(Annexure A)

INTEGRATED PROJECT REPORT

On

MANTIS - HELPING YOU IN IMPROVING YOUR MENTAL HEALTH

Submitted in partial fulfilment of the requirement for the
Course Integrated Project (CS 203) of

COMPUTER SCIENCE AND ENGINEERING
B.E. Batch-2019

in

JUNE-2022

Submitted By

Under the Guidance of:
DR. DEEPAK AHLAWAT
ASSISTANT PROFESSOR

SHRUTI GUPTA
Roll. No. 1910991937

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
CHITKARA UNIVERSITY
PUNJAB

(Annexure B)

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(Annexure –C)

CERTIFICATE

This is to be certified that the project entitled "Mantis-helping you in improving your mental health" has been submitted for the Bachelor of Computer Science Engineering at Chitkara University, Punjab during the academic semester January 2022- May-2022 is a bonafide piece of project work carried out by "Shruti Gupta– 1910991937" towards the partial fulfillment for the award of the course Integrated Project (CS 203) under the guidance of "Dr. Deepak Ahlawat" and supervision.

Dr. Deepak Ahlawat

(Assistant Professor, C.S.E)

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(Annexure –D)

CANDIDATE'S DECLARATION

I, **Shruti Gupta– 1910991937,** B.E.-2019 of the Chitkara University, Punjab hereby declare that the Integrated Project Report entitled **"Mental Health Predictor"** is an original work and data provided in the study is authentic to the best of my knowledge. This report has not been submitted to any other Institute for the award of any other course.

Shruti

Shruti Gupta
ID No 1910991937

Place : Rajpura
Date : 26 June 2022

ABSTRACT

Behavioural health disorders, specifically depression, are a serious health concern in the United States and worldwide. The consequences of unaddressed behavioural health conditions are multifaceted and have impact at the individual, relational, communal, and societal level. Despite the number of individuals who could benefit from treatment for behavioural health concerns, their difficulties are often unidentified and unaddressed through treatment. Technology carries unrealized potential to identify people at risk for behavioural health conditions and to inform prevention and intervention strategies. Drawing upon data from the National Longitudinal Study of Adolescent Health (Add Health, n=3782), this project has two aims related to advancing understanding of technology's potential value in behavioural health: 1) to develop a forecasting procedure that can be used to identify youth who are at risk of reporting a depression diagnosis as adults based on a set of input variables; and 2) to understand the developmental trajectories of depression for youth.

To address the first aim of this project, random forest methodology was used to derive the forecasting algorithm. The second aim was pursued with Generalized Additive Model analysis to estimate relationships between presence of a reported depression diagnosis as an adult and youth characteristics. Findings from this study indicate that it is feasible to use a forecasting tool to identify individuals at risk of being diagnosed with depression, which can facilitate early intervenion and improved outcomes. Gender, race, and receiving counselling as a youth were the most important predictors of having a reported depression diagnosis as an adult. This dissertation addresses the role of health disparities, specifically gender and race, related to depression and mental health treatment.

In sum, this dissertation highlights how a machine learning forecasting tool could be used to inform prevention strategies and understanding of factors associated with receiving a depression diagnosis. This study presents and discusses these findings in addition to offering important implications for future research and practice to identify and prevent behavioural health conditions such as depression.

(Annexure -E)

ACKNOWLEDGEMENT

It is my pleasure to be indebted to various people, who directly or indirectly contributed in the development of this work and who influenced my thinking, behaviour and acts during the course of study.

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Shruti Gupta

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(Annexure –F)

CONTENTS

CHAPTER 1

INTRODUCTION

Machine learning (ML), a method of data analysis in which computers "learn" to independently modify or adapt their actions (e.g., make predictions) to produce more accurate decisions and results, has emerged as a powerful analytic tool for large and complex datasets As such, ML lends itself to the processing of disease biomarkers and has been Implemented in medical diagnostic tools ranging from the detection and classification of tumors, to providing a differential diagnosis of neurodegenerative diseases with similar presentations ML methods have reliably demonstrated an increase in prediction accuracy when compared with older, more conventional statistical techniques or physician-based expert systems. In parallel, ML techniques have been applied to examine affective display differences exhibited during emotion states, such as facial expression and vocal prosody, through audio and video-based analysis. These advances have generated a new field of research which has successfully used ML techniques, such as support vector machines ,regression ,and neural networks ,for automatic recognition of emotion using audio visual data from conventional databases and recently more naturalistic environments..

Moreover, ML has also been extended to investigate verbal and nonverbal affective abnormalities associated with psychiatric disorders and has gone on to successfully classify those presenting with and without a given diagnosis. This is a substantial advancement given that prior to the advent of ML, identifying divergences in affect-related behaviours relied exclusively on labor-intensive, rater-based analysis , thus leaving findings more susceptible to bias. ML-based techniques show incredible promise for psychiatric diagnostics through harnessing observable affect-related behaviours through highly objective methods. In fact, observable affect-related behaviours are commonly used by mental health professionals to assist in psychiatric diagnostics, often through non-structured methods that result in general, qualitative data (e.g., 'flat' or 'broad' affect). However, the majority of current algorithms still require some level of human intervention such as labor-intensive manual labelling or hand classification of data in order to extract useful features prior to analysis.

These steps render current algorithms-based analysis time-consuming as well, ultimately hampering feasible application of current ML techniques in clinical settings.
We sought to investigate the possibility of developing a method that combines advanced ML-based techniques in combination with automated data collection procedures to identify clinical depression in a demographically diverse population. We chose to begin this effort with depression for two reasons.

First, the prevalence and impact of depression is staggering. Depression is the leading cause of disability in the United States for individuals ranging from 15 to 44.3 years of age (NIMH). Major depressive disorder (MDD), a psychiatric disorder characterized by experiencing depressed mood or anhedonia most of the day nearly every day for a period of two weeks or more, affects upwards of 16.1 million American adults annually, roughly 6.7% of the United States population (NIMH). Distress from clinically elevated depression is often accompanied with suicidal ideation and attempt (WHO).

Nearly 800,000 individuals worldwide die as the result of suicide each year, making it the second leading cause of death in individuals 15 to 29 years of age. Second, verbal and nonverbal affective abnormalities demonstrated by individuals with depression are well-documented and lend themselves to ML-based processing. Depressed individuals possess significant differences in facial expressions and everyday vocabulary use (e.g., absolutist words.

When compared with healthy individuals. In addition, speaking behaviours and voice acoustic characteristics have been closely linked to depressive state, recovery time course from depression and treatment response. This research provides a solid foundation of 'behavioural biomarkers' that may be used to identify clinically elevated depression using audio visual data. Hence, we designed a web-based evaluation that can be completed quickly (~5 min), and requires no manual labelling that takes into account all of the above-mentioned modalities. In addition, we created a new ML-based algorithm that leverages, and extends, the behaviourally relevant findings to identify depression using naturalistic audio visual data. This comprehensive methodology (AiME) was developed to minimize human intervention, thereby enhancing feasibility, scalability, and potential applications in clinical settings.

