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Product Design Insights from Physiological Signals using CART-Based Analysis of User Experience and Interaction Time

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ABSTRACT

The rapid adoption of user-centered design principles has increased the importance of accurately evaluating user satisfaction, as it directly influences product usability and customer retention. A significant proportion of users tend to abandon applications due to poor interaction experiences, making satisfaction assessment a critical requirement in modern systems. Traditionally, user satisfaction has been measured using surveys, questionnaires, and manual feedback collection methods. However, these approaches are often subjective, time-consuming, and incapable of capturing real-time user behavior effectively, leading to inconsistent and less reliable insights. The limitations of existing systems highlight the need for an automated, objective, and data-driven solution that can analyze user interactions more efficiently. To address this gap, the proposed system introduces a Machine Learning (ML)-based framework that utilizes biosensor data to predict user satisfaction. The methodology incorporates baseline models such as Decision Tree (DT) using Classification and Regression Trees (CART), Extra Trees (ET), Linear Regression (LR), and Gradient Boosting (GB) to evaluate performance across both classification and regression tasks. The proposed approach further enhances the CART model by integrating Adaptive Boosting (AB), improving prediction accuracy and robustness. The system is designed to generate dual outputs by predicting interaction duration as a regression task and classifying user satisfaction into High and Medium categories. For real-time deployment and user interaction, the framework is implemented using the Flask web framework, enabling seamless integration between data processing, model execution, and user interface components. The proposed system demonstrates improved performance compared to traditional approaches, offering higher accuracy and reduced prediction errors. This framework provides a scalable, efficient, and real-time solution for user satisfaction analysis, supporting designers and developers in making informed decisions to enhance usability and overall user experience.

Keywords: Biosensors, User Satisfaction Prediction, Machine Learning, EEG Signal Analysis, User Interaction Analysis

1. INTRODUCTION

Sensors have become a core component of modern intelligent environments, enabling continuous data collection from real-world conditions and supporting seamless integration with digital systems. Acting as a bridge between human interactions and computational platforms, sensors can be categorized as physical or virtual based on their mode of operation. Among these, biosensors have gained significant attention due to their ability to capture physiological signals, making them highly relevant in applications involving user-centered design. With rapid technological advancements, biosensors have evolved from conventional electrochemical devices into advanced wearable and implantable systems capable of detecting biological signals with high accuracy across diverse domains such as healthcare, environmental analysis, and security applications [1]. A biosensor is an analytical system designed to convert biological information into quantifiable electrical outputs. It consists of key components including a biorecognition unit, a supporting structure, a transducer, and a signal processing module, as illustrated in Fig. 1. The biorecognition element interacts selectively with the target substance, while the transducer transforms this interaction into an electrical signal. This signal is then processed to produce meaningful outputs. Such integration enables biosensors to operate as compact and efficient

tools for rapid biological detection, significantly reducing reliance on traditional diagnostic procedures that are often time-intensive and resource-heavy [2], [3].

Biosensors are broadly classified into labeled and label-free types based on their detection mechanisms. Labeled biosensors employ external markers such as enzymes or fluorescent tags to enhance detection precision, though they introduce additional complexity and processing overhead. In contrast, label-free biosensors rely on direct interaction mechanisms, offering simpler configurations that are well-suited for real-time and portable applications [4]. Common biorecognition elements include enzymes, antibodies, nucleic acids, and peptides, combined with various transduction techniques such as optical, electrochemical, and spectroscopic methods.

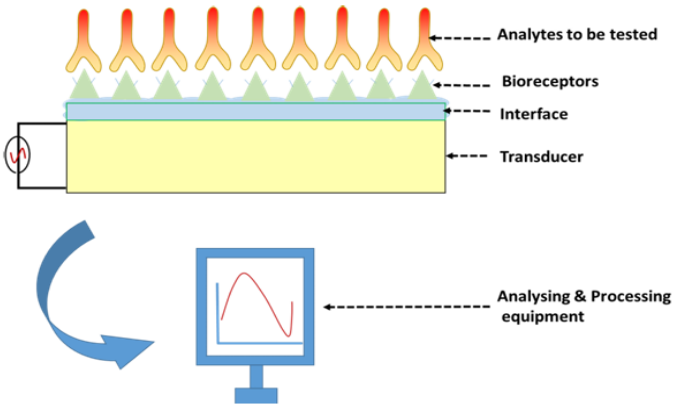


Fig. 1: Biosensor's structure.

