Optimization of Depression Level Detection Based on Noninvasive Parameters with Artificial Neural Network

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Abstract

We optimized the measurement of depression levels by developing an instrument that processes four physical parameters non-invasively with an Artificial Neural Network (ANN). High-accuracy detection instruments help establish a diagnosis to realize early and appropriate prevention and treatment of depression. Depression among students tends to increase, which has an impact on reducing productivity and even attempting suicide. It can reduce the quality and quantity of the productive age generation. The selection of non-invasive physical parameters, namely heart rate, hours of sleep, respiratory rate, and blood oxygen, considers practical aspects for the examiner and the subject examined. This research uses an exploratory method to develop an ANN-based tool for detecting student depression levels. The ANN-based Depression Detector (dANN) input layer harvests data from measurements of the four parameters. Then, the ANN hidden layer processes and studies the data in depth to present five levels of depression in the output layer. Learning results using Loss Graphs show that dANN reduces prediction errors or training iterations at Epochs greater than 130 or offers high accuracy after reaching Epoch 130. DANN prioritized high accuracy in practical measurements. dANN has the potential to be further developed by integrating psychological parameter data, considering that depression is multifactorial. The result of classification reported a precision of 1.0. This felicitating value presents the success of learning and training on dANN. Furthermore, dANN will be built on a web basis to improve performance by implementing an expert system.

Keywords: Depression Level, Noninvasive, Physical Parameters.

1 Introduction

Modern lifestyles and needs psychologically influence the human mind, leading to depression and mental stress (Vitriol et al., 2014). Based on WHO data, around 1 billion people experience mental disorders, and more than 300 million people suffer from depression worldwide (James et al., 2018;

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World Health Organization, 2017; World Mental Health Day: An Opportunity to Kick-Start a Massive Scale -up in Investment in Mental Health, n.d.). Depression significantly affects quality of life, corresponding to its influence on a person's thinking and mental development (Andrade et al., 2003; Liu et al., 2020). Linearly around 800,000 people commit suicide each year (World Health Organization, 2017). The exact causes of depression are not fully understood but have been linked to neurotransmitter imbalances, hormonal abnormalities, genetic vulnerabilities, and stressful environmental conditions that lead to a variety of psychomotor depressive symptoms (Sobin & Sackeim, 1997)

The prevalence rate of depression in college students has been reported to be higher than that found in the general population and has been suggested to increase over time (Ceyhan et al., 2009; Newman et al., 1996). In 2002, mental disorders were estimated to account for nearly half of the total disease burden of youth in the United States (Eisenberg et al., 2007). A meta-analysis conducted by Ibrahim et al. (Ibrahim et al., 2013) also reported that the prevalence rate of depression among American, Canadian, and European students ranged from 10% to 85%, with a weighted average prevalence of 30.6%. In a systematic review study extracted from data from 43 countries, most of the depression among medical students was reported at 27.2%, with a percentage of suicidal thoughts of 11.1% (Rotenstein et al., 2016). Another study estimated that the overall prevalence of depressive symptoms among university students during the COVID-19 pandemic was 34% (Deng et al., 2021). It should be noted that this observed increase is not much more significant than pre-pandemic prevalence as it is based mainly on data from Chinese students, not global data.

Students face complex tasks and problems that, due to depression, is allegedly related to a lack of academic motivation, which can continue to give rise to suicidal thoughts. A decrease in academic motivation can be seen from the presence of burnout, lack of enthusiasm and desire to excel, and decreased level of information absorbed to a reduction in the ability of individual students to demonstrate learning (Hidajat et al., 2020; Hysenbegasi et al., 2005; Setiyoaji et al., 2021). Various kinds of treatments for student productivity and academic quality have been proposed in previous studies (Parno et al., 2021; Setiyoaji et al., 2021; Suganda et al., 2023). However, a comprehensive response to mental health issues is still much needed (Strunk et al., 2021; World Health Organization, 2017).

