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Stress detection through wearable sensors: a convolutional neural network-based approach using heart rate and step data

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ABSTRACT

With the current technological advancements, particularly in sensing technologies, monitoring various health aspects, including heart rate, has become feasible. The problem addressed in this study is the need for effective stress detection methods to mitigate the significant consequences of high-intensity or long-term stress, which impacts safety and disrupts normal routines. We propose a stress detection system developed based on the convolutional neural network (CNN) method to address this. The study involves university students aged 20–22, focusing on mental stress. The dataset encompasses parameters such as heart rate, footsteps, and resting heart rate recorded through a smartwatch with 149,797-row data. Our results indicate that the CNN model achieves an 84.5% accuracy, 80.9% precision, 79.8% recall, and an 80.4% F1-score, confirming its efficacy in stress classification. The confusion matrix further validates the model's accuracy, particularly for classes 1 and 2. This research contributes significantly to the development of an effective and practical stress detection method, holding promise for enhancing well-being and preventing stress-related health issues.

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1. INTRODUCTION

People generally desire control in their lives, but as they age, they often experience more losses than gains [1]. With advancing age, individuals must make strategic choices about where to invest their energy and resources. Both theoretical and empirical work suggests that social interactions are greatly valued throughout one's life. Eric's research shows that while adults perceive a decrease in their control over non-social stressors as they age, this reduction is not evident in the context of social stressors. This finding implies that socioemotional aspects remain robust, maintaining their significance in the lives of older adults.

Stress constitutes a ubiquitous component of everyday existence, encountered by the majority of individuals across diverse contexts and modalities. Nonetheless, exposure to high intensity or prolonged stress can compromise safety and perturb the regularity of daily activities. Early identification of mental stress is crucial for averting a plethora of health issues that stress may precipitate [2].

It is crucial to detect mental stress early, as it can prevent the emergence of numerous health problems related to stress. Stress can primarily be categorized into acute stress and chronic stress. The release of stress hormones such as cortisol can lead to unhealthy habits such as smoking addiction, consuming unhealthy food, and the use of medication that potentially increases health risks, including a decline in the immune system, increased blood pressure, brain disorders, heart attacks, strokes, violence, suicide, and even an elevated risk of cancer [2].

Heart rate monitoring was investigated using the heart rate variability (HRV) technique, specifically focusing on mental stress detection through photoplethysmography (PPG). This study employed the support vector machine (SVM) for classification, drawing on low frequency (LF), high frequency (HF), and the LF/HF ratio metrics from HRV's frequency domain analysis. LF metrics were observed to escalate under conditions of mild/low stress. In contrast, HF metrics increased during mild/low and moderate stress levels, implicating both the autonomic nervous system (ANS) and sympathetic nervous system (SNS). Additionally, stress levels and the LF/HF ratio progressively rose from mild to severe stress conditions. Analysis of 15 subjects labeled 3 types baseline, amusement and stress revealed detection accuracies of 75.21%. Analysis of same data with 2 class (stress and non-stress) resulting accuracies of 88.56%. 3 classes and 2 classes are using hybrid convolutional neural network (CNN) to detect stress [3].

Tharion *et al.* [4] discussed the analysis of heart rate variability as a stress detection method. This research calculated heart rate variability using both time-domain and frequency-domain methods. The results showed that heart rate variability could serve as a good indicator for detecting stress [5]. Shu *et al.* [6] investigated the use of heart rate variability as an indicator of stress in emotion recognition. The study demonstrated that changes in heart rate could be utilized to identify emotions such as neutral, sad and happy using emotional stimulus from video clips.

Over two decades, stress and depression have been detected as prominent global public health concern [7]. It is a mental condition that arises when an individual experiences an inability to meet their needs or expectations, resulting in pressure. This pressure can affect both mental and physical health, as well as individual productivity [8]. Moreover, stress refers to the mental imbalance faced by an individual due to the presence of pressure. This pressure arises from the individual's inability to meet their needs or expectations, which can stem from both internal and external demands. Emotional reaction will consist of denial symptoms and pangs of strong emotion such as traumatic images [9].

