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RESEARCH ARTICLE

Detection and Classification of Teacher-Rated Children's Activity Levels Using Millimeter-Wave Radar and Machine Learning: A Pilot Study in a Real Primary School Environment

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of the Graduate School of Engineering, Kyoto University, under Approval No. 202219.

ABSTRACT Traditional assessments of children's health and behavioral issues primarily rely on subjective evaluation by adult raters, which imposes major costs in time and human resource to the school system. This pilot study investigates the utilization of millimeter-wave radar coupled with machine learning for the objective and semi-automatic detection and classification of children's activity levels, defined as restlessness, within a real classroom environment. Two objectives are pursued: confirming the feasibility of restlessness detection using millimeter-wave radar and applying standard machine learning method for restlessness classification. The experiment involves a nine-day observational study, using two radar systems to monitor the activities of 14 children in a primary school. Radar data analysis involves the extraction of distinctive features for restlessness detection and classification. Results indicate the successful detection of restlessness using millimeter-wave radar, demonstrating its potential to capture nuanced body movements in a privacy-protected manner. Machine learning models trained on radar data achieve a classification accuracy of 100%, outperforming other methods in terms of non-invasiveness, lack of body restraint, multi-target applications, and privacy protection. The study's contributions extend to children, parents, and educational practitioners, emphasizing non-invasiveness, privacy protection, and evidence-based support. Despite limitations such as a short monitoring duration and a small sample size, this pilot study lays the foundation for future research in non-invasive restlessness detection using non-contact monitoring technologies. The integration of millimeter-wave radar and machine learning offers a promising avenue for efficient and ethical trait assessments in real-world educational environments, contributing to the advancement of child psychology and education. This work supports efforts for non-contact monitoring of children's activity holding promise such as non-invasive, privacy protection, multi-targets, objective evaluation, and computer-aided screening.

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INDEX TERMS Machine learning, millimeter-wave radar, non-contact monitoring, real school environment, restlessness.

I. INTRODUCTION

In the modern world in which school-based education is universal or mainstream, children spend as much waking hours in school as at home. In such societies, schools play a key role in promoting children's health, as well as providing education. For example, in Japan, school-based daily health observation system has been broadly implemented, which has been utilized to screen for a wide range of physical and mental health issues [1], [2]. At present, school-based health observations, particularly for mental health and behavioural issues, primarily rely on subjective evaluation by schoolteachers, health professionals in schools such as school doctors, nurses, psychologists and social workers, or children themselves. Though effective it is, such subjective evaluation, often based on a standardized questionnaire, poses several major challenges to the school system.

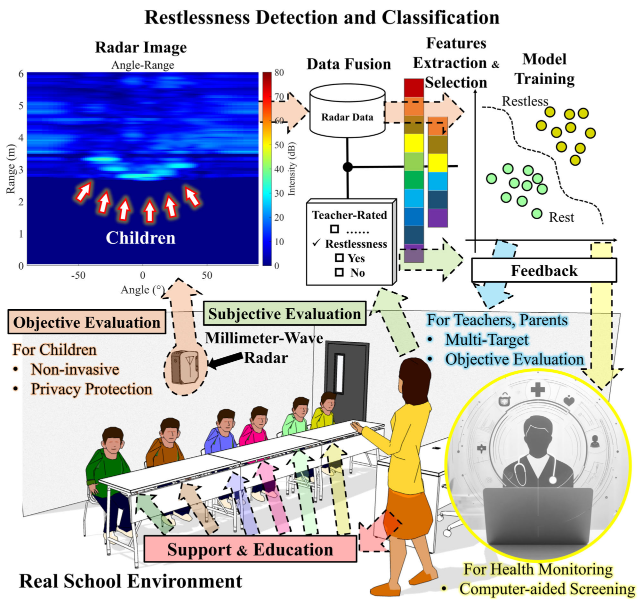


FIGURE 1. Study concept and vision.

One of the major challenges is the time and human re- sources required for collecting and analyzing questionnaire data, alongside many school activities happening every day [3]. Many schools may not have sufficient time to conduct survey, and to collate, analyze, evaluate and feedback questionnaire data, or sufficient expertise for teachers to interpret and understand the results [4]. In addition, particularly younger children may not possess sufficient metacognitive skills to monitor their own mental condition [5], which puts a major limitation on self-reported measurements.

To overcome these challenges, objective measurement of children's mental and behavioural states is in dire need. For example, wearable devices, which can monitor activity levels as well as physiological states such as heart rates, are sometimes seen as a 'game changer' in monitoring children's health at school. However, several issues such as discomfort in wearing devices for long hours, protecting personal information while sharing data in school, as well as the financial cost to provide such devices to each child, are seen as barriers for implementing such system to the classrooms.

Recent advancements in commercial millimeter-wave radar, known for their precision in distance and micro-movement measurements [6], [7], present new possibilities to overcome such limitations for wearable devices and enables implementation of objective health monitoring system in the classrooms. These millimeter-wave radar systems could be deployed for applications like vital sign monitoring [8], [9], gesture recognition [10], behavior detection [11], and human pose estimation [12]. Leveraging the millimeter-wave radar's adeptness at sensing environmental changes through electromagnetic waves, it not only captures a diverse array of body movements but also ensures privacy protection simultaneously [13], [14]. Given these inherent characteristics, there is a justifiable expectation that the use of millimeter-wave radar could introduce a novel approach to detect children's mental and behavioral states in real school environments.

We conducted a proof-of-concept study to implement millimeter-wave radar systems in a real classroom, monitor children's daily activities, and examine whether the recorded children's activity levels predict teacher-based evaluation of children's behavioural traits. We targeted a teacher-rated behavioural rating scale, the Strength and Difficulties Questionnaire (SDQ) [15] and its second item (SDQ 2: Restless, overactive, cannot stay still for long) represent overall activity levels of children evaluated by the teachers. We investigated whether the level of body movement measured by millimeter-wave radar systems can predict activity levels evaluated subjectively by teachers.

Furthermore, we learned that machine learning (ML), which has found extensive application in computer-aided diagnosis for analyzing both imaging and non-imaging data [16]. However, how to apply ML for restlessness classification using millimeter-wave radar in a realistic classroom setting has not been previously explored. Once adequately trained with relevant features, ML has the potential to serve as a supplementary opinion or provide supporting information in the school-based evaluation process, thereby mitigating the workload for teachers, school-based healthcare professionals and children [17]. The identification of specific features from millimeter-wave radar data, successfully validated to be informative for classifying restlessness, holds the promise of training ML models to develop a computer-aided screening system for children's activity levels.

Therefore, the objective of this pilot study is to propose a non-invasive, multi-target monitoring approach for the detection and classification of children's activity levels, which we define as 'restlessness' in children within a real classroom environment, using millimeter-wave radar. Figure 1 visually articulates our research concept and vision. Briefly, our study has two purposes: Purpose 1: Confirming the feasibility of restlessness detection using millimeter-wave radar in a real classroom environment. Purpose 2: Applying standard machine learning algorithm and training machine learning models for restlessness classification, incorporating both subjective and objective evaluations.

To achieve these objectives, we conducted a nine-day observational experiment in a real primary school setting. During the experiment, the regular activities of the children were recorded using two millimeter-wave radar systems. Subsequently, the radar data underwent analysis, and distinctive features were extracted for classification through ML techniques. Given the millimeter-wave radar's capacity to measure micro-body movement, velocity, and angle, achievable through multiple-input and multiple-output (MIMO) antenna arrays, and the potential use of carefully selected features for ML-based detection and classification, this study puts forth the following hypotheses: Hypothesis 1: Millimeter-wave radar could serve as a tool for monitoring restlessness in daily classroom environments. Hypothesis 2: Restlessness measured using millimeter-wave radar could be leveraged to distinguish between children who are evaluated to be restless by teachers, and those who are not.

