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# Parkinsons Disease Detection Using Machine Learning Algorithm: A Review of Literature

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***Abstract:*** ***Parkinson's disease (PD), or simply Parkinson's is a long-term degenerative disorder of the central nervous system that mainly affects the motor system. A quantitative analysis of handwriting samples would be valuable as it could supplement and support clinical assessments, help monitor micrographic, and link it to PD. Such an analysis would be especially useful if it could detect subtle yet relevant changes in handwriting morphology, thus enhancing solution of the detection procedure. We can find several works that attempt at dealing with this problem out there, most of them make use of datasets composed by a few subjects only. In this study, we conducted a literature review of studies that applied machine learning models to movement data to diagnose PD published*** **in 2019***, using the PubMed and IEEE Xplore databases, to provide a comprehensive overview of data modalities and machine learning methods that have been used in the diagnosis and differential diagnosis of Parkinson's disease. In this research, we investigated their goals, data sources, data kinds, machine learning methodologies, and associated outcomes.*

***Keywords: Review of Literature, Parkinson disease, Machine Learning, SVM, Decision Tree, KNN, Linear Regression, time stamp, LSTM, Deep-ML-CNN, pressure, Cross validation.***

## I. INTRODUCTION

Parkinson's disease (PD) is a degenerative neurological illness that is persistent. The primary etiology of Parkinson's disease is uncertain. However, it has been shown that a mix of environmental and genetic variables play a crucial role in the development of Parkinson's disease [1]. It is a well-known fact that around one million individuals in the United States suffer from Parkinson's disease, while approximately five million people globally suffer from Parkinson's disease. As a result, it is critical to forecast Parkinson's disease in its early stages so that therapy may be planned ahead of time. Non-motor and motor symptoms are the two forms of Parkinson's disease symptoms. Many individuals are aware of motor symptoms since they can be seen with the naked eye. Resting tremor, slowness of movement (bradykinesia), postural instability (balance issues), and stiffness are examples of cardinal symptoms [2]. People are generally familiar with Parkinson's disease's motor symptoms, but an increasing amount of research is being done to predict Parkinson's disease from non-motor symptoms that precede the motor ones. If an accurate and timely prognosis is achievable, a patient can receive appropriate therapy at the appropriate time Nonmotor symptoms taken into account include Rapid Eye Movement (REM), Sleep Behaviour Disorder (RBD), and olfactory loss Developing machine learning models that can aid in illness prediction can play a critical role in early detection. In this work, we used the PubMed and IEEE Xplore databases to perform a literature analysis of papers that applied machine learning models to movement data to diagnose PD published in 2019 & 2018 to offer a thorough overview of data modalities and machine learning algorithms used in the diagnosis and differential diagnosis of Parkinson's disease. We evaluated their aims, data sources, data types, machine learning approaches, and associated outcomes in this study.

## II. JUSTIFICATION OF THE STUDY

Parkinson's disease (PD) is a neurological illness that affects a person's movements, and may cause tremors, slowness of movement, muscle stiffness and imbalance as well as changes in speech and writing skills [3]. One of the most challenging tasks when dealing with PD diagnosis is whether to use visual and/or signal based information from patient exams. As aforementioned, previous works have used high-end image technology (MRI) for such purposes, but being expensive and may be invasive enough to the patient as well. Additionally, most signal-based datasets for PD recognition are small and biased, which may not reject the real world. In order to overcome such shortcomings, we need to develop a new dataset composed of images. Proper research can enhance the performance of the above-mentioned problem domains. For these reason we need to to measure and compare the performance with the previous studies.

 

## III.OBJECTIVES WITH SPECIFIC AIMS

In this study, we will use the PubMed and IEEE Xplore databases to conduct a literature review of papers that applied machine learning models to movement data to diagnose PD published in 2019, in order to provide a comprehensive overview of data modalities and machine learning algorithms used in the diagnosis and differential diagnosis of Parkinson's disease.In this study, we will assess their objectives, data sources, data kinds, machine learning methodologies, and associated outcomes.

TABLE I: SOURCE OF DATA & PERFORMANCE METRIC OF THE INCLUDED STUDIES

| Source of data | Performance metric |
|---|---|
| independent recruitment of human participants<br>PPMI database<br>PhysioNet<br>mPower database<br>Others<br>(1 PPMI + Sheffield Teaching Hospitals NHS Foundation Trust;<br>1 PPMI + Seoul National University Hospital cohort;<br>1 UCI + collected from participants | Accuracy<br>Sensitivity (recall)<br>Specificity (TNR)<br>AUC<br>MCC<br>Precision (PPV)<br>NPV<br>F1 score<br>Others<br>(7 kappa; 4 error rate; 3 EER; 1 MSE; 1 LOR; 1 confusion matrix; 1 cross validation score; 1 YI; 1 FPR; 1 FNR; 1 G-mean; 1 PE; 5 combination of metrics) |

TABLE II: RELATED WORKS

| Type of Diagnosis ,Source of data | Objectives | Machine learning method(s) | Outcomes | Year | References |
|---|---|---|---|---|---|
| Diagnosis and differential diagnosis,Collected from participants | Classification of PD, HC and other neurological stance disorders | Ensemble method of 7 models (logistic regression, KNN, shallow and deep ANNs, SVM, random forest, extra-randomized trees) with 90% training and 10% testing data in stratified k-fold cross-validation | 8-class classification accuracy = 82.7% | 2019 | [4] |
| Diagnosis,Collected from participants,Collected from participants | Classification of PD from HC | SVM (linear, quadratic, cubic, Gaussian kernels), ANN, with 5-fold cross-validation | Classification with ANN:<br>Accuracy = 89.4%<br>Sensitivity = 87.0%<br>Specificity = 91.8%<br>Severity assessment with ANN:<br>Accuracy = 95.0%<br>sensitivity = 90.0%<br>Specificity = 99.0% | 2019 | [5] |
| Diagnosis,Collected from participants | Classification of PD, HC and PD, HC, IH | SVM, random forest, naïve Bayes with 10-fold cross | Random forest:<br>HC vs. PD:<br>Accuracy = 0.950 | 2019 | [6] |

