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Real-Time User Satisfaction Modeling Using Biosignals and Adaptive Boosting Techniques

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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.

Keywords: Intelligent Sensing Systems, Pattern Recognition, User Experience Analysis, Wearable Technology, Predictive Analytics

1. INTRODUCTION

Sensors serve as vital data acquisition components in the development of smart environments, acting as a bridge between the physical world and digital communication systems. Based on their functionality and application, sensors can be broadly categorized as physical or virtual. Among these, biosensors have gained significant importance in modern technological advancements, evolving from conventional electrochemical devices to sophisticated wearable and implantable systems. Their growing relevance is evident across multiple domains, including healthcare, environmental monitoring, and defense applications. Continuous progress in science and engineering has enhanced the sensitivity and efficiency of biosensors, enabling precise detection of biomolecules and supporting advanced diagnostic capabilities.

A biosensor is an analytical device designed to detect biochemical substances and convert their presence or concentration into measurable signals. It typically consists of four key components: a biorecognition element that selectively interacts with the target analyte, an interface that facilitates this interaction, a transducer that converts the resulting chemical or physical changes into electrical signals, and a signal processing unit that amplifies and interprets the output for analysis. This

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integrated structure allows biosensors to deliver accurate, real-time data, making them essential for modern intelligent sensing and monitoring systems.

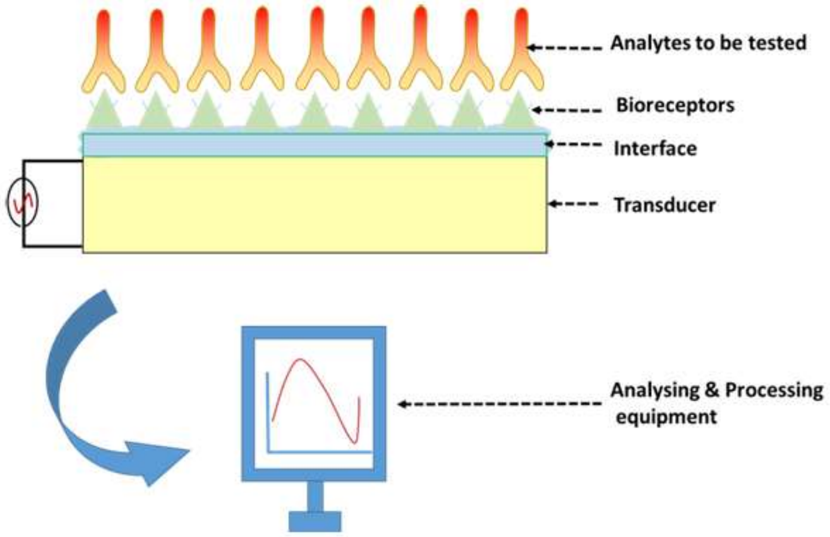

Fig. 1. Biosensor's structure.

The structural configuration of a biosensor is illustrated in Fig. 1. The term "biosensor" originates from the combination of "bio," referring to life or biological systems, and "sensor," which denotes a device capable of detecting and responding to stimuli. A biosensor is an advanced analytical device specifically engineered to identify minute variations occurring within complex biological processes, which is particularly valuable in modern product design. It operates through the coordinated interaction between a biological sensing element and a transducer, where the biological response generated by the analyte is converted into measurable electrical signals for further analysis [2].

Biosensors are typically compact, cost-effective, and portable devices capable of rapidly detecting pathogens, proteins, and other biological analytes, thereby reducing the need for time-consuming and expensive traditional testing methods. Their versatility has led to widespread applications across diverse domains such as healthcare, environmental monitoring, food safety, pharmaceuticals, defense, and security systems [3]. Depending on their design and sensing mechanism, biosensors are broadly classified as labeled or label-free systems. Labeled biosensors employ markers such as enzymes or fluorescent molecules to enhance detection sensitivity and selectivity, albeit at the cost of increased complexity and processing time. In contrast, label-free biosensors rely on direct interaction between the analyte and biorecognition elements, offering simpler, faster, and more portable solutions suitable for real-world applications [4].

