Human Activity Recognition for Identifying Bullying and Cyberbullying: A Comparative Analysis Between Users Under and over 18 Years Old

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Abstract: The smartphone is an excellent source of data. Sensor values can be extrapolated from the smartphone. This work exploits *Human Activity Recognition (HAR)* models and techniques to identify human activity performed while filling out a questionnaire that aims to classify users as Bullies, Cyberbullies, Victims of Bullying, and Victims of Cyberbullying. The paper aims to identify activities related to the questionnaire class other than just sitting. The paper starts with a state-of-the-art analysis of HAR to arrive at the design of a model that could recognize everyday life actions and discriminate them from actions resulting from alleged bullying activities (*Questionnaire Personality Index*). Five activities were considered for recognition: Walking, Jumping, Sitting, Running, and Falling. The best HAR activity identification model was applied to the dataset obtained from the *"Smartphone Questionnaire Application"* experiment to perform the analysis. The best model for HAR identification is CNN.

1 INTRODUCTION

Identifying and recognizing human activities is called *Human Activity Recognition (HAR)*. These actions can vary, such as walking, sitting, falling, etc... (Carrera et al., 2022a; Vincenzo Dentamaro et al., 2020). Each requires *Artificial Intelligence (AI)* algorithms to analyze and classify raw data collected from devices like smartphones or smartwatches. According to (Minh Dang et al., 2020a), the latter has sensors that can capture data during activities. This data can classify and recognize activities (Minh Dang et al., 2020a).

The paper being a social and person problem, comes under the world of health and well-being (Angelillo, Balducci, et al., 2019; Angelillo, Impedovo, et al., 2019; Cheriet et al., 2023; Gattulli, Impedovo, Pirlo, & Semeraro, 2023; D. Impedovo et al., 2012; Donato Impedovo et al., 2021).

These devices can monitor users' mental and physical states with their sensors. Within an *IMU (Inertial Measurement Unit)*, an electronic device consists of accelerometers, gyroscopes, and occasionally magnetometers; these sensors are combined. To determine the number of axes on which the measurement of each sensor used is made, an n-axis IMU can be created, where the number of axes are the sum of the axes on which the measurement of each sensor is made. For example, when a three-axis accelerometer and a three-axis gyroscope are integrated, this is called a six-axis IMU. If the magnetometer is included, speak of a 9-axis IMU (Thomas et al., 2022; Zhang et al., 2022).

One of the fundamental sensors is the triaxial accelerometer, but other sensors, such as the triaxial gyroscope and magnetometer, are also used. Specifically:

1. The *Accelerometer* detects linear motion and gravitational force by measuring acceleration along the three axes: X, Y, and Z;
2. The *Gyroscope* measures the rate of rotation of a body about the X, Y, and Z axes;
3. The *Magnetometer* is used to detect and measure geomagnetic fields, which are only sometimes useful for HAR purposes; therefore, it is only sometimes included among the sensors used (Straczkiewicz et al., 2023).

Research on HAR is advanced, but few studies have recognized bullying actions over other activities. Most studies have focused on recognizing actions of physical violence, such as punching or pushing (Twyman et al., 2010). For this reason, datasets for

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recognizing bullying activities are less common than those for recognizing more general human activities. A fall can indicate a bullying action experienced (Twyman et al., 2010). A real-world example is a boy falling due to direct pushes or hits.

This paper focused on the recognition of bullying activities such as falling, an activity little considered in other studies, and other activities in line with other studies in the field. This paper aims to identify activities performed during the completion of a questionnaire by an experimental group of high school student's 18-year-olds, about 16 years, and an experimental group of college student's over-18-year-old, about 19 years, in Italy.

The study aims to achieve several objectives.

1. To understand and study the most widely used techniques in the state of the art of Human Activity Recognition and then use them for Bullying Detection systems, which deal with identifying and recognizing cases of bullying.
2. To compare the results obtained on this experimental group of under-18-year-olds and analyze any differences from the over-18-year-old group (Gattulli, Impedovo, Pirlo, & Sarcinella, 2023).

To achieve these goals, the literature was studied to understand the typical architecture of a Human Activity Recognition system, commonly used sensors, and the most relevant activities to be recognized. Next, dataset creation techniques were studied, and a public dataset was considered. Once this information was understood, a dataset containing data generated by the triaxial accelerometer for five different activities (*Walking, Running, Jumping, Sitting, and Falling*) was performed by nineteen participants. This dataset, named *"Uniba Dataset,"* was later compared with one of the best-known public datasets in the literature, *UniMiB SHAR*. The aim is to distinguish activities resulting from bullying from *Activities of Daily Living*. Next, SHAR studied smartphone-based methods to combine the activities in the datasets to the final label given by the questionnaire (*Bully, Cyberbully, Victim of Bullying, and Victim of Cyberbullying*).

