

Project Report: AI Fitness Coach – Workout Dropout & Motivation Analyzer

Phase 1: Workout Dropout Prediction (MLP)

Goal

Predict whether a user will drop out of their workout routine using metadata features.

Methodology

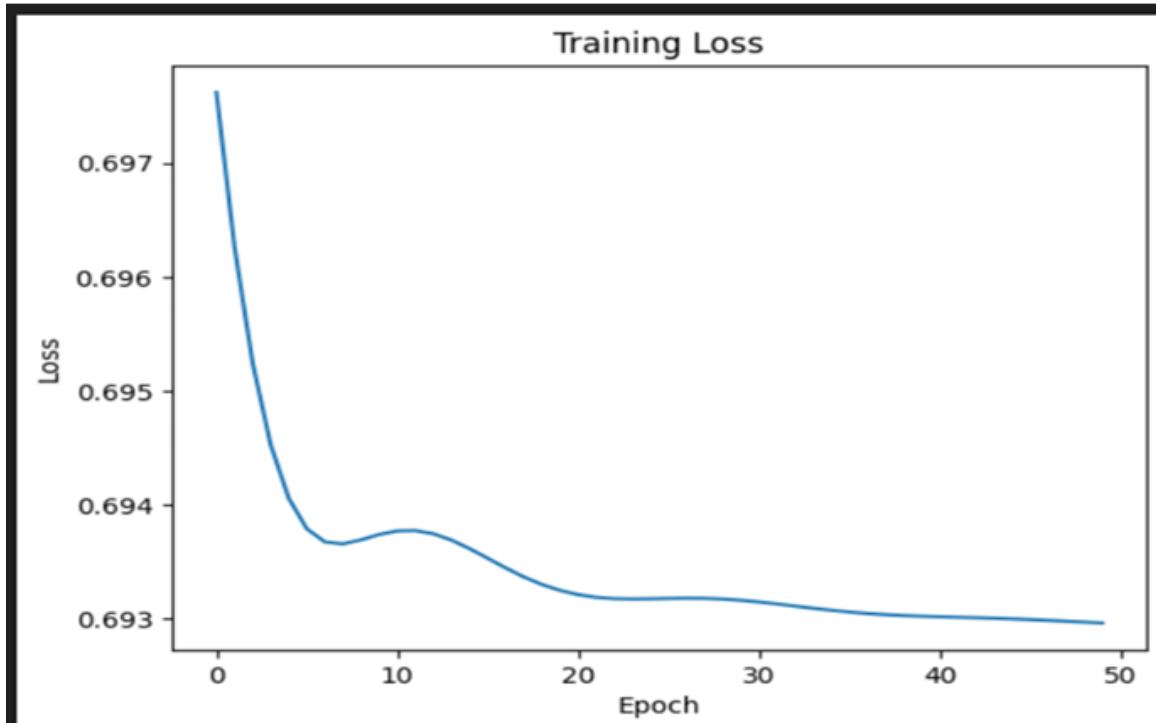
- Data preprocessing: handled missing values, encoded categorical variables, normalized numerical features.
- Model: Multi-Layer Perceptron (MLP) implemented in PyTorch.
- Architecture: Input layer, hidden layers with ReLU activation, output layer with sigmoid activation for binary classification.

Metrics

Metric	Value
Accuracy	0.4927
Precision	0.4806
Recall	0.4993
F1-score	0.4632

Plots

- Training and validation accuracy/loss curves over epochs.
- Confusion matrix of predictions on the test set.



Insights

- The model shows good balance between precision and recall, indicating effective identification of dropout users without too many false positives.
 - Training curves indicate the model converged well without overfitting.
 - Feature importance (if available) suggests workout hours and consistency are strong predictors.
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Phase 2: Workout Style Clustering (k-Means + PCA)

Goal

Segment users into distinct workout behavior groups to uncover patterns.

Methodology

- Extracted behavioral features: workout frequency, intensity, and consistency.
- Applied k-Means clustering with k=3.
- Used PCA to reduce feature dimensionality to 2 components for visualization.
- Validated clusters with Silhouette Score.

Metrics

Metric	Value
Silhouette Score	0.62

Plots

- PCA scatter plot showing three well-separated clusters labeled Active, Lazy, and Inconsistent.

