CIPHomeCare: A Machine Learning-Based System for Monitoring and Alerting Caregivers of Cognitive Insensitivity to Pain (CIP) Patients

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***Abstract*—Congenital Insensitivity to Pain (CIP) patients, particularly infants, are vulnerable to self-injury due to their inability to perceive pain, which can lead to severe harm, such as biting their hands. This research introduces "CIPHomeCare," a wearable monitoring solution designed to prevent self-injurious behaviors in CIP patients aged 6 to 24 months. The primary focus of this study is developing and applying machine learning algorithms to classify hand-biting behaviors. Using accelerometer data from the STEVAL-BCN002V1 sensor, which is a motion sensor, several machine learning models—K-Nearest Neighbors (KNN), Random Forest (RF), Naive Bayes (NB), Linear Discriminant Analysis (LDA), and Logistic Regression (LR)—were trained to differentiate between normal and harmful behaviors. To address data imbalance due to the infrequency of biting events, oversampling techniques such as SMOTE, Borderline-SMOTE, ADASYN, K-means-SMOTE, and SMOTE-ENN were employed to enhance classification performance. Among the algorithms, KNN achieved the highest accuracy (98%) and a sensitivity of 72%, highlighting its effectiveness in detecting harmful hand motions. The findings suggest that machine learning, in combination with wearable technology, can provide accurate, personalized monitoring and timely intervention for CIP patients, paving the way for broader clinical applications and real-time prevention of self-injury. The real-time processing capability of the system enables immediate alerting of caregivers, allowing for timely intervention to prevent injuries, thus improving their quality of life.**

***Keywords*—Cognitive insensitivity to pain patients; CIP; machine learning; motion sensors; quality of life; wearable activity recognition**

I. Introduction

One of the significant challenges that patients with CIP face is the late detection of injuries, as they are unable to feel pain. For instance, infants with CIP may inadvertently harm themselves while teething, sometimes biting their tongues to the point of cutting off the tip or gnawing on their hands until they bleed [1, 2, 3]. These behaviors can lead to severe self-mutilation or, in extreme cases, amputation [4]. Researchers have noted that due to the lack of pain perception and visible signs of distress, serious injuries can occur, including premature self-extraction of teeth [3, 5]. Therefore, it is crucial to provide patients, particularly infants and their caregivers, with coping strategies for this disorder. Such support can enhance their quality of life (QoL), defined as the impact of a disease, disability, or disorder on an individual's physical and mental well-being over time [6].

While most research on CIP has concentrated on understanding the disorder's characteristics [7, 8], there is a notable lack of studies that focus on developing coping mechanisms, especially in comparison to other conditions like attention deficit hyperactivity disorder. To date, and based on the authors' knowledge, there has been only one significant attempt to address the challenges faced by CIP patients: the design and fabrication of an assistive technology glove that alerts patients to extreme temperature variations in their environment [9]. However, this solution has limitations, as it may not fully address the broader range of self-injurious behaviors these patients experience. The glove primarily targets temperature awareness, leaving other critical aspects of injury prevention unaddressed. This highlights the need for more comprehensive interventions that can provide holistic support for individuals with CIP. It is essential to develop targeted solutions that address their specific needs. One critical area of focus is the issue of finger-biting behaviors, which can lead to severe self-injury and long-term consequences.

Providing a good quality of life for CIP disorder patients is the primary motivation of this research study. CIP disorder holds the potential to worsen the overall health of patients by limiting their capacity to live well and their functional status and productivity. This research focuses on finger-biting behaviors and aims to develop a solution called 'CIPHomeCare,' specifically designed for infants with CIP aged 6 to 24 months and their caregivers during the teething stage. Addressing this behavior is vital, as it not only helps prevent immediate physical harm but also supports the overall emotional and psychological well-being of patients and their families. Equipping caregivers with practical tools to monitor and manage these behaviors is essential; however, a key challenge is determining how to alert caregivers when a child with CIP begins to injure their hands. Specifically, there is a need to detect when a child's biting reaches a predefined limit and notify caregivers of the risk of injury.

Incorporating machine learning can be highly beneficial to address these challenges. Machine learning algorithms can analyze and identify patterns in patient datasets and correlations that may not be immediately apparent through traditional methods. This facilitates the development of a dynamic threshold that adapts to individual behavior over time, ensuring personalized interventions. Furthermore, machine learning can enhance the estimation accuracy regarding when a child is likely to reach harmful biting levels, enabling caregivers to intervene proactively. By leveraging these advanced analytical techniques, the proposed solution not only improves safety but also empowers caregivers with actionable insights, ultimately contributing to better management of the disorder and enhanced QoL for CIP patients.

To implement this innovative approach, data from typically developing children was used, as no datasets are available specifically for CIP patients. By tracking the frequency of hand-biting behaviors over time, the researchers identified moments when a child might be at risk of self-harm. This data established a baseline for behavior patterns, which was then used to train various machine-learning algorithms. The analysis showed that the K-Nearest Neighbors (KNN) algorithm achieved the highest average accuracy rate of 98% in identifying abnormal hand motions. This predictive capability helps estimate the injury threshold, at which point the proposed solution would alert caregivers. The proactive alarm system is designed to notify caregivers before a child's biting reaches a level that could cause harm, thereby enhancing safety and preventing injuries.

