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Examining Factors for Anxiety and Depression Prediction

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Abstract— Mental health conditions, such as anxiety and depression, are a significant public health concern that can have significant impacts on an individual's quality of life, relationships, and overall well-being. In recent years, data science and machine learning techniques have emerged as important tools for early detection for mental health issues. This research aims at understanding the factors leading to anxiety and depression and implement predictive modelling for improving the accuracy and efficiency of early mental health diagnoses. Tabular DNN outperformed ANN and other machine learning classifiers by approximately 30%. Overall, our findings suggest that deep learning tabular models have the potential to improve the accuracy and efficiency. Thereby helping in early mental health diagnoses so that accessible and convenient support to individuals in need in context of this work.

Keywords— Mental health, anxiety, depression, neural networks, DNN, ANN, classifiers

I. INTRODUCTION

Millions of people worldwide suffer from anxiety and depression. Depression is characterised by intense feelings of despair, gloom, and sadness. It is more than just a "bad mood," but a persistent feeling that a person cannot control and that interferes with daily activities and functioning. Depression is expected to overtake heart disease as the leading cause of death by 2023. Depression can appear in a variety of forms, and symptoms can range from mild to severe. Depression is a common mental health issue. The symptoms manifest themselves in four key areas of human work: emotional, cognitive, physical, and behavioural, with mood problems being the most visible manifestation, among others. Changes in nutrition or weight, disturbed sleep and insomnia, decreased energy, a sense of shame, disordered thinking, focusing, and decision-making, persistent death thoughts, and suicidal ideation are all symptoms of depression. Anhedonia, or a loss of interest in previously enjoyable activities, is a factor in social disengagement.

Everyone experiences anxiety at some point in their lives. Anxiety is the unpleasant and uncomfortable feelings that a person experiences when confronted with stressful or frightening situations. Anxiety can be triggered by a variety of factors, mostly as a result of stress. Anxiety symptoms can occur as psychological, physical, or environmental issues. Anxiety can manifest itself in various ways, including but not limited to excessive worrying and fear, restlessness, overly emotional responses, as well as negative thoughts. While some people appear calm, they experience headaches and excessive sweating [1-2].

In recent years, the importance of mental health in society has been given more importance, and data science has played a crucial role in understanding and addressing mental health issues. Big data and machine learning techniques have allowed researchers to analyse large amounts of data, such as electronic medical records, social media posts, and survey responses, to find patterns and trends that can be used to develop new mental health interventions. They have been used to identify risk factors for mental health disorders, like poverty, trauma, and social isolation, and to create targeted interventions to address these factors.

Data science has also been used to improve the accuracy and efficiency of mental health diagnoses. Machine learning algorithms, for example, have been developed to help mental health professionals accurately identify and diagnose mental health disorders using a combination of clinical data and patient self-reported data. This can reduce the burden on mental health professionals and improve the quality of care for patients. In addition to its contributions to research and clinical practice, data science has also played a role in promoting mental health awareness and reducing stigma. Social media platforms, for example, have used data science to identify and intervene in cases of online harassment, which can have a negative impact on mental health. Data science has also been used to create mental health apps and online resources that provide self-assessment tools and resources for people struggling with mental health issues. Overall, data science has had a

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significant impact on the field of mental health and is only beginning to be recognized for its potential to address mental health challenges. As data science techniques continue to evolve, it is likely that they will continue to play a key role in improving mental health care and promoting mental health awareness in society. Thus, the implementation of machine learning and AI in mental health has the potential to improve the accuracy and efficiency of diagnoses, as well as provide accessible and convenient support to individuals in need [3].

The predictive findings using artificial intelligence and data analytics aid in the early detection of high-risk medical conditions in patients [4-5]. In case of mental disorders, healthcare providers can forecast the likelihood of mental diseases and provide appropriate treatment outcomes with the assistance of ML approaches, which can aid probable behavioural biomarkers. These techniques aid in the visualisation and interpretation of large amounts of healthcare data [6]. The visualisation aids in the development of an effective hypothesis for the diagnosis of mental disorders. The traditional clinical diagnostic approach for depression does not accurately identify the complexity of the depression. Using ML methods, the composition of symptoms associated with mental disorders such as depression and anxiety can be easily detected and predicted [7].

