Analysing Gait Patterns of Parkinson's Disease Patients to Predict Freezing of Gait (FoG) Using Machine Learning Algorithms

Prannaya Gupta · Nallapuraju Ananya · Ye Chen Rui

Abstract Parkinson's Disease (PD) is a neurodegenerative disease that affects the substantia nigra, a region in the brain. It causes many hindrances to activities of daily living (ADL). A debilitating symptom of PD is Freezing of Gait (FoG), where patients are unable to move forward despite intention of walking. The forward momentum of the torso can often lead to patients falling, causing serious medical consequences. Prior work has explored the use of gait tests, medical questionnaires and inertial measurement units to predict FoG. In this research, work has been done to perform a comprehensive review of various input formats, signal processing algorithms and machine learning algorithms to predict such FoG events. A novel method for image representation via autoscaling and RGB pixelation has been introduced, in addition to raw signal data and the Moore-Bachlin algorithm for Freeze Indices. We find that a 2-dimensional convolutional neural network (CNN) performs the best on scaled images, attaining state-of-the-art accuracy of 99.50% and sensitivity of 99.65%. We integrate this model into an Android application which can be used by patients and doctors to predict and track freeze events over a period of time. This can help doctors diagnose patients and gauge the severity of the disease, so as to prescribe medication.

Keywords Freezing of Gait · Parkinson's Disease · Machine Learning · Cloud Computing

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1 Introduction

Parkinson's Disease (PD) is a progressive neurodegenerative disorder that affects the substantia nigra, a key region within the basal ganglia of the brain. It largely results in the progressive loss of dopamine neurotransmitters in various locations in the body, and generally leads to a poorer connection between the central nervous system and the muscles (Braak et al. (2004)). This results in several motor symptoms and gait abnormalities, ranging from primary motor symptoms such as tremors, bradykinesia and rigidity and a loss of postural reflexes, to secondary motor symptoms such as reduction in stride length, shuffling of gait, step festination and freezing of gait (Ferster et al. (2015); Nutt et al. (2011)).

Freezing of Gait (FoG) is a secondary motor symptom of Parkinson's Disease, and is one of the most debilitating effects of PD. FoG involves a brief episodic absence or marked reduction of forward progression of the feet despite the intention to walk (Ferster et al. (2015)). The forward momentum possessed by the patient is often held up by the torso, while the feet remain firmly in place, causing patients to fall, which can lead to serious social and clinical consequences (Bloem et al. (2004)). In general, this effect interferes with daily activities, and significantly impacts the quality of life of patients (Moore et al. (2007)).

The World Health Organisation (WHO) estimated in 2019 that roughly 8.5 million individuals among us live with PD, although recent studies suggest that this number has since increased to more than 10 million. Many of the patients afflicted by PD also suffer from FoG.

Hence, individuals afflicted by FoG need to be kept safe. This research aims to use machine learning algorithms on FoG datasets in order to classify FoG moments. We also propose a novel image representation method for feature selection. We also aim to utilise these models via an Android App designed to help patients track their FoG moments.

2 Background

2.1 FoG Characterization

Currently, FoG can be characterized via gait tests including the timed up and go (TUG) test (Podsiadlo and Richardson (1991)) and the Hoehn and Yahr (H&Y) scale (Hoehn and Yahr (1967)), or individual questionnaires. The H&Y Scale utlises individual questionnaires too, notably the six-question Freezing of Gait Questionnaire (FoG-Q, Rozenfeld et al. (2017)), which utilises a 5-point scale to rank symptom severity. However, it is to be noted that these tests are highly inefficient in measuring FoG due to environmental triggers, medication and the patient's mental state.

2.2 Utilisation of IMUs in Gait Analysis

In our prior literature, the role of IMUs in Gait Analysis has been well-established. Ferster et al. (2015) utilised 9-axial (accelerometer, gyroscope and magnetometer) IMUs at the shanks of participants in order to determine various gait parameters including the stride length and stride duration. A similar approach was also adapted by Pinto et al. (2019) to determine the stride time.

