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**ORIGINAL RESEARCH ARTICLE**

# Determination of stress obtained from sensor-based wearable measurements using VGG16 deep learning model

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## ABSTRACT

There are many researches carried out for different purposes on human-computer interactions. One of them is related to stress-related activity detection. Today, in people with disorders whose activity is not understood or misunderstood, the correct detection of the relevant movement can be vital in some cases. It may be more advantageous to use physiological signals in the body in determining the type of activity. Due to these important situations, two different research applications were carried out within the scope of this study in order to automatically detect four different types of stress, namely Neutral, Emotional, Mental, and Physical. For both applications, the data was first converted to images as a preprocessing. In the first stage of the research, the images of the standard dataset were presented to the VGG16 deep learning model. As a result, the highest accuracy rate was obtained as 67% for class 1 Neutral activation. In the second part of the study, an application was performed using the Isolation Forest Algorithm on the existing image data to remove outliers. The new dataset obtained were presented to the same model and detailed analyses were made. Accordingly, the maximum accuracy value was 97% in Physical activity. In the same application, the average rate for all activities was 82.5%. Briefly, the research contributes to the literature by demonstrating the significant impact of outliers on system performance through image transformations of existing time series physiological signals.

***Keywords:*** stress determination; physiological signals; deep learning; VGG16

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## 1. Introduction

As authors, we define the state of "being active" as showing activity, that is, an action that creates a change compared to the previous situation. However, according to the definition in the Oxford English Dictionary; "active (adjective and noun): Characterized by busy or lively activity; engaging or ready to engage in physically energetic pursuits; alert, lively; busy"[1]. In the same dictionary, activity is "The state of being actively occupied; brisk or vigorous action; busyness, liveliness, vigor"[1]. In short, the words active and activity generally mean movement and change. In daily life, many physical, emotional and mental activities such as talking, thinking, walking, jumping, sad, laughing, crying, getting angry, being afraid, being happy can cause changes in different physiological signals in our body[2–7]. For example, it is known that there are differences in heart signals compared to normal as a result of sudden or any emotional change[8]. In another study, changes in facial muscle signals were investigated in the detection of emotional mimic expressions in order to perform human-computer interaction more meaningfully and accurately[9].

In the literature, various physiological signals, data read from sensors placed in the environment, and methods for utilizing these as input are employed in studies conducted for purposes such as activity detection, identification, or determination. One of them is about the presence and type of physical activity as a result of evaluating the data collected from sensors such as heat, temperature, humidity, and movement in an environment within the scope of the Internet of Things or in smart home systems[10,11]. For the same purpose, thanks to wearable smart systems equipped with sensors, activity detection is possible thanks to signals such as electrocardiogram (ECG), electromyogram (EMG), Thoracic Electrical Bio-impedance (TEB), Electro Dermal Activity (EDA) that change as a result of any activity in the human body[12–16]. There are also studies using the heart rhythm rate change parameter extracted from ECG signals for emotional and human activity identification[8,17–20]. However, the common feature of these studies is to extract the properties of the obtained signals in the frequency and time domain by applying some techniques. In addition, various feature selection methods have been applied in order to make more precise evaluations. In a different study, evaluations were made on ECG, EDA, and body temperature to determine the stress situation in the body[21]. The researchers processed the signals obtained from the skin to detect four different emotional states and presented the obtained features to some machine learning algorithms[22]. In a similar study, stress detection was also added for the same purpose[23]. In a doctoral thesis[24], the author proposed a hybrid technique for selecting features extracted from physiological signals obtained in human activity detection. In another paper[25], many physiological signals such as heart, muscle, and respiration were obtained with wearable sensors, and their sensitivity to stress responses was investigated. In an interesting study, the authors evaluated different measurements together to determine the energy consumed as a result of the activity[26]. In the research carried out on electroencephalography (EEG) as a different signal type, the situations exposed to different stress factors were examined and classified with support vector machines[27]. In the literature, there are many studies conducted to detect stress and activity[28–33]. The common points of all of them were to record some physiological data through the necessary sensors, extract features from them, select features, and classify them.

