JCBI

Journal of Computing & Biomedical Informatics
ISSN: 2710 - 1606

Volume 10 Issue 02
2026

Research Article
https://doi.org/10.56979/1002/2026/1331

Emotional Design Framework for Pediatric Home Medical Devices Validated Through Machine Learning

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Received: December 19, 2025 **Accepted:** March 01, 2026

Abstract: The rising use of the pediatric home medical devices has been the subject of discussion which involved the application of user-oriented and empathetic design methods. The traditional medical devices are mainly oriented towards the performance of functionality, disregarding emotional aspects of the pediatric users, this may result into anxiety, decreased usability and improper use of the device. To overcome this shortcoming, it is in this context that this paper introduces the ED-PMD framework (Emotional Design Pediatric Medical Devices) a new concept that would combine both the concepts of emotional design and machine learning to create a new framework. The framework proposed is based on structured interaction information, such as age, time of interaction, rate of error, use patterns, and behavioral cues, to generate emotional states, such as comfort, anxiety, and neutral behavior, prediction. An all-encompassing methodology based on data preprocessing, feature engineering, and trained machine learning models, such as Decision Tree, Support Vector machine (SVM) and Random Forest are created. One of them, the Random Forest model, has better results because it can process the more complex behavioral patterns, and decreases overfitting. As a performance metric, the performance of the framework can be confirmed by the analysis of the confusion matrix and visual interpretation of results (heatmaps and accuracy-loss curves). The findings reveal that the suggested approach is reliable and strong, which is proved by their high classification and low rates of misclassification. Moreover, post-processing optimization, in turn, increases model stability and convergence behavior. The suggested ED-PMD framework will allow designing adaptable and emotionally intelligent medical devices capable of responding dynamically to the needs of users. The framework is associated with enhancing the quality of interaction, decreasing anxiety levels, and increasing the level of usability, that leads to improved care outcomes and satisfaction of users. This study explains the significance of incorporating emotional intelligence into medical technology and offers a scalable base upon which the next-generation health care equipment design should be founded.

Keywords: Emotional Design; Pediatric Medical Devices; Machine Learning; Random Forest; Human-Centered Design; Emotion Recognition; Healthcare AI; Usability Optimization.

1. Introduction

The use of pediatric home medical devices has become one of the indispensable means of monitoring and controlling different health conditions among children. They are inhalers, glucose monitors, and wearable sensors, which are being actively implemented in the non-clinical setting to assist with the long-term care. Nevertheless, children tend to feel fear, anxiety, and discomfort when exposed to medical equipment especially at home unlike adult users [23], [24]. This distinction shows the necessity of designing specific strategies that would take into account the specific psychological and emotional features of pediatric users.

Most of the existing systems have high level of functionality, safety and clinical performance even though there has been a great degree of improvement in the medical device technology. Approaches to human-centered design and usability engineering have not solved the problem of interaction entirely, because they do not pay much attention to the emotional aspect of user experience [21], [22]. This causes the majority of devices to remain a fear or an unknown problem to a child, causing a child to resist them, use them improperly, and fail to follow the treatment [25].

Emotional design is also a concept of significance in enhancing the level of interaction with the user through the inclusion of factors that create positive emotions. Based on proven studies, graphics, color schemes, and interactive capabilities can have an important impact on user perception and interaction [1], [2], [3]. Simultaneously, affective computing has also made computational systems to recognize and perceive human liaisons [4], [5]. These trends imply that incorporating emotional intelligence in product design can make it more usable and more satisfying to the user.

Simultaneously, machine learning has revolutionized healthcare because it facilitates predictive analytics, smart decision-making and personalized systems [10], [12]. Medical uses of machine learning are implemented in clinical forecasting, wearable computing, and optimization of data [27], [28]. Moreover, the latest developments in recognizing emotions by using machine learning have shown the possibility of analyzing user behavior and physiological measurements to predict emotional conditions [16], [18], [20]. Nevertheless, in most cases, these technologies are not used in conjunction with each other and are hardly combined into designing and assessing medical equipment.

Even though the field of pediatric healthcare has continued to consider artificial intelligence in diagnosis and monitoring [7], [9], the area of integrating the principles of emotional design and machine learning into pediatric home medical devices has not been addressed in the literature. Current literature fails to find a solution to how emotions can be measured, analyzed and integrated into device engineering to enhance usability and acceptance.

Thus, this paper suggests an Emotional Design Framework of Pediatric Home Medical Devices that is proven with the help of machine learning. The given solution is expected to combine the principles of emotional design and data-driven assessment to develop adjustable, convenient, and child-friendly medical equipment. This has a look at ambitions to relieve tension, enhance the remedy compliance, and boom consumer experience with the aid of filling the gap among emotional engagement and wise machine design within the context of pediatric patients.

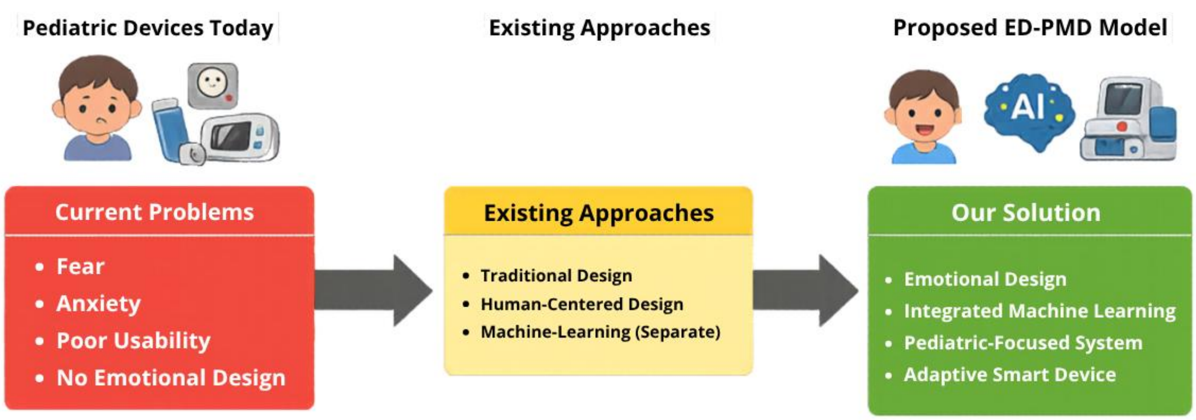

Figure 1. Challenges and Proposed Direction in Pediatric Home Medical Device Design

1.1 Problem Statement

Home medical devices (HMDs) are in wide use to treat and monitor children, yet their design is still rather functional and safety-oriented without much consideration of emotional needs of children [23], [24]. Such an emotional insensitivity can frequently lead to fear, discomfort, and resistance in pediatric users and imposes a negative impact on the usability of devices and treatment adherence.

