beats2beats: Activity-Driven Music Playlist Recommendation System Using Wearable Sensor Data

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Introduction

- Recommending a music that is suited to what a person is currently doing is a non-trivial task.
- Current music recommender algorithms depend on data collected from the user to build a profile which require long-term usage of the system.
- **The Gap:** Very little focus on recommender systems that do not rely on long-term user profiling.
- **Untapped Potential:** Integration of these systems to the physical metrics collected by sensors of modern smart devices.
- **Major Contribution:** Leverage real-time sensor readings of smart watches to predict current user activity and recommend a playlist that would appropriately match the user's activity.

Objective

The main objective of this study is to construct a music recommendation system that will take into account the physical activity that a user is currently doing.

Specifically, this study aims to:

- Identify the activity that is being performed by a user based on sensor data.
- Construct a playlist of songs according to the user's current activity.

Methodology

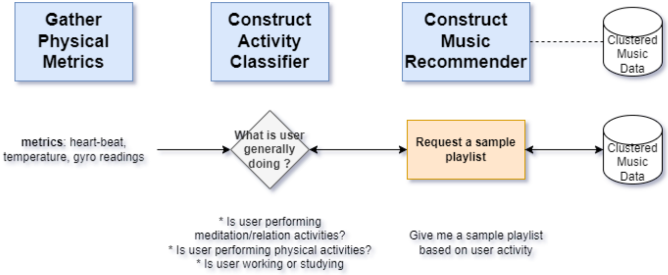


Figure: General Workflow of Music Recommendation

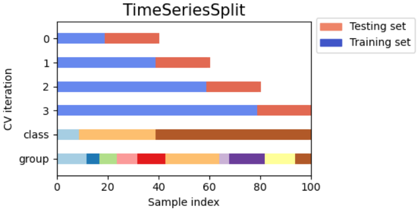
The general workflow of music recommendation starts with classifying the physical metrics (sensor data) into activity types. Based on the activity type, recommendation follows by sampling and filtering music from already clustered music database.

Human Activity Classifier

Observations from the PAMAP2 dataset: Sensor readings every 0.01 second for over 10 hours from 9 test subjects performing 18 distinct activities

- Sensor readings were **aggregated per second** for a total of 27,360 observations
- Activities were grouped into **three clusters**: Relaxation, Focused, Physical

11 Features from Wrist Sensor: heart rate, temperature, 3D acceleration, 3D gyroscope data, and 3D magnetometer data



Music Data Feature Selection and Labeling

Dataset: 301 Total Features from 13129 tracks from FMA Data.
8 Audio Features from echonest dataset: acousticness, danceability, energy, instrumentalness, liveness, speechiness, tempo and valence are used for training.
Genre Labels: Music Genres are used to initially label/tag tracks into target classifications.

Table: Genre-based Music Clusters.

Cluster 0: Relaxation [1][2][3]	**Cluster 1: Focus** [1] [2] [3] [1]	**Cluster 2: Physical** [2] [3] [4]
Classical	Old-Time / Historic	Rock
	International	Electronic
	Pop	Jazz

Results

Human Activity Classifier

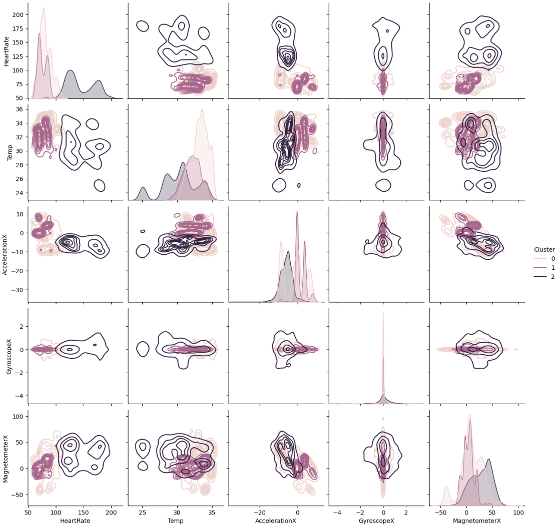


Figure: Pair Plot of Selected Features in PAMAP2 Data.

Human Activity Classifier

Table: Performance metrics of trained classifiers on PAMAP2 Data.

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	0.76	0.86	0.76	0.74
ANN	0.80	0.90	0.80	0.81

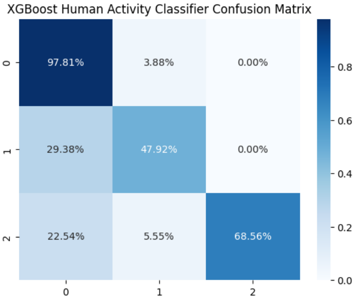


Figure: Confusion Matrix for XGBoost (Left) and ANN (Right) Classifiers trained on PAMAP2 Data.

Human Activity Classifier

Table: Hyperparameters of the best performing ANN classifier on the PAMAP2 data.

Hyperparameters	**Value**
Number of hidden layers	3
Number of neurons	$[11, 64, 32, 16, 3]$
Hidden Layer Activation Function	tanh
Output Layer Activation Function	softmax
Learning Rate	0.001

Music Recommendation

Figure: Pair Plot of Audio Features in FMA Data.

Music Recommendation

Table: Performance metrics of trained classifiers on FMA Data.

Model	Accuracy	Precision	Recall	F1 Score
XGBoost	0.86	0.86	0.86	0.86
AdaBoost	0.79	0.80	0.79	0.79
KNN	0.78	0.78	0.78	0.78

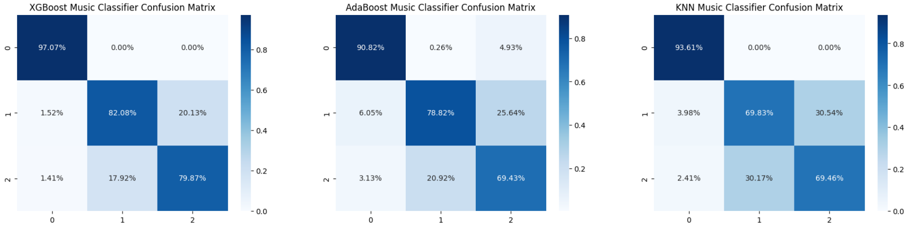


Figure: Confusion Matrix of Different Models of Music Classifier

Conclusion and Future Work

This study was able to construct **two classifiers:** one classifier predicts the type of activity that is currently being performed by the user and another classifier outputs a playlist of songs that is appropriate for the user's activity. The **Artificial Neural Network** was the human activity classifier with the best performance while the **XGBoost classifier** had the best performance in recommending a music playlist.

Future work can involve building an **end-to-end hardware prototype** making use of wearable sensors to implement the trained recommendation system. Moreover, **user studies** can also be conducted to evaluate satisfaction, playlist relevance, and engagement, as well as compare the user evaluations with that of other music recommendation systems.

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