Labyrinth: Fayoum Journal of Science and Interdisciplinary Studies 3 (2025) 2 in press

Fayoum University

Contents lists available at Egyptian Knowledge Bank

Labyrinth: Fayoum Journal of Science and Interdisciplinary Studies

Journal homepage: https://lfjsis.journals.ekb.eg/

Touching the Difference: A Deep Learning Approach to Child-Adult Detection Based on Touch Gestures

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ARTICLE INFO

Keywords:

Age Group Classification
Child Detection
Touch Gestures
Smartphone
Behavioral Analysis

ABSTRACT

Accurately distinguishing between children and adults based on smartphone interaction behaviors is essential for enabling safe and personalized digital experiences. This study addresses the need for automated child-adult detection by leveraging advanced interaction analysis techniques. We employed two distinct neural network architectures (MLP and DL4j) to classify users as children or adults. These models were trained and evaluated using three datasets: Tap-Gesture, Stroke-Gesture, and the Combined-Gestures dataset comprising both interaction types. Using a diverse dataset of 198 participants across various ages and demographics, the models extracted a set of discriminative features from raw touch data, achieving high classification accuracy across all datasets. The results highlight the effectiveness of our models: the MLP model achieved its best performance on the stroke dataset with an AUC of 90% and an EER of 19.04%, while the DL4j model reached an AUC of 91% and an EER of 17.33% on the same dataset. This research offers valuable insights for the development of personalized applications, security systems, and accessibility tools, contributing to the creation of safer and more inclusive digital environments.

1. Introduction

Smartphones have become an important device, serving as essential tools for communication, education, entertainment, and daily tasks. As mobile devices increasingly integrate into the lives of users of all ages, personalizing interactions to suit different age groups has become an important focus. Children, in particular, represent a growing segment of smartphone users [1], so automatic personalization, which can be performed automatically by detecting whether the user is a child or an adult, can improve the quality of digital interaction. Content, features, and security measures can be tailored to specific age groups (e.g., children and adults) to create a more secure and appropriate digital environment. For example, social networks can protect children from inappropriate content by automatically detecting it, rather than relying on traditional age verification methods, such as birth date entry, which can be bypassed by entering a false date [2]. Touch gesture analysis provides a more robust and accurate solution. Similarly, parental controls can be activated for children to ensure a safe and appropriate digital experience, particularly in households with shared devices between children and adults [3]. Additionally, accessibility features can be optimized based on age, enhancing user experience and independence [4].

This paper utilizes touch gesture patterns to distinguish between adult and child users using novel deep learning models. Our models can accurately classify users based solely on their touch behavior by analyzing how they interact uniquely with their devices. We collected a diverse dataset containing touch gestures from different users of different ages to train and evaluate our models. This paper introduces two deep learning models, a Multilayer Perceptron (MLP) and a DeepLearning4j (DL4J) network with an LSTM layer. These models extract features from the raw touch data, enabling them to identify differences between adult and child gestures. The experimental results demonstrate the effectiveness of our approach, achieving high accuracy in classifying users. This research can be beneficial for the future of AI systems. By enabling precise user age classification, our model can contribute to the development of more personalized, secure, and accessible digital experiences for users of all ages.

Few studies have explored using deep learning for the detection of child users based on their behavior. One notable study [5] focused on analyzing gestures such as scrolling, swiping, and pinching. By representing these gestures as images, the researchers employed transfer learning techniques with pre-trained Convolutional Neural Networks (CNNs) to extract meaningful features and accurately classify users based on their age. Another study by Lin et al. [6] took a different approach, collecting multi-finger interactions, accelerometer, and gyroscope data while participants played mobile games.

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DOI: 10.21608/ifjsis.2025.387680.1117
Received 11 June 2025; Received in revised form 8 October 2025; Accepted 11 October 2025
Available online XX October 2025

Deep Neural Networks (DNNs) and CNNs were utilized to classify users into age groups with high accuracy. While [7] adopted a more holistic approach, collecting unrestricted touchscreen interactions and various sensor readings. A combination of heuristic feature selection and deep learning was employed to identify relevant features and classify users into age groups.

