*i*Journals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 10 Issue 8 August 2022

Teenager Depression Diagnosis Using Physical and Algorithmic Deep Learning Methods (RNN)

Minjae Kim

Choate Rosemary Hall

jkim23@choate.edu

DOI: 10.26821/IJSHRE.10.8.2022.100803

ABSTRACT

Recently, the suicide rate among teenagers has risen to the point that it has become a massive societal issue. Suicide stems from depression; as such, it is critical to diagnose depression in children and adolescents early and to address the mental issue promptly. However, it is difficult for people to realize that what they're going through is indeed depression, leading to many people developing depression without knowing what is happening. In this research paper, I propose a method of detecting early signs of depression that takes both physical and mental factors into account. Depression causes physical changes within the body in a variety of ways. The paper discusses which physical devices can be introduced to measure these changes. There are also various forms and tests that may be used to "grade" a person on a standardized scale of depression. Since patients must manually respond to the questions, I have categorized this procedure as a physical system. We may deduce the severity of the condition from the information that individuals submit naturally, in addition to obtaining responses from them. Deep learning can be employed to carry out this procedure. To be more precise, I applied RNN to implement binary text classification. The evaluation used real data to demonstrate its practicality. The study closes with suggestions for enhancing the system.

1. INTRODUCTION

Depression is an emotional response budding from disappointment in our lives or suffering a significant loss. People from all age groups, noticeably children and adolescents, can develop depression. Normally, depression is transient and passes quickly, but if it advances to the level of a severe mental issue, it lasts a long time and is tough to overcome on one's own. Detecting and treating depression in children and adolescents in a timely way is therefore crucial. Depression symptoms in children are comparable to depression symptoms in adults: Sorrow, a sense of helplessness, and so on and so forth... However, children, unlike adults, do not adequately articulate their emotions. Children do not understand concepts such as "self-esteem," "guilt," and "attention." As a result, in the case of youngsters, this feeling is frequently not appropriately conveyed and is exhibited via behaviors. Aside from major symptoms such as changes in diet or sleep patterns, the following behavioral changes are likely signs of childhood depression: a sudden decline in academic performance, the act of wiggling, moving back and forth, or constantly pulling or rubbing one's hair, skin, clothing, etc.; also, speaking slowly or monotonously, irritation for unknown reasons, sudden yelling and complaining, etc. Depression was once thought to be caused by a dissonance of important neurotransmitters in the brain. For example, research has revealed that serotonin promotes cognitive dissonance, sleep disorders, irritation, and anxiety, whereas norepinephrine impacts conscious awakening, fatigue, and depression. Additionally, adrenocortical hormones are implicated in depression. It is also important to note that a common trend in people with depression is to have a family history of depression. Children born to depressed parents are three times more likely to go through depression than average people. The matching percentage in identical twins is 70%. This data reinforces the notion that depression is a hereditary condition. Much research has been conducted to determine the impact of the family environment on depression. Parents who are alcoholics or drug addicts cannot meet their children's needs regularly. The loss of a parent due to death or divorce is a traumatic event for children, and stress from long-term health issues of parents, siblings, or children themselves is also a major influence. Children who are subjected to psychological or physical abuse by their parents, as well as sexual abuse, are more sensitive to depression. Aside from the ones listed here, there are several more causes of depression. Furthermore, children who have grown up in a stable family with ample affection may suffer from depression. Therefore, scientists are aware that genetic, biochemical, and environmental variables all contribute to depression.

Mental health medicine and medical treatment for children who are depressed are crucial. For children to continue to study efficiently and have harmonious interpersonal interactions in the future, mental health medicine provides good assistance. When compared to adults, children react quite well to therapy for depression. Psychotherapy is an extremely successful treatment for childhood depression. Children learn how to properly communicate their feelings or emotions, as well as how to cope with depression or stress from their surroundings, through treatment. Many studies have shown that antidepressants are effective in treating depression. This is more beneficial, however, when done by a pediatric psychiatrist as part of a comprehensive treatment plan that includes play therapy, psychotherapy, cognitive behavioral therapy, and family therapy.

