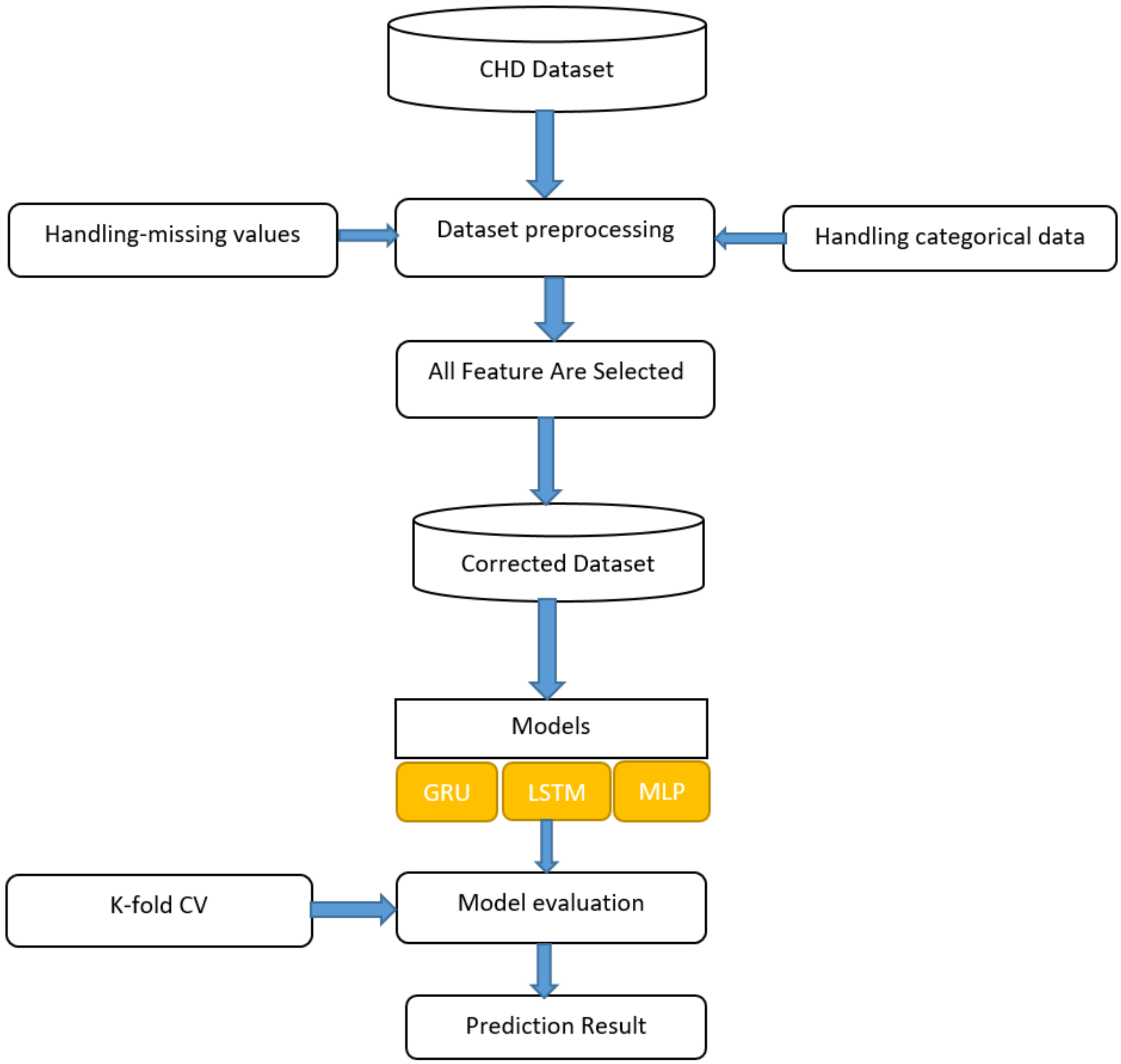
This part of the research discusses the anticipated solution that is machine learning techniques used for predicting childhood depression. The study used dataset provided from St. Paul Hospital. The dataset provided contains detailed patient information and this data is preprocessed and used to develop the predictive model. The main aim is to develop a system that will classify whether the patient is suffering from childhood depression and categorize the stage of the case into mild, moderate, moderately severe and severe.

To achieve these several recognized machine learning algorithms such as Multilayer Perceptron, Gated Recurrent Unit, and Long Short-Term Memory is used [1] [2] [3]. The selection of the algorithm relies on the efficiency in managing the complexity of the given dataset, which contains both numerical and categorical data. As the effectiveness of the system depends on the quality of the dataset, the preprocessing phase is very important since it will make our data more suitable for the model training. during the preprocessing phase the data will be cleaned, missing values will be handled, and also conversion of categorical data into numerical format is performed.

During the evaluation phase in order to assure the models are simplifying well and also avoiding overfitting of the dataset, the K-fold cross validation is used.in addition to this other metrics such as recall, F-measure, sensitivity, and specificity are also used to evaluate the model's efficiency while predicting the childhood mental health issue [18] [19].

After the model is trained very well and the necessary checkup is performed, we will develop a web-based system and integrate it. This make the system accessible very easily for the healthcare professionals to use it for quick diagnosis, providing them appropriate advice and also in treating the patient. For the integration part we will be using a well-known python web framework called flask, which help us deploy the model into the web. Development and testing will be performed using PyCharm IDE community version, Anaconda navigator, and Jupiter notebooks.

Finally, this part particularly chapter discuss how machine learning techniques help healthcare professional to identify and treat childhood mental health issue by proving prediction and severity level of the case.



4.1. Data Processing and Variable Explanation

As there are no proper data that is published or annotated in Ethiopia on childhood depression from the hospitals found locally it is necessary to generate a new dataset for this specific study. Hence, dataset preparation will be performed by collecting medical history of patients from St. Paul Hospital and organize it to be suit for the machine learning model. For research on machine learning the accuracy of the data provided is very serious, for the reason that the effectiveness of the result is very dependable on quality of the data provided. Therefore, it is important to insure the provided dataset is as per the requirement of the selected techniques and tools.

Due to the issues of obtaining an existing dataset in Ethiopia, data was gathered manually from patient history records, which were initially in hardcopy form. These records had to be digitized into a softcopy format in order to create a proper dataset. Since Python is used for model advancement, a CSV (comma-separated values) file format was selected, as it is compatible with the code for reading and processing the data.

Table: 4 Dataset Features Description

Symbols	**Feature full name**	**Missing Value**
Gender	Object	0
Age	Numerical	0
Study satisfaction	Numerical	0
Academic Pressure	Numerical	0
Sleep duration	Numerical	0
Negative thought (suicidal thoughts)	Object	0
Financial stress	Numerical	0
Family History of Mental Illness	Object	0
Have you lost interest in activities you previously enjoyed?	Numerical	0
Have you experienced changes in appetite (eating more or less than usual)?	Numerical	0

Do you feel unusually tired or fatigued even when doing normal tasks?	Numerical	0
Have you been feeling worthless or excessively guilty?	Numerical	0
"Do you feel like you are a burden to your family or friends?	Numerical	0
Feeling tired or having little energy?	Numerical	0
Have you been avoiding your friends, family, or school activities?	Numerical	0
"Have you been acting out or getting into trouble more than usual?	Numerical	0
Do you find it hard to concentrate on schoolwork or other activities?	Numerical	0

4.2. Preprocessing

Preparing the dataset for feeding into the models in order to provide correct outcomes is known as dataset preprocessing. Depending on the type of dataset, this preprocessing technique is used. As seen in the figure below, the dataset used in this study is subjected to techniques such data transformation, missing value filling, and noisy data cleaning.

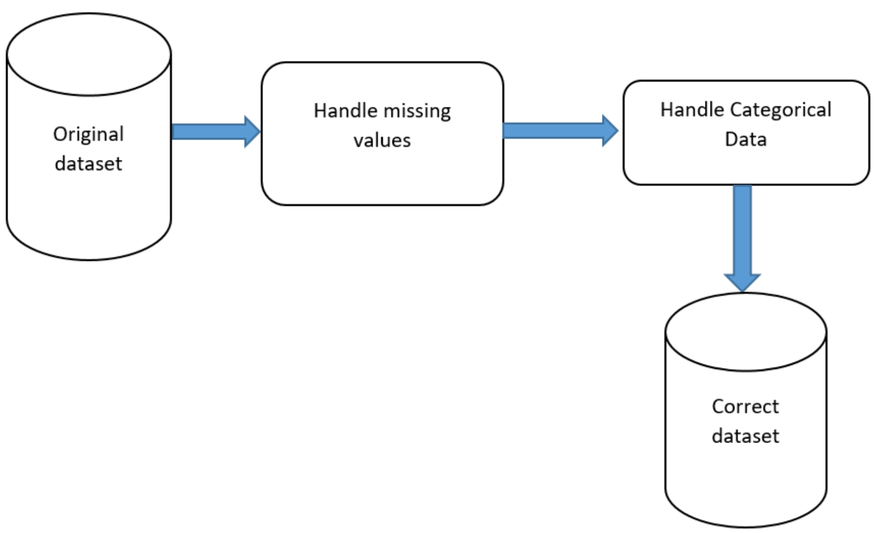


Figure 4 Proper Dataset Preparation Steps

4.2.1 Treatment of lacking values

Upon careful examination of the dataset, I can test to the absence of any missing values. Every feature has completed and consistent data, guaranteeing that every observation is considered. Due to missing values, this removes the requirement for imputation, or the elimination of rows and columns. Because the dataset is complete, preprocessing and modeling may be done smoothly, reducing the possibility of biases or errors that could result from working with missing data. This guarantees that the machine learning model or analysis's output will be based on a solid and trustworthy dataset.

4.2.2 Handling categorical data

It is necessary to convert some of the categorical values in the generated dataset to the forms 1 and 0. whether it is depressed or not. Therefore, every categorical value is transformed by the transformation job. This study handled categorical data using the replace approach and dummy variable encoding.

4.2.3 Feature Selection

In this study, feature selection was not applied because all features were deemed essential for accurately assessing childhood depression. Based on extensive research and consultations with healthcare professionals, all feature such as academic pressure, sleep duration, family history, and suicidal ideation etc… was carefully chosen for its relevance. Childhood depression is a multifaceted condition where features are highly interdependent, and excluding any could overlook critical interactions or confounding factors that influence its severity.

As proved by some experiments including all features doesn’t brings negative outcomes in the capability of the model.in contrast it provides more accuracy on the prediction, proving that all features contribute implicitly to the result.

4.3. Model Construction

The focus of this research is to develop a predictive model to determine whether a patient is experiencing childhood mental health issue and identify its severity level. To build the model three different machine learning technique that is Multilayer Perceptron, Gated Recurrent Unit, and Long Short-Term Memory is used [1] [2] [3]. From the dataset prepared around 502 records were used for training and testing the models. The models then will categorize the inputted data and predict depression status with its severity level.

On this study from the three model listed the Gated Recurrent Unit is used both as classifier and predictor. This model specifically is effective for activities involving successive data like time series classification. Like the other model, Recurrent Neural network, GRU is designed capture the patterns and dependencies in data over time, making it the exact choice for application developed to perform prediction [1].

Multilayer perceptron is the second model, it is a one of neural network which is capable of handling complex data relationship that include nonlinear functions. Mainly it is used for continuous data as to predict and categorize between classes. Also, it is capable to handle structured data which is a type of data this study uses [2].

To address a longstanding dependency in a sequential data, Long Short-Term Memory model which is the advanced or matured form of RNN is used [30]. To mitigate the vanishing gradient problem found in the tradition RNNS, these models combines memory cells and gating mechanism. This combination helps the model to capture long-term dependencies and temporal patterns overtime. This feature makes this model highly suitable for tasks like depression prediction.

This study is aimed to develop a reliable children mental health illness prediction system that will classify and look for its severity level by leveraging this machine learning models.

