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Leveraging AI for Mental Health Intervention: Detecting Depression in Youth and Adults

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Abstract:
The ubiquitous presence of modern technology and the pervasive influence of social media have dramatically reshaped how individuals interact and function globally. With mobile phone usage reported at of the time, digital platforms and emerging technologies are constantly evolving, presenting both beneficial and detrimental impacts on the public. While social media offers numerous positive effects, it is simultaneously associated with negative outcomes that affect the current state of mental health.

In response to the growing mental health crisis, particularly the risk of suicide, Machine Learning (ML) and Artificial Intelligence (AI) models are being deployed to detect depression in both youth and adults. The inherent strength of ML models lies in their capacity to learn from large-dimensional datasets, enabling them to identify complex, useful patterns within vast amounts of data to facilitate intelligent decision-making. This research is fundamentally motivated by the need to inform future studies and interventions aimed at comprehending the manifestation and impact of depression on the mental well-being of young people and adults.

Keywords- Social Media, Mental Health, Suicide, Machine Learning (ML), Artificial Intelligence (AI), Depression Detection, Youth Depression, Adult Depression, Large-dimensional Datasets, Intelligent Decision-making.

1. Introduction

Annual global statistics reveal a staggering public health crisis, with approximately 800,000 individuals dying by suicide each year. This makes suicide the fourth leading cause of death specifically among individuals aged 15–29 years, according to the World Health Organization (WHO). Furthermore, the underlying condition of depression can lead to significant physical and emotional problems that severely impair an individual's ability to work.

1.1 Depression

Depression is a remarkably common disorder, impacting over a million individuals globally. The American Psychiatric Association (APA) defines it as a significant and widespread medical condition that negatively affects a person's feelings and thought processes. Fortunately, major depression is treatable.

The disorder is a key contributing factor to suicide in both adolescents and the elderly. Those experiencing a late onset of depression face particularly complex risk factors. The global rise in depression has been further compounded by the COVID-19 epidemic, with the stress of the pandemic leading to increased rates of the disorder worldwide.

Beyond traditional stressors, social media significantly influences mental health. Individuals' minds are easily affected, leading to issues such as depression, anxiety, low self-confidence, sleeplessness, and general anxiety. Despite its high prevalence, depression is also associated with a high incidence

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of mortality rates and ranks among the most common disorders.The signs and symptoms of depression are descripted in the Figure 1

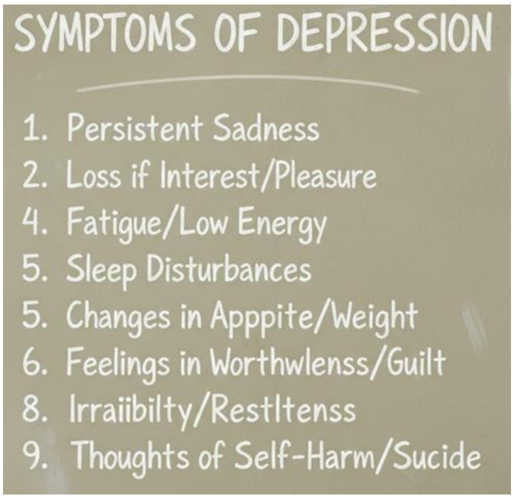

Figure 1. Signs and symptoms of depression

1.2 Cause of people Death

Depression encompasses a variety of clinical subtypes, which may include neurotic, dysthymia (or dysthymic), endogenous, melancholia (or melancholic), atypical, seasonal, psychotic, postpartum, and unipolar depression.

Functional disability and death can be rooted in conditions such as chronic obstructive pulmonary disease, liver sickness, neurologic illness, cancer, and chronic pain, impacting individuals across all races and genders. In the context of national health, Figure 2 highlights the ten leading causes of death in the United States in 2020. This data is compiled and released in a report by the National Centre for Disease Control and Prevention.

1	State	Sex	Race/Ethnicit	Age Group	First Year	Last Year	Rank	Cause of Death	Deaths
2	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	1	Unintentional I	15117
3	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	2	Homicide	6466
4	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	3	Suicide	6062
5	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	4	Malignant Neo	1306
6	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	5	Heart Disease	870
7	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	6	COVID-19	501
8	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	7	Congenital Ano	384
9	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	8	Diabetes Mellit	312
10	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	9	Chronic Low. R	220
11	United Sta	Both Sexe:	All Races,	15-24 yrs	2020	2020	10	Complicated Pr	191
12	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	1	Unintentional I	31315
13	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	2	Suicide	8454
14	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	3	Homicide	7125
15	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	4	Heart Disease	3984
16	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	5	Malignant Neo	3573
17	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	6	COVID-19	2254
18	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	7	Liver Disease	1631
19	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	8	Diabetes Mellit	1168
20	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	9	Cerebrovascula	600
21	United Sta	Both Sexe:	All Races,	25-34 yrs	2020	2020	10	Complicated Pr	594
22	United Sta	Both Sexe:	All Races,	35-44 yrs	2020	2020	1	Unintentional I	31057
23	United Sta	Both Sexe:	All Races,	35-44 yrs	2020	2020	2	Heart Disease	12177

Figure 2.The ten leading causes of death in the United States in 2020 for all races and both sexes.

