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Machine Learning Approaches in Photoplethysmography-Based Sleep Stage Classification

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Introduction

- Sleep is critical for health and cognitive function.
- Traditional **Polysomnography (PSG)** is accurate but intrusive, expensive, limited to a single night.

Need for long-term, at-home sleep monitoring.

Using a single-sensor PPG with Machine Learning to classify sleep stages

Wake

Light

Deep

REM

Problem Statement and Motivation

- PSG is costly and impractical for continuous monitoring, while PPG offers a cheaper alternative for detecting sleep disorders like hyperpnea
- Models like KNN, SVM, and RF show limited accuracy, motivating the use of ensemble models for better sleep stage classification.
- Compared several ensemble machine learning classifiers like .F

Goal

Enhancing the accuracy of PPG-based four-stage sleep classification through machine learning models.

Literature Review

Existing Work

- **Wu et al. (2020)**: **62%** accuracy (SVM-ANN).
- **Motin et al. (2023)**: **72.39%** accuracy using Random Forest.

Gap Identified

- Limited use of advanced models like **CatBoost and XGBoost.**
- Insufficient feature optimization and hyperparameter tuning.

Dataset Pre-procesing

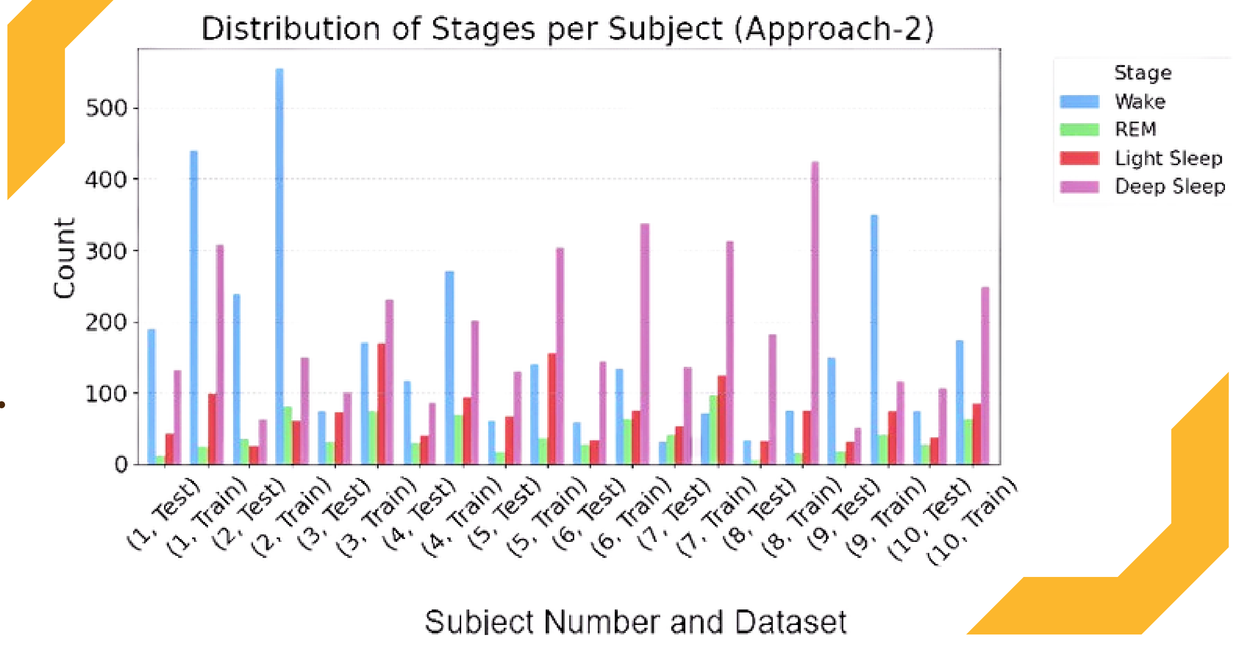
Dataset

- 10 subjects, 7-10 hours per night.
- 30-second epochs labeled using R&K scoring.
- Mapped to 4 sleep stages: Wake, Light, Deep, REM.