The literature reviewed highlights the increasing importance of physiological signals and sensor data in understanding human activities and states. Researchers have used a wide range of sensors, from environmental indicators such as temperature and motion to wearable devices that capture complex signals such as ECG and EMG. These studies are not limited to activity detection but extend into the nuanced area of stress assessment and emotional states. What unites these is a systematic process of data acquisition, feature extraction, and classification techniques. The trend towards multimodality approaches, such as simultaneous assessment of various physiological measures, points to the evolving complexity of research methodologies. Additionally, the integration of advanced technologies such as EEG expands the scope of inquiry by providing insights into stressors that may escape traditional sensor-based approaches. These studies highlight the transformative potential of physiological data in shaping the ever-expanding landscape of health monitoring and behavior analysis, playing a key role in shaping future applications in health, well-being, and beyond. In this paper, the VGG16 deep learning model was used to detect four different stress-related activities, namely Neutral, Emotional, Mental, and Physical. For this purpose, feature groups extracted from ECG, TEB, and EDA signals obtained by wearable sensor hardware[15,16,34]. In addition, dataset was updated as a result of outlier data analysis for each class using the isolation forest algorithm. As a result of this step, more successful results were obtained compared to the previous stage. Briefly, the contribution of the research to the literature is to prove and show how effective outliers can be on system performance through image transformations of existing time series physiological signals. The study provides numerical results affirming the necessity of outlier data detection in any data collected for diverse purposes.

The remaining parts of the paper are as follows: detailed explanations about the research flow, the dataset used, the deep learning model, and outlier data detection are given in the Material and Methods section. In the experimental results section, evaluation criteria, result tables, and comments are given. The general evaluation and discussion of the results and future studies are mentioned in the discussion and conclusion section.

## 2. Material and methods

In this research, using the VGG16 deep learning model, four different stress-related activities were classified over the image equivalents of the data in time series format. In summary, the block diagram containing the steps within the scope of the study was briefly presented in **Figure 1**.

