CS-C4100 Digital Health and Human Behavior, Depression Analysis

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1 Introduction

Depression, a formidable medical condition affecting nearly one in 10 adults annually and more commonly observed among women, presents itself with a spectrum of symptoms. These include persistent feelings of sadness, emptiness, and anxiety, often accompanied by changes in weight, sleep patterns, and a loss of interest in once-enjoyable activities. Its severity is evaluated based on the intensity, duration, and impact of these symptoms on social and occupational functioning.[1]

Fortunately, promising treatment ability exists through psychological and pharmacological interventions. In exploring new avenues for early detection, the measurement of motor activity emerges as a potential diagnostic system. Body sensors, adept at collecting vast health-related data, offer the capability to monitor daily steps, caloric expenditure, heart rate, and activity levels continuously.

The repercussions of depression encompass not only emotional turmoil but also significant physical and economic challenges. Reduced daytime activity and heightened nocturnal activity patterns often characterize this condition.

This severe mental disorder, distinct in its symptoms from bipolar disorder, manifests through disrupted biological rhythms influenced by environmental factors.[2] These disruptions can stem from lifestyle choices conflicting with natural daylight cycles, seasonal changes, social rhythm alterations, and other triggers linked to genetic vulnerabilities.

Understanding the nuances of depression, its varied manifestations, and the potential of objective measures such as actigraph recordings to observe its impact remains an ongoing pursuit in psychiatric research.

Given the risks and challenges associated with depression, timely diagnosis can initiate the treatment process. However, as mentioned earlier, accurate and timely diagnosis is crucial due to the widespread symptoms. In this article, we aim to utilize the data collected here[3], encompassing individuals with depression (the condition group) and those without depression (the control group). We intend to investigate whether, through recorded activities, we can diagnose depression in individuals. Further elaboration on the questions addressed in this article will be discussed in the Problem Formulation section. The Dataset

Description section will elucidate the data structure and its various aspects. Subsequently, in the Methods section, we will delve into the procedures applied to the data and discuss the outcomes obtained in the Results and Conclusion section.

2 Problem Formulation

The identification and timely diagnosis of depression remain pivotal challenges in healthcare due to its multifaceted nature and the subjective interpretation of symptoms. While depression manifests through a spectrum of psychological, emotional, and physical manifestations, its accurate and prompt diagnosis stands as a critical juncture in ineffective intervention.[4]

The diagnostic process heavily relies on subjective assessments conducted through clinical interviews and self-reported surveys. However, these methods often encounter limitations due to individual variations in expressing and interpreting symptoms, leading to potential misdiagnosis or delayed identification of the condition.

In light of these challenges, this study aims to address the need for a more objective and reliable diagnostic approach for depression. Leveraging advancements in technology, particularly the utilization of body sensors capable of recording and analyzing various physiological parameters, we seek to explore whether quantifiable data related to daily activities, such as motor activity patterns, heart rate variability, and sleep rhythms, can serve as reliable markers for the identification of depression.

Furthermore, we aim to ascertain the effectiveness of these objective measures in distinguishing between individuals diagnosed with depression (the condition group) and those without depression (the control group). By establishing robust correlations between recorded activities and the presence or absence of depressive symptoms, this research endeavors to contribute to the development of more accurate, timely, and objective diagnostic tools for depression.

The ultimate goal is to pave the way for a more standardized, accessible, and efficient diagnostic methodology that can complement conventional diagnostic approaches, thereby enhancing the precision of identifying depression and facilitating prompt and appropriate interventions for individuals affected by this debilitating condition.

3 Dataset Description and Cleaning Data

The dataset comprises two distinct folders, housing data for the control and condition groups. Each patient's information is stored in a CSV file, encompassing actigraph data collected over time. The columns within these files include (Figure 1):

- Timestamp: Recorded at one-minute intervals. (numerical)
- Date: Denotes the date of measurement. (numerical)

- Activity: Indicates the activity measurements captured by the actigraph watch. (numerical)

	timestamp	date	activity
0	2003-03-18 15:00:00	2003-03-18	60
1	2003-03-18 15:01:00	2003-03-18	0
2	2003-03-18 15:02:00	2003-03-18	264
3	2003-03-18 15:03:00	2003-03-18	662
4	2003-03-18 15:04:00	2003-03-18	293

Figure 1: data table for control 1

Supplementary to the actigraph data, the "scores.csv" file contains MADRS scores and various patient attributes, encompassing (Figure 2):