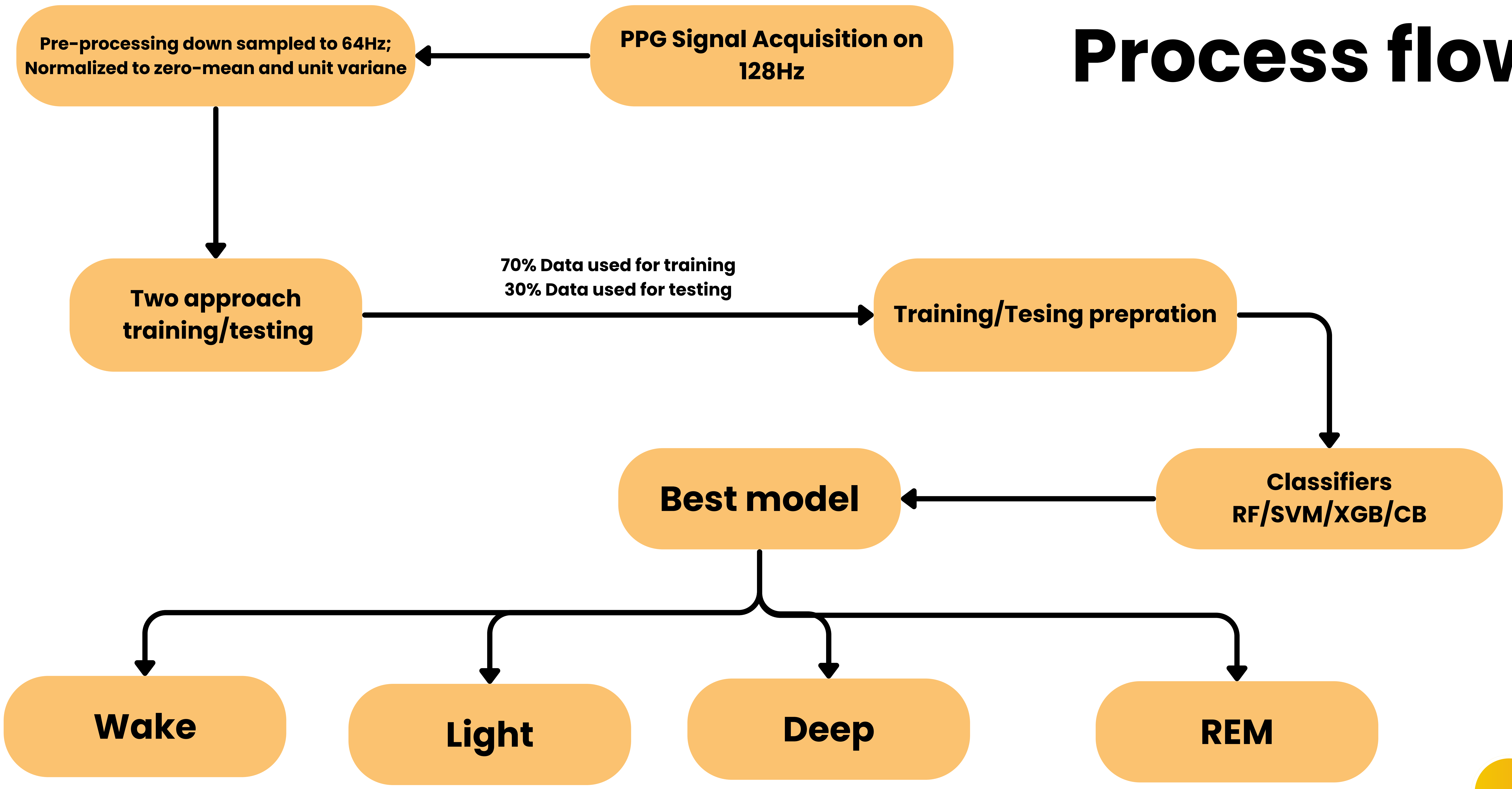
Subject No.	Total Segments	Wake	Light	Deep	REM
Subject 1	1246	629	439	142	36
Subject 2	1212	795	214	87	116
Subject 3	924	245	331	243	105
Subject 4	909	388	288	134	99
Subject 5	909	202	434	221	52
Subject 6	872	192	482	108	90
Subject 7	864	102	448	177	137
Subject 8	844	108	608	101	27
Subject 9	833	500	168	105	60
Subject 10	815	247	356	121	91
Total	9428	3408	3768	1445	807

Preprocessing

- Down-sampled PPG signals: **128Hz → 64Hz.**
- Z-score normalization for feature scaling.
- Feature reduction: Statistical analysis → **72 features** retained.



