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Affectionate real-time assistant: Development of a pressure-sensitive infant holding monitoring system

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Abstract: This paper presents the development of the Affectionate Real-Time Assistant (A.R.A), a pressure-sensitive infant holding monitoring system designed to enhance neonatal safety. The system employs five pressure pads integrated with an Arduino Uno to capture pressure distribution data from six distinct infant holding postures. Data were collected from 33 participants, including 12 parents, 11 non-parents, and 10 neonatal medical professionals. Machine learning algorithms were applied to classify holding postures accurately. Additionally, a NodeMCU module and an MPU6050 accelerometer and gyroscope sensor were incorporated to detect excessive tilting and shaking, which can prevent Shaken Baby Syndrome (SBS) and milk aspiration. Real-time feedback and alerts are delivered through the Blynk IoT platform, enabling caregivers to monitor and adjust infant handling promptly. Survey results from 20 parents informed system requirements, emphasizing the need for user-friendly, real-time safety monitoring. Experimental evaluation demonstrates the system's effectiveness in posture classification, tilt detection, and shaking prevention, highlighting its potential as a practical tool for improving infant care. Future work will focus on expanding sensor capabilities and refining machine learning models for broader application.

Keywords: *Infant health risk, Infant holding, Infant monitoring systems, IoT, Machine learning, Milk aspiration, Neonatal safety, Shaken baby syndrome.*

1. Introduction

Neonatal safety remains a critical concern worldwide, with infant mortality and injury risks such as Sudden Infant Death Syndrome (SIDS) [1, 2] Milk Aspiration [3] and Shaken Baby Syndrome (SBS) [4] posing significant challenges to caregivers and healthcare providers. Advances in biosensor technology and Internet of Things (IoT) platforms have enabled continuous, real-time monitoring of infant physiological parameters and environmental conditions, improved early detection of health issues and enhancing caregiving practices [5-8]. However, current infant monitoring systems predominantly focus on vital signs and gross movement detection, often overlooking the nuanced assessment of infant handling and posture, which are crucial factors influencing infant safety and comfort. Motivated by these gaps, this study aims to develop an innovative system that directly monitors infant holding postures through pressure-sensitive sensing, integrated with machine learning [9] and IoT technologies to provide caregivers with actionable, real-time feedback.

Despite the proliferation of infant monitoring devices, there is a lack of effective solutions that objectively and continuously assess caregiver-infant physical interactions, particularly the detection of unsafe infant holding postures that can lead to injury or distress. Existing wearable [10] and camera-based systems primarily track general motion or physiological signals but do not adequately capture the pressure distribution patterns associated with different holding postures. Moreover, preventive mechanisms to detect and alert caregivers about excessive tilting or shaking which are the key contributors to SBS and milk aspiration are insufficiently integrated into current monitoring platforms.

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This gap limits caregivers' ability to receive timely warnings and intervene to ensure infant safety during handling.

The primary objective of this study is to design and implement a training and educational system - A.R.A (Affectionate Real-Time Assistant), a pressure-sensitive infant holding monitoring system that:

- Accurately captures and classifies multiple infant holding postures using an array of pressure sensors.
- Integrates machine learning algorithms to analyse pressure data for real-time posture classification.
- Incorporates sensor modules to detect excessive tilting and shaking to provide preventive alerts against Shaken Baby Syndrome and Milk Aspiration.
- Delivers real-time feedback and notifications to caregivers through an IoT platform (Blynk), facilitating immediate corrective actions.

The scope includes conducting a caregiver survey to identify key safety concerns and system requirements, developing a hardware prototype with pressure pads interfaced to Arduino Uno and NodeMCU ESP8266 microcontrollers, collecting and analysing data from diverse participant groups, and evaluating system performance in realistic holding scenarios.

This study employs a mixed-methods approach combining qualitative and quantitative data collection with hardware prototyping and machine learning analysis. Initially, a survey was conducted with 20 parents to gather insights on neonatal safety concerns and expectations from infant monitoring systems. These findings informed the design specifications for the hardware system, which consists of five pressure pads attached to a baby doll to simulate infant holding postures. Pressure data were collected from 33 participants (12 parents, 11 non-parents, and 10 neonatal medical professionals) across six distinct holding postures. The data were processed and classified using machine learning techniques to develop accurate posture recognition models. Additionally, a NodeMCU ESP8266 module and MPU6050 Accelerometer and Gyroscope sensor was integrated to monitor tilting angles, excessive shaking and trigger alerts to prevent unsafe handling. The entire system communicates with the Blynk IoT platform to provide caregivers with real-time feedback and visualizations, enabling proactive infant care.

2. Literature Review

This section reviews existing research related to infant safety, posture monitoring technologies, and AI-based caregiving support systems. It highlights current gaps in the literature and provides context for the development of a real-time infant-holding monitoring solution.

Several studies have explored caregiver perspectives and concerns regarding neonatal safety and infant care practices through survey methodologies. These investigations typically assess parental awareness of risks such as Sudden Infant Death Syndrome (SIDS) [11] and Shaken Baby Syndrome (SBS) [12] as well as their attitudes toward infant monitoring technologies. Survey results often highlight the need for real-time, user-friendly monitoring systems that provide actionable feedback to caregivers, emphasizing safety and ease of use. Surveys conducted with caregivers reveal a generally positive attitude toward remote in-home monitoring systems, especially those that are non-invasive and user-friendly, such as wearable smart suits and sensing bands [13]. However, many existing surveys focus primarily on general infant health monitoring rather than specific infant handling or posture concerns, indicating a gap in understanding caregiver needs related to physical infant holding and positioning.

Wearable and embedded systems for infant monitoring have seen notable progress in recent years. Products like Owlet® Dream Sock [14] and Mimo Wearable Baby Monitor - Smart Clothing Lab [15] focus on physiological tracking (heart rate, oxygen levels, breathing), while posture detection has primarily been explored in areas such as elder care and physical therapy. Technologies such as pressure sensors, accelerometers, and smart textiles have enabled the detection of motion, orientation, and pressure distribution.

In a related context, studies have demonstrated how flexible sensors combined with machine learning can classify body movements and posture changes in rehabilitation settings [16, 17]. Similarly, posture-correcting wearables for adults using accelerometer and gyroscope data have proven effective in training users to adjust their body alignment. However, such solutions are seldom applied to infant-care interactions, where the wearable must be designed for the caregiver, not the infant.

A variety of hardware-based infant monitoring systems have been developed, leveraging sensors such as accelerometers, cameras, pressure mats, and physiological monitors to track infant health and behaviour [18]. A broad spectrum of hardware solutions has been developed to monitor infant health and behaviour using various sensor modalities. Wearable accelerometers and inertial measurement units (IMUs) have been employed to detect infant carrying and movement patterns, providing valuable data on gross motor activity [19]. Camera-based systems enable posture recognition and emotion detection, leveraging machine learning algorithms to interpret visual and auditory cues [5, 20]. Pressure-sensitive mats and smart cradles equipped with environmental and physiological sensors offer non-invasive monitoring of vital signs such as heart rate, temperature, and humidity [19, 21]. IoT integration allows these devices to transmit real-time data to caregivers via mobile applications and cloud platforms, enhancing accessibility and responsiveness [5, 22].