- Number: Unique patient identifier. (categorical)
- Days: Number of days measured. (numerical)
- Gender: Coded as 1 or 2 for female or male. (numerical)
- Age: Grouped into specific age brackets. (categorical)
- Afftype: Categorization into bipolar II (1), unipolar depressive (2), or bipolar I (3). (categorical)
- Melanch: Presence of melancholia (1) or absence (2). (categorical)
- Inpatient: Indicates inpatient (1) or outpatient (2) status. (categorical)
- Edu: Education categorized by years. (categorical)
- Marriage: Married or cohabiting (1), single (2). (categorical)
- Work: Working or studying (1), unemployed/sick leave/pension (2). (categorical)
- Madrs1: Initial MADRS score at the start of measurement. (numerical)
- Madrs2: MADRS score at the end of the measurement. (numerical)

	number	days	gender	age	afftype	melanch	inpatient	edu	marriage	work	madrs1	madrs2
0	condition_1	11	2	35-39	2.0	2.0	2.0	6-10	1.0	2.0	19.0	19.0
1	condition_2	18	2	40-44	1.0	2.0	2.0	6-10	2.0	2.0	24.0	11.0
2	condition_3	13	1	45-49	2.0	2.0	2.0	6-10	2.0	2.0	24.0	25.0
3	condition_4	13	2	25-29	2.0	2.0	2.0	11-15	1.0	1.0	20.0	16.0
4	condition_5	13	2	50-54	2.0	2.0	2.0	11-15	2.0	2.0	26.0	26.0
5	condition_6	7	1	35-39	2.0	2.0	2.0	6-10	1.0	2.0	18.0	15.0

Figure 2: data table for control and condition group

The dataset involves motor activity recordings from 23 patients diagnosed with unipolar and bipolar depression (condition group). Five individuals were hospitalized during data collection, while 18 were outpatients. Clinicians assessed the severity of ongoing depression using the MADRS scale at the onset and conclusion of motor activity recordings.

Additionally, the dataset includes actigraphy data from 32 non-depressed individuals (control group), comprising 23 hospital employees, five students, and four former patients without current psychiatric symptoms. In the condition group's "score" section, out of 23 data entries, we have three NaN values in "melanch" and one missing value in "edu." In the control group, only the columns "days," "gender," and "age" have values, while the rest contain NaNs. Therefore, we cannot use the other columns for comparison between groups. However, for intra-group comparisons within the condition group, we can still utilize the other columns.

As observed in the figures 3, the Actigraphy data exhibits considerable noise, indicating the necessity for data-smoothing techniques. Certain days exhibit activity patterns that raise suspicion, potentially indicating non-wear periods or anomalies within the dataset. Hence, a rigorous data cleaning and preprocessing stage becomes imperative.

After data cleaning, we will proceed with further refinement by eliminating days exhibiting sub-threshold activity (with a threshold set at 75 units). This step aims to maintain within-day variability while excluding days with insufficient activity levels. Additionally, we intend to enhance data smoothness by implementing a moving average filter (employing a 20-minute window) to generate a more refined version of the dataset. This filtering process is designed to remove high-frequency noise effectively. (Figure 4)