The representation of depression is multifactorial, with the construction of psychological and physiological factors that superimpose and interact (Sau & Bhakta, 2017). The pathophysiology of depression shows that this disorder has an impact on metabolic disorders, the immune system, and the nervous system, as well as the hypothalamus, pituitary, and adrenal glands (Verma, 2012), as well as autonomic nervous system dysfunction related to heart rate (Hartmann et al., 2019). The results of intensive exploratory research show that depression is represented by abnormalities in physical parameters such as temperature (Jiang et al., 2022; Rausch et al., 2003), hours of sleep (Dong et al., 2022; Kim & Lee, 2018; Uzer & Gulec, 2020), oxygen in the blood (Burtscher et al., 2022), and blood parameters (Verma, 2012). Blood parameters are examined invasively, requiring special treatment and skilled personnel. Meanwhile, measurements of the physical parameters of temperature, heart rate, oxygen levels, and length of sleep are carried out non-invasively to make them more efficient, user-friendly, and WYSIWYG (what you see is what you get).

Previous studies have succeeded in studying and predicting the level of depression through imaging and the use of various machine learning algorithms (Kholili et al., 2022) (Patel et al., 2016), one of which is an Artificial Neural Network (ANN). ANN makes decisions by analyzing unstructured data with pattern recognition (Roy & Chakraborty, 2013), like a human brain network (X. S. Yang & He, 2016). The ANN method develops interactive effects between variables through pattern recognition between related variables and has no presumptions.

Systematical literature shows that the multifactorial characteristics of depression (Sau & Bhakta, 2017) are very suitable for ANN, which has succeeded in identifying depression through the classification of various physical factors that cause it (Erguzel et al., 2016; Park, 2020; Qiu et al., 2021; Sau & Bhakta, 2019; J. P. Yang et al., 2021). In 2012, Puthankattil and Joseph (Puthankattil & Joseph, 2012) used ANN to classify normal and depressed signals based on electroencephalography (EEG) signals and obtained an accuracy of 98.11%. Another study by Sau and Bakhta (Allahyari, 2019) accurately predicted the level of depression using the ANN model from sociodemographic factors and morbidity conditions. The accuracy level of the constructed ANN model is 97.2%.

The success of preventing and curing depression depends on the results of a diagnosis that provides recommendations for medical action and/or psychological assistance. The correct diagnosis really depends on the results of the detection of depression. The implementation of artificial intelligence with ANN has succeeded in increasing the accuracy of measuring depression levels, unfortunately processing data with ANN deep learning currently only processes one physical parameter, while the success of the detection results will be better if carried out in multi-dimensional physics from several non-invasive physical parameters as an effort to prioritize patient comfort. Based on the motivation that has been stated, an algorithm for detecting the level of depression using a non-invasive physical database is needed. This research is part of ongoing research that will integrate the psychological dimension and its measurement and develop hardware and software integrated instrumentation with website facing that interacts with respondents as an expert system.

2 Method

The diagnostic depression instrument has developed as exploration research that arranged in Figure 1 as follows.

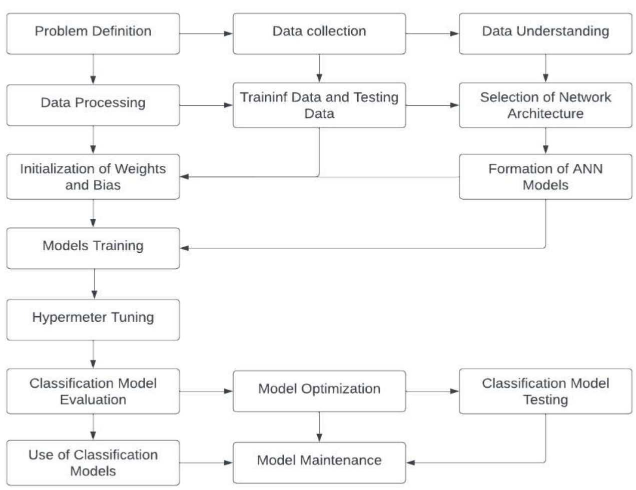

Figure 1: Exploration Scheme for Developing dANN Instrument

Preparation of Datasets

It acquired physical data from a depression-level dataset on the kaggle.com page. The exploration and preprocessing of data are carried out, including cleaning, filtering, and sorting raw data. The next stage is dividing and labeling the data into two parts for the training and testing processes. The training and testing data amount is configured according to the ratio of 80 20. From this preparation stage, a dataset that is ready to be processed will be obtained.

