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Embedded Wearable IoT System for Child Safety Based on Hybrid Deep Learning Classification

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ABSTRACT

The integration of the Internet of Things (IoT) into everyday life is revolutionizing personal safety and health monitoring. In increasingly busy and distracting urban environment, ensuring child safety exponentially growing to become a serious concern. The objective of this study is to design a wearable IoT system, helping keep track of a child's location and health to support early emergency action. For the child's safety, a simple tracking system app was designed that helps parents set boundaries and receive real time notifications whenever their child leaves the designated area, detected through GPS. To assess health-related risks, the system collects and analyzes seven key physiological and motion signals: acceleration (accel_x, accel_y, accel_z), gyroscopic movement (gyro_x, gyro_y, gyro_z), and heart rate. To improve detection of health anomalies such as minor seizure, a hybrid deep learning framework consisting of convolutional neural networks (CNN) and long short-term memory (LSTM) networks was developed and trained using modified version of the SHAR-100-20 dataset which simulates human activity in individuals with disabilities. A total of 300,000 measurements were sampled from the modified version of the data and divided into 70% for the training and 30% for the testing to train and apply cross validation for evaluation purposes. The proposed system achieved an excellent 99% accuracy in detecting minor seizures. It surpassed other tracking systems by providing better detection rates, greater awareness of what is happening and faster responses. Moreover, the flexible structure is supporting the use in elderly and medical care monitoring, supplying a complete framework for monitoring health and location in an effective way, and offering a comprehensive solution for real-time health and location tracking.

1. INTRODUCTION

All over the world, more people are concerned about children because the number of public incidents and child disappearances is increasing. Every year, research shows that 64% of all abduction cases involved children, and one child goes missing every two minutes in the European Union [1]. The Malaysian National Crime Record Center found that child-related crimes went up by 10.5% from 2019 to 2020 [2]. The serious numbers highlight the need for solutions that quickly safeguard children in all environments. Using printed wristbands, surveillance cameras and centrally controlled systems for children has shown it is difficult to offer quick answers to security issues [3]. Such systems often cannot stop major incidents in places where there are many visitors, for example in museums and schools [4, 5]. As a consequence, new research has turned towards using GPS, GSM and wireless communication modules together with the Internet of Things (IoT) to design advanced monitoring systems. Some experts suggest that wearable devices that include GPS and GSM technology could send updates on a child's location to parents, either through text or mobile application alerts [6-8]. Advanced tracking solutions now use both RFID for indoor positioning and GPS for outdoor tracking [9], along with techniques such as Time of Arrival, Angle of Arrival and Received Signal Strength [10].

A growing number of healthcare experts believe that human action recognition (HAR) technologies are very helpful for continuously monitoring patients with neurological illnesses. Hence, smart monitoring systems and patterns recognition for different applications are vital [11-16]. In this context, artificial intelligence and deep learning have achieved impressive results across various domains of applications, making them promising tools for improving health monitoring [17, 18]. Spotting seizures, for example, is a crucial part of such monitoring systems, as failure to do so can place a person's life at risk. An important difficulty is that seizure-related events in HAR datasets are much less common than other activities which worsens the performance of traditional classification algorithms. To address this, we proposed an embedded system with hybrid architecture that processes sensors input frames by integrating convolutional neural networks (CNNs) for spatial feature extraction with long short-term memory (LSTM) for temporal sequence analysis. New developments used in wearables help identify and address health problems early which benefits those individuals—primarily children—susceptible to health emergencies. Furthermore, we put into practice biometric sensors and anomaly detection models incorporated into a wearable smart watch on an ESP32 microcontroller according to our system. While previous works only used geofencing [19-21], our system monitors both the child's and parent's device location in real time to send an alert when the child walks into an unsafe area. With the simple Flutter-tracker app for parents, they can track the satellite's condition, set alert distances and receive instant notifications, helping meet the rising need for user-friendly parenting tools.

In addition, the system allows mobile usage and compatibility with various environmental setups since static RFID or Wi-Fi nodes are replaced by a flexible ESP32-based system that uses GPS and GSM for communication. The access to biometric and location details is allowed only to the school's authorized members. With real-time monitoring, biometric analysis and intelligent detection, our system offers a powerful and flexible method for keeping children safe today. A patron can expand the foundation to elderly care, long-term health care and supportive health care when emergencies arise. The proposed method presents valuable contortions including the following:

1. A comprehensive framework leveraged the tracking capabilities of location and health status by integrating biometric sensors into a smartwatch.

2. The system offers a dual location monitoring mechanism for both child and parent using GPS and developed mobile app with flexible configuration of the safe zones.

3. The proposed model combined CNN and LSTM to integrate the spatial features with the temporal sequence pattern to recognize health anomalies, particularly seizures, in children based on their movements and heart rate.

4. The designed system can be extended easily to scalable use, such as elderly care, long-term patient monitoring, and emergency health interventions.

2. LITERATURE REVIEW

This section presents a detailed analysis of past investigations along with recent procedural methods which resolve similar issues within the research scope of this study. Understanding previous research enables us to understand the value of our work by placing its significance in the scientific body of knowledge.

