Handwriting Detection Test (HWDT): Android Application for the Recognition of Neurodegenerative Diseases

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Abstract: Nowadays there is an increase in the global incidence of dementia, with over 55 million reported cases worldwide. In Italy, the number is estimated to exceed 1 million individuals. According to evidence, a therapeutic approach in the pre-clinical stages involves conducting screening tests to identify changes in the handwriting process. This paper aims to propose an E-Health app named Handwriting Detection Test (HWDT). The proposed app is a smart-screening solution that reduces time and waiting periods in the interaction between experts and patients. We implemented screening tests derived from recent advances or ongoing research. The paper highlights the significant role of handwriting behavior and explains the design and development phases of the proposed system. This approach offers a more efficient and technologically advanced method for early detection and monitoring of cognitive changes associated with neurodegenerative impairments.

1 INTRODUCTION

Artificial Intelligence (AI) and Behavioral Biometrics systems play increasingly pivotal role in health-related issue detection. Behavioral Biometrics tools have opened avenues for groundbreaking advancements in healthcare diagnostics and monitoring: These tools can be used as digital sentinels, providing a proactive approach to healthcare by flagging potential issues long before they manifest in overt symptoms.

In recent times, behavioral biometrics tools have largely impacted Dementia studies by offering a new approach to improve individual's quality of life. This is particularly true in the assessment of Neurodegenerative Disorders (ND; Cheriet et al., 2023),defined as an incurable and heterogeneous group of medical conditions which lead to progressive modifications of the ability to carry out essential functions with cognitive dysfunction and behavioral impairment (Dugger & Dickson, 2017; Lamptey et al., 2022; Wilson et al., 2023). To date, clinical criteria are employed to assess cognitive impairments (Gómez-Río et al., 2016; Mordhorst et al., 2022): practitioners employ screening tests or comprehensive neuropsychological assessments, supported by medical information, or neurological exams to move from a "possible" to a "probable" diagnosis(Menéndez-González, 2023; Hansson, 2021).

Evidence shows that the most prevalent neurodegenerative conditions refer to Alzheimer's Disease (AD) and Parkinson's Disease (PD). In this regard, literature provides valid instruments to investigate changes in cognitive functions. Current evidence states that The Mini-Mental State Examination (MMSE; Folstein et al., 1975)or Montreal Cognitive Assessment (MOCA; Nasreddine et al., 2005) are the most used for cognitive screening (Tsoi et al., 2015) even if MoCA is preferred because it assesses executive function and visuospatial abilities (Siqueira et al., 2019; Hoops et al., 2009).

The paper is structured as below. The second part is related to a brief overview about intelligent tools and applications related to our research purpose. The third section is focused on the architecture and development phases of the Handwriting Detection Test (HWDT) which is the core of this work. The last section (4) illustrates the conclusions and planned future work.

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1.1 Alzheimer’s Disease

Alzheimer's Disease (AD) represents the most common form of Dementia. AD people from the early onset mainly suffer from cognitive (e.g. memory, comprehension, language, attention, reasoning, and judgment) and functional (e.g. behavioral) deficits (Kumar et al., 2022) the severity of which shifts according to the disease stage. Indeed, data shows that AD is classify into three stages: preclinical, mild and dementia-stage (Abbatantuono et al., 2023; Albert et al., 2011). Individuals in the transitional stage between aging and dementia are diagnosed with Mild Cognitive Impairment (MCI; Petersen, 2016), defined as a progressive pathological condition that increases the likehood to develop AD disease (Shigemizu et al., 2020; Calub et al., 2023; Chen et al., 2022; Iachini et al., 2009).

AD can be assessed by combining information through biomarkers (Hansson, 2021) or imaging techniques such as Structural Magnetic Resonance Imaging (MRI; Afzal et al., 2021). Moreover, neurological exams and cognitive and functional assessments are use in order to obtain a comprehensive evaluation of patients. Traditional methods for diagnosis of dementia rely on medical history, physical examination, or neurological testing (Ritchie et al., 2017; Weintraub et al., 2018) resulting partially subjective evaluations. However the existing treatments can only postpone the progression of the disease.

This highlight the need to diagnostic them as early as possible. In this regard, the analysis of alterations in handwriting has proved to be fundamental in early diagnosis and assessment of disease progression (Impedovo et al., 2019).

