Abstract—We overview recent research in Child-Computer Interaction and describe our framework ChildCI intended for: i) generating a better understanding of the cognitive and neuromotor development of children while interacting with mobile devices, and ii) enabling new applications in e-learning and e-health, among others. Our framework includes a new mobile application, specific data acquisition protocols, and a first release of the ChildCI dataset (ChildCIdb v1), which is planned to be extended yearly to enable longitudinal studies. In our framework children interact with a tablet device, using both a pen stylus and the finger, performing different tasks that require different levels of neuromotor and cognitive skills. ChildCIdb comprises more than 400 children from 18 months to 8 years old, considering therefore the first three development stages of the Piaget’s theory. In addition, and as a demonstration of the potential of the ChildCI framework, we include experimental results for one of the many applications enabled by ChildCIdb: children age detection based on device interaction. Different machine learning approaches are evaluated, proposing a new set of 34 global features to automatically detect age groups, achieving accuracy results over 90% and interesting findings in terms of the type of features more useful for this task.

Index Terms—Child-Computer Interaction, Computer Vision, e-Health, e-Learning, ChildCIdb, Age Detection

I. INTRODUCTION

CHILDREN are becoming one of the latest (and youngest) users of the technology based on touch interaction. They have more and more access to mobile devices on a daily basis. This fact is demonstrated in recent studies of the literature [1], showing that over 75.6% of the children are exposed to mobile devices between the age of 1 to 60 months. This aspect has been exacerbated by the COVID-19 outbreak in 2020. With a large percentage of the academic institutions around the world now in lockdown, virtual education has temporally replaced traditional education to a very large extent using specific e-Learning mobile applications in which children interact with them to improve their knowledge and skills [2], [3]. However, and despite the importance of the topic, the field of Child-Computer Interaction (CCI) is still in its infancy [4], [5].

Our work aims at generating a better understanding of the way children interact with mobile devices during their development process. Children undergo many different physiological and cognitive changes as they grow up, which reflect in the way they understand and interact with the environment. According to Piaget’s theory [6], there are four different stages in the development of the children: i) Sensorimotor (from birth to 2 years old), focused mainly on the evolution of the motor control such as fingers and gestures, and the acquisition of knowledge through sensory experiences and manipulating objects; ii) Preoperational (2-7 years), children are getting better with language and thinking, improving also their motor skills; iii) Concrete Operational (7-11 years), their thinking becomes more logical and organized, but still very concrete; and iv) Formal Operational (adolescence to adulthood), they begin to think more about moral, philosophical, ethical, social, and political issues that require theoretical and abstract reasoning.

Currently, most studies in the field of CCI are focused on the Preoperational and Concrete Operational stages (2-11 years), pointing out that children’s touch interaction patterns are different compared with adults [7]–[10]. As a result, different guidelines should be considered for the proper design and development of children mobile applications, considering their incipient physiological and cognitive abilities [11]–[14].

In this article we present our framework named ChildCI, which is mainly focused on the understanding of CCI with applications to e-Health [15] and e-Learning [16], among others. In particular, the present study introduces all the details regarding the design and development of a new child mobile application, the specific acquisition protocol considered, and the first capturing session of the ChildCI dataset (ChildCIdb). In the scenario considered, children interact with a tablet device, using both a pen stylus and also the finger, performing different tasks that require different levels of neuromotor and cognitive skills. Unlike most previous studies in the literature, our analysis considers the first three stages of the Piaget’s theory in order to perform an in-depth analysis of the children development process. Additionally, ChildCI is an on-going project in which children will be captured in multiple sessions along their development process (from 18 months to 8 years old), being possible to extract very relevant insights. The main contributions of this study are as follow:

• An overview of recent works studying touch and stylus interactions performed by children on screens, remarking the publicly available datasets for research in this area and the improvements over them of our contributed ChildCIdb.
• Design and development of a novel child mobile application composed of 7 tests grouped in three different...
categories (emotional state, touch, and stylus). Different levels of neuromotor and cognitive skills are required in each test to measure the evolution of the children in each Piaget’s stage. By doing so, we are able to connect the children’s performance on finger and stylus with their level of cognitive and motor development according to their age.

- A first release of the new ChildCI dataset\(^1\) (ChildClDb v1), which is planned to be extended yearly to enable longitudinal studies. This is the largest publicly available dataset to date for research in this area with 438 children in the ages from 18 months to 8 years old. In addition, the following aspects are considered in the acquisition of the dataset: \(i\) interaction with screens using both finger and pen stylus, \(ii\) the emotional state of the children during the acquisition, \(iii\) information regarding the previous experience of the children with mobile devices, \(iv\) the children’s grades at the school, and \(v\) information regarding the attention-deficit/hyperactivity disorder (ADHD).