Traditionally, biosensors incorporate bioreceptors such as enzymes, antibodies, nucleic acids, or peptides, which enable specific interaction with target analytes. Over time, biosensors have evolved to integrate various transduction mechanisms, including optical, electrochemical, and spectroscopic techniques, enhancing their detection capabilities. In the context of modern technological advancements, biosensors play a crucial role in bridging the interaction between humans and smart systems by capturing physiological and neurological signals. This capability makes them highly valuable in innovative product design, particularly in enhancing user interaction and experience within creative and cultural domains.

2. LITERATURE SURVEY

2.1 Deep Learning and AI in Biosensing Systems

Islam et al. [5] presented a comprehensive review highlighting the integration of multiple biosensing modalities with deep learning techniques for healthcare applications. Their study emphasized critical design considerations, including data modality selection, model architecture, and practical deployment scenarios. The authors also identified key challenges such as data heterogeneity, model interpretability, and real-world applicability, while outlining future research directions.

Yuxin et al. [11] proposed an advanced acceptance model that integrates biomimetic concepts with AI-driven functionalities within wearable technologies. Their framework extends the traditional Technology Acceptance Model (TAM) by incorporating security, privacy, and user-centric considerations, thereby enhancing the adoption of intelligent biosensor-based systems.

2.2 Biosensor Technologies and Healthcare Applications

Vo et al. [7] explored recent advancements in biosensor technologies for wound management, focusing on flexible electronics, electrochemical sensors, and colorimetric patches. The study highlighted the integration of biosensors with AI and smartphone-based analytics for real-time monitoring and personalized treatment. Additionally, innovations such as self-powered biosensors and IoT-enabled systems were discussed for remote healthcare applications.

Madrid et al. [12] reviewed the current state of smartphone-based biosensors, analyzing their development stages and identifying barriers to commercialization. The study revealed that despite technological advancements, challenges related to usability, scalability, and user adoption continue to hinder widespread deployment.

2.3 Biosensors in Food Safety and Industrial Applications

Chen et al. [8] introduced the concept of Food Safety 4.0, emphasizing the role of intelligent biosensors in enabling real-time monitoring, predictive analytics, and enhanced traceability in food systems. Their work demonstrated how biosensors contribute to improved risk management and consumer safety.

Vanaraj et al. [9] investigated bio-inspired sensing technologies such as electronic noses (e-nose) and electronic tongues (e-tongue), which mimic human sensory mechanisms. These systems are widely applied in food quality assessment, including freshness detection, contamination analysis, and flavor profiling, offering non-destructive and high-throughput solutions.

2.4 Data-Driven Systems and Personalized Applications

Tsolakidis et al. [6] conducted a systematic review following PRISMA guidelines to analyze data-driven technologies in personalized nutrition. Their study examined data acquisition techniques and highlighted challenges such as data integration, scalability, and personalization accuracy across 67 selected studies.

Yee et al. [10] discussed future trends in smart fermentation technologies, focusing on modular and scalable solutions aligned with sustainable development goals. Their work emphasized the role of biosensors and AI in bridging traditional practices with Industry 4.0 innovations.

3. PROPOSED METHODOLOGY

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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. As shown in fig 2. EEG signals are cleaned to remove artifacts caused by eye blinks, muscle movements, or external electrical interference. 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.