1.2 Parkinson's Disease

Parkinson's Disease (PD) is defined as a neurodegenerative and multisystemic condition (Chahine et al., 2020) and involve both functional, cognitive and behavioral disorders. In particular, PD symptomatology in mainly related to motor impairments, e.g. Akinesia; Rigidity; Tremor; Postural instability, bradykinesia, tremors, gait/balance issues (Armstrong & Okun, 2020; Marino et al., 2019) and non-motor symptoms, e.g. difficulties in sleep and attention (Jankovic, 2008), cognitive decline (Bosboom et al., 2004), a reduced ability detect smells, voice changes (Aouraghe et al., 2023). Researchers have identified different PD stages from early to advanced (Carrarini et al., 2019; Hoehn & Yahr, 1967).

According to Movement Disorder Society-PD criteria (MDS-PD), the diagnosis relies on clinical assessment (Heinzel et al., 2019), involving a thorough examination of medical history and neurological evaluations (Bloem et al., 2021). Thus, the diagnosis is challenging: clinical assessment is the gold standard, supported by brain imaging approaches and biomarker-supporter diagnostic tools widely used as valid approaches to confirm suspected PD (Tolosa et al., 2021).

Despite the extensive use of standardized assessment tools in healthcare, several studies highlight that the handwriting analysis is powerful for the ability to detect subtle changes in cognitive functioning even in the early stages of neurodegenerative diseases (Aouraghe et al., 2023; Drotár et al., 2016; J. Zhang et al., 2023).

The present work aims to provide an app based on a battery of digital screening based on handwriting task solutions. In addition, several aspects were considered, including the level of education of users, the feasibility of testing and the context of use.

2 RELATED WORK

Nowadays, e-health health tools are employed to investigate individual health conditions (Sblendorio et al., 2023). The literature highlighted the significant role that handwriting analysis can play in assessing clinical conditions, including neurodegenerative diseases (Aouraghe et al., 2023; Chai et al., 2023; Faundez-Zanuy et al., 2021).

Handwriting results from an elaborate human activity involving cognitive, kinesthetic, and perceptual-motor components (Cilia et al., 2019). Handwriting tools can capture information starting based on an individual’s performance in handwriting tasks to distinguish healthy subjects from people affected by ND (Angelillo et al., 2019a; Angelillo et al., 2019b; Impedovo et al., 2012; Pirlo & Impedovo, 2013).These tools provide more information compared to traditional assessment (pen-and-paper tests) which remains a good method to evaluate health status.

In this work, we focus on the value of handwriting performance analysis. Indeed, the adoption of a smart Pen on a digital screen provides data about the individual’s abilities in performing tasks (axis coordinates, position, pressure, and time information) (Ardimento et al., 2021; Aversano et al., 2020; Faundez-Zanuy et al., 2020). The integration of digital tools such as smart devices or mobile apps allows objective, real-time monitoring, and more comprehensive information about an individual's health status, also taking an active role in managing their health (Wicks et al., 2014).

In neurodegenerative conditions, signs of difficulties or alterations in handwriting i.e., micrography, slower movements, or tremors are related to pathology's biomarkers (Impedovo & Pirlo, 2018; Gattulli et al., 2023a; Gattulli et al., 2023c). De Stefano et al. (2019) emphasize using handwriting tasks allows to capture of essential features, including spatial organization and fine motor control abilities, and the type of movement (e.g., in-air). For such problem, several pattern recognition algorithms have been developed over the years ranging from shallow learning techniques to advanced deep learning techniques such as wave nets and transformers(Cannarile et al., 2022; Carrera et al., 2022; Dentamaro et al., 2018; Impedovo et al., 2019; Impedovo et al., 2021).

The existing evidence regarding the development of applications for detecting impairments in ND is still limited. Lauraitis et al. (2019) propose an Android app designed to identify prodromal signs of neurodegenerative impairment and enhance decision support in medical contexts, achieving 86.4% accuracy. The model's primary focus is to recognize signs of both motor and cognitive impairment by using a touch-and-visual task. The data used in the study were gathered from both healthy individuals and patients in the early stages of the disease. The methodology involved the implementation of a back-propagation neural network classifier.

In a study, Chandra et al. (2021) collected data on patients using an Apple pen to capture parameters including pressure and speed. Participants were invited to perform drawing (spiral and infinity symbol) and cognitive (recall) tasks. Handwriting tools show the advantage of detecting also signs of prodromal impairment. For this purpose, Rosenblum et al., 2021)introduced a smart tool called "DailyCog", an app to identify MCI in PD patients. The app investigates cognitive abilities by exploiting simple and daily tasks. Indeed, includes everyday tasks and tests for the evaluation of executive functions, visual-spatial, and motor abilities.