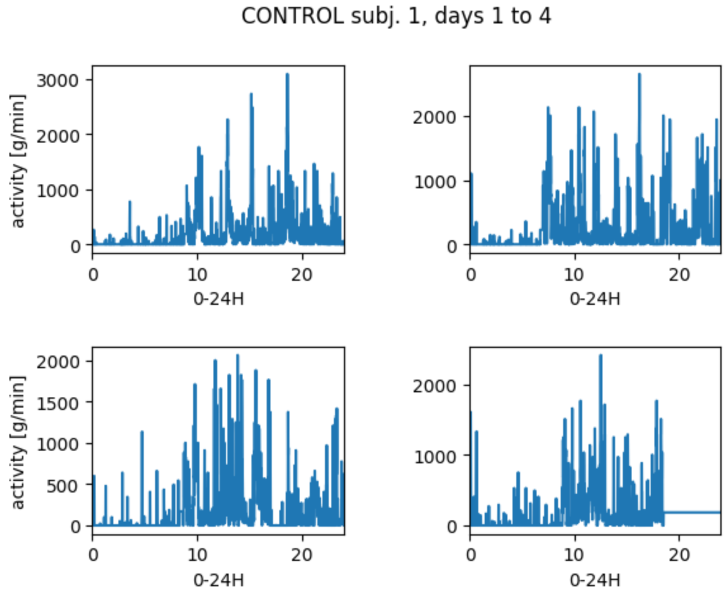

Figure 3: Noisy data for Subject 1 in control group

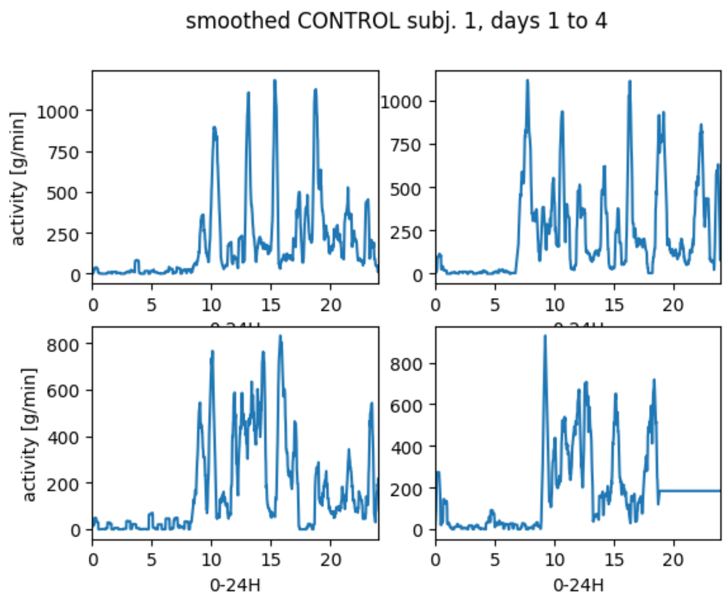

Figure 4: Smooth data for Subject 1 in control group

Upon completion of these cleaning and filtering procedures, the dataset should demonstrate a noticeable improvement in clarity and a reduction in noise, rendering it more suitable for subsequent analyses and more accurate interpretations. We can see the comparison before and after smoothing data in the figure 5.

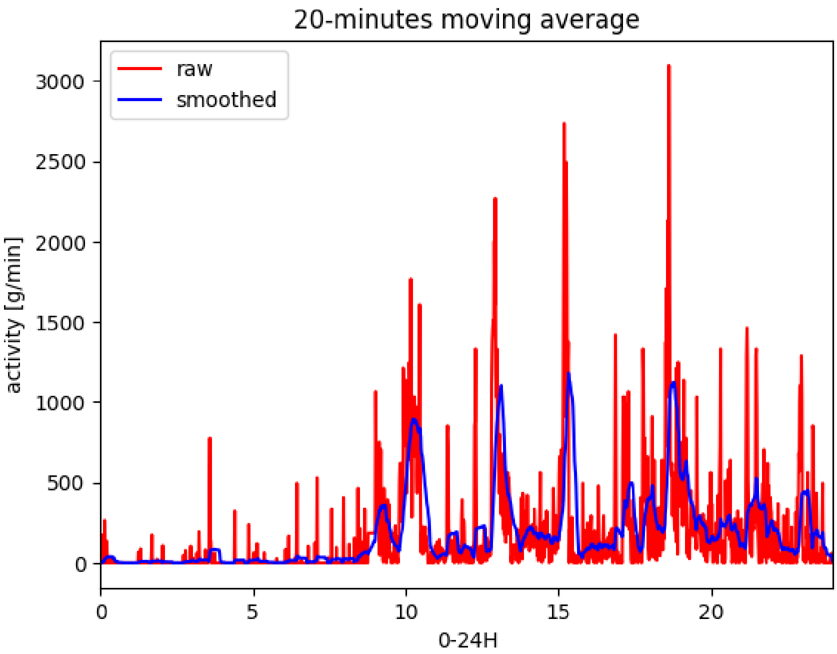

Figure 5: Comparison between noisy and smoothed data for subject 1 in control group

4 Methods

We aim to uncover statistical variances between groups or subgroups within the datasets, primarily focusing on distinctions between individuals with depression and healthy controls.