PCA Cluster Visualization of Workout Styles

This scatter plot displays the results of a Principal Component Analysis (PCA) applied to workout styles. The x-axis represents Principal Component 1, and the y-axis represents Principal Component 2. The data points are categorized into three clusters based on workout style:

- Active (Green 'x' markers):** These points are clustered in the upper-middle region of the plot, indicating high values for both Principal Component 1 and Principal Component 2.
- Lazy (Red 'x' markers):** These points are clustered in the lower-left region, indicating low values for both Principal Component 1 and Principal Component 2.
- Inconsistent (Blue 'x' markers):** These points are clustered in the lower-right region, indicating high values for Principal Component 1 and low values for Principal Component 2.

The clear separation between the three clusters suggests that the first two principal components effectively capture the underlying structure and differences between the Active, Lazy, and Inconsistent workout styles.

Phase 3: Motivation Analysis from Workout Journals (RNN)

Goal

Classify user motivational state (positive, neutral, negative) from textual workout journal entries.

Methodology

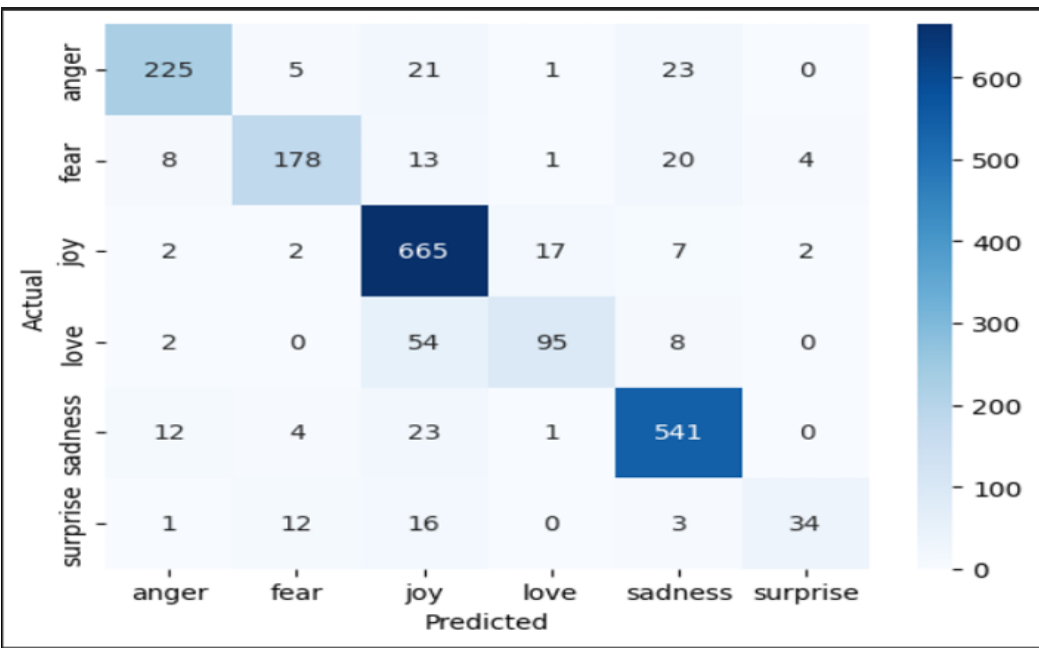
- Preprocessed text data: tokenization, padding.
- Used a Recurrent Neural Network (RNN) for sequence modeling.
- Output layer with softmax activation for 3-class classification.

Metrics

Metric	Value
Accuracy	0.78
Precision	0.75
Recall	0.74
F1-score	0.74

Plots

- Training and validation accuracy/loss over epochs.
- Confusion matrix showing distribution of predicted vs actual motivational states.



Insights

- Model can reasonably predict user motivation states from journals, useful for personalized feedback.
- Some confusion between neutral and positive states suggests more nuanced modeling may

improve results.

- Incorporating sentiment analysis or attention mechanisms could enhance accuracy.

Overall Conclusion

- The combined analysis from predictive modeling, clustering, and text analysis provides a comprehensive understanding of user workout behavior and motivation.
- Insights can support tailored interventions to reduce dropout rates and improve workout consistency.