- Experimental framework using machine learning techniques to demonstrate the research potential of our contributed ChildClDb. In particular, we focus on the task of children age group detection while colouring a tree (named Drawing Test). A new set of 34 global features are proposed to automatically detect the age group, achieving interesting insights.

The remainder of the article is organised as follows. Sec. [II] summarises previous studies carried out in touch and stylus interactions performed by children. Sec. [III] describes all the details of ChildClDb, including the design and development of the mobile application, the specific acquisition protocol, and the first capturing session. Sec. [IV] develops an experimental framework using machine learning techniques and ChildClDb for the task of children age group detection. Finally, Sec. [V] draws the final conclusions and points out future work.

II. RELATED WORKS

Different studies have evaluated the interaction of the children with mobile devices. Table I shows a comparison of the most relevant studies in the literature ordered by the age of the subjects, including information such as the number of children considered in the study, the type of acquisition tool, etc.

The first thing we would like to highlight is the lack of publicly available datasets in the field. To the best of our knowledge, the novel dataset presented in this study (ChildClDb) is the only available dataset to date together with the dataset presented in [13]. Therefore, ChildClDb is one of the main contributions of this study, not only due to the large number of children captured (438), but also to other many aspects such as the age of the children (from 18 months to 8 years), acquisition tool (touch and stylus), emotional state information, ADHD information, etc.

Analysing the studies focused on the first stage of the Piaget’s theory (Sensorimotor, 0-2 years), to the best of our knowledge the work presented by Crescenzi and Grané in [14] is the only one available. This is mainly produced due to the difficulties when capturing data from children in that age range (e.g., they sometimes do not want to play with the mobile devices). The focus of their study was to analyse how children under 3 years old interact with mobile devices, using commercial apps related to drawing and colouring tasks. They concluded that children under 3 adapt their gestures to the content of the apps and suggested that the use of app tools (e.g., color palette) may begin from 2 years.

Many studies have focused on the second stage of the Piaget’s theory (Preoperational, 2-7 years), paying special attention to the ability to perform gestures on multi-touch surfaces. In [17], the authors proposed a set of 8 different tasks to measure the ability of the children to perform gestures. They concluded that children in the age 2-3 are able to perform simple gestures such as tap and drag and drop but also other complex ones such as one- and two-finger rotation, scale up and down, etc. A similar research line was studied in [18], reviewing 100 touchscreen apps for preschoolers. In addition, the authors found that children above 3 are able to follow in-app audio instructions and on-screen demonstrations.

An interesting article in this line is the work presented by Vatavu et al. in [13]. In that work the authors captured and released to the research community a dataset composed of 89 children (3-6 years) and 30 young adults. They analysed the way children interact with mobile devices, showing significant improvements in children’s touch performance as they grow from 3 to 6 years. Also, the authors proposed different guidelines for designing children applications. Similar conclusions have been obtained in other studies in the literature [19], [22].

Mobile devices have also been studied as a way to teach children, in particular through digital game-based learning (DGBL) applications. In [21], the authors investigated whether DGBL can improve the creativity skills in preschool children (3-6 years). Nine different games were considered in the study, concluding that DGBL can potentially affect children’s ability to develop creative skills and critical thinking, knowledge transfer, acquisition of skills in digital experience, and a positive attitude toward learning. Similar conclusions were extracted in [23] when asking children to solve puzzle games.

Considering that children and adults typically use different interaction patterns on mobile devices, some studies have proposed the development of automatic systems to detect age groups. This research line has many different potential applications, e.g., restrict the access to adult contents or services such as on-line shopping. In [9], the authors presented an automatic system able to detect children from adults with classification rates over 96%. This detection system is based on the combination of features based on neuromotor skills, task time, and accuracy. The dataset released in [13] was considered in the experimental framework. In a related work, Acien et al. proposed an enhanced detection system including global features from touch interaction [10].

