EXPLORING TRANSFER LEARNING FOCUSED ON PHYSIOLOGICAL SIGNALS FOR EMOTION RECOGNITION

An Undergraduate Research Scholars Thesis

by

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TABLE OF CONTENTS

Page

ABSTRACT 1

DEDICATION 2

ACKNOWLEDGMENTS 3

NOMENCLATURE 4

CHAPTER

I. INTRODUCTION 5

II. METHODS 7

- Datasets 7
- Domain Adaptation 7
- Neural Network Model 8

III. RESULTS 9

- Visualizing Overall Results 10
- Visualizing Results by Subject 12

IV. CONCLUSION 34

REFERENCES 35

ABSTRACT

Exploring Transfer Learning Focused on Physiological Signals for Emotion Recognition

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Recent work in the area of automatic emotion recognition has leveraged a large amount of publicly available data with transfer learning techniques to detect emotion on low-resource data. Previous work demonstrated that the use of maximum independence domain adaptation and transfer component analysis show promise in generalizing on unseen domains. While the accuracy increases are significant, they remain below within-dataset models. Other research concluded that a subspace alignment auto-encoder (SAAE) is useful for domain adaptation and is more effective than current techniques. Despite the encouraging results of these studies, more work needs to be done to extend this to real-world brain computer interaction (BCI) applications. The primary goal of this thesis is to develop transfer learning techniques that leverage existing data and attempt to generalize them on unseen domains accurately enough for real-world applications. If the proposed endeavor is successful, emotion recognition for real-life applications will not need to include large amounts of data from the target domain since transfer learning techniques will be able to accurately generalize on unseen domains.

DEDICATION

I would like to dedicate this thesis to my dear friends Aashish, Kim, and James who have constantly been by my side and taught me that there’s never a bad time to be a bit of a joker.

ACKNOWLEDGMENTS

I would like to thank my advisor Dr. Theodora Chaspari for allowing me to research with her through this year and encouraging me to perform my best. Her guidance and support have been absolutely invaluable. At the beginning of the fall semester, I did not have the faintest inkling of what machine learning was. After taking her class and performing research with her, I can safely say that I know much more than I ever thought possible.

I would also like to acknowledge the entire HUman Bio-Behavioral Signals (HUBBS) Lab for a great year. I had never been exposed to research before and their inquisitive nature and positivity at each of the lab meetings has made my experience wonderful. I also would like to thank Kexin for helping me throughout the year as well. He has provided much needed guidance and I would not have been able to complete this thesis without him.

NOMENCLATURE

SEED	SJTU Emotion EEG Dataset
DEAP	Dataset for Emotion Analysis of Physiological Signals
PS	Per Subject Normalization
AD	Across Dataset Normalization

CHAPTER I

INTRODUCTION

The ability to recognize emotion can play a large role in people's daily lives and can provide a number of benefits across a wide range of disciplines. It can be used in harmony with music therapy to help alleviate pain and depression or can be used to recognize public speaking anxiety in order to recommend techniques to help alleviate it [7], [8]. The goal of this thesis is to provide a way to accurately recognize emotion given electroencephalogram (EEG) data.

While emotion recognition has many beneficial applications for humans, the ability to actually train a model that is accurate enough to be used in these applications is a challenge. We do have access to in-lab datasets that provide EEG signals that are labelled according to what emotion a participant feels but there is not a lot of data available overall. Given this, the machine learning systems that are created often have trouble generalizing between training and testing, as well as on unseen data.

The challenge to generalizable machine learning systems is a difficult one but can be overcome with emerging transfer learning techniques. Transfer learning involves training a model on one data set and testing the model on a different yet similar dataset. Rather than splitting a single data set into training and testing portions, this process allows us to utilize more data when creating a model, therefore increasing the likelihood that the model can generalize on unseen data. Recent work in the area of emotional recognition involved comparing transfer learning techniques on publicly available datasets and an introductory study to cross-dataset adaptation [1]. This preliminary study demonstrated that the use of maximum independence domain adaptation and transfer component analysis show promise in regards to generalizing on unseen domains, with accuracy increases from 7.25 to 13.40 percent. While these increases are significant, they remain below within-dataset models. In order to allow for real-world application, more studies are required in order to fine tune the transfer approaches for increasing the accuracy between datasets [1]. Other work included the proposal of a component called the subspace alignment auto-encoder (SAAE). This research involved using an EEG dataset and comparing subject-to-subject and session-to-session evaluations using current transfer learning techniques and the new one proposed. Results concluded that SAAE is useful for domain adaptation and more effective than current techniques in some cases but more research needs to be done to extend this to real-world brain computer interaction (BCI) applications [2].

In this thesis, we develop transfer learning techniques that leverage existing data and attempt to generalize machine learning systems on unseen domains accurately enough for real-world applications. In order to evaluate whether transfer learning can bring substantial improvement in existing models, we gathered baseline accuracies on in-domain experiments in two datasets and then compared these accuracies with the accuracies gathered when performing between the two datasets. Results indicate that transfer learning allowed the machine learning system to generalize on unseen data yielding 10% relative improvement over in-domain experiments in one of the two datasets. Results are discussed in relation to limitations of the proposed algorithms and in the light of potential ways of improvement as part of the future work.

CHAPTER II

METHODS

Datasets

The public Dataset for Emotion Analysis of Physiological Signals (DEAP) [4] and SJTU Emotion EEG Dataset (SEED) [5] were used throughout this research and are outlined below.

DEAP

The electroencephalogram (EEG) and peripheral physiological signals of 32 participants were gathered as each participant watched 40 one-minute long excerpts of music videos [4]. Each participant rated each video in terms of level of arousal, valence, like/dislike, dominance, and familiarity.

SEED

The EEG signals of 15 participants were gathered as each participant watched each of 15 Chinese film clips. Each film was labeled beforehand as either negative, positive, or neutral. A total of 15 trials were conducted for each film [6].

Domain Adaptation

Both of the above datasets have labeled data but are labeled in different ways, meaning that they are domain-specific. This allowed us to verify the effectiveness of transfer learning techniques. A neural network was trained on both of the datasets and the following domain adaptations were performed: subject-to-subject used both of the datasets (DEAP → DEAP) and (SEED → SEED). In order to check the validity of using transfer learning techniques, the following domain adaptations were also performed: (DEAP → SEED) and (SEED → DEAP).

Neural Network Model

Two neural networks were trained and tested on the DEAP and SEED data sets and utilized the open-source Python neural network library Keras and the machine learning library Scikit-learn.

Four neural networks were trained and tested, one each for (DEAP → DEAP), (SEED → SEED), (DEAP → SEED), and (SEED → DEAP). In order to find the best hyperparameters for each of the networks, a five-fold cross validation was used with the training data. After these were found, a leave-one-out cross validation was used to test the trained model.

Fine Tuning

So as to perform transfer learning for the (DEAP → SEED) and (SEED → DEAP) domain adaptations, fine tuning was needed. After training each network on their respective datasets, DEAP and SEED, the last layer of each was frozen and then retrained using a five-fold cross validation on the dataset that was adapted to. After this, a leave-one-out cross validation was used to verify the fine tuned network

Normalization

Normalizing the data when training the model was used in order to have data within the same range across both domains, DEAP and SEED. Two normalization techniques were used and a model was trained on each. Normalization across the entire data set and normalization per subject were used.

CHAPTER III

RESULTS

In reference to Table 1, in-domain models after normalizing the data per subject for DEAP and SEED provided better results compared to population-wide normalization, with the model trained on SEED performing much better than the model trained on DEAP, having an accuracy of 0.6341 and 0.3782 respectively. Utilizing transfer learning on the domain of DEAP to SEED did not yield better results in comparison to the in-domain model trained on SEED for normalization per subject or normalization across all data. However, transfer learning did yield better results on the domain of SEED to DEAP when normalizing per subject. Normalizing across all data on this domain performed worse than the baseline accuracy found for DEAP.

Table 1. Accuracies across each of the domains and normalizations

Domain	**Normalization**	**Unbalanced Accuracy**
DEAP	across all subjects data	0.3304
SEED	across all subjects data	0.3082
DEAP	per subject	0.3782
SEED	per subject	0.6341
SEED → DEAP	per subject	0.4387
SEED → DEAP	across all subjects data	0.3333
DEAP → SEED	per subject	0.5126
DEAP → SEED	across all subjects data	0.5526

Visualizing Overall Results

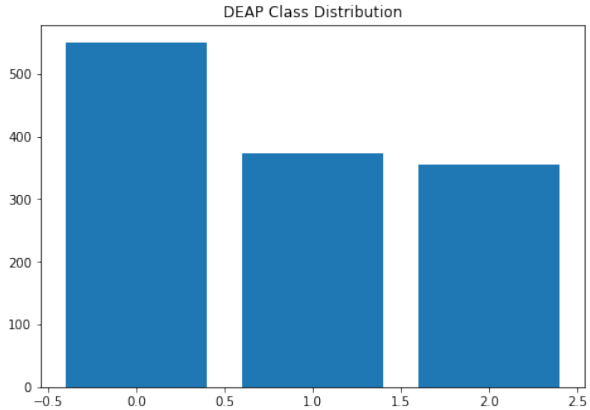

Figure 1. DEAP Class Distribution (0, 1, 2)

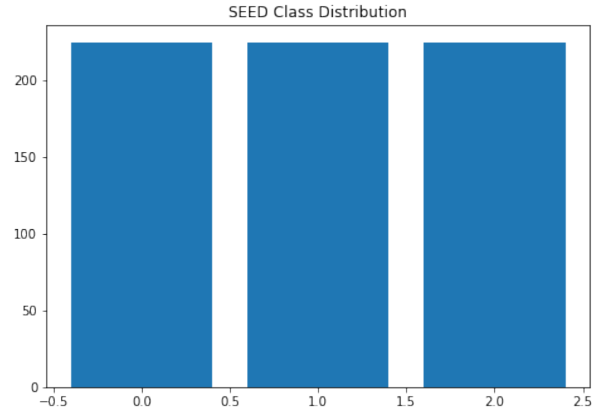

Figure 2. SEED Class Distribution (0, 1, 2)