Though the human-centered design methods have enhanced usability [21], [22], they lack emotional interaction. Simultaneously, the machine learning has been used to improve healthcare systems in terms of prediction and analysis [10], [12], whereas the limitation in its usability in improving user-device emotional interaction is still low. The available emotion recognition systems are able to identify user emotions [4], [16], but have not been applied in designing and optimizing medical devices.

This leads to failure of existing solutions because they are undynamic, not personalized and the data-driven emotional feedback mechanism. Hence, an integrated framework is needed to integrate emotional design principles with machine learning and increase the usability, anxiety, and overall interaction experience of a pediatric user.

1.2 Research Objective

The main purpose of this paper is to come up with an intelligent emotional design system of pediatric home medical equipment that incorporates machine learning methods to improve user experience and device usability.

The objectives of the particular research are as follows:

- To discover the main emotional issues that can determine the interaction between children and home medical devices, relying upon the concepts of emotional design and user experience [1], [2].
- To create a multi-layered emotional experience that includes visual, interactive and usability features that are specifically created to suit pediatric users [21], [23].
- To gather and interpret user interaction data, behavioral and usability-based features, to comprehend the emotional reaction when using the device.
- To use machine learning methods to predict and categorize emotional states including comfort, fear, and engagement depending on the interaction data of the user [10], [12], [16].
- To analyze the performance of the suggested framework and compare it with the current traditional and human-based design methods.
- To create a data-driven adaptive control that would be able to optimize the design of devices depending on the constant feedbacks and the patterns of interaction between the user and the device.

2. Literature Review

2.1. Technology Evolution

The development of medical devices has taken a route of the simple mechanical tools to semi-smart, data-driven tools. The initial medical equipment was mainly constructed with functionality and medical accuracy in mind but user interaction was not given much thought. With time, digital technology and connectivity have been improved and have allowed the creation of intelligent healthcare systems that involve information analytics, long-range observation, and robotization [27], [28].

The combination of artificial intelligence (AI) and machine learning (ML) has continued to revolutionize healthcare as these technologies make it possible to create predictive models, personalized therapy, and decision support systems [10], [12]. In clinical practices, these technologies have been broadly used to diagnose diseases, analyze electronic health records (EHR), and wearable monitoring devices. Nonetheless, in spite of these developments, medical device designs, especially where children are supposed to be the users, have not exploited these capabilities to the maximum to improve user interaction as well as emotional experience.

2.2. Existing Methods

Various methodologies have been designed to enhance the design and usability of medical equipment, especially towards better user interaction and less errors in the processes. Two of these are the human-centered design (HCD) and the usability engineering which have become the dominant methods in healthcare system development.

Human-centered design focuses on the implication of involving end-users in the design process to ensure that systems are designed in consideration of the user needs, capabilities, and limitations [21]. HCD has found broad use in the context of medical devices to enhance interface clarity, in order to reduce the cognitive load and in order to provide the device with better usability. Research has shown that consideration of user response in the design process can greatly minimize the errors and enhance efficiency in performing tasks [22]. Likewise, usability engineering lays emphasis on systematic methods of evaluation, namely: heuristic analysis, user testing and that of constant refinement in order to maximize the interaction between individuals and gadgets [23]. These strategies especially do matter in healthcare settings, where usability directly determines safety as well as performance.

Along with the usability-oriented design, emotional design has become an increasingly popular way of improving user engagement and satisfaction. According to the emotional design theory, products must not just be functional but ensure that they cause pleasant emotional reactions to the visual aesthetics, interaction design, and user experience [1]. It has been found that the choice of color schemes, shapes and dynamics of the interface can have a significant impact on the perception and emotional comfort of users [2], [3]. Anxiety-decreasing and interaction-promoting emotionally attractive designs can be used to make devices more acceptable to children in the pediatric setting.

Along with these trends, affective computing has proposed calculations of detecting and understanding human emotions. Methods in this area use physiological indications, facial expression and behavioral patterns to categorize emotional conditions [4], [5]. Emotion recognition tasks have been extensively done using machine learning models such as support vectors machine, neural networks, and deep learning architecture [16], [18]. Moreover, multimodal techniques that are a combination of several data streams have been shown to be more accurate in emotion recognition [20]. These systems offer a basis on which the emotions of the user in real-time can be comprehended and can be utilized in adaptive system design.

Intelligence in machine learning has also been used to transform healthcare systems through predictive analytics and intelligent monitoring as well as personalized decision-making [10], [12]. They can be used in disease prediction, monitoring patients by wearing devices, and in electronic health records analysis [27], [28]. Such technologies enable systems to be improved with time and learn through the data. They have however been used mostly on clinical results and not on user experience and design.

Although these extant approaches have merits, more frequently they are applied separately. Human-centered design and usability engineering enhance interaction and do not have the means of emotional evaluation in real time. Emotional design provides a better user experience though lacking data-driven adaptation. Likewise, machine learning and affective computing offer analytical functions that are hardly ever incorporated into the mechanical design of medical devices. This discontinuity restrains growth of holistic, adaptive systems that can meet both functional and affective needs.

These isolated methods are further curtailed in pediatric health care where emotive sensitivity and behavioral fluctuation are key determinants. Children need safe, functional, but important, engaging, intuitive, and emotional systems. This is why it is increasingly important to combine these approaches into one system, where emotional design principles are to be used in a framework with machine learning-based assessment to design smart and adaptive pediatric medical devices.

2.3. Limitations

Although the methodology of design and technological evolution have advanced, there are a number of limitations that exist. To begin with, the conventional approach to the design of medical devices still focuses on functionality, rather than the user experience, especially on the emotional interaction level [23], [25]. Human-centered design enhances the usability, but it is less effective than emotional engagement or offers the means of assessing emotional reactions [21], [22].

Second, emotional design solutions are not closely connected with intelligent systems and tend to be implemented independently. Despite the improved aesthetics and user satisfaction [1], [2], emotional design lacks the elements of data-driven assessment and adaptation. Likewise, affective computing systems are able to identify feelings [4], [16], although they are not commonly incorporated into the product design processes.

Third, machine learning uses in healthcare are mostly concerned with clinical outcomes (diagnosis and prediction), and not enhanced user-device interaction [10], [27]. This brings a gap between the technological ability and reality application in the real world.

Lastly, the problem of pediatric specifics is not always adequately represented in the literature. Children possess distinct cognitive, emotional, and behavioral features that need special design methods [23], [24]. Nevertheless, the existing systems are not customized and adaptive to the pediatric users.