Fear, worry, and stress are natural reactions to perceived or real threats, as well as to uncertainty and the unknown. As a result, dread is natural and comprehensible in the context of situations like COVID-19. While the threat of infection looms overhead, daily lives were also affected changing the realities within and thus affecting physical and well-being of people. COVID-19 saw an exponential increase in mental health issues around the globe [8-9]. Therefore, we analysed the mental health data as a part of this work to gain insights about the factors leading to anxiety and depression. Moreover, we also tried to model the possibilities of mental health issues using various machine learning algorithms for early detection.

II. Background

Anxiety and depression are complex conditions that can be influenced by a variety of factors, including intrinsic factors such as genetics and personality traits, and extrinsic factors such as social support and stress. It is important to understand the specific factors that contribute to anxiety and depression to develop effective interventions and support for individuals who may be struggling with these conditions. The COVID-19 pandemic has had a significant impact on mental health, with many individuals experiencing increased levels of stress and anxiety due to social isolation, financial strain, and other pandemic-related challenges. It is important to investigate the additional factors that may lead to anxiety and depression in pandemic-like situations to develop targeted interventions and support for individuals who may be at risk of these conditions. Machine learning algorithms can be trained to analyse large amounts of data, such as electronic medical records and patient self-report, to identify patterns and trends that can inform the development of new mental health interventions. By using machine learning techniques to predict anxiety and depression in individuals based on identified risk factors, it may be possible to develop personalised interventions and support for those at risk of these conditions. This research will be important for improving the accuracy and efficiency of early mental health diagnoses, for providing accessible and convenient support to individuals in need.

III. Related Work

This section provides insights about existing work in the domain of mental health and well-being in general and use of machine learning techniques for analysis and detection. Happiness is usually cited as a crucial result of life quality and a trait of those who have good adjustment and function. People who are content are less likely to report having a mental health problem. Understanding how important people think happiness is to them is less definite and inconsistent. Happiness seems to have benefits and risks for outcomes related to mental health, depending on how it is valued or prioritised. This research in [10] investigates the relationship between the importance of happiness and outcomes related to mental health, as well as whether this relationship is influenced by how much people value happiness. The investigation included dual data sample - a community sample (n = 248) and a sample of university students (n = 413). Anxiety and depression symptoms as well as psychological distress were used to operationalize mental health. Happiness and the emphasis that people placed on happiness were linked to negative mental health outcomes. Happiness level and mental health were more significantly correlated in multi-variate analysis. The interaction between happiness and importance of happiness showed that people's importance of happiness moderated the influence of happiness. Results in terms of mental health are highly correlated with overall happiness and, to a lesser extent, with the importance of happiness. Among individuals who placed a higher value on happiness, there was a stronger correlation between happiness and mental health.

When young people seeking mental health care attempt to switch between child and adolescent mental health services (CAMHS) and adult mental health services (AMHS) their care is frequently disrupted. This is due to the lack of agreement on what constitutes best practices for intervention success to some extent. In [11], the author's purpose was to involve patients, carers, and clinicians in prioritising essential elements of smooth CAMHS-AMHS transitions that can be used in the development or assessment of transition therapies. In order to identify key elements of effective CAMHS-AMHS transitions, a Delphi research was carried out. Three impartial expert panels made up of children, parents, and clinicians ranked and offered feedback on the significance and viability of key CAMHS-AMHS transitions components in accordance with the principles of patient-oriented research. Components that received at least 70% support from any panel and were deemed practicable or significantly advanced to the next stage. As a result, a list of 26 essential CAMHS-AMHS transitional elements had been developed. These elements could be used in the planning, execution, or assessment of interventions aimed at enhancing the transitional experiences and outcomes for young people receiving mental health care. Throughout the whole research process, youth and families participated in an advising position as experts, lending their crucial insights to the planning and execution of this study as well as the interpretation of the results.

Reference [12] tackled the issue related to the prediction of Generalised Anxiety Disorder (GAD) and Major Depressive Disorder (MDD) by re-analysing data from an observational study with a novel machine learning pipeline. The machine learning algorithms under review were XGBoost, Random Forest, SVM, K-nearest-neighbours, and a neural network that was optimised using Bayesian hyper-parameter optimization. Every model has been trained using a 5-fold validation technique. A total of 4,184 undergraduate students undertook a general health screening as well as a psychiatric evaluation for MDD and GAD. For model training, fifty-nine biomedical and demographic features from the general health survey, as well as a set of engineered features, were used. On a held-out test set, the model performed well, with an AUC of 0.73 (sensitivity: 0.66, specificity: 0.7) for GAD and MDD, respectively. Also, Shapley Additive Explanation (SHAP) values used to determine which features had the greatest impact on disease prediction. It also aids in the calculation and visualisation of feature importance in this complex model. The SHAP kernel explainer accepts data and a prediction function from the user and returns the relative importance of each feature for each subject. The leading predictors of MDD were contentment with living standards and having government health insurance; the top predictors of GAD were up-to-date vaccinations and marijuana use. According to the findings of a study published in the Journal of Clinical Epidemiology and Biomarkers, machine learning algorithms have a reasonable predictive performance in detecting GAD and MDD based on the Datasets provided. These findings could be used in future studies in order to assist in the early diagnosis of MDD and GAD.

