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Automated Child Detection on Smartphones through Behavioral Analysis Techniques

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Abstract: The use of internet-connected devices like smartphones and tablets has become integral to daily life, raising significant privacy and safety concerns for young users. Automatically distinguishing child users can empower devices to filter inappropriate content and provide a safer online environment. In this paper, we introduce *kidDetect*, a novel framework that detects children on smartphones by analyzing their distinctive interaction behavior, including touch dynamics and device holding patterns. We conducted a study with 198 participants, collecting touch and sensor data non-invasively as they used various applications. Our findings confirm that children exhibit statistically unique behaviors. By leveraging these patterns, we developed classifiers that achieve strong performance in child detection, with an AUC of 0.93 for swipe gestures and 0.90 for tap gestures.

Keywords: Child Detection, Behavioral Analysis, Smartphone Interaction, Touch Gestures, Sensor Data, Parental Control Systems

1 Introduction

Using internet became a must in all fields of our life specially after COVID-19 not only for adults but also for children. Approximately 80% of children use smartphones to access the internet almost daily, according to a survey conducted in 19 European countries with data collected from 25,101 children [1]. But, letting kids use internet-connected devices can raise several parenting concerns, such as exposure to adult content, cyberbullying, and the risk of encountering online predators [2]. Restrictions on children's internet use are necessary to lower the risks they face while using it. Applications for parental control can be used to impose these restrictions, but they need to be manually activated before we can give the device to the kids. This can be forgotten, especially if the device can be shared by different users at different ages [3]. Beside restriction on phone, apps that employ age verification methods, such as social media apps (i.e. Facebook, Instagram, etc.) should choose more robust techniques because they are circumvented by providing a fictitious birthdate [4]. So, detecting the age of the user automatically will increase the reliability of parental control and the robustness of the age verification techniques of apps. As a result, children can utilize smartphones in a safer entertainment environment.

In this study we introduce *kidDetect* a framework for automatically detecting children on smartphone through behavior analysis. Our approach is based on observing the behavioral variations between adults and children while using smartphones. Since children typically have smaller and weaker hands and tend to be more active and move around compared to adults, there are noticeable distinctions in the size, speed, and strength of their touches on the screen, as well as in how they hold the phone steadily. These distinctions can be extracted from data recorded from the screen touch and built-in sensors of the phone. In our field study, we were able to recruit 198 participants who used the phone freely without any interfering from us and our system collected their touches and sensor data. We used four distinct methods to train the classifiers. In the first, we trained classifiers with features extracted from touches. In the second, we trained classifiers with features extracted from sensor data. In the third, we trained classifiers using sensor features, particularly those obtained during screen touches. Finally, we trained classifiers using different fused grouped of sensors and gestures features. Our main contributions are as follows:

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– We introduce *KidDetect*, a novel framework that automatically identifies child users on smartphones by analyzing their touch and sensor interaction patterns. By using non-invasive data collection methods, this framework offers a practical and reliable solution to differentiate between children and adults.
– To better understand children's internet usage, risks they face, and parental strategies, we conducted an online survey among social media groups. The survey specifically focused on children aged 3 to 12, providing valuable insights into how children navigate the digital world and how parents manage online safety concerns.
– We carried out an in-depth study involving 198 participants (children and adults), capturing their real-world interactions with smartphones in a natural setting. The data collected includes diverse touch gestures, along with accelerometer and gyroscope sensor readings, offering a comprehensive look at behavior patterns across different age groups.
– KidDetect has the potential to significantly improve digital entertainment environments, particularly through practical applications such as enhancing parental control systems, implementing age-appropriate content filtering, and bolstering privacy protection for children using smartphones and other digital devices.

The rest of the paper is structured as follows: section 2 covers relevant research on various methods for detecting children on smart devices. The next section describes our methodology as section 3.1 presents the findings of our online survey. Section 3.2 provides details about our data collection process, including participant and study procedure details. Section 3.3 explains how we differentiate between children and adults using touch data, including the gestures and features we considered. Section 3.4 describes how can we differentiate between children and adults using sensor data and which sensors and features could be used. Section 3.5 explains how we differentiate between children and adults by fusing touch and sensor features. The classifiers and metrics that we used in our study are covered in section 3.6. The results are shown in section 4. Our study is discussed in section 5.

2 Related work

Age detection is used in the fields of authentication and security in personal devices like smartphones and tablets [5]. Due to the development of the hardware of these devices, researchers have investigated the feasibility of utilizing biometric data obtained from sensors, cameras, or microphones to determine the user's age [6]. Techniques in this field of study are based on examining features that can be extracted from the user's face, voice, or even behavior while using the device, such as touches on the screen, or motions made while holding it [7].

Face and speech features were used as a base for age detection [8,9,10,11,12]. However, to use the camera and microphone, these approaches require user permission, and external factors have a significant impact on how well they work. Users might, for instance, be silent while using the device or be surrounded by noise. Additionally, it could be challenging to get a good enough picture for classification (i.e., image may be distorted, show only a portion of the user's face, or affected by the amount of light [3]. Thus, the need arises for a different classification scheme based on other features.

In order to classify the user's age without requiring the use of a camera or microphone, touch-based and sensor-based techniques were proposed. For instance, Vatavu et al [13]examined how kids interacted with smartphones and tablets and gathered touch data from 30 young adults and 89 kids between the ages of 3 and 6. The data set was publicly available for research community and was used in some touch-based classification techniques to detect if the user of the device is a child or an adult [14,15,16]. Features were extracted from tap gestures and a Bayes' rule classifier was trained to reach 86.5% and 99% accuracy when classifying a single touch and more than 7 consecutive touch events, respectively [14]. Hernandez-Ortega et al. [15] trained an SVM classifier that achieved 96% correct classification by using the Sigma-Lognormal model to extract features from drag and drop gestures. Acien et al. [16] also employed the sigma-lognormal model and the SVM classifier. However, the focus of the study was on tap and swipe gestures. Additionally, an active user detection (AUD) algorithm was proposed, which could identify children during an ongoing interaction session. Methods employing this dataset require further feature analysis. Rasheed et al. [17] conducted a study to identify children on smart phone and formulated a data set collected from 30 children under 6 years and 30 adults. They used various classification models to extract features from six distinct touch gestures. The age of the children, the size of the data set, and the non-realistic way in which the data was collected all placed limitations on these studies on touch-based techniques. Li et al., [18] also formulated their own data set from 17 children aged from 3 to 11 years and 14 adults, which is also limited by age and size, using only tap and swipe touch gestures. They suggested the aged detection system iCare, which can identify children with an accuracy of 84% and 97% with just one swipe and eight consecutive swipes, respectively. Hossain and Haberfeld [19] aimed to evaluate how well tap gestures work for age estimation and age group detection. They collected data from participants aged from 5 to 61 years, to conduct a data set from 262 user sessions for both phone and tablet. The best age group detection accuracy for phones and tablets, respectively, was 73.66% and 82.28%, according to the study. Tolosana et al. [20] collected different touch gestures using fingers and pen stylus and formulated their public data set called ChildCIdb v1 that contain more than 400 children from

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18 months to 8 years old, then they utilized this data set in a framework that can accurately identify three age groups with over 90% accuracy. Tolosana et al. [20] study was extended by Ruiz-Garcia et al. [21] to explore more features and do more analysis that enhanced accuracy to achieve more than 93%. Pulfrey and Hossain [22] collected gesture data on using smart phone and tablet from subjects aged from 5 to 61 years old but they focused only on zoom-in and zoom-out gestures. From Zoom gestures, they extracted features, then trained a classifier to estimate the age of the user with 90% accuracy for smartphones and 91% accuracy for tablets. Hossain [23] used the dataset used in [22] to conduct a comprehensive study using zoom gestures to assess the impact of training data size on age estimation accuracy. His findings demonstrated a significant positive correlation, indicating that larger datasets can substantially improve age prediction performance. Guarino et al. [24] collected data on swipe, scroll, pinch-to-zoom, and drag-and-drop touch interactions from 49 children under 16 and 98 adults. They used gesture data in a different way, it was converted into image representations capturing details like finger pressure and movement characteristics, then Convolutional Neural Networks (CNNs) with transfer learning techniques were employed to analyze these gesture images for gender (male/female) and age group (child/adult) classification. Scrolling gestures yielded the best individual performance (0.81 accuracy for gender, 0.96 for age group).