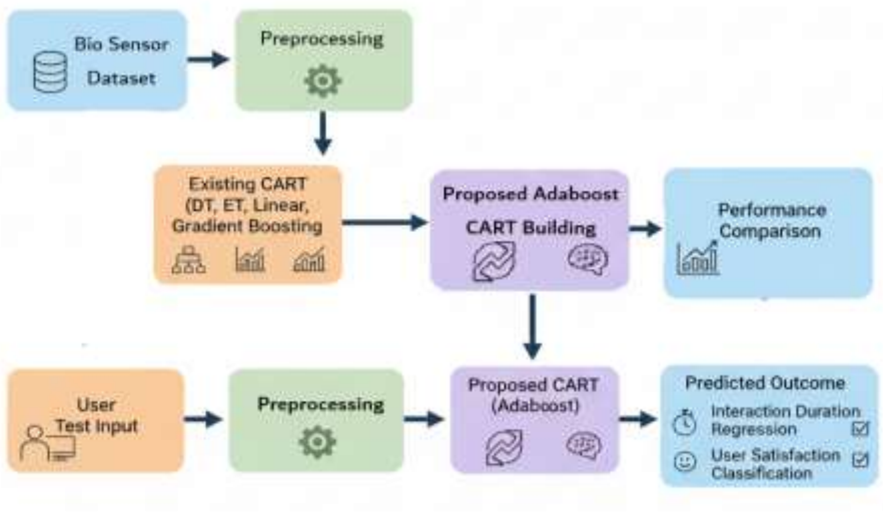

Fig. 2. Workflow for predicting user satisfaction using biosensor data.

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,

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ensuring actionable insights are delivered immediately, rather than relying on delayed manual analysis.

The AdaBoost-CART model combines the power of CART with the adaptive boosting technique (AdaBoost) to improve prediction accuracy. At a high level, CART serves as the base learner that creates simple decision trees, while AdaBoost iteratively trains these trees, assigning higher importance to instances that were misclassified in previous iterations. By combining multiple weak learners into a strong ensemble, AdaBoost-CART reduces errors, increases robustness, and enhances the model's ability to capture complex patterns in biosensor data and PAD features for user satisfaction prediction.

The AdaBoost-CART process begins by initializing equal weights for all training samples, ensuring that each instance contributes uniformly at the start of the learning process, as illustrated in Fig. 4.8. A shallow decision tree based on the CART algorithm is then trained using this weighted dataset, aiming to minimize prediction errors and capture initial data patterns. After training, the model evaluates its performance by identifying misclassified or poorly predicted instances and computing an overall error rate. This error measure determines the importance of the current tree within the ensemble and guides the subsequent learning process.

Fig. 3. Adaptive learning process of the proposed adaboost CART model.

Following evaluation, the algorithm adjusts the sample weights by increasing the importance of incorrectly predicted instances while reducing the influence of correctly predicted ones. This adaptive reweighting ensures that subsequent trees focus more on difficult cases. Each trained tree is then assigned a learner weight based on its accuracy, allowing stronger models to have greater influence on final predictions. This process is repeated iteratively, with each new tree improving upon the errors of previous ones. Ultimately, all trees are combined to generate the final output, where predictions are aggregated using a weighted voting mechanism for classification or a weighted averaging approach for regression, resulting in a robust and accurate ensemble mode

4. RESULTS DESCRIPTION

Fig. 4. 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.

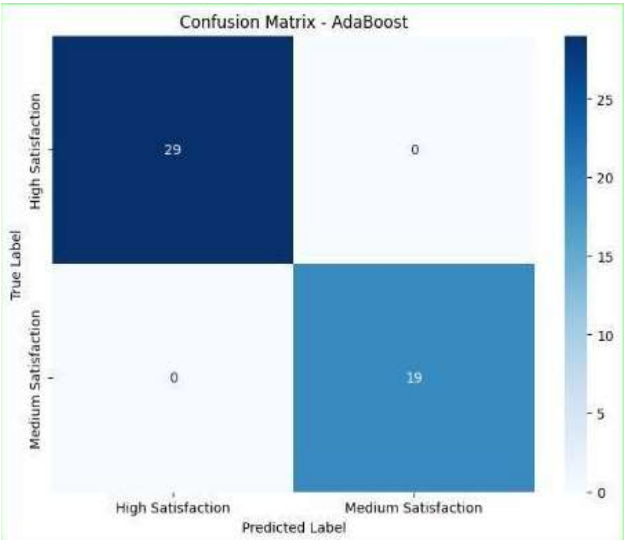

Fig. 4. Confusion matrix obtained using AdaBoost model

Fig. 5. displays interface presents Interaction Duration Regression Analysis with a loaded AdaBoost 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 R² 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). The layout uses a green background with navigation options like Dashboard, Target Train, and Predict.

