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Problem Statement

Body-Focused Repetitive Behaviors (BFRBs), including hair pulling, skin picking, and nail biting, are repetitive self-directed actions associated with anxiety and OCD, and to study these, the wrist-worn Helios device equipped with IMUs, thermopiles, and time-of-flight sensors was used to record participants performing 18 gestures (8 BFRB-like and 10 non-BFRB) across four body positions, following a structured sequence of hand transition, brief pause, and gesture execution to evaluate the added value of the extra sensors in detecting BFRB-like movements.

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Motivation

Body-Focused Repetitive Behaviors (BFRBs), such as hair pulling, skin picking, and nail biting, are under-detected repetitive actions linked to anxiety and OCD that can cause significant physical and psychosocial harm; developing wearable devices like Helios, which combine motion, heat, and proximity sensors, can improve detection of these behaviors, enabling early intervention, better monitoring, and enhanced understanding of mental health patterns.

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Key Contribution

- Feature extraction from IMU, Thermophile & ToF.
- Building a pipeline for testing our proposed ML models and finding the best fit.
- Use of XgBoost to increase the accuracy of the best model from above.
- Use of 1D CNN to look for better model from the given datasets.

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Method
Part-1 (Preparation)

Data processing and feature extraction

- Importing required libraries to process the train, test files.
- Extraction of IMU, Thermophile & ToF features for training.
- Data pipeline for merging the extracted features to train the proposed models.

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Method
Part-2 (Training begins)

Model training and further improvement

- Using different ML models like Random Forest, Decision Trees, Logistic Regression, KNN algo & Voting Classifier.
- Training the prepared data on these models to find the best out of these five to find the best one.
- Further, using XGBoost to improve the accuracy of the best model obtained.
- Next step -> Next slide....

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Method
Part-3 (Exploring Deep Learning)

Further training using CNN's & other

- Building a 1D CNN model to look for improvements in the validation_accuracy.
- Hypertuning the parameters of the 1D CNN model to improve the val_accuracy by 2-5%.
- Trying LSTM to check for some improvements.

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Results

I) Comparison of proposed models

Logistic Regression

```
Logistic Regression Macro F1 Score (Validation): 0.5703
```

K-Nearest Neighbours

```
k-Nearest Neighbors Macro F1 Score (Validation): 0.4765
```

Decision Trees

```
Decision Tree Macro F1 Score (Validation): 0.4839
```

Random Forest

```
Random Forest Macro F1 Score (Validation): 0.6864
```

Voting Classifier

```
Voting Classifier Macro F1 Score (Validation): 0.5216
```

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Results
II) XGBoost, 1D CNN & Some LSTM’S

XGBoost

```
Optimized XGBoost Macro F1 on Validation: 0.7074
```

1D CNN

```
Validation Accuracy: 0.5550102249488753
Validation Macro F1: 0.5687377856456846
```

1D CNN(with hypertuned params)

```
Validation Accuracy: 0.6343558282208589
Validation Macro F1: 0.645763211839946
```

GCN, GAT, CNN2D & CNN3D

```
▶ Training GCN ...
Epoch 5/80: loss=0.694, Macro=0.333, Acc=0.500
Epoch 10/80: loss=0.692, Macro=0.333, Acc=0.500
■ Early stop at epoch 12

▶ Training GAT ...
Epoch 5/80: loss=0.684, Macro=0.333, Acc=0.500
Epoch 10/80: loss=0.690, Macro=0.333, Acc=0.500
■ Early stop at epoch 12

▶ Training CNN2D ...
Epoch 5/80: loss=0.692, Macro=0.333, Acc=0.500
Epoch 10/80: loss=0.694, Macro=0.333, Acc=0.500
Epoch 15/80: loss=0.695, Macro=0.333, Acc=0.500
■ Early stop at epoch 18

▶ Training CNN3D ...
Epoch 5/80: loss=0.689, Macro=0.333, Acc=0.500
Epoch 10/80: loss=0.689, Macro=0.333, Acc=0.500
■ Early stop at epoch 12
```