Adolescent suicide has recently risen to the point where it has become a social problem. Teenagers nowadays encounter a variety of difficulties, including value confusion, academic pressure, anxiety about the future, and friendship. Teenagers' challenges are exacerbated by the disintegration of traditional culture, turmoil in the family structure, and fast socio-cultural changes. Some teenagers who do not respond adequately to these issues may think suicide is the only option. It can be inferred that children who suffer from suicidal thoughts are depressed. Adolescents suffering from depression are unhappy, struggle with internal confusion, and have a decline in confidence and self-worth. These mental conflicts might lead to suicide due to feelings of helplessness and fury. 90% of kids who consider suicide believe that their friends or family do not understand them. So, despite their loneliness, they refuse to communicate to their parents about their tragedies, disappointments, and failures. Some parents dismiss their children's despair and complaints as character flaws. Consequently, teenagers with depression believe that their emotions have been disregarded, and they are resentful towards other people. Depressed teens frequently seek relief from those who share their sentiments of grief and despair. Some adolescents, for example, are engrossed in music that represent their insanity, self-destructive rage, and suicidal thoughts. Teenagers must be taught that depression is treatable. Parents or instructors who downplay these difficulties, especially in the case of teenagers experiencing depression for the first time, do not realize that their situation is insurmountable if left untreated, and could eventually lead to suicide.

However, these methods of combating depression miss an important component: the capacity to correctly deal with and detect depression before it takes hold in one's thinking. While the health recommendations and medicines described above can assist with depression treatment, they cannot prevent depression from occurring in the first place. To address the issue at its root, it is necessary to devise methods and techniques for detecting escalating sadness and stress. Forms and surveys are two current methods of preventative detection. There are several forms and tests available to assess the depression levels of an individual taking the test, including the Patient Health Questionnaire-9 (PHQ-9), Beck Depression Inventory (BDI), Zung Self-Rating Depression Scale, and Hamilton Rating Scale for Depression (HRSD). These measures are highly effective for evaluating depression levels, but they are missing

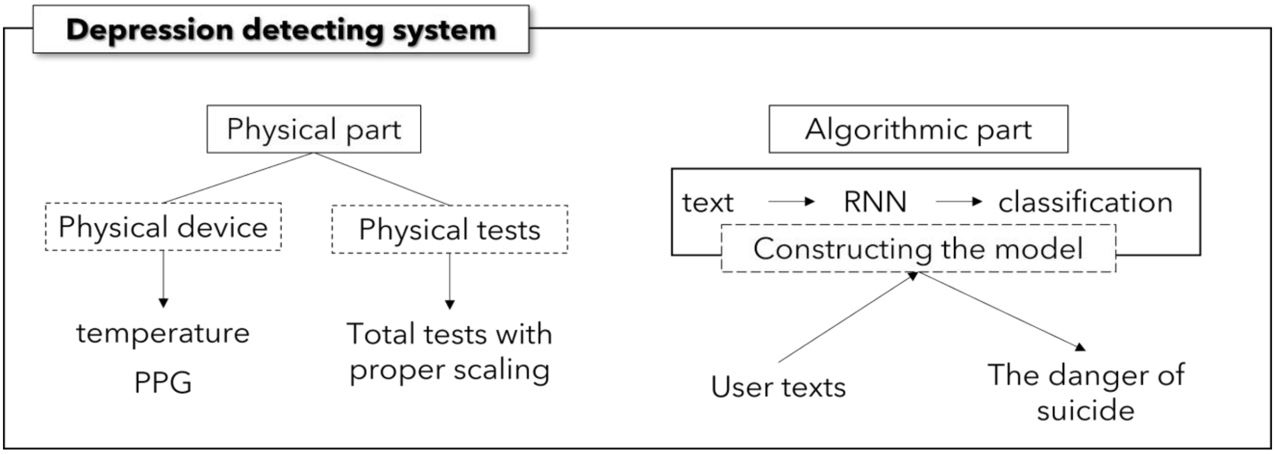

Fig 1: Model of Depression Detection System

an important aspect: the physical effects of this mental burden.