Later, Bachlin et al. (2010) explores placing triaxial accelerometers at the trunk, shank and thighs. Alam et al. (2017) analysed the vertical ground reaction force using force insoles in patients' shoes. Kuhner et al. (2017) explored using motion capture systems to characterize FoG events, which ensured reduction in latency of data signal processing.

The above literature confirms the success of utilising accelerometers, gyroscopes, and force insoles to effectively differentiate FOG from normal gait and has greatly helped in designing the proposed approach for this study.

2.3 Public Dataset Analysis

It is crucial to perform a systematic review of the existing datasets that exist for exploration in the field of FoG detection. For the context of this research, only accelerometer datasets have been identified as they can be measured on an Android Phone. Three key datasets have been identified, as represented in Table 1. These datasets each provide us with Acceleration readings in the X, Y and Z axes.

Name of Dataset	Source	Locations	Participant Count
DaphNET	Bachlin et al. (2010)	Shank, Trunk and Thigh	10
PDBioStampRC21	Adams et al. (2020)	Trunk, Hand and Thigh	34
mPower	Bot et al. (2016)	Thigh	9520

Table 1: A review of existing datasets

2.4 The Moore-Bächlin Algorithm for Freeze and Energy Indices

In prior literature, a parameter known as the Freeze Index (FI) has been established to minimize the feature set of a dataset while maintaining a large part of the temporal features. This algorithm has been further elaborated on via the Moore-Bächlin Algorithm (Moore et al. (2008); Bachlin et al. (2010)), which computes a corresponding Energy Index (EI), which can be used to isolate low-power conditions (e.g. walking). The FI and EI, as restablished in Mikos et al. (2018), can be isolated via the following algorithm:

$$F(a,b) = \int_a^b |A(f)|^2 df = \sum_{n=\left\lceil \frac{N}{f_{sr}} \times a \right\rceil}^{\left\lfloor \frac{N}{f_{sr}} \times b \right\rfloor} |A[n]|^2$$

$$FI = \frac{F(3,8)}{F(0.5,3)}, \qquad EI = F(0.5,8)$$

Here, the function $A(f)$ represents the Fourier Transform of the Signal, with $A[n]$ representing the corresponding Discrete Fast Fourier Transform (DFFT) computed over N frequencies and f_{sr} is the sampling rate frequency.

Bachlin et al. (2010) utilised this algorithm and isolated walking situations given $EI \geq 2^{11.5}$. Following this, if the FI value is higher than 1.5, they classified the signal as a freeze moment.

2.5 Image Representation via Continuous Wavelet Transform

Both Shi et al. (2020) and Shi et al. (2022) utilised Continuous Wavelet Transforms (CWTs) on their own collections of data and generated scalograms that were then inputted in a Convolutional Neural Network (CNN). This CNN was then trained on these scalogram images and a final prediction model was developed.

2.6 Prior Work

In our prior work (Nallapuraju et al. (2022)), the DaphNet Dataset and GPU-Assisted Support Vector Machines (SVMs) were utilised to predict *"freeze events"*. Via the aforementioned Moore-Bächlin Algorithm, the Freeze and Energy Indices (FI and EI) were identified. These values were then trained via a SVM model to predict whether a given event is a freeze event. The final model was set up with an Arduino prototype to detect freeze events by raising a small shrill noise.

3 Methodology

3.1 Data Collection and Engineering

In this study, both the aforementioned DaphNET and the PDBioStampRC21 datasets (Adams et al. (2020)) are explored, which provide data readings from PD and non-PD patients. We utilise only readings from the thigh for the convenience for those utilising the mobile app.

Following the data retrieval, we window the DaphNET data over a window of size $N = 256$, which gives us a large set of readings. An example of a positive-negative duo is as represented in Figure 1. A noticeable shift can be observed with major fluctuations in acceleration due to the freeze event.