According to health psychology research, three factors can trigger stress, involving physical-biological stressors such as challenging-to-treat illnesses or physical disabilities, psychological stressors encompassing negative thoughts or feelings of frustration, and social stressors related to disharmonious relationships among individuals, in society, or within the family. The impacts of stress on health include stress hormone release, increased heart rate, and respiratory rate [10]. Stress can also lead to symptoms such as headaches and difficulty sleeping, as well as an increased risk of health disorders such as hypertension and digestive problems [11].

Stress is a complex phenomenon that can affect an individual's physical and mental well-being [12]. In many cases, acute stress can trigger the "fight or flight" response, which is useful for dealing with emergency situations. However, when stress persists into chronicity, the body experiences excessive pressure, negatively impacting the health system. Chronic stress can impair the immune system, increase the risk of heart disease, and even accelerate the aging process. Additionally, stress can affect sleep quality, concentration, and daily productivity, leading to mental health problems such as anxiety and depression [13].

In IEEE Access, Taskasaplidis *et al.* [14] has reviewed many stress detection methods, one of which uses heart rate on a Fitbit wearable sensor. Khoo *et al.* [15] reviewed all multimodal mental health detection, one of them using HRV and Khoo *et al.* also shows that modality fusion techniques for concatenating feature representations as a single input to learn high-level representations can be used in dense and fully connected layers with attention mechanisms like CNN, multi-head attention network, and transformer. Chalmers *et al.* [16] using a wearable device entitled "Stress watch: the use of heart rate and heart rate variability to detect stress: a pilot study using smart watch wearables," has similar research with a different variable, which is heart rate variability (HRV) and resting heart rate (RHR). Chalmers *et al.* [16] has shown that HRV cannot be measured individually, it must consider the RHR baseline while anxiety and stress state to ensure additive acute stress. Sim *et al.* [17] uses a CNN to detect stress with five classes (no response, not stressed, a bit stressed, moderate, a lot, and extremely), resulting in 79.25% AdaBoost approach accuracy Fontes *et al.* [18] used CNN to improve HRV-based acute stress detection, resulting in a 95.83% accuracy.

Considering the serious impact of stress on human health, the author conducted research to detect mild stress using the CNN method. This approach aims to integrate several relevant data layers, such as heart rate, footstep, and resting heart rate, as primary parameters in the stress detection process. This integration is expected to provide a more holistic understanding of stress conditions and evaluate CNN's performance in managing and analyzing heart rate data. The results of this study are anticipated to contribute significantly to developing more effective and practical stress detection methods. Our research can be implemented in wearable health monitoring devices to provide users with real-time stress detection and management. This can be particularly useful in workplace wellness programs, where employers can offer personalized stress management strategies to employees based on their stress levels. Our approach utilizes commonly available sensors in wearable devices, such as heart rate monitors and accelerometers. This ensures that our method can be implemented without significant additional costs, making it accessible to a wide range of users.

The evaluation of the CNN model achieves an 84.5% accuracy, 80.9% precision, 79.8% recall, and an 80.4% F1-score. The confusion matrix further validates the model's accuracy, particularly for classes 1 (stress) and 2 (no stress). The novelty of this research lies in utilizing three variables that have not been previously employed in any known studies. Stress will reduce the number of footsteps, as mentioned by Brockmann and Ross [19]. Altini and Plews [20] conducted research in 5 years for a longitudinal study of HRV at rest (RHR) and stress. These results confirm the efficacy of the proposed stress detection system and its potential to contribute significantly to the development of more effective and practical stress detection methods.

2. METHOD

In the design phase of the system constructed in this research, a system is developed to analyze the implementation of a stress detection system using the CNN method. This phase involves creating a structured plan that outlines the necessary steps for building and evaluating the stress detection system. The research is divided into several stages that align with the block diagram depicted in Figure 1, ensuring a systematic approach to the development process.