The first aim of this project is to develop a forecasting procedure that can be used to identify youth who are at risk of developing a depressive disorder as an adult and could benefit from prevention or support services. This procedure seeks to predict whether a youth will have a diagnosed behavioural health condition, specifically depression as an adult, based on a set of input variables. The second aim of this study is to understand the developmental trajectories of depression for youth. This study addresses the following research questions drawing upon data from the National Longitudinal Study of Adolescent Health (Add Health): How well do random forests forecasts perform in terms of predicting which youth will report a depression diagnosis as an adult? What features distinguish youth with depressive symptoms who report a depression diagnosis as an adult from youth with depressive symptoms who do not report a depression diagnosis as an adult?

1.1 Motivation For Work

Depression is diagnosed using conventional approaches which include Physical Diagnosis and Behavioural Diagnosis. These methods do not consider social media data which have proved to be used by patients to interact with peers because of their support and ability to understand someone's experience, while maintaining a comfortable emotional distance. We want to use social media to make the diagnosis process more holistic by providing an additional avenue of inputs for the professional in the form of social media posts and to reduce time and effort in the process of diagnosing a person's mental health condition by automating the analysis of the social media posts.

1.2 Problem Statement

Evaluation of emotional health using mental health screening test and suggest steps to overcome the present stage because most people are reluctant to seek help due to concerns about unwanted interventions, time, cost, and perceived stigma. 1 in 7 Indigenous people suffered from mental health issues like anxiety, depression in 2021. These include depression, anxiety disorders, schizophrenia, bipolar disorders, idiopathic developmental intellectual disability, conduct disorders, and autism. The contribution of mental disorders to the total disease burden has doubled in India from 1990 to 2021, indicating the need for implementing effective strategies to control this increasing burden. Mental illnesses contribute significantly to the burden of disease in India as reported by this study. There is an urgent need to strengthen mental health services, integrate these with general healthcare, and remove barriers such as stigma and access to treatment. Students are facing mental health issues and the larger problem is the lack of awareness and the influence around the term mental health, we are looking for methods to make students more aware about mental health issues and clearing the influence around it.

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CHAPTER 2

LITERATURE SURVEY

2.1 INTRODUCTION

Over the years, stress, anxiety, and modern-day fast-paced lifestyles have had immense psychological effects on people's minds worldwide. The global technological development in healthcare digitizes the scopious data, enabling the map of the various forms of human biology more accurately than traditional measuring techniques. Machine learning (ML) has been accredited as an efficient approach for analysing the massive amount of data in the healthcare domain. ML methodologies are being utilized in mental health to predict the probabilities of mental disorders and, therefore, execute potential treatment outcomes. This review paper enlists different machine learning algorithms used to detect and diagnose depression.

The ML-based depression detection algorithms are categorized into three classes, classification, deep learning, and ensemble. A general model for depression diagnosis involving data extraction, pre-processing, training ML classifier, detection classification, and performance evaluation is presented. Moreover, it presents an overview to identify the objectives and limitations of different research studies presented in the domain of depression detection. Furthermore, it discussed future research possibilities in the field of depression diagnosis. Social media channels, such as Facebook, Twitter, and Instagram, have altered our world forever.

People are now increasingly connected than ever and reveal a sort of digital persona. Although social media certainly has several remarkable features, the demerits are undeniable as well. Recent studies have indicated a correlation between high usage of social media sites and increased depression. The present study aims to exploit machine learning techniques for detecting a probable depressed Twitter user based on both, is/her network behaviour and tweets. For this purpose, we trained and tested classifiers to distinguish whether a user is depressed or not using features

extracted from his/her activities in the network and tweets. The results showed that the more features are used, the higher are the accuracy and F-measure scores in detecting depressed users.

This method is a data-driven, predictive approach for early detection of depression or other mental illnesses. This project main contribution is the exploration part of the features and its impact on detecting the depression level.

2.2 EXISTING METHODS

Over the years, there have been numerous studies on the use of ML to amplify the scrutiny of mental disorders. In the authors present a history of depression, imaging, and ML approaches. It also provides reviews on researchers that have used imaging and ML to study depression. The algorithms under review are SVM (linear kernel), SVM (nonlinear kernel), and relevance vector regression. Only one mental health domain (MHD) is used to analyse in this survey. This study did not mention depression screening scales, and there is no comprehensive comparison of algorithms. Surveyed mental health monitoring systems (MHMS) using ML and sensor data in mental disorders. This project also analysed supervised, unsupervised, semi-supervised, transfer, and reinforcement learning which were applied in the domains of mental well-being, including depression, anxiety, bipolar disorder (BD), migraine, and stress. However, this project only presents a brief review of the cases about MHMS and applications. Compared ML based brain imaging classification and prediction research studies for diagnosing. Major depression disorder (MDD) and BD were analysed, combined with the utilization of the MRI data. SVM, LDA, GPC, DT, RVM, NN, and LR algorithms are under review in this project. However, depression screening scales used in different studies are not mentioned. It only focuses on MDD and BD-based research studies. Analysed five ML algorithms; SVM, Gradient Boosting Machine (GBM), RF, Naïve Bayes, and KNN were applied in the domains of mental disorders. It included PTSD, schizophrenia, depression, ASD, and BD studies. This study reviewed the limited number of ML algorithms and did not specify the advantages of using a particular ML approach.

The authors analysed Facebook data to detect depression-relevant factors. The Facebook user's data were analysed using LIWC. Four supervised learning ML approaches were applied to the acquired data: DT, KNN, SVM, and an ensemble model. Experimental results indicated that DT yielded better classification accuracy. Presented a brief review of generic AI-based applications for mental disabilities and an illustration of AI-based exploration of biomarkers for psychiatric disorders. The study reviewed three major approaches for brain analysis for psychiatric disorders, magnetic resonance imaging (MRI), electroencephalography (EEG), and kinesics diagnosis, along with five AI methods, Bayesian model, LR, DT, SVM, and DL. In this, we have used DL methodology to extract a representation of depression cues in audio and video to detect depression.

This review has introduced the databases and described objective markers for automatic depression estimation (ADE) to sort out and summarize their work. Furthermore, they reviewed the DL methods (DCNN, RNN, and LTMS) for automatic depression detection to extract the representation of depression from audio and video. Finally, they have discussed challenges and promising directions related to the automatic diagnosis of depression using DL approaches.

CHAPTER 3

METHODOLGY

3.1 Methodology for Depression Diagnosis

The detection methodology involves a series of processes, including the data extraction, the pre-processing of the extracted data, feature extraction methods for selecting the required set of features for identifying symptoms of depression, and ML classifiers for classifying the input data into defined data categories. This section discusses each of these steps and the different methods and approaches used for implementing each step.

3.1.1 Pre Processing Algorithms

1. Linear Discriminant Analysis (LDA): LDA is a dimensionality reduction approach that removes redundant features by transforming them from a spatial space onto a lower-dimensional space. LDA reduces the dimensions in each dataset, retains the most important features, and achieves higher class separability.

2. Synthetic Minority Oversampling Technique (SMOTE): SMOTE is a statistical oversampling technique to obtain a synthetically class-balanced dataset. It provides a balanced class distribution that develops synthetic patterns from the minority class.