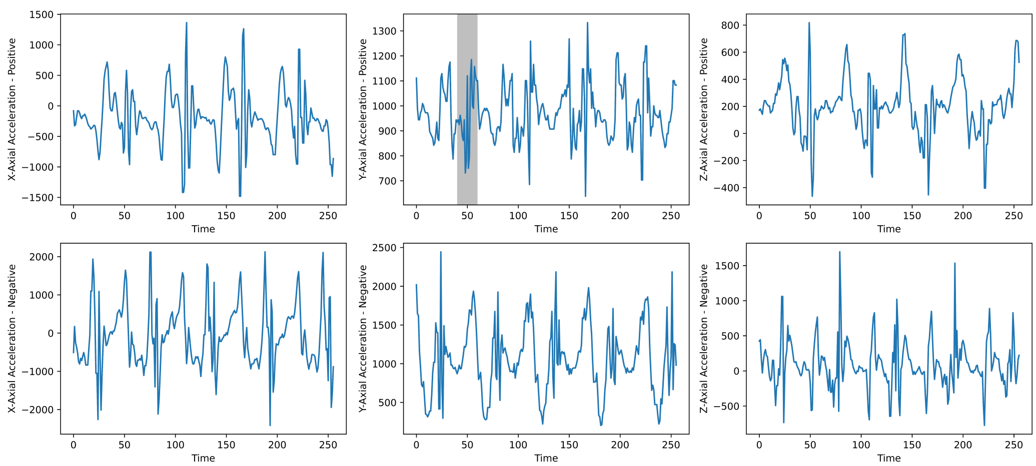


Fig. 1: Generated Windows of Size $N = 256$.

3.2 Data Manipulation

We manipulate these windows via two key methods, firstly the Moore-Bächlin Algorithm and a novel image generation algorithm of our design.

3.2.1 Freeze Indices

Using the aforementioned Moore-Bächlin Algorithm, we isolate the FI values for all three axial accelerometer readings, giving us a `FreezeX`, `FreezeY` and `FreezeZ`. A diagram of this generation schematic is shown in Figure 2.

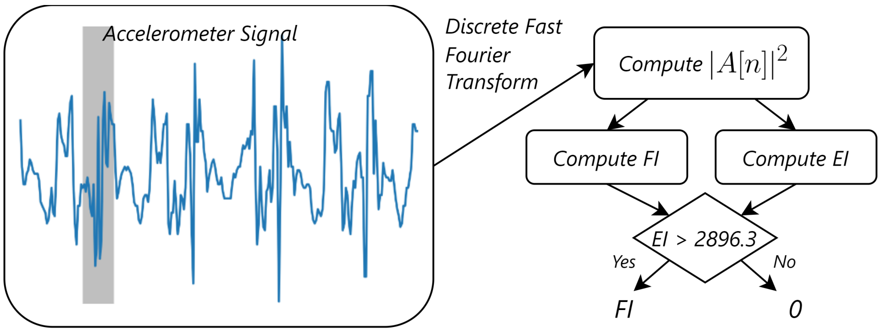
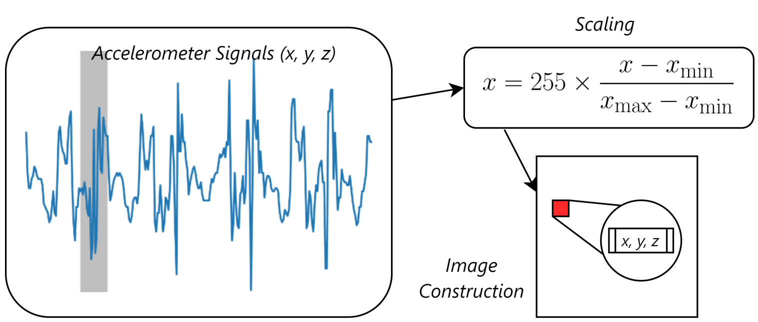


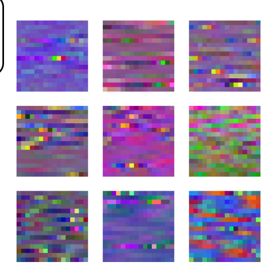
Fig. 2: Freezing Index Pipeline

3.2.2 Image Generation

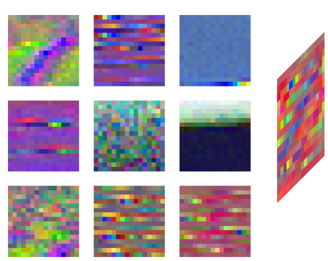
We introduce a new novel yet simplistic method for data manipulation, which converts the triaxial readings into RGB images via min-max scaling and represents each data point as a pixel in a 2D image. This provides us with a set of images over which we can use various Computer Vision Algorithms. Examples of images generated and the generation pipeline are shown in Figure 3.