Process flow



Methodology – ML Pipeline

01 Data Splitting

Approach-1: 70/30% split for training/testing
Approach-2: Subject-wise split

02 Machine Learning Models

SVM, RF, XGBoost, CatBoost

03 Hyperparameter Tuning

Grid Search and Randomized Search

04 Model Evaluation

Accuracy, Precision, Recall, F1-Score, ROC-AUC

Model Implementation

01 Extreme Gradient Boosting (XGB)

Max depth = 9,
learning rate = 0.05.

02 Categorical Boosting (CB)

Bagging temperature,
depth = 9, learning rate =
0.2898.

Hyperparameter Tuning

03 Random Forest (RF)

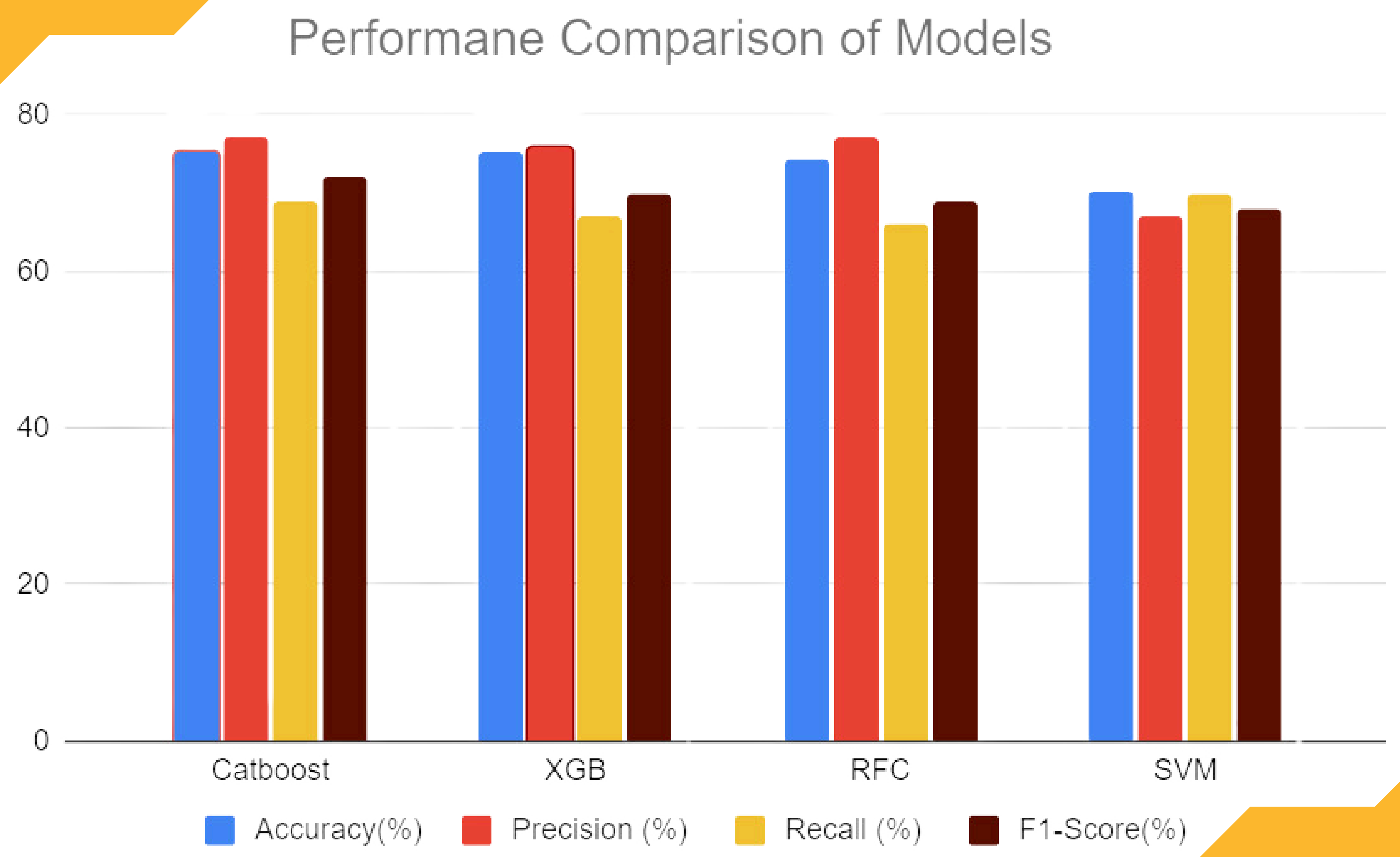
RBF kernel, class balancing.

