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IMPROVED PHOTOPLETHYSMOGRAPHY-BASED FOUR-STAGE SLEEP CLASSIFICATION WITH EXPLAINABLE AI-DRIVEN MACHINE LEARNING

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AUTHOR





Tasnim Ferdous
Lecturer
Computer Science and Engineering
BRAC University

Reshad Ul Karim
Student
Computer Science and Engineering
BRAC University

Abrar Samin
Student
Computer Science and Engineering
BRAC University

Sammam Mahdi
Student
Computer Science and Engineering
BRAC University

Dr. Aniqua Nusrat Zereen
Assistant Professor
Computer Science and Engineering
BRAC university

INTRODUCTION

- **Sleep classification is vital for cognitive and physical health.**
- **Traditional PSG methods: Accurate but expensive, intrusive, and single-night monitoring.**

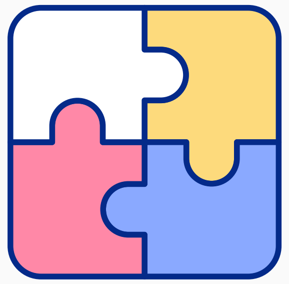
SOLUTION

PPG-based sleep monitoring with Machine Learning (ML).

CHALLENGE

Need for feature optimization without compromising accuracy.

OUR APPROACH



Use Explainable AI (XAI) to identify the most important features, reducing model complexity.

RESEARCH MOTIVATION

Addressing sleep disorders like sleep hypoApnea.

Growing demand for affordable, at-home sleep monitoring solutions.

Feature engineering and lightweight models are critical for single-sensor systems.

UNIQUENESS

- Use of XAI for feature reduction and interpretability.
- High accuracy with reduced computational costs.

RELATED WORKS AND GAPS

- Existing studies achieved accuracy up to 72.39% using RF and SVM.

CHALLENGES IDENTIFIED

- Complex feature sets (72+ features).
- Black-box nature of ML models.

GAPS

- Lack of explainability and lightweight feature optimization.

OUR CONTRIBUTIONS

- Reduced features (42) using XAI.
- Improved accuracy (75.54%) with CatBoost.

CONTRIBUTIONS

Systematic evaluation of SVM, RF, XGBoost, and CatBoost.

Achieved 75.54% accuracy with CatBoost using only 42 features.

Implementation of Explainable AI (XAI) to identify the most significant features.

Improved performance with reduced computational complexity.

STATE OF THE ART SUMMARY TABLE

	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	κ	Dataset	Method
Wu et al. (2020)	62	-	-	-	0.41	Private(N=31)	PPG with SpO2, 55 features, SVM-ANN
Motin et al. (2023)	70.19 ± 0.32	-	-	62	-	Private(N=10)	PPG, 72 features, SVM
Motin et al. (2023)	72.39 ± 0.48	-	-	62	-	Private(N=10)	PPG, 72 features, RF
Motin et al. (2023)	72.23 ± 0.38	-	-	65	-	Private(N=10)	PPG, 72 features, KNN
Proposed Model	75.54	76	76	76	0.59	Private(N=10)	PPG, 42 features, CatBoost with XAI
Proposed Model	75.93	76	76	76	0.6	Private(N=10)	PPG, 56 features, XGBoost with XAI
Proposed Model	75.82	76	76	75	0.6	Private(N=10)	PPG, 51 features, RF with XAI
Proposed Model	71.4	72	71	72	0.5	Private(N=10)	PPG, 48 features, SVM with XAI

