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Estimation of Worker Stress Considering Differences in Listening Tempo

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ABSTRACT

This study was aimed at constructing a machine learning model to estimate the increase or decrease in stress experienced by workers when listening to music. In the experiment, six participants listened to beats of 7 different BPM while inputting text and were asked to complete questionnaires regarding their biometric data, music preferences, and music listening habits. Consequently, a model with an AUC $\approx$ 0.98 was constructed. However, the possibility of class labeling was suggested, and increasing the diversity of the dataset was found necessary. Stress estimation is a key in developing a system related to music that can help reduce stress and improve work productivity.

Keywords: Mental stress, Music therapy, Productivity, Biometric measurements, Machine learning

INTRODUCTION

In recent years, an interest in stress reduction and suppression has grown against the backdrop of a stressful society. It has been confirmed that the number of workers' compensation cases for mental disorders is actually on the increase due to the progression of a stressful society (Mizushima and Honma, 2023). To consider countermeasures against stress, understanding the level of stress is important; for this, stress estimation using machine learning has been used. In a previous study on stress estimation (Suzuki and Sato, 2020), a driver was assumed to be driving in the absence of external stimuli, such as listening to music, and the stress and relaxation states were estimated with an accuracy rate of ~73% using an index based on the heart rate variability. However, in recent years, increasing number of people have started listening to music while working owing to the diversification of work styles and spread of music players. In addition, the effects of listening to music on stress suppression (Kikuta, 2010) and motivation to work (Abe and Aragaki, 2010) have been confirmed, indicating that listening to music is closely related to stress changes among workers. Therefore, this study was aimed at estimating the increase or decrease in stress among people who listen to music while working. In this study, we focused on the "tempo" of the music. Tempo is the most important factor affecting the impression of music (Ralph, 1935), and listening to "beat sounds" with a strong tempo component has been confirmed to have a stress suppression effect (Kamise, 2022). However, these previous studies did not take into account individual differences in music preference and music listening habits, and the large influence of these individual differences is considered to be an issue. In this study, we considered the extraction of features that include individual differences to be effective for this issue, and we used machine learning to construct a model for estimating the increase or decrease in the stress of workers, while listening to beat sound.

An Experiment to Obtain Biometric Information of Workers While Listening to a Beat Sound

A dataset was created to construct a model for estimating the increase/decrease in the stress of a worker while listening to sound. The experimental flow and setup are shown in Figures 1 and 2, respectively. Six male students in their 20s participated in the experiment. The participants were seated with their heads fixed 75 cm from the monitor while listening to beats through headphones. The experiment was explained to the participants and their consent was obtained prior to the experiment. No compensation was paid for participation in this study. During the experiment, the pupil diameter and heart rate of the participants were measured using a gaze meter (Tobii Pro Spectrum, manufactured by Tobii Technology) and a multiorganization measurement sensor (WEB-1000, manufactured by Nihon Kohden). The target task was a text input task, in which all the task sentences written in Japanese were typed in hiragana, as shown in Figure 3. The tempo of the beats was set as the experimental condition. A total of seven experimental conditions were set, where the participants were asked to listen to beats of 30–210 BPM with an increment of 30 BPM. The set BPM encompassed the BPM of commonly heard music.

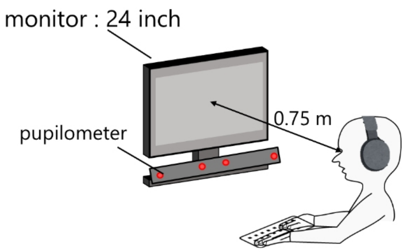


Figure 1: Experimental setup.

Instruction Practice	Question	Equipment Installation	Rest	Task **15 sec×7 condition(BPM)×20 times**	Question

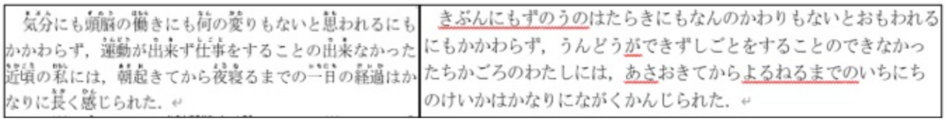
Figure 2: Experimental procedures.