Sensor-based technique to detect the age of the user was used by Gillani et al. and Khabir et al. [25,26]. Their proposed technique depends on detecting age through walking while holding the device. They extracted features from gait cycles using data from accelerometer and gyroscope sensors. In addition to the age detection the gender was detected through the analyses of the sensor data while walking using deep learning approach [27,28]. However, walking only is insufficient because the user can use the device while sitting or in any other situation. Davarci et al. [29] also used sensor-based technique but they extracted features from data collected from accelerometer sensor while tapping randomly on the device. Zhang et al. [30] proposed a method that would use sensory data only gathered during screen unlocking and phone calls to identify children users on the phone. They used features extracted from data collected from accelerometer, magnetic field, and light sensors in their classifier that reached precision of 94.8 % to identify children users. But they collected data from small number of users as the number of participants in their study was 35 participants only.

Both touch-based and sensor-based techniques were presented by [3,31] to detect the presence of a child in the front of the smart device based on touch gestures and sensors. For instance, Nguen et al., [3] found that the system could detect children using touch gestures, accelerometer, gyroscope, and rotation sensors' data but the performance was better when combining touch gestures with sensor. The scenario for collecting data was in a real-life settings for using device but was limited by the number of subjects as they consisted of 25 children aged from 5.5 to 12 years and 25 adults. While Cheng et al., [31] extended the work done by [18] by adding new features extracted from accelerometer and gyroscope sensors, increasing the size of the data set to reach 62 children aged from 3 to 17 years and 38 adults. They could achieve 96.6% and 98.3% child identification accuracy using only a single swipe and three consecutive swipes, respectively.

3 Methodology

3.1 Child on the internet survey

We conducted an online survey at the beginning of our study to find out how children access the internet, which devices they use the most, how old the children who use the internet are, what activities do they engage in online, what risks they face, and how parents manage those risks (see Appendix). The survey results guided us in some of the study's issues.

Online social media groups on Facebook and WhatsApp in Egypt were used to administer the survey. There were 160 participants in the survey. We asked them to respond to the survey's questions if they were parents of children between the ages of 3 and 12. Approximately 77% of children between the ages of 3 and 8—roughly equal numbers of children at each age—and the remaining children, aged 9 to 12. It was discovered that 97.5% of children use the internet. With 81.9% of children using a smartphone to access the internet, smartphones were the most popular device, followed by tablets and computers. Therefore, we carried out our study using a smartphone. Additionally, we discovered that roughly half of the kids owned their own devices, and the other half shared them with adults (see figure 1).

As part of the study, the children's intentions regarding internet use were also investigated. we found that they use it mainly for entertainment 78.1%, gaming 68.8%, learning 33.1%, doing school homework 14.4%, and messaging 13.3% as shown in figure 2. Our development of a smartphone scenario to gather our dataset was aided by these findings. The most popular apps that the parents indicated in the survey were also used to determine which apps to use. We found that children access to the internet almost daily, as 73.4% of them access to the internet every day while the rest access to the internet one day or few days a week. The time that was spent on the internet in one session varies from child to another as it begins from less than one hour to 6 hours, two parents mentioned that their children use it for 10 hours! which is a very long time. Approximately 50% of parents reported that they keep an eye on their kids when

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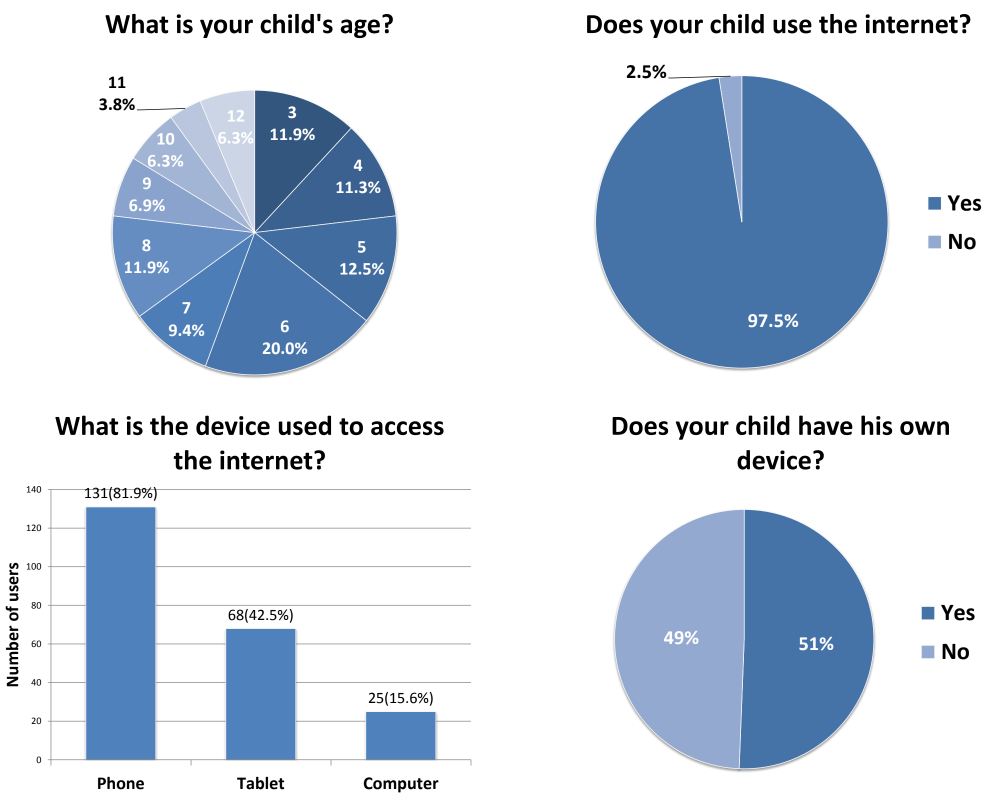

Fig. 1: Findings of our survey for children's ages, the percentage of children who access the internet, and the used devices.

Fig. 2: Findings of our survey for the activities that children practice on the internet.

they use the internet, 44% said they monitor their kids occasionally, and the remaining parents said they don't watch their kids at all. The parental control applications were not used among most of the parents as 80% of them do not use any parental control application to control the usage of the smartphone. About 63% of parents noticed a negative impact on their children after using the internet, like distraction, violence, bad mood, sleep disorders, and introversion. About 21% of parents mentioned that their children exposed to inappropriate content for their age while 19% were not sure about that. Exposure to annoying or inappropriate advertisements while using the Internet was mentioned by about 31% of the parents while 27% of them were not sure.