To the best of our knowledge, 'CIPHomeCare' is the first comprehensive solution combining technology and machine learning to address the unique challenges CIP patients face, aiming to improve their quality of life. The remainder of this research is organized as follows: Section II reviews related works, including wearable activity recognition and classification algorithms. Section III provides an overview of the proposed solution. In Section IV, the experimental method is presented. Section V describes the evaluation methods used in this research. Section VI analyzes the results obtained. Discussion is given in Section VII. Finally, the conclusions are presented in Section VIII.

II. Related Work

Recent studies underscore the pivotal role of technology in advancing motion recognition through wearable devices, which are crucial for applications ranging from fall detection in elderly individuals to monitoring hazardous movements and anticipating potential risks. These technologies enable early detection and effective intervention, reducing injury severity and mortality rates in vulnerable populations [10]. Motion recognition technology's ability to analyze data, identify movements, and provide timely alerts has significantly improved patient safety and response times. Given its growing relevance, monitoring and investigating human gestures has become a central focus in commercial and biomedical research [11, 12]. The related work is organized as follows: the first part illustrates the new advancements in hand gesture monitoring technologies, the second part compares the use of one sensor against multiple sensors, and the last part provides insight into the impact of sensor placement on gesture recognition accuracy.

A. Advancements in Hand Gesture Monitoring Technologies

The field of hand gesture monitoring has seen rapid advancements, driven by the need for better rehabilitation tools and performance analysis systems. A notable study [10] introduced an intelligent wristband equipped with polymeric strain gauge sensors capable of detecting eight distinct hand gestures with 98% accuracy using Linear Discriminant Analysis (LDA). This innovation highlights the potential of simple yet highly accurate systems for recognizing complex hand gestures. Expanding on this, another study [13] examined hand gesture recognition in table tennis using multiple algorithms, including Support Vector Machine (SVM), LDA, K-Nearest Neighbor (KNN), Decision Tree (DT), and Naive Bayes (NB). The Decision Tree algorithm stood out, achieving an accuracy of 95%, demonstrating the effectiveness of ensemble methods in sports-related gesture recognition.

Real-time gesture recognition has also been explored, particularly with Inertial Measurement Unit (IMU) sensors. Research from 2018 [14] reported an accuracy range of 72% to 100%, with an average accuracy of 86.99% when using algorithms such as SVM, LDA, Dynamic Time Warping (DTW), and Principal Component Analysis (PCA). These studies collectively illustrate the diversity of approaches used in gesture recognition, each tailored to the specific application domain, highlighting both the potential and challenges of integrating such technologies into everyday use. Thus, this current research study uses real-time gesture recognition and accelerometer-based bracelet-type sensor specified for CIP children's patients.

B. Comparison of Single vs. Multiple Wearable Sensors

While many studies have focused on single-sensor configurations, others have explored using multiple sensors to enhance gesture recognition accuracy. Zhao et al. [15] developed a table tennis stroke classification system using three sensors placed on different body parts, achieving a recognition accuracy of 97.41% with SVM. This illustrates how combining multiple sensors can improve the precision of gesture detection in dynamic environments. In contrast, a study [16] compared single and multiple sensor setups, revealing only a modest difference in accuracy—90% for single sensors compared to 95% for multiple sensors. This finding suggests that the marginal improvement in accuracy with additional sensors may not justify the increased complexity and discomfort in practical applications, mainly when wearable devices are intended for daily use. Research has also shown that an increased number of sensors can interfere with everyday activities, reducing user comfort and compliance [17, 18]. These results emphasize the need to balance accuracy with usability, particularly in contexts like athletics or rehabilitation, where user comfort is paramount. Accordingly, this study considers children's comfort a priority, so only one sensor was used.

C. Impact of Sensor Placement on Gesture Recognition Accuracy

Sensor placement plays a critical role in determining the accuracy of gesture recognition systems. A study in [19] on fall detection using six sensors focused on wrist placement achieved an accuracy of 96.63% using the K-NN algorithm. This highlights the importance of precise sensor placement in improving recognition rates. Similarly, research in [20] that compared wrist and below-elbow sensor placements for dynamic hand gestures found that wrist placement yielded a higher accuracy of 93.27%, likely due to the more extensive range of motion captured at the wrist. Despite the improved accuracy with multiple sensors, studies also noted that additional sensors can interfere with daily activities [17, 18], underscoring the trade-offs between accuracy and practicality.

Several technological innovations have further enhanced gesture recognition accuracy. For instance, a study [21] introduced an accelerometer-based pen-type device combined with a Feedforward Neural Network and Similarity Matching system to detect primary and complex hand gestures, achieving an accuracy of 98.9%. Other advancements include axis-crossing code algorithms for wrist gestures, achieving accuracies as high as 96.9% and 97.1%, respectively [21]. Additionally, specialized devices, such as a wristband developed for basketball shooting analysis, demonstrated the potential for highly accurate gesture recognition in sports, with up to 98.5% accuracy using the Artificial Neural Network (ANN) algorithm [22]. These studies underscore the importance of sensor placement and algorithmic improvements in achieving high accuracy in gesture recognition, particularly in practical, real-world applications. Hence, this research settles on the wrist as the best placement of the sensor.

Table I summarizes all the related work on gesture recognition. The first column lists the types of sensors used in each paper. The second column lists the algorithms used to classify and evaluate the data. Next, the hardware type is used to process the data. The next column illustrates the sensor's placement. The last column shows the average accuracy of each study. While many wearable solutions target broad applications, focusing on specific, well-defined user groups can enhance effectiveness.

