AUTOMATIC PAIN RECOGNITION SYSTEM FOR DENTAL PATIENTS USING MACHINE LEARNING

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ABSTRACT

Dental patients often struggle to effectively communicate their pain during treatment where they rely on their gestures and physical movements. This may disturb the treatment process from the dentists. This patient self-reporting method also can be subjective and inconsistent. In this study, we present a machine learning-based automatic pain recognition system designed to objectively recognize the pain levels in dental patients. The bio-signals comprising heart rate obtained from Electrocardiography (ECG), muscle activities extracted from Electrocardiography (EMG), and brain activity derived from Electroencephalography (EEG) have been extracted using the AD-8232 sensor for ECG and the BITalino sensor kit for EMG and EEG recordings. These signals have been normalized and classified by a machine learning classifier into "High pain," "Mild pain," and "No pain" categories. The dataset has been collected from 8 subjects. Two electrodes are placed on the arms, and one is positioned on the right leg to perform the ECG data collection. In EEG data collection, the electrodes are placed on the participant‘s forehead to capture the brain's electrical activity. The electrodes used to collect EMG data are placed on the jaw muscles. The system underwent training and testing using the bio-signals as input data and the pain levels as the output. Python served as the programming language for machine learning training, while the open-source integrated development environment (IDE) Jupyter Notebook has been employed as the primary platform for the model development. Eight distinct machine learning algorithms have been utilized for the model training, including Random Forest Classifier, K-Neighbors Classifier, Bagging Classifier, Decision Tree Classifier, Logistic Regression, SGD Classifier, Linear SVC, and ADA Boost Classifier. Random Forest model demonstrated the best performance, achieving the highest accuracy of 65.1%. This research contributes to automatic pain assessment in dental treatment using machine learning.

KEY WORDS: *Automatic Dental Pain Recognition, Machine Learning, Bio-signals, Electrocardiography (ECG), Electromyography (EMG), Electroencephalogram (EEG).*

1. INTRODUCTION

The experience whenever a tooth is injured, or gum is inflamed is unpleasant. Dentin, possesses sensory pain mechanisms that respond to stimuli. Pain perception varies from person to person. Among dental conditions, toothache ranks as one of the most common acute pains, alongside pericoronitis, alveolar osteitis, and apical periodontitis. [1].

Usually, it is difficult for the dentist to detect whether a patient is really in pain while providing the treatment. Most of the patients also, due to feeling nervous, signifies that they are in pain although they are actually not. This gives a false indication to the doctors and affects the smoothness of the treatment. One of the methods for automatic pain detection is by using physiological signals recorded by wearable technology which are the electrocardiography (ECG), electroencephalogram (EEG) and electromyography (EMG). Heart rate (HR) and heart rate variability (HRV) are related to the autonomic nervous system, which controls internal body functions without us knowing. They can be measured using an electrocardiogram (ECG) and are used to gauge pain intensity. While heart rate (HR) is studied most often in pain research, sometimes researchers also look at heart rate variability (HRV), which shows how heart rate changes over time or between different frequencies [2].

Electroencephalography (EEG), as a hotspot in cognitive neuroscience, has been one of the most progressed in the field of pain detection. EEG contains a wealth of information, including pain data [3]. Electroencephalography (EEG) has garnered interest as a low-cost, user-friendly method for evaluating brain function in pain recognition with a high temporal resolution [4]. When it comes to the diagnosis of facial muscle during orthodontic treatment, EMG is crucial in addressing issues linked to the neuromuscular approach and facial pain that arises from using functional appliances. EMG is more frequently used in dentistry to treat temporomandibular joint (TMJ) abnormalities, dysfunctional TMJ, dystonia, head and neck muscular diseases, cranial nerve lesions, and seizure disorders. Typically, surface electromyography (EMG) records muscle activity from the skin's surface across the muscle using two electrodes in order to evaluate muscle function [5].

In the last decade, automatic pain recognition has moved from being a hypothesis to a crucial field of research. Due to this reason, some research has focused on applying artificial intelligence (AI) to categorize or detect different levels of pain based on auditory inputs. Although facial and body occlusions are commonly seen in infants, these techniques are particularly pertinent to analyse their cries as the more precise means of determining the discomfort that these babies are experiencing. Nonetheless, there's still a big difference in adult patients' voice-based pain detection [6]. Patients use the visual analogue scale (VAS) to express the intensity of their pain by drawing a line on a horizontal scale and anchoring it at each end with phrases such as "no pain" and "the worst pain imaginable". This and similar procedures are popular because they are simple, fit the need to assign a numerical value to the experience of pain, and frequently produce data that confirms expectations [7].

