Project 2 Report

Introduction:

This project aims to evaluate the classification performance of traditional machine learning (KNN, SVM, and Random Forest) and deep learning (MLP) models on human motion data from the PSU-TMM100 Taiji-Quan dataset. The goal is to compare these classifiers with and without Fisher Projection (LDA) for dimensionality reduction, assess their robustness using Leave-One-Subject-Out (LOSO) cross-validation, and identify the most discriminative features using both filter and wrapper methods.

The dataset consists of three versions (SET1, SET2, and SET3) with different padding sizes (N = 100, 200, 300) and includes 39 pose classes (38 key poses and one transition pose). Each sample contains 68 features representing Euler angles (x, y, z) and confidence scores from 17 body joints. The classifiers will be trained and tested under different configurations, with performance metrics such as accuracy, precision, recall, and F1-score analyzed across LOSO iterations. Additionally, confusion matrices will be examined to understand classification errors, and the most discriminative body joints will be identified to improve motion classification efficiency.

Dataset and Preprocessing:

The dataset consists of three variations—SET1, SET2, and SET3—each corresponding to different window sizes (N = 100, 200, 300). It contains motion capture data from 10 subjects performing Taiji-Quan, with each sample representing one of 39 pose classes (38 key poses + 1 transition pose). Each data point includes 68 features derived from 17 body joints, capturing their Euler angles (x, y, z) and confidence scores.

For preprocessing, Euler angles are normalized to the [0,1] range to ensure consistency across features. Missing values, particularly in confidence scores, are either removed or replaced to maintain data integrity. Fisher Projection (LDA) is applied to reduce dimensionality and enhance classification performance. The dataset is split using Leave-One-Subject-Out (LOSO) cross-validation, where models are trained on data from 9 subjects and tested on the remaining subject in an iterative manner to evaluate generalization across individuals.

Classifiers and Feature Selection:

The classification task employs both classical machine learning models and deep learning approaches. Random Forest is used as the traditional classifiers with varying numbers of estimators. For deep learning, a Multi-Layer Perceptron (MLP) is implemented with different architectures (1, 2, and 3 hidden layers) and with a variation of the parameters, using ReLU activation and the Adam optimizer to improve training stability and convergence.

Feature selection is performed using a filter-based approach, where features are ranked based on their ANOVA F-score. The most discriminative features are calculated using F-scores for each feature and selecting the top-K most relevant ones. This helps in reducing dimensionality and retaining only the most important features for classification. This combination ensures that the model is trained in the most informative features, enhancing both accuracy and computational efficiency.

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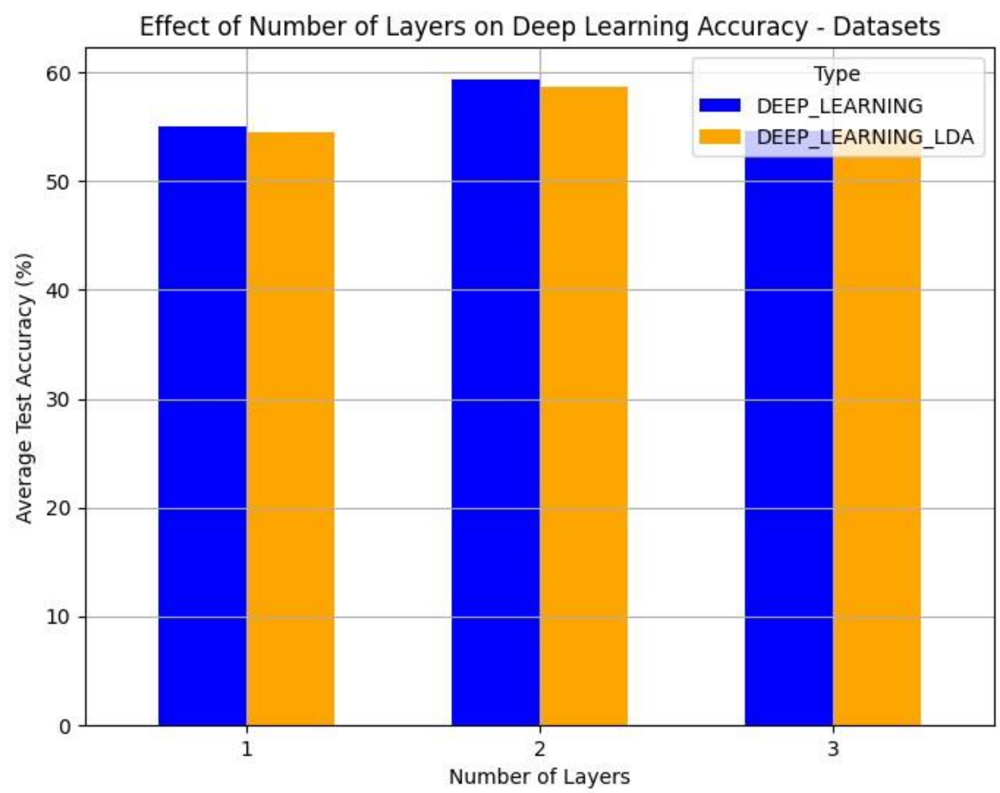
Experimental Setup:

The experimental setup follows a Leave-One-Subject-Out (LOSO) cross-validation approach, where models are trained on data from 9 subjects and tested on the remaining subject, ensuring a robust evaluation across all 10 subjects. The classification performance is assessed by computing the mean and standard deviation of accuracy across these iterations. Additionally, models are trained and tested with and without Fisher Projection (LDA) to analyze the impact of dimensionality reduction on classification accuracy. Accuracy is compared across different classifiers and datasets to evaluate their effectiveness in human motion classification.

Results & Analysis:

- The classification rates on ALL three datasets using the two types of classifiers (classic v deep learning) separately using tables and figures (e.g. bar graph) while varying their respective parameters w and w/o Fisher projection etc.



I have varied the number of layers for the MLP and found it gives better results if there are 2 layers.