Isa et al. [22] proposed child-tracking system incorporates GPS for time-based position tracking while Bluetooth operates for nearness alerts. The Arduino MEGA functions as the main controller while triggering the transmission of child GPS data as text messages after Bluetooth disconnects. This system failed to perform biometric monitoring as well as incorporate intelligent behavior prediction functions. Taha et al. [23] illustrated how an Arduino connected to a GPS/GSM device allows tracking of children and notifies their caregivers by SMS. However, the device did not measure heart rate or movement, it was unable to act if there's an emergency. Secondly, since there is no mobile app, all user interaction and management depend completely on SMS. Marhoon et al. [24] designed a child monitoring system wherein smart bracelets with ESP8266 chips to help parents monitor their children through their smartphones. Combined hardware and software elements to notify parents the moment the child strayed further than a marked 50 meters. If the child travelled beyond a predefined distance, the system played a sound and sent the position by SMS with a link to Google Maps. In the test range, the solution managed to track and alert both ends in real time. However, the system can't use biometric monitoring, it cannot be used for health or emergency purposes. Because it needs a strong internet connection for GPS updates and sending out messages, the system can be less reliable for users in remote areas or places with bad access to the internet.

Al-Hussaini and Mitchell [25] introduced a flexible machine learning method for the detection of seizures using EEG readings from wearable devices. By focusing on class balance and using feature extraction in Random Forest classifiers, the study demonstrated how the system can be understandable and gave an accuracy of 93.7%. An energy-efficient neural network for embedded systems was shown by another contribution, EpiDeNet [26]. The model, which focused on reducing energy usage while maintaining detection quality, obtained over 91% accuracy using CHB-MIT EEG data, making it appropriate for continuous monitoring in wearable devices. The system used EEG only and did not support other biometric signals. Gelbard-Sagiv et al. [27] studied a different method for making wearable EEGs better by improving the arrangement of electrodes. The idea was to use less memory in the design by using fewer electrodes and still attain a strong 89% detection accuracy. Shirt sensors was used to measure sleep biomarkers from patients who might seize [28]. UC San Diego's team found that their SVM model with an AUC of 0.80 might let sleep features be added to pre-seizure warning systems. Strongly depends on night-time rest and cannot do its work when you are awake or up. A complete seizure prediction system utilized a selection of wearable sensors that monitor ECG, PPG and EEG [29]. The study revealed that when physiological info is included, model performance is greatly enhanced and SVM classifiers predicted 94.3% correctly. They utilized standard methods (SVM), not including those from deep learning methods. Table 1 shows a comprehensive comparison of some of the previous work.

Table 1. Literature review of previous works

Reference	System Type	Technology Used	Additional Features	Limitations	Accuracy
[22]	child tracking	GPS + Bluetooth + Arduino MEGA	SMS alerts when Bluetooth disconnects	Bluetooth dependency, poor long-range tracking, no biometric or ML	Not specified
[23]	child tracking	GPS + GSM + Arduino	low-cost tracking via SMS	No heart rate or movement monitoring, no mobile app, risk of losing device, prepaid SIM dependency	Not specified
[24]	child tracking	ESP8266 + GPS + GSM + buzzer/LED	distance alert + mutual alarms on devices	No biometric monitoring, high power consumption, needs strong internet	Not specified
[25]	seizure detection	EEG + ML (Random Forest)	class balancing + feature extraction	EEG only	93.7%

[26]	seizure detection	EEG + Energy-efficient Neural Net	low power consumption + high accuracy	supports EEG only	> 91%
[27]	seizure detection	EEG + Electrode Optimization	reduced electrodes for lower memory usage	focuses on electrode placement, not model improvement	89%
[28]	seizure prediction	SVM + Shirt Sensors (sleep biomarkers)	nighttime sleep-based seizure prediction	not effective when awake or active	AUC = 0.80
[29]	seizure prediction	ECG + PPG + EEG + SVM	multi-sensor physiological data fusion	uses traditional SVM, no deep learning	94.3%

3. SYSTEM OVERVIEW

This section presents the details of the proposed system and all its components: hardware, software, and machine learning algorithms implementation to predicate child's pattern behavior.

3.1 Hardware implementation

The proposed embedded system is designed as a wearable IoT which include sensing, tracking, and communication. This section presents the main components and focusing on the system functions. The central microcontroller ESP32-C3 SuperMini is used to process data and controls communication with sensors. To track motion and orientation of the child GY-521 (MPU6050) is used. SIM800L Module (SIM800L BO1) is utilized to send and receives SMS or data over mobile networks [30]. ATGM336H GPS Module is responsible for providing real-time geographic coordinates. The Pulse oximeter and heart-rate sensor MAX30102 is designed for monitoring blood oxygen levels and heart rate [31]. The system is powered by Li-Po Battery (3.3V, 1100 mAh). Figure 1 shows the proposed system. Figure 2(a) and (b) show the pub top and bottom layer.

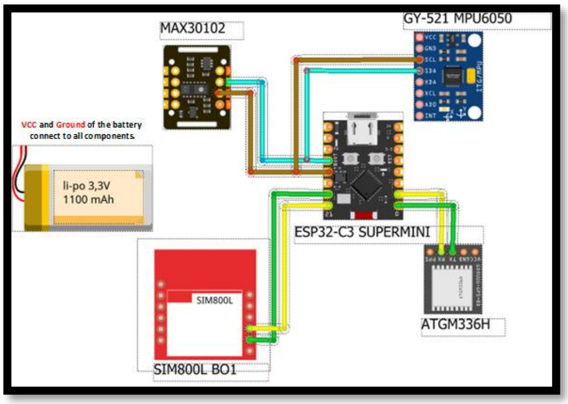
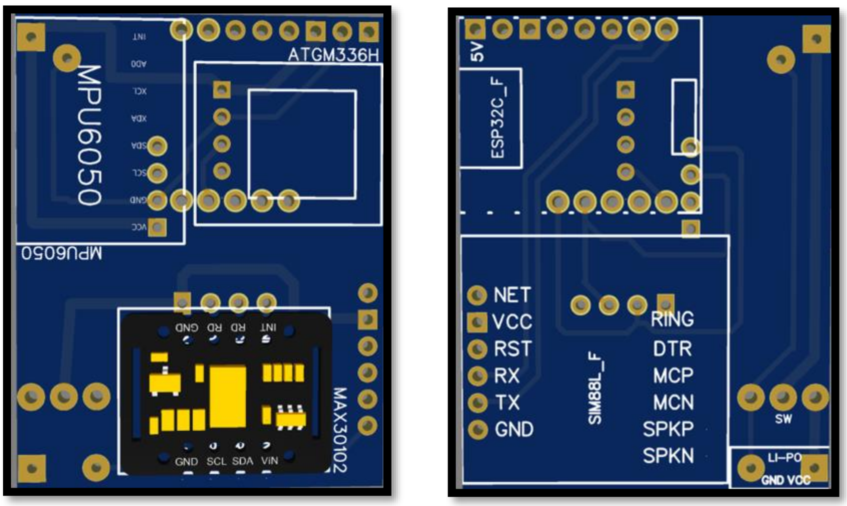


