TremorSense: Tremor Detection for Parkinson's Disease Using Convolutional Neural Network

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***Abstract*—Parkinson's Disease (PD) hand tremors are common symptoms in all stages of PD. PD tremors have a severe influence on patients' daily quality of life. Wearable technology can be used to help detect, quantify, and mitigate these PD tremors. Among the wearable technology, PD tremor detection is the primary step for further analysis and treatment using wearable devices. Some researchers have explored PD rest tremor detection. However, less research has been done concerning postural tremor and action tremor detection, which are difficult to classify only using frequency-domain features. In this paper, we propose TremorSense, a PD tremor detection system to classify Parkinson's Disease hand tremors. TremorSense utilizes accelerometers and gyroscopes as wearable sensors on patients' wrists to collect data from 30 PD patients. We develop the TremorSense Android application that connects the sensors via Bluetooth to save the data. Furthermore, we design an 8-Layer Convolutional Neural Network (CNN) to classify PD rest, postural, and action tremors. We evaluate the CNN model with self-evaluation, cross-evaluation and leave-one-out evaluation, and the accuracies for all three evaluations are greater than 94%.**

***Index Terms*—Parkinson's Disease, Tremor Detection, Wearable Device, Convolutional Neural Networks**

I. Introduction

Parkinson's Disease (PD) currently affects more than 10 million people worldwide, and the number of people afflicted is expected to increase each year [1]. PD is marked by a continuous degeneration of the central nervous system (CNS) and has four main motor symptoms: postural instability, rigidity, bradykinesia, and frequent tremors [2]. PD tremors are involuntary rhythmic oscillations [3], usually occurring in the hands and/or fingers of PD patients. Consequently, these tremors cause general motor difficulties resulting in a reduced quality of daily life for PD patients.

Before we can design a system to quantify or mitigate tremor symptoms, we must first accurately detect tremor events in PD patients. There are three types of PD tremors: resting, postural, and action tremors [4]. Each type of tremor has unique characteristics: rest tremors happen when patients are relaxed and stable; postural tremors occur when patients are static with specific poses; action tremors appear when patients perform daily activities. Currently, PD tremors cannot be completely cured, but several methods exist to reduce the severity of tremors in PD patients. Conventional clinical approaches that treat PD and PD tremors are drug treatments, such as Levodopa [5], as well as brain surgery called deep brain stimulation [6]. Less invasive methods, such as psychological treatments, are meant to reduce patient stress [7], and simple vibration devices [8] have been shown to reduce the severity of PD tremors as well. Wearables, such as other different vibration devices, have also been explored to mitigate the tremors [9]. PD vibration devices can be easily integrated and are less invasive than the two common clinical treatments.

Researchers have investigated different sensors such as accelerometers [10]–[13], gyroscopes [14], EMG [15], and other sensors [16], [17] for use in tremor detection. Also, researchers explored threshold-based algorithms [18]–[24] and machine learning algorithms [10]–[13] in tremor detection. Existing research cannot simultaneously classify all three types of tremors accurately since most of them only use frequency-domain features. However, the frequency-domain features of some daily activities are similar to the features of PD tremors. This makes it hard to detect and classify tremor accurately. Furthermore, the moving time window for the tremor classification of existing works is typically greater than two seconds, with more time delay when detected in real-time. In this paper, we will address the following research questions:

RQ1: How can we detect three types of tremors accurately?

RQ2: Can we use a shorter time window size to reduce the time delay?

In this paper, we proposed TremorSense to accurately detect the three types of PD tremors using an 8-Layer Convolutional Neural Network (CNN). We collected data from 30 PD patients via accelerometer and gyroscope sensors on both wrists and the TremorSense Android application. We divided the sensor data with a window size of 1.28 seconds and a sliding window size of 0.64 second. In total, we used 20,226 tremor instances and 20,226 no tremor instances, and fed them into an 8-Layer CNN model. The TremorSense CNN model can accurately classify instances as *'tremor'* or *'no tremor'*. Our contributions are summarized as follows:

- We used Ultigesture (UG) sensors and developed the TremorSense Android application to collect tremor data from 30 PD patients in a clinical user study.
- We designed an 8-Layer CNN model to classify all types of PD tremor events. We evaluated the CNN model with self-evaluation, cross-evaluation and leave-one-out evaluation, and the accuracies for all three evaluations are greater than 94%.
- We used 1.28 seconds as window size and 0.64 second as a sliding window to divide data, which is shorter than what was used in current PD tremor detection research. This allows for the classification of shorter tremor events. It can also potentially reduce the detection time delay with real-time classification in future work.

This paper is organized as follows. First, in Section 2, we present data collection, including sensors that we use, TremorSense application development, and parameters and demographics of our dataset. In Section 3, we discuss how we process the sensor data and our CNN model design, and show the evaluation performance of our CNN model. In Section 4, we introduce related works about tremor detection. In Section 5, we present the discussion and future work. Lastly, we summarize our conclusions in Section 6.