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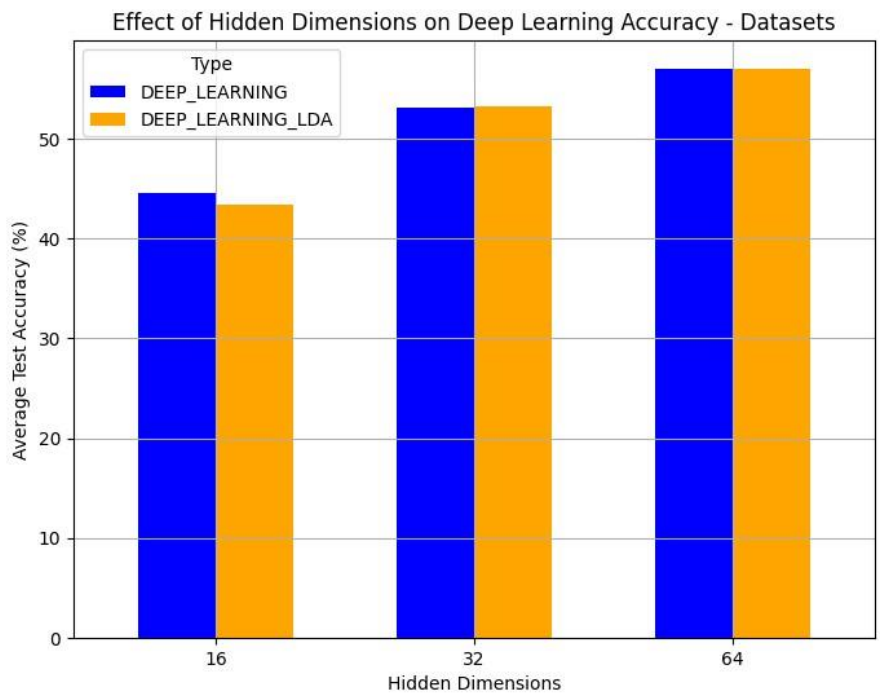
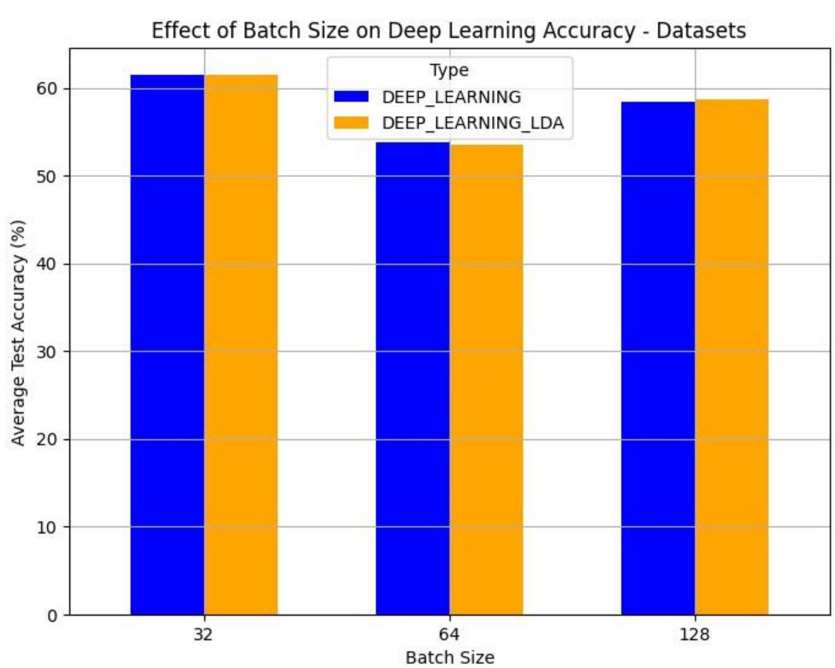


By varying the number of hidden dimensions for each layer, I have observed that the performance is becoming better with an increasing number of hidden dimensions. However, due to the computational constraints of my machine, I have used at max 64 hidden dimensions for each layer.



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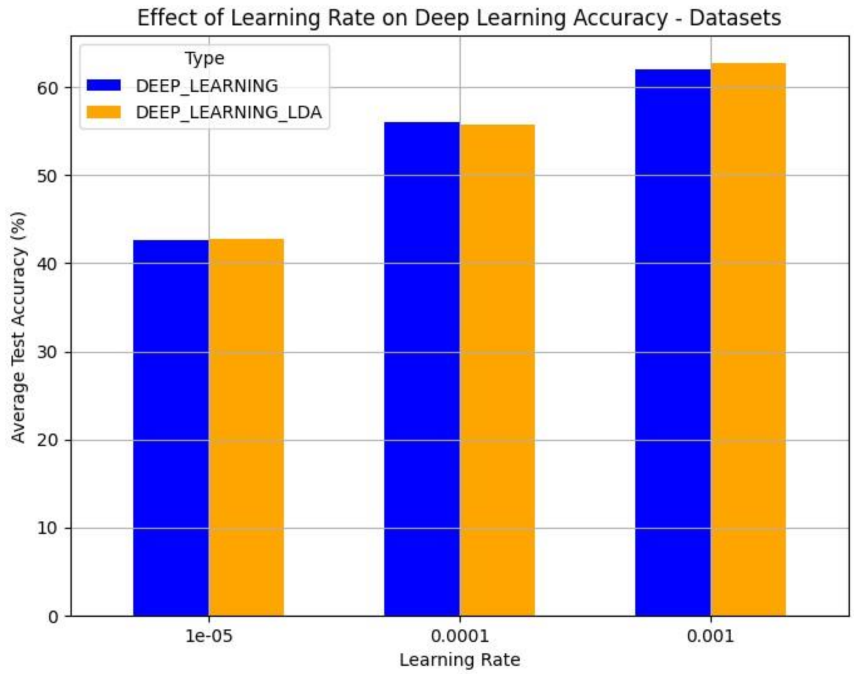
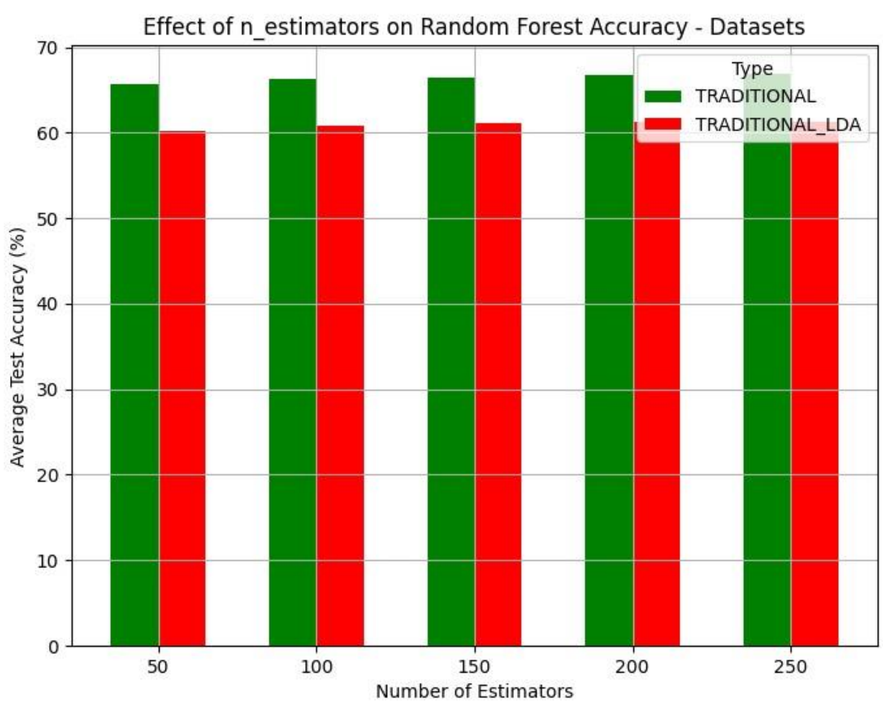
For batch size, I have selected 32 as it gives the optimum result compared to others.



