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Mental Disorder Screening Via Wearable Internet Of Things: Deep Neural Network Approach

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Abstract

Mental health problems are becoming a significant international health issue, and a late diagnosis has, in most cases, caused serious social, economic, and clinical impacts. Early detection is consequently a requirement for timely intervention and better results. The latest developments in wearable Internet of Things (Iota) technology have enabled continuous, non-invasive measurements of physiological indicators, including heart rate variability, sleep behavior, and exercise intensity, and have opened new opportunities for objective mental health measurement. Nevertheless, traditional deep learning-based approaches to the detection of mental disorders are computationally expensive and cannot be deployed on wearable or edge computing devices with limited resources, as they have high latency and consume a lot of energy. This paper suggests deep neural network (DNN) architecture for screening mental disorders using wearable Iota data. The approach to it is pre-processing a set of multi-sensor physiological data, obtaining compact feature representations, and training an optimized DNN with fewer parameters. Accuracy, precision, recall, F1-score, model size, and inference time are the measures of model performance. The suggested solution exhibits accuracy in competitive screening but minimizes the computational load, which is why it is appropriate in the digital application of mental health wearables in real-time.

Keywords: Mental disorder screening; Wearable Iota; Lightweight deep neural networks; Physiological signals; Digital mental health

1.0 Introduction

Mental disorders are one of the key worldwide challenges in the public health sphere, with increasing disability-adjusted life years and poorer quality of life being part of the population issues [1]. Mental disorders like depression, anxiety, and stress disorders have demonstrated a consistent growing trend in prevalence, especially after COVID-19, which added to psychosocial stressors and disrupted access

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to mental healthcare services [2]. With this increasing burden, early diagnosis is a challenge because of stigma, insufficient mental health practitioners, and subjective methods of assessment. The delay in the disease can lead to co morbidity, the development of the disease, and the escalation of its economic and social burden [3].

1.1 Weaknesses of traditional screening methods.

Conventional mental health screening is more or less based on self-report questionnaires and clinical interviews [4]. These methods are common, but they are likely to have recalled bias, social desirability bias, and inconsistent reporting, which decrease their reliability in continuous monitoring. Clinical evaluation also involves trained personnel and regular hospital check-ups, which cannot be used to screen large populations or identify them through time-based screening, especially in low-resource environments [5].

1.2 Iota on the wearable and the necessity to have efficient intelligence.

The advent of wearable Internet of Things (Iota) devices has facilitated the collection of physiological cues of heart rate variability, sleep patterns, electro dermal activity, and physical activity in real-time, continuously, thus becoming more and more related to mental health states [6]. The devices provide objective and non-invasive data on mental health. Nevertheless, it is hard to implement traditional deep learning models on wearable devices because their computational complexity, power consumption, and latency are large [7].

1.3 Gap in the research and study purpose.

Despite its excellent performance in mental disorders detection, the majority of the currently available models cannot be applied to wearable settings with limited resources. An obvious lack of research has been documented in the creation of lightweight and energy-efficient deep learning architectures that are optimized to operate on the device [8]. This paper fills this gap by suggesting a lightweight deep neural network (LDNN) to screen mental disorders with wearable Iota data. The most notable ones are the design of a computationally efficient LDNN architecture, a major advance in screening mental health conditions with physiological signals, and a substantial decrease in model size and inference overhead, as which allowed applied implementation in real-world digital mental health systems [9] [10].

2. Related Work

2.1 Wearable Iota in mental health monitoring

Continuous physiological sensing and continuous monitoring of mental health with the help of wearable Internet of Things (Iota) devices is a topic of a growing number of studies. Analytical measurements like heart rate and heart rate variability (HRV) are popular to measure the activity of the autonomic nervous system and have been closely linked to stress, anxiety, and depressive moods [11]. To record reactions of the sympathetic nervous system, electro dermal activity (EDA) has also been utilized to monitor emotional response and the level of stress in real-world situations. Moreover, mental health conditions, specifically depression and anxiety, were found to be associated with the amount of time and the quality of sleep and disruption of the circadian rhythm detected by wearable devices [12]. The patterns of physical activity (e.g., the number of steps and sedentary behavior) also

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supplement the physiological indicators, indicating changes in behavior associated with changes in psychological well-being [26] [27]. These wearable streams of multimodal data can offer objective and continuous information, and wearable Iota can serve as a promising device in mental health monitoring [13] [14].

