

# Depressed Patients Identification using Cardiovascular Signals

M. Sami Zitouni<sup>1</sup>, Ahsan Khandoker<sup>2</sup>

<sup>1</sup>University of Dubai, Dubai, United Arab Emirates

<sup>2</sup>Khalifa University, Abu Dhabi, United Arab Emirates

## Abstract

*In this study, we present a deep learning based framework for the identification of Major Depressive disorder (MDD) patients from cardiovascular signals. In this work, multi-modal cardiovascular signals, including electrocardiogram (ECG) and finger photoplethysmography (PPG), are used. The signals were collected from 60 subjects for 10 minutes, out of whom 30 were diagnosed with MDD by a psychiatric, and 30 were healthy. The signals are pre-processed and segmented into 30 seconds segments to be able to perform the identification in half a minute window, which proved to be sufficient in this work. Then, time-frequency analysis is performed on the signals for feature extraction and then a recurrent neural network architecture based on Long Short-Term Memory (LSTM) networks is utilized for the identification of the MDD patients. The results demonstrated a robust performance with an accuracy of 85.7%. This study can be considered an advancement towards the involvement of artificial intelligence tools in the assisted diagnosis and monitoring of mental diseases, and reducing their risk and impact on human daily life.*

## 1. Introduction

Persistent feeling of low mood, sadness, low self esteem, and worthlessness, loss of interest in outside stimuli, sleeping trouble, increased fatigue, and suicidal thoughts are all characteristics and signs of the mental illness known as Major Depressive disorder (MDD). A variety of factors can trigger depression, including genetics, hormones, environment, and socio-cultural influences [1]. MDD is associated with the risk of comorbidities, such as cardiovascular disease, as it can be a risk factor for its pathogenesis, where the two conditions are known to have similar causative factors including inflammation and oxidative stress [2]. Thus, physiological signals captured from the cardiovascular system embodies cues of MDD development. The clinical diagnosis of MDD is mainly based on self reported experiences and mental status examination through psychiatric interview questionnaires, as well as

ruling out physical conditions with similar symptoms [3]. Therefore, an automated artificial intelligence based tool can play a crucial role in assisting the diagnosis of MDD, as well as continuous monitoring of the mental health status and the development of MDD through wearables, to avoid severe depression cases associated with significant self neglect and risk of harm to self or others, as well as allow early and proper intervention. Studies have continually shown that MDD is associated with poorer quality of life and increased morbidity and mortality. In the developed world, coronary artery disease (CAD) is a leading cause of mortality, and when a patient suffers from cardiac disease and MDD together, the prognosis for both worsen. Further, the risk of developing CAD is proportional to the severity of depression. MDD also confer a higher chance of developing coronary heart disease (CHD), and a CHD patient with MDD has an increased risk of poorer cardiovascular consequences including myocardial infarction. MDD leads to a higher risk of mortality in patients suffering comobrid CHD, while the presence of MDD is a bad prognostic factor for those who suffered myocardial infarction as it dramatically increases the risk of cardiac mortality [4]. Automated identification of depressed patients using physiological signals is mainly implemented using measurements of brain activity through electroencephalogram (EEG), or cardiovascular activity, such as ECG and PPG. Methods based on EEG reported high performances and had the overall highest accuracies out of the clinical sensing MDD detection solutions [5]. EEG-based studies mainly focused on differentiating depressed patients from healthy controls [6–8]. However, for active and continuous monitoring of depressed patients, EEG sensors can be invasive and require special setup for wearing and recording, which is unpractical and a burden for already distressed people. On the other hand, cardiovascular signals can be collected using commonly used non-invasive wearables, such as smart watches, making them more practical for automated diagnosis and continuous monitoring. Additionally, MDD is usually associated cardiac arrhythmia or abnormal heart rhythms, and ECG is commonly used for its detection [9]. Thus, methods were developed recently for the detection and diagnosis of depressed patients us-

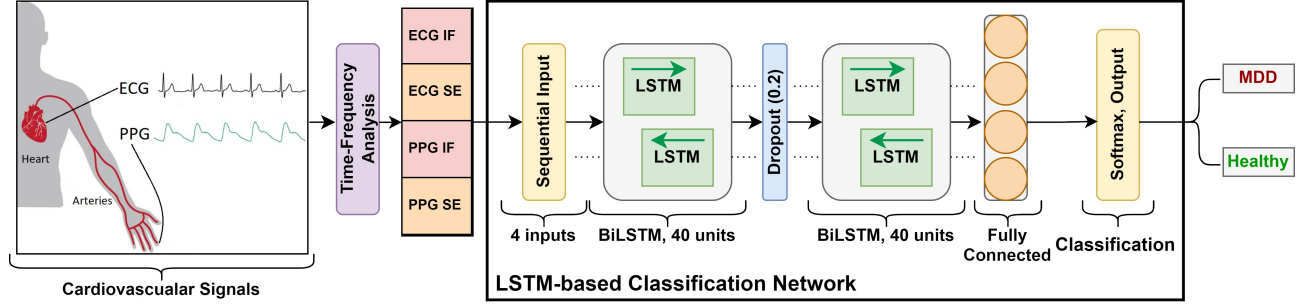


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ing ECG [10], PPG [11], and heart-rate variability (HRV) [12, 13]

