Real-Time Fall Prevention using Learned Gait Analysis with Smartphone Sensor Data

Shruti Badrish
Redmond High School
Redmond, WA, USA
shrutibadrish@gmail.com

***Abstract*—Falls are well known to be a leading cause of injury and injury-related deaths, especially in the elderly and in those with neurological disorders. Every year, one in four older adults experiences a fall, and every 11 seconds, someone is treated in an emergency department for a fall-related injury. In this work, we aim to prevent falls and save lives by using smartphones to detect and alert people when their risk of falling increases. Existing solutions in this space primarily focus on fall detection (i.e., getting speedy assistance after a fall), or are specialized to work for patients with specific disorders. Instead, we propose a novel approach to fall prevention based on analyzing *gait variance* using standard smartphone sensor data. By classifying gait patterns as steady or unsteady, we develop a machine learning model based on time series analysis, using an LSTM-based recurrent neural network. Our model can effectively infer unsteady gait with a test accuracy of 96.6%, using a small window of accelerometer and gyroscope sensor data captured by a smartphone. This work can enable us to detect and alert people of impending falls, thereby potentially saving lives. It also opens up opportunities for adaptive learning based on individual user patterns and feedback, for greater fall prediction accuracy.**

***Index Terms*—fall prevention, machine learning, gait, smartphone, sensor, data processing**

I. Introduction

The Centers for Disease Control and Prevention (CDC) reports that falls are the leading cause of injury and injury-related deaths among adults aged 65 years and older in the United States [2]. Every year, one in four older adults experiences a fall, and every 11 seconds, someone is treated in an emergency department for a fall-related injury. Falls can lead to serious injuries such as hip fractures, head trauma, and lacerations, which can result in hospitalization, loss of independence, and even death. Each year at least 300,000 older people are hospitalized for hip fractures.

A large body of research in this space focuses on *fall detection*, which focuses on automatically detecting that someone has fallen, so that post-fall assistive measures such as calling emergency personnel can be automatically performed. However, given the seriousness of this problem and its severe consequences on the subsequent quality of life for a fragile demographic, it is of vital importance that we design practical yet proactive techniques to prevent the occurrence of falls in the first place.

As the first step towards a solution. we make the observation that smartphones have become a ubiquitous part of adult life today. According to Pew Research Center, the share of Americans that own a smartphone is now 85%, up from just 35% in 2011 [1]. Further, a vast majority of smartphones carry sensors such as accelerometers and gyroscopes. Accelerometers detect the orientation of the smartphone, whereas gyroscopes track rotation or twisting movements of the device. All sensor readings can be captured and processed in real time by phone apps and downloaded for processing on computers.

Second, we observe the existence of a correlation between the *gait* of an individual and their risk of suffering a fall. Gait is defined as the walking pattern of an individual. It is long known that irregularities in one's gait can be effectively used to predict fall risk [9], [16]. A number of factors can cause such irregularities, such as the development of neurological disorders, injuries, impairment, sudden onset dizziness, and substance abuse. These irregularities are in turn highly likely to lead to falls.

In this paper, we propose a new method for fall prevention based on the detection of gait irregularities through smartphone accelerometer and gyroscope sensor data. The overall approach is as follows: we study a corpus of normal and abnormal gait patterns and use machine learning to create a time-sequence-based deep learning model called LSTM (for long short-term memory) [6] that can detect abnormal gait. We can then use this learned model to perform inference over smartphone sensor readings collected and processed in real time using the smartphone. The result of inference can then be used by an app on the phone to provide timely (within few seconds in the ideal case) warnings such as audible alerts and messaging family members. This can lower the likelihood of a subsequent fall, and prove to be a vital tool for preventing falls before they occur.

The rest of this paper is organized as follows. We describe our methodology in Section II, covering data collection, preprocessing, analysis, and training using an LSTM model. We report results in Section III showing the accuracy of our solution and its ability to perform inference on unseen test data in real time. We survey related work in Section IV and conclude in Section V.