Machine learning techniques have been widely explored for age estimation based on user behavior on touch-based devices. Tolosana et al. [8] investigated children's interactions with tablets, analyzing gestures such as tapping, dragging, zooming, and coloring. They utilized Support Vector Machines (SVM) for classification, demonstrating the potential of gesture features to distinguish age groups. Ruiz Garcia et al. [9,10] build on this study by expanding the feature set and analyzing a larger dataset of children's tablet interactions, employing Hidden Markov Models (HMM) to improve classification accuracy. Hossain and Pulfery [11,12] examined touch gestures, including hold time, finger size, and pressure, using Support Vector Regression (SVR) for age estimation and Logistic Regression for age group classification. Similarly, Zaccagnino et al. [13] explored a broader range of gestures, such as scrolling, swiping, tapping, dragging, pinching, and keystrokes, and applied classifiers like Random Forest for age detection. Recent work by Sait et al. [14] focused on different gestures, such as tapping, swiping, typing, zooming, and measuring finger size, using gyroscope readings. Using K-Nearest Neighbors (KNN), they demonstrated the feasibility of classifying users based solely on finger size. Complementing these efforts, Vatavu et al. [15] adopted a Bayes' rule classifier to distinguish single and multiple touch events. Hernandez Ortega et al. [16] and Acien et al. [17] explored the use of SVM classifiers with the Sigma-Lognormal model, extracting features from gestures such as dragging, dropping, tapping, and strokes to improve classification accuracy. Moreover, Rasheed et al. [18] explored different machine learning models to extract and classify features from six distinct touch gestures, while Li et al. [19] introduced the iCare system, which utilizes multiple classifiers to identify children based on tap and stroke gestures.

Prior work demonstrates the effectiveness of touch interactions for age classification, but often relies on controlled settings and traditional ML. To address this, we propose a deep learning approach that classifies children and adults directly from raw touch gestures, using real-world data to achieve high accuracy. The contributions of this study are as follows:

- A novel touch-based method for automated child/adult classification using deep learning is proposed.
- Two neural network architectures for gesture-based user classification are designed and compared.
- We collected a novel dataset of smartphone touch gestures from users across a wide age range, including children (3-12 years) and adults (19-65 years).

The rest of this paper is organized as follows: Section 2 details the methodology, including data collection, preprocessing, and model design. Section 3 presents experimental results and evaluation. Section 4 discusses the implications and limitations of the findings. Section 5 concludes the paper and outlines directions for future research.

2. Materials and Methods

2.1. Data Acquisition and Preprocessing

To construct our dataset, we collected interaction data from 198 participants, including both children and adults, in accordance with ethical research standards as in [3,19]. For minors, informed parental consent was obtained before participation. Table 1 presents the age distribution of the participants. To capture realistic user interaction data, we developed a custom data collection framework and deployed it on a Google Pixel XL smartphone. Participants were asked to engage in typical smartphone tasks that simulate real-world usage scenarios, including watching videos, playing mobile games, and browsing social media applications. The framework was designed to log comprehensive touch interaction data, including Timestamps, Screen Cartesian coordinates (X, Y), Pressure levels, Application context, and Gesture metadata.

An online preprocessing pipeline was implemented concurrently with data collection, which involved several stages to prepare the raw touch data for analysis. The pipeline first performed data cleaning by removing incomplete records and invalid touch events. Next, gesture segmentation separated continuous touch streams into individual gestures, which were then classified as either a tap or a stroke. A tap gesture is defined as a brief and isolated touch event where the finger contacts the screen momentarily without any significant movement. In contrast, a stroke gesture (also referred to as a slide or swipe) involves a continuous motion across the screen, with the user's finger dragging along the display surface. This was followed by normalization to scale numerical features to standard ranges. Finally, the pipeline performed feature extraction in real-time to calculate the spatial, temporal, and dynamic features described below.

Following gesture collection and feature extraction, we constructed three distinct datasets:

1. Tap-Gesture Dataset: Contains only tap gesture data.
2. Stroke-Gesture Dataset: Contains only stroke gesture data.
3. Combined- Gestures Dataset: Integrates both tap and stroke gestures data.

Through careful participant selection, the design of comprehensive usage scenarios, and meticulous data preprocessing, we established a robust foundation for the subsequent feature extraction and model training processes.

Table 1: Participants' age distribution.