3. Linguistic Inquiry and Word Count (LIWC): LIWC is a text analysis technique for understanding different emotional, subjective, and structural components present in the spoken and written speech patterns.

4. Hidden Markov Model (HMM): HMM is a probabilistic model used to capture and describe information from observable sequential symbols. In HMM, the observed data are modelled as a series of outputs generated by several internal states.

3.2 Feature Extraction Methods

Feature selection is a technique in which those features are selected that are the most accurate predictors of the target variable.

1. SelectKBest: SelectKBest is a feature extraction approach that retains relevant features and drops unwanted features in the given input data. It is a univariate feature selection approach based on the univariate statistical analysis. It combines the univariate statistical test with selecting the K-number of features based on the statistical result between the variables.
2. Particle Swarm Optimization (PSO): PSO is a computational process for optimizing nonlinear functions by developing the candidate solution in a repetitive pattern based on a defined quality measure. The general concept of the PSO algorithm is inspired by the swarm actions of birds, flocking, and schooling in nature.

3. Maximum Relevance Minimum Redundancy (mRMR): mRMR is a feature selection approach that manages multivariate temporal data without compressing previous data. The algorithm selects features with the most relevant class and the least correlation between redundant classes. It provides significantly improved class predictions in extensive datasets.

4. Boruta: Boruta is a feature selection approach designed around a Random Forest classification. Boruta is used for extracting all the relevant variables by removing less relevant features, using the statistical analysis iteratively.

5. RELIEFF: RELIEFF algorithm is one of the most successful filtering feature selection methods. RELIEFF algorithm is used to eliminate the redundant features.

3.3 Requirements

Hardware Requirements:

- RAM: 4 GB
- Storage: 500 GB
- CPU: 2 GHz or faster
- Architecture: 32-bit or 64-bit

Software Requirements:

- Python 3.5 in Google Colab is used for data pre-processing, model training and prediction.
- Operating System: windows 7 and above or Linux based OS or MAC OS

Functional requirements:

Functional requirements describe what the software should do (the functions). Think about the core operations.

Because the "functions" are established before development, functional requirements should be written in the future tense. In developing the software for Depression Analysis, some of the functional requirements could include:

- The software shall accept the tw_spydata_raw.csv dataset as input.
- The software should shall do pre-processing (like verifying for missing data values) on input for model training.

Non-Functional requirements:

Product properties:

- Usability: It defines the user interface of the software in terms of simplicity of understanding the user interface

CHAPTER 4

DISCUSSION

This study aimed to develop a forecasting tool that can be used to identify youth at risk of being diagnosed with depression as an adult. Additionally, this study investigated the developmental trajectories of depression for youth. The following section discusses the findings of this study within the context of prior research and realworld applicability. Implications of this study and limitations are also discussed.

4.1 Depression Forecasting Tool

This study is a preliminary step towards the integration of technology solutions into the treatment of behavioural health conditions. This study demonstrated the feasibility of developing a forecasting procedure that can be used as a tool for identifying youth who are at risk of being diagnosed with depression as an adult. Using a set of input variables collected from youth, this tool did a good job of forecasting which youth would not have a reported depression diagnosis as an adult with a 92% accuracy rate. This procedure was able to cut the error rate in half when classifying no diagnosis. Specifically, race, gender, youth depression score on the CES-D, receiving counselling as a youth, youth self-esteem, and youth suicidal ideation were the most important factors in terms of forecasting accuracy. If an algorithm like this one were replicated, these factors may be variables to consider including.

Whenever a method or idea that deviates from traditional approaches is proposed, providing a proof of concept to demonstrate practicality is an important first step. Therefore, the feasibility finding is important in demonstrating how technologybased approaches, such as machine learning algorithms, have the potential to improve the identification, assessment, and treatment of behavioural health conditions such as depression.

Despite major scientific advances in the United States, behavioural health difficulties remain a persistent problem for millions of Americans and many people never engage in treatment. According to Mental Health in America's 2019 State of Mental Health in America report, since last year there has been an increase in the percentage of individuals who report serious thoughts of suicide and an increase in the number of individuals who report experiencing at least one major depressive episode.

Mainstream media has also recently drawn attention to the commonness of mental health difficulties after numerous celebrities and people in the public eye died by suicide. Now more than ever, we need to do better to ensure that people who are struggling get connected to the care that they need and deserve. While technology and machine learning strategies are not a silver bullet for behavioural health disorders, this study provides evidence for the potential of using a forecasting tool as a prevention mechanism and strategy to identify individuals who could benefit from receiving mental health services. Specifically, a tool like this one could help identify people who are likely to be diagnosed with depression in the future. Early identification is key to prevention and prior research has shown that intervening early rather than waiting for symptoms to further develop is beneficial (Ginsburg et al., 2014; Wolk, Kendall, & Beidas, 2015).

Despite knowing the importance of identifying behavioural health problems early, significant identification challenges exist, and many disorders often go undiagnosed (U.S. Department of Health & Human Services, 1999; Williams, Klinepeter, Palmes, Pulley, & Foy, 2004). A forecasting tool such as this one has the potential to help providers identify individuals at risk for depression and aligns with recent work being done by researchers at Virginia Tech where Chiu and colleagues are attempting to use Artificial Intelligence and machine learning algorithms to diagnose mental illness (Zarley, 2019). Compared to physical health conditions, where blood tests and X-rays can be used to diagnose conditions, diagnosing behavioural health conditions is often much more subjective. The article highlights how challenging it is to quantify feelings and "measure the mind," making it difficult to diagnosis mental illness using the DSM guidelines. This work provides hope that machine learning can positively impact our understanding and treatment of behavioural health conditions.

If we think about the process of treatment for behavioural health conditions, an individual often experiences or exhibits symptoms of a condition and either is referred to services or seeks services independently (identification). The individual is then engages in an assessment with a provider, which informs diagnosis and next steps. Next, the individual engages in services to treat their condition (treatment). While this description may be over-simplified, and in practice may not be so linear, the point is that identification is typically the first step. Early detection is key to prevention and identifying problems early reduces the chance of long-term disability associated with behavioural health problems (Williams, Klinepeter, Palmes, Pulley, & Foy, 2004). Hence, when thinking about prevention and early intervention strategies, a machine learning tool, such as this one could be used to identify people at risk of developing depression.

4.2 Depression Trajectories

The second aim of this study was to advance the understanding of developmental trajectories of depression for youth. Specifically, using longitudinal data, this study explored what differentiates youth with symptoms of depression who go on to report a depression diagnosis as an adult from youth with symptoms of depression who do not go on to report a depression diagnosis as adult. The main finding from this study related to youth depression trajectories was that race and gender were the most important factors in terms of who would have a reported depression diagnosis as an adult. Longitudinal data were used to examine these trajectories from youth to adulthood. Smokowkoski and team (2014) highlight how even though developmental mental health research is about trajectories and change over time, most research in the area is cross-sectional rather than longitudinal.