The paper is structured as follows: *Section 2* contains the state-of-the-art Human Activity Recognition analysis focusing on the Smartphone-based category. *Sections 3 and 4* provide a detailed analysis of the Datasets, Features, and Classifiers used. *Section 5* discusses the solution implemented in the experiment. *Section 6* is analyzing the results obtained and discuss the strengths and weaknesses of the proposed model. *Section 7* provides the conclusions.

2 STATE OF ART

In this section, several studies on Human Activity identification are viewed and analyzed. A new type of human activity detection approach is considered that combines potential abnormal activities performed while filling out a questionnaire to identify attitudes associated with bullying or cyberbullying by the individual.

Many studies still need to include the feature extraction and selection phase; some examples of this type of study are given below. The investigation (Minarno et al., 2020) uses a triaxial gyroscope and accelerometer to recognize the daily actions of thirty volunteers. The researchers (Minarno et al., 2020) examined daily life actions, such as lying down, standing, sitting, walking, and going down or upstairs, including *Decision Tree, Random Forest,* and *K-Nearest Neighbor*. Some classifiers have excellent performance with up to 98 percent accuracy without implementing a feature selection and extraction step.

Testing is done using three public datasets: the *UMAFall* (Casilari et al., 2017), *UniMiB SHAR* (Micucci et al., 2017), and *SisFall* (Sucerquia et al., 2017). The latter is a publicly available dataset that is only sometimes considered because it uses only Inertial Measurement Units to collect data.

The study presents An interesting example (Dehkordi et al., 2020), in which a 75% overlap is applied on a two-second sliding window. According to the study, there are two types of actions: static actions, in which the global coordinates of the body do not change, and dynamic actions, in which the whole body is in motion. Ten users were considered. They were each given a smartphone to hold in their dominant hand and instructions on what to do. The smartphone's triaxial accelerometer (either a *Samsung Galaxy* or an *LG Nexus*) collected data at 50 Hz. The classification phase took place with the implementation of many classifiers, including *Support Vector Machine, Decision Tree,* and *Naïve Bayes*. The latter two performed the best by achieving 98% average accuracy between static and dynamic task recognition.

2.1 Recognition of Acts of Bullying or Violence

The vision-based approach can identify bullying or violent actions in human activity detection. According to the study (Minh Dang et al., 2020b), sensor-generated data are more difficult to obtain. There are two categories of data: RGB and RGB-D. The second type of data offers higher accuracy than RGB data but is less used because it is more complex and expensive. This study also emphasizes how vital the pre-processing and feature extraction stages are. Classifiers are trained on datasets consisting of movies or frames to determine whether or not there are violent situations in the described scene. After a thorough analysis by the authors regarding several classifiers, the most efficient one turns out to be CNN, with an accuracy ranging from 93.32% to 97.62%.

Researchers have combined sensor-based activity recognition and voice tone emotions to recognize activities (Zihan et al., 2019). In this study (Ye et al., 2018), sensors used in smartphones and smartwatches were used for sensor-based activity recognition. To reduce the size of the feature matrix, some features were extracted a priori and then selected using the principal component analysis algorithm. *Mel Frequency Cepstral Coefficients (MFCC)*, a representation of the short-term power spectrum of a sound, were used to calculate features for emotion recognition by voice. The classifier used is a K-Nearest Neighbors. Cross-validation results showed 77.8 percent accuracy for sensor-based systems and 81.4 percent for audio-based systems.

Also considered were studies in which public datasets are used. The first example considered is the study (Amara et al., 2021) that used the *UMAFall* and SisFall Datasets created with 38 volunteer participants. The data created were then divided: 20% is devoted to examination, 30% to validation, and 50% to training. In pre-processing, activities are assigned a label to determine whether they are daily activities or falls. As a result, the classification is binary, and the number of instances in the classes needs to be more balanced. *UMAFall* is used only with these class-unbalanced methods with binary classification in the fall detection domain.

Some studies, also conducted by the authors of this paper, have used smartphone-based sensor methods to deal with cyberbullying. Indeed, the smartphone is an excellent source of information. An anomaly detection analysis characterized by human behavior can be performed using smartphone sensor values using machine learning techniques.