Class	Age	No. of users
Children	3-5	14
	6-9	60
	10-12	31
Adults	19-29	45
	30-39	30
	40-65	18

2.2. Feature Extraction and Analysis

Feature extraction serves as a critical step in transforming raw touch data into meaningful representations that capture age-related behavioral differences [15,18]. These differences stem from distinct motor control patterns, where developmental variations in coordination, precision, and cognitive processing lead to discernible disparities in how children and adults interact with touchscreens [19]. Motivated by these behavioral distinctions, this study focuses on extracting a targeted set of features designed to capture discriminative patterns across the spatial, temporal, and dynamic dimensions of touch interaction [20,21]. The selected feature categories are summarized in Table 2. A detailed description of the collected features is provided in the following subsections, including specific hypotheses for how each category distinguishes child and adult interaction patterns.

Table 2: Extracted features for touch gesture.

Feature category	Extracted features
Spatial	Up and down (x, y) coordinates
Temporal	Interstroke duration, gesture duration
Trajectory	Displacement, average curvature, gesture length
Pressure & size	Up, down, minimum, maximum, average
Acceleration & Velocity	Maximum velocity, average velocity

2.2.1. Spatial Features

The spatial features include the x and y coordinates of touch points, capturing the real-time positions of the user's touch on the screen. These coordinates are essential for identifying interaction patterns such as finger movements and gesture distances.

- Distance Between Two Points:

$$D_{i,j} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \quad (1)$$

, where (x_i, y_i) and (x_j,y_j) are the coordinates of two touch points.

2.2.2. Temporal Features

Temporal features reflect the timing aspects of user interactions. We extracted temporal features, such as interstroke duration (i.e., the time between consecutive gestures) and gesture duration (i.e., the total time of a single gesture). These features are essential as they help differentiate users based on the speed and frequency of their touch interactions. For instance, children may exhibit slower gestures compared to adults.

- Gesture Duration represents the time between the first and last touch point:

$$Duration = t_{end} - t_{start} \quad (2)$$

, where t_{start} and t_{end} are the times of the first and last touch, respectively.

- Interstroke Duration represents the time between consecutive gestures:

$$Interstroke\ Duration = t_{start}^{(n+1)} - t_{end}^{(n)} \quad (3)$$

, where $t_{start}^{(n+1)}$ and $t_{end}^{(n)}$ represent the start time of the next gesture and the end time of the current gesture, respectively.

2.2.3. Trajectory Features

The trajectory features include measures of displacement, average curvature, and gesture length. These features track the path of the touch across the screen and are useful for distinguishing between users. Younger users, in general, tend to make less precise and shorter gestures with greater curvatures.

- Displacement is the straight-line distance between the starting and end points of the gesture:

$$D_{disp} = \sqrt{(x_{end} - x_{start})^2 + (y_{end} - y_{start})^2} \quad (4)$$

, where (x_{start}, y_{start}) and (x_{end}, y_{end}) are the starting and ending positions of the gesture, respectively.

- Average Curvature represents the amount of deviation of the touch line from being a straight line, and is calculated based on the following formula:

$$K = \frac{|X'Y'' - Y'X''|}{(X'^2 + Y'^2)^{\frac{3}{2}}} \quad (5)$$

, where X and Y are row vectors of points in the stroke, and K represents the row vector of curvatures for each point in the stroke, and then we calculate the average of K to represent $S_{curvature}$ as follows:

$$S_{curveture} = \frac{1}{N}\sum_{i=1}^{n} K_i \quad (6)$$

- Gesture Length represents the total distance covered during the gesture:

$$L_{gesture} = \sum_{i=1}^{N-1} D_{i,i+1} \quad (7)$$

, where $D_{i,i+1}$ is the distance between consecutive touch points, and N is the total number of touch points in the gesture.

2.2.4. Pressure and Size Features

We captured pressure and size data during each touch interaction, including measures of up, down, minimum, maximum, and average pressure applied on the screen. These features offer insights into how the user interacts with the device physically, with children potentially using less pressure and having smaller touch areas than adults.

- Maximum Pressure:

$$P_{max} = max(P_1, P_2, \ldots, P_n) \quad (8)$$

, where P_i represents the pressure at the i-th touch point, and n is the total number of touch points in the gesture.

- Average Pressure:

$$P_{avg} = \frac{1}{n}\sum_{i=1}^{n} P_i \quad (9)$$

, where P_i is the pressure at the i-th touch point.

2.2.5. Acceleration and Velocity Features

Finally, we extracted acceleration and velocity features, including the maximum velocity and average velocity of the touch gestures. These metrics are essential for identifying differences in gesture dynamics, such as children generally exhibiting faster, less controlled movements than adults.