The researchers in [13] proposed a new diagnostic methodology that tests rigorously for differences in cognitive biases among anxious and depressed individuals. The machine learning tool used for this research is designed to detect complex non-linear high-dimensional interactions that may help to make predictions. The ones based on decision tree algorithms were intended to be sensitive enough to classify participants into four groups (high anxiety and low depression levels [HA], high depression and low anxiety levels [HD], high anxiety and depression levels [HAD], and low anxiety and depression levels [LAD]). The prediction model for differentiating between symptomatic participants revealed a 71.44% prediction accuracy for the former (sensitivity) and 70.78% for the latter (specificity). 68.07% and 74.18% prediction accuracy were obtained for a two-group model with high depression/anxiety, respectively. The analysis also revealed which specific behavioural measures helped predict anxiety versus depression.

NLP approaches analyse acoustic and linguistic aspects of human language derived from text and speech, and they can be combined with machine learning approaches to classify depression and its severity. In the research conducted by [14] a model to predict anxiety and depression symptoms is designed. A set of speech data is used as input into this framework. The data set used for the experiment was pre-processed in order to remove noise and make the original data set more consistent. The different machine learning approaches used on the dataset include Naïve Bayes, Random Forest, and Support Vector Machines (SVM). It is vital to classify the data. The accuracy of these machine learning algorithms was recorded as 97% for SVM, 78% for Random Forest and 76% for Naïve Bayes.

Seafarers frequently suffer from a multitude of mental illnesses. The authors in [15] used machine learning techniques to predict the existence of anxiety and depression among seafarers. They used five different machine learning classifiers to predict anxiety and depression among seafarers and discovered that the CatBoost classifier outperformed the others.

In [16], the Depression, Anxiety, and Stress Scale questionnaire was used to collect data from employed and unemployed people from various cultures and groups in order to apply these algorithms (DASS 21). Five separate machine learning algorithms predicted anxiety, depression, and stress on five levels of severity - these are particularly well adapted to predicting psychological issues due to their high accuracy. Following the application of the various approaches, the confusion matrix revealed that classes were unbalanced. As a result, the f1 score metric was added,

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which assisted in identifying the best accuracy model as the Random Forest classifier among the five used algorithms. The specificity parameter also demonstrated that the algorithms were particularly sensitive to unfavourable outcomes. Machine learning algorithms were used in this study to assess five different levels of anxiety, depression, and stress intensity. A standard questionnaire was used to collect data, which measured common anxiety, depression, and stress symptoms (DASS-21). Following that, five different classification techniques – Decision Tree (DT), Random Forest Tree (RFT), Naïve Bayes, Support Vector Machine (SVM), and K- Nearest Neighbour (KNN) – were used. Although Random Forest was shown to be the best model, the accuracy of Naïve Bayes was found to be the highest. Because this challenge resulted in imbalanced classes, the best-model selection was based on the f1 score, which is employed in imbalanced partitioning scenarios. The current psychiatric diagnosis is based on self-reports, which are vulnerable to personal biases. As a result, data-driven solutions that improve accuracy and specificity would be extremely beneficial to the diagnosis process.

The authors in [17] looked at six different machine learning classifiers that used a variety of socio-demographic and psychological data to determine whether or not a person was depressed. In addition, three distinct feature selection approaches were utilised to extract the most relevant features from the dataset: Select K-Best Features (SelectKBest), Minimum Redundancy and Maximum Relevance (mRMR), and the Boruta feature selection algorithm. The Synthetic Minority Oversampling Technique (SMOTE), which minimises the class imbalance of the training data, was utilised to improve accuracy in predicting depression. With an accuracy of 92.56%, the AdaBoost classifier with the SelectKBest feature selection algorithm topped all other approaches. Other evaluation criteria such as sensitivity, specificity, accuracy, F1-score, and area under the curve (AUC) of multiple models have also been calculated in order to determine the best efficient model for predicting depression.