Figure 1. The proposed system



(a) Top layer (b) Bottom layer

Figure 2. The Pcb top and bottom layers for the proposed system

3.2 Software design

A cross-platform IDE application known as Arduino integrated development environment (IDE), is used to program the proposed micro controller, as exists primarily in Java coding language to operate on Windows and macOS and Linux platforms. Within the IDE code can be edited via a text editor that supports features including text movement capabilities and text search tools and formatting assistance while also providing single-step functions for Arduino boards including our micro controller Esp32-C3 Super Mini program compilation and upload processes.

In addition, Flutter tracking application was used. The mobile application delivered a pair of essential values to the ESP32 which includes the guardian's present GPS position and the security distance selected by the user (10, 15, 20 or 25 meters). The ESP32 obtains GPS coordinates from itself as well as from the received guardian data to perform the distance calculation between both points. The ESP32 sends an instruction to the SIM800L module so it initiates a GSM call to the guardian's phone after calculating distance measurements exceed the defined limit.

If the child moves beyond the predefined threshold, the system marks the child's location as outside the safe zone. After that, the child's movement with heart rate are continuously monitored, and these signals are sent to the AI unit to predicate the health status of the child by estimating the pattern behavior using the trained hydride model.

The ESP32 maintains a continuous data transfer to the mobile application that includes the location, quantitative reports of heart rate combined with oxygen level readings, motion information, and the decision of the AI unit to predicate the type behaviors (Normal, Pre-Seizure, and Seizure). The mobile application presents real-time health information and shows the GPS positions of both child and guardian at the same time. User interaction with locations is possible through the map view which utilizes OpenStreetMap integration from the flutter map plugin. The application implements real-time connection monitoring to maintain system reliability. The selected architecture allows microcontrollers such as ESP32 to execute an efficient communication protocol which uses minimal resources as well as the Flutter interface enables user-friendly interaction as shown in Figure 3. Note that the readings of the sensors are not shown as the system was in the disconnection state from the internet. Figure 4 shows a flowchart which demonstrating the overall process and the steps of the proposed system.

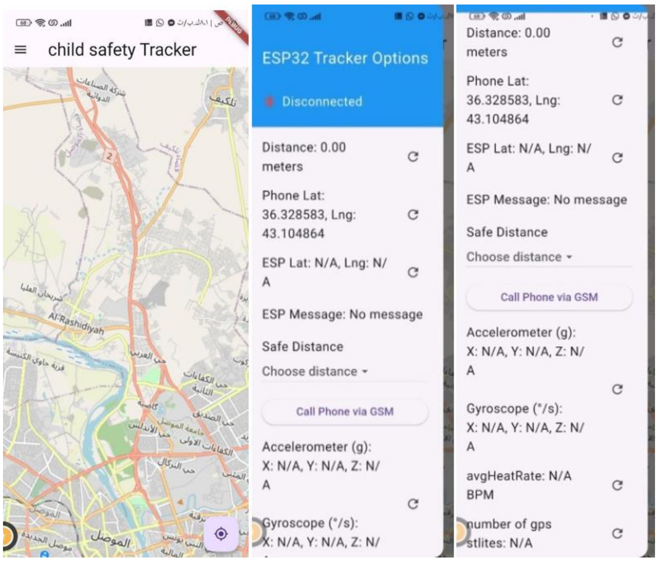


Figure 3. Child safety tracker platform

3.3 Machine learning implantation

Artificial intelligence and machine learning techniques have gained a prominent status and are now extensively applied across a wide range of fields. Thus, AI and ML methods can contribute significantly to resolving diverse issues of daily real-life challenges. Activity monitoring and human behavior analysis are considered as essential tasks in numerous types of practical applications in modern life. Human patterns understanding can be used in wide range of applications including healthcare, smart homes, surveillance systems, and security systems. For example, monitoring specific patterns in physical activities and behavioral responses may be very useful to detect anomalies such as medical emergencies, psychological distress, or even unauthorized behavior. The automation of this process with the integration of artificial inelegance techniques is crucial to achieve speed, accuracy, and adaptability.

