Optimized Convolutional Neural Network Transfer Learning Method for Stress Emotion Classification

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Abstract: Stress management plays an essential role in predicting stress levels and diagnosing to avoid its effects on certain individual's socio-economic life. To achieve efficient stress prediction, a hybrid Deep Belief Network and Transfer Learning (DBNTL) method was proposed. Though DBNTL learn domain exact features on the top layers, but it decrease the change among the two domain distributions of different layers. Hence this paper proposes a novel Optimized Convolutional Neural Network and TL (OCNNTL) method that supports OCNN-based classifier on small-scale emotion and stress data domains. This novel model requires two domains that distribute similar OCNN. Two distribution models Marginal Distribution Discrepancy (MDD) at similar layers and Joint Distribution Discrepancy (JDD) of various layers helps OCNN to learn higher quality features at the top layers even the different emotion and stress domains contain similarity elements on feature-level. The OCNNTL layers are trained equally, so it measures both MDD of one layer and JDD of multiple layers. Moreover, a precise trade-off of these two discrepancies can increase transferability between emotion-stress domains. At last, the experimental outcomes exhibit the efficiency of OCNNTL method as compared to the CNN and DBNTL-based stress emotion classification methods.

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1. Introduction

Normally, stress is the response of the human skin to the external forces. Different physical and emotional tasks are triggered in stressful situations. The bruising on the skin happens as an individual age raise significantly with stress. Chronic stress weakens the skin's defense systems and reduces the strength of immune and cardiovascular systems in a human body. The immunity of an individual becomes weaker and a stressed person is possibly less resistant to illness and chronic diseases like hypertension, asthma or diabetics. Many physiological variables associated with the hormones are measured easily. For stress analysis, non-invasive measures such as variation in respiration rate, respiration patterns or skin conductance are more suitable and precise than the physical signs that include facial expressions, speech or vocal changes and changes in gesture patterns [1].

Stress is triggered by external atmospheric pressures that exceed the tolerant capacity of a person. Opinions of depression or nervousness are the fundamental source of stress. Chronic stress creates permanent fluctuations in the physiological systems of a person and long-term diseases are grown like asthma diabetics and hypertension. In usual conditions, automated nervous model controls hormones to maintain the immunity and cardiovascular activities of a person [2]. To forecast and measure the accurate operation of the hormonal system, numerous non-invasive methods are developed that involve the analysis of biomedical signals generated with respect to the stress. As a result, automated stress or emotional classification methods are developed that classifies the emotions, stress and feelings [3]. On the other hand, the challenge of stress emotion classification remains difficulty by its interdisciplinary behavior.

Usually, automated stress emotion classification is executed by estimating different person's skin related features or changes of the electric impulses in the nervous system. The common well-known methods are electroencephalography [4], Skin Conductance Response (SCR) [5], blood pressure, respiration rate [6], etc. From this viewpoint, Masood & Alghamdi [7] modelled the disparity in stress severity using a deep learning model that classifies the mental stress. A wireless sensor was deployed to monitor respiration rate difference, SCR and breathing pattern irregularities. A group of protocols was designed by various cognitive experiments that engage persons in a sequence of mental activities with various challenges. The person feels stress that differs in severity while undergoing these challenges. A deep breathing method was executed before and after every cognitive experiment for relaxing the user from stress. Besides, neural signals were used to extract the cerebral features. Moreover, CNN was applied to train and validate the input datasets for identifying the stress behaviors and their severity. Nonetheless, the data acquisition process was highly expensive and the classification accuracy was not highly effective.

Therefore, Banerjee et al. [8] designed the DBNTL method for diagnosing Post-Traumatic Stress Disorder (PTSD) in which DBN combines three categories of features and TL solves the small data size problem. The TL was aimed at passing data from a rich-label source domain to another weak-label target domain. Also, more domain-invariant features were learned by the DBN. But, as DBNs learns domain specific features on the top layers, it reduces the shift between two domain distributions of different layers.

Hence in this paper, a new OCNNTL method is suggested that supports CNN-based classifier on small-scale emotion and stress data domains. This OCNNTL method requires two domains that distribute similar features for emotion and stress labels. As various emotion-stress feature domain contain similarity elements on feature-level, distributing similar OCNN learns higher quality features at top layers. Also, the MDD at similar layers and JDD of various layers are considered. The OCNNTL layers are trained equally, so it measures both MDD of one layer and JDD of multiple layers. Moreover, an accurate trade-off of these two discrepancies can increase transferability between emotion-stress domains.

