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# A Dual-Stream ML Model for Estimating Interaction Time and Satisfaction Categories in Product Design

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## ABSTRACT

The rapid rise of user-centered product design has increased the need for understanding user satisfaction through objective measures. According to recent studies, over 65% of organizations report product usability as a key factor in customer retention, while 75% of users disengage after unsatisfactory interactions. Traditional manual surveys and subjective feedback mechanisms are time-consuming and often biased, providing limited real-time insights into user experience. To address this gap, this study proposes a Machine Learning (ML)-based framework that leverages biosensor data for predicting user satisfaction. Existing methods such as Classification and Regression Trees (CART) using Decision Tree (DT), Extra Trees (ET), Linear Regression (LR), and Gradient Boosting (GB) serve as baseline models. The proposed method introduces a CART framework with Adaptive Boosting (AdaBoost), enhancing both regression and classification performance. The output comprises two dimensions: interaction duration prediction (regression) and user satisfaction classification (High and Medium categories). Experimental results demonstrate that the proposed model significantly reduces error rates and improves accuracy compared to existing methods, ensuring robust predictions. This methodology offers a scalable and intelligent solution to quantify user satisfaction in real time, supporting designers, manufacturers, and product developers in delivering more engaging and user-friendly systems.

**Key Words**: Product Design Analytics, Machine Learning, Predictive Modeling, User Satisfaction Classification, Behavioral Data Analysis

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## 1. INTRODUCTION

Sensors are excellent information-gathering devices for the deployment of smart towns because of their unique position at the interface between the analog world humans live in and basic communication organizations. Depending on the application context, sensors are characterized as physical or virtual. Biosensors play a significant role in product design, having progressed from traditional electrochemical biosensors to wearable and implantable biosensors. Biosensors are a popular topic in today’s scientific community. With advancements in science and technology, biosensors have become more sensitive and capable of detecting biomolecules in various fields, including medical, environmental, and military [1]. A biosensor is a device able to convert chemical data derived from biomolecule concentrations into usable analytical signals. It essentially constitutes four constructions consisting of elements of the sensing bind, which exactly binds with the analyte being tested; an interface offering a working location for the elements of a biosensor; converting

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chemical or physical data resulting from the collaboration between the elements of sensing with the analyte into electrical signals; and amplification and processing of these signals together with an interface circuit designed for data processing and analysis.

The biosensor's structure is represented in Fig. 1. The term "biosensor" is derived from two words: "bio," an abbreviation for biology or life, and "sensor," indicating a device or system that measures and responds to stimulants. A biosensor is a highly advanced analytical instrument that has been precisely designed to detect subtle changes occurring within complex biological processes, an essential feature in product design. It converts these small fluctuations into recognizable electrical signals. At the core, this biosensor utilizes the synergistic interaction of this biological sensing element with a transducer, itself an integral part of the conversion of biological information into measurable electrical signals [2]

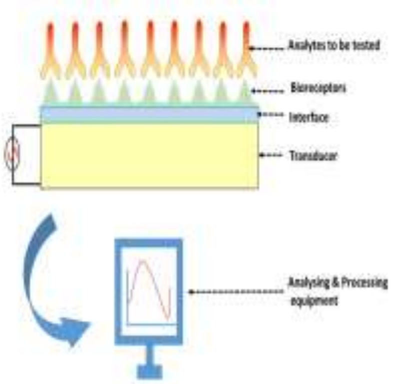


Fig. 1: Biosensor's structure.

Biosensors are low-cost and portable devices that can detect pathogens, proteins, and other analytes in a matter of instants, establishing new possibilities for innovation in product design. They intend to eliminate the time and high cost of expertise involved in testing processes that, in certain industries, cost more to acquire. Biosensors form a rapidly developing multidisciplinary field, potentially transforming consumer, health care, and industrial testing. These devices have provided solutions to a variety of applications, including food safety and processing, drug growth, disease detection, defense, biomedicine, environmental monitoring, and security [3].

Biosensors are designed based on the target analyte and transduction process and are characterized as labeled or label-free based on their label use. Labelled biosensors utilize a reporter for identifying analytes such as enzymes, electroactive chemicals, or fluorescent molecules. Labels improve signal amplification and selectivity for sensing but occur at a higher cost and longer sensing time. Label-free approaches rely on bio recognition elements (BRE) to recognize targets, and their basic design makes them ideal for portable devices and adaptable in product design [4].

According to the traditional definition, biosensors are sensors that make use of a bioreceptor, such as nucleic acid, peptide, enzyme, antibody, etc. Biosensors have developed into many kinds of transducers, such as spectroscopic, optical, and electrochemical biosensors [5]. In today's rapidly developing technology environment, product design prioritizes strengthening links between people and things to improve usefulness and emotional involvement. Biosensors can measure physiological and neurological responses, making them a game changer. This research aims to develop a biosensor-driven design approach to improve interaction and user experience in creative and cultural product design.