The primary focus of early pain assessment research is on the merging of biological data based on the BioVid Heat Pain Database (BVDB) and facial expression from multiple models [8]. For instance, Werner et al. [9] used multi-model signals and a random forest classifier to identify the degree of discomfort. Random forest classifier was used by Kächele et al. [10,11] to continuously forecast pain intensity. However, tracking various facial regions is necessary for facial expression-based pain identification, which can be difficult and time-consuming in clinical settings. Autonomic nervous system is greatly impacted by pain, which alters heart rate and electrodermal activity (EDA) [12]. The bio-physiological signals enter the BioVid Heat Pain Database (BVDB) by: first, through the electrodermal activity (EDA), also known as skin conductance (SC) or galvanic skin response (GSR), that evaluates the changes in the electrical properties of the skin, which exhibits a strong correlation with emotional state [8]; second, electrocardiogram (ECG), which records heart electrical activity and provides information on the heart function [13]; and third, the trapezius muscle activates, indicating a high level of stress that is common during pain stimulation [8,14].

Promising outcomes in pain recognition have been seen by deep learning models using physiological inputs. Lopez-Martinez et al. applied ECG signal properties to multi-task neural networks with two hidden layers, one shared and one person-specific [15]. These neural networks outperformed single-task neural networks in terms of performance. Wang et al. [16] suggested deep hybrid classifiers based on Recurrent Neural Networks to classify the severity of pain. They employed a bidirectional Long Short-Term Memory (LSTM) network to combine manually created features with the temporal dynamic properties of physiological inputs.

Pain severity in healthy people can be classified using several machine learning algorithms. Logistic regression, support vector machines (SVM) with different kernels, and other traditional techniques are used to develop models that distinguish between no pain and increasing levels of pain. Heart Rate Variability (HRV) may show how healthy people's autonomic systems respond to pain stimuli [17].

This paper presents the development of a low-cost and simple pain recognition system for patients under dental treatment. Bio-signal data, including the ECG, EEG, and EMG, have been collected. A machine-learning-based pain recognition system has been developed and tested. The rest of the paper is organized as follows: Section 2 describes the methodology of the system, involving data collection and machine learning. The results, and discussion are presented in Section 3, and finally the conclusion is drawn in Section 4.

2. METHODOLOGY

Electroencephalogram (EEG), electromyography (EMG), and electrocardiography (ECG) are selected as target signals. The process begins by gathering data from the subject as shown in the flow chart. The pain levels output is classified into "High pain," "Mild pain," and "No pain" using a machine learning classifier.

The first step of the system development is "Data collection: from (ECG, EMG, EEG)" as shown in Figure 1. Following data collection, the bio signals such as ECG, EMG, EEG are extracted and before being fed into the machine learning classifier, the feature values from the ECG, EEG and EMG signals are normalized. The system progresses to the application of machine learning algorithms to develop the model and classify the pain level.

Subsequent decision nodes assess the pain level, " If the machine learning model determines the pain level is high, the process leads to a "high pain" outcome. If not, the system proceeds to the next decision node, "if the pain level medium" resulting in a "medium pain". If the pain level is neither high nor medium, the final decision node "there no pain" leads to a "no pain" outcome.