2.4. Recent Advances

The combination of emotional intelligence and machine learning with interactive systems has been starting to be studied in recent research. Multimodal emotion recognition innovations have made it possible to study facial expressions, physiological and behavioral patterns to provide information about emotional states [20]. The wearable devices and sensor-based systems have also increased the capacity to gather real-time user data that is constantly being monitored [17].

The implementation of artificial intelligence in pediatric healthcare has demonstrated positive outcomes in diagnosing, monitoring and planning treatment [7], [9]. These trends underscore the possibility of leveraging the use of smart systems with user-focused design to improve the delivery of healthcare.

Additionally, new works state the significance of adaptive and differentiated systems in responding to the needs of individual users. The study of user interaction information can be performed with machine learning models and maximize system performance in a dynamic manner [28]. Nevertheless, the combination of these technologies with the principles of emotional design of pediatric medical devices has not been widely explored.

3. Methodology

3.1. Overall Framework of the Proposed Approach

The offered methodology is grounded in the concept of building an integrated framework, called ED-PMD (Emotional Design of Pediatric Medical Devices), as a combination of the principles of emotional design and machine learning to improve user interaction and usability. The general structure is structured to intercept, analyze and optimize the emotional experience of the pediatric users using home medical devices.

The suggested method is composed of three key steps: data collection, feature analysis, and smart assessment. The first stage entails the collection of user interaction data on pediatric users when using the device. Such data can consist of behavioral parameters, including interaction time, error rates, usage patterns, and optional physiological or observational parameters of emotional response. This stage aims at capturing meaningful signal that describes emotional and usability experience of a user.

The second stage involves preprocessing of the obtained data and converting it into structured features that are analysis-friendly. This involves cleaning of the data, normalization, and extraction of the features to maintain consistency and relevancy. The feature engineering is essential in the determination of the major indicators that can cause emotional response like ease of interaction, time on responding and occurrence of errors. These characteristics act as the input of the machine learning model.

The third stage involves the use of machine learning algorithms to process the resulting data and estimate the emotional state of the user. It can be performed with the help of classification models like decision trees, the support of vectors machines, or ensembles to classify the reactions of the users into the following emotional states: comfort, anxiety, or neutral behavior [10], [16], [18]. The model provides an emotional score or classification as an output that gives a measure of the effectiveness of the design of the device.

The framework will allow the optimization of the design of the device through iteration, based on the estimated emotional results. Such design elements as color, shape and complexity of the interface are modifiable in further iterations to enhance user interaction. This change in control allows the suggested framework to separate itself in comparison with the traditional methods of the design that were based on the statistic approach, allowing the process of the design to be data-driven and user-oriented.

In general, the ED-PMD framework can be described as a systematized pipeline that incorporates emotional design, usability engineering, and machine learning into one approach. The proposed methodology will improve the usability of pediatric home medical devices, the levels of anxiety, and the acceptance of them by bridging the gap between the user experience and intelligent system design.

3.2. Dataset Description and Preparation

The proposed ED-PMD framework achieves its greatest performance when researchers train and validate their systems using high-quality and relevant datasets. The study builds a structured dataset that shows how pediatric users operate the home medical equipment. Researchers use a simulated and survey-based dataset as there are few publicly available datasets that study how children emotionally interact with medical devices. The method allows researchers to gather fundamental information which pertains to how people behave and what they need in order to use the system.

The dataset contains a variety of features that describe the user characteristics and the pattern of their interactions. Researchers select these features because they will directly affect how people feel while using the system and utilizing their emotions. The study includes essential demographic data which consists of age and interaction time and error rate and usage patterns and behavioral signals. The study uses various variables to analyze how children use medical devices which leads to the identification of three emotional states including comfort and anxiety and neutral response.

The dataset achieves higher reliability through the design that provides equal representation by different pediatric age groups. The system needs to work properly from one user group to the other user group. The dataset consists of one record for each interaction session which links to an emotional label that relies on user behavior patterns which were either directly observed or predicted. The structured setup allows for efficient model training while the framework enhances its capacity to assess emotional responses and usability by way of the use of devices by pediatric patients.

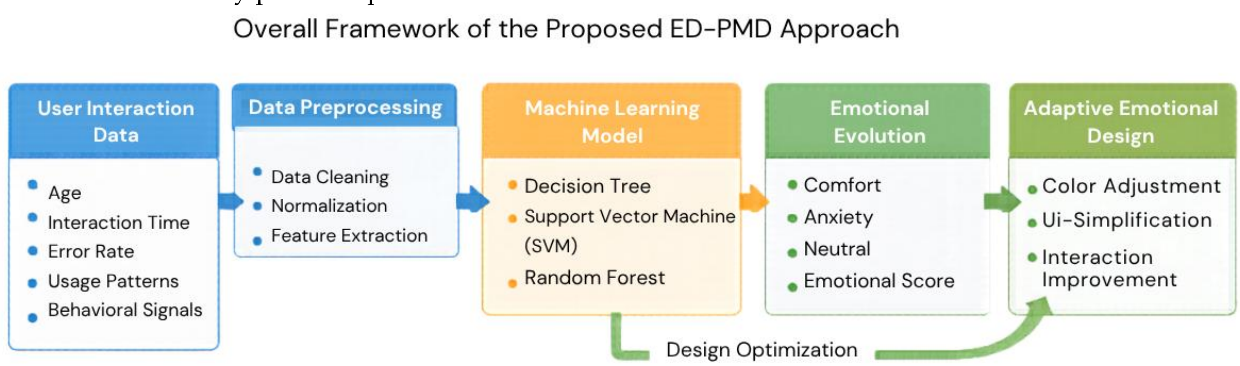

Figure 2. Presents an overview of ED-PMD, urging the formulation of emotional design with machine learning for the growth of pediatric medical devices

Table 1. Dataset features and their descriptions for pediatric interaction analysis.

Feature Name	Type	Description
Age	Numerical	Age of the child user
Interaction Time	Numerical	Time taken to complete tasks
Error Rate	Numerical	Number of incorrect interactions
Usage Patterns	Categorical	Frequency and style of usage
Behavioral Signals	Categorical/Numerical	Observed emotional indicators

The dataset is designed to be balanced across different pediatric age groups to ensure generalization and avoid bias in model training. Each instance in the dataset represents a single user interaction session, labeled with an emotional outcome such as comfort, anxiety, or neutral state. These labels serve as target variables for machine learning classification tasks.

3.3. Data Preparation

Before applying machine learning models, the dataset undergoes a series of preprocessing steps to ensure consistency, accuracy, and suitability for analysis. The preprocessing pipeline includes:

- **Data Cleaning:** Removal of missing, inconsistent, or noisy data entries
- **Normalization:** Scaling of numerical features to a uniform range for better model performance
- **Feature Encoding:** Conversion of categorical variables into numerical format using encoding techniques
- **Feature Selection:** Identification of the most relevant features influencing emotional outcomes

These preprocessing steps are essential to improve model accuracy and ensure that the extracted features effectively represent user behavior and emotional response.