Despite these advances, most existing systems primarily focus on physiological monitoring or general movement detection rather than detailed assessment of infant holding postures. The ability to detect unsafe handling practices, such as excessive tilting or shaking that can lead to Shaken Baby Syndrome, remains underdeveloped in current hardware solutions [19, 23]. Moreover, while some systems incorporate machine learning for emotion or cry analysis, integration of pressure-based sensing specifically for posture classification and real-time preventive feedback is limited. Most commercial devices also lack access to raw sensor data, restricting their utility for complex research or personalized training applications [24]. These limitations highlight opportunities for developing comprehensive systems that combine pressure sensing, machine learning classification, and IoT-enabled real-time feedback to enhance neonatal safety and caregiver support.

The reviewed literature reveals several gaps that motivate the present study. First, there is a lack of systems that directly measure and classify infant holding postures using pressure-based sensing, which can provide more precise and immediate assessment of caregiver-infant interactions. Second, existing solutions rarely incorporate preventive modules aimed at mitigating risks such as excessive tilting or shaking during infant handling. Third, comprehensive integration of machine learning algorithms with IoT-enabled real-time feedback tailored to caregiver needs is underdeveloped. Addressing these gaps by combining pressure-sensitive hardware, machine learning classification, and IoT feedback mechanisms [25] can significantly enhance neonatal safety monitoring and caregiver support.

3. Survey Methodology and Findings: Defining Caregiver Requirements

To support this research, a detailed survey was conducted among parents and guardians in Malaysia to understand their experiences, concerns, and practices related to infant safety and care. The goal was to gather both qualitative and quantitative data to know about current childcare methods, levels of safety awareness, and areas needing improvement in helping to address gaps in existing child healthcare research.

The survey included various topics such as knowledge of safe handling practices, use of childcare products, sleeping and feeding habits, emergency readiness, and familiarity with safety devices. In addition, selected respondents participated in interviews to provide deeper insights into the factors influencing their caregiving decisions and routines.

3.1. Survey Design and Participant Demographics

A total of 20 individuals took part in the survey. As shown in Figure 1, 55% were parents of a single child, while 45% had multiple children. This suggests that many participants were first-time parents—a relevant factor since they may have different levels of knowledge and preparedness regarding infant safety.

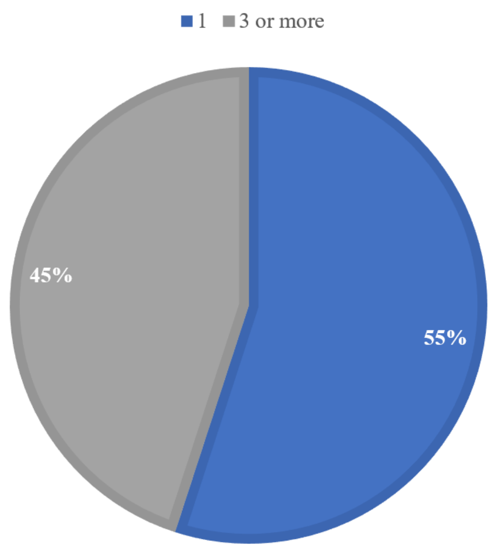

Figure 1.
Number of children (pie chart).

The survey also highlighted concerns about handling babies. According to Figure 2, 70% of respondents worried about how they or others held their infants. Figure 3 provides a breakdown of these concerns, with the most common being safety risks (80%), discomfort to the baby (65%), improper carrying techniques (55%), and excessive shaking (50%). These results point to a heightened awareness of handling risks and emphasize the need for improved education on safe practices.

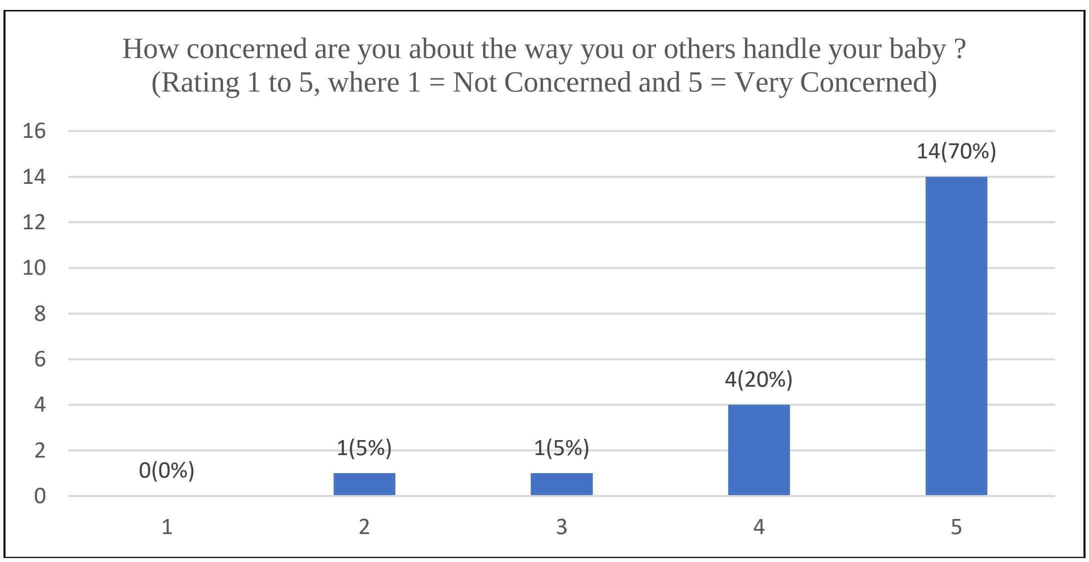

Figure 2.
Concern of baby handling (bar chart).

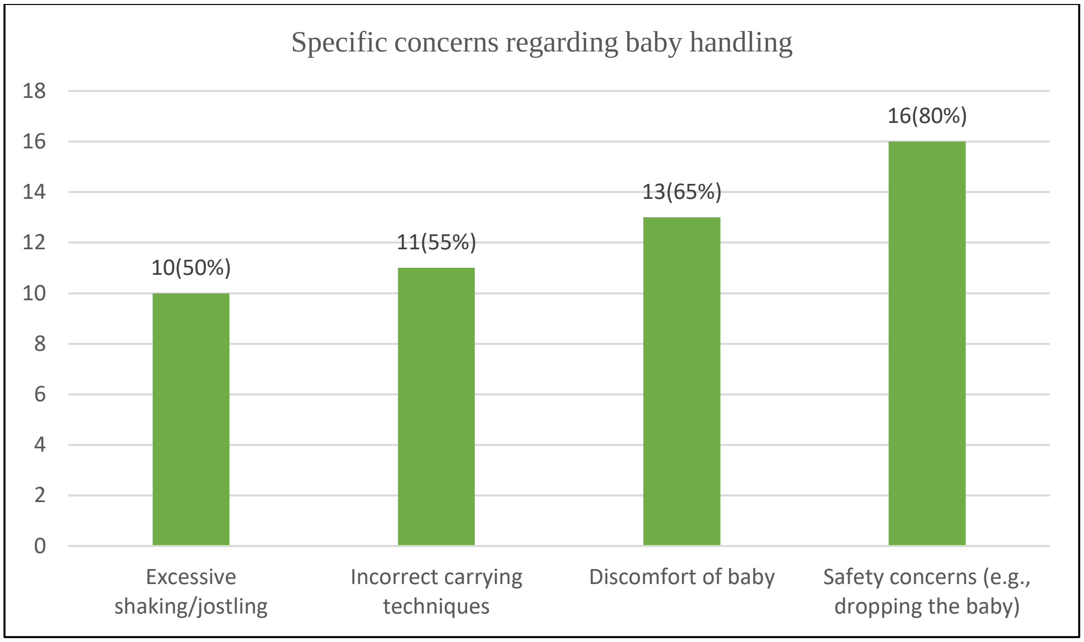

Figure 3.
Specific concerns regarding baby handling (bar chart).