3.2 Experimental study

3.2.1 Participants

Our study recruited a total of 198 participants, comprising 105 adults and 93 children. Adult participants were required to sign a consent form prior to the study, while children provided assent with parental consent. The children were recruited from local schools and kindergartens, and the adult volunteers came from a variety of backgrounds. Child participants, aged 3 to 12, were selected in accordance with the Children's Online Privacy Protection Rule (COPPA) definition [32]. Adult participants ranged from 19 to 71 years of age (see Table 1). All participant data were encrypted and anonymized.

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Table 1: participants in our study

Age groups	No. of subjects	No. of males	No. of females
Preschoolers (3-5)	14	9	5
School age (6-12)	91	47	44
Young adults (19-39)	75	41	34
Middle-aged adults (40-59)	14	4	10
Older adults (+60)	4	2	2
Total	198	103	95

3.2.2 Apparatus

In our study, we developed a comprehensive framework to facilitate the collection of a new dataset tailored for child and adult detection based on behavioral interaction patterns. For this purpose, we used two Google Pixel XL smartphones, each featuring a 5.5-inch display and running Android 10. These devices were instrumented with our custom-built framework, alongside the study-specific app designed to gather touch and sensor data. The smartphones were chosen for their consistent hardware specifications, ensuring uniform data collection across participants. The instrumented framework operates at the system level, capturing detailed touch interaction data directly from the Android operating system (OS). For each interaction, including gestures like swipes, taps, and long presses, the framework records precise touch points, pressure, speed, and movement trajectories. In addition to touch data, the app also continuously logs accelerometer and gyroscope sensor readings, enabling us to capture movement and orientation changes during smartphone use. This dual-layer data collection approach allows for the comprehensive analysis of both fine-grained touch interactions and broader physical movements, such as phone stability and usage patterns.

To ensure data consistency and accuracy, the framework was configured to work in the background without interrupting the natural use of the device. All data was anonymized and securely stored on the device before being transferred to a central server for further analysis. The selected smartphones were utilized in natural, real-world scenarios, allowing participants to interact with pre-installed apps as they normally would. This setup ensured that the data collected reflected authentic user behavior, providing a reliable dataset for training our classification models.

3.2.3 Study procedure

First, we take approvals for participation in our study, explain to participants what to do and familiarize them with the smart phone. Then participants were given the smart phone instrumented with our framework *KidDetect* and the study app to record their behavior to train our classifier by simulating real-life smartphone use. The results of the online survey that was conducted at the beginning of our study were used to set up this scenario. Children use the mobile for watching videos, playing games and learning. Therefore, we selected the most widely used apps by kids and created the scenario below, which will be completed by kids and adults alike with minimal differences. The tasks are as follows:

1. Launch the "YouTube" app, search for a video, and spend a few seconds watching it. Do this again for multiple videos. Children who could not search for a video we seeded suitable ones for them.
2. Launch the Talking Tom game, interact with the cat for a short while, then access the mini-games section to play one game for Jigsaw Puzzles, Hit The Road, and Cake Tower. Each mini game requires the user to do a certain gesture. In the first mini-game, the player should drag and drop the pieces of the jigsaw to form a picture. In the second, the player should move a car right and left by sliding his finger on the screen. In the last one, the player taps the screen to construct a cake tower.
3. Launch "khan academy kids" educational app to complete a math, reading, and logic lesson. Similar to the game these lessons require the user to do certain gestures: tap, swipe, and drag and drop (this step for children only).
4. Login to Facebook, post something on the wall, browse the page, like and comment on some posts, then logout (this step is only for adults).
5. Unlock the camera and move freely to capture some pictures in different directions.
6. Go through the photos in the gallery by opening it.

3.2.4 Data collection

The touch data comprises the time of the touch as well as the real and relative x and y coordinates of the touch on the screen. It also includes the size, pressure, and package name of the program that the touch was made in, as well as the action code for the touch, which indicates whether it is an up, down, or move action. The instrumented code also extracts gesture features at the same time. The study app creates an ID for each participant after recording his or her age and gender. It then saves touch data and extracts gesture features from the OS, labeling them with the ID. A background-operating service in the study app gathers data from the accelerometer and gyroscope sensors. Our

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system is configured to use the UI sampling rate, which is supported by the Android operating system.

To efficiently gather sufficient data without rapidly draining the battery or consuming excessive storage, we selected a sampling rate that falls in the middle of the available range. During each session, the service records the sensor type, the values for x, y, and z axes, and the corresponding timestamp for when the data was collected. Similar to the touch data, sensor data is saved and labeled with the participant's ID. All participants remained anonymous, as we only recorded their age and gender. Figure 3 shows the study app's interface and how the resulting data was automatically organized into unique, timestamped directories for each participant session, ensuring structured and non-invasive storage. Figure 4 shows samples of the raw touch and sensors data captured during the study.

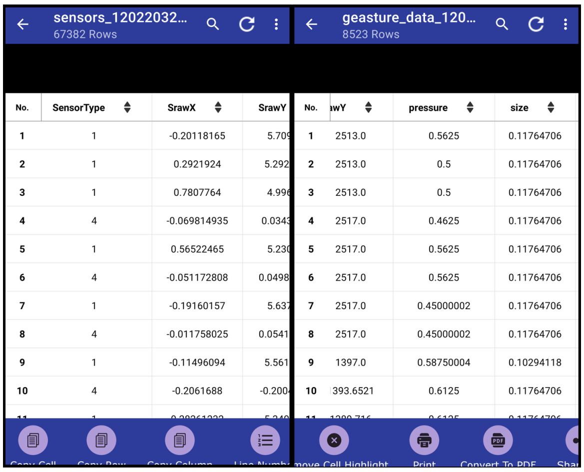

Fig. 4: Samples of the raw touch and sensors data captured during the study.

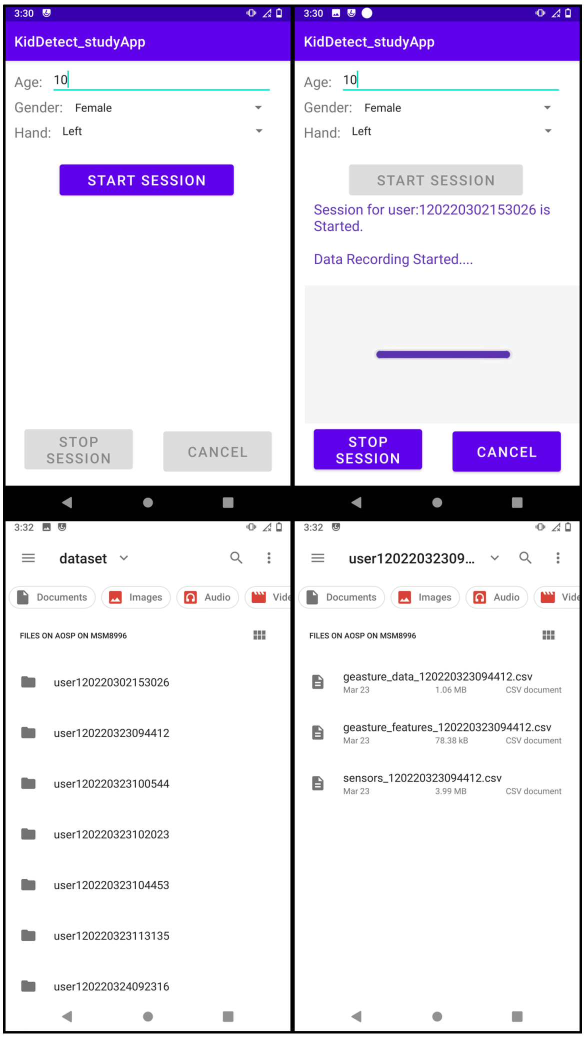

Fig. 3: Study app interface and its generated session file structure for recorded sensor and touch data.