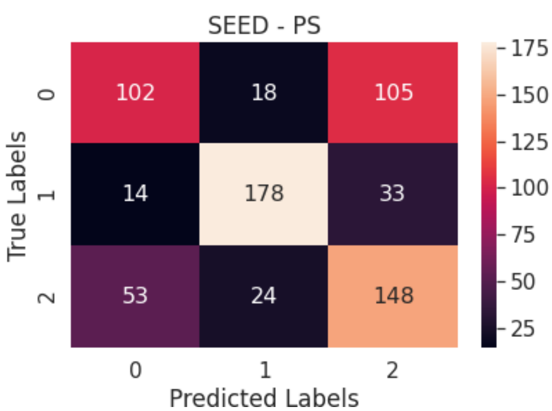

Figure 3. SEED – PS confusion matrix

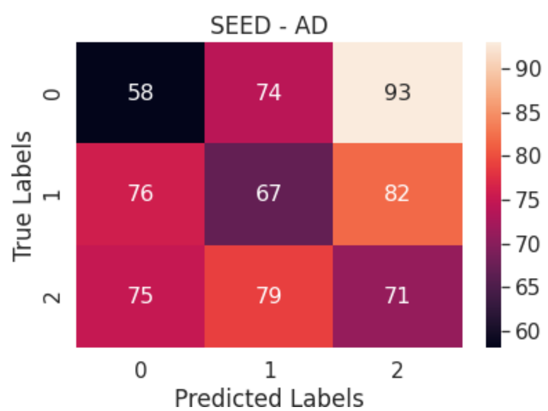

Figure 4. SEED - AD confusion matrix

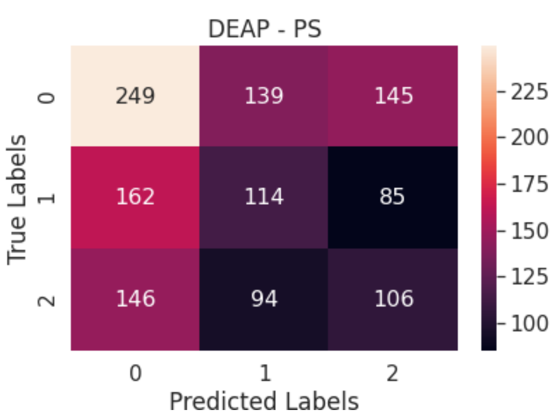

Figure 5. DEAP - PS confusion matrix

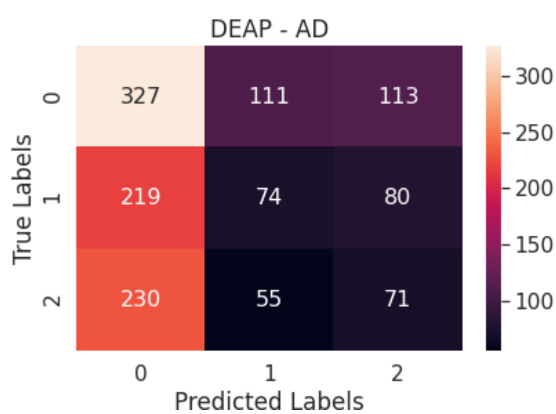

Figure 6. DEAP - AD confusion matrix

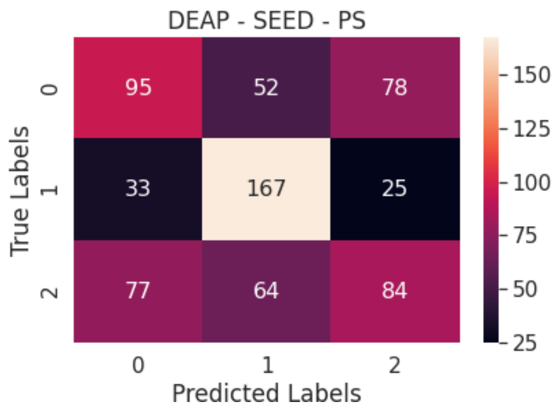

Figure 7. DEAP to SEED – PS confusion matrix

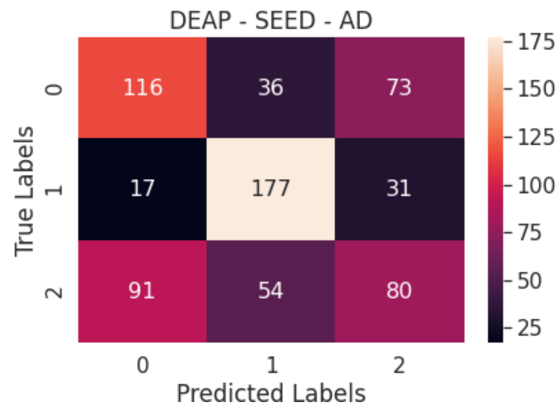

Figure 8. DEAP to SEED – AD confusion matrix

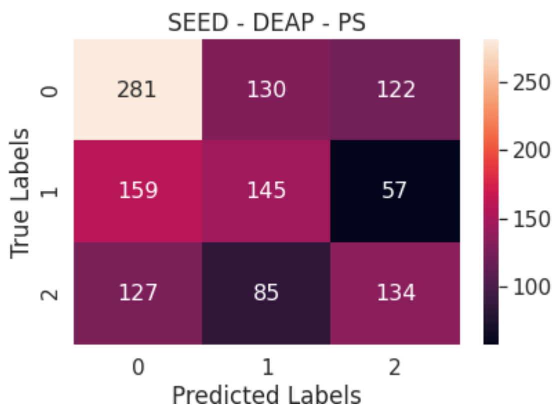

Figure 9. DEAP to SEED – PS confusion matrix

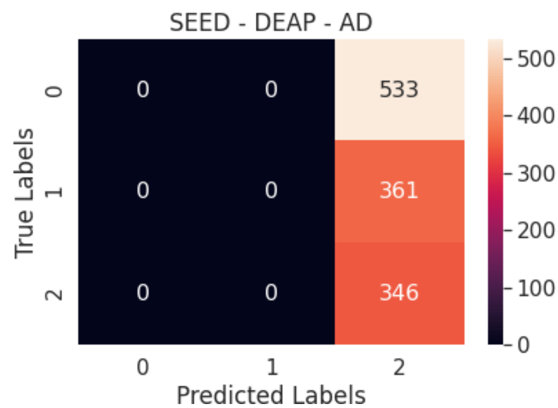

Figure 10. SEED to DEAP – AD confusion matrix

The above matrices are known as confusion matrices. The diagonal starting from the upper left that goes down to the lower right are the number of times that our models predicted the correct value. For example, in the SEED - PS matrix, 0 was correctly predicted 102 times. Looking at these matrices as an entire idea show us that the per subject normalization performed better on average than the across dataset normalization. We can also further support our conclusion that the SEED → DEAP transfer learning outcomes faired worse than their counterpart. As we can see from the SEED → DEAP - AD matrix, the model predicted ‘2’ for every sample. This may infer that our model has been overfitted or improperly tuned. In an ideal scenario, each of our matrices would display the same distribution as seen in Figure 1 (DEAP Class Distribution) and Figure 2 (SEED Class Distribution).

Visualizing Results by Subject

SEED → DEAP per subject - normalization per subject

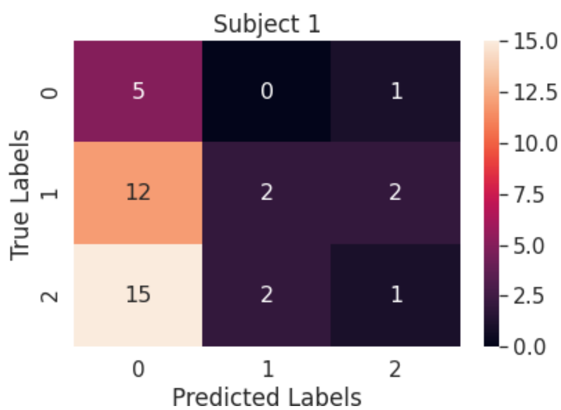

Figure 11. SEED to DEAP – PS Subject 1 confusion matrix

Figure 12. SEED to DEAP – PS Subject 2 confusion matrix

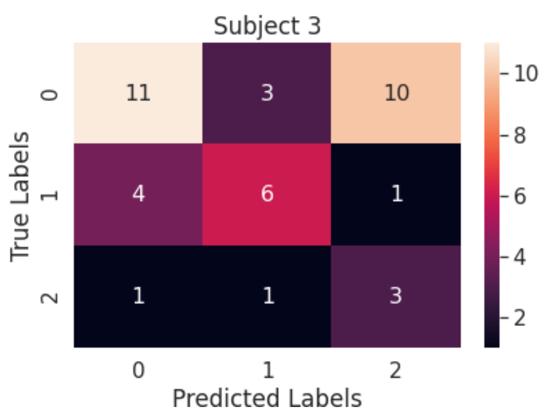

Figure 13. SEED to DEAP – PS Subject 3 confusion matrix

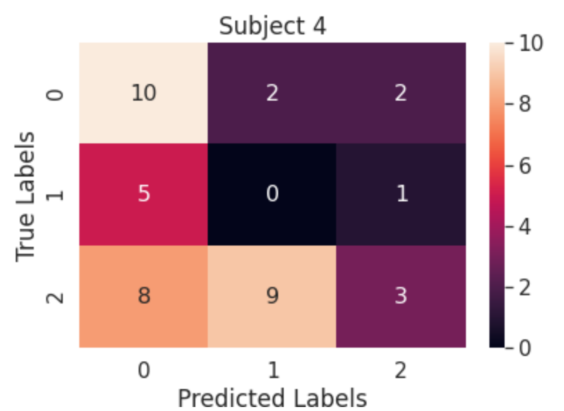

Figure 14. SEED to DEAP – PS Subject 4 confusion matrix

Figures 11, 12, 13, and 14 are the confusion matrix outputs for subjects 1, 2, 3, and 4.

SEED → DEAP per subject - normalization per subject - continued

Figure 15. SEED to DEAP – PS Subject 5 confusion matrix

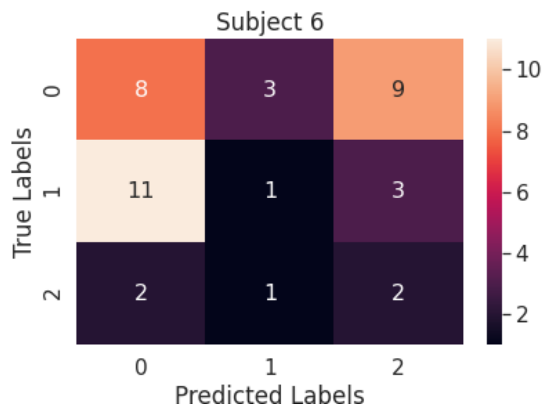

Figure 16. SEED to DEAP – PS Subject 6 confusion matrix

Figure 17. SEED to DEAP – PS Subject 7 confusion matrix

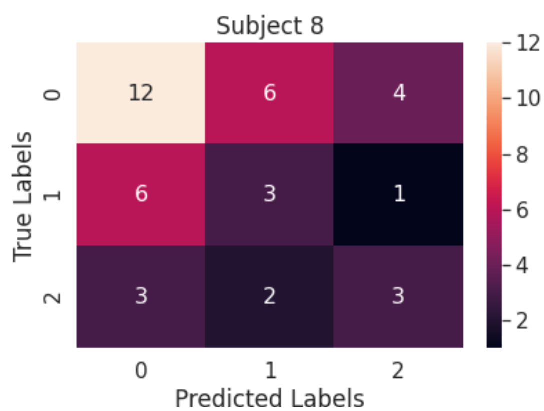

Figure 18. SEED to DEAP – PS Subject 8 confusion matrix

Figures 15, 16, 17, and 18 are the confusion matrix outputs for subjects 5, 6, 7, and 8.