Reference [18] focuses on the psychological impact of the pandemic, for which researchers employed convenience sampling and a web-based quantitative questionnaire that includes the 7-item Generalised Anxiety Disorder Scale (GAD-7) and other basic information. According to the results of the General Anxiety Disorder Scale, two-thirds of college students who answered the survey showed some level of anxiety, ranging from mild to moderate to severe. The respondents' gender had some bearing on their worry throughout the pandemic. In [19], a mathematical approach using supervised machine learning is is presented utilizing bio-signals in a randomised controlled trial. Bagged Trees was deduced as the best classifier obtaining an accuracy score of over 80%.

Kumar et al. (2020) used eight machine learning algorithms to predict the development of psychological issues such as anxiety, depression, and stress using data from the online DASS42 application. Eight algorithms were used to predict five different severity degrees of anxiety, despair, and stress. There are four types of algorithms: probabilistic, nearest neighbour, neural network, and tree-based. For the prediction of varying severity levels of anxiety, depression, and stress, a hybrid classification algorithm was used. The same procedures were used on another dataset gathered by the authors, DASS21. The prediction accuracy obtained by utilising the hybrid algorithm was higher than that obtained by using single methods, although the radial basis function network, which falls under the category of neural network, yielded the highest accuracy [20].

IV. Methodology

The 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 anxiety and depression, and training the deep learning models to make predictive analysis. This section discusses each of these steps and the different methods and approaches used for implementation.

A. *Data Description*

This analysis made use of the nationwide COVID-19 Impact Survey from the Data Foundation [21]. It included information from the COVID-19 Impact Survey, which provides statistics on the economic well-being, social dynamics, and physical and mental health of Americans as a result of the coronavirus pandemic. Estimates for the entire United States, along with 10 states and 8 urban regions, are provided by the probability-based survey, which was carried out by the National Opinion Research Center (NORC) at the University of Chicago for the Data Foundation. States that fall under this category include California, Colorado, Florida, Louisiana, Minnesota, Missouri, Montana, New York, Oregon, and Texas. Urban areas include Atlanta, Baltimore, Birmingham, Chicago, Cleveland, Columbus, Phoenix, and Pittsburgh. Data was gathered in three phases (April, May, and June, 2020) to give a picture of the effects of the global pandemic on the economy, employment, and physical and mental health in the United States during each period. The three phases consist of several cross-sectional studies. For each wave, data was gathered over the course of a week, with interviews conducted in both English and Spanish. First, a representative sample of American households was chosen at random from the NORC National Sample Frame at the University of Chicago, and they were subsequently

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contacted via mail, email, phone, and field interviewers in the United States. Each household with one or more adult roommates had one participant selected at random (family, friend, partner). All members who requested it had access to the survey either online or over the phone with a NORC telephone researcher. The dataset aims to offer a continuous evaluation of the public's perception, health, and economic position throughout the outbreak in order to see how things are changing. When a wealth of data is accessible, it will be possible to monitor changes in issues like COVID-19 symptoms and financial situation over time. The survey's three main research topics are physical health, financial and economic health, and social and mental health. The survey questions covered a wide range of indications, such as mental health, working from home, communication, COVID-19 symptoms, persistent medical conditions, behavioural components, and many more. Data from weeks 1, 2, and 3 (April 20–26, 2020, May 4–10, 2020, and May 30–June 8, 2020, respectively) were accessible and incorporated for this investigation. Combining different columns or factors would tell us a brief explanation how it would help in determining the cause of increase in mental health issues. Since the type of data affects the kind of statistical analysis that can be done on it, we delved deeply into the nature of the data in order to characterise and analyse it. Different graphs and frequency were made to describe the data. It seems like the analysis would be used to work on those factors and moreover prepare us for the next pandemic. After collecting the data, processing and cleaning up the accumulated data were left of the data preparation and processing step. Making sure the data you require is actually accessible to you for processing was one of the phase's crucial components. Collecting useful data and starting the data analytics lifecycle were the first steps in the data preparation phase. Creating data sets for testing, training, and production reasons were part of the data analytics architecture at this stage. To analyse the data, we relied on tools and a variety of techniques. After some analysis (in the trial phase) we pointed out the key findings and checked if the analysis is helping us to determine what factors are affecting the mental health issues.