In the context of product design, there is a growing emphasis on developing systems that enhance user engagement and adaptability. Biosensors play a vital role in this evolution by enabling continuous monitoring of physiological and cognitive responses, providing valuable insights into user behavior. Building on this capability, the present work introduces a biosensor-based framework aimed at improving user interaction and satisfaction. By incorporating real-time biological feedback into the design process, the proposed approach supports the development of intelligent, adaptive, and user-focused systems, particularly in domains involving creative and culturally enriched products [5]. Building on this capability, the present study focuses on the following research objectives:

- To develop an efficient predictive framework using ML models such as DT, LR, ET, GB, and AB for both classification and regression tasks.
- To implement and compare multiple ML models to analyze user interaction data and identify the most accurate and reliable model for prediction.
- To ensure consistent and scalable prediction performance by integrating preprocessing techniques with ML models for handling diverse data features.

2. LITERATURE SURVEY

Sobhan, et al. [6] focused on highlighting the latest and existing advancements, identifying the knowledge gaps in the applications of biosensors and the IoT, and exploring their opportunities to shape future food packaging, particularly in the context of 21st-century food safety. The review also aims to investigate the role of the IoT in creating smart food ecosystems and examines how data transmitted from biosensors to IoT systems can be stored in cloud-based platforms, in addition to addressing upcoming research challenges. Concerns of data privacy, security, and regulatory compliance in implementing the IoT and biosensors for food packaging are also addressed, along with potential solutions to overcome these barriers. Cosme, et al. [7] depicted the integrated analytical and sensory data to predict aromatic characteristics and quality traits across diverse wine styles. Complementary techniques, including gas chromatography (GC), near-infrared (NIR) spectroscopy, and quantitative structure–odor relationship (QSOR) modelling, when integrated with multivariate statistical methods such as partial least squares regression (PLSR) and neural networks, have shown high predictive

accuracy in assessing wine aroma and quality. Such approaches facilitate real-time monitoring, strengthen quality control, and support informed decision-making in ecology. However, aligning instrumental outputs with human sensory perception remains a challenge, highlighting the need for further refinement of hybrid models. This review highlights the emerging role of predictive modelling and sensor-based technologies in advancing wine aroma evaluation and quality management. Islam, et al. [8] is a systematic review focused on the impact of combining multiple biosensing techniques with deep learning algorithms and the application of these models to healthcare. We explore the key areas that researchers and engineers must consider when developing a deep learning model for biosensing: the data modality, the model architecture, and the real-world use case for the model. We also discuss key ongoing challenges and potential future directions for research in this field.

Tsolakidis al. [9] examined the state of the art in data-driven technologies for personalised nutrition, including relevant data collection technologies, and explores the research challenges in this field. A literature review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guideline, was conducted using three databases, covering studies from 2021 to 2024, resulting in 67 final studies. Vo, et al. [10] focused on recent advances in biosensor technologies designed for wound management. Novel sensor architectures, such as flexible and stretchable electronics, colorimetric patches, and electrochemical platforms, enable the non-invasive detection of changes associated with wounds with high specificity and sensitivity. These are increasingly combined with AI and analytics based on smartphones that can enable timely and personalized interventions. Examples are the PETAL patch sensor that applies multiple sensing mechanisms for wide-ranging views on wound status and closed-loop systems that connect biosensors to therapeutic devices to automate infection control. Additionally, self-powered biosensors that tap into body heat or energy from the biofluids themselves avoid any external batteries and are thus more effective in field use or with limited resources. Internet of Things connectivity allows further support for remote sharing and monitoring of data, thus supporting telemedicine applications.