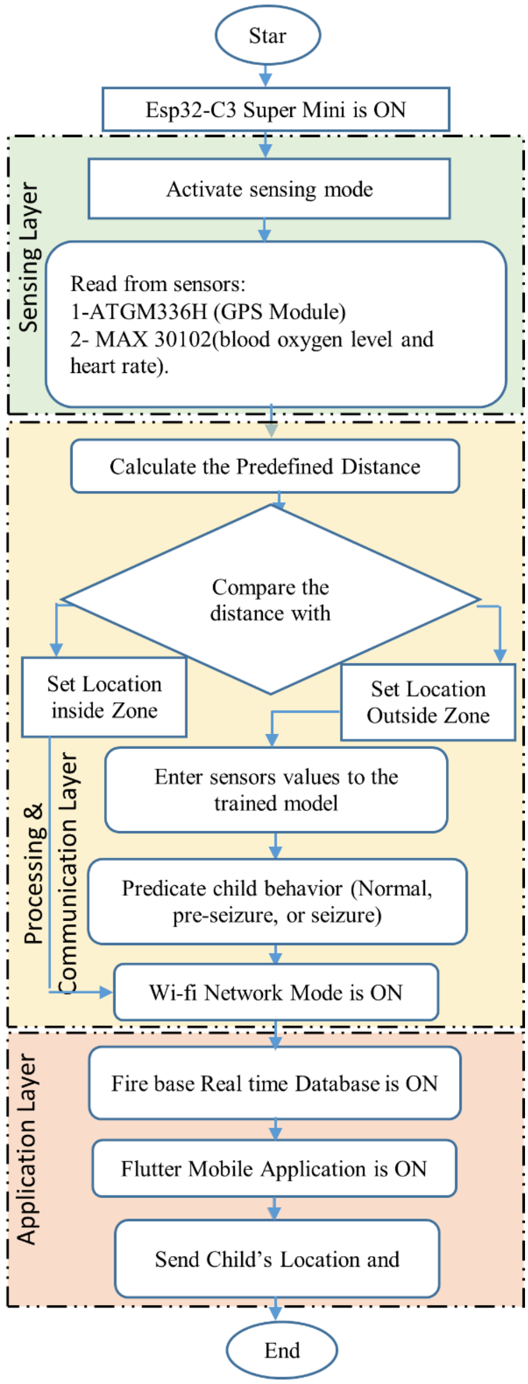


Figure 4. Flowchart of the proposed system

On the other hand, mentoring children's activities and their behaviors is very important task for parents, caregiver, and educators because it ensures their safety, offers the required support, and provides greater peace of mind. Therefore, we tended to present an automatic system based on AI to predict kids' activities and detects any abnormal or risky behavior. For this purpose, we utilized SHAR-100-20 dataset as the primary source of the activity classification to provide the necessary data to train our system. SHAR-100-20 is publicly available dataset collected from 100 participants, designed to simulate 20 classes of physical activities for human actions recognition. We used this particular dataset because it offers a set of very comprehensive variety of activities which are highly relevant to safety mentoring for children's behaviors. initially, we modify the dataset by restructuring the original output labels of the data to accommodate them for the training part of our system. To achieve that, a certified medical expert was consulted to reclassify the original twenty classes into three types of activities: normal, pre-seizure, and seizure. Then after that we sample 100,000 recordings for each class.

After the modification, the data labels were consolidated into three behavioral categories: normal, pre-seizure, and seizure of 300,000 measurements, few samples from the data are shown in Figure 5. The primary reason of this transformation was to align the dataset with the core objective of our activity recognizer model.

	accel_x	accel_y	accel_z	gyro_x	gyro_y	gyro_z	heart_rate	class
0	1.599165	-3.134336	-19.407838	2.399959	-7.166784	12.945217	145.878481	pre_seizure
1	0.108474	-1.338545	-19.373011	-0.905540	-5.001971	-9.932420	159.253031	pre_seizure
2	2.691323	-0.901463	-16.966700	-9.755911	-7.886016	-5.048401	154.926879	pre_seizure
3	4.323601	-3.099938	-15.757118	-5.221432	-0.466844	12.231996	176.520251	pre_seizure
4	-1.015163	1.685492	-16.179450	0.744402	-12.862677	0.151253	147.628421	pre_seizure

Figure 5. Few samples from the dataset

The learning process of our system can be divided into two steps. Firstly, we used the raw data of the collected sensors of acceleration (accel_x, accel_y, accel_z), gyroscopic movement (gyro_x, gyro_y, gyro_z), and heart rate. For this particular step, we utilized traditional methods of machine learning process where the input of the trained models is a vector of seven parameters and the output is the predication of the behavioral type. To perform the training process, we split the modified data into training part and testing part. We used the training segment of the data to apply the learning process of the predication models.

To evaluate the performance of the learned models, we applied cross validation strategy throughout the training process. A 10-fold cross validation technique was used by randomly dividing the dataset ten times into 70% to 30% segments ratio. In each iteration, we used the training portion to build the predication model, while the remaining portion of the data was utilized to measure the classification accuracy and the other evaluation metrics. Finally, the performance of the trained model was calculated by averaging the results across all ten iterations to provide a comprehensive assessment of its effectiveness.

A broad spectrum of classification methods has been proposed by researchers to improve the recognition performance, each algorithm exhibits unique characteristics, strength and limitations. Consequently, determining the best candidate classification technique for particular dataset and task can be both challenging and demanding task. To overcome this problem, we explored wide range of classification algorithms by training around 18 different models. The implemented classification techniques can be categorized into linear, nonlinear, single classification and ensemble of classification methods. Logistic Regression, Linear Discriminant Analysis, and Support Vector Machine were trained to build predication models as linear classifiers. On the other hand, Decision Tree, Quadratic Discriminant Analysis, and K Nearest Neighbors were trained as non-linear models. Additionally, we extended the scope of the training to include ensemble of classifiers by training Extra Trees Classifier, Random Forest Classifier, and Ada Boost Classifier. The primary objective of deploying various classification techniques is to achieve comprehensive comparative analysis.

The aforementioned classifiers have demonstrated their effectiveness across different types of applications involving static data and tabular input, where each measurement is considered entirely independent. However, these types of classification approaches do not consider the temporal history of the input and rely solely on the current state of entered data sensors. Hence, they are practically unsuitable for problems involving time series inputs, where data pattern and its dependencies are essential factors for accurate classification. Behavior monitoring using physiological signal analysis can be considered as time series problem where the input features are time dependent. In this analysis, the temporal relationship between sensors measurements observations can be very crucial for the classification performance. Therefore, we used in the next phase of our project time series models to implement the predication models.