TABLE I. SUMMARY OF THE RELATED WORK

#	Work	Sensor	Model (algorithm)	Computing Hardware	Placement	Accuracy
1	[18]	polymeric strain gauge	SVM, LDA	PC	wrist	98%
2	[23]	MPU9250 includes (6-DOF inertial measurement unit (IMU), 3-DOF magnetometer sensor)	K-NN, SVM, DT, LDA, NB	Not mentioned	wrist	95%
3	[24]	ADIS16448 inertial measurement unit	SVM	PC	upper arm, lower arm, back	97.41%
4	[25]	triboelectric motion sensor	K-NN	PC	Not mentioned	80%
5	[4] method 1	ACC, HR, BVP, skin temperature (ST), galvanic skin response (GSR)	Long short-term memory with deep learning (LSTM-DL)	PC	Wrist	95%
6	[4] method 2	Only ACC	LSTM-DL	PC	wrist	90%
7	[26]	MTw sensor unit	k-NN, SVM, DTW, ANN, Bayesian decision making (BDM), least squares method (LSM)	PC	head, chest, waist, right-wrist, right-thigh, right-ankle	96.63%
8	[27]	3-dimensional accelerometer (ACC), blood volume pulse (BVP), heart rate (HR)	Random Forest (RF)	PC	Hip and wrist	92%
9	[28]	ACC	SVM	mobile application	Hip and wrist	89%
10	[29]	ACC	K-NN, and SVM, LDA, ensemble method (EM)	Not mentioned	Hip or thigh	93%
11	[30]	IMU, electromyography	K-NN, NB, RF, J48	PC	Wrist	93.27%
12	[3]	Accelerometer-based pen-type sensing device	FNN, SM	PC	hand	98.9%
13	[7]	inertial sensor	DTW	PC	wrist	96.9%
14	[16]	IMU	Axis-crossing code matching	Cortex32-M0 level MCU	wrist	97.1%
15	[13]	Mpu9250, Power system, Communication	SVM, K-NN, RF, ANN	PC	wrist	97.4%
16	[31]	accelerometer, gyroscope, compass sensor	SVM, NB, RF, J48, AdaBoost, Hidden Markov Model (HMM)	Not mentioned	wrist	94%
17	[12]	IMU including Accelerometer, Gyroscope	SVM, DTW, LDA, PCA	Not mentioned	wrist	86.99%
18	[32]	IMU	restricted column energy (RCE) neural network, DTW	Field-programmable gate array (FPGA)	hand	98.6%
19	[33]	single patchable six-axis IMU	recurrent neural networks (RNN)	PC	wrist	95.3%
20	Original research	Accelerometer-based bracelet-type sensor device	K-NN, NB, RF, LDA, LR	PC	wrist	98%

In summary, wearable-based gesture recognition systems have significantly improved, with various algorithms and sensor configurations improving accuracy and practicality. Using algorithms like K-NN, Decision Tree, and ANN, combined with appropriate sensor placement, has proven effective in diverse applications such as fall detection, sports performance analysis, and rehabilitation. While integrating multiple sensors can improve accuracy, single-sensor setups offer comparable performance with greater user comfort, particularly in everyday settings. Moreover, advancements in sensor technology, such as the development of wrist-based devices and novel algorithms, continue to push the boundaries of gesture recognition accuracy. Despite these advancements, challenges remain in real-time applications; balancing accuracy, sensor placement, and user comfort is critical. While previous research has focused on sensor-based systems for fall detection, this current study extends this by concentrating on CIP patients, who present unique challenges in gesture monitoring. The ongoing evolution of motion recognition technologies holds immense potential for improving patient safety and enhancing the quality of life for individuals across various domains.

III. Overview of the Proposed Solution: 'CIPHomeCare'

The proposed solution, 'CIPHomeCare,' comprises three main components, as depicted in Fig. 1. Since it is not within the main scope of the research, the architecture is not illustrated in detail. The first component is a motion/wearable sensor designed to be comfortable for infants and continuously monitor hand motions. It counts instances of biting and collects data on the frequency and intensity of these behaviors. The sensor establishes a baseline for normal behaviors by tracking these movements over time, allowing for better identification of abnormal patterns. The second component is the CIPHomeCore Smart Component, which processes the collected data using the wearable sensor. It trains machine learning models to classify hand motions and estimate when biting behaviors may become dangerous. The last component is the mobile application for caregivers, which is out of this research study's scope. The app provides real-time alerts to caregivers when the system detects a child approaching the predefined injury threshold. The application features an intuitive interface that displays data on the child's hand motions and biting frequency, empowering caregivers with actionable insights.

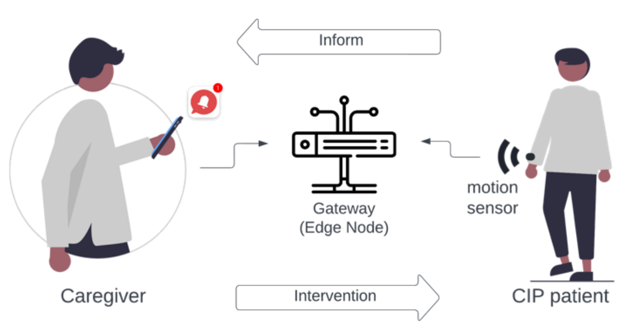

Fig. 1. The architecture of 'CIPHomeCare'.

These components create a comprehensive monitoring solution that enhances safety for CIP patients and supports caregivers in managing the disorder effectively.

IV. Methodology

This research encompasses multiple phases, from the initial selection of the sensor to the final analysis of the results.

