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A Gamified Assessment Platform for Predicting the Risk of Dementia + Parkinson's disease (DPD) Co-Morbidity

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Abstract

Population aging is becoming an increasingly important issue around the world. As people live longer, they also tend to suffer from more challenging medical conditions. Currently, there is a lack of a holistic technology-powered solution for providing quality care at an affordable cost to patients suffering from co-morbidity. In this paper, we demonstrate a novel AI-powered solution to provide early detection of the onset of Dementia + Parkinson's disease (DPD) co-morbidity, a condition which severely limits a patient's ability to live actively and independently. We investigate useful in-game behaviour markers which can support machine learning-based predictive analytics on patients' risk of developing DPD co-morbidity.

1 Introduction

Parkinson's disease (PD) and dementia are chronic neurodegenerative diseases where symptoms progressively deteriorate with no cure currently available. PD patients exhibit motor symptoms like tremor, rigidity, bradykinesia, abnormal gait [Nussbaum and Ellis, 2003]. Dementia patients exhibit cognitive deficits like long-term memory loss, difficulty in reasoning, decline in visual and spatial abilities, and depression [Nussbaum and Ellis, 2003]. Research has shown that dementia develops in over 80% of PD patients after 20 years [Hely *et al.*, 2008]. This has been attributed to the possible spread of PD pathology (i.e., Lewy-body-type degeneration) to the hippocampus and cerebral cortex which are the main regions that experience atrophy in Alzheimer's disease [Emre, 2003]. Suffering from dementia and Parkinson's disease at the same time, i.e. DPD co-morbidity, drastically decreases quality of life for patients. This puts a massive strain on both economy and healthcare infrastructure to care for these patients. Neurodegenerative diseases have an increased onset with age. With many countries facing an aging population, this is a pressing problem that needs immediate addressing.

The diagnosis of PD and dementia is usually based on multi-source data, including laboratory, clinical and behavioral data, and requires the knowledge and opinions from multiple healthcare professionals, such as physio-therapist, psychologist, and memory disorder specialist. Due to its intricate nature, the diagnosis process is highly subjective with different healthcare professionals having different views on the severity of symptoms. As a result, machine learning methods have been used to provide a more objective assessment, to aid the doctor in reaching a diagnosis. Models are trained using a variety of biomarkers from clinical records to neuroimaging scans. For PD assessment, research has mainly focused on detecting psychomotor symptoms using body worn sensors. Analysis is carried out on the sensor signals to identify discriminative patterns related to slowness in movement [Iakovakis *et al.*, 2018], tremor [Joundi *et al.*, 2011] and abnormal gait [Aung *et al.*, 2013]. As for dementia assessment, researchers have explored various cognitive-related biomarkers, such as measuring brain atrophy from neuroimaging scans [Zhang *et al.*, 2011] and test results of computerized test batteries [Zeng *et al.*, 2018].

The pervasiveness of smartphone devices in the last decade has provided a cost-effective diagnostic tool accessible by everyone. Most smartphones come equipped with sensors like accelerometers and gyroscopes to record physiological signals when carrying out various assessments related to motor and cognitive well-being. There have been a few successful work that showed the potential of using smartphones as an accessible and longitudinal monitoring tool for self-diagnosis of PD [Stamate *et al.*, 2017; Schwab and Karlen, 2019; Zhang *et al.*, 2019a]. Most of the current smartphone-based assessments are focused on either PD or dementia individually, with a lack of studies on monitoring and predicting DPD co-morbidity.

2 Gamified Assessment Platform

This paper presents a prototype for detecting early signs of DPD co-morbidity through a mobile assessment platform (video link[1]). It consists of six gamified assessments which assess the patient on both motor and cognitive impairments (see Figure 1). They are specially designed to capture severity of symptoms related to DPD co-morbidity. Since current medical literature indicates a high probability of PD patients developing dementia [Hely *et al.*, 2008], most of our assessments are PD related (Fig. 1 (a) - (e)). The mini-games

[1]https://youtu.be/-AJvGDgwYrg

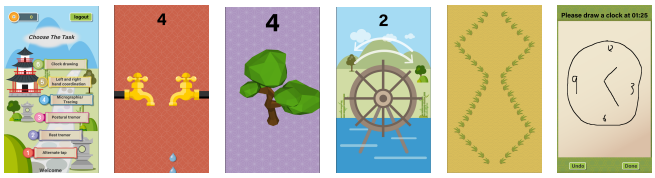


Figure 1: Screenshots of the mini-test in the DPD assessment App: (a) main page, (b) finger tapping, (c) tremor (rest, postural), (d) micrographia, (e) coordination, and (f) clock drawing

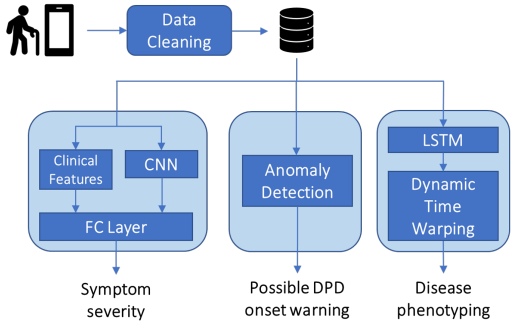


Figure 2: AI engine for analyzing data collected from the DPD co-morbidity mobile assessment platform

are designed in collaboration with doctors and researchers from Pacific Parkinson's Research Centre. Each of them is designed for assessing one characterizing symptom of PD, such as tremor, micrographia, and left-right hand coordination. The clock drawing test is a widely used clinical test for screening cognitive impairments [Shulman, 2000]. A digitalized version with automatic scoring system is designed for assessing dementia symptoms (Fig. 1(f)).