For learning rate, 0.001 is selected as I found better results with this.



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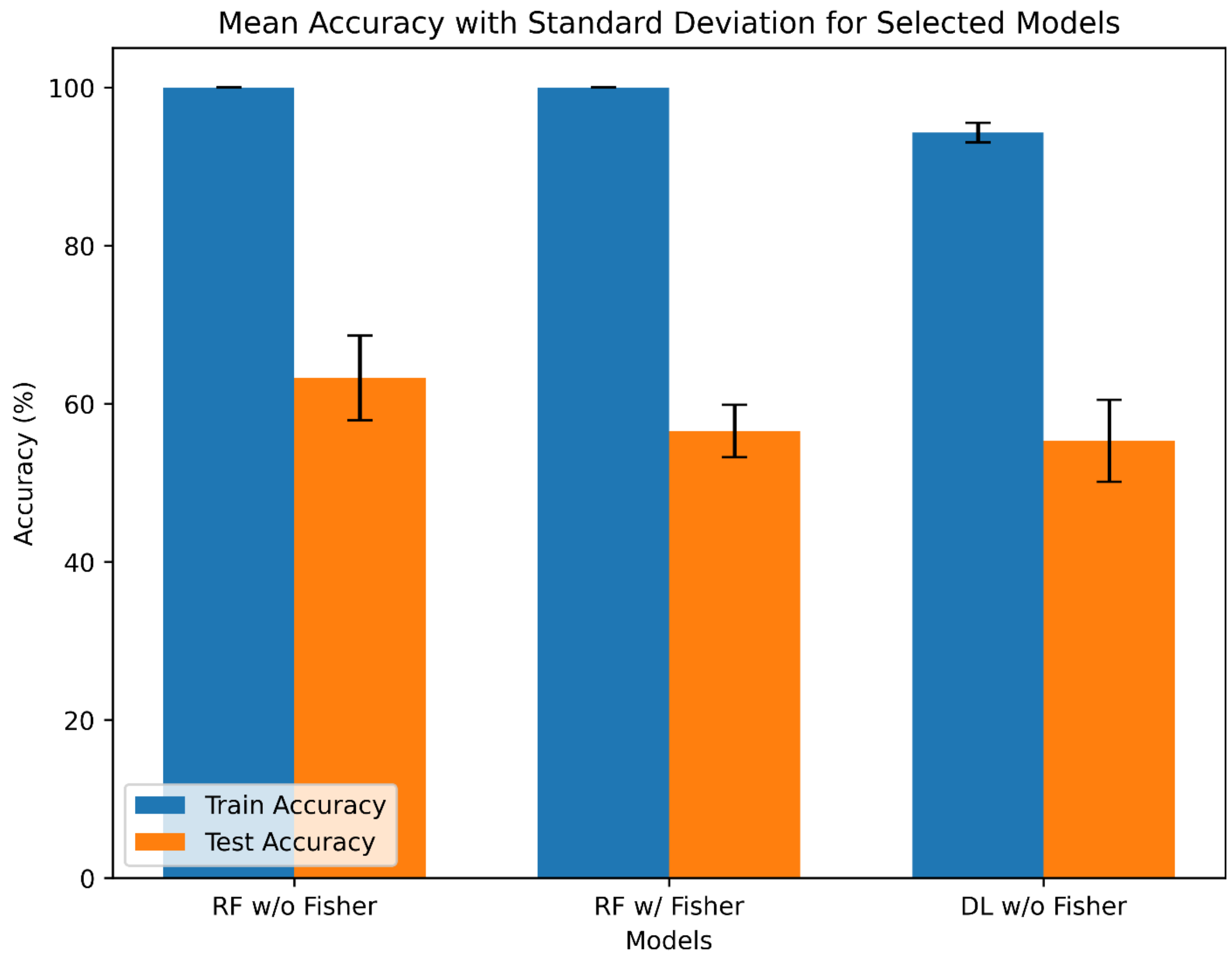
For traditional machine learning, I have used random forest classifier and varied the number of estimators parameter. I have observed that after 150, the result does not improve that much. Hence, I have selected 150 as the model parameter for later simulations.

- Pick TOP 3 from each of the two approaches above, Report the results (both training and testing) in different ways.

I have selected Random Forest Classifier w and w/o Fisher projection with 150 as the number of estimators, and Deep Learning model w/o Fisher projection as the top three classifiers with 2 layers, 64 hidden dimensions, 32 as batch size and 0.001 as the learning rate, and run the model for 20 epochs.

Best classifier -



I have found that traditional random forest classifier without Fisher projection works the best compared to other two I have selected.