SEED → DEAP per subject - normalization per subject - continued

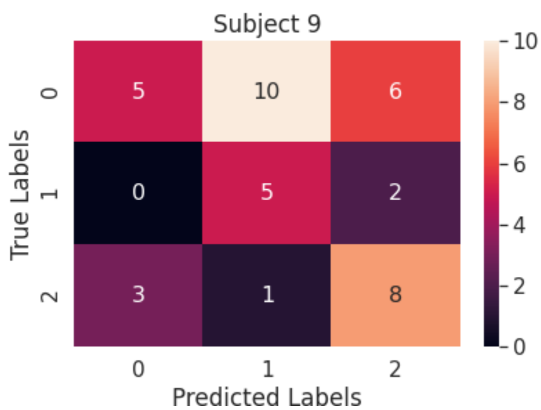

Figure 19. SEED to DEAP – PS Subject 9 confusion matrix

Figure 20. SEED to DEAP – PS Subject 10 confusion matrix

Figure 21. SEED to DEAP – PS Subject 11 confusion matrix

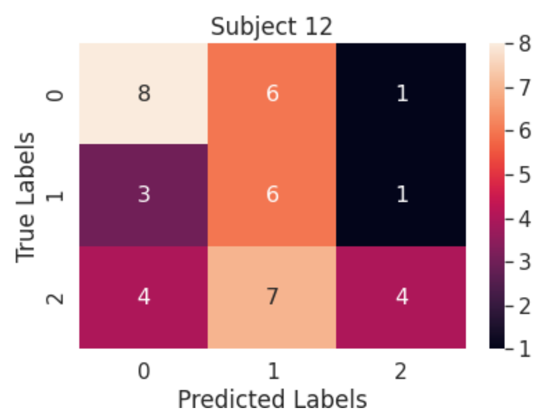

Figure 22. SEED to DEAP – PS Subject 12 confusion matrix

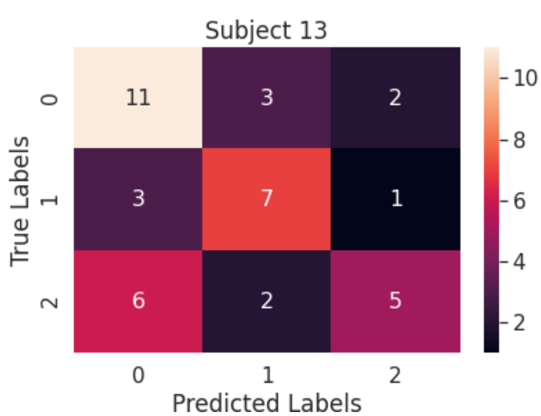

Figure 23. SEED to DEAP – PS Subject 13 confusion matrix

Figure 24. SEED to DEAP – PS Subject 14 confusion matrix

SEED → DEAP per subject - normalization per subject - continued

Figure 25. SEED to DEAP – PS Subject 15 confusion matrix

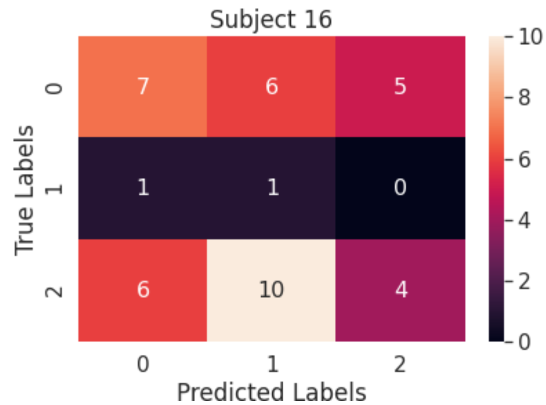

Figure 26. SEED to DEAP – PS Subject 16 confusion matrix

Figures 19 through 26 are the confusion matrix outputs for subjects 9 through 16.

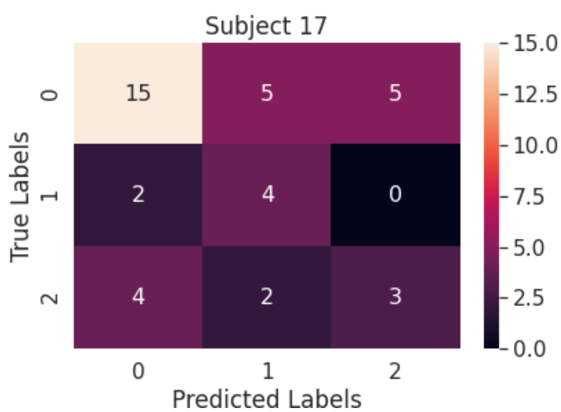

Figure 27. SEED to DEAP – PS Subject 17 confusion matrix

Figure 28. SEED to DEAP – PS Subject 18 confusion matrix

SEED → DEAP per subject - normalization per subject - continued

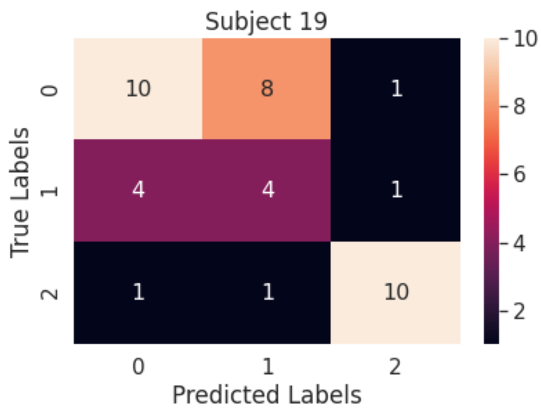

Figure 29. SEED to DEAP – PS Subject 19 confusion matrix

Figure 30. SEED to DEAP – PS Subject 20 confusion matrix

Figure 31. SEED to DEAP – PS Subject 21 confusion matrix

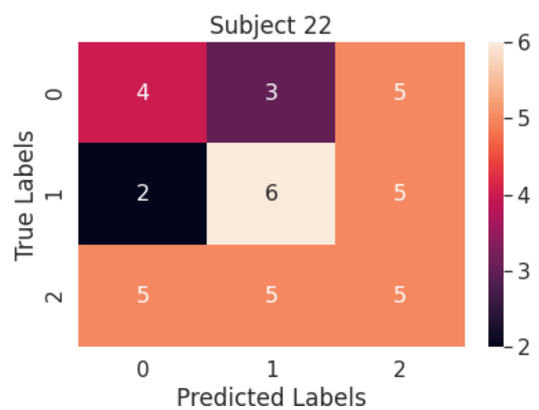

Figure 32. SEED to DEAP – PS Subject 22 confusion matrix

Figure 33. SEED to DEAP – PS Subject 23 confusion matrix

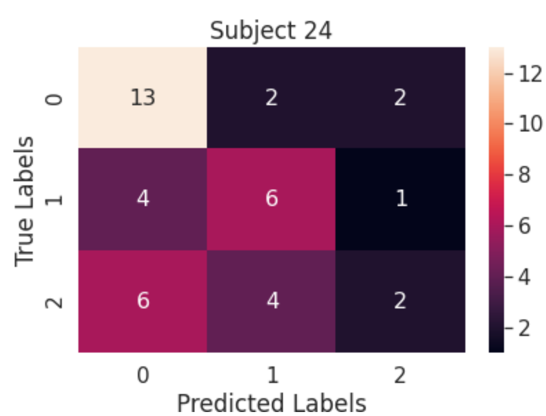

Figure 34. SEED to DEAP – PS Subject 24 confusion matrix

SEED → DEAP per subject - normalization per subject - continued

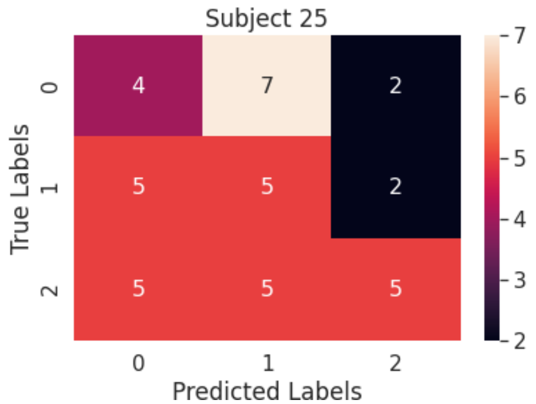

Figure 35. SEED to DEAP – PS Subject 25 confusion matrix

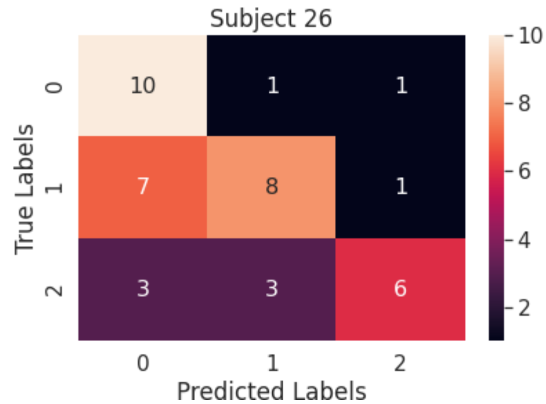

Figure 36. SEED to DEAP – PS Subject 26 confusion matrix

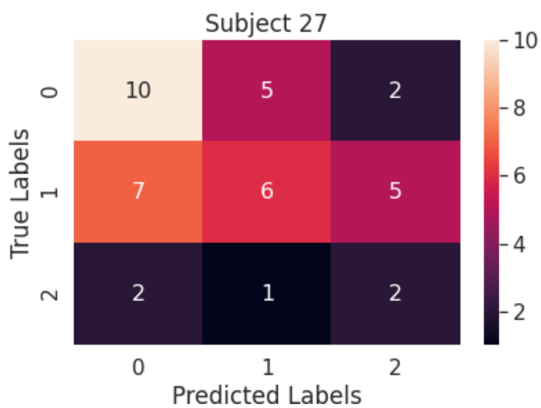

Figure 37. SEED to DEAP – PS Subject 27 confusion matrix

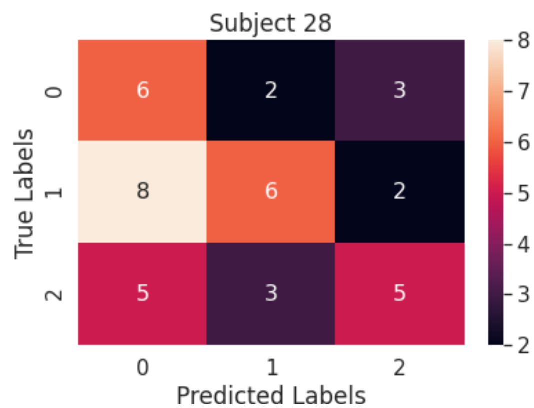

Figure 38. SEED to DEAP – PS Subject 28 confusion matrix

Figures 27 through 38 are the confusion matrix outputs for subjects 17 through 28.