To the best of our knowledge, this study represents the first attempt to detect restlessness in children within a real classroom environment using millimeter-wave radar. Given the pressing need for monitoring children's health and behavioral conditions within school environment, this pilot study is envisioned to make the following significant contributions: **Key contribution to children: Non-invasive, privacy protection**. By adopting a non-invasive approach, this study prioritizes the well-being of children, while ensuring their activities remain unrestricted. The emphasis on privacy protection allows for self-management, enabling children to comprehend their behavior without concerns about privacy issues. **Key contribution to parents, teachers, and school-based professionals: Multi-targets, objective evaluation**. Providing parents and teachers with more comprehensive information about children's behavior at school. The implementation of a multi-target sensing system for restlessness measurement aims to alleviate the burden on teachers. Objective information contributes to evidence-based support and education for children, enhancing classroom management. **Key contribution to health monitoring within schools: Computer-aided screening**. Recognizing the time constraints and shortage of trained specialists available for schools, the introduction of a ML-based computer-aided screening offers the potential for more efficient and objective behavioral monitoring. This technology has the capacity to assist school-based professionals in making faster and more accurate assessments, which would lead to early targeted intervention.

Additionally, we conducted a comparative analysis of our proposed approach against existing ones. This comparison aims to furnish readers with a more comprehensive understanding of the advantages and limitations associated with different methodologies. Simultaneously, with the goal of stimulating further research within this domain, our discussion extends to both technical and social perspectives. By addressing technical considerations, we aim to contribute to the refinement and enhancement of methodologies in this field. Furthermore, our exploration of social aspects seeks to inspire broader conversations and investigations into the broader societal implications of employing such technologies in real-world settings.

II. METHODS

A. SUBJECTS AND EXPERIMENT

We conducted a nine-day recording of class activities in a primary school using millimeter-wave radar systems, spanning from March 6th to 17th, 2023, with the participation of 14 children.

Figure 2 (a) provides an overview of the experiment. To minimize disruption to normal school activities, children were instructed to behave freely in regular seating patterns, either a U pattern or a random pattern corresponding to the school activity (Fig. 2 (b)). Two radar systems were positioned at the back of the classroom, as illustrated in Fig. 2 (c). Radar 1 was placed in the left corner of the classroom, 3.6 m from the left edge of the table, 4.7 m from the right edge of the table, and at a height of 1.78 m. Radar 2 was positioned in the right corner, 5.1 m from the left edge of the table, 4.5 m from the right edge of the table, and at a height of 0.9 m. To mitigate the environmental factors that can affect the radar performance, we installed the radar systems on the top of the shelves away from obstacles. From the installed radar systems, we confirmed that the whole classroom could be covered by the radar beam in advance. Controlled by individual laptops through self-written programs, each radar initiated measurements automatically every day at 08:00 a.m. and stopped at 04:00 p.m.

Following the observation experiment, two teachers completed the SDQ, which comprises five scales related to emotional, conduct, peer, prosocial problems, and hyperactivity. In this study, we only focused on the items related to restlessness, which is SDQ 2: restless, overactive, cannot stay still for long. SDQ 2 is scored on a scale from 0 to 2, where 0 indicates 'not true', 1 indicates 'somewhat true', 2 indicates 'certainly true'. Children are labeled to be restless if either/both teacher(s) answered 1 or 2 to this item.

Data selection is depicted in Fig. 3. The analysis focused on data collected when children seated in the U pattern (as shown in Fig. 2 (b)) to ensure both radars recorded the activities. Thus, eight children were excluded from the analysis because they could not be recorded by the two radar at the same time. Six children's data were utilized

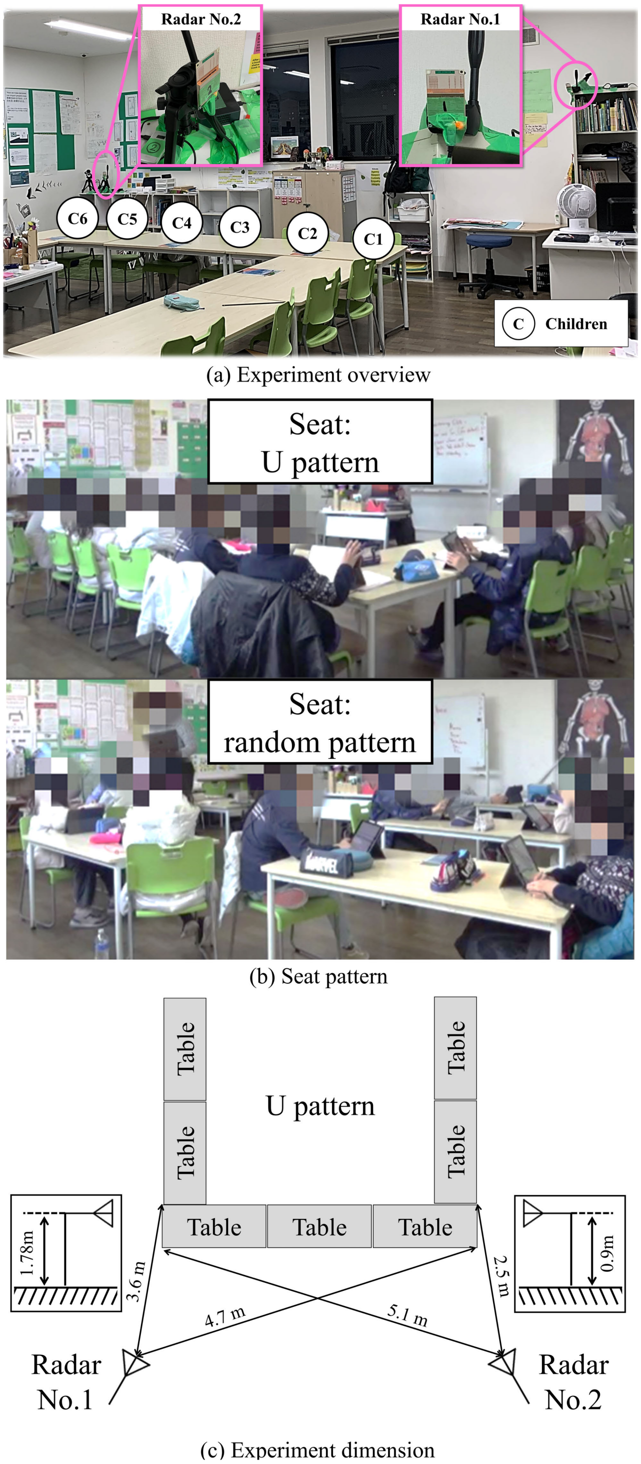


FIGURE 2. Experiment overview, seat pattern and dimension.

for restlessness detection. Additionally, for training the ML model, only data where radar analysis matched the SDQ 2 results were used. Consequently, data from four children were used for restlessness classification.

Written informed consent for participation was provided by the participants and participant's legal guardians. All participants agreed to the privacy policy. Participation was entirely voluntary, and students were informed of their right to opt out at any point during the process. This study was approved by the Ethics Committee of the Graduate School of Engineering, Kyoto University (No. 202219).