- Velocity is the rate of change in position:

$$V = \sqrt{(X')^2 + (Y')^2} \quad (10)$$

, where X and Y are the row vectors of points in the stroke and V is the row vector of velocities at each point.

- Acceleration is the rate of change of velocity:

$$a(t) = \frac{dV(t)}{dt} \quad (11)$$

, where $a(t)$ is the acceleration at time t, and $\frac{dV(t)}{dt}$ is the first derivative of velocity.

- Maximum Velocity:

$$Vmax = max(V_1, V_2, \ldots, V_n) \quad (12)$$

, where V_i is the velocity at the i-th time point.

- Average Velocity:

$$V_{avg} = \frac{1}{n}\sum_{i=1}^{n} V_i \quad (13)$$

, where V_i is the velocity at the i-th time point.

To improve the model's efficiency and accuracy, we applied feature engineering techniques to eliminate redundant features. This process reduces dataset dimensionality and enhances computational performance without compromising analytical accuracy. Pearson correlation analysis was used to detect and remove highly correlated features from the dataset.

2.3. Model Architecture and Implementation

To classify touch interaction data as originating from either a child or an adult, we implemented and evaluated two distinct neural network architectures using the Weka framework. The hyperparameters for both models were optimized through an iterative process of empirical testing, where various configurations were evaluated to select the values that yielded the best performance on our validation set. Both models were independently trained and evaluated on the Tap-Gesture, Stroke-Gesture, and Combined-Gestures datasets. Performance was assessed using standard classification metrics, which are detailed in the results section.

2.3.1. Network 1: Multilayer Perceptron (MLP)

The first model utilized a traditional Multilayer Perceptron (MLP) architecture, chosen for its proven effectiveness in learning non-linear relationships from feature vectors. The MLP was configured with multiple hidden layers to enable progressive abstraction of touch interaction patterns. The specific hyperparameters, finalized through empirical testing, are summarized in Table 3. The model was trained on the preprocessed datasets to identify discriminative features that distinguish between child and adult touch interactions.

Table 3: MLP Model Configuration.

Parameter	Learning rate	Momentum	Hidden layers	Epochs	Batch size
Value	0.1	0.2	5, 10, 20	500	500

2.3.2. Network 2: Deep Learning 4j (DL4j)

The second model was implemented using the DeepLearning4j (DL4j) library and incorporated a Long Short-Term Memory (LSTM) layer. This architecture was selected for its capacity to capture temporal dependencies inherent in the sequential nature of touch gesture data. The network's configuration, optimized for stable training and effective sequence modeling, is detailed in Table 4. The DL4j model was trained on the same preprocessed datasets to capture more complex and sequential patterns in touch behavior than the MLP.

Table 4: DL4j Model Configuration.

Parameter	Optimizer	Learning Rate	Epochs	Input Layer	Hidden Layer	Output Layer
Value	Adam	0.001	10	Dense (22 neurons, ReLU)	LSTM (10 neurons, ReLU)	Dense (2 neurons, Softmax)

3. Results

3.1. Overview

This section presents experimental results evaluating the effectiveness of the proposed model for classifying users as children or adults based on touch gesture data. The experiments were conducted using a labeled dataset of user interaction records, as described in Section 2.1. The primary objective is to assess the model's ability to accurately distinguish between child and adult users by analyzing features derived from their interaction behaviors. To ensure the robustness and generalizability of the results, the dataset was partitioned into training, validation, and test sets.

The evaluation process involves dividing the dataset into training, validation, and test sets, using a structured data partitioning strategy to prevent data leakage and ensure unbiased performance evaluation. The model is trained on the training set, validated during the training phase to monitor overfitting or underfitting, and finally evaluated on an independent test set to assess its generalization capability.

To comprehensively evaluate the performance of our child/adult classification model, we employed a diverse set of standard evaluation metrics. Each metric offers distinct insights into specific aspects of the model's behavior:

- Accuracy: Measures the overall correctness of the model predictions.
- Precision: Assesses the proportion of correctly identified positive instances among all instances predicted as positive.
- Recall (Sensitivity): Evaluates the model's ability to identify all actual positive instances.
- F1-Score: Provides a harmonic mean of precision and recall, especially useful in cases of class imbalance.
- AUC (Area Under the Curve): Measures the model's ability to distinguish between the two classes across various threshold settings.
- EER (Equal Error Rate**)**: Identifies the point at which the false acceptance rate equals the false rejection rate, offering a balanced trade-off measure.