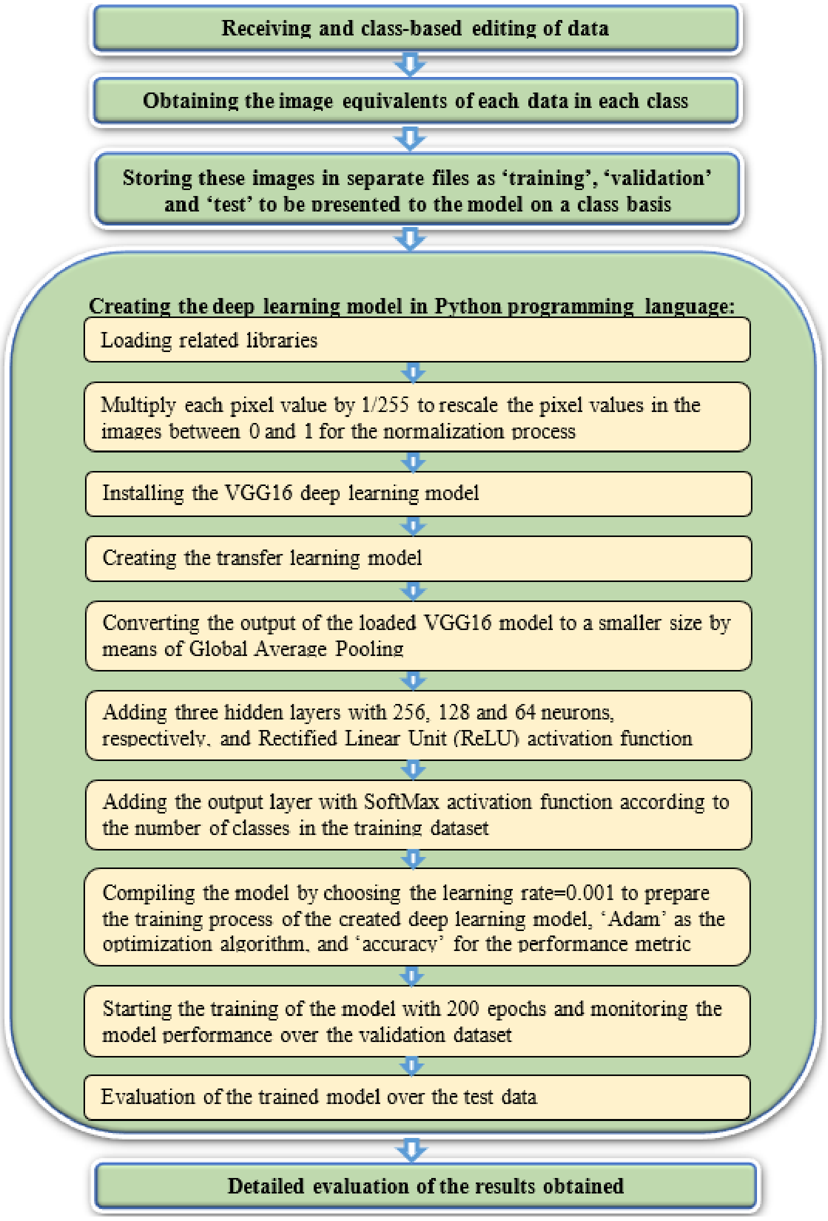


**Figure 1.** Block diagram with research steps.

These process steps were run again for the new dataset created after the detection of outliers, which is the second stage of the study. Then, the experimental results obtained as a result of the second stage were evaluated comparatively.

### 2.1. Used dataset

The dataset were used to determine four stress-related activities, namely Neutral (Class 1), Emotional (Class 2), Mental (Class 3), and Physical (Class 4)[15,16,34]. Neutral and Emotional activities from these classes were obtained from signals recorded during the viewing of the relevant time periods of three different movies[34]. Although the data for Class 3 was collected while playing two different games mentioned in the same reference, for class 4 it consisted only of data while going up and down the stairs. This dataset consist of a total of 4480 samples, each of which consists of 533 features. Of the 533 features specified, 174 were obtained from ECG signals, 151 from TEB, 104 from EDA data from arm, and the other 104 from EDA data from subjects' hands[15,16,34]. While sampling frequency was taken as 100 Hz for EDA and TEB from the signals used in the data collected from 40 subjects, 250 Hz was used for the ECG signal. Detailed information about the dataset used by Mohino-Herranz et al.; Mohino-Herranz and Gil-Pita et al.; UCI Machine Learning Repository[15,16,34]. Data distribution graphs for each of the classes in the dataset used are given in **Figure 2**.

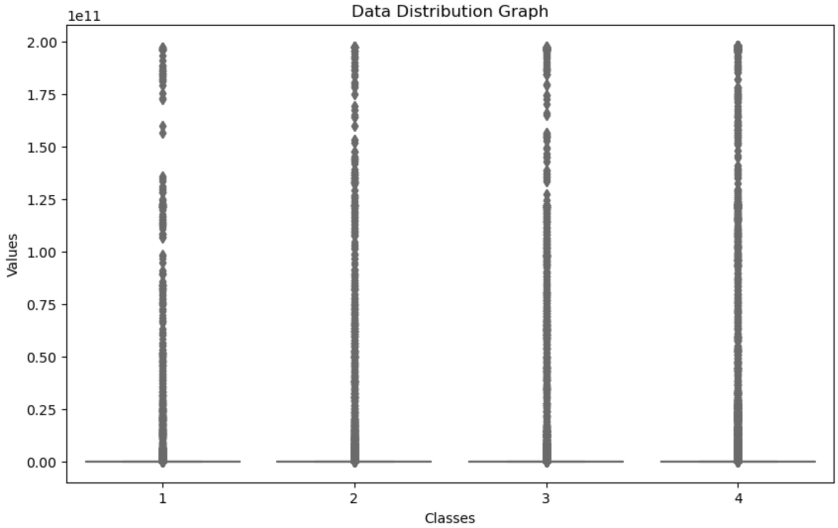


**Figure 2.** Data distribution graphs for four classes.

Accordingly, when the data distributions of the four classes are examined, it is seen that the distribution between the classes has similar characteristics and ranges. This situation has the effect of making the distinction between classes difficult. Therefore, machine learning algorithms offer convenience in solving similar problems.

For this research, each data in the form of a time series in the size of 1 × 533 in the dataset was firstly converted into images of 256 × 256 size one by one. During the transformation of time series data into images, each data was sequentially presented to a small algorithm that was written. Within the scope of this algorithm, the received data was first displayed as a "figure" and then the dimensions of this "figure" were resized as 256 × 256. Finally, this resulting "figure" was stored in a folder for later use. Thus, an "image" based dataset was obtained. An example representation of each class from the data converted to images is given in **Figure 3**.