The researchers (Gattulli, Impedovo, Pirlo, & Sarcinella, 2023) use *Human Activity Recognition (HAR)* models and techniques to identify human activity performed while filling out a questionnaire using a smartphone application that aims to classify users as Bullies, Cyberbullies, Bullying Victims, and Cyberbullying Victims. The work aims to discuss an innovative smartphone method that integrates the results of the cyberbullying and bullying questionnaire (*Bully, Cyberbully, Bullying Victim, and Cyberbullying Victi*m) and the human activity performed. At the same time, the individual fills out the questionnaire. The work begins with state-of-the-art analysis of HAR to arrive at the design of a model capable of recognizing actions of daily life and distinguishing them from those that might result from alleged bullying. Five activities were considered for recognition: *Walking, Jumping, Sitting, Running, and Falling* (Castro, Dentamaro, et al., 2023). The best HAR activity identification model is applied to the dataset derived from the *"Smartphone Questionnaire Application"* experiment to perform the previously described analysis. The work presented in the following paper is the precursor (Gattulli, Impedovo, Pirlo, & Sarcinella, 2023) to the one present.

Another work analyzed is that of (Gattulli, Impedovo, & Sarcinella, 2023), which analyzes a method of *Detection Anomaly,* an essential process for identifying a situation different from the ordinary. The following study analyzes anomalies in the human behavioral domain observed when filling out a questionnaire on bullying and cyberbullying. This work analyzes smartphone sensor data (*Accelerometer, Magnetometer,* and *Gyroscope*) to use anomaly detection techniques to identify anomalous behaviors used during questionnaire completion in an Android application. To understand any polarizing content suggested during the use of the application and identify users who exhibit abnormal behaviors, which could be expected of classes of users, psychology and computer science work together to analyze and detect any latent patterns within the dataset under consideration (Gattulli, Impedovo, & Sarcinella, 2023).

3 DATASET

The datasets used during this experiment are as follows:

DatasetUniba. The creation of this dataset took place in a controlled environment with nineteen participants, including thirteen males and six females (Gattulli, Impedovo, Pirlo, & Sarcinella, 2023). Each participant performed eight different actions divided into the two categories previously described:

ADL:

- *Walking;*
- *Running;*
- *Hopping;*
- *Sitting;*
- *Falling (forward, backward, right, and left).*

Only accelerometer-generated data were collected using a smartphone placed in each participant's right pocket, with the screen facing the body. This was done at a sampling rate of 200 Hz using the Android application. The collected raw data were then sent to a server in *TXT format* to be reprocessed and converted to *CSV format*. Each task was performed several times (two or three). Each trial was 15 seconds long. The falls were performed on a mattress placed on the floor.

The CSV file is divided into three columns: the first column contains the user ID, the second contains the activity performed, the third contains the Timestamp in milliseconds from the start of the action, and the next three contain the three triaxial accelerometer values X, Y, and Z.

DatasetUniba Resampled. A resampled version of the DatasetUniba.

UniMiB SHAR. Dataset consisting only of values obtained from the accelerometer. Recognized activities are again divided into two categories:

Falling:

- Falling forward;
- Falling backward;
- Falling to the right;
- Falling to the left;
- Falling by hitting an obstacle;
- Falling with protective strategies;
- Falling backward without protective strategies;
- Syncope.

ADL:

- *Walking;*
- *Running;*
- *Climbing stairs;*
- *Descending stairs;*
- *Jumping;*
- *Lying down from a standing position;*
- *Sitting.*

For each activity, there are 2 to 6 trials for each user. For the actions with two trials, the smartphone in the right pocket is used in the first and the left in the second. For actions with six trials, the first three have the smartphone in the right pocket and the others in the left pocket. Data are provided in windows of 51 or 151 samples around an original signal peak higher than 1.5g, with g being the acceleration of gravity. The best results obtained in the experimentation performed from this dataset are with a K-NN in the ADL-only category.

In all datasets, all activities are considered anomalous except the sitting activity.

4 METHODS

The machine learning models used are:

- **CNN**, a convolutional, feed-forward neural network, consisting in this case of 3 ReLU layers, each alternating with a pooling layer for simplifying the output obtained from the previous layer, whose practical goal is to reduce the number of parameters the network must learn. After these, a flattened layer is used for linearizing the output, and a SoftMax layer is used for the classification.
- **LSTM**, a type of RNN, differs from CNN networks because of the addition of *feedback* layers, whose peculiarity is the ability to learn from long-time sequences and then maintain memory. This network is structured by 2 LSTM layers, alternating with a Dropout layer. Then, the actual layers are devoted to the prediction of relu and SoftMax.
- **Bi-LSTM** is a particular type of LSTM network that is practically trained to make predictions not only on past knowledge but also on future knowledge and then go backward with the predictions. Unlike the LSTM network, which can learn unidirectionally.