04 Support Vector Machine (SVM)

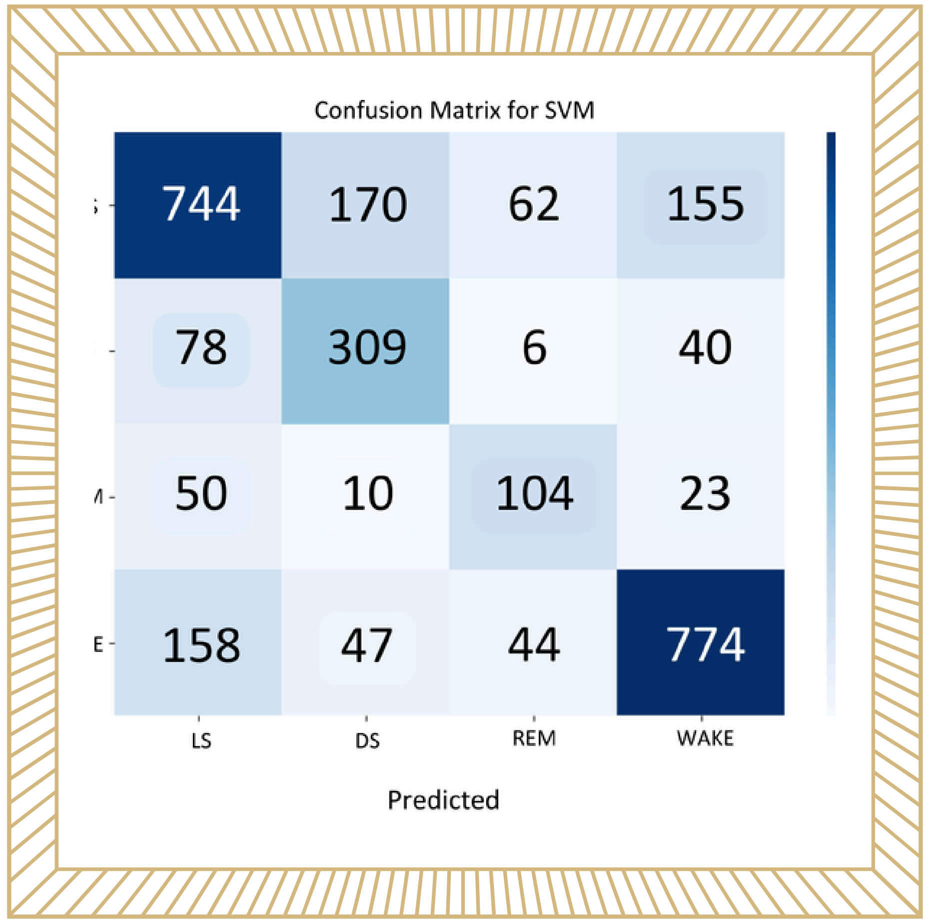
RBF kernel, class balancing.

Hyperparameter tuning significantly improved model performance.