When asked about their confidence in carrying an infant, 45% felt assured, while 55% were unsure as shown in Figure 4. Those who felt uncertain mainly cited worries about head and neck support and the potential harm from incorrect cradling, especially for newborns.

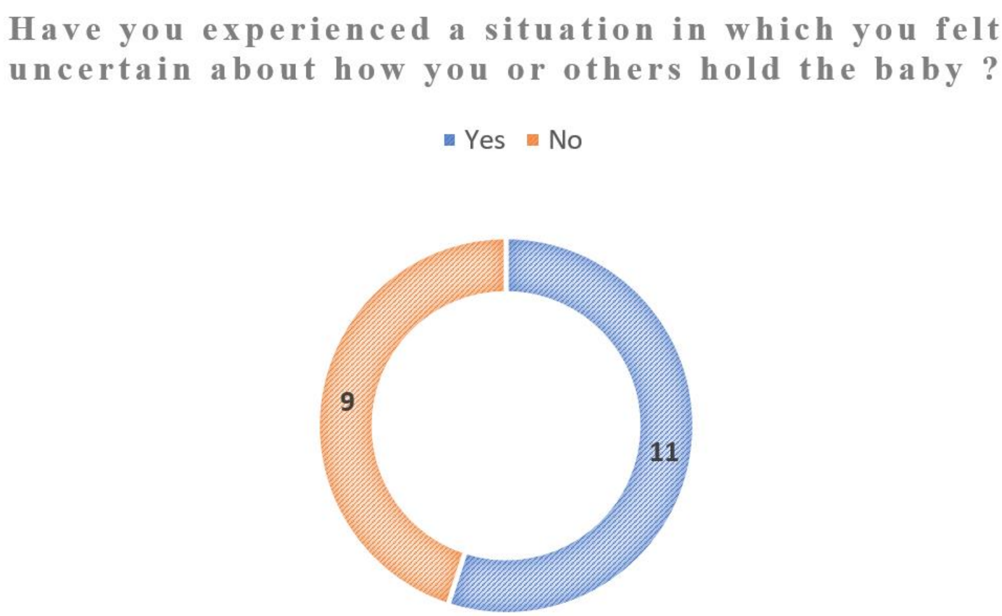

Figure 4.
Uncertainty on how to carry or handle baby (pie chart).

Awareness of monitoring technologies for baby handling was generally low; 70% of participants were unaware of such solutions as shown in Figure 5. However, 45% expressed interest in adopting a device that monitors handling and issues alerts for excessive shaking as shown in Figure 6.

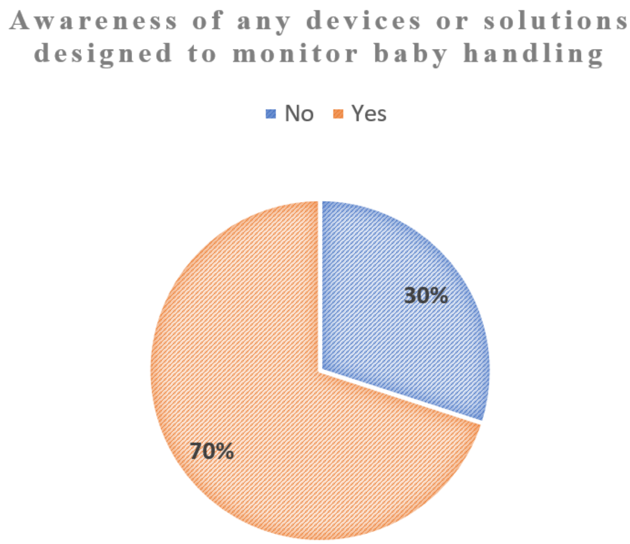

Figure 5.
Awareness of baby handling technologies (pie chart).

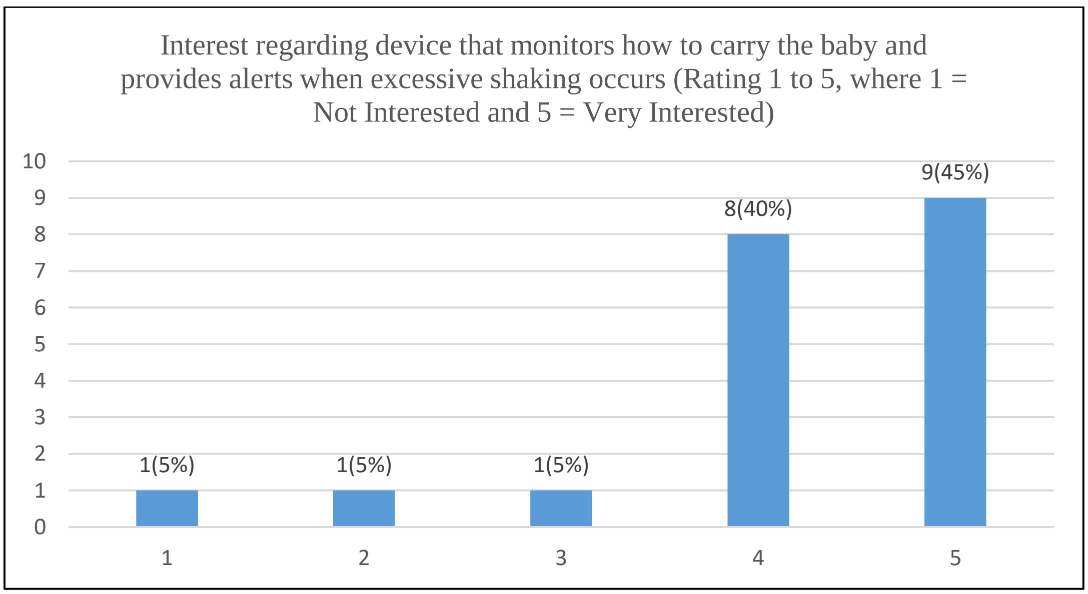

Figure 6.
Interest regarding device that monitors how to carry the baby and provides alerts when excessive shaking occurs (bar chart).

Lastly, Figure 7 outlines the features that participants valued most in a monitoring device. The top three were: real-time alerts for excessive movement (85%), a user-friendly mobile interface (80%), and built-in educational content on safe handling (80%). These preferences indicate a strong demand for an all-in-one, accessible solution that not only ensures safety but also enhances caregiver knowledge and confidence.