1.3 Depression Prevention strategies

Preventing depression involves a multifaceted approach influenced by numerous factors. To effectively mitigate the risk in both men and women, it is crucial to ensure smooth maintenance of individual aspects, including attitude, knowledge, age, coping skills, and genetics.

Supportive social structures also play a vital role. Family members can contribute significantly by fostering good mental health and financial stability, which in turn helps reduce depressive tendencies. Furthermore, environmental factors are important, as a green environment and healthy food are known to improve mental health.

The pervasive influence of social media presents a nuanced challenge; it contains both beneficial and harmful information, meaning the likelihood of depression can fluctuate based on an individual's usage patterns. Lastly, community stressors like academic pressure can also be a direct cause of depression. Figure 3 details these various spheres of influence for avoiding depression in youth.

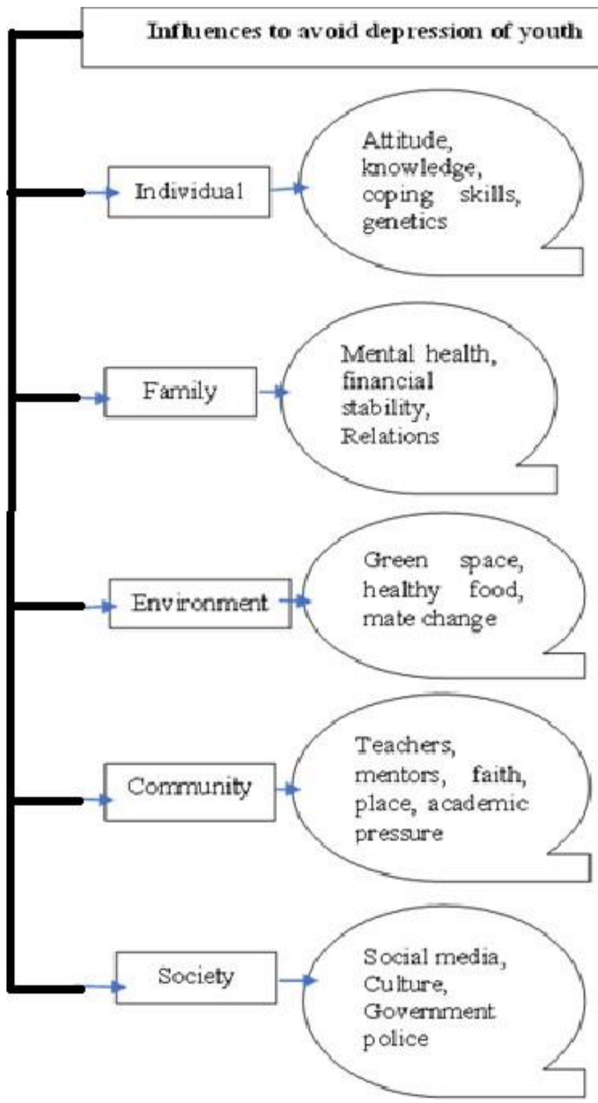

Figure 3 Factors influence to avoid the depression of youth

2. Related Works

Growth of hyperactivity disorder and depression in adolescents [1].Hence, depression risks creating cognitive emotions in the human being. The implicit and explicit degrees are used as self-report. Patients also investigate repeated maladaptive and little use of adaptive behaviours. This research focused on risk assessment and prevention approaches to depression. The Survey of mental health report [2] assessed the impact of expressive disorders on children and adolescents in Australia. The effect of individual mental disorders on work with family and friends in school and at work can indicate the severity of disorders. The 4–17 age groups of children had 8% of mild disorder and adolescents had 3% of moderate and 42% of severe disorder. This report provides information about service and support. Youth used various forms of support to deal with their behaviours and emotional issues. Sergio G et al. [3] employed machine learning algorithms such as Logistic Regression Classifiers (LOGREG), Support Vector Machines (SVM), Multinomial Nave Bays (MNB), and K-Nearest Neighbours (K-NN).Models are implemented using Python and use map and radius pattern techniques to detect anxiety and depression patterns in text processing. The algorithm SS3 provides 61% of F-measure and 63% of precision performance.

The author [4] focused on multi-parametric Remote Measurement Technologies (RMTs). It includes wearable devices and smartphone apps for symptom tracking. The author can provide a protocol to find depression symptoms and notifications with the help of technical as RMTs. Though smart phone data is collected by an app and a faith device. This scientific report [5] describes the impression of the COVID-19 sickness on cognitive conditions and indications. It provides information about the prevalence of suicidal thoughts and behaviours and mental health service access. This survey shows the pooled resultof data about data analyses, which contain a comparison with prevalence of pre-pandemic situations. The experiments are conducted by time series analysis of monthly movements in twenty onecountries. Depression is a general health problem due to intellectual difficulties. Kshirsagar et al. [6] investigated the unique model that can be analysed through deep learning methods with convolution neural networks. This model used more parameters for image emotion analysis to validate the performance of the classifier, and the model produced 74% of the results. This research used a hypothesis that a person with a depression measure value, which indicate the whether individuals are depressedor not depressed. But this approach has not been tested in high resolution photos.