Not only the screen interaction using the finger has been studied as a way to interact with mobile devices. Different studies have considered the stylus for the acquisition tool. In [20], Remi et al. studied the scribbling activities executed by children of 3-6 years. They considered the Sigma-Lognormal writing generation model [9], [28] to analyse the motor skills, [source: https://github.com/BiDAlab/ChildClDb_v1]
TABLE I: Comparison of different studies focused on the interaction of the children with mobile devices.

| Study                           | Age of Participants | # Participants | Acquisition Tool | Emotion | ADHD | Public |
|--------------------------------|---------------------|----------------|------------------|---------|------|--------|
| Crescenzi and Grané (2019)     | 14-33 Months        | 21             | Finger           | No      | No   | No     |
| Nacher et al. (2015)           | 2-3 Years           | 32             | Finger           | No      | No   | No     |
| Hiniker et al. (2015)          | 2-5 Years           | 34             | Finger           | No      | No   | No     |
| Abdul-Aziz (2015)              | 2-12 Years          | 33             | Finger           | No      | No   | No     |
| Vatavu et al. (2015)           | 3-6 Years           | 89             | Finger           | No      | No   | Yes    |
| Vera-Rodriguez et al. (2020)   | 3-6 Years           | 89             | Finger           | No      | No   | [13]   |
| Acien et al. (2019)            | 3-6 Years           | 89             | Finger           | No      | No   | [13]   |
| Remi et al. (2015)             | 3-6 Years           | 60             | Stylus           | No      | No   | No     |
| Behnamnia et al. (2020)        | 3-6 Years           | 7              | Finger           | No      | No   | No     |
| Hussain et al. (2016)          | 4-6 Years           | 10             | Finger           | No      | No   | No     |
| Huber et al. (2016)            | 4-6 Years           | 50             | Finger           | No      | No   | No     |
| Woodward et al. (2016)         | 5-10 Years          | 30             | Finger           | No      | No   | No     |
| Nacher et al. (2018)           | 5-10 Years          | 55             | Finger           | No      | No   | No     |
| Tabatabaey-Mashadi et al. (2015)| 6-7 Years         | 178            | Stylus           | No      | No   | No     |
| Anthony et al. (2014)          | 6-17 Years          | 44             | Finger           | No      | No   | No     |
| McKnight and Cassidy (2010)    | 7-10 Years          | 80             | Finger/Stylus    | No      | No   | No     |
| Laniel et al. (2020)           | 8-11 Years          | 25             | Stylus           | No      | Yes  | No     |
| Anthony et al. (2016)          | <12 Years           | 24             | Finger           | No      | No   | No     |
| ChildCIdb (Present Study)      | 18 Months - 8 Years | 438            | Finger/Stylus    | Yes     | Yes  | Yes    |

concluding that there are significant differences in the model parameters between ages. Stylus has also been considered in [26] to analyse the correlation between the performance of polygonal shape drawing and the levels in handwriting performance. The study revealed that there are details in the children’s drawing strategy highly related to the handwriting performance. Recently, Laniel et al. proposed in [27] a new measure of fine motor skills, the Pen Stroke Test (PST) in order to discriminate between children with and without attention-deficit/hyperactivity disorder (ADHD). This test is also based on the parameters of the Sigma-Lognormal model, providing preliminary evidences that the PST may be very useful for detecting ADHD.

Finally, we also include in Table [1] the description of our ChildCIdb presented in this study, for completeness.

III. ChildCIdb Description

A. Acquisition: Year 1

ChildCIdb is a novel Child-Computer Interaction dataset. This is an on-going dataset collected in collaboration with the school GSD Las Suertes in Madrid, Spain. This article presents the first version of ChildCI dataset (ChildCIdb v1), which comprises one capturing session with 438 children in total in the ages from 18 months to 8 years, grouped in 8 different educational levels according to the Spanish education system. All parents provided informed consent for their child’s participation. Table [11] provides the statistics of ChildCIdb regarding the number of children associated to each educational level, and also the gender and handedness information. As can be seen, the number of children captured increases with the educational level, being levels 2 and 3 the levels with less subjects. As commented before, this is produced due to: i) less children are grouped in the same class, and ii) the acquisition is usually more difficult as they are very young. Regarding the gender statistics of the ChildCIdb, 50% of the children were male/female whereas for the handedness, 84% were right-handed, although this factor is not completely defined until they are 5 years old [29].

In addition to the gender and handedness information, the following personal information was acquired during the acquisition process.
enrolment stage: \(i\) date of birth, and if he/she is premature (gestation period of less than 37 weeks), \(ii\) whether he/she is a child with ADHD, \(iii\) whether he/she has ever used any mobile device before the acquisition, and \(iv\) his/her educational grades. All this information enriches the project, being possible to research in several interesting lines, e.g., is there any relationship between the way children interact with the devices and their grades?

### B. Yearly Acquisition Plan

ChildCIdb is planned to be extended yearly to enable longitudinal studies. The same children considered in ChildCIdb v1 will be acquired as they grow up and move to the different educational levels (from 18 months to 8 years). Therefore, future versions of ChildCIdb will be extended to: \(i\) new children that are registered to the educational level 2 of the school GSD Las Suertes in Madrid, Spain, and \(ii\) new acquisition sessions for the children already captured in previous versions of ChildCIdb (up to 8 years old).

