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Automated Sleepiness Detection via EEG Brainwave Analysis: A Nonlinear Ensemble Approach with Optimized Hyper-Tuning Strategies

K. Srujan Raju[1], Roopa R[2], Penubaka Balaji [3, *], T. Ravi Kumar[4], Dr. K. Reddy Madhavi[5], Dr. C. Sateesh Kumar Reddy[6]

[1]Dean (T&P) & HOD, Dept. of CSE, CMR Technical Campus, Hyderabad. Email: ksrujanraju@gmail.com

[2]Assistant professor, Computer Science & Engineering (Data Science), Madanapalle Institute of Technology & Science, Madanapalle. Email: roopa509@gmail.com

[3, *] Assistant Professor, Department of CSE, K L University, Vaddeswaram, Guntur, Andhra Pradesh, India. Email: penubakabalaji.cse@gmail.com

[4]Associate Professor, Department of CSE, Aditya Institute of Technology and Management, Tekkali. Email: ravi.4u.kumar@gmail.com

[5]Professor, AI&ML, School of Computing, Mohan Babu University, Tirupati, A.P., India. Email: kreddymadhavi@gmail.com

[6] Assistant Professor (Senior level), Advanced CSE, School of Computing & Informatics, Vignan's Foundation for Science, Technology and Research, Vadlamudi, Guntur-522213. Email: satishreddic@gmail.com

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Abstract:

Introduction: Automated sleepiness detection plays a vital role in ensuring driving-related safety, monitoring physical well-being, worker safety, and various other applications. The ability to detect and respond to signs of sleepiness is essential in preventing accidents and improving overall safety and productivity.

Objectives: The primary objective of this work was to explore avenues for enhancing the performance of automated sleepiness detection systems using advanced machine learning techniques. Specifically, the study aimed to determine the improvement potential in accuracy through the application of fine-tuning techniques across several machine learning algorithms.

Methods: A range of machine learning algorithms, including LightGBM, XGBoost, CatBoost, Extra Trees Classifier (ETC), and Random Forest (RF), were employed to evaluate their effectiveness in sleepiness detection. Fine-tuning techniques were applied to these boosting algorithms to assess their impact on performance improvements.

Results: The results revealed significant performance enhancements, particularly for boosting algorithms. CatBoost emerged as the top performer, achieving an accuracy score of 83%, demonstrating its capability in the domain of sleepiness detection. The improvements achieved through fine-tuning were substantial across all algorithms evaluated.

Conclusions: This study highlights the potential of advanced machine learning techniques to make meaningful contributions to automated sleepiness detection systems. The results underscore the importance of fine-tuning in boosting algorithm performance and suggest a growing role for such technologies in improving safety, health, and productivity in various domains.

Keywords: EEG, Brainwave Data, Sleepy Driver, Machine learning, Ensemble Learning.

1. Introduction

As humans, sleep is essential for our performance, learning abilities, and overall physical health, and a typical human spends one-third of his lifetime sleeping [1]. Sleepy driving remains a global concern, responsible for countless car accidents and the tragic loss of tens of thousands of lives annually [2]. Studies show that up to 20% of all traffic accidents, and even up to 50% on certain roadways, can be attributed to driver sleepiness, and it is estimated to result in 1,200 fatalities and 76,000 injuries annually [3]. Sleepiness is a common problem that can cause fatigue and impair our ability to stay alert and focused, especially at work. Inadequate sleep significantly contributes to fatigue, leading to sleepiness and reduced productivity and safety. Therefore, it is essential to identify and address the underlying causes of sleepiness and fatigue to promote better alertness and safety in our daily lives [4]. Long-distance driving poses a particular risk, often causing drowsiness, further compounded by the widespread issue of drowsy driving. Signs of sleepiness include drooping eyelids, frequent yawning, eye rubbing, nodding heads, wakefulness, and rapid eye movement [4].