Major depression and substance use disorders [7] cause suicidal behaviour in young people. Internationally, suicide is an example of a community health problem. The World Health Organization estimated 703 000 deaths by suicide annually in 2021 in the Americas by an increased rate of 17%. In the high-income country of Canada, 90% of young people will commit suicide in 2021.

Millions of citizens internationally suffer from depression. Evaluation, delighting, and avoiding recurrence requires near-term identification of symptoms of depression. This can be improved through machine learning. The proposed intelligent techniques to identify depression through long-term and short-term memory of recurrent neural networks with the TensorFlow deep learning tool. The depression and suicide dataset used for analysis is taken from the kaggle website. It classifies the depression and non-depression categories for a given depressed dataset. Depression influences the young and aged equally to somatic disease, and the association is mutual [8]. This study suggested that as white matter changes on MRI, it processes dysfunction. Exercise and nutrition ideas are motivated to avoid depression. The author suggested using electroconvulsive therapy to be safe for geriatric patients. This research recommends the electronic health record and Internet-based testing to analyse the depression of young and old people.

Suicides are commonly associated with depression, which occurs due to economic causes, social causes, and un-curable diseases. Various suicide prediction models have been developed [9]. Now a day who commit suicide of individual is significantly increased. The range of 35–54 years of age was fourth, and women age of 75 had the highest tendency to commit suicide. The number of suicides in Japan increased during the COVID-19 pandemic [10]. Preventive measures are essential, which are published by a national policy agency. The Granger Causality Test (GCT) and Vector AutoRegression (VAR) models are applied to predict the suicides. In this model not provides, information about which age people may commit suicide. versus the age at which they look for suicide-related in sequence may differ. But, Tablets, computers and smartphones are used for searching to identify mental health depression people [11-13] and describe the usage of Internet-based Depression Treatment and blended cognitive-behavioral therapy, different psychotherapies for treating depression. The behavioural activation for depression is to engage less in pleasant activities, which indications of increased depressed mood.

This review gives data about the model of social networking service (SNS) utilisation and its connection with SNS addiction among university students [14]. SNS and mental health status, consisting of nervousness and miserable symptoms. This study helps to reduce SNS addiction by conducting activities for cognitive-behavioural techniques. Cognitive behavioural therapy (CBT) is the gold standard of therapy treatment [15], which presents a chance for intellectual behavioural psychotherapists for remote areas through videoconferencing to help the patients. This research focuses on people with depression symptoms. Internet-based involvement assures improved access to cerebral physical condition care for a larger public people and in additional distant places. The authors [16] demonstrated the performance of the model for different mental treatments and depression prevention. The treatment standardisation of measurement time is a challenge in this model.

The aspects of pandemic and mental health present current evidence-based responses and recovery work internationally for health care providers and policy-makers [17-18]. In setting up and preserving a therapeutic alliance [19-21], which is essential to working together with the patient when making treatment decisions. Also, considering the patients' preferences is essential to avoid depression disorder. Suicide risk must be carefully assessed in all patients with major depressive disorder. This evaluation contains information about symptom identification, means, plans, common medical situations, and family history of suicide.

During COVID-19, maintaining the mental health of people needed some good actions. Pay attention to providing telecounselling remotely to frontline health-care workers and households affected by depression and anxiety. Substance use disorders, neurological conditions, and suicide risk are all examples of mental health conditions [22]. This survey reports that the worldwide economy loses an additional US$ 1 trillion per year due to depression and anxiety. Depression disturbs 264 million individuals in the world. The more common stages of symptoms of depression and anxiety have been found in several countries. In Ethiopia, an estimated 33% of symptoms, Canada 47%, China 50% and Pakistan 42% come from depression. Priority attention needs to be given to guarding and supporting the human rights of members of the public suffering from bad mental health conditions due to depression. Authors [23-25] described depression and psychological distress through a correlation between the psychological distress score and comorbidities.

For children, students, and staff, frequently gathering, analysing, and performing on data is a very vital role for academic requirements, health requirements, and mental health issues [26-37]. Hence, planning and implementation (student placements and hospitalization) regarding the need for guide lines to the people This research reports how to take decision making when depression is causing children, students, and staff in schools and universities. Connect data review to goals and outcomes.

Grade retention, climate surveys, school specialists, learning outcomes, and mental health services are all possible sources of data. Authors give recommendations for raising quires. It can be understood by Figure 4 through enhancing workforce capacity among the students.

Figure 4 motivating the students without depression

Md. Zia Uddin et al. investigated the framework using text mining with a recurrent neural network (RNN) of deep learning concepts to detect depression [38]. The concept of RNN is applied to time-sequential data. It contains recurrent connections between current state history and hidden states. For data visualisation purposes, linear discriminant analysis is applied.Lee et al. [39] acknowledged the unipolar and bipolar depression and Nero imaging subtypes are identified from the brain image features.

4. Outcome analysis

Umme et al.[40] conducted an analysis of depression in children aged 4–17 years using the Young Minds Matter (YMM) dataset. This analysis focused on family activities and socio-economic issues to detect depression and successfully achieved high precision.

The study utilized the Random Forest (RF) algorithm for classification. The RF method works by splitting the dataset into numerous subsets and applying a decision tree algorithm to each of these splits. The final prediction is determined through a voting mechanism among all the individual decision trees.