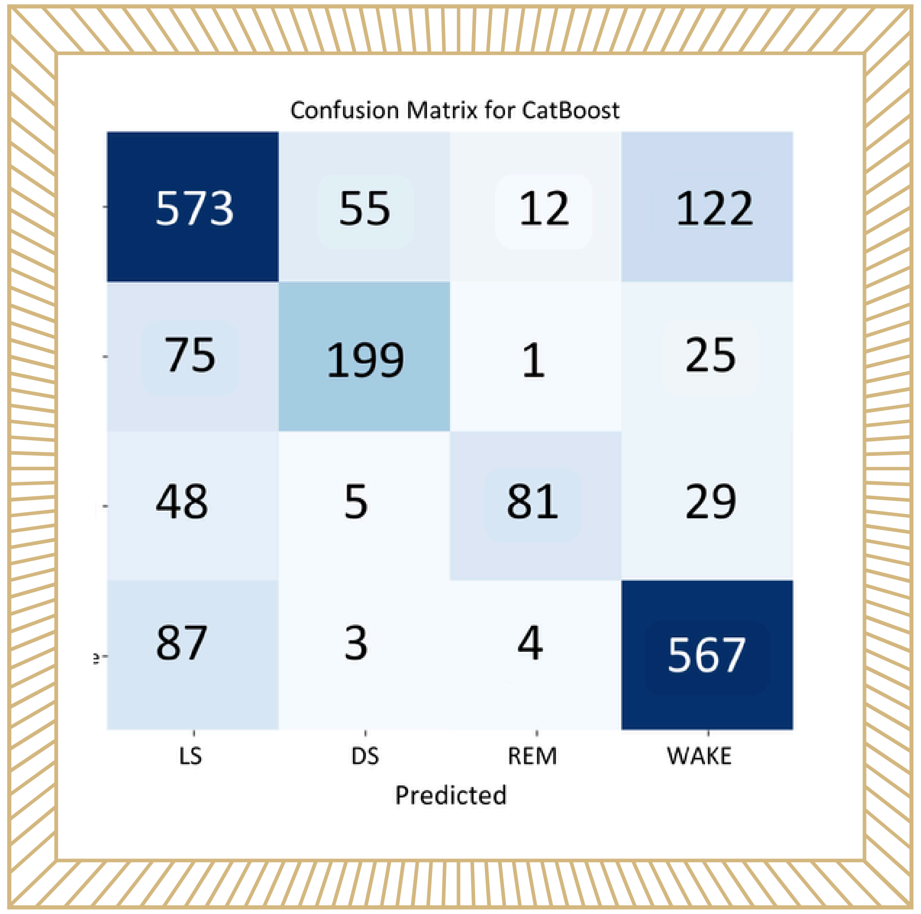
Results and Performance Evaluation



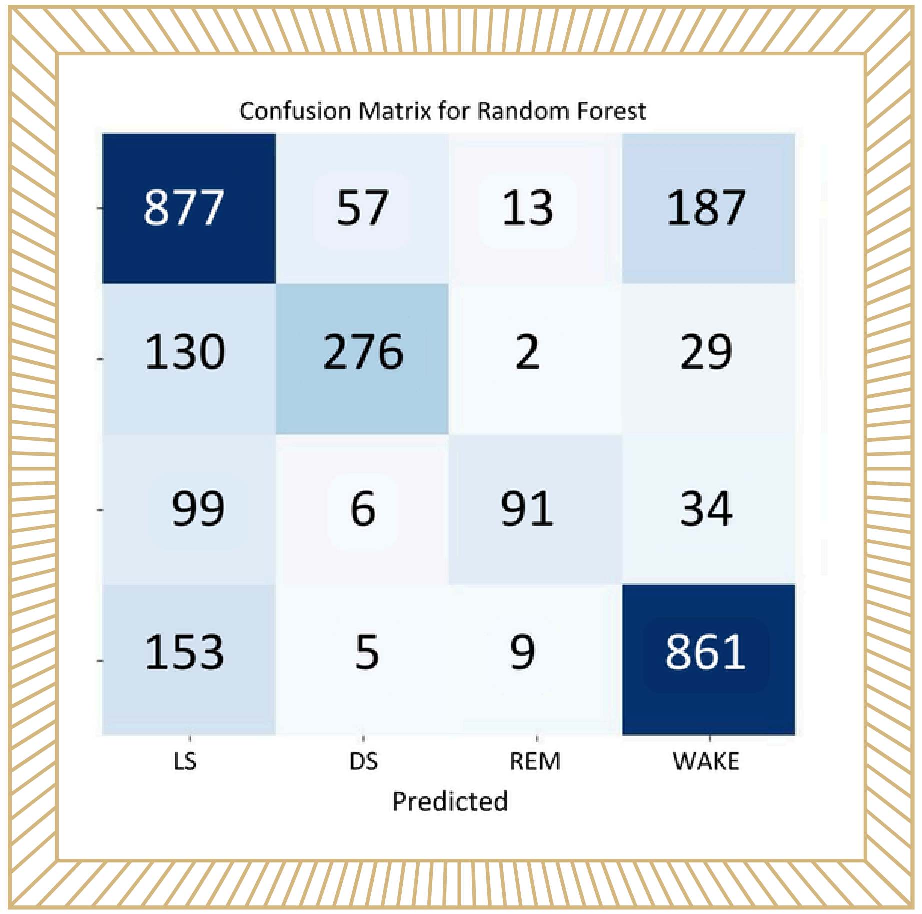
Confusion Matrix



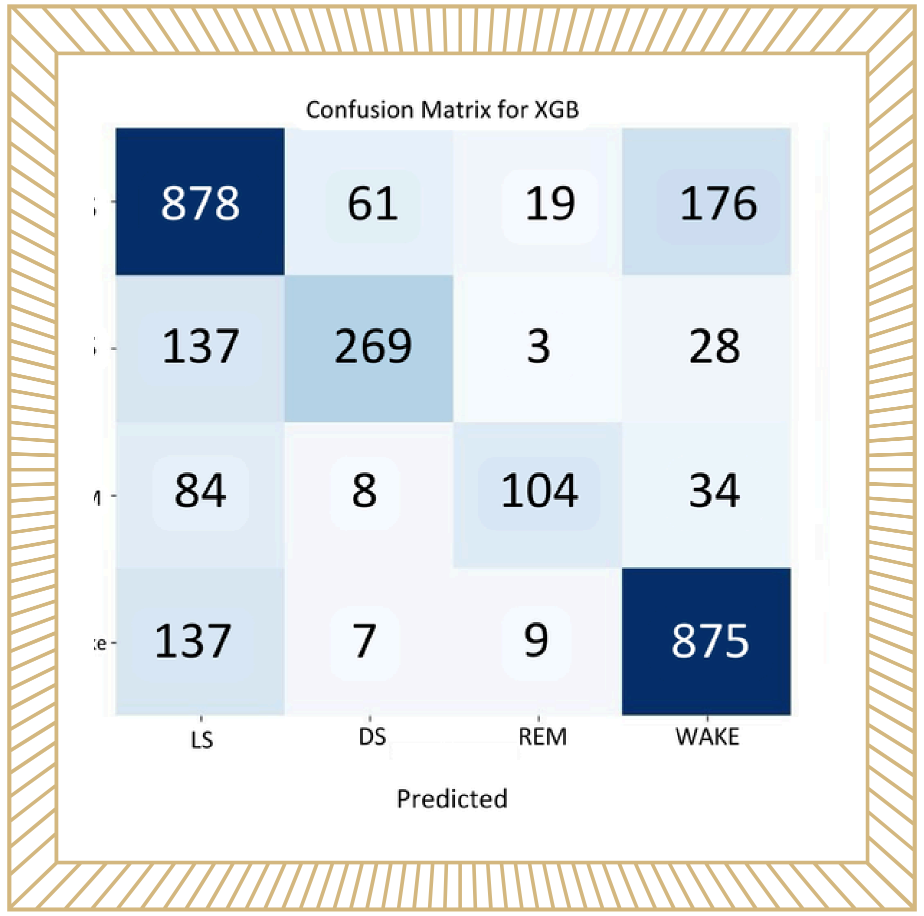
XGB



CB

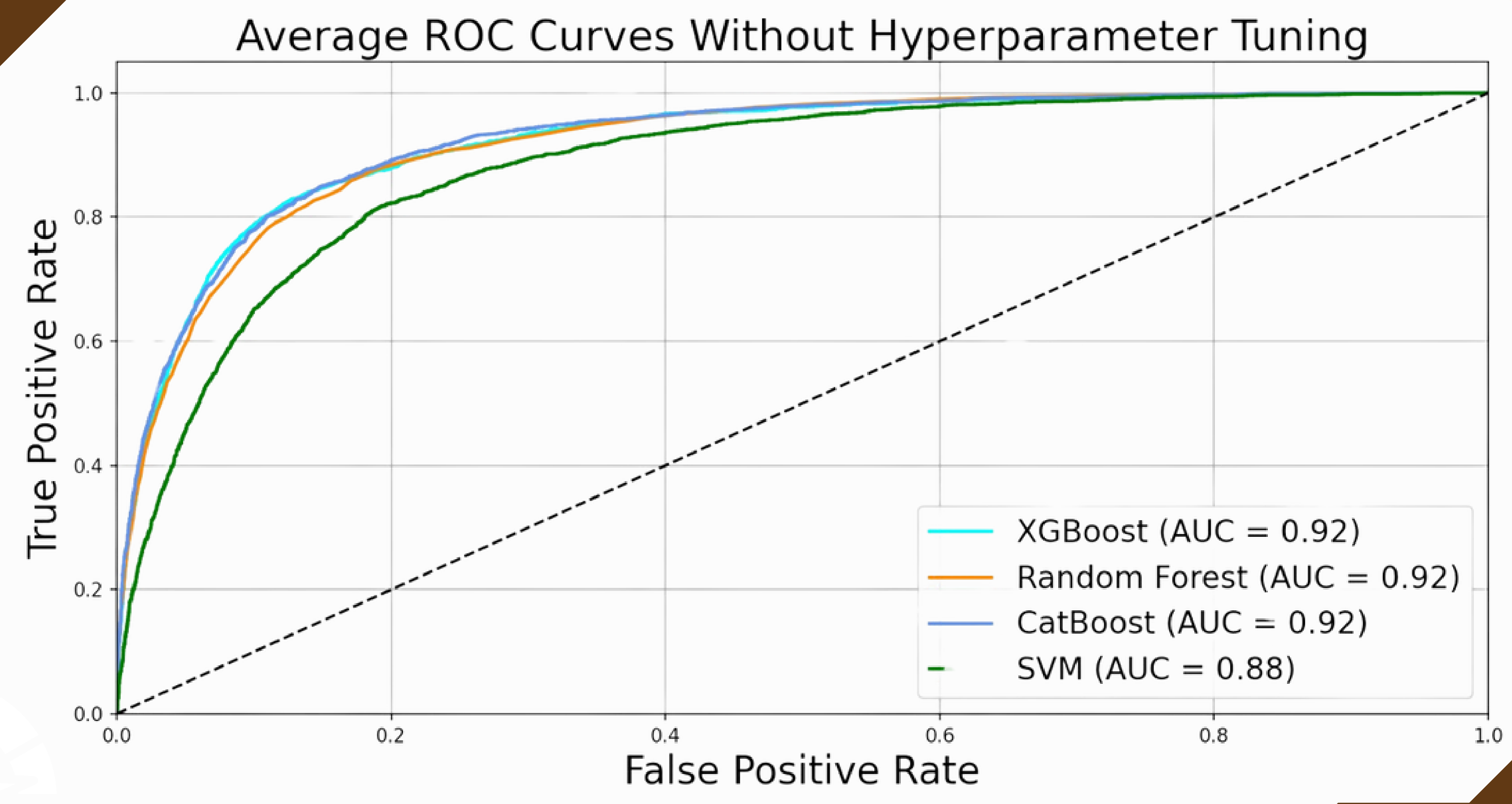


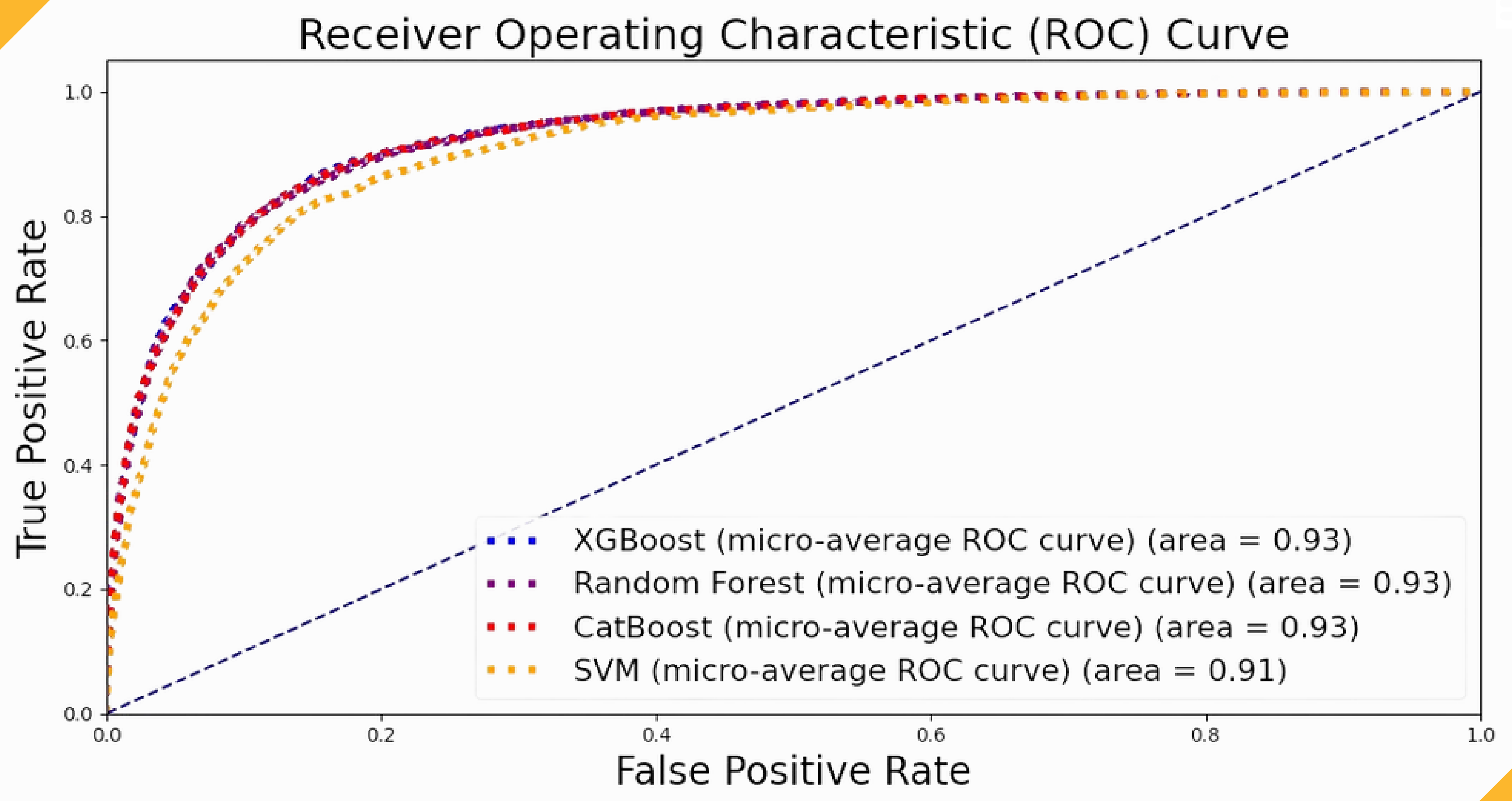
RF



SVM

ROC curve before hyperparameter tuning