II. Methods

The objective of this study is to categorize the walking patterns of individuals who walk with a steady walking pattern that is characteristic of a normal gait and those who have an unsteady walking pattern which is indicative of an abnormal

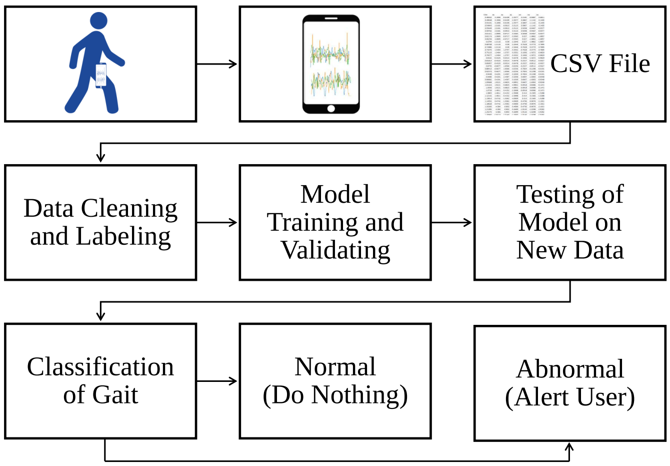

Fig. 1. Flowchart of the Gait Classification process

gait putting them at a higher risk for falls. This classification was done based on sensor data collected from the smartphone they carried. Specifically, this study collected smartphone accelerometer and gyroscope readings from participants while they walked normally and with varying types of gait, including simulated abnormal gaits. The data was used to create a machine learning model to distinguish abnormal gait patterns from normal gait patterns. The model was trained and tested through the use of an LSTM machine learning model. Fig. 1 provides a flow chart of the process.

A. Data

The mobile application 'Physics Toolbox Sensor Suite' was used to collect smartphone sensor (accelerometer and gyroscope) data. The data was exported into a comma-separated value (CSV) file format. Accelerometers and gyroscopes are two of many sensors present in most smartphones, and measure the dynamics of the phone along the x, y, and z axes. Specifically, the linear accelerometer measures linear acceleration in m/s^2, and the gyroscope measures angular rotational velocity in rad/s. Together, the sensors reflect the smartphone user's motion, and can be used to determine their gait pattern. The data was collected at a 50 Hz sample rate in order to optimize the amount of data that needs to be processed by the model and thus reduce computation time.

B. Data Collection

This study builds on past works for human activity recognition (HAR). The participant is assumed to be walking, and the raw accelerometer and gyroscope data is collected through smartphone sensors. Participants in the study were of a range of ages, from adolescents to adults. All participants were healthy and were capable of walking for the whole three-minute interval, and exhibited a normal gait. All data collected and activities performed in the study were done with prior consent from participants. During data collection, each participant carried a smartphone in their right front pocket. The participants were instructed to walk in 3-minute intervals, during which they performed several variations of walking. Specifically, they walked three times in their normal walking pattern for 3 minutes each time at different speeds. Additionally, they walked for 3 minutes with their left shoe on and right shoe off, with the left shoe raised by 4cm and repeated the same this time with the right shoe on and raised by 4cm and left shoe off. Finally, they walked for another 3 minutes with the left knee unbent during their walk. These walking patterns were chosen to simulate the antalgic gaits [3] and left leg pegged patterns. The walking patterns are summarized in Table I. The data collected included x, y, and z angular velocities and linear accelerations, which were measured 50 times per second and exported for analysis. This data is saved in CSV files. The file names include the word "normal" or "abnormal" based on the walking it corresponds to, to help with data preprocessing.

C. Data Pre-Processing

Each CSV file corresponds to a single participant and contains data collected during various walking conditions. For each file, the data is preprocessed by removing null values, converting the accelerometer and gyroscope values to floating point values, and assigning a 'normal' or 'abnormal' label. This cleaned data is appended into the a pandas dataframe. The resulting dataframe contains all the cleaned and labeled data from all the participants, which we use for training our model.