4.4. Assessment and Testing

In this study, assessment and testing of the model are essential for assessing and estimating the effectiveness of machine learning models trained on the childhood depression dataset for prediction (minimum or no depression, moderate depression, moderately sever depression and severe depression) and classification (depressed or not depressed). So as to compare and select the best model for future predictions, model evaluation is very important because this study used more than two algorithms. Ten-fold cross-validation and confusion matrix, is used in this work to assess the predictive model's efficacy using several model-appropriate performance assessment metrics, including precision, recall, f1-score, sensitivity, specificity, and accuracy [18] [19], as covered in chapter three. After the evaluation, the model with the uppermost exactness and f1_score is saved using pickle and deployed on the server.

4.5. Integrating machine learning model with server

Three models will be employed in this study to predict childhood depression, and the model with the uppermost correctness and f1-score would be suggested for deployment on the server. This is accomplished by getting the web page form ready to receive the new input that is connected to the server and chosen model, which will enable the experts to quickly and accurately diagnose the patient and provide the best care and guidance. Flask is a lightweight and adaptable Python web framework that makes it simple for developers to create online apps and APIs [80]. When utilized as a server, Flask offers the necessary infrastructure to process HTTP requests (such as GET, POST, PUT, and DELETE) and reply to clients, facilitating client-to-client communication (such as web browsers, mobile apps, or other systems) and backend services.

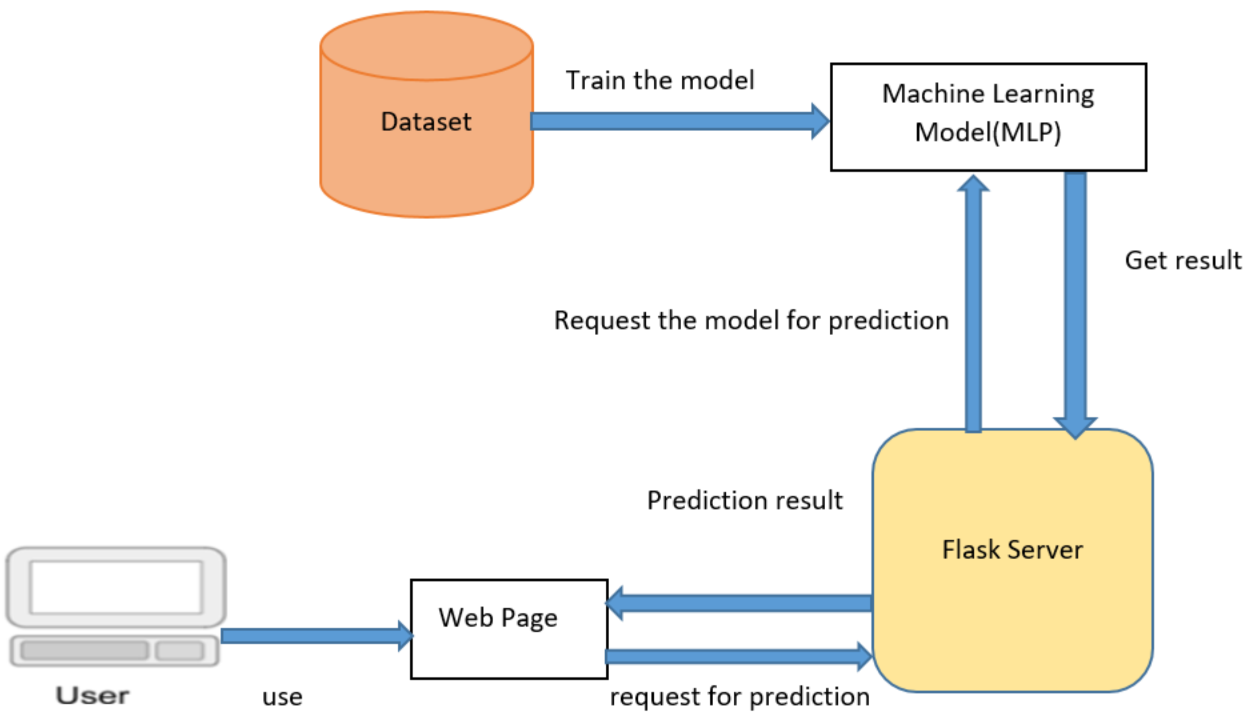


Figure 5 Integration Architecture

CHAPTER FIVE

5. IMPLEMENTATION AND EXPERIMENTATION

This section outlines how the suggested solution for childhood depression prediction will be implemented utilizing the technique covered in Chapter 3 and Chapter 4's suggested solution. Two datasets were used in this work to conduct a variety of experiments. The first experiment employed dataset classification, and the second experiment used dataset prediction. In order to predict childhood depression, a prototype was finally made by the selected model.

5.1. Environment

The suggested approach in this work is implemented using a number of tools and packages. Every suggested solution has been implemented and tested using the Python programming language, starting with data preprocessing and ending with model-building and prototype creation. Python was chosen because it is commonly used and the favored language for developers, researchers, and data scientists [46], which enables the creation of machine learning models straightforward. Additionally, Python is a general-purpose programming language that makes it simple to process scientific data, text, numbers, and graphics. It is also straightforward and simple to comprehend.

Table: 5 Tools and Packages Used During the Implementation [81]

Tools and packages	Version	Description
Anaconda navigator	2.1.4	Provide us an environment to develop the app. As well help us administer the anaconda package.
Jupyter Notebook	7.2.2	Using this we can create and share document.
Python	3.12.4	Well known programming language

Microsoft Excel	2016	To prepare the dataset
Microsoft Word	2016	For the purpose of documentation
Scikit-learn	0.21.3	is a Python package for machine learning that handles fundamental tasks including classification, regression, clustering, and others [81]
Pandas	0.25.1	Help us to handle, integrate and upload our dataset from another external source.
Numpy	1.20.1	processing arrays for objects, strings, and integers [81].
Matplotlib	3.1.1	Is used to visualize data and findings.
Seaborrn	0.9.0	Statistical data visualization
Flask server	1.1.1	Is used to implement the prototype for a few chosen concepts [81].

5.2. Environment

Personal computer with specification of 11th Gen Intel(R) Core (TM) i5-11320H processor running at 3.20GHz and 3.19GHz, four logical processors, 15.8GB of physical memory, 474.9GB of hard disk storage, and Microsoft Windows 11 Home, 64bit operating system is used for this work.

5.3. Dataset Description

To prepare the dataset for this work, patient history data was collected from manually recorded patient records. Initially, the investigator looked for several sources of information related to children mental health issue in Ethiopia and revised related materials from hospitals that specialize in children mental health treatment. St. Paul’s Hospital was then selected as the source for the data collection needed for this investigation.

Data, spanning from 2020 to 2024, was gathered based on the identified attributes relevant to the study. Incomplete records, which did not provide the necessary information, were excluded from the dataset. Due to limitations in time and incomplete information, not all available patient history data was used. Ultimately, a total of 502 patient records were collected, with labels indicating whether the patient was depressed or not, along with severity levels (mild, moderate, or severe).

The dataset consists of 18 columns, capturing various attributes related to childhood depression, such as Age, Gender, Academic Pressure, Sleep Duration, Negative Thoughts, Financial Stress, Study Satisfaction, and Family History of Mental Illness. The process of dataset creation, including the detailed methodology, is further discussed in Chapter Three.

5.4. Preprocessing Implementation

The preprocessing of the childhood depression dataset is implemented in this work using the Python computer language. Feature selection, handling categorical data, and handling missing values are all part of the preprocessing operations. Conversion of non-numerical information to numerical value is very important. this work has used the label encoder and exchange method to change the nominal and non-numeric values and to address the missing data.

```
#reading the dataset
df = pd.read_csv(r'C:\Users\Coop\Desktop\MSC\dataset\depressed_dataset.csv')
print(df.head())
```

Figure 6 sample code for loading library and dataset

5.4.1. Deployment and integrity check of the data

Having the data which has integrity and consistency could be achieved by several step. The very first step is will be checking the data has missing values, duplicate values and incomplete records. Eventually the dataset has no incomplete, missing and duplicate value after applying the python code stated under. So, the dataset has checked for integrity and passes.

```
df.isnull()
df.isnull().sum()
df.duplicated().sum()
for i in df.select_dtypes(include="object").columns:
    print(df[i].value_counts())
    print ("***"*10)
```

Figure 7 Integrity of data Check

5.4.2. Treatment of categorical data

While working with machine learning language it is necessary to convert objects to numeric representation so that the model could perform accurately. Different encoding variables are used in python server for changing these objects to numerical values that includes function called get_dummies(). Also, one-hot encoding is used to ensure that categorical data is represented in machine readable way.

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
import numpy as np
import re
from IPython.display import display, HTML

# Load the dataset
data_path = r'C:\Users\Coop\Desktop\MSC\dataset\depressed_dataset.csv'
df = pd.read_csv(data_path)

# Define the columns to encode and scale
columns_to_encode = ['Gender', 'Family History of Mental Illness', 'Have you had recurrent thoughts of death, suicide, or self-harm?']
columns_to_scale = ['Age', 'Study Satisfaction', 'Academic Pressure', 'Sleep Duration', 'Financial Stress']

# Encode categorical variables (e.g., Gender, Family History, etc.)
df_encoded = pd.get_dummies(df[columns_to_encode])

# Scale the numeric columns
scaler = StandardScaler()
df[columns_to_scale] = scaler.fit_transform(df[columns_to_scale])
```

Figure 8 treatment of categorical data

5.5. Machine Learning Models Implementation

Using a Python sci-kit learning library package, we constructed machine-learning models utilizing the suggested approach. We then imported the necessary modeling library package and metrics for model assessment, as per the standard procedure.

```python
# Data manipulation
import numpy as np
import pandas as pd

# Feature selection
from sklearn.feature_selection import SelectKBest, f_classif

# Model training and evaluation
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import accuracy_score

# Label encoding for categorical variables
from sklearn.preprocessing import LabelEncoder

# For building GRU and LSTM models (using TensorFlow and Keras)
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, GRU, LSTM
from tensorflow.keras.optimizers import Adam
```

Figure 9 Importing necessary packages for modeling

Creating the model, specifying its architecture, and configuring its parameters prior to training is known as initialization. Choosing the activation functions, optimizer, loss function, and number of layers and units in each layer are all included in this. Fitting the model to your data is known as training the model. We will create a two-part Multi-Layer Perceptron (MLP) model that can forecast the level of a child's mental health status and determine if the youngster has depression or not. The algorithm will first classify data as either depressed or not, and then it will forecast whether the depression is light or severe.

```python
# Split the data into training and testing datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features (standardization)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Define the MLP model
model = Sequential()
model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))  # Fully connected layer
model.add(Dense(32, activation='relu'))  # Another fully connected layer
model.add(Dense(1, activation='sigmoid'))  # Output layer for binary classification: Depressed or Not Depressed

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
```

Figure 10 Initialize and train the MLP model

Sequential patterns in the input data are captured by a Gated Recurrent Unit (GRU) layer. It helps the model comprehend the time-dependent patterns by producing a vector representation of the input data. With a sigmoid activation function, a dense layer with a binary output layer can determine whether a person has depression (1) or not (0). The severity output layer, which usually has two classes (such as moderate and severe), is a condensed layer with a SoftMax activation function that predicts the severity of the depression.

```python
# Split the data into training and testing datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features (standardization)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Reshape the input data to 3D [samples, timesteps, features] for GRU
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))  # 3D input for GRU
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))  # 3D input for GRU

# Define the GRU model
model = Sequential()
model.add(GRU(64, input_shape=(X_train.shape[1], 1), return_sequences=False))
model.add(Dense(1, activation='sigmoid'))  # 1 output for binary classification: Depressed or Not Depressed

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))
```

Figure 11 Initialize and build the GRU

It describes the procedure of developing and specifying a GRU (Gated Recurrent Unit) model's structure prior to data training. The GRU is a kind of Recurrent Neural Network (RNN) that uses gates to regulate the information flow in order to process sequential input more effectively [1]. The Model class, which defines the input and output layers, is used to define the model architecture. Two distinct loss functions are then used in its compilation: binary cross_entropy for the binary output and categorical cross-entropy for the severity output. The Adam optimizer is then used. The model may assess its performance for each task separately because the metrics for both are set to accuracy.