ROC Curve after hyperparameter tuning

- **Tuned models achieved higher AUC values.**
- **CatBoost and XGBoost: AUC = 0.93.**
- **SVM improved to 0.91 after tuning.**

Discussion and limitation

- Dataset Size and Generalizability
- Integration of Advanced Techniques like ExplainableAI
- Lack of Deep Learning Models
- Future Work on Dataset Expansion

State of the art comparison

	Accuracy	Precision	Recall	F1-Score	K	Method
Wu et al.[2020] [23]	62	-	-		0.41	PPG with SpO2, 55 features, SVM-ANN
Motin et al.[2023] [16]	70.19 ± 0.32	-	-	62	-	PPG, 72 features, SVM
Motin et al.[2023] [16]	72.39 ± 0.48	-	-	62	-	PPG, 72 features, RF
Motin et al.[2023] [16]	72.23 ± 0.38	-	-	65	-	PG, 72 features, KNN
Proposed Model	75.29	77	69	72	0.58	PPG, 72 features, CatBoost
Proposed Model	75.15	76	67	70	0.58	PPG, 72 features, XGBoost
Proposed Model	74.41	77	66	69	0.57	PPG, 72 features, RF
Proposed Model	70.2	67	70	68	0.5	PPG, 72 features, SVM

Thank You!