D. Data Visualization

Data visualization is carried out by plotting the accelerometer and gyroscope data against time. A clear difference is visible in the normal and abnormal walking gaits. Figures 2 and 3 show samples of normal and abnormal gait data respectively.

E. Data Analysis

A Long Short-Term Memory (LSTM) network was trained on this data in order to classify the gait into one of the two categories. It was implemented using the Python Keras Sequential API.

An LSTM is a type of recurrent neural network (RNN) [11] used for sequence prediction. LSTMs are designed to handle sequential data, such as (as used in this project) time-series data. They do so by processing the data one element at a time, while maintaining a memory of previous elements. The model we implemented has four layers.

The first layer in the model is an LSTM layer with 128 units. This layer is a type of RNN that allows the model to learn and remember long-term dependencies in the input data, making it well-suited for sequential data such as time series.

The second layer is a dropout layer [13] with a rate of 0.5. This layer randomly drops out half of the units in the previous layer during each training iteration, which helps to prevent overfitting and improve generalization performance.

The third layer is a dense layer with 64 units and a rectified linear unit (ReLU) activation. The ReLU function returns 0

TABLE I
WALKING GAITS

Gait style	Description
Normal brisk	Participants walk in their normal walking pattern at their usual pace.
Normal fast	Participants walk in their normal walking pattern at a fast pace.
Normal slow	Participants walk in their normal walking pattern at a slow pace.
Left antalgic	Participants walk with their left shoe on for a height difference of 4cm between their legs.
Right antalgic	Participants walk with their right shoe on for a height difference of 4cm between their legs.
Left pegged (straight) leg	Participants walk without bending their left knee.

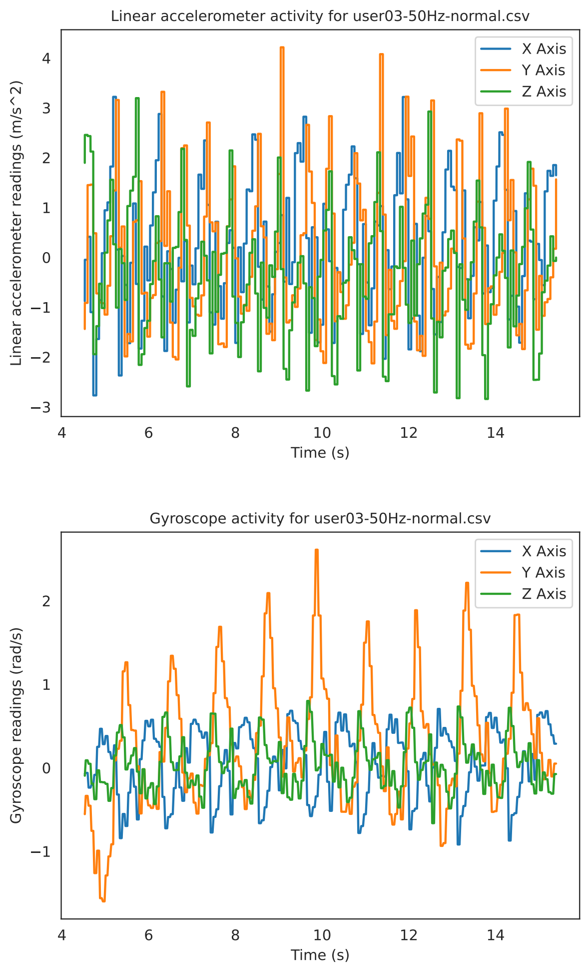

Fig. 2. Example graphs of linear accelerometer and gyroscope readings for normal gait.