SEED → DEAP per subject - normalization per subject - continued

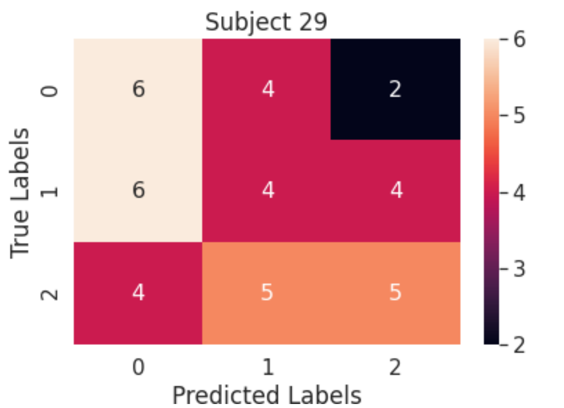

Figure 39. SEED to DEAP – PS Subject 29 confusion matrix

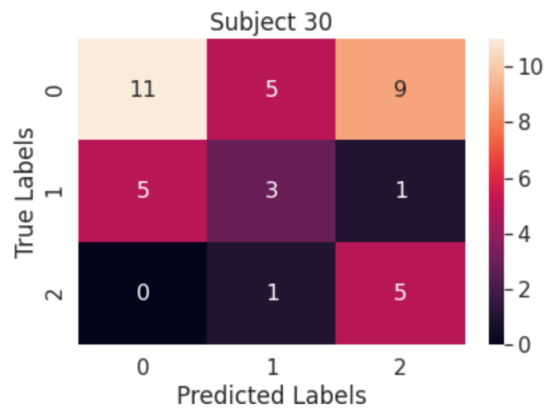

Figure 40. SEED to DEAP – PS Subject 30 confusion matrix

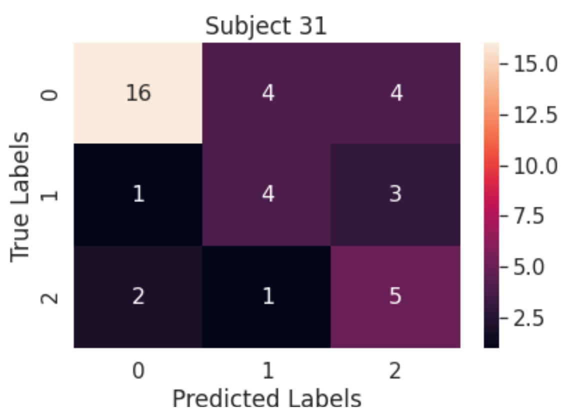

Figure 41. SEED to DEAP – PS Subject 31 confusion matrix

Figures 39 through 41 are the confusion matrix outputs for subjects 29 through 31.

SEED → DEAP per subject - normalization across all data

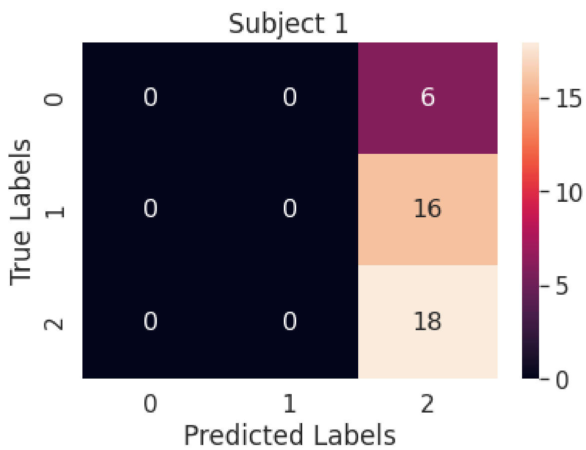

Figure 42. SEED to DEAP – AD Subject 1 confusion matrix

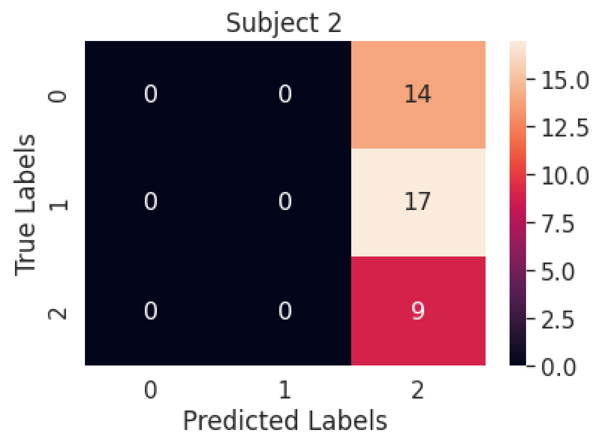

Figure 43. SEED to DEAP – AD Subject 2 confusion matrix

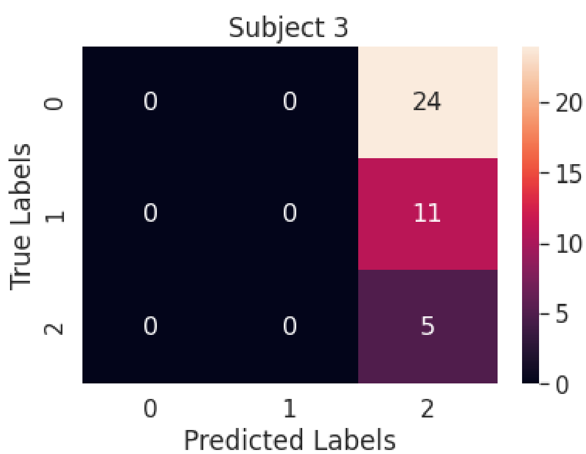

Figure 44. SEED to DEAP – AD Subject 3 confusion matrix

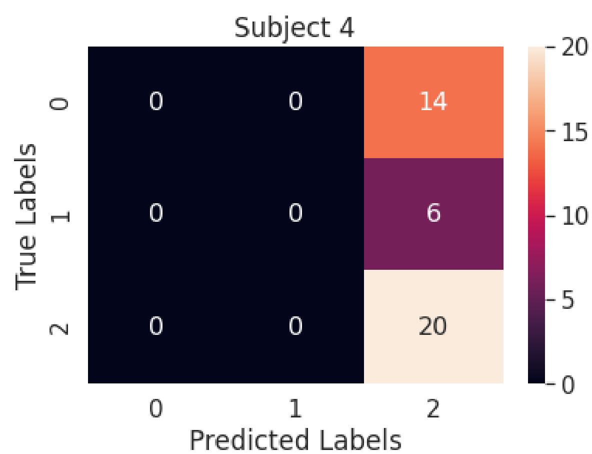

Figure 45. SEED to DEAP – AD Subject 4 confusion matrix

SEED → DEAP per subject - normalization across all data - continued

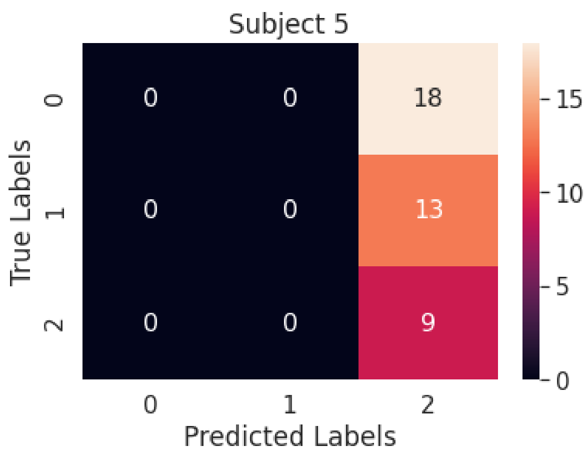

Figure 46. SEED to DEAP – AD Subject 5 confusion matrix

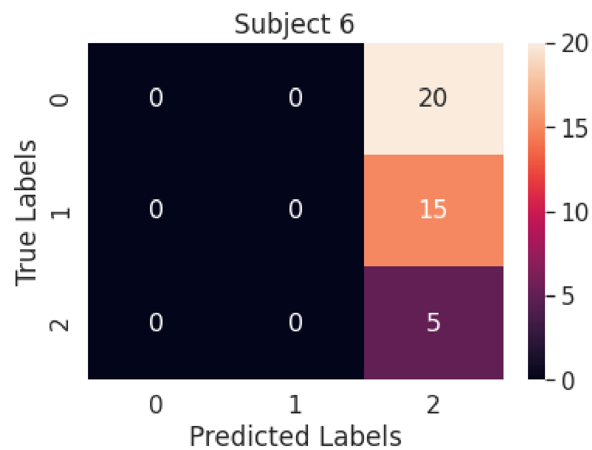

Figure 47. SEED to DEAP – AD Subject 6 confusion matrix

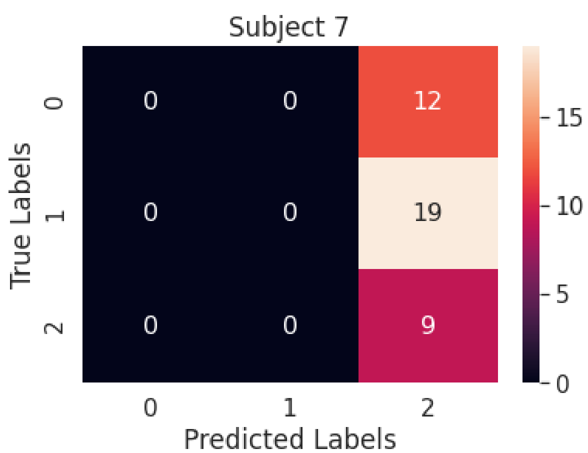

Figure 48. SEED to DEAP – AD Subject 7 confusion matrix

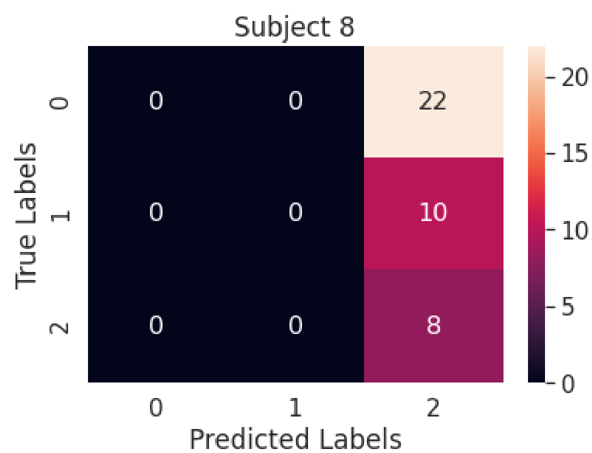

Figure 49. SEED to DEAP – AD Subject 8 confusion matrix

Figures 42 through 49 are the confusion matrix outputs for subjects 1 through 8.