II. Data Collection

We collected the sensing data and video ground truth for the tremor activities from 30 PD patients with the help of the medical professionals from Virginia Commonwealth University (VCU). Our study is part of a tremor vibration study conducted by VCU. The sensing data was collected from a single three-axis accelerometer and a single three-axis gyroscope. For data collection, we employed the commonly used tremor rating scales: UPDRS and Fahn-Tolosa-Marin, to collect three types of PD tremor events. Specifically, we used 11 UPDRS activities and 3 Fahn-Tolosa-Marin scale activities as shown in Table I. During data collection, we used an Android smartphone to record the ground truth video for tremor events labeling. In this section, we present the details of the tremor rating scales and the activities we use in the study. We also describe the equipment and application that we utilized to collect tremor data, and explain the parameters and demographics of our dataset.

TABLE I: **Scales and Activities**

Number	Scale	Activity
1	UPDRS	Finger Tapping
2	UPDRS	Hand Movements
3	UPDRS	Pronation-Supination
4	UPDRS	Toe Tapping
5	UPDRS	Leg Agility
6	UPDRS	Arising From Chair
7	UPDRS	Gait
8	UPDRS	Postural Stability
9	UPDRS	Postural Tremor of the Hands
10	UPDRS	Kinetic Tremor of The Hands
11	UPDRS	Rest Tremor Amplitude
12	Fahn-Tolosa-Marin	Handwriting
13	Fahn-Tolosa-Marin	Drawing
14	Fahn-Tolosa-Marin	Pouring Water

A. *Activities*

Tremor Rating Scales are frequently used clinical methods to assess PD tremor severity. Among them, Unified Parkinson's Disease Rating Scale (UPDRS) [25], [26] and Fahn-Tolosa-Marin Scales [27] are currently the most selected approaches in clinical facilities to quantify the PD tremors. The UPDRS has four parts: non-motor experiences of daily living, motor experiences of daily living, motor examination, and motor complications. The professionals assess each activity and apply a score between 0 and 4 for the patient. The scores represent different tremor severities: Normal (0), Slight (1), Mild (2), Moderate (3), and Severe (4). In our study, we choose the activities from UPDRS that are most closely related to tremor quantification. The Fahn-Tolosa-Marin rating scale includes daily activities such as handwriting, drawing, pouring water, etc. PD patients commonly suffer hand tremors during daily activities. Thus, we choose 11 activities from the motor examination portion of UPDRS and three activities from Fahn-Tolosa-Marin scales, as shown in Figure 2. The following introduces the details of these 14 activities that are employed in our study:

1) Finger Tapping: The patient taps the index finger on the thumb ten times as quickly and as far as possible. Note that this is done on the same hand, and the patient performs it on the right hand and left hand separately.
2) Hand Movements: The patient makes a tight fist with the arm bent at the elbow so that the palm faces the examiner. The patient opens the hand ten times as fully and as quickly as possible. Note that this is done on the same hand, and the patient performs it on the right hand and left hand separately.
3) Pronation-Supination Movements of Hands: The patient extends the arm out in front of his/her body with the

(a) (b) (c) (d) (e) (f) (g)

(h) (i) (j) (k) (l) (m) (n)

Fig. 2: **Data Collection: (a) Finger Tapping; (b) Hand Movements; (c)Pronation-Supination Movements of Hands; (d) Toe Tapping; (e) Leg Agility; (f) Arising From Chair; (g) Gait (Freezing of Gait); (h) Postural Stability; (i) Postural Tremor of the Hands; (j) Kinetic Tremor of the Hands; (k) Rest Tremor Amplitude; (l) Handwriting; (m) Drawing; (n)Pouring Water.**

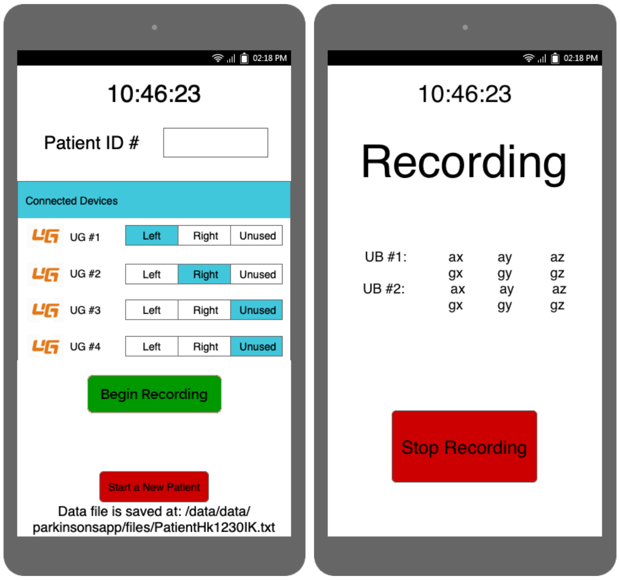
palms down. The patient turns the palm up and down alternately ten times as fast and as fully as possible. Note that this is done on the same hand, and the patient performs it on the right hand and left hand separately.