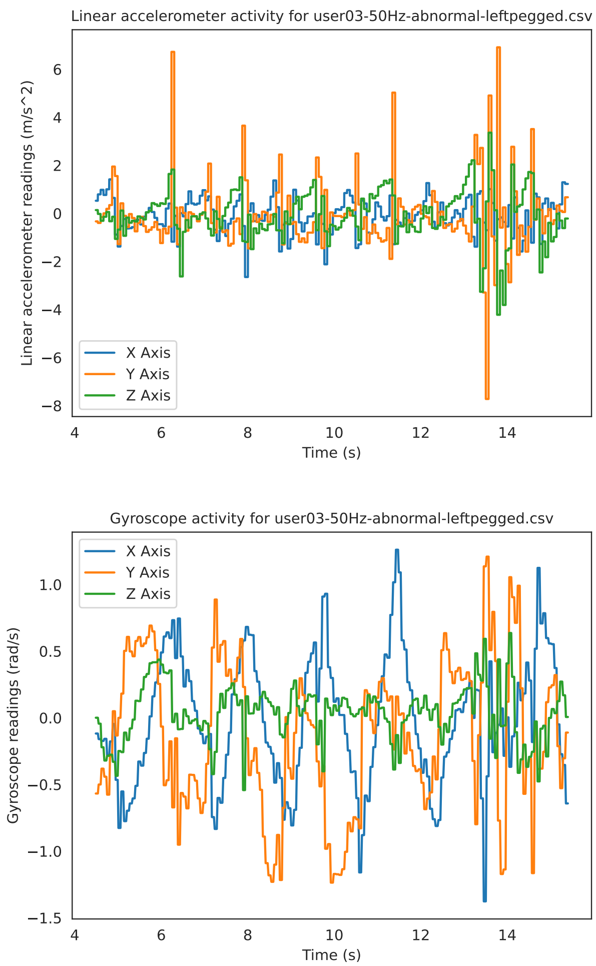

Fig. 3. Example graphs of linear accelerometer and gyroscope readings for abnormal gait.

for negative values and is linear for positive values. It can be written as $f(x) = \max(0, x)$.

The fourth and final layer is a softmax layer with a number of units equal to the number of classes in the output (i.e., 2). This layer computes the probability of each class given the input data and ensures that the probabilities sum to one.

Ultimately, this model classifies sequential data into one of two classes using an RNN with an LSTM layer, dropout for regularization, and dense and softmax layers for classification. Figures 4 and 5 show a visualization of the model.

Data is classified and trained over 10 second intervals with a 1.0 second sliding window. We chose 10 second intervals of data to make sure that a slight change in gait in otherwise normal walking does not get flagged as abnormal. The number of training epochs was set to 200. The number of epochs in LSTM training is the number of times the algorithm goes through the entire training dataset during the training process. We found that going beyond 200 epochs provided diminishing accuracy returns as compared to the time taken to train the model. Additionally, overfitting can occur if the number of