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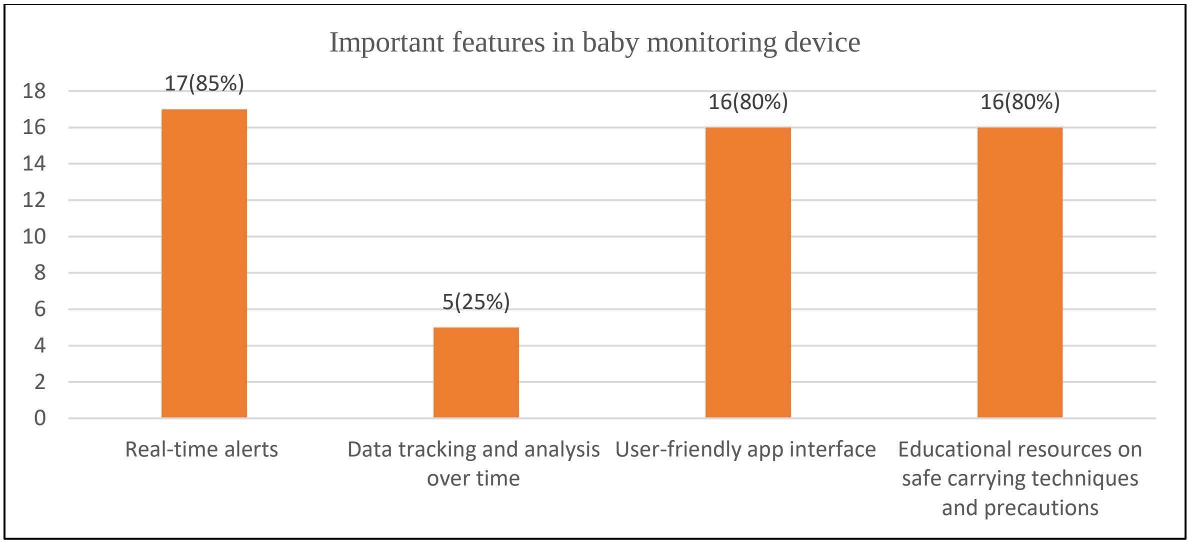

Figure 7.
Important features in monitoring device (bar chart)

In summary, these demographic and perceptual findings offer valuable insights into the current state of parental knowledge and the lack of support tools. They also serve as a foundation for designing targeted interventions and technologies to encourage safer infant care practices.

3.2. Key Findings: Quantitative and Qualitative Analysis

The combined survey and experimental findings offer key insights into current infant-holding practices and the potential role of smart monitoring in enhancing safety. Among the 20 surveyed parents, 70% reported concerns regarding baby handling, citing safety risks (80%), infant discomfort (65%), improper techniques (55%), and excessive shaking (50%). While 55% expressed confidence in holding their baby, 45% were uncertain, particularly about supporting the head and neck. Awareness of existing monitoring technologies was limited (70% unaware), though 45% showed interest in adopting such devices. Preferred features included real-time alerts for excessive movement (85%), a user-friendly mobile interface (80%), and integrated educational content (80%).

An experimental evaluation involving 33 participants (12 parents, 11 non-parents, and 10 neonatal professionals) revealed distinct differences in infant-holding posture across groups based on pressure sensor data from six standardized positions. Medical professionals served as a reference group due to their clinical experience, though not assumed to be flawless. Notably, non-parents exhibited broader sensor pad coverage, indicating heightened caution and adherence to instructions, likely due to inexperience. In contrast, parents showed lower coverage, potentially reflecting habitual familiarity. These patterns suggest that experience level influences holding technique. Qualitative insights further revealed that first-time parents often rely on intuition, while non-parents lacked clinical knowledge but followed instructions closely. These findings underscore the need for a real-time, AI-driven monitoring system that provides corrective feedback and educational guidance

4. System Design and Implementation: From Requirements to Prototype

This section outlines the development process of the proposed infant-holding monitoring system, from initial requirements gathering to functional prototype realization. It details the hardware and software components, integration strategies, and design decisions that shaped the system architecture.

4.1. System Architecture and Functional Overview

The proposed system comprises two primary subsystems working in tandem to monitor infant handling posture and motion: a pressure-sensitive classification unit for holding posture detection and a tilt-shake detection module for movement analysis. Sensor data is processed by microcontrollers (Arduino Uno and NodeMCU ESP8266), analysed using trained machine learning models, and transmitted wirelessly to the Blynk IoT dashboard. The architecture supports real-time classification of both holding type and correctness, alongside alerts for excessive tilting or shaking, thereby ensuring holistic monitoring of infant safety.

4.2. Component Selection and Justification

- Pressure Sensor Pads (PadA to PadE): Chosen for their flexibility and responsiveness in detecting subtle pressure variations across critical support regions on the baby doll (head, neck, spine, limbs).
- Arduino Uno: Used for capturing analog sensor readings and transmitting serial data to the processing interface. Its simplicity and reliable analog-to-digital conversion make it ideal for prototyping.
- NodeMCU ESP8266: Chosen for its built-in Wi-Fi capabilities and compact design. Integrated with the MPU6050 sensor to monitor tilt and shake, it relays data to the Blynk IoT dashboard wirelessly.
- MPU6050 Accelerometer & Gyroscope: Selected for its 6-axis measurement capability to detect dangerous angles or sudden shaking motions [26].
- Blynk IoT Platform: Offers real-time visualization and alerting via a mobile dashboard without the need for custom app development [25].

4.2.1. Implementation Details: Hardware and Software Development

The Arduino Uno is connected to five pressure sensors that are calibration and connected via analog pins (A0–A4). These readings are collected every second and transmitted via serial communication to a PC for preprocessing and ML inference. Simultaneously, the ESP8266 collects tilt and motion data from the MPU6050 and communicates with the Blynk cloud [27]. The software components include Arduino IDE for embedded code, Python (Jupyter Notebook) for Machine Learning inference, and Blynk for visualization. The pressure pad composition is shown in Figure 8 while the schematic diagrams are shown in Figure 9 and Figure 10.