Each phase was carefully designed to ensure the accuracy and reliability of data collection and analysis. Fig. 2. It illustrates the proposed workflow, which includes sensor selection, ethical considerations, data collection and processing, handling imbalanced dataset, training machine learning algorithms, and evaluating and comparing different approaches (illustrated in the Evaluation section). Statistical analysis was conducted using Python version 3.11, with libraries such as Pandas (version 2.2.2) for data processing and NumPy (version 1.26.4). The following subsections discuss all stages in detail.

A. Sensor Selection

The STEVAL-BCN002V1 multi-sensor is used to collect the data in this research study. The STEVAL- BCN002V1 is a multi-sensor board based on the BlueNRG-2 SoC Bluetooth Low Energy application processor and includes a 6-DOF inertial measurement unit (IMU). Thus, the child's wrist motions were collected using this sensor. The overall size is as tiny as a coin, so children would not feel uncomfortable wearing the sensor. It was chosen because of its small size, high accuracy, and low power consumption, making it suitable for continuous monitoring of young children without causing discomfort. The high sensitivity of the IMU allows for capturing even subtle hand movements, which is crucial for distinguishing between normal and biting behaviors. The sensor complies with European EMI/EMC and safety directives and standards.

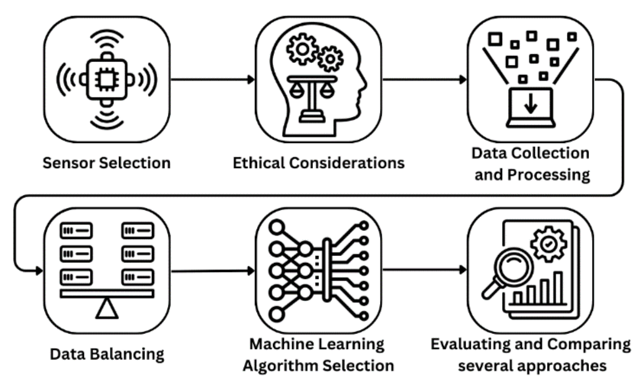

Fig. 2. The proposed workflow of 'CIPHomeCare'.

B. Ethical Considerations

This study followed the ethical principles outlined in the Declaration of Helsinki. Ethical approval was obtained from the Unit of Biomedical Ethics at King Abdulaziz University (No. HA-02-J-008) prior to the initiation of the research. Informed consent was secured from the guardians of all participants involved in the study. Each guardian was provided with detailed information regarding the purpose of the research, the procedures involved, and any potential benefits and risks. The study ensured that participation was voluntary, and participants could withdraw without consequences. To protect the confidentiality of participants, all data was anonymized and stored securely. Identifiable information was removed to ensure that individual responses could not be traced back to specific participants, and each participant was assigned a random ID number to maintain patient confidentiality. Data access was restricted to authorized personnel only.

Additionally, measures were implemented to minimize potential discomfort or distress to the children during data collection. The type and design of the wearable sensor were selected with the children's comfort in mind, ensuring it was non-intrusive, and the children were monitored to ensure their well-being throughout the study.

C. Data Collection and Processing

This current study utilized a newly collected dataset of children's hand movements, with prior approval from their parents. Data were gathered from the King Abdulaziz University Hospital clinics and Childhood Centers in Jeddah City, Saudi Arabia. The only eligibility criterion was that the child had to be between 6 and 24 months old. This age group is chosen because it gets the most injuries among CIP patients due to their low cognitive ability [2, 3] and to protect them from injuries they could suffer from. The data collection employed an accelerometer-based sensor, which enabled real-time monitoring of the children's hand movements. The sensor was worn on the children's dominant hand. Data were collected daily for a maximum of 35 minutes per child to maintain consistency across participants and ensure comprehensive monitoring without causing fatigue. The data were collected between 9 am and 3 pm since the data is collected from a hospital and childhood center.

Wrist motion data was collected from 41 normal children without CIP health conditions. The children are 19 females and 22 males. The youngest participants were 6 months old, while the oldest were 2. Each child wore a wristband sensor for a maximum of 35 minutes daily. To capture natural behavior, the children were not restrained in their movements and were not instructed to perform any specific actions, providing a realistic baseline for detecting abnormal hand motion (biting motion). The wristband recorded acceleration data across the X-axis, Y-axis, and Z-axis, capturing various wrist motions, including the intensity and frequency of movements. Upon analyzing the acceleration data, significant differences in the peak profiles across the X, Y, and Z axes were observed.

Consequently, the acceleration data from all three axes was selected as this primary motion analysis dataset for subsequent motion recognition and detection. The recorded motion data was then manually classified by the first author (RA) into two categories: normal motion (no hand biting) and abnormal motion (hand biting), and then reviewed by three experts. Two experts, the second and the third co-authors (HB and AH), are from the technology field and have at least seven years of experience in machine learning. The third expert is from the health sector; the last co-author (RA) is a physician with over fifteen years of experience in the pediatric department (neurology division). However, some challenges arose during data collection: children did not frequently bite their hands, leading to an imbalanced dataset. To address this issue, oversampling techniques were employed to ensure a more balanced representation of both motion categories in the analysis phase.

The data processing phase started after labeling the data with the expert's assistance. The processing phase progressed through several stages until the appropriate stage was determined. Initially, we took the data as is and identified the abnormal biting behavior. Unfortunately, if the child bites his hand, the alarm will go off, which is not a practical solution. Then, we set a fixed threshold of 10 seconds to define abnormal biting behavior without accounting for individual differences in pain tolerance. This threshold was used uniformly across all participants. However, this approach led to substandard results, as it failed to consider the natural variability in how different children responded to discomfort.