The performance of the RF algorithm was highly effective in identifying metal depression in patients, yielding a detection rate of in 10-fold cross-validation and in 5-fold cross-validation. The sequential flow of the RF algorithm and the statistical cross-validation results are illustrated in Figure 5 and Figure 6, respectively.

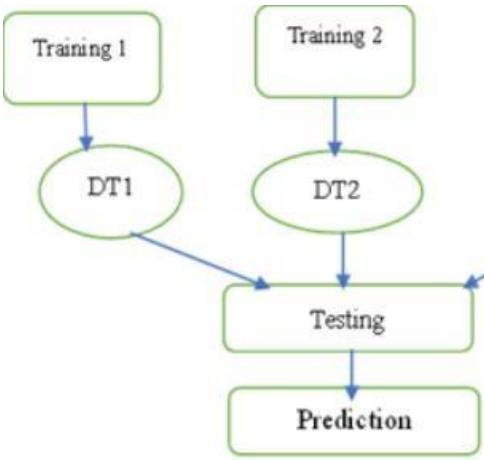

Figure 5 Flow of RF Algorithm

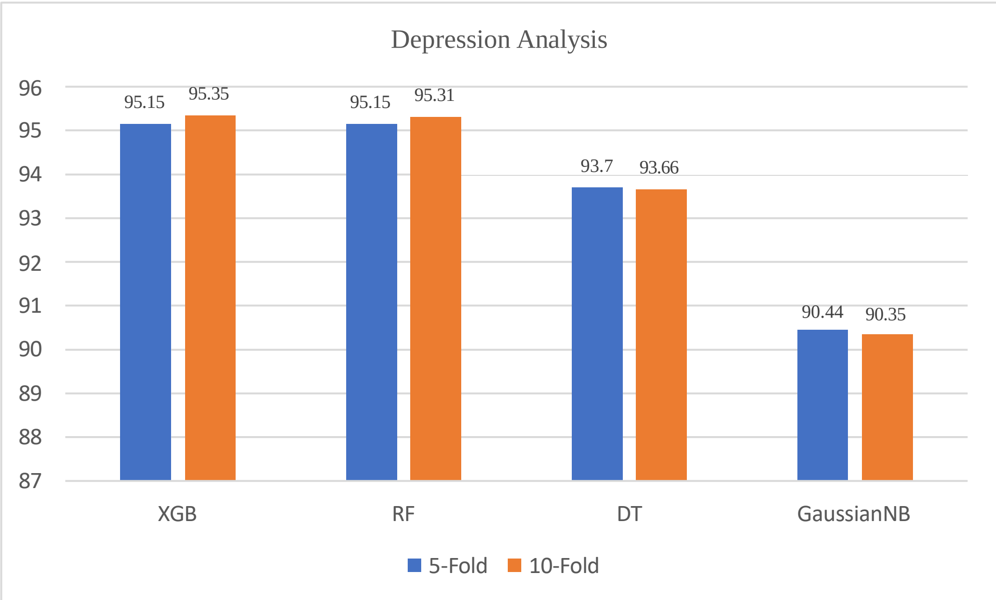

Figure 6 Statistical analysis of Depression using Young Minds Matter dataset