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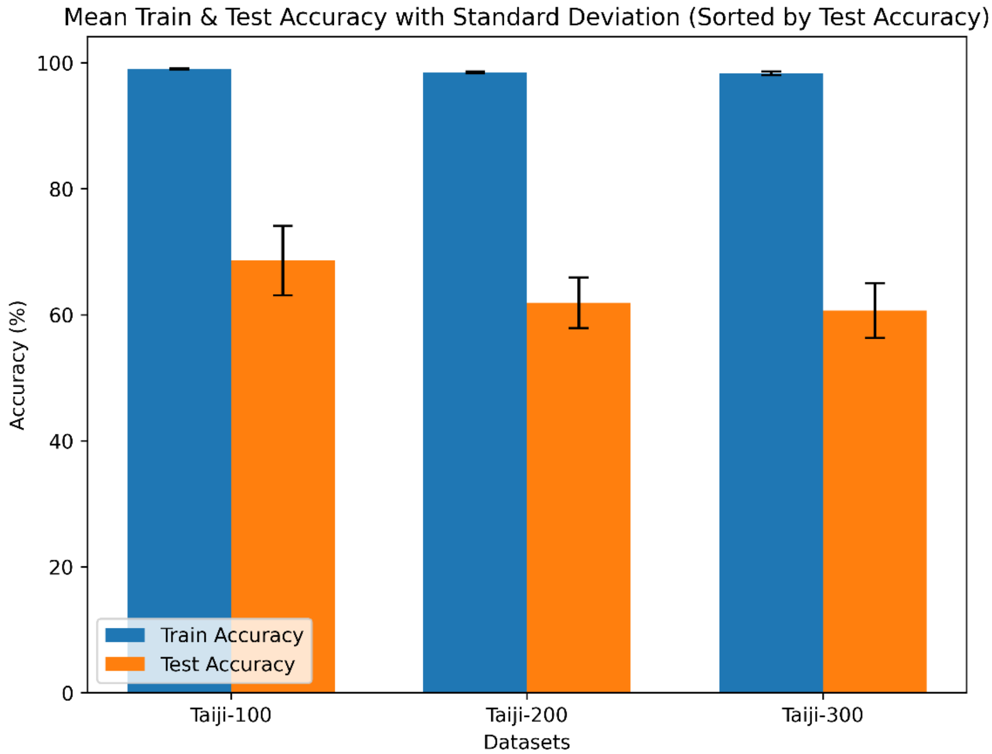
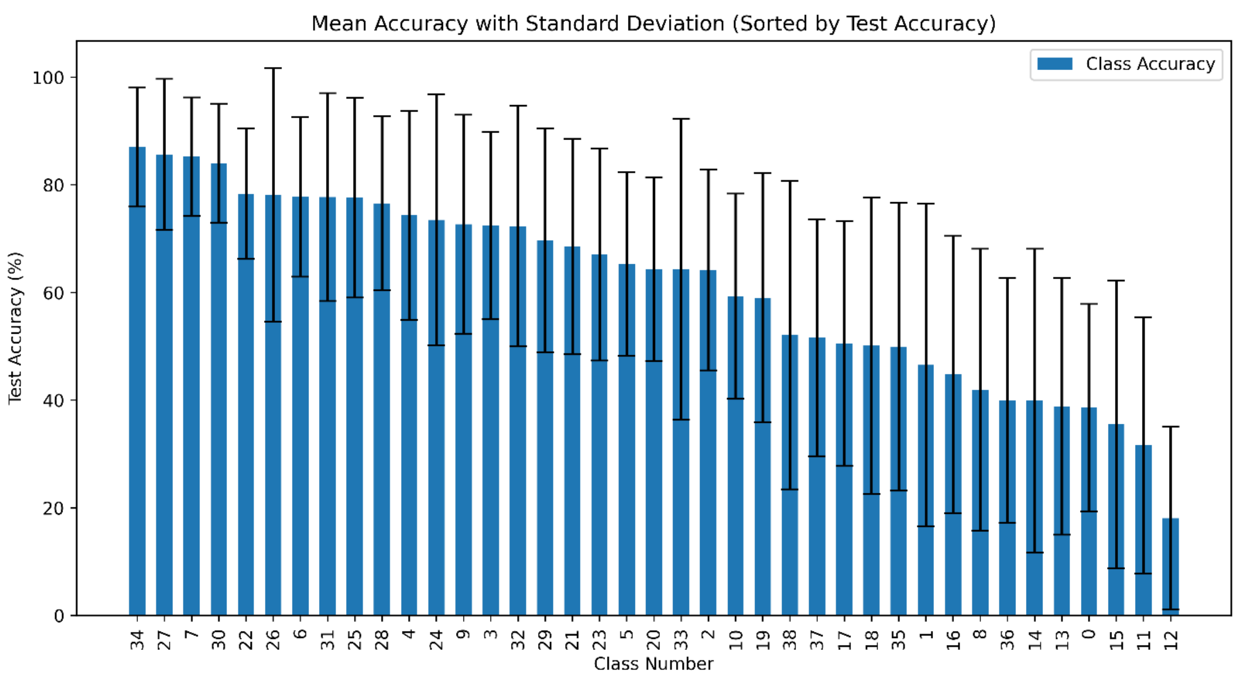
Best dataset –



The dataset with N = 100 performs the best of the three datasets.