### C. Software Application

An Android mobile application was implemented for the acquisition, which comprises 7 different tests grouped in 3 main blocks: \(i\) emotional state, \(ii\) touch, and \(iii\) stylus. Fig. 1 shows some examples of the different interfaces designed in ChildCI for each test, before and after their execution. As the participants are children, and keeping in mind they are not able to focus on the task for a long time, we decided to develop a brief and interactive acquisition application in order to keep their attention as much as possible in a limited amount of time. Thus, we decided to set up a maximum time for each test as indicated in Fig. 1 being 5 minutes the maximum time for the complete acquisition. In case the child is not able to finish each test in the maximum time set for it, the application automatically moves to the next test.

In the first block, the main goal is to capture the emotional state of the children before the beginning of the acquisition (Test 0 - Emotional State Self-Assessment Test). Three faces with different colours and facial expressions were represented on the screen, asking the children to touch one according to their emotional state. Table III shows the statistics of the emotional state analysis per educational level for the first version of ChildCIdb. As can be seen, most children were in a good mood before the beginning of the acquisition (78%). It is also interesting to remark the high number of children between 1-3 years that did not provide any information about their emotional state (DK/DA). This information will be also very interesting for the project to see any relationship between the children mood and the way they interact with the devices.

After the end of the first block related to emotional state analysis, it starts the second block focused on the analysis of the children motor and cognitive skills using their own finger as a tool. This new block is indicated to the children through an image example. The second block comprises 4 different tests with different levels of difficulty to see the ability of the children to perform different hand gestures and movements. The maximum time of each test is 30 seconds. We describe next each of the tests:

- **Test 1 - Tap and Reaction Time:** the goal is to touch one mole at a time in order to see the ability of the children to perform tap gestures (gross motor skills) and their reaction times. Once the mole is touched, it disappears from that position and appears in another position of the screen. In total, 6 different moles must be touched for the end of the test. Just a single finger is needed to complete the task.
- **Test 2 - Drag and Drop:** the goal is to touch the carrot and swipe it to the rabbit. This test is designed to see the ability of the children to perform drag and drop gestures (fine motor skills). In order to facilitate the comprehension of the test and motivate the children, an intermittent blue arrow is shown in the screen until the children touch the carrot. Just a single finger is needed to complete the task.
- **Test 3 - Zoom In:** the goal is to enlarge the rabbit and

### TABLE II: Statistics of the ChildCIdb dataset regarding the number of children associated to each educational level, and the gender and handedness information.

| Educational Level | # Subjects | Gender | Handedness |
|-------------------|------------|--------|------------|
|                   |            | Male   | Female     | Right | Left | Both | Unknown |
| 2 (1-2 Years)     | 18         | 8      | 10         | 12    | 3    | 2    | 1        |
| 3 (2-3 Years)     | 36         | 14     | 22         | 30    | 3    | 3    | 0        |
| 4 (3-4 Years)     | 50         | 29     | 21         | 38    | 5    | 7    | 0        |
| 5 (4-5 Years)     | 66         | 32     | 34         | 58    | 6    | 1    | 1        |
| 6 (5-6 Years)     | 93         | 53     | 40         | 83    | 8    | 0    | 2        |
| 7 (6-7 Years)     | 77         | 35     | 42         | 69    | 8    | 0    | 0        |
| 8 (7-8 Years)     | 98         | 48     | 50         | 79    | 15   | 0    | 0        |
| **Total**         | **438**    | **219**| **219**    | **369**| **48**| **17**| **4**    |

### TABLE III: Statistics of the emotional state analysis per educational level for the ChildCIdb. DK/DA stands for “does not know/does not answer”.

| Educational Level | Happy | Normal | Sad | DK/DA |
|-------------------|-------|--------|-----|-------|
| 2 (1-2 Years)     | 3     | 3      | 1   | 11    |
| 3 (2-3 Years)     | 19    | 1      | 7   | 9     |
| 4 (3-4 Years)     | 39    | 0      | 2   | 9     |
| 5 (4-5 Years)     | 52    | 2      | 0   | 12    |
| 6 (5-6 Years)     | 83    | 1      | 1   | 8     |
| 7 (6-7 Years)     | 63    | 2      | 6   | 6     |
| 8 (7-8 Years)     | 83    | 4      | 0   | 11    |
| **Total**         | **342**| **13**| **17**| **66**|
Block 1: Emotional State Analysis

Test 0 - Emotional State Self-Assessment Test: 10 seconds max.

