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Review Article

Parkinson's Disease Detection Using Deep learning approach based on Wearable Sensor-Based Daily Monitoring

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ABSTRACT

Parkinson's disease (PD) is a movement disorder characterized by motor dysfunction commonly bradyphemia, tremor, rigidity, akinesia, or slowness of movement. Noting that motor states can fluctuate in PD the primary aim of this current paper was to differentiate multiple states using wearable sensors in the patients and detection of this PD based on deep learning (CNN). Methodology: In this paper, the researchers recorded the signals of the accelerometer and gyroscope fixed on the wrist of PD in their regular daily functioning after using this dataset collection. The deep learning architecture developed was to optimize a CNN for analyzing the sensor data for motor status like rest, tremor, and dyskinesia. Results and Conclusion: The availability of high accuracy in defining different degrees of motor state was achieved through the deep learning algorithm hence providing a high option in monitoring pd symptoms. These outcomes also show and suggest the possibility and practicality of the wearable sensor for daily activity monitoring for the identification of PD. It can also provide appropriate information to patients other than doctors regarding their sickness which gives them a platform to effectively handle Parkinson's disease patients. The error has been determined to be within the vicinity of 98%.

1. INTRODUCTION

Parkinson's disease (PD)[1-5] is a movement disorder characterized by motor dysfunction commonly bradyphemia, tremor, rigidity, akinesia, or slowness of movement. This is because, once the symptoms of the disease manifest it becomes tough to handle the situation as the disease has developed and progressed[6-8]. Noting that motor states can fluctuate in PD the primary aim of this current paper was to differentiate multiple states using wearable sensors in the patients and detection of this PD based on deep learning (CNN). Methodology: In this paper, the researchers recorded the signals of the accelerometer and gyroscope fixed on the wrist of PD in their regular daily functioning after using this dataset collection[9-13]. The deep learning architecture developed was to optimize a CNN for analyzing the sensor data for motor status like rest, tremor, and dyskinesia. Results and Conclusion: The availability of high accuracy in defining different degrees of motor state was achieved through the deep learning algorithm hence providing a high option in monitoring pd symptoms. These outcomes also show and suggest the possibility and practicality of the wearable sensor for daily activity monitoring for the identification of PD[14-15]. It can also provide appropriate information to patients other than doctors regarding their sickness which gives them a platform to effectively handle Parkinson's disease patients. According to the authors of the disclosed investigations, the error has been determined to be within the vicinity of 98%. Further research work needs to be done so that findings that have already been made can be imposed and the efficiency of the sensor can be improved to be effectively used in clinical practice.

2. LITERATURE REVIEW

Nearly Recently, Several Multimodal Detection of Parkinson's Disease Daily are monitoring using Wearable Sensors i.e. A TelePark, a multimodal telehealth solution, was designed to address the deficiencies of separate systems in 12 individuals with Parkinson's disease over 12 weeks. The system employs video visitation, a smartphone application, a

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camera system, and wearable sensors. The structured training encompassed the installation of equipment and online educational sessions. The study revealed a high level of adherence, with 79% of participants completing the questionnaires, 62% confirming their prescription use, and 33% using the electronic Hauser diary. It could be seen that the overall quality of life was not affected and that more patients are needed to provide information about the effect of the remedy on motor signs as stated in [16].

The researchers looked at whether ANS activity registered back from a wearable sensor could be used to predict the reduction in the effectiveness of L-dopa in individuals. In this case, the patients with Parkinson's disease and L-dopa-treated patients will be asked to keep a diary of their 'on-off' state for 24 hours. At the same time, they were also mandatorily requested to wear a portable ANS sensor, known as the E4 wristband®, that monitored features including Skin Conductance (EDA), Heart Rate (HR), Blood Volume Pulse (BVP), and Skin temperature (TEMP). For the prediction of the wearing-off (WO) period, a method combining empirical mode decomposition (EMD) with regression analysis was used. To obtain the best results, when we employed such individually designed models as tested by cross-validation, we can get a correlation of more than 90% when comparing with the OFF state reported by the patients and the reconstructed signals. A combined condition, in which the same ASR metrics were used for all subjects, yielded no statistically significant results. The paper proofs of concept research that shows that the Autonomic Nervous System (ANS) index can be used to determine the on/off phenomena in PD patients under the L-dopa medication. However, it is crucial to calibrate these measurements on an individual basis.

Further investigation is required to determine if individuals may detect wearing-off before they are consciously aware of it, as described in the study [17]. The article introduces a sophisticated scene categorization technique that utilizes cricket scenarios and employs a pre-trained AlexNet Convolutional Neural Network (CNN) model. The strategy demonstrates a 99.26% accuracy on a smaller dataset and surpasses other deep learning models. Among the experiments conducted, the AlexNet CNN method exhibits the most favorable outcomes [18]. An SPNet, based on deep learning, can identify mathematical operations in sports footage by analyzing high-level visual feature sequences and utilizing 3D convolution networks. The technique surpasses the anticipated SPNet, obtaining an average accuracy of 76% on the SP-2 dataset and 82% on the C-sports dataset. It demonstrates the highest performance for observations, movement, and posture activities, as given in reference [19].

The summary will cover both classic remote sensing image segmentation approaches and deep learning-based methods employed in the semantic segmentation of remote sensing images. Pre-processing and boosting procedures are frequently employed in data preparation approaches. Ultimately, this study examines and predicts the problems and future paths for research in this particular area. This study aims to advance the boundaries of knowledge and offer valuable material for academics interested in furthering this area of inquiry [20].