B. Data – Exploration, Insights & Correlations

The data was gathered over a three-month period, and each month's results are presented separately. In total, 8,769, 8,952, and 7,491 people participated in the poll in each of the months of April, May, and June 2020 respectively. For this study the datasets from the three months were combined and the total respondent count reached 25,212. This consists of 56% females and 44% of male respondents, Fig. 1.

For this study, approximately 60% of participants had an average annual income of approximately $50,000 over a three-month period, which is consistent with the average annual household income in the United States, Fig. 2. Additionally, 52.5% of participants had a bachelor's degree or higher, Fig. 3. These data suggest that the sample is representative of the general population in terms of income and education level, Fig. 4.

The respondents in this dataset expressed concern about one or more of the mental health indicators. 37.60% of respondents who provided mental health markers mentioned feeling uneasy, anxious, or on edge. 38.02% (9,588) felt pessimistic about the future, 38.22% (9,639) expressed despair, and 37.95% (9,571) reported loneliness, presented from Fig. 4 – Fig. 6. Only 9.62% (2,425) of those surveyed claimed to have experienced at least one physical symptom related to the coronavirus pandemic, such as sweating, breathing difficulties, nausea, or a racing heart .

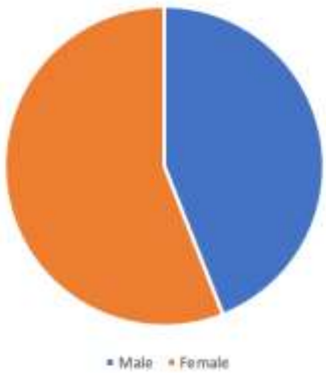

Fig. 1 Gender Ratio

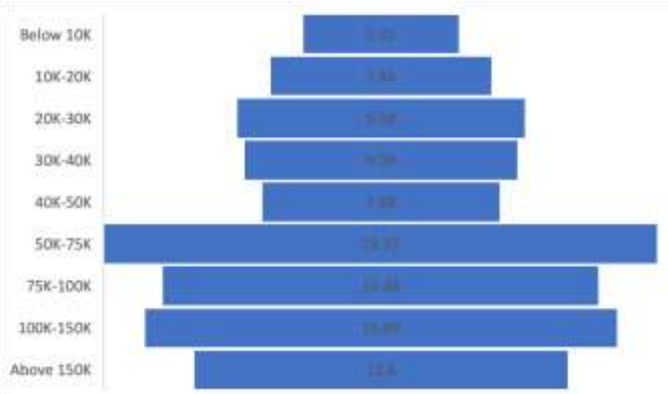

Fig. 2 Annual Household Income

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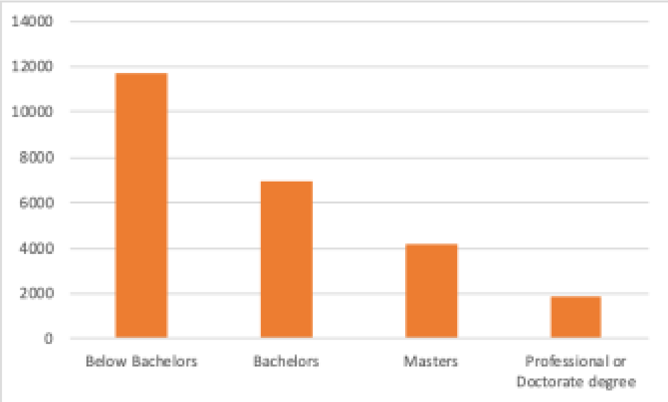

Fig.3 Level of Education

Correlational analysis can give insight on intricate real-world relations, assisting researchers in formulating hypotheses and making predictions. This section – Fig. 8 & Fig. 9, report the relationships between a self-reported anxiety column and depression column with other columns. The top three correlated columns with depression anxiety, hopelessness and loneliness. However, physical changes, hopelessness and loneliness showed highest correlation with the self-reported anxiety column.