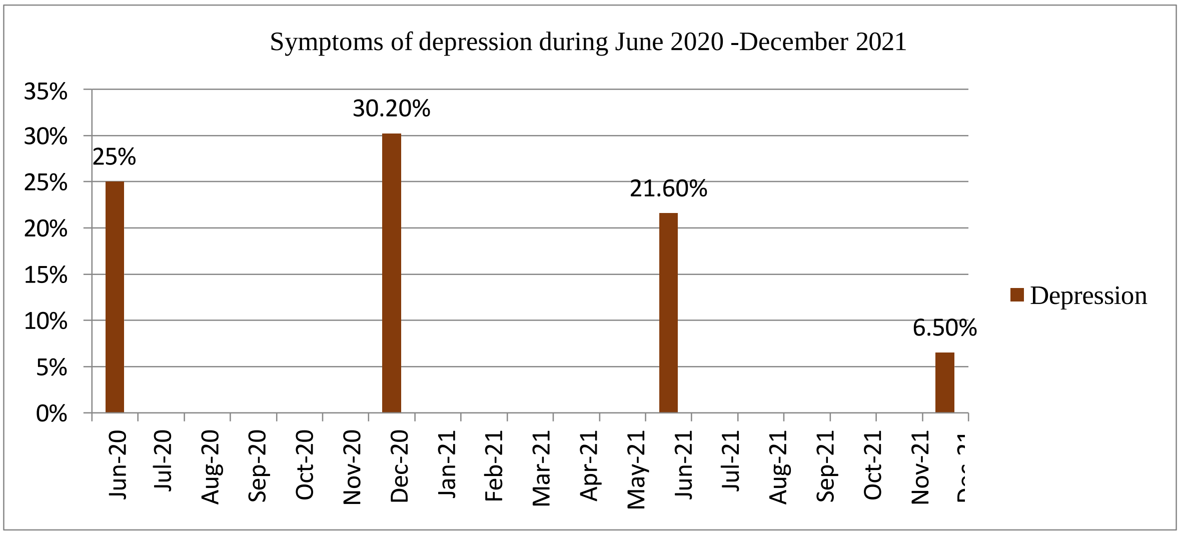

Figure 7 Pandemic causes spike in depression

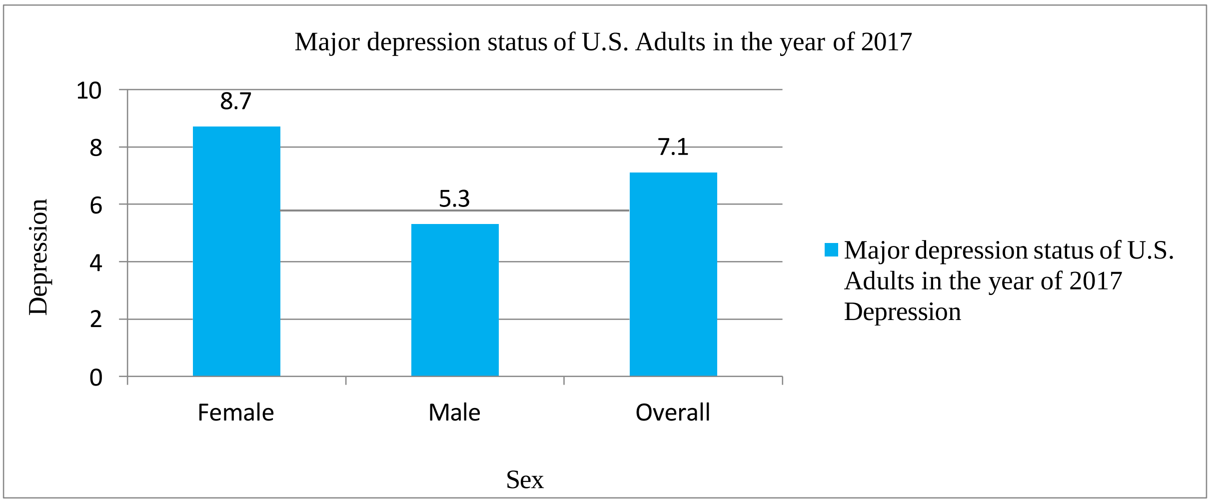

Figure 8 Major depression status of U.S. Adults in the year of 2017 based on sex

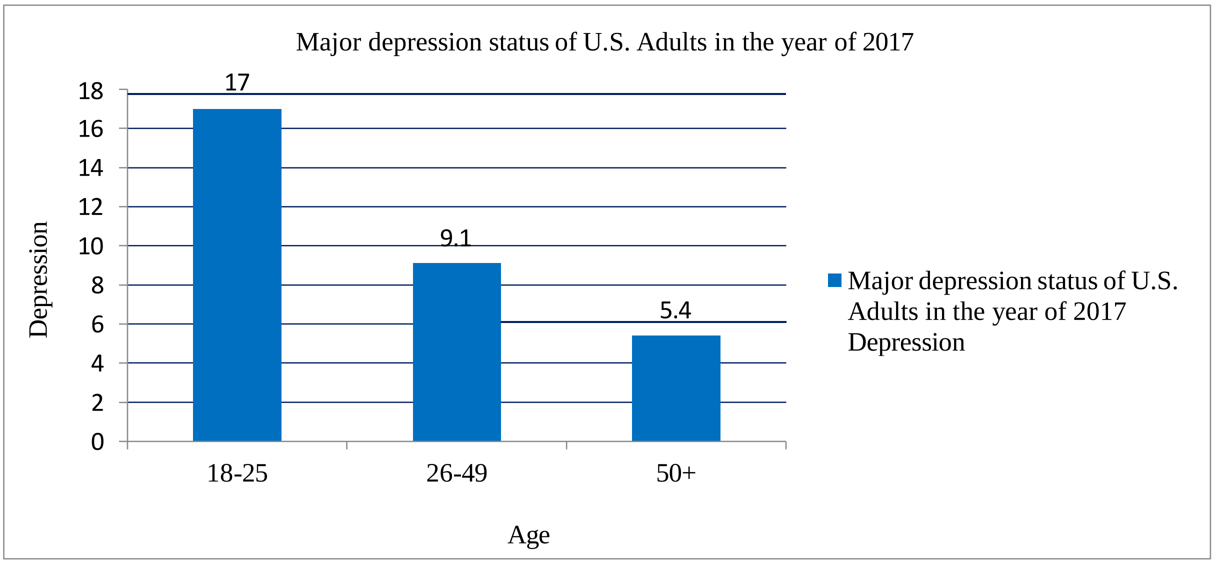

Figure 9 Major depression status of U.S. Adults in the year of 2017 based on Age

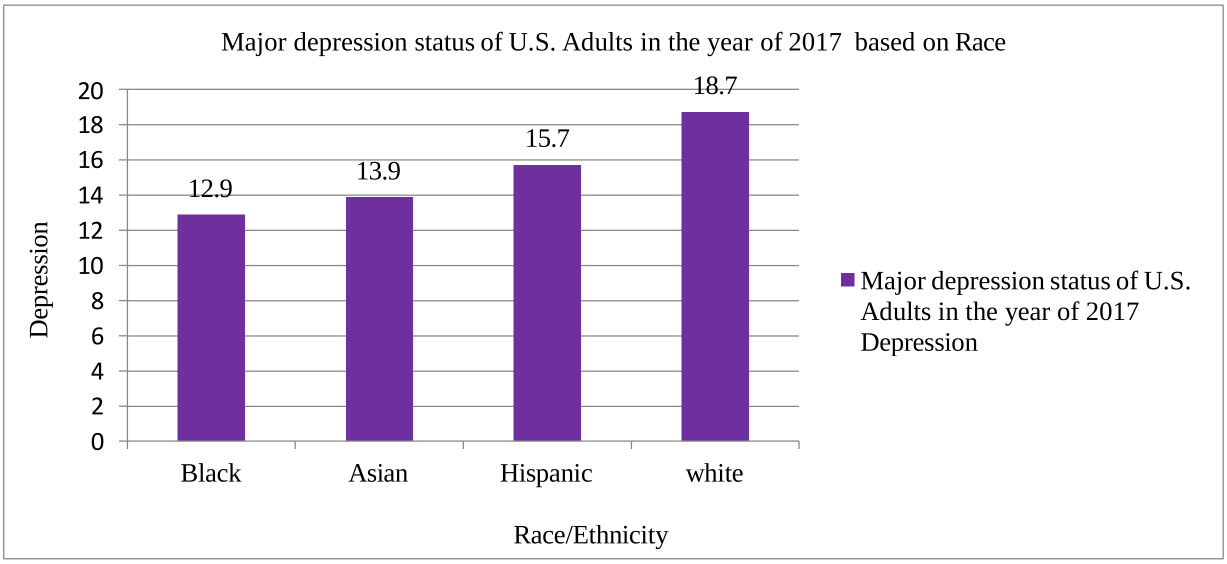

Figure 10 Major depression status of U.S. Adults in the year of 2017 based on ethnicity