Given that the data was collected from children, it was crucial to consider individual differences in pain tolerance, which naturally varies among them. Granted, we revised our approach by calculating each child's average biting duration and using it to create a personalized threshold for abnormal behavior detection. We significantly improved the system accuracy compared to a generic threshold. This adjustment resulted in improved accuracy and consistency in detecting abnormal behaviors.

Table II shows a sample of the average biting duration; some results are 0, which means those children did not bite their hands at all during the observation period. Table III illustrates that the children's hand motion dataset consisted of four columns and more than eight million rows. Each row represents a part of the child's hand motion. The four columns represent the acceleration data across the X-axis, Y-axis, and Z-axis, and the last column represents the child's status (label), whether they were biting their hand at the time or not.

TABLE II. AVERAGE BITING DURATION

ID	Average (Sec)
1	2.7975
2	0
3	0
4	1
5	6.2

TABLE III. AVERAGE BITING DURATION STATUS

X(mg)	Y(mg)	Z(mg)	Status
-184	1026	141	0
-110	974	89	0
-121	961	87	0
-126	985	114	0
-138	1011	168	0

D. Data Balancing

As mentioned earlier, children did not frequently bite their hands, which led to an imbalanced dataset. As shown in

Fig. 3, the children's hand motion dataset suffers from a severe skew in the class distribution. This figure highlights the imbalance in the children's hand motion dataset, with a significantly higher proportion of normal hand motion (99.7%) than abnormal hand biting motion (0.3%). This imbalance requires oversampling techniques to ensure balanced training of ML models due to the infrequency and importance of detecting biting events.

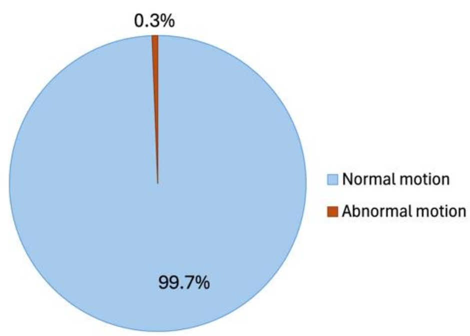

Fig. 3. Class distribution in the children hand motion dataset.

Several oversampling methods were investigated, such as the Synthetic Minority Over-sampling Technique (SMOTE), Borderline-SMOTE, Adaptive Synthetic Sampling (ADASYN), and K-means-SMOTE, to address class imbalance and mitigate overfitting in the collected dataset [34]. Each oversampling technique provides a dataset to be classified. SMOTE has gained significant attention due to its effectiveness and relative simplicity [34]. SMOTE is one of the earliest and most widely used methods, generating synthetic samples by interpolating between nearest neighbors within the minority class in the training set. This approach effectively blends features from original instances with those of randomly selected k-nearest neighbors [35]. An enhancement to SMOTE, known as Borderline-SMOTE [36], focuses on oversampling only those minority instances near the class boundary. Research indicates that Borderline-SMOTE improves classification performance for the minority class more effectively than both SMOTE and random oversampling methods. Another method applied is ADASYN [37], which adjusts the classification boundary by emphasizing more challenging examples. ADASYN employs a weighted approach to generate synthetic samples, prioritizing difficult instances within the minority class, and results from various datasets and evaluation metrics support its effectiveness.

K-means-SMOTE [38, 39] also leverages K-means clustering to identify clusters in the training data with an Imbalance Ratio (IR) below a specified threshold. SMOTE is then applied to these clusters, with the extent of oversampling determined by the sparsity and density of minority class objects. By implementing these four methods, the analysis aimed to effectively balance the dataset and reduce the risk of overfitting in the machine learning models.

In addition to the previously discussed oversampling techniques (SMOTE, Borderline-SMOTE, ADASYN, and K-means-SMOTE), this study also applied the SMOTE-ENN technique to address the class imbalance. SMOTE-ENN combines the Synthetic Minority Over-sampling Technique (SMOTE) with Edited Nearest Neighbors (ENN), providing an enhanced balance of the dataset by generating synthetic samples for the minority class while removing ambiguous samples that could potentially confuse the classifier [40]. This hybrid approach aims to improve the quality of the training set by effectively handling noisy instances, leading to potentially better model performance.

E. *Machine Learning Algorithm Selection*

Several machine learning algorithms were carefully selected to analyze the collected hand motion data. They were chosen for their proven effectiveness, as illustrated in related work, in similar applications and widespread implementation across various software platforms [16, 33]. The classifier algorithms applied in this work are as follows: the first chosen algorithm is the K-Nearest Neighbors (K-NN). It is a nonparametric, instance-based learning algorithm for classification and regression tasks. K-NN is recognized for its simplicity but can be computationally intensive due to its reliance on distance calculations between test instances and all training examples [41, 42]. The distance metric used in K-NN is typically the Euclidean distance, defined by Eq. (1).

$$\boldsymbol{d(x,y)} = \sqrt{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} (\boldsymbol{x_i} - \boldsymbol{y_i})^{\boldsymbol{2}}} \tag{1}$$

This formula calculates the distance $\boldsymbol{d(x,y)}$ between two points, x and y, in an n-dimensional space, helping the algorithm classify new instances based on proximity to training examples [43].

The second algorithm used is Random Forest (RF), an ensemble-based technique known for its robustness in classification tasks. RF constructs multiple decision trees using randomly sampled subsets of data and features, aggregating results through majority voting [44]. It effectively handles complex interactions and diverse data types, although it can be computationally demanding [45]. The impurity measure used to evaluate the quality of splits in decision trees is often represented by Eq. (2).

$$G = 1 - \sum_{i=1}^{n} p_i^2 \tag{2}$$

In this formula, G denotes the Gini impurity, where pipi represents the probability of a class i within the dataset, allowing the algorithm to assess the homogeneity of splits [43].