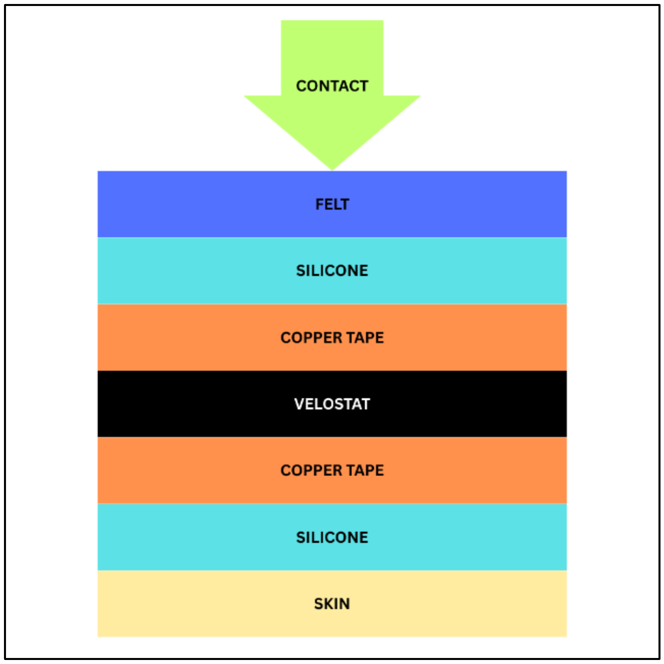

Figure 8.
Pressure pad components

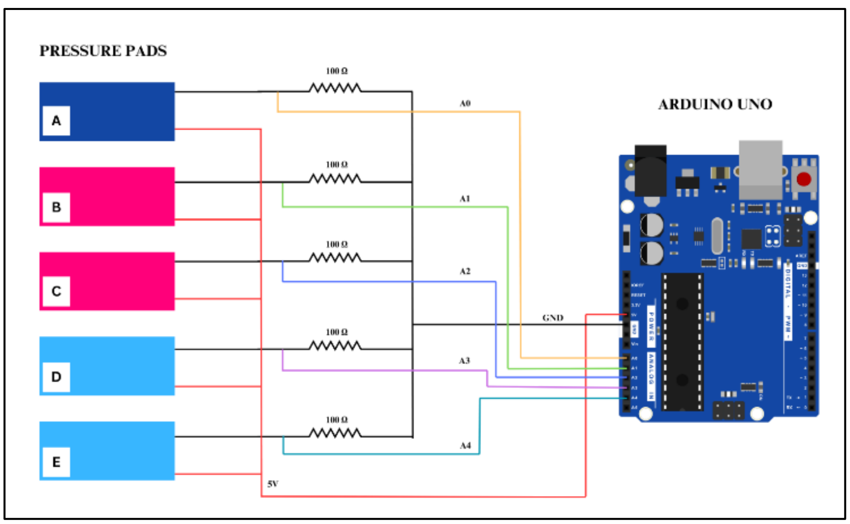

Figure 9.
Circuit Diagram of Pressure Pads connection to Arduino Uno.

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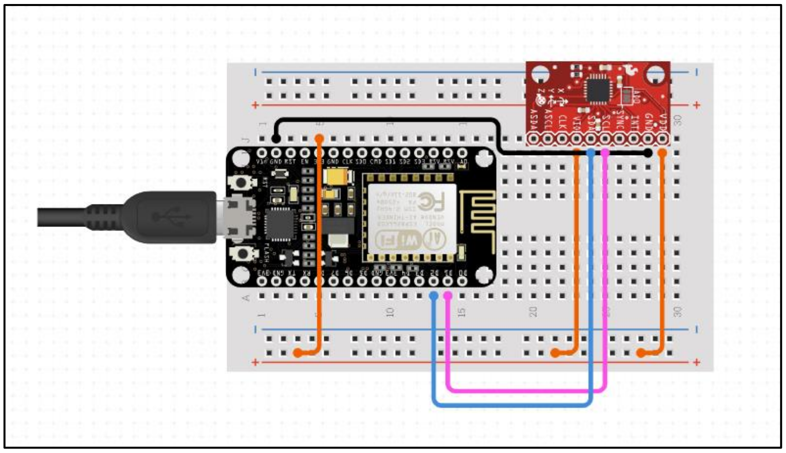

Figure 10.
Circuit Diagram of Sensor with ESP8266 NodeMCU V3.

4.2.2. Processing and Communication Layer
The data processing is bifurcated:

1. Holding Posture Data: Analog pressure values are interpreted by a trained XGBoost model [28] to classify both holding type (multiclass) and posture correctness (binary). This is done offline during training, but in deployment, can be ported to real-time Python inference scripts.
2. Tilt & Shake Detection: Real-time tilt angle is calculated using trigonometric functions on accelerometer data. Classification is as follows:

- Safe: >30°
- Moderate: 30°–50°
- Dangerous: >50°

Shake detection is based on a threshold (acceleration >3 m/s^2). Data is transmitted via Wi-Fi using the Blynk.virtualWrite() API.

4.2.3. Feedback and Interface Layer
The feedback system is hosted on the Blynk mobile dashboard:

- V0: Gauge widget for tilt angle
- V1: LED widget for danger level (Green/Yellow/Red)
- V2: Terminal/notification for shake alerts
- V3/V4/V5: Additional widgets for handling type, correctness status, or visual indicators

This configuration ensures both visual and text-based alerts are accessible to caregivers in real time as shown in Figure 11 to Figure 13.

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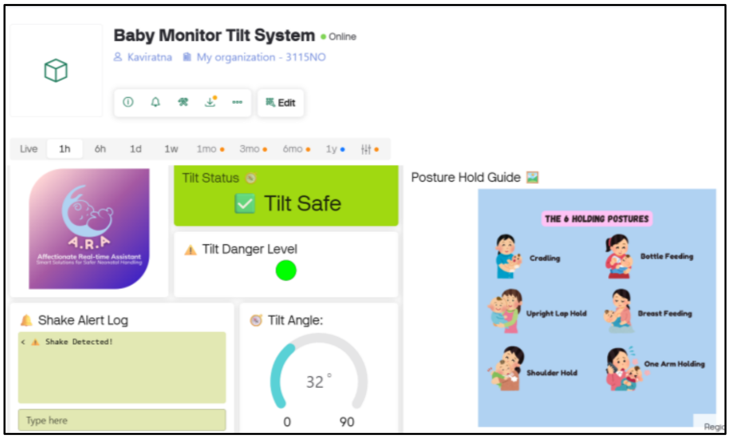

Figure 11.
Dashboard interface when tilt in safe range.

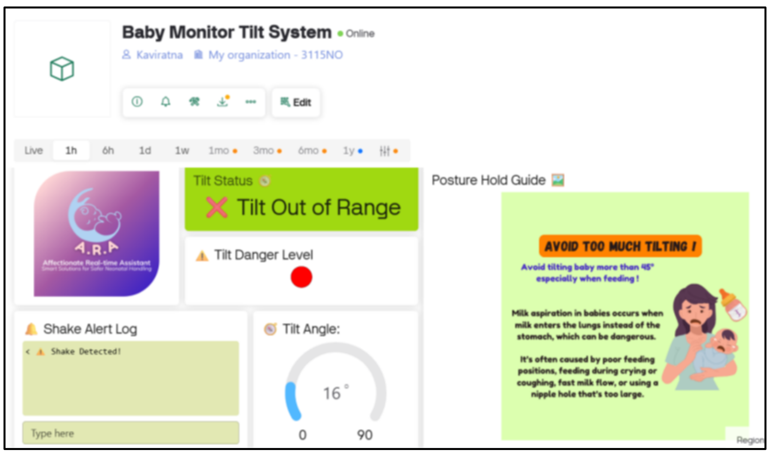

Figure 12.
Dashboard interface when tilt not in safe range.

Figure 13.
Notification received on phone when shaking detected.

4.3. Implementation Details: Hardware and Software Development

This subsection presents the technical implementation of the system, focusing on both hardware assembly and software development. It describes the integration of pressure sensors and motion modules with microcontrollers, as well as the programming logic used for data acquisition, processing, and user interface deployment.

4.3.1. Materials and Components

Table 1 presents a comprehensive list of all hardware and material components used in the development of the prototype system, along with detailed descriptions of their roles and functions within the overall architecture.

Table 1.
List of components and their description.