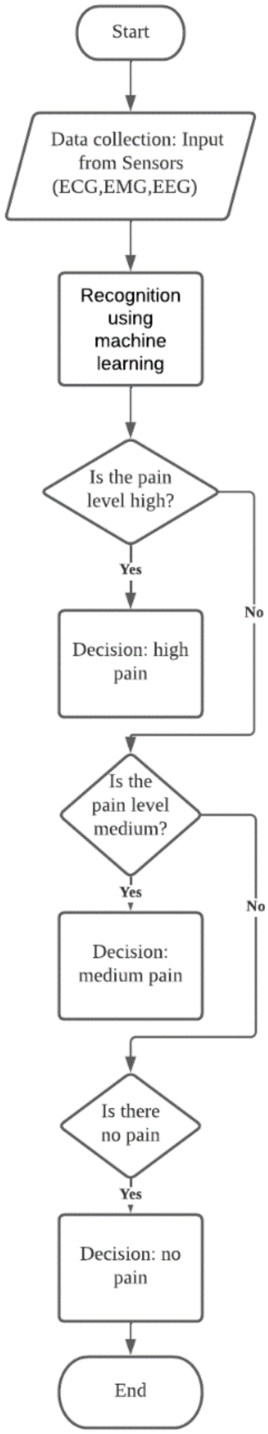

Figure 1: Flowchart illustrating the whole system

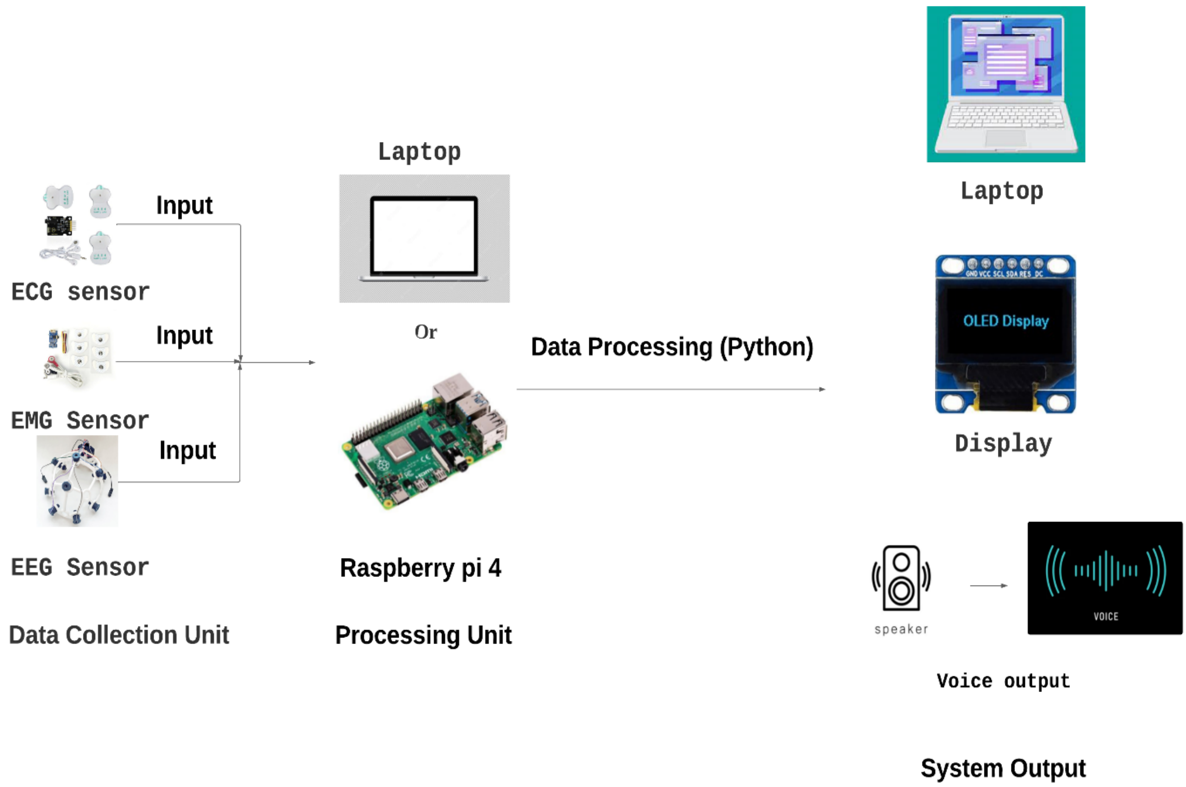

Figure 2: Block Diagram

The block diagram as shown in Figure 2 depicts a schematic representation of a biomedical data acquisition and processing system for the pain recognition system. ECG, EEG and EMG sensors serve as the data collection unit, capturing bio signals. The captured signals from the sensors are then fed into a Raspberry Pi 4, which acts as the processing unit, and the data is processed on a laptop. The model training and testing are executed using Python programming language, a common choice for data analysis due to its extensive libraries and frameworks that support scientific computing.

The output of the data processing is displayed on three types of devices: a laptop screen, which likely provides a comprehensive visual interface for detailed data examination; a display, which provides a more compact and immediate visual representation and a voice output which enhances user comfort; and provide a better understanding about the estimated pain level. This integration allows users to understand the system output easier, by receiving auditory feedback alongside visual cues.