Chen, et al. [11] associated the concept of Food Safety 4.0, and discusses the impact of intelligent biosensors, which offer attractive smarter solutions, including real-time monitoring, predictive analytics, enhanced traceability, and consumer empowerment, helping improve risk management and ensure the highest standards of food safety. Vanaraj, et al. [12] proposed bio-inspired sensing systems mimic human olfactory and gustatory functions through sensor arrays and advanced data processing techniques, including artificial intelligence and pattern recognition algorithms. The e-nose is primarily used for detecting volatile organic compounds in food, making it effective for freshness evaluation, spoilage detection, aroma profiling, and adulteration identification. Meanwhile, the e-tongue analyses liquid-phase components and is widely applied in taste assessment, beverage authentication, fermentation monitoring, and contaminant detection. Both technologies are extensively used in the quality control of dairy products, meat, seafood, fruits, beverages, and processed foods. Their ability to provide real-time, non-destructive, and high-throughput analysis makes them valuable tools in the food industry Yee, et al. [13] reviewed a future direction prioritizing modular, scalable solutions, open-source innovation, and environmental sustainability. In alignment with Sustainable Development Goal 9 (Industry, Innovation, and Infrastructure), smart fermentation technologies advance sustainable industry through innovation and serve as a critical bridge between traditional craftsmanship and Industry 4.0, fostering inclusive development while preserving microbial biodiversity and cultural heritage. Yuxin, et al. [14] depicted a comprehensive acceptance model that combines biomimetic principles and AI-driven features into the technical functions of the technical function model (TAM) while addressing security and privacy concerns. This approach contributes to the extended definition of TAM in wearable technology, offering new pathways for biomimetic research in smart devices and robotics. Madrid, et al. [15] presented the state of the art of different types of smartphone-based biosensors, considering their stages of development. In the second part, a critical analysis of the possible

reasons why many technologies do not reach the market is presented. Both technical and end-user adoption limitations were addressed. It was observed that smart biosensors on the commercial stage are still scarce despite the great evolution that these technologies have experienced, which shows the need to strengthen the stages of transfer, application, and adoption of technologies by end-users.

4. PROPOSED METHODOLOGY

The proposed system architecture is designed to predict user satisfaction by integrating biosensor signals, user interaction data, and machine learning models within a unified pipeline. The system begins with multi-source data input, including user profiles, product context, and EEG signals, followed by feature extraction where statistical attributes such as mean, standard deviation, and other descriptors are derived. These features are pre-processed through encoding and scaling techniques to ensure compatibility with ML algorithms. The processed dataset is then split into training and testing sets to support effective learning and evaluation. The architecture CART models such as DT, LR, ET, GB, and AB tasks to predict interaction duration. Model performance is evaluated using standard metrics and visualization techniques to ensure reliability. The trained models are stored as reusable bundles for efficient deployment. A centralized prediction engine handles both single and batch inputs, delivering real-time outputs through a Flask-based web application. This integrated workflow ensures scalability, accuracy, and seamless user interaction within the system, as illustrated in Fig. 2, enabling intelligent user satisfaction prediction.