3.2.5 data preprocessing

The raw data must be preprocessed before using it in our classifier after collection. Online preprocessing was carried out for touch data while it was being collected. The touch events were analyzed to determine the type of gesture—tap or swipe—and to extract features for each one. The raw sensor data was processed offline after ending all sessions. First it was sorted by time and the gravity forces were excluded from it. Then we computed the magnitude for every sample and applied the forward-backward digital filtering: cascaded second-order filtering on data to reduce noise. Then we extracted features from the preprocessed data. Sensory data was divided into windows from which two methods of feature extraction are available. The first method of division was based on time, and the second was based on gestures to obtain sensory information between each touchdown and up.

3.3 Detecting children using touch data

Smart phone operates by making different types of touches or gestures like tapping or sliding with your finger on its screen. The way a user touches the screen will vary depending on their age because children's and adults' hands differ in size and strength. Compared to adults, children's gestures are typically weaker and smaller on the screen. Additionally, there are differences between the long touches on screens that children and adults make, such as dragging and dropping [13]. With the help of this feature, we can create a model that uses touch data from the smartphone screen to identify children users.

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3.3.1 Gesture selection

There are many types of gestures that can be made to operate the smart phone device. There are single-touch gestures that can be made by single finger like tap, double tap, and swipe. Multi-touch gestures that can be made by more than one finger like zoom in, zoom out, and rotation. In selecting the appropriate gesture to work on, we took a few factors into account. Both adults and kids should be able to perform the gesture easily, and most mobile apps should support it. Furthermore, it is imperative that the gesture possesses sufficient behavioral information to differentiate between adults and children [31]. So, in our study, we made use of tap and swipe gestures.

3.3.2 Gesture features extraction

We do some actions when we touch smart phone screen. Tap gestures have two actions: touch down and touch up, while swipe gestures have three actions touch down, touch move, and touch up. The location of the finger, the pressure applied to the finger, and the area of the screen that the finger touched can all be recorded by the smart phone for each action [31]. We can extract features from these actions that can be utilized for user differentiation in authentication or age detection. Since tap has less actions than swipe it has less features. From tap we extracted 16 features. Four features for position: downX, upX, downY, and upY. Five features for each pressure and size area: up, down, max, min, and average. Two features for the time that the tap takes: duration and interswipe duration. From swipe we extracted 22 features. 16 features as in tap beside three features for velocity and acceleration: average velocity, max velocity, and average acceleration. Three features for swipe shape: length, displacement, and average curvature as shown in table 2 [33,34,31]. We trained classifier with different features selections to see how features affect the accuracy of classification. For swipe we trained the classifier with all features, then we trained the classifier with all features, excluding the position features due to their consideration as highly personal features in prior studies [3]. For tap we trained the classifier with all tap features, then we trained the classifier without position features. Finally, we trained the classifier with all features including the features of velocity, acceleration, and shape that were assigned to swipe as we noticed that some children do not tap fast on the screen so the tap could take some features of swipe.

3.4 Detecting children using sensor data

In this section, we propose an approach of detecting children using sensor data. We observed that children hold and move the device in a different way from adults. Children are more active and move their hands and bodies while holding the device more than adults. Also, they interact with apps not only by their fingers but also with their entire body specially while playing games. Young children have weak and small hands that can not hold the device in a stable way. Sensors on smartphones like accelerometer and gyroscope can be used to record the changing motion of the device that can be then used to differentiate between children and adults. Figure 5 illustrates how sensor recorded differences between an adult and a child when they made a single tap or swipe while using the phone in the same situation. Adult's tab shows slight change in magnitude while child's tap shows noticeable ups and downs in magnitude (see figure 5a). Adult's swipe is shorter and more stable than child's swipe (see figure 5b).

3.4.1 Sensor selection

There are sensors built into smartphones, such as motion, position, and environmental sensors. Motion sensors like accelerometer, gyroscopes, linear acceleration and rotational vector sensors measure acceleration and rotational forces of the device along three axis x, y and z. Two motion sensors—the accelerometer and gyroscope—were chosen for our study because their data can be used to effectively extract a robust feature set for the detection process [3]. The gyroscope measures the rate of rotation around each of the three physical axes, while the accelerometer sensor measures the device's velocity change rate over time along the three axes.

3.4.2 Sensor features extraction

Sensory data were used in many applications like human activity recognition, authentication, age and gender detection. Achieving high classifier performance is challenging when perform training with raw sensor data streams only, as individual sensor values often fall short of fully capturing user behavior. To address this limitation, descriptive features are commonly extracted from multiple time windows, each representing a segment of the raw data. This approach allows for more understanding of user behavior and enhances the classifiers' ability to perform effectively [35,36,37,3]. Accordingly, we extracted the same feature set that Nguyenet et al. [3] had extracted. First, we removed gravity forces from the sensor data because they cause the data to inaccurately reflect changes in smartphone motion [36]. The magnitude was then calculated for the axes x, y, and z using the formula mag= $\sqrt{x^2+y^2+z^2}$. Lastly, we extracted eight features: mean, standard deviation (std), variance (var), min, max, root-mean-square deviation, skewness and kurtosis for each time window for 4 axes: x, y, z, mag. In total over each sensor, 32 features for each window were extracted.

We also divided sensory data by gestures as we recorded sensory data only between every down action

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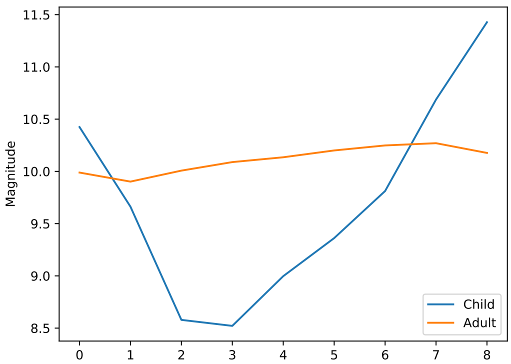
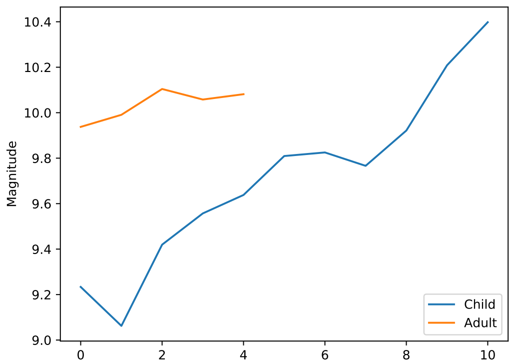
Table 2: Extracted features for tap and swipe gestures.

Features group	Features
Position	downX, upX, downY, upY
Pressure	up, down, max, min, average
Size area	up, down, max, min, average
Time	duration, interswipe duration
Velocity and acceleration	average velocity, max velocity, average acceleration
Shape	length, displacement, average curvature



(a) tap.



(b) swipe.

Fig. 5: The difference between child's and adult's single gesture using sensor data.

and up action, to minimize storage and computational time consumption. We also aimed to determine whether sensor data recorded while holding and using the phone would yield the same classification accuracy as data recorded while only tapping or swiping on the screen. The same features that were used in time windows were also used in gesture windows.

3.5 Detecting children using touch-sensor fusion

This section proposes a child detection approach that integrates touch with sensor features. We extracted two feature sets: one characterizing the touch gesture itself and another capturing sensor data associated with the touch event. We used in this approach the same features groups with highest performance that were extracted in the previous two approaches of detecting children using touch data and using sensor data. The impact of sensor-gesture combinations on the fusion process was investigated. Specifically, we evaluated the performance when fusing the following groups: accelerometer with swipe gestures, accelerometer with tap gestures, gyroscope with swipe gestures, gyroscope with tap gestures, all sensors with swipe gestures, all sensors with tap gestures, and all sensors with all gestures.

