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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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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 proposing an algorithm for restlessness classification through machine learning. 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.

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 be-

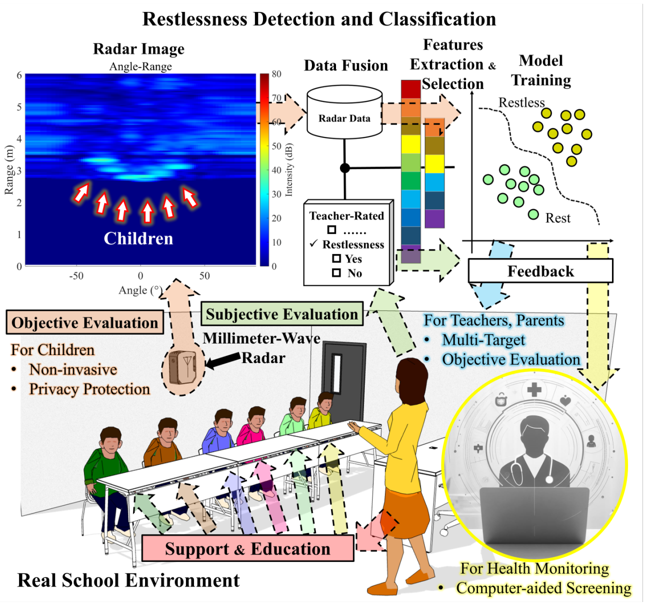


FIGURE 1. Study concept and vision.

havioural 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.

One of the major challenges is the time and human resources 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 over- come 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 employed machine learning (ML), which has found extensive application in computer-aided diagnosis for analyzing both imaging and non-imaging data [16]. 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: Proposing an algorithm and training a ma- chine learning model for restlessness classification, incorporating both subjective and objective restlessness 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

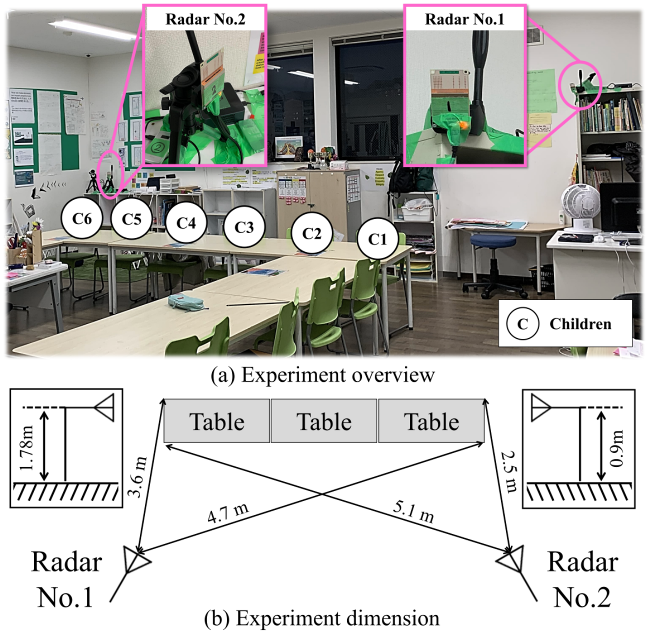


FIGURE 2. **Experiment overview and dimension.**

were instructed to behave freely in regular seating patterns, either a U pattern or a random pattern corresponding to the school activity. Two radar systems were positioned at the back of the classroom, as illustrated in Fig. 2 (b). 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, 2.5 m from the right edge of the table, and at a height of 0.9 m. 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, pro-social 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 Figure 3. The analysis focused on data collected when children were seated in the U pattern to ensure both radars recorded the activities. Additionally, for training the ML model, only data where radar analysis matched the SDQ 2 results were used. Consequently, data from six children were utilized for restlessness detection, and 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. This study was approved

