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Research Paper

Improving Sleep Disorder Diagnosis Through Optimized Machine Learning Approaches

Naga Chaitanya Rani[1]

V.L. Niharika[2], V. Vyshnavi[3]

[1]Managing Director of Spypro Security Solutions, Hyderabad, Telangana, India.

[2]Student, Department of AIML, Bapatla Engineering College, Bapatla, AP, India

[3]Student, Department of AIML, Bapatla Engineering College, Bapatla, AP, India

Corresponding author: Email:vniharika0096@gmail.com

ABSTRACT:

Due to their impact on health, sleeping disorders such as obstructive sleep apnea and insomnia should be properly diagnosed. In this work, machine learning models are optimized with the help of the Sleep Health and Lifestyle dataset of Kaggle, which is selected to predict sleep disorders. ANOVA is used in feature selection, and SMOTEENN resampling is used in dealing with imbalance between classes. Additional features are engineered by seven foundation classifiers, including RF, Gradient Boosting, Gaussian Naive Bayes, KNN, DT, LR, and SVM. A number of ML algorithms are then tested. The engineered Voting Classifier is the most successful, as it has accuracy. Accuracy of Stacking Classifier is lower in the event of using original features. Making decisions about the model using Explainable AI tools such as LIME and SHAP enhances the transparency and makes clinical decisions.

"**KEY WORDS:** Sleep Disorder, Machine Learning, Feature Engineering, SMOTEENN, Classification, Ensemble Learning, Explainable AI"

1. INTRODUCTION

Sleep is critical to both physical and mental wellbeing to recuperate, control significant functions and maximize brains. Every person should get enough rest particularly sensitive groups such as children and the elderly. Temporal sleep deprivation may result in reduction of focus, memory and risk of accidents whereas chronic sleep deprivation may result in cardiovascular disease, diabetes, depression and obesity. Treating and understanding sleep disturbances is one of the best healthcare issues.

The sleep quality is evaluated by the wakefulness, N1, N2, N3, and the REM sleep stages. The brain waves and the physiological responses differ according to the stage. Wakefulness is alertness of the brain, however N1 and N2 are deeper stages of light sleep.

The deepest state of the non-REM stage is known as N3 which is the physical recovery and REM sleep has vivid dreams and activities of the brain such as waking up. Proper categorization of these stages is used to diagnose insomnia and sleep apnea.

This is analyzed mostly based on polysomnography (PSG) that requires a lot of resources and can easily be subject to human error. Data-driven and automated techniques are vital in the detection and diagnosis of sleep disorder.

2. LITERATURE SURVEY

1.Optimizing Sleep Disorder Classification Using Bayesian Optimization:

The Gradient Boosting Classifiers enhance the classification of sleep problems in this research. The data is pre-treated to guarantee quality and the aspects to be addressed include health and lifestyle. The Bayesian Optimization increases the performance and optimizes model parameters.

Optimization enhances the performance of the models and the results of the diagnostic process since the accuracy increased to 92.92 to 94.44.

2.Advanced Neural Networks for Sleep Disorder Classification

An AD-ANN is developed by means of CNN, RNN, and ensemble. The model is meant to process spatial and temporal sleep data. Standard datasets that are trained include Sleep-EDF and PhysioNet. The model achieved 98.2 percent accuracy, precision, and recall in the stages of sleep. The method allows the diagnosis of sleep disorder on a scale and at an accurate rate.

3.Revolutionizing Sleep Disorder Diagnosis: A Multi-Task Learning Approach

The proposed paper proposes a CNN-based multi-task learning model to enhance the diagnosis of sleep problems. Rather than using complex PSG, it uses EEG signals to save both time and money. The model uses STFT and CWT time-frequency images.

It enhances the accuracy by integrating Genetic Algorithm and Q-learning forecasts. The 98% precision of the model demonstrates its effectiveness and accuracy to identify sleep problems with the help of the automated system.