4) Toe Tapping: The patient places the heel on the ground in a comfortable position while sitting, and then taps the toes ten times as big and as fast as possible. Note that this is done on the same foot, and the patient performs it on the right foot and left foot separately.
5) Leg Agility: The patient places the foot on the ground in a comfortable position while sitting, and then raises and stomps the foot on the ground ten times as high and as fast as possible. Note that this is done on the same leg, and the patient performs it on the right leg and left leg separately.
6) Arising From Chair: The patient crosses his/her arms across the chest, and then stands up from the chair.
7) Gait: The patient walks at least ten meters (30 feet), and then turns around and returns to the examiner.
8) Postural Stability: Examiner stands behind the patient and pulls the patient briskly towards the examiner with enough force to displace the center of gravity so that patient must take a step backwards.
9) Postural Tremor of the Hands: The patient stretches the arms out in front of his/her body with palms down for ten seconds.
10) Kinetic Tremor of the Hands: With the arm starting from the outstretched position, the patient performs at least three finger-to-nose maneuvers with each hand reaching as far as possible to touch the examiner's finger. Note that this is done on the same hand, and the patient performs it on the right hand and left hand separately.
11) Rest Tremor Amplitude: This has been placed purposefully at the end of the examination to allow the rater to gather observations on rest tremors that may appear at any time during the exam. This includes when quietly sitting, during walking and during activities when some body parts are moving but others are at rest. The patient is scored the maximum amplitude that is seen at any time as the final score.
12) Handwriting: The patient uses his/her dominant hand to write his/her name and several other sentences.
13) Drawing: The patient uses both hands to draw a straight line and traces a circle maze with a pencil.
14) Pouring Water: The patient uses both hands to pour water from a cup to another cup.

Fig. 3: **UG Sensor band: A combination of accelerometer, gyroscope, magnetometer**

B. Sensors and Tremor-Band Application

We deployed two UG sensors [28], as shown in Figure 3, one on each of the patient's wrists to record tremor data. We developed an Android application denoted PAT and implement it on a Google Pixel 3 to record our UG sensor data. The sampling rate of PAT is 100Hz. PAT collected the data from



(a) Main Screen (b) Recording Screen

Fig. 4: **TremorSense Application**

UG sensors via Bluetooth in real-time, and we transfer our data to a PC for offline analysis. Our app has two states: Main Screen (4a), and Recording Screen (4b).

Main Screen: When the application is launched, the user can see the home screen. On this screen, the user can enter the patient ID number, and select which UG bands pertain to each wrist used in the study. Then, they can start the individual data collection and view the location where the data file is saved.

Recording Screen: The user can see this screen once they have begun recording data. On this screen, the user can view live data streaming from the UG wristbands and stop the data recording after completing data collection for a patient.

In our study, we use a camera to record all activities and tremor events for each patient. UG sensors can record data using UNIX time. Therefore, the data saved by PAT App has UNIX time labels. We label each activity start and end time, tremor event start and end time, and whether an activity has a tremor on right or left hand. We label these tremor events using UNIX time, which synchronizes with sensor data.

C. Dataset

Parameters: We conducted our data collection in a clinical environment. Before the patient took the UPDRS test, we asked them to fill out their demographical information in a questionnaire, which we present in demographics later. Following this, we asked the patients to wear our UG sensor on both wrists, and perform UPDRS activities and Fahn-Tolosa-Marin activities. We repeated this process three times for each patient. After each repetition, the doctor assessed a rating score to evaluate the tremor severity. The tremors occurred during testing activities and transition times. We labeled the data based on the video ground truth for the occurrence of tremors and the duration of tremor. The labels are used to extract the tremor instances to feed into our CNN model for tremor classification.

TABLE II: Patient Demographics

Characteristics	Details
Number of Patients	30
Gender Proportion	18 Males / 12 Females
Range of Patient Current Age	45 - 84 Years old
Average of Patient Current Age	67.43 Years old
Range of PD Symptom Onset Age	35 - 82 Years old
Average of PD Symptom Onset Age	58.63 Years old
Range of PD Diagnosed Age	38 - 82 Years old
Average of PD Diagnosed Age	60.73 Years old
Range of Disease Duration	0 - 24 Years
Average of Disease Duration	8.80 Years
Range of UPDRS Score	0 - 3

Demographics: We administered a questionnaire before the study for the following basic statistics: age, gender, PD symptom onset age, PD diagnosis age, and years since PD Diagnosis, as shown in Table II. We recruited 30 patients in our study, including 18 males and 12 females. On average, our patients are 67.43 years old, with the youngest being 45 years old to the oldest being 84 years old. The average age of PD symptom starting age is 58.63 years old, with the youngest from 35 years old to the oldest 82 years old. The average PD diagnosis age is 60.73 years old, and the range is from 38 years old to 82 years old. Based on the above information, we calculated the average PD duration since PD symptoms start, which is 8.80 years old, and the range of PD duration, which is from 0 years to 24 years. The range of the tremor severity score is from 0 to 3. This shows that the PD patients in our dataset have different ages, PD symptom durations, and different PD severity stages.