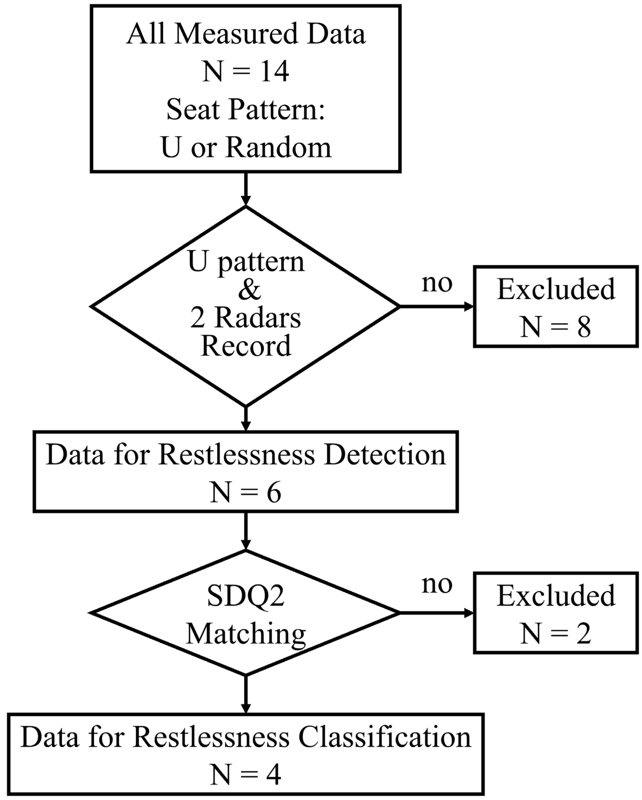


FIGURE 3. Flowchart of data selection.

B. RESTLESSNESS DETECTION AND CLASSIFICATION

In this study, we used the same frequency-modulated continuous wave (FMCW) radar system as used in our previous study (T14RE_01080108_2D, S-Takaya Electronics Industry, Okayama, Japan) to record children's activity [18]. This radar system is based on IWR1443 (Texas Instruments), which is a self-contained and single-chip device that simplifies the implementation of millimeter-wave sensors in the band of 77 to 81 GHz band with up to 4 GHz continuous chirp [19]. The parameters for the radar system can be found in Table 1. The radar parameters such as the output power, antenna gain, and installation position were set to comply with the standards stated in the Radio Radiation Protection Guidelines (RRPG) of the Ministry of Internal Affairs and Communications of the Japanese Government, which takes sufficiently large safety factors into consideration. The standard values in the RRPG are on a par with the values released by International Commission on Non-Ionizing Radiation Protection. For these reasons, the possibility of adverse events such as health implications is considered sufficiently low.

The main structure of the radar system is illustrated in Fig. 4 (a) and (b). This radar system includes three transmit (TX) and four receive (RX) radio frequency (RF) components, analog and digital components including analog-to-digital converters (ADCs), digital signal processors (DSPs), and micro-controllers (MCUs). Because the millimeter-wave radar transmits signals with a wavelength that is in the millimeter range (about 4 mm), this radar system has the ability to detect movement that are as small as a fraction of a millimeter.

The fundamental concept in FMCW millimeter-wave radar system is the transmission of an electromagnetic signal that object reflects in its path. The signal used in FMCW millimeter-wave radar has the frequency that increases linearly with time, this is called a chirp. The chirp is characterized by a start frequency 77 GHz, bandwidth (B) 3.6 GHz, and chirp time 120 µs (see Fig. 4 (c) left part) [20]. The radar system first generates a chirp, and is transmitted by a transmit antenna, after reflecting by an object, the chirp is captured by the receiver antenna. A mixer combines both signals to produce an intermediate frequency (IF) signal. An example of the process is shown in Fig. 4 (c) upper diagram. Let Δf be the difference frequency between receiving and transmitting signals, and slope of chirp frequency S, then the time delay (τ) can be mathematically derived as:

$$\tau = \frac{\Delta f}{S} = \frac{2d}{c}, \tag{1}$$

where d is the distance to the detected object, and c is the speed of light.

Angle detection in FMCW millimeter-wave radar is illustrated in Fig. 4 (d) by reference [21]. The receiver has received the reflected signal with the phase difference $\Delta\phi$, the distance between antenna is l, wave length is λ. Then the L in Fig. 4 (d) is $L = l \sin\theta$, because delta $\Delta\phi = (2\pi L)/\lambda$, then the angle of an object θ can calculate by:

$$\theta = \sin^{-1}\left(\frac{\lambda\Delta\phi}{2\pi l}\right). \tag{2}$$

Next, the complex radar image $I_0(t, r, \theta)$ is calculated following the methodology outlined in our previous study [8] as follows:

$$I_0(t, r, \theta) = \boldsymbol{\omega}^{\mathrm{H}}(\theta)\boldsymbol{s}(t, r), \tag{3}$$

where t, r, and θ represent time, range, and angle, respectively. The superscript H is the complex conjugate transposition of the matrix, and $\boldsymbol{\omega}(\theta) = [\boldsymbol{\omega}_0, \boldsymbol{\omega}_1, \ldots, \boldsymbol{\omega}_{K-1}]^{\mathrm{T}}$, here, $\boldsymbol{\omega}_k(\theta) = \mathrm{e}^{-\mathrm{j}\pi k \sin\theta}$, $K = 12$ is the number of elements in the virtual array, $k = 0, 1, \ldots, K-1$, where we assume $l = \lambda/2$.

In a real classroom, there are multiple reflective surfaces and objects that may cause multipath interference. However, most of these objects are stationary, so the resulting clutter is static, meaning it does not change over time. In contrast, the echoes from the target children vary over time. To remove this static clutter, we use a time averaging method to obtain the complex radar image $I_c(t, r, \theta)$ as follows:

$$I_c(t, r, \theta) = I_0(t, r, \theta) - \frac{1}{T_c}\int_{t-T_c}^{t} I_0(\tau, r, \theta)\,\mathrm{d}\tau, \tag{4}$$

here, T_C is set to 10 s. This approach effectively reduces the influence of stationary objects in the classroom, ensuring that the results in this study are minimally affected by interference from these reflective surfaces or objects.

Finally, the power of the complex radar image is time-averaged to obtain the radar image $I_p(t, r, \theta)$ as follows:

$$I_p(t, r, \theta) = \frac{1}{T_P}\int_{t-T_P}^{t} |I_c(\tau, r, \theta)|^2\,\mathrm{d}\tau, \tag{5}$$

here, T_P is set according to the monitoring period.

Figure 5 illustrates the restlessness detection processing. After obtaining the radar image I_P using Eq. 5 (angle-range in Fig. 5 (a)), we manually select the region of interest (ROI) and define the point with the maximum intensity value (Fig. 5 (b)). Subsequently, we extract the coordinates (rows and columns) and count the number of occurrences of each coordinate and its proportion within the observation time. An example of relatively stable activity over 400 s is shown in Fig. 5 (c). Both the row and column coordinates of the point with maximum intensity value almost stay in the same, with coordinate (6, 11) occupying 94% of the monitored duration. This indicates that, during 94% of the observation period, the child remained in almost the same position. In contrast, Fig. 5 (d) presents an example of restlessness. Neither the row nor the column coordinate remains constant, and the most frequent coordinate was (5, 10), accounting for only 25% of the entire monitored duration. This implies that the child could not maintain the same position for more than 25% of the observation period, indicative of restlessness. Thus, for restlessness feature extraction, we used the ratios of the top five most frequently appeared coordinates each day as features. Higher values indicate greater stability in the child's activity. Subsequently, for restlessness classification, we employed these features, which exhibited significant differences when compared to subjective evaluation results,

TABLE 1. Parameters of T14RE FMCW Radar.