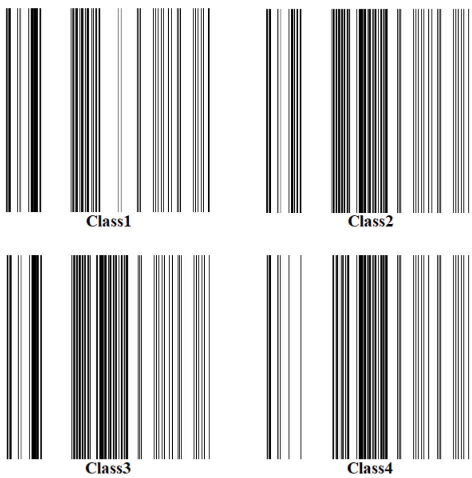


**Figure 3.** Sample images for each class.

When **Figure 1** is carefully examined, the visual differences between the classes can be understood. However, it is not possible to evaluate them manually and artificial intelligence-based systems are needed.

## 2.2. VGG16 deep learning architecture

In image processing studies, Convolutional Neural Network (CNN) is generally a preferred deep learning model, and VGG16 is an architecture derived from this CNN model. This architecture was first developed by the "Visual Geometry Group" (VGG) at Oxford University and takes its name from the abbreviation of this group. The use of multiple sequential convolution and pooling layers in this architecture makes the VGG16 model stand out in deep learning architectures. Since the CNN model is generally effective in recognizing patterns in images, the VGG16 architecture derived from these networks is a very successful model in this context[35].

Transfer learning is that machine learning methods store the information obtained during the solution of a problem and use this information when another problem is encountered. With the Transfer Learning approach, models that show higher success and learn faster can be developed using less training data[36]. As mentioned above, deep learning architectures such as VGG16 can be used in different tasks thanks to these features that are pre-trained and learned on large dataset. The basic architecture of VGG16 consists of 5 layers and these layers are as follows: input layer, convolutional layers, max-pooling layers, fully connected layers, and output layer[37]. In the input layer, images are given to the input of the model with RGB (Red, Green, Blue) color channels, usually $224 \times 224$ pixels in size. In the next layer, VGG16 consists of 13 consecutive convolution layers. Each convolution layer is created with sequential $3 \times 3$ dimensional filters, and then the ReLU activation function is applied in each layer. These convolution layers produce various feature maps to determine the features of the image. The next layers are the max-pooling layers and between each of the three sequential convolution layers, there are $2 \times 2$ dimensional max-pooling layers of 2 steps. These layers help reduce feature map size and reduce computational overhead[38,39]. In the next layers, the result is reached with fully connected layers. VGG16 has 3 fully connected layers. These layers are used for assigning features to classes and calculating the probability distribution of the results. In the last of these layers, there are as many neurons as the number of classes, and the Softmax activation function is generally used. In this way, the image results in probabilities of belonging to different classes[38,39].

## 2.3. Isolation forest algorithm for outlier detection

The expectation of a researcher from the data he will work on is to be able to obtain inferences with high accuracy and reliability. One of the important problems that undermine the data processing and this expectation afterward is the outlier values in the dataset. The observation that is significantly far from the range of the majority of observations in the processed dataset is called an outlier. Outliers look different from the rest of the observations in the dataset and can therefore be identified. If the dataset used in the studies are not cleaned of outliers, the processing steps may become blurred and the quality of the desired outputs may decrease. For this reason, the discrete data in the dataset to be used must be determined before starting scientific studies and it must be decided what to do with these data[40,41].

There are many methods in the literature that can be used for outlier detection. One of them, Isolation Forest, is a fast and effective unsupervised learning method and works by assuming that outliers tend to be more isolated. The basic idea of this algorithm is based on decision trees and is built on the expectation that outlier data points will follow a longer path through many random trees[42,43]. The Isolation Forest algorithm estimates the isolation time of each data point and uses these estimates as a score. Points that are isolated faster get lower scores, and points that take longer to isolate are given higher scores. These scores are then used to identify outliers. Outliers tend to have a larger score because they are not isolated by shorter paths[42,43].

# 3. Experimental results

In this study, first of all, 20% of the used dataset was allocated for testing, with equal samples from each class. Then, an adjustment was made on the remaining samples to be 80% training and 20% validation. Accordingly, there are 896 images in total, 224 for each class in the test set, a total of 720 images, 180 for each class in the validation set, and finally, there are 716 images for each class in the training set, a total of 2864 images. After the outlier detection application carried out in the second stage of the research, the test, validation, and training dataset consist of 804,648, and 2576 data in total (with an equal number of images in each class), respectively.