Component	Description
Arduino Uno	Reads analog input from pressure sensors and transmits to PC for ML inference.
ESP8266 NodeMCU	Handles real-time tilt and shake detection via Wi-Fi using the Blynk IoT app.
MPU6050 Sensor	Detects 3-axis tilt angle and acceleration for shake detection.
Pressure Sensor Pads	Custom-built using felt, silicone, copper tape, and Velostat layers to detect distributed pressure.
Blynk IoT App	Displays tilt angle, shake alerts, and posture classification in real time.
Baby Mannequin	Simulates a 3–4 kg infant for realistic posture testing.
USB Cable, Breadboard, Jumper Wires	Used for prototyping and circuit assembly.
Laptop (Jupyter Notebook)	Runs the machine learning models and processes serial input from Arduino.

4.3.2. Assembly

The development of the system involved several key steps in both hardware integration and software configuration. The custom pressure sensors were constructed by sandwiching a Velostat sheet between two conductive layers of copper tape, forming a pressure-sensitive pad capable of detecting varying force levels [29]. These pads were then connected to the Arduino Uno, which served as the primary microcontroller for analog signal acquisition. Meanwhile, the MPU6050 accelerometer and gyroscope module was interfaced with the ESP8266 NodeMCU, enabling wireless tilt and shake detection.

To ensure reliable data transmission and stable readings, resistors were incorporated into the circuit design where appropriate. Firmware development and sensor programming were carried out using Arduino IDE, while data collection and preprocessing were performed using Google Colab for machine learning integration. For real-time feedback, the Blynk IoT platform was configured to receive data from the ESP8266 and display posture classification results, tilt angle, and shake alerts directly on the user's mobile device. The circuit set up on the baby mannequin is illustrated in Figure 14.

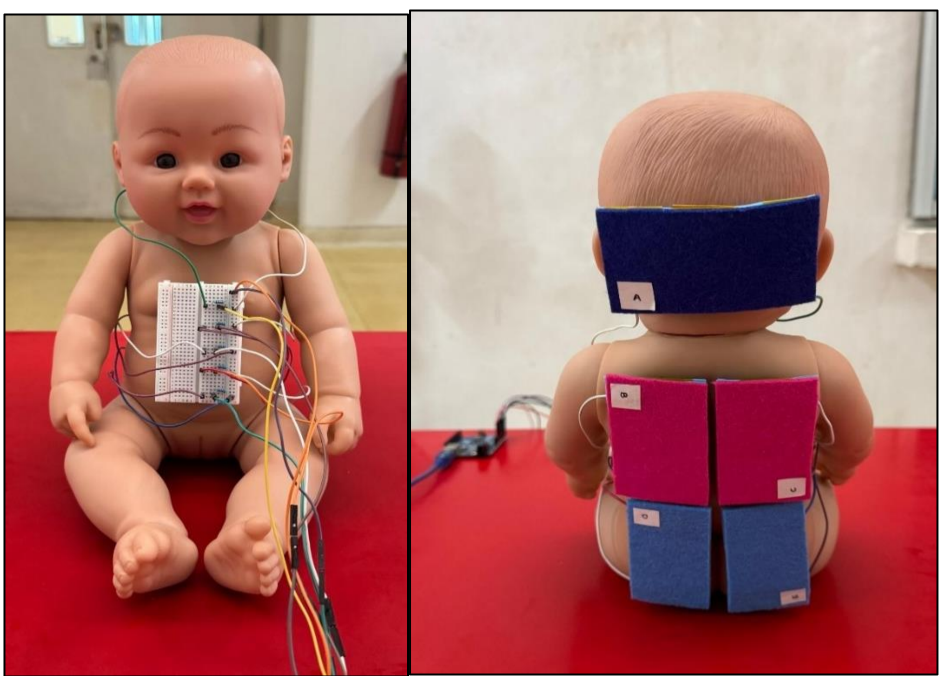

Figure 14.
Frontal (left) and Side (right) View of Circuit Set Up on Baby Mannequin.

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The data collection process was carried out involving a total of 33 participants. To ensure a broad and representative understanding of infant-holding practices, participants were categorized into three distinct groups: 12 parents, 11 non-parents, and 10 medical professionals (comprising 5 doctors and 5 nurses) with direct experience in neonatal care. This categorization was intended to capture a range of handling techniques and familiarity levels, thereby enriching the dataset with diverse infant-care perspectives.

Each participant was instructed to perform six standardized infant-holding positions based on recommended caregiving techniques as detailed in Table 2. For every trial, the posture was evaluated and labelled as either "Correct" or "Incorrect", according to predefined safety and ergonomic criteria relevant to neonatal support particularly regarding head, neck, and spinal alignment.

During each holding instance, pressure sensor data was collected using multiple pressure-sensitive pads placed strategically on a baby mannequin. The recorded data included timestamped pressure values, along with annotated metadata such as participant group, specific holding position, and the evaluated posture label. This data was initially logged in a structured Excel spreadsheet and subsequently exported in CSV format for further analysis.

All data was processed using Python in a Jupyter Notebook environment. The labelled dataset was cleaned and prepared for training a supervised machine learning model. A classification algorithm was implemented to analyse sensor input and distinguish between correct and incorrect infant-holding postures. The end goal of this model was to facilitate real-time posture evaluation through an interface that can provide instant feedback to caregivers, thereby improving infant safety practices.

Ethical considerations were carefully observed throughout the data collection process. All participants were informed about the study's purpose, procedures, and use of anonymized data for research and system development. Consent was obtained from each participant prior to data collection. No real infants were involved in the study; instead, a standardized baby mannequin was used to simulate realistic holding scenarios while eliminating any ethical risks associated with infant involvement.

Table 2.
Position number and their types.

Position Number	Position Type
1	One Arm Holding
2	Cradling
3	Upright Lap Hold
4	Shoulder Hold
5	Breast Feeding
6	Bottle Feeding

5. Results and Performance Analysis

This section presents the outcomes of the system evaluation based on both survey responses and experimental data. It analyses the system's performance in detecting infant-holding postures and assesses user feedback to validate its effectiveness and usability using machine learning.

The evaluation of the system was conducted through a two-stage supervised machine learning pipeline, which classified both the type of infant-holding position and its correctness based on pressure data. The data was collected from 33 participants: 12 parents, 11 non-parents, and 10 medical professionals (5 doctors and 5 nurses), each performing six standardized holding types. These included One Arm Hold, Cradling, Upright Lap Hold, Shoulder Hold, Breast Feeding, and Bottle Feeding. Each holding instance was manually labelled as "Correct" or "Incorrect" according to predefined ergonomic and safety guidelines.

Sensor data were recorded using five pressure pads (Pad A–E), and the raw readings were tagged with metadata (participant type, holding position, and posture label). The data was cleaned and encoded using Python and pre-processed into training-ready format. Features included raw pad values and encoded participant types. The models were implemented using XGBoost classifiers [30] after comparing between the support vector machines (SVM) [31] and Random Forest [32] for model performance as shown in Figure 15, selected for their robustness with small to medium-sized structured datasets.