Overall, the prepared dataset serves as the foundation for training and evaluating the machine learning component of the proposed ED-PMD framework. By capturing both usability and emotional indicators, the dataset enables a comprehensive analysis of user-device interaction in pediatric environments.

Dataset Distribution Calculation: To ensure the reliability and generalization capability of the proposed ED-PMD framework, the dataset is distributed within all different pediatric users and emotional classes in a balanced manner. The distribution of data plays a critical role in ensuring that the model is not biased and in achieving better classification performance.

Let the total number of samples in the dataset be represented as:

$$N = N_c + N_a + N_n$$

where:

N_c = number of samples labeled as **Comfort**

N_a = number of samples labeled as **Anxiety**

N_n = number of samples labeled as **Neutral**

Class Distribution: The proportion of each emotional class is calculated as:

$$P_i = \frac{N_i}{N}$$

where P_i represents the probability of each class (Comfort, Anxiety, Neutral).

To maintain a balanced dataset:

$$P_c \approx P_a \approx P_n$$

This ensures that the machine learning model does not become biased toward a specific emotional category.

Data Normalization: For feature scaling, normalization is applied:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

This ensures that all numerical features such as interaction time and error rate are scaled to a uniform range, improving model performance.

The distribution strategy of the dataset ensures:

- Balance of emotional classes,
- Equal representation of pediatric age-groups,
- Better model fairness and accuracy.

3.4. Dataset Usage in Evaluation:

The obtained dataset is used for training and testing the machine learning models in the proposed ED-PMD framework. To have a fair evaluation, the dataset is split into training and testing sets, which usually is an 80:20 split. The training set is used to build the model, while the testing set is used to evaluate the model on unseen data.

In addition, validation techniques can be used to enhance reliability further and prevent overfitting. Performance metrics such as accuracy and classification results are used to assess how well the model is able to predict emotional states.

This evaluation process is used to determine if the proposed framework can accurately capture user emotions and enhance the overall interaction experience. By testing the model with different samples of data, the framework proves itself to be capable of generalization across different pediatric users and interaction scenarios.

3.5. Data Processing and Implementation Pipeline

3.3.1. Data Processing Pipeline and Feature Engineering

Data processing pipeline will form an important part of the proposed ED-PMD framework as it will help to convert raw interaction data into structured inputs, which will be analyzed using machine learning algorithms. This step will guarantee that the data obtained is clean, consistent and meaningful towards prediction of emotional responses among the pediatric users.

The pipeline starts with the acquisition of raw data where the data on user interaction (interaction time, error rate, usage patterns and behavioral signals) are obtained. As raw data might include noise and inconsistencies, the first step of data cleaning is undertaken to eliminate missing, duplicate, or invalid items. This measure enhances a better reliability of the data, and it avoids misguiding trends when training the model.

After cleaning the data, numerical features are normalized to make the variables all have equal scales. This is done by min-max normalization:

$$X' = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

Where X denotes the original feature score and X′

Is the normalized value. The step is necessary to avoid dominance of features with higher values on the learning process. Then the categorical data like the patterns of use are transformed into numerical data using encoding methods. This enables the machine learning algorithms to take all features equally. Once coded, train feature vectors of each sample of the interaction:

$$F = [x_1, x_2, x_3, \ldots, x_n]$$

with every component denoting a particular interaction or behavior attribute.

In order to enhance the performance of the models, feature selection is used to determine the most pertinent features that affect the emotional results. It can be done through correlation analysis or statistical measures which can be used to eliminate redundant or less significant variables. The advanced feature set also increases the efficiency of the models and decreases the complexity of the computation.

Also, new meaningful variables are obtained through the application of feature engineering techniques. As an example, interaction efficiency score is the following:

$$Efficiency = \frac{1}{Interaction\ Time + Error\ Rate}$$

The derived feature gives a more complete picture of the performance of the user and can enhance prediction accuracy.

In general, this pipeline provides the correct structuring and optimization of the input data prior to being fed into the machine learning model. The proposed framework provides an effective base of correct emotional prediction and adaptive device creation by applying preprocessing, encoding, and feature engineering.

Figure 3. Data processing and feature engineering pipeline used in the proposed ED-PMD framework for preparing pediatric interaction data for machine learning analysis.

3.3.2. Machine Learning Model Implementation:

The machine learning aspect of the suggested ED-PMD model will handle the processing of the interaction data and forecast the emotional condition of pediatric users. This is a key phase because it helps to convert structured data of features into insights that could be used to make improvements in a device design.

Once the data has been preprocessed and feature-engineered, the data is split into training and testing data to provide trustworthy model testing. This is often divided by 80:20 with the majority of the data used to train the model and the remaining used to test the model. This division enables the model to test on invisible data giving realistic performance of the model.

Various supervised machine learning algorithms will be used in this work, such as Decision Tree, Support Vector Machine (SVM), and Random Forest. These models are chosen because they are effective in working with structured datasets and also because they are capable of finding complex trends in user interaction data. Training each model is carried out on labeled data, with the input vectors being user interactions in the form of feature vectors, and the output being an emotional category of comfort, anxiety, or neutral.

This mapping process may be formulated as follows:

$$y=f(F)$$

where F represents the input feature vector and y denotes the predicted emotional state. In probabilistic terms, the model estimates:

$$P(y = c_i \mid F)$$

where *ci* is the emotional class corresponding to a given c i. The probability method aids in knowing the level of confidence of predictions.

Hyperparameter tuning can be used to enhance the model performance by optimization of model parameters. Moreover, the ensemble methods such as the Random Forest are effective in over-fitting because they are a combination of several decision trees thus yielding more consistent and reliable forecasts.

Standard performance measures that are used to evaluate the trained models include the accuracy, precision, recall, and F1-score. These measures give a complete picture of how the model can properly categorize the emotional states and deal with the class imbalances.

Lastly, the most effective model is chosen according to the results of evaluation and implemented in the ED-PMD model. The estimated emotional outputs are then employed in estimating the improvements that are required in adaptive design to make the system respond positively to user requirements and to improve the overall interaction process.