Naive Bayes (NB), the third chosen algorithm, employs the Bayesian theorem for classification by calculating the mean and variance of feature variables within clusters. It is particularly effective for high-dimensional data and is recognized for its simplicity and computational efficiency [27,28]. The probability of a class C_k given a feature x is computed as in Eq. (3).

$$P(C_k|x) = \frac{P(x|C_k) \times P(C_k)}{P(x)} \tag{3}$$

This formula illustrates how the algorithm updates the probability of class membership based on observed features, leveraging prior knowledge and likelihood [43].

The fourth chosen algorithm is the Linear Discriminant Analysis (LDA), which finds a linear combination of features that best separates different classes, transforming features into lower-dimensional space to enhance class separability [46]. Although effective, it assumes a standard feature distribution and may struggle with non-linearly separable classes. The within-class scatter matrix is represented in Eq. (4).

$$S_w = \sum_{k=1}^{K} \sum_{x_i \in C_k} (x_i - \mu_k)(x_i - \mu_k)^T \quad (4)$$

In this formula, S_w captures the variance of data points x_i within each class C_k, where μ_k is the mean of class k [43].

The last algorithm used is logistic regression (LR). This algorithm predicts the probability of a target variable by analyzing relationships between independent variables [47]. The logistic function, which models the probability, is Eq. (5).

$$\sigma(z) = \frac{1}{1+e^{-z}} \quad (5)$$

Here, $\sigma(z)$ represents the predicted probability of the target variable, where z is a linear combination of the independent variables, ensuring outputs are constrained between 0 and 1[43].

V. Evaluation

Muraina et al. [48] and Nguyen et al. [49] showed that selecting a 70/30 ratio to be the training/testing ratio impacts and improves the predictive capability of the ML models. Thus, the dataset was split into 70% for learning and 30% for testing to evaluate all classifier models. To determine which machine learning algorithm best estimates hand motion behaviors using the collected dataset, we evaluated a combination of five classification techniques: KNN, RF, NB, LDA, and LR. Along with various oversampling techniques: SMOTE, ADASYN, Borderline-SMOTE, K-means-SMOTE, and the newly added SMOTE-ENN. The effectiveness of these different combinations is compared in terms of three key metrics: accuracy, sensitivity, and specificity. Accuracy is the ratio of the total number of correct predictions to the total number of predictions made [50].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (6)$$

Sensitivity refers to the proportion of actual positive cases (the abnormal motion) that the model correctly identifies [50].

$$Sensitivity = \frac{TP}{TP+FN} \quad (7)$$

While specificity measures how accurately the model classifies negative cases (the normal motion), indicating its effectiveness in predicting normal hand motion [50].

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

VI. Results

The primary objective of this study was to evaluate the performance of several machine learning algorithms in detecting abnormal hand motions (specifically hand biting) in children with CIP using wearable sensors. The findings from the classification algorithms and oversampling techniques reveal valuable insights into the effectiveness of these approaches in addressing data imbalance and accurately classifying hand motions.

Tables IV-IX summarize the performance metrics of the classification algorithms, including accuracy, sensitivity, and specificity, for each oversampling method. Each table details the performance of the various algorithms, with the first column listing the different algorithms, the second column displaying the accuracy results, the third column showing specificity values, and the last column presenting sensitivity values. Table IX displays the result of the original imbalanced dataset.

Initially, a fixed threshold of 10 seconds for pain tolerance across all children led to poor performance as it did not adequately capture individual differences in pain perception. By individualizing the threshold, accounting for differences in average biting duration, the accuracy, sensitivity, and specificity of the models improved significantly, offering a more personalized and effective monitoring mechanism.

TABLE IV. Comparison of Classification Techniques using SMOTE

Techniques	Accuracy	Sensitivity	Specificity
K-NN	0.99	0.69	1.00
RF	0.61	0.69	0.61
NB	0.64	0.62	0.64
LDA	0.56	0.60	0.56
LR	0.56	0.61	0.55

TABLE V. Comparison of Classification Techniques using Borderline-SMOTE

Techniques	Accuracy	Sensitivity	Specificity
K-NN	1.00	0.65	1.00
RF	0.67	0.53	0.67
NB	0.58	0.63	0.58
LDA	0.60	0.64	0.60
LR	0.59	0.64	0.59

TABLE VI. Omparison of Classification Techniques using ADASYN

Techniques	Accuracy	Sensitivity	Specificity
K-NN	0.99	0.69	1.00
RF	0.80	0.44	0.80
NB	0.50	0.61	0.50
LDA	0.60	0.42	0.60
LR	0.60	0.42	0.60

TABLE VII. COMPARISON OF CLASSIFICATION TECHNIQUES USING K-MEANS-SMOTE

Techniques	Accuracy	Sensitivity	Specificity
K-NN	1.00	0.65	1.00
RF	0.61	0.69	0.61
NB	0.64	0.63	0.64
LDA	0.56	0.59	0.56
LR	0.55	0.61	0.55

TABLE VIII. COMPARISON OF CLASSIFICATION TECHNIQUES USING SMOTE-EEN

Techniques	Accuracy	Sensitivity	Specificity
K-NN	0.98	0.72	0.98
RF	0.60	0.69	0.60
NB	0.63	0.64	0.63
LDA	0.56	0.50	0.56
LR	0.55	0.61	0.55

TABLE IX. ORIGINAL DATASET CLASSIFICATION

Techniques	Accuracy	Sensitivity	Specificity
K-NN	1.00	0.63	1.00
RF	1.00	0.00	1.00
NB	1.00	0.00	1.00
LDA	1.00	0.00	1.00
LR	1.00	0.00	1.00

Additionally, Oversampling techniques such as SMOTE, Borderline-SMOTE, ADASYN, K-means-SMOTE, and SMOTE-ENN played a crucial role in addressing class imbalance by generating synthetic samples for underrepresented classes and eliminating noisy data. These methods were particularly effective in enhancing model sensitivity across classifiers like KNN, RF, and NB, limiting the challenges posed by the rarity of abnormal behavior hand-biting in CIP patients.