These metrics collectively offer a comprehensive assessment of the model's classification performance, robustness, and generalization ability. The results underscore the importance of feature selection and hyperparameter optimization, which contribute significantly to achieving competitive accuracy compared to existing approaches.

3.2. MLP Model Results

We evaluated the performance of the MLP model for child/adult classification across three datasets: Tap-Gesture, Stroke-Gesture, and Combined-Gestures datasets. Table 5 summarizes the classification performance in terms of Accuracy, Precision, Recall, F1-score, AUC, and EER.

The MLP model exhibited its highest performance on the Stroke-Gesture dataset, achieving an accuracy of 82.83%, a precision of 83%, a recall of 82.80%, an F1-score of 82.90%, an AUC of 90%, and an EER of 19.04%. Comparatively, performance on the Tap-Gesture and Combined-Gestures datasets was lower. The Tap-Gesture dataset achieved an accuracy of 74.79%, while the Combined-Gestures dataset reached 77.43% accuracy in child/adult classification, as shown in Table 5 and Figure 1.

These results indicate that for the MLP model, stroke gestures carry more distinguishing information for child-adult detection compared to tap gestures or their combination.

3.3. DL4j Model Results

The DL4j model demonstrated overall superior performance in child/adult classification compared to the MLP model, particularly on the Stroke-Gestures dataset. The model's performance across the three datasets is summarized in Table 6.

It achieved its best results on the Stroke-Gesture dataset with an accuracy of 84.61%, a precision of 84.30%, a recall of 84.60%, an F1-score of 84.30%, an AUC of 91%, and an EER of 17.33%. The Tap-Gesture dataset produced a slightly lower performance with an accuracy of 75.46%, while the Combined-Gestures dataset yielded an accuracy of 77.33%. These results, as visualized in Figure 2, confirm the effectiveness of the DL4j architecture in capturing complex interaction patterns.

The DL4J model's consistent advantage over the MLP model indicates that more advanced architectures are better equipped to capture the intricate patterns present in touch gesture data.

Table 5: Performance of the MLP model for child/adult classification on the three datasets (Tap-Gesture, Stroke-Gesture, and Combined-Gestures).

Dataset	Accuracy	Precision	Recall	F1-Score	AUC	EER
Tap-Gesture	74.79%	74.80%	74.80%	74.80%	83.00%	25.11%
Stroke-Gesture	82.83%	83.00%	82.80%	82.90%	90.00%	19.04%
Combined-Gestures	77.43%	77.50%	77.40%	77.10%	87.00%	22.58%

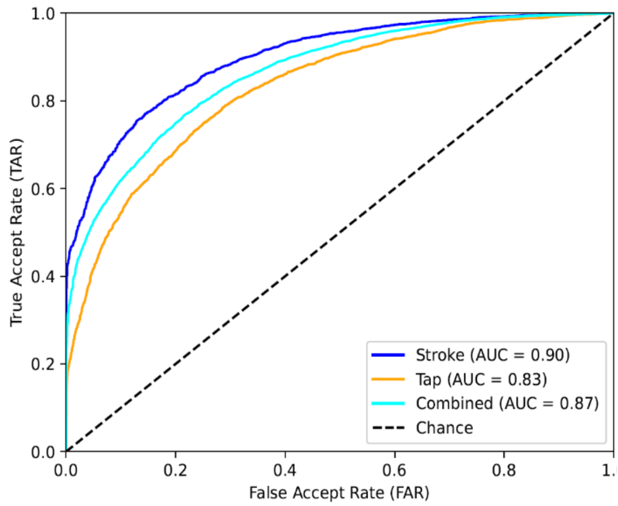

Figure 2: ROC curves evaluating MLP model performance in child/adult classification using (a) stroke gestures, (b) tap gestures, and (c) combined gestures.