To tackle this problem, researchers worldwide have tirelessly developed driver sleepiness detection systems to improve road safety for drivers and passengers. In biomedical signals, physiological indicators such as EEG for brain wave activity, ECG to monitor heart rate, EMG to track muscle activity, and EOG to record eye movements are essential in diagnosing sleep-related disorders [5]. EEG is a powerful and predictive component among these indicators due to its direct brain activity measurement [6]. Electroencephalography involves using specialized equipment to record brain bioelectrical activity across different states, including baseline sleep, wakefulness, mental stress, and various activations [7]. This versatile approach allows for investigating brain-behavior across numerous scenarios, enabling the potential detection of brain-related disorders. Recent research has focused on EEG driver simulator studies, planning to develop an EEG-based fatigue countermeasure algorithm and evaluate its dependability in detecting distinct stages of tiredness through offline data analysis. This research explores EEG signals to identify and manage driver sleepiness, significantly contributing to road accidents.

The goal is to develop an intelligent system using Machine Learning that will play a crucial role in classifying different levels of drowsiness, thus promoting safer roads. While previous studies have relied mainly on EEG monitoring for sleepiness detection, this approach seeks to go beyond those limitations by introducing a new ML framework tailored to the unique challenges of EEG Brainwave Data, using cutting-edge techniques to advance the field. The aim is to provide a more robust solution to a problem that poses a serious threat to road safety. VIJAYPRIYA et al. [8] proposed a novel approach for drowsiness classification using the MCNN (Multi-scale Convolutional Neural Network) framework utilizing the YAWDD and NTHU-DDD datasets.

The Flamingo search algorithm (FSA) was combined with MCNN to optimize features with the MCNN-based FSA model, gaining approximately 98.38% accuracy for the YAWDD dataset and 98.26% for NTHU-DDD, surpassing conventional methods by around 6%. A hybrid model for detecting drowsiness was presented in another study [9], and the model combined non-intrusive and invasive approaches by leveraging AI-based Multi-Task Cascaded Convolutional Neural Networks (MTCNN) to detect facial features and Galvanic Skin Response (GSR) sensors to gather physiological data.

The fusion of these measures resulted in an overall efficacy of 91% in identifying the transition from wakefulness to drowsiness in drivers, as evaluated in a simulated environment. According to [10], a new non-invasive and real-time system has been created to detect driver drowsiness using visual features from a camera mounted on a dashboard.

The system uses facial landmarks and face mesh detectors to detect regions of interest and removes mouth aspect ratio, eye aspect ratio, and head pose features. These features are then passed through three different classifiers - a random forest, a sequential neural network, and a linear support vector machine. The system was evaluated on the National Tsing Hua University driver drowsiness detection dataset, and it achieved a remarkable detection accuracy of up to 99%, which effectively alerts and mitigates drowsy driving instances. Another study [3] took a more superficial, non-intrusive approach by focusing on a single wrist device for comfortable wear by drivers for drivers' drowsiness detection, analyzing physiological skin conductance (SC) signals, and testing three ensemble algorithms. The Boosting algorithm was the most effective, achieving an accuracy rate of 89.4% for detecting drowsiness.