4. From Narratives to Diagnosis: SleepCare Platform

SleepCare, a ML application, categorizes sleep issues by utilizing unstructured narrative data in the form of physician notes, online forums and telehealth reports. In the elderly, sleep problems are usual, and these problems may reduce cognitive abilities and life quality. Other diagnostic methods are required since polysomnography is costly and not affordable.

The given strategy categorizes textual descriptions of sleep into clinical outcomes: stress-related, neurodegenerative, and respiratory disorders with the help of the NLP. It is a three-step classification pipeline and includes Multinomial Naïve Bayes, SVM with word embeddings and transformer-based BERT model to take into account syntactic and contextual information.

The model was tested with 475 tagged sleep narratives with the help of cross-validation. The SVM based BERT-based model was 81% accurate and had equal performance across classes.

3. PROPOSED SYSTEM

The proposed solution applies the best machine learning on the Sleep Health and Lifestyle data on Kaggle to enhance the diagnosis of sleep disorders. Data preparation deals with missing values, codes category variables and standardizes continuous variables. ANOVA will choose the most significant predictors, and SMOTEENN will solve the problem of the class imbalance and enhance the reliability of the classification.

Models, such as RF, Gradient Boosting, Gaussian Naive Bayes, K-Nearest Neighbors, Decision Tree, Logistic Regression, and Support Vector Machine, introduce seven new features in the feature space as a result of feature engineering.

It is trained on Logistic Regression, RF, DT, SVM, Extra Trees, Extreme Gradient Boosting, Gradient Boosting, LightGBM, CatBoost, AdaBoost, Naive Bayes, Voting Classifier, and Stacking Classifier. A precise and valid system of predicting sleep problems is developed.

4. METHODOLOGY

To forecast and detect sleep disorders effectively and in a real-time, the presented Sleep Disorder Detection System is implemented based on machine learning that encompasses the data collection, preprocessing, feature engineering, model construction and deployment.

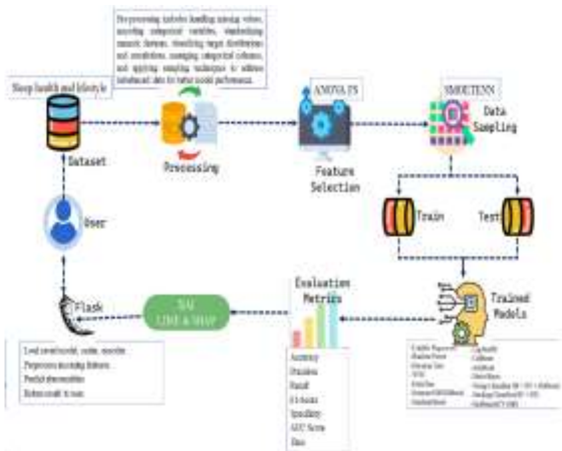
The methodology is based on pipelines to ensure dependability, scalability and interpretability.

Develop an effective, well-organized machine learning platform.

To accurately forecast sleeping difficulties on health and lifestyle data.

Enhance early diagnosis and reduction in cost of diagnosis.

Implement a healthcare solution.



4.1 Problem Identification

The initial phase is the identification of sleep disorder healthcare problems.

PSG is both costly and time consuming and needs infrastructure in the hospital.

4.2 Dataset Acquisition

The system employs physiological and lifestyle information of the Sleep Health and Lifestyle Dataset. Choose such significant characteristics as BMI, stress, sleep duration, and physical activity.

4.3 Exploratory Data Analysis (EDA)

The data set structure and attributes are displayed using Exploratory Data Analysis. The analysis of statistical distribution, correlation, and imbalance of statistics are considered.

4.4 Data Preprocessing

Data presentation enhances the quality of data and the reliability of models.

Eliminate redundancies, remove values, encode nominal data, and standardize numeric variables.All these measures clean and normalize data to be used in machine learning.

4.5 Feature Selection (ANOVA)

ANOVA is applied to select the best predictors. Significant attributes such as stress level, sleep duration and BMI are maintained and insignificant or insignificant attributes are removed.This improves model performance and predictive power.