2. Literature Survey

Maxhuni et al. [9] developed a stress prediction approach using the combination of TL, Semi-Supervised Learning (SSL) and ensemble methods. The SSL was applied to learn the subjects with missing data. The subjects were grouped according to the trained decision trees similarity. Also, ensemble method was used for enhancing the accuracy. But, it has high complex to combine several objective and subjective data streams.

Song & Kim [10] designed a DBN-based stress classification that utilizes the Korea National Health and Nutrition Examination Survey (KNHANES VI) database. Through this model, the stress was classified by evaluating the stress-related physical action and lifestyle information of people under 19 and 80 years based on people who were normally stressed and those who were not stressed. Also, DBN was processed as a feature of the lifestyle data and physical action that were reviewed to be meaningful in evaluating stress. But, it was not suitable to estimate the level of stress subcategory cases.

Sriramprakash et al. [11] developed a detector for identifying the stress in working people. At first, physical signals of many people were obtained via Galvanic Skin Response (GSR), Electrocardiogram (ECG), etc. Then, the required features which represented the stress level in working individuals were extracted from the acquired signals using Welch’s algorithm. After that, these features were classified as stressed and normal person by the Support Vector Machine (SVM) and K-Nearest Neighbor (KNN) algorithms. Conversely, it has less accurateness.

Luo et al. [12] designed an Improved Grasshopper Optimization Algorithm (IGOA) for predicting the economic stress. At first, Gaussian mutation was explored to raise the diversity of the population that renders GOA more capable of regional searching. After that, the Levy flight mechanism was performed for increasing the randomness of the movement of the search agent that enhances the GOA's global capacity for exploration. Also, GOA was executed with opposition-based learning to make search solution space effectively. Moreover, efficient kernel extreme learning was used based on the GOA to predict the economic stress. Conversely, the time complexity was high.

Jawharali & Arunkumar [13] recommended an Electro Oculo Graphy (EOG) that considers Artificial Neural Network (EOG-ANN) for prediction and prevention of stress levels through EEG signals. In EOG-ANN, the noise in the signals were eliminated via auto regressive filtering process for diminishing the classification error. After that, the time-domain features in the signals were extracted and fed to the ANN to classify the stress level. But, the processing time was high for large-scale dataset.

Shaw et al. [14] presented a general method for personalized predictive modeling of students stress level. The data was considered as time-series and the temporal patterns contained in student data were detected. By feature engineering, this method can able to deal with long and irregular sequences. The data multi-resolution nature was addressed through histogram of categorical inference values. At last, a personalized framework was created for every student during leveraging data from all students. In contrast, the stress level of new students were not classified.

He et al. [15] designed CNN for accurately detecting the acute cognitive stress with five sessions. At first, the data was gathered from 12 men and 8 women aging from 18 to 35 years. In the odd number of sessions, the people were requested to sit still and relax. During these sessions, a headset played relaxing music so the participants could relax the most. In the even number of sessions, the people were requested to execute mathematical analysis which was displayed in the front monitor. Finally, the answer of the people was analyzed using CNN for detection acute cognitive stress. But, the classification performance was not effective.

3. Proposed Methodology

This section explains the OCNNTL method for classifying the stress and emotions in detail. Initially, the freely accessible dataset i.e., Wearable Stress and Affect Detection (WESAD) dataset is acquired. This dataset contains ECG, Blood Volume Pulse (BVP), electromyogram (EMG), Electrodermal Activity (EDA), body temperature and respiration along with triaxial acceleration signals sampled at 700Hz. Here, the ECG signal is recorded by the common three-point ECG. The EDA signal is recorded on the rectus abdominis which allows the patient to move as freely as possible. Typically, EDA is the property of an individual body that causes continuous discrepancy in the electrical features of the skin. Moreover, all patients wore the Empatica E4 on their non-dominant hand to record BVP (64Hz) and EDA (4Hz). The respiration is recorded via a respiration inductive plethysmograph sensor. These data are helpful for extracting both stress and emotion-domain features. But, the key distinguish of stress and emotion is the fluctuations in SCR from EDA signals i.e., the negative emotions like anger, fear and depression are termed as stress. In contrast, the emotions include amusement, pride and embarrassment. The recorded signal is stored locally to extract the most significant features with a specified interval.