This study found that the factors which most influenced whether youth would have a reported depression diagnosis as an adult the most were if the youth identified as White, female, and had ever received counselling as a youth. From a prevention standpoint, this finding is not overly useful, but is consistent with previous research about individuals who get diagnosed with depression most often. Specifically, research consistently shows that women are almost twice as likely to experience and be diagnosed with depression compared to men (Mayo Clinic, 2019; Whiteman, Ruggiano, & Thomlison, 2016). Furthermore, behavioural health conditions such as depression are often underdiagnosed and under-treated among people who identify as Black or African American and Hispanic/Latino/a compared to people who identify as White (Stockdale, Lagomasino, Siddique, McGuire, & Miranda, 2008; Young, Klap, Sherbourne, & Wells, 2001).

While this finding is not novel and does not provide new insight as to understanding why, among a group of young people with depression symptoms, some report a depression diagnosis as an adult and others do not, it does perhaps highlight an important and larger issue of health disparities and who has access to health services. The National Institutes of Health (2014) defines health disparities as, “differences that exist among specific population groups in the United States in the attainment of full health potential that can be measured by differences in incidence, prevalence, mortality, burden of disease, and other adverse health conditions.”

Despite design or methodology, research has consistently found that individuals who identify as White are healthier than people who identify with almost all other racial groups (except individuals who identify as Asian; National Center for Health Statistics, 2016). Research also shows that while these disparities exist in various areas of health including life expectancy, heart disease, infant mortality, and obesity, behavioural health disparities also exist (Baciu et al., 2017; Safran et al., 2009). Individuals, particularly people who identity as Black/African American, are less likely to ask questions with their healthcare providers and less likely to request information about their health (Patel & Bakken, 201; Eliacin et al., 2016).

While rates of mental health conditions are similar across different ethnic/racial groups, the consequences of these conditions are often worse for individuals who do not identify as White (APA, 2017). Additionally, individuals who do not identify as White are less likely to receive behavioural health services. A 2015 report found that among individuals with any mental health conditions, 48% of people who identify as White received treatment, 31% of people who identity as Black or African American received treatment, 31% of people who identify as Hispanic received treatment, and 22% of people who identify as Asian received treatment (AHRQ, 2016). Recent work has also shown that the mental health of Black/African American youth needs more attention as the suicide rate for Black/African American youth is increasing compared to suicide rates for other children of the same age. A 2015 study showed that suicide rates were twice as high for Black/African American youth compared to White youth ages five to eleven (Bridge et al., 2015). While people across different racial/ethnic groups are less likely to seek treatment compared to their White counterparts, research also suggests that once they enter treatment, they are more likely to end treatment early (Cook et al., 2015; Fortuna et al., 2010).

While many factors may explain racial disparities in health care, within the context of this study, a factor that is important to consider involves differences in trust or distrust in healthcare providers. The degree to which an individual seeks out medical care and health services, retains long term relationships with healthcare providers, and adheres to treatment is greatly influenced by the level of trust and therapeutic relationship between the individual and provider (Boulware, Cooper, Ratner, LaVeist, & Powe, 2016; Hall, Dugan, Zheng, & Mishra, 2001; Peterson, 2002). Healthcare providers' cultural awareness in practice, as well as perceived racial bias and levels of empathy have also been associated with contributing factors for not using health services (Constatine, 2007; Cooper et al., 2012; Thomspon & McCable, 2012). Gender also plays a role in help-seeking behaviors. On average, women are more likely to use behavioural health care services than men (Matheson et al., 2014; SAMSHA, 2015).

Since Weissman's landmark article in the 1970s which noted differences in depression by gender, a significant amount of research has explored this disparity (Wesissman & Klerman, 1977; Salk, Hyde, & Abramson, 2017). An array of factors and interactions of factors, including biological differences (e.g., hormonal, neurological, and genetic considerations) and psychosocial factors (e.g., socioeconomic resources, traumatic experiences, coping skills, and personality) have been found to influence gender differences in depression (Afifi, 2007; Salk, Hyde, & Abramson, 2017). Other research has proposed that the increased prevalence of depression among women is related to how women perceive and respond to stress (Kelly, Tyrka, Anderson, Price, & Carpenter, 2008). Compared to men, women are more likely to report experiencing greater anxiety and sadness from stress (Chaplin et al., 2008). Women are also more likely than men to experience trauma and experience negative consequences associated with stress (Chaplin et al., 2008; Keyes et al., 2012; Kucharska, 2017; Matud, 2004). Gender has been found to moderate the relationship between trauma and mental health symptoms, with a stronger association among women than men (Breslau & Anthony, 2007; Kucharska, 2017).

In addition to gender and race, having received counselling as a youth was also an important factor related to reporting a depression diagnosis as an adult. This finding could be attributed to the fact that if a person received counselling for a mental health concern as a youth, they may be more likely to seek services again if struggling with a mental health concern as an adult. This explanation aligns with prior research showing that prior positive experiences with mental health treatment predict future service engagement (Maulik, Eaton, & Bradshaw, 2011). However, this finding also highlights the importance of adolescent mental health treatment as a point of early intervention and prevention of depression in adulthood.

Despite scientific advancements in recent years, the quality of mental health treatment has not improved, and in some circumstances, has worsened (Hayes, Marston, Walters, King, & Osborn, 2017). This gap in treatment quality can be partially attributed to the lack of a systematic approach to measuring quality (Kilbourne et al., 2018). Further, the behavioural health field does not have an agreed upon set of quality indicators for psychosocial treatments (Pincus, Spaeth-Rublee, & Watkins, 2011).

Over 650 Evidence Based Treatments (EBTs) for various behavioural health concerns have been developed and tested in an effort to improve mental health treatment for youth (Chorpita et al., 2016). However, despite the abundance of EBTs, they are typically not delivered in community-based mental health clinics (Gyani, Shafran, Myles, & Rose, 2014; Zima et al., 2005). Research findings examining the effectiveness of youth mental health services delivered in community-based settings have also been mixed (Southam-Gerow et al, 2010; Weisz et al, 2012).

On average, less than half of individuals who report depression receive adequate treatment (Kessler et al., 2005). In fact, most people with depression receive treatment from primary care providers instead of mental health professional (Bilsker, Goldner, & Jones, 2007). Guidelines from the American Psychiatric Association suggest a person diagnosed with depression should receive treatment that includes antidepressant medication and/or psychotherapy for at least four to eight weeks. Studies have found that 30% to 79% of individuals in treatment for mood disorders such as depression receive treatment that does meet the threshold of minimally adequate care (Duhouz, Fournier, Gauvin, & Roberge, 2012; Eisenberg & Chung, 2012; Stein et al., 2013; Wang et al., 2005). Despite this large range found across studies, Puyat and colleagues (2016) note that this evidence highlights that many individuals with depression receive inadequate treatment. Additionally, their study found that men and younger adults had higher odds of receiving minimally adequate treatment relative to women and older adults (Puyat, Kazanjian, Golder, & Wong, 2016). Overall, the finding related to receiving counselling among youth and a reported depression diagnosis as an adult suggests that it would be helpful to further examine mental health counselling in adolescence, including access to evidence-supported treatments, outcomes, and implication for mental health in adulthood.