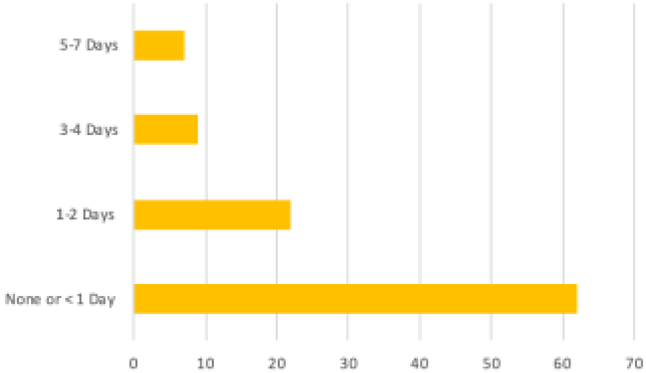

Fig. 4 Anxiety & Nervous Feelings

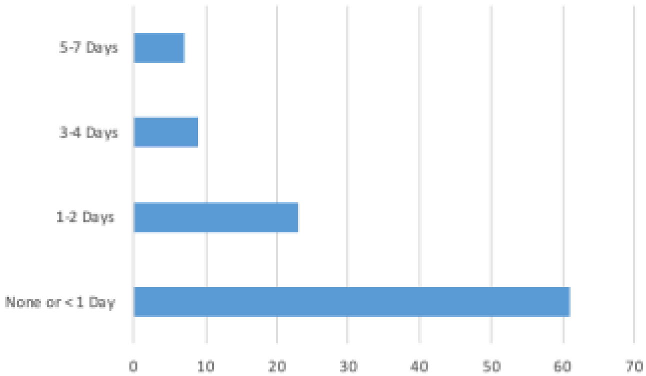

Fig.5 Depression

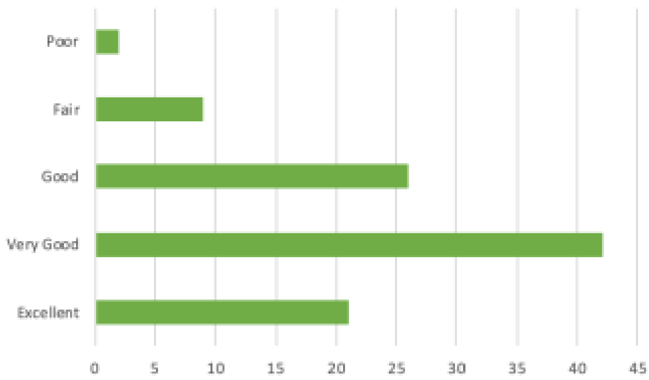

Fig. 6 Physical Health

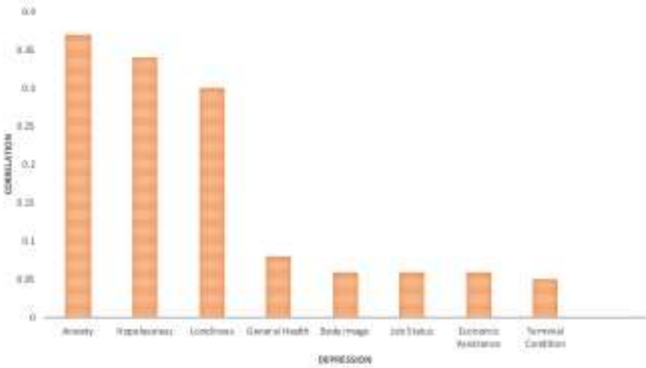

Fig. 7 Depression – Top 8 Correlated Columns

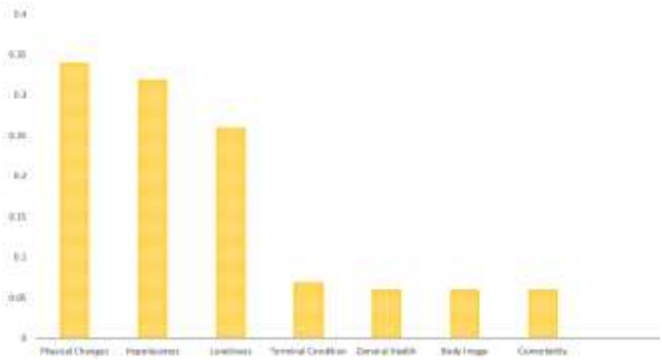

Fig. 8 Anxiety – Top 7 Correlated Columns

C. *Feature Selection*

The data analysis revealed the correlation of the self-reported anxiety and depression columns with 7 and 8 columns respectively, as represented in Fig.7 and Fig. 8. Hence the final model is trained with these features only. Analysis shows that anxiety, hopelessness and loneliness significantly contribute to depression. It can be noted that hopelessness and loneliness are also highly correlated with anxiety which in turn causes depression. Although other features such as general health, body image, economic

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conditions, etc don't generally present a direct high correlation score, but they have an impact on each other which eventually affects the top 3 columns in both anxiety and depression. Since the data is tabular in nature, features are well defined, highly organized and self-explanatory in relation to the target column based on domain knowledge and expertise. Hence, techniques such as embedded NSGA2 + Bi-Directional + GR, filter based NSGA2 +GR, filter based NSGA3 + GR, etc are not required for such data. The idea of feature selection in non-tabular data is usually based on presence of feature noise, under-representation and irrelevance in prediction. The nature of structured tabular data overcomes these issues by default. Therefore, statistical correlation tests form a better alternative for feature selectin in tabular data.