2.1 DATA COLLECTION

The dataset has been collected from 8 subjects, for three distinct levels of pain: No pain, Mild Pain, and High Pain. The data collection process involved the simultaneous recording of three types of bio signals: ECG, EEG, and EMG. Subsequently, a machine learning model has

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been developed to recognize pain levels based on the recorded bio signals. In this study, real-time data collection was conducted employing the BITalino setup to capture EEG and EMG data, while the AD8232 ECG monitoring sensor interfaced with Arduino facilitated ECG data acquisition. Data analysis, visualization, and interpretation have been carried out using Open Signal, Arduino IDE, and Jupyter Notebook software. Both the BITalino and AD8232 ECG monitoring hardware systems were instrumental in acquiring data throughout the experimentation phase. Figure 3 shows the ECG monitoring system comprised of an Arduino R-3 microcontroller, an ECG module (AD8232), a breadboard, and jumper wires. The ECG module is connected to the body via electrodes.

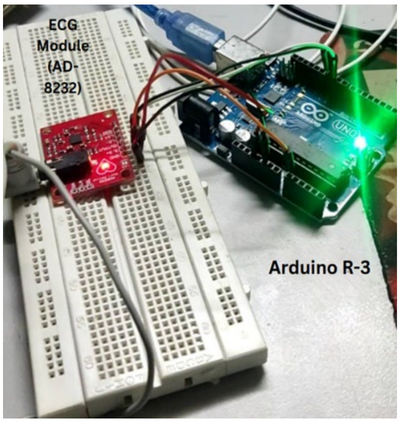

Figure 3: ECG Sensor Setup

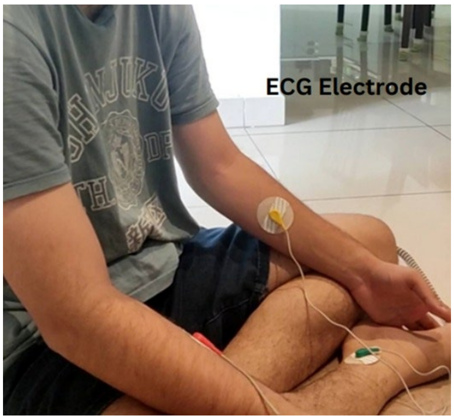

Figure 4: ECG Sensor Setup

The subjects are attached with ECG electrodes as shown in Figure 4. The electrodes are small, with round patches attached to the skin. In the ECG setups, the AD8232 ECG Sensor module is used together with Arduino to record the ECG. The AD8232 is equipped with signal conditioning block for ECG applications and can interface with microcontrollers like the Arduino for data acquisition. Two electrodes are placed on the arms and the one is positioned on the right leg to perform the data collection of the electrical activity at the heart.

Figure 5: Analog ECG Signal

Figure 5 shows an ECG (Electrocardiogram) analogue signal. The graph displays the electrical activity of the heart over time. The line graph indicates different aspects of the heart's electrical signals. The electrocardiogram (ECG) signal has been acquired through the sampling frequency (fs) of 500 Hz. The analogue ECG signal has been pre-processing using MATLAB software. MATLAB facilitates the filtration of waves through bandpass filters. Peak detection or signal thresholding methods are used to identify the peaks of the waves. The interpretation phase represents the concluding stage of the recoded ECG signals

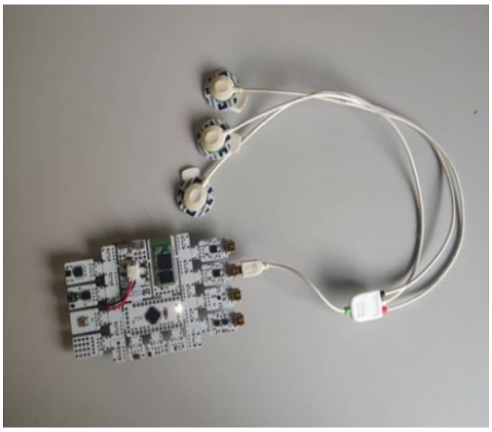

Figure 6: EEG & EMG Sensor Setup (BITalino Controller)

Figure 7: EEG Sensor placement

The BITalino EEG sensor and controller device are used to capture different brain wave patterns. The electrodes are positioned to record brain waves such as alpha, beta, gamma, and delta. The optimal electrode placement on the scalp can be seen in Figure 7, ensuring accurate signal detection. The BITalino EEG sensor is shown in Figure 6, providing a clear view of the device. This EEG sensor setup and electrode placement are used for understanding the brain activity and record the brain weaves during the dental pain. In EEG data collection, the electrodes are fixed to the participant‘s heads to capture the brain's electrical activity. Using the BITalino controller, EEG signals are recorded. While electrodes are commonly positioned on the forehead to capture specific brain activities, standard practice involves the placement of multiple electrodes across the scalp [18].

