

Cost-Effective Predictive Modeling for Student Mental Health Using Readily-Available Data

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Abstract—The mental health of post-secondary students is a critical public health issue, with alarming rates of psychological distress, suicidal thoughts, and behaviors on university and college campuses. Predictive modeling can be utilized for the analysis of student mental health to better understand current students' mental state. These predictions are often made using large surveys collected from students or participants to use the survey questions as features and then predict based on a target question related to mental health. The expensive nature of collecting data this way can be prohibitive for some institutions, and due to the scale and potential data processing required, the predictions made using those data could be too late for any proactive approaches to tackle the mental health of students. To address this, it is worth investigating the predictive performance of readily available data to predict student mental health as a means of accurately representing an institution's student body. In this paper, we show that readily-available data can be used to predict mental health with competitive accuracy compared to other experiments done in the literature that utilize more expensively collected data with neural network models.

Index Terms—Predictive Modeling, Neural Networks, Student Mental Health

I. INTRODUCTION

Mental health of post-secondary students is an important public health issue [1], with alarming rates of psychological distress and suicidal thoughts in college and university campuses. Recent studies indicate that suicidal thoughts and behaviors (STB) are prevalent among college students, with lifetime estimates for suicidal ideation, plans, and attempts reported as 22.3% for suicidal ideation, 6.1% for suicidal plans, and 3.2% for suicide attempts, respectively [1]. Identifying students at risk for mental health and social problems early in their academic journey is critical to a large-scale improvement in student wellness and academic success.

Given the critical role mental health plays in student overall well-being, many post-secondary students struggle with issues that significantly influence their academic performance [10]. Knowing when students are struggling can help institutions

allocate mental health resources accordingly or take other appropriate measures to mitigate some of the effects of students' deteriorated mental health. Anticipating the mental health status of a student population is something that has been studied through predictive modeling using neural networks for many different mental health outcomes, such as depression or general mental health and well-being (e.g. [15]).

Oftentimes, when predicting mental health, these models rely on data collected from student surveys or even national surveys for more general mental health predictions [2]–[4]. These surveys are often quite detailed to capture a vast amount of latent factors (i.e., features) that can contribute towards the accurate prediction of a target, in these cases, mental health status of a student.

However, collecting a thoroughly representative sample of such surveys presents significant challenges. A large number of students are often needed to get significant data, many of whom may lack the time or energy to complete the surveys due to the demands of their academic life. To encourage participation, financial incentives can be offered to students, although students who struggle with their mental health may find it particularly difficult to engage and respond. Furthermore, the time required to collect, preprocess and analyze these data can result in delays, potentially rendering any intervention too late to have a meaningful impact during periods of heightened poor mental health.

The time and effort that are required to collect these data, along with the cost an institution may incur to acquire it, for example, hiring an agency to carry out the survey, make this process quite expensive. Data in this form are also not very streamlined in that large-scale surveys as these are potentially only collected once a year as many student mental health surveys tend to be and even less frequently like with national health reports. This infrequency would be detrimental to any proactive approach that aims to address student mental health.

This leads to the concept of cost-effective data information

that is readily available, frequently updated, and locally relevant, ensuring that it accurately reflects the lived experiences of students within a given institution. Cost-effective data sources, such as regional pricing indexes, housing market trends, or environmental metrics, offer a viable alternative to traditional surveys.

Building on this, we have developed Artificial Neural Network (ANN) and Deep Neural Network (DNN) models using readily available, cost-efficient, and reliable datasets released by the Canadian government [12]. These datasets provide an alternative to traditional survey methods, offering frequent updates and local relevance. In this study, ANN and DNN were selected due to their proven effectiveness in capturing complex, non-linear relationships between environmental factors and mental health outcomes. Unlike traditional machine learning models such as Random Forest, XGBoost, or support vector machine (SVM), neural networks excel in handling high-dimensional data and can model intricate patterns that are often present in mental health datasets. In addition, ANN and DNN have been widely used in similar predictive modeling tasks in the literature, demonstrating competitive performance in regression tasks. Although other models could be considered in future work, ANN and DNN were chosen for their ability to provide a robust baseline to evaluate the predictive power of readily available environmental data.