SEED → DEAP per subject - normalization across all data - continued

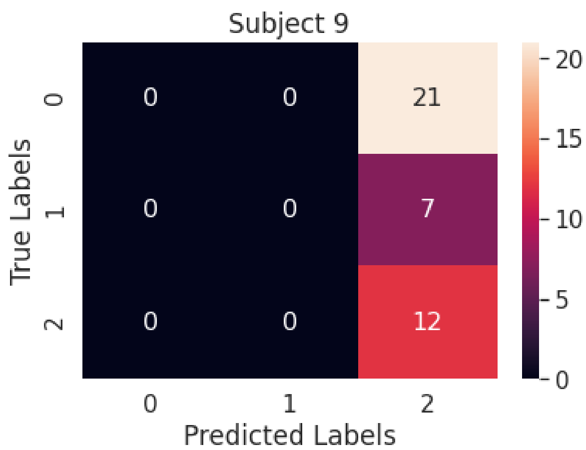

Figure 50. SEED to DEAP – AD Subject 9 confusion matrix

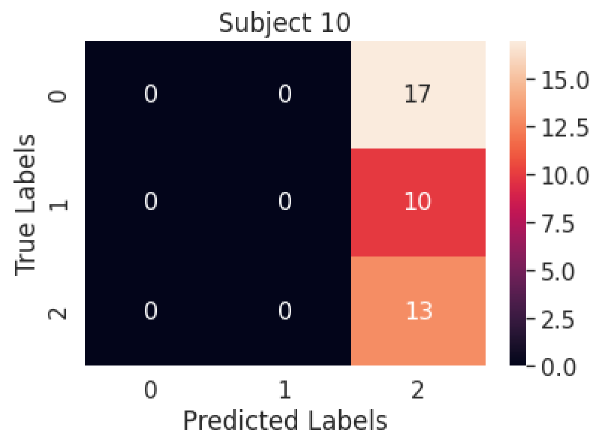

Figure 51. SEED to DEAP – AD Subject 10 confusion matrix

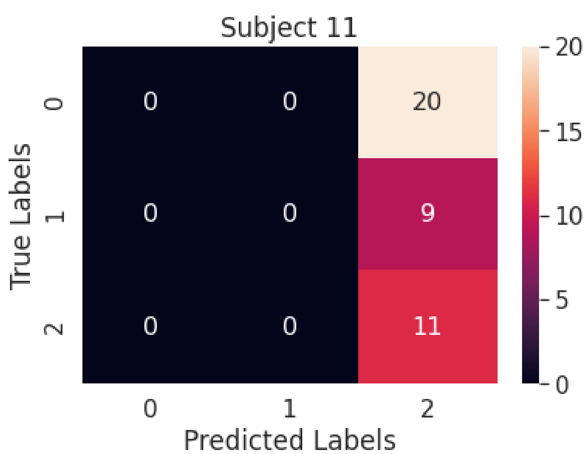

Figure 52. SEED to DEAP – AD Subject 11 confusion matrix

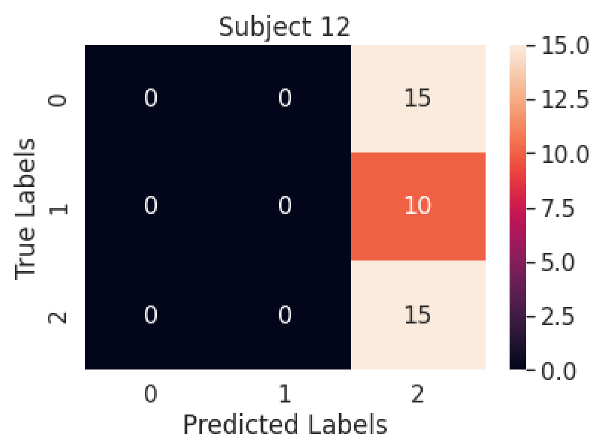

Figure 53. SEED to DEAP – AD Subject 12 confusion matrix

SEED → DEAP per subject - normalization across all data - continued

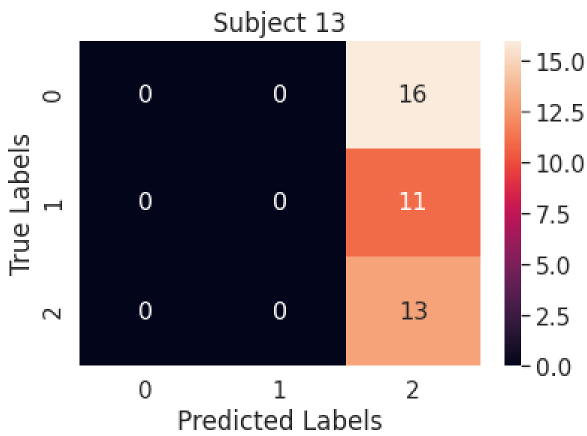

Figure 54. SEED to DEAP – AD Subject 13 confusion matrix

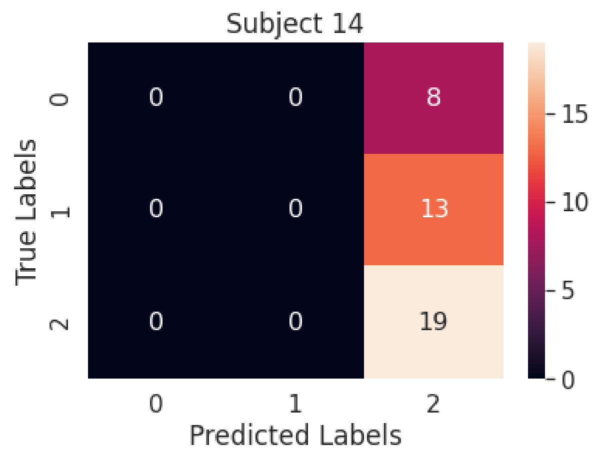

Figure 55. SEED to DEAP – AD Subject 14 confusion matrix

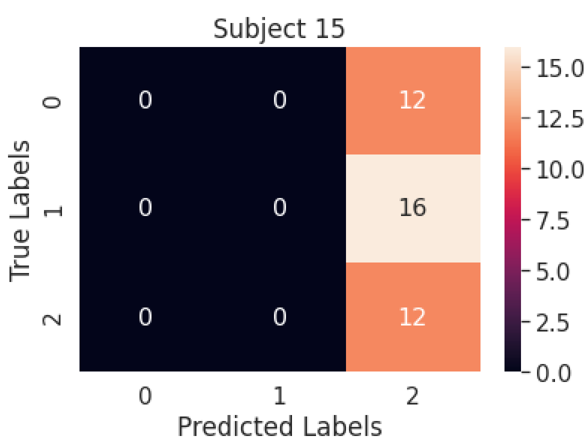

Figure 56. SEED to DEAP – AD Subject 15 confusion matrix

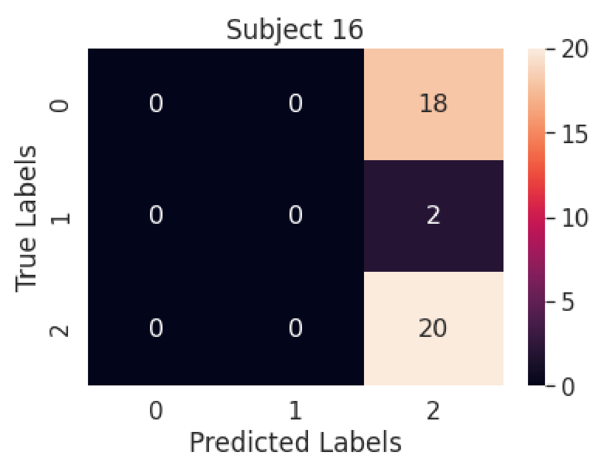

Figure 57. SEED to DEAP – AD Subject 16 confusion matrix

Figures 50 through 57 are the confusion matrix outputs for subject 9 through 16.