Use the Finger!

Block 2: Touch Analysis

Test 1 - Tap and Reaction Time: 30 seconds max.
Test 2 - Drag and Drop: 30 seconds max.
Test 3 - Zoom In: 30 seconds max.
Test 4 - Zoom Out: 30 seconds max.

Use the Stylus!

Block 3: Stylus Analysis

Test 5 - Spiral Test: 30 seconds max.
Test 6 - Drawing Test: 2 minutes max.

Fig. 1: Examples of the different interfaces designed in ChildCI for each test, before and after their execution, including the maximum time set up in each of them. Three main acquisition blocks are considered: i) emotional state, ii) touch, and iii) stylus. Representative video recordings of the different educational levels are available at [https://github.com/BiDAlab/ChildClcb_v1](https://github.com/BiDAlab/ChildClcb_v1).
put it inside the two red circles for a short time. This test is designed to: i) analyse the ability of the children to perform scale-up (zoom-in) gestures, and ii) analyse the precision of the motor control of the children when trying to put the rabbit inside the two red circles (fine motor skills). In order to facilitate the comprehension of the test, two intermittent outer arrows are depicted until the children touch the surface close to the rabbit. The rabbit can be only enlarged/shortened using two fingers. No displacement of the rabbit along the screen is allowed to facilitate the test, only the size of the rabbit can be modified.

- **Test 4 - Zoom Out**: the goal of this test is similar to Test 3 but in this case children have to perform scale-down (zoom-out) gestures. Two fingers are needed to complete the test (fine motor skills).

After the end of the second block related to the children touch analysis, it starts the third block aimed to analyse the ability of the children using the pen stylus. This is indicated to the children through an image example showing a pen stylus. This block comprises the following 2 tests:

- **Test 5 - Spiral Test**: the goal of this test is to go across the spiral, from the inner part to the outer part, trying to keep it always in the area remarked in black colour. Once the children finish the test, they must press the button “Next” to move to the following test. The maximum timer set up for this test is 30 seconds. A similar version of this test is widely used for the detection of Parkinson’s disease and movement disorders [30].

- **Test 6 - Drawing Test**: the goal of this test is to colour the tree in the best way possible. Once the children decided to finish the test, they must press the button “Next”. This last test ends the acquisition. The maximum timer set up for this test is 2 minutes.

These tests are designed to investigate the cognitive and neuromotor skills of the children while performing actions with their own fingers or using the pen stylus, and also analyse their evolution with time. The research results that can be obtained by analysing ChildCI will be very valuable to better understand the current skills of the children in this society dominated by mobile devices.

**D. Acquisition Protocol**

Currently, ChildClIdb comprises one acquisition session. The following principles were applied for the acquisition of the data:

- The same tablet device (Samsung Galaxy Tab A 10.1) was considered during all the acquisition process in order to avoid inter-device problems, e.g., different sampling frequencies [31], [32].

- All children performed the same tests in the same order (from Test 0 to Test 6) regardless of their educational level. This will allow us to perform a fair evaluation of the children inside a specific educational level and also between different ones.

- No help was provided to the children apart from the instructions indicated on the screen before the beginning of each test. For children under 3 years old, oral instructions were also given following the conclusions extracted in [13].

- Children performed each test by themselves, without any other help.

- The acquisition was carried out inside the normal class, one at a time, and always with the child sitting far from the other children to avoid distractions, and with the device over a table. Children were allowed to move the device freely to feel comfortable.

- The acquisition was controlled from a distance by a supervisor at all times in order to control the proper flow of the acquisition.

**IV. Example Application: Age Detection**

This section analyses quantitatively one of the many different potential applications of ChildClIdb. In particular, we focus on the popular task of children age group detection based on the interaction with mobile devices [7], [9], [10], [33]. Due to the large volume of information captured in ChildClIdb, we focus in this section only on the analysis of the Test 6 (Drawing Test) based on the way children colour a tree. Fig. 2 shows some examples of the Drawing Test performed by different children age groups.

The organisation of this section is as follows: Sec. IV-A describes the experimental protocol. Sec. IV-B describes the age group detection systems proposed in this study. Finally, Sec. IV-C provides the results achieved.

**A. Experimental Protocol**

The experimental protocol proposed in this study has been designed to detect three different groups of children: Group 1 (children of educational levels 2 and 3, i.e., 1-3 years), Group 2 (children of educational levels 4, 5, and 6, i.e., 3-6 years), and finally Group 3 (children of educational levels 7 and 8, i.e., 6-8 years).