Individuals experiencing depression displayed evident motor function differences in comparison to healthy controls. Notably, both the speed and volume of hand movements were diminished. Additionally, our findings revealed a direct correlation between the severity of depression and the reduction in movement volume.[5]

The conventional perception links the depressive state to decreased daytime motor activity, heightened variability in activity levels, and simpler activity patterns compared to individuals in good health. Nonetheless, contradictory motor activity patterns have been noted in some bipolar and unipolar depressed patients. These patterns entail increased mean activity levels, reduced variability, and a heightened complexity in activity patterns, resembling those observed in individuals experiencing manic episodes.[6]

Depression often manifests with indications hinting at disruptions in circadian rhythms. These signs encompass early morning awakening, shifts in mood throughout the day, alterations in sleep patterns, changes in the timing of temperature fluctuations, and peaks in cortisol levels. Interpersonal social rhythm therapy aims to enhance the management of interpersonal relationships and stabilize crucial social cues. This therapy incorporates regulating sleep and wakes schedules, meal timings, and the timing of social engagements to promote stability.[7]

We plan to employ the Wilcoxon Sum of Rank Test, which is suitable for comparing means between two groups, particularly for parameters that don't follow a normal distribution. We'll utilize this test to formulate statistical hypotheses regarding the reduction in activity. Our analysis will focus on three activity-related variables: maximum activity, mean activity, and circadian rhythms.

For circadian rhythms analysis, the gold standard approach involves fitting a cosine wave pattern across a 24-hour period. This method allows us to evaluate and characterize circadian variations effectively.

5 Results

The average level of activity (Figure 6) demonstrates noticeable differences between the subjects in the control group and those in the experimental condition, a finding that aligns with results from previous studies. Intriguingly, the activity levels during the night appear to be similar for both groups. This similarity could potentially explain why their circadian rhythms, or internal biological clocks, are not misaligned, as has been reported in some research.

To elaborate, "mean activity" refers to the average level of activity of the subjects. When this mean activity shows differences between control and condition subjects, it suggests that the condition being tested significantly affects the subjects' activity levels.

"Circadian rhythms" are physical, mental, and behavioral changes that follow a daily cycle. They respond primarily to light and darkness in an organism's environment. If the circadian rhythms were "out of phase," it would mean that the subjects' biological clocks are not synchronized with each other. However, the comparable night activity between the control and condition subjects indicates that their circadian rhythms are not out of phase, contrary to what some studies have suggested [8]. This could be due to the fact that the condition being tested does not significantly affect the subjects' activity levels during the night.

Several variables demonstrate distinct group patterns in the figures (Figure 8 and 7) presented, notably in parameters such as daily mean and maximum activity levels and the MESOR. However, certain variables related to circadian cycles, specifically the acrophase, depict more ambiguous distinctions between the groups. Rigorous statistical tests are imperative to validate our hypotheses derived from these observations.

In this analysis, we employ the Wilcoxon rank sum test, a robust non-parametric test suitable for non-normally distributed data. Our chosen significance level, set at $p = 0.05$, allows us to rigorously examine differences between each group based on the characteristics observed in the figures. This statistical approach enables a comprehensive evaluation of the distinct groupings observed in the data, particularly emphasizing the discrepancies in circadian rhythm-related variables, thereby offering a more nuanced understanding of the observed distinctions.