## 2. Methodology

### 2.1. Subjects and Dataset

In this study, 30 patients with a primary diagnosis of MDD were included, as well as 30 control subjects. A consultant psychiatrist made the diagnoses using the mini-international neuropsychiatric interview (MINI) [14], and the structured interview guide for the Hamilton Depression Rating Scale (HAM-D) [15] was used to assess the severity of clinical depression. All patients included in this study were diagnosed as MDD at their first visit to the psychiatric clinic and signals were recorded only from unmedicated MDD patients. The control group was interviewed by the psychiatrist to check whether they had to go through any psychiatric assessment. The control subjects in this study were not required to complete MINI interview and other questionnaire since they declared that they had no previous history of psychiatric disease. MDD patients completed valid and reliable self-report ratings of depression (21-item beck depression inventory BDI), anxiety (general anxiety disorder GAD7), and stress severity (patient health questionnaire PHQ-9), while control subjects only completed PHQ-9 rating [3]. Table 1 summarizes the demographics of both depressed and control subjects, as well as their psychiatric ratings. Cardiovascular signals' ECG and PPG were recorded for an average of 10 minutes for each subject with a sampling frequency of  $1kHz$ .

### 2.2. Time-Frequency Analysis

Compared to raw ECG and PPG signal, extracted features in form of time-frequency moments can improve the performance of the classifier as they are more distinctive. In the proposed method, time-frequency analysis is applied to extract information of the signals' spectrograms by computing the Instantaneous Frequency (IF) and spectral Entropy (SE) in the time domain. Each of the computed IF and SE of the input ECG and PPG signals is used as a one-

Table 1. Subjects' demographics and psychiatric scores.

Variable	MDD	Control
Subjects	30	30
Gender male (%)	7 (23%)	11 (37%)
Age (yrs)	$33.73 \pm 8.49$	$31.63 \pm 10.97$
Height (cm)	$161.87 \pm 7.15$	$159.07 \pm 8.96$
BMI ( $kg/m^2$ )	$26.78 \pm 5.99$	$24.29 \pm 3.59$
WC (cm)	$86.17 \pm 15.92$	$76.57 \pm 9.48$
SBP (mmHg)	$112.00 \pm 13.75$	$110.50 \pm 10.86$
DBP (mmHg)	$72.00 \pm 8.47$	$69.83 \pm 6.76$
PHQ-9	$19.00 \pm 5.64$	$1.87 \pm 1.46$
BDI	$35.27 \pm 12.02$	N/A
GAD7	$16.03 \pm 6.15$	N/A

dimensional sequential feature to input to the LSTM-based classification network. Figure 1 illustrates the proposed method for depressed patients identification. First, ECG and PPG signals are segmented into 30 second inputs, and then time-frequency analysis is performed. IF measures the time dependent frequency of the input cardiovascular signals as the first moment of their power spectrograms. In this work, 524 time windows were used and the time estimates correspond to the centers of the time windows. On the other hand, SE estimates the uniformity of energy distribution in the frequency-domain of the signals based on their power spectrograms. For SE estimation, 524 time windows are used as well to obtain feature sequences with the same size. In addition to the IF and SE feature being more distinctive than using raw signals, the input sizes are reduced from 30000 (30 seconds times  $1kHz$ ) to 524 values. The input sequences are then standardized before feeding them to the classifier.

### 2.3. LSTM-based Classification Network

In this study, An LSTM-based network is utilized for the classification of the input cardiovascular signals of subjects into healthy or depressed. It can be seen in the literature that LSTM models perform well for classifying sequential