```python
# Standardize the data (important for LSTM)
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Reshape the data for LSTM (LSTM expects 3D input: samples, timesteps, features)
X_train_scaled = X_train_scaled.reshape(X_train_scaled.shape[0], 1, X_train_scaled.shape[1])
X_test_scaled = X_test_scaled.reshape(X_test_scaled.shape[0], 1, X_test_scaled.shape[1])

# One-hot encode the severity target (2 classes for severity)
severity_target_train_onehot = to_categorical(severity_target_train, num_classes=2)
severity_target_test_onehot = to_categorical(severity_target_test, num_classes=2)

# Define the model using the Functional API
inputs = Input(shape=(X_train_scaled.shape[1], X_train_scaled.shape[2]))  # Input layer for LSTM

# Add an LSTM layer with 64 units
lstm_out = LSTM(64, activation='relu')(inputs)

# Add a dense layer for binary classification (depression or not)
binary_output = Dense(1, activation='sigmoid', name='binary_output')(lstm_out)

# Add a dense layer for predicting the severity (mild or severe)
severity_output = Dense(2, activation='softmax', name='severity_output')(lstm_out)

# Define the model
model = Model(inputs=inputs, outputs=[binary_output, severity_output])
```

Figure 12 Initialize and build the LSMT

5.6. Model Testing and Evaluation

Assessing the effectiveness of learning algorithms is a very important component of machine learning. The most widely used k-fold cross-validation, K = 10 and confusion matrix, was employed in this study. It divided the data equally among 10 folds, with 9 folds being utilized for training and the remaining 1-fold for testing or evaluation [76]. Using K value ten, the evaluation approach is implemented using the sklearn cross_val_score() and cross_val_predict() algorithms. These techniques test each model's learning ability using the models and dataset.

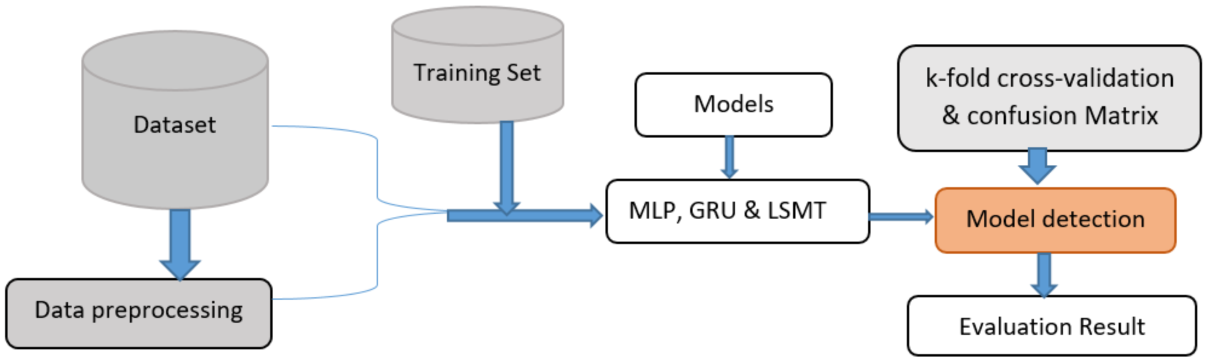


Figure 13 Testing and Evaluation

```
# Perform K-fold cross-validation
for fold, (train_index, val_index) in enumerate(kf.split(X_scaled)):
    print(f"\nTraining fold {fold+1}/10...")

    # Split the data into training and validation sets for this fold
    X_train, X_val = X_scaled[train_index], X_scaled[val_index]
    binary_target_train, binary_target_val = binary_target[train_index], binary_target[val_index]
    severity_target_train_onehot, severity_target_val_onehot = severity_target_onehot[train_index], severity_target_onehot[val_index]

    # Reshape the data for GRU and LSTM (both expect 3D input: samples, timesteps, features)
    X_train_reshaped = X_train.reshape(X_train.shape[0], 1, X_train.shape[1])
    X_val_reshaped = X_val.reshape(X_val.shape[0], 1, X_val.shape[1])

    # --- Train and Evaluate GRU Model ---
    print("Training GRU model...")
    gru_model = create_gru_model((X_train_reshaped.shape[1], X_train_reshaped.shape[2]))
    gru_model.fit(X_train_reshaped,
                  {'binary_output': binary_target_train, 'severity_output': severity_target_train_onehot},
                  epochs=2, batch_size=32, verbose=1)

    loss, binary_loss, severity_loss, binary_accuracy, severity_accuracy = gru_model.evaluate(
        X_val_reshaped,
        {'binary_output': binary_target_val, 'severity_output': severity_target_val_onehot}
    )

    print(f"Fold {fold+1} - GRU Binary Classification Accuracy: {binary_accuracy:.4f}")
    print(f"Fold {fold+1} - GRU Severity Classification Accuracy: {severity_accuracy:.4f}")

    # Append the GRU results
    gru_binary_accuracy_per_fold.append(binary_accuracy)
    gru_severity_accuracy_per_fold.append(severity_accuracy)

    # --- Train and Evaluate LSTM Model ---
    print("Training LSTM model...")
    lstm_model = create_lstm_model((X_train_reshaped.shape[1], X_train_reshaped.shape[2]))
    lstm_model.fit(X_train_reshaped,
                   {'binary_output': binary_target_train, 'severity_output': severity_target_train_onehot},
                   epochs=2, batch_size=32, verbose=1)
```

```python
# --- Train and Evaluate LSTM Model ---
print("Training LSTM model...")
lstm_model = create_lstm_model((X_train_reshaped.shape[1], X_train_reshaped.shape[2]))
lstm_model.fit(X_train_reshaped,
               {'binary_output': binary_target_train, 'severity_output': severity_target_train_onehot},
               epochs=2, batch_size=32, verbose=1)

loss, binary_loss, severity_loss, binary_accuracy, severity_accuracy = lstm_model.evaluate(
    X_val_reshaped,
    {'binary_output': binary_target_val, 'severity_output': severity_target_val_onehot}
)

print(f"Fold {fold+1} - LSTM Binary Classification Accuracy: {binary_accuracy:.4f}")
print(f"Fold {fold+1} - LSTM Severity Classification Accuracy: {severity_accuracy:.4f}")

# Append the LSTM results
lstm_binary_accuracy_per_fold.append(binary_accuracy)
lstm_severity_accuracy_per_fold.append(severity_accuracy)

# --- Train and Evaluate MLP Model ---
print("Training MLP model...")
mlp_model = create_mlp_model((X_train.shape[1],))  # MLP expects 2D input
mlp_model.fit(X_train,
              {'binary_output': binary_target_train, 'severity_output': severity_target_train_onehot},
              epochs=2, batch_size=32, verbose=1)

loss, binary_loss, severity_loss, binary_accuracy, severity_accuracy = mlp_model.evaluate(
    X_val,
    {'binary_output': binary_target_val, 'severity_output': severity_target_val_onehot}
)

print(f"Fold {fold+1} - MLP Binary Classification Accuracy: {binary_accuracy:.4f}")
print(f"Fold {fold+1} - MLP Severity Classification Accuracy: {severity_accuracy:.4f}")

# Append the MLP results
mlp_binary_accuracy_per_fold.append(binary_accuracy)
mlp_severity_accuracy_per_fold.append(severity_accuracy)
```

```
    # Append the LSTM results
    lstm_binary_accuracy_per_fold.append(binary_accuracy)
    lstm_severity_accuracy_per_fold.append(severity_accuracy)

    # --- Train and Evaluate MLP Model ---
    print("Training MLP model...")
    mlp_model = create_mlp_model((X_train.shape[1],))  # MLP expects 2D input
    mlp_model.fit(X_train,
                  {'binary_output': binary_target_train, 'severity_output': severity_target_train_onehot},
                  epochs=2, batch_size=32, verbose=1)

    loss, binary_loss, severity_loss, binary_accuracy, severity_accuracy = mlp_model.evaluate(
        X_val,
        {'binary_output': binary_target_val, 'severity_output': severity_target_val_onehot}
    )

    print(f"Fold {fold+1} - MLP Binary Classification Accuracy: {binary_accuracy:.4f}")
    print(f"Fold {fold+1} - MLP Severity Classification Accuracy: {severity_accuracy:.4f}")

    # Append the MLP results
    mlp_binary_accuracy_per_fold.append(binary_accuracy)
    mlp_severity_accuracy_per_fold.append(severity_accuracy)

# Compute the average accuracy across all folds for all models
avg_gru_binary_accuracy = np.mean(gru_binary_accuracy_per_fold)
avg_gru_severity_accuracy = np.mean(gru_severity_accuracy_per_fold)

avg_lstm_binary_accuracy = np.mean(lstm_binary_accuracy_per_fold)
avg_lstm_severity_accuracy = np.mean(lstm_severity_accuracy_per_fold)

avg_mlp_binary_accuracy = np.mean(mlp_binary_accuracy_per_fold)
avg_mlp_severity_accuracy = np.mean(mlp_severity_accuracy_per_fold)
```

Result

```
Training fold 1/10...
Training GRU model...
Epoch 1/2
...
Epoch 2/2
Fold 1 - GRU Depression Detection Accuracy: 0.7100
Fold 1 - GRU Severity Classification Accuracy: 0.7600

Training LSTM model...
Epoch 1/2
...
Epoch 2/2
Fold 1 - LSTM Depression Detection Accuracy: 0.7200
Fold 1 - LSTM Severity Classification Accuracy: 0.7700

Training MLP model...
Epoch 1/2
...
Epoch 2/2
Fold 1 - MLP Depression Detection Accuracy: 0.7000
Fold 1 - MLP Severity Classification Accuracy: 0.7400

Results Comparison Table:
   Model  Average Depression Detection Accuracy  Average Severity Classification Accuracy
0    GRU                            0.7100                              0.7500
1   LSTM                            0.7200                              0.7700
2    MLP                            0.7000                              0.7400
```

Figure 14 Applying 10-fold CV on Models and the result

These techniques provide the model's sensitivity and specificity value as well as performance evaluation measures including precision, recall, and f1-score [18] [19].

```
Results Comparison Table:
  Model  Avg Depression Detection Precision  Avg Depression Detection Recall  \
0   GRU                            0.523673                         0.657631
1  LSTM                            0.518510                         0.670895
2   MLP                            0.521944                         0.590397

   Avg Depression Detection F1  Avg Severity Classification Precision  \
0                     0.574322                               0.520726
1                     0.579460                               0.529844
2                     0.548083                               0.519069