3.6 Classifiers and Metrics

We used four classifiers in our study: Random Forests (RF), K-nearest neighbors (KNN), logistic regression, and Support Vector Machine (SVM). RF is an ensemble learning method that combines multiple decision trees to make predictions. Each decision tree is trained on a random subset of the training data, and the final prediction is determined by aggregating the predictions of all the individual trees. RF classifiers are known for their ability to handle high-dimensional data, handle both numerical and categorical features, and provide robustness against overfitting [38]. The KNN classifier is a machine learning algorithm that uses the class labels of a new data point's K closest neighbors in the training dataset to determine the class label for that data point. It uses distance metrics to compute the similarity between data points and predicts the class label by looking at the labels that appear most frequently among the closest neighbors. Logistic regression is a classifier used for binary classification tasks. It models the relationship between the input features and the probability of belonging to a specific class using a logistic function. It is a linear model that makes predictions based on the weighted sum of the input features. SVM is a machine learning classifier that works by finding an optimal hyperplane that separates different classes in the data,

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maximizing the margin between them. SVMs can handle both linearly separable and non-linearly separable data by using kernel functions to transform the data into higher-dimensional space. [39]

In all experiments to evaluate the performance of our classifier we divided our dataset into training set and testing set. We used 10-fold cross validation. By using sklearn's HalvingRandomSearchCV, we were able to tune the classifier's parameters to achieve optimal performance.

We employed the commonly used metrics of Area Under the Curve (AUC) , Equal error rate (EER), precision, recall, and F1 score to assess the classifier's performance. AUC represents the area under the ROC curve which describes the relation between the true positive rate and the false positive rate at various threshold values [40]. EER is the point at which the false acceptance rate and false rejection rate are equal. The lower the equal error rate value, the higher the accuracy of the classifier. Precision represents the proportion of true positive predictions out of all positive predictions made by the model. In simpler terms, precision indicates how well a model avoids false positives. Recall represents the proportion of true positive predictions out of all actual positive instances in the data. In simpler terms, recall indicates how well a model captures all the positive instances. F1 score is the harmonic mean of precision and recall, and it ranges from 0 to 1, with 1 being the best possible score. A higher F1 score indicates a better balance between precision and recall, reflecting a more accurate classifier [41].

4 Results

In this section, we present the results of our suggested techniques for utilizing touch and sensor data to classify children and adults. For the classification task, as previously indicated, we used four classifiers. For touch data, we trained the classifiers using features extracted from single swipe and single tap. The results indicated that the RF classifier exhibited the highest performance with lower errors for both swipe and tap gestures. The RF classifier achieved an AUC of 0.91 with an EER of 0.18 for swipe gestures, and an AUC of 0.83 with an EER of 0.26 for tap gestures. The KNN classifier followed, achieving an AUC of 0.83 with an EER of 0.23 for swipe gestures, and an AUC of 0.81 with an EER of 0.21 for tap gestures. Then, logistic regression and Support Vector Machine (SVM) classifiers performed similarly and obtained lower results compared to RF and KNN classifiers for both swipe and tap gestures (see figure 6). Furthermore, we trained the four classifiers using features extracted from sensors. The RF classifier yielded the best results, achieving an AUC of 0.85 with an EER of 0.25 for accelerometer data, and an AUC of 0.72 with an EER of 0.34 for gyroscope data. The SVM classifier ranked second for accelerometer data, achieving an AUC of 0.84 with an EER of 0.29, while the logistic regression classifier ranked third for gyroscope data, achieving an AUC of 0.68 with an EER of 0.36 (see figure 7). For the RF classifier, which showed the best performance among all models, we will present detailed results for touch, sensor, and fusion models in the following sections.

4.1 Touch results

Both tap and swipe gesture features were used to classify age. We found that swipe can classify age more accurately than tap (see figure 8). To investigate the relationship between features and classification accuracy, we trained a classifier with different feature selections. For swipe gesture, the classifier achieved an AUC of 0.91 with an EER of 0.18 when trained with all features (see table 2). Excluding the position features from the swipe classifier resulted in a decrease in accuracy, with an AUC of 0.82 and an EER of 0.26. The presence of position features significantly influenced the accuracy of classification (see figure 8b). For tap gesture, the classifier achieved an AUC of 0.79 with an EER of 0.28 when trained with all tap features. Excluding the position features from the tap classifier resulted in a further decrease in accuracy, with an AUC of 0.71 and an EER of 0.35. Training the classifier with all features, including velocity, acceleration, and shape features assigned to swipe, achieved the best accuracy, as it achieved an AUC of 0.82 with an EER of 0.27 (see figure 8a). Table 3 shows the values of precision, recall, F1 score, AUC, and EER metrics for all touch models with different features selections.

4.2 Sensor results

We used data of accelerometer and gyroscope to classify age in two ways. In the first method, we divided sensory data into sets of time window of size 1 second and extracted features for each time window. In the second method, we divided sensory data by gesture and extracted features for each gesture window. We trained the classifier and found that accelerometer is more accurate than gyroscope in classification. We also found that we can use gesture window instead of time window as it gave better results for both accelerometer and gyroscope. The classifier achieved for accelerometer an AUC of 0.82 with an EER of 0.28 and an AUC of 0.85 with an EER of 0.25 for time window and gesture window respectively, while it achieved for gyroscope an AUC of 0.68 with an EER of 0.38 and an AUC of 0.71 with an EER of 0.35 for time window and gesture window respectively (see figure 9). The values of precision, recall, F1 score, AUC, and EER metrics are displayed for each sensor model with various feature selections in table 4.

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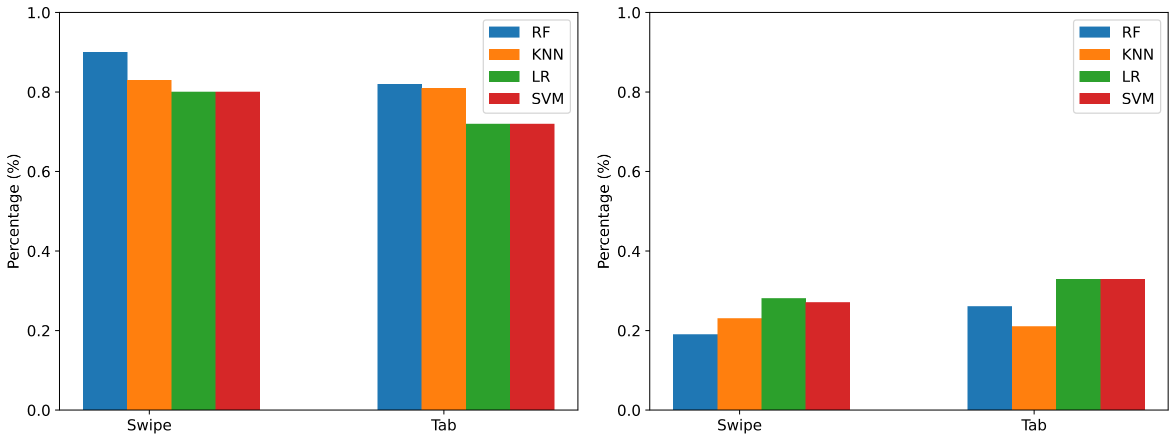
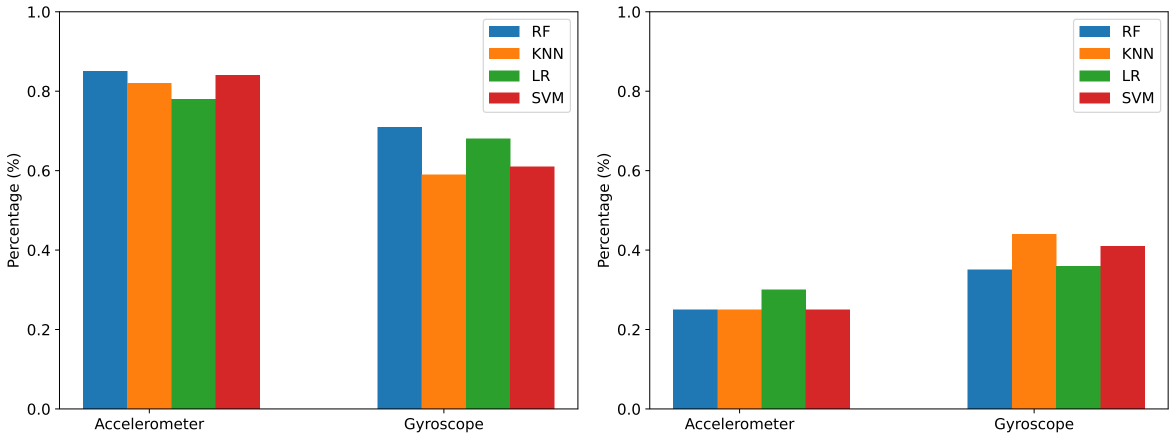