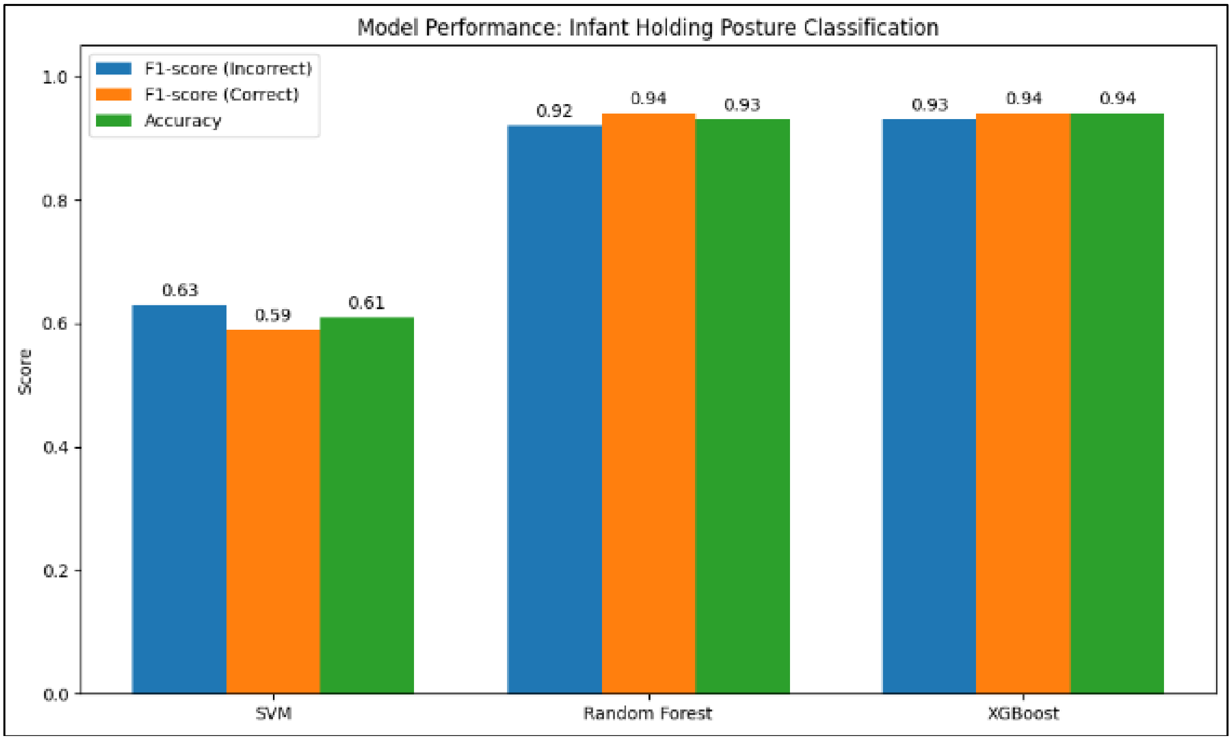

Figure 15.
Model Performance: Infant Holding Posture Classification.

5.1. Classification Accuracy

Two separate classification models were developed: Model 1 is the Holding Type Classifier, and Model 2 is the Correctness Classifier. The first model was trained to identify the holding position. Due to inconsistencies in the raw labels (e.g., "Cradling" vs. "Cradling "), similar classes were merged into five unified holding types. Using an 80:20 stratified train-test split, the XGBoost model achieved a classification accuracy of 83%. Performance was evaluated using precision, recall, and F1-score for each holding class. Figure 16 displays a bar chart of classification accuracy across all five classes. The highest scores were observed in One Arm Hold and Cradling, while Shoulder Hold showed slightly lower precision due to overlapping pad pressure with Upright Hold.

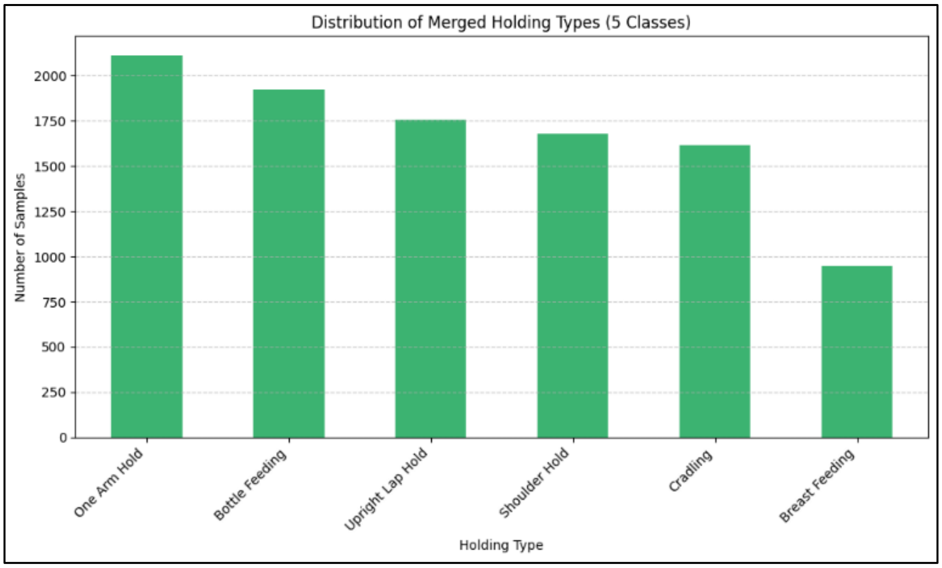

Figure 16.
Distribution of Merged Holding Types (5 Classes).

The second model used the predicted holding type, pressure values, and participant type as input features to classify the posture as either "Correct" or "Incorrect." This binary classification achieved an impressive accuracy of 93%, with balanced precision and recall. Figure 17 shows the confusion matrix for the XGBoost training model. The correctness classifier was particularly effective in identifying incorrect postures, a critical requirement for real-time feedback systems.

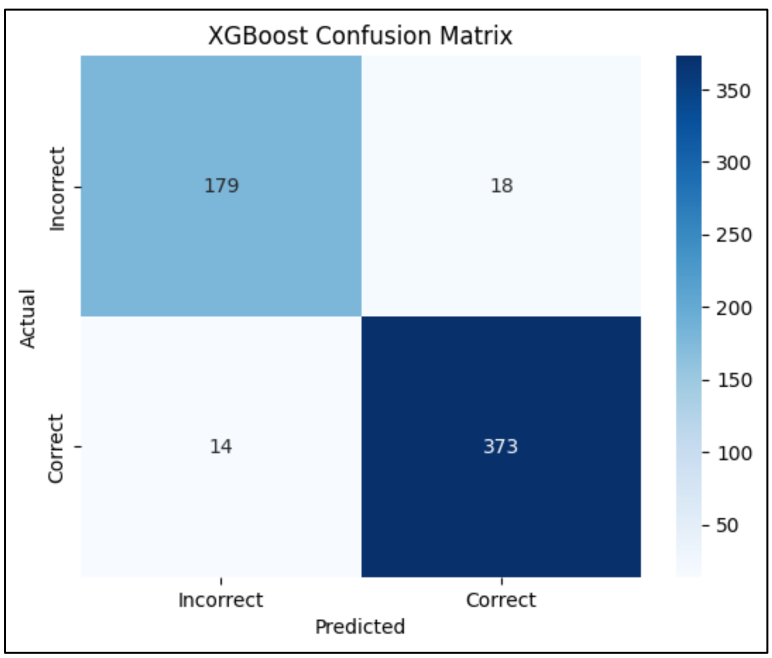

Figure 17.
XGBoost Confusion Matrix.