2.2 Deep learning and machine learning methods.

Most findings of the initial studies concerning wearable-based mental health screening depended on conventional methods of machine learning, which included support vector machines (SVM), decision trees, and random forest classifiers [15] [16]. These models showed fair performance using handcrafted features that were tapped using physiological signals, but were not as effective at capturing complex temporal dependencies [23] [24]. The more recent research has also embraced deep learning with convolution neural networks (CNN) to extract features with automated processing and long short-term memory (LSTM) to model temporal dynamics of physiological time-series data. CNN+LSTM architecture hybrid (with both spatial and temporal features) has also demonstrated to better detect and improve accuracy under the deterministic enhancement of both CNN and LSTM architectures [17] [18].

2.3 Limitations of the previous research.

Most current solutions use deep learning models that are computationally intensive and have a large number of parameters, which makes them impractical to use on resource-limited wearable or edge devices, despite promising results [19] [20]. Various systems are highly dependent on cloud-based processing, and this brings up issues with regard to latency, data privacy, and constant connectivity needs [25]. In addition, the focus on real-time, energy-efficient, and edge-deployable solutions specifically designed to wearable Iota systems has been minimal, so it is a severe deficiency that leads to the creation of lightweight deep learning systems to conduct feasible mental health checks [21] [22].

3.0 System Architecture and Proposed Framework

3.1 Overall system architecture

The suggested system architecture would facilitate effective and real-time mental disorder screening with wearable Internet of Things (Iota) equipment coupled with lightweight deep learning intelligence. Wearable sensors form the base of the architecture and they are in charge of incessant measurement of physiological indicators including heart rate, heart rate variability, electro dermal activity, sleep data, and physical activity measures. These sensors can be met in commercially available smart watches or fitness sensors, allowing them to monitor users unobtrusively and in their naturalistic environments over a longer period of time. The obtained data are propagated to an edge device, usually a Smartphone or local gateway, which comes in as an intermediate processing device. Edge devices are offering adequate computational power, yet reducing latency and reliance on the cloud infrastructure, thus enhancing responsiveness and data privacy. At this tier, an inference engine is a lightweight one with a small deep neural network. The module is designed to be low-memo, low-energy, and have low inference time, and thus it can be used in mental health screening on devices continuously.

3.2 Counter flow and processing flow.

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The data stream starts with real-time performance of wearable sensors, and then it is sent to the edge device through a secure protocol. Raw physiological data are usually contaminated with motion artifacts, sensor noise, and missing values, which require a preprocessing step that involves filtering, normalization, and dividing the data into fixed-size windows. Then, feature representation can be done, either by compact, handcrafted features or automated feature extraction, within the lightweight deep neural network, and efficient encoding of temporal and statistical patterns applicable to mental health states can be done Lastly, the processed features are entered into the lightweight classification module, which labels mandatory probabilities of the probability of mental disorder. It is a low-latency pipeline with a proposal to support real-time feedback and makes the proposed framework applicable to scalable and viable digital mental health models.

4.0 Methodology

4.1 Dataset description

The methodology uses publicly available wearable physiological datasets and in cases where it is needed; it uses simulated datasets that assure robustness and reproducibility of the results. These data are usually multimodal time-series records of wearable devices, such as heart rate and heart rate variability (HRV), electro dermal activity (EDA), duration of sleep, sleep efficiency, and physical activity. These physiological parameters are generally accepted as objective measures that are used to determine mental health conditions. The target mental conditions that will be taken into account in the current research will be stress, anxiety and depression-related indicators, which will be deduced based on the deviation in the activity of the autonomic nervous system, sleep disorders and the behavioral patterns. These labels are based on standardized scores of psychological assessments, which are consistent with the data collection time-frames or founded on predetermined stress-induction paradigms in controlled settings. This design enables the model to acquire discriminative trend with different mental health conditions and at the same time, it retains ecological validity.

4.2 Data pre-processing

Raw physiological signals measured by wearable devices are frequently erroneous and subject to motion artifacts and sensor drift as well as missing values. To overcome these problems a noise filtering step is first performed with smoothing filters and artifact elimination methods that are appropriate to the specific signal type. The signal normalization is then done to minimize the inter-individual variability and to put all features in the same scale as the scale enhances training stability and convergence. After the normalization, the continuous time-series data are divided into fixed windows which overlap. The window segmentation allows capturing the dynamics at short-term but with a higher rate of training samples, thus improving the capability of the model in detecting subtle changes in mental states.