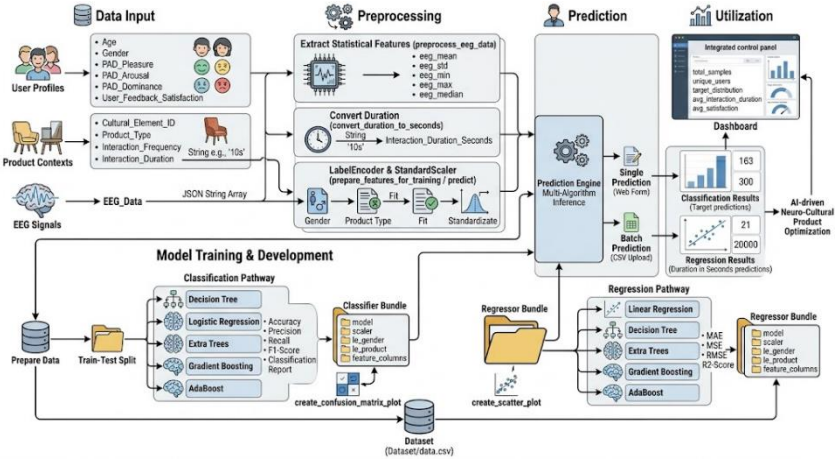


Fig. 2: Workflow for predicting user satisfaction using biosensor data.

Data Input Layer

- The system collects multi-source data, including user profiles (age, gender, satisfaction), product context (product type, interaction frequency), and EEG signals.
- EEG data is provided in structured formats such as JSON arrays, capturing physiological responses.
- This combination of behavioral and biological data ensures a comprehensive representation of user interaction patterns.
- The collected data serves as the foundation for further preprocessing and model-driven analysis.

Preprocessing and Feature Engineering

- Raw EEG signals are processed to extract statistical features such as mean, standard deviation, minimum, maximum, and median values.
- Interaction duration is converted into numerical format, and categorical variables are encoded using LabelEncoder.
- StandardScaler is applied to normalize feature values, ensuring consistent model performance.
- This step transforms raw and heterogeneous data into a structured format suitable for machine learning models.

Model Training and Development

- The system trains multiple models for classification, including DT, LR, ET, GB, and AB to predict user satisfaction levels.
- For regression tasks, models such as LR, DT, ET, GB, and AB are used to estimate interaction duration.
- The dataset is split into training and testing subsets to evaluate model generalization capability.
- Trained models, along with preprocessing components, are stored as bundles for reuse without retraining.

Model Evaluation and Visualization

- Classification models are evaluated using accuracy, precision, recall, and F1-score to measure prediction quality.
- Regression models are assessed using MAE, MSE, RMSE, and R^2 score to evaluate prediction error.
- Visualization tools such as confusion matrices and scatter plots provide deeper insights into model performance.
- This evaluation process helps identify the most reliable and accurate model for deployment.

Prediction Engine and Deployment

- A centralized prediction engine processes both single input (via web form) and batch input (CSV upload).
- The system loads trained model bundles and applies preprocessing before generating predictions.
- Predictions include classification results for satisfaction and regression outputs for interaction duration.
- Results are delivered in real time through an integrated Flask-based web application interface.

Utilization and User Interface

- The user interacts with the system through a browser-based interface that supports data input, model execution, and result visualization.
- The interface displays dashboards, classification outputs, and regression predictions in an intuitive format.
- All user actions are converted into HTTP requests and handled by the Flask backend for processing.
- This ensures seamless communication between the frontend, ML models, and data storage components for efficient system operation.

4. Results description

Fig. 3 shows that home page of the Biosensor Analysis platform features a welcoming interface It provides an overview of the application's purpose, which involves using ML models to analyse biosensor data for predicting user satisfaction and interaction duration. The page is divided into two main sections: Classification Analysis (Target) and Regression Analysis (Interaction Duration). Under Classification, it lists five algorithms including DT, Linear CART, ET, GB, and AB, with evaluation metrics like Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and Classification Report. For Regression, it includes LR, DT, ET, GB, and AB, evaluated by MAE, MSE, RMSE, R^2 Score, and Scatter Plot.