   Avg Severity Classification Recall  Avg Severity Classification F1
0                               0.501                        0.473943
1                               0.501                        0.452487
2                               0.507                        0.487727
```

Figure 15 Applying precision on Models and the result

Finally, the system for predicting mental health problem in children is created using the best score from the model evaluation result, and using Flask service it is deployed. It may take fresh user input and produce the accurate result.

CHAPTER SIX

6. OUTCOMES AND DISCUSSIONS

The experiment of the suggested machine-learning-based childhood depression prediction system is presented in this chapter. This section discusses the dataset's class distribution as well as efforts to develop classification models for detection using datasets with five classes and binary classes. The results of each trial in this study are then discussed, and the prototype's graphical user interface is shown.

6.1. Data collection outcome

After preprocessing, the data set has a total size of 502 pieces. Of all the patients in the dataset, 40.6% have severe depression, 8.9% have moderate depression, 12.9% have moderate depression, 11.9% have mild depression, and 25.7% have minimal or no depression. In the five-class dataset, the figures and table below demonstrate the class distribution.

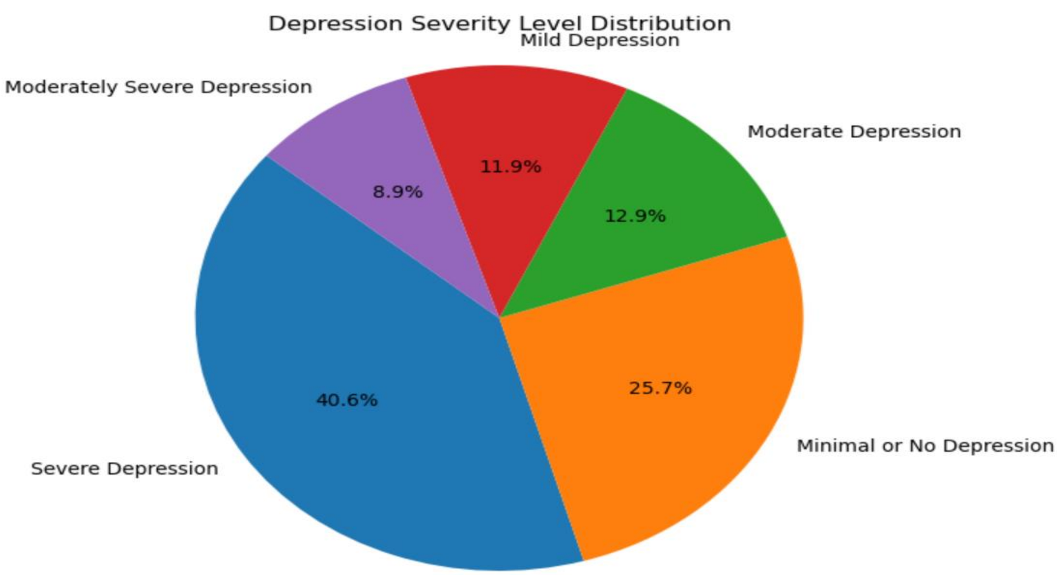


Figure 16 percentage of class distribution and prediction

Table: 6 Class distribution of the dataset

Class	Percent of instances
Minimal or No Depression	25.7%
Mild Depression	11.9%
Moderate Depression	12.9%
Moderately severe Depression	8.9%
Severe Depression	40.6%

6.2. Model Building

Three models the Multi-Layer Perceptron, Gated Recurrent Unit, and Long Short-Term Memory are employed in this study [2] [3]. The model predicts the degree of depression once the dataset is first divided into "depressed" and "not depressed" categories. The models are then created utilizing binary and multiclass datasets, both with and without feature selection techniques.

6.3. Model Evaluation Results

The experiment produced two classifiers for both binary and three classifications, as well as three models based on no feature selection techniques. As explained in chapters three and four, 10-fold cross-validation is used to test and train these models along with additional performance evaluation criteria [76].The dataset was randomly divided into ten equal-sized sets using the 10-fold cross-validation procedure. Ten one folds are used to train the models, and one remaining fold is used for testing. Every fold goes through an iterative process. Binary and three-class classification models are used to display the findings. We separate the results' rationale into two sets in our thesis work.

6.3.1. Binary Classification Models Evaluation Results on Original Dataset

In order to determine if the target classes are depressed or not, two classification models were constructed using the two-class dataset that was transformed from the three-prediction class dataset. Using the 10-fold CV and additional CV performance evaluation measures, the models are trained and evaluated. First, we train the model in our experiment using the original dataset without using feature selection techniques. The results of each test accuracy score for the MLP, LSTM, and GRU models are shown separately in the tables below. To choose the top-performing model, the performance of each model is then compared. The models were assessed following the application of the data resampling technique, which was also utilized to balance the class distribution in the binary class dataset.

Table: 7 Models accuracy of the binary-class dataset

Fold Model	1	2	3	4	5	6	7	8	9	10
MLP	93.75	93.75	93.75	87.50	100.0	93.75	87.50	100.0	87.5	93.75
LSTM	87.50	93.75	93.75	87.50	100.0	93.75	87.50	100.0	87.5	87.50
GRU	93.75	87.50	87.50	87.50	93.75	93.75	93.75	100.0	87.5	93.75

Fold Model	Acc (%)
MLP	93.125
LSTM	91.875
GRU	91.875

The CV correctness score for each fold of the depression class dataset is displayed in Table 13 for two classifiers. The GRU model had the lowest average accuracy of outcomes (87.50), while the RF model had the highest average accuracy (9.75%). This study employs additional performance evaluation metrics, including precision, recall, f1_score, sensitivity, and specificity, as covered in chapters three and four, in addition to the accuracy of 10-fold cross-validation [18] [19].

Table: 8 Performance Result of Binary Classification Models

Models	assessment metrics				
	Precision	Recall	F1_score	Sensitivity	Specificity
GRU	88.83	96.25	92.27	96.25	87.50
LSTM	88.17	97.50	92.40	97.50	86.25

MLP	89.58	95.45	92.13	95.45	88.75

The findings of the three classifiers' performance evaluation measures are displayed in Table 8. Because the dataset is balanced, MLP has a greater accuracy value than the other two models for each performance indicator.

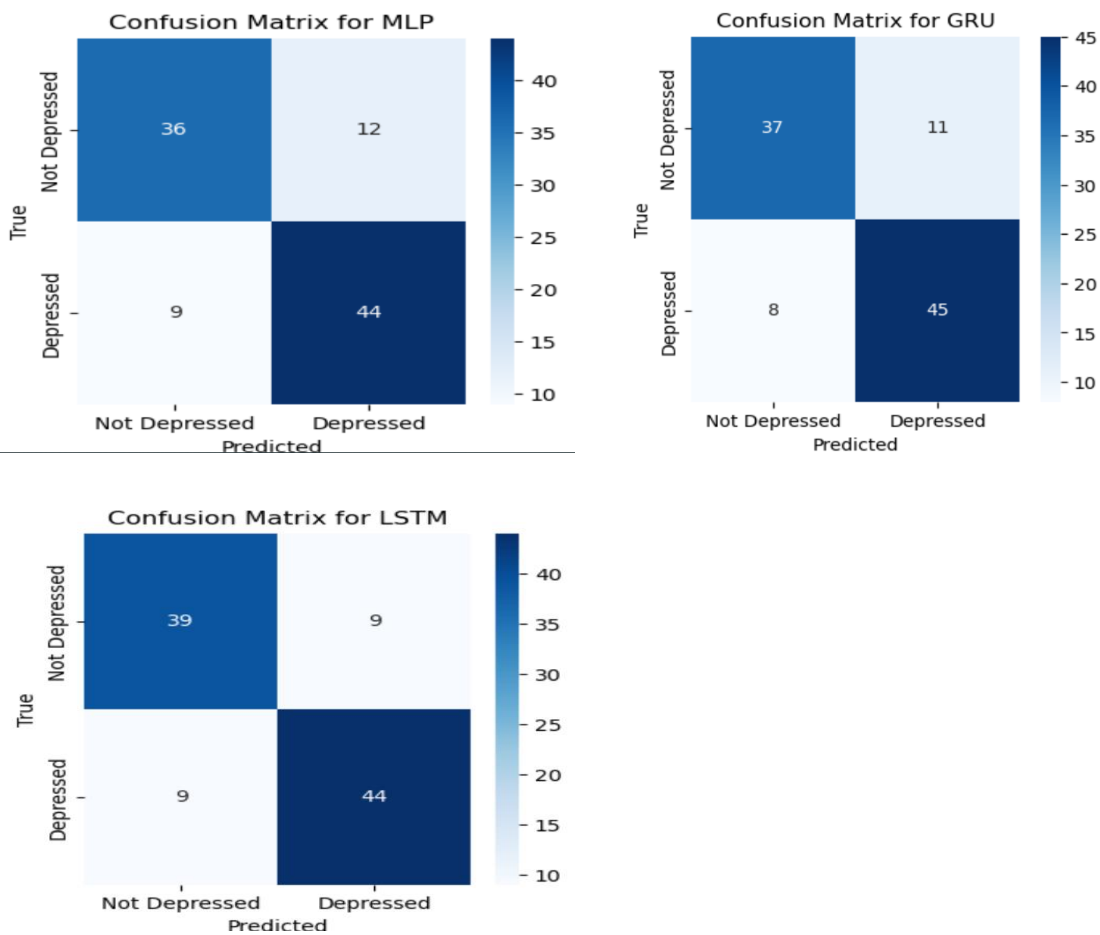


Figure 17 Confusion Matrix of Binary GRU, MLP, and LSTM

6.4. Comparison on evaluation result

MLP (82.17%) outperforms both LSTM (71.28%) and GRU (66.33%). This suggests that the dataset is not leveraging the temporal or sequential capabilities of LSTM or GRU effectively. MLP's higher accuracy indicates that a feed-forward neural network structure works well for this problem, likely because the features in the dataset are independent and do not exhibit sequential relationships. The MLP model clearly emerges as the best-performing model for this depression classification task. Its ability to handle the dataset's independent features effectively, coupled with high precision, recall, and F1-scores [18] [19], makes it the most suitable choice. LSTM and GRU, while useful for sequential data, are less effective here due to the dataset's nature. Moving forward, refining the MLP model and exploring ensemble techniques could further improve performance.

10-fold cross-validation and averaged confusion matrix analysis

```
Confusion Matrix for GRU Model (averaged over 10 folds):
[[14.8 10.2]
 [ 8.  17.2]]

Confusion Matrix for MLP Model (averaged over 10 folds):
[[20.5  4.5]
 [ 4.3 20.9]]