SEED → DEAP per subject - normalization across all data - continued

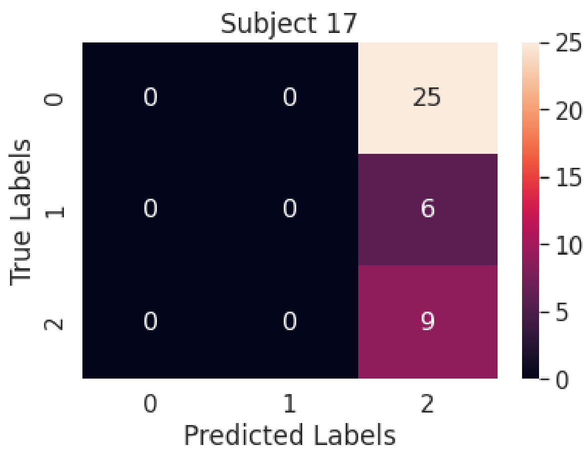

Figure 58. SEED to DEAP – AD Subject 17 confusion matrix

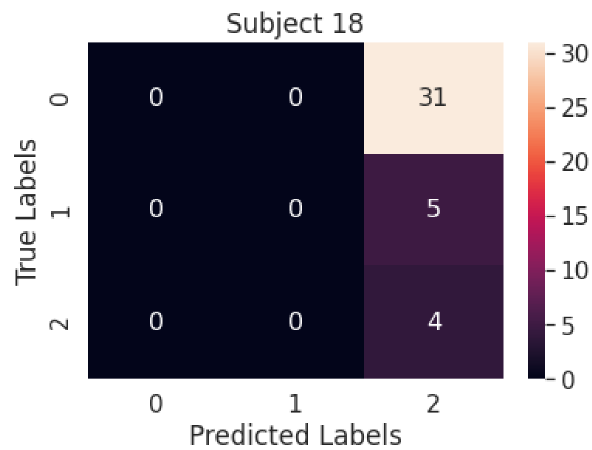

Figure 59. SEED to DEAP – AD Subject 18 confusion matrix

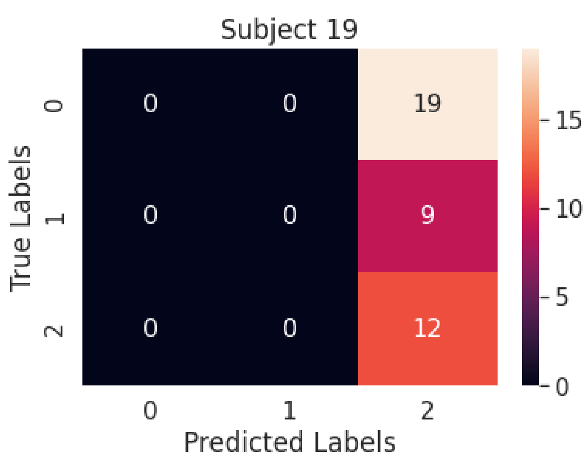

Figure 60. SEED to DEAP – AD Subject 19 confusion matrix

Figure 61. SEED to DEAP – AD Subject 20 confusion matrix

SEED → DEAP per subject - normalization across all data - continued

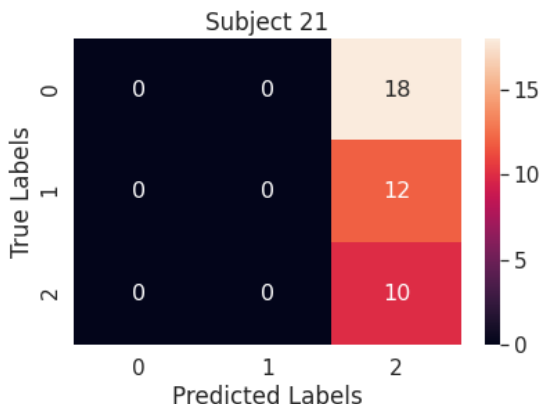

Figure 62. SEED to DEAP – AD Subject 21 confusion matrix

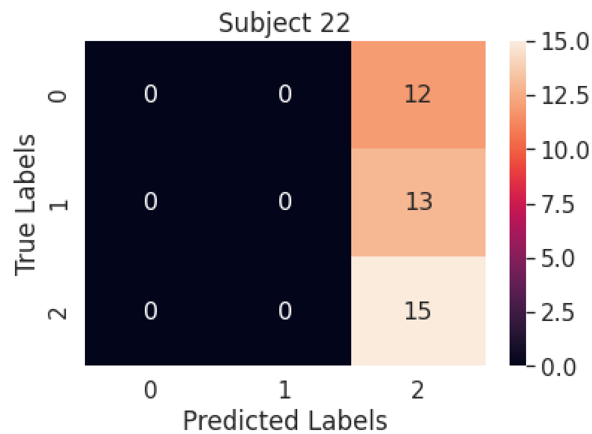

Figure 63. SEED to DEAP – AD Subject 22 confusion matrix

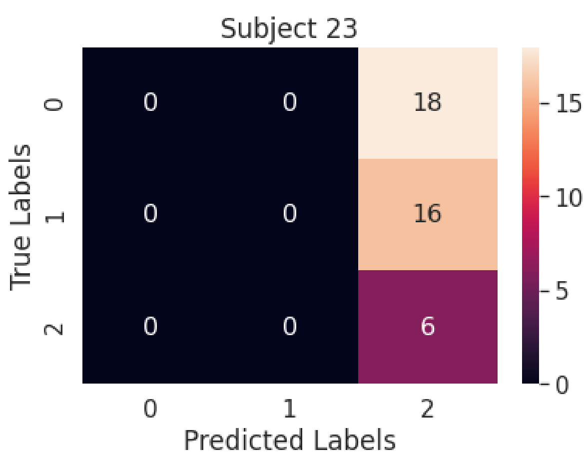

Figure 64. SEED to DEAP – AD Subject 23 confusion matrix

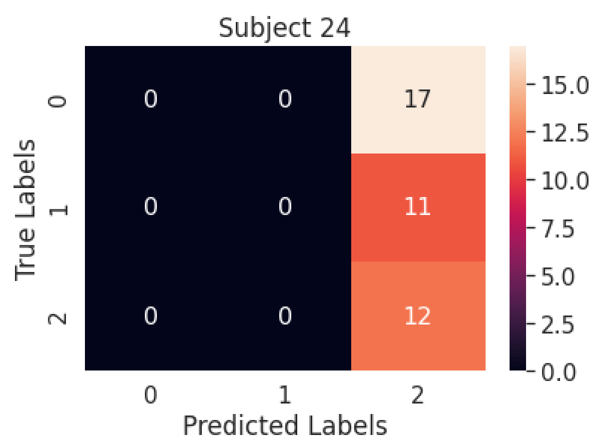

Figure 65. SEED to DEAP – AD Subject 24 confusion matrix

Figures 58 through 65 are the confusion matrix outputs for subjects 17 through 24.

SEED → DEAP per subject - normalization across all data - continued

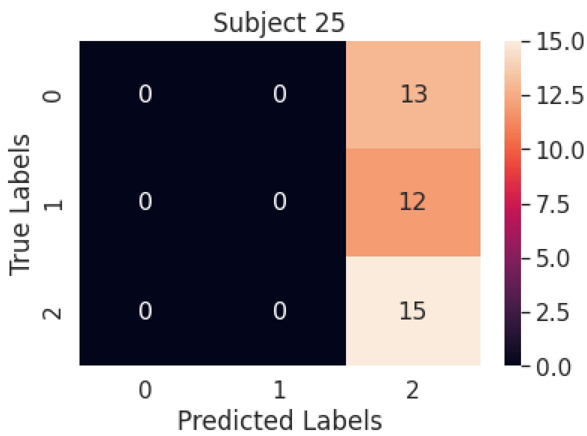

Figure 66. SEED to DEAP – AD Subject 25 confusion matrix

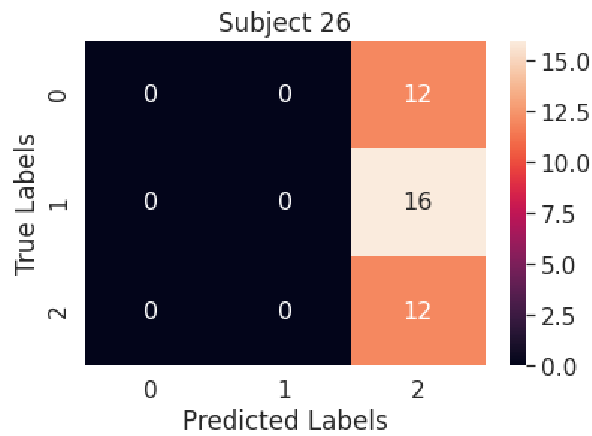

Figure 67. SEED to DEAP – AD Subject 26 confusion matrix

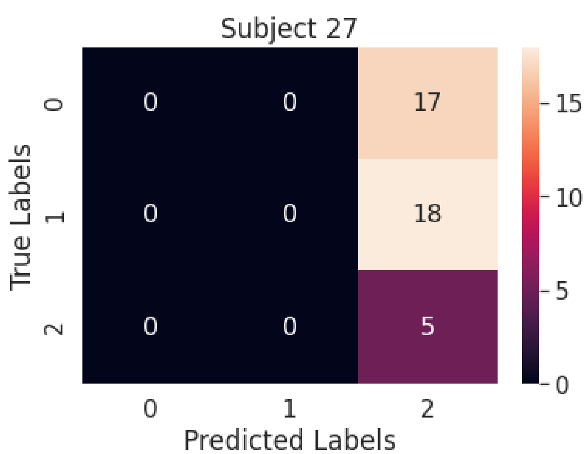

Figure 68. SEED to DEAP – AD Subject 27 confusion matrix

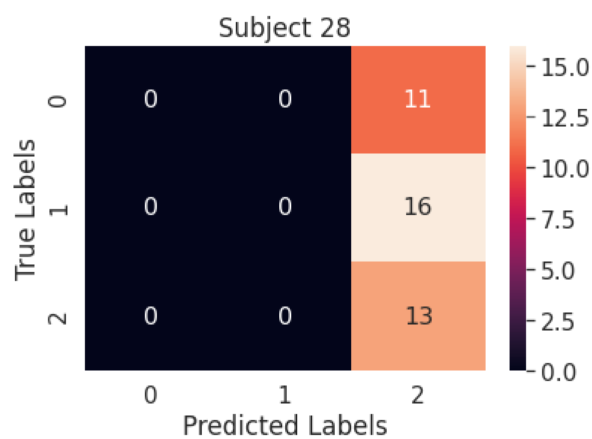

Figure 69. SEED to DEAP – AD Subject 28 confusion matrix

SEED → DEAP per subject - normalization across all data - continued

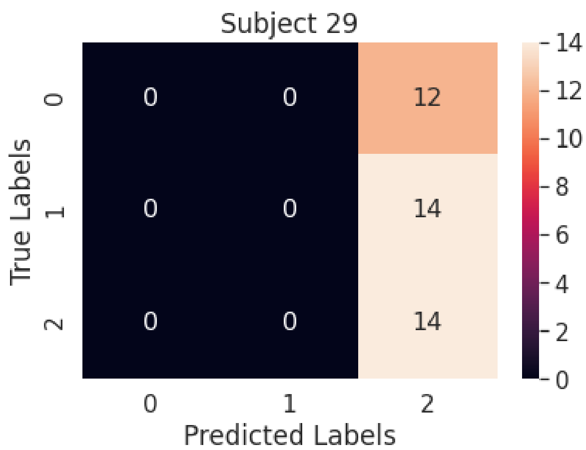

Figure 70. SEED to DEAP – AD Subject 29 confusion matrix

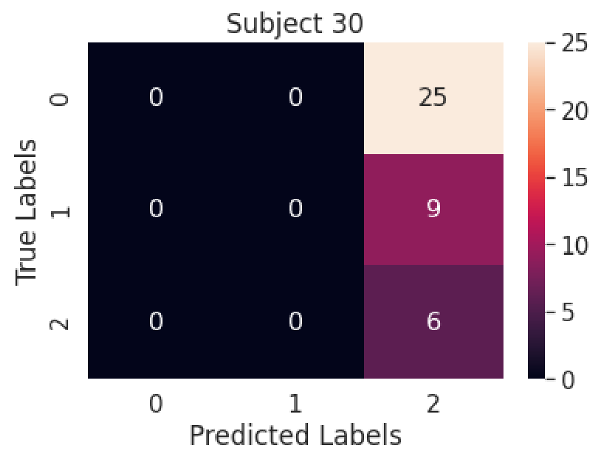

Figure 71. SEED to DEAP – AD Subject 30 confusion matrix

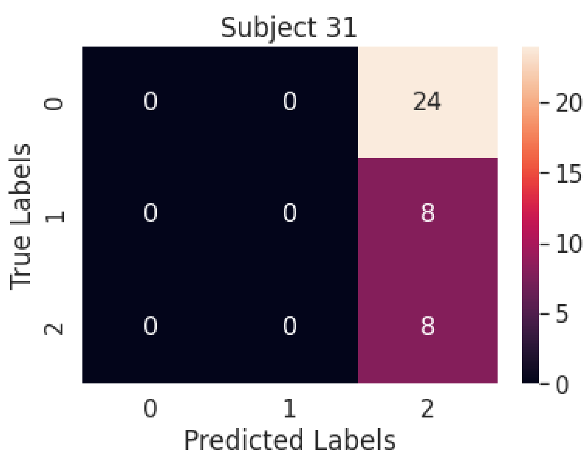

Figure 72. SEED to DEAP – AD Subject 31 confusion matrix

Figures 66 through 72 are the confusion matrix outputs for subjects 25 through 31.