Before the experiment, participants were asked to respond to a subjective questionnaire regarding their music preferences and music listening habits. The items were: frequency of “Do you usually listen to music in your daily life” five-point grading scale, frequency of “Do you usually listen to music while working” to five-point grading scale, and tempo of “Tempo of music you usually listen to” to six-point grading scale. The respondents were asked to respond to six-point grading scale “the tempo of the music I usually listen to.” The BPM condition set in this study was used as a boundary criterion for the tempo stage, where 30 BPM and ≥210 BPM were not used as a boundary for the stage owing to their rarity. The data on the questionnaire results were converted into dummy variables (referred to as Q-results in this paper).

Analysis and Data Preprocessing Methods

Pupil Diameter

Pupil diameter is a biological parameter controlled by the autonomic nervous system (Hara, 2012). It was used as an index of stress in this study. Mydriatic pupils indicate a state of stress (tense state), and contracted pupils indicate a state of relaxation (restful state). In addition, pupil diameter data require processing of missing data due to blinking. In this study, we detected the blinking eye from the fluctuation before and after the missing pupil diameter data (Ronen, Avishai and Noga, 2018) and linearly interpolated the pupil diameter data during eye blinking, as shown in Figure 4. In this study, the stress value was defined as the pupil diameter during the task minus the pupil diameter at rest, and a negative value was classified as class 0 (low-stress group) and a positive value as class 1 (high-stress group).



気分にも頭脳の働きにも何の変りもないと思われるにもかかわらず，運動が出来ず仕事をすることの出来なかった近頃の私には，朝起きてから夜寝るまでの一日の経過はかなりに長く感じられた。	きぶんにもずのうのはたらきにもなんのかわりもないとおもわれるにもかかわらず，うんどうができずしごとをすることのできなかったちかごろのわたしには，あさおきてからよるねるまでのいちにちのけいかはかなりにながくかんじられた。

Figure 3: Experimental tasks (problem statement and sample responses).

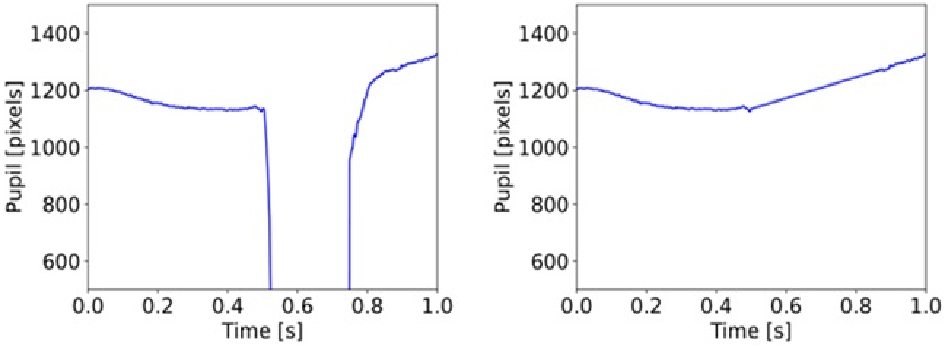


Figure 4: Blink interpolation processing image.

Electro-Cardiogram (ECG)

An electrocardiogram is an index that records the electrical activity of the heart and can be expressed as heart rate or analyzed as heart rate variability to treat it as an index of autonomic nervous system activity. In this study, the noise caused by respiration and body movements was removed and used as the heart rate data.

Entire Data Set

As the data scales were variable, standardization was performed to unify data scales.

Model Building and Performance Evaluation Methods

We used neural networks to construct a model for estimating the increase or decrease in the stress of a worker while listening to sound. A two-class classification model was constructed to estimate whether stress increases or decreases. Neural networks are multilayered and can hierarchically extract features. A neural network can also model nonlinear functions and is a learning method that excels in nonlinear relationships and pattern learning. The structure of the model is shown in Figure 5. The input and output layers are both one layer. We developed a two-class classification model; therefore, a sigmoid function was used as the activation function of the output layer. The hidden layer consisted of two fully-coupled layers, and the ReLu function was used as the activation function for all bonded layers. The binary cross-entropy was used as a loss function, and the optimization method was Adaptive Moment Estimation (Adam), which combines the momentum and Root-Mean-Square Propagation (RMSProp). The confusion matrix, Receiver Operatorating Characteristic curve (ROC), and Area Under the Curve (AUC) were used to evaluate the performance of the model.

Confusion Matrix

The confusion matrix is a square matrix, as shown in Figure 6, and is used to evaluate the model performance in machine-learning classification problems. For each element, we denote Positive if the actual value is positive, Negative if the actual value is negative, True if the prediction of the agrees with the actual value, and False otherwise. The outcome was TP if the model correctly predicted the actual value as Positive. It was FP if the model incorrectly predicted the actual value as Positive. Conversely, it was FN if the model incorrectly predicted the actual value as Negative, and TN if the model correctly predicted the actual value as Negative.