While depression can be detected, it is crucial to know if it is causing any side effects within a person's psyche. Therefore, my idea is to build an application that uses such questionnaires and a physical measuring device. It is hard to correctly quantify and measure an individual's depression levels and what could happen depending on these levels in stand-alone approaches. Furthermore, each form has different questions, which may result in different outcomes if the same person takes each test. As such, combining questions to precisely identify a person's depression level would be extremely beneficial. While these forms may help us comprehend a person's mental state, they are far from sufficient. These emotional mood swings can be harmful to the body; thus, it is essential to understand the physical changes that occur from depression and how a person is physically feeling at any time. The application we propose performs a variety of functions using much of the same technology that is commonly used today, such as determining if a person's blood flow is pumping at a faster or slower pace and monitoring their body temperature.

For the methods above, patients should answer the questions manually or wear a device. Due to these manual actions, I put this process as a physical system. This aspect of the proposed system not only receives the response from the user, but also helps to infer the level of illness from the text that the user wrote naturally. This process can be executed by adopting deep learning. To be specific, I applied RNN to implement binary text classification. To show practicality, the evaluation was conducted with real data. The paper concludes with suggestions to improve the system.

The physical component of the system is introduced in Chapter II. The RNN-based algorithmic element of the system is described in Chapter III. Chapter IV contains the evaluation. Chapter V has the conclusion and future efforts.

2. PHYSICAL METHODS

Depression may physically affect your body in a variety of ways. For starters, depression raises cortisol levels. Cortisol, often known as the stress hormone, causes blood pressure and heart rate to rise. As a result, depression indirectly increases heart rate, causing blood to flow more quickly through the organ. Another physical side effect of depression is a malfunctioning thermoregulation system. Depression has been linked to an increase in core temperature as well as an inability to sweat well, resulting in unstable thermoregulation, according to research. These physical symptoms of depression may be evaluated using various sensors such as the Apple Watch and thermometer technology.

2.1 Heart Rate Sensor

To begin, heart rate monitors employ several technologies to accurately determine how rapidly our hearts beat. Most heart rate monitors that we wear in our daily lives use PPG (photoplethysmography) technology, which involves beaming light into our skin and detecting the quantity of light dispersed by blood flow. PPG sensors require four different components. First, optical emitters that transmit light waves into the skin are required. Second, a photodetector catches and measures the light refracted by our blood, then converts the data into usable information. Third, an accelerometer monitors the velocity of light and blood flow and combined with the photodetector results, is used to track our heart rates. Finally, PPG-specific methods are implemented to further turn the data into usable heart rate values. These algorithms may then be tweaked to monitor additional biometric variables like blood oxygen levels and blood pressure. This technology is used by the Apple Watch to correctly monitor heart rates ranging from 30 to 210 beats per minute. It is necessary to recall certain physics to understand how Apple watches function. Blood is red because it reflects red light and absorbs other colors, such as green. To measure heart rate, Apple Watches use green LEDs. When a person's heart beats, the blood flow (and absorption of green light) increases. Between heartbeats, the blood flow and absorption rate of green are lower. The Apple Watches can correctly estimate how many times one's heart beats per minute by flashing the LED lights at an extremely high pace.

2.2 Measuring Body Temperature

In terms of monitoring body temperature, current technology has proven useful in delivering reliable data without the usage of medical technology or equipment. Apps that can take one's temperature simply by scanning their fingerprint (putting a finger on their phone screen) or thermometers that can plug into their phone's headphone port to monitor temperature are more accessible than ever before. It's also worth noting that kids experience emotional ups and downs all the time as a natural part of puberty. As such, sadness is frequently ignored as a natural consequence of puberty, leaving these young people without appropriate assistance or direction. These measuring methods are very crucial in keeping young adolescents safe and identifying whether they are depressed.

2.3 Methods of Testing

There are a variety of forms and tests that may be administered to determine a person's specific level of depression. These forms employ a set of standards, like a grading system, and utilize the grade or rating a person obtained to assess depression levels. The Patient Health Questionnaire-9 (PHQ-9) [1, 2], the Beck Depression Inventory (BDI) [3, 4], and the Zung Self-Rating Depression Scale [5] are examples of these forms.