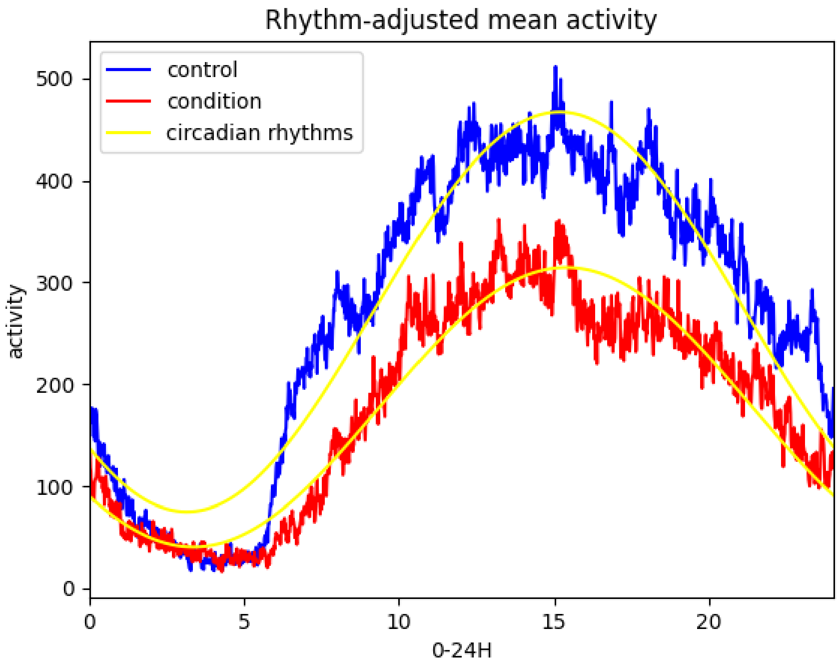

Figure 6: Average level of activity

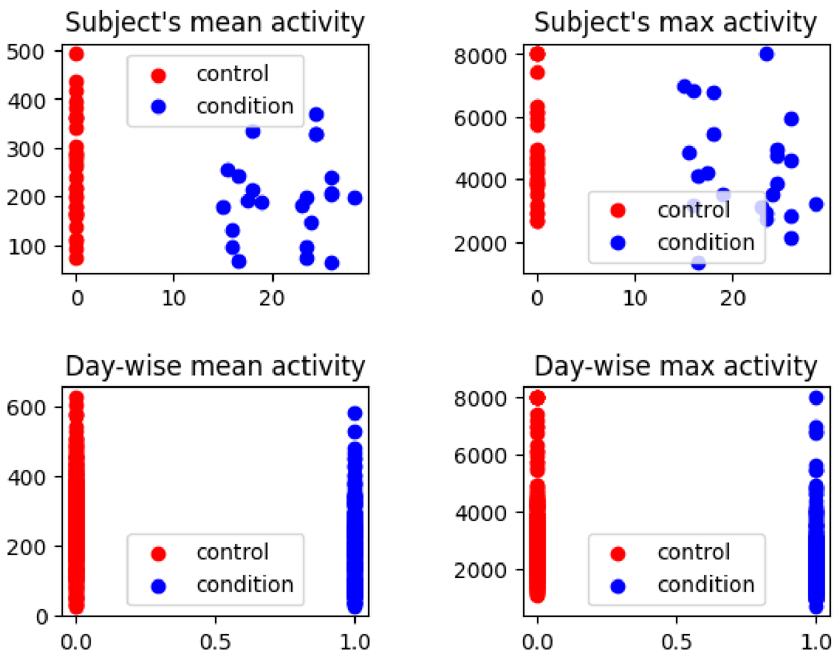

Figure 7: Statistical difference between control and condition group in day activity and mean activity

