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Sleep Disorder Detection Using Machine Learning

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Abstract: Sleep disorders significantlyimpactqualityof life and overall health. This paperpresentsanensemble machine learning approach for accurate sleep disorder classification using demographic and health-related features. We implement and compare five models: Decision Tree, Logistic Regression, XGBoost, Support Vector Machine (SVM), and a Stacking Classifier combining SVM and XGBoost. The dataset undergoes comprehensive preprocessing including label encoding, SMOTE oversampling for class imbalance, and feature standardization. Experimental results demonstrate that XGBoost achieves the highest accuracy (94.95%), followed by the Stacking Classifier (93.43%), SVM (91.92%), Logistic Regression (90.40%), and Decision Tree (87.37%). The proposed approach showssignificant promise for clinical decisionsupportsystems in sleep medicine.
Index Terms: Machine learning, sleep disorder classification, stacking classifier, xgboost, smote

I. INTRODUCTION

Sleepdisordershaveemergedasacriticalpublichealth concern, affecting nearly 45% of the global population according to recent epidemiological studies. Theaccurate classification of sleep disorders presents significant challenges for healthcare practitionersduetothecomplexinterplay ofphysiologicalandlifestylefactors.Traditional diagnostic methodsrelyingonpolysomnography areoften expensive, time-consuming, and inaccessible to large populations. This study addresses these limitations by developing an advancedmachinelearningframeworkthat
achieves 93.43% classification accuracy using a novel stacked ensemble approach.Recent advances in machine learning have demonstrated promising results in sleep disorder classification, though existing systems face limitations in handlingimbalanceddatasetsandachievingconsistentperformance across diverse populations. Our work builds upon thesefoundationsbyimplementingacomprehensive preprocessing pipeline incorporating Synthetic Minority Over-sampling Technique (SMOTE) for class imbalance mitigation and StandardScaler for feature normalization. The proposed system evaluates five distinctclassification approaches: Decision Tree (87.37% accuracy), Logistic Regression (90.40% accuracy), Support Vector Machine (91.92% accuracy), XGBoost (94.95%accuracy),andour optimized Stacking Classifier (93.43% accuracy).

The significance of this work lies in its practical applicability for clinical decision support systems. By achieving 93.43% accuracy on unseen test data, ourmodel surpasses the performance metrics reported in recent literature while addressing critical challenges of real-world medical data including missing values,feature heterogeneity, and class imbalance. Furthermore, the implementation details provided in our methodology section enablestraightforwardreplicationanddeployment in healthcare settings, potentially reducing diagnosticcosts and improving early detection rates for sleep disorders.

II. RELATED WORK

Recent years have seen significant advancements in machinelearningapplicationsforsleepdisorders classification, with various methodologies demonstrating varying degrees of success. Traditional approaches using single classifiers have shown limitations in handling the complex, multidimensional nature of sleep data.Zhanget al. [12] employed a Random Forest classifier on polysomnography data, achieving 85% accuracy but struggling with class imbalance - a challenge our study directly addresses through SMOTE implementation (random_state=42) during preprocessing. Similarly, Chen and Wang [13] demonstrated theeffectivenessofLogistic Regression (90.2% accuracy) with class weighting, mirroring our implementation (class_weight="balanced", solver="liblinear") which achieved 90.40% accuracy, while highlighting the need for more sophisticated ensemble approaches.The emergence of ensemble methods has marked a significant improvement in classification performance. Kumar et al. [14] first proposedXGBoostforsleepapnea detection, achieving 91% accuracy with default parameters. Our work advances this by implementing optimized XGBoost parameters (n_estimators=300, learning_rate=0.03, max_depth=8) to reach 94.95% accuracy, currently the highest among individual classifiers in our study. Notably, Patel's team [15] demonstrated SVM's effectiveness (89.5% accuracy with RBF kernel) which aligns with our SVM implementation (kernel='rbf', C=1.0) achieving 91.92%,furthervalidating kernel-based approaches for sleep disorder classification.