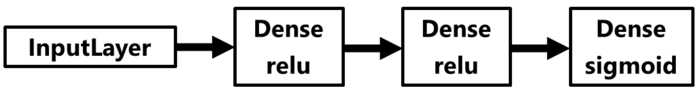


Figure 5: Model structure.

The confusion matrix summarizes the results in tabular form. Using this confusion matrix, the model performance can be evaluated in more detail by calculating the indices using formulae (1)–(4), where Accuracy is the percentage of correct responses among all predictions, Precision is the percentage of correct responses among those predicted as Positive, and Recall is the percentage of correct responses among the actual responses. F1 is the harmonic mean of Precision and Recall. For example, in the case of a model that estimates the presence of cancer based on a radiograph, a high Recall value is required because the risk of missing a cancer even though it is actually present is higher than the risk of incorrectly pointing out a cancer even though it is not present. Thus, the confusion matrix and the four values calculated from it indicate the relationship between the model predictions and actual class labels.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = \frac{2 \times Recall \times Precision}{Recall + Precision} \tag{4}$$

ROC Curve, AUC

The ROC curve visualizes the relationship between the true positive rate (TPR) and false positive rate (FPR), as shown in Figure 7, where TPR is the percentage of correctly identified positives that were actually positive, and FPR is the percentage of incorrectly identified positives that were actually negative. FPR is the percentage of cases incorrectly judged as Positive when being actually Negative. Using these indices, the ROC curve evaluates the model performance at different thresholds and helps determine the correct balance. AUC stands for the area under the curve and represents the area under the ROC curve; AUC takes values from 0 to 1. AUC = 0.5, when the model randomly assigns data, and the closer the maximum value to 1, the

		Prediction	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Figure 6: Confusion matrix.

better the classification ability of the model. As a rule of thumb, AUC $\geq$ 0.9 indicates a very good classifier, $\geq$0.8 a good classifier, $\geq$0.7 a satisfactory classifier, $\geq$0.5 a poor classifier, and <0.5 the opposite, showing lesser than random classification performance.

Result and Discussion

Among the two models constructed, in Model 1, the BPM of the sound heard (hereinafter referred to as Beat BPM) and the value obtained by subtracting the normal heart rate from the heart rate during the experiment (hereinafter referred to as heart rate (task-rest)) were set as explanatory variables. In Model 2, the Q-results were added to the explanatory variables in Model 1.

Model 1 (Explanatory Variables: Beat BPM, Heart Rate (Task-Rest))

Figure 8, Table 1, and Figure 9 show the confusion matrix, four indices calculated using the confusion matrix, and ROC curve for Model 1, respectively. The lower-right panel in Figure 9 shows that the AUCs for class labels 0 and 1 were approximately 0.76. This indicated that the model could roughly estimate the increase or decrease in stress. However, according to the results in Table 1, data that should be class 1 (high-stress group) were often misclassified as class 0 (low-stress group). In addition, the number of samples for each label was slightly skewed, indicating a room for improvement.

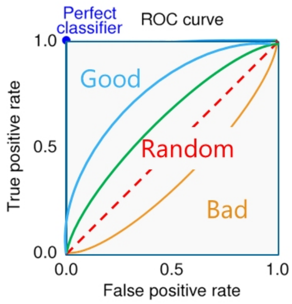


Figure 7: ROC curve.

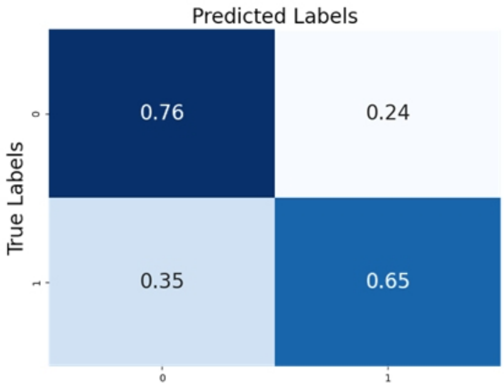


Figure 8: Confusion matrix of model1.

Table 1. Model1 performance evaluation metrics.