3. DEEP LEARNING NEURAL NETWORKS

Deep Learning (DL) is a machine learning subject that teaches computers what people do in nature, such as when a person comprehends and learns from his personal experience. Methods that employ computations to learn data information directly without depending on predetermined equations to be used as a model are included in standard automated learning algorithms. They are well-known for their ability to detect picture patterns [20]; for example, they can distinguish faces, ears, and iris, read text from video clips, and recall car numbers from license plates [16]. They can also be employed by assistive drivers in conjunction with certain approaches for driving detection from traffic signals or identifying persons crossing the street. Deep learning outperforms other machine learning algorithms, according to the trial findings. In addition, sub-sampling layers give better results using CNN a, timing, and clarity for the images [21,30].

The neural network learning process is the neural network model that can perform a certain function by modifying its internal parameters. The learning process of the neural network model may be accomplished by continually attempting to match the input data to the associated target value, and many iterations until it achieves or approaches the target value. After a sufficient number of test encounters, an internal model will be developed to anticipate new input scenarios.[22].

In general, neural network may be trained in two ways:

1. ***Supervised Learning:*** There are two types of patterns in this learning algorithm: input patterns and desired or goal output patterns. These two sets of patterns can be provided by an outside individual known as the instructor or automatically by the system (self-supervised).
2. ***Unsupervised Learning:*** The output layer of this learning system is taught to respond to pattern clusters in the input layer. Unlike the last learning method, this one does not start with a list of target patterns.
3. ***Convolutional Neural Networks (CNNs).***
   CNNs have emerged as an effective deep-learning technology for assessing and processing visual data such as photos and videos. Every formation of CNNs is engineered to extract and recognize diversified details from the given input signals which in turn makes them highly proficient in some of the applications including the classification of images, image division, and identification of objects. Various CNNs are designed almost

similarly to mimic the human visual system; which is purely a network of neurons that identifies and analyzes data from visuals. CNNs duplicate this biological architectural unit by using 'layers of computational neurons' called convolution layers that perform tasks such as convolution and pooling on the given input data to perform information extraction [24].
CNNs were created by mimicking the visual cortex of the human brain which comprises two parallel neuron circuits which help detect objects/images. CNN incorporates this mechanism through the utilization of artificial neurons referred to as convolution layers that are connected to work in aspects such as convolution and pooling for extraction of relevant data from input data. CNNs have significantly transformed every computer vision application where they are employed and have almost gotten to a level of similar performance in picture categorization, object detection, and image generation. Due to their capability to train and abstract hierarchical features from the input visuals, the assistance of such vehicles has been deemed pertinent in numerous applications such as self-driving cars, medical image diagnosis, and facial recognition.
Besides, the CNNs have been used not only for image processing but also natural and time series analysis data. CNNs have demonstrated possible performance in these areas also and smoothening of concept through a slight change in architecture and inclusion of certain layers like recurrent or attention procedures.
CNN has a few initial layers, which are then followed by several layers though the number may not be the same for all the CNNs. The main layers in a CNN architecture are [25]:

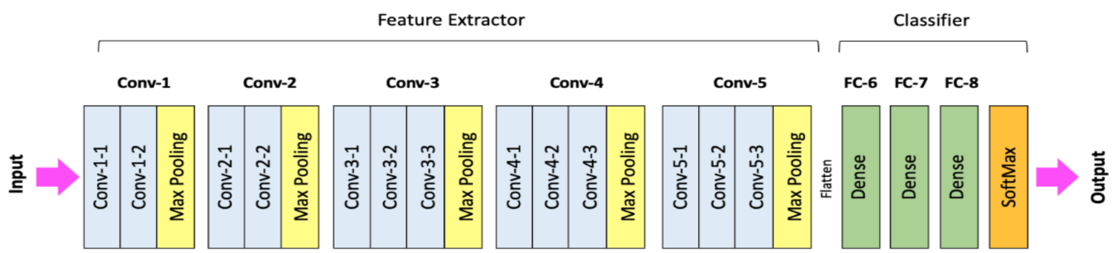


Fig. 1. Layes of CNN

- ***Convolutional Layers:*** These layers apply to the input data a series of learnable filters (also known as kernels). Each filter extracts unique information by conducting element-wise multiplication and summation on the input. To capture distinct elements at different spatial locations, several filters are utilized. Feature maps are the output of the convolutional layers.

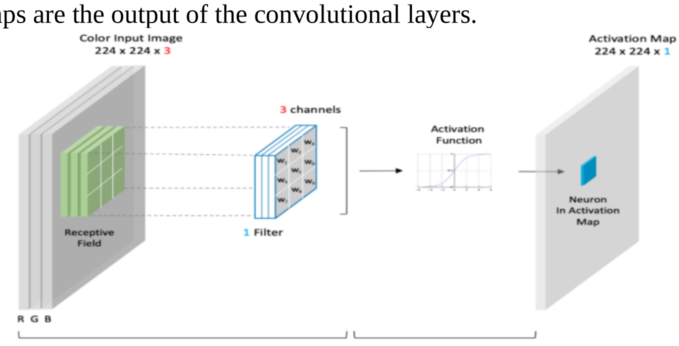


Fig. 2. Convolutional Layers

- ***Activation Layers:*** An activation function is applied element-by-element after each convolutional layer to inject non-linearity into the network. ReLU (Rectified Linear Unit), sigmoid, and hyperbolic tangent are examples of common activation functions (tanh). Because of its simplicity and efficacy in avoiding the vanishing gradient problem, ReLU is frequently employed.
- ***Pooling Layers:*** These layers sample the spatial dimensions of the feature maps from the bottom up, minimizing computing complexity and identifying the most important characteristics. Max Pooling, which picks the largest value inside a pooling window, and Average Pooling, which takes the average value, are two popular pooling approaches.