Bringing it all together, the finding that what differentiates youth with symptoms of depression who receive a reported depression diagnosis as an adult from youth with depression symptoms who do not receive a reported depression diagnosis as an adult are factors such as identifying as female, identifying as White, and having received counselling as a youth highlights the underlying issue of health disparities. Rather than helping to understand the developmental trajectories of depression, this finding may reflect the question of who is likely to seek services for a behavioural health condition such as depression. In practice, to receive a depression diagnosis, an individual must go through a series of steps. First, a person must have a perceived or identified need; second, the person has to find and make an appointment with a provider; and finally, the person has to visit a healthcare provider for treatment. Given what we know about rates of diagnosis among different groups and differences in help-seeking behaviours, it makes sense that access to care and differences in who is likely to seek help in the first place is a plausible explanation for this finding. Past studies have found that individuals who identify as Black/African American or Latino/a are less likely to have access to quality care and treatment given the availability of providers where they live (Blanco et al. 2007; Hasnain-Wynia et al. 2007).

Connecting this finding to the first aim of the study, it demonstrates the importance of and need to identify individuals at risk of having a behavioural health condition in a universal and non-stigmatizing way. Together, these findings also highlight the importance of using a health promotion framework when talking about behavioural health. While most people would not second guess seeking care for a broken bone or another serious physical health concern, it would be ideal if this belief could also hold true for behavioural health symptoms.

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CHAPTER 5

CODE IMPLEMENTATION

Importing the Required Libraries:

- import numpy as np
- import pandas as pd
- import matplotlib.pyplot as plt
- import seaborn as sns

Importing the Dataset:

When running python programs, we need to use datasets for data analysis. Python has various modules which help us in importing the external data in various file formats to a python program. In this example we will see how to import data from excel sheet using pandas to a python program.

- df=pd.read_excel('Health Data.xlsx')

Using the Dataset:

As soon as we import the dataset, we see the number of rows and columns present in the dataset using "shape" function

- dt.shape

To check the first 5 rows and last 5 rows of the dataset we use head() and tail() function respectively.

- dt.head()
- dt.tail()

Filtering the Dataset:

Dropping some columns which are not needed in our model prediction

Drop the columns by using the drop method.

- columns_to_drop=['Region','I have my regular access to the internet','I am currently employed at least part-time','I am on section 8 housing','I receive food stamps','Annual income from social welfare programs','I have a gap in my resume','Total length of any gaps in my resume in\xa0months.','Household Income','Device Type']
- df.drop(columns=columns_to_drop,inplace=True)

We see that in one of our columns, the price is given the US dollars , but as we are in INDIA and so we change that column to rupee by multiplying the column with the 70.

- df['Annual income (including any social welfare programs) in Rupee']=df['Annual income (including any social welfare programs) in USD']*70

Now we drop that US column from our dataset.

- df.drop('Annual income (including any social welfare programs) in USD',axis=1,inplace=True)

Analysing the Dataset:

Now to get the information of our data, we use the info function to get the information on our data

- df.info()

To check if any null value is present in our dataset or not.

- df.isnull().sum()

Filling up the Null Values:

We see that there are many null values present in the columns so we drop some null values and some we fill the values by taking out the mean.

- for i in df:
-     if i=='Education' or i=='Age' or i=='Gender':
-     df[i].dropna()
-    else:
-    df[i].fillna(df[i].median(),inplace=True)

To check whether all the null values have been filled or either removed.

- df.isnull().sum()

Prediction Column:

As we want the prediction from this column so we keep this column

- y=df['I identify as having a mental illness']

We drop the column on which prediction is to be made.

- df.drop('I identify as having a mental illness',axis=1,inplace=True)

To we check first 20 rows of our dataset

- df.head(20)

Finding Correlation between our Columns:

We try to find the corelation between our data by using corelation function.

- df.corr()

After finding the correlation, we use the heatmap present in seaborn library to visualize the corelation in the graphical format. To get the clear view of the correlation in the graphical format, we also use the matplotlib library to set the axis of the figure obtained.

- fig = plt.figure(figsize=(22,20))
- fig.add_axes([0,0,1,1])
- ax = fig.get_axes()[0]
- sns.heatmap(df.corr(), ax=ax, vmin=-1, vmax=1, annot=True)

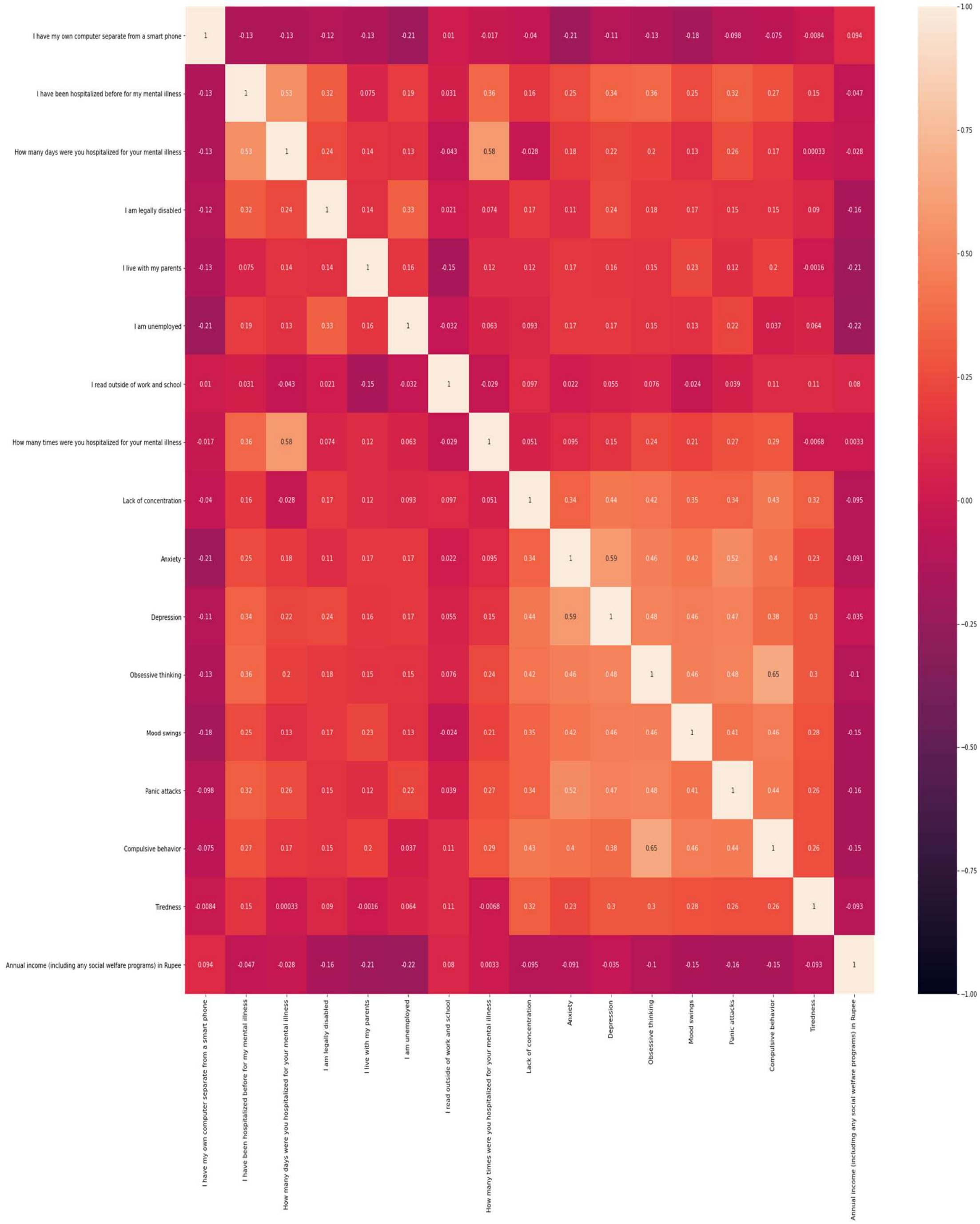

Figure 5.1 Correlation between the columns

5.1 LABEL ENCODING

Now as we know that the computer only understands the binary language ie 0 and 1, so we need to covert some coloumns of our data into the 0 and 1 format. To do this, we use the library present in the sklearn known as LabelEncoder.