## 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

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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

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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.

## 3. PROPOSED METHODOLOGY

The proposed system integrates biosensor-driven feature extraction with an advanced CART framework, enhanced by AdaBoost, to predict user satisfaction during product interaction accurately. The methodology begins with signal acquisition from biosensors, primarily EEG, which captures real-time brain activity during product interaction. Alongside EEG, interaction logs such as clicks, navigation paths, task completion times, and demographic data (age, gender, and product type) are collected to create a multi-dimensional dataset reflecting both physiological and behavioural aspects of user experience. Once collected, the biosensor and interaction data undergo preprocessing and normalization. EEG signals are cleaned to remove artifacts caused by eye blinks, muscle movements, or external electrical interference.

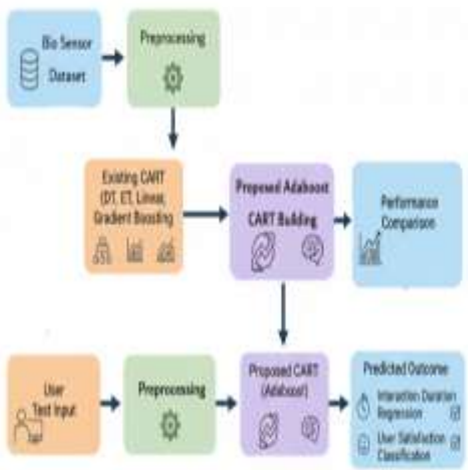

Fig. 2. Workflow for predicting user satisfaction using biosensor data.

Statistical features including mean, standard deviation, minimum, maximum, and median are extracted from the EEG signals to transform raw physiological data into meaningful inputs for machine learning. Interaction metrics are scaled, and categorical variables are encoded using Label Encoding or One-Hot Encoding, ensuring all features are compatible with the CART-AdaBoost framework. Missing or inconsistent data is handled via imputation techniques to maintain dataset integrity. The core of the methodology is the AdaBoost-enhanced CART model, which addresses both regression and classification tasks simultaneously. In this dual-output architecture, the CART base learners act as weak classifiers or regressors. AdaBoost iteratively combines these weak learners, focusing on instances that were previously mis predicted, thereby improving overall accuracy and robustness. Regression is employed to predict interaction duration, providing insights into temporal engagement, while classification predicts user satisfaction levels (e.g., High, Medium), capturing qualitative emotional responses. To further improve prediction quality, feature importance evaluation and selection are applied. Tree-based methods inherent to CART help identify the most influential features, allowing the system to prioritize EEG-derived signals and critical behavioural metrics.

Finally, the system supports real-time deployment and user feedback analysis. Trained AdaBoost-CART models are saved along with preprocessing transformers to allow seamless prediction on new incoming data. A web interface built with Flask enables dynamic input of EEG and interaction metrics, producing instant predictions for both duration and satisfaction. This real-time capability allows industries to adapt product features, personalize user experiences, and optimize engagement, ensuring actionable insights are delivered immediately, rather than relying on delayed manual analysis.

## 4. RESULTS DESCRIPTION

Fig. 3 shows that home page of the Biosensor Analysis platform features. It provides an overview of the application's purpose, which involves using machine learning 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 Decision Tree, Logistic Regression, Extra Trees, Gradient Boosting, and AdaBoost, with evaluation metrics like Accuracy, Precision, Recall, F1-Score, Confusion Matrix, and Classification Report. For Regression, it includes Linear Regression, Decision Tree, Extra Trees, Gradient Boosting, and AdaBoost, evaluated by MAE, MSE, RMSE, $R^2$ Score, and Scatter Plot.

Fig. 3. Home page for biosensor analysis.

Fig. 4 displays the 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

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(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

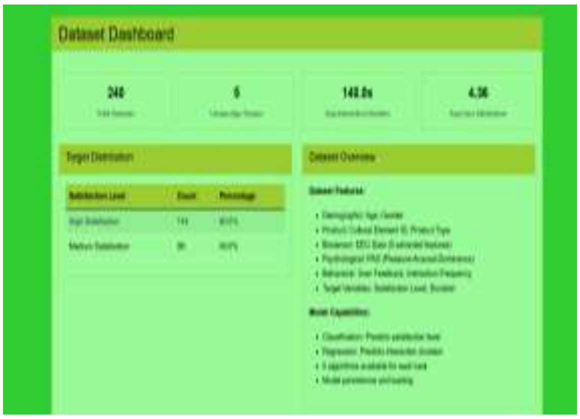


Fig. 4. Dataset dashboard for biosensor analysis.

Fig. 5 shows that the AdaBoost 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 AdaBoost the top performer for predicting user satisfaction levels from biosensor data in this analysis.