3 SYSTEM ARCHITECTURE: HANDWRITING DETECTION APPLICATION

The overall application's architecture illustrates the interaction between the prospective user and the device, which is a supportive tool for carrying out key activities. This approach directs users to utilize a single device, and once chosen it needs to be linked to a local database for storing and manipulating user data. Additionally, the device communicates with a server component for data transmission and result retrieval. This approach aligns partially with the MVC pattern (Model-View-Controller; Utpatadevi et al., 2012),which involves dividing the software structure of an application into three components:

- Model. Essential component for data management;
- View. Component that will manage the output of the previously authenticated user interface.
- Controller. Component in charge of management features.

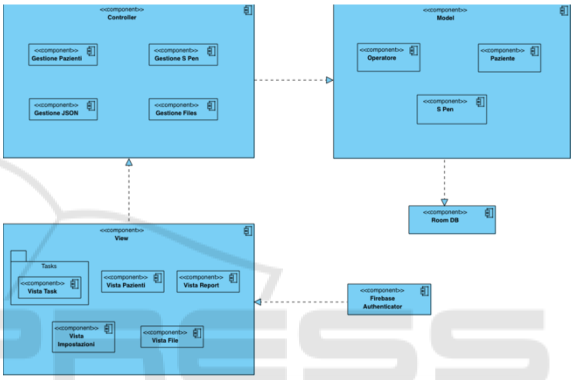

Figure 1: Application architecture.

The Model component is responsible for the acquisition and storage of data; the Controller must allow interface updates in case of input, modification, or removal of this data, updating the View component that will be shown to the user. For the implementation aspect, the use of libraries is crucial to improve the app's functionality. Choices include OkHttp for efficient network operations management, GSON for JSON data manipulation, MPAndroidChart for graphical result representation, and Room Persistence Library for easy access to local SQlite database data. In addition, Google's Firebase Authentication SDK ensures secure access to the application through different user authentication modes.

3.1 Authentication and Patient Management

User authentication is the initial interface that will be shown to the user. A CardView has been integrated to show editable fields. In the Activity section, the user can register by clicking on the appropriate TextView, which redirects to the User Registration Activity.

Both processes are connected to Firebase service methods, implemented within the project's scale, and configured through the google-service.json file in the application directory.

In case of a new registration, a filter has been set to fill in all the fields shown in the CardView; otherwise, the system notify the user with the help of a Toast (dynamic widget for messages). Once communication between the device and the Firebase service occurs, checks will be carried out with the condition, followed by the isSuccesful() method, which will be successful only if the access or registration is successful; otherwise an error will be notified. In Firebase Authentication, the user information object includes the credential entered when filling in the editable fields on the interface, resulting in the addition of a property called UUID (Universally Unique Identifier), used to identify so that identification is possible within the application uniquely.

After logging in, users have access to the following Activities. Managing authentication operations involves creating a FirebaseAuth object and using it to verify the user's authentication status by declaring a FirebaseUser object.

Figure 2: Access activity and user registration.

The process of adding patient data takes place by creating a local database in the application, using the Data Access Object (DAO) design pattern to separate the data access logic from the rest of the application.

The Room library is integrated to facilitate the implementation of the database with a UUID generated during authentication. The database management class declares the entities involved, such as patients and business data. CRUD operations (Create, Read, Update, Delete) are declared by methods in the class, allowing data to be added, removed, updated, and deleted. For the insertion of patient data, a Activity similar to that of recording is used, with a CardView containing widgets such as Spinner and radiobutton to select gender options.

After completing the fields, the user can confirm the addition, and receive a notification about entering the data in the Patients table of the database. CRUD operations are defined in an interface, allowing further future database management operations to be added. Subsequently, the operator can manage patient data through an Activity called ListPatient, which displays the list of registered patients.

Operations are implemented with the use of an AlertDialog widget, which allows the operator to read patient information and perform operations such as removal, testing or demo.

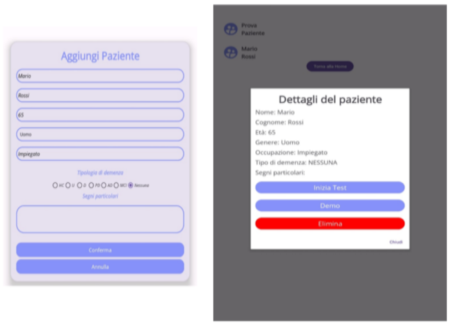

Figure 3: Additional patient information.

3.2 Task

After reviewing the drawing and writing activities, it is presents a concise vision of how the proposed screening test should be carried out. Considering potential unfamiliarity with technology, it's been incorporated a demo phase with simple tasks to allow them to become familiar with the system, before proceeding with the complete test. The demo phase comprises three activities: written word production, horizontal and vertical point connection, and replication of a square shape. This phase, intended to be user-friendly, spans approximately 4 minutes.