Label	Precision	Recall	F1	Number of samples
0	0.59	0.76	0.66	83
1	0.81	0.65	0.72	127

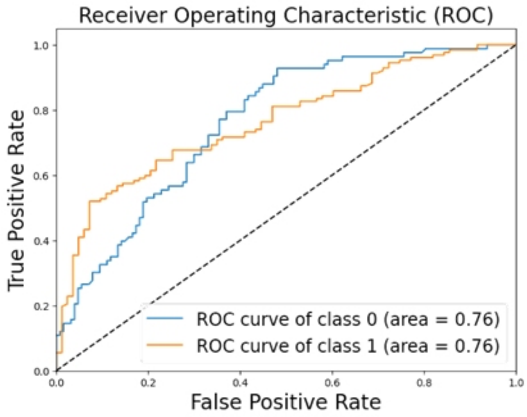


Figure 9: ROC curve of model1.

Model 2 (Explanatory Variables: Beat BPM, Heart Rate (Task-Rest), Q-Results)

Figure 10, Table 2, and Figure 11 show the confusion matrix, four indices calculated from the confusion matrix, and ROC curve of Model 2, respectively. According to Table 2, all four indices calculated from the confusion matrix were high for both classes 0 and 1. The lower-right panel in Figure 11 indicates that the AUC for both class labels 0 and 1 was approximately 0.98. Therefore, this model could estimate an increase or decrease in stress with high probability. However, owing to the question of whether music preferences and listening habits affected the results to this extent, we rechecked the details of the data. Consequently, we found a large amount of data of several individuals to correspond to one of the classes, suggesting the possibility of class individualization. Therefore, estimating increases or decreases in stress is possible by identifying individuals from the data. Model 1 with thin individual identifiers exhibited a medium level of classification performance, whereas Model 2 with strong individual identifiers exhibited very high performance. Issues related to class gerrymandering can be attributed to the small number of participants in Experiment (6) and the fact that music preferences and habits are important factors in explaining individual differences and also strongly associated with individuals. To solve this problem, increasing the diversity of the dataset is necessary by increasing the number of participants in the experiment rather than acquiring more data per participant.

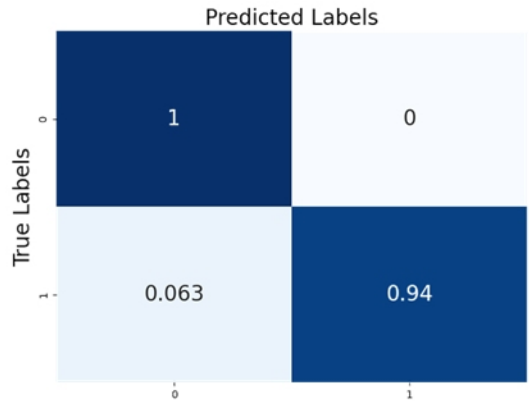


Figure 10: Confusion matrix of model2.

Table 2. Model1 performance evaluation metric.

Label	Precision	Recall	F1	Number of samples
0	0.91	1	0.95	83
1	1	0.94	0.97	127

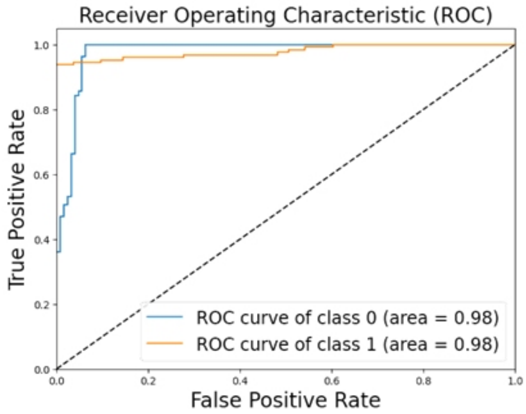


Figure 11: ROC curve of model2.

CONCLUSION

In this study, we conducted an experiment to obtain biometric information of workers who listened to beats with headphones while typing sentences. The experiment was aimed at constructing a model to estimate the increase or decrease in stress in workers who listened to sounds. In addition, we administered a questionnaire survey on music preferences and listening habits. Consequently, we constructed a model with AUC ≈ 0.76, which roughly estimated the increase or decrease in stress. However, the model can be improved further in terms of reducing the misclassification tendency and bias in the number of samples. The model with music preference and listening habits added as explanatory variables showed a very high classification performance; however, the results indicated a possibility of class labeling, indicating the need to improve the diversity of the dataset. Expanding the dataset to increase diversity is expected to improve the validity and classification performance of the model. Although the two model we constructed could estimate the increase/decrease in stress for the most part, it could not evaluate the work performance. In the future, constructing an estimation model of work performance and combining it with the stress increase/decrease estimation model is expected to lead to the proposal of a BPM system that can reduce stress and improve performance. This model will contribute to the improvement of daily work productivity.

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