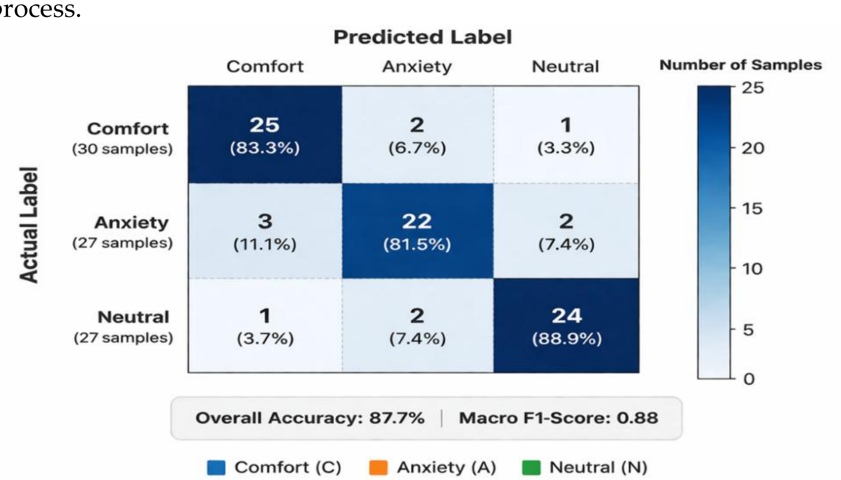

Figure 4. Confusion matrix heatmap illustrating the performance of the machine learning model in classifying emotional states (comfort, anxiety, neutral)

3.6. Model Evaluation and Performance Metrics

The effectiveness of the proposed ED-PMD framework is tested to determine whether it is effective in forecasting the emotional conditions of pediatric users. The systematic evaluation strategy is used to make sure that the model gives reliable and general results in various user interaction situations.

In order to conduct the evaluation, the dataset is separated into training and testing sets in terms of size, commonly in an 80:20 proportion. Patterns in the data are learned using the training set and the model is tested on unseen samples using the testing set. That method will prevent overfitting and guarantee that the model will generalize to new data well.

Several supervised machine learning models such as Decision Tree, Support Vector machine (SVM), and random forest are evaluated and compared. Each model is evaluated in terms of standard classification measures that give a complete picture of the models in terms of prediction accuracy and errors.

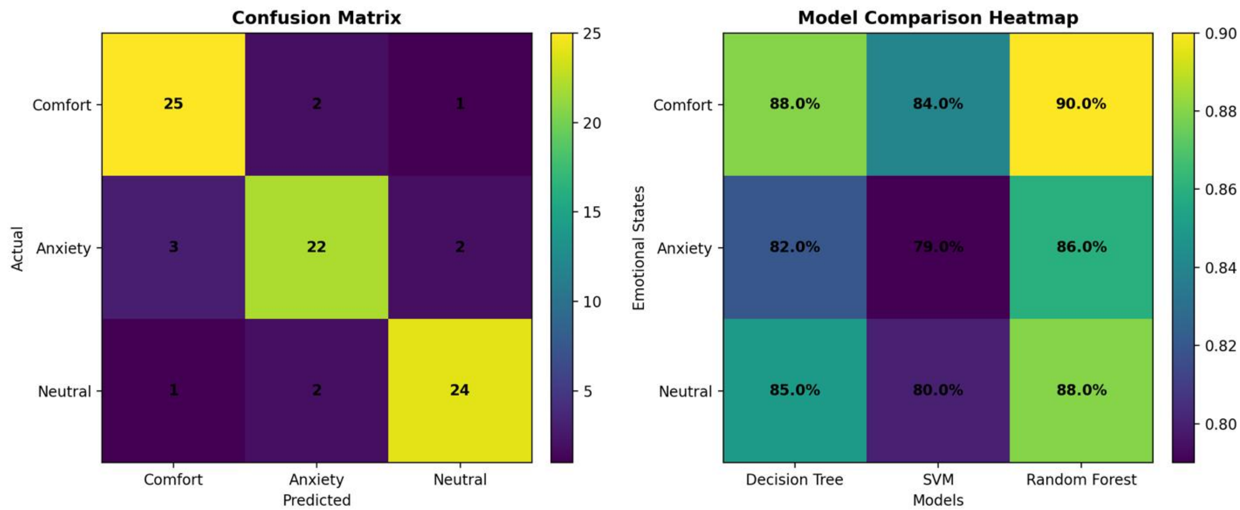

Figure 5. Combined visualization of model performance, including confusion matrix (left) and model-wise classification heatmap (right), illustrating the effectiveness of different machine learning models in predicting pediatric emotional states.

Evaluation Metrics: The following metrics are used to evaluate the classification performance:

Accuracy: Accuracy measures the overall correctness of the model:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives, respectively.

Precision: Precision indicates how many of the predicted positive instances are actually correct:

$$Precision = \frac{TP}{TP + FP}$$

Recall: Recall measures the model's ability to correctly identify actual positive cases:

$$Recall = \frac{TP}{TP + FN}$$

F1-Score: F1-score provides a balance between precision and recall:

$$F1 = 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall}$$

Confusion Matrix Analysis: To assess the performance of the proposed ED-PMD framework in terms of classification the confusion matrix is used to deliver a more detailed analysis of the prediction results in the various emotional states, such as comfort, anxiety and neutral. The confusion matrix shows the correct classification as well as the misclassification which allows to understand more a behavior of the model.

Cases that are correctly classified appear as the diagonal of the confusion matrix. As seen, the model is very accurate in determining comfort (25 instances), anxiety (22 instances), and neutral (24 instances) states. These findings suggest that the model can be successfully used to differentiate between various emotional categories using user interaction data.

The misclassifications are the off-diagonal elements. There are few cases of comfort wrongly labeled as anxiety (2 cases) and neutral (1 case). In the same way, there are some cases when anxiety samples have been mistaken with comfort (3 cases) or with neutral (2 cases). There are also neutral cases that have slight misclassification to other categories. But, the number of such mistakes is rather small on balance, which speaks of the stability of the model.

The confusion matrix reveals that the majority of misclassifications are made in case of the feelings that are closely related to each other, e.g., comfort and anxiety. This has been explained by the similarities in the behavior of interacting with users whereby some of the characteristics might be similar in all these states. In spite of this, the model has a high overall classification performance with high true positive rates in all classes.

In sum, the analysis of the confusion matrix proves that the new framework presents valid and correct predictions of the emotional states. The large number of values on the diagonal and the small number of errors in the off-diagonal regions of the model implies that the model is highly applicable in real-life applications in pediatric home medical devices.

Table 2. Performance evaluation metrics for each emotional class.