DATASET PRE-PROCESING

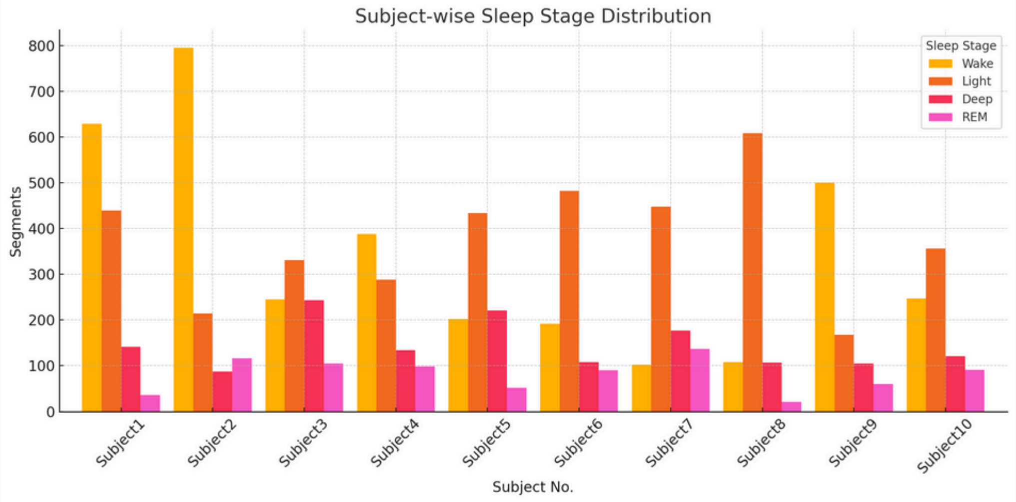
DATASET

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

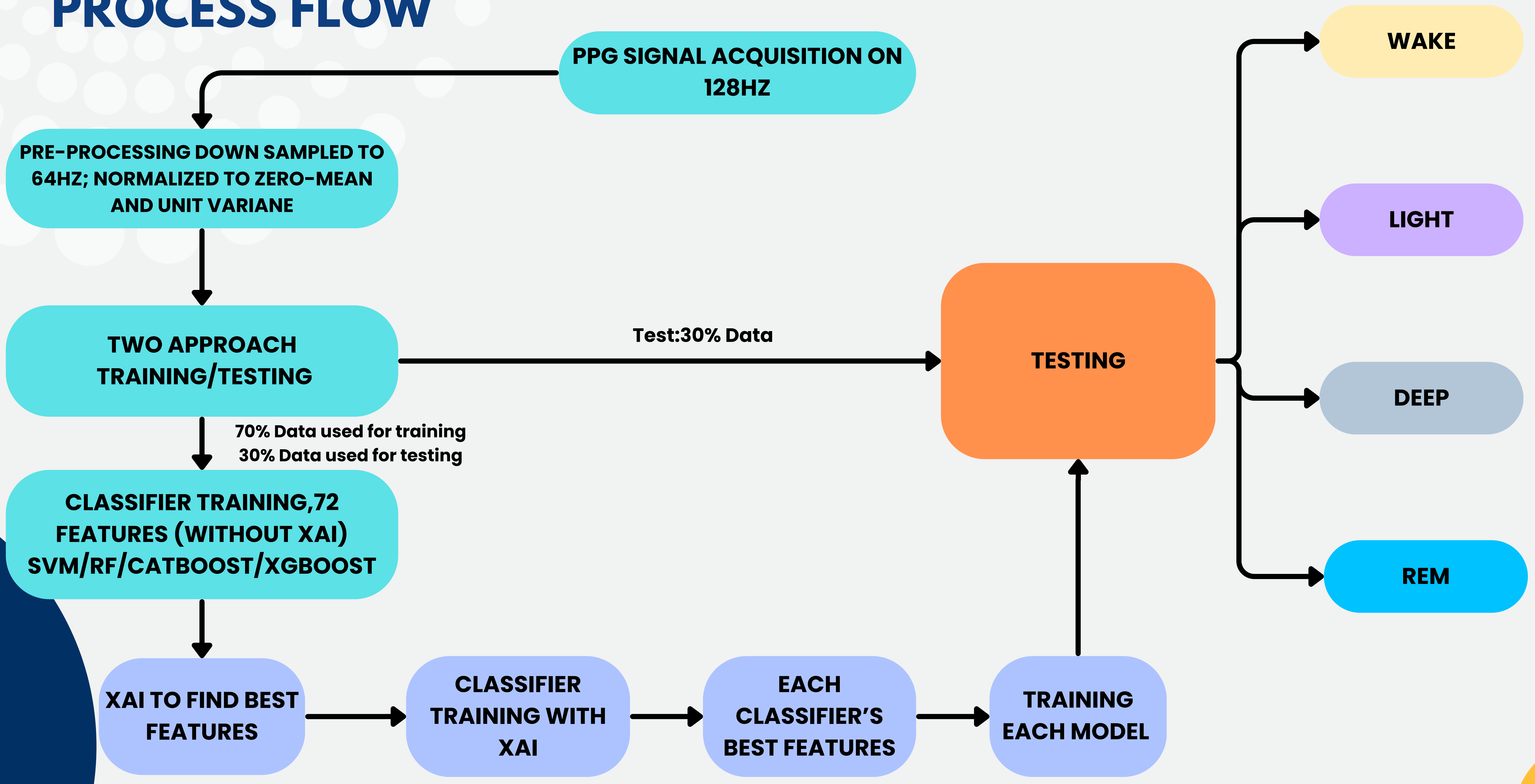
Subject No.	Total Segments	Wake	Light	Deep	REM
Subject 1	1246	629	439	142	36
Subject 2	1212	795	214	87	116
Subject 3	924	245	331	243	105
Subject 4	909	388	288	134	99
Subject 5	909	202	434	221	52
Subject 6	872	192	482	108	90
Subject 7	864	102	448	177	137
Subject 8	844	108	608	101	27
Subject 9	833	500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