2.3.1 PHQ-9

The Patient Health Questionnaire-9 is a self-administered depression screening tool based on modern criteria. It is one of the initial methods used to measure the extent of depression in a patient and pinpoint particularly troubling aspects of the patient's diagnosis. The available options for responses vary from "not at all" to "most of the time."

2.3.2 BDI

The Beck Depression Inventory is a 21-question survey that examines people's attitudes and symptoms of depression. This assessment, which is extensively used by both doctors and patients, measures the severity of both cognitive and physical depression. However, the BDI has certain shortcomings. The lack of universally applicable standards leads to subjective interpretations.

2.3.3 Zung Self-Rating Depression Scale

The Zung Self-Rating Depression Scale is a 20-question inventory designed to assess the intensity of a person's depression. Each question is scored on a scale of 1-4.

3. ALGORITHMIC SYSTEM

In addition to physical approaches, I also investigated an algorithmic system in this study.

3.1 RNN

A recurrent neural network (RNN) is a sequence model that processes inputs and outputs in units of sequence. When considering a translator, an input is a sentence that is a sequence of words that you need to translate. The translated sentence that corresponds to the output is also a word sequence. Sequence models are models that are designed to process sequences. Since it is a structure that may take inputs and outputs regardless of the length of the sequence, it is possible to design a structure in a variety of flexible ways [4].

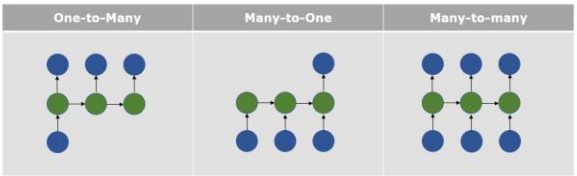

Fig 2: Relations of RNN

The work of reasoning whether the chance of suicide for a person is high by looking at student writings may be done using the Many-to-One RNN in Figure 2 above. Text categorization takes input for all time steps, but only the final time RNN cell outputs a hidden state, posing a challenge for proceeding to the output layer and selecting the correct response through the activation function. This is known as the Binary Classification problem, in which the correct answer is chosen from two options, and the Multi-Class Classification problem, in which the correct answer is picked from three or more options. You must use the activation function and the loss function that correspond to the problem for these two problems. For binary classification issues, utilize the sigmoid function as the output layer's activation function and binary_crossentropy as the loss function.

3.2 Text Classification using RNN

Supervised learning is used for text classification, where the training data consists of data that has been labeled with the correct answer in advance. In other words, the machine is a system that examines the questionnaire with the proper answer written on it thoroughly and anticipates and answers future questions that do not contain the correct response [5]. The training data in the spam mail classifier, for example, comprises of the contents of the email and a label indicating whether the email is legitimate or spam. Assume you have around 20,000 email samples in the format [text, class]. This data, which includes 20,000 email samples, includes text data containing the contents of the emails as well as a label indicating whether the data is spam or not. It consists of two columns. Suppose the system learned from the 20,000 email sample data. If the data is correct and the model is well-designed, the learned model predicts the precise label even if the training data lacks email text.

4. EVALUATION

First, I present the dataset in the evaluation chapter as well as how I implemented it in Python with pseudo codes. Section C contains the overall findings, which include a histogram of text length, logistic regression of the dataset - how many were 0 (did not commit suicide), 1 (committed suicide), and metric assessments of model loss and model accuracy.

4.1 Dataset

The dataset utilized in the RNN evaluation contains text messages as well as the result of whether the author succumbed to suicide. Table 1 below shows a sample of the entire dataset.

Table 1. a sample of the entire dataset

text	**class**
Honetly idkI dont know what im even doing here. I just feel like there is nothing and nowhere for me...	did not commit suicide
[Trigger warning] Excuse for self inflicted burns*I do know the crisis line and used it after when I...	committed suicide
It ends tonight.I can't do it anymore. I quit.	committed suicide

The data contains about 3,000 texts and the label (committed suicide, didn't commit suicide).