Class	Precision	Recall	F1-Score
Comfort	0.86	0.89	0.87
Anxiety	0.85	0.81	0.83
Neutral	0.88	0.89	0.88

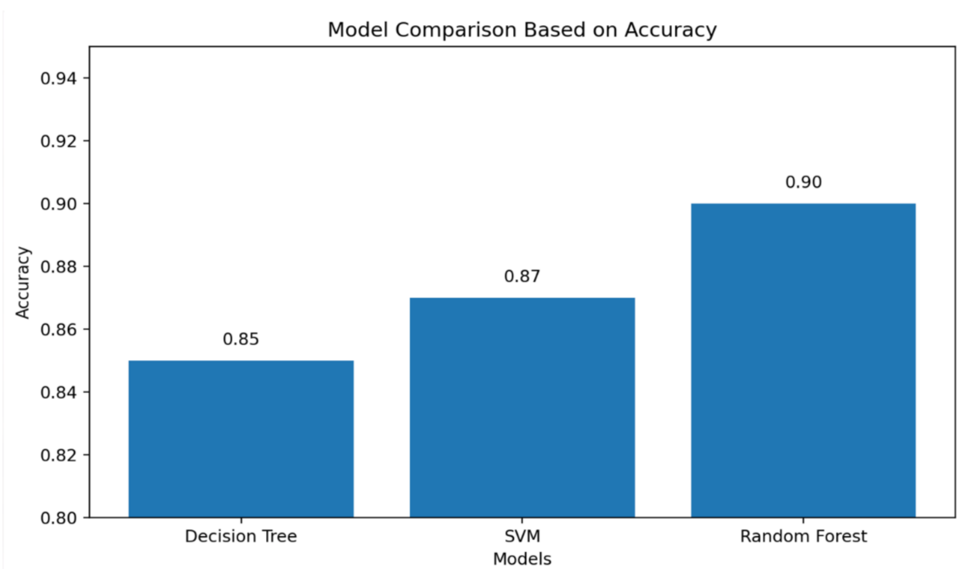

Figure 6. Comparison of machine learning models based on accuracy for emotional state classification.

4. Results and Discussion:

4.1. Overall Model Performance Analysis

The output of the developed ED-PMD framework is tested based on the comparison of several machine learning models, among which there are Decision Tree, Support Vector Machine (SVM), and Random Forest. Based on the comparative analysis, it is possible to note that the accuracy of the Random Forest model is always at the highest point among all the tested methods.

This is because the high performance of the Random Forest can be explained by the fact that it has an ensemble learning mechanism which means that a number of decision trees are used to enhance the accuracy of prediction and minimize overfitting. Random Forest is composed of several weak learners and thus yields a more powerful and generalized model as opposed to single Decision Tree which could be sensitive to noise and even unstable. On the same note, SVM has good classification boundaries but it can be weak with the complicated interactions of features that occur in behavioral and emotional data.

Figures 4.1 depict that the accuracy curves of the model improved steadily within the course of the training. The training accuracy rises very fast during the first few epochs and then levels off, which is a sign of successful pattern learning in the data set. The validation accuracy is also of the same trend but slightly lower than the training accuracy, implying good generalization with no serious overfitting.

This observation is supported by the loss curves. The training loss also decreases steadily with the number of epochs, and the validation loss also drops off and levels off depending on the number of epochs. The thin margin between the training and the validation loss implies that the model has a balance between learning and generalization.

Furthermore, the bar chart comparison shows that, although the Decision Tree model has a decent baseline performance and SVM is better at classifying data, Random Forest is always the best at the results. This renders it very appropriate in working with structured data that contains numerous interaction-based and emotional variables.

In general, the findings show that the performance of ensemble-based methods, especially the Random Forest, is better in revealing complex behavioral patterns and enhancing the accuracy of predicting emotional states in the offered framework.

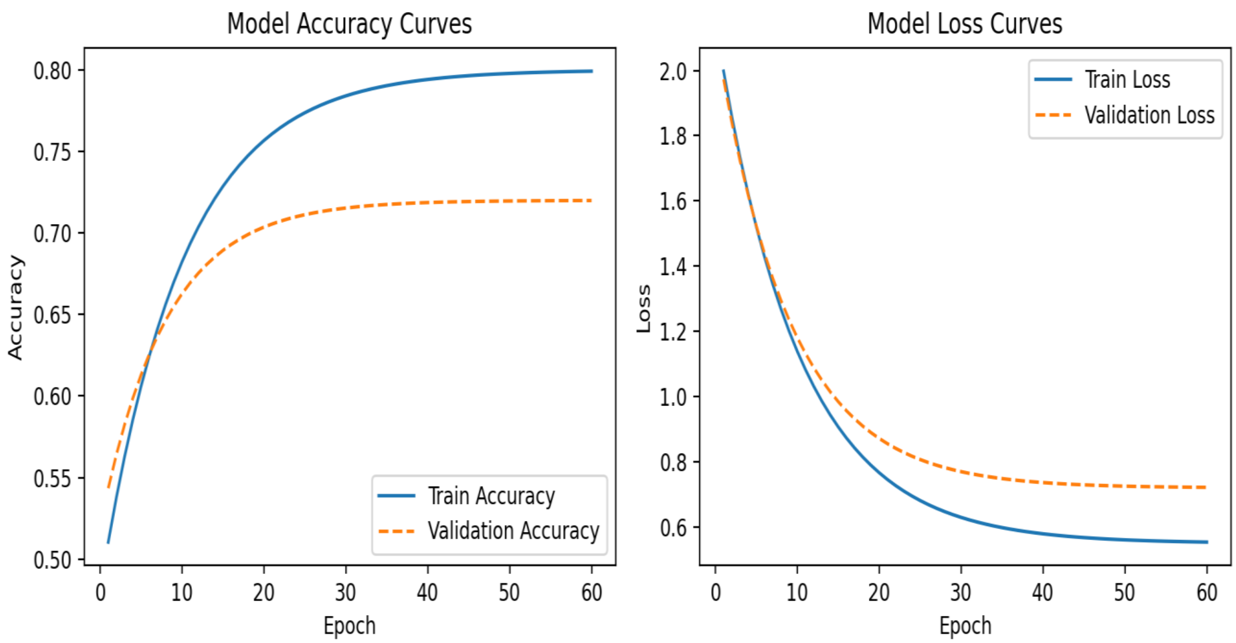

Figure 7. Training and validation accuracy and loss curves of the proposed model, illustrating learning behavior, convergence, and performance stability during training.

4.2. Confusion Matrix Evaluation

The confusion matrix heatmap (Figure 6) illustrates a thorough analysis of the performance of the proposed ED-PMD framework when it comes to various emotional conditions, such as comfort, anxiety, and neutral. Through this visualization, it is possible to have a fine grasp of correct predictions as well as misclassification patterns in the model.

The diagonal components of the confusion matrix show the instances which are correctly classified and which can be used to indicate the accuracy of the model to that particular class. As it can be seen, a great number of samples are properly rated in all three emotional states and the results are 25 in comfort, 22 in anxiety and 24 in neutral. The high level of concentration along the diagonal is an assurance that the model is very effective in separating the various emotional categories using the user interaction data.