2. Methodology

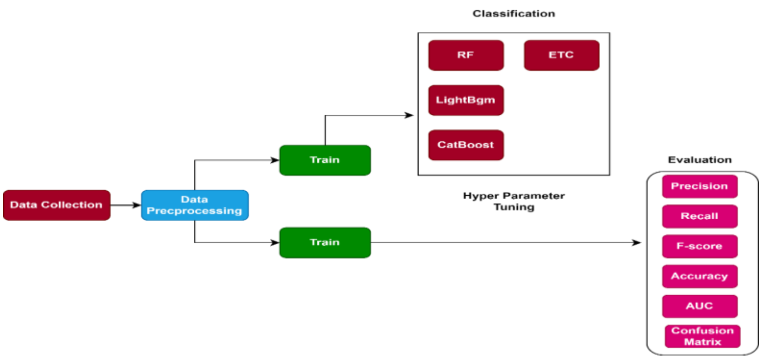

Figure 1. The overall framework of our research

2.1. Dataset Description

The original dataset was obtained from Kaggle, a publicly available platform. The dataset includes EEG signal data gathered from four awake or asleep drivers under controlled conditions. To collect the data, each driver wore a NeuroSky MindWave headset, which is a single-channel EEG device that measures the voltage between an electrode on the forehead (frontal lobe) and two additional electrodes—one acting as a ground and the other as a reference, placed on each earlobe. During data collection sessions, the individuals were instructed to remain awake or asleep. The original dataset contains 3,735 data. We divided the dataset for training and testing purposes. The transformed training set consists of 2,614 data, and the test set includes 1,121 data.

2.2. Classification

To classify the driver as sleepy and awake, we used several ML classifiers. All classifiers were used first without tunning, and later, we tuned the classifiers. We used LightGBM, CatBoost, Extreme

Gradient Boosting (XGBoost), Extra Trees Classifier (ETC) and Random Forest (RF). The hyperparameter tuning of all classifiers is shown in Table 1. The hyperparameter process is shown graphically in Figure 2. All of the classifiers are described below:

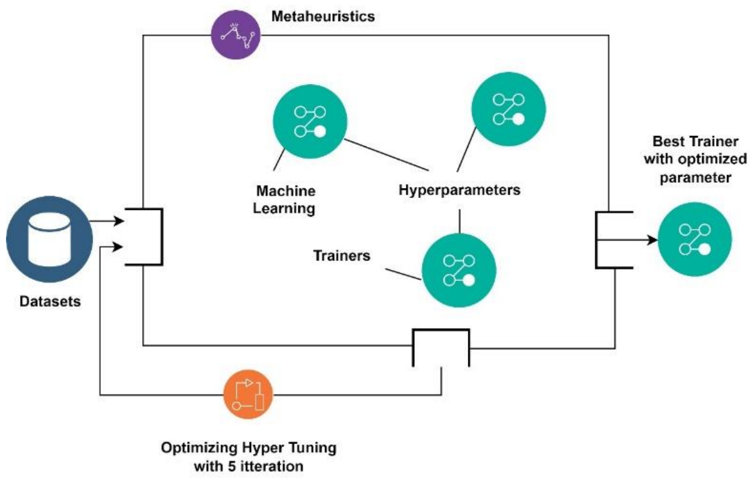

Figure 2. Hyperparameter tuning process

LightGBM: LightGBM is a powerful and efficient gradient-boosting framework for large-scale ML tasks. It is particularly well-suited when memory efficiency is crucial. It uses a technique called “Leaf-wise” tree growth, which differs from traditional depth-wise growth. In the leaf-wise approach, the tree is grown by expanding the leaf, giving the maximum loss function reduction. This leads to a more balanced tree and reduces the number of levels, which can significantly improve training speed. Our research used the num leaves parameter in grid search tuning. The classifier is also dependent on ‘n’ estimator values, and for this, it is also included in the grid search.

Catboost: In this study, we employed advanced ML techniques to enhance the accuracy of our driver drowsiness detection system. Specifically, we utilized the CatBoost classifier. CatBoost works by optimizing a loss function by adding weak learners (in this case, decision trees) to the ensemble. For a binary classification problem, the objective function for CatBoost is typically the binary cross-entropy loss, which is defined as:

$$L_{(y,p)} = -\frac{1}{N} \sum_{i=1}^{N} [\, y_i \,.\log(p_i) + (1 - y_i) \cdot \log(1 - p_i)]$$

Where: N is the entire number of samples. yi is the sample of true label i. pi is the expected probability that sample i belongs to class 1. In the context of CatBoost, the model aims to minimize this loss function by adjusting the parameters, including the hyperparameters like learning rate, depth of trees, and regularization terms. A grid search approach systematically explored parameters such as depth, rate of learning, iterations, l2 leaf reg, and count of the border. The parameter depth controls the highest depth of the decision trees in the CatBoost ensemble. The learning rate parameter influences the step size during the optimization process. The parameter iterations define the number of boosting rounds, affecting the overall complexity of the ensemble. Additionally, l2 leaf reg and border count were fine-tuned to mitigate overfitting and enhance the robustness of the model.