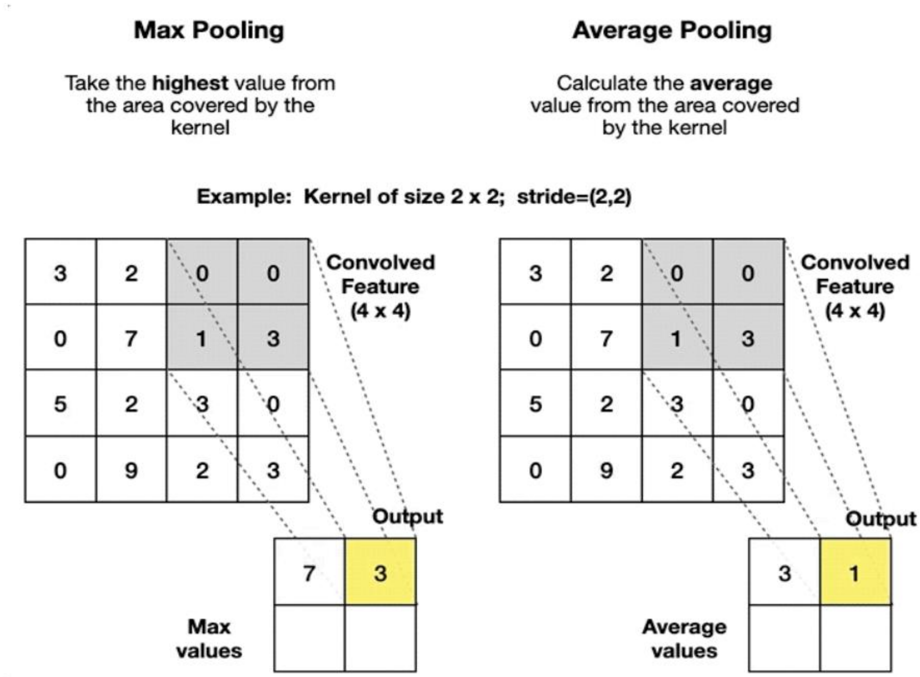


Fig. 3. pooling layer

- Fully connected layers, sometimes referred to as thick layers, establish connections between each neuron in the previous layer and every neuron in the current layer. Completely interconnected layers execute the ultimate categorization or prediction task. To calculate the probabilities for each class, the output of the final fully connected layer is commonly fed into a softmax activation function.

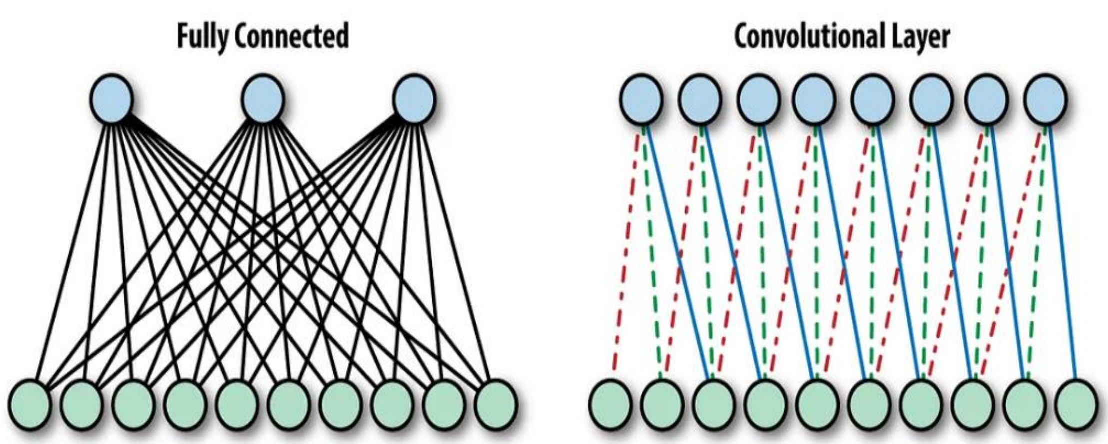


Fig. 4. Fully Connected

- ***Dropout Layers:*** Dropout is a regularization technique used to mitigate overfitting. During training, dropout layers randomly remove a fraction of neurons, which encourages the network to develop more resilient features by preventing excessive dependence on individual neurons.

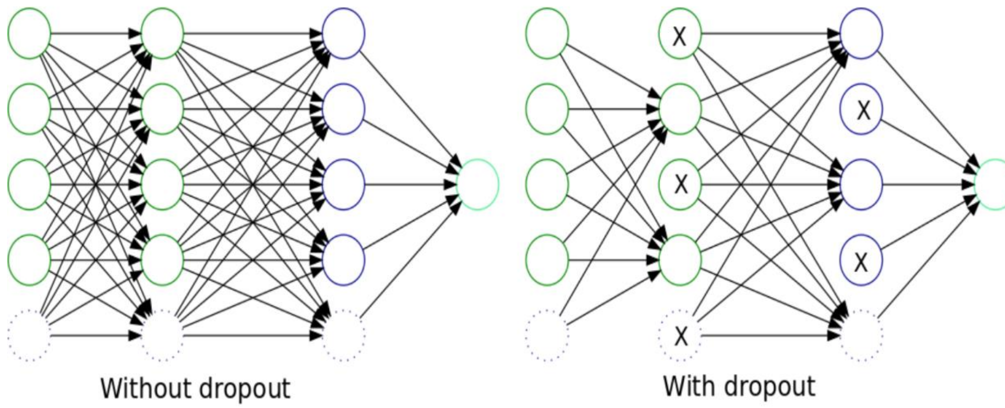


Fig. 5. Dropout Layers

- The output layer of the Convolutional Neural Network (CNN) is responsible for generating the final output of the network. The choice of activation function in this layer is contingent upon the specific task being performed, with softmax being employed for multi-class classification and sigmoid for binary classification.