Model	T14RE
Size (mm)	W50 × D4.7 × H85
Center Frequency (GHz)	79
Wavelength (mm)	3.8
Bandwidth (GHz)	3.6
Range Resolution (mm)	44.7
Sampling Frequency (Hz)	100
TX Power (dBm)	24
Number of Transmitting Elements	3
Number of Receiving Elements	4
Number of Virtual Elements	12
Angular Resolution (deg)	8.5
Chip Time (μs)	120

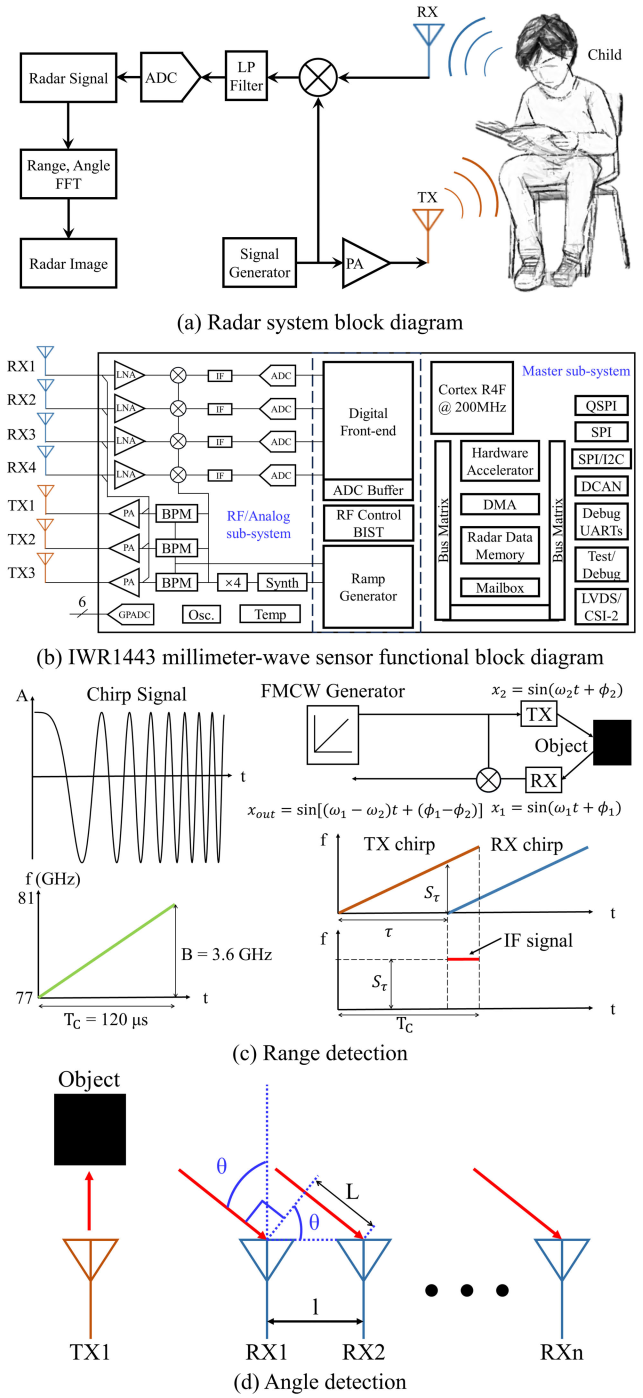


FIGURE 4. **Radar system and fundamental concept. (a) The radar system block diagram in our study. (b) The IWR1443 millimeter-wave sensor functional block diagram, re-write referenced [19]. (c) The chirp signal and range detection. (d) Angle detection, considering the distance between antenna is $\lambda/2 = 1.9$ mm, we can assume that the reflected signal of each receiver is parallel.**

to train ML models. A total of 34 ML models were trained using 5-fold cross-validation, 70% data for training and 30% for test, employing the machine learning toolbox in MATLAB version R2023a.

C. STATISTICAL ANALYSIS

The mean, median, and standard deviation of all features were computed. The normality of the data was assessed using the Shapiro-Wilk test. For the analysis of five features across six children over nine days, one-way repeated ANOVA (RMANOVA) was employed. If the assumption of normality was not violated, parametric RMANOVA was conducted; otherwise, non-parametric RMANOVA (Friedman's repeated ANOVA) was applied. Additionally, a test of sphericity was performed for parametric RMANOVA. Effect size (ω^2) was calculated, with interpretations as follows: $\omega^2 \leq 0.01$ indicates a trivial effect, $0.01 < \omega^2 \leq 0.06$ suggests a small effect, $0.06 < \omega^2 \leq 0.14$ indicates a medium effect, and $\omega^2 > 0.14$ implies a large effect. Post hoc testing was conducted only when RMANOVA revealed a significant difference, and Bonferroni correction was applied.

Independent T-test was used for features selection. The normality of data was assessed using the Shapiro-Wilk test. Equality of variances (Levene's) was tested. If the assumption of normality or variances was violated, non-parametric T-test (Mann-Whitney) was applied, otherwise, parametric T-test was applied. Cohen's d and Rank biserial correlation (R_B) effect size was calculated. Cohen's $d \leq 0.2$ indicates a trivial effect, $0.2 <$ Cohen's $d \leq 0.5$ suggests a small effect, $0.5 <$ Cohen's $d \leq 0.8$ indicates a medium effect, and Cohen's $d > 0.8$ implies a large effect. $R_B \leq 0.1$ indicates a trivial effect, $0.1 < R_B \leq 0.3$ suggests a small effect, $0.3 < R_B \leq 0.5$ indicates a medium effect, and $R_B > 0.5$ implies a large effect. The significance level was set at $\alpha < 0.05$. All statistical analyses were performed using JASP (version 0.18.1.0, The Netherlands).

III. RESULTS

A. RESTLESSNESS DETECTION

After excluding the time when children sat randomly, the total monitoring time during the U seat pattern for nine days was 443.3 minutes for radar 1 and 434.8 minutes for radar 2. The discrepancy in monitoring time between the two radars resulted from some missing radar data during the long-term monitoring. Additionally, data taken when radar systems were obstructed by another child or teacher standing in front of them were excluded from the analysis. The monitoring time used for data analysis is summarized in Table 2.

Figure 6 illustrates the results of five features for radar 1 and radar 2. The p-values of the Shapiro-Wilk test for radar 1 features 3 and 4, and radar 2 features 1 and 4 did not show significant differences (all $p > 0.05$), thus parametric RMANOVA was performed for these features (see Table 6 in Appendix A). Other features were tested using the Friedman test (see Table 7 in Appendix A). In summary, the results suggest that C1 had the longest time staying still among the children. C5 showed a lower still index value compared to C2, C3, and C4 did, indicating more frequent