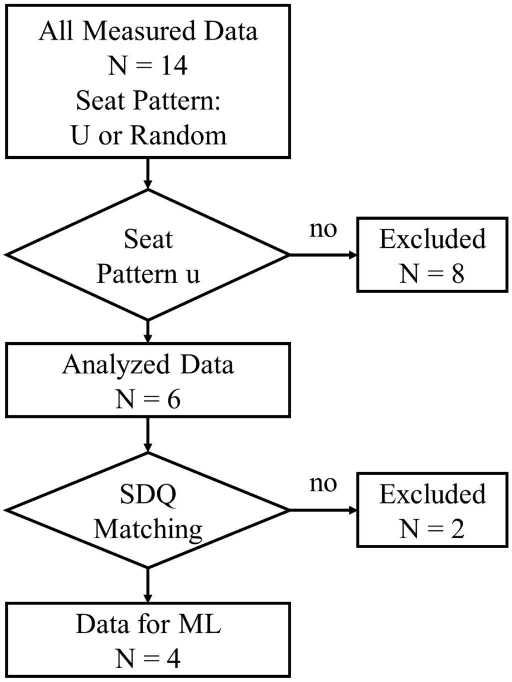


FIGURE 3. Flowchart of data selection.

by the Ethics Committee of the Department of Electrical Engineering, Kyoto University (No. 202219).

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 [18] (T14RE_01080108_2D, S-Takaya Electronics Industry, Okayama, Japan) to record children's activity. The parameters for the radar system can be found in Table 1. The main structure of the radar system is illustrated in Figure 4. The radar image, denoted as $I_p(t, r, \theta)$, was calculated following the methodology outlined in our previous study [8], where t, r, and θ represent time, range, and angle, respectively.

TABLE 1. Parameters of T14RE FMCW Radar

Modulation	T14RE
Size (mm)	W50 × D4.7 × H85
Center Frequency (GHz)	79
Wavelength (mm)	3.8
Bandwidth (GHz)	3.6
Range Resolution (mm)	45
Sampling Frequency (Hz)	100
TX Power (dBm)	24
Number of Transmitting Elements	3
Number of Receiving Elements	4
Number of Virtual Elements	12

Figure 5 illustrates the restlessness detection processing. After obtaining the radar image (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)).

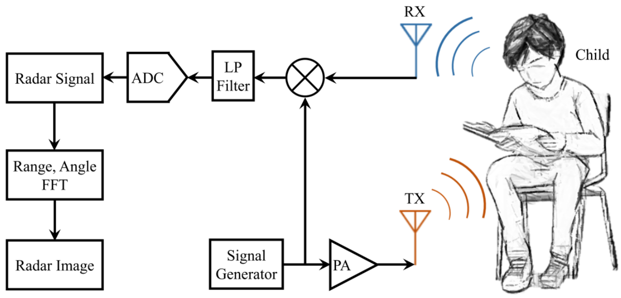


FIGURE 4. Radar system block diagram.

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 seconds 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. For restlessness classification, 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, 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: $\omega^2 < 0.01$ indicates a trivial effect, $0.01 < \omega^2 < 0.06$ suggests a small effect, $0.06 < \omega^2 < 0.14$ 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