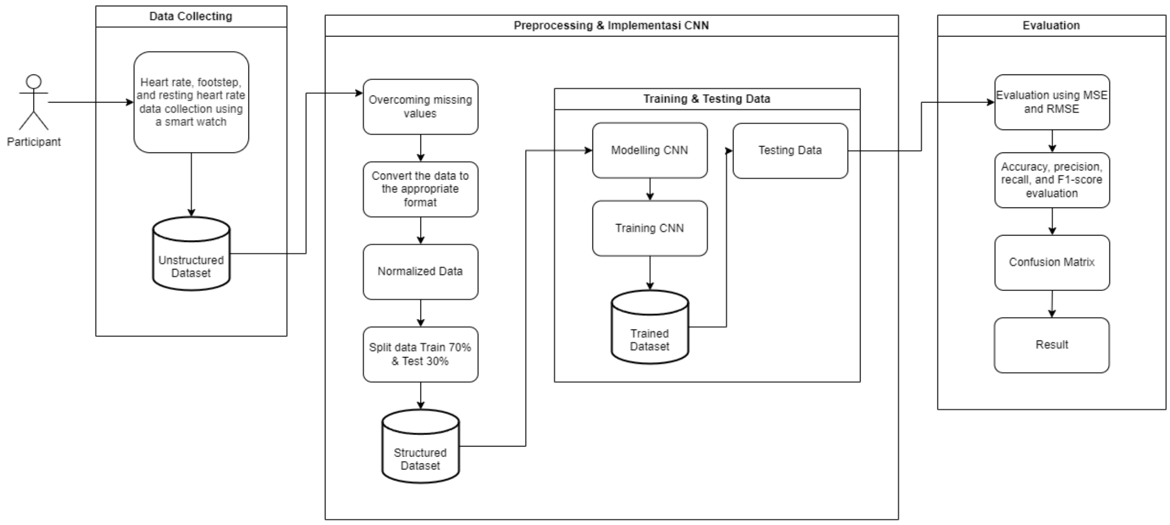

Figure 1. Data collection, preprocessing, CNN implementation, and evaluation processes

2.1. Data Collection

In the design of this system, the main focus is to detect heart rate, footstep, and resting heart rate as key parameters to identify the level of stress. The first process involves data collection. Data collection was conducted on 10 participants who are Telkom University students aged between 20 and 22 years, with the identified type of stress being mental stress. This data includes information on heart rate, the number of steps (footsteps), and resting heart rate measured using the Fitbit Charge 3 smart watch.

This system, built on smartwatch technology, is designed to enhance our understanding of mental stress by focusing on three key parameters. It captures real-time physiological responses, providing immediate and accurate data about stress levels. This approach ensures researchers can analyze mental stress more effectively within the studied population, leading to better insights and potential interventions.

2.2. Preprocessing

The preprocessing stage helps ensure that the data used to train the model is clean, relevant, and ready for use in the training and testing processes [21]. In this stage, processes such as handling missing values, labeling data, converting data into appropriate formats, data normalization, and splitting data into training and testing data are carried out. The processes in this stage can be seen in Figure 2.

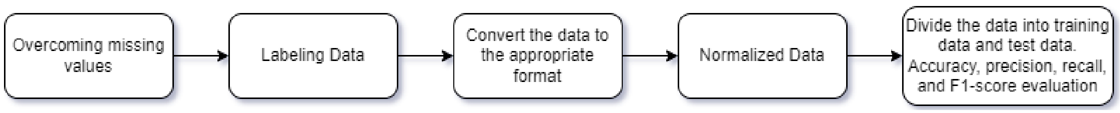

Figure 2. The preprocessing flow starts with removing noise and divides the data into training and test data

2.3. Convolutional neural network

Convolutional neural network (CNN) stands out as a specialized architecture within artificial neural networks, meticulously crafted for processing structured data [22]. Comprising distinct layers, CNN possesses the innate ability to autonomously and hierarchically discern features from input data. The convolutional Layer, with its convolution operations, excels in extracting intricate features by scanning minute portions of the input using filters or kernels. This facilitates the detection of specific patterns, enabling the model to acquire a nuanced understanding of the data's hierarchical structures. The layer, incorporating the rectified linear unit (ReLU) activation function, contributes by eliminating negative values in the convolution results, recognizing intricate patterns and forming abstract data representations. The pooling layer strategically reduces the spatial dimensions of the convolutional layer outputs, mitigating computational complexity and preventing overfitting. Finally, the fully connected layer amalgamates information from preceding layers, serving as a decisive classifier for tasks like stress classification based on heart rate, culminating in a comprehensive and sophisticated data analysis. The main formula related to the convolution operation in a CNN can be seen in (1).

$$S(ii,jj) = (I * K)(ii,jj) = \sum_{mm} \sum_{nn} I(mm,nn) \cdot K(ii - mm, jj - nn) \quad (1)$$

When, $S(ii,jj)$ is the pixel at position (ii,jj) in the convolution result matrix. $I(mm,nn)$ is the pixel value at position (mm,nn) in the input (image or data matrix). $K(ii - mm, jj - nn)$ is the value of the filter (kernel) at position $(ii - mm, jj - nn)$. $\sum_{mm}$ dan $\sum_{nn}$ are symbols for summing up all the pixel values in the convolution operation.