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The XGBoost confusion matrix demonstrates its effectiveness in classifying holding postures. The model correctly identified 373 "Correct" instances and 179 "Incorrect" instances. It had a low number of misclassifications, with only 18 false positives and 14 false negatives.

Figure 18 shows the classification report for this model, demonstrating a macro-average F1-score of 0.94 and a strong ability to generalize across different user groups.

Classification Report:

	precision	recall	f1-score	support
0	0.93	0.91	0.92	197
1	0.95	0.96	0.96	387
accuracy			0.95	584
macro avg	0.94	0.94	0.94	584
weighted avg	0.95	0.95	0.95	584

Figure 18.
Classification Report for XGBoost.

5.2. System Response Time

While model inference was initially tested offline, integration with the ESP8266 NodeMCU microcontroller enabled real-time deployment. Sensor readings were streamed to the Blynk IoT platform at a rate of one update every 1000 milliseconds (1 second). Testing showed the system could generate and transmit predictions within 1 second, allowing near-instantaneous feedback. For the shaking and tilting detection module, the system reliably triggered alerts when the tilt angle exceeded ±45° or shake intensity crossed a defined threshold, helping to mitigate risks associated with Shaken Baby Syndrome (SBS).

5.3. Comparative Analysis: Aligning System Performance with Survey-Derived Expectations

The system's design and results were benchmarked against expectations derived from the parent survey. According to survey results, 70% of parents expressed concern over baby handling, 50% feared excessive shaking, and 85% prioritized real-time alerts as a desired feature. The system delivered on all three fronts by offering automated posture detection, shake/tilt monitoring, and real-time mobile alerts.

Interestingly, although medical professionals were used as the reference group for defining correct posture, analysis revealed that non-parents showed broader pressure pad coverage during holding tasks. This may reflect increased caution and attentiveness among those with less experience. In contrast, parents exhibited more compact pressure distribution, possibly indicating routine handling confidence. These patterns are illustrated in a dashboard form in Figure 19, which visualizes average total pressure coverage across participant groups.

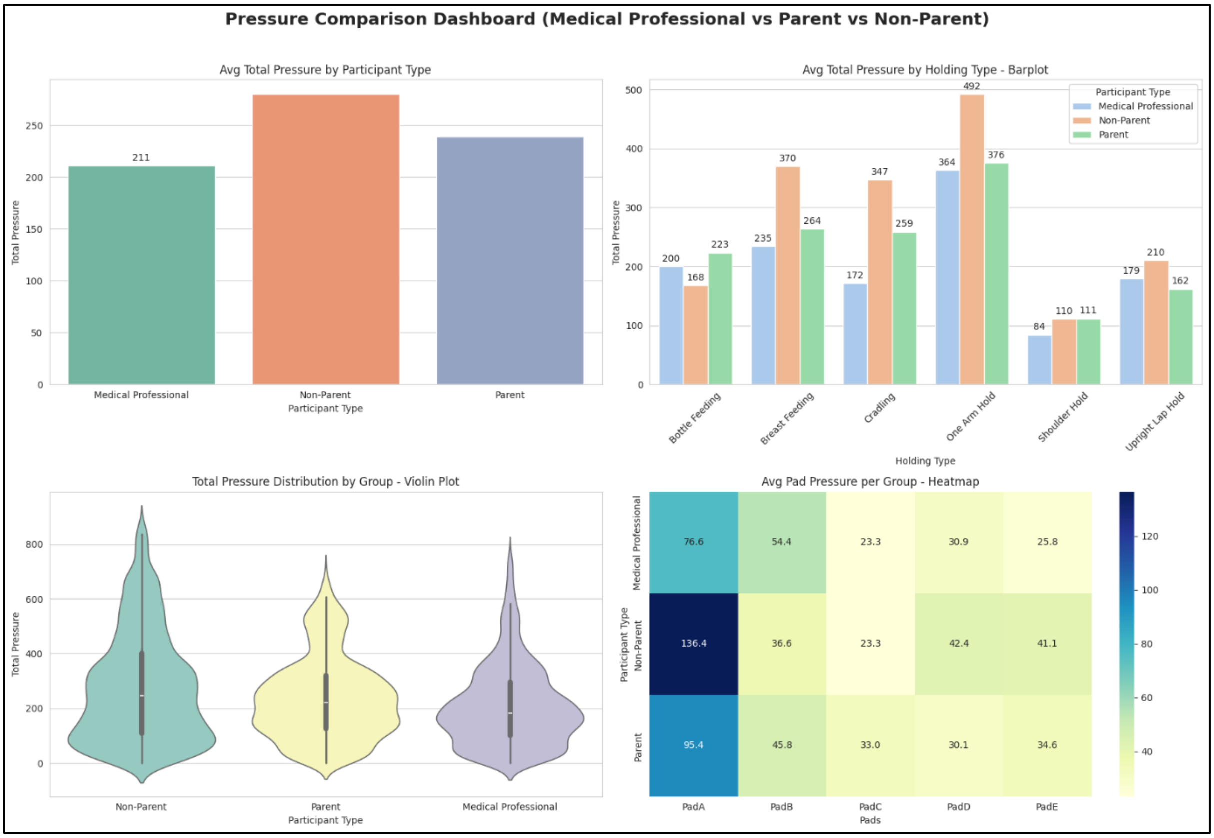

Figure 19.
Pressure Comparison Dashboard (Medical Professional vs Parent vs Non-Parent).

This comprehensive dashboard compares pressure data across all three participant types: medical professionals, non-parents, and parents. The top-left bar chart shows that non-parents apply the highest average total pressure, followed by parents, and then medical professionals. The top-right bar plot details the average total pressure for each holding type across the three groups. The bottom-left violin plot illustrates the total pressure distribution for each participant type, and the bottom-right heatmap shows the average pressure per pad for each group, providing a holistic view of pressure dynamics.

The results validate both the technical robustness and real-world applicability of the system. The high classification performance, low latency, and alignment with user expectations make it a promising tool for improving infant safety and guiding untrained caregivers.

6. Conclusion and Future Work

This study presents the development of the Affectionate Real-Time Assistant (A.R.A), a pressure-sensitive infant holding monitoring system that combines machine learning and IoT technologies. It classifies six baby-holding types and identifies whether each posture is correct or potentially harmful, based on sensor data from 33 participants, including parents, non-parents, and medical professionals. A separate survey involving 20 parents explored attitudes toward smart baby care technologies. The trained XGBoost classifiers achieved high accuracy for both posture type and correctness detection. Integration with Blynk IoT enabled real-time monitoring of excessive tilting and shaking which are key factors in preventing Shaken Baby Syndrome (SBS) and milk aspiration.

Despite promising performance, the system faced several limitations. Variations in pressure application across users caused inconsistencies in readings, and clinical validation was not feasible due to ethical and logistical barriers. As a training and educational tool, A.R.A does not replace expert supervision and is limited by its dataset and the use of a baby doll, which may not fully reflect real-life biomechanics. Overlapping pressure patterns in multi-class classification highlighted the need for improved sensor placement and preprocessing. Some caregivers may also require guidance to interpret IoT feedback effectively. Lessons learned include the importance of consistent data labelling, the sensitivity of pressure sensors, and the complexity of posture classification. Future work will involve expanding the dataset and improving sensor ergonomics and the user interface.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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