XGBoost: XGBoost is an ensemble learning algorithm known for its high performance and efficiency in various ML tasks, including classification. The core principle behind XGBoost lies in optimizing a regularized objective function, which can be represented as follows:

$$L(\theta) = \sum_{i=1}^{n} L_{(y_i,\hat{y}i)} + \sum_{k=1}^{K} \Omega\,(f_k\,)$$

– L(θ) is the function of loss, which measures the discrepancy between true labels yi and predicted values yˆi.

– The first term Pn i=1 L(yi , yˆi) represents the data loss, where L denotes the differentiable convex of the loss function (e.g., binary cross-entropy for classification). The second term PK k=1 Ω(fk), is the regularization term, which penalizes the complexity of the model. It's a sum of all the trees in the ensemble, where Ω is a regularization function specific to each tree.

The hyperparameters provided, including learning rate, gamma, and max depth, are crucial in shaping the behavior of the XGBoost model. The learning rate is a crucial parameter that regulates the size of the steps taken during the optimization process; also, gamma defines the lowest loss reduction required to split a node, and max depth defines the depth of a separate tree, exploiting the model's complicatedness.

ETC: We implemented the ETC, an ensemble learning method that extends the capabilities of conventional decision trees. The Extra Trees approach introduces an additional layer of randomness by randomly selecting features and thresholds at each split, thereby mitigating overfitting and enhancing the model's robustness to noise. Mathematically, the Extra Trees Classifier operates by considering a random subset of features and choosing a random threshold for splitting at each node, which introduces additional variance and strengthens the classifier's resilience. For hyperparameter optimization, we conducted a thorough grid search exploring various values for critical parameters, including criterion, max depth, min samples split, min samples leaf, and max features. This meticulous tuning aimed to strike an optimal balance between model complexity and predictive accuracy, resulting in a highly effective classifier for discerning driver drowsiness. The mathematical formulation of the Extra Trees Classifier's objective function involves a loss term.

$$\sum_{i=1}^{n} L_{(yi,\widehat{yi})}$$

That quantifies the discrepancy between true labels yi and predicted values yˆi and a regularization term that penalizes model complexity.

$$\sum_{k=1}^{K} \Omega(f_k)$$

Table 1. Hyper tunning of all classifiers

Methods	Hyper Tunning
Lightgbm	type of boosting: ['gbdt','dart', 'goss','rf'] leaves of num: [30, 50, 100] learning rate: [0.01, 0.05, 0.1]

	n_estimators: [100, 200, 500] fraction of feature: [0.8, 0.9, 1.0] fraction of bagging: [0.8, 0.9, 1.0] freq of bagging: [1, 3, 5]
Catboost	learning rate: [0.001, 0.01, 0.1] gamma: [1, 5, 10] max depeth: [10,20,30]
XGboost	depth: [6, 8, 10] learning rate: [0.01, 0.05, 0.1] Iterations: [100, 200, 500] l2 leaf reg: [3, 5, 7] , border count: [32, 64, 128]
ETC	criterion: ['gini', 'entropy','log loss'] depth: [None, 10, 20, 30, 40, 50] min samples split: [2, 4, 6, 8, 10] min_samples leaf: [1, 2, 3, 4, 5] max features: [None, 'sqrt', 'log2']
RF	n estimators: [50,100,200] max depth: [None, 10, 20, 30] min samples split: [2, 5, 10] min samples leaf: [1, 2, 4] , max features: ['auto', 'sqrt', 'log2']