4.6 Feature Engineering

Feature engineering is beneficial in terms of data representation. We extract new characteristics, group continuous variables and create health risk indicators.

The changes unveil latent trends and enhance the diagnosis of sleep problems.

4.7 Class Imbalance Handling (SMOTEENN)

SMOTEENN contains imbalance in category classes. In this approach, synthetic samples are generated by means of SMOTE and ENN, and noisy data are removed.

This ensures the model training constitutes rare cases such as sleeplessness and sleep apnea.

1179 characters | 165 words

4.8 Train-Test Split

There are training and testing sets of data to evaluate the model generalization.

This helps to remove overfitting and guarantees the performance of the models on unknown data.

4.9 Model Training

There are numerous machine learning algorithms trained on the processed dataset. The models are taught sleeping problem patterns such as excessive stress and sleeplessness or high BMI and sleep apnea. The hyperparameter adjustment is used to optimize model performance.

4.10 Ensemble Optimization

Voting or stacking methods Ensemble techniques raise the accuracy and stability of the forecasts.

The numerous models are employed in these strategies to give more precise predictions.

4.11 Model Evaluation

Trained models are evaluated with the help of Standard measures such as Accuracy, Precision, Recall, and F1-Score.

In medical use, recall is necessary so as not to miss disorder cases.

4.12 Explainable AI (LIME and SHAP)

The most commonly used explainable AI methods to interpret the model predictions are SHAP and LIME. These are the methods that define feature relevance and predict.

This enhances transparency and aids medical practitioners to comprehend projections.

4.13 Model Saving

Saving and reusing of trained model later.

The trained model is not re-trained, thus making the system to be deployed efficiently.

4.14 Deployment (Flask and SQLite)

The system is deployed using flask and SQLite.

The web interface allows individuals to input health data to make predictions.The database contains the information and prediction results of users to be referred to later.

4.15 User Input Module

The user interface gathers structured real-time health data. Information is checked and processed and then transmitted to the prediction engine.

4.16 Real-Time Prediction

The system is used to forecast after preprocessing user input based on the model that has been trained.

5. RESULTS AND DISCUSSION

The proposed Sleep Disorder Detection System was experimented with a high number of machine learning models and features. Accuracy, Precision, Recall, F1-Score and Specificity performance measures were evaluated.

5.1 Performance Evaluation

The results of the experiments indicate that class balancing and feature engineering can enhance prediction. Model training performance was better with engineered features as compared to original features with the Voting Classifier having an accuracy of 97.3%.

ML Model	Accuracy	Precision	Recall	F1 Score	Specificity	AUC Score	Time
Eng - Logistic Regression	0.893	0.888	0.846	0.862	0.911	0.957	0.0540
Eng - Random Forest	0.973	0.956	0.958	0.958	0.989	0.973	0.0981
Eng - Decision Tree	0.973	0.958	0.958	0.958	0.989	0.973	[illegible]
Eng - SVM	0.733	0.689	0.714	0.700	0.858	0.973	0.0194
Eng - ExtraTree	0.973	0.958	0.958	0.958	0.989	0.973	0.0693
Eng - Extreme GB	0.973	0.959	0.958	0.958	0.989	0.973	[illegible]
Eng - Gradient Boosting	0.973	0.958	0.958	0.958	0.980	0.973	0.1947
Eng - LightGBM	0.973	0.958	0.958	0.958	0.989	0.973	[illegible]
Eng - CatBoost	0.973	0.956	0.958	0.958	0.989	0.973	1.4842
Eng - AdaBoost	0.973	0.956	0.958	0.958	0.989	0.973	0.0583
Eng - Naive Bayes	0.773	0.553	0.646	0.594	0.823	0.973	0.0015
Eng - Voting Classifier	0.973	0.958	0.958	0.958	0.989	0.973	0.2368
Eng - Stacking Classifier	0.947	0.924	0.947	0.932	0.977	0.973	0.7387
Eng - GridSearch CV	0.947	0.951	0.958	0.950	0.875	0.973	7.3517

The Stacking Classifier was also good with 88% accuracy using the original features and even higher using the designed features.