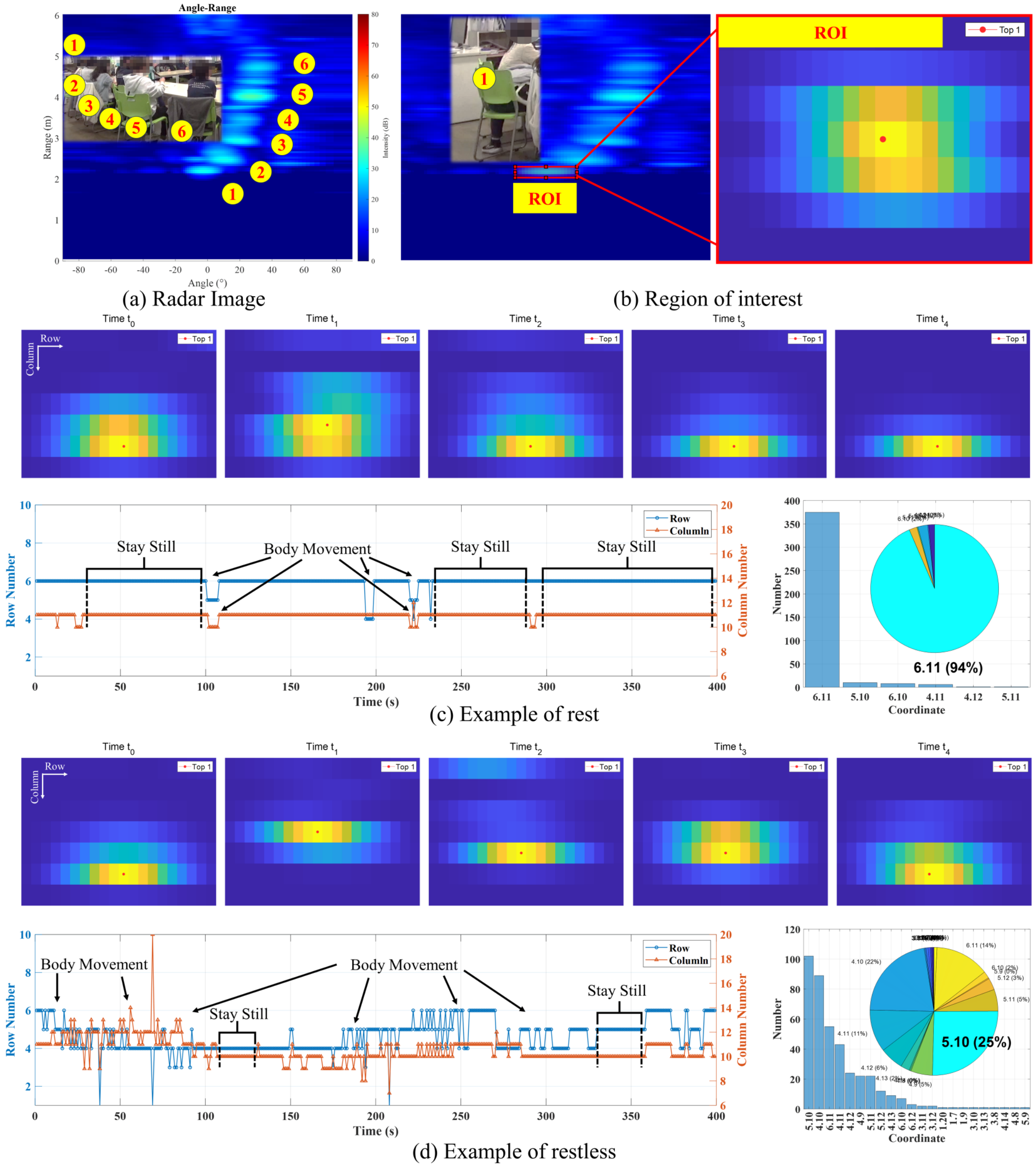


FIGURE 5. Data processing. (a) Example of radar image, horizontal axis represents angel (°), vertical axis represents range (m). (b) Example of ROI for one child. Red square represents the chosen ROI, red circle represent the maximum intensity point in the ROI. (c) Example of rest for 400 sec. (d) Example of restlessness for 400 sec. 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 sec.

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 < 0.2 indicates a trivial effect, $0.2 <$ Cohen's d < 0.5 suggests a small effect, $0.5 <$ Cohen's d < 0.8 indicates a medium effect, and Cohen's d > 0.8 implies a large effect. $R_B < 0.1$ indicates a trivial effect, $0.1 < R_B < 0.3$ suggests a small effect, $0.3 < R_B < 0.5$ 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.