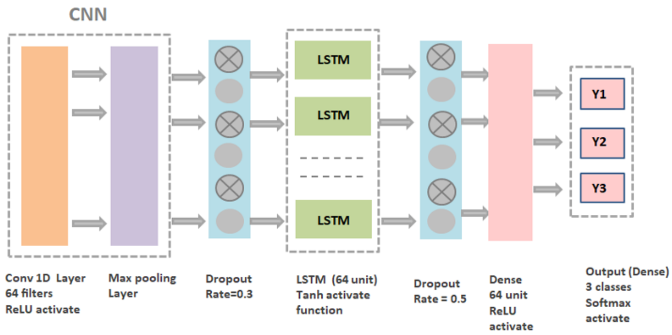


Figure 6. The proposed model architecture

Table 2. Proposed model configuration

Layer No.	Type	Configuration	Activation
1	Conv1D	Filters = 64, Kernel = 4, Stride = 1	ReLU
2	MaxPooling1D	Pool Size = 2	--
3	Dropout	Rate = 0.3	--
4	LSTM	Units = 64	Tanh/Sigmoid
5	Dropout	Rate = 0.3	--
6	Dense	Units = 64	ReLU
7	Dense	Units = 64	Softmax

In order to capture the sequential temporal patterns across time domain of the input sensors, we aggregated 20 consecutive samples to create a single window of input segment. This window of input allowed the classification models to learn not only from the data measurements individually but also from the temporal patterns throughout multiple steps over time. The segmented time-windows of the inputs were used to train types of deep learning architectures: a pure CNN to capture the local spatial features across the temporal window, a pure RNN to capture the sequential dependencies relationships of the temporal patterns, and finally a hybrid CNN-RNN architecture network to leverage both local spatial features and temporal sequence learning capabilities. This hybrid architecture model allowed a comprehensive analysis to accommodate spatial and temporal features learning. Figure 6 shows the block diagram of the proposed hybrid architecture network. Table 2 illustrates the details configuration of the proposed network.

3.4 Evaluation process

In order to evaluate the trained models, we used Accuracy, precision, recall, and F1-score (as shown in the following equations) with predication time, size of the model, and number of learnable parameters (for deep learning model). The evaluated metrics can provide a complete analysis and illustrated a trade-off between efficiency and accuracy. The next section presents the results details of the conducted experiments.

$$Accuracy\ \% = \frac{TP + TN}{TP + TN + FP + FN} \times 100 \quad (1)$$

$$Precision\ \% = \frac{TP}{TP + FP} \times 100 \quad (2)$$

$$Recall\ \% = \frac{TP}{TP + FN} \times 100 \quad (3)$$

$$F1 - Score\ \% = \frac{2 \times Precision \times Recall}{Precision + Recall} \times 100 \quad (4)$$

4. RESULTS AND EVALUATION

4.1 Results of machine learning algorithms

This section presents comprehensive details of the all experiments conducted in the proposed work. The ultimate goal of this comparison is to find the best candidate classification algorithm and to build the most effective model for recognizing different patterns in child behavior. The results of our experiments can be divided into two types regarding the nature of the data handling. Firstly, we treated the inputs samples measurements independently. For this type of analysis, we trained traditional machine learning methods using cross validation methods. We used 10-fold validation method by splitting the dataset into training and testing segment using 70%:30% ratio. Table 3 shows a comprehensive analysis of the obtained results of the conducted experiments in our project.

Table 3. Results of comparison

Model	Accuracy	Recall	Prec.	F1-Score	Execution Time
Light Gradient Boosting Machine	0.9622	0.9622	0.9647	0.9624	1.9310
Random Forest Classifier	0.9578	0.9578	0.9593	0.9579	0.2080
Extreme Gradient Boosting	0.9567	0.9567	0.9588	0.9568	0.3260
Extra Trees Classifier	0.9567	0.9567	0.9587	0.9568	0.1640
CatBoost Classifier	0.9544	0.9544	0.9564	0.9546	5.6520
Gradient Boosting Classifier	0.9522	0.9522	0.9558	0.9525	0.5200
Decision Tree Classifier	0.9344	0.9344	0.9374	0.9342	0.0320
Quadratic Discriminant Analysis	0.8722	0.8722	0.8762	0.8688	0.0420
K Neighbors Classifier	0.8678	0.8678	0.8931	0.8658	0.0620
Ada Boost Classifier	0.8500	0.8500	0.8556	0.8499	0.2280
Naive Bayes	0.8489	0.8489	0.8560	0.8442	0.0520
Gaussian Process Classifier	0.8444	0.8444	0.8782	0.8405	1.1230
MLP Classifier	0.8433	0.8433	0.8519	0.8428	0.2870
Linear Discriminant Analysis	0.7244	0.7244	0.7225	0.7143	0.0230
Ridge Classifier	0.7178	0.7178	0.7164	0.7040	0.0270
Logistic Regression	0.6956	0.6956	0.6921	0.6854	0.0610
SVM - Radial Kernel	0.5767	0.5767	0.8092	0.5557	0.2120
SVM - Linear Kernel	0.5011	0.5011	0.5076	0.4222	0.0370
Dummy Classifier	0.3333	0.3333	0.1111	0.1667	0.0540

To ensure a better evaluation, we calculated the accuracy, recall, precision, and F1-score metrics. Additionally, we computed the execution time of each of the all trained models to assess the speed of the predication and the suitability for real-time applications.