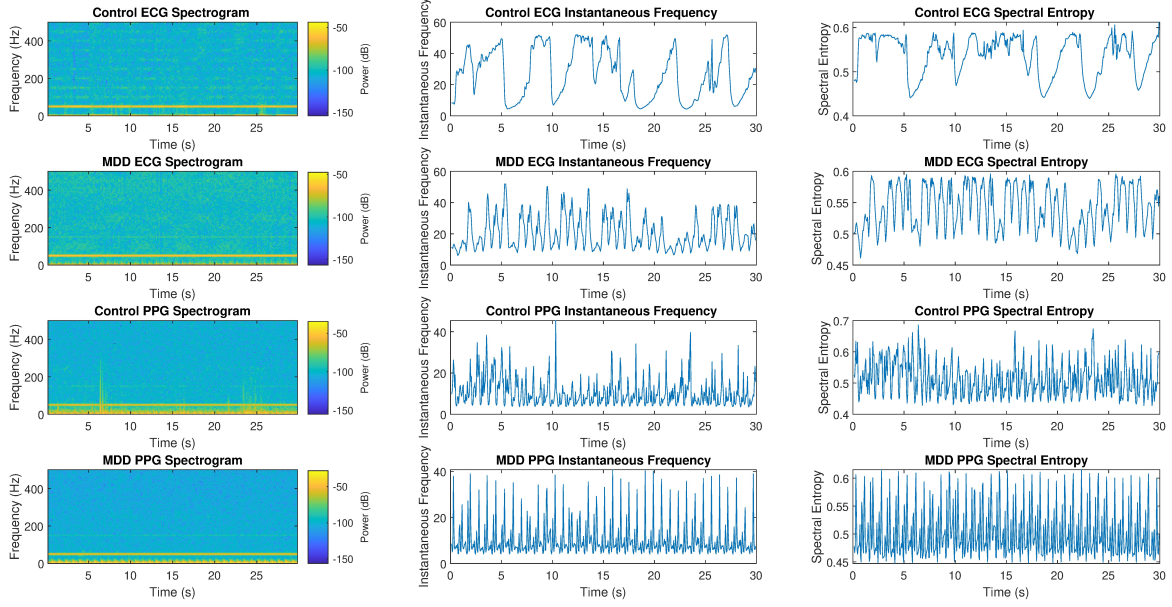


Figure 2. Example ECG and PPG spectograms of MDD and control subjects with the extracted ECG IF, ECG SE, PPG IF, and PPG SE signals.

features in depression identification techniques [6]. The used LSTM-based classification network is shown in Figure 1, where the layers of the network and their parameters are given. This network has a two bidirectional LSTM layers, each of which has 40 hidden units, and a dropout layer between them, with a probability of 0.2. The input layer has 4 sequential inputs corresponding to ECG IF, ECG SE, PPG IF, and PPG SE signals. A fully connected layer and a softmax layer with two outputs are used for classification into MDD or healthy. Since equal number of control and MDD subjects were used, the data were balanced with very minimal bias. For 60 subjects, the total number of data samples were 1264, each corresponds to 30 seconds of ECG and PPG signals. A 4-fold cross validation setup was implemented in a subject dependant manner. The hyperparameters used include an initial learning rate of 0.005, 200 max epochs, a mini batch size of 30, and a drop factor of 0.2 at half of the max epochs, with adam optimizer.

### 3. Results

This section presents the obtained results from the proposed depressed patients identification framework. Figure 2 demonstrates example ECG and PPG signals' spectograms of an MDD and a control subject, in addition to extracted ECG IF, ECG SE, PPG IF, and PPG SE signals after applying the time-frequency analysis on 30 seconds segments. As it can be observed, the IF and SE signals are clearly distinctive between the MDD and control subjects for both ECG and PPG signals, in comparison to the

Table 2. Performance evaluation of the proposed depressed patients identification method (%).

Accuracy	Sensitivity	Specificity	Precision	F1-Score
85.7	87.4	83.8	85.9	86.6

raw versions, where their spectograms hardly shows differences. Table 2 shows the performance evaluation from the 4-fold cross validation results for classifying data belonging to either MDD patient or control. The presented framework achieved a high and robust performance of 85.7% accuracy, 87.4% sensitivity, 83.8% specificity, 85.9% precision, and 0.866 f1-score. Figure 3 shows the confusion matrix of the classification results. Figure 4 displays the ROC curve with highlighted 95% confidence interval. The obtained results shows the ability of the proposed framework in robustly identifying depressed patients using 30 seconds segments of cardiovascular signals.

		Confusion Matrix	
True Class	Control	124	24
	MDD	21	146
		Control	MDD
		Predicted Class	

Figure 3. Confusion matrix of classification results.

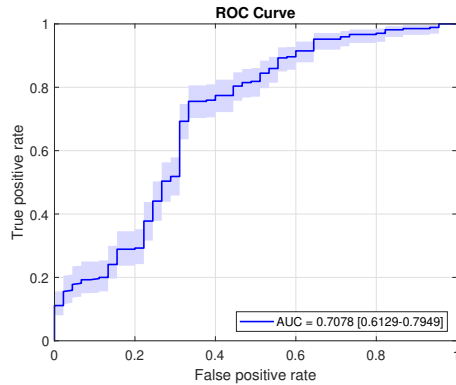


Figure 4. ROC curve showing classification performance and AUC value with 95% confidence interval.

## 4. Conclusion

This paper presented a method for the identification of depressed patients using cardiovascular signals. The dataset used contained ECG and PPG signals, that were collected from 60 subjects, divided equally into 30 MDD patients and 30 control subjects. Time-frequency analysis was implemented through estimating IF and SE from raw ECG and PPG signals, to obtain distinctive sequential features. An LSTM-based classification network with bi-directional LSTM layers was utilized for the classification of time dependent sequential features. The 30 seconds input segments of cardiovascular signals were classified into either MDD patient or healthy subject. The achieved results showed a robust and promising performance. Future work will include the use of respiratory signals along with cardiovascular signals, as well as classifying the detected MDD patients based on the severity of the depression, where a classification network is trained based on the acquired psychiatric and self-report ratings of depression.

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Address for correspondence:

M. Sami Zitouni

College of Engineering and IT, University of Dubai, United Arab Emirates

mzitouni@ud.ac.ae