The outputs obtained as a result of the experimental researches were first evaluated on the 4-class confusion matrix. The confusion matrix was created according to the actual and predicted class labels. As a result, True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN) numbers of the test dataset were obtained. TP rate, FP rate, Specificity, Precision, F1 score and accuracy[44] values were calculated over these parameters. The formulas of some of them are as follows[44]:

$$TPrate = \frac{TP}{TP + FN} \tag{1}$$

$$FPrate = \frac{FP}{FP + TN} \tag{2}$$

$$Specificity = \frac{TN}{TN + FP} \tag{3}$$

$$Precision = \frac{TP}{TP + FP} \tag{4}$$

$$F1score = \frac{2TP}{2TP + FP + FN} \tag{5}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{6}$$

In addition to these evaluation criteria, Cohen’s Kappa score[45] is also calculated. Finally, the loss and accuracy graphs for the training and validation of the outlier detection application, where the best results were obtained, were drawn. Thanks to these graphs, the performance changes of the training phase of the relevant model according to the epochs can be observed[46–48].

In the first phase of the study, the highest performance results for training and validation over 200 epochs were 70.15% and 69.44%, respectively. Confusion matrix obtained for the test data is given in **Figure 4**.

When the confusion matrix given in **Figure 4** is examined, it is understood that class3 performs better in terms of TP number and class 1 performs better in terms of TN. Other performance outputs obtained for the test data are given in **Table 1**.

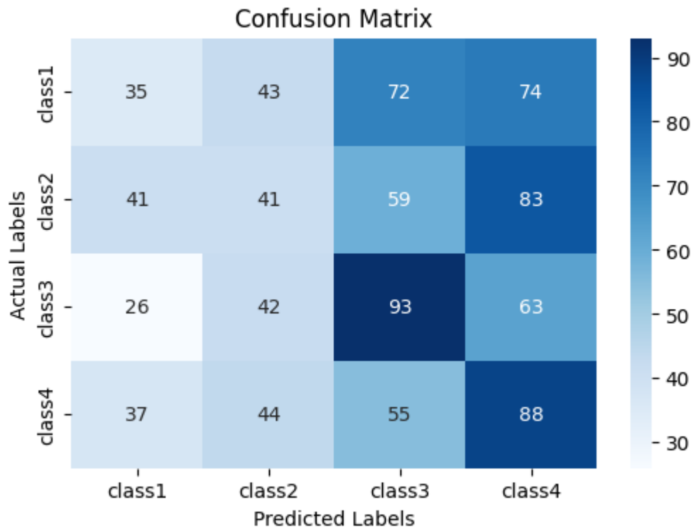


**Figure 4.** The confusion matrix obtained for the test dataset in the first phase of the research.

When **Table 1** is analyzed on a class basis; although class 1 outperformed others in terms of FP, TN, FP rate, specificity, kappa, and accuracy, the performance of class 3 was better for TP, FN, TP rate, precision, and F1 score. These two classes were followed by class 2 and class 4 in terms of accuracy. The average accuracy rate of the system was obtained as 64.3%. For the first stage of the study, test performances were also evaluated using VGG19, ResNet50, and DenseNet121 models under the same conditions. Accordingly, the result of 61.4% for the VGG19 model was followed by ResNet50 and DenseNet121 models with 60.3% and 58.4%. Since VGG16 achieved the best performance outputs for the first stage among all models, the next stages of the research were continued with this model.

**Table 1.** The test results for the first stage of this research.

| **Classes** | **TP** | **FP** | **TN** | **FN** | **TP rate** | **FP rate** | **Specificity** | **Precision** | **Kappa** | **F1 score** | **Accuracy** | **Mean accuracy** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| class 1 | 35 | 104 | 568 | 189 | 0.16 | 0.15 | 0.85 | 0.25 | 0.57 | 0.20 | 0.67 | 0.643 |
| class 2 | 41 | 129 | 543 | 183 | 0.18 | 0.19 | 0.81 | 0.24 | 0.54 | 0.21 | 0.65 | |
| class 3 | 93 | 186 | 486 | 131 | 0.42 | 0.28 | 0.72 | 0.33 | 0.53 | 0.37 | 0.65 | |
| class 4 | 88 | 220 | 452 | 136 | 0.39 | 0.33 | 0.67 | 0.29 | 0.47 | 0.33 | 0.60 | |

As a result of outlier detection applied in the second stage of the research, the dataset was presented to the same model. The loss and accuracy graphs obtained over 200 epochs for training and validation from these datasets are presented in **Figure 5**.