Preparation of ANN-based algorithms

After preparing the dataset that will be used, the ANN-based flow or algorithm construction is carried out. The architecture of the ANN network is based on a quantitative model that is most adaptable to every possibility. Flow of the ANN-based diagnostic model algorithm. From this stage, we will obtain the ANN-based depression diagnostic model construction path.

Training Models

At this phase, the Artificial Neural Network (ANN) algorithm undergoes training by utilizing a preprocessed dataset. The learning process takes place during this stage. Enhancing the prediction accuracy of Machine Learning models involves regular training. To allow the algorithm to adapt to the correct relative weights, the model weights are initialized randomly. The backpropagation algorithm reverses the consequences by utilizing the output error.

During forward propagation, neurons are activated by the softmax activation function. The weight ratio is taken randomly at the beginning of the learning process. The process stops when the process has reached the maximum scheduled Epoh value or scheduled error value. The stored collection of proportional weights is used as the weight ratio in the testing process. In design, the artificial neural network model mimics the workings of the human brain. The ANN construction consists of 3 layers: the input layer, the output layer, and the hidden layer, which processes the input layer, which the output layer can receive.

3 Result and Discussion

Data Collection

In this research, we created a system for pattern recognition and early detection data based on a group of noninvasive physical data. Noninvasive physical data on depression consists of data proven to directly influence student depression, namely heart rate, temperature, sleep time, and oxygen levels in the blood. This process has two stages, with the first stage carrying out pattern recognition by finding the best architecture of the model ANN. The training and data testing process is carried out to obtain the best model for depression parameters based on groups of physical data. The second stage involves early detection using the Artificial Neural Network architectural pattern created in the first stage. The testing process is carried out by entering new data that matches the depression data to see the analysis of the early depression detection tool.

Data Definition

Depression variables based on physical and psychological data are criteria that serve as a reference for decision-making in assessments using an Artificial Neural Network. Variables are identified by examining how the data is influenced by the investigation at hand. The selection criteria are derived from insights gathered from Kaggle datasets. The variables in early detection are based on noninvasive physical data groups in Table 1.

Table 1: Noninvasive Physical Data Groups

No	variabel	Nama Kriteria
1	x1	Heart Rate
2	x2	Temperature
3	x3	Sleep Hours
4	x4	Blood Oxygen

Design of Artificial Neural Network Architecture

The architecture used to detect depression based on non-invasive physical data is backpropagation with feedforward learning. In general, the ANN structure has three layers: the input layer, the hidden layer, and the output layer. Furthermore, this hidden layer helps the network to recognize a more significant number of input patterns than a network that does not have a hidden layer.

The Artificial Neural Network architecture uses two activation functions. The activation function is as follows.

1. ELU (Exponential Linear Unit) is currently the at the forefront of activation function technology due to its versatility across various scenarios. Widely employed in hidden layers and output layers, especially when the response variable is continuous and has greater significance beyond zero. ELU introduces a non-zero output for negative input values, which helps prevent dead neurons and encourages the network to learn more robust representations.
2. Softmax is currently considered a state-of-the-art technology in various applications. This function is widely favored for its ability to handle multiple classes efficiently. It transforms the raw output scores into a probability distribution across multiple classes, making it particularly suitable for classification tasks. Its utilization in the output layer ensures that the model outputs probabilities for each class, allowing for clear and interpretable predictions.

Artificial Neural Network Architecture has model parameters and corresponding parameters so that the network learns better and faster. These adjustment parameters are referred to as hyperparameters.