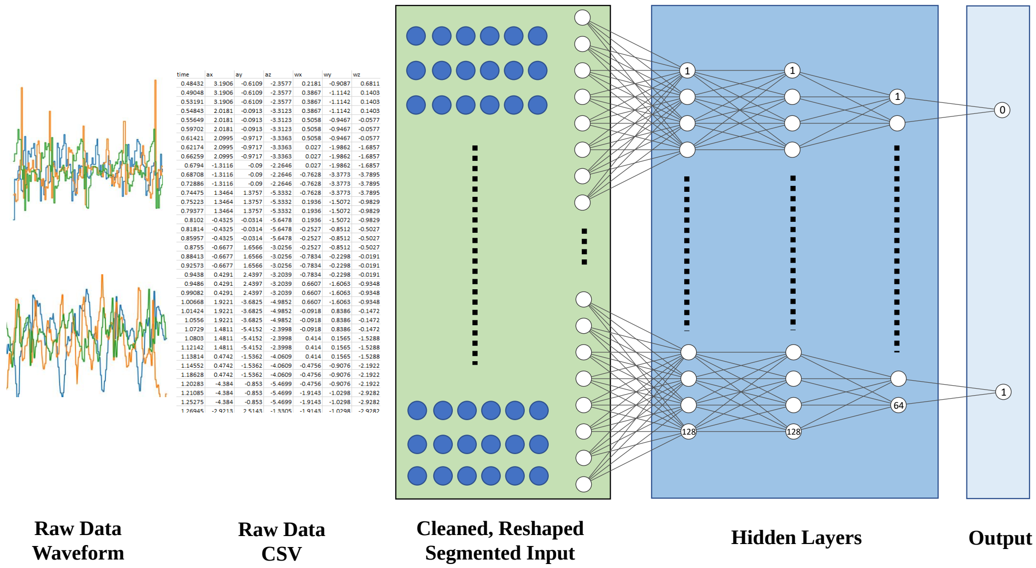

Fig. 4. Visualization of the LSTM RNN model

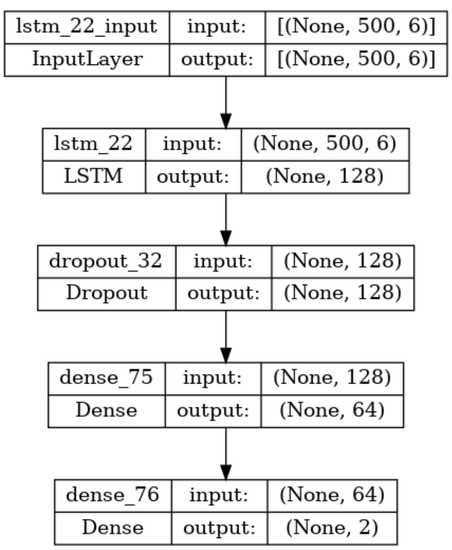

Fig. 5. Visualization of the LSTM RNN model

epochs is too high, which can lead to poor generalizability for new data.

III. Results

This system for monitoring one's gait was used to detect irregularities and, thus, the likelihood of a future fall. The model was trained over the pre-determined training data, for 200 epochs (Figure 6).

The accuracy of the trained model (i.e., the percentage of data that is classified correctly) is 96.6%. The loss of the trained model is computed using a cross-entropy loss function, defined as $L(y, \hat{y}) = -\left[y \log(\hat{y}) + (1-y)\log(1-\hat{y})\right]$, where y is the true label (either 0 or 1) and $\hat{y}$ is the predicted probability of the positive class. In our case, the loss is calculated to be 0.127.

Figure 7 depicts the confusion matrix for the model, in which positive is defined as abnormal gait, which provides further information on the model's performance. Each square in a confusion matrix depicts one of four possible outcomes: true positive (TP, top left), false positive (FP, bottom left), false negative (FN, top right), or true negative (TN, bottom right). These values can be used to calculate the model's precision, recall, and F-score.

The precision of a model is defined as how many predicted positive cases were actually positive, or

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

The precision value for this model is 0.963. The recall of a model is defined as how many positive cases were predicted as positive, or

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

The recall value for this model is 0.979. The F-score of a model is defined as the harmonic mean of recall and precision, or

$$\text{F-score} = \frac{2 \times \text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}}$$

The F-score value for this model is 0.971.

From the confusion matrix, it can be seen that the model predicts the type of gait with great accuracy.

IV. Related Work

The paper [5] provides a good survey of prior work.

Sensors such as inertial measurement units [4] or hall-effect sensors [3] have been previously used for gait analysis.

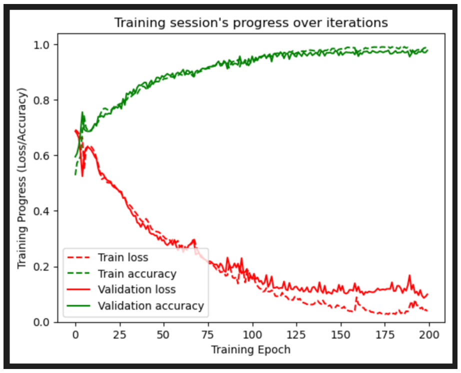

Fig. 6. Model training accuracy and loss model over epochs.