3. Results and Discussion

In this section, we will thoroughly examine the effectiveness of different prismatic ML models and provide detailed insights and analysis of each model's performance. We will use different performance criteria to evaluate the models, such as accuracy (Acc.), area under the receiver operating characteristic curve (AUC), recall (Rec.), precision (Prec.), F1-score (F1), Cohen's kappa measure (Kappa), Matthew's correlation measure (MCC), and total training time (TT) in seconds (Sec.). The classifier's performance before hyper-tuning is shown in Table 2. CatBoost demonstrated the highest accuracy at 80% among the models evaluated for driver drowsiness detection. This suggests that 80% of the samples were correctly classified, indicating a robust overall performance. The Lightgbm and XGboost accuracy is the same. They achieved 79% accuracy. The worst accuracy is gained by RF (77%). However, ETC performs better than RF and fewer than the other three classifiers. Regarding recall, which measures the proportion of actual drowsy states correctly identified, CatBoost achieved a commendable score of 72%. This indicates that the model effectively identified drowsy states in drivers. Lightgbm and XGboost recall values are the same as CatBoost. However, the worst performer classifier in this case is ETC (66%). RF is the second-highest performer here (67%). Moreover, CatBoost showed a high precision score of 79%, implying that when it predicted a drowsy state, it was correct 79% of the time. This is a vital metric for applications like driver safety, where false alarms can be costly. However, the ETC precision value is more significant than Lightgbm, XGboost, and RF.ETC achieved the precision performance as Catboost. The F1 score, the harmonic mean of prec and rec, was calculated at 75%. This balanced metric demonstrates CatBoost's ability to strike a favorable compromise between prec and rec. Additionally, CatBoost exhibited an impressive AUC of 88%. This metric is crucial as it measures the model's ability to distinguish between alert and drowsy states, making CatBoost particularly adept at this task. The Kappa statistic, which measures agreement between the model's predictions and the actual labels, is 58%. This indicates a substantial level of agreement beyond random chance. The Matthews Correlation Coefficient (MCC) of 59% further corroborates CatBoost's predictive solid capabilities. MCC is particularly valuable as it considers true positives, true negatives, false positives, and false negatives. These metrics collectively provide a comprehensive assessment of the model's performance. However, it is worth noting that CatBoost took slightly longer for predictions, with a time taken of 2.78 seconds.

Table 2. Performance of the classifiers

Model	Acc.	AUC	Rec.	Prec.	F1	Kappa	MCC	TT(Sec.)
Catboost	0.80	0.88	0.72	0.79	0.75	0.58	0.59	2.78
Lightgbm	0.79	0.87	0.72	0.77	0.74	0.57	0.57	0.53
Xgboost	0.79	0.87	0.72	0.77	0.74	0.56	0.57	0.58
ETC	0.78	0.86	0.66	0.79	0.72	0.54	0.55	0.46
RF	0.77	0.86	0.67	0.77	0.72	0.53	0.54	0.88

Table 3. Performance of the classifiers after hyper-tunning

Model	Acc.	Rec.	Prec.	F1	Best Param
Catboost	0.83	0.78	0.81	0.80	learning rate : 0.1 gamma:5 , max depth: 30
Lightgbm	0.80	0.74	0.79	0.77	boosting type: rf, leaves of num: 50, learning rate: 0.05, n estimators: 500 fractions of feature: 0.8, fraction of bagging: 1.0, freq of bagging: 5
Xgboost	0.80	0.74	0.79	0.77	depth: 6, learning rate: 0.1, iterations: 500, l2 leaf reg: 7, border count:32
ETC	0.79	0.70	0.80	0.75	criterion: entropy, max depth: 10 min samples split: 8, min samples leaf: 5, max features: log2
RF	0.78	0.70	0.78	0.74	n estimators:10 max depth: None , min samples split: 5 min samples leaf: 2 max features: sqrt

However, it is worth noting that CatBoost took slightly longer for predictions, with a time taken of 2.78 seconds. While computational efficiency is an essential consideration in applications where accuracy and discrimination ability are paramount, CatBoost's slightly longer prediction time may be an acceptable trade-off. Comparatively, LightGBM and XGBoost exhibited similar performance metrics. Both models achieved an AUC of 87%, indicating robust discriminatory power.