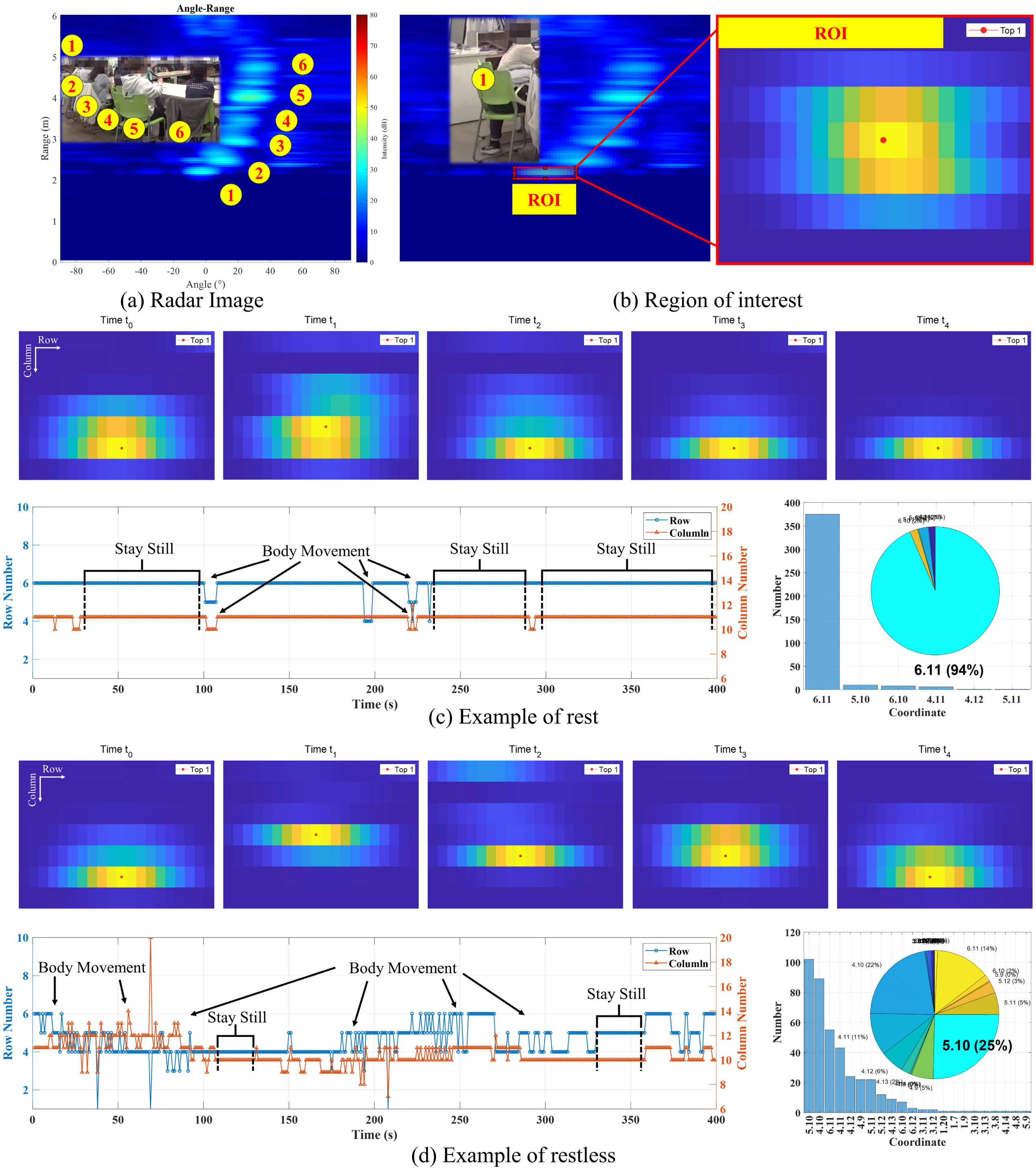


FIGURE 5. **Data processing. (a) Example of radar image, horizontal axis represents angle (°), vertical axis represents range (m). (b) Example of ROI for one child. Red square represents the chosen ROI, red circle represent the maximum intensity point in the ROI. (c) Example of rest for 400 s. (d) Example of restlessness for 400 s. Blue line with circle markers represents the number of row where maximum intensity point appears, red line with triangle makers represents the number of column where maximum intensity point appears. Bar and pie charts illustrate the number of occurrences of each coordinate and its proportion during 400 s.**

body movements. Details of the restlessness detection can be found in Tables 5–10 in Appendix A.

The results of the subjective evaluation of restlessness are presented in Table 3. According to the SDQ 2 results, C1, C3, and C5 were labeled to be resting, C2, C4, and C6 were labeled to be restless. Radar results confirmed that C2 showed more active characteristics than C1; however, C5 showed more active characteristics than C4 from radar image

TABLE 2. Result of monitoring time.

Monitoring Day	Radar No. 1	Radar No. 2
1	47.6	46.6
2	118.8	116.8
3	95.5	95.3
4	44.3	43.8
5	14.0	14.0
6	29.5	29.5
7	30.8	29.0
8	31.0	31.0
9	31.8	28.8
Total monitoring time (min)	**443.3**	**434.8**

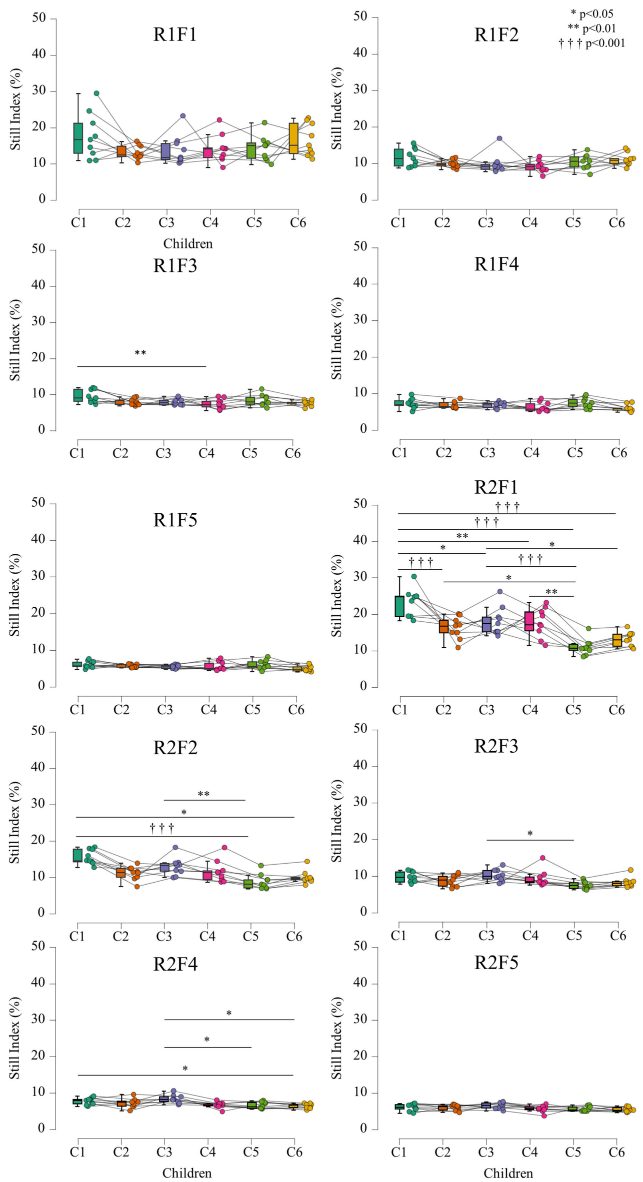


FIGURE 6. **Results of restlessness detection. Horizontal axis represents children, vertical axis represents still index (%).**

TABLE 3. SDQ2 item results.