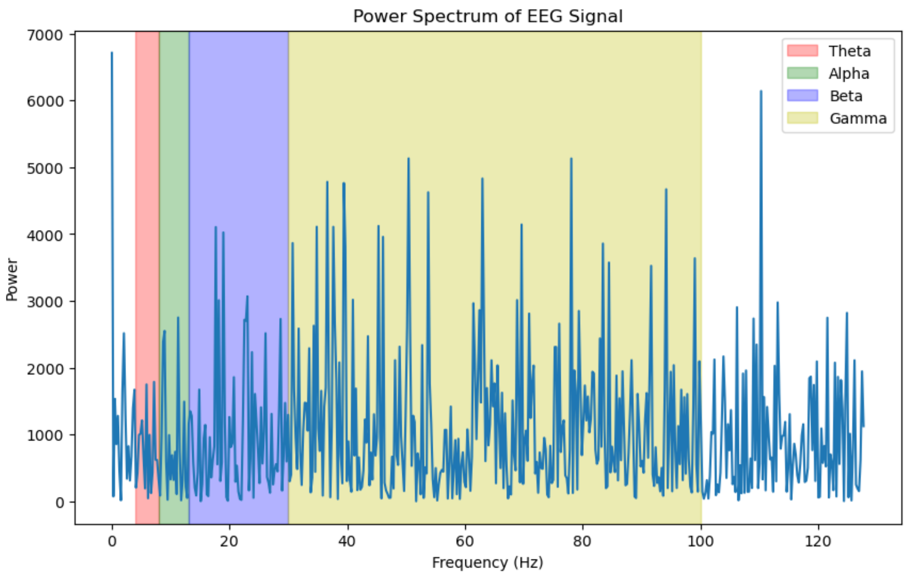

Figure 8: Analog EEG Signal

The graph in Figure 8 shows a waveform of the EEG signal, which represents the brain waves of a person. The signal is composed of four distinct waveforms, each corresponding to a specific frequency range of brain waves: theta, beta, alpha, and gamma. The theta waveform is the lowest frequency range, typically associated with relaxed states or drowsiness. In the image, the theta waveform is relatively small and spans from the left to the right side of the graph [19].

The beta waveform is the next highest frequency range, typically associated with alertness and focus. In Figure 8, the beta waveform is larger and more prominent, occupying a significant portion of the graph from the left to the right side. The alpha waveform is the next frequency range, typically associated with relaxed wakefulness. In Figure 8, the alpha waveform is smaller than the beta waveform and is located between the theta and beta waveforms. The gamma waveform is the highest frequency range, typically associated with cognitive processing and attention [20]. In Figure 8, the gamma waveform is the smallest and is located towards the right side of the graph.

Figure 9: EMG Sensor Placement

Figure 6 shows the setup for the EMG data collection with a sensor using BITalino controller and electrodes. The electrodes are positioned on the skin to detect the electrical signals produced by muscle activity. The BITalino Controller acts as the interface between the sensor and the recording device. Figure 9 shows the placement of the BITalino controller with electrodes for EMG which is attached to detect facial muscle activity. The electrodes are placed on the jaw muscle so that they can detect the tension of the jaw muscle for dental pain detection. The BITalino controller is used to monitor and record the electrical signals generated by his facial muscles in response to dental pain. The electrodes are situated on the subject's cheek and beneath the chin, suggesting the monitoring of muscles engaged in jaw movements.

2.2 MACHINE LEARNING

A machine learning model has been developed for the automated prediction of pain. Various machine learning algorithms are used to train the model, including Random Forest, K-Neighbors, Bagging, Decision Tree, SGD (Stochastic Gradient Descent), Logistic Regression, Ada Boost, Linear SVC (Support Vector Classifier), and Multinomial Naive Bayes. It collects bio signals from the subject, such as ECG, EEG, and EMG. The purpose is to forecast the subject's pain level, which is classified into three categories: "No Pain," "Mild Pain," and "High Pain." The model's goal is to reliably predict pain levels by examining bio signals.