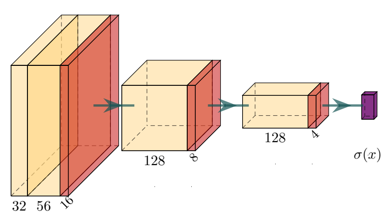
(a) Image Generation Pipeline



(b) FoG Images



(c) Non-FoG Images



(d) CNN Architecture.

Fig. 3: Image Generation Pipeline

3.3 Machine Learning

In prior literature, Aich et al. (2018) conducted a comprehensive review of Machine Learning Algorithms to predict FoG and non-FoG moments, namely the Support Vector Machine (SVM), k-Nearest Neighbour (kNN), Decision Tree (DT) and Naïve Bayes (NB). In our research we utilise various methods on the various data representations proposed, which are listed in Table 2. We train various GPU-assisted and TPU-assisted models via Kaggle Notebooks, Google Cloud and Google Colaboratory and come up with three approaches to review FoG detection.

Method	Shape	Models Trained
Method 1: Signal Input	`(768,)`	SVM, Random Forest (RF), kNN, Neural Network (NN), 1D Convolutional Neural Network (CNN)
Method 2: Freeze Indices	`(3, )`	SVM, RF, kNN, NN
Method 3: Image Generation	`(16, 16, 3)`	2D-CNN (See Figure 3)

Table 2: Methods to develop feature vectors.

4 Results

4.1 Method 1 - Signal Input

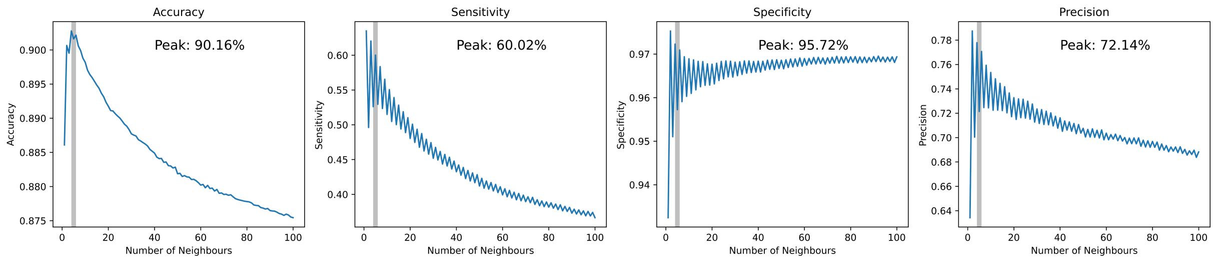
Upon training on the Signal Input, we observe that, consistent with the observations in Aich et al. (2018), the SVM Architecture actually performs the best, at a resounding 91.21% accuracy, which is close to the SVM from Aich et al. (2018) that reached a 91.42% accuracy. The SVM, however, has a terrible recall rate and is far surpassed by a 1D-CNN, which is currently our best performing model. Upon running this data through Google Cloud's AutoML pipeline, we achieve a model that surpasses all these. The results are highlighted in Table 3.