Children (gender)	Restlessness Evaluation	
	Teacher A	Teacher B
1 (G)	0	0
2 (G)	0	1
3 (G)	0	0
4 (G)	0	1
5 (B)	0	0
6 (B)	0	1

G: girl, B: boy
SDQ 2: Restless, overactive, cannot stay still for long
0: Not true, 1: somewhat true, 2: certainly true

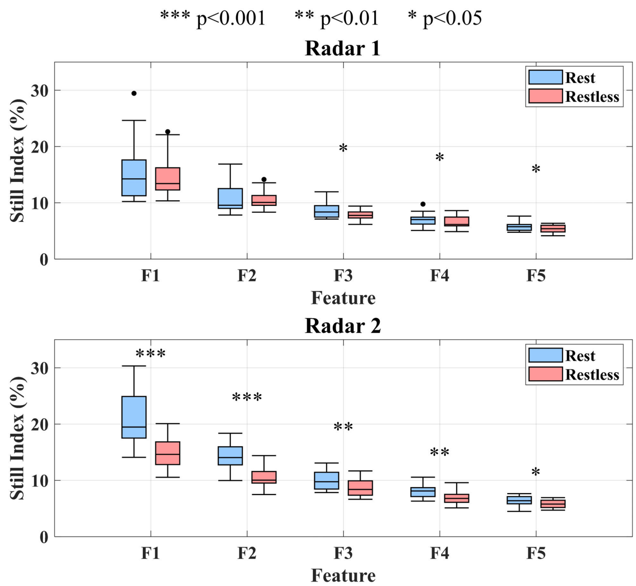


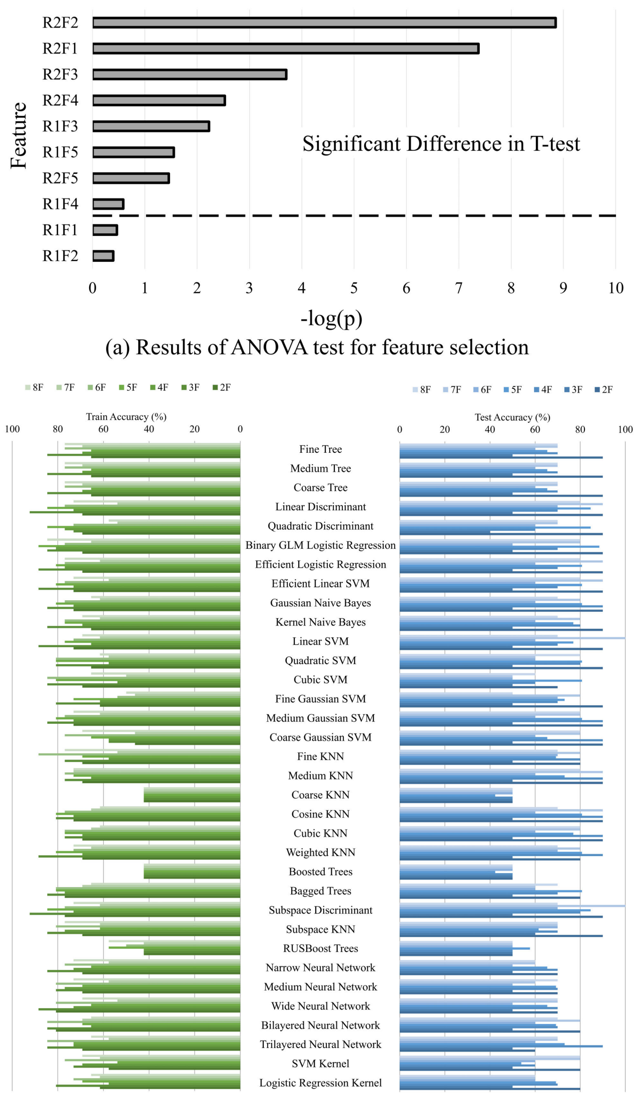
FIGURE 7. **Results of ten features for restlessness classification. Horizontal axis represents features, vertical axis represents still index (%). Red box represents Rest group, red box represents Restless group.**

analysis, which is the opposite to the subjective evaluation. Therefore, for restlessness classification, only the data that aligns with both radar and questionnaire results were used. This means that C1 and C3 were labeled as group 'rest', C2 and C6 were labeled as group 'restlessness'.

B. RESTLESSNESS CLASSIFICATION

The pair samples T-test was conducted to analyze 10 features from rest and restless groups, aiming to select suitable features for ML. Fig. 7 illustrates the chosen features for ML- based classification. Features 3, 4 and 5 of radar 1, and all features of radar 2 showed significant differences. Details about features selection can be found in Appendix B from Table 11 to Table 15.

Fig. 8 illustrates the selection of features and the classification accuracy of ML using different features. Because there were eight features from two radar systems that showed significant difference, we calculated the ANOVA p-value for these features, and use $-\log(p)$ to rank importance of each feature. As shown in Fig. 8 (a), feature 2, 1 and 3 from radar 2 showed the highest importance, followed by feature 4 from radar 2, features 3 and 5 from radar 1. Thus, we used



(a) Results of ANOVA test for feature selection

(b) Results of restlessness classification

FIGURE 8. Results of restlessness classification using machine learning models. (a) Features selection, (b) Machine learning training and test accuracy.

the features from top 2 to top 8 (total 7 feature pattern, 8F indicates top 8, 7F indicates top 7, and so forth) to train the ML models. Among the tested ML models, two of them showed the highest accuracy of 100% in classifying rest and restlessness (see Fig. 8 (b)).

We compared the accuracy of our method to other ML methods for classifying restless, referencing [22]. We selected the highest accuracy from different methods in each study, including MRI (Magnetic Resonance Imaging), EEG (Electroencephalogram), ECG (Electrocardiogram), MEG (Magnetoencephalography), questionnaire, game simulation, accelerometer, actigraphy, pupillometric, and Twitter (a total of 83 studies). The results are summarized in Table 4. In addition to accuracy, we compared these models using four other indices: non-invasive, body restraint, multi-target, and privacy protection. Generally, our method achieves a classification accuracy of 100% and outperforms other methods when considering non-invasiveness, lack of body restraint, potential for multi-target applications, and privacy protection.

IV. DISCUSSION

This pilot study aimed to explore the feasibility of utilizing millimeter-wave radar for the detection and classification of restlessness in children within a real classroom environment. The experiment, conducted over nine days in a primary school setting, involved two millimeter-wave radar systems to monitor the regular activities of 14 children. The collected radar data underwent analysis, and distinctive features were extracted for restlessness detection and classification through ML techniques.

The study's initial objective, confirming the feasibility of restlessness detection using millimeter-wave radar in a real classroom environment, yielded encouraging results. The radar's precision in capturing distance and micro-movement measurements proved instrumental in monitoring the diverse array of body movements exhibited by children. Notably, the privacy protection aspect inherent in millimeter-wave radar technology ensures a balance between data richness and ethical considerations in sensitive environments. Restlessness, as measured by teacher-rated questionnaire, was successfully detected through the radar's capability to sense environmental changes. The inherent capacity of the radar to capture nuanced body movements addresses the limitations associated with traditional wearable actigraphy devices, offering valuable insights into real-life scenarios.

The second objective, applying standard machine learning algorithm and training machine learning models for restlessness classification, marked a significant advancement in the study. The utilization of specific features derived from millimeter-wave radar data demonstrated promising results in distinguishing between resting and restless individuals. The selected features, such as the ratios of the top five most frequently appeared coordinates, played a crucial role in achieving a classification accuracy of 100% through ML models. A comparative analysis of our proposed radar system and ML outcomes against existing literature shows the advantages and limitations of different methodologies. The non-invasive, multi-target, and privacy-protected features of our method position it favorably against other approaches, contributing to both technical advancements and societal considerations.

To the best of our knowledge, this study represents the first and only instance where FMCW millimeter-wave radar technology has been employed for the detection of restlessness. In contrast to traditional approaches that rely on vital signal monitoring [23], [24], [25], which necessitate the attachment of sensors to the body, rendering prolonged monitoring uncomfortable, our proposed approach utilizing millimeter-wave radar presents a promising non-invasive and

TABLE 4. Restlessness classification summary.