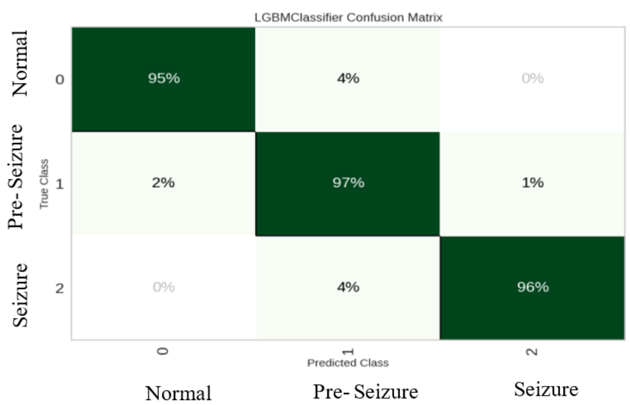


Figure 7. Confusion matrix of the trained model

As illustrated in the Table 3, the trained classifiers were ranked in descending order based on the accuracy metric. Notably, Light Gradient Boosting Machine classifiers achieved superior performance offering accuracy of 96% predication rate. Furthermore, we determined the confusion matrix of the learned model to provide the predication rate for each class individually, this result is shown in Figure 7. In order to achieve features analysis, we evaluated the significant of inputs feature to determine their relative contribution on predication performance.

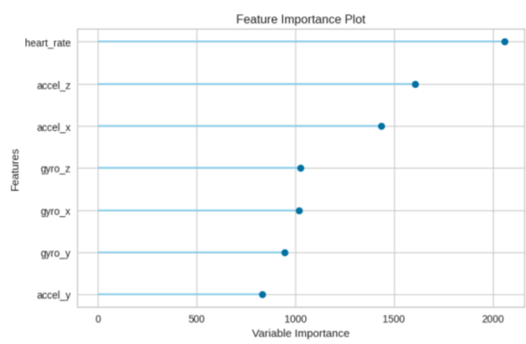


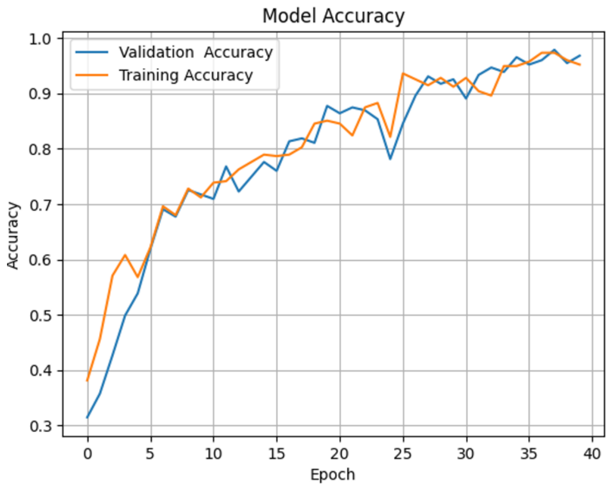
Figure 8. The significant of feature in the dataset

Evaluating feature importance provides the contribution of each feature in the dataset and measure their ranks. The result of the feature ranking analysis is presented in Figure 8.

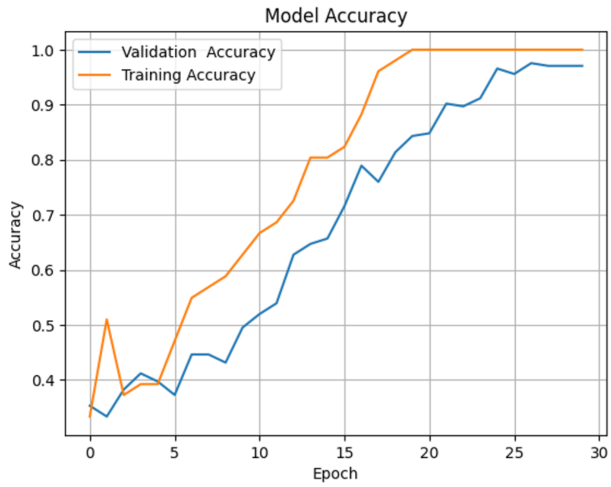
In the second phase of our project, we focused on capturing temporal dynamics of the input sensors. To achieve this goal, the input features were processed to represent the temporal pattern by segmenting continuous data stream into windows of 20 consecutive measurement. These samples were created by aggregating consecutive measurements samples to form a single instance to reflect the short-time behavioral. Each one of these accumulated windows presented one label to describe the children behavioral state and predict one pattern from three classes (Normal, Pre- Seizures, and Seizure).

As we mentioned before, the conventional machine learning methods cannot handle temporal states of the sequential data because they lack the mechanism to model time-based dependencies. This characteristic makes them unfit for particular tasks involving patterns classification where the time and the sequence of the observations play crucial role. Therefore, we trained deep learning models with capabilities of capturing temporal dynamic. More specifically, we used three different architectures of deep learning models: CNN, RNN, and CNN-RNN. First, Convolutional Neural Networks (CNNs) was trained to extract spatial and local features predict the correct behavior and detect seizer. Additionally, we trained Recurrent Neural Networks (RNNs) model to capture the sequential nature of the data. Finally, we used hydride model by combining CNN and RNN architectures to accommodate the strength points of both networks. The hybrid model gains the potential of leveraging the features extraction capability of CNN with the capacity of the RNN to learn the temporal dynamic of the sequential inputs.