III. Tremor Detection Model & Evaluation Results

The TremorSense overview is shown in Figure 5. TremorSense collects accelerometer and gyroscope data from UG sensors and the TremorSense Android application. Based on the ground-truth labeling, we use a sliding window to divide the data into instances of *'tremor'* and *'no tremor'*. Both the *'tremor'* and *'no tremor'* instances are fed into the 8-Layer CNN for tremor classification. This CNN model is designed for a binary classification problem, and the output is *'tremor'* or *'no tremor'*. In this section, we introduce signal processing, CNN classification model design, and its evaluation results.

TABLE III: Data Segmentation Instances

Label	Rest	Postural	Action	Total
Tremor	15049	1206	4011	20226
No Tremor	17705	504	2017	20226

A. Signal Processing

The raw data collected from UG sensors includes three-axis accelerometer data, three-axis gyroscope data, and the UNIX timestamp labels of each data point. We manually labelled the ground truth videos and transformed the time labels into UNIX

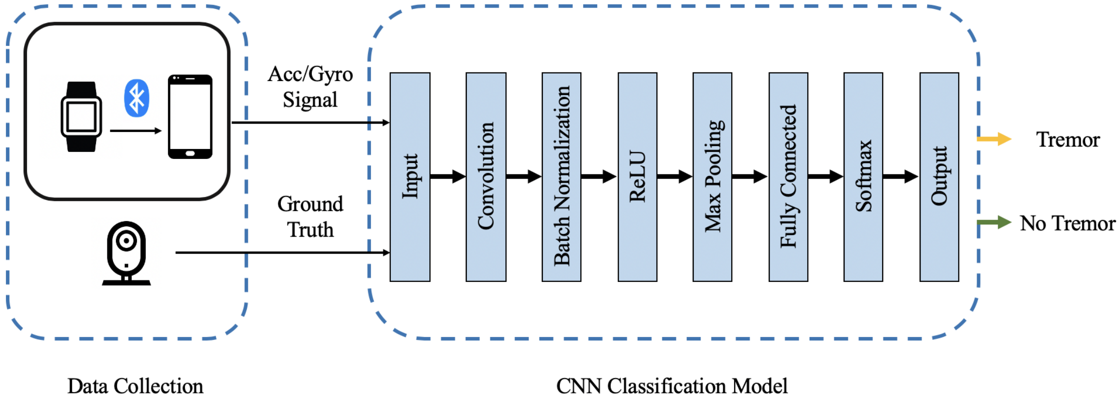


Fig. 5: **TremorSense Overview**

timestamps, which can be synchronized with sensor data. The tremor events consist of rest tremors, postural tremors, and action tremors. Since the duration of tremor events is from below three seconds to several minutes, we decide to use a 1.28 second time window and a 0.64 second sliding window to divide the raw data into instances. Each instance includes 128*6 data points. The columns consist of the accelerometer x-axis, accelerometer y-axis, accelerometer z-axis, gyroscope x-axis, gyroscope y-axis, and gyroscope z-axis, respectively. The columns have 128 data points for each axis of sensors. We extracted the *'tremor'* instances and *'no tremor'* instances based on ground truth labeling. The total number of instances of the different types is shown in Table III. In total, we have 20,226 *'tremor'* instances, including 15,049 rest tremor instances, 1,206 postural tremor instances, and 4,011 action tremor instances.. To balance the dataset, we also have 20,226 *'no tremor'* instances, including random selected 17,705 rest instances, all 504 postural activity instances, and all 2,017 other activity instances.

B. CNN Classification Model Design

In this section, we present our 8-Layer CNN design for tremor classification. We use a CNN to classify tremor instances because it learns parameters and features effectively for complex problems. Because action and postural tremors have similar frequency domain features as activities performed in our study, tremor classification becomes difficult. Our CNN efficiently solves this problem by training the parameters and learning features directly from the time-domain.

Note, in the TremorSense CNN model, each instance is a two-dimensional six-axis accelerometer and gyroscope data. Therefore, we use two-dimensional data as the input to our CNN model. In the following subsections, we present Input Layer, Convolution Layer, Batch Normalization Layer, Rectified Linear Unit (ReLu) Layer, Fully Connected Layer, Softmax Layer, and Classification Output Layer, respectively.

1) Input Layer: The Input Layer takes the instances that we described in the previous subsection. The size of each input to the CNN model is $(128*6)$, and each instance consists of 768 data points. The goal of our CNN model is to classify whether each instance is *'tremor'* or *'no tremor'*. The Input Layer does not learn parameters and features. This Layer mainly prepares data input for the other following CNN Layers.

2) Convolutional Layer: In our CNN model, we use one convolution Layer, which can work efficiently with our dataset without consuming many computing resources. Convolutional Layer substitutes matrix multiplications with convolution computations. TremorSense employs two-dimensional convolution:

$$S(i,j) = (I*K)(i,j) = \Sigma_m \Sigma_n I(m,n)K(i-m,j-n) \quad (1)$$

Where I is the input, and K is the Kernel. [29]

In image classification with CNNs, researchers typically use more kernels to extract more features from all pixels to enhance classification accuracy. Our input instances are similar to two-dimensional images. Thus, TremorSense uses 32 two-dimensional kernels with a size of $3*3$ and a stride of one in both horizontal and vertical directions. Stride means the number of data points that a kernel shifts over for each convolution. For each input instance, the Convolutional Layer creates a feature map by adding a bias term along with the kernel. The kernels generate the same number of feature maps in the Convolutional Layer output. As the Convolutional Layer shares the same feature maps for all input instances, the training and testing computation overhead decrease significantly. Therefore, CNNs are effective in dealing with complex problems such as image classification, autopilot, etc..