(a) (b)

Fig. 6: Evaluation of the KidDetect framework for swipe and tap gestures across four models: Random Forest (RF), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM). Subplot (a) presents the Area Under the Curve (AUC) values, while subplot (b) illustrates the Equal Error Rate (EER) values. The figure highlights the performance differences between classifiers in distinguishing between child and adult smartphone users based on behavioral patterns.



(a) (b)

Fig. 7: Performance evaluation of the KidDetect framework using accelerometer and gyroscope data across four models: Random Forest (RF), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Support Vector Machine (SVM). Subplot (a) displays the Area Under the Curve (AUC) values, and subplot (b) presents the Equal Error Rate (EER) values. The figure compares the classifiers' ability to differentiate between child and adult smartphone users based on sensor data during smartphone interactions.

4.3 Sensor-touch fusion results

We examined the impact of different fusion groups on classification: accelerometer+swipe, gyroscope+swipe, all sensors+swipe, accelerometer+tap, gyroscope+tap, all sensors+tap, and all sensors+all gestures. We found that fusion generally improved classification for both swipes and taps compared to using them alone (see figure 10). For swipe gesture alone the classifier achieved an AUC of 0.91 with an EER of 0.18. Fusion with accelerometer and both sensors achieved the best classification performance with almost same results, as they achieved an AUC of 0.93 with an EER of 0.16. While fusion with gyroscope didn't significantly improve performance (similar to swipe alone) (see figure 10a). For tap gesture alone the classifier achieved an AUC of 0.83 with an EER of 0.26. Fusion with both sensors achieved the highest performance with an AUC of 0.90 with an EER of 0.20.

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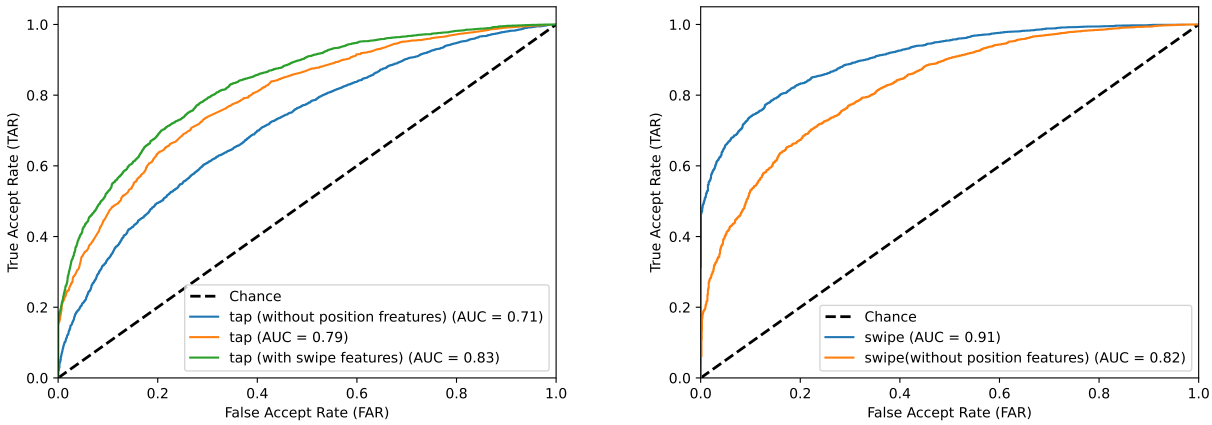

(a) tap. **(b)** swipe.

Fig. 8: the ROC curve for gestures with different feature selections.

Table 3: Metrics for RF classifier for touch data.

Used features	Precision	Recall	F1 score	AUC	EER
Swipe features	0.84	0.92	0.88	0.91	0.18
Swipe without position features	0.79	0.93	0.86	0.82	0.26
Tap features	0.75	0.60	0.66	0.79	0.28
Tap without position features	0.66	0.54	0.59	0.71	0.35
Tap with swipe features	0.75	0.68	0.72	0.83	0.26

Table 4: Metrics for RF classifier for sensory data.

Sensor	Precision	Recall	F1 score	AUC	EER
Accelerometer (time window)	0.73	0.90	0.81	0.82	0.28
Accelerometer (gesture window)	0.79	0.81	0.80	0.85	0.25
Gyroscope (time window)	0.65	0.87	0.74	0.68	0.38
Gyroscope (gesture window)	0.70	0.93	0.80	0.71	0.35

While fusion with accelerometer achieved an AUC of 0.88 with an EER of 0.22. Similar to swipe, fusion with gyroscope didn't significantly improve performance (see figure 10b). Fusing all sensors and gestures achieved an AUC of 0.91 with an EER of 0.17. The values of precision, recall, F1 score, AUC, and EER metrics are displayed for all fusion groups in table 5.

5 Discussion

Based on the above results we can say that detecting children on smartphone can be made automatically by analyzing their behavior while using the phone like touching the screen and holding the phone. Touching screen includes swipe and tap gestures, using only a single swipe or tap we can detect children. The study demonstrated that swipe gestures are more effective than tap gestures in classifying age. The presence of position features significantly improves the accuracy of classification for both swipe and tap gestures. Children have shorter fingers which exhibit a higher tendency to touch the edges of the screen compared to adults, thereby the position features significantly influence the accuracy of classification. The inclusion of additional features for tap, such as velocity, acceleration, and shape, improves the overall accuracy of the classifier. This finding confirmed our observation during data collection, that children sometimes make slower taps that have some features of swipe.