The main contributions of this study are:

- **Development of Models Using Government-Released Data:** We build predictive models, including ANN and DNN using reliable datasets released by Statistics Canada [12]. These models demonstrate the feasibility of using publicly available data to address challenges in predicting student mental health outcomes.
- **Creation of a Mental Health Index as a Target Variable:** We construct a novel target variable, the Student Mental Health Index, by aggregating and averaging multiple relevant parameters to represent overall mental health.
- **Analysis of Predictive Power of Cost-Effective Data:** We evaluate the effectiveness of using easily obtainable, cost-effective and reliable data for predicting student mental health outcomes.
- **Correlation with Environmental Factors:** We examine how various environmental factors, which can be accessed with minimal effort or resources, correlate with mental health indicators.
- **Comparison with Expensive Data Collection Methods:** We compare the predictive effectiveness of our approach with existing methods in the literature that rely on costly and resource-intensive data collection techniques.

The rest of this paper is organized as follows. Section II describes related work in the field of mental health prediction model. Section III provides an overview of the data collection process. Section IV describes the model design. Section V presents the experimental results, and Section VI concludes the paper.

II. RELATED WORK

This section focuses on related work in mental health prediction models, focusing on studies that evaluate various approaches, including the use of data from physical sensors, facial expressions, and questionnaire surveys from institutions [2], [3], national databases [4], and other participants [5]–[9]. It also examines the application of machine learning techniques, such as classifiers and neural networks, to improve the accuracy of the prediction.

Many studies have used standard training/validation/test splits, with a common configuration being 70% for training, 10% for validation, and 20% for testing [7], ensuring a robust evaluation of model performance.

Table 1 summarizes some of the neural network models previously used for mental health prediction, along with their prediction accuracy and the types of data used. The table also highlights the target predictions made by each model, providing an overview of existing approaches and their outcomes.

Nguyen and Byeon [9] identified stress, sleep, and income as key predictors of depression using interpretable model-agnostic explanations. Wu et al. [8] highlighted environmental factors, including fire safety and accident risks, as significant contributors to urban mental health in London. Baek and Cheung [7] utilized Context-DNN on Korea National Health data, considering factors such as physical health and socioeconomic status. Cheung and Teo [6] applied ANN and DNN to tech industry survey data, incorporating work-related stressors, achieving accuracies of 0.786 and 0.799, respectively. These studies demonstrate the effectiveness of neural networks in mental health prediction, leveraging environmental and socioeconomic factors.

However, the work of [4]–[10] primarily relies on survey-style data, which is not only costly but also time-intensive to collect. While these models yield strong results, their dependence on such data limits their ability to provide real-time predictions. In contrast, our approach leverages environmental data obtained from Canadian government statistics [12], allowing for more frequent and real-time monitoring. This approach supports quicker, more proactive mental health interventions. Our ANN and DNN models, with accuracies of 0.846 and 0.878 respectively, which demonstrates competitive performance when compared to survey-based models as shown in Table II.

III. DATASET AND DATA COLLECTION

This section provides an overview of the datasets that are used and the data collection process, focusing on environmental factors and mental health data used in our study.

A. Dataset

In this paper, datasets released by the Canadian government [12] are used to develop prediction models. Although this study focuses on Canadian data, the proposed approach can be adapted to other regions using similar publicly available datasets. Many countries collect and publish environmental

TABLE I
NEURAL NETWORK MODELS PERFORMANCE IN LITERATURE

Network Type	Data Collected	Prediction Target	Accuracy	Reference
ANN	United States National Health and Nutrition Examination Survey; 5,000 participants from 2011 - 2020	Depression - yes or no	0.706	Lee & Kim [4]
ANN	Swedish Twin Child and Adolescent Twin Study; 7638 twin pairs	Mental Health Problems - yes or no	0.705	Tate et al. [5]
ANN	Open Sourcing Mental Illness in Tech Survey	Mental Health Problems - yes or no	0.786	Cheung & Teo [6]
DNN	Korea National Health and Nutrition Examination Survey; 39,255 participants	Risk of Depression - 0.00 - 1.0	0.855	Baek & Cheung [7]
DNN	Korea Centers for Disease Control and Prevention's Community Health Survey; 36,258 participants in 2020	Experienced Depression - yes or no	0.899	Nguyen & Byeon [9]
DNN	Open Sourcing Mental Illness in Tech Survey	Mental Health Problems - yes or no	0.799	Cheung & Teo [6]
Context - DNN	Korea National Health and Nutrition Examination Survey; 39,255 participants	Risk of Depression - 0.00 - 1.0	0.955	Baek & Cheung [7]