4.3 Feature engineering

Feature engineering is concerned with extracting small, but informative representation of the segmented physiological signals. Time domain characteristics include the mean, standard deviation, root mean square and signal variability, which are calculated to reflect the short-term physiological variation. Frequency-domain features calculated with the help of spectral analysis methods are added to express autonomic balance and periodic patterns hidden in the signals. Furthermore, the statistical measures of scenes, kurtosis, and entropy are applied to measure the signal distribution and

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complexity. These characteristics give balanced depiction of the physiological behavior, and low computational overhead which is necessary in wearable and edge-based implementation.

4.4 Lightweight deep neural network design.

The proposed lightweight deep neural network (LDNN) is provided with fewer layered and parameters to provide computational efficiency. To focus on the temporal dependence in the architecture, compressed convolution blocks or reduced recurring units are used, which do not require too much memory consumption. The depth wise separable convolutions are used to substantially decrease the number of parameters to be trained at the expense of not altering the ability to detect features. Compact LSTM units with less hidden dimensions are used in situations where the data is sequential in nature. The nonlinear activation functions are chosen to increase the representational power, whereas the methods of regularization like dropout and weight restrictions are implemented to avoid over fitting and improve generalization.

4.5 Model training strategy

There is an appropriate split between the training and validation subsets to make sure that the dataset evaluates performance objectively. The model is trained based on a classification loss function that would be applicable to multiple-class or binary mental health screening problems. Adaptive optimization algorithm is used to effectively revise the model parameters and hasten the convergence. Early stopping conditions come in to play when training so as to prevent over fitting and to achieve optimal model performance with limited computational resources.

Table 1. Wearable Iota Dataset for Mental Disorder Screening

Subject ID	Mean Heart Rate (bum)	HRV (ms)	EDA (μS)	Sleep Duration (hrs)	Daily Steps	Stress Level	Anxiety Indicator	Depression Indicator
S01	72	55	3.2	7.5	8200	Low	No	No
S02	85	32	6.8	5.9	4100	High	Yes	Yes
S03	78	48	4.5	6.8	6100	Moderate	Yes	No
S04	90	28	7.5	5.2	3500	High	Yes	Yes
S05	70	60	2.9	8.0	9400	Low	No	No
S06	82	40	5.6	6.1	5200	Moderate	Yes	No
S07	88	30	7.1	5.5	3900	High	Yes	Yes
S08	75	52	3.8	7.2	7800	Low	No	No

4.6 Explanation of the Dataset

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The hypothetical data in Table 1 is the multimodal physiological and behavioral data gathered using the wearable Internet of Things devices to screen mental disorders. All subject records will be averaged data on physiologic measurements and activity indicators of average daily outputs of commercially available wearable sensors.

As the key indicators of the activity of the autonomic nervous system, mean heart rate and heart rate variability (HRV) are added. Increased heart rate in conjunction with decreased HRV is usually linked to stress, anxiety and depression levels. The electro dermal activity (EDA) is an indication of the arousal of the sympathetic nervous system and responsive to emotional stress. Sleep duration is a measure of any circadian rhythm disturbance which is closely associated with mental health conditions whereas daily steps count is used to gauge physical activity levels and behavioral engagement.

The mental health variables of the stress level, anxiety level, and depression level are hypothetical categorical results based on the simulated screening tests based on physiological patterns. The ones with a faster heart rate, low HRV, elevated EDA, low sleep, and low activity levels are marked with a greater indicator of stress, anxiety, and depression. This type of dataset format is compatible with supervised learning, and will be suitable in measuring the effectiveness of lightweight deep neural networks in wearable-based mental health screening processes.