Figure 11, Figure 12, and Figure 13 show the depression status of U.S. adults in the year 2020, based on sex, age, and race, respectively. Based on gender, females had the highest rate of mental depression with 10.7% and adults aged 18–25 were highly affected in the year 2020. Based on race, black people are extremely affected due to mental depression in the year 2020.

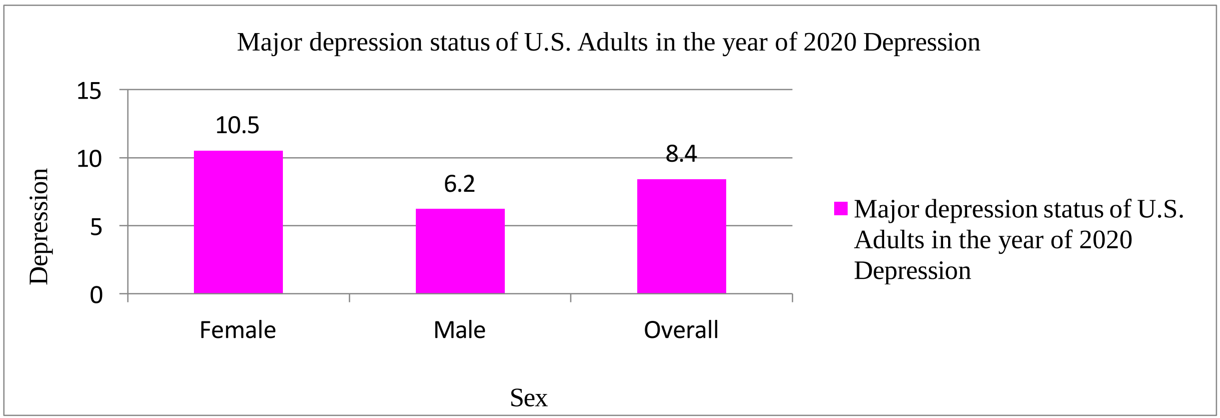

Figure 11 Major depression status of U.S. Adults in the year of 2020 based on Sex