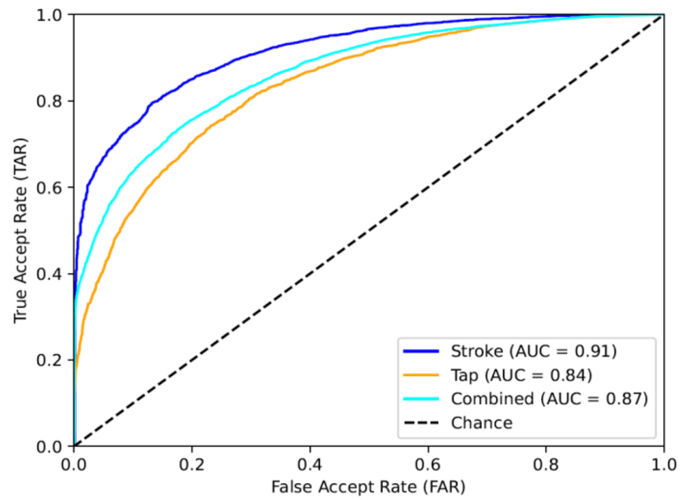

Figure 2: ROC curves evaluating DL4j model performance in child/adult classification using (a) stroke gestures, (b) tap gestures, and (c) combined gestures.

Table 6: Performance of the DL4j model for child/adult classification on the three datasets (Tap-Gesture, Stroke-Gesture, and Combined-Gestures).

Dataset	Accuracy	Precision	Recall	F1-Score	AUC	EER
Tap-Gesture	75.46%	75.40%	75.50%	75.40%	84.00%	24.59%
Stroke-Gesture	84.61%	84.30%	84.60%	84.30%	91.00%	17.33%
Combined-Gestures	77.33%	78.30%	77.30%	77.40%	87.00%	22.48%

4. Discussion

This study investigated the feasibility of using touch gesture data to distinguish between child and adult users on smartphones. Touch interaction data was collected from a diverse group of participants, and meaningful features were extracted to train two neural network models: a traditional Multilayer Perceptron (MLP) and a Deep Learning 4j (DL4j) model incorporating an LSTM layer. The superior performance of stroke gestures can be attributed to their richer dynamic characteristics. Unlike simple taps, strokes contain continuous motion information, including velocity profiles, acceleration patterns, and trajectory curvatures that more effectively reveal age-related differences in motor control. Children typically exhibit less smooth, more variable stroke motions with irregular velocities and greater curvature, reflecting the development of fine motor skills. These complex temporal-spatial patterns provide a more discriminative signature than the relatively uniform characteristics of tap gestures.

Both neural network architectures (MLP and DL4j) demonstrated powerful performance in classifying users, with the DL4j model slightly outperforming the MLP. This improved performance can be attributed to the DL4j model's deeper architecture and the LSTM layer's ability to capture temporal dependencies, allowing for more effective modeling of touch gesture sequences. However, the study is not without limitations. Although the dataset was diverse, its generalizability could be enhanced by including a larger number of participants across a broader range of age groups and demographic profiles. Moreover, the exclusive reliance on touch gesture data may restrict the model's robustness in real-world scenarios, where other behavioral cues—such as typing patterns or screen navigation habits—may also provide valuable signals.

5. Conclusions

This study examined the potential of utilizing touch gesture data to distinguish between child and adult users on smartphones. Through the analysis of a diverse dataset of touch interactions, we demonstrated that stroke gestures provide a more informative and discriminative representation of user behavior compared to tap gestures or a combination of both. Two neural network architectures—Multilayer Perceptron (MLP) and Deep Learning 4j (DL4j)—were employed to classify users based on their touch behavior. While both models achieved promising results, the DL4j model consistently outperformed the MLP due to its ability to capture temporal dependencies through its LSTM layer. These findings have important implications for the development of more secure, adaptive, and personalized mobile systems, enabling devices to tailor settings, content, and interactions to the needs and preferences of individual users. For future work, further investigation could include exploring additional feature sets and leveraging alternative deep learning architectures, such as Convolutional Neural Networks (CNNs), to capture spatial patterns in touch data better. Moreover, applying data augmentation techniques may enhance the diversity of the training data and improve model generalization. Finally, the development of adaptive, useraware systems capable of learning and evolving with individual behavior over time would further enhance the accuracy and reliability of user classification in dynamic environments. Moreover, research should consider the integration of multimodal data, such as voice input, facial recognition, or motion sensor data, to build more comprehensive and accurate user classification systems. Such enhancements could significantly improve the applicability and reliability of child/adult detection in practical smartphone environments.

Author Contributions

Asmaa M. Elsify: Conceptualization, methodology design, software development, data curation, writing—original draft preparation, and project administration. Alaa Elnashar: Methodology design, validation, visualization, and supervision—review and editing. Ahmed Mahfouz: Conceptualization, methodology design, software development, supervision, and writing—review and editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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