Label Encoding refers to converting the labels into a numeric form so as to convert them into the machine-readable form. Machine learning algorithms can then decide in a better way how those labels must be operated. It is an important pre-processing step for the structured dataset in supervised learning.

- from sklearn.preprocessing import LabelEncoder

We apply the label encoder on our 3 coloumns which have the categorical values.

- education=LabelEncoder()
- age=LabelEncoder()
- gender=LabelEncoder()

Transforming the columns:

As we know that the machine only understands the binary language, so to make our columns understandable to the machine, we transform into the binary language.

So we transform the values of these columns into the 0 and 1 format

- df['Education']=education.fit_transform(df['Education'])
- df['Age']=age.fit_transform(df['Age'])
- df['Gender']=gender.fit_transform(df['Gender'])

Now we check that If the numerical values are added, we check the first 5 rows.

- df.head()

Standardizing Data:

It is is the process of converting data to a common format to enable users to process and analyze it. Most organizations utilize data from a number of sources; this can include data warehouses, lakes, cloud storage, and databases. It is is the process of rescaling the attributes so that they have mean as 0 and variance as 1.

The ultimate goal to perform standardization is to bring down all the features to a common scale without distorting the differences in the range of the values.

To do this, we use the library present in the sklearn known as StandardScaler.

- from sklearn.preprocessing import StandardScaler
- ss=StandardScaler()

Now we will transform our dataset by Standard scaler by using fit_transform.

- df2=ss.fit_transform(df)

Validating the model:

Now we need to divide the data for the training and testing of our model.

The standard for dividing the dataset into Training and Testing is mostly 70:30 or 75:25 or 80:20. But we will divide the dataset into the 80% for Training and 20% for the Testing.

We will not directly assign the data linearly, but instead we will shuffle the dataset and then assign because then only we will know that if our model is right or not.

So firstly we will import train_test_split from the Sklearn library.

- from sklearn.model_selection import train_test_split

Now we will divide the data and shuffle it by using train_test_split.

- X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

Training the Logistic regression model:

Logistic regression is a process of modelling the probability of a discrete outcome given an input variable. The most common logistic regression models a binary outcome; something that can take two values such as true/false, yes/no, and so on. Logistic regression is a statistical analysis method to predict a binary outcome, such as yes or no, based on prior observations of a data set. A logistic regression model predicts a dependent data variable by analysing the relationship between one or more existing independent variables.

Now we train our dataset using the Logistic Regression algorithm.

- from sklearn.linear_model import LogisticRegression
- lr=LogisticRegression()

Now we input our data into the Logistic Regression which we had made the data from the train test split.

- lr.fit(X_train,y_train)

Now we prdict the result from our model. Here 0 is right and 1 is negative.

- y_pred=lr.predict(X_test)
- y_pred

Accuracy:

Now we check the accuracy of our result using the accuracy_score. For using this, we need to import it from the sklearn.

- From sklearn.metrics import confusion_matrix,precision_score,recall_score,accuracy_score
- accuracy_score(y_test,y_pred)

here we get the accuracy score of the 82%.

```
accuracy_score(y_test,y_pred)
```

```
0.8208955223880597
```

Figure 5.2 Accuracy Score of Model

1.2 CONFUSION MATRIX

It is a performance measurement for machine learning classification problem where output can be two or more classes. It is a table with 4 different combinations of predicted and actual values.

The confusion matrix consists of four basic characteristics (numbers) that are used to define the measurement metrics of the classifier. These four numbers are:

1. TP (True Positive):
2. TN (True Negative):
3. FP (False Positive):
4. FN (False Negative:

It is extremely useful for measuring Sensitivity, Precision, Specificity, Accuracy.

Confusion matrices represent counts from predicted and actual values. The output "TN" stands for True Negative which shows the number of negative examples classified accurately. Similarly, "TP" stands for True Positive which indicates the number of positive examples classified accurately. The term "FP" shows False Positive value, i.e., the number of actual negative examples classified as positive; and "FN" means a False Negative value which is the number of actual positive examples classified as negative. One of the most commonly used metrics while performing classification is accuracy.

Accuracy

The accuracy of a model (through a confusion matrix) is calculated using the given formula below.

- Accuracy = ((TP + TN) /(TP + TN + FP + FN)).

Precision

Precision or the positive predictive value, is the fraction of positive values out of the total predicted positive instances. In other words, precision is the proportion of positive values that were correctly identified

- Precision = ((TP) / (TP + FP))

Specificity

Specificity gives the fraction of negative values out of the total actual negative instances. In other words, it is the proportion of actual negative cases that are correctly identified. The FP rate is given by (1 – specificity).

- Specificity = ((TN) / (TN + FP))

Sensitivity

Sensitivity, recall, or the TP rate (TPR) is the fraction of positive values out of the total actual positive instances (i.e., the proportion of actual positive cases that are correctly identified).

- Sensitivity aka Recall = ((TP) / (TP + FN))

We now also plot the confusion matrix of the predicted and the tested values.

- cf_matrix=confusion_matrix(y_test,y_pred)
- sns.heatmap(cf_matrix, annot=True)

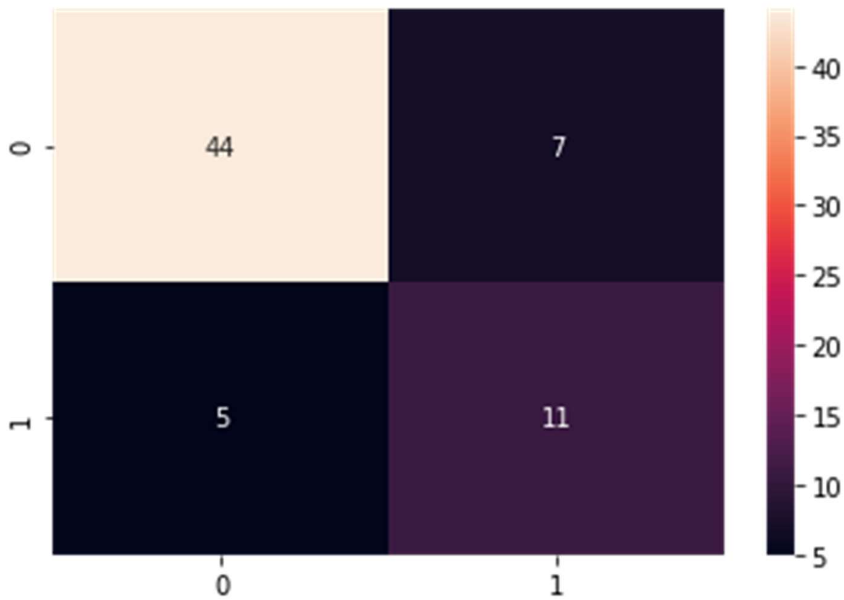

Figure 5.3 Confusion Matrix Between Predicted and Tested Values

In the confusion matrix, we also plot recall score and precison score as explained above.