The current version of ChildClIdb (v1) has been divided into development (80%) and evaluation (20%) datasets, which comprise separate groups of subjects. The development dataset is used to train the age group detection systems whereas the evaluation dataset is finally used to test the trained systems on realistic conditions (new unseen subjects not used during the development stage). As the number of samples available in Group 1 and 3 is less than the Group 2, the data augmentation technique SMOTE of Imbalanced-Learn toolbox[34] was considered only during the development stage to balance and better train the models. For the final evaluation, only real samples of ChildClIdb are considered. To better estimate the skill of the machine learning models proposed, k-fold cross validation is used in this experimental framework with k=5. Final results provide the average values of the 5 fold cross validation.

**B. Age Group Detection Systems**

Different machine learning approaches are studied in this work. The proposed age group detection systems comprise

https://imbalanced-learn.org/stable/
three main modules: feature extraction, feature selection, and classification. The specific parameters of each approach are selected over the development dataset.

1) Feature Extraction: a set of 148 global features are extracted for each acquisition. From the total features extracted, 114 features are based on preliminary studies in the field of Human-Computer Interaction (HCI) and related with Time, Kinematic, Direction, Geometry, and Pressure information [34]–[36]. The remainder 34 features (denoted as Drawing features) are originally presented in this study and designed for the specific Drawing Test (colouring a tree). Table IV describes this novel set of 34 global features, which extracts relevant information such as the length of the drawing strokes, and the number of times the children colour outside the margin of the tree, among many others.

2) Feature Selection: the following approaches are studied to select the most discriminative features from the total 148 global features originally extracted:

- Fisher Discriminant Ratio (FDR): it measures the discriminative power of each independent global feature. The value increases with the inter-class variability and decreases with the intra-class variability. In our experiments, we select the subset of global features whose FDR values are higher than 0.05.

- Sequential Forward Floating Search (SFFS): this algorithm aims to select the optimal feature subset for a specific optimisation criteria while reducing the number of possible combinations to be tested. Therefore, this algorithm offers a suboptimal solution as it does not take into account all possible feature combinations, although it does consider correlations between features, achieving high-accuracy results [37]. The specific implementation considered in this study is publicly available in MLxtend.

- Genetic Algorithm (GA): this algorithm is inspired by Charles Darwin’s theory of natural evolution by relying on biologically inspired operations such as mutation, crossover, and selection; and it finds good application for feature selection in handwriting biometrics [38]. We consider the genetic algorithm originally presented in [39]. This algorithm has been completely programmed in this study from scratch, including aspects such as parallel execution to speed up the feature selection process. Our implemented code using Python is publicly available in GitHub. In our experiments, we consider the following parameters: random generations = 100, population = 200, crossover rate = 0.6, mutation rate = 0.05.

3) Classification: different classifiers are studied in our experimental framework. All of them are publicly available in Scikit-Learn [37]. In addition, for each classifier, the optimal parameters are selected after an in-depth search over the development dataset using the class GridSearchCV of Scikit-Learn.

http://rasbt.github.io/mlxtend/
https://github.com/BiDAlab/GeneticAlgorithm
https://scikit-learn.org/stable/
Naive Bayes (NB): this is a simple probabilistic classifier based on Bayes’ theorem with the “naive” assumption of conditional independence between every pair of features given the value of the class variable.

Logistic Regression (LR): this is a statistical classifier that models the probability of a certain class using logistic functions. In our experiments, we consider L2 regularisation.

K-Nearest Neighbours (K-NN): this is a non-parametric method in which an event is assigned to the class most common among its k nearest neighbours. In our experiments the number of neighbours is 5, and the algorithm used to compute the nearest neighbours is BallTree.

Random Forest (RF): this is an ensemble learning method that fits a number of decision tree classifiers at training time and outputs the class that is the mode of the classes of the individual trees. In our experiments, the number of trees in the forest is 100, the maximum depth of the tree is 75, and the function to measure the quality of the split is gini.

AdaBoost (AB): it combines multiple “weak classifiers” into a single “strong classifier”. It begins by fitting a classifier on the original dataset and then fits additional copies of the classifier on the same dataset but where the weights of incorrectly classified instances are adjusted such that subsequent classifiers focus more on difficult cases. We consider here the AdaBoost-SAMME approach presented in [40] with 50 maximum number of estimators.

Support Vector Machines (SVM): this is a popular learning algorithm that constructs a hyperplane or set of hyperplanes in a high- or infinite-dimensional space that best separates the classes. In this case, we have selected regularization with 0.1, polynomial kernel with degree 3 and coefficient scaled.