A CNN's general structure often consists of stacking numerous convolutional layers, then pooling layers, and lastly fully linked layers. The network may learn hierarchical representations of the input data using this design, collecting low-level characteristics in early layers and high-level features in subsequent levels.
It is crucial to note that based on the job and dataset, the particular architecture and layer configurations may change. To enhance performance for individual applications, researchers frequently experiment with alternative layer configurations, kernel sizes, and hyperparameters [26]:

- A named static data pattern is classified.
- Data pattern classification with a time-varying probability density function.
- Signal processing applications that use waveforms as data models
- Unsupervised algorithms for unlabeled data sets, for example.

4. WEARABLE SENSOR

Wearable sensors have transformed the worlds of healthcare and human activity monitoring by collecting data in a continuous, non-invasive, and real-time manner. These sensors are frequently incorporated into wearable devices such as smartwatches, fitness trackers, and patches. They may collect physiological, biomechanical, and environmental data, allowing for a variety of applications in healthcare, sports performance monitoring, and wellness tracking.[27].
Smart wearables have progressed with the aspects of health screening, especially for chronic diseases. They provide constant monitoring of several body attributes such as pulse, blood pressure, temperature, and blood oxygen level without invasive techniques and visits to hospitals or clinics. It equally provides an early understanding of the pathologies, correct interferences, and enhances patient care.
The three primary uses include physiological monitoring, physical activity, and motion tracking devices. Some of them include steps and pace counts, speed-ups, and product placement for encouraging physical activity, analysis of gait, and assessment of postures. And useful in occasions that establish the level of fitness, monitor the performance of a patient undergoing a rehabilitation program, and minimize the occurrence of injuries. [28].

5. THE PROPOSED METHOD

The proposed method for daily monitoring is based on wearable sensors for conditional detection of Parkinson's disease in MATLAB, where an environment through MATLAB assumes the presence of a recoil device sensor, and we generate data randomly. The system was trained on real data, so the system with virtual sensors for the affected person and the unaffected person. The diagram of proposed method is shown in Figure (6).