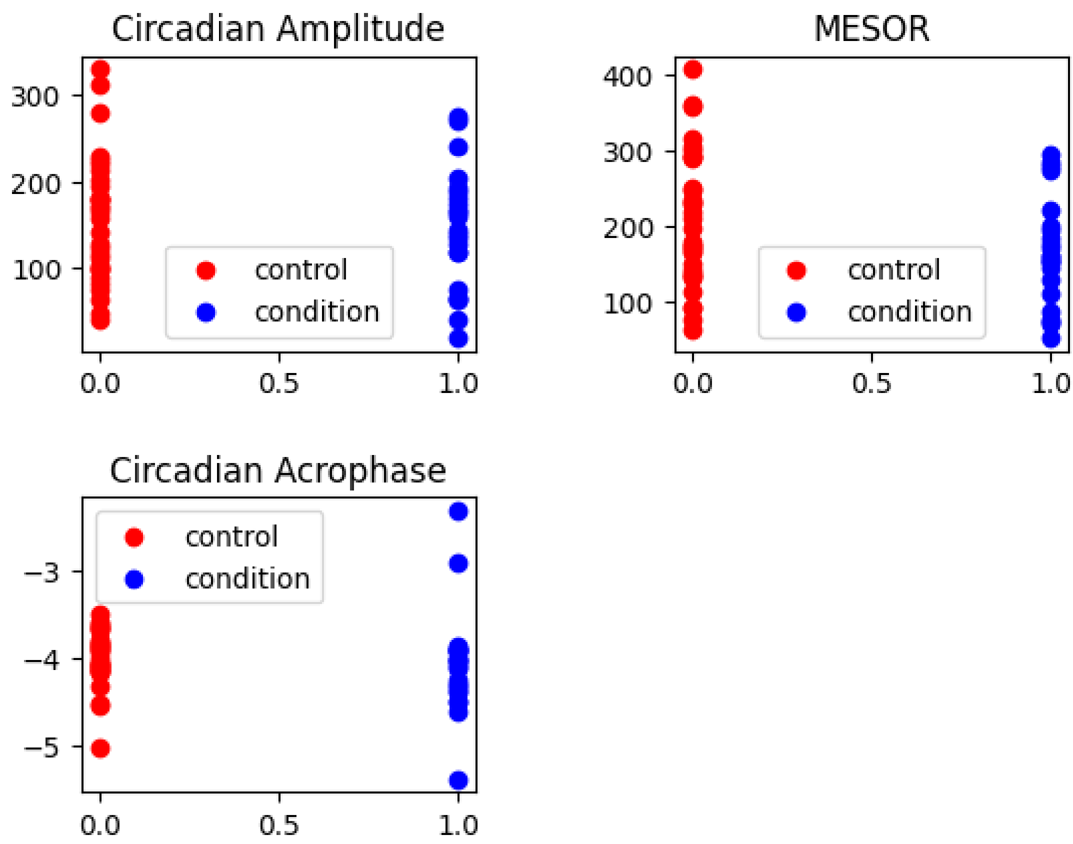

Figure 8: Statistical difference between control and condition group in circadian amplitude, MESOR, circadian acrophase

Category	p-value	Status
day-wise mean	3.46E-30	Rejected
subject-wise mean	0.06788781976	Accepted
day-wise max	4.93E-16	Rejected
subject-wise max	0.242475467	Accepted
subject-wise Acrophase	0.1125426692	Accepted
subject-wise Cycle Amplitude	0.6207203844	Accepted

Table 1: Calculation of p-value for each hypothesis

The results from the hypothesis testing revealed noteworthy distinctions across various categories. Specifically, the day-wise mean activity exhibited a substantial difference between groups, evident from the remarkably low p-value (3.46×10^{-30}) obtained, indicating a rejection of the null hypothesis. Conversely, while the subject-wise max activity demonstrated statistical equality (0.242475467), the day-wise max activity did not, as depicted by its considerably low p-value (4.93×10^{-16}). This discrepancy between day-wise and subject-wise maximum activity may stem from subject-wise maximum values being more susceptible to noise spikes or outliers within the dataset.

Certain studies have implemented more rigorous data-cleaning approaches by removing non-plausible high measurements, which could account for the disparity in results between these parameters.

Regarding the acrophase samples, the statistical analysis did not reveal significant distinctions (0.1125426692), suggesting that the hypothesis asserting that the cycles of depression and control groups are not out of phase holds true. However, it's essential to note that while the obtained p-value indicates a lack of statistical significance, a slightly higher value (approximately 11%) might suggest that more significant, more representative datasets could yield different or more nuanced outcomes. This underscores the potential impact of dataset size and representation on the observed statistical results.

6 Conclusion and Discussion

In conclusion, this study sheds light on the complexities of diagnosing depression and the potential of leveraging technological advancements to develop more objective diagnostic tools. Depression, a prevalent and debilitating condition, presents multifaceted symptoms impacting various aspects of an individual's life. Accurate and timely diagnosis remains pivotal for effective intervention and treatment.

Through the exploration of motor activity patterns and physiological parameters using body sensors, this research aimed to identify reliable markers for the identification of depression. The dataset analysis revealed distinct differences between control and depressed subjects, particularly in parameters related to activity amplitudes. The most substantial variations were observed in amplitude, both in terms of maximum and mean activity levels.

Notably, our findings did not indicate phase shifts in activity rhythms between control and depressed groups, contradicting some existing studies' suggestions. This lack of disparity in activity rhythms may imply a consistent alignment in biological clocks between the groups despite the observed differences in activity levels.

While these insights provide valuable groundwork, further extensive studies are warranted to validate these findings. However, even at this preliminary stage, these observations hold promise. They may potentially serve as rudimentary indicators prompting lifestyle adjustments when consistent depressive conditions emerge over time.

It's crucial to acknowledge the limitations of this study, notably the relatively small dataset size and the need for more extensive investigations with larger and more diverse populations. These limitations underscore the necessity for continued research endeavors to solidify and expand upon these preliminary findings.

In essence, this study underscores the potential of utilizing objective measures such as motor activity patterns to aid in identifying and understanding depression. As technology continues to advance, incorporating these objective markers into diagnostic methodologies holds promise for enhancing the accuracy and timeliness of identifying depression, thereby facilitating more effective interventions and ultimately improving outcomes for individuals affected by this challenging condition. For future studies, investigating the potential of machine learning algorithms to analyze complex activity patterns and identify unique signatures associated with depressive states presents an intriguing area for future exploration. Leveraging these advanced analytical techniques could lead to the development of more precise and personalized diagnostic tools.

References

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