- recall_score(y_test,y_pred)
- precision_score(y_test,y_pred)

```
recall_score(y_test,y_pred)
```

0.6875

```
precision_score(y_test,y_pred)
```

0.6111111111111112

Figure 5.5 Precision Score of Model

In this model we have accuracy of 82.08% on test data and recall score of 0.6875 and precision rate of 0.611.

We will prefer going for more recall value as we want less False Negative.

1.3 RANDOM FOREST CLASSIFIER

Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model.

Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset. Instead of relying on one decision tree, the random forest takes the prediction from each tree and based on the majority votes of predictions, and it predicts the final output.

So now we import the Random Forest Classifier from the sklearn library.

- from sklearn.ensemble import RandomForestClassifier
- rf=RandomForestClassifier()

Now we input our data into the Random Forest Classifier which we had made the data from the train test split.

- rf.fit(X_train,y_train)

Now we prdict the result from our model. Here 0 is right and 1 is negative.

- y_pred2=rf.predict(X_test)
- y_pred2

Now we check the accuracy of our result using the accuracy score.

- accuracy_score(y_test,y_pred2)

here we get the accuracy score of the 89%.

In the confusion matrix, we also plot recall score and precision score as explained above.

- recall_score(y_test,y_pred2)
- precision_score(y_test,y_pred2)

```
accuracy_score(y_test,y_pred2)
```

```
0.8955223880597015
```

Figure 5.6 Accuracy Score of Model

```
recall_score(y_test,y_pred2)
```

```
1.0
```

Figure 5.7 Recall Score of Model

```
precision_score(y_test,y_pred2)
```

```
0.6956521739130435
```

Figure 5.8 Precision Score of Model

We now also plot the Confusion Matrix of the predicted and the tested values.

- cf_matrix2=confusion_matrix(y_test,y_pred2)
- sns.heatmap(cf_matrix2, annot=True)

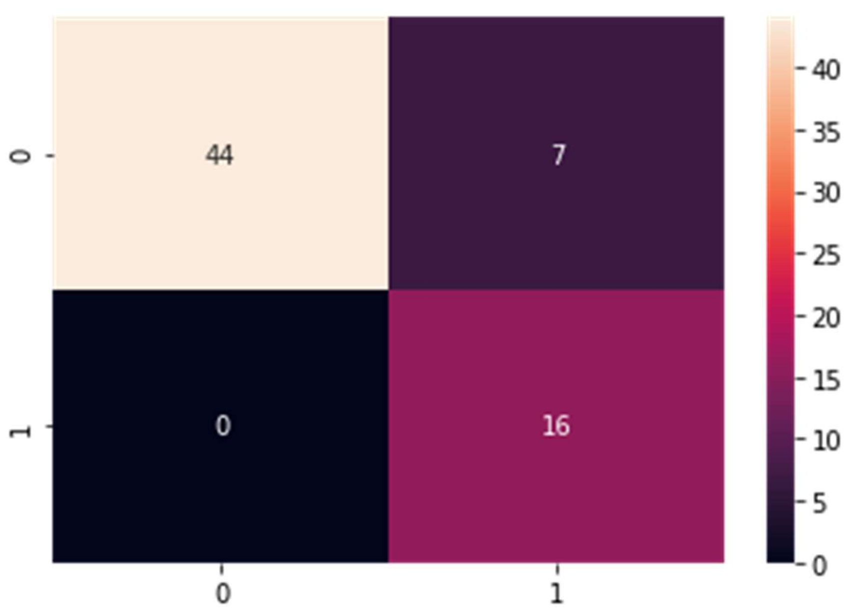

Figure 5.9 Confusion Matrix Between Predicted and Tested Values

LIMITATIONS OF THE PROJECT

Because this study is one of the first to use machine learning strategies within the context of the prevention of depression, it is exploratory by nature. Hence, there are a few limitations worth noting. First, this study relies on self-report data for all variables, and, therefore, responses may be subject to social desirability bias, or answering questions in ways seen as socially acceptable. Additionally, self-report surveys could be impacted by a respondent's mood that day and how the individual perceives and remembers past events or experiences. Second, the outcome and main variable of interest for both aims of this study was presence of a reported depression diagnosis as an adult. Specifically, the question asked, "Has a doctor, nurse or other health care provider ever told you that you have or had depression?" Therefore, the outcome variable is dependent on individuals accurately reporting whether they have received a depression diagnosis. As we know, depression can go underdiagnosed, so it is possible that some individuals may have experienced depression, but never sought help for it or were never diagnosed, and, therefore, responded no to this question. Thus, depression diagnosis in this study may be underreported. Third, as this study relies on secondary data from Wave I and Wave IV of the Add Health study, only variables collected in the original study were available for this study. As such, some important variables related to the development of depression such as parental incarceration, parental mental health, and childhood abuse information were not available for this study. Fourth, the alpha values for some measures such as maternal attachment, maternal involvement, autonomy from parents, and neighbourhood connection were low, which indicates that these measures have a questionable level of internal consistency. Finally, the results from this machine learning forecasting procedure may be different by race and gender. If a tool such as this one were to be used in practice, it would be important to explore potential differences in performance. Despite these limitations, this study contributes to research related to depression among youth and young adults and to the field of social policy and practice as it

1) provides support for the concept of using a machine learning forecasting tool to identify individuals with behavioural health conditions, such as depression,

2) offers insight into the development of a depression diagnosis for youth while emphasizing the role that health disparities and access to care play, and

3) highlights the importance of early detection and universal screening for behavioural health conditions.

IMPLICATIONS

The findings from this study have important implications for further research and practice. First, future research that addresses this study's limitations is needed. For example, rather than relying on individuals' self-report of a depression diagnosis, one could administer a depression assessment tool that is used to diagnose depression. It would be important to determine how forecasting skill and accuracy would compare when depression diagnosis is measured differently. Additionally, future research which replicates this study is also needed to validate the findings and accuracy of this study.

Specifically, results should be explored for differences in performance related to gender and race. Finally, while risk factors for developing behavioural health conditions have been studied in depth, less is known about protective factors that promote good health and well-being (Banyard, Hamby, & Grych, 2017). Hence, additional research is needed to address this gap in knowledge as understanding these distinguishing features is critical to informing prevention strategies and programs.