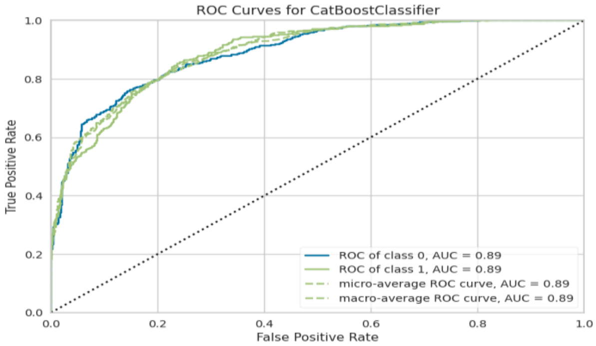

Figure 3. ROC curve for CatBoostClassifier after hypertuning

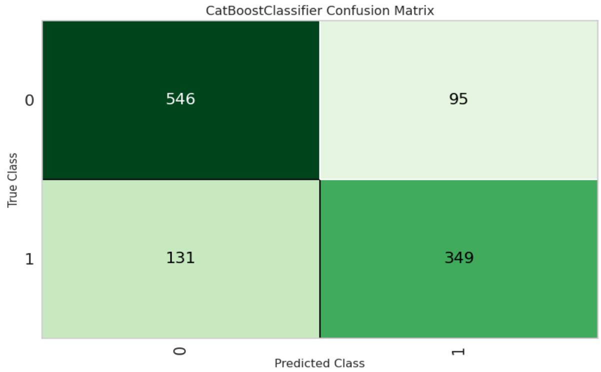

Figure 4. Confusion matrix for CatBoostClassifier

They both attained an accuracy of 79%, demonstrating overall solid correctness in classification. Additionally, LightGBM and XGBoost showcased balanced recall and precision scores, emphasizing their proficiency in identifying drowsy states. One notable advantage of LightGBM and XGBoost was their computational efficiency. LightGBM recorded a time of 0.53 seconds, while XGBoost was slightly higher at 0.58 seconds. These models offer swift predictions, which is crucial for real-time applications.

The ETC displayed competitive results with an AUC of 86% and an accuracy of 78%. ETC demonstrated notable precision at 79%, indicating a high proportion of correctly predicted drowsy states. However, it exhibited a lower recall of 66%, suggesting a slightly reduced ability to identify drowsy states compared to other models. Regarding computational efficiency, ETC excelled with a time of 0.46 seconds, making it an excellent choice for applications where rapid predictions are critical. While RF exhibited a slightly longer time of 0.8 seconds, it remains a viable option for applications where computational efficiency is less critical than precision and recall.

In summary, CatBoost excelled in discrimination ability and overall performance, making it a strong contender for driver drowsiness detection despite a slightly longer prediction time. LightGBM and XGBoost demonstrated similar strong performance, with notable computational efficiency. The ETC and RF also performed well, particularly in precision and computational efficiency. Finally, Catboost performed best in all evaluation criteria, but its computational efficiency is much higher than other classifiers. We have performed hyper-tuning processes after applying the baseline classifier. The parameters and the values of hyper-tuning of all the classifiers are presented earlier. Now, we will present the impact of hyper-tuning. At the hyper-tunning process, we performed 5-fold cross-validation. Table 3 presents the impact of the hyper-tuning of all classifiers. This Table shows the precision, recall, and f-score values. We will also show the best param of all classifiers.