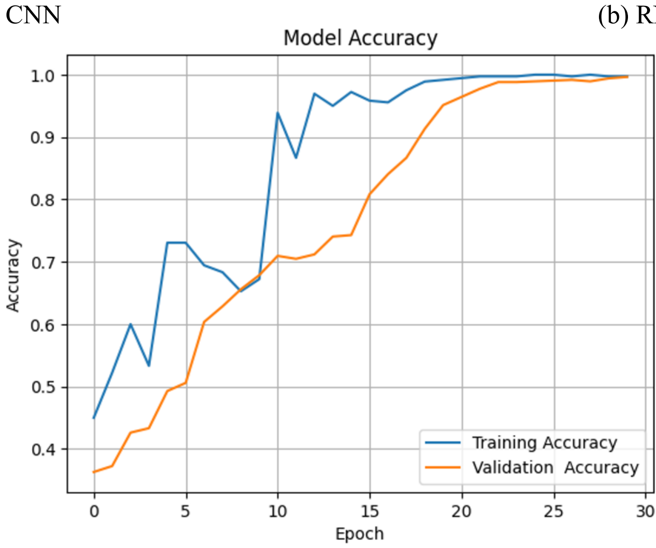
To evaluate the performance of the three proposed networks, we divided the dataset into two section of 70% for the training and 30% for the testing. For the training configuration, Adam optimizer was used to train the model with an adaptive learning rate technique. The training started at 0.001 learning rate and then it was adjusted dynamically based on validation performance to help reducing the effect of the overfitting problem and accelerating convergence. The models were learned using a batch size of 32 using categorical cross-entropy to compute the loss function as suitable measurement for multi-class classification. The training and the validation accuracy were computed during the training process to observe the convergence process, the results learning process are shown in the Figures 9(a)-(c). Additionally, we computed the confusion matrix, Figures 10(a)-(c) show these results. Furthermore, we measured the recall, precision, F1-score, number of the parameters, size, and predication time for proposed networks, Table 4 illustrates a comprehensive comparison of the trained models.



(a) CNN

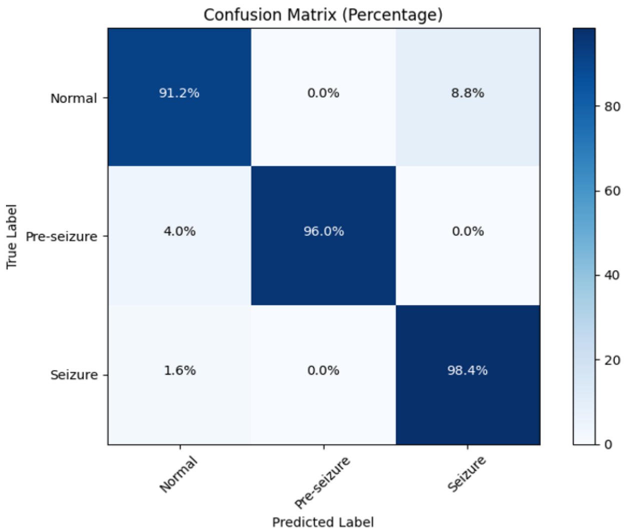


(b) RNN

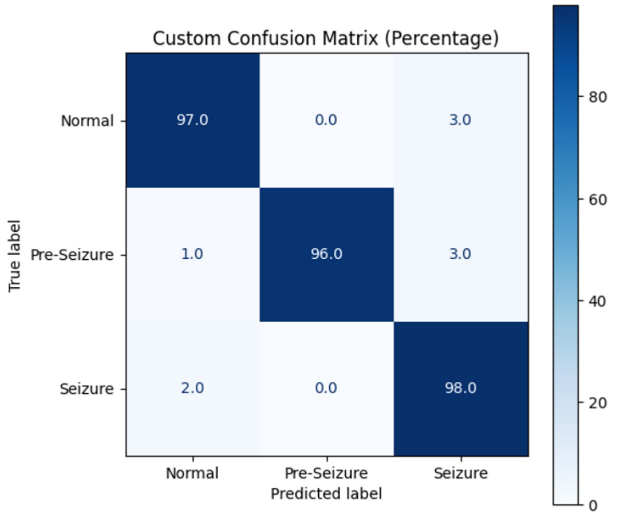


(c) CNN+RNN

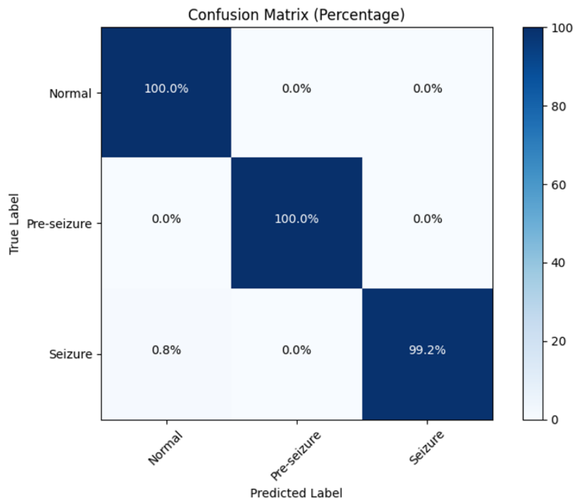
Figure 9. The accuracy measurements during the training



(a) CNN



(b) RNN



(c) CNN +RNN

Figure 10. Confusion matrix of the trained models

Table 4. Results of comparison of the deep learning models

Model	Accuracy	Recall	Prec.	F1-Score	No of Parameters	Size of Model	Execution Time
CNN	0.95211	0.95673	0.95335	0.95207	26755	0.10 MB	0.624
RNN	0.9730	0.97763	0.97225	0.96170	22787	0.09 MB	0.549
CNN+RNN	0.99720	0.99739	0.99733	0.99765	39235	0.15 MB	0.882