Each of these models was used in different combinations with the various datasets. Starting with CNN, it was noted that remarkable performance was achieved compared with LSTM and Bi-LSTM.

5 EXPERIMENTATIONS

The experiment is organized into several stages:

- Data pre-processing;
- Extraction of data generated by the sensors;
- Classifier training;
- Activity recognition;
- Comparing results with data from users under 18 years old with results from users over 18 years old.

The pre-processing phase was carried out to prepare the data for further processing to simplify the classification of activities. Specifically:

- Activities that were not relevant (in the case of *UniMiBSHAR*) were removed;

- Activities were renamed and grouped into a more manageable and meaningful set. For example, the various types of falls (right, left, front, and back) were aggregated into a single activity representing each type of fall;
- The data were appropriately adapted into a three-dimensional form for input into a CNN.

The second phase of the experiment involved a data feature extraction phase by which only the accelerometer values were extracted from the text files from the sensors of the devices used by the users when filling out the questionnaire. Values generated by the magnetometer and gyroscope were then discarded. The row of interest (X, Y, and Z coordinates) was placed within a data structure offered by the Python Pandas library, called a data frame. Each coordinate triple (X, Y, Z) also specified the questionnaire screen in which that movement was recorded. This procedure obtained a series of CSV files used in the following steps to make predictions. The entire process was repeated for all users participating in all test phases (Test1, Test2, Test3) except a few who needed to be considered because they had not completed the entire questionnaire.

In phase three, the chosen HAR classifiers are trained with three HAR datasets: *UniMiB SHAR* (Micucci et al., 2017), *DatasetUniba*, and *DatasetUniba Resampled*, a sampled version of Dataset Uniba. In the fourth phase, through the HAR model, the activities performed using the results of the first phase are predicted for each user. The fifth phase compares the results obtained on college students over 18 and those obtained on high school students under 18. This way, the differences between the two groups of participants are analyzed.

6 RESULTS

Our research methodology focused on evaluating a variety of Deep Learning datasets and model combinations to determine the most effective configuration (Cannarile et al., 2022; Donato Impedovo et al., 2019, 2023). Various model and dataset combinations were used to evaluate their performance to complete the offline training phase. *Table 1* shows the results, including the overall users' accuracy averages and F1-scores.

It is critical to note that these values represent the averages for each user in the dataset, which was trained using the Leave One Out technique. The latter technique ensures a reliable training process in which each user is isolated during model training. This allows us to evaluate the system's performance under more realistic and generalizable conditions. In this way, we provide a comprehensive assessment of the predictive capabilities of our model for the dataset in question.

Table 1: Accuracy results and F1_Score averages.

Model	Dataset	Average Accuracy	Average F1-Score
CNN	**DatasetUniba**	**0,915**	**0,901**
CNN	**UniMiBShar**	**0,998**	**0,996**
CNN	DatasetUniba Resampled	0,659	0,459
LSTM	DatasetUniba	0,865	0,819
Bi-LSTM	DatasetUniba	0,891	0,855

Below is a comparison of the results obtained by high school students under 18 and college students over 18 (Figure 1- 4).

Legend (Figure 1-2): *Bullying (blue), Victim of Bullying (orange), Cyberbully (gray), Victim of Cyberbullying (yellow).*

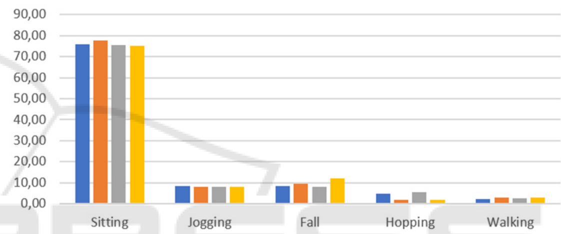

Figure 1: Recognized activities for high school students under 18 years.

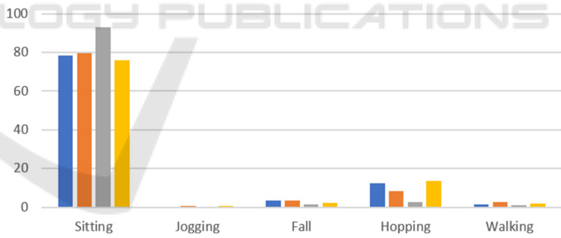

Figure 2: Recognized activities of college students over 18 years by category.