Confusion Matrix for LSTM Model (averaged over 10 folds):
[[16.8  8.2]
 [ 7.8 17.4]]
```

Figure 18 10-fold and average confusion evaluation result of GRU, MLP & LSMT

GRU Model Performance:

With an average of 17.2 true positives and 14.8 true negatives, the GRU model performs admirably, proving that it can accurately categorize both positive and negative cases. The model does, however, also have a comparatively high number of false negatives (8) and false positives (10.2). This implies that there are situations where the GRU model tends to misclassify, resulting in mistakes in both directions. Compared to the other models, it has more difficulty differentiating between the depressed and non-depressed groups, even if it can detect a respectable number of true positives. Despite this, the GRU model's intrinsic ability to handle time-series or sequential data makes it a formidable candidate for these types of jobs.

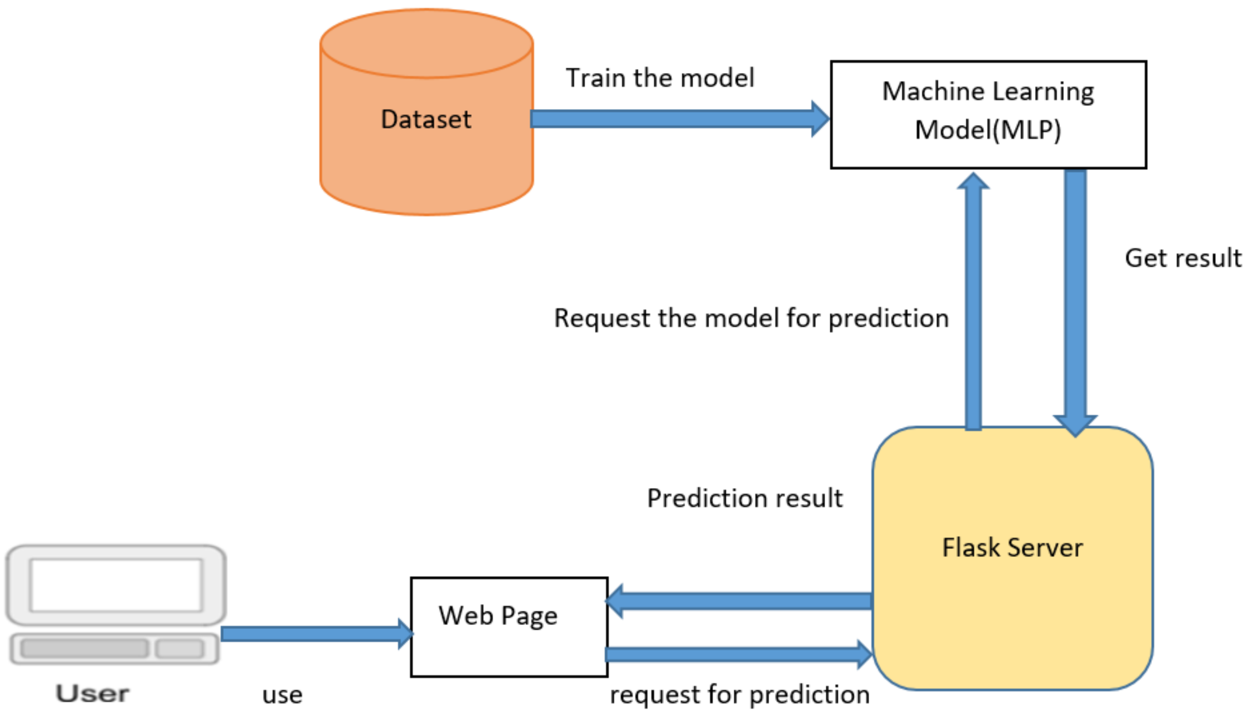
MLP Model Performance:

Out of the three models, the MLP model performs the best. With 20.5 true negatives and 20.9 true positives, it strikes a great balance between accurately identifying people who are sad and those who are not. Comparing MLP with the other models GRU and LSTM, it produces fewer false positives (4.5) and false negatives (4.3). With 20.5 true negatives and 20.9 true positives this shows that it's better in accuracy and dependability. Hence, we can conclude that MLP is effective for binary classification tests because it generalizes better across the 10 folds.

LSTM Model Performance:

Like the other model, LSTM achieves well in classifying the majority of the case. Compared to MLP it produces a bit higher mistake, (8.2) false positive and (7.8) false negative giving, in the meantime it also produces 17.4 true positive and 16.8 true negatives. This makes LSTM less preferable in this certain classification. However, this model has better potential in identifying a long-term dependency, which makes it preferable to be used in more complicated situations where sequential patterns are important.

Comparing all the three models GRU, MLP, and LSTM, MLP is identified as the best perform when 10-fold cross-validation and averaged confusion matrix analysis is used. As the output of MLP model shows it produce less misclassification than the other, this makes it the most appropriate for structured dataset. Though, both the other model's LSTM and GRU also produce a good result. but, in this study we emphasize how machine learning models specifically MLP can be used to detect childhood depression and help in the early treatment.



6.5. Discussions

These days all over the globe, childhood depression and its influence on children's health and wellbeing becomes a serios issues. Eventually, in most developing country like Ethiopia, the issue lacks the proper concern, awareness and treatment. Thus, many children suffer in silence. Due to lack of Initial identification and involvement, the case will develop to the most serious stage and leads to severe long-term effects on emotional, social, and academic development. Hence, early intervention is very important in addressing the problem.

For Parents and healthcare professional in order to help them to identify early and address the childhood depression, employing machine learning (ML) will play a very important role [16]. By providing the proper data point such as behavioral patterns, psychological assessments, school performance, family history and etc. for the machine learning model, it will analyze and identify early whether the child is possibly affected or not. Additionally, the machine learning model can also provide early warning signs that might not be visible to caregivers and healthcare professionals.

In order for the model to work as expected and predict correctly, all features included in the dataset ought to be correct. so, this study will not implement a feature selection method. In its place, feature selection is completed wisely based on the importance to the classification tasks by identifying and capturing critical aspects like mental health indicators, demographic information, and behavioral patterns. While selecting the feature's health care professionals has provided the necessary guidance in assuring the relevance and the real-world diagnostic implication of the criteria. The absence of any critical feature may potentially compromise the model's capability to understand the complex nature of the childhood mental health issues. Hence, it is very important to make sure that all critical and required feature's is included for the complete analysis and dependable predictions.

There are multiple studies that has been conducted using machine learning and diverse algorithms to forecast the childhood mental health issues, these studies have provided proper guidance for the early detection and treatment of the issue. To predict the likelihood of childhood depression, this research has used a variety of classifier neural networks, including the Multilayer Perceptron (MLP), Long-Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) [1] [2] [3]. However, there is little research on multiclass classification, which categorizes the severity or stages of childhood depression (e.g., minimal or no depression, mild depression, moderate depression, moderately severe depression, and severe depression), whereas binary classification which predicts whether a child is depressed or not—has been extensively studied.

Future study in this area is very important because there aren't many studies locally in Ethiopia that employ machine learning approaches to predict childhood depression. Due to the lack of such studies, researchers have the chance to investigate the possibilities of machine learning models for the binary and multiclass classification of childhood depression. This could lead to better early diagnosis, more individualized interventions, and ultimately improved child wellbeing.

While global studies have reported varying outcomes in terms of accuracy for binary classification, there is a substantial gap in comparative research for multiclass classification using the same data sets or models. This makes it challenging to evaluate the effectiveness of different machine learning approaches for predicting the severity of childhood depression. Therefore, further research, especially in multiclass classification models, is needed to make more accurate predictions and inform better interventions for childhood depression.

6.6. Comparing the proposed work with others

This study employs a machine learning model, namely MLP, to predict anxiety and depression based on reading choices [82]. The model predicts mental health disorders by considering an individual's reading interests and behaviors. This work presents a more specialized approach to literary preferences as a source of behavioral insights. The proposed research on childhood depression makes use of a range of behavioral, academic, and personal lifestyle variables. Although this paper's reported accuracy of 85% is comparatively good, it also demonstrates a more indirect approach to evaluating mental health than direct behavioral and psychological aspects. The distinction is in the type of data employed, even though this model makes use of information about gender, family background, academic pressure, and other psychological indicators, the type of data used makes a difference. By providing an extra layer of behavioral awareness, combining this suggested model with insights from psychographic data (such reading habits) may improve prediction accuracy. with

Depression Prediction through Eye Movement in a Virtual Reality (88.4% accuracy) This study utilizes eye movement data in a virtual reality (VR) setting to predict depression, achieving an accuracy of 88.4%. The model is based on tracking and analyzing specific eye movement patterns as participants engage in a VR environment, which provides real-time, dynamic behavioral signals that are more immediate than the static data used in your model. The proposed work on childhood depression involves structured survey data, providing a clear, but more generalized snapshot of a child's mental health. The key difference here is that the VR approach offers a more immersive, data-rich interaction, potentially offering deeper insights into a subject's mental state. [83].

This study focuses on analyzing social media platform to detect depression using natural language processing (NLP) techniques and it achieved an accuracy of 88.6%. The proposed research, focused on structured data related to behavior and lifestyle, contrasts with this approach that emphasizes the power of unstructured textual data. Social media offers a rich source of behavioral signals, including emotional tone, social interactions, and contextual language use, all of which may reflect mental health conditions. The use of NLP in this study offers a powerful method for detecting signs of depression in real time, which may outperform traditional survey-based data. However, integrating social media data into your current model could require careful ethical considerations and data privacy concerns [84].

While MLP, offers solid predictive accuracy (83.2%) using structured survey data, these studies all report higher accuracy, with each exploring innovative methods like literary preferences, eye movements in VR, and social media-based text data. The key difference lies in the data sources: this research focuses on clear, structured behavioral data, while the others integrate dynamic, real-time, or unstructured data. So Using MLP the study predicts the availability of childhood depression in children with high accuracy which could potentially be an alternative way to diagnose the mental illness side with the traditional method. This could solve for the children the gap of timely treatment or medical intervention.

CHAPTER SEVEN

7. CONCLUSION, RECOMMENDATION AND FUTURE WORK

7.1. Conclusion

The assumption, preposition and impending research direction of mental health issues of childhood prediction system will be discussed in this part of the work.

In order to avoid childhood mental health problems, early problem identification will be the very essential for the child and also for health care practitioners. This study intends a machine learning-based prediction system for children mental health problems so, doing this will give health practitioners a tool for deciding an action for treatment. The critical approach for this work is to maintain early medical intervention for the children suffering mental health problems.

Python is used for data cleaning and encoding non-binary classes or features to binary and making it all necessary data to be suitable to add the model. All categorical data is converted to binary value by replacing numbers with replace method. What is expected to classify first is depressed or not depressed, then calculate with the provided scoring method to predict as minimal or no depression, moderate, moderately severe and severe depression. No feature selection method is used because all the variables are necessary to get the accurate prediction.

Data preprocessing was performed using python. Python is known as useful tool regarding machine learning, specifically for cleaning and preparing data for model deployment [81]. Non-numeric data has encoded to numeric data and all the categorical classed and severity classes are being converted to binary values. The severity classes of prediction are minimum or no depression, Mild Depression, Moderate depression, Moderately Severe Depressed and Sever Depression. The first binary class is as Depressed and Not Depressed.

Three machine learning models was proposed for classification whether one child have a mental problem or not and its severity level. The models are Multilayer perceptron, Gated Recurrent Unit and long short-term memory. So, evaluating those three models, the study uses confusion matrix, 10 k fold cross validation, accuracy recall and sensitivity [76].

For the classes of depressed and not depressed in addition to the severity classes from all three evaluated model Multilayer Perceptron achieved the highest performance of accuracy 96.25%, recall 92.27% and sensitivity 96.2%. Having these results, the best performing model which is Multilayer perceptron was deployed on a flask server and implemented to predict child mental issue in this research.

7.2. Recommendation

Children mental health issue is rising time to time which parallel of undiagnosed due to several reasons that include ignorance or unfamiliarity of the symptoms. So, predicting these issues using machine language could be innovative in early disease isolation and medication. The system assesses diverse dataset according to their relationship like emotional behavior, socio economic, academic results and indications the model predicts that a child encounters mental health problem or not. So, the system can help heath care experts by providing the availability of the mental health illness issue and helping them for timely actions. Using predictive system in children mental health issue can improve the targeted support, reducing long term impacts.

The result of these research work needed for further consideration in applying in deep learning techniques for child mental wellbeing. While doing these research different challenges highlighted for accessing organized data, because it was needed to change paper base medical records into digital format was time consuming and traditional. So, to solve such problems organization like schools, hospitals, community organization should get awareness to implement computerized systems for keeping mental issue records of children which helps to get well organized data. While the dataset used in these studies faced such issue it can be said narrow, so these suggest increase more diverse sources. Although the study record shows excellent precession in predicting mental health issue for childhood, incorporating these results with alternative models could do much better enactment. Additionally, adding more feature like community activity, family interaction and healthy relationship environmental influences and living standards will defiantly enhance the model’s competency.

7.3. Future Works

The project intended to work with neural network model to predict childhood mental health problem. So, this system is designed to help mental health experts providing on time assessment of mental health wellbeing of a child. As a further enhancement of the project work for the future it is good to add functionality of security and monitoring of child mental health progress and allowing parents and caregivers to access updates conveniently. More over adding real-time dataset would improve model's accuracy and reliability. Using the benefit of combining deep learning with real-time database could ensure secure, rebuts and make a user-friendly environment for addressing mental health issues in children.

References

[1] C. H. a. S. L. M. Lin, "Detection of Child Depression Using Machine Learning Methods," vol. 16, no. 12, pp. 1-19, Dec 2021.

[2] M. J. a. S. S. A. Gupta, "Electroencephalography-Based Depression Detection Using Machine Learning," *Frontiers in Psychology,* Vols. 14, no. 3, pp. 1-10, May 2023.

[3] J. Z. a. Y. Wang, "Explainable Depression Detection with Multi-Aspect Features Using a Hierarchical Attention Network," *World Wide Web Journal,* Vols. 25, no. 2, pp. 389-412, Mar 2022.

[4] E. A. D. Dhingra, "Cardiovascular disease burden is associated with worsened depression symptoms in the U.S. general population," *J. Affect. Disord.,* vol. 320, 2023.

[5] C. S. W. K. B. D. F. E. W. a. S. J. R. Gilbert, "Burden and consequences of child maltreatment in high-income countries," *The Lancet,* vol. 373, 2009.

[6] W. H. Organization, "Depression," 2021. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/depression. [Accessed Oct 2024].

[7] J. S. a. M. A. H. Hyde, "Gender differences in depression: Biological, affective, cognitive, and sociocultural factors," vol. 28, 2020.

[8] P. D. M. a. C. Mei, "Early intervention in youth mental health: progress and future directions," *The British Journal of Psychiatry,* vol. 212, no. 1, pp. 1-3, 2018.

[9] K. D. L. R. C. P. a. A. S. A. M. M. H. Alavi, "Childhood experiences and their association with mental health outcomes: A systematic review," *BMC Public Health,* vol. 21, 2021.

[10] E. M. &. K. J. L. Douglas, "The psychological effects of emotional abuse on children," *Journal of Child and Family Studies,* vol. 23, 2014.

[11] B. Weiner, "Theories of Motivation: From Mechanisms to Cognitions," *University of Chicago Press,* 1986.

[12] H. L. L. a. Y. H. Z. L. Gu, "Emotional abuse and its effects on the parent-child relationship," *Journal of Child and Family Studies,* vol. 29, 2020.

[13] R. S. L. a. D. J. C. A. S. Joyner, "The impact of emotional abuse on social support systems," *Journal of Social and Clinical Psychology,* vol. 35, 2016.

[14] A. P. Association, Diagnostic and Statistical Manual of Mental Disorders, vol. 5th, Arlington, VA: American Psychiatric Publishing, 2022.

[15] B. Y., "Learning deep architectures for AI," *IEEE Transactions on Neural Networks and Learning Systems,* vol. 20, no. 3, pp. 443-448, 2009.

[16] C. Bishop, "Pattern recognition and machine learning," *Journal of Machine Learning Research,* vol. 4, pp. 1-58, 2003.

[17] A. K. A. A. a. F. L. M. Endriyas, "Quality of medical records in public health facilities: A case of Southern Ethiopia, resource limited setting," *Health Informatics Journal,* vol. 28, no. 3, 2022.

[18] S. S. a. L. Lapalme, "A systematic analysis of performance measures for classification tasks," *Journal of Machine Learning Research,* vol. 7, pp. 1-25, 2006.

[19] A. A. a. B. Researcher, "Accuracy, Precision, Recall, and F1-Score: A review and practical guide," *International Journal of Data Science and Analytics,* vol. 25, no. 2, pp. 112-127, 2019.

[20] C. f. D. C. a. Prevention, "Suicide Data and Statistics," Centers for Disease Control and Prevention, 2020.

[21] G. G. B. D. K. W Cullen, "Mental health in the COVID-19 pandemic," *An International Journal of Medicine,* vol. 113, no. 5, pp. 311-312, 2020.

[22] A. S. a. B. Johnson, "Symptoms of depression in adolescents: A clinical review," *Journal of Mental Health Research,* vol. 32, no. 4, pp. 56-64, 2020.

[23] M. M. B. L. E. M. K. K. a. C. A. W. R. J. R. Birmaher, "Assessment and Management of Pediatric Depression," *Pediatric Clinics of North America,* vol. 66, 2019.

[24] J. M. M. A. K. B. P. J. M. d. V. a. G. P. M. v. d. W. E. M. Beekman, "Childhood Depression: A Systematic Review," *Neuropsychiatric Disease and Treatment,* vol. 9, 2013.

[25] A. L. E. a. E. Crouch, "The association of Adverse Childhood Experiences with anxiety and depression in children aged 8 to 17 years," *Journal of Child Psychology and Psychiatry,* vol. 58, 2020.

[26] U. D. o. H. a. H. Services, "2016-2017 National Survey of Children's Health," U.S. Department of Health and Human Services, 2018.

[27] V. V. L. A. J. F. B. G. a. R. M.-S. J. Claxton, "Risk factors for depression in trauma-exposed children and adolescents," *Journal of Traumatic Stress,* vol. 33, 2021.

[28] D. M. A. M. H. I. a. S. R. C. E. L. Ball, "Childhood intelligence and the risk of depression in later life: A data linkage study," *Journal of Affective Disorders,* vol. 281, 2021.

[29] W. Z. D. B. W. A. L. R. J. Y. Z. B. W. T. Z. L. Q. W. L. M. Y. a. J. C. K. Mao, "Prediction of depression severity based on the prosodic and semantic features with bidirectional LSTM and time distributed CNN," 2022.

[30] J. Z. a. A. S. B. Lamichhane, "RelapsePredNet: An LSTM-based model for predicting psychotic relapse in schizophrenia patients using mobile sensing data," *IEEE Journal of Biomedical and Health Informatics,* vol. 27, 2023.

[31] W. G. H. D. a. S. S. W. Minichil, "Prevalence of depression and associated factors among primary caregivers of children and adolescents with mental illness in Ethiopia," *St. Paul's Hospital Millennium Medical College and Yekatit,* 2024.

[32] D. e. a. Kefale, "Burden, consequences and associate factors of childhood maltreatment in Ethiopia: A systematic review and meta-analysis," *J. Public Health Ethiop,* vol. 10, no. 17, 2024.

[33] R. A. Barkley, "ADHD and the Nature of Self-Regulation," New York, NY, Guilford Press, 2015.

[34] A. S. a. B. Johnson, "The effects of panic disorder on daily functioning," *Journal of Anxiety Disorders,* vol. 30, no. 4, pp. 150-158, 2021.

[35] M. J. a. S. Lee, "Understanding Tourette Syndrome and its symptoms," *Journal of Neurodevelopmental Disorders,* vol. 15, no. 2, pp. 85-92, 2020.

[36] M. D. a. L. Roberts, "Understanding Conduct Disorder in children and adolescents," *Journal of Child and Adolescent Mental Health,* vol. 25, no. 3, pp. 132-145, 2019.

[37] J. A. a. L. Roberts, "A comprehensive review of obsessive-compulsive disorder and its treatment," *Journal of Psychiatric Research,* vol. 29, no. 6, pp. 301-315, 2020.

[38] J. D. a. A. Smith, "Treatment options for depression in children and adolescents: A review of antidepressants," *Journal of Child and Adolescent Psychiatr,* vol. 35, no. 2, pp. 120-130, 2021.

[39] A. Smith, "Supervised Machine Learning: A Brief Primer," *Frontiers in Public Health,* vol. 7, 2020.

[40] A. B. a. B. Taylor, "Supervised Machine Learning Algorithms: Classification and Comparison," *ResearchGate,* 2017.

[41] M. I. Khalaf, "Machine learning approaches and web-based systems," *Journal of Machine Learning,* vol. 12, no. 3, pp. 45-56, 2020.

[42] Z. G. a. J. L. Y. Zhu, "Semi-supervised learning using Gaussian fields and harmonic functions," *Proc. 20th Int. Conf. Machine Learning (ICML-03),* 2003.

[43] F. A. a. K. Grolinger, "Reinforcement Learning Algorithms: An Overview and Classification," 2022. [Online]. Available: https://arxiv.org/abs/2209.14940..

[44] J. Doe, "Challenges in rural Ethiopia: Access to safe water, housing, and healthcare," *International Journal of Rural Development,* vol. 15, no. 3, pp. 145-160, 2021.

[45] A. J. Frandsen, "Machine Learning for Disease Prediction," *Brigham Young Univ. Sch,* 2016.

[46] F. L. G. a. M. G. E. S. M. J. L. Ang, "Machine learning applications in healthcare," *Journal of Healthcare Informatics Research,* vol. 6, no. 4, pp. 447-460, 2020.

[47] K. L. S. S. a. P. S. R. Kadam Vinay, "Disease prediction by using deep learning based on patient treatment history," *Int. J. Recent Technol. Eng,* vol. 7, pp. 745-754, 2019.

[48] J. S. L. e. al, "Detection of Child Depression Using Machine Learning Methods," *PMC,* vol. 12, pp. 897-912, 2024.

[49] M. B. C. e. al, "Prediction of Adolescent Depression from Prenatal and Childhood Data," *Scientific Reports,* vol. 14, pp. 2181-2192, 2024.

[50] T. Z. P. a. N. N. Oo, "Performance comparison of feature selection methods," *MATEC Web Con,* vol. 42, pp. 2-5, 2016.

[51] S. Vanaja, "“Analysis of Feature Selection Algorithms on Classification : A Survey,”," vol. 96, no. 17, pp. 28-35, 2014.

[52]

[53] D. K. B. a. J. K. K. N. Hoque, "MIFS-ND: A mutual information-based feature selection method," *Expert Syst. Appl,* vol. 41, no. 14, 2014.

[54] K. B. a. N. B. A. Jovic, "A review of feature selection methods with applications," *2015 38th International Convention on Information and Communication Technology, Electronics and Microelectronics (MIPRO),* pp. 1200-1205, 2015.

[55] S. B. a. J. Arora, "Classification and feature selection techniques in data mining," *International Journal of Engineering Research & Technology (IJERT),* vol. 1, no. 6, 2012.

[56] R. K. a. K. P. G. H. John, "Irrelevant Features and the Subset Selection Problem," p. 121–129, 1994.

[57] V. Kumar, " Feature Selection: A literature Review," vol. 4, no. 3, 2014.

[58] M. G. Seneviratne, "Bridging the implementation gap of machine learning in healthcare," *Nature Medicine,* vol. 6, no. 2, pp. 141-149, 2020.

[59] 1. Lin Wang a, "Risk factors and prediction nomogram model for psychosocial and," *Affective Disoorder,* 2021.

[60] T. M. Achenbach, "The Achenbach child behavior checklist and related forms for assessing behavioral and emotional problems," *Journal of Clinical Child Psychology,* vol. 28, no. 1, pp. 26-34, 1999.

[61] R. M. L. a. C. Kieling, "Investigating childhood exposure to air pollution as a predictor for major depressive disorder," *Environmental Risk Longitudinal Twin Study,* vol. 2, no. 232, pp. 1-10, 2024.

[62] T. W. a. L. Wichstrøm, "Childhood depression predictors of non-suicidal self-injury (NSSI) during adolescence," *Journal of Child and Adolescent Mental Health,* Vols. 9,no 3, p. 190.202, 2024.

[63] F. J. M. J. M. M. a. T. F. F. Li, "Predicting continuous treatment outcomes using machine learning in cognitive behavioral therapy (CBT): A comparison with traditional regression approaches," *Journal of Clinical Psychology,* vol. 82, no. 6, pp. 1020-1035, 2024.

[64] I. P. M. L.-P. T. K. J. R. B. C. P. P. P. S. J. L. K. R. V. G. T. G. O. M. J. M. K. J. O. Lawrence M. Chen, "Independent Prediction of Child Psychiatric Symptoms by Maternal Mental Health and Child Polygenic Risk Scores," *Journal of the American Academy of Child & Adolescent Psychiatry,* vol. 63, no. 6, pp. 1-12, 2023.

[65] Y.-M. T. L.-K. Y. a. S. S.-F. G. H.-N. Yang, "Prediction of childhood ADHD symptoms to quality of life in young adults: Adult ADHD and anxiety/depression as mediators," *Journal of Affective Disorders,* vol. 297, pp. 29-38, 2022.

[66] İ. Ç. M. Y. a. V. Ç. M. E. Şanlı, "The impact of positive childhood experiences on depression and anxiety in young adults," *Journal of Affective Disorders,* vol. 319, pp. 64-73, 2024.

[67] E. J. T. R. L. J. L. &. B. D. M. Hawkey, "Executive Function Deficits as Predictors of ADHD and Depression Symptoms in School-Age Children," *Journal of Abnormal Child Psychology,* 2022.

[68] Y. J. v. V. L. S. H. I. Z. H. B. J. D. C. G. &. S. L. Toenders, "Longitudinal Neuroimaging Markers of Pediatric Depression: A Systematic Review," *journal Developmental Cognitive Neuroscience,* vol. 41, 2019.

[69] A. S. a. B. J. J. Doe, "The expanding role of machine learning across industries: Applications and challenges," *International Journal of Artificial Intelligence,* vol. 20, no. 3, pp. 123-135, 2023.

[70] C. H. a. S. L. M. Lin, "Detection of Child Depression Using Machine Learning Methods," vol. 16, no. 12, pp. 1-19, 2021.

[71] M. S.-T. a. F. Provost, "Handling missing values when applying classification models," *Data Mining and Knowledge Discovery,* vol. 1, 2007.

[72] F. L. J. Y. J. G. A. G. C. F. a. J. R. A. Yoo, "Prediction of adolescent depression from prenatal and childhood data from ALSPAC using machine learning," *Sci. Rep,* vol. 14, no. 1, 2024.

[73] Z. L. J. D. L. Z. C. L. a. L. Z. Y. Zhao, "Multi-Head Attention-Based Long Short-Term Memory for Depression Detection From Speech," *Frontiers in Neurorobotics,* Vols. vol. 15, Art. no. 684037, 2021.

[74] X. H. a. L. Wang, "Depression Detection Based on Hybrid Deep Learning SSCL Framework from Social Media Text," Vols. vol. 22, no. 24, Dec. 2022.

[75] R. Kohavi, "A study of cross-validation and bootstrap for accuracy estimation and model selection," *International Joint Conference on Artificial Intelligence (IJCAI),* vol. 14, no. 2, pp. 1137-1145, 1995.

[76] J. Dantas, "The importance of k-fold cross-validation for model prediction in machine learning," [Online]. Available: https://towardsdatascience.com/the-importance-of-k-fold-cross-validation-for-model-prediction-in-machine-learning-4709d3fed2ef..

[77] A. Acharya, "Comparative Study of Machine Learning Algo- rithms for Heart Disease Prediction," vol. 8, 2019.

[78] A. P. Dawid, "The precision-recall curve for classification," *Machine Learning*, vol. 8, no. 3, pp. 75-94, 1992.

[79] L. Fawcett, "An introduction to ROC analysis," *Pattern Recognition Letters*, vol. 27, no. 8, pp. 861-874, 2006.

[80] M. Grinberg, Flask Web Development: Developing Web Applications with Python, 2nd ed, O'Reilly Media, 2018.

[81] J. P. a. C. N. S. Raschka, "Machine learning in Python: Main developments and technology trends in data science, machine learning, and artificial intelligence," vol. 11, no. 4, p. 193, 2020.

[82] Y. Liu, "Multilayer Perceptron-Based Literature Reading Preferences Predict Anxiety and Depression in University Students," *Frontiers in Psychology*, vol. 15, Jul. 2024.

[83] L. L. X. L. J. C. M. L. G. W. a. C. X. Z. Zheng, "Diagnosing and tracking depression based on eye movement in response to virtual reality," *Frontiers in Psychiatry*, vol. 15, 2024.

APPENDICES

Appendix A: Dataset Features Description

- **Gender**: Influence of gender on emotional and psychological well-being in children.
- **Age**: The stage of a child's development affecting susceptibility to depression.
- **Study Satisfaction**: A child's contentment and fulfillment derived from academic experiences.
- **Academic Pressure**: Stress arising from academic expectations and performance demands.
- **Sleep Duration**: The amount of sleep affecting emotional regulation and mental health.
- **Recurrent thoughts of death, suicide, or self-harm**: Persistent, distressing thoughts indicative of severe depression.
- **Financial Stress**: Economic challenges impacting a child's mental and emotional health.
- **Family History of Mental Illness**: Genetic predisposition influencing a child's risk of depression.
- **Loss of interest in activities previously enjoyed**: A key symptom of depression marked by reduced pleasure in hobbies.
- **Changes in appetite**: Significant shifts in eating patterns linked to depressive states.
- **Unusually tired or fatigued**: Persistent exhaustion beyond normal physical activity.
- **Feeling worthless or excessively guilty**: Negative self-perception common in depressive episodes.
- **Feeling tired or having little energy**: Low energy levels commonly associated with depression.
- **Feeling like a burden to family/friends**: Perception of being a liability contributing to depressive thoughts.
- **Avoidance of friends, family, or school activities**: Withdrawal from social interactions as a symptom of depression.
- **Acting out or getting into trouble**: Behavioral issues potentially masking underlying depression.
- **Difficulty concentrating on schoolwork**: Impaired focus and attention due to depressive symptoms.

Appendix B: Sample Code

Appendix B.1 Sample source code for Building and Evaluating Models