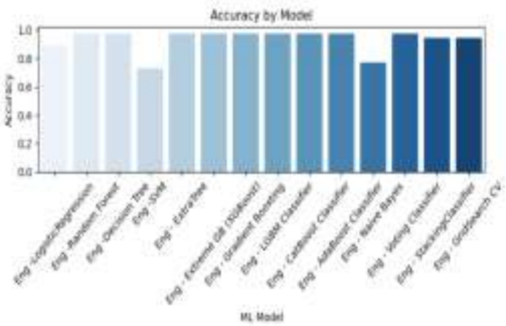
ML Model	Accuracy	Precision	Recall	F1 Score	Specificity	AUC Score	Time
Eng - Logistic Regression	0.973	0.958	0.958	0.958	0.989	0.956	0.0820
Eng - Random Forest	0.973	0.958	0.958	0.958	0.989	0.974	0.0046
Eng - Decision Tree	0.973	0.958	0.958	0.958	0.989	0.974	0.0012
Eng - SVM	0.973	0.958	0.958	0.958	0.988	0.974	0.0025
Eng - ExtraTree	0.973	0.958	0.958	0.958	0.988	0.974	0.0098
Eng - Extreme GB	0.973	0.958	0.958	0.958	0.988	0.974	0.2305
Eng - Gradient Boosting	0.973	0.958	0.958	0.958	0.989	0.974	0.0545
Eng - LightGBM	0.973	0.958	0.958	0.958	0.989	0.974	0.0842
Eng - CatBoost	0.973	0.958	0.958	0.958	0.989	0.974	0.4249
Eng - AdaBoost	0.973	0.958	0.958	0.958	0.989	0.974	0.0314
Eng - Naive Bayes	0.773	0.555	0.646	0.594	0.828	0.974	0.0810
Eng - Voting Classifier	0.973	0.958	0.958	0.958	0.989	0.974	0.1803
Eng - Stacking Classifier	0.973	0.958	0.958	0.958	0.989	0.974	0.5799
Eng - GridSearch CV	0.973	0.958	0.958	0.958	0.989	0.974	5.4550

Simple models such as Naive Bayes did not do well, therefore, pointing at the need of sophisticated ensemble techniques.

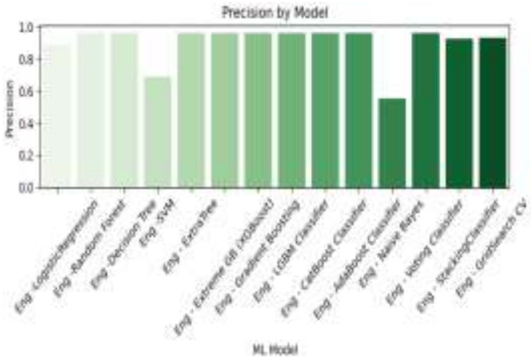
5.2 Comparative Analysis

Models were compared by use of graphs as:

- **Accuracy comparison graphs**

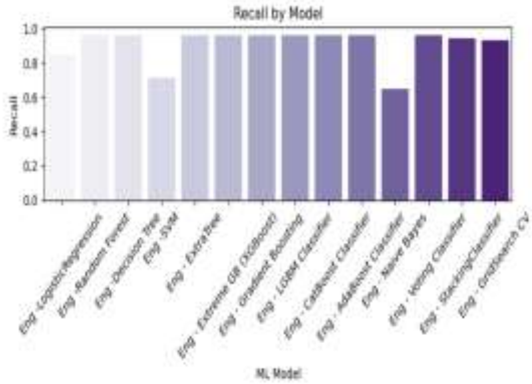


- **Precision comparison graphs**

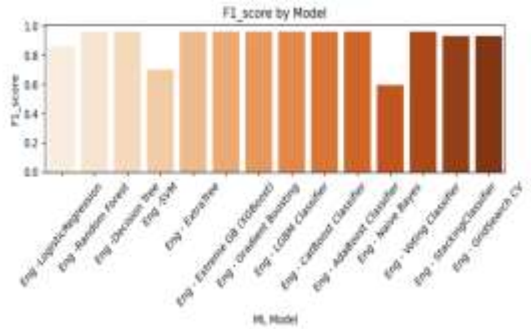


The graphical study demonstrates that engineered features enhance performance. Trained models on reduced and optimized feature sets have a higher level of accuracy, and generalization.

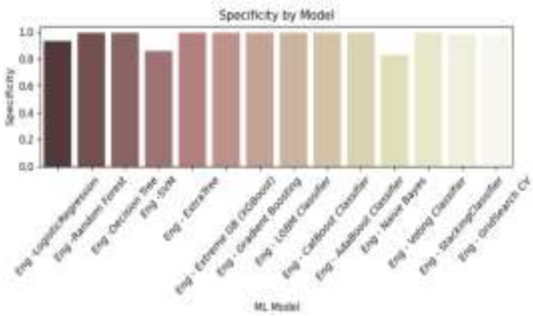
- **Recall comparison graphs**



- **F1-score comparison graphs**



- **Specificity comparison graphs**



The comparisons reveal that ensemble models are better than the single machine learning methods. Compared to models that were trained using original features, performance focuses on feature selection and transformation.

5.3 Impact of Data Processing Techniques

Relevant features, noise reduction and enhanced efficiency of the model were identified in the ANOVA feature selection method. The SMOTEENN resampling method addressed imbalance in classes and trained models that are not frequent. Such techniques significantly enhanced the level of recollection and this is important in medical diagnosis in order to prevent cases of disorders.

5.4 System Output and Visualization

The interface can also be entered by users who can input their health data and get quick projections.

The screenshots of the system prove:

- Input form for user data
- Output of prediction (type of sleep disorder)
- Clear and comprehensible results.

This makes the system user-friendly and not only accurate to the non-technical users.

5.5 Discussion

The results indicate the combination of:

- Feature engineering
- Ensemble learning
- Explainable AI techniques

delivers a pertinent and valid system of sleep disorder forecasting.

Such explainability methods as LIME and SHAP provide the means to see the impact of features on predictions, which increases trust. The system is more efficient and cheaper as compared to the traditional diagnostic methods used.

6.CONCLUSION

The prediction of sleep problems was accurately represented by engineered characteristics, machine learning models, and resampling. The ANOVA feature selection and SMOTEENN class balancing improved ability of the model to differentiate normal and pathological sleeping patterns.

Several engineering characteristics obtained after the application of the algorithm enhanced predicted performance. The model that was most accurate at 97.3 was the Voting Classifier making it reliable. Stacking Classifier was less efficient using original features, which proves the effectiveness of feature engineering.

Elucidable AIs such as LIME and SHAP were used to determine key factors to contribute to making any model more interpretable. The findings indicate that the proposed approach is an accurate, reliable, and interpretative predictor of sleep disorders.

7.FUTURE SCOPE

Through the inclusion of information on physiological features associated with sleep such as the EEG, ECG and breathing rates, additional research can enhance the suggested system. This enhances model generalization and strength.Auto-generated features and complex temporal associations on sleep data can be realized by deep learning techniques of CNNs and RNNs.

Inclusion of lifestyle traits, health history and wearable device activities into sleep disorder prediction may also enhance the accuracy and reliability.More sophisticated optimization techniques such as Bayesian parameter optimization and ensemble techniques can enhance the model performance.

In order to diagnose and treat the sleep disorders at an early stage, developing real time deployment frameworks to undertake on-going monitoring and practical healthcare applications can be helpful.