D. *Modelling*

For modelling the data was subjected to both machine learning and deep learning models in order to determine the best modelling technique. Linear Regression (LR), Random Forest Classifier (RF), Ridge Classifier (RIDGE), and Gradient Boosting Classifier (GBC) constitute the machine learning models used in this work. ANN and DNN were used as neural network modelling. DNN, Pytorch Tabular is used to train the mode. Pytorch Tabular provides several advantages over building a model from the ground up or using a pretrained model such as automatic optimal learning rate finder, easier training and evaluation interface, easier model architecture configuration, build in metrics tracking and build in evaluation metrics. The neural network model architecture for anxiety and depression model are illustrated in Fig. 9 – Fig. 11. ANN using multiclass regression was used as an alternative for comparison. Multiclass regression was used as it provides highly interpretable coefficients that quantify the relationship between your features and your outcome variable.

E. *Predictive Performance*

The performances of the models are evaluated in terms of accuracy and harmonic mean. The model trained using the deep neural network outperforms the model using artificial neural network. The outputs generated through the deep neural network show higher rates of accuracy.

Table 1 presents the performances of the models. The proposed DNN model performs at an accuracy of over 90% for both anxiety and depression. ANN shows almost 30% lesser performance for the same. The harmonic mean between the two for both anxiety and depression also presents DNN outperforming by over 20-30%.

TABLE I
PERFORMANCE ANALYSIS

Model	Accuracy	F1	Precision	Recall
Anxiety				
LR	0.67	0.64	0.63	0.36
RF	0.67	0.63	0.62	0.31
RIDGE	0.68	0.64	0.63	0.43
GBC	0.67	0.64	0.64	0.39
ANN	0.62	0.71	0.71	0.71
DNN	0.91	0.91	0.91	0.91
Depression				
LR	0.67	0.65	0.64	0.48
RF	0.68	0.64	0.63	0.46
RIDGE	0.68	0.64	0.64	0.49
GBC	0.68	0.65	0.64	0.48
ANN	0.63	0.66	0.67	0.66
DNN	0.96	0.96	0.96	0.96

V. DISCUSSION & CONCLUSION

This research used Tabular DNN, ANN, LR, RF, RIDGE, and GBC classifiers for early prediction and early detection of mental health problems such as anxiety and depression. Only 9.62% (2,425) of those surveyed claimed to have experienced at least one physical symptom related to the coronavirus pandemic, such as sweating, breathing difficulties, nausea, or a racing heart. However, physical changes to oneself especially sudden and social constructs such as hopelessness and loneliness presented highest correlation with self-reported anxiety data. Anxiety along with day to day social requirements are found to be extremely important for mental well-being of individuals as the best means of safeguard from depression. The model training involves top correlated features. Pytorch Tabular provides several advantages over building a model from the ground up or using a pretrained model such as automatic optimal learning rate finder, easier training and evaluation interface, efficient model tuning and architecture configuration for tabular data.

The model trained using the deep neural network outperforms all other classifiers by almost an 40% accuracy margin. The harmonic mean also suggests that the DNN is better at predicting anxiety and depression as it supersedes all machine learning classifiers and ANN by almost 30%. The tabular DNN is able to predict accurately every 9 out of 10 times & almost 10 out of 10 times for anxiety and depression respectively.