After getting the best result of hyper-tuning, we used the best performer, CatboostClassifier, to show the AUC curve. Figure 3 shows the ROC curve for our classifier, with three lines representing the ROC curves for class 0, class 1, and the micro-average. The AUC value for all three curves is 0.89, indicating that our classifier has high accuracy and can correctly identify most positive instances and avoid false alarms. The result proved that after hyper-tuning, the value is increased. The confusion matrix is shown in Figure 4. The kappa and MCC value of the Catboost classifier is seen in Figure 5 after hyper-tuning. After tuning, the value increased by almost 6% for MCC and kappa evaluation metrics.

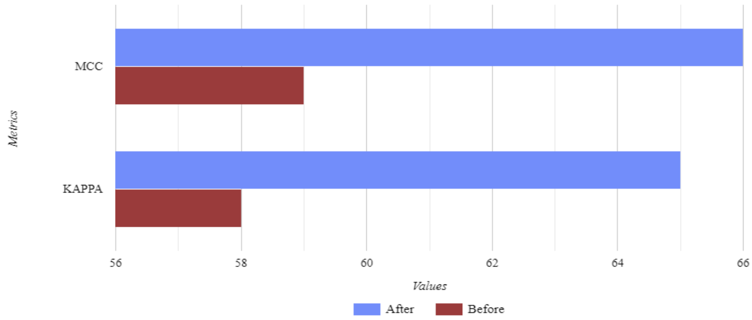

Figure 5. Kappa and MCC value of CatBoostClassifier after hyper tuning

4. Conclusion

Detecting sleepiness cannot be overstated, especially when safety is paramount. Recently, there has been a growing interest in using machine learning algorithms to detect drowsiness automatically. Our study delved deep into this topic, using brainwave EEG waves to evaluate the performance of various ML algorithms such as CatBoost, LightGBM, XGBoost, ETC, and Random Forest. We evaluated the performance of these algorithms using distinct metrics such as acc, prec, rec, and F1-score. We improved their performance significantly after making some minor adjustments to the models. The CatBoost model, in particular, showed great potential with an accuracy of 80% even before hyper-tuning. However, we saw some exceptional results after hyper-tuning the CatBoost model. With an accuracy of 83%, CatBoost outperformed all the other models by a considerable margin. This highlights the importance of fine-tuning and CatBoost's natural ability to detect sleepiness. One of the most significant takeaways from our study is the potential of machine learning methods in drowsiness detection. Despite having a very short dataset, the adjusted CatBoost model showed excellent outcomes, which bodes well for real-world applications. From the perception of the applied outcome, a hybrid-based approach is suggestive of a more improved and stable model. The implications of our study are vast, particularly in situations where worker safety, performance optimization, and safety are top priorities. The study and use of these models in practical settings may lead to increased production and better health and safety outcomes in various sectors. Overall, our findings may contribute to the further improvement of bringing new concepts for model building and help to implement a system for safety.

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BIOGRAPHIES OF AUTHORS

Dr. K Srujan Raju is currently working as Dean of Training and Placement and Heading Department of Computer Science & Engineering at CMR Technical Campus. He obtained his Doctorate in Computer Science in the area of Network Security. He has more than 20+ years of experience in academics and research. His research interest areas include Computer Networks, Information Security, Data Mining, Cognitive Radio Networks, Image Processing, and Other Programming Languages. Dr. Raju worked on 2 projects funded by the Government of India under CSRI & NSTMIS and has also filed 16 patents and 4 Design Patents out of which 4 Design Patents, 3 Utility Patents and 1 copyright in software granted by Indian Patent Office, edited more than 24 books published by Springer Book Proceedings of AISC series, LAIS series and others which are indexed by Scopus also authored books in C Programming & Data Structure, exploring to the Internet, Hacking Secrets, contributed chapters in various books and published more than 100 papers in reputed peer-reviewed Journals and International Conferences. Dr. Raju was invited as Session Chair, Keynote Speaker, Technical Program Committee member, Track Manager, and reviewer for many National and International conferences also appointed as subject Expert by CEPTAM DRDO – Delhi & CDAC. Dr. Raju is a member of various professional bodies and received a Significant Contributor Award and Active Young Member award from the Computer Society of India also served as a Management Committee Member, State Student Coordinator & Secretary of CSI – Hyderabad Chapter. Presently he is a research Consultant to a few engineering and pharmacy colleges and a Mentor of Thub Telangana. He can be contacted at email ksrujanraju@gmail.com.