and socioeconomic data, such as consumer price indices, housing market trends, and tuition fees, which can serve as proxies for mental health predictors. For example, the United States Bureau of Labor Statistics [16], Eurostat in the European Union [17], Office of National Statistics UK [18] and national statistical agencies in other countries provide comparable datasets. The key lies in identifying region-specific factors that significantly impact student mental health and ensuring that the data is locally relevant. By customizing the model to incorporate these region-specific variables, the approach can be generalized to different geographic and demographic contexts, making it a versatile tool for institutions worldwide.

B. Environmental Factors

Publicly available, government-released data provides a cost-effective, accurate, and reliable source of information for educational institutions. These data are often tailored to local demographics, which makes them very useful for predicting the mental health outcomes of students in specific regions.

In our study, we used several environmental factors, including various Consumer Price Indices (CPI) [12], to gain insights into students' lives and their potential mental states. These indices include metrics such as food prices, personal health expenses, recreation costs, and other essential indicators that reflect the financial and social well-being of a student. Additionally, we incorporated other reported metrics, such as tuition fees and rental market data, which have significant impacts on students' lives in post-secondary institutions.

The data used to train our models came from diverse and credible sources, including:

- Average tuition fees for both domestic and international students, sourced from the Statista Research Department [13], [14].

- Rental averages and medians, obtained from the Canada Mortgage and Housing Corporation.
- Consumer Price Indices, published by the Government of Canada through Statistics Canada, specifically for the province of Ontario.

All data were collected in the period 2011–2017 to align with the mental health data used in our study.

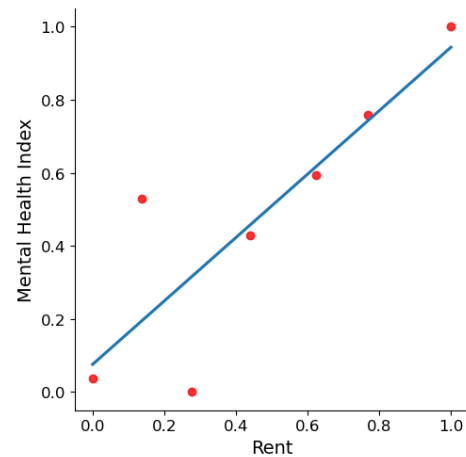


Fig. 1. Correlation Between Mental Health Index and Rental Price

To create the target variable of the mental health index, we averaged the parameters that provide a comprehensive measure of student mental health. This index served as the dependent variable for our predictive models. To evaluate how well the mental health index performs, we have plotted its correlation with the average rental price. Figure 1 illustrates this correlation, showing that the mental health index is performing well.