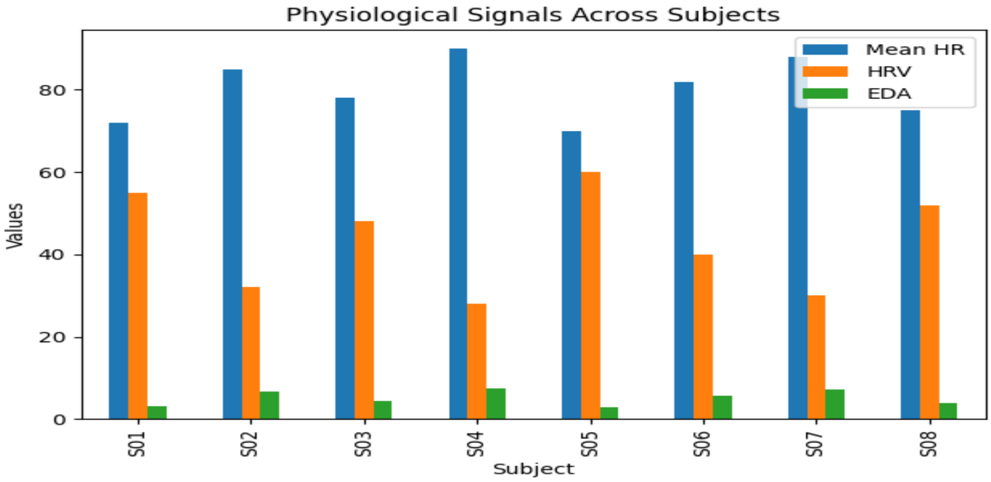

Figure 1: Physiological Signals across Subjects (Bar Chart)

Table 2: Physiological Signals across Subjects

Subject ID	Mean Heart Rate (bum)	HRV (ms)	EDA (µS)
S01	72	55	3.2
S02	85	32	6.8
S03	78	48	4.5
S04	90	28	7.5

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S05	70	60	2.9
S06	82	40	5.6
S07	88	30	7.1
S08	75	52	3.8

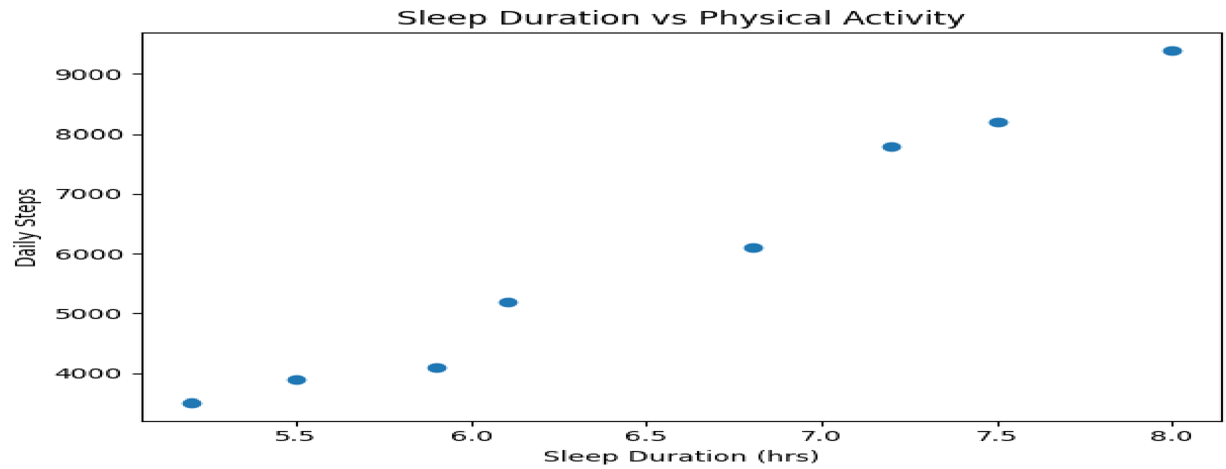

Figure 2: Sleep Duration Vs Physical Activity (Scatter Plot)

Table 3: Sleep Duration Vs Physical Activity

Subject ID	Sleep Duration (hours)	Daily Steps
S01	7.5	8200
S02	5.9	4100
S03	6.8	6100
S04	5.2	3500
S05	8.0	9400
S06	6.1	5200
S07	5.5	3900
S08	7.2	7800