The equation (1) describes the convolution process between the input (*I*) and the filter (*K*), resulting in the convolution matrix *S*. Afterward, this convolution result can be operated with an activation function, such as the ReLU function, and undergo layers of pooling and fully connected layers to generate the final output [23].

2.4. Evaluation phase

Evaluating CNN models in the context of a specific task can be done using various performance metrics [23]. These metrics provide a quantitative framework for assessing the model's effectiveness, enabling researchers to identify strengths and areas for improvement. Below is a brief explanation of some commonly used evaluation metrics, highlighting their relevance in analyzing model performance within different tasks.

2.4.1. Confusion matrix

A confusion matrix is a matrix table used in the evaluation of the performance of a classification model. The confusion matrix provides a comprehensive overview of how well a classification model can predict the correct target classes and analyzes the types of errors made by the model [24]. The matrix is composed of four key components: true positives (TP), which reflect correctly predicted positive instances; true negatives (TN), indicating instances accurately identified as negative; false positives (FP), representing cases incorrectly classified as positive despite belonging to the negative class (Type I error); and false negatives (FN), which denote positive instances misclassified as negative (Type II error). These elements provide a detailed breakdown of the model's classification performance, allowing for a thorough analysis of its accuracy and the types of errors it makes in predicting target classes [25]. By using these four main cells, the confusion matrix can be stated in Table 1.

Table 1. Table explaining the confusion matrix

		Actual value	
		Positive	Negative
Predictive value	Positive	True positive (TP)	False negative (TN)
	Negative	False negative (FN)	True negative (TN)

The confusion matrix aids in calculating various classification evaluation metrics such as accuracy, recall, precision, and F1-score [26]. By utilizing the values from the confusion matrix cells, we can better understand the classification model's performance across different aspects. The accuracy, recall, precision, and F1-score calculations can be observed in (2) to (5).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad (2)$$

Accuracy measures how often the model provides correct predictions overall. It is expressed as the total correct predictions (true negative and true positive) ratio to the total number of samples.

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

Precision measures how precise the model is in predicting the positive class. It is expressed as the ratio of true positive to the total positive predictions (false positive and true positive).

$$Recall = \frac{TP}{(TP + FN)} \tag{4}$$

Recall measures the model's ability to detect all instances of the actual positive class. It is expressed as the ratio of true positive to the total instances of the positive class (true positive and false negative).

$$F1 - Score = 2\,\frac{Precision * Recall}{Precision + Recall} \tag{5}$$

The F1-score represents the harmonic mean between precision and recall, offering a balanced measure that encompasses both. F1-score achieves a high value if and only if both precision and recall have high values.

3. RESULTS AND DISCUSSION

3.1. Implementation preprocessing

The outcomes of the data preprocessing stage are detailed in sections 3.1.1 to 3.1.5. These sections cover the results from handling missing values, implementing data labeling, converting data formats, normalizing data, and splitting the data, which collectively constitute the preprocessing steps for this research. Each step is critical to ensuring the dataset's quality and suitability for analysis, ultimately enhancing the reliability and accuracy of the results presented in subsequent sections.

3.1.1. Results from overcoming missing values

The main objective of this stage is to clean and prepare the data for further analysis or modeling. In this phase, the dataset is evaluated using the $isnull().sum()$ function to identify the number of missing values in each column. Subsequently, rows containing missing values are removed using the drop a function, and the modified dataset is stored back in the variable "data." This action is taken to cleanse the dataset from rows with missing values. After this process, another evaluation using $isnull().sum()$ is conducted to ensure that the dataset used is free from missing values. Ultimately, this piece of code aims to handle and eliminate missing values in the dataset before proceeding to the analysis or modeling stage. The outcomes of this stage can be observed in Figure 3.

```
id           0
dateTime     0
bpm          0
step         0
kelelahan    0
dtype: int64
id           0
dateTime     0
bpm          0
step         0
kelelahan    0
dtype: int64
```

Figure 3. Results of the missing value removal stage

3.1.2. Implementation of labeling data

This process aims to provide labels to the data based on the interview results from participants, assigning the label "*ya*" (yes) for feeling stress and "*tidak*" (no) for not feeling stress, which will be subsequently converted to "*ya*" with a value of 1 and "*tidak*" with a value of 0. The outcomes of this labeling process are presented in Table 2.