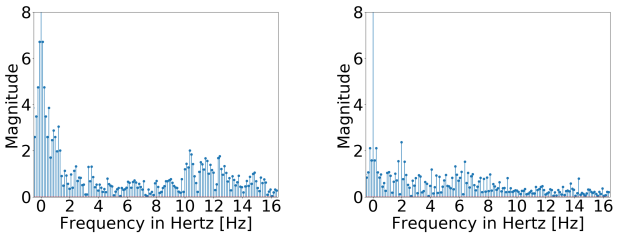
3 AI Engine

Data collected from the various tasks can then be used for 1) daily symptoms monitoring, 2) early warning of potential progression from PD to dementia, and 3) discovering disease phenotypes which could complement medical research into DPD progression and pathology. An overview of the AI engine is shown in Figure 2.

Monitoring Symptoms

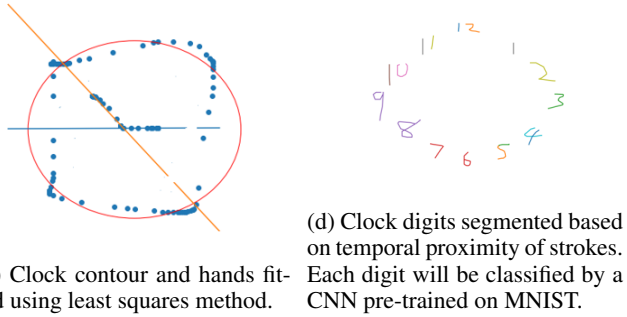
As the assessments are self-administered without any form of clinical supervision, the data collected are likely to be noisy. Filtering of data is crucial, as using noisy data for training will affect model performance. We train a binary classifier to filter out data points that do not follow assessment protocol (e.g., large segments of stationary signals).

The data collected from each test comes in the form of 1D signals. We make use of a combination of both clinically driven and data driven features. For the clinical features, we used feature engineering to extract specific traits found in each disease, refer to Figure 3. In PD, resting tremor occurs in the range of 4-6 Hz [Thenganatt and Louis, 2012]. We first apply Fast Fourier Transformation (FFT) [Heideman *et al.*, 1984] and filter out signals not in this range. Patients with dementia are known to suffer from spatial and recall deficits. As such, clinical features for the clock drawing test involve assessing how well the clock is drawn. We first segment the handwritten digits based on the temporal proximity of strokes. A Convolutional Neural Network (CNN) [LeCun *et al.*, 1995] pre-trained on the MNIST dataset [LeCun *et al.*, 2010] is then used to recognise each digit. The hands and contour of the clock are fitted using a least squares method. Scoring will be done based on the digits being at the correct position with respect to the hour and minute hands. For the data driven features, we use a CNN to extract local invariant patterns from the raw sensor signals. The clinical features from each test are then concatenated with the data driven features to train a deep learning model in an end-to-end manner. An overall disease state can be calculated by combining the performance scores from all tests.



(a) Rest tremor frequency distribution after FFT.

(b) Postural tremor frequency distribution after FFT.



(c) Clock contour and hands fitted using least squares method.

(d) Clock digits segmented based on temporal proximity of strokes. Each digit will be classified by a CNN pre-trained on MNIST.

Figure 3: Clinical features extracted for PD (a,b) and dementia (c,d)

Early Warning

Based on the longitudinal signals collected, we compare how a patient's symptoms differ on a monthly or daily basis. Relative intra-patient comparison is more reliable than a direct inter-patient comparison. It is normal for different individuals to have varying level of performance on the various tests. This could be due to familiarity with the task or naturally slower reflexes. Large decrease in relative performance will be a bigger source of concern and prompt intervention is required. We detect significant drops in performance using a window averaging approach, where a pre-defined threshold is set and any score difference across windows that exceed this value will trigger a warning to the patient.

Discovering Phenotypes

The longitudinal data collected from each patient can also be used as a way to cluster the patients. The user's historical per-

formance across tasks are combined to form a feature vector at each time point. The history is encoded using a Long-short term memory network (LSTM) [Hochreiter and Schmidhuber, 1997] which is trained in an unsupervised manner like in [Zhang *et al.*, 2019b]. As each patient joins the study at different time points, it is likely that intra-patient temporal sequences are out of sync. We used Dynamic Time Warping [Berndt and Clifford, 1994] to align the different representations temporally before obtaining a similarity score based on Euclidean distance. This allows us to discover different types of DPD progression patterns that can occur.

4 Conclusion

In conclusion, our gamified assessment platform provides a new paradigm for monitoring and managing neurodegenerative diseases. In the future, we will collaborate with healthcare professionals to test the platform with both healthy seniors and DPD co-morbidity patients to collect longitudinal datasets that can be used by AI researchers for exploring diagnosis and progression prediction of PD and dementia, and by medical researchers for studying DPD co-morbidity.

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