Study	Method	Features	Machine Learning	Non-invasive	No Body Restraint	Multi-target	Privacy Protection	Accuracy (%)	Sample Size
[23]	MRI	FCF	AE	-	-	-	+	99.6	627(267)
[24]	EEG	PSR-PSO	NPC	-	-	-	+	100	97(47)
[25]	ECG	Entropy	Ensemble	-	-	-	+	87.2	123(45)
[26]	MEG	Coherence	Kernel SVM (RBF)	-	-	-	+	92.7	50(25)
[27]	Questionnaire	CPRS	Linear SVM	+	+	-	-	100	35(23)
[28]	Performance	CPT	Random Forest	+	-	-	+	87	458(213)
[29]	Accelerometer	End-to-end	CNN	+	+	-	+	98.6	red148(73)
[30]	Actigraphy	28 metrics	SVM (unspecified)	+	+	-	+	83.1	155(44)
[31]	Pupillometric	Eye vergence	Kernel SVM (RBF)	+	-	-	-	96.3	92(43)
[32]	Twitter	Topic	SVM (unspecified)	+	+	-	-	76	2061(1032)
[33]	RGBD	DTW	GMM	+	+	+	-	94.4	6(3)
Ours	**FMCW Radar**	**7 still index**	**Linear SVM**	+	+	+	+	**100**	**4(2)**

+ represents the method is capable, - represents the method is incapable
Sample Size: Total (Restlessness)

nonrestrictive solution, offering a user-friendly alternative for long-term monitoring applications. The study by Lee et al. [13] proposed a novel assessment of hyperactivity in young individuals with Attention Deficit Hyperactivity Disorder (ADHD) using impulse-radio ultra-wideband (IR-UWB) radar technology. Their findings indicated that the average activity function differed between children with and without hyperactivity, with those exhibiting hyperactive behavior displaying elevated activity levels, corroborating our observations. However, it is noteworthy that their research endeavor involved a relatively brief monitoring period of 22 minutes, substantially shorter than the duration of our study, which spanned over 400 minutes. Our nine-day real classroom environment experiment has yielded valuable data pertaining to the daily activity patterns of children, facilitating a deeper understanding of their behavioral dynamics. It is common to establish a baseline activity level prior to the commencement of the experiment, as it serves as a crucial reference point for the data. However, in the context of real-world school environment monitoring, implementing such a baseline measurement presents considerable challenges, as it is imperative to minimize disruptions to the normal flow of school activities. Conversely, in the present study, we detected children's restlessness through the lens of the ratio of still time rather than relying solely on activity level. Consequently, the necessity for a baseline measurement is rendered less critical within the parameters of our methodological approach.

With the increasing adoption of millimeter-wave radar in various technological and biomedical engineering applications, the health implications and biological effects on humans have garnered considerable attention from researchers. Generally, the biological effects of millimeter-waves on living organisms can be categorized into thermal and non-thermal effects [34]. Specifically, the biothermal effect is related to the substantial presence of water molecules in organisms, such as skin and corneal tissues [35]. Given that millimeter-waves are classified as non-ionizing radiation, implying that they lack sufficient energy to ionize atoms or molecules, and considering that the children were seated at a minimum distance of 2 m from the radar during the study, it is reasonable to conclude that the millimeter-wave radar did not exert any detectable thermal effects. Yaekashiwa et al. found no observable changes in human skin fibroblast cells after exposure to millimeter-wave radiation in the frequency range of 70-300 GHz [36], further substantiating the absence of biogenetic damage caused by the non-thermal effects of millimeter-waves. Moreover, millimeter-wave radar technology has been widely employed in applications aimed at enhancing children's safety and well-being, including presence detection systems to prevent incidents of children being left unattended in vehicles and succumbing to heatstroke [37], monitoring of children's sleep stages [38], and detection of vital signs in children [39]. There may be concerns regarding the potential impact of excessive monitoring on children's emotional well-being, such as feelings of being overly controlled or a violation of privacy [40], [41]. However, to the best of our knowledge, there is no direct evidence indicating that the use of millimeter-wave radar affects children's psychological or mental health. On the contrary, recent studies suggest that millimeter-wave radar holds significant potential as an effective tool for monitoring mental stress [42] and recognizing emotions [43].

The proposed approach to measure childre's restlessness is designed to be minimally affected by a fast movement, as the activity levels are evaluated based on time variations in echo intensity rather than Doppler frequency. Using Doppler frequency would require target velocities to remain below the Nyquist velocity, which is determined by the sampling frequency. However, this limitation does not apply to our approach. Nevertheless, our method involves incoherent averaging, as shown in Eq. 5. If a target moves beyond the spatial resolution within the averaging period T_p, the resulting radar image $I_{\rm p}(t, r, \theta)$ will become less focused, which would negatively impact the accuracy of the approach. Basically, the radar's spatial resolution is defined in both range (distance) and angular (azimuth) directions. As shown in Table 1, the range resolution is 44.7 mm, and the angular resolution is 8.5 degrees. For example, at a distance of 3.0 m, the spatial resolution determined by the angular resolution equates to approximately 445 mm. Therefore, at 3.0 m, the combined spatial resolution is about 445 mm by 45 mm. If the distance between two children exceeds this spatial resolution, the radar echoes can be separated, allowing the system to distinguish between them. However, if the children are closer than the spatial resolution, the echoes will merge, and our approach will be unable to accurately estimate their individual activity levels. Developing a technique that maintains robustness even with fast-moving targets is a topic of great interest, which we hope to explore in future research. Moreover, since distinguishing between closely located children is challenging at the current spatial resolution, future work could aim to improve radar resolution. Developing these enhancements would increase the system's applicability in crowded settings, making it more robust in real-world classroom scenarios.

A pertinent concern in this pilot study involves the dynamic and spontaneous nature of children's activities and the potential implications of deploying millimeter-wave radar technology within a lively classroom setting. Ethical, Legal, and Social Issues (ELSI) are paramount in research that involves monitoring children's behavior. To address these concerns, we provided comprehensive explanations and obtained informed consent from both children, parents teachers, and school management prior to the experiment. Additionally, during the post-interview phase, we collected feedback on the radar measurement process from teachers, parents, and the students themselves, capturing a range of perspectives, both positive and negative. We did not include this result in the main manuscript because it is beyond the scope of the study. However, readers can find the interview results in Appendix C. Importantly, our interview results indicate no evidence that the technology or experimental process adversely affected students' natural behaviors within the school environment. As we consider scaling up our study, we recognize the necessity of further addressing ELSI concerns. This includes ensuring that students have the right to opt out of the measurement and guaranteeing that the information collected is not utilized for personal evaluation purposes, such as academic grading or internal assessments. Upholding these ethical standards is essential to preserving the integrity of childhood experiences and ensuring that technological interventions do not compromise children's health or freedom.

In this pilot study, we employed standard machine learning models to assess the feasibility of using features derived from millimeter-wave radar for classifying children's restlessness. Our primary goal was to evaluate whether these radar-derived features could effectively support classification tasks. By applying standard machine learning models, we confirmed that these features provided an acceptable level of accuracy for this initial classification purpose. From our literature review, we found that among the various machine learning modes, SVM is one of the most popular methods, and applying SVM for restlessness classification has shown high accuracy (often > 90%, as shown in Table 4). This is reasonable, as SVM has been proven to be a powerful supervised learning algorithm used for classification tasks across various domains [44]. Among the different types of SVM, most researchers have employed either linear SVM ([27] and ours) or kernel SVM ([26], [31]). The main difference between linear SVM and kernel SVM lies in how they handle the data and the type of decision boundaries they can create. Linear SVM assumes that the data can be divided by a 2-D straight line or a hyperplane in higher dimensions, making it suitable for linear separable data. On the other hand, kernel SVM extends this concept by applying a kernel function (such as polynomial or radial basis function (RBF)) to map the data into higher dimensional space. This transformation allows kernel SVM to create complex decision boundaries, making it suitable for handling non-linearly separable data.