In this research, 8 subject's bio signals have been recorded. At this stage of study, we were unable to get the data from real dental patients. Therefore, we have taken the data from individuals who are having no pain, mild pain, and high pain to represent data for the different pain levels. However, this study still shows the feasibility of the proposed technique for detecting pain automatically and the data from real dental patients' need to be collected in the future study to imply a realistic automatic pain recognition system for dental patients. The recorded bio signal underwent pre-processing before being used to train the model. Training has been carried out using 80% of the pre-processed data, while the remaining 20% was used for testing.

Random Forest is a collection of many decision trees. Each tree is trained on a randomly selected portion of the training data. To identify the best split for each node in the tree, only a randomly chosen subspace of the feature space is considered. Notably, the trees in the random forest are fully grown and not pruned. Random forests have proven successful in a variety of application domains, providing benefits such as high predictive accuracy and fast training and prediction timeframes [21,22]. The random forest can effectively manage the complex correlations and variability found in bio-signal data.

The K-Neighbors Classifier algorithm divides data into categories based on its proximity to other data points. As a single tree model, Decision Tree Classifier is more prone to overfitting than its ensemble counterparts. Decision trees can capture complicated patterns, but they may lack generalizability when dealing with data variability, resulting in inferior performance in the context of this study [23]. Logistic Regression is a simple model that predicts probabilities using a logistic function. While effective in linear connections, its effectiveness in this case may be limited due to the nonlinear and multidimensional structure of bio-signals, making it difficult to accurately capture pain levels [24]. Stochastic Gradient Descent (SGD) is used to solve large-scale, sparse machine learning problems. While it is economical, its performance may be influenced by feature scaling sensitivity and the requirement for careful parameter optimization, resulting in unpredictability in its efficiency for pain recognition [25]. The Linear Support Vector Classifier performs well in high-dimensional spaces, but it may struggle with the nonlinear patterns found in bio-signal data, potentially resulting in lower accuracy compared to more complicated models [26].

3. RESULT AND DISCUSSION

The random forest algorithm achieved an accuracy of 65.1% with a prediction time of 2.1 seconds. The model exhibited a recall of 0.56, suggesting sensitivity to the dataset. Additionally, F1 score of 0.56 is attained, indicating a well-balanced trade-off between precision and recall.

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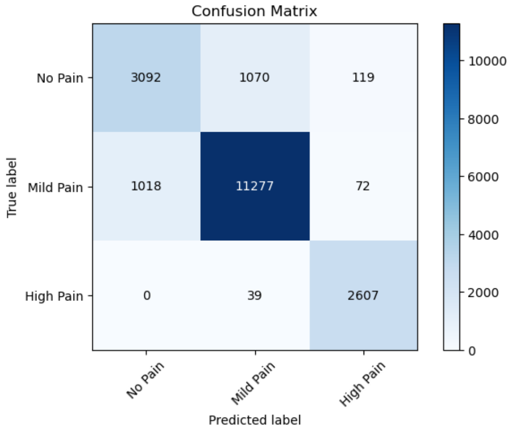

Figure 10: Confusion Matrix

Figure 10 displays a confusion matrix, which is a table used to evaluate the performance of a classification model. In this confusion matrix, the class "No Pain" has been correctly predicted 3092 times, while 1070 instances of "No Pain" have been inaccurately predicted as "Mild Pain", and 119 instances have been inaccurately predicted as "High Pain". For the class "Mild Pain", 11277 instances have been correctly predicted. However, 1018 instances of "Mild Pain" have been inaccurately predicted as "No Pain", and 72 instances have been inaccurately predicted as "High Pain". Lastly, for the class "High Pain", all instances (2607) have been correctly predicted. There are no instances inaccurately predicted as other classes.