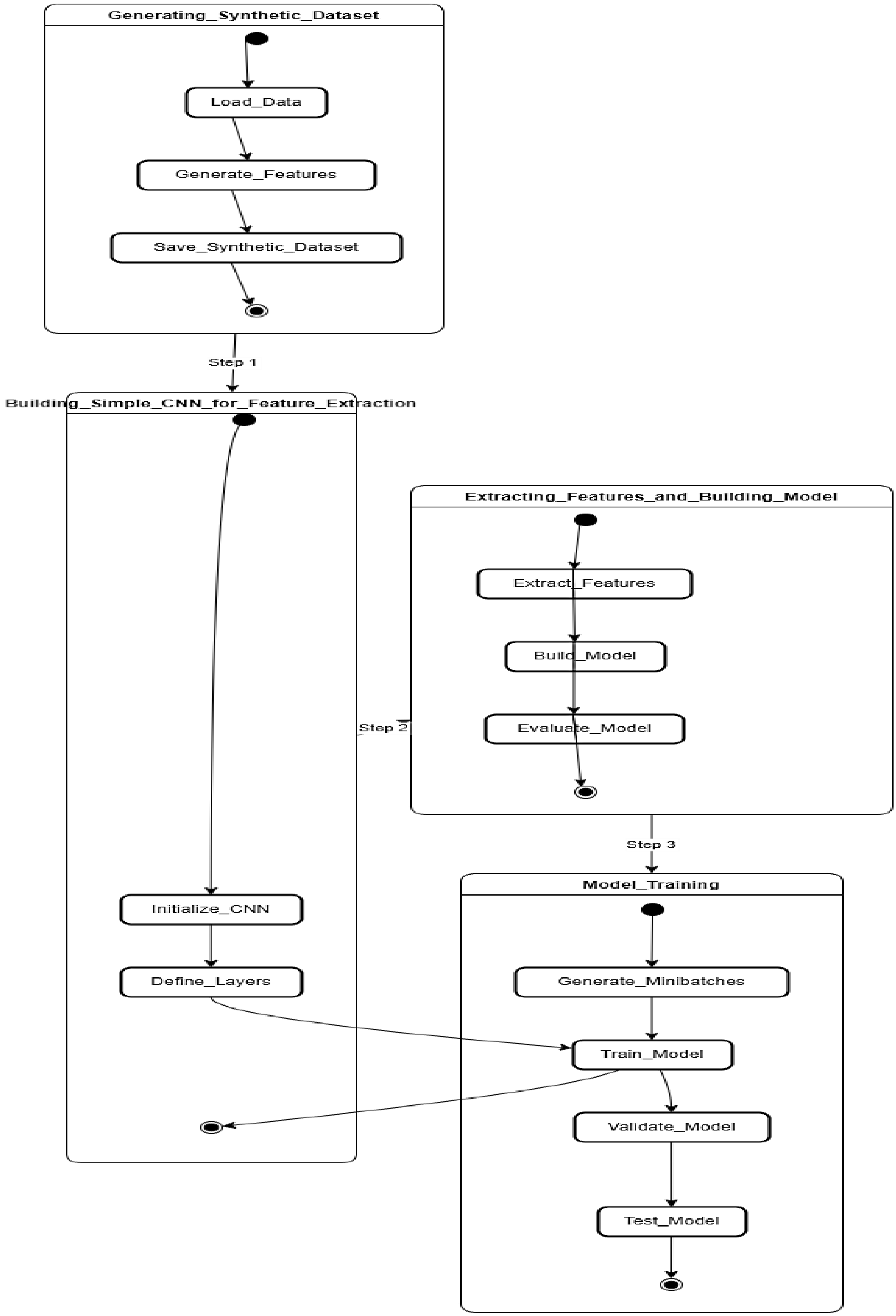


Fig. 6. State Diagram of Proposal Method

5.1. Data Collection

Obtain measurements from motion tracking devices like accelerometers and gyroscopes that the PD patients use during their day-to-day activities. This should be done with several patients to get data from a diverse patient population to improve generalization.

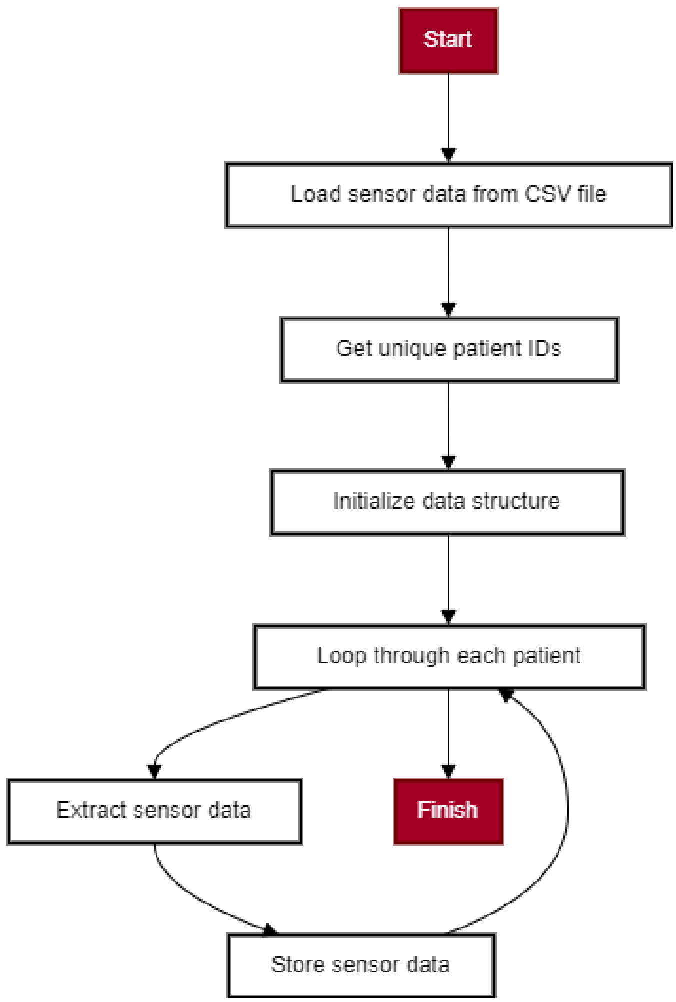
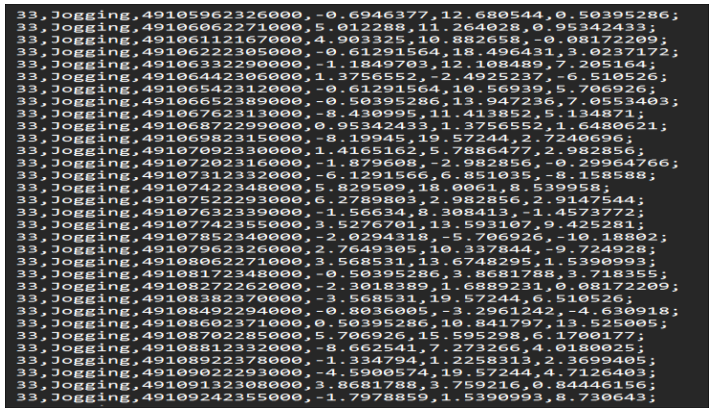


Fig. 7. Flowchart of Data Collection

5.2. WISDM Dataset

Classifying biometric time series data is the current goal. dubbed the "WISDM Smartphone and Smartwatch Activity and Biometrics Dataset." Wireless Sensor Data Mining is referred to as WISDM. The dataset was created by the Fordham University Department of Computer and Information Science in New York. 51 individuals participated in 18 routine tasks, and the researchers utilized the accelerometer and gyroscope sensors on a smartphone and smartwatch to record data. Every participant completed each task for three minutes, for a total of 54 minutes of data collection. This repository's dataset has a detailed explanation [29][30]. But if you would rather see the actual data, you can view the entire dataset here.
As mentioned earlier, a compact dataset is used, consisting of the following six activities:

1. represents walking
2. represents running,
3. represents climbing stairs,
4. represents sitting,
5. represents standing, and
6. represents kicking a soccer ball.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33,Jogging,49105962326000,-0.6946377,12.680544,0.50395286;
33,Jogging,49106062271000,5.012288,11.264028,0.95342433;
33,Jogging,49106112167000,4.903325,10.882658,-0.08172209;
33,Jogging,49106222305000,-0.61291564,18.496431,3.0237172;
33,Jogging,49106332290000,-1.1849703,12.108489,7.205164;
33,Jogging,49106442306000,1.3756552,-2.4925237,-6.510526;
33,Jogging,49106542312000,-0.61291564,10.56939,5.706926;
33,Jogging,49106652389000,-0.50395286,13.947236,7.0553403;
33,Jogging,49106762313000,-8.430995,11.413852,5.134871;
33,Jogging,49106872299000,0.95342433,1.3756552,1.6480621;
33,Jogging,49106982315000,-8.19945,19.57244,2.7240696;
33,Jogging,49107092330000,1.4165162,5.7886477,2.982856;
33,Jogging,49107202316000,-1.879608,-2.982856,-0.29964766;
33,Jogging,49107312332000,-6.1291566,6.851035,-8.158588;
33,Jogging,49107422348000,5.829509,18.0061,8.539958;
33,Jogging,49107522293000,6.2789803,2.982856,2.9147544;
33,Jogging,49107632339000,-1.56634,8.308413,-1.4573772;
33,Jogging,49107742355000,3.5276701,13.593107,9.425281;
33,Jogging,49107852340000,-2.0294318,-5.706926,-10.18802;
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33,Jogging,49109132308000,3.8681788,3.759216,0.84446156;
33,Jogging,49109242355000,-1.7978859,1.5390993,8.730643;
```

Fig. 8. Sample of WISDM DATASET

5.3. Pre-processing

Remove artifacts and noise from the data collected from the sensors through a preprocessing step. To prepare the data for further analysis processes such as filtering, normalization, and feature extraction should be taken into consideration.

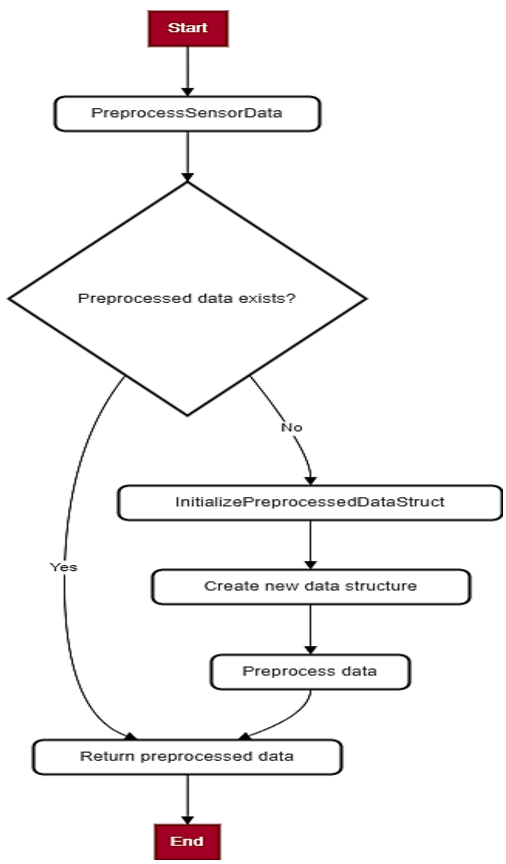

Fig. 9. Flowchart of Preprocessing Model

5.4. Feature Extraction

Remove artifacts and noise from the data collected from the sensors through a preprocessing step. To prepare the data for further analysis processes such as filtering, normalization, and feature extraction should be taken into consideration.

5.5. Model Training using the CNN

The steps of model training are listed as below:
Step1. Specify the number and types of layers, such as convolutional layers, activation layers (e.g., ReLU), pooling layers (e.g., max pooling), and fully connected layers.
Step2. Configure hyperparameters and set the learning rate, batch size, number of epochs, and regularization techniques (e.g. dropout) to control model training.
Step3. Initialize the CNN model, Create an instance of the CNN model using the defined architecture.
Step4. Training loop: Iterate through the training dataset multiple times (epochs) and update the model's parameters using optimization algorithms like gradient descent and backpropagation.
Step5. Monitor loss and accuracy, Evaluate the model's performance on the training set by computing the loss function (e.g., cross-entropy) and accuracy metrics. Adjust hyperparameters if necessary.

5.6. Model Validation

Validate the trained CNN model using the testing dataset. Evaluate its performance using various metrics such as accuracy, precision, recall, and F1 score. Adjust the model and hyperparameters if necessary to optimize performance.

5.7. Model Testing

Apply the trained CNN model to unseen data from Parkinson's Disease patients to assess its generalization and real-world performance. Evaluate the model's ability to accurately detect and classify different motor symptoms.

6. EXPERIMENTAL RESULTS

In our experience, as shown below, found that 70 %samples were trained 30 samples were tested, and the diagnosis was revealed whether the person was infected or not. Thus, the results below and the graph show the accuracy rate that we reached, which is 98%, and this gives good and effective results.