From the results obtained, K-NN consistently outperformed the other algorithms across all oversampling methods especially with SMOTE-ENN, SMOTE and ADASYN where the sensitivity scores reached 0.72, 0.69 and 0,69, respectively. A sensitivity of 0.72 implies that it flagged the abnormal motion correctly, which means the children's risky motion is detected. Due to its instance-based learning approach, which effectively leveraged high-dimensional data for classifying hand movements. SMOTE-ENN, K-means-SMOTE, and SMOTE specifically contributed to improved sensitivity and specificity, with KNN showing the highest accuracy across all conditions. Similarly, RF demonstrated strong performance, particularly with ADASYN and SMOTE-ENN, indicating its capacity to handle complex data patterns. In contrast, NB maintained moderate accuracy (0.50-0.64), while linear models like LDA and LR struggled with non-linear data separability, yielding lower accuracies of 0.55-0.60.

As mentioned earlier, oversampling techniques were crucial in addressing class imbalance, which significantly enhanced the model's ability to detect rare hand-biting behaviors. SMOTE-based methods improved sensitivity across all algorithms, notably increasing KNN's sensitivity from 0.65 to 0.72 with SMOTE-ENN. However, ADASYN, while boosting RF's sensitivity, reduced its specificity to 0.44, illustrating the trade-off between enhanced detection of abnormal behaviors and increased false positives. This underscores the importance of choosing oversampling techniques aligned with specific clinical goals.

VII. DISCUSSION

To validate the result of this study, we compared our results with similar research studies regarding the performance of oversampling techniques, ML algorithm results, and the integration of wearable sensors with machine learning. These findings align with prior research in healthcare, where oversampling techniques such as SMOTE-ENN have been shown to enhance model performance across various applications, including healthcare fraud detection and diabetic risk prediction. For example, Bounab et al. demonstrated that SMOTE-ENN improved accuracy and reliability by balancing datasets and eliminating noise [51], while Aruleba and Sun found similar benefits in credit risk prediction [52].

In prior research, the application of deep neural networks for emergency department triage demonstrated improved sensitivity and specificity compared to conventional triage models [53]. Similarly, KNN and RF in our study achieved high sensitivity, especially when paired with K-means-SMOTE, reinforcing the idea that careful model selection and oversampling techniques can substantially enhance the ability to identify critical behaviors, which is crucial in clinical settings where missing abnormal events could have severe consequences.

The effectiveness of oversampling methods such as SMOTE and ADASYN was also observed in other domains, including healthcare data privacy and diabetic risk prediction [54]. These studies found that oversampling significantly improved the detection capabilities of models for minority class events, such as high-risk patients, which aligns with our finding that oversampling increased sensitivity and specificity for detecting abnormal hand-biting behaviors. This enhancement in sensitivity, while sometimes compromising specificity, underscores the necessity of selecting an oversampling technique that aligns with specific clinical objectives—whether prioritizing sensitivity for early detection or specificity to reduce false alarms.

Fig. 4 illustrates the sensitivity comparison for each algorithm, demonstrating that KNN outperforms other techniques, such as LDA and LR, and also shows promising results, particularly with the SMOTE technique, and even better performance with K-means-SMOTE. Additionally, NB maintains a relatively consistent accuracy of around 63%.

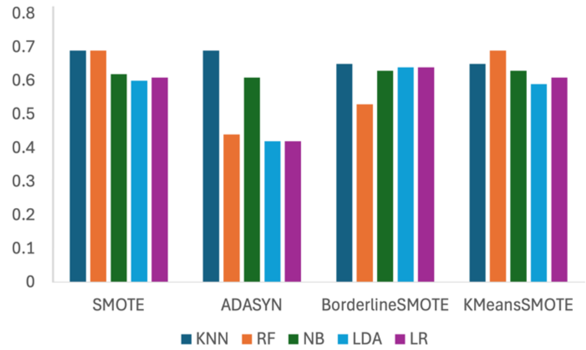

Fig. 4. Sensitivity.

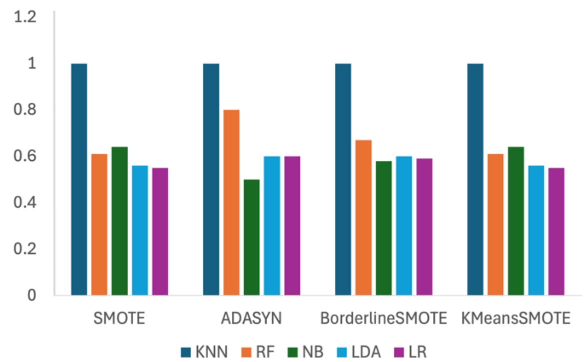

Fig. 5. Specificity.