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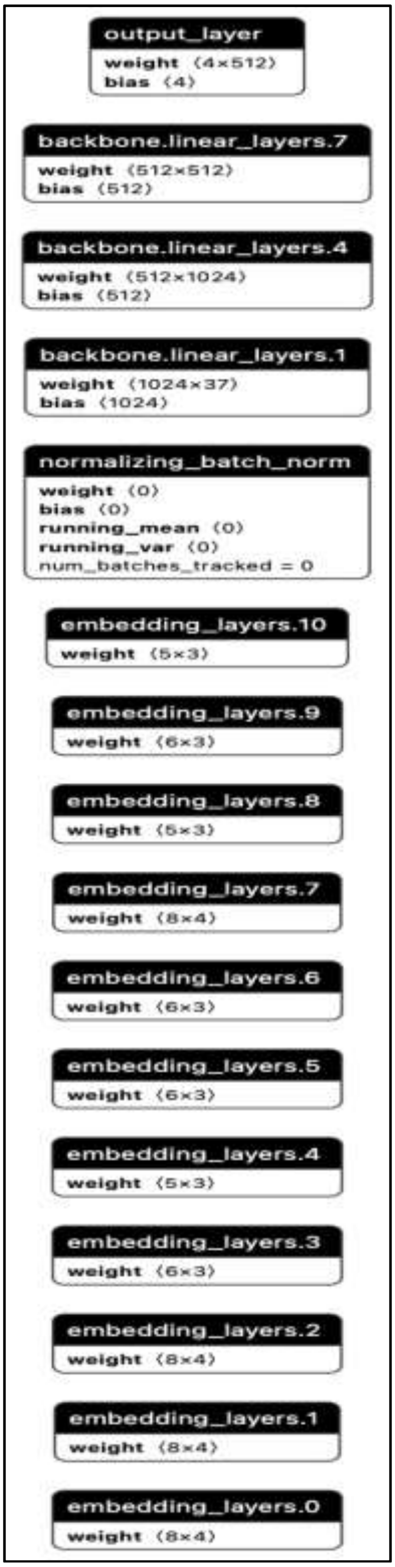

Fig. 9 DNN Architecture - Anxiety

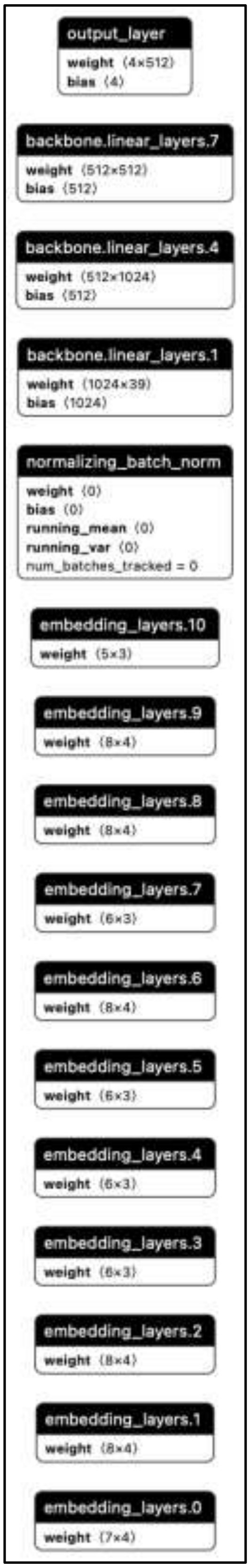

Fig. 10 DNN Architecture – Depression

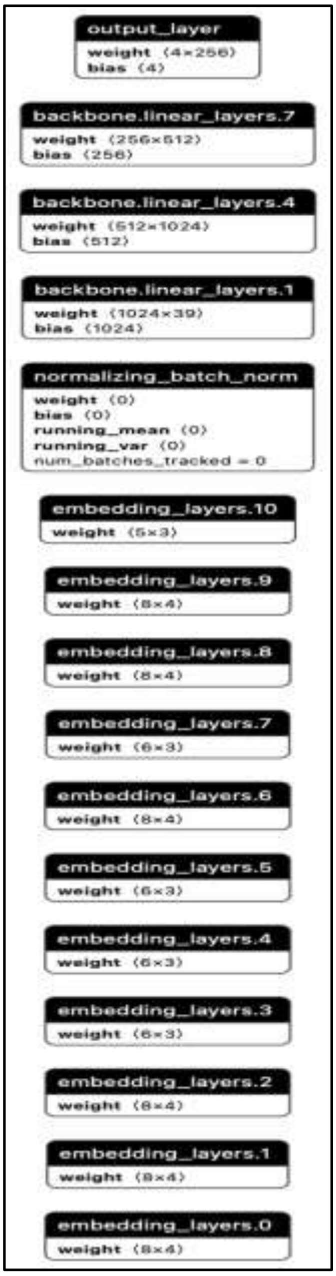

Fig. 11 ANN Architecture – Anxiety & Depression

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CONFLICT OF INTEREST

The author(s) declare that there is no conflict of Interest

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