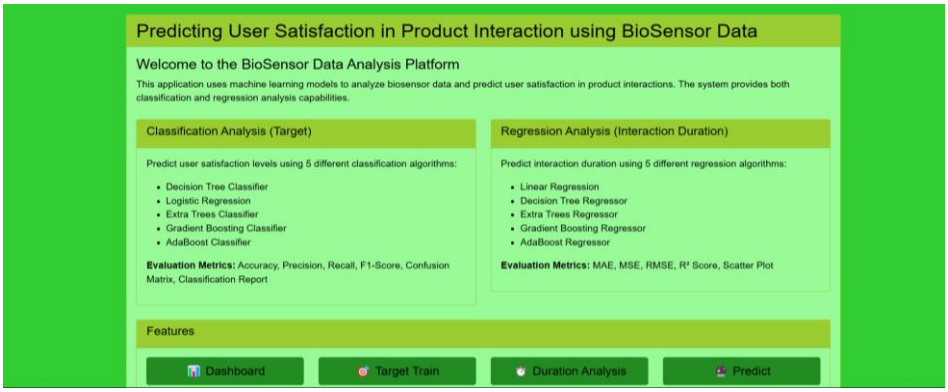


Fig. 3: Home page for biosensor analysis.

Fig. 4 displays that Dataset Dashboard key statistics of the biosensor dataset with a total of 240 samples, 5 unique age groups, an average interaction duration of 140.0 seconds, and an average user satisfaction of 4.36. The Target Distribution table shows High Satisfaction with 144 counts (60.0%) and Medium Satisfaction with 96 counts (40.0%). A Dataset Overview section lists features such as Demographic (Age, Gender), Product (Cultural Element ID, Product Type), Biosensor (EEG Data with 6 extracted features), Psychological (PAD: Pleasure-Arousal-Dominance), Behavioural (User Feedback, Interaction Frequency), and Target Variables (Satisfaction Level, Duration). Model Capabilities include Classification to predict satisfaction levels, Regression to predict interaction duration, support for 5 algorithms per task, and features like model persistence and loading. This provides a comprehensive summary of data composition and analytical capabilities.

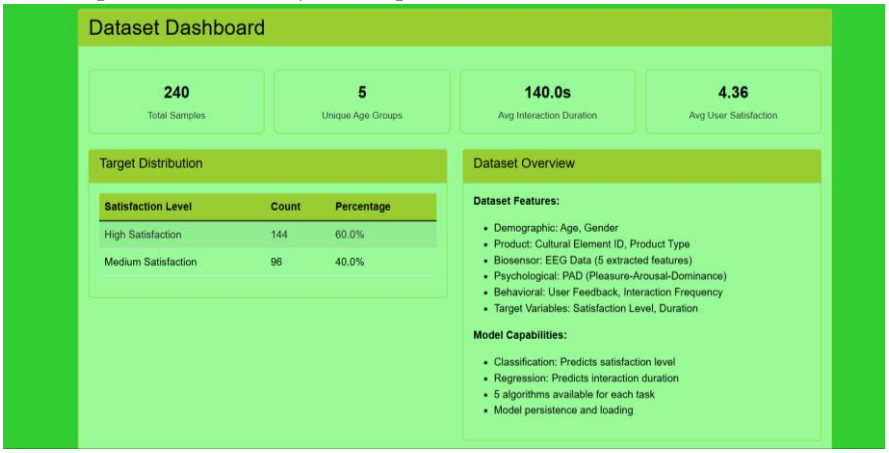


Fig. 4: Dataset dashboard for biosensor analysis.