8.REFERENCES

[1] Khanmohmmadi, S., Khatibi, T., Tajeddin, G., Akhondzadeh, E., & Shojaee, A. (2025). Revolutionizing sleep disorder diagnosis: A Multi-Task learning approach optimized with genetic and Q-Learning techniques. *Scientific Reports*, *15*(1), 16603.

[2El-Kenawy, E. S. M., Ibrahim, A., Abdelhamid, A. A., Khodadadi, N., Abualigah, L., & Eid, M. M. (2024). Predicting sleep disorders: leveraging sleep health and lifestyle data with dipper throated optimization algorithm for feature selection and logistic regression for classification. *Computational Journal of Mathematical and Statistical Sciences*, *3*(2), 341-358.

[3] Chandra, S. O., Jenefa, A., Thiyagu, T. M., & Vidhya, K. (2025, June). Enhancing Diagnostic Precision: Advanced Neural Networks for Sleep Disorder Classification. In *2025 3rd International Conference on Self Sustainable Artificial Intelligence Systems (ICSSAS)* (pp. 1097-1102). IEEE.

[4] Frantzidis, C. A. (2025). From Narratives to Diagnosis: A Machine Learning Framework for Classifying Sleep Disorders in Aging Populations: The sleepCare Platform. *Brain Sciences*, *15*(7), 667.

[5] Panda, N. R., Paramanik, S., Raut, P. K., & Bhuyan, R. (2025). Prediction of sleep disorders using Novel decision support neutrosophic based machine learning models. *Neutrosophic Sets and Systems*, *82*(1), 19.

[6] T. S. Alshammari, "Applying machine learning algorithms for the classification of sleep disorders," IEEE Access, vol. 12, pp. 36110–36121, 2024.

[7] X. Xiao, Y. Rui, Y. Jin, and M. Chen, "Relationship of sleep disorder with neurodegenerative and psychiatric diseases: An updated review," Neurochemical Res., vol. 49, no. 3, pp. 568–582, Mar. 2024.

[8] M. Braun, S. Dietz-Terjung, U. Sommer, C. Schoebel, and C. Heiser, "Stated patient preferences for overnight at-home diagnostic assessment of sleep disorders," Sleep Breathing,vol.28,no.5,pp. 1939–1949,Oct.2024.

[9].A.Şenol,T.Talan,andC.Aktürk,"Anewhybri dfeaturereductionmethod by using MCMSTClustering algorithm with various feature projection methods: A case study on sleep disorder diagnosis," Signal, Image Video Process., vol. 18, no. 5, pp. 4589–4603, Jul. 2024.

[10] I. A. Hidayat, "Classification of sleep disorders using random forest on sleep health and lifestyle dataset," J. Dinda: Data Sci., Inf. Technol., Data Anal., vol. 3, no. 2, pp. 71–76, Aug. 2023.

[11] W.Z.T.Tareq, "Sleep disorders detection and classification using random forests algorithm," in Decision Making in Healthcare Systems. Cham, Switzerland: Springer, 2024, pp. 257–266.

[12] Z. Zhang, T. B. Conroy, A. C. Krieger, and E. C. Kan, "Detection and prediction of sleep disorders by covert bed-integrated RF sensors," IEEE Trans. Biomed. Eng., vol. 70, no. 4, pp. 1208–1218, Apr. 2023.

[13] A. Wadichar, S. Murarka, D. Shah, A. Bhurane, M. Sharma, H. S. Mir, and U. R. Acharya, "A hierarchical approach for the diagnosis of sleep disorders using convolutional recurrent neural network," IEEE Access, vol. 11, pp. 125244–125255, 2023.

[14] Wara, T. U., Fahad, A. H., Das, A. S., & Shawon, M. M. H. (2025). A systematic review on sleep stage classification and sleep disorder detection using artificial intelligence. *Heliyon*, *11*(12).

[15] E. R. Widasari, K. Tanno, and H. Tamura, "Automatic sleep disorders classification using ensemble of bagged tree based on sleep quality features," Electronics, vol. 9, no. 3, p. 512, Mar. 2021.