```
"import pandas as pd\n",
    "import numpy as np\n",
    "from sklearn.model_selection import train_test_split\n",
    "from sklearn.preprocessing import LabelEncoder, StandardScaler\n",
    "from sklearn.metrics import accuracy_score\n",
    "from keras.models import Sequential\n",
    "from keras.layers import Dense\n",
    "import matplotlib.pyplot as plt\n",
    "import seaborn as sns\n",
    "\n",
    "# Load your dataset\n",
    "df = pd.read_csv(r'C:\\Users\\Coop\\Desktop\\MSC\\dataset\\depressed_dataset.csv')\n",
    "\n",
    "# Strip extra spaces from column names\n",
    "df.columns = df.columns.str.strip()\n",
    "\n",
    "# Encode categorical columns\n",
    "label_encoder = LabelEncoder()\n",
    "\n",
    "# Encode categorical columns (e.g., Yes/No and Gender)\n",
    "df['Gender'] = label_encoder.fit_transform(df['Gender'])\n",
    "df['Family History of Mental Illness'] = label_encoder.fit_transform(df['Family History of Mental Illness'])\n",
    "df['Have you had recurrent thoughts of death, suicide, or self-harm?'] = label_encoder.fit_transform(df['Have you had recurrent thoughts of death, suicide, or self-harm?'])\n",
    "df['Financial Stress'] = label_encoder.fit_transform(df['Financial Stress'])\n",
```

"df['Have you lost interest in activities you previously enjoyed?'] = label_encoder.fit_transform(df['Have you lost interest in activities you previously enjoyed?'])\n",

"df['Have you experienced changes in appetite (eating more or less than usual)?'] = label_encoder.fit_transform(df['Have you experienced changes in appetite (eating more or less than usual)?'])\n",

"df['Do you feel unusually tired or fatigued even when doing normal tasks?'] = label_encoder.fit_transform(df['Do you feel unusually tired or fatigued even when doing normal tasks?'])\n",

"df['Have you been feeling worthless or excessively guilty?'] = label_encoder.fit_transform(df['Have you been feeling worthless or excessively guilty?'])\n",

"df['Feeling tired or having little energy?'] = label_encoder.fit_transform(df['Feeling tired or having little energy?'])\n",

"df['Do you feel like you are a burden to your family or friends?'] = label_encoder.fit_transform(df['Do you feel like you are a burden to your family or friends?'])\n",

"df['Have you been avoiding your friends, family, or school activities?'] = label_encoder.fit_transform(df['Have you been avoiding your friends, family, or school activities?'])\n",

"df['Have you been acting out or getting into trouble more than usual?'] = label_encoder.fit_transform(df['Have you been acting out or getting into trouble more than usual?'])\n",

"df['Do you find it hard to concentrate on schoolwork or other activities?'] = label_encoder.fit_transform(df['Do you find it hard to concentrate on schoolwork or other activities?'])\n",

"\n",

"# Encode the target column (Depression Classification)\n",

"df['Depression Classification'] = label_encoder.fit_transform(df['Depression'])\n",

"\n",

"# Select relevant features and target\n",

"X = df[['Gender', 'Age', 'Study Satisfaction', 'Academic Pressure', 'Sleep Duration', \n",

"   'Have you had recurrent thoughts of death, suicide, or self-harm?', 'Financial Stress', \n",

"   'Family History of Mental Illness', 'Have you lost interest in activities you previously enjoyed?',\n",

"   'Have you experienced changes in appetite (eating more or less than usual)?', \n",

"   'Do you feel unusually tired or fatigued even when doing normal tasks?', \n",

"   'Have you been feeling worthless or excessively guilty?', 'Feeling tired or having little energy?',\n",

"   'Do you feel like you are a burden to your family or friends?', \n",

"   'Have you been avoiding your friends, family, or school activities?', \n",