Table 2. Results from the data labeling

ID	DateTime	bpm	step	Feeling stress
ID001	2023-09-23 00:00:02	99	0	No
ID001	2023-09-23 00:00:07	98	0	No
ID001	2023-09-23 14:47:12	104	10	Yes
ID001	2023-09-23 14:47:17	107	10	Yes

3.1.3. Data format conversion

In this stage, adjustments to the data format are made. There are a series of data type conversions (casting) for columns in the dataset. Firstly, the columns $'bpm'$ (heart rate per minute), $'step'$ (number of steps), $'kelelahan'$ (fatigue label), and $'dateTime'$ (time) are converted to the integer data type using the $'astype'$ (int) function. This converts the values in these columns into integers, facilitating further processing and analysis. The code for the format adjustment can be seen in Figure 4.

```
data['bpm'] = data['bpm'].astype(int)
data['step'] = data['step'].astype(int)
data['kelelahan'] = data['kelelahan'].astype(int)
data['dateTime'] = data['dateTime'].astype(int)
```

Figure 4. Code for the data format conversion stage

3.1.4. Normalized data

In this stage, data normalization is performed using min-max scaling. Normalization is the process of transforming data so that its values fall within a specific range, in this case, the range between 0 and 1 [27]. $hr\_normalized = (hr - hr\_min)/(hr\_max - hr\_min)$,

$$hr\_normalized = \frac{(hr - hr\_min)}{(hr\_max - hr\_min)} \tag{6}$$

$$step\_normalized = \frac{(step - step\_min)}{(step\_max - step\_min)} \tag{7}$$

3.1.5. Split data

In this stage, the dataset is divided into two main subsets: training data (train) and testing data (test). The chosen proportion allocates 70% of the data to training the model (X_train and y_train) and the remaining 30% to testing or evaluating the model's performance (X_test and y_test). This split ensures a balanced approach, allowing the model to learn effectively while providing sufficient data for an unbiased evaluation of its predictive accuracy and generalization capabilities.

3.2. Results from the CNN model

The results of the CNN model implementation are visualized using a graph of the model's loss, consisting of two lines: the blue line representing the training loss and the red line representing the validation loss. The training loss is the error value produced by the model when trained with the training data. The training loss will continue to decrease as the training iterations progress. This suggests the model is improving its ability to identify patterns within the training dataset. Then, the validation loss is the error value produced by the model when tested with validation data. The validation loss will also decrease as the training iterations progress, but the decrease will be slower than the training loss. This indicates that the model is approaching its limit in recognizing patterns in the training data. The graph for the model loss can be seen in Figure 5.

Based on the graph, it can be concluded that the CNN model has successfully achieved good accuracy. This is evident from the significant decrease in both training loss and validation loss as the training iterations progress. At the 60th epoch, the training loss and validation loss reach values of 0.12 and 0.14, respectively. These low loss values indicate that the CNN model can recognize patterns in the training data with high accuracy.

Based on Figure 6, it can be concluded that the results of the CNN implementation are quite good. This is evident from the training accuracy and validation accuracy values, reaching 85% and 82.5%, respectively. Training accuracy is the model's accuracy when trained with training data [28]. Validation accuracy is the model's accuracy when tested with validation data. High accuracy values indicate that the CNN model is capable of recognizing patterns in both training and validation data effectively.