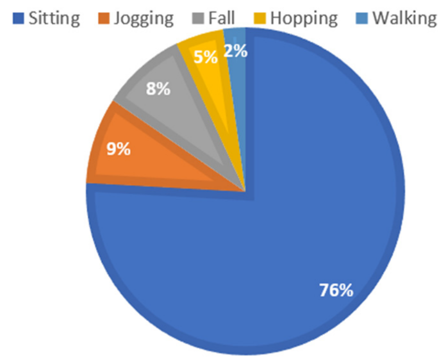

Figure 3: Activity percentages of high school students under 18 years.

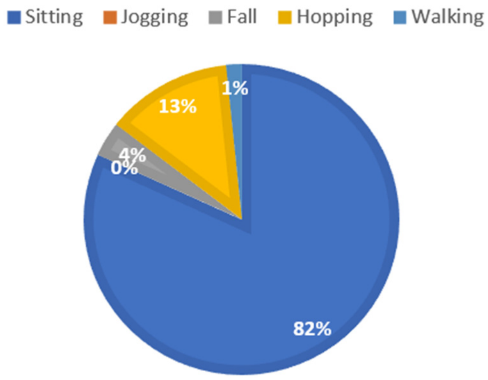

Figure 4: Percentages of college student activity over 18 years.

Looking at the results obtained, some psychological and scientific observations could be made:

- **Cyberbullies** under 18 years old showed abnormalities in the initial part of the questionnaire, with jumping, falling, and running activities while watching videos related to the feelings they experienced. **Cyberbullies** over 18 years, on the other hand, were considered “quieter” as they spent most of their time sitting in higher percentages than the other categories;

- **Bullies**, among high schoolers under 18 years, showed running and falling as prevalent abnormal activities. Among those over 18 years, on the other hand, the prevalent abnormal activity shown was jumping. These abnormal activities were recorded, particularly during the questionnaire phases composed of the *QuizActivityButtons/DomestionsVideos*;

- **Bully victims under 18 years showed more remarkable abnormal phases** during *QuizActivityButtons* but with prevalent falling and running activities. For those over 18 years, the abnormal phase is mainly characterized by jumping activities;

- The **Victims of CyberBullies** Under 18 years, as well as the bullies, recorded falling and running as their main abnormal activity, particularly during the *QuizActivityButton/DomestionsVideo* phase. Victims Over 18 years, on the other hand, were the only users who showed abnormalities in the early part, as well as **Cyberbullies** in our experiment.

In general, frequent abnormal running and falling activities were observed in the sample of high school students under 18 years, while hopping activities were less frequent and walking activities were almost nonexistent. Among college students over 18 years, on the other hand, the predominant abnormal activity recorded was hopping, while the other activities, except sitting, were infrequent.

In addition, the questionnaire could be reduced to only those questions about the category of **bully** to be identified. In both experiments, in the case of **bullies and victims** of bullies, the *QuizActivityButton* activities would suffice, thus removing the initial part of submitting videos and related questions.

For the **Bullies Under 18 years**, questions regarding the running activity were more discriminating:

- *Bullying*: the frequency with which bullying was done (stealing items, discriminating against someone because of disability/skin color/sexual orientation, pushing);

- *Cyberbullying*: in what environment it occurs, how many incidents have been suffered, and how many text messages containing insults have been received.

For the fall activity, questions regarding.

- *Habits*: rules imposed by parents and control internet use, whether cyberbullying has been discussed in the classroom.
- *Bullying*: If you intervene if you see a case of bullying in action, how often you were bullied and the frequency you were bullied (Physical, Verbal, Behavioral, and Threats).

Victims of bullying under 18 years recorded abnormal fall activities in responding to questions concerning:

- *Bullying*: whether one has been subjected to threats, exclusion, physical violence, false rumors about oneself, discrimination because of one's skin/culture, theft, or damage to one's belongings.

- *Cyberbullying*: the frequency with which you have been bullied through messages, media, websites, and e-mails; the frequency with which you have been ignored online; whether someone has impersonated you, received false news about you, impersonated you on social media or with your address book contacts.

Regarding Cyberbullies under 18 years, questions regarding the following were found to be discriminating for the fall activity.

- *Bullying*: whether one has been subjected to threats, exclusion, physical violence, false rumors about oneself, discrimination because of one's skin/culture, theft, or damage to one's belongings.