In this study, our aim was to investigate the utility of standard machine learning models in the novel context of radar-based restlessness classification—rather than to innovate in machine learning algorithms themselves. Our study's novelty lies in its application context—integrating machine learning with radar data to tackle classroom restlessness detection, which has unique practical challenges. However, we acknowledge that these standard models may not reflect the most recent advancements in machine learning, and our study's optimizations were limited to feature selection and cross-validation. Emerging state-of-the-art methods, such as meta-learning models [45], CNN-LSTM multimodal foundation models [46], graph neural networks [47], and transformer-based architectures [48], [49], offer significant potential to enhance classification performance in future applications. These advanced approaches are particularly relevant, as they can better capture complex spatial-temporal relationships, process multimodal data more effectively, and may yield additional insights and improved accuracy. In future research, we aim to explore the applicability of these advanced models to radar-based restlessness classification. For instance, meta-learning approaches could enable rapid adaptation to new patterns in radar data through one-shot or few-shot learning capabilities [45]. CNN-LSTM models may provide a robust framework for handling multimodal features and complex scenes [46]. Likewise, graph neural networks and transformer-based architectures have shown promise for capturing intricate spatial and temporal dependencies in radar data [47], [48], [49]. Integrating these models into our framework could improve resilience against environmental interference, enhance accuracy, and deepen understanding of behavioral patterns in radar-based monitoring.

The study's contributions extend beyond technical advancements to address practical implications for various stakeholders. For children, the non-invasive nature of the approach prioritizes their well-being and ensures unrestricted activities, while the emphasis on privacy protection fosters a sense of autonomy. Parents, teachers, and school policymakers stand to benefit from the implementation of a multi-target system for restlessness measurement. The objective information provided by millimeter-wave radar contributes to evidence-based support and education for children, which would complement health and behavioural monitoring traditionally conducted by teachers and school-based health professionals. Additionally, the ML-based computer-aided screening offers potential efficiency in clinical assessments, addressing the global shortage of trained specialists.

This pilot study acknowledges several limitations that should be considered for a comprehensive understanding of its findings. First, the study focused on a limited set of school activities during the observed days. As restlessness could manifest under wider range of school activities which may not be limited to the recorded period of time during the school days, future research could explore restlessness during various class activities. This would provide a more nuanced understanding of how contextual factors influence children's activity levels. Second, the small sample size of six children analyzed for restlessness detection and the further reduction to only four children for ML model training due to matching with subjective evaluation results pose challenges to the generalizability of the findings. Overfitting is a critical issue in machine learning, particularly with small sample sizes, as models can become overly specialized to the training data, limiting model generalizability. To mitigate this risk, we employed several robust strategies: (1) We implemented a 5-fold cross-validation during the training process, a widely accepted technique that helps prevent overfitting by iteratively partitioning the data into training and validation subsets, thereby ensuring the model is evaluated on unseen data. (2) As illustrated in Fig. 8 (b) on the manuscript, we have reported not only the training accuracy but also the testing accuracy. This crucial step allows for the direct assessment of potential overfitting, as a significant lower testing accuracy compared to training would be indicative of overfitting. (3) Feature selection was performed to identify and retrain only the most informative predictors for the classification. This technique commonly referred to as removing features in machine learning, reduces model complexity and acts as a regularization strategy, mitigating overfitting tendencies. Collectively, these rigorous measures provided robust safeguard against overfitting, despite the limited sample size. While we acknowledge the inherent challenges posed by small datasets, we believe that our proposed methodology has thoughtfully addressed and controlled overfitting problem. Nevertheless, caution is warranted in interpreting the results, and future studies with larger and more diverse participant groups are crucial to validate and extend the conclusions drawn from this pilot study. It is also important to notice that in the real classroom, there were multiple reflective surfaces causing multipath interference. Because of such multipath effects, the radar signal contains artifacts that do not correspond to the actual target children, even we removed the static clutter in the radar signal processing. Despite this, our results indicate that the radar-based measurement has a potential to evaluate children's activity levels when considering the non-invasiveness, lack of body restraint, potential for multi-target applications, and privacy protection. Our next step is to develop a signal processing method to suppress such multipath effect to improve the performance of our approach.

The variation in SDQ results between two teachers highlights a potential source of bias, possibly influenced by differences in cultural background. One teacher, a local Japanese national, is responsible for overseeing the entire class, while the other teacher is an English instructor from an overseas region. Since both teachers spend a significant amount of time interacting with the children on a daily basis, it was presumed that they possessed sufficient familiarity with the children to accurately rate the SDQ questionnaire. To address the potential bias in subjective evaluations between teachers, we adopted an approach where children were labeled as "restless" if either or both teachers answered 1 (somewhat true) or 2 (certainly true) on the SDQ 2. This method was designed to minimize bias by avoiding reliance on just one teacher's evaluation. While this helps to control bias, we recognize that it is difficult to completely eliminate bias in any subjective assessment. As such, future research should aim for a larger and more diverse survey, incorporating additional perspectives, such as parental input during at-home evaluations. This would help further reduce bias and enhance the robustness of the restlessness assessments. The study's analysis focused solely on the range direction of radar data, limiting the examination of special movements such as head movements and potential classmate influences. Future research could explore improvements in radar parameters and algorithms to address these limitations and provide a more comprehensive understanding of children's activities.

Despite these limitations, this pilot study serves as a pioneering exploration of a non-invasive approach to monitoring children's school activity using millimeter-wave radar technology. The study anticipates the continued development of this technology, emphasizing its potential for non-invasive mental health measurements in real classroom environments. Moreover, given that the trait of restlessness overlaps with clinical definition of a developmental condition, Attention Deficit and Hyperactivity Disorder, similar technology could be utilized for screening such clinical conditions within the school environment. However, note that several major barriers exist on such screening, such as ethical issues on screening children's trait within school environment, ownership of children's data, legal and ethical issues on child protection, as well as technological challenges requiring for further refinement of recording and analyzing methodologies [50]. Future research endeavors should address technical challenges, including random body movement and the development of robust algorithms for vital signal analysis from millimeter-wave radar systems.

V. CONCLUSION

In conclusion, this pilot study demonstrates the potential of millimeter-wave radar and ML in revolutionizing the assessment and classification of restlessness in children. The integration of advanced technology not only addresses the limitations of traditional methods but also introduces a novel, efficient, and ethical approach to restlessness detection in real-world educational settings. As technology continues to advance, further research in this domain is warranted to refine methodologies, enhance accuracy, and explore the broader societal implications of implementing such innovative technologies in the field of child psychology and education.

DATA AVAILABILITY STATEMENT

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

AUTHOR CONTRIBUTIONS

Tianyi Wang: Conceptualization; Formal Analysis; Methodology; Software; Visualization; Writing–Original Draft Preparation; Writing–Review & Editing.

Takuya Sakamoto: Data Curation; Investigation; Software; Validation; Writing–Review & Editing; Supervision.

Yu Oshima: Investigation; Data Curation.

Itsuki Iwata: Methodology; Software.

Masaya Kato: Investigation.

Haruto Kobayashi: Investigation.

Manabu Wakuta: Conceptualization; Project Administration; Supervision.

Masako Myowa: Funding Acquisition; Investigation.

Tokomo Nishimura: Investigation: post-interview; Writing–Review & Editing.

Atsushi Senju: Writing–Review & Editing; Funding Acquisition; Project Administration.

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CONFLICT OF INTEREST

The authors declare the research was conducted in the absence of any commercial or financial relationship that could be construed as a potential conflict of interest.

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