Besides touching the screen, the movement of the phone while usage can also be used to detect children. Movement changes can be recorded by mobile sensors. The results indicate that the accelerometer outperformed the gyroscope in classifying age. Dividing sensory data for feature extraction by time or by gesture (i.e., only while touching screen) can be useful, but dividing by gesture gives more accurate results and reduces the

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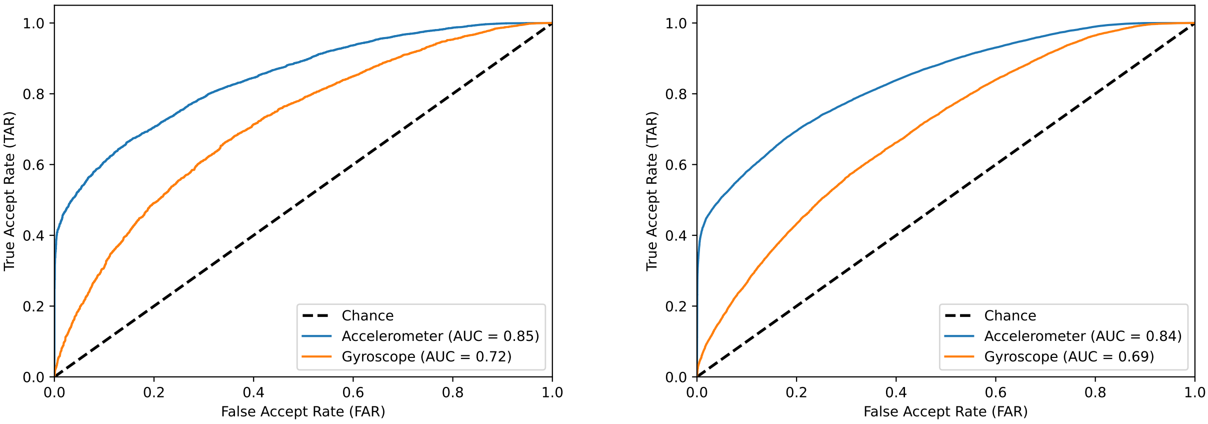
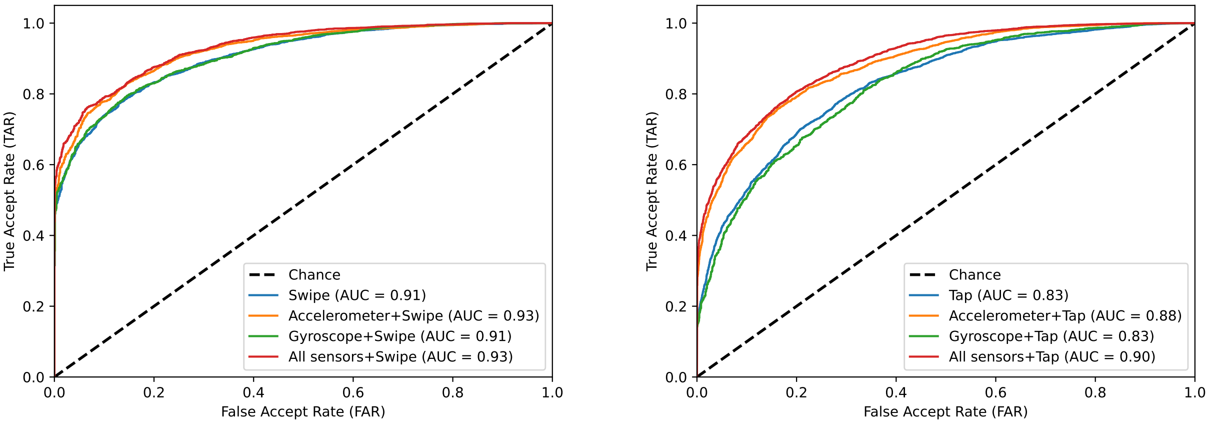


(a) Gesture window. **(b)** Time window.

Fig. 9: the ROC curve for sensors with different window selections.



(a) Swipe gesture. **(b)** Tap gesture.

Fig. 10: the ROC curve for different sensor-touch fusion groups.

computation time. Detecting children using touch data is more accurate than detecting children using sensor data. Figure 11a shows the best performance for single models in our study.

Fusing gestures with sensors enhances the classification process. For both swipe and tap gestures fusion with accelerometer improves the accuracy of classification. While fusion of gyroscope with tap or swipe has no significant improvement on classification. Merging both sensors with tap enhanced the classification accuracy, but with swipe has no significant enhancement. Fusing all sensors with all gestures is not effective as it decreased the accuracy of classification compared by fusing swipe gesture only with sensors. Figure 11b shows the performance for all fusion models in our study.

We think that parents should be more aware of how to protect their children from any possible risk that could face them while using the internet. Also, they must minimize screen time especially most of children access the internet for entertainment and gaming. Research community, developers, and content creators also should pay attention to how to provide children a safer environment while using the internet, as they make up a large number of internet users. Sharing the same device between adults and children could raise the possibility of the exposure of children to adults only content. We think that our study will be helpful in that field, as detecting the

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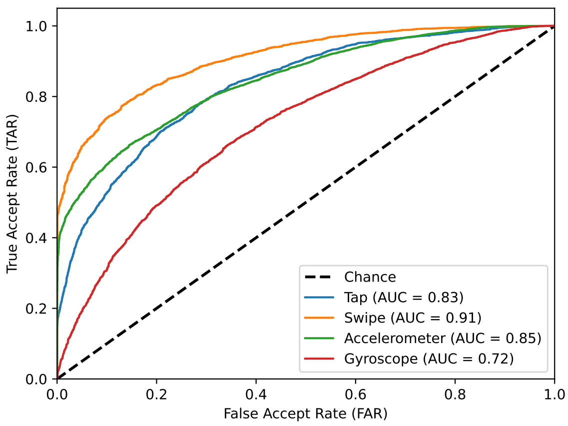
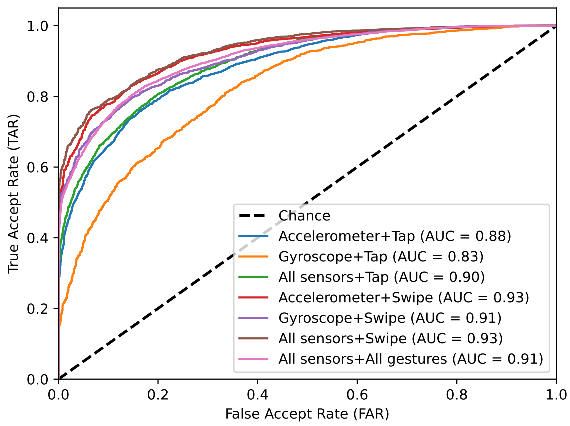
Table 5: Metrics for RF classifier for sensor-touch fusion.

Fusion group	Precision	Recall	F1 score	AUC	EER
Accelerometer+swipe	0.88	0.92	0.90	0.93	0.16
Gyroscope+swipe	0.84	0.95	0.89	0.91	0.18
All sensors+Swipe	0.86	0.95	0.90	0.93	0.16
Accelerometer+tap	0.82	0.74	0.78	0.88	0.22
Gyroscope+tap	0.76	0.80	0.78	0.83	0.26
All sensors+tap	0.84	0.72	0.77	0.90	0.20
All sensors+ all gestures	0.85	0.84	0.84	0.91	0.17



(a) AUC of single models.



(b) AUC of fused models.

Fig. 11: the ROC curve for all models.

age of the user is a first step in a system that could automatically configure the device to be suitable for children or adults.

5.1 Comparison with related work

In this section we compare our study with the related studies that use touch and/or sensory data in child/adult classification. We take in our consideration data collection and classification performance. Comparing the performance with other studies is hard due to differences in methodologies, the structure of the collected datasets and the selected features, so we take only the similar points to our study from each study. We show the performance for studies that used smartphones to make child/adult classification using single gesture and/or single sensor window.