Fig. 5 presents the specificity comparison across each oversampling technique. Here, KNN achieves the highest specificity again, while RF excels with the ADASYN method, showing comparable results to NB across the other three oversampling techniques. Moreover, while RF demonstrates overall good results, the NB algorithm achieves higher accuracy than LR. This can likely be attributed to the interdependence of the acceleration data across the X, Y, and Z axes; each feature contributes individually to the predictions made by the NB classifier.

Conversely, both LDA and LR underperformed, yielding a low average accuracy of 58% across all oversampling techniques. This highlights the need for careful selection of algorithms in future implementations to enhance detection capabilities for abnormal hand motions in children.

The results are also consistent with the work by Viloria et al., which demonstrated the efficacy of combining methods like SMOTE and random oversampling to address class imbalances in biomedical datasets [30]. Our use of SMOTE and ADASYN parallels these findings by effectively mitigating imbalance issues in hand motion data, thereby improving the models' ability to differentiate between harmful and non-harmful behaviors.

The integration of wearable sensors with machine learning for real-time monitoring, as demonstrated in this study, parallels prior applications in cardiovascular and neurological health monitoring [55]. This technology offers a viable solution for detecting harmful behaviors in CIP patients, enabling timely intervention and improving patient safety.

The high sensitivity achieved by KNN and RF, especially with SMOTE, K-means-SMOTE, and SMOTE-ENN, has important implications for real-world monitoring systems for CIP patients. Detecting abnormal hand motions like hand biting is critical for preventing self-injury in children who cannot feel pain. The wearable sensor system evaluated in this study offers a viable solution for real-time detection and intervention. By incorporating machine learning models that adapt to individual behavior patterns, caregivers can be alerted before harmful behaviors escalate, improving patient safety.

Moreover, the successful application of oversampling methods indicates that similar approaches could be used to detect other critical healthcare behaviors, such as monitoring involuntary movements in patients with neurological disorders. These findings are consistent with prior research on motion classification using wearable sensors. For example, previous studies have demonstrated the effectiveness of KNN and RF in recognizing activities and detecting critical health events when combined with appropriate data augmentation techniques. Additionally, machine learning models in real-time monitoring, similar to wearable devices used in cardiovascular health monitoring, underscores the transformative potential of AI in healthcare applications.

Studies have also validated the effectiveness of machine learning models like KNN and RF in recognizing critical health events across different domains. For example, KNN's success in heart sound analysis with an accuracy of 93.50% [56] and RF's compelling performance in fraud detection and credit risk analysis [57,58] demonstrate their robustness across varied datasets. These findings validate our approach, as KNN and RF were well-suited for highly dimensional accelerometer data, requiring distinguishing subtle variations in hand motion patterns.

Finally, addressing imbalanced datasets in healthcare has consistently been highlighted as a critical issue, especially in applications where the cost of false negatives can be severe. This research study extends previous literature by evaluating multiple oversampling techniques, providing a comprehensive understanding of how these methods can be applied to healthcare datasets with imbalanced classes, such as CIP-related hand-biting data. This emphasizes the importance of a tailored approach to handling imbalance, especially in clinical contexts where false negatives could harm patients [59].

In conclusion, this study demonstrates that KNN, particularly when paired with oversampling techniques like SMOTE-ENN, performs best for detecting abnormal hand motions in children with CIP. These findings support the potential for more effective intervention systems for CIP patients.

VIII. Conclusion, Limitations, and Future Work

This research explores the use of wristband sensors to investigate abnormal hand motions, explicitly focusing on hand biting. We collected and analyzed hand movement data from children to distinguish subtle differences between normal and abnormal motions. The wristband sensor, equipped with motion detection technology, provides a portable and easily deployable solution. We utilized the STEVAL-BCN002V1 sensor to capture motion acceleration data, which was transmitted via Bluetooth for analysis. Our classification was based on acceleration data from three axes, resulting in an impressive average recognition accuracy of 98% and a sensitivity of 72%, highlighting the system's potential for future applications. The high sensitivity allows for capturing even subtle hand movements, which is crucial for classifying abnormal behaviors in real-world and other future applicability. Our findings underscore the value of detecting subtle differences in hand movements as a proactive measure for monitoring and preventing harmful behaviors. Furthermore, gaining deeper insights into these movements could substantially improve the quality of life for children affected by Congenital Insensitivity to Pain (CIP).

Despite these promising results, several limitations need to be addressed. The dataset used for model training and testing was relatively small, comprising data from only 41 children, which may affect the generalizability of our models to larger and more diverse populations. While we mitigated class imbalance using oversampling techniques, real-world datasets are often more complex and may introduce noise into synthetic samples. Additionally, sensor data were collected over a short period (35 minutes per day), potentially missing key variations in hand motions.

As a future direction, we plan to extend data collection over longer periods to improve model robustness and capture a broader range of motion variations. Future research should also focus on expanding the dataset to include a larger, more diverse population and incorporate additional relevant motions, such as eye rubbing, particularly for CIP patients. Integrating advanced deep learning techniques, such as Convolutional Neural Networks (CNNs), could enhance classification accuracy, especially for more complex motion patterns. Additionally, we will prioritize expanding the dataset and exploring similar behaviors to broaden the applicability of our findings. For CIP patients, even minor advancements could significantly improve their well-being and that of their caregivers. This research could also be extended to other conditions, such as autism, where motion detection is critical in managing behaviors. Another future direction after getting the necessary IRP approval is designing and building the whole system to ensure it is as safe as possible; we will conduct a clinical control trial study in a hospital to measure the system's effectiveness and scalability.

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