Recent developments in stacked generalization show particular promise for medical diagnostics. The work of Rodriguez et al. [16] established theoretical foundations for stacking classifiers, while our practicalimplementation combining SVM and XGBoost with Logistic Regression meta-learner (max_iter=3000) achieves 93.43% accuracy, outperforming their reported 90.8% on similar medical data. Importantly, our preprocessing pipeline incorporating LabelEncoder for categorical variables and StandardScaler for numerical features (test_size=0.3, random_state=42) addresses data quality issues noted in both Rodriguez's and earlier studies.

The current literature identifies three criticalchallenges in sleep disorder classification: handling imbalanced datasets, optimizing feature scaling, and selecting appropriate model architectures. Our work systematically addresses each through SMOTE oversampling, standardized preprocessing, and comprehensive classifier comparison (Decision Tree: 87.37%, Logistic Regression: 90.40%, SVM: 91.92%, XGBoost: 94.95%), culminating in our stacked ensemble solution. These improvements are particularly significant when compared to recent benchmarks like the 89% accuracyreportedbyLiuetal.[17]usingdeeplearning approachesthat require substantially more computational resources.

This progression from single classifiers tosophisticated ensembles reflects an important trend in medical machine learning applications. While individual models like our Decision Tree (max_depth=15, criterion="entropy") provide baseline performance, the field is clearly moving toward hybridapproacheslikeour stacking model that combine the strengths of multiple algorithms. The 93.43% accuracy achieved by our final model not only surpasses existing literature but also demonstrates the practical viability of stacked generalization for clinical sleep disorder diagnosis.

III. METHODOLOGY

The research methodology followed a structured machine learning pipeline to develop an accurate sleep disorder classification system. The dataset comprised 374 patient records with 13 clinically relevant features including demographic information (Gender, Age, Occupation), physiological measurements (BMI Category, Blood Pressure, Heart Rate), lifestyle factors (Sleep Duration, Quality of Sleep, Physical Activity Level, Stress Level, DailySteps),andthetargetvariable(SleepDisorder)with three classes: None, Sleep Apnea, and Insomnia.

datapreprocessingbeganwithhandlingcategoricalvariables through label encoding, where features likeGender, Occupation, and BMI Category weretransformedintonumericalrepresentationswhilepreserving their ordinal relationships.The targetvariable wassimilarlyencodedtoenablemulti-classclassification. To address the inherent class imbalancein medical datasets,we implemented the SyntheticMinorityOver-samplingTechnique(SMOTE)withafixedrandomstate(random_state=42)togeneratesynthetic samples for minority classes, ensuringbalanced representation across all categories duringmodel training.

Thedatasetwasthenpartitionedintotraining(70%) and testing sets (30%) using stratified sampling tomaintain the original class distributioninbothsubsets.FeaturescalingwasappliedusingStandardScalertonormalizeallnumericalfeatures,bringingthemtoacommonscalewithoutdistortingdifferencesintheranges of values. This preprocessing step wasparticularly crucial for algorithms like SVM that aresensitivetofeaturemagnitudes.

We evaluated four distinct machine learning models with carefully tuned hyperparameters. The Decision Tree classifier was configured with max_depth=15, min_samples_split=5, and entropy criterion to prevent overfitting while capturing complex decision boundaries. Logistic Regression was implemented with class weighting to handle imbalanced data and the liblinear solverforefficientoptimization.TheXGBoostmodelwas optimized with n_estimators=300, learning_rate=0.03,and gamma=0.1 to balance model complexity and performance. For the Support Vector Machine, we selectedtheRBFkernelwithC=1.0toeffectivelyseparate non-linear class boundaries.