For the running activity, the questions are covered.

- *Cyberbullying*: the frequency with which acts of cyberbullying such as threatening and abusive texting/emails, sending violent, embarrassing, or intimate media, threatening online, making silent or intimidating phone calls, and spreading false rumors about other people.

For the skipping activity, the questions covered:

- Emotions were felt when watching some videos and asking general questions.

For the **Cyberbullies over 18 years**, questions regarding:

- *Cyberbullying*: specifically, the frequency with which acts of bullying were carried out through messages, media, phone calls, and e-mails.

Victims of Cyberbullying Under 18 years recorded abnormal running activities for the following questions:

- *Cyberbullying*: the frequency with which acts of cyberbullying such as threatening and abusive texting/emails, sending violent, embarrassing, or intimate media, threatening online, making silent or intimidating phone calls, and spreading false rumors about other people.

In addition, abnormal fall activities have been recorded:

- *Bullying*: threats, exclusion, physical violence, false rumors about oneself, discrimination because of one's skin/culture, theft of or damage to one's belongings were experienced.
- *Cyberbullying*: how often you have been bullied via messages, media, websites, and e-mail, how often you have been ignored online, whether someone has impersonated you, received false rumors about you, impersonated you on social

Victims of cyberbullying over 18 years, on the other hand, recorded abnormal activities during the initial part concerning The emotions felt when watching some videos and general questions.

7 CONCLUSIONS

In this work, *Human Activity Recognition (HAR)* models are used to examine the behavior exhibited by high school students under 18 years old and college students over 18 years old while performing a questionnaire. The distinguishing feature of this research is the use of accelerometer sensors built into smartphones, which allowed us to record users' behaviors in detail.

This technique allowed us to analyze the actions of individuals, distinguishing between different movements and actions. They are considered *"abnormal,"* all those behaviors beyond simply sitting, focusing on more dynamic or unusual activities or movements that could provide significant information about students' emotional state or active participation while filling out the questionnaire.

By using HAR models in this context, we could better understand the behavioral patterns formed during the interaction with the questionnaire and find attractive cues for evaluating the responses.

In this research, we used accelerometer technology innovatively, which allowed us to improve our analysis capabilities and offered new perspectives for interpreting and monitoring student behavior in scientific research contexts.

We can conclude these experiments by saying that we achieved our goals, namely:

- It was possible to use appropriate DL models to perform HAR on data generated by sensors on a smartphone, all after comparing different models and datasets to achieve optimal accuracy. The best performance was obtained with a *Convolutional Neural Network (CNN) with DatasetUniba* and *UniMiBSHAR datasets*;
- The results obtained in this experiment on an experimental group of high school students under 18 years were compared with those obtained from college students over 18 years.

Participants under 18 did a lot more running and falling, but they did less jumping than their over-18-year-old counterparts, who said jumping was one of the most frequent unusual things they did.

Both groups spent most of their time sitting, with 76 percent of participants under 18 years and 82 percent over 18 years. The two groups spent the same amount of time on other activities, except jumping, an unusual behavior commonly seen by the under-18-

year-old participants but never seen by the over-18-year-old participants.

This view allows us to observe how the under-18-year-olds are particularly active and active compared to their over-18-year-old peers. This difference in behavior could be because young people are more sensitive and concerned about bullying. Their greater involvement in the complex social dynamics that foster bullying could be the reason for this interest.

Implementing more advanced cybersecurity measures, such as data encryption, could be expected. More excellent protection of sensitive information can be ensured through modern techniques, helping preserve privacy and prevent harmful phenomena such as online bullying. In this context, cybersecurity becomes essential to ensure a safer and more secure digital environment, particularly considering how actively young people are involved in online activities (Carrera et al., 2022b; Castro, Impedovo, et al., 2023; V. Dentamaro et al., 2021; Vincenzo Dentamaro et al., 2018; Galantucci et al., 2021).