Best classified classes –



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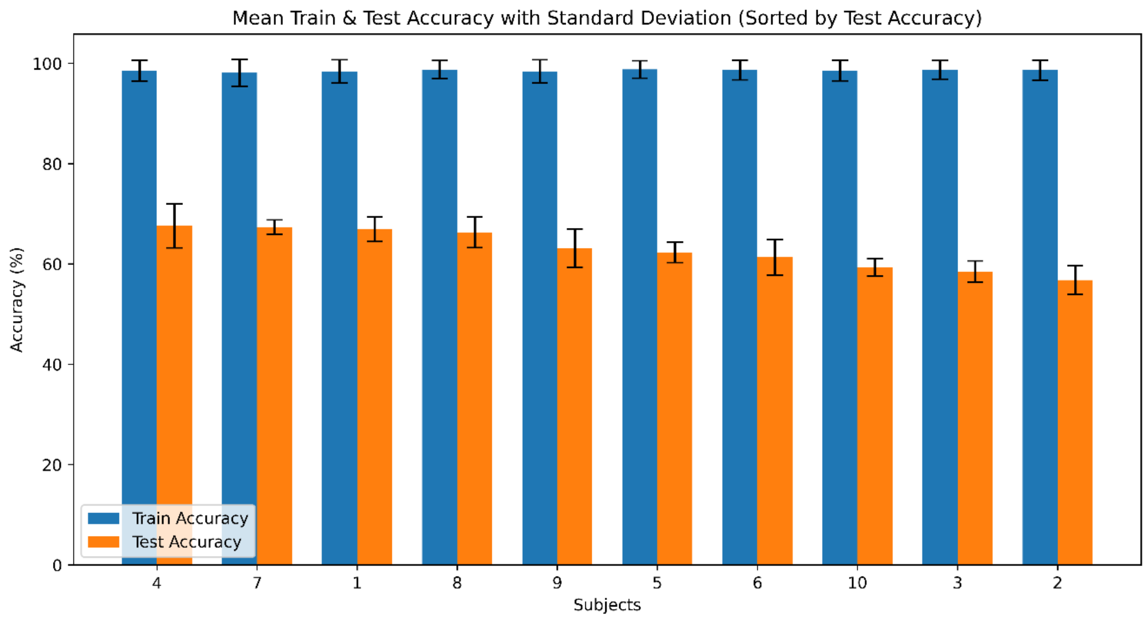
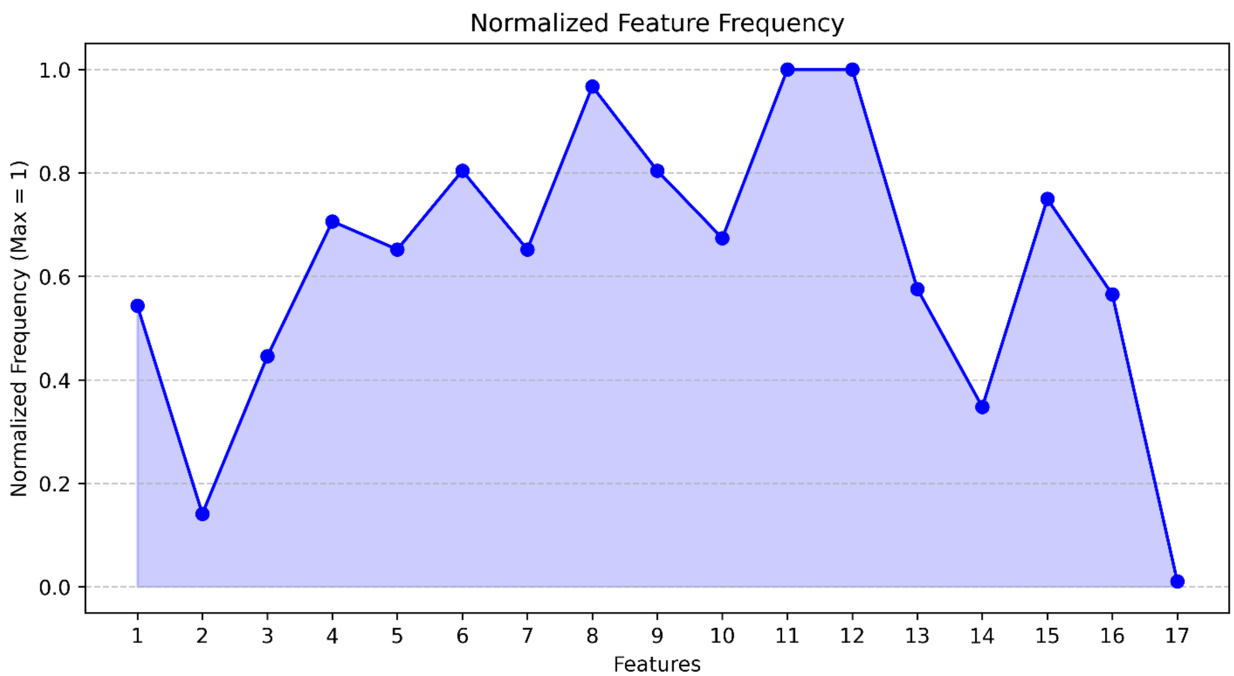
I have plotted the classified class test accuracies in a descending order and found that class number 34, 27, 7 and 30 are the easiest classes to classify compared to other classes.

Best subjects –



Although the test accuracies for the subjects does not vary that much, subject number 4, 7, 1 and 8 are the best subjects in terms of accuracy.

Best body joint features –



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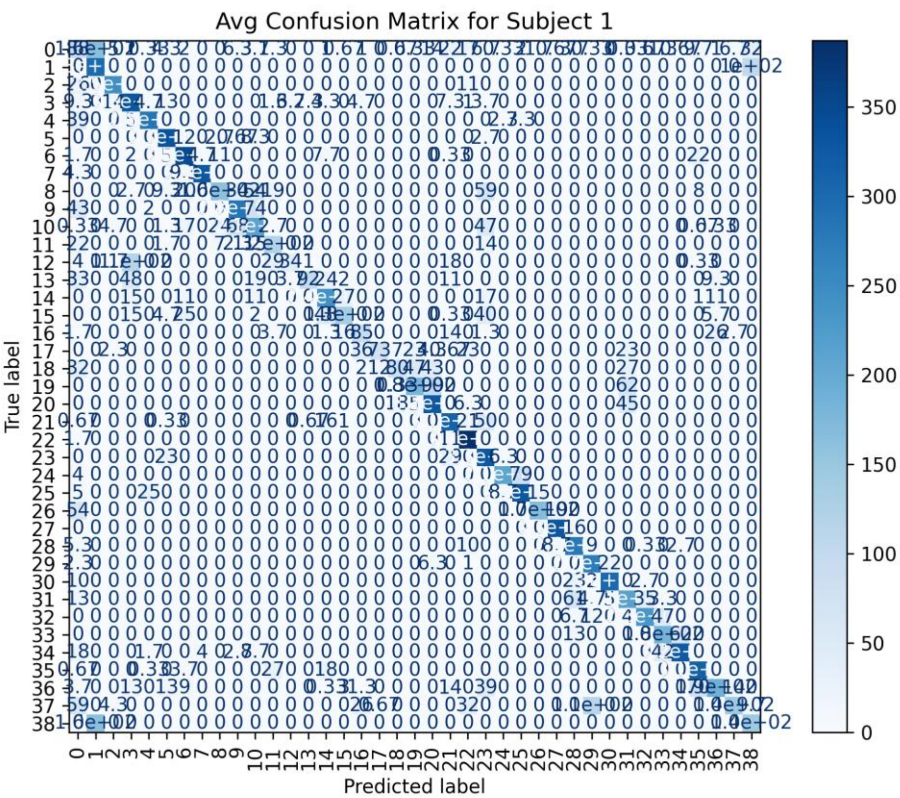
I have found that left knee (11), left ankle (12), right knee (8), right ankle (9) and left wrist (6) are the most discriminative features.

Confusion matrices –

I have selected the random forest classifier without Fisher projection for calculating the confusion matrices for 10 subjects.