Subsequently, participants complete the screening tests in digital version, expected for about 15 minutes. The specified timeline reflects an optimal trajectory for cognitively healthy individuals.

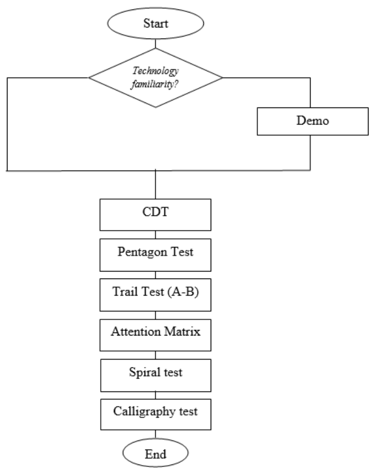

Figure 4: Flow chart of design application.

Screening test:

• Clock Drawing Task (CDT): is a cognitive functions screening measure. As a detective tool, the test evaluates a range of cognitive abilities including several executive functions. The task consists of the replication of an analogical clock with numbers and dials (Handzlik et al., 2023; Schejter-Margalit et al., 2021).

• Pentagon Drawing Test (PDT): the test is a sub-component of the MMSE test to evaluate visuospatial function. The evaluation concerns the accuracy of the drawing, the symmetry and the correct position of the angles (Hosseini-Kivanani et al., 2023).

• Trail Making Test (TMT): The test requires to connect a sequence of targets to evaluate working memory, attention, visual-conceptual and visual-motor tracking. It is composed of two performance tasks: one phase involves only numerical targets (1, 2, 3, …), the other phase requires to alternate between numbers and letters (1, A, 2, B, …) (Zhang et al., 2023)

• Attentional Matrices test (AMT): The Attentional Matrix test aims to evaluate selective attention during a visual task. It consists in a grid of numbers or words where the subject is invited to cancel a certain number of target variables (Gattulli et al., 2022; Gattulli et al., 2023a; Gattulli et al., 2023b).

• Spiral Drawing and Copying Test: In this task, individuals are required to replicate or copy the Archimedes spiral. Indeed, it is used particularly in assessing motor abnormalities (Thakur et al., 2023).

• Handwriting: this task consists of a simple non-sense words task. Authors suggest to employ the pattern involves the repetition of the word "le". Evidence shows that signs of degradation in handwriting has been observed during repeated actions (Impedovo et al., 2019).

3.3 Data Input Acquisition

When the patient starts one of the screening test tasks, a *BottomNavigationView* widget is displayed. This widget allows the operator to navigate linearly during the execution of the different tasks, allowing you to return to the previous task, proceed to the next or cancel the test by pressing on the icon representing a "home", which reports to the Dashboard.

To collect input data generated with the stylus, the SpenEventManager class is used, a Java class that handles pen events. This class adopts the methods of MotionEvent, the standard class of Android for the recognition of user input types, allowing the filtering of data to be acquired. Unlike the BottomNavigationView, with which you can also interact using the palm of your hand, to represent the path traced with the stylus, a custom view has been implemented within the various layouts, providing a virtual drawing area. The *DrawingView* class extends the View class and initializes objects like Paint, to set the background color, and *SpenEventManager*, to get the data for the graphic representation. When capturing generated events, it is critical to recognize cases of *onHover* or ontouch data, using an Enum variable to track the status of the stylus relative to the screen. The data captured by *MotionEvent* includes the x and y coordinates, the time stamp, the tilt, the press and the button used. This data represents a single point on the screen and is converted to a custom format, stored as JSON and saved locally in the application. The manipulation of this data, through the CustomFormatConverter.java class, is essential to adapt them to the needs of the artificial intelligence algorithm, ensuring accuracy and relevance in analysis and predictions.

After conversion, the new string is again encapsulated in a JSON file and saved locally on the device. The saved files are accessible to the operator via the File Explorer option in the Dashboard, which shows a list of folders related to registered patients and, within them, the test files performed with indication of the date and time. To manage folder creation and file saving, a file management logic has been implemented with variables that consider the relative path.

During the early stages of development, the execution of the drawing was not fluid. The drawing, or "pattern", was created by touching the screen with the stylus, generating a "Canvas" inside a "Path" object. At this stage, there was a delay in the execution of complex drawings. To overcome this difficulty, the RDP (Ramer-Douglas-Peucker) algorithm has been implemented, which simplifies the representation of a line by removing non-significant intermediate points. The algorithm selects key points, calculates the distance between the intermediate points and the straight line between the key points, keeping only the significant points. The integration of this algorithm, instead of using a Bitmap object, optimizes efficiency based on the device. The code presents a main cycle that simplifies the path, obtaining simplified coordinates and adding them to the simplified path with a specific sampling distance.