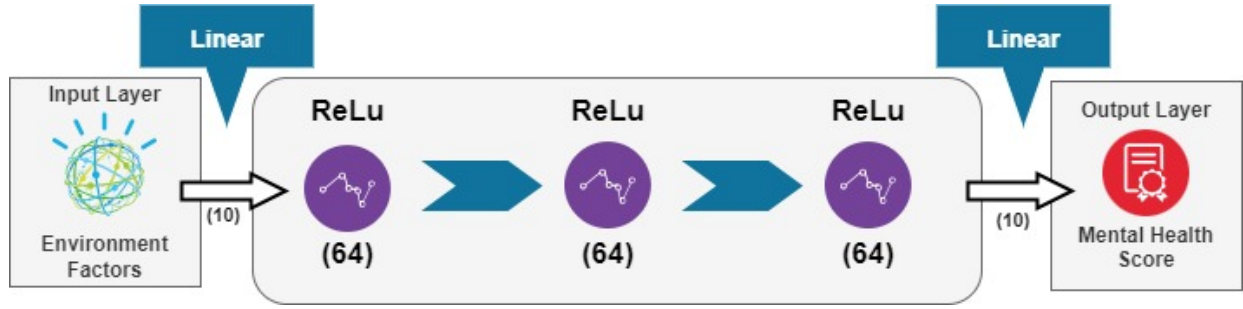


Fig. 2. Proposed DNN Model Architecture

C. Mental Health

In order to utilize the proposed environmental factors that we obtained through publicly available data, we require continuous mental health data to train a prediction model. We used a study [11] on mental health among post-secondary Canadian students, which is our target demographic. The study gathered data from 2011-2017 on certain mental health outcomes such as the prevalence of persistent stress, or feeling poorly, among other attributes that we then combined and averaged over the number of reported outcomes to obtain a score representing the severity of mental health scaled from 0 to 100 with 100 being the most severe, with the entire population having all the mental health afflictions that were reported. Our goal is to predict a score or measure of how well or poorly the mental health of students is at a given point in time, and from this score, we can allocate relevant resources or act accordingly to provide support to the affected student.

IV. PROPOSED PREDICTION MODEL DESIGN

This section describes the design of the neural network models used to predict mental health scores based on environmental factors.

In similar experiments centered on the prediction of mental health, artificial and deep neural networks have been commonly used, with the primary goal of classifying mental health outcomes into binary categories, such as the presence or absence of a disorder. However, our study takes a different approach in that it aims to evaluate the effectiveness of cost-efficient environmental factors in predicting a continuous mental health score, which is derived from a combination of various mental health indicators. Unlike binary classification tasks, our predictive model addresses the complexity of a continuous outcome, framing the problem as a regression task to capture the nuanced relationship between environmental factors and mental health. This approach provides a more comprehensive understanding of mental health fluctuations and allows for more precise predictions that can guide proactive interventions.

Figure 3 illustrates the complete workflow of our proposed model, from environmental data collection to prediction. This framework highlights key steps, including feature selection, normalization, model design, and prediction, which are described in detail below.

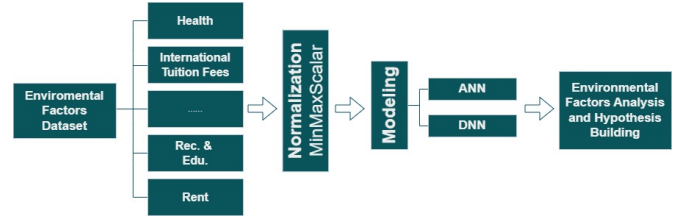


Fig. 3. Workflow of the Proposed Prediction Model Architecture

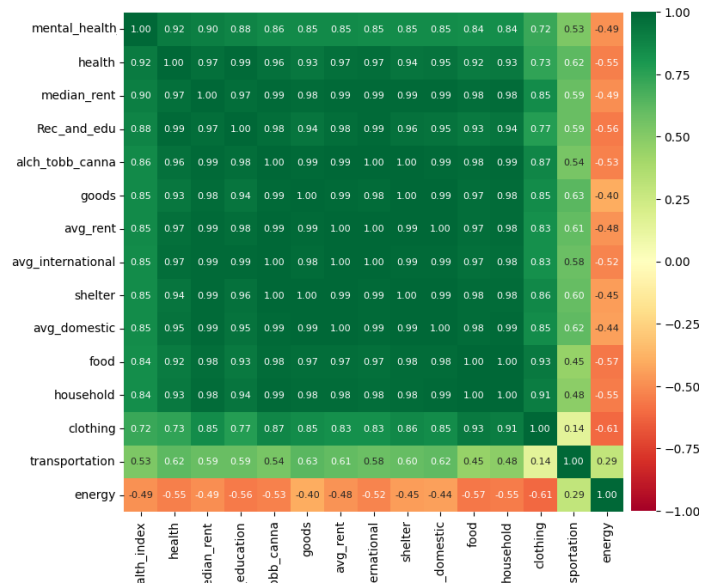


Fig. 4. Correlation Heat-map of Environmental Factors with Mental Health

We first identify which features are the most conducive to optimal model training. As we are faced with a regression problem, some feature selection methods such as LASSO are not available to us, and so we opt to evaluate these features on their correlation to the target variable. As shown in Figure 4, many of these environmental factors are strongly correlated with mental health, and we can see that things such as the cost of health services or rent are more strongly correlated with mental health, possibly showing that one's inability to pay for these facilities can greatly decrease their mental health by inducing high levels of stress and anxiety.