As show in the Table 4, the hybrid CNN+RNN architecture outperformed the solo architecture by achieving 0.99 of accuracy. The superiority of the performance indicates the effectiveness of leveraging convolutional and recurrent layers for capturing both spatial and temporal behavioral patterns of the learned features. Additionally, the trained RNN model achieved an accuracy of 97% with relatively fast execution time of 0.5 milliseconds (ms), while maintaining a light weight model with 22,787 parameters with very compact model size of 0.09 MB. On the other hand, the standalone CNN offered 95% accuracy with reasonable response time of 0.6 milliseconds, the model allocated 26,755 parameters with a manageable model size of 0.1 MB. Even though, the hybrid CNN+RNN model consumes a relatively large size (when it is compared to stand-alone models CNN and RNN) of 0.15MB with the longest execution time (882 ms), it stands out to be the most effective dependable network model by achieving exceptional accuracy and balanced precision-recall performance. The obtained results emphasized that with combining the CNN and RNN models offered trade-off between the speed and the predicative accuracy. Hence, the proposed hybrid model provided resilient and accurate solution for real-time child behavioral recognition task.

4.2 Optimized power management and battery endurance evaluation

In the development of the proposed embedded system, a precise energy assessment was essential to determine the operational longevity of the device. The hardware includes an ESP32-C3 microcontroller Ultra-Low-Power SoC with RISC-V Single-Core CPU Supporting 2.4 GHz Wi-Fi and Bluetooth LE, GPS unit, MPU6050 accelerometer, MAX30102 pulse sensor, and a SIM800L GSM module. Each component exhibits specific power and current consumption behavior across operational states such as sleep, idle, and active as shown in Table 5. These values can be obtained from the module datasheet or by measurement. The system draws its power from a 1100 mAh lithium-battery.

Table 5. Battery lifetime and energy consumption

Module	Sleep (mA)	Idle (mA)	Active (mA)
ESP32-C3 SuperMini	2.1	28	40
ATGM336H GPS	0	10	100
MPU6050 (GY-521)	0.01	1.0	4.0
MAX30102	0.9	1.0	3.5
SIM800L (GSM)	1.8	19	108

To calculate the battery lifetime, the current values for sleep, idle and active should be considered as below:

- Sleep: MCU in light sleep, SIM in low-power mode, and GPS powered down.
- Idle: MCU awake with a low duty cycle sensor reads (1 Hz), GPS maintaining fix, SIM on but not transmitting.
- Active: data sampling from sensors at 50–100 Hz, GPS refreshing location, SIM800L performing Tx (SMS/voice/data) or active TCP session.

To model the system's energy footprint, two operating scenarios were defined:

Scenario 1 – Device Remains Within Defined Safe Zone: In this scenario, the device does not exceed the configured geographical threshold, meaning the SIM800L communication module remains inactive throughout operation. The energy demands are dominated by the sensing and control modules: We assume the sensors sample rate to be every 1 s; GPS query every 5 s; SIM idle (no TX). The breakdown of duty cycle is every minute. The ESP32 would be active for 10% of the time to read the sensors data and upload with a sleep for 90%. GPS active for 20% of the time, otherwise low- power. MPU6050/MAX30102 both are active for 10%. By taking the values from Table 5 (active and sleep) values and calculating the current in each module with the assumed duty cycle, the average total current for all modules would be 29.259 mA. The battery life time can be calculated by dividing the battery capacity by the average current and the life time would be 37.6 hour. This number depends on duty cycles chosen and the GPS current. For example, if the GPS keeps always on, the battery life time will be less.

Scenario 2 – Device Exits Safe Zone: Once the system crosses the defined boundary, it triggers the SIM800L module, which significantly increases power usage due to GSM transmission. The SIM800L, during active communication, consumes up to 108 mA per session. This results in a total average current to be 135.459 mA and a shorter battery lifespan of about 8.1 hour, due to the added energy burden from cellular data transmission. This dual-scenario evaluation enables intelligent power budgeting and offers insights into optimization strategies. These may include selective module activation, adaptive sampling intervals, and the implementation of low-power sleep states. Long-term improvements may leverage techniques such as energy harvesting or hardware-level optimization to extend device autonomy.

5. CONCLUSIONS AND FUTURE WORKS

This study introduced a comprehensive IoT-based wearable system that integrates GPS tracking and biometric monitoring to ensure child safety and support early detection of medical emergencies. By combining real-time location tracking with a hybrid CNN-LSTM model trained on synthetic modified HAR data, the proposed system effectively monitors children's movement and health status. The system achieved a high seizure detection accuracy of 99%, demonstrating the robustness of the deep learning model, especially. Compared to existing child tracking solutions, our approach offers a broader feature set enabling not only precise geofencing alerts but also health anomaly detection, all within a power-efficient and user-friendly framework. The implementation on ESP32, along with mobile support via a Flutter tracking app, ensures flexibility, low power consumption, and compatibility across environments. The dual-tracking capability of both child and guardian enhances situational awareness and allows for quick response in emergencies. Furthermore, the system's adaptability paves the way for potential applications beyond child safety, including elderly care and continuous health monitoring for individuals at risk. Overall, this research contributes a novel, practical, and scalable solution that bridges the gap between safety and health monitoring, meeting the growing demand for intelligent, wearable technology in real-life safety-critical scenarios.

Even though that we achieved promising results, we should acknowledge several limitations in our project. For example, the current implementation of our app and the deployed prototype are not fully matured and need more development. Additionally, the current system should be tested against real-world condition to evaluate the system effectiveness under outdoor/indoor and critical scenarios.

Future work can focus on completing the whole design to improve the deployment of the prototype, app functionalities, and expand the testing modes to cover real world scenarios. Additional directions for future research to include further development of the proposed system by integrating annotative techniques such as explainable AI approaches, data transfer security and privacy methods, different nodes implementation as a wireless sensor network, and energy optimization algorithms to extended the battery life time.

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