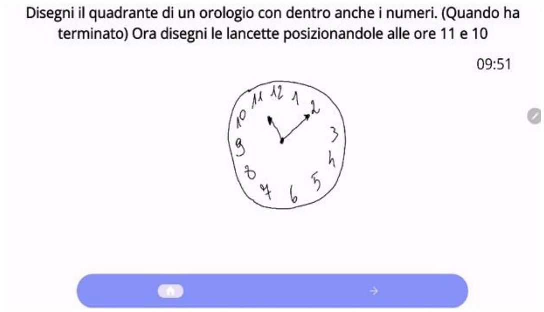

Figure 5: Example of task.

3.4 Sending Data to the Web Service

The process described is about sending samples for screening testing to a web service. Using the OkHttp library, a connection to the server is opened via a Runnable object. Files in the directory are iterated and sent to the microservice via an asynchronous thread, showing the user an upload interface. During iteration, progress is monitored via a progress bar.

For each JSON file, a Callback object is created to handle successful notification or any errors, such as IOException in case of problems reading the file or InterruptedException for thread handling.

3.5 Final Report

To develop an interface to visualize the results, methods have been implemented to represent the speed, pressure and acceleration data obtained during the drawing tasks. The results are presented through a table using the *ReciclerView* component, extracted from a Room database. Given the complexity of the data (15 tasks in one session), a *ReciclerView* with an Adapter was chosen to efficiently handle large datasets.

To improve the representation, the MPAndroidChart library was introduced to create a Radar Chart, allowing multidimensional visualization of prediction data on a series of rays. The graph includes a static red line to indicate the minimum gap for the severity index of the disease and a blue line to represent data that exceeds the gap. Crossing the red line indicates a potential dementia patient. In addition, tables containing kinematic data specific to each task have been implemented, using a class that extends *ReciclerView.Adapter*.

When the report is presented, the tables show data related to the task, such as drawing a clock or copying two pentagons, along with their kinematic values.

3.6 AI Service

The Web Server is fundamental in the internet infrastructure, separating calculation and data evaluation from the device. The AI Service uses different systems, allowing the creation of an environment with a framework to receive data, make predictions and obtain numerical results. Machine Learning, part of AI, develops algorithms to learn from past data. It adopts supervised learning, classification in specific context. It follows a structured life cycle: problem study, data collection and preparation, choice of model.

MLOps (Machine Learning Operations) facilitates the implementation, management and maintenance of Machine Learning models, ensuring a smooth transition from development to deployment.

METHODS: the Random Forest algorithm was implemented for classification. Studies show an average accuracy of 94.5%, exceeding individual Decision Trees (92.5%).

SET UP: The algorithm is evaluated considering the speed in the execution of drawing tasks as biomarker.

Kinematic features such as the Fourier Discrete Transform are used for the Maxwell-Boltzmann speed profile and distribution to recognize deficits related to neurodegenerative diseases.

4 CONCLUSION

This paper introduces innovative E-Health tools to detect signs of neurodegenerative impairment. Specifically, an Android App was developed to collect data on individual performance in handwriting tasks. The App includes a battery of standardized tests that measure performance by testing different cognitive domains. The instrument has demonstrated its effectiveness in acquiring data generated by digital pens.

The AI application's model has exhibited positive outcomes in classification avoiding values exceeding the "minimum gap" threshold, as indicated in the radar chart. Moreover, the model can detect individuals with no form of ND and classify them as healthy. During user evaluation scales conducted in the testing phases, favorable results emerged regarding usability and user satisfaction with the interface implemented in the prototype.

Despite the results, this work presents some limits. The current configuration lacks of immediate communication between the server and the application, leading to delays exceeding 5 minutes in obtaining results from the artificial intelligence model. Recognizing its early stage of development, there is a concerted effort to craft a prototype ready for user deployment. This step aims to assess functionalities and interactions, providing an initial glimpse into the application's performance.

Further studies could implement a framework that manages requests made by the application to the microservice. This approach aims to reduce the current computational burden and response time imposed on the device. The adaptability in the Android development environment is noteworthy, allowing scalability across various hardware resources. This flexibility enables the testing of the prototype on different products with varying hardware characteristics, offering a broader perspective on its performance and usability.

The insights gained from these observations will guide potential enhancements in subsequent iterations, ensuring the continuous refinement and optimization of the application.

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