REFERENCES

Amara, M. I., Akkouche, A., Boutellaa, E., & Tayakout, H. (2021). A Smartphone Application for Fall Detection Using Accelerometer and ConvLSTM Network. 2020 2nd International Workshop on Human-Centric Smart Environments for Health and Well-Being (IHSH), 92–96. doi: 10.1109/IHSH51661.2021.9378743

Angelillo, M. T., Balducci, F., Impedovo, D., Pirlo, G., & Vessio, G. (2019). Attentional Pattern Classification for Automatic Dementia Detection. IEEE Access, 7, 57706–57716. doi: 10.1109/ACCESS.2019.2913685

Angelillo, M. T., Impedovo, D., Pirlo, G., & Vessio, G. (2019). Performance-Driven Handwriting Task Selection for Parkinson's Disease Classification. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11946 LNAI, 281–293. doi: 10.1007/978-3-030-35166-3_20/COVER

Cannarile, A., Dentamaro, V., Galantucci, S., Iannacone, A., Impedovo, D., & Pirlo, G. (2022). Comparing Deep Learning and Shallow Learning Techniques for API Calls Malware Prediction: A Study. Applied Sciences 2022, Vol. 12, Page 1645, 12(3), 1645. doi: 10.3390/APP12031645

Carrera, F., Dentamaro, V., Galantucci, S., Iannacone, A., Impedovo, D., & Pirlo, G. (2022a). Combining Unsupervised Approaches for Near Real-Time Network Traffic Anomaly Detection. Applied Sciences 2022, Vol. 12, Page 1759, 12(3), 1759. doi: 10.3390/APP12031759

Carrera, F., Dentamaro, V., Galantucci, S., Iannacone, A., Impedovo, D., & Pirlo, G. (2022b). Combining Unsupervised Approaches for Near Real-Time Network Traffic Anomaly Detection. Applied Sciences 2022, Vol. 12, Page 1759, 12(3), 1759. doi: 10.3390/APP12031759

Casilari, E., Santoyo-Ramón, J. A., & Cano-García, J. M. (2017). UMAFall: A Multisensor Dataset for the Research on Automatic Fall Detection. Procedia Computer Science, 110, 32–39. doi: 10.1016/j.procs.2017.06.110

Castro, F., Dentamaro, V., Gattulli, V., & Impedovo, D. (2023). Fall Detection with LSTM and Attention Mechanism. WAMWB 2023 Advances of Mobile and Wearable Biometrics 2023.

Castro, F., Impedovo, D., & Pirlo, G. (2023). A Medical Image Encryption Scheme for Secure Fingerprint-Based Authenticated Transmission. Applied Sciences 2023, Vol. 13, Page 6099, 13(10), 6099. doi: 10.3390/APP13106099

Cheriet, M., Dentamaro, V., Hamdan, M., Impedovo, D., & Pirlo, G. (2023). Multi-speed transformer network for neurodegenerative disease assessment and activity recognition. Computer Methods and Programs in Biomedicine, 230. doi: 10.1016/J.CMPB.2023.107344

Dehkordi, M. B., Zaraki, A., & Setchi, R. (2020). Feature extraction and feature selection in smartphone-based activity recognition. Procedia Computer Science, 176, 2655–2664. doi: 10.1016/j.procs.2020.09.301

Dentamaro, V., Convertini, V. N., Galantucci, S., Giglio, P., Palmisano, T., & Pirlo, G. (2021). Ensemble consensus: An unsupervised algorithm for anomaly detection in network security data. CEUR WORKSHOP PROCEEDINGS, 2940, 309–318. Retrieved from https://ricerca.uniba.it/handle/11586/377597

Dentamaro, Vincenzo, Impedovo, D., & Pirlo, G. (2018). LICIC: Less Important Components for Imbalanced Multiclass Classification. Information 2018, Vol. 9, Page 317, 9(12), 317. doi: 10.3390/INFO9120317

Dentamaro, Vincenzo, Impedovo, D., & Pirlo, G. (2020). Fall detection by human pose estimation and kinematic theory. Proceedings - International Conference on Pattern Recognition, 2328–2335. doi: 10.1109/ICPR48806.2021.9413331

Galantucci, S., Impedovo, D., & Pirlo, G. (2021). One time user key: A user-based secret sharing XOR-ed model for multiple user cryptography in distributed systems. IEEE Access, 9, 148521–148534. doi: 10.1109/ACCESS.2021.3124637

Gattulli, V., Impedovo, D., Pirlo, G., & Sarcinella, L. (2023). Human Activity Recognition for the Identification of Bullying and Cyberbullying Using Smartphone Sensors. Electronics 2023, Vol. 12, Page 261, 12(2), 261. doi: 10.3390/ELECTRONICS12020261

Gattulli, V., Impedovo, D., Pirlo, G., & Semeraro, G. (2023). Handwriting Task-Selection based on the Analysis of Patterns in Classification Results on Alzheimer Dataset. IEEESDS'23: Data Science Techniques for Datasets on Mental and Neurodegenerative Disorders.