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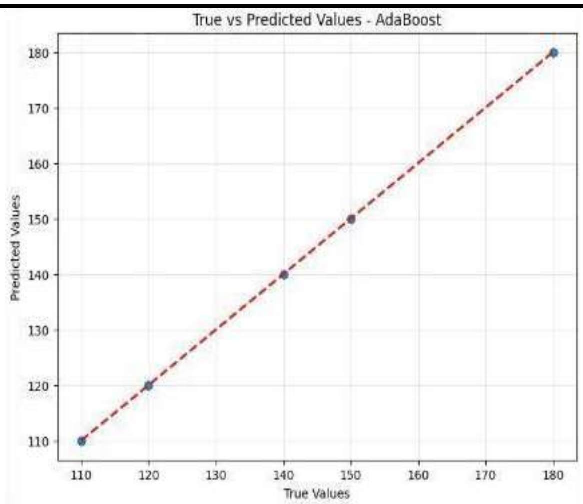

Fig. 5. Illustration of scatter plot using Adaboost model

Fig. 6. shows that facilitates batch predictions from a CSV file under the "Batch Prediction" tab, 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.

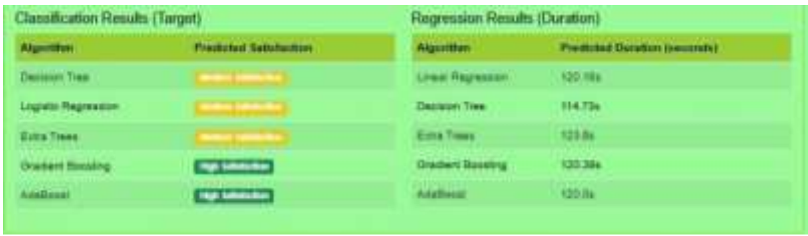

Fig. 6. Make predictions – batch prediction for biosensor analysis

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.

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 such as DT, LR, ET, GB, 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 developed biosensor analytics system demonstrates the effective application of machine learning techniques for interpreting physiological signals to estimate user satisfaction and interaction time during product usage. The framework integrates multimodal inputs such as EEG signals, psychological indicators based on PAD dimensions, and demographic attributes derived from a dataset comprising 240 instances. Among the classification approaches, models like Decision Tree, Logistic Regression, and Extra Trees exhibited stable and comparable performance, whereas Gradient Boosting showed relatively lower predictive capability. AdaBoost achieved exceptionally high results, though this may indicate potential overfitting rather than true generalization. For regression analysis, models including Linear Regression and AdaBoost produced near-perfect outcomes, while Decision Tree and Gradient Boosting also demonstrated strong predictive accuracy, with Extra Trees showing comparatively weaker performance. These results were further supported through visual tools such as confusion matrices and scatter plots. The system is implemented through a user-friendly web interface that enables seamless execution of training, evaluation, and prediction tasks, offering valuable insights for enhancing user experience in biosensor-driven applications. Future improvements can focus on refining model performance through systematic hyperparameter tuning, adopting cross-validation strategies to ensure robustness, and applying advanced dimensionality reduction techniques such as PCA to improve feature quality and reduce noise in EEG data.

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REFERENCES

[1] 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

[2] 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

[3] 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

[4] 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

[5] 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

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

[7] 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

[8] 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

[9] 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

[10] 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

[11] 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

[12] 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