3) Batch Normalization Layer: We employ a Batch Normalization Layer to improve CNN training speed and apply feature maps to an activation function in the ReLU Layer. The Batch Normalization Layer can reduce the sensitivity to network initialization, which helps avoid overfitting. Eq. 2 shows the normalized activation. The function normalizes the

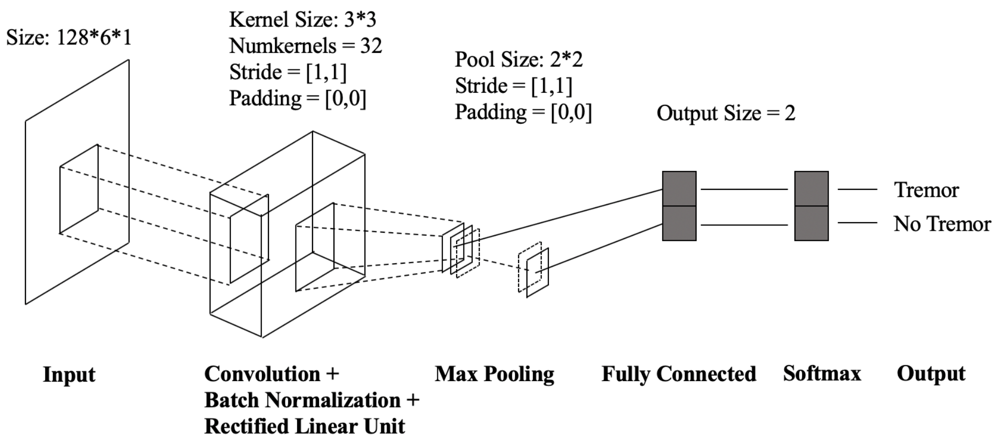


Fig. 6: **Convolutional Neural Network Layers**

input x_i over a mini-batch for each input instance. And the output of the batch normalization Layer is Eq. 3.

$$\hat{x_i} = \frac{(x_i - \mu_B)}{(\sqrt{\sigma_B^2 + \epsilon})} \tag{2}$$

where μ_B and σ_B are the mean and variance of the mini-batch [30].

$$y_i = \kappa \hat{x_i} + \rho \tag{3}$$

where κ is the scale factor, ρ is the offset, and $\hat{x_i}$ is the normalized activation in Eq. 3 [30].

4) Relu Layer: The Rectified Linear Unit (ReLU) layer is a widely used non-linear activation function following the Batch Normalization Layer [29]. The ReLU Layer uses a threshold function to set all the negative input values to zero as Equation 4:

$$f(x) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases} \tag{4}$$

The ReLU layer does not change the size of the input. Since negative inputs are set to zero, only a certain number of neurons are activated. It is more computationally efficient compared with traditional activation methods like Sigmoid and Tanh functions.

5) Max Pooling Layer: The Max Pooling Layer is mainly for down-sampling the output of the ReLU Layer. Max Pooling Layer returns the max value of the inputs within a pooling rectangular filter. TremorSense uses $2*2$ pooling size and $1*1$ stride size. The goal of the Max pooling Layer is to decrease learning parameters in the following Layer and reduce over-fitting. Typically, Convolutional Layer, Batch Normalization Layer, ReLU Layer, and Max pooling Layer are combined as one unit. Multiple units may be needed in more complex classification problems.

6) Fully-connected Layer: The Fully-connected layer is an essential component of our CNN model that classifies the input with all the features from previous layers. The Fully-connected layer of our CNN model goes through its backpropagation process to decide the most accurate weights. Each neuron determines weights that prioritize the most relevant label and votes for the classification decision. The output of the Fully-connected layer generates the final probability for each class, which is *'tremor'* and *'no tremor'* in our CNN model.

7) Softmax Layer: The Softmax Layer performs the softmax function to the output from the Fully-connected Layer. The function returns the probability for each instance belonging to each class, *'tremor'* and *'no tremor'*. The classification results are based on the probability that the Softmax Layer generates.

8) Classification Output Layer: Our Classification Output Layer consists of two classes, which are *'tremor'* and *'no tremor'*. Since researchers mainly care about whether tremors events happen or not when they are doing daily activities, the input instances are classified into binary categories. In the next section, we discuss the classification results of the TremorSense CNN model.

C. Evaluation Results

In this subsection, we perform self-evaluation, cross-evaluation, and leave-one-out evaluation to demonstrate the performance of our TremorSense CNN model. We use the 30 patients data that we introduced in Section 2. We employ Precision, Recall, F1 Score, and Accuracy to validate our CNN model performance.