Gattulli, V., Impedovo, D., & Sarcinella, L. (2023). Anomaly Detection using smartphone Sensors for a Bullying Detection. WAITT 2023 - 1st Workshop on Artificial Intelligence for Technology Transfer.

Impedovo, D., Pirlo, G., Sarcinella, L., Stasolla, E., & Trullo, C. A. (2012). Analysis of stability in static signatures using cosine similarity. Proceedings - International Workshop on Frontiers in Handwriting Recognition, IWFHR, 231–235. doi: 10.1109/ICFHR.2012.180

Impedovo, Donato, Dentamaro, V., Abbattista, G., Gattulli, V., & Pirlo, G. (2021). A comparative study of shallow learning and deep transfer learning techniques for accurate fingerprints vitality detection. Pattern Recognition Letters, 151, 11–18. doi: 10.1016/J.PATREC.2021.07.025

Impedovo, Donato, Dentamaro, V., Pirlo, G., & Sarcinella, L. (2019). TrafficWave: Generative deep learning architecture for vehicular traffic flow prediction. Applied Sciences (Switzerland), 9(24). doi: 10.3390/APP9245504

Impedovo, Donato, Pirlo, G., & Semeraro, G. (2023). Next Activity Prediction: An Application of Shallow Learning Techniques Against Deep Learning Over the BPI Challenge 2020. IEEE Access, 11, 117947–117953. doi: 10.1109/ACCESS.2023.3325738

Micucci, D., Mobilio, M., & Napoletano, P. (2017). UniMiB SHAR: A dataset for human activity recognition using acceleration data from smartphones. Applied Sciences (Switzerland), 7(10). doi: 10.3390/app7101101

Minarno, A. E., Kusuma, W. A., Wibowo, H., Akbi, D. R., & Jawas, N. (2020). Single Triaxial Accelerometer-Gyroscope Classification for Human Activity Recognition. 2020 8th International Conference on Information and Communication Technology, ICoICT 2020. doi: 10.1109/ICOICT49345.2020.9166329

Minh Dang, L., Min, K., Wang, H., Jalil Piran, M., Hee Lee, C., & Moon, H. (2020a). Sensor-based and vision-based human activity recognition: A comprehensive survey. Pattern Recognition, 108, 107561. doi: 10.1016/J.PATCOG.2020.107561

Minh Dang, L., Min, K., Wang, H., Jalil Piran, M., Hee Lee, C., & Moon, H. (2020b). Sensor-based and vision-based human activity recognition: A comprehensive survey. Pattern Recognition, 108. doi: 10.1016/j.patcog.2020.107561

Straczkiewicz, M., Huang, E. J., & Onnela, J. P. (2023). A “one-size-fits-most” walking recognition method for smartphones, smartwatches, and wearable accelerometers. Npj Digital Medicine 2023 6:1, 6(1), 1–16. doi: 10.1038/s41746-022-00745-z

Sucerquia, A., López, J. D., & Vargas-Bonilla, J. F. (2017). SisFall: A fall and movement dataset. Sensors (Switzerland), 17(1). doi: 10.3390/s17010198

Thomas, B., Lu, M. L., Jha, R., & Bertrand, J. (2022). Machine Learning for Detection and Risk Assessment of Lifting Action. IEEE Transactions on Human-Machine Systems, 52(6), 1196–1204. doi: 10.1109/THMS.2022.3212666

Twyman, K., Saylor, C., Taylor, L. A., & Comeaux, C. (2010). Comparing children and adolescents engaged in cyberbullying to matched peers. Cyberpsychology, Behavior and Social Networking, 13(2), 195–199. doi: 10.1089/CYBER.2009.0137

Ye, L., Wang, P., Wang, L., Ferdinando, H., Seppänen, T., & Alasaarela, E. (2018). A Combined Motion-Audio School Bullying Detection Algorithm. International Journal of Pattern Recognition and Artificial Intelligence, 32(12). doi: 10.1142/S0218001418500465

Zhang, Y., Wang, L., Chen, H., Tian, A., Zhou, S., & Guo, Y. (2022). IF-ConvTransformer: A Framework for Human Activity Recognition Using IMU Fusion and ConvTransformer. Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies, 6(2), 88. doi: 10.1145/3534584

Zihan, Z., & Zhanfeng, Z. (2019). Campus bullying detection based on motion recognition and speech emotion recognition. Journal of Physics: Conference Series, 1314(1). doi: 10.1088/1742-6596/1314/1/012150

APPENDIX

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