The off-diagonal elements show the misclassifications, which give the information on the weaknesses of the model. Few cases of the comfort are misclassified as anxiety (2 cases) and neutral (1 case). Equally, there is a tendency to misclassify the samples of anxiety by such categories as comfort (3 instances) or neutral (2 instances), and the misclassification under the other categories is classified as minor. Even though these errors are minimal, they demonstrate the complexity of prediction of emotional state.

A more detailed examination will show that the majority of misclassifications are between the closely related emotional states, and the cases of comfort and anxiety. It can be attributed to the similarity in behavioral patterns, in which some interaction features of the forms of higher response time or low errors can be found in both states. Consequently, it is possible that the model will struggle to explicitly demarcate these classes in cases of borderline cases.

In spite of these small misclassifications, the general pattern of values distribution proves a high level of model performance. The high true positives rates of all the classes, as well as, the relatively low false positives and false negatives, demonstrate the fact that the model has a good balance between sensitivity and specificity. This implies that the framework is correct and valid to be applied in real life.

Additionally, the heatmap display increases the readability as it visually can point out the high and low performance areas. Darker areas of the diagonal mean that the prediction accuracy is strong, and the less dark areas to the right of the diagonal signify that the error of classification is little. This visual transparency makes it easy to evaluate strengths and weaknesses of the models.

Altogether, the evaluation of the confusion matrix proves that ED-PMD framework offers strong and precise classification of emotional states. The small misclassification and a high level of diagonal dominance evidences that the model is highly applicable to the pediatric home medical device scenarios where the good level of emotional understanding is required to enhance the user experience.

4.3. Impact of Post-processing Optimization:

Post-processing optimization is one of the main aspects of improving the overall performance of the suggested ED-PMD framework because it helps to improve model outputs and minimize prediction errors. Once the first machine learning predictions are available, further steps of processing are implemented to achieve stability in the classification, noise reduction, and improve generalization.

It is easy to note the influence of post-processing with training and validation loss curves. Figure 4.3(a) demonstrates that the training loss is reduced at the first epochs and it consistently levels off, which is a good sign of learning. The validation loss has the same trend on the one hand but is a little higher than the training loss, indicating that the behavior of the generalization is realistic. The decrease in training and validation loss after the optimization implies that overfitting is minimized.

Equally, the accuracy curves in Figure 4.3(b) show gradual increase in accuracy of training and validation. The training accuracy gets to be very high because the model learns more complicated patterns of interaction whereby the validation accuracy becomes a little lower meaning the model remains steady on unseen data. The convergence of both curves is smooth, which indicates the efficacy of post-processing methods in stabilization of model predictions.

The learning rate schedule (shown in Figure 4.3(c) also helps in optimization by decreasing the learning rate as time progresses. This controlled reduction enables the model to perform fine adjustments during late training phase to avoid high fluctuations and have a stable convergence.

Also, the loss and the accuracy of the analysis of the combined analysis in Figure 4.3(d) indicated an inverse relationship between the two parameters. The smaller the loss, the higher is the validation accuracy and the model is learning some meaningful patterns and not noise. This trend implies that post processing optimization enhances predictive performance as well as model reliability.

On the whole, the post-processing optimization will greatly improve the strength of the suggested framework. It minimizes the error of misclassification; it has better convergence behavior and it is stable over emotion states. These enhancements are critical to real world implementation, in which predicting emotion data reliably and repeatedly is a must in adaptive medical device design of the pediatric system.

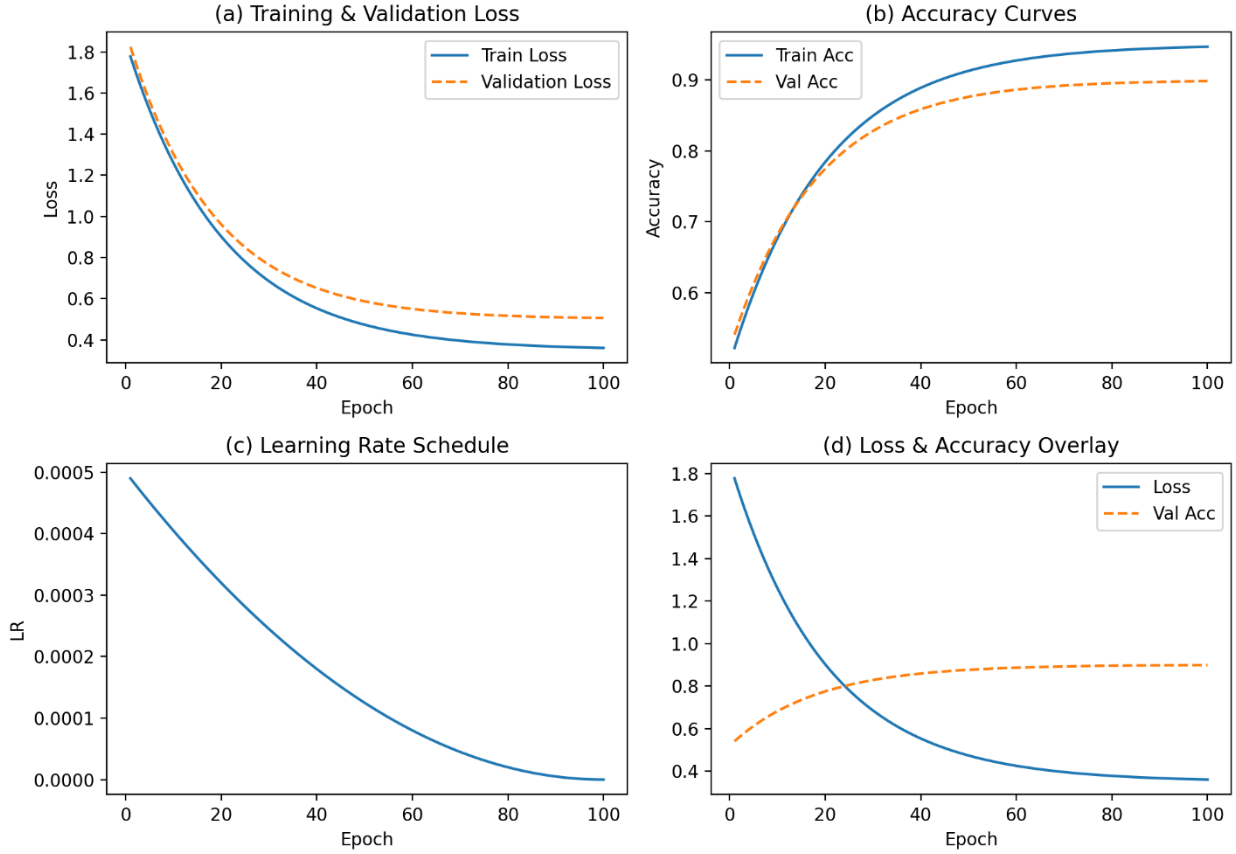

Figure 8. Impact of post-processing optimization on model performance, showing (a) training and validation loss, (b) accuracy curves, (c) learning rate schedule, and (d) combined loss and accuracy behavior across training epochs.