Roopa R is an Assistant Professor in the Department of CSE- Data Science at Madanapalle Institute of Technology & Science. Pursuing Ph. D at S V University, Tirupati. She received B. Tech in 2006 and M. Tech in 2013 from the JNTU Anantapur University. She has 10 years of teaching experience. Research areas include Deep Learning, Machine Learning, Big data and Image processing.

Dr Penubaka Balaji is a Assistant Professor in Computer Science & Engineering (Honors), K L University (K L E F - Deemed to be University), Vaddeswaram, Guntur. He has 19.5 years of abundant experience in Teaching, and research. He has 18 years of experience in Engineering Colleges and 1.5 years of experience in K L University. He has published several papers in international & national journals and conferences, and reviewed several Scopus journals. He is qualified in GATE. He has received her B.Tech (CSIT) degree from Jawaharlal Nehru Technological University Hyderabad, M.Tech (CSE) degree from Jawaharlal Nehru Technological University Anantapuramu Anantapur and Ph.D. from K L University (K L E F), Vaddeswarm in *"Classic Reputational Trust Assessment-An Opinion Mining Technique for Trust Evaluation of E-Commerce Applications*".

Dr. T. Ravikumar obtained his Ph.D. in Computer Science and Engineering from GITAM-A Deemed-to be University, Visakhapatnam, India, 2020. He received his M. Tech in Computer Science and Engineering from JNT University, Hyderabad in 2008. He is having 15 years of teaching experience in various Engineering Colleges. Presently he is working as an Associate Professor in the Department of CSE, at Aditya Institute of Technology and Management. He is having more than 20 publications in various reputed international journals and conferences . His current research interest includes Machine Learning, IoT, Software Engineering and Artificial intelligence**.**

Dr. K. Reddy Madhavi, completed B.Tech from SV University, Tirupati, M.Tech from JNTU Hyderabad and Ph.D from JNTU, Anantapur and currently working as Associate Professor, Sree Vidyanikethan Engineering College, Tirupati. She has filed and published 21 National and International Patents and few of them granted too. To her profile she has 35 International journals/conferences indexed in SCI/Scopus/Web of Science and published edited/authored books and book chapters. She is the Convener of "DST SERB Sponsored International Conference on Data Science, Intelligent Computing and Cyber Security". She has undergone a course on Design Thinking in collaboration with IUCEE EPICS Purdue University, USA. She is also an Innovation Ambassador associated with IIC, MHRD, Govt.of India. She is acting as a reviewer and program committee member for many International and National conferences and journals. She is acting as Session Chair/Co-chair for many symposia and conferences, delivered expert talks too. She has received "Young Women Scientist award by Dr. Abdul Kalam Educational Trust during the Academic Year 2019-20 and "Young Researcher Award" at CHSN-2020 at JNTUK.

Dr.C. Sateesh Kumar Reddy, Assistant Professor (Senior Level), Advanced CSE, Vignan's Foundation for Science, Technology & Research, Vadlamudi, Guntur, Andhra Pradesh, India. He has worked in the fields of embedded systems and signal processing for over 12 years, first as an Embedded Engineer and later as an Assistant Professor and Researcher. The author has more than 11 years of academic experience, during which time he has created and taught courses on embedded system design to students in graduate level. His area of interest is embedded systems, ERTOS, Signal Processing, Computing, Machine learning and deep learning applications.