MODEL TRAINING AND FEATURE SELECTION

- Ranked and reduced features to optimize performance
- CatBoost achieved best accuracy (42 features)
- Iterative Feature Selection: Testing performance across subsets of features

WITHOUT XAI

Model	No. of Features	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	72	74.41	77	66	69
SVM	72	70.20	67	70	68
XGB	72	75.15	76	67	70
CB	72	75.29	77	69	72

WITH XAI

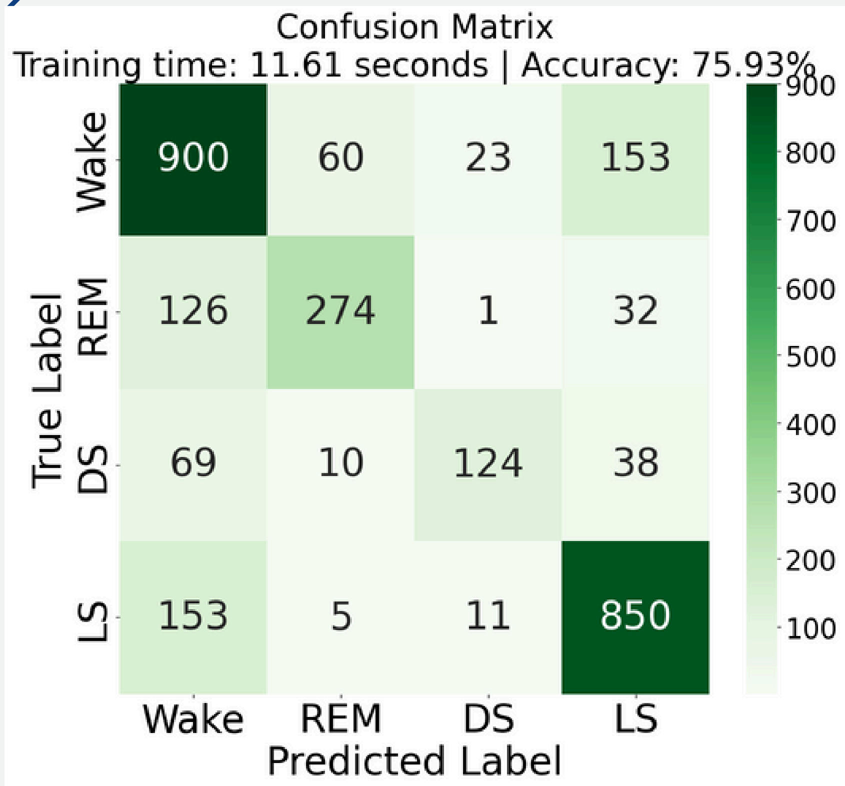
Model	No. of Features	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RF	51	75.82	76	76	75
SVM	48	71.40	72	71	72
XGB	56	75.93	76	76	76
CB	42	75.54	76	76	75