Figure 5. Model loss graph on CNN

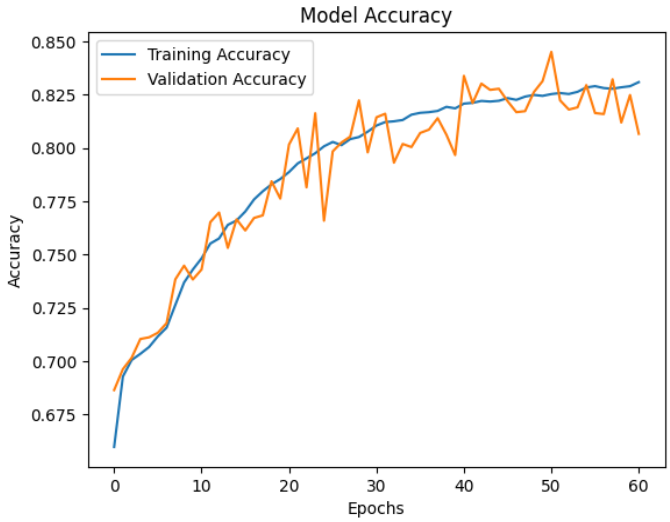

Figure 6. Model accuracy graph on CNN

3.3. Evaluation

The model evaluation stage includes accuracy, precision, recall, F1-score, and confusion matrix. Each of these metrics offers a unique perspective on the model's performance, assessing its ability to predict target values accurately and classify data effectively. By combining these metrics, a comprehensive understanding of the model's strengths and weaknesses is achieved, facilitating a more interpretation of its predictive and generalization capabilities.

3.3.1. Accuracy, recall, precision, and F1-score

The accuracy result indicates that the CNN model can correctly predict the target for 84.5% of the total data. The precision value shows that the CNN model can predict the actual target for 80.9% of the total actual targets. The recall value indicates that the CNN model can predict all actual targets for 79.8%. The F1-score value shows that the CNN model predicts the target well, balancing precision and recall, with a score of 80.4%. Further details can be seen in Figure 7.

3.3.2. Confusion matrix

Based on the confusion matrix plot from CNN, it can be concluded that the CNN model is capable of predicting classes with good accuracy. This is evident from the high diagonal values in the confusion matrix, namely 23,708 for class 1 and 14,274 for class 2. The diagonal values in the confusion matrix represent the number of correctly predicted instances. The complete Confusion Matrix results can be seen in Figure 7.

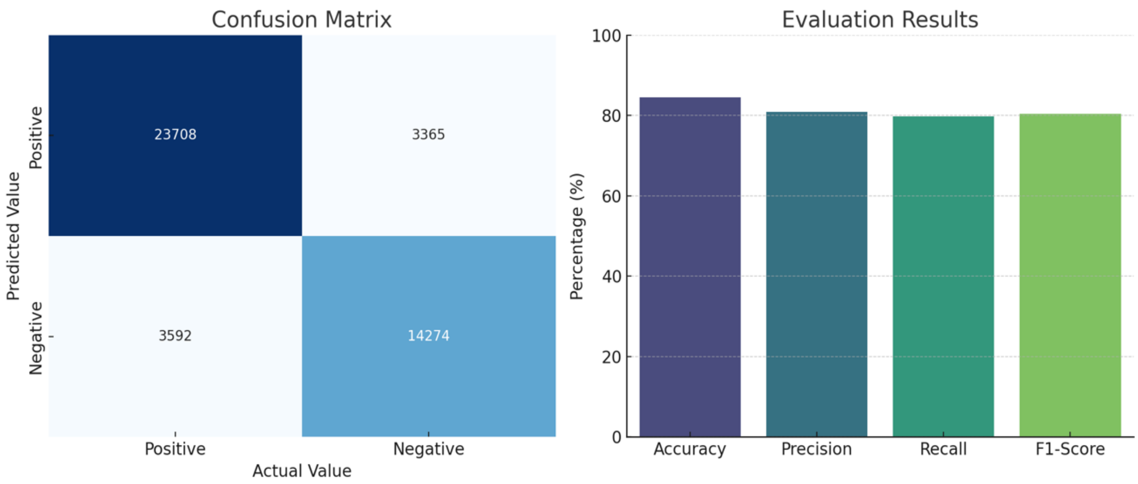

Figure 7. Complete confusion matrix and evaluation result

4. CONCLUSION

This study aims to detect stress based on heart rate using the CNN method. The evaluation results of the model achieved an accuracy of 84.5%, precision of 80.9%, recall of 79.8%, and an F1-score of 80.4%. The confusion matrix indicates that the model can predict classes 1 and 2 well, with high diagonal values. As a future research direction, this study could serve as a foundation for further exploration into integrating additional factors to enrich heart rate data and adding more subjects and types of stress. This could enhance the accuracy and applicability of the model in more complex stress situations.

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