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**

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

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

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 analysis, which is the opposite to the subjective evaluation. Therefore,

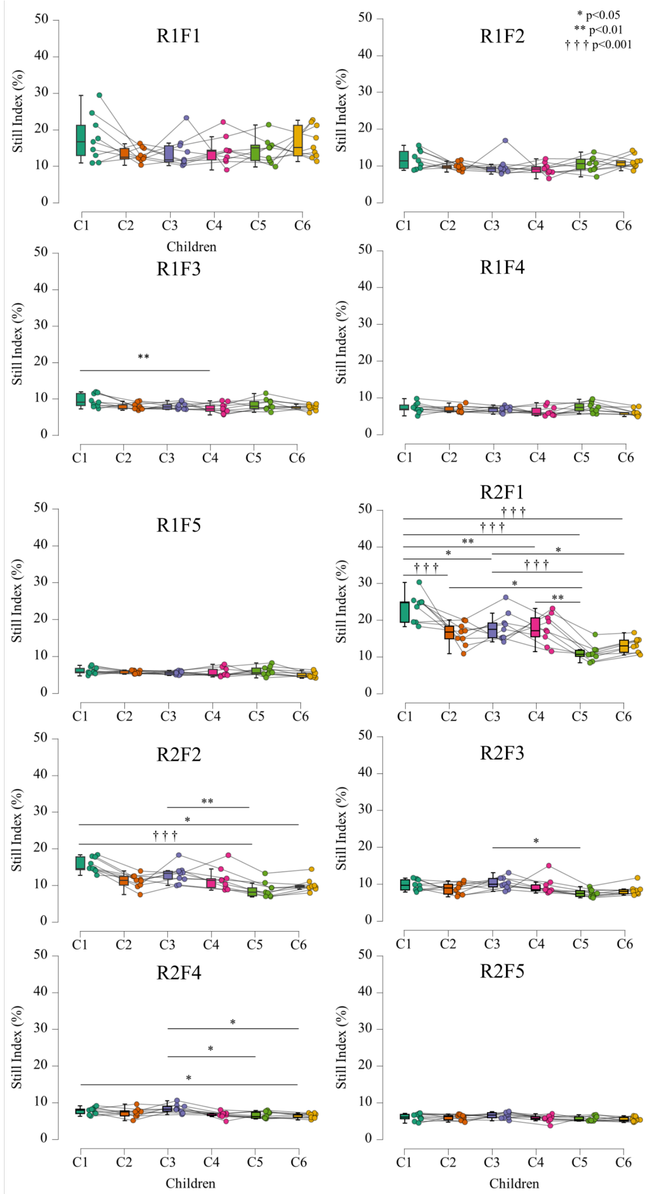


FIGURE 6. Results of restlessness detection. Horizontal axis represents children, vertical axis represents still index (%).

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 was 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 Tables 11 to 15.