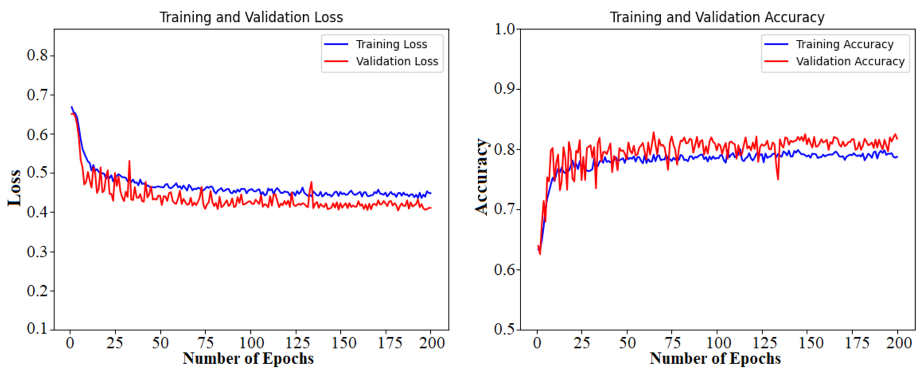


**Figure 5.** Loss and accuracy graphs of the training and validation dataset in the second phase of the research.

When the loss and accuracy graphs in **Figure 5** are examined, it is seen that as the epoch number increases, the loss value decreases for both datasets, while the accuracy increases. Loss values represent the estimation errors of the model separately for the training and validation dataset. The regular decline curve shows that the model has been trained successfully and that the distortions in the data have been eliminated as much as possible. After the training process was completed, the system evaluation was made on the test data and the confusion matrix in **Figure 6** was obtained.

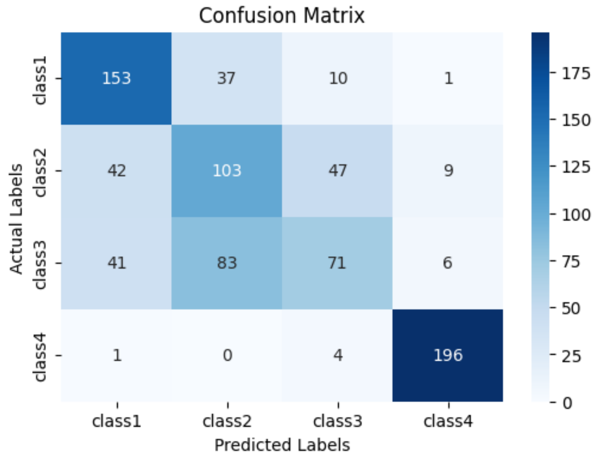


**Figure 6.** Loss and accuracy graphs of the training and validation dataset in the second phase of the research.

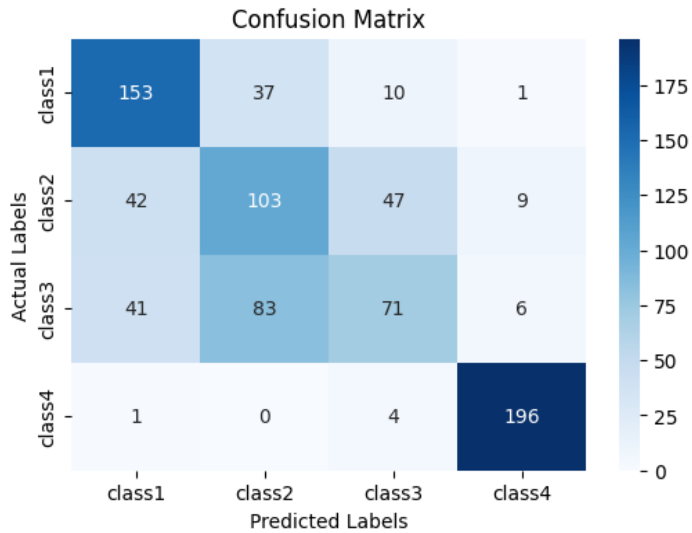


**Figure 7.** The confusion matrix obtained for the test dataset in the second phase of the research.

When the confusion matrix in **Figure 7** is examined, it is clearly seen that the most successful predictions are obtained in class 4. While 196 of the 201 data in this class were predicted correctly, 4 of them were labeled as class 3 and 1 of them as class 1. By following this class 1, 153 data are correct and others are incorrect. However, inferences made from the multi-class confusion matrix are given in **Table 2** in order to make a more detailed analysis about the classes.