MODEL PERFORMANCE WITH XAI

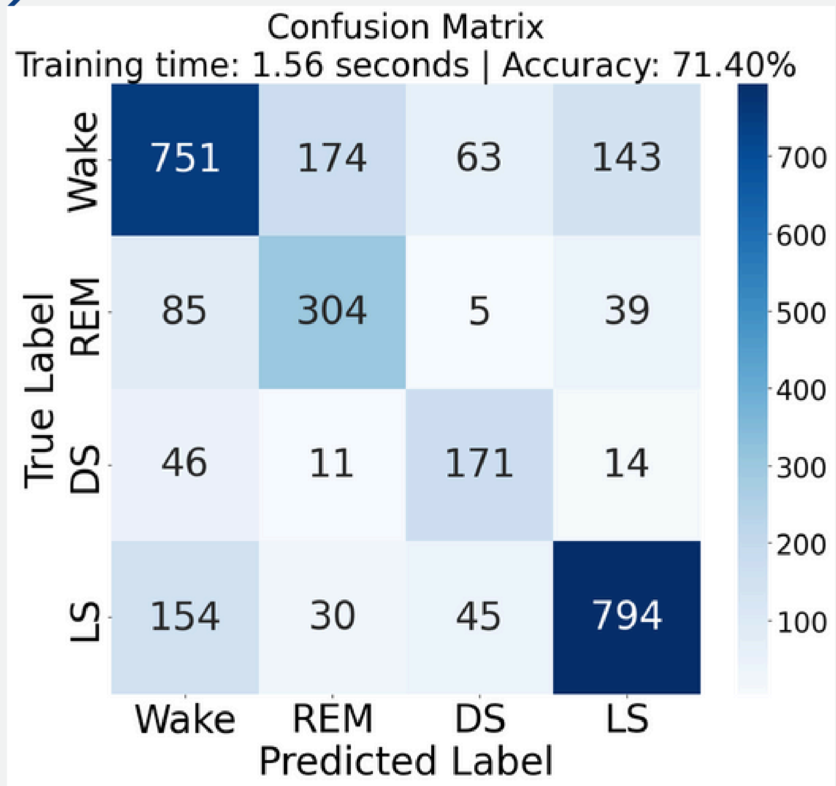
- **RF** — Accuracy = 75.82% with 51 features
- **SVM** — Accuracy = 71.40% with 48 features
- **XGBOOST** — Accuracy = 75.93% with 56 features
- **CATBOOST** — Accuracy = 75.54% with 42 features

