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.

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

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

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

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.

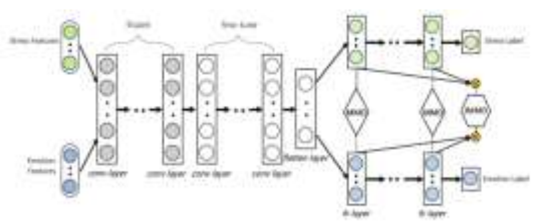

Figure 1: Overall Architecture of OCNNTL Method

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

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

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:

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

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

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		
Actual Class		Positive	Negative
	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).

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

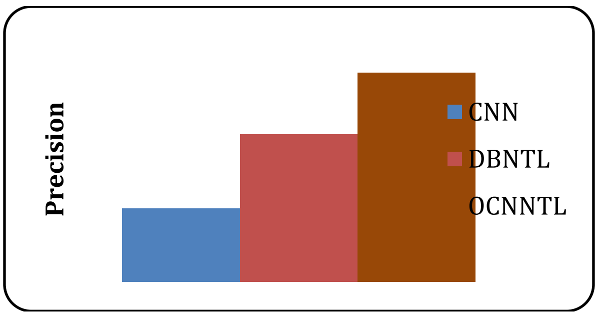

Figure 2: Comparison of Precision

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.

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

$$= \frac{TP}{TP + FN}$$

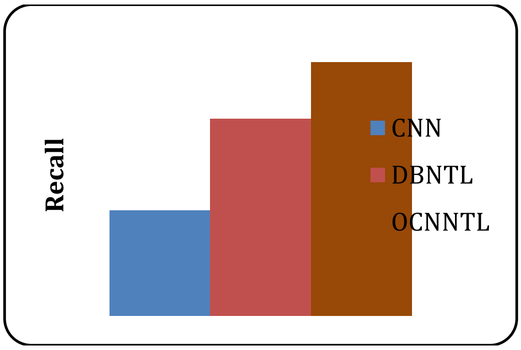

Figure 3: Comparison of Recall

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.

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

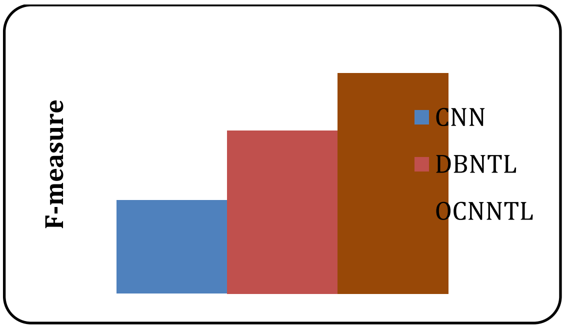

Figure 4: Comparison of F-measure

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.

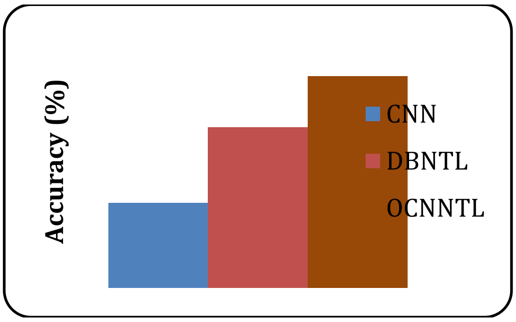

Figure 5: Comparison of Accuracy

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.

References

[1] T. Pereira, P.R. Almeida, J.P. Cunha, and A. Aguiar, Heart rate variability metrics for fine-grained stress level assessment, *Computer Methods and Programs in Biomedicine*, Vol. 148, 2017, pp.71-80.

[2] R. Castaldo, P. Melillo, U. Bracale, M. Caserta, M. Triassi, and L. Pecchia, Acute mental stress assessment via short term HRV analysis in healthy adults: A systematic review with meta-analysis, *Biomedical Signal Processing and Control*, Vol.18, 2015, pp.370-377.

[3] A. Dzedzickis, A. Kaklauskas, and V. Bucinskas, Human emotion recognition: review of sensors and methods, *Sensors*, Vol. 20, No.3, 2020, pp. 592.

[4] B. Kaur, D. Singh, and P.P. Roy, EEG based emotion classification mechanism in BCI, Procedia Computer Science, Vol.132, 2018, pp. 752-758.

[5] A. Liapis, C. Katsanos, D. Sotiropoulos, M. Xenos, and N. Karousos, Recognizing emotions in human computer interaction: studying stress using skin conductance, In IFIP Conference on Human-Computer Interaction, Springer, Cham, 2015, pp. 255-262.

[6] Q. Zhang, X. Chen, Q. Zhan, T. Yang, and S. Xia, Respiration-based emotion recognition with deep learning, Computers in Industry, Vol.92, 2017, pp.84-90.

[7] K. Masood, and M.A. Alghamdi, Modeling mental stress using a deep learning framework, IEEE Access, Vol. 7, 2019, pp. 68446-68454.

[8] D. Banerjee, K. Islam, K. Xue, G. Mei, L. Xiao, G. Zhang, and J. Li, A deep transfer learning approach for improved post-traumatic stress disorder diagnosis, Knowledge and Information Systems, Vol. 60, No.3, 2019, pp. 1693-1724.

[9] A. Maxhuni, P. Hernandez-Leal, L.E. Sucar, V. Osmani, E.F. Morales, and O. Mayora, Stress modelling and prediction in presence of scarce data, Journal of Biomedical Informatics, Vol. 63, 2016, pp. 344-356.

[10] S.H. Song, and D.K. Kim, Development of a stress classification model using deep belief networks for stress monitoring, Healthcare Informatics Research, Vol.23, No.4, 2017, pp. 285-292.

[11] S. Sriramprakash, V.D. Prasanna, and O.R. Murthy, Stress detection in working people, Procedia Computer Science, Vol. 115, 2017, pp. 359-366.

[12] J. Luo, H. Chen, Y. Xu, H. Huang, and X. Zhao, An improved grasshopper optimization algorithm with application to financial stress prediction, Applied Mathematical Modelling, Vol. 64, 2018, pp.654-668.

[13] B. Jawharali, and B. Arunkumar, Efficient human stress level prediction and prevention using neural network learning through EEG signals, International Journal of Engineering Research and Technology, Vol. 12, No.1, 2019, pp. 66-72.

[14] A. Shaw, N. Simsiri, I. Deznaby, M. Fiterau, and T. Rahaman, Personalized student stress prediction with deep multitask network, arXiv preprint arXiv:1906.11356 2019.

[15] J. He, K. Li, X. Liao, P. Zhang, and N. Jiang, Real-time detection of acute cognitive stress using a convolutional neural network from electrocardiographic signal, IEEE Access, Vol. 7, 2019, pp.42710-42717.