1) Self-Evaluation: For self-evaluation, we trained and tested our model using the data from each patient. We run 5-fold cross-validation for each round of training and testing. Since we trained and tested our model using the same data for each patient, the classification results were supposed to achieve the best score among all evaluation results. As expected, the overall precision, recall, F1 score, and accuracy are 93.31%,

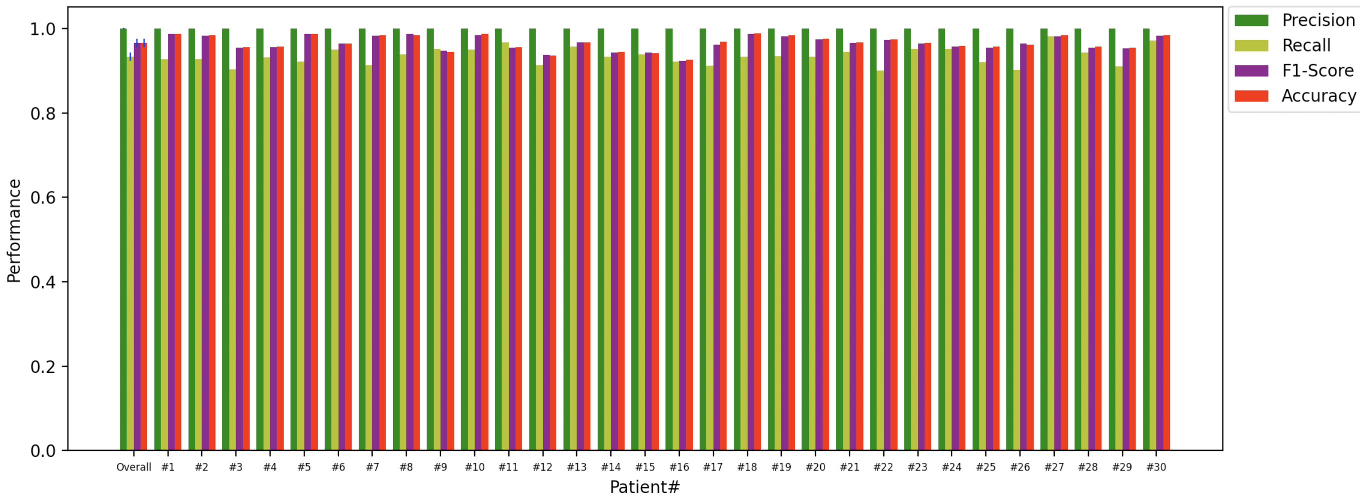


Fig. 7: **Overall Self-Evaluation Results**

100%, 96.54%, and 96.65%, respectively. The overall standard deviation for precision, recall, F1 score, and accuracy are 0, 0.03, 0.02, and 0.02, respectively. Figure 7 shows the overall average with standard deviation error bars and the individual self-evaluation results for 30 patients.

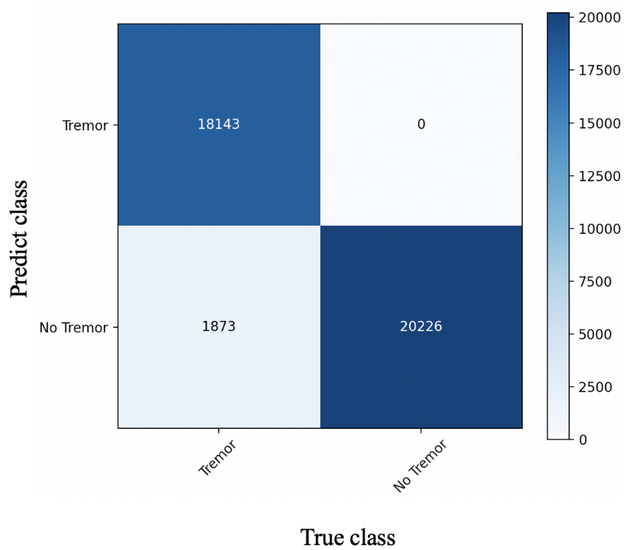


Fig. 8: **Confusion Matrix of the Cross-Evaluation Test**

2) Cross-Evaluation: For cross-evaluation, we trained and tested our model on using the data from all patient data. We also run 5-fold cross-validation for each round of training and testing. The overall precision, recall, F1 score, and accuracy are 90.64%, 100%, 95.09%, and 95.35%, respectively. Figure 8 shows the confusion matrix of cross-evaluation results.

3) Leave-One-Out-Evaluation: For leave-one-out-evaluation, we trained our model using data from 29 patients and tested our model with the data from the single remaining patient. The overall precision, recall, F1 score, and accuracy are 88.58%, 100%, 93.95%, and 94.29%, respectively. Even though the leave-one-out evaluation accuracy is around 2% worse than self-evaluation, and 1% worse than cross-evaluation, the performance is still strong with an accuracy above 94%. The overall standard deviation for precision, recall, F1 score, and accuracy are 0, 0.02, 0.02, and 0.02, respectively. Figure 9 shows the overall average with standard deviation error bars and the individual leave-one-out-evaluation results for 30 patients.