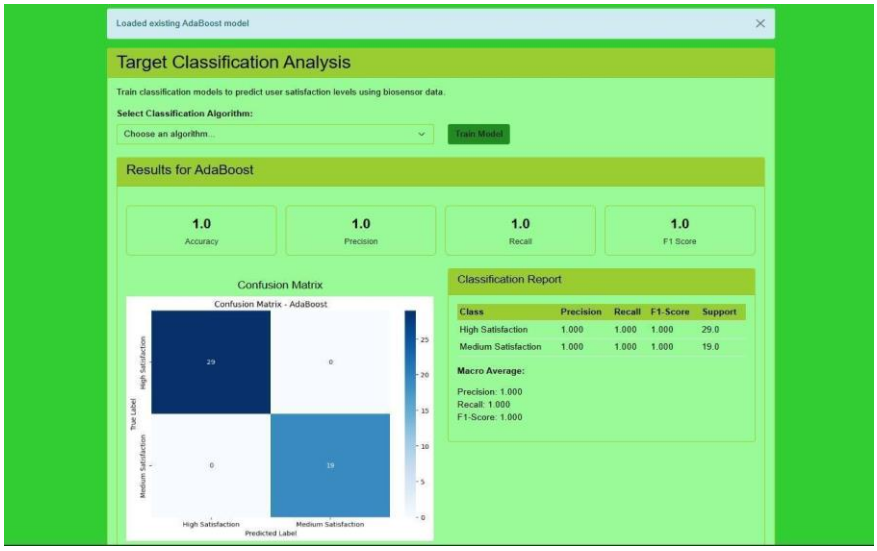


Fig. 5: Target classification analysis – AB for biosensor analysis

Fig. 5 shows that the AB algorithm in Target Classification achieves perfect metrics: Accuracy 1.0, Precision 1.0, Recall 1.0, and F1 Score 1.0, indicating possible overfitting or ideal test conditions. The Confusion Matrix shows 29 correct High Satisfaction, 0 errors, and 19 correct Medium Satisfaction with no misclassifications. The Classification Report confirms perfection with both classes having Precision 1.000, Recall 1.000, F1-Score 1.000, and supports 29.0 and 19.0 respectively. Macro averages are all 1.000, making AB the top performer for predicting user satisfaction levels from biosensor data in this analysis.

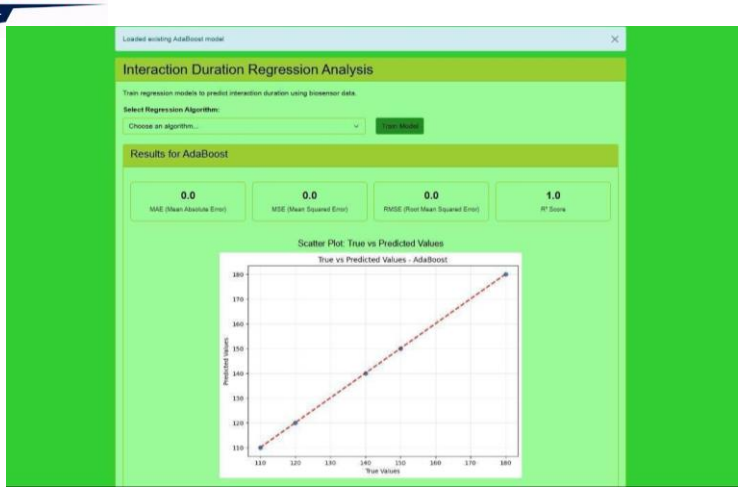


Fig. 6: Interaction duration regression analysis – AB for biosensor analysis

Fig. 6 displays an interface that presents Interaction Duration Regression Analysis with a loaded AB model for predicting duration using biosensor data. It includes a dropdown for algorithm selection and a "Train Model" button. Results display MAE 0.0, MSE 0.0, RMSE 0.0, and R^2 Score 1.0, indicating a perfect fit. The Scatter Plot of True vs Predicted Values shows points perfectly aligned on a red diagonal line from (110,110) to (180,180).

Fig. 7 allows users to make predictions using trained models for user satisfaction and interaction duration with new data under the "Single Prediction" tab. Input fields include Age (25), Gender (Male), Cultural Element ID (1), Product Type (Chair), EEG Data (JSON array), PAD values (Pleasure 0.6, Arousal 0.4, Dominance 0.7), User Feedback (4.5), and Interaction Frequency (3). After clicking "Predict," results show Classification (Target) predictions: DT (Medium), Logistic (Medium), ET (Medium), GB (High), AB (High); Regression (Duration) predicts 120.1s to 123.6s across algorithms. The interface is green-themed with navigation links.