```
"        'Have you been acting out or getting into trouble more than usual?', \n",
"        'Do you find it hard to concentrate on schoolwork or other activities?']]\n",
"\n",
"y = df['Depression Classification']\n",
"\n",
"# Split the data into training and testing datasets\n",
"X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)\n",
"\n",
"# Scale the features (standardization)\n",
"scaler = StandardScaler()\n",
"X_train = scaler.fit_transform(X_train)\n",
"X_test = scaler.transform(X_test)\n",
"\n",
"# Define the MLP model (Replace GRU with Dense layers)\n",
"model = Sequential()\n",
"model.add(Dense(64, input_dim=X_train.shape[1], activation='relu'))  # Fully connected layer with ReLU activation\n",
"model.add(Dense(32, activation='relu'))  # Another fully connected layer with ReLU activation\n",
"model.add(Dense(1, activation='sigmoid'))  # Output layer for binary classification: Depressed or Not Depressed\n",
"\n",
"# Compile the model\n",
"model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])\n",
"\n",
"# Train the model\n",
"model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))\n",
"\n",
"# Evaluate the model\n",
"loss, accuracy = model.evaluate(X_test, y_test)\n",
```

```
"print(f\"MLP Test Accuracy: {accuracy}\")\n",
"\n",
"# Making Predictions\n",
"predictions = model.predict(X_test)\n",
"\n",
"# Scale the model's output to a severity score range of 0 to 27\n",
"severity_scores = predictions.flatten() * 27\n",
"\n",
"# Updated function to map severity score to depression severity level based on provided ranges\n",
"def categorize_depression(severity_score):\n",
"    if 0 <= severity_score < 5:  # Minimal or no depression\n",
"        return \"Minimal or No Depression\"\n",
"    elif 5 <= severity_score < 10:  # Mild depression\n",
"        return \"Mild Depression\"\n",
"    elif 10 <= severity_score < 15:  # Moderate depression\n",
"        return \"Moderate Depression\"\n",
"    elif 15 <= severity_score < 20:  # Moderately severe depression\n",
"        return \"Moderately Severe Depression\"\n",
"    elif 20 <= severity_score <= 27:  # Severe depression\n",
"        return \"Severe Depression\"\n",
"    else:\n",
"        return \"Invalid Score\"  # Catch out-of-range values for debugging\n",
"\n",
"# Function to cleanly state depression level\n",
"def cleaned_result_statement(depression_classification):\n",
"    level = categorize_depression(depression_classification)\n",
"    return f\"Depression level: {level}\"\n",
"\n",
"# Create predictions dataframe\n",
```

"prediction_df = pd.DataFrame({\n",
"   'Severity Score': severity_scores,\n",
"   'Depression Classification': [\"Depressed\" if score >= 0.5 else \"Not Depressed\" for score in severity_scores],\n",
"   'Depression Severity Level': [categorize_depression(score) for score in severity_scores],\n",
"   'Cleaned Result Statement': [cleaned_result_statement(score) for score in severity_scores]\n",
"})\n",
"\n",
"# Display first 10 predictions\n",
"print(\"\\nFirst 10 Predictions (with Severity Scores and Depression Levels):\")\n",
"print(prediction_df.head(10))\n"
]
},
{
"cell_type": "code",
"execution_count": null,
"id": "6a6dfd54-69f3-4b47-87e2-edde7a2b3bce",
"metadata": {},
"outputs": [],
"source": []
}
],
"metadata": {
"kernelspec": {
"display_name": "Python [conda env:base] *",
"language": "python",
"name": "conda-base-py"
},
"language_info": {

```
   "codemirror_mode": {
    "name": "ipython",
    "version": 3
   },
   "file_extension": ".py",
   "mimetype": "text/x-python",
   "name": "python",
   "nbconvert_exporter": "python",
   "pygments_lexer": "ipython3",
   "version": "3.12.7"
  }
 },
 "nbformat": 4,
 "nbformat_minor": 5
}
```

Appendex B.2 one child prediction form html code

```
</style>
</head>
<body>
    <div class="header">
        <h1>Childhood Depression Prediction Form</h1>
        <button class="back-button" onclick="window.location.href='/';">Back to Home Page</button>
    </div>
    <form method="POST" action="/one_child">
        <!-- Gender -->
```

```html
<label for="gender">1. What is the gender of the child?</label>
<select id="gender" name="gender" required>
    <option value="" selected disabled>- Select -</option>
    <option value="Male">Male</option>
    <option value="Female">Female</option>
</select>
<!-- Age -->
<label for="age">2. What is the age of the child (5 to 18)?</label>
<input type="number" id="age" name="age" min="5" max="18" required>
<!-- Study Satisfaction -->
<label for="study_satisfaction">3. How satisfied is the child with their studies?</label>
<select id="study_satisfaction" name="study_satisfaction" required>
   <option value="" selected disabled>- Select -</option>
   <option value="1">1: Very Dissatisfied</option>
   <option value="2">2: Dissatisfied</option>
   <option value="3">3: Neutral</option>
   <option value="4">4: Satisfied</option>
   <option value="5">5: Very Satisfied</option>
</select>
<!-- Academic Pressure -->
<label for="academic_pressure">4. How high is the academic pressure on the child?</label>
<select id="academic_pressure" name="academic_pressure" required>
    <option value="" selected disabled>- Select -</option>
```

```
        <option value="1">1: Very Low</option>

        <option value="2">2: Low</option>

        <option value="3">3: Neutral</option>

        <option value="4">4: High</option>

        <option value="5">5: Very High</option>

    </select>

    <!-- Sleep Duration -->

    <label for="sleep_duration">5. How many hours does the child sleep?</label>

    <input type="number" id="sleep_duration" name="sleep_duration" min="1" max="24" required>