3.1. Feature Extraction

The fluctuations in SCR is robustly triggered by stress or emotional stimulation. So, given an influence of the SCR's profile from EDA signals, feature extraction is executed via statistics associated with the amplitude, first and second order derivative of the EDA signal given in Table 1.

Table 1: Extracted EDA Features

Types	Detailed Features
Raw SCR(i.e., SCR obtained from the raw EDR signal)	Amplitude: mean First derivative, second derivative: max, min, max of total value and mean value
Wavelet coefficients	Max, mean, standard variance and median

Similarly, features associated with the mean, variance including other features listed in Table 2 are extracted from the ECG signals.

Table 2: Extracted ECG/BVP Features

Types	Detailed Features
Raw ECG/ BVP signals	Mean and standard variance of the heart rate; R peak value: Electrical power fluctuation between R peak & baseline; Q peak value: Electrical power fluctuation between Q peak & baseline; S peak value: Electrical power fluctuation between S peak & baseline; QRS interval: Time variation between QRS offset-onset points; PR interval: Time duration from the inception of the P wave to the QRS initial point; QT interval: Time duration from the QRS initial point to the T wave stop point; ST interval: Time taken from the QRS ending point to the T wave initial point; RR interval (Heart rate): Interval between two R-peaks; Mean, variance;
Wavelet coefficients	Min, max, mean and standard variance.

The R-peak is detected via the Daubechies8^{th} level wavelet coefficients. By pass through the window function from the left and right side of R-peak, the Q and S-peaks are initiated and situated the negative peaks. By pass through the left side of the Q peak, the peak value is noticed as the P-peak. Likewise, by pass through the right side of the S-peak, the peak value is noticed as the T-peak. Also, the average is computed via the mean of all data in each ECG signal. Variance is helpful to determine how much fluctuation of a value from the mean.

By using BVP signal, the heart rate is estimated along with their respective mean and standard variance. Normally, heart rate is the count of R peak/time unit or number of times the heart beats per time units. The heart rate is computed by measuring distance between two R peaks in ECG/BVP signal. Likewise, respiration rate is the count of breaths by human takes per unit time or the speed at which breathing occurs. It is computed via the RR intervals$(\mathrm{RR_i}, \mathrm{i} = 1, \dots, \mathrm{n}-1)$. Also, the mean and standard variance of the inhalation or exhalation are measured. Table 3 lists the features extracted from these physical signals.

Table 3: Extracted Features from Respiration Signals

Types	Detailed Features
Raw respiration signal	Mean and standard variance of inhalation and exhalation duration, respiration rate.
Wavelet coefficient s	Max, mean, standard variance, median and number above zero.

Thus, both stress and emotion-domain features are extracted and fed to the OCNNTL classifier to classify the stress emotional activities into three classes include stress, neutral and amusement.

3.2. Novel Optimized CNN and TL for Stress/Emotion Analysis

For given stress features domain$\mathrm{F_S} = \{(\mathrm{x_i^S}, \mathrm{y_i^S})\}_{\mathrm{i}=1}^{\mathrm{n_S}}$ and emotion features domain$\mathrm{F_E} = \{(\mathrm{x_i^E}, \mathrm{y_i^E})\}_{\mathrm{i}=1}^{\mathrm{n_E}}$ where$\mathrm{n_S} \gg \mathrm{n_E}$, the TL method is used for optimizing the standard CNN with $\mathrm{F_S}$ and $\mathrm{F_E}$ and enhancing its classification efficiency in$\mathrm{F_E}$.This OCNNTL minimizes the domain distribution discrepancy at the Fully-Connected (FC) layers when training the CNN with $\mathrm{F_S}$ and $\mathrm{F_E}$ simultaneously.