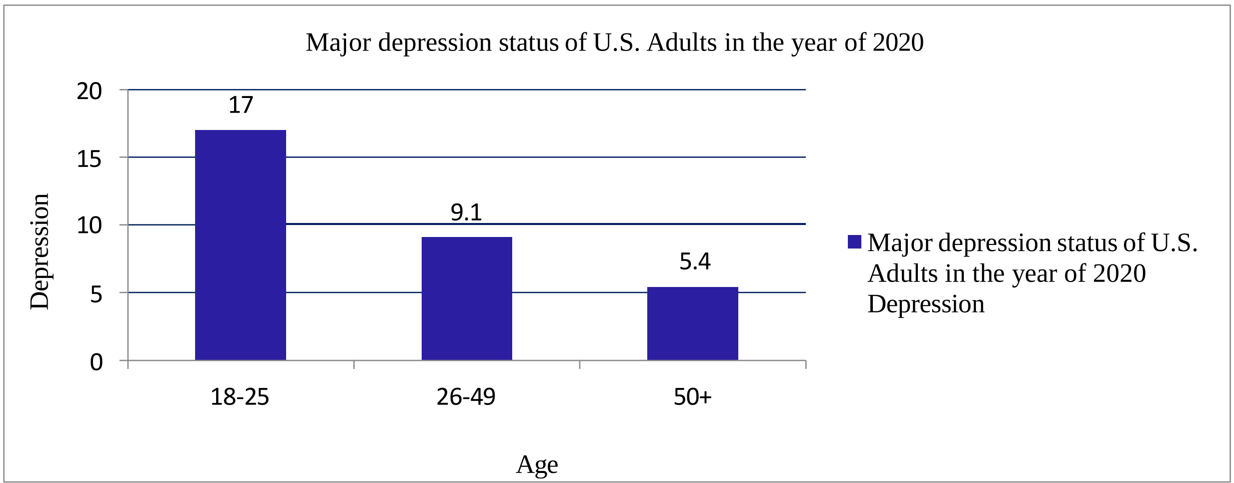

Figure 12 Major depression status of U.S. Adults the year of 2020 based on Age

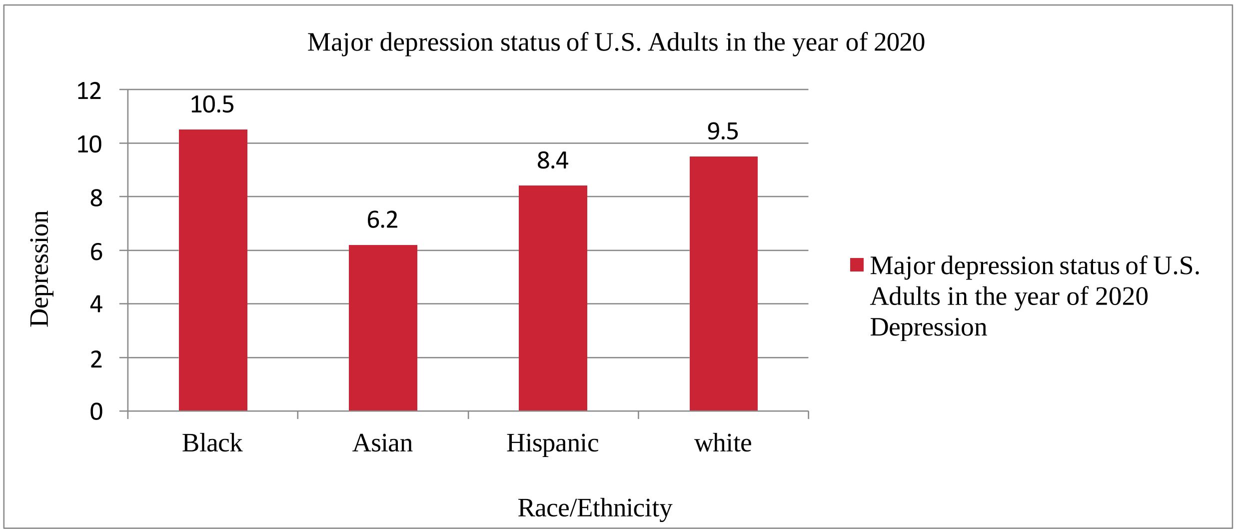

Figure 13 Major depression status of U.S.adults the year of 2020 based on race

Figure 14 Figure 15 and Figure 16 show the depression status of U.S. adolescents in the year 2020, based on sex, age, and race, respectively. Based on gender, females had the highest rate of mental depression with 25.2% and adults aged 50+ were highly affected in the year 2020. Based on race, white people are extremely affected due to mental depression in the year 2020.

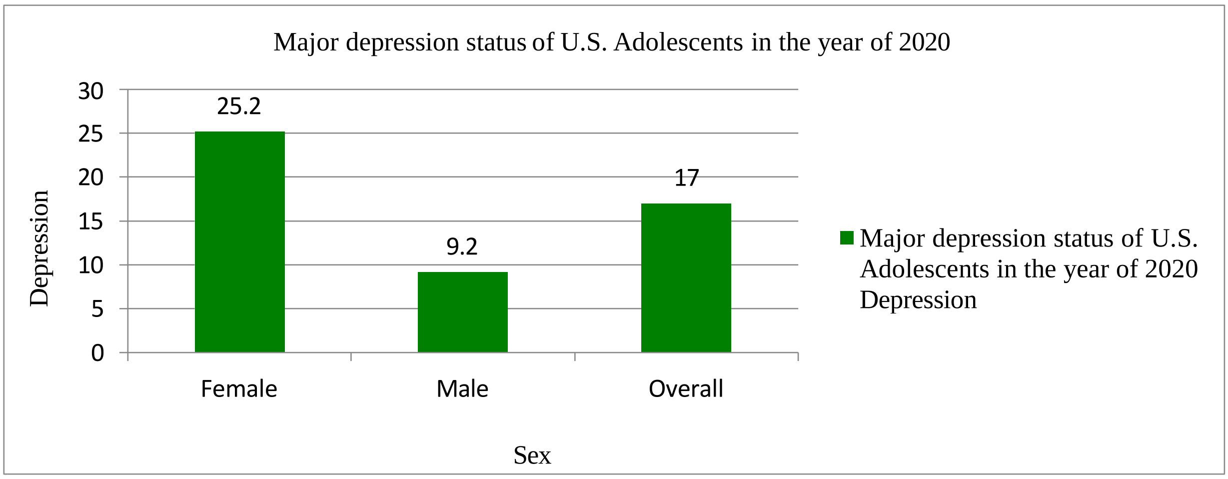

Figure 14 Major depression status of U.S. Adolescent in the year of 2020.