Model used with Method 1	Accuracy (%)	Recall (%)	Precision (%)
Google Cloud AutoML Model	**93.70**	49.89	80.79
Support Vector Machine (SVM)	**91.21**	29.29	82.14
1D Convolution Neural Network (CNN)	90.88	**78.03**	52.97
Neural Network with 3 Hidden Layers	90.36	38.67	52.39
Random Forest (RF)	90.06	14.56	89.42
Big Single-Hidden-Layer Perceptron	90.03	61.59	50.09
Neural Network with 4 Hidden Layers	90.00	0.01	20.00
Small Single-Hidden-Layer Perceptron	89.91	50.47	49.54
k-Nearest Neighbours (kNN)	88.67	8.51	51.99
Logistic Regression	87.98	0.04	0.79
Neural Network with 2 Hidden Layers	84.20	75.34	36.08

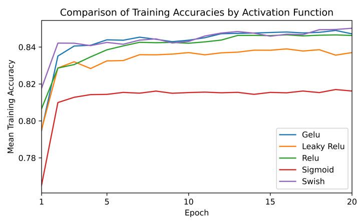
Table 3: Results from Method 1.

4.2 Method 2 - Freeze Indices

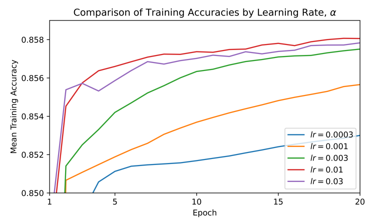
For Method 2, we trained various models over the three freeze index values. We experimented with kNNs and observed a change in accuracy while varying the number of neighbours in the model. The peak reached an accuracy of 90.16%, which towers over the 85.2% determined from the kNN from Aich et al. (2018). We also train various neural networks, comparing over activation functions,



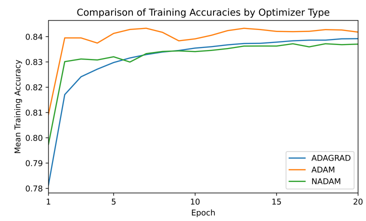
(a) Comparison of KNN Parameters



(b) Comparision of Activations



(c) Comparision of Learning Rates



(d) Comparision of Optimizers

learning rates and optimizers and observe that a neural network with the Swish activation and a learning rate of $\alpha = 0.01$ under the Adam optimizer performs the best, with an accuracy of 86.17%. The final results are summarised in Table 4.

Model used with Method 2	Accuracy (%)	Recall (%)	Precision (%)
***k*NN** - Best Performing	**90.28**	**52.61**	**77.79**
Random Forest	88.43	38.65	74.98
Neural Network (Swish, Adam, $\alpha = 0.02$)	86.17	25.12	63.96
SVM (Gaussian Kernel)	86.08	18.46	70.20
LogReg	84.77	9.12	59.80
SVM (Linear Kernel)	84.45	0.44	64.63

Table 4: Results from Method 2.

4.3 Method 3: Image Generation

We design a deep convolutional neural network (CNN) to be trained over the generated images (see Figure 3 for more details regarding the architecture). This CNN fared extremely well, hitting a resounding accuracy of **99.50%**, beating every other model we have trained so far and hitting state-of-the-art. The model achieves a sensitivity of 99.65% and a precision of 95.63% over 20 epochs, outperforming Aich et al. (2018) by 7%.

4.4 Our Final Application

We develop a final Android Application that utilises this CNN model internally to predict FoG. This is done via the enabling of a "Walk Mode", where users can place their phones into their pocket (ideally representative of the thigh-point readings) and simply walk, and the accelerometer in the phone is automatically used to monitor freeze events. These freeze events are logged onto Firebase Cloud Storage as CSVs and can be later viewed via the "Freezes" page. The entire app ecosystem is displayed in Figure 4.

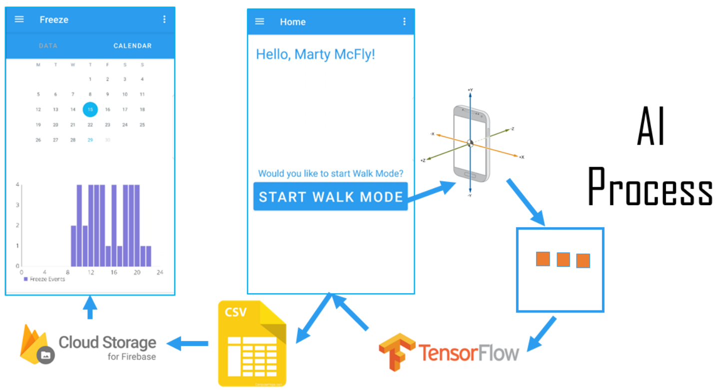


Fig. 4: Our Android Application.