Consider J be the cross-entropy loss function. Instinctively, if $\mathrm{F_S}$ is applied to increase the efficiency of a CNN on$\mathrm{F_E}$, both $\mathrm{F_S}$ and $\mathrm{F_E}$are applied to train similar OCNN together. But, in emotion analysis domain, a discrepancy is constantly existed between domain distributions $\mathrm{P_1}(\mathrm{X^S})and\mathrm{P_2}(\mathrm{X^E})$. But now, the transferability reduces at the FC layers by passing the stress features from common to domain-specific via OCNN. Thus, this OCNNTL method minimizes the domain shift at FC layers from the below perspectives:

- Minimizing $\mathrm{MDD}\{\mathrm{P_1}(\mathrm{Z^{Si}}), \mathrm{P_2}(\mathrm{Z^{Ei}})\}_{\mathrm{i}\in\mathrm{G}}$ in an one layer at a time;
- Reducing JDD$\mathrm{P_1}(\mathrm{Z^{S1}}, \dots, \mathrm{Z^{S|G|}})and\mathrm{P_2}(\mathrm{Z^{E1}}, \dots, \mathrm{Z^{E|G|}})$ of different layers.

The features at FC layers are $\{\mathrm{Z^{Si}}\}_{\mathrm{i}\in\mathrm{G}}and\{\mathrm{Z^{Ei}}\}_{\mathrm{i}\in\mathrm{G}}$. Here, G indicates a group of selected FC layers to be aligned for joint distribution. Normally, G contain all the FC layers of the OCNN

Minimizing MDD via Maximum Mean Discrepancy (MMD)

MMD is applied for confirming whether two distributions $\mathrm{P_1}(\mathrm{X^S})$ and$\mathrm{P_2}(\mathrm{X^E})$ are identical. Its assumption is $\mathrm{E_{P_1}}[\mathrm{f}(\mathrm{X^S})] = \mathrm{E_{P_2}}[\mathrm{f}(\mathrm{X^S})]$when$\mathrm{P_1} = \mathrm{P_2}$. It is applied to determine the distribution similarity as:

$$D(P_1, P_2) \triangleq \left(E_{P_1}[f(X^S)] - E_{P_2}[f(X^S)]\right) \tag{1}$$

In Eq. (1), F stands for the functional set. Also, the MDD is minimized as:

$$D_G(P_1, P_2) \triangleq \frac{1}{n_S^2}\sum_{i=1}^{n_S} \sum_{j=1}^{n_S} \prod k(z_i^S, z_j^S) + \frac{1}{n_E^2}\sum_{i=1}^{n_E} \sum_{j=1}^{n_E} \prod k(z_i^E, z_j^E) - \frac{2}{n_S n_E}\sum_{i=1}^{n_S} \sum_{j=1}^{n_E} \prod k(z_i^S, z_j^E) \tag{2}$$

In Eq. (2), characteristic kernel k is the Gaussian kernel function.

Minimizing JDD via Joint Maximum Mean Discrepancy (JMMD)

The JMMD is computed to minimize the JDD of two domains as follows:

$$D_G(P_1, P_2) \triangleq \|C_{Z^{S,1:|G|}}(P_1) - C_{Z^{E,1:|G|}}(P_2)\|^2 \tag{3}$$

In Eq. (3), $C_{Z^{S,1:|G|}}(P_1)$ and $C_{Z^{E,1:|G|}}(P_2)$ are the feature embedding in Hilbert space.

$$C_{Z^{*,1:|G|}} = \frac{1}{n_*}\sum_{i=1}^{n_*} \otimes_{l=1}^{G} \phi^l(x_i^E) \tag{4}$$

In Eq. (4), $* \in \{S, E\}$. If Gaussian kernel is used, then $D_G(P_1, P_2)$ is computed as follows:

$$D_G(P_1,P_2) \triangleq \frac{1}{n_S^2}\sum_{i=1}^{n_S}\sum_{j=1}^{n_S}\prod_{l\in G} k^l(z_i^{Sl}, z_j^{Sl}) + \frac{1}{n_E^2}\sum_{i=1}^{n_E}\sum_{j=1}^{n_E}\prod_{l\in G} k^l(z_i^{El}, z_j^{El}) - \frac{2}{n_S n_E}\sum_{i=1}^{n_S}\sum_{j=1}^{n_E}\prod_{l\in G} k^l(z_i^{Sl}, z_j^{El}) \tag{5}$$