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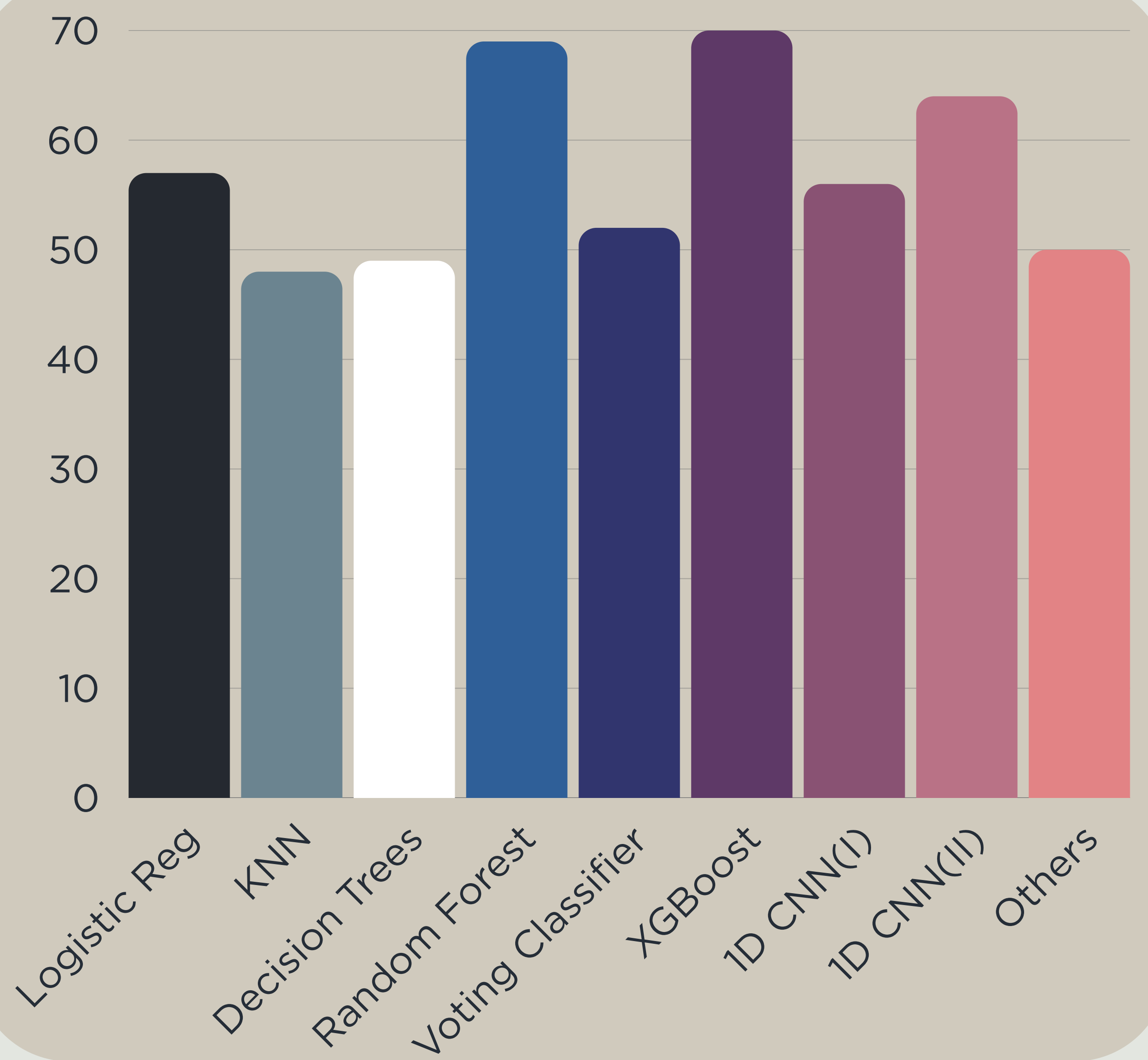
Conclusion



Key Points

- From the graph we can clearing see that Random Forest optimised using XGBoost performs the best.
- In short the for these type of datasets i.e. (.csv files) Random Forest is the effective choice.

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Conclusion
Future Enchancements

What is the planning?

- Train the models used on larger datasets and make the models robust.
- Using more deeper models to obtain more valuable results.
- Investigate long-term patterns of BFRBs to better understand mental health impacts.
- Develop real-time monitoring and alert systems for early intervention (if time permits).