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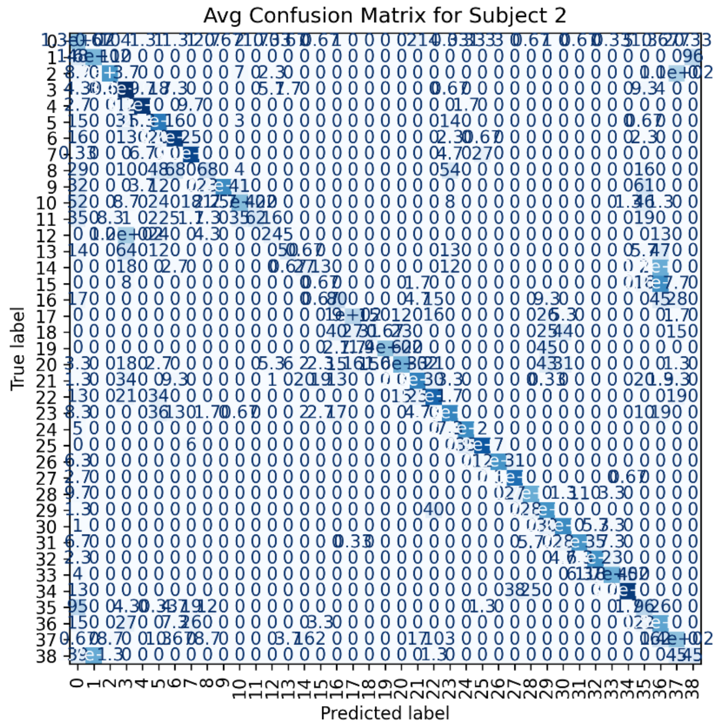

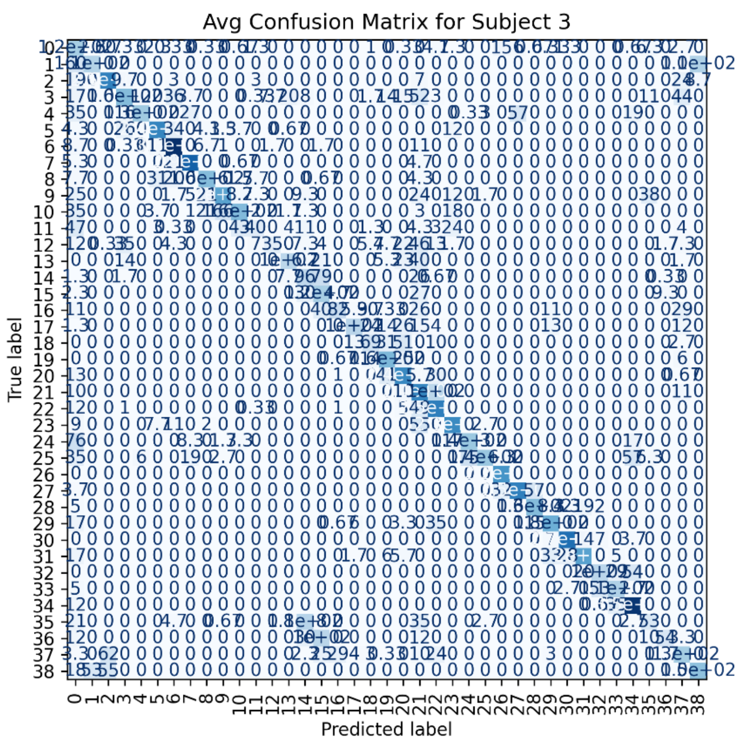

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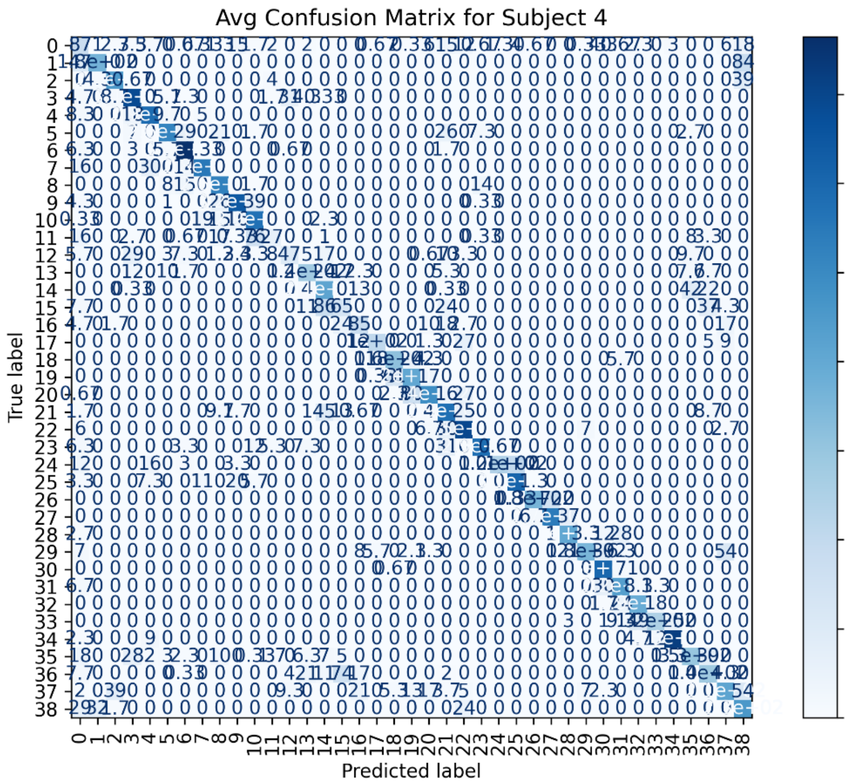