Mahesh Ganji. (2025). Enhancing Oracle Cloud HR Reporting Through AI-Driven Automation. Journal of Science & Technology, 10(6), 28–36. https://doi.org/10.46243/jst.2025.v10.i06.pp28-36

[17] Todupunuri, A. (2025). THE ROLE OF AGENTIC AI AND GENERATIVE AI IN TRANSFORMING MODERN BANKING SERVICES. American Journal of AI Cyber Computing Management, 5(3), 85–93. https://doi.org/10.64751/ajaccm.2025.v5.n3.pp85-93

[18] Todupunuri, A. (2025). Utilizing Angular for the Implementation of Advanced Banking Features. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.5283395

[19] Sushma Babburi. (2025). Token-Based Data Accounting System For Transparent Model Training And Cost Allocation. American Journal of AI Cyber Computing Management, 5(4), 463–474. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp463-474

[20] Snigdha Gaddam. (2025). SOFTWARE STACK PREPARED FOR AI TRANSITIONING FROM MODULES TO MODELS. American Journal of AI Cyber Computing Management, 5(4), 451–462. https://doi.org/10.64751/ajaccm.2025.v5.n4.pp 451-462

[21]Gaddam, S. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.

[21]Bajarang Bhagwat, V. (2023). Optimizing Payroll to General Ledger Reconciliation: Identifying Discrepancies and Enhancing Financial Accuracy. JOURNAL OF ADVANCE AND FUTURE RESEARCH, 1(4). https://doi.org/10.56975/jaafr.v1i4.501636

[22]Suhasnadh Reddy Veluru, Sai Teja Erukude, and Viswa Chaitanya Marella. 2025. Multimodal Detection of Fake Reviews using BERT and ResNet-50. In 2025 4th International Conference on Innovative Mechanisms for Industry Applications (ICIMIA). IEEE, 877–882.

[23]Doragacharla, V. R. (2026). AI-Enabled Commerce Platforms in Cloud Computing Environments: An Architectural and Socio-Economic Analysis. Journal of Computational Analysis & Applications, 35(1).

[24]Jay Bharat Mehta. (2025). AUTONOMOUS PATCH VALIDATION FOR ZERO-DAY EXPLOITS IN ENTERPRISE CLOUDS. International Journal of Applied Mathematics, 38(4s), 1270–1285. https://doi.org/10.12732/ijam.v38i4s.685

[25]Reddy, S. K. (2025). Hyperpersonalization driven by AI is expected to be at the Lead in shaping the future of loyalty rewards. Journal of Emerging Technologies and Innovative Research.

[26]Reddy, S. K. R. Developing a Modular AI Framework to Enhance Scalability and Personalization in Next-Generation Reward Platforms.

[27]Poojari, R. (2026). Privacy-Preserving Generative AI in Healthcare Systems Using Federated Learning Approaches. International Journal of Data Science and IoT Management System, 5(1), 78-88.

[28]Kalae, U. K. (2021). Enhancing data analytics and reporting efficiency using Power BI and SQL in cloud computing environments. Journal of Computational Analysis and Applications, 29(6), 2021. https://doi.org/10.48047/jocaaa.2021.29.06.48

[29]Kalae, U. K. (2025). Optimizing cost-effective cloud data pipeline orchestration across multiple cloud providers. Journal of Information Systems Engineering and Management, 10(63s), e726–e741.

[30]Saikumar, B. (2023). Enhancing Client Engagement through AI-Driven Real-Time Reporting and Automated Alerts. International Journal of Enhanced Research in Science, Technology & Engineering, 12(11), 111–117. https://doi.org/10.55948/ijerste.2023.1115

[31]Saikumar, B. (2024). Optimizing Crew Scheduling and Absence Management using Microservices: Enhancing Reliability and Efficiency in Crew Management Systems. International Journal of Enhanced Research in Management & Computer Applications, 13(11),50–55. https://doi.org/10.55948/ijermca.2024.0116