The top ten most correlated features were selected based

on their strong relationship with the target variable, ensuring that only the most relevant data points are used for prediction. The dataset was split using an 80/20 ratio for training and testing, a widely accepted approach that strikes an effective balance between model training and evaluation. Using 80% of the data for training allows the model to learn sufficiently from a large dataset, while holding back 20% as a test set ensures the model's ability to generalize to unseen data, helping assess its robustness and minimize overfitting.

To further enhance the model performance and ensure that each feature contributes equally to the learning process, we applied min-max normalization. This normalization method transforms the values of each feature into a fixed range, typically between 0 and 1, preventing features with larger numeric ranges from overshadowing those with smaller ranges. By scaling the data, we ensure that the model does not favor any specific feature due to its inherent scale, which is critical for neural networks.

In both the ANN and DNN architectures, ReLU activation was chosen for hidden layers due to its superior ability to handle non-linearity while mitigating the vanishing gradient problem that is common in deep networks, as shown in Figure 2. The ANN model consists of a single dense hidden layer with 64 units, while the DNN uses three layers, as shown in Figure 2, each with 64 units, followed by a final output layer with one unit and a linear activation function for regression tasks. Both models were compiled with the Adam optimizer, known for its efficiency in handling sparse gradients, and configured with default hyperparameters (learning rate = 0.001, beta1 = 0.9, beta2 = 0.999, epsilon = 1e-07, amsgrad = False), and training was performed over 500 epochs with a batch size of 1 and was trained to minimize the mean squared error (MSE) loss function to refine the predictions of the model.

V. EXPERIMENTAL RESULTS

We compared the accuracy of our ANN and DNN compared to other similar experiments carried out using, for the most part, survey-style questionnaires predicting mental health as a classification problem with our regression problem. The experiments were conducted using Python in a Jupyter Notebook environment, leveraging libraries such as TensorFlow, NumPy, scikit-learn. The models were trained on a standard GPU setup, which allowed for efficient processing of the neural networks.

Figure 5 presents the accuracy and training loss over the first 20 epochs of the model training process. As shown in Figure 5, accuracy improves consistently with each epoch, while loss decreases, indicating that the model is learning and improving its performance.

Figure 6 presents the Mean Absolute Error (MAE) over epochs for the ANN and DNN models. As shown in Figure 6, the MAE of both models decreases progressively with each epoch, indicating an improvement in the model predictions.

As such, we define our accuracy as the relative error measured using the absolute value of the true value subtracted from the mean absolute error over the true value. This accuracy measure will give us a sense of how close our predicted value

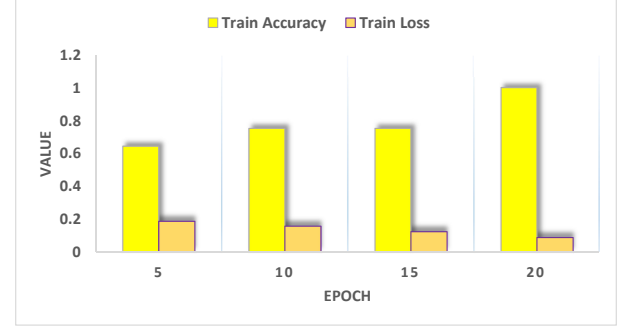


Fig. 5. Accuracy of the Proposed Model

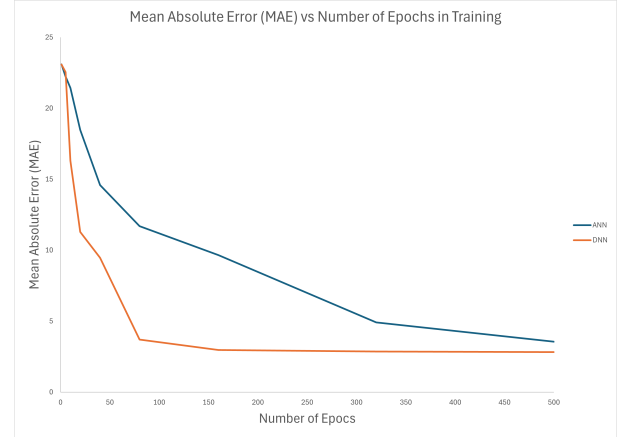


Fig. 6. Mean Absolute Error over Epochs

is to the true mental health score. We compare this measure of accuracy with the average accuracies of similar experiments for a given type of neural network.