**Table 2.** The test results for the second stage of the research.

| Classes | TP | FP | TN | FN | TP rate | FP rate | Specificity | Precision | Kappa | F1 score | Accuracy | Mean accuracy |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| class 1 | 153 | 84 | 519 | 48 | 0.76 | 0.14 | 0.86 | 0.65 | 0.79 | 0.71 | 0.84 | 0.825 |
| class 2 | 103 | 120 | 483 | 98 | 0.52 | 0.19 | 0.81 | 0.46 | 0.64 | 0.49 | 0.73 | |
| class 3 | 71 | 61 | 542 | 130 | 0.36 | 0.10 | 0.90 | 0.54 | 0.69 | 0.43 | 0.76 | |
| class 4 | 196 | 16 | 587 | 5 | 0.98 | 0.02 | 0.97 | 0.93 | 0.97 | 0.95 | 0.97 | |

The average accuracy rate for the test data in the second stage was calculated as 82.5%. As can be seen in **Table 2**, class 4 gave the best results in all performance criteria. Class 4, which had the worst performance in the first stage, was the best in the second stage. It is thought that the reason for this is mostly the detection and elimination of disruptive data in this class. Likewise, higher results were obtained for the other classes compared to the previous stage. The fact that Kappa and F1 score values for class 4 are very close to 1 indicates that the classification performance is very close to perfect. When other classes were evaluated in terms of accuracy, class 4 was followed by class 1, class 3, and class 2, respectively. When the whole table is examined, it is clearly understood that the outlier detection application affects the results positively.

## 4. Discussion and conclusion

The determination of the type of activity in research and applications carried out under the name of human-computer interaction increases its importance day by day. Especially for patients whose activity they want to perform is not understood, the correct determination of the relevant activity can be vital in some cases. Detection of stress through some physiological signals in the body may be more advantageous for those with the aforementioned disorders. For these reasons, it is considered important to automatically identify certain stress, especially through relevant signals.

In this study, two different research applications were carried out to detect four different stress, namely Neutral, Emotional, Mental, and Physical. A dataset consisting of 4480 samples with 533 features obtained from references[15,16,34] was used for related applications. Features in this dataset are extracted from ECG, EDA, and TEB signals. All samples in the used dataset were first converted to images. The first stage of the research was to present the images of the standard data to the VGG16 deep learning model. As a result, the highest accuracy rate was obtained as 67% for class 1 Neutral activation. In the second part of the study, an outlier detection application was performed using the Isolation Forest Algorithm on the available data. The new dataset obtained were presented to the same model and detailed analyses were made. Accordingly, the maximum accuracy value was 97% in Physical activity. In the same application, the average rate for all activities was 82.5%.

The significant increase in the results thanks to the outlier detection applied in the second stage is related to the detection of some of the data that has a disruptive effect on the system. In the first stage, the highest performance was obtained for the Neutral activity, but in the next, for the Physical. The activity with the highest increase compared to the first stage was Physical. This shows that the disruptive components in the dataset of this activity have been largely eliminated. It is seen that the activity with the second highest rate of improvement is the first. Then others followed.

As with any research, this study has some limitations. The first of these is the limited number and variety of data. Especially in deep learning applications, having more data contributes to better learning of the model. The second is about applying outlier detection from each class equally to avoid class imbalance in the research. As a result of this application, which was carried out at an equal rate, a high rate of improvement was achieved in one class, while it was limited in another. Therefore, outlier detection can be done at different rates for each class. However, the class imbalance that may occur in the data due to this difference should not be ignored.

In terms of future studies, the variety of stress can be increased by expanding the same dataset. In addition, research can be carried out on different deep-learning models and outlier detection algorithms. Most importantly, performing studies on original existing and different signals can lead to the emergence of remarkable research.

## Author contributions

Conceptualization, CY and SY; methodology, CY and SY; software, CY and SY; validation, CY and SY; formal analysis, CY; investigation, CY and SY; resources, CY; data curation, CY and SY; writing—original draft preparation, CY and SY; writing—review and editing, CY and SY; visualization, CY and SY; supervision,

CY and SY; project administration, CY and SY; funding acquisition, CY. All authors have read and agreed to the published version of the manuscript.

## Conflict of interest

The authors declare no conflict of interest.

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