5 Discussions and Conclusions

Based on the research conducted in this study, we conclude that the 2D CNN over the post-processed window of triaxial accelerometer data performs the best in terms of accuracy and sensitivity, and beats both Aich et al. (2018) and Shi et al. (2020, 2022). Furthermore, a small-scale Android App has been developed that is able to track FoG events.

With the increasing prevalence of PD amongst the elderly population in Singapore, more elderlies are at the risk of falling and injuring themselves in cramped spaces (eg HDB, Corridors etc). The developed algorithm and application can help predict such falls so that such damage can be mediated in time.

6 Future Work

Further work can be done to explore the use of actual gait parameters such as Stride Length and Stride Duration in prediction when computing the gait freeze moment. In addition, since we have developed the prototype application, we can explore phasing it into medical testing with Parkinson's patients in order to determine the effectiveness of the algorithm. We can also consider emitting noises via earbuds to the patients in order to ease patients during FoG by conducting auditory biofeedback.

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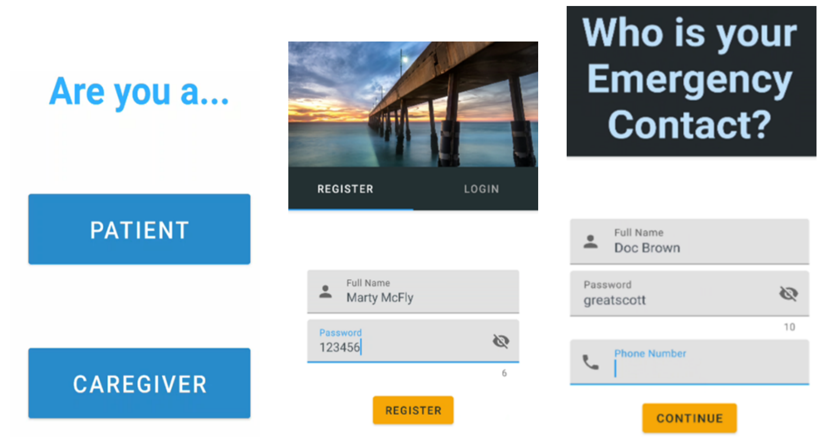
A Images of Android App

A.1 Authentication Portal

Authentication has been implemented via Firebase Cloud Firestore. There is a distinction for Caregivers and Patients, and patients are supposed to insert the contacts of their caregivers so that they can be notified in case of falls.