This Artificial Neural Network model is a Sequential model consisting of several Dense and Dropout layers. The model has more than 2.5 million trainable parameters, allowing it to learn more complex representations of the input data. This model has an input layer with dimensions not described in the text. The Dense layers following the input layer have various output sizes, with the number of units increasing from 32 to 1024. The Dropout layer is used to avoid overfitting by randomly turning off some units during training. This model is used for tasks involving classification with an output layer of size 5, which may reflect different categories or classes. This model has a complex structure and is suitable for tasks requiring a deep understanding of the input data.

```
Model: "sequential_9"
 Layer (type)                Output Shape              Param #
=================================================================
 dense_98 (Dense)            (None, 32)                160
 dense_99 (Dense)            (None, 64)                2112
 dense_100 (Dense)           (None, 128)               8320
 dropout_32 (Dropout)        (None, 128)               0
 dense_101 (Dense)           (None, 512)               66048
 dense_102 (Dense)           (None, 1024)              525312
 dense_103 (Dense)           (None, 512)               524800
 dropout_33 (Dropout)        (None, 512)               0
 dense_104 (Dense)           (None, 512)               262656
 dense_105 (Dense)           (None, 1024)              525312
 dense_106 (Dense)           (None, 512)               524800
 dropout_34 (Dropout)        (None, 512)               0
 dense_107 (Dense)           (None, 128)               65664
 dense_108 (Dense)           (None, 64)                8256
 dense_109 (Dense)           (None, 32)                2080
 dropout_35 (Dropout)        (None, 32)                0
 dense_110 (Dense)           (None, 5)                 165
=================================================================
Total params: 2,515,685
Trainable params: 2,515,685
Non-trainable params: 0
```

Figure 2: Neural Network Architecture Models

Defining Output

At this phase, the anticipated outcome involves establishing a framework for identifying optimal parameters to detect depressive tendencies using non-intrusive sets of physiological data. The test results are as follows:

a. To find out early detection of depression based on physical and psychological data groups. The output of this early detection is the best architectural pattern for detecting depression based on physical data groups.
b. Categorization of training and testing outputs that consisted of five levels, as listed in Table 2.

Table 2: Depression Category Data

No	Depression Level
1	Normal
2	Medium Low
3	Medium
4	Medium High
5	High

Training and Validation

Following are the results of training and validation of the Artificial Neural Network architecture.

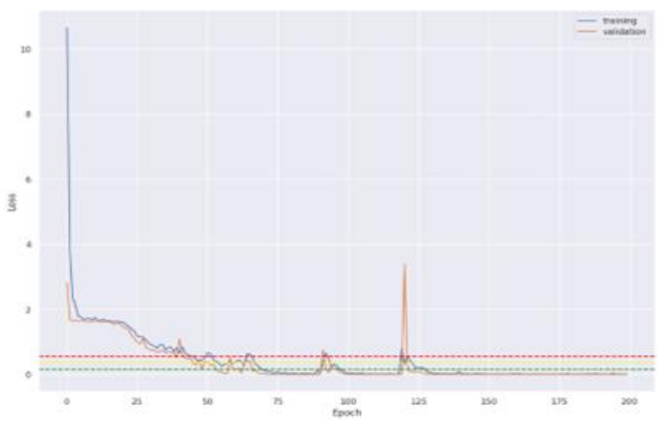

Figure 3: Architectural Training and Validation Loss Graph

Figure 4: Graph of Architectural Training and Validation Accuracy

Loss and accuracy graphs are essential visual tools in evaluating artificial neural networks (ANN) during testing. The loss graph depicts the extent to which the network succeeds in reducing prediction errors over time or training iterations, Figure 3. The main goal is to see loss decrease over time, which shows that the web is learning and improving its performance. Meanwhile, the accuracy graph reflects the extent to which the network can make correct predictions on test data as described in Figure 4. If accuracy improves over time, the network is better at classifying data. However, it is also crucial to assess whether there is a notable discrepancy between the accuracy of the training and validation data, as this could suggest overfitting. By analyzing these two graphs, we can measure the performance of the ANN and determine whether the model is suitable for the given task.

Classification

```
4/4 [==============================] - 0s 11ms/step
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        25
           1       1.00      1.00      1.00        25
           2       1.00      1.00      1.00        27
           3       1.00      1.00      1.00        22
           4       1.00      1.00      1.00        27

    accuracy                           1.00       126
   macro avg       1.00      1.00      1.00       126
weighted avg       1.00      1.00      1.00       126
```

Figure 5: Classification Report

Our classification report shows a precision of 1.0 as suggests that it is apparent, Figure 5. This encouraging value shows the success of learning and training on dANN. Classification report is an essential metric in evaluating the performance of a classification model (Yang, X. S., & He, X. 2016). When the accuracy, precision, and recall values reach 1.0, the classification model has done a perfect job predicting the different classes. An accuracy value of 1.0 means that the model predicted all samples correctly, without errors.

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