TABLE II
COMPARISON OF NEURAL NETWORK TYPES

Type	Avg. Acc of Models in Literature	Our Acc	MAE
ANN	0.732	0.846	3.58
DNN	0.851	0.878	2.83

As shown in Table II, the classification-based ANN and DNN models that utilize survey style data have an accuracy of 0.732 and 0.851 respectively. Our model that uses environmental factors collected from publicly available sources [12]–[14] can compete with these basic models on its mental health outcome with an accuracy of 0.846 and 0.878 obtained from averaging 10 model training runs.

Figure 7 and Figure 8 illustrate the regression performance metrics of the ANN and DNN models, respectively, including MSE, MAE, and Root Mean Squared Error (RMSE).

VI. CONCLUSION AND FUTURE WORK

This research demonstrates the potential to use readily available and cost-effective environmental data to predict student mental health with accuracy comparable to traditional

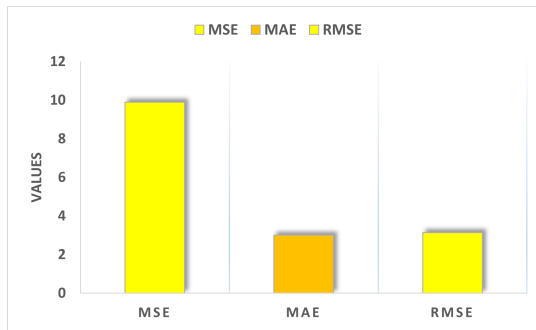


Fig. 7. ANN Model Metrics

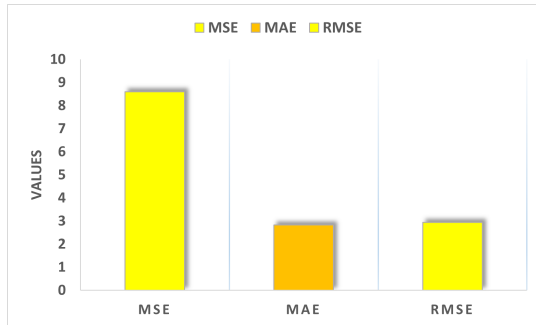


Fig. 8. DNN Model Metrics

survey-based approaches. Using ANN and DNN, the study highlights how publicly accessible data, such as consumer price indices and rental trends, can effectively model mental health outcomes. These findings provide an innovative solution to the challenges of high costs, delays, and limited scalability associated with survey-based methods, enabling institutions to adopt proactive and timely measures to support student well-being. Future research will focus on integrating more recent and locally relevant in-house mental health data to refine and validate the predictive models further. The development of novel neural network architectures tailored for this purpose will also be explored to enhance prediction accuracy. In addition, the study will investigate combining individual-level student information with environmental factors to assess personalized mental health risks. Expanding the scope of data sources and applying these models in diverse demographic and geographic settings will provide deeper insights and broaden the applicability of this approach.

Although this study demonstrates the potential of using readily available data and ML models to predict student mental health, it is crucial to address the ethical implications of such applications. The use of AI in mental health prediction raises concerns about data privacy, potential biases in the data, and the risk of misinterpretation of the model output. For example, biases in environmental or socioeconomic data could lead to unfair targeting or misallocation of resources, while privacy concerns may arise if individual-level data are used without proper consent. Furthermore, the predictions made by these models should not be seen as definitive diagnoses but

rather as tools to guide proactive interventions. Responsible AI practices, such as ensuring transparency, fairness, and accountability in the development and deployment of models, are essential to mitigate these risks. Future work should also explore the ethical frameworks and guidelines necessary to ensure that AI-driven mental health interventions are used responsibly and equitably across diverse populations and regions.

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