DEAP → SEED per subject - normalization per subject

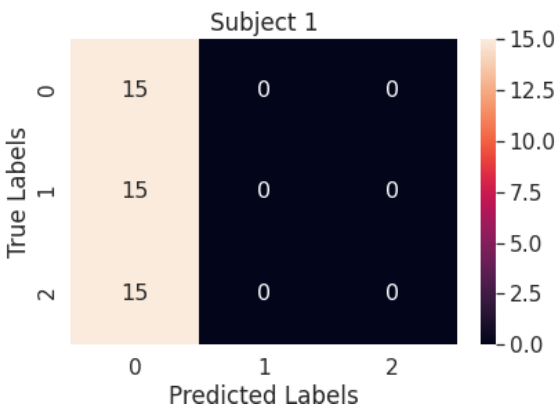

Figure 73. DEAP to SEED – PS Subject 1 confusion matrix

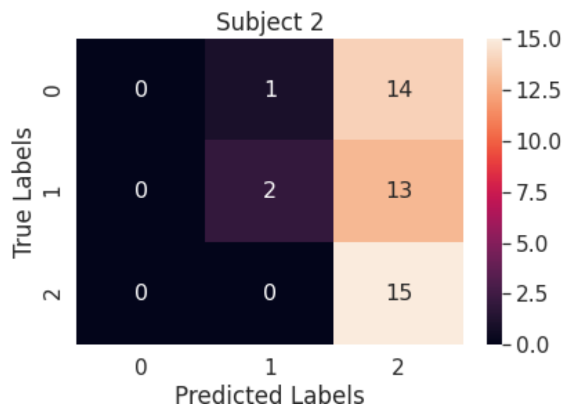

Figure 74. DEAP to SEED – PS Subject 2 confusion matrix

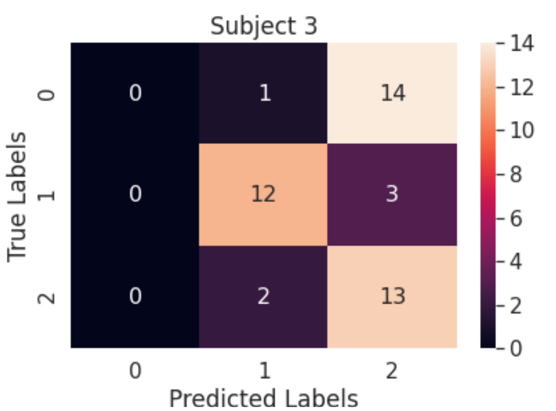

Figure 75. DEAP to SEED – PS Subject 3 confusion matrix

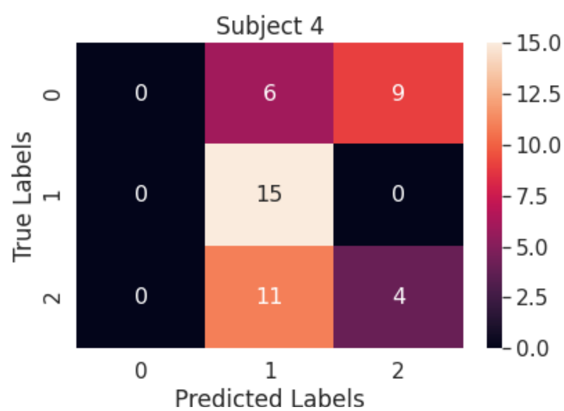

Figure 76. DEAP to SEED – PS Subject 4 confusion matrix

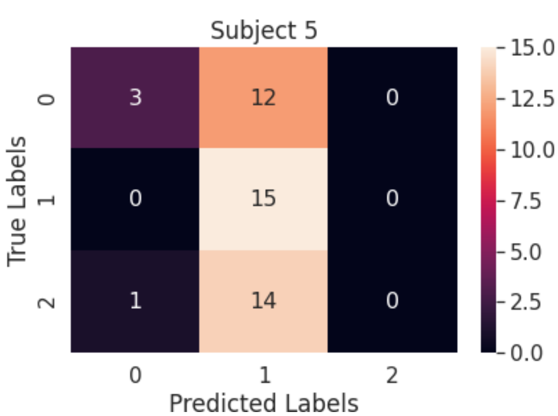

Figure 77. DEAP to SEED – PS Subject 5 confusion matrix

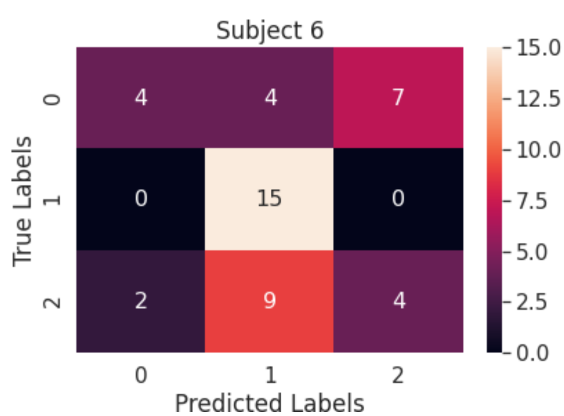

Figure 78. DEAP to SEED – PS Subject 6 confusion matrix

DEAP → SEED per subject - normalization per subject - continued

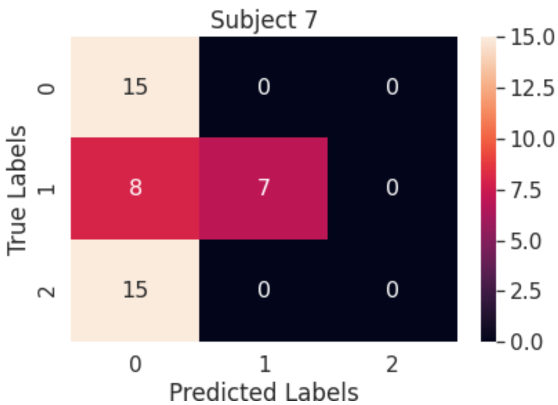

Figure 79. DEAP to SEED – PS Subject 7 confusion matrix

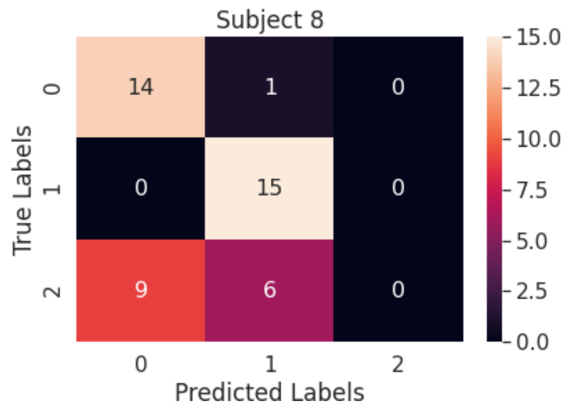

Figure 80. DEAP to SEED – PS Subject 8 confusion matrix

Figure 81. DEAP to SEED – PS Subject 9 confusion matrix

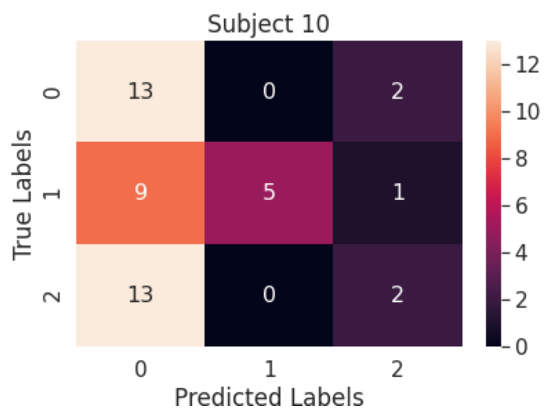

Figure 82. DEAP to SEED – PS Subject 10 confusion matrix

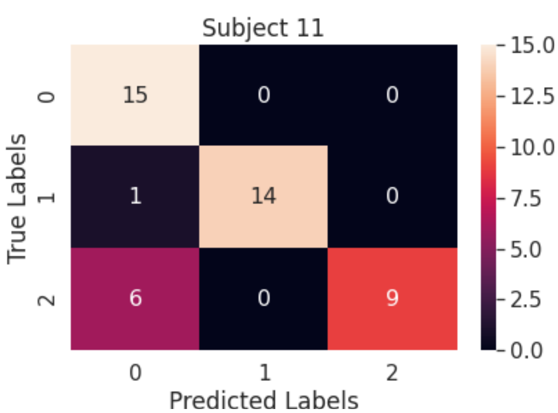

Figure 83. DEAP to SEED – PS Subject 11 confusion matrix

Figure 84. DEAP to SEED – PS Subject 12 confusion matrix

Figures 73 through 84 are the confusion matrix outputs for subjects 1 through 12.

DEAP → SEED per subject - normalization per subject - continued

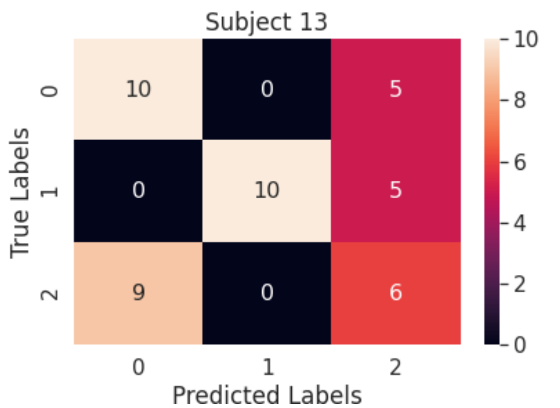

Figure 85. DEAP to SEED – PS Subject 13 confusion matrix

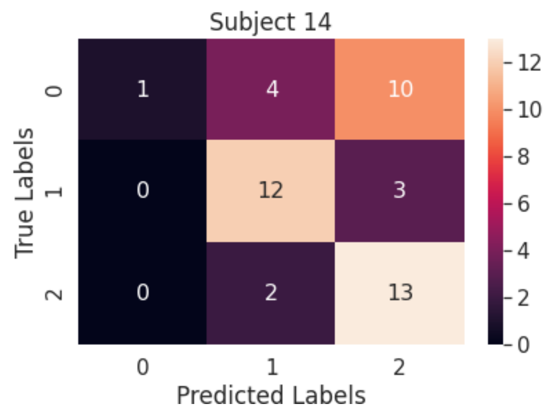

Figure 86. DEAP to SEED – PS Subject 14 confusion matrix

Figure 87. DEAP to SEED – PS Subject 15 confusion matrix

Figures 85 through 87 are the confusion matrix outputs for the subjects 13 through 15.