	Algorithm	Accuracy: Test	Precision: Test	Recall: Test	F1 Score: Test
0	RandomForestClassifier	0.65052	0.564671	0.565391	0.564855
1	KNeighborsClassifier	0.64200	0.561086	0.574755	0.564362
2	BaggingClassifier	0.63760	0.550880	0.545020	0.542867
3	DecisionTreeClassifier	0.63132	0.535953	0.536837	0.536392
4	SGDClassifier	0.50052	0.511900	0.549750	0.481757
5	LogisticRegression	0.63216	0.531343	0.426353	0.430173
6	AdaBoostClassifier	0.63004	0.348132	0.357687	0.308544
7	LinearSVC	0.63120	0.377098	0.334044	0.259729
8	MultinomialNB	0.63120	0.210400	0.333333	0.257970

Figure 11: Model Accuracy

Figure 11 presents performance metrics, including accuracy, precision, recall, and F1 score, for various machine learning algorithms applied to a classification task. Each algorithm has been trained and evaluated on a dataset, but specific details about the dataset, such as its size, features, and target variable, are not provided.

Based on the metrics, the Random Forest emerges as the most suitable algorithm for this machine learning model. With an accuracy of 0.65, precision of 0.56, recall of 0.56, and F1 score of 0.56, it demonstrates the highest performance across all evaluated metrics. This algorithm's strength lies in its ability to handle complex datasets effectively, maintain robustness against overfitting, and provide balanced precision and recall values, resulting in a high F1 score. Thus, it offers a reliable solution for accurate classification tasks, making it the preferred choice based on all performance indicators.

Best Accuracy: 0.651 - RandomForestClassifier
Best F1 Score: 0.565 - RandomForestClassifier
Best Precision: 0.565 - RandomForestClassifier
Best Recall: 0.575 - KNeighborsClassifier

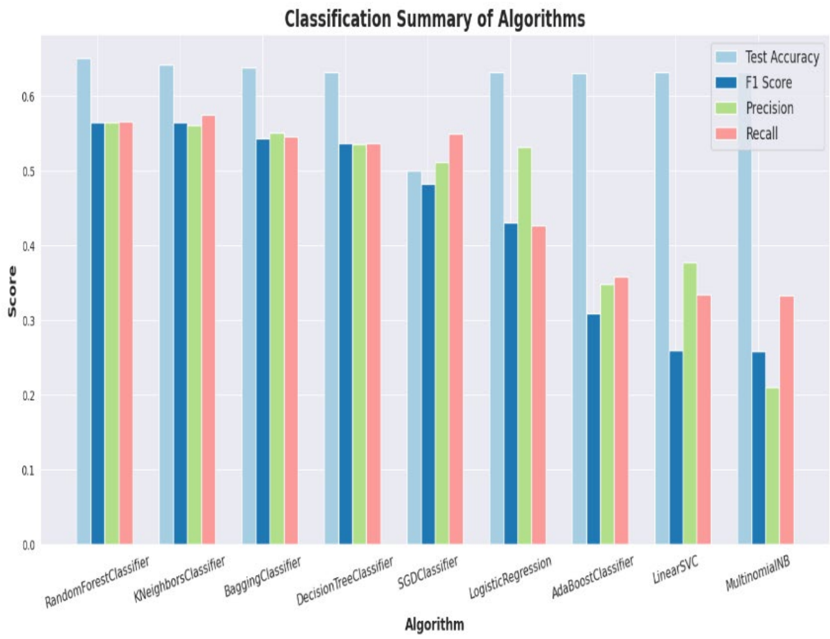

Figure 12: Classification Summary of Models

In Figure 12, each algorithm is listed along the horizontal axis, and the vertical axis represents the score, ranging from 0 to approximately 0.7. The comparative analysis of machine learning algorithms is presented, where each algorithm is plotted against test accuracy, F1 score, precision, and recall metrics. The Random Forest Classifier emerges as the top performer, with the highest scores across most metrics, including an accuracy of 0.651, an F1 score of 0.565, and a precision of 0.565. However, the K-Neighbours Classifier stands out with the highest recall score of 0.575. Despite variations in performance, none of the other algorithms surpass the Random Forest Classifier in terms of test accuracy, F1 score, or

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precision. The legend in the upper right corner succinctly summarizes the best-performing algorithms for each metric, highlighting the Random Forest Classifier as the leader in accuracy, F1 score, and precision, while the K-Neighbours Classifier excels in recall. This visualization aids in selecting the most suitable algorithm for specific tasks based on performance metrics.