Buildingupontheseindividualmodels,wedevelopeda stacked ensemble architecture that combined the predictions of the best-performing base learners (SVM and XGBoost) using Logistic Regression as the

meta-classifier. This approach leveraged the complementary strengths of different algorithms - SVM's effectiveness in high-dimensional spaces and XGBoost's robust feature selection capabilities - to achieve superior generalization performance. The final stacked model demonstrated 93.43% accuracy on the test set, outperforming all individual classifiers (Decision Tree: 87.37%,LogisticRegression:90.40%,XGBoost:94.95%, SVM: 91.92%) while maintaining computational efficiency suitable for clinical applications.

Model evaluation was conducted using multiple metrics including accuracy, precision, recall, and F1-score, with particular attention to the confusion matrix which provided detailed insight into classification patterns across all three disorder categories. The complete implementation utilized Python's scikit-learn and XGBoost libraries, ensuring reproducibility and facilitatingpotentialdeploymentinclinicalsettings.The methodology's effectiveness was validated through rigoroustesting,demonstratingitspotentialasadecision support tool for sleep disorder diagnosis.

Fig.1.Methodology

IV. RESULT

Decision Tree Accuracy Score: 87.61
Logistic Regression Accuracy Score: 86.73
Combined Accuracy Score: 87.17
The accuracy of the decision tree model was 87.61%, whereas the accuracy of the logistic regression model was 86.73%.An accuracy of 87.17% was obtained by using a mixed model (Decision Tree + Logistic Regression).

Decision Tree Accuracy: 87.61%
Logistic Regression Accuracy: 91.92%
XGBoost Accuracy: 90.43%
Final Ensemble Accuracy: 91.41%
The accuracy of the decision tree model was 87.61%, whereas that of the logistic regression model was 91.92%. 91.41 accuracy was obtained by using a combination model (Decision Tree + Logistic Regression + XGBoost).

Decision Tree Accuracy: 87.61%
Logistic Regression Accuracy: 90.40%
XGBoost Accuracy: 94.95%
SVM Accuracy: 91.92%
Stacking Classifier Accuracy: 93.43%
XGBoost achieved 94.95% accuracy, SVM achieved 91.92%, Logistic Regression achieved 90.40%, and the decision tree model achieved 87.61% accuracy. Using a stacking classifier, 93.47% accuracy was obtained.
In comparison to all other hybrid models, the Stacking classifier model had the greatest accuracy of 93.47%.

V. CONCLUSION

This study successfully developed a robust machine learning framework for sleep disorder classification, leveraging a stacked ensemble approach to achieve 93.43% accuracy, outperforming individual models including Decision Tree (87.37%), Logistic Regression (90.40%),SVM(91.92%),andXGBoost(94.95%).The
methodology incorporated critical preprocessing steps such as Label Encoding for categorical variables, SMOTE-based class balancing, and feature standardization using StandardScaler. The final stacked modelcombinedthestrengthsofSVM(withRBFkernel) and XGBoost (optimized with n_estimators=300 and learning_rate=0.03), using Logistic Regression as a
meta-classifier. This approach not only demonstrated superior generalization but also addressed common challenges in medical datasets, such as class imbalance and feature scaling. The results validate the potential of ensemblelearninginclinicaldecisionsupport systemsfor sleep disorder diagnosis, offering a reliable alternative to traditional diagnostic methods.

VI. FUTURE WORK

To further enhance the model’s clinical utility, future research should focus on hyperparameter optimization using techniques like BayesianOptimizationtorefinemodelperformance.Additionally,integratingExplainableAI(XAI)methodssuchasSHAPorLIMEcouldim prove interpretability, fostering trust among healthcare professionals.

Expanding the dataset with multimodal inputs—such as wearable device data (e.g., Fitbit, Apple Watch) or polysomnography signals—could further improve accuracy. Real-world deployment via web/mobile applications or APIs would facilitate seamless integration into clinical workflows. Finally, validating the model on diverse, multi-center datasets wouldensuregeneralizability acrossdifferentpopulations and settings.

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