Multi-Layer Perceptron (MLP): this is a class of feed-forward Artificial Neural Network (ANN). It consists of three or more layers (an input and an output layer with one or more hidden layers) of non-linear activation nodes. Each node is connected to every node in the following layer (fully-connected). In our study, we have considered four hidden layers with 100, 200, 200, and 100 neurons for each hidden layer, respectively. In addition, Adam optimiser is considered with default parameters (learning rate of 0.001) and a loss function based on cross-entropy.

C. Experimental Results

1) Results: Table IV shows the results achieved in terms of age group classification Accuracy (%) over the final evaluation dataset of ChildClidb for the different feature selection and classification approaches considered.

We first analyse the results achieved by each feature selection technique. As can be seen, the algorithm SFFS provides the best results in all cases (83.38% average accuracy), followed by the Genetic Algorithm (79.23% average accuracy). The FDR algorithm provides the worst average accuracy results (73.00%). This seems to be produced because the FDR feature selection technique is based on the discriminative power of each independent feature. No correlations between features are considered in the selection process.

Analysing the results achieved by each classification approach, SVM, Random Forest, and MLP provide the best results with 90.45%, 88.69%, and 85.98% accuracies, respectively. Other simpler classifiers such as Naive Bayes and K-NN provide much worse results (69.63% and 71.24% accuracies, respectively).

Finally, we compare the results achieved with the state of the art. To the best of our knowledge, this is the first study that focuses on the classification of children age groups (from 18 months to 8 years) based on the interaction with mobile devices. Previous studies were focused on a simpler task, i.e., classification between children (3-6 years) and adults [7], [9], [10], achieving in the best cases classification accuracy results of 96.3%. Comparing that result achieved in a simpler task with the results achieved in the present study (accuracy results over 90%), we can conclude that: i) good results are achieved, proving the soundness of the proposed age group classification systems, and ii) the possibility to distinguish with high-accuracy results between different children age groups.

| # | Feature Description | # | Feature Description |
|---|---------------------|---|---------------------|
| 1 | $N$ (draw outside the tree margin) | 2 | $N$ (pen-downs) |
| 3 | $N$ (time samples inside the tree margin) | 4 | $N$ (time samples outside the tree margin) |
| 5 | $N_{\text{max}}$ (pen-down time samples) | 6 | $T_{\text{mean}}$ (pen-down) |
| 7 | $T_{\text{mean}}$ (pen-down) | 8 | $T_{\text{mean}}$ (pen-down) |
| 9 | $T_{\text{max}}$ (pen-down) | 10 | $N_{\text{max}}$ (pen-up time samples) |
| 11 | $T_{\text{min}}$ (pen-up) | 12 | $N_{\text{max}}$ (pen-up time samples) |
| 13 | $T_{\text{min}}$ (pen-up) | 14 | $T_{\text{mean}}$ (pen-up) |
| 15 | Mean (X-coordinate spatial position) | 16 | Mean (Y-coordinate spatial position) |
| 17 | Std (X-coordinate spatial position) | 18 | Std (Y-coordinate spatial position) |
| 19 | $N$ (changes in drawing direction) | 20 | $M_{\text{ax}}$ (X-coordinate spatial position) |
| 21 | $M_{\text{in}}$ (X-coordinate spatial position) | 22 | $M_{\text{ax}}$ (Y-coordinate spatial position) |
| 23 | $M_{\text{in}}$ (Y-coordinate spatial position) | 24 | End test before time? (Yes/No) |
| 25 | $T$ (drawing inside the tree margin) | 26 | $T$ (drawing outside the tree margin) |
| 27 | $T$ (drawing) | 28 | $T$ (not drawing) |
| 29 | $T$ (drawing inside the tree margin) / $T$ (drawing) | 30 | $T$ (drawing outside the tree margin) / $T$ (drawing) |
| 31 | $T$ (drawing inside the tree margin) / $T$ (drawing outside the tree margin) | 32 | $T$ (drawing) / $T$ (Test) |
| 33 | Draw anything? (Yes/No) | 34 | $N$ (time samples) |

TABLE IV: Novel set of 34 global features (denoted as Drawing features) proposed in this study for the task of colouring a tree (Test 6 - Drawing Test). $N$ stands for number and $T$ for time.
TABLE V: Results achieved in terms of age group classification Accuracy (%) over the final evaluation dataset of ChildCIdb for the different feature selection and classification approaches considered in the experimental framework. We remark in bold the best result achieved.

| Feature Selection | Naive Bayes | Logistic Regression | K-NN | Random Forest | AdaBoost | SVM | MLP |
|-------------------|------------|---------------------|------|---------------|----------|-----|-----|
| FDR               | 69.63      | 73.99               | 71.24| 75.56         | 68.27    | 75.58| 76.72|
| SFFS              | 78.09      | 82.22               | 81.98| 88.69         | 76.28    | 90.45| 85.98|
| GA                | 77.86      | 81.30               | 77.86| 80.37         | 73.98    | 81.51| 81.76|