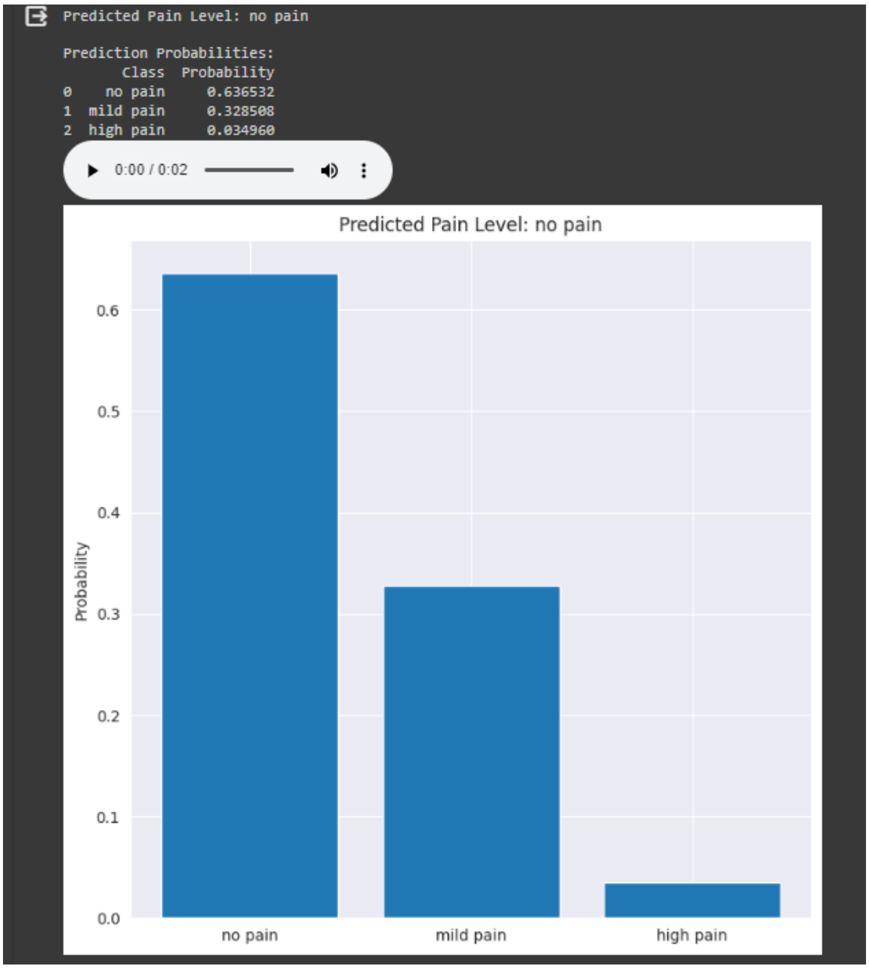

Figure 13: Final output of the system

Figure 13 shows the final output, featuring both a graph and a voice output indicating the predicted pain level. The bars on the graph are positioned at different heights, reflecting the various pain levels. At the beginning, the final output of the system is shown as "No Pain." Subsequently, the model presents the probabilities of the other two pain level categories. Finally, the system articulates the final output both graphically and vocally. The graph visually represents the results of the pain assessment, with the 'No Pain' category exhibiting the highest peak, indicating a predicted pain level of "No Pain." Combined with voice output, the graph serves as a valuable tool for easily understanding of the pain level.

The study achieves an accuracy of 65.1%. In future study, the data needs to be collected from real dental patients with various levels of pain during the treatment and the training and testing needs to be repeated using these data to represent a more practical and realistic automatic pain detection for dental patients. A larger dataset is also needed and the usage of

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other bio-signals and sophisticated machine learning models can be applied to boost the system's performance.

4. CONCLUSION

In conclusion, this study presents a simple and low-cost pain recognition system in dental treatment. Three types of biosensors, which are the heart rate (ECG), muscle activity (EMG), and brain activity (EEG), have been used for the pain recognition system for dental treatment. The bio signals were captured using AD-8232 for ECG, BITalino sensor kit for EMG and EEG recordings from different subjects. The system provides an objective assessment of pain, classified into "High pain," "Mild pain," and "No pain" categories. A variety of machine learning algorithms had been employed and Random Forest Classifier emerged as the most effective, achieving an accuracy of 65.1%. Overall, this study contributes significantly to the advancement of intelligent pain assessment methodologies, offering potential implications in dental care. Future works involves the utilization of the data obtained from real patients in a hospital environment for the model training and testing to obtain a more accurate result. Medical-grade equipment also need to be used for a more reliable data collection process.

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