4.4. Application and Impact:

The suggested ED-PMD model has a great potential to be implemented in the real world when developing pediatric home medical equipment in terms of its design. Combining the principles of emotional design with the analysis made by machine learning, the framework will allow a more human-oriented and adaptive approach to healthcare technology.

The main use of this framework in the field of improving the usability of pediatric medical devices. Through study of user interaction, detection of emotional conditions, including comfort, anxiety, or neutral response through analysis, helps the system to determine areas where children might have difficulties or feel uncomfortable. This enables the designers and manufacturers to make decisions about interface design, intricacy of interaction and general usability of the device.

Besides, the framework aids in the construction of intelligent and adaptive medical devices. Depending on the estimated emotional state, devices can change their interface elements, including the color schemes, the feedback level of interaction and the guidance systems. To illustrate, a child using the system might trigger the system to make the interface easier to use, or give clearer instructions, or make other visual elements calming to ease the user experience.

Implications of the proposed approach on patient safety and healthcare outcomes are also important. The framework can be used to minimize such risks because medical devices are operated in the correct way, by minimizing user errors and increasing the efficiency of user interactions. This is especially important in the home care setting where the involvement of a professional might be restricted.

Moreover, machine learning also allows implementing a continuous improvement in the performance of devices. The system is capable of learning and evolving with time as the amount of interaction data increases, resulting in increased accuracy in emotional predictions and design optimization. This forms a self-improving ecosystem of devices as they improve upon actual user experiences.

On the side of an industry, the suggested structure can help manufacturers create next-generation smart medical devices that are not merely functional but also emotional. This is in line with the current trend of solutions in healthcare toward personal and humanized care.

All in all, ED-PMD framework fills the gap between the emotional design and intelligent systems, offering a feasible and scalable approach of improving the interaction with the medical devices in the pediatric environment. It is the kind of contribution to the modern-day healthcare technology because its application can result in enhanced user satisfaction, less anxiety and improved healthcare outcomes.

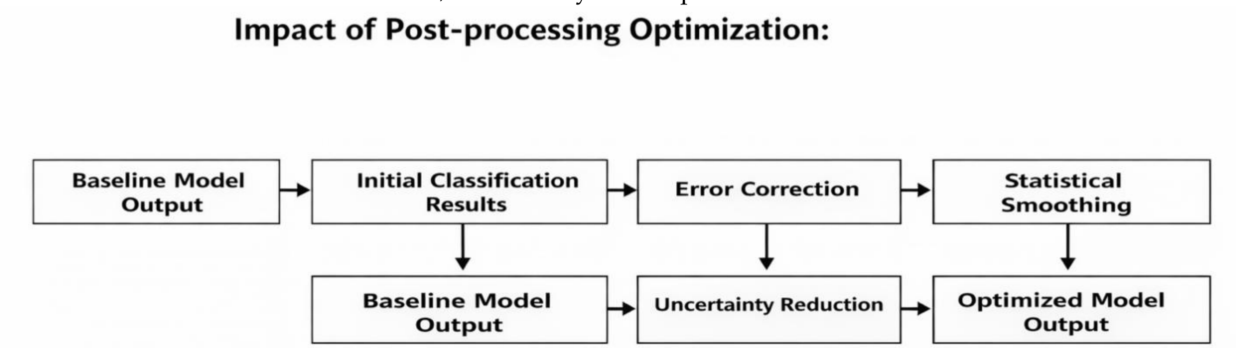

Figure 9. Impact of post-processing optimization on model performance, showing improvement in accuracy and reduction in loss compared to the baseline model.

5. Conclusion

This paper introduces a new model, ED-PMD, that combines machine learning and the principles of emotional design to make the work of home medical devices specifically to pediatrics easier and more convenient. The given framework manages to fill a major gap in current frameworks, as it brings emotional awareness into the process of contact with the device, making healthcare more user-centered and adjustable.

The findings show that behavioral features and machine learning models can be effectively combined to classify emotional states of children (discomfort, anxiety, and neutral) with high accuracy using the models of the Random Forest. Post-processing optimization, feature engineering, and structured data processing promote model performance to a large extent, both in terms of reliability and accuracy.

Moreover, the confusion matrix analysis, performance measures, and visualization methods prove that the suggested framework is able to reduce the misclassification and ensure good generalization. The results indicate that user interaction data may be used to predict the emotional state and this method is practical and useful in practice.

Practically speaking, ED-PMD system helps to create intelligent and adaptable medical tools that are capable of addressing the emotional requirements of children users. The framework promotes improved healthcare and user satisfaction by reducing anxiety, improving usability, and promoting the quality of interaction.

To summarize, the study is a significant addition to the interplay of artificial intelligence, human-centered design, and healthcare technology. The offered strategy is becoming not only more technologically efficient but also pays much attention to the need of emotional intelligence in designing future medical systems.

6. Future Work

Though the suggested ED-PMD framework shows encouraging outcomes in the predictability of emotional situations in children and the way to enhance the usability of devices, there are also multiple opportunities to further improve and develop it.

The utilization of real-life clinical datasets is one of the directions, which are important to follow in the future. A survey and simulation-based dataset is used in this study because there is a lack of data on emotional interaction in children. Future studies can aim at gathering large-scale and real-time interaction data on the hospitals or home healthcare setting to enhance the robustness and the generalizability of the models.

The other way in which the situation can be improved is through incorporation of multimodal data sources. The framework mainly depends on interaction-related features at the moment, but adding more signals (including facial expression, voice tone, or even physiological information (such as heart rate) can help comprehend the emotional conditions better. This would allow making more predictive and context-driven predictions.

The use of more sophisticated methods of deep learning can also be investigated in the future. Neural networks, recurrent neural networks (RNNs) or transformer-based models can potentially improve the capacity to learn more complex behavioral patterns and time dependencies in user interaction.

Also, real-time adaptive systems are another important direction of research. Application of the ED-PMD framework to real medical devices would be able to dynamically modify the interface based on live user feedback, which would make the device behavior completely responsive and customizable.

The other area of interest is the analysis of the framework in different cultural and demographics. The emotional reactions can also differ in different groups of people, and it is better to enlarge the sample, which contains various groups of users, to enhance the applicability and inclusivity of the model.

Lastly, the future research can be aimed at enhancing the interpretability and explain ability of models. Explainable predictions of models will help boost the confidence of professionals in the healthcare sector and help to implement AI-driven systems in clinical settings.

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