4) Comparison with Existing Work: In our CNN evaluation results, the accuracy is above 94%, and the F1 score is above 93%. Compared with existing research in PD tremor detection, TremorSense achieves a higher accuracy greater than 94%, while Zhang et al. [12] reach 75% and Fraiwan et al. [11] reach 81%. Moreover, TremorSense uses 1.28 seconds as the window size, while Zhang et al. [12] utilize multiple windows with sizes greater than 30 seconds. TremorSense has a shorter delay in tremor detection. It shows the robust and convincing results of our CNN model.

IV. Related Work

In recent years, there are increasing research topics in PD tremor detection and quantification. Researchers have explored different sensors in tremor detection such as accelerometers and Electromyography (EMG), and algorithms in tremor classification such as Support Vector Machine (SVM) and Neural Network (NN). Existing works mainly collected data on randomly selected daily activities that are not as clinically relevant as TremorSense. Also, the accuracies of existing tremor detection models are lower than 90%.

In 2017, Zhang et al. [12] used accelerometers and machine learning algorithms to detect tremors in PD patients' daily activities. They collected data based on six UPDRS activities and nine daily activities. The accuracies of their classification models are around 75%. They also used multiple windows with sizes greater than 30 seconds to segment their data. Compared with them, TremorSense provides more comprehensive

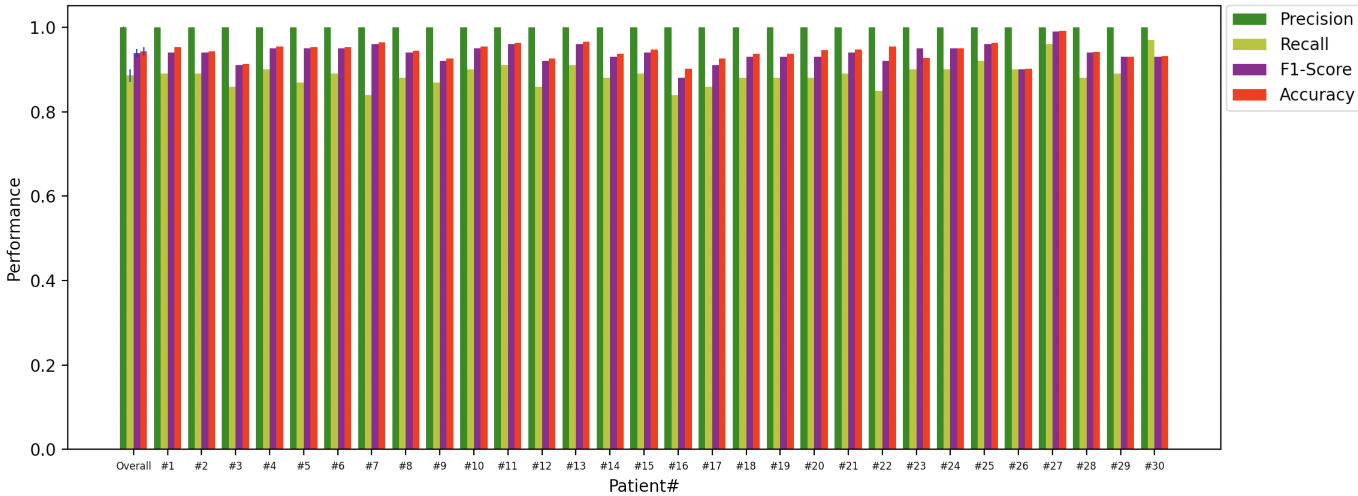


Fig. 9: **Overall Leave-one-out Evaluation Results**

TABLE IV: **Related Work Parkinson's Disease Tremor Detection**

Reference	Year	Sensor*	Patients	Time Window	Classifier**	Performance
[16]	2016	Laser	18	NaN	Threshold	NaN
[14]	2018	Acc & Gyro	NaN	NaN	Threshold	NaN
[10]	2015	Electrodes	8	2s	NN/Clustering	89.5%
[15]	2017	EMG	10	2s	HMM	82.0%
[17]	2018	Electrodes	12	2s	ML	70.0%
[11]	2016	Accelerometer	21	NaN	ANN	81.0%
[12]	2017	Accelerometer	5	30s	SVM/NN	75.0%
[13]	2018	Accelerometer	6	3s	RF/MLP	88.7%
TremorSense	**2021**	**Acc & Gyro**	**30**	**1.28 seconds**	**CNN**	**>94%**

* Acc: Accelerometer; Gyro: Gyroscope.
** RF: Random Forest; MLP: Multi-Layer Perceptron; SVM:Support Vector Machine; NN: Neural Network; HMM: Hidden Markov Model; ML: Machine Learning; ANN: Artificial Neural Network; CNN: Convolutional Neural Network.