CONFUSION MATRICES

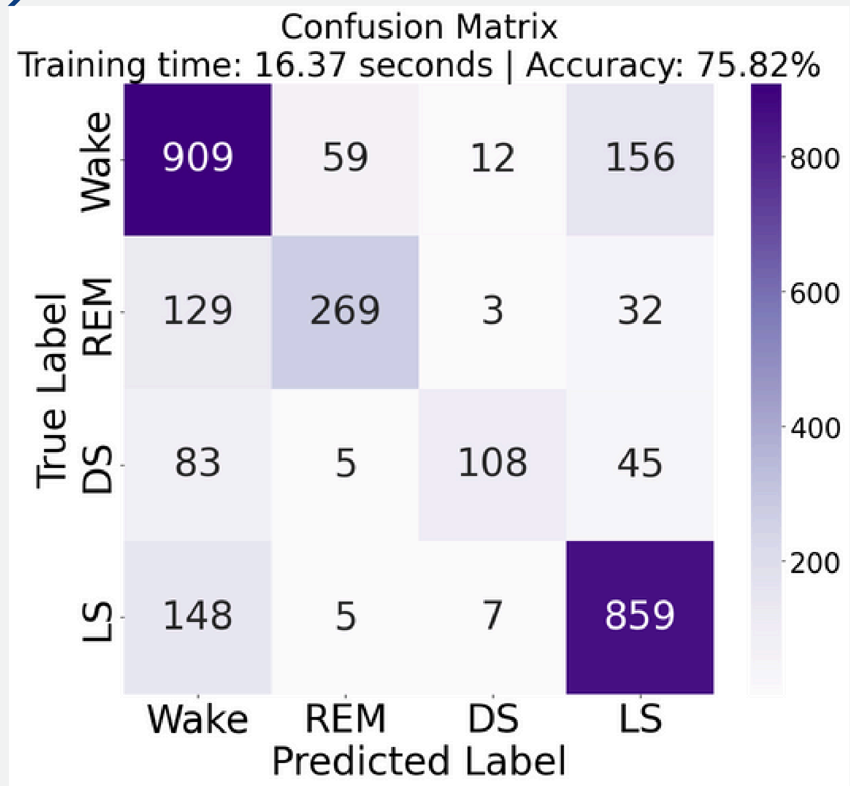
RF



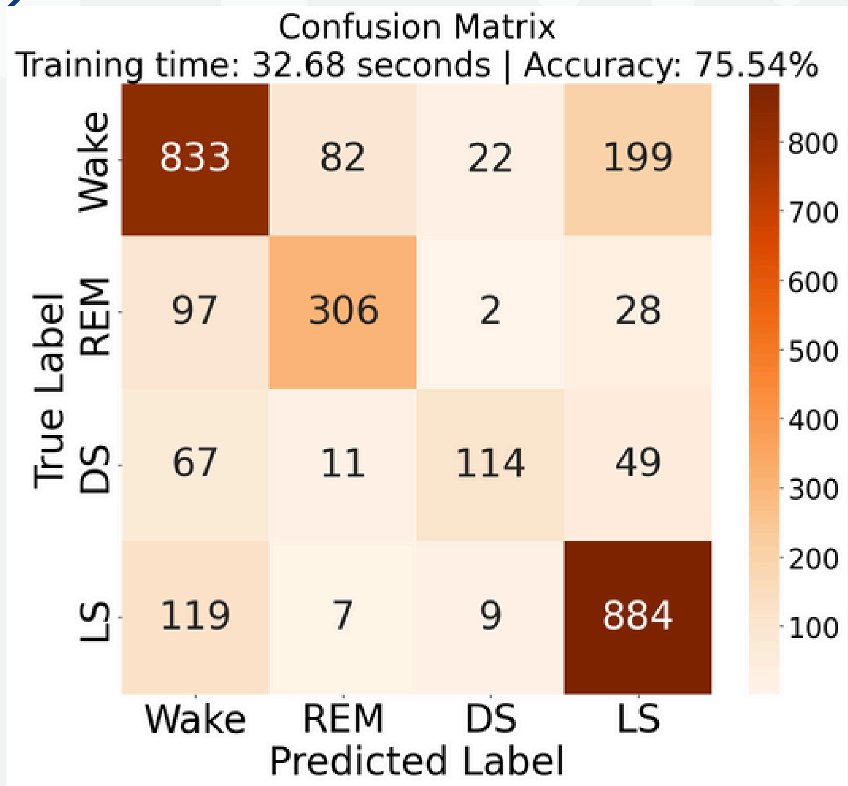
SVM



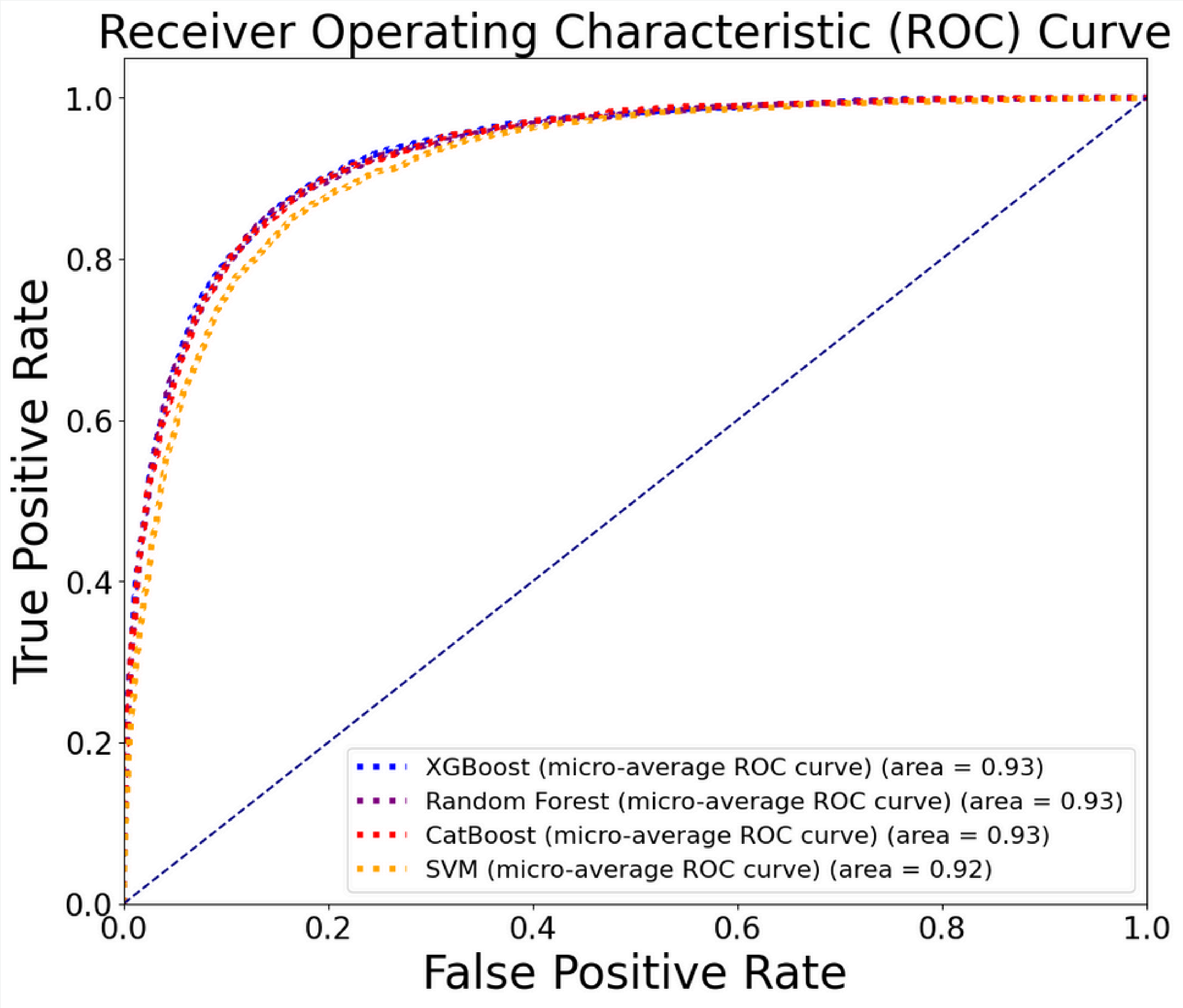
XGBOOST



CATBOOST



ROC CURVE ANALYSIS



- CatBoost, XGBoost, RF: 0.93
- SVM: 0.92

DISCUSSION

IMPROVED PERFORMANCES	UNIQUENESS	STRENGTHS	LIMITATIONS	FUTURE WORK
CatBoost with 42 features achieves state-of-the-art accuracy (75.54%).	Use of XAI for explainability and feature reduction.	• Reduced computational costs. • Lightweight model suitable for wearable devices.	• Small dataset (10 subjects). • Need for larger datasets for deep learning models.	• Integrate deep learning with transfer learning. • Expand dataset for broader generalizability.

THANK YOU

FOR ATTENDING OUR PRESENTATION