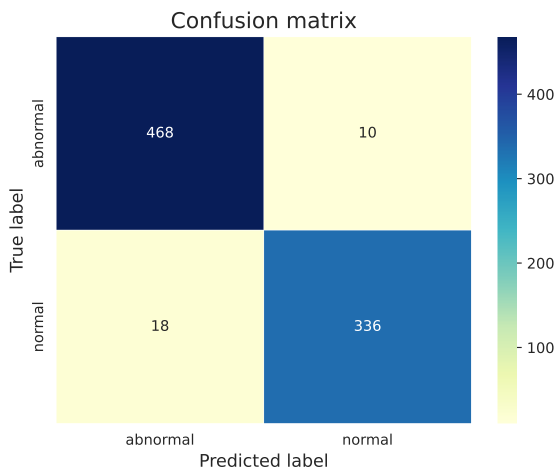

Fig. 7. Confusion matrix for trained model performance on testing data.

However special sensors can be cumbersome to carry around for the sole purpose of fall detection. This work utilizes smartphone sensors to solve a similar problem, thus increasing the accessibility of the gait analysis method.

In [18], the authors propose smartphone-based gait recognition as a less obtrusive way to capture biometric information, compared to fingerprints, iris, face, and voice recognition. In [15] the authors used a 2D convolution neural network to detect abnormal gait in walking patterns using smartphone data. In [17], a person's drunken gait is determined using a deep neural network algorithm, achieving a 79% test accuracy. In [10], accelerometer data is used to identify gait changes in Parkinson's patients by using a random forest model which achieves a 92.5% test accuracy. This work generalizes such work to solve a broader problem, fall detection, and uses an LSTM model to achieve a higher accuracy of 96.6%.

Fall detection systems [14] solve a related problem: detecting falls in order to help the elderly and their caregivers, and subsequently triggering alarms and notifying emergency services. However, these systems focus on detecting a fall after it has occurred. This research focuses on preventing falls before they occur.

Many existing fall prevention systems assess users' medical and behavioral histories and surveys to predict the likelihood of a fall [12]. This work does not currently use user information.

There are two related works that focus on using smartphones in predicting falls [7], [8]. Their work takes a feature extraction approach: they combine the horizontal accelerometer signals with pitch and roll data to create 4 tilt-invariant signals, and extract 3 quantitative features from these signals to create a feature vector. The system uses a decision tree classifier to sort the data into classes based on the features of the training data. Their results show that this approach works best only if the user's data was a part of the training process. For new data, the system accuracy is poor. In contrast, this system uses an LSTM-based approach and is able to classify data from a user whose data was not used while training with a high accuracy.

V. Conclusions and Future Work

The results show that smartphone accelerometer and gyroscope sensor data can be used as an accurate and effective predictor of gait variance. The LSTM model is able to predict normal, abnormal, and irregular gait gait with a test accuracy of 96.6%, a precision of 0.979 and a recall of 0.963. These values indicate the strong possibility of using smartphone data to detect falls, as irregular gait is a common predictor of falls.

These results also have many future implications. By increasing the number of epochs the model trains for as well as the amount of participants in the study, the model can predict steady and unsteady gait patterns with a higher accuracy. Additionally, adaptive learning can be used to personalize the model to the user, thereby making it more accurate. As future work, we plan to integrate our model into a smartphone app that can perform machine learning inferencing in real time in order to provide fall alerts. We also plan to allow users to report falls and upload their smartphone sensor data, so that we can better train our model to detect falls in the real world.

Acknowledgment

I would like to thank CSRSEF for providing the opportunity to work on and present a research project. I also thank my parents for providing educational resources to investigate the problem, and my family for providing test data for use in the project.

References

[1] Demographics of mobile device ownership and adoption in the united states, pew research center. https://www.pewresearch.org/internet/fact-sheet/mobile/.

[2] Keep on your feet - preventing older adult falls. https://www.cdc.gov/injury/features/older-adult-falls/index.html.

[3] C. Chheng and D. Wilson. Abnormal Gait Detection Using Wearable Hall-Effect Sensors. *Sensors (Basel)*, 21(4), Feb 2021.