- **Computing Platforms:** The experiments included the daily tracking of the early detection of Parkinson’s disease with wearable devices on an HP EliteBook computer installed with an Intel Core i7-3840QM CPU clocked at 2. 80GHz. MATLAB was used for system implementation, which entailed learning models training/and testing. When dissecting this movie, one can use 80GHz as the computing platform. The experiments were based on early detection of Parkinson’s disease using wearable technology to constantly monitor the affected individuals. In the system implementation, the researchers incorporated Matlab as the language to perform the computations. There was a Matlab-based system that provided training and testing of multiple learning models to enable the early detection of Parkinson’s disease.
- **Data division:** In this research paper, a synthetic data set was created, which assumed was collected by using wearable devices. In addition to the synthetic data, global data was also used for training the system. The training data comprised 70% of the total data, while the remaining 30% was used for testing the system.
- **Feature Extraction for CNN:**The input data used for the current analysis were preprocessed and transformed for the cnn model with feature extraction to achieve appropriate learning and classification as shown in Table (1).

TABLE I. FEATURE EXTRACTION USING CNN

-0.13431	-0.4915	0.027395	-0.26836	0.108752	-0.27023	0.239045	-0.85319	-0.5885
0.273191	-0.12118	0.067486	-0.45112	-0.84859	-0.75478	-0.57567	-0.07094	-0.37293
-0.0463	0.379746	-0.02503	-0.07191	-0.78905	-0.12609	-0.36412	-0.26104	-0.70768
-0.3375	-0.26369	-0.75535	-0.12844	-0.72482	-0.42134	-1.1829	-0.26225	0.244212
0.936831	0.189632	-0.28849	-0.48943	-0.25594	0.001054	-0.19927	-0.25236	-0.20042
0.347528	0.035516	0.261273	0.087982	0.047352	0.654003	-0.53879	-0.30976	0.079572
0.492053	0.105197	-0.23143	0.13343	0.293024	-0.16053	-0.42854	-0.36494	0.395644
0.947644	-0.49073	0.506949	-0.46069	-0.0304	0.114567	-0.98488	-0.19472	-0.17667
-0.28653	-0.4971	-0.39384	-0.07163	-0.55335	-0.36145	-0.07705	0.382864	0.390508
-0.15718	-0.13586	0.737467	-0.01993	-0.53504	-0.31794	0.173278	0.289932	0.082892
-0.27418	0.55787	1.181361	0.193159	-0.71843	0.016174	-0.73766	-0.16159	-0.66712
-0.31353	-0.12076	0.073987	0.084574	-0.28544	0.184709	-0.02119	-0.28612	-0.00921
0.270538	0.129948	0.460395	-0.83897	0.085969	-0.32955	0.095431	-0.28392	0.957902
-0.39491	0.450397	-0.61568	-0.11014	-0.69776	0.029595	-0.29406	-0.57999	-0.51351
0.32089	-0.03997	0.663601	-0.36888	0.195468	0.701156	-0.06526	-0.46879	-1.07722
0.511058	-0.7028	0.100806	-0.69251	-0.24738	-1.09507	-0.04009	1.367761	-0.36963
-0.07226	-0.31766	-0.1314	0.125336	0.696916	0.49862	0.376929	-0.33758	-0.36393
0.247161	0.293677	0.448469	-0.19099	-0.02331	0.855762	-0.09197	-0.18557	-0.7555
-0.50829	0.669175	-0.13721	0.410355	0.845928	-0.44666	0.415406	-0.50459	-0.16707
0.299544	-0.67847	0.252546	-0.53619	-0.31989	-0.20819	-0.0581	0.045828	-0.14212

- **Training of CNN:** The CNN model was trained using one CPU only and the time taken was recorded as shown below. First of all, the input data was pre-processed to bring the data into the format suitable for the model. Then it was the training phase which involved layers through the epochs and computed different characteristics at the mini-batch and the validation level. Such metrics comprised accuracy, loss function, and the base learning rate. The training steps were provided; this included the epoch number, iteration count, time taken, accuracy and loss of the mini-batches, validation accuracy and loss, and the current base learning rate.