evaluations by employing 11 clinically relevant UPDRS activities and 3 Fahn-Tolosa-Marin activities, and TremorSense achieves the accuracies above 94% with different evaluation methods. The window size of TremorSense is 1.28 seconds, which classifies shorter tremor events. Fraiwan et al. [11] used the accelerometer in a smartphone to detect PD tremor events based on daily activities. They used Artificial Neural Networks (ANNs) as a classifier to distinguish tremors with an accuracy of 81%. They collected 30 seconds of data for 21 patients with a sampling rate of 9-11 Hz, which indicated that they only had around 6,300 data points in total. Compared with them, TremorSense is more clinically relevant and accurate. Also, TremorSense has 31,067,136 (40452*128*6) data points used for training and testing. In 2018, Zhang et al. [13] utilized CNNs and Mel-frequency cepstral coefficients (MFCCs) to extract the frequency-domain features and fed them into Random Forest (RF) and Multi-Layer Perceptron (MLP) models. They briefly introduced their methods in a two-page paper, which provide little details on implementation and evaluation.

Some existing works [10], [15], [17] focus on recognizing only PD rest tremors. Camara et al. [10] employed electrodes to measure local field potentials (LFPs which are signals from a large group of cells in the brain) and NN to detect the PD rest tremor with an accuracy of 89.5%. Hirschmann et al. [15] utilized EMG signals and Hidden Markov Models (HMMs) to recognize PD rest tremor events with an accuracy of 82%. Yao et al. [17] also used LFP signals and machine learning algorithms to classify PD rest tremors with an accuracy of 70%. Compared with them, these works collect data when patients were only rest while TremorSense uses clinical UPDRS and Fahn-Tolosa-Marin activities to collect tremor events. TremorSense can also classify three types of tremors: rest tremors, postural tremors, and action tremors with higher accuracy. In addition, some researchers used threshold-based methods to recognize hand tremor events [14], [16]. These works collected the data of daily activities from non-PD patients. They did not evaluate the performance of their models. In comparison, TremorSense evaluates its model on 30 real PD patients with 14 clinical relevant activities. We summarize and compare tremor detection related research with TremorSense, as shown in Table 4. The table includes the papers published in recent years with different tremor types, sensors or signals, patient numbers, time windows, classifiers, and performance.

Researchers have also employed sensing methods to detect and quantify PD hand tremors such as electromagnetic motion trackers [31], [32], electromyography (EMG) [33], [34], accelerometers [10]–[13], gyroscopes [35], [36], and touch sensors [37]–[39]. Based on the data from the sensors, several works have been done on tremor severity quantification such as tremor frequency analysis [40], [41], tremor amplitude analysis [36], [42] and tremor severity assessment [19], [24]. These works use conventional methods to detect the tremors with a certain frequency range. Some researchers [18]–[24] use 3.5 Hz - 7.5 Hz to extract rest tremors and 4 Hz - 12Hz extract postural tremors. However, the main frequency components of some activities are in the same range as the frequency of tremor events. For example, the frequency of UPDRS (3.4) Finger Tapping without tremors are typically in the range of 2Hz - 5Hz, which overlaps with the range of tremors and lead to misclassifications. TremorSense can avoid these misclassifications by using both accelerometer and gyroscope time-domain features.

V. Discussion and Future Work

TremorSense uses the CNN model and time domain data to classify the tremor events. The features that the CNN used are not so manifest as frequency-domain features, which may not be friendly to domain researchers. However, only frequency domain features may not be enough to classify the tremors when PD patients perform daily activities. The frequency of some daily activities is in the same range as as the frequency of tremors, which are very hard to classify when only using frequency-domain features. TremorSense classifies three types of PD tremors, and most misclassifications come from action tremors. To further address this research question, we intend to explore more on both the time-domain and frequency-domain features of some specific misclassified action tremors in future work.

TremorSense uses accelerometers and gyroscopes as sensors to collect data. Both sensors are unintrusive and portable wearable devices that are best for tremor detection in the home environment and clinical environment. However, other sensors such as EMG, EEG, etc. can be further explored in the future. Theses clinical sensors can provide better features for domain researchers and have the potential to find tremor treatment and mitigation approaches.

PD tremor detection is a necessary procedure in PD tremor quantification and treatment, especially for wearable devices. Researchers need to automatically detect all three types of PD tremors accurately when patients participate in PD tremor severity quantifications. Some wearable devices, such as vibration devices, demand accurate tremor detection to provide appropriate mitigations and treatments. We propose to use TremorSense in our tremor assessment and quantification system in future work.

VI. Conclusion

In this paper, we proposed TremorSense, a PD tremor detection system, to classify PD tremor events when PD patients perform daily activities. We employed UG sensors and develop the TremorSense Android application to collect data from 30 PD patients in a clinical user study. We divided the time domain sensor data with 1.28 seconds and design an 8-Layer Convolutional Neural Network (CNN) classifier. We evaluated our CNN model with self-evaluation, cross-evaluation and leave-one-out evaluation, and the accuracies for all three evaluations are greater than 94%. The results validated that TremorSense can accurately classify PD rest tremors, postural tremors, and action tremors.

VII. Conflict of Interest

Dr. Pretzer-Aboff has financial interest in Resonate Forward, LLC, a company with commercial interests in technology. This conflict has been reviewed and managed by VCU.

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