Fig. 5. Target classification analysis – AdaBoost for biosensor analysis

Fig. 6. displays interface presents Interaction Duration Regression Analysis with a loaded AdaBoost model for predicting duration using biosensor data, where the Results includes 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: Decision Tree (Medium), Logistic (Medium), Extra Trees (Medium), Gradient Boosting (High), AdaBoost (High); Regression (Duration) predicts 120.1s to 123.6s across algorithms.

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Fig. 6. Interaction duration regression analysis – AdaBoost for biosensor analysis


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

Fig. 8. shows that facilitates batch predictions from a CSV file under the Batch Prediction using trained models for satisfaction and duration. Users upload a CSV file, with a note that it should exclude target columns and follow a specified format including Age, Gender, Cultural Element ID, Product Type, EEG Data, PAD, User Feedback, Satisfaction, Interaction Frequency. Expected CSV format details are provided, with EEG data in JSON array format. Results display Classification (Target) and Regression (Duration) predictions for uploaded data, with algorithms like Decision Tree and AdaBoost listed. The layout features a green theme and navigation options.

Table 1 presents the performance comparison of five classification models—Decision Tree, Logistic Regression, Extra Trees, Gradient Boosting, and AdaBoost—based on their accuracy, precision, recall, and F1-score. Among the models, AdaBoost achieves perfect performance, scoring 1.0000 across all metrics, indicating exceptionally strong predictive capability on the given dataset. Logistic Regression and Extra Trees 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 behavior. The Decision Tree model performs moderately with an accuracy of 0.5625, while Gradient Boosting shows relatively lower precision but acceptable recall. Overall, the table highlights significant variation across models, emphasizing AdaBoost as the highest-performing classifier in this evaluation.


Fig. 8. Make predictions – batch prediction for biosensor analysis

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Table. 1: Comparison of classification models

| Model | Accuracy | Precision | Recall | F1 Score |
|---|---|---|---|---|
| Decision Tree | 0.5625 | 0.7922 | 0.5625 | 0.5162 |
| Logistic Regression | 0.7292 | 0.8392 | 0.7292 | 0.7246 |
| Extra Trees | 0.7292 | 0.8392 | 0.7292 | 0.7246 |
| Gradient Boosting | 0.6042 | 0.3650 | 0.6042 | 0.4551 |
| AdaBoost | 1.0000 | 1.0000 | 1.0000 | 1.0000 |

Table. 2: Comparison of regression models

| Model | MAE | MSE | RMSE | $R^2$ Score |
|---|---|---|---|---|
| Decision Tree | 2.3142 | 11.7170 | 3.4230 | 0.9791 |
| Linear Regression | 0.0000 | 0.0000 | 0.0000 | 1.0000 |
| Extra Trees | 11.8983 | 167.9224 | 12.9585 | 0.6998 |
| Gradient Boosting | 1.7054 | 4.0712 | 2.0177 | 0.9927 |
| AdaBoost | 0.0000 | 0.0000 | 0.0000 | 1.0000 |

Table 2 compares the performance of five regression models—Decision Tree, Linear Regression, Extra Trees, Gradient Boosting, and AdaBoost—using MAE, MSE, RMSE, and $R^2$ Score as evaluation metrics. The results indicate that Linear Regression and AdaBoost deliver perfect predictive performance, achieving zero error across MAE, MSE, and RMSE, along with an $R^2$ score of 1.0000. Gradient Boosting 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 Decision Tree model shows moderate performance with slightly higher errors but still maintains a high $R^2$ value of 0.9791. In contrast, Extra Trees 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. Overall, the table highlights large performance differences, with Linear Regression and AdaBoost emerging as the most accurate regression models for predicting interaction duration.

## 5. CONCLUSION

The Biosensor Analysis platform effectively utilizes machine learning algorithms to analyse biosensor data for predicting user satisfaction levels and interaction durations in product interactions, incorporating features like EEG data, PAD psychological metrics, and demographic details from a dataset of 240 samples. Classification models such as Decision Tree, Logistic Regression, and Extra Trees achieved consistent accuracy of 0.7292 with F1 scores around 0.7246, while Gradient Boosting underperformed at 0.6042 accuracy, and AdaBoost delivered perfect metrics (1.0 across all), highlighting its superior fit albeit with overfitting concerns. In regression tasks, Linear Regression and AdaBoost attained ideal $R^2$ scores of 1.0 with zero errors, Decision Tree scored 0.9791, Gradient Boosting 0.9927, and Extra Trees lagged at 0.6998, as visualized through confusion matrices and scatter plots. The intuitive, green-themed web interface supports model training, evaluation, and predictions, proving valuable for user experience insights in biosensor applications. Performance improvements can be realized through hyperparameter optimization using Research to boost weaker models, implementing k-fold cross-validation for better generalization and reduced variance, and advanced feature selection techniques like PCA on EEG data to minimize noise and enhance overall predictive accuracy across all algorithms.

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