4.2 Implementation

The evaluation (RNN) was performed in Python using Keras. Google Colab was used for the evaluation.

*i*Journals: International Journal of Software & Hardware Research in Engineering (IJSHRE)
ISSN-2347-4890
Volume 10 Issue 8 August 2022

Table 2. Pseudo code of RNN

Pseudo code of RNN	
1	construct an RNN model
2	set text as train data
3	fit the model
4	evaluate the model with test data
5	modify the layers and do the fitting repeatedly

Note that I conducted preprocessing with Word Embedding before beginning the RNN process. First, I constructed an RNN model using SimpleRNN(). I designated 80% of the real data as training data. I tested the model with 20% of the real data (test data) while varying the echo. I experimented with dense layers to modify the hidden layer construct.

4.3 Results

4.3.1 Histogram of Length

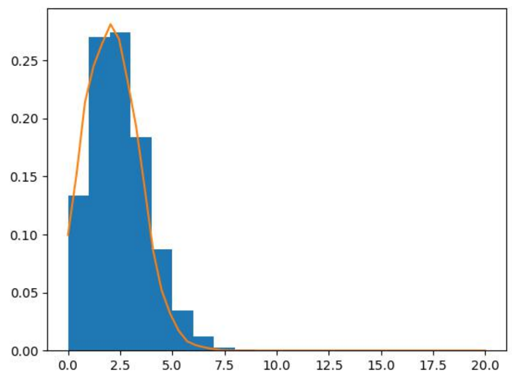

Fig 5: Histogram of length

Figure 5 above displays a histogram of the length of the texts. The axis X scaling factor is equal to 0.1 times the length. And the numbers on Axis y are scaled according to the length with 0.001. As you can see, the data texts are scarcely more than 75 words. Since the data was extracted from short-form SNS, the lengths range between 10 and 50 words.

4.3.2 Logistic Regression of Local DB

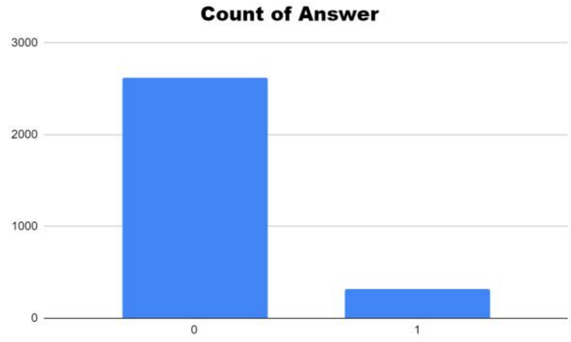

Fig 6: the result of logistic regression

Figure 6 depicts the distribution of real data. Users who did not commit suicide wrote 85 percent of the data. The others were written by suicide victims.

4.3.3 Model Evaluation

Fig 7: The accuracy of the model

I adjusted the model to account for 8 echoes. As seen in Figure 7, the accuracy increases with echo in both the training and test data.

Fig 8: The loss of the model

Figure 8 describes how the loss decreases as the echo increases.

5. CONCLUSION

In this paper, I propose a method of detecting early signs of depression that takes both physical and mental factors into account. The paper discusses what physical devices may be employed, as well as the many forms and tests that can be used. Not only did I consider such physical methods, but I also developed algorithmic methods that can use the patients' natural texts using RNN. The model evaluation is attached.

I present two methods for extending the physical aspect of this system. First, we may use linear regression to forecast uncertain data to sensing values. Second, preprocessing is required for appropriate scaling of the combined tests.

The text classification could be accomplished with LSTM or one of the other deep learning methods. Additionally, various data types can be used. For example, consider the mood in a daily selfie or the emotions in fonts.

6. REFERENCES

[1]. K Kroneke et al, The PHQ-9: validity of a brief depression severity measure, 2001

[2]. AT Beck et al, Beck depression inventory (BDI-II), 1996

[3]. JT Biggs et al, Validity of the Zung self-rating depression scale, 1978

[4]. T Mikolov, Recurrent neural network based language model, 2010

[5]. P Liu, Recurrent neural network for text classification with multi-task learning, 2016