DEAP → SEED per subject - normalization across all data

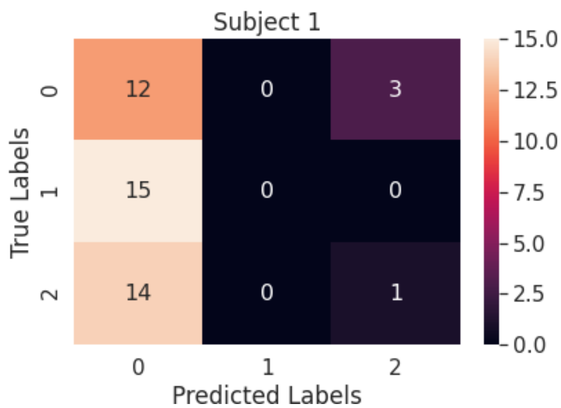

Figure 88. DEAP to SEED – AD Subject 1 confusion matrix

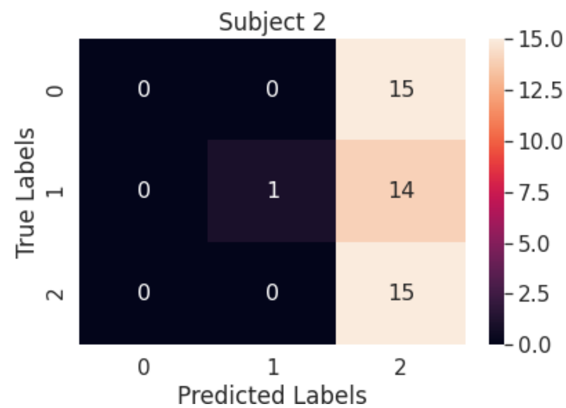

Figure 89. DEAP to SEED – AD Subject 2 confusion matrix

Figure 90. DEAP to SEED – AD Subject 3 confusion matrix

Figure 91. DEAP to SEED – AD Subject 4 confusion matrix

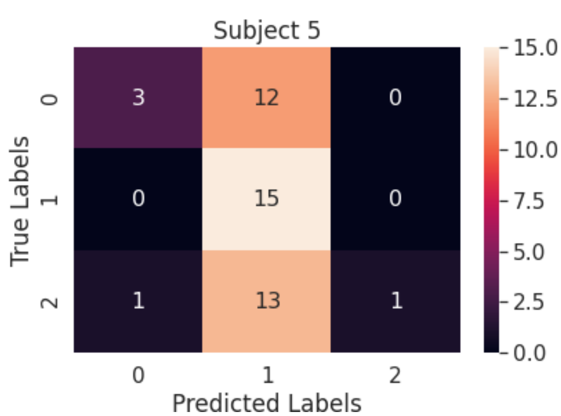

Figure 92. DEAP to SEED – AD Subject 5 confusion matrix

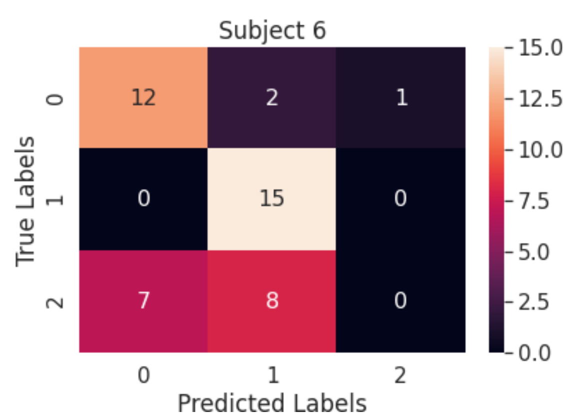

Figure 93. DEAP to SEED – AD Subject 6 confusion matrix

DEAP → SEED per subject - normalization across all data - continued

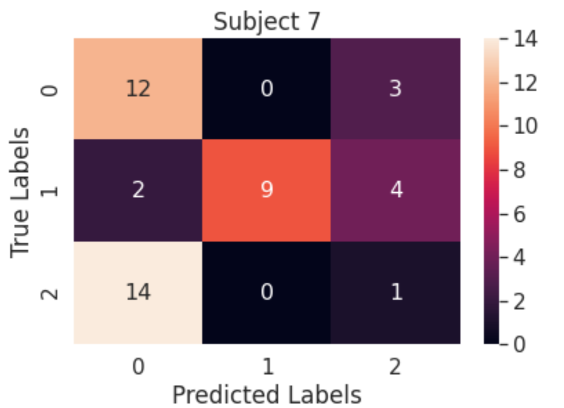

Figure 94. DEAP to SEED – AD Subject 7 confusion matrix

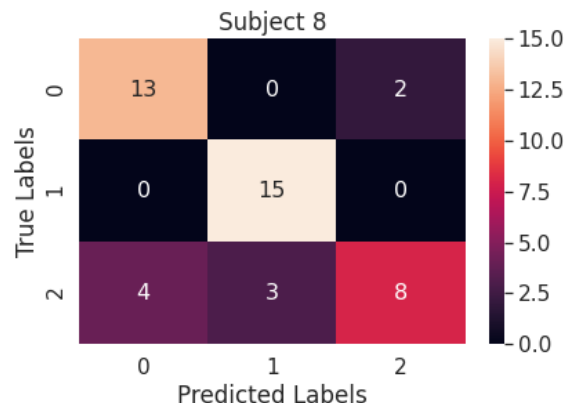

Figure 95. DEAP to SEED – AD Subject 8 confusion matrix

Figures 88 through 95 are the confusion matrix outputs for subjects 1 through 8.

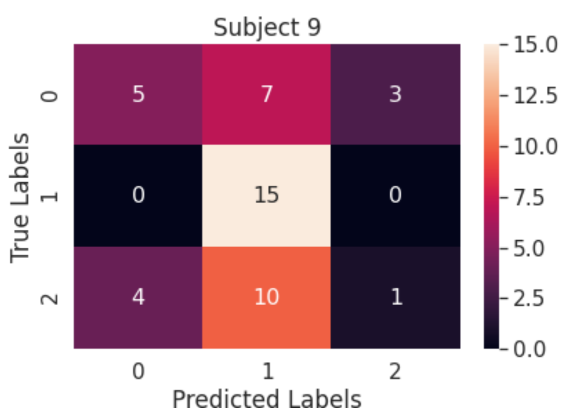

Figure 96. DEAP to SEED – AD Subject 9 confusion matrix

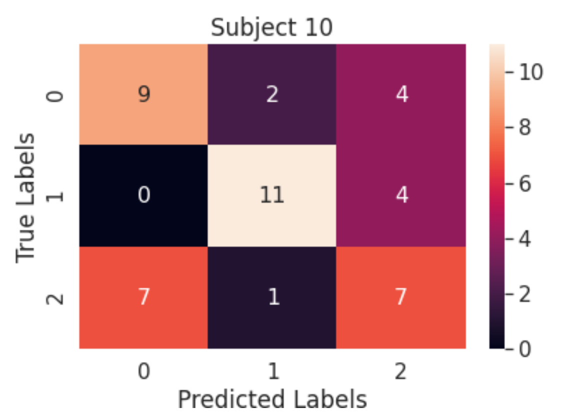

Figure 97. DEAP to SEED – AD Subject 10 confusion matrix

DEAP → SEED per subject - normalization across all data - continued

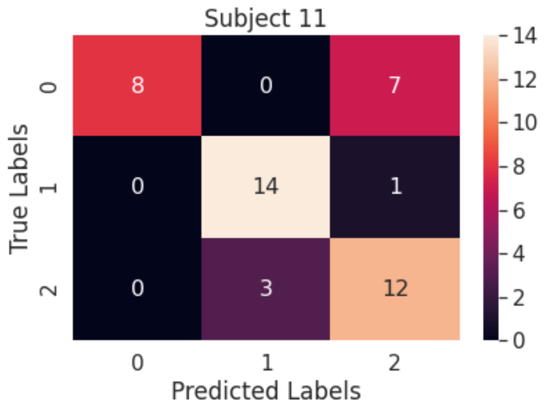

Figure 98. DEAP to SEED – AD Subject 11 confusion matrix

Figure 99. DEAP to SEED – AD Subject 12 confusion matrix

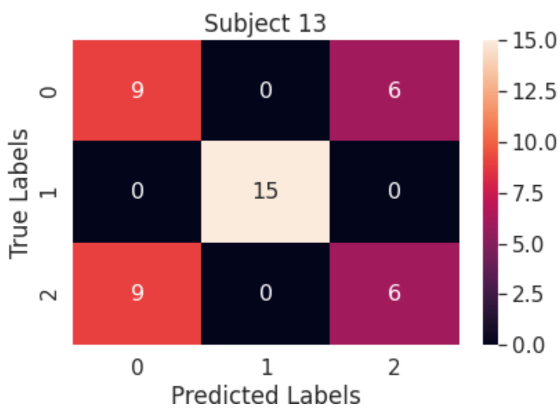

Figure 100. DEAP to SEED – AD Subject 13 confusion matrix

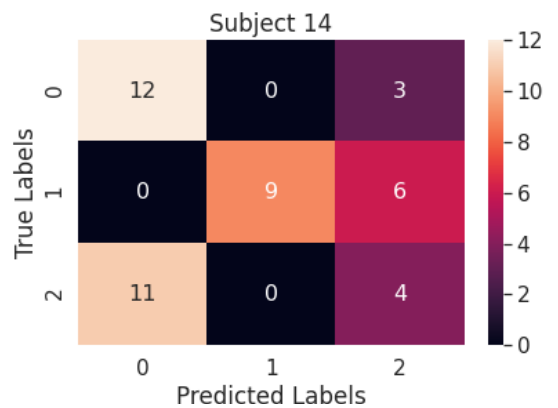

Figure 101. DEAP to SEED – AD Subject 14 confusion matrix

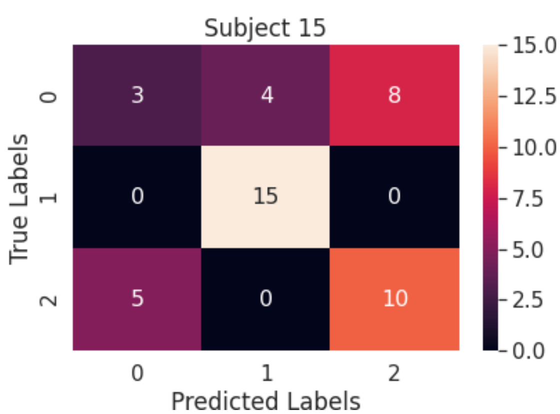

Figure 102. DEAP to SEED – AD Subject 15 confusion matrix

Figures 96 through 102 are the confusion matrix outputs for subjects 9 through 15.

The above portion shows the confusion matrices for each subject across the four transfer learning methods and two normalization techniques. As we can conclude from the above data, the DEAP → SEED transfer learning methods performed much better than the DEAP → SEED methods. Furthermore, we can further support our conclusion that the per subject normalization technique is much better than the across dataset technique. The SEED → DEAP method that used normalization across the entire dataset indicates that this is a valid conclusion.

CHAPTER IV

CONCLUSION

In this paper we explored performing transfer learning techniques across two publicly available datasets in an attempt to generalize unseen data well enough for real-world applications. We also investigated two normalization methods, per subject and entire dataset. We concluded that transfer learning is relatively beneficial in comparison to traditional machine learning methods. We also concluded that per subject normalization performs better than across dataset normalization. While these conclusions were made, the accuracies obtained through our experiments were not as high as we would have hoped. Because of this, more work needs to be done in the realm of transfer learning in order to apply emotion recognition to real-world applications.

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