Collecting dataset that contains touch data from children is a challenging process as it is not easy to deal with children specially young ones, as far as we know, our dataset is one of the biggest and more balanced datasets that contains both touch and sensor data for children and adults using real-life scenario. In studies that used only touch data, Hossain and Haberfel [19] and Pulfery and Hossain [22] collected data from 103 children as we do but we used larger range of ages as their children aged from 5 to 12 while our children aged from 3 to 12, also we have more balanced numbers from different ages. Our number of adults (95 adults) exceeds theirs (21 adults). The first study collected taps while tapping on buttons on the screen, and the second study collected zoom in and zoom out gestures while doing some predefined tasks. Then comes the dataset conducted by Vatavu et al. [14] and used by Acien et al. [16] and Hernandez et al. [15] with data collected from 89 children and 30 adults, but the ages of children were limited (3 to 6 years). The smallest dataset was conducted by Li et al.[18] with 17 children and 14 adults.

For studies that used only sensors to detect children while touching the phone, Davarci et.al. [29] collected a dataset that close to ours in number of participants as they collected data from 100 children and 100 adults. But they collected only accelerometer data while tapping randomly on the screen of the phone. Zhang et al. [30] collected sensory data from accelerometer, magnetic field and light sensors, from only 12 children and 38 adults while unlocking and answering the phone.

Studies that collected both touch and sensory data were made by Cheng et al. [31] and Nguyen et al. [3].

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Table 6: Comparison table between our study and related studies in child/adult classification

study	Data set			Collected data	Best performance for single gesture/window
	participants	Age by years	Collection scenario		
Acien et al.[16]	89 child 30 adult	3 to 6 25	Static	Touch: Tap, swipe	Accuracy: swipe 94.1% tap: 85.4%
Hernandez et al. [15]	89 child 30 adult	3 to 6 25	Static	Touch: Swipe	Accuracy: 96%
Hossain and Haberfeld [19]	103 child 17 between 21 adult	5 to 12 13 to 17 18 to 61	static	Touch: Tap	Accuracy: 73.63%
Li et al. [18]	17 child 14 adult	3 to 13 20 to 59	Real-life	Touch: Tap, swipe	AUC:swipe: 0.90 tap: 0.88
Pulfrey and Hossain [22]	103 child 17 between 21 adult	5 to 12 13 to 17 18 to 61	Static	Touch: Zoom in, zoom out	Accuracy: 90%
Rasheed et. al [17]	30 child 30 adult	<6 >18	Static	Touch: Tap, swipe, slide, rotation, zoom in, zoomout.	Accuracy: swipe: 86.6% tap: 85.4%
Vatavu et. al. [14]	89 child 30 adults	3 to 6 >25	Static	Touch: Tap	Accuracy: 86.5%
Davarci et. al. [29]	100 child 100 adult	3 to 11 12 to 50	Static	Touch: Tap Sensor: Accelerometer	Accuracy: 85.3%
Zhang et. al. [30]	12 child 23 adult	5 to 77	Real-life	Touch: Swipe, answering phone Sensor: Accelerometer, magnetic field, light	Precision: 94.80% Recall: 94.83%
Cheng et. al. [31]	62 child 38 adult	3 to 17 18 to 59	Real-life	Touch: Tap, swipe Sensor: Accelerometer, Gyroscope	AUC:swipe: 0.99 tap: 0.94
Nguyen et. al. [3]	25 child 25 adult	2.5 to 12 24 to 66	Real-life	Touch: Tap, swipe Sensor:Accelerometer, Gyroscope, rotation, linear acceleration	AUC: Stroke: 0.83 tap: 0.68 sensor window:0.99
Our study	103 child 95 adult	3 to 12 19 to 71	Real-life	Touch: Tap, swipe Sensor: Accelerometer, Gyroscope	AUC: swipe: 0.93 tap: AUC: 0.90 sensor window:0.85

The first study collected taps, swipes and data of accelerometer and gyroscope from 62 child aged from 3 to 17 years old and 38 adults, while the second study collected taps, swipe, and data of accelerometer, gyroscope, rotation, and acceleration sensors from 25 children aged from 2.5 to 12 years old and 25 adults. Data in both studies were collected by phone in a real-life manner. Our study came out with promising results as it has good performance results with only single gesture and single sensor window in comparison with other studies. The closet study to ours is Nguyen et al. [3], they achieved an AUC of 0.83 for stroke and an AUC of 0.68 for tap while we achieved an AUC of 0.91 for swipe and an AUC of 0.83 for tap, after fusion results enhanced to an AUC of 0.93 for swipe and an AUC of 0.90 for tap. Li et al. [18] achieved an AUC of 0.90 for swipe and an AUC of 0.88 for tap. The rest of studies used different metrics for evaluation of classification. Table 6 shows data collection and performance comparison between our study and the related studies.

6 Conclusion

Our study focused on distinguishing between child and adult smartphone users by analyzing behavioral differences during real-life smartphone interactions. We collected data from 198 participants, including children aged 3 to 12 and adults aged 19 to 71, capturing a range of touch gestures and sensor data. By examining differences such as touch size, speed, strength, and phone stability, we extracted meaningful features from both touch and sensor data during interactions. These features were used to train machine learning models, which achieved promising results: an AUC of 0.91 for swipe gestures, 0.83 for tap gestures, 0.85 for accelerometer data, and 0.72 for gyroscope data. When combining touch gestures with sensor data, performance improved, reaching an AUC of 0.93 for swipe and 0.90 for tap gestures.

These findings highlight the potential of our approach, KidDetect, in enhancing parental control systems and age verification techniques, ensuring safer online experiences for children. By leveraging automatic user detection, this framework addresses significant privacy and security concerns, providing an additional layer of protection for children against inappropriate content, cyberbullying, and online threats.

Future research will focus on refining our techniques to improve classification accuracy and robustness. The integration of deep learning approaches and expanding the model to include more detailed age group

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classification will be explored to further enhance the framework's effectiveness.

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9 Competing interests

No competing interest is declared.

10 Author contributions statement

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

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Appendix

Child on the Internet Survey Questions

1. What is your child's age? (Choose from 3 to 12 years).
2. Does your child use the Internet? (Yes or No).
3. What is the device used to access the Internet? (a) Smartphone; (b) Tablet; (c) Computer.
4. What is the most used device? (a) Smartphone; (b) Tablet; (c) Computer.
5. Does your child have his own device? (Yes or No).
6. Which activities does your child practice while using the Internet? (a) School homework; (b) Learning; (c) Entertaining; (d) Games; (e) Messaging.
7. What are the names of the most used applications, whether in social media, games, education, or any other programs? (Write them by name from most used to least used).
8. How often does your child use the internet? (a) once a week; (b) More than once a week; (c) Daily.
9. How many hours does your child spend on the internet at one time?
10. Do you monitor your child while using the Internet? (Yes, No or Sometimes).
11. Do you put one of the parental control applications on the device used by your child? (Yes or No).
12. Does your child have a social media account? (Yes or No).
13. Do you notice any negative impact on your child through his use of the Internet? (Yes or No).
14. If your answer is yes in the previous question, what these negative effects?

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15. Is your child exposed to age-inappropriate content (for adults only) while using the Internet? (Yes, No or I don't know).
16. If your answer is yes in the previous question, mention where this content was exposed and what type of content.
17. Is your child exposed to annoying or inappropriate advertisements while using the Internet? (Yes, No or I don't know).
18. If your answer is yes in the previous question, mention where these advertisements were shown and what is its type?
19. Does your child meet strangers through his use of the Internet? (Yes, No or I don't know).
20. If your answer is yes in the previous question, mention how does your child meet them?
21. What are your biggest concerns about your child's use of the Internet, and what are your suggestions to provide a safe environment for him while using the Internet?

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