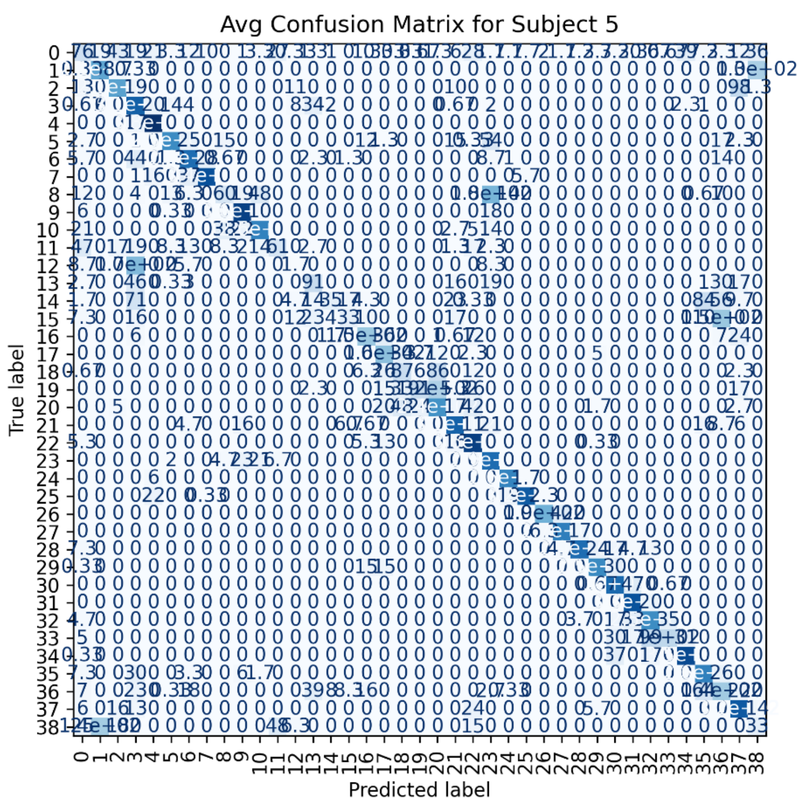

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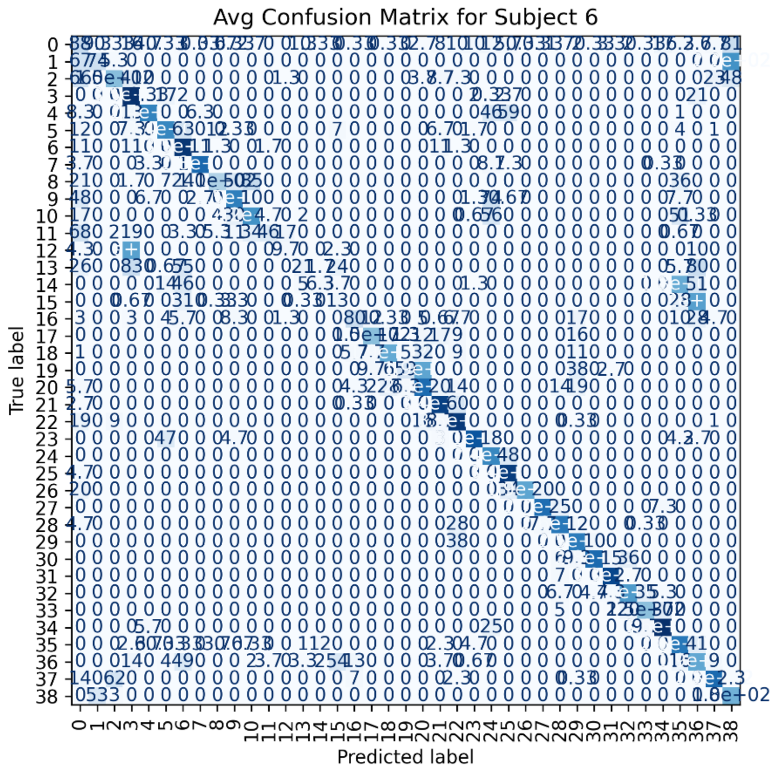

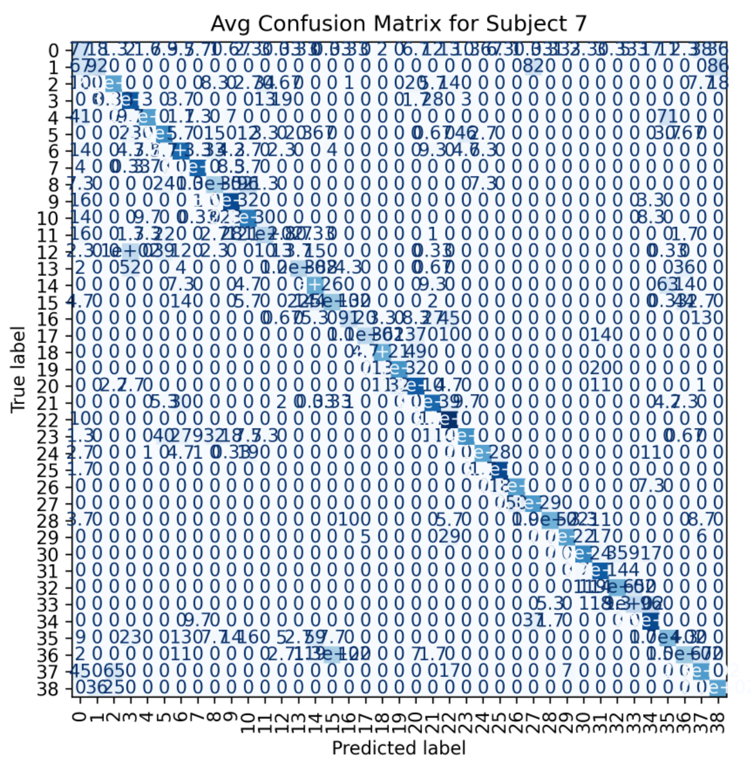

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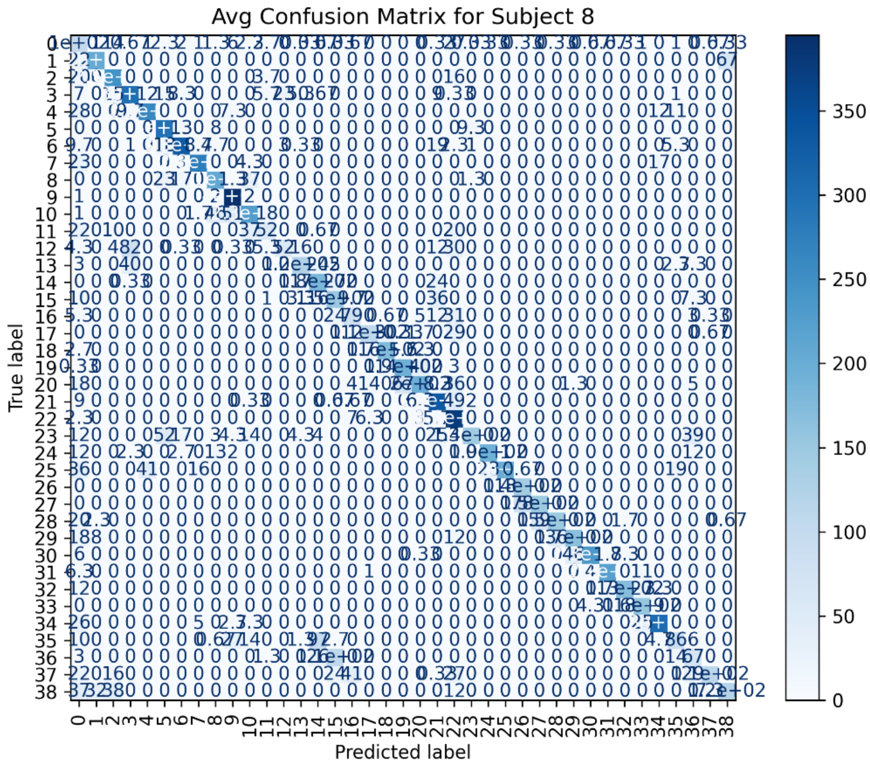