In addition to future research, the findings from this study have important practice implications. First, this study demonstrated that it is feasible to develop a forecasting tool that can be used to identify mental health difficulties. While this tool relied on a specific set of input variables and is likely not to be exactly replicated, a similar tool could be developed depending on the data and information one had available. A tool like this one could be implemented in various practice settings including a primary care clinic, behavioural health organization, or even at the behavioural healthcare system level. In the primary care setting, a tool like this one may be specifically helpful in identifying people with underlying behavioural health conditions and beginning conversations about the importance of mental health and how it also impacts our physical health. While this application may deviate from standard practice, with some training it could be feasible.

Similarly, a behavioural health or social service organization could implement a similar tool using existing data that are collected from individuals as part of the standard intake process to identify individuals who are most at risk to ensure that they remain engaged in treatment or have access to services. Integrating a tool like this one in standard care and combining provider expertise/clinical judgement with data and/or a decision support tool has the potential to improve patient outcomes. Decision support tools take into account client information (e.g. demographics or clinical data) to offer personalized treatment (Graham, James, & Spertus, 2018).

CONCLUSION

In sum, this dissertation highlights how a machine learning forecasting tool could be used to inform prevention strategies and factors associated with receiving a depression diagnosis. Findings from this study indicate that it is feasible and practical to use a forecasting tool to identify individuals at risk of being diagnosed with depression. Machine learning tools have the potential to improve the diagnosis and treatment of behavioural health conditions and subsequently may help individuals live healthier lives. Additionally, this dissertation emphasizes the role health disparities, specifically gender and race, may play in seeking care and having access to quality mental health treatment. Future research is needed to better understand the developmental trajectories of depression for youth and what differentiates youth with depression symptoms who are diagnosed with depression as an adult from youth with depression symptoms without a depression diagnosis as an adult. More attention and work focusing on health promotion and prevention should also be considered. This study presents and discusses these findings in addition to offering important implications for future research and practice to identify and prevent behavioural health conditions such as depression.

Hence, as providers and as a health system, more attention and effort need to be given to strategies that build mental health literacy and reduce the stigma associated with mental health conditions. Health promotion and prevention initiatives that focus on stress, wellbeing, and mental health literacy have demonstrated positive outcomes and greater level of social and emotional competencies (Fenwick-Smith, Dahlberg, & Thompson, 2018; O'Reilly, Svirydzenka, Adams & Dogra, 2018). However, less is known about long-term impact of these initiatives, and more research is needed to further evaluate their effectiveness (O'Reilly, Svirydzenka, Adams & Dogra, 2018).

As our healthcare system is working towards achieving the Triple Aim of improved patient experience of care, improved population health, and reduction in cost, investing in solutions to better identify people in need of behavioural health services and focusing on health promotion and prevention strategies have the potential to help achieve the Triple Aim and ensure that all individuals are equipped with the opportunity and tools to live a healthy life.

xThis project defines a binary classification problem as identifying whether a person is depressed, based on his tweets and Twitter profile activity. Different machine learning algorithms are exploited and different feature datasets are explored. Many pre processing steps are performed, including data preparation and aligning, data labelling, and feature extraction and selection. The SVM model has achieved optimal accuracy metric combinations; it converts an extremely nonlinear classification problem into a linearly separable problem. Although the DT model is comprehensive and follows understandable steps, it can fail if exposed to brand-new data. This study can be considered as a step toward building a complete social media-based platform for analysing and predicting mental and psychological issues.

FUTURE WORK

We propose some possible future study directions in this part, based on the review of prior research in the preceding section.

1. A larger data sample is required:
   The majority of prior depression detection research utilized a small sample size. A small sample size is useful for building a prediction model, while a bigger sample size is important for constructing a more accurate model that works well throughout the population. When a large sample size is used to train a model, it allows for a greater diversity of depressed patients to be included, perhaps leading to models with real therapeutic value. When a few studies use bigger datasets, the methods will most likely alter and show more developed approval metrics. The k-fold cross-validation technique, in particular, may be employed with higher k-values to allow for larger test sets on which to test prediction models and increase generalizability.

2. Learning methods:
   Various learning techniques give a better outcome in different situations; therefore, choosing the right one is crucial. Unlabelled data may sometimes help develop a prediction model for a large sample size with little data. As a result, the first step is to determine if the incoming data are labelled, unlabelled, or a combination of labelled and unlabelled data. As a result, employing an unsupervised, supervised, or semi-supervised learning technique will be determined. The second phase is dependent on the learning method's objective, which must be addressed. The last stage is to identify whether the input is linear or nonlinear; linear data are helpful when the dataset is small to prevent overfitting, whereas nonlinear data are important when the dataset is big. The last step is to choose a learning technique to limit the options. The technique for picking the best learning method is to assess various factors such as complexity, flexibility, computation time, optimization ability, and so on, and then choose the best one. If you have too many learning method choices, evaluate the performance of each technique on the provided data; if you just have a few, simply change the default model to make it more appropriate for learning the given data.

3. Clinical application:
   Long-term, creating a predictive model aims to find a method that can improve accuracy. However, such a scenario is unlikely to arise in the next few years, since SVM and a few other supervised learning algorithms are presently trustworthy and seem to be around in this area of research.

Regardless, after a sufficiently strong method has been thoroughly authorized via preliminary considerations, showing its efficacy, and determining whether it will benefit patients or not, its progression to clinical preliminaries will be critical. Future clinical trials should ensure that machine learning methods efficiently identify depressed individuals who are unlikely to respond to the current specialist under investigation. Clinicians' use of this information improves patient outcomes (for example, diminished inactivity among determination and reduction).

4. Collaboration of research groups:
   With the significant progress among different disciplines, collaboration with other disciplines is crucial for ADE. For affective computing, relevant fields include psychology, physiology, computer science, ML, etc. Thus, researchers should borrow each other's strengths to promote ADE's advances. For audio-based ADE, the deep models only represent the depression scale from audios. The deep models capture patterns only from facial expressions specific to video-based ADE. Notably, physiological signals also contain significant information closely related to depression estimation. Accordingly, different researchers should study together to build multimodal-based DL approaches for clinical application.

5. Availability of databases:
   Because of the sensitivity of depression data, it is difficult to gain various data for estimating the scale of depression. Hence, the availability of data is a major issue. First, as opposed to the facial expression recognition task, database availability is scarce up to the present day. Given the literature review, one can note that the widely used depression databases are AVEC2013, AVEC2014, and DAIC-WOZ. Notably, AVEC2014 is a subset of AVEC2013. Second, there is no multimodal (i.e., audio, video, text, physiological signals) database to learn comprehensive depression representations for ADE. The existing databases consist of two or three modalities. Though the DAIC database comprises three modalities (audio visual and text), the organizer has not provided the original videos of DAIC, leading to a certain inconvenience for ADE. Third, the limited size of the datasets limits the research in depression prediction, especially when using DL technologies. For instance, AVEC2013 only contains 50 samples for training, development, and test set. Effective methods to augment the limited amount of annotated data are called to address his bottleneck. Fourth, the criteria for data collection should be standardized. At present, different organizers adopt a range of conditions, equipment, and configurations to collect multimodal data.

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