```
Training on a single CPU.
Initializing input data normalization.
|============================================|
| Epoch | Iteration | Time Elapsed | Mini-batch | Validation | Mini-batch | Validation | Base Learning |
|       |           | (hh:mm:ss)   | Accuracy   | Accuracy   |    Loss    |    Loss    |     Rate      |
|============================================|
|     1 |         1 |     00:00:08 |      4.00% |     10.00% |     3.4729 |     2.6303 |        0.0010 |
|     5 |         5 |     00:00:17 |     92.00% |     98.00% |     1.6498 |     1.0060 |        0.0010 |
|============================================|
Training finished: Max epochs completed.
Training on a single CPU.
|============================================|
| Epoch | Iteration | Time Elapsed | Mini-batch | Validation | Mini-batch | Validation | Base Learning |
|       |           | (hh:mm:ss)   | Accuracy   | Accuracy   |    Loss    |    Loss    |     Rate      |
|==========================================|
|     1 |         1 |     00:00:06 |     94.00% |     98.00% |     0.7997 |     0.7498 |        0.0100 |
|    20 |        20 |     00:00:06 |     98.00% |     98.00% |     0.7348 |     0.6325 |        0.0100 |
|==========================================|
Training finished: Max epochs completed.
Activities through which Parkinson's was identified:
```

Index	Activity
1	{'Eating Soup' }
2	{'Eating Sandwich' }
3	{'Jogging' }
4	{'Jogging' }
5	{'Eating Chips' }
6	{'Eating Pasta' }
7	{'Jogging' }
8	{'Drinking from Cup'}
9	{'Writing' }
10	{'Clapping' }

Accuracy on the test set: 98.000000%
CNN Model - Accuracy: 90.000000%
CNN Model - Precision: 98.00000%
CNN Model - Recall: 94.0000000%
CNN Model - F1-Score: 97.00010%

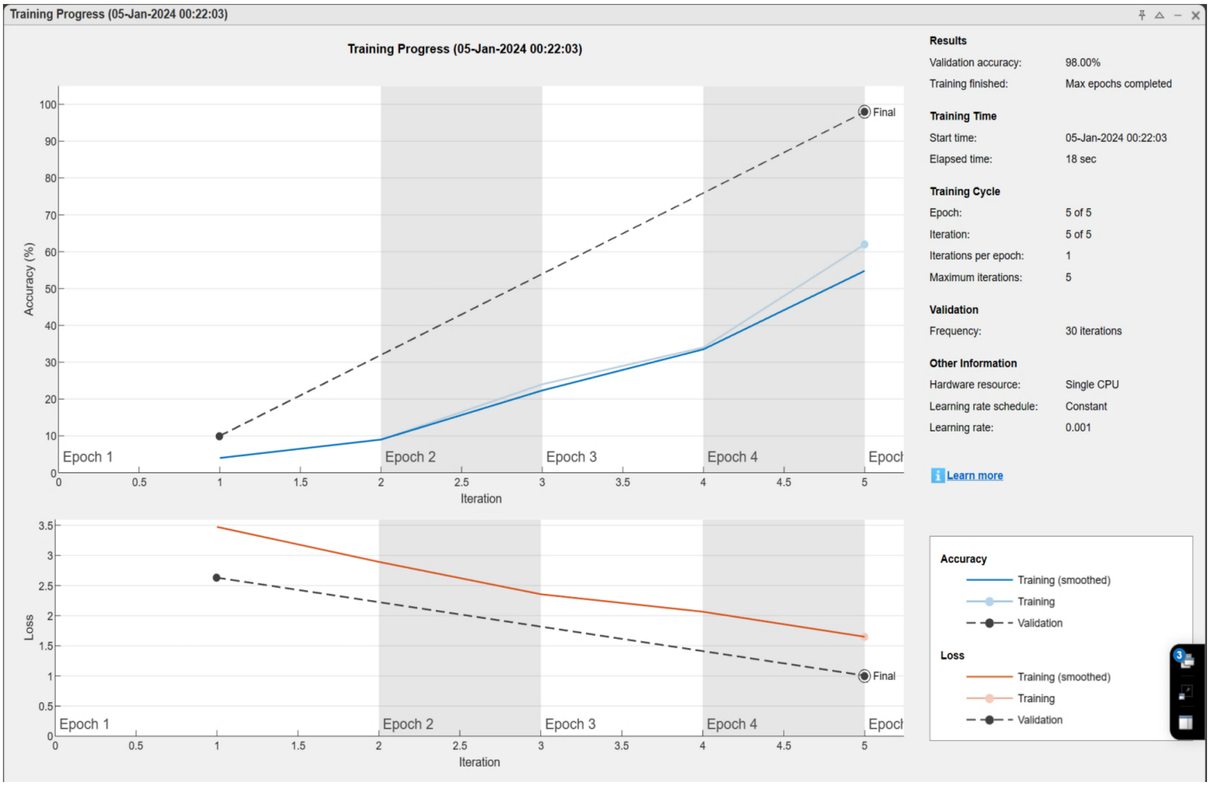

Fig. 10. The Accuracy of this project

The results are evaluated and compared with other works results from literature as shown in Table (2). It can be seen that our proposed method is outperformance of other exiting works.

TABLE II. COMPARISON BETWEEN PROPOSED METHODS AND PREVIOUS RESEARCH.

Ref.	Method	Database	Accuracy
[16]	Multimodal telehealth system (video visits, smartphone app, camera, wearable sensors)	12 Parkinson's disease patients	Consistent adherence: 79% for questionnaires, 62% for medication, 33% for electronic diaries. No effect on quality of life. A larger cohort is needed to establish the effect on motor symptoms.
[17]	Wearable sensor to predict L-dopa wear-off in Parkinson's	L-dopa treated Parkinson's patients	90% correlation between patient documented OFF state and reconstructed signal using individual models. The pooled model is not statistically significant. More research is needed for pre-awareness wear-off detection.
[17]	High-quality scene classification using pre-trained AlexNet CNN	Cricket scenario dataset	99.26% accuracy, outperformed other deep learning models.
[18]	Deep learning-based SPNet detects mathematical operations in sports footage	SP-2 dataset, C-sports dataset	The average accuracy of 76% on SP-2 and 82% on C-sports, the best performance for observations, movement, and posture activities.
[19]	Summary of traditional and deep learning-based remote sensing image segmentation methods	N/A	N/A - Literature review paper analyzing challenges and future directions.
Our method*	Wearable sensor to deep learning (CNN) in Parkinson's	WISDM Dataset and generation dataset	98% accuracy.

7. CONCLUSIONS

Placing accelerometers and gyroscopes on the wrists of individuals with Parkinson's disease enables convenient and non-invasive monitoring of their motor symptoms. The machine learning method that was built showed a high level of accuracy in categorizing various motor states, such as rest, tremor, and dyskinesia. This was achieved by building a dataset that mimicked data collected from a device or computer and training the system using a worldwide dataset called the WISDM Dataset.

Wearable sensor-based monitoring can enhance the management of Parkinson's disease by offering real-time input to patients and physicians and facilitating tailored treatment programs. It provides the opportunity to identify symptoms at an early stage, enabling prompt intervention and modification of treatment procedures. Furthermore, the ongoing

surveillance of symptoms associated with Parkinson's disease might yield significant data for the sake of researching and advancing new therapy methodologies.
Further study is required to authenticate the findings and enhance the sensor technology for feasible application in clinical environments. Longitudinal studies with bigger cohorts are crucial to ascertain the dependability and efficacy of wearable sensor-based monitoring. Furthermore, it is crucial to tackle obstacles such as data protection, user acceptance, and system usability to achieve widespread use of this technology.
the regular monitoring of Parkinson's disease patients using wearable sensors has the potential to significantly enhance their quality of life and improve the management of this intricate neurological condition.

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Conflicts Of Interest

The author's disclosure statement confirms the absence of any conflicts of interest.

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