Stress Emotion Classification using OCNNTL Classifier

In OCNNTL classifier, both MMD and JMMD are integrated into the FC layers of the OCNN where MMD is computes the MDD and JMMD computes the JDD for emotion-stress domains. Figure 1 shows the overall architecture of OCNNTL. This illustrates that the MDD is computed at FC layer with MMD and JDD is computed at the FC layer and softmax layer with JMMD. Because various stress-emotion domains comprise similarity components on stress or emotional-level, allocating similar OCNNTL learns higher quality stress emotion features at first-layers. The MDD of similar layers and JDD of various layers are considered. The OCNNTL layers are trained mutually, so both marginal distribution $P(Z^l)$ of one layerand joint distribution $P(Z^1, ldots, Z^l)$ of various layers are considered. An accurate trade-off of these two discrepancies improves the transferability between emotion-stress domains.

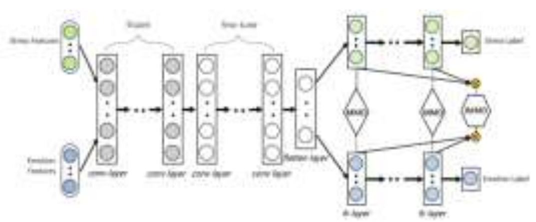

Figure 1: Overall Architecture of OCNNTL Method

The optimization procedure reduces MMD and JMMD of FC layers when fine-tuning CNN with $F_S$andF_E. The loss factor is:

$$L = L_S + L_E + \lambda D_G(P_1,P_2) + \eta \sum_{i\in G} D_i(P_1,P_2) \tag{6}$$

In Eq. (6),$D_i(P_1,P_2)$ is the MMD loss at i^{th} FC layer, λ and η are two trade-off parameters. Also,L_S and L_E are the classification loss factors for F_S andF_E and they are:

$$L_S = \frac{1}{n_S}\sum_{i=1}^{n_S} J\left(f(x_i^S), y_i^S\right) \tag{7}$$

$$L_E = \frac{1}{n_S}\sum_{i=1}^{n_E} J\left(f(x_i^E), y_i^E\right) \tag{8}$$

4. Experimental Results

In this section, the OCNNTL method is implemented in MATLAB 2017b using WESAD dataset (described in Section 3) and its efficiency is compared with the CNN, DBNTL methods in terms of precision, recall, f-measure and accuracy. Total instances in WESAD dataset is 63000000. In this experiment, totally 9000 instances only considered. The selected instances are divided into 1500 instances of each class for training and 1500 instances of each class for testing. The confusion matrix for each class is found separately, and then the average value of predicted results for OCNNTL is depicted in Table 4.

Table 4: Confusion Matrix for 4500 Test Data Instances

		Predicted Class	
		Positive	Negative
Actual Class	Positive (1500 for each class)	True Positive **1390**	False Negative **100**
	Negative(3000 for other class)	False Positive **110**	True Negative **2900**

4.1. Precision

It is computed according to the amount of correctly classified stress and emotional classes at True Positive (TP) and False Positive (FP).

$$Precision = \frac{No.of\ correctly\ classified\ stress/emotion\ classes}{No.of\ correctly\ classified\ stress/emotion\ classes + No.\ of\ incorrectly\ classified\ stress/emotion\ classes} = \frac{TP}{TP+FP}$$

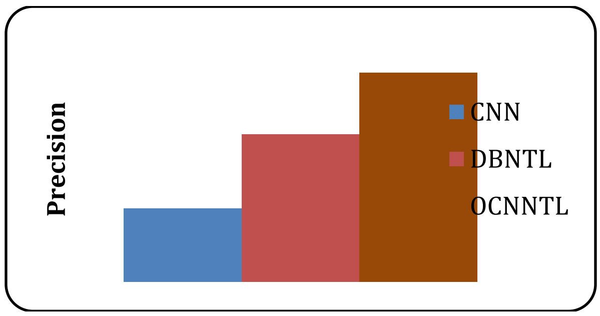

Figure 2: Comparison of Precision

In Figure 2, the precision values for CNN, DBNTL and OCNNTL methods are illustrated. This analysis observes the precision of OCNNTL is 2.78% and 6.32%increased as compared to DBNTL and CNN methods, accordingly.