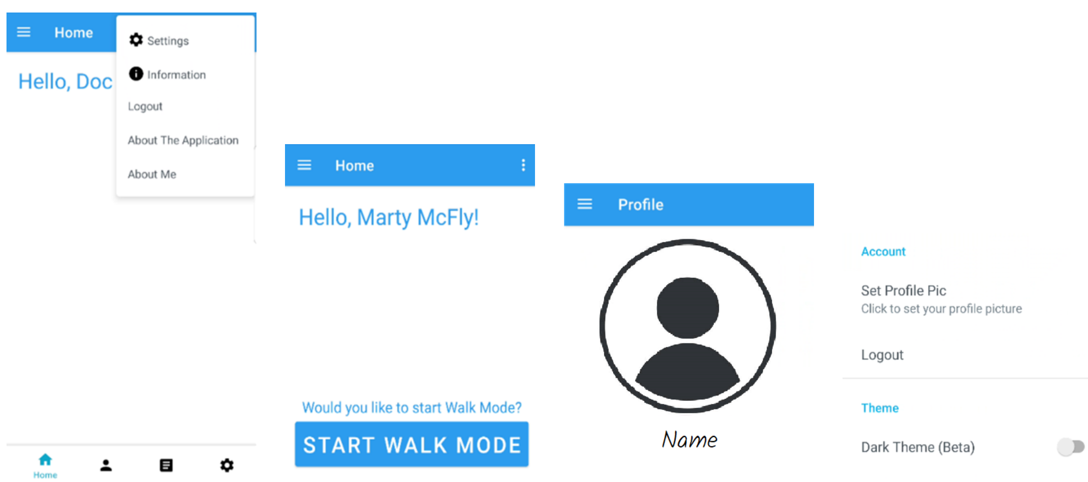


(a) Selection Process (b) Auth Process (c) Setup Process

Fig. 5: Authentication Portal

A.2 Main Application Features

An empty home page (to be populated with analytics) is our intro to the app for caregivers. We also have a "Walk Mode" implemented for patients, wherein users are advised to put their phones in their pockets and walk to monitor freeze events. Navigation is done via a Bottom Navigation Bar.

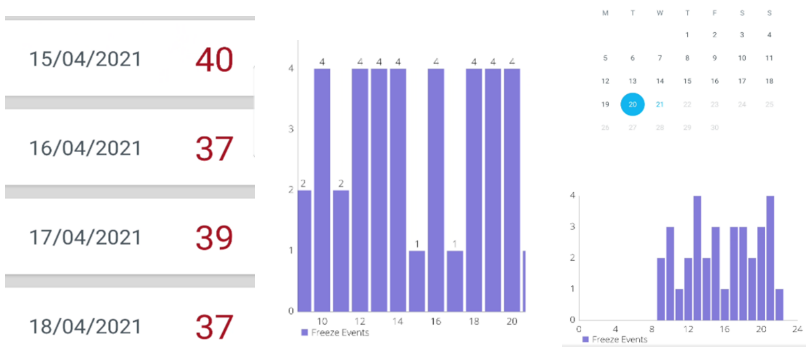


(a) Main Page (Doctor) (b) Main Page (Patient) (c) Profile Page (d) Settings Page

Fig. 6: Main Pages

A.3 Freeze Archives

There are pages that log freeze data, pulling from Firebase Cloud Storage.

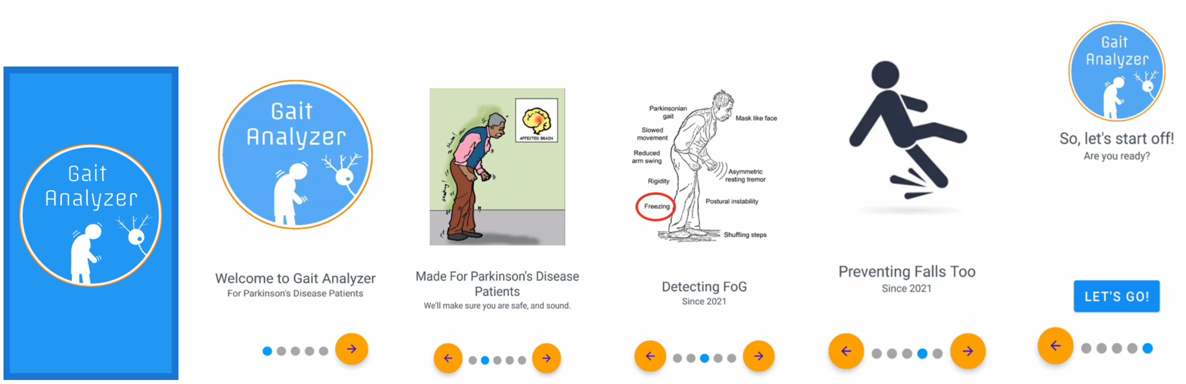


(a) Main Data Listing (b) Graph of Daily Data (c) Calendar-based Data

Fig. 7: Freeze Archives

A.4 Onboarding Pages

In addition, onboarding pages have been implemented to give users an understanding of the situation and the app's purpose.



(a) Splash (b) Pg 1 (c) Pg 2 (d) Pg 3 (e) Pg 4 (f) Pg 5

Fig. 8: Onboarding