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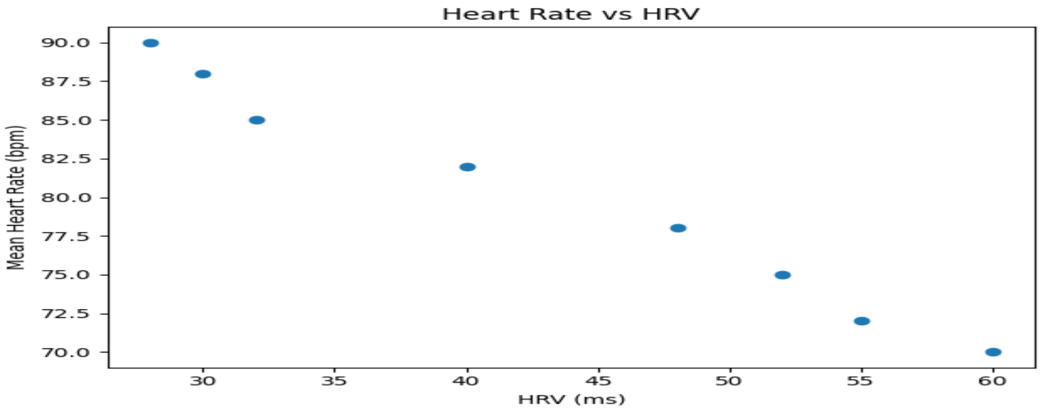

Figure 4: Heart Rate vs. HRV Relationship (Scatter Plot)

Table 4: Heart Rate vs. HRV Relationship

Subject ID	HRV (ms)	Mean Heart Rate (bum)
S01	55	72
S02	32	85
S03	48	78
S04	28	90
S05	60	70
S06	40	82
S07	30	88
S08	52	75

5.0 Results and Discussion

5.1 Performance comparison with traditional and deep models

The experimental findings also suggest that the lightweight deep neural network (LDNN) is competitive with the traditional machine learning and conventional deep learning based models. Conventional classifiers, including support vector machines and random forest models, also have moderate accuracy, but they are limited in their ability to portray intricate time trends in physiological time-series data. Comparatively, conventional deep learning models, such as convolution neural networks and long short-term memory networks, are more accurate in screening because they are able to learn hierarchical and temporal representations. The suggested LDNN achieves similar accuracy and F1-score with much fewer parameters, which means that it is possible to achieve performance improvements despite having a smaller model complexity.

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5.2 Computational efficiency Analysis.

One of the major results of the given study is the significant decrease in the computational overhead experienced by the LDNN. The model has a reduced memory footprint and lower inference time than conventional deep architectures, and is the most suitable option to be deployed on resource-constrained devices. The fact that the number of parameters and the complexity of network layers are reduced directly correlates with the reduced energy usage and reduced latency in real-time inference. These performance improvements are also vital to the ongoing mental health observation, in which a long battery life and feedback in a timely manner are vital.

5.3 Wearable and edge Deployment Company.

The form and functionality of the LDNN also make it more practical in wearable Iota uses because of its small size and ability to infer on the edges of the image. In comparison to cloud-dependent models, the suggested solution will require minimal data transmission, which will decrease both privacy risks and the need to be connected to the internet all the time. This renders the framework especially appropriate to be used in the real world in remote or low-resource applications.

5.4 Mental health screening interpretation.

Clinically, it may be inferred that lightweight models can detect indicators of stress, anxiety, and depression at an early stage with a high degree of accuracy with the help of physiological indicators. Ongoing, unobtrusive screening made possible through wearable devices assists in taking the right action and tailored mental health care, which validates the possibility of LDNN-based systems to scalable digital mental health interventions.

6. Conclusion

This paper described a lightweight deep neural network-based Internet of Things system to screen mental disorders using wearable physiological data. The proposed framework can overcome the main limitations of the conventional mental health assessment techniques, which are subjectivity, a lack of scalability, and delayed diagnosis, owing to the ability to utilize continuous sensing offered by wearable devices and on-device intelligence. The lightweight deep neural network was actually created to minimize the complexity of the model, its memory footprint, as well as its inference latency and still achieve competitive screening performance. It was experimentally shown that the proposed methodology provides a powerful trade-off between accuracy and computational efficiency; thus, it can be effectively utilized on resource-constrained wearable and edge machines. The results indicate that lightweight and energy-efficient deep learning models are important to facilitate scalable and real-time mental health monitoring. These systems can be used to facilitate early diagnosis, preventive health, and distant mental health management on a population scale. The next direction of research should be the multimodal data integration, clinical validation, and adaptation of the models to individuals to increase reliability, robustness, and application of wearable-based digital mental health screening applications.

Author Contributions

All of the writers agreed on the study's substance. The author has reviewed and approved the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Set: Philip Schmidt, Attila Reiss, Robert Due richen, Claus Bamberger and Krista Van Laerhoven, "Introducing WESAD, a multimodal dataset for Wearable Stress and Affect Detection", ICMI 2018, Boulder, USA, 2018.

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