4.2. Recall

It is calculated according to classification of the stress or emotional classes at TP and False Negative (FN) rates.

$$Recall = \frac{No.of\ correctly\ classified\ stress/emotionclass}{No.of\ correctly\ classified\ stress/emotion\ classes + No.of\ incorrectly\ classified\ non-stress/emotion\ classes} = \frac{TP}{TP+FN}$$

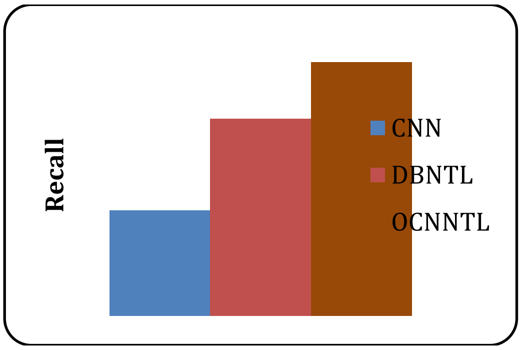

Figure 3: Comparison of Recall

Figure 3 shows the recall values for CNN, DBNTL and OCNNTL methods. This analysis indicates the recall of OCNNTL method is 1.53% and 4.49% increased as compared to the DBNTL and CNN methods, respectively.

4.3. F-measure

It is the harmonic average of both precision and recall.

$$F-measure = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}$$

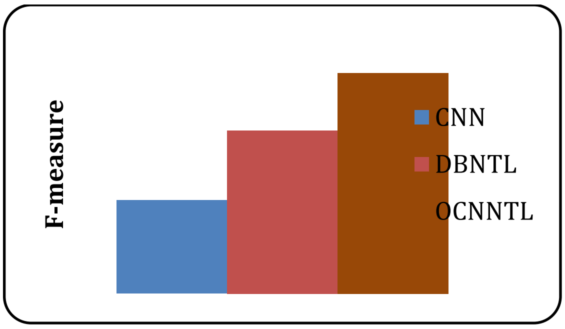

Figure 4: Comparison of F-measure

In Figure 4, the f-measure values for CNN, DBNTL and OCNNTL methods are shown. This analysis notices the f-measure of OCNNTL is 2.44% and 5.59% increased as compared to the DBNTL and CNN methods, accordingly.

4.4. Accuracy

It is the ratio of exact classification of stress or emotional classes over the overall number of trails executed.

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

TP measures an outcome where the OCNNTL exactly classifies the stress/emotional classes as stress/emotional.

FP measures an outcome where the OCNNTL inexactly classifies the stress/emotional classes as non-stress/emotional.

FN measures an outcome where the OCNNTL inexactly classifies the non-stress/emotional classes as stress/emotional.

True Negative (TN) measures an outcome where the OCNNTL exactly classifies the non-stress/emotional classes as non-stress/emotional.

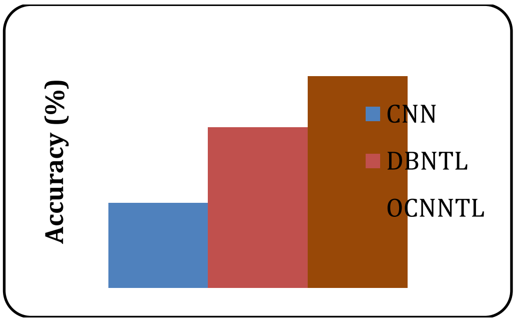

Figure 5: Comparison of Accuracy

Figure 4 shows the accuracy values for CNN, DBNTL and OCNNTL methods. This analysis addresses the accuracy of OCNNTL is 1.31% and 3.33% increased as compared to the DBNTL and CNN methods, respectively.

5. Conclusion

In this paper, an OCNNTL method is suggested for increasing the accuracy of stress emotion classification via OCN Non small-scale emotion and stress domains. It requires emotion- and stress-feature domains that share identical OCNN. As various emotion-stress domain contain similarity elements on feature-level, assigning similar CNN learns a high-quality features at the top layers. Also, the MDD at similar layers and JDD of various layers are considered. The OCNNTL layers are trained equally, so it considers both MDD of one layer and JDD of multiple layers. Moreover, the transferability between emotion-stress feature domains is increased via deciding an accurate trade-off between MDD and JDD. To end, the experimental outcomes proved that the OCNNTL method achieves higher accuracy as compared to the DBNTL and CNN methods for stress emotions classification.

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