Fig. 3: Number and type of global features selected for each machine learning approach studied. (Color image.)
2) Feature Selection Analysis: this section analyses the type of global features selected for each of the machine learning approaches studied. Fig. 3 shows the number of global features selected for each category (Time, Kinematic, Direction, Geometry, Pressure, and Drawing) [34]. For the FDR feature selection approach, a single subset of features is selected for all classifiers as this feature selector is independent of the classifier. For the SFFS and GA approaches, a different subset of features is selected for each classifier and feature selection approach. In all cases, we select the optimal feature vector that provides the best accuracy results in development.

Analysing the FDR approach, global features related to the Kinematic, Geometry, and Drawing information are predominant with percentages of 26.7%, 28.9%, and 28.9%, respectively. In total, 45 out of the 148 global features are selected in the optimal feature subset.

Regarding the SFFS approach, the features selected are very different depending on the specific classifier considered. For example, for simpler classifiers such as Naive Bayes, features related to the Time information are predominant (27.3%). Nevertheless, when we consider more sophisticated classifiers such as SVM, Random Forest, and MLP, features related to the Kinematic, Geometry, and Drawing information outweigh other types of features, being able to better exploit the non-linearity of the features and to achieve higher accuracy results (SFFS (Naive Bayes) = 78.09% vs. SFFS (SVM) = 90.45%). On average, 64 global features are selected using the SFFS approach. Similar trends are observed for the GA selection approach, with an average of 67 global features selected.

Finally, we also include in Fig. 4 the average percentage of features selected per category. In general, we can see that the novel features related to the Drawing information are the most selected ones with an average 24.2%. This result proves the success of the novel features designed in this study for the task of children age group detection. Other features based on the Geometry (20.3%) and Kinematic (18.5%) information of the children while interacting with the devices are also very important to distinguish between different age groups. However, information related to the Direction and Pressure performed by the children while colouring the tree seems not to be discriminative to distinguish between children age groups. These results prove the existence of different patterns in the motor control process of the children with the age such as the velocity and acceleration while performing strokes. These insights also agree with the physiological and cognitive changes across age discussed in Piaget’s theory [6].

V. Conclusions

This article has presented a preliminary study of our framework named ChildCI, which is aimed at generating a better understanding of Child-Computer Interactions with applications to e-Health and e-Learning, among others.

In particular, in this article we have presented all the details regarding the design and development of a new child mobile application, the specific acquisition protocol considered, and the first capturing session of the ChildCI dataset (ChildCIdb v1), which is publicly available for research purpose. In the scenario considered, children interact with a tablet device, using both the pen stylus and also the finger, performing different tasks that require different levels of motor and cognitive skills. ChildCIdb v1 comprises over 400 children in the ages from 18 months to 8 years, considering therefore the first three stages of the motor and cognitive development of the Piaget’s theory.

In addition, we have demonstrated the potential of ChildCIdb including experimental results for one of the many possible applications: children age group detection. Different machine learning approaches have been studied, proposing a new set of 34 global features to automatically detect the age group, achieving accuracy results over 90% and interesting findings in terms of the type of features more useful.

Future work will be oriented to: i) extend ChildCIdb with more participants and acquisition sessions, ii) analyse and improve the accuracy of the children age group detection systems using the remaining tests of ChildCIdb not considered in the present article, iii) study the application of other feature and signal representations of the drawing and screen interaction beyond the ones tested here with special emphasis in recent deep learning methods [41], iv) develop child-independent interaction models for the different test from which child-dependent behaviours can be derived [42], v) correlate the interaction information with the meta-data stored in the dataset like learning outcomes and ADHD [43], vi) combine the information provided by the multiple tests using information fusion methods [44], vii) exploit ChildCIdb in other research problems around e-Learning [16] and e-Health [15], [45], and viii) compare the insights achieved in ChildCI with previous studies focused on the traditional children cognitive development based on Piaget’s theory [6].

Acknowledgements

This work has been supported by projects: PRIMA (H2020-MSCA-ITN-2019-860315), TRESPASS-ETN (H2020-MSCA-ITN-2019-860813), BIBECA (MINECO/FEDER RTI2018-101248-B-I00), and Orange Labs. This is an on-going project carried out with the collaboration of the school GSD Las Suertas in Madrid, Spain.

https://github.com/BiDaLab/ChildCIdb_v1
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