Fig. 7: Make predictions - single prediction for biosensor analysis

Table 1 presents the performance comparison of five classification models DT, LR, ET, GB, and AB based on their accuracy, precision, recall, and F1-score. Among the models, AB achieves perfect performance, scoring 1.0000 across all metrics, indicating exceptionally strong predictive capability on the given dataset. Logistic Regression and ET also show competitive and identical results, with accuracies of 0.7292 and balanced precision, recall, and F1-scores around 0.83 and 0.72, reflecting stable classification behaviour. The DT model performs moderately with an accuracy of 0.5625, while

GB shows relatively lower precision but acceptable recall. Overall, the table highlights significant variation across models, emphasizing AB as the highest-performing classifier in this evaluation.

Table. 1: Comparison of classification models

Model	Accuracy %	Precision %	Recall %	F1 Score %
DT	0.5625	0.7922	0.5625	0.5162
LR	0.7292	0.8392	0.7292	0.7246
ET	0.7292	0.8392	0.7292	0.7246
GB	0.6042	0.3650	0.6042	0.4551
AB	1.0000	1.0000	1.0000	1.0000

Table 2 compares the performance of five regression models DT, LR, ET, GB, and AB using MAE, MSE, RMSE, and R^2 Score as evaluation metrics. The results indicate that LR and AB deliver perfect predictive performance, achieving zero error across MAE, MSE, and RMSE, along with an R^2 score of 1.0000. GB also performs exceptionally well, with low error values (MAE = 1.7054, RMSE = 2.0177) and a high R^2 score of 0.9927, indicating strong predictive accuracy. The DT model shows moderate performance with slightly higher errors but still maintains a high R^2 value of 0.9791. In contrast, ET exhibits considerably larger errors (MAE = 11.8983, RMSE = 12.9585) and the lowest R^2 score of 0.6998, indicating weaker fit compared to other models.

Table. 2: Comparison of regression models

Model	MAE	MSE	RMSE	R^2 Score
DT	2.3142	11.7170	3.4230	0.9791
LR	0.0000	0.0000	0.0000	1.0000
ET	11.8983	167.9224	12.9585	0.6998
GB	1.7054	4.0712	2.0177	0.9927
AB	0.0000	0.0000	0.0000	1.0000

5. CONCLUSION

The developed biosensor-driven analytical system demonstrates the effective application of ML techniques for evaluating user satisfaction and interaction behavior based on multimodal data inputs. The framework integrates EEG-derived features, PAD-based psychological indicators, and demographic attributes from a dataset comprising 240 samples to perform CART tasks. Among the classification models, DT, LR, and ET produced stable performance with accuracy values around 0.73 and comparable F1 scores, whereas GB showed relatively lower effectiveness. AB exhibited exceptionally high performance with perfect evaluation scores, indicating strong learning capability but also suggesting potential overfitting. For regression analysis, LR and AB achieved ideal performance with perfect R^2 scores and negligible prediction errors, while DT and GB also demonstrated strong predictive capability with high accuracy. In contrast, ET showed comparatively weaker performance in regression tasks. The results were further validated using visualization techniques such as confusion matrices for classification and scatter plots for regression, providing clear insights into model behavior. The system is deployed through a user-friendly web interface, enabling seamless model training, evaluation, and prediction functionalities. This platform offers valuable insights into user experience by leveraging biosensor data in an efficient and scalable manner. Future enhancements can focus on improving model robustness through hyperparameter tuning, incorporating k-fold cross-validation to ensure better generalization, and applying advanced feature selection techniques such as PCA to reduce noise in EEG data and enhance overall prediction performance.