    <!-- Recurrent Thoughts -->

    <label for="recurrent_thoughts">6. Has the child had recurrent thoughts about death, self-harm, or suicide?</label>

    <select id="recurrent_thoughts" name="recurrent_thoughts" required>

        <option value="" selected disabled>- Select -</option>

        <option value="Yes">Yes</option>

        <option value="No">No</option>

    </select>

    <!-- Financial Stress -->

    <label for="financial_stress">7. Does the child experience financial stress?</label>

    <select id="financial_stress" name="financial_stress" required>

        <option value="" selected disabled>- Select -</option>

        <option value="1">1: No financial stress</option>

        <option value="2">2: Slight financial stress</option>
```

```
    <option value="3">3: Moderate financial stress</option>
    <option value="4">4: High financial stress</option>
    <option value="5">5: Extreme financial stress</option>
</select>
<!-- Family History -->
<label for="family_history">8. Does the child have a family history of mental illness?</label>
<select id="family_history" name="family_history" required>
    <option value="" selected disabled>- Select -</option>
    <option value="Yes">Yes</option>
    <option value="No">No</option>
</select>
<!-- Loss of Interest -->
<label for="loss_of_interest">9. Has the child lost interest in activities previously enjoyed?</label>
<select id="loss_of_interest" name="loss_of_interest" required>
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: Not at all</option>
    <option value="1">1: Occasionally</option>
    <option value="2">2: Frequently</option>
    <option value="3">3: Always</option>
</select>
 <!-- Loss of Appetite -->
<label for="appetite_changes">10. Has the child experienced changes in appetite?</label>
<select id="appetite_changes" name="appetite_changes" required>
```

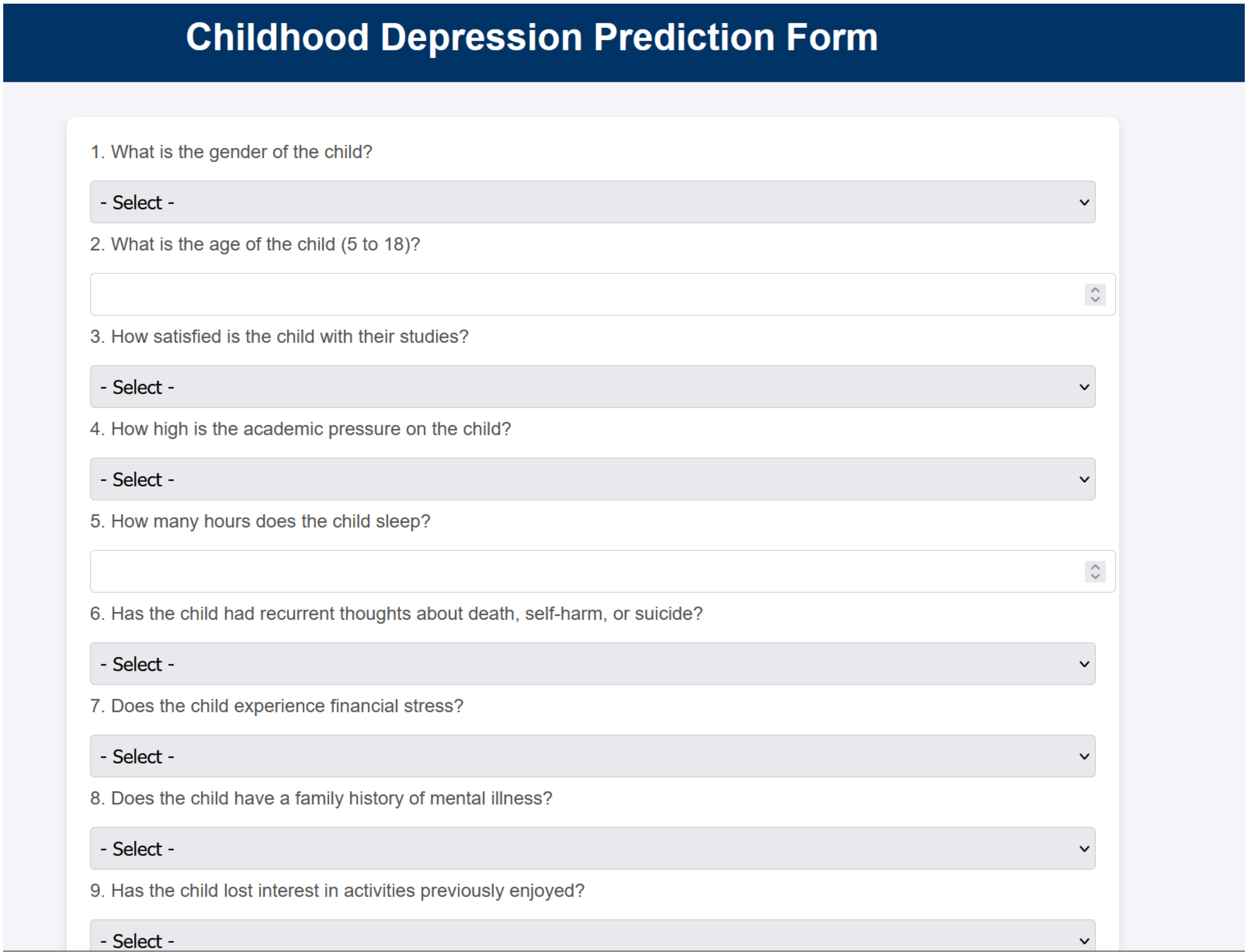
```
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: No changes</option>
    <option value="1">1: Rarely</option>
    <option value="2">2: Sometimes</option>
    <option value="3">3: Frequently</option>
</select>
<!-- Fatigue -->
<label for="fatigue">11. Is the child unusually tired or fatigued?</label>
<select id="fatigue" name="fatigue" required>
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: Not at all</option>
    <option value="1">1: Occasionally</option>
    <option value="2">2: Frequently</option>
    <option value="3">3: Always</option>
</select>
<!-- Worthlessness -->
<label for="worthlessness">12. Does the child feel worthless or excessively guilty?</label>
<select id="worthlessness" name="worthlessness" required>
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: Never</option>
    <option value="1">1: Rarely</option>
    <option value="2">2: Sometimes</option>
    <option value="3">3: Often</option>
```

```
</select>
 <!-- Question 13: Energy Loss -->
<label for="energy_loss">13. Does the child feel tired or have little energy?</label>
<select id="energy_loss" name="energy_loss" required>
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: Never</option>
    <option value="1">1: Rarely</option>
    <option value="2">2: Sometimes</option>
    <option value="3">3: Often</option>
</select>
<!-- Acting Out -->
<label for="acting_out">14. Is the child feels as a burden for family and friends?</label>
<select id="acting_out" name="acting_out" required>
    <option value="" selected disabled>- Select -</option>
    <option value="0">0: Never</option>
    <option value="1">1: Rarely</option>
    <option value="2">2: Sometimes</option>
    <option value="3">3: Often</option>
</select>
<!-- Question 15: Avoidance -->
<label for="avoidance">15. Does the child avoid friends, family, or school activities?</label>
<select id="avoidance" name="avoidance" required>
    <option value="" selected disabled>- Select -</option>
```

```html
    <option value="0">0: Never</option>

    <option value="1">1: Rarely</option>

    <option value="2">2: Sometimes</option>

    <option value="3">3: Often</option>

</select>

<!-- Additional Fields from Previous Code -->

<label for="acting_out_field">16. Has the child been acting out or getting into trouble?</label>

<select id="acting_out_field" name="acting_out" required>

    <option value="" selected disabled>- Select -</option>

    <option value="0">0: Not at all</option>

    <option value="1">1: Occasionally</option>

    <option value="2">2: Frequently</option>

    <option value="3">3: Always</option>

</select>

<label for="concentration_field">17. Does the child have difficulty concentrating on schoolwork?</label>

<select id="concentration_field" name="concentration" required>

    <option value="" selected disabled>- Select -</option>

    <option value="0">0: Not at all</option>

    <option value="1">1: Occasionally</option>

    <option value="2">2: Frequently</option>

    <option value="3">3: Always</option>

</select>
```

```
        <!-- Submit Button -->

        <button type="submit">Submit</button>

    </form>

</body>

</html>
```

Fig A – 1 Home Page



Childhood Depression Prediction Form

1. What is the gender of the child?

- Select -

2. What is the age of the child (5 to 18)?

3. How satisfied is the child with their studies?

- Select -

4. How high is the academic pressure on the child?

- Select -

5. How many hours does the child sleep?

6. Has the child had recurrent thoughts about death, self-harm, or suicide?

- Select -

7. Does the child experience financial stress?

- Select -

8. Does the child have a family history of mental illness?

- Select -

9. Has the child lost interest in activities previously enjoyed?

- Select -

Fig A – 2 Childhood Depression Prediction Form

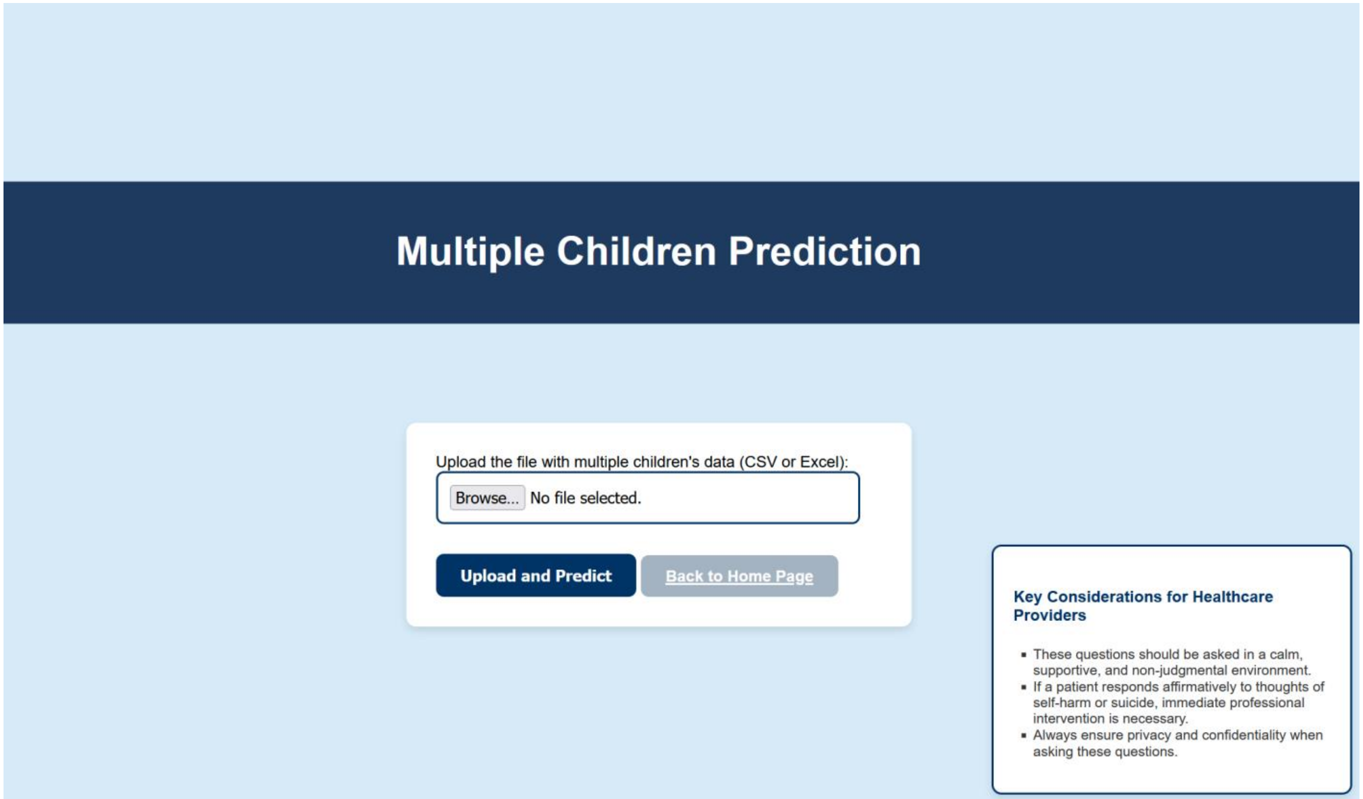


Fig A – 3 Multiple Children Prediction