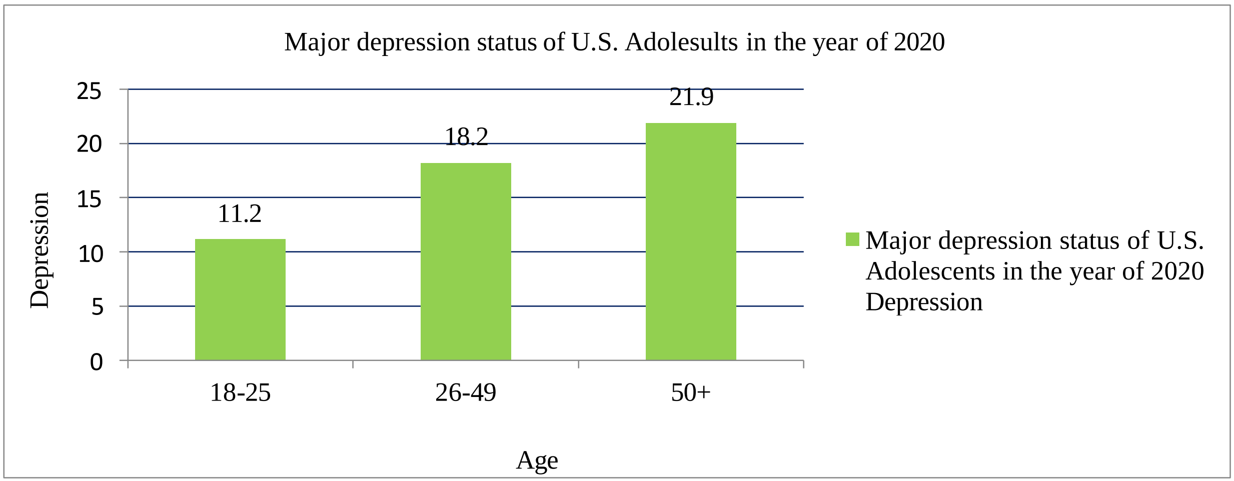

Figure 15 Major depression status of U.S. Adolesults the year of 2020.

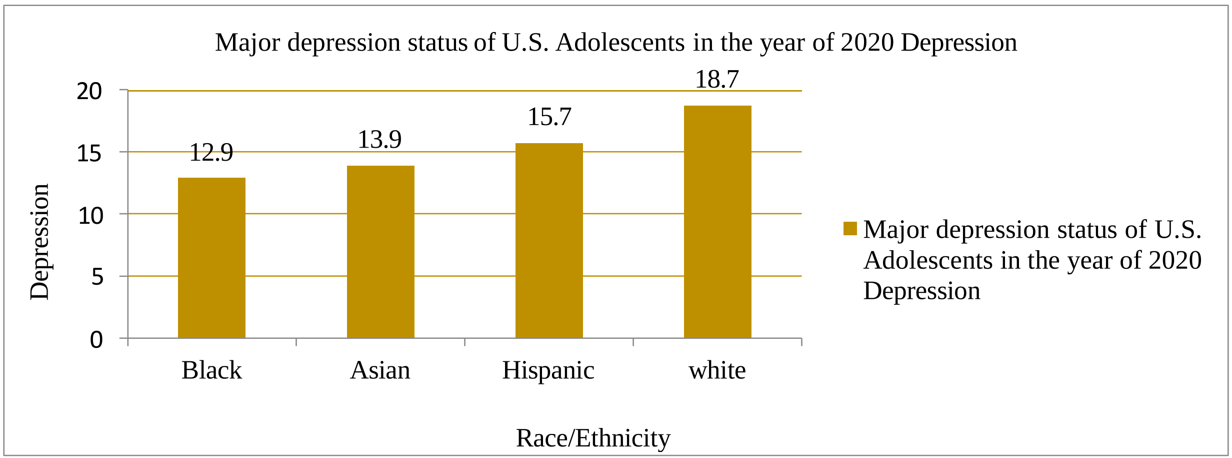

Figure 16 Major depression status of U.S. Adolesults the year of 2020 based on race

5. Conclusion and Future directions

The premature detection of mental health depression in children and adolescents is vital, as it enables the initial diagnosis necessary for their advancement in educational, community, and developmental spheres. Among adults aged 50 and older, mental health depression disorders stand as prominent causes of illness and incapacity. For the youth population, particularly adolescents aged 15–29 years, the elevated rate of suicide remains the fourth primary reason for death.

The consequences of failing to adequately address adolescent and adult mental health conditions are far-reaching, leading to compromised mental health and restricted opportunities for adults to lead fulfilling lives. The findings of this research exploration can therefore be applied to facilitate the timely diagnosis of the disease and the introduction of treatment at an early stage.

Future investigations might focus on the early detection of mental health depression through the continued development and application of artificial intelligent algorithms.

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