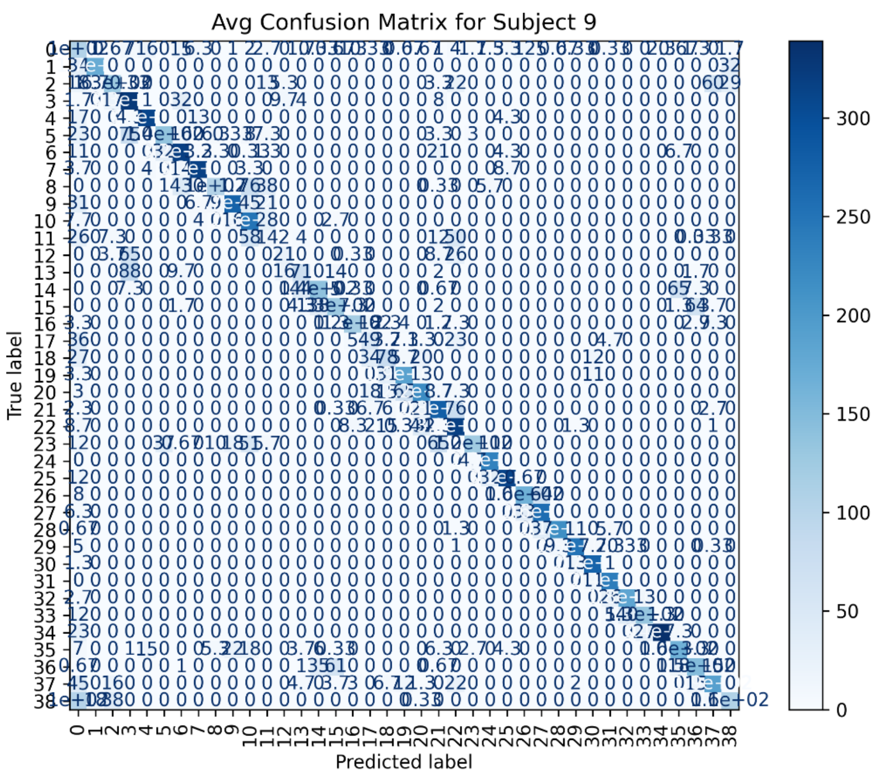

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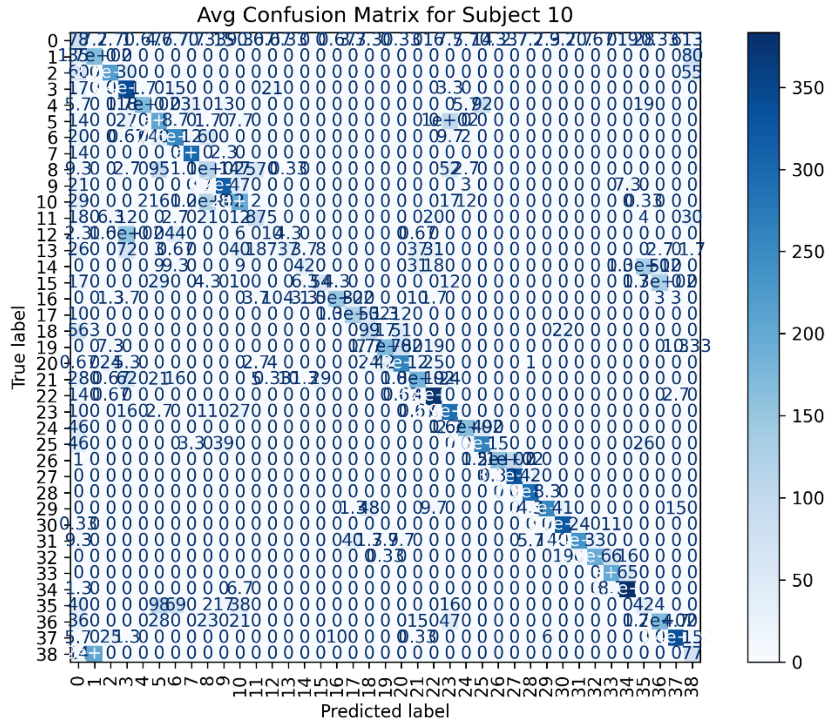

Analysis –

The classification performance varied across different models, with the Random Forest classifier without Fisher Projection (LDA) achieving the highest accuracy among all tested approaches. The MLP model with two hidden layers and 64 hidden units per layer performed better and increasing the number of hidden dimensions further improved results. However, due to computational constraints, a maximum of 64 hidden units per layer was used. Batch size of 32 and a learning rate of 0.001 provided optimal results for deep learning training. For Random Forest, increasing the number of estimators improved performance up to 150 trees, beyond which additional trees did not yield significant gains.

The impact of Fisher Projection was mixed. While dimensionality reduction helped in some cases, it also led to loss of useful information, resulting in slightly lower accuracy for certain models. Notably, Random Forest performed better without Fisher Projection, while MLP showed comparable performance with and without projection depending on the dataset. Among the three datasets, SET1 (N = 100) achieved the best classification results, suggesting that a smaller context window led to improved recognition of key poses.

Further analysis of class-wise performance revealed that Classes 34, 27, 7, and 30 were the easiest to classify, likely due to their distinct motion patterns. Subject-wise classification showed relatively stable results, with Subjects 4, 7, 1, and 8 achieving the highest accuracy, indicating more consistent movement patterns that the models could learn effectively. Additionally, feature selection identified left knee (joint 11), left ankle (joint 12), right knee (joint 8), right ankle (joint 9), and left wrist (joint 6) as the most discriminative features. These joints appear to play a critical role in distinguishing different Taiji movements, making them essential for classification.

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Conclusion:

The analysis demonstrates that traditional machine learning models, particularly Random Forest, outperformed deep learning models for this classification task. While MLP benefitted from deeper architecture and increased hidden units, Random Forest without Fisher Projection remained the most robust model overall. The dataset with N = 100 (SET1) produced the highest accuracy, indicating that a smaller context window leads to better classification. The easiest-to-classify poses and most discriminative joints highlight key movement patterns essential for human motion analysis.