[4] Trupti Gujarathi and Kalyani Bhole. Gait analysis using imu sensor. In *2019 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*, pages 1–5, 2019.

[5] Mohammad Ashfak Habib, Mas S. Mohktar, Shahrul Bahyah Kamaruzzaman, Kheng Seang Lim, Tan Maw Pin, and Fatimah Ibrahim. Smartphone-based solutions for fall detection and prevention: Challenges and open issues. *Sensors*, 14(4):7181–7208, 2014.

[6] Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural Comput.*, 9(8):1735–1780, nov 1997.
[7] Akm Jahangir Alam Majumder, Farzana Rahman, Ishmat Zerin, William Ebel, and Sheikh Iqbal Ahamed. iPrevention: Towards a novel real-time smartphone-based fall prevention system. In *Proceedings of the 28th Annual ACM Symposium on Applied Computing*, SAC '13, page 513–518, New York, NY, USA, 2013. Association for Computing Machinery.
[8] Akm Jahangir Alam Majumder, Ishmat Zerin, Miftah Uddin, Sheikh I. Ahamed, and Roger O. Smith. SmartPrediction: A real-time smartphone-based fall risk prediction and prevention system. In *Proceedings of the 2013 Research in Adaptive and Convergent Systems*, RACS '13, page 434–439, New York, NY, USA, 2013. Association for Computing Machinery.
[9] Muyinat Y. Osoba, Ashwini K. Rao, Sunil K. Agrawal, and Anil K. Lalwani. Balance and gait in the elderly: A contemporary review. *Laryngoscope Investigative Otolaryngology*, 4(1):143–153, 2019.
[10] Albert Pierce, Niklas König Ignasiak, Wilford K. Eiteman-Pang, Cyril Rakovski, and Vincent Berardi. Mobile phone sensors can discern medication-related gait quality changes in Parkinson's patients in the home environment. *Computer Methods and Programs in Biomedicine Update*, 1:100028, 2021.
[11] D. E. Rumelhart, G. E. Hinton, and R. J. Williams. *Learning Internal Representations by Error Propagation*, page 318–362. MIT Press, Cambridge, MA, USA, 1986.
[12] S. Sato, T. Kakamu, T. Hayakawa, T. Kumagai, T. Hidaka, Y. Masuishi, S. Endo, and T. Fukushima. Predicting falls from behavioral and psychological symptoms of dementia in older people residing in facilities. *Geriatr Gerontol Int*, 18(11):1573–1577, Nov 2018.
[13] Nitish Srivastava, Geoffrey Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. Dropout: A simple way to prevent neural networks from overfitting. *J. Mach. Learn. Res.*, 15(1):1929–1958, jan 2014.
[14] Carlo Tacconi, Sabato Mellone, and Lorenzo Chiari. Smartphone-based applications for investigating falls and mobility. In *2011 5th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*, pages 258–261, 2011.
[15] Md Shahriar Tasjid and Ahmed Al Marouf. Leveraging smartphone sensors for detecting abnormal gait for smart wearable mobile technologies. *International Journal of Interactive Mobile Technologies (iJIM)*, 15(24):pp. 167–175, Dec. 2021.
[16] Joe Verghese, Anne Felicia Ambrose, Richard B. Lipton, and Cuiling Wang. Neurological gait abnormalities and risk of falls in older adults. *Journal of Neurology*, 257:392–398, 2010.
[17] Tirra Hanin Mohd Zaki, Musab Sahrim, Juliza Jamaludin, Sharma Rao Balakrishnan, Lily Hanefarezan Asbulah, and Filzah Syairah Hussin. The study of drunken abnormal human gait recognition using accelerometer and gyroscope sensors in mobile application. In *2020 16th IEEE International Colloquium on Signal Processing Its Applications (CSPA)*, pages 151–156, 2020.
[18] Qin Zou, Yanling Wang, Qian Wang, Yi Zhao, and Qingquan Li. Deep learning-based gait recognition using smartphones in the wild. *IEEE Transactions on Information Forensics and Security*, 15:3197–3212, 2020.