Fig. 8 illustrates the selection of features and the classi-

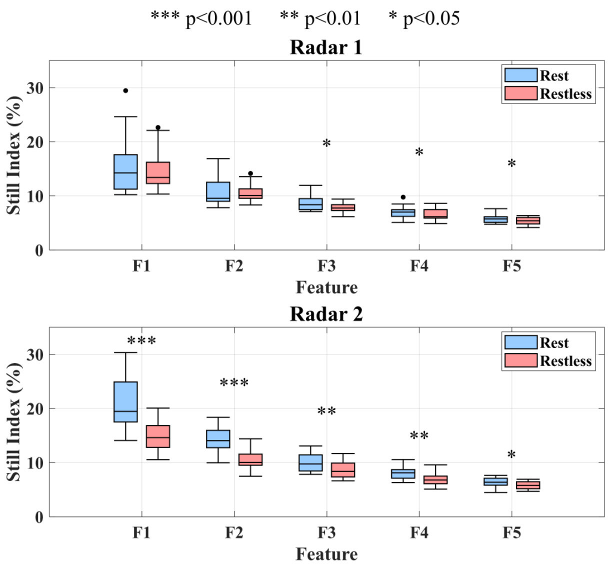


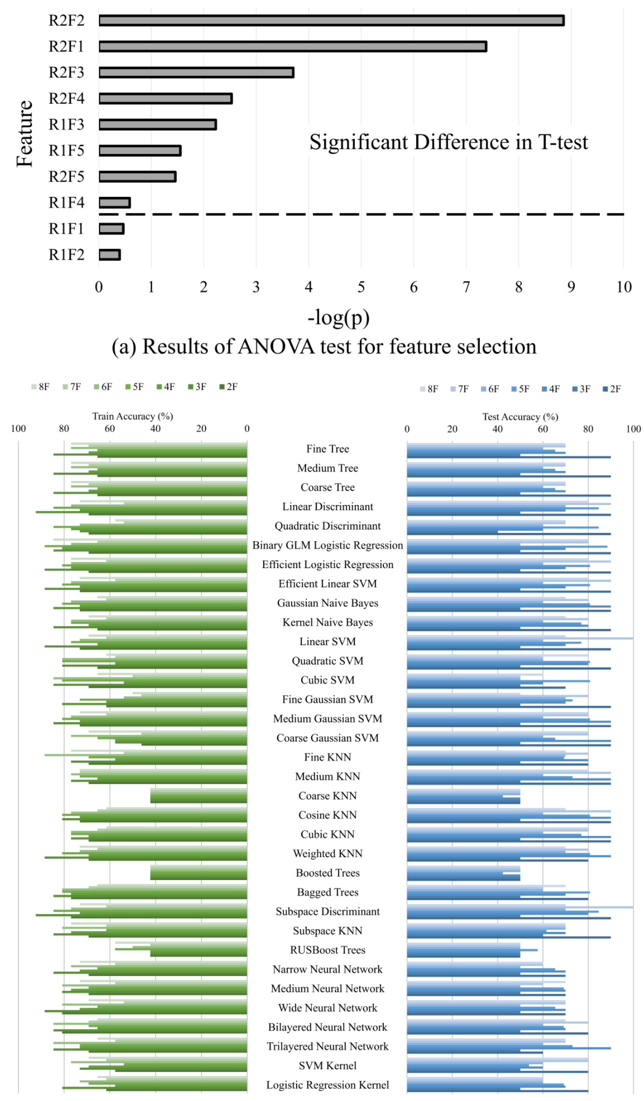
FIGURE 7. **Results of ten features for restlessness classification. Horizontal axis represents features, vertical axis represents still index (%). Red box represents Rest group, red box represents Restless group.**

fication accuracy of ML using different features. Because there were eight features from two radar 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 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 [19]. We selected the highest accuracy from different methods in each study, including MRI, EEG, ECG, MEG, 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



(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.**

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

TABLE 4. Restlessness Classification Summary

Study	Method	Features	Machine Learning	Non-invasive	No Body Restraint	Multi-target	Privacy Protection	Accuracy (%)
[20]	MRI	FCF	AE	-	-	-	+	99.6
[21]	EEG	PSR-PSO	NPC	-	-	-	+	100
[22]	ECG	Entropy	Ensemble	-	-	-	+	87.2
[23]	MEG	Coherence	SVM	-	-	-	+	92.7
[24]	Questionnaire	CPRS	SVM DT	+	+	-	-	100
[25]	Performance	CPT	Random Forest	+	-	-	+	87
[26]	Accelerometer	End-to-end	CNN	+	+	-	+	98.6
[27]	Actigraphy	28 metrics	SVM	+	+	-	+	83.1
[28]	Pupillometric	Eye vergence	SVM	+	-	-	-	96.3
[29]	Twitter	Topic	SVM	+	+	-	-	76
[30]	RGBD	DTW	GMM	+	+	+	-	94.4
Ours	**FMCW Radar**	**7 still index**	**Linear SVM**	+	+	+	+	**100**

+ represents the method is capable, - represents the method is incapable

with traditional wearable actigraphy devices, offering valuable insights into real-life scenarios.

The second objective, proposing an algorithm and training a ML model 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.

The study's contributions extend beyond technical advancements to address practical implications for various stake- holders. 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. Firstly, 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. 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. 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. The variation in SDQ results between two teachers high- lights a potential source of bias, possibly influenced by differences in cultural background. Future research should consider a larger and more diverse survey scale, including input from parents during at-home evaluations, to mitigate potential biases and enhance the robustness of 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 (ADHD), 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 techno- logical challenges requiring for further refinement of recording and analyzing methodologies [31]. 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.

ETHICS STATEMENT

This study was approved by the Ethics Committee of Department of Electrical Engineering, Kyoto University, No. 202219.

AUTHOR CONTRIBUTION

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.

Tomoko Nishimura: 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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