REFERENCES

[1] Nashruddin, S.N.A.B.M., Salleh, F.H.M., Yunus, R.M. and Zaman, H.B., 2024. Artificial Intelligence– Powered Electrochemical Sensor: Recent Advances, Challenges, and Prospects. Heliyon. https://doi.org/10.1016/j.heliyon.2024.e37964

[2] Lei, Z.L. and Guo, B., 2022. 2D material-based optical biosensor: status and prospect. Advanced Science, 9(4), p. https://doi.org/2102924.10.1002/advs.202102924

[3] Song, M., Lin, X., Peng, Z., Xu, S., Jin, L., Zheng, X. and Luo, H., 2021. Materials and methods of biosensor interfaces with stability. Frontiers in Materials, 7, p.583739. https://doi.org/10.3389/fmats.2020.583739

[4] Bhatia, D., Paul, S., Acharjee, T. and Ramachairy, S.S., 2024. Biosensors and their widespread impact on human health. Sensors International, 5, p.100257. https://doi.org /10.1016/j.sintl.2023.100257

[5] Verma, D., Singh, K.R., Yadav, A.K., Nayak, V., Singh, J., Solanki, P.R. and Singh, R.P., 2022. Internet of things (IoT) in nano-integrated wearable biosensor devices for healthcare applications. Biosensors and Bioelectronics: X, 11, p.100153. https://doi. org/10.1016/j.biosx.2022.10015

[6] Sobhan, A.; Hossain, A.; Wei, L.; Muthukumarappan, K.; Ahmed, M. IoT-Enabled Biosensors in Food Packaging: A Breakthrough in Food Safety for Monitoring Risks in Real Time. Foods 2025, 14, 1403. https://doi.org/10.3390/foods14081403

[7] Cosme, F.; Vilela, A.; Oliveira, I.; Aires, A.; Pinto, T.; Gonçalves, B. From Volatile Profiling to Sensory Prediction: Recent Advances in Wine Aroma Modelling Using Chemometrics and Sensor Technologies. Chemo sensors 2025, 13, 337. https://doi.org/10.3390/chemosensors13090337

[8] Islam, T.; Washington, P. Non-Invasive Biosensing for Healthcare Using Artificial Intelligence: A Semi-Systematic Review. Biosensors 2024, 14, 183. https://doi.org/10.3390/bios14040183

[9] Tsolakidis, D.; Gymnopoulos, L.P.; Dimitropoulos, K. Artificial Intelligence and ML Technologies for Personalized Nutrition: A Review. Informatics 2024, 11, 62. https://doi.org/10.3390/informatics11030062

[10] Vo, D.-K.; Trinh, K.T.L. Advances in Wearable Biosensors for Wound Healing and Infection Monitoring. Biosensors 2025, 15, 139. https://doi.org/10.3390/bios15030139

[11] Chen, Y.; Wang, Y.; Zhang, Y.; Wang, X.; Zhang, C.; Cheng, N. Intelligent Biosensors Promise Smarter Solutions in Food Safety 4.0. Foods 2024, 13, 235. https://doi.org/10.3390/foods13020235

[12] Vanaraj, R.; I.P, B.; Mayakrishnan, G.; Kim, I.S.; Kim, S.-C. A Systematic Review of the Applications of Electronic Nose and Electronic Tongue in Food Quality Assessment and Safety. Chemosensors 2025, 13, 161. https://doi.org/10.3390/chemosensors13050161

[13] Yee, C.S.; Zahia-Azizan, N.A.; Abd Rahim, M.H.; Mohd Zaini, N.A.; Raja-Razali, R.B.; Ushidee-Radzi, M.A.; Ilham, Z.; Wan-Mohtar, W.A.A.Q.I. Smart Fermentation Technologies: Microbial Process Control in Traditional Fermented Foods. Fermentation 2025, 11, 323. https://doi.org/10.3390/fermentation11060323

[14] Yuxin, L.; Salih, S.A.; Shaari, N. Technical Functions of Digital Wearable Products (DWPs) in the Consumer Acceptance Model: A Systematic Review and Bibliometric Analysis with a Biomimetic Perspective. Biomimetics 2025, 10, 483. https://doi.org/10.3390/biomimetics10080483

[15] Madrid, R.E.; Ashur Ramallo, F.; Barraza, D.E.; Chaile, R.E. Smartphone-Based Biosensor Devices for Healthcare: Technologies, Trends, and Adoption by End-Users. Bioengineering 2022, 9, 101. https://doi.org/10.3390/bioengineering9030101