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| | | validation | F-measure = 0.947<br>HC + IH vs. PD:<br>Accuracy = 0.917<br>F-measure = 0.912<br>HC vs. IH vs. PD:<br>Accuracy = 0.789<br>F-measure = 0.796 | | |
| Diagnosis,Collected from participants | Classification of PD from HC | Deep-MIL-CNN with LOSO<br>or RkF | With LOSO:<br>Precision = 0.987<br>Sensitivity = 0.9<br>specificity = 0.993<br>F1-score = 0.943<br>With RkF:<br>Precision = 0.955<br>Sensitivity = 0.828<br>Specificity = 0.979<br>F1-score = 0.897 | 2019 | [7] |
| Diagnosis,Collected from participants | Classification of PD from HC | LSTM, CNN-1D, CNN-LSTM with 5-fold cross-validation and a training-test ratio of 90:10 | CNN-LSTM: Accuracy = 83.1%<br>Precision = 83.5%<br>Recall = 83.4%<br>F1-score = 81%<br>Kappa = 64% | 2019 | [8] |
| Diagnosis,Collected from participants | Classification of PD from HC | Naïve Bayes, KNN, SVM<br>with leave-one-out cross validation | SVM: Accuracy = 95%<br>Precision = 0.951<br>AUC = 0.950 | 2019 | [9] |
| Diagnosis and differential diagnosis,Collected from participants | Classification of PD, HC and IH | SVM-polynomial, random<br>forest with 5-fold cross validation | HC vs. PD, random forest: Precision = 1.000<br>Recall = 1.000<br>Specificity = 1.000<br>Accuracy = 1.000<br>F-measure = 1.000<br>Multiclass classification (HC vs. IH vs. PD), random forest:<br>Precision = 0.930<br>Recall = 0.911<br>Specificity = 0.956<br>Accuracy = 0.911<br>F-measure = 0.920 | 2019 | [10] |
| Diagnosis,PhysioNet | Classification of PD from HC and assess the severity of PD | 1D-CNN, 2D-CNN, LSTM,<br>decision tree, logistic regression, SVM, MLP | 2D-CNN and LSTM accuracy = 96.0% | 2019 | [11] |
| Diagnosis,PhysioNet | Classification of PD from HC | SVM-Gaussian with 3- or<br>5-fold cross validation | Accuracy = 100%, 88.88%, and 100% in three test groups | 2019 | [12] |
| Diagnosis,PhysioN | Classification of PD | SVM-linear, KNN, naïve | SVM, KNN and decision | 2019 | [13] |

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| et | from HC | Bayes, LDA, decision tree<br>with leave-one-out cross validation | tree accuracy = 96.8% | | |
| Diagnosis,PhysioNet | Classification of PD from HC | KNN, CART, decision tree,<br>random forest, naïve Bayes, SVM-polynomial, SVM-linear, K-means, GMM with leave-one-out<br>cross validation | SVM:<br>Accuracy = 90.32%<br>Precision = 90.55%<br>Recall = 90.21%<br>F-measure = 90.38% | 2019 | [14] |
| Diagnosis,PhysioNet | Classification of PD from HC | DCALSTM with stratified<br>5-fold cross validation | Sensitivity = 99.10%<br>Specificity = 99.01%<br>Accuracy = 99.07% | 2019 | [15] |
| Differential diagnosis,<br>,Collected from participants | Classification of PD from MSA | SVM with leave-one-out-cross validation | MSA vs. PD: 2019<br>Accuracy = 0.79<br>Sensitivity = 0.71<br>Specificity = 0.86<br>MSA vs. HC:<br>Accuracy = 0.79<br>Sensitivity = 0.84<br>Specificity = 0.74<br>MSA vs. subsample of PD:<br>Accuracy = 0.84<br>Sensitivity = 0.77<br>Specificity = 0.90 | 2019 | [16] |
| Differential diagnosis,Collected from participants | Classification of PD from MSA | SVM with leave-one-out-cross validation | Accuracy = 77.17%<br>Sensitivity = 83.33%<br>Specificity = 74.19% | 2019 | [17] |
| Diagnosis,Collected from participants | Classification of PD from HC | CNN with 85 subjects for<br>training and 9 for testing | Training accuracy = 95.24%<br>Testing accuracy = 88.88% | 2019 | [18] |
| Diagnosis and differential diagnosis,Collected from participants | Classification of PD, PSP, MSA-P and HC | CNN with train-validation<br>ratio of 85:15 | PD:<br>Sensitivity = 94.4%<br>Specificity = 97.8%<br>Accuracy = 96.8%<br>AUC = 0.995<br>PSP:<br>Sensitivity = 84.6%<br>Specificity = 96.0%<br>Accuracy = 93.7%<br>AUC = 0.982<br>MSA-P:<br>Sensitivity = 77.8%<br>Specificity = 98.1% | 2019 | [19] |

 

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| | | | Accuracy = 95.2%<br>AUC = 0.990<br>HC:<br>Sensitivity = 100.0%<br>Specificity = 97.5%<br>Accuracy = 98.4%<br>AUC = 1.000 | | |
| Diagnosis,Collected from participants | Classification of PD from HC | Boosted logistic regression with nested cross-validation | Accuracy = 76.2%<br>Sensitivity = 81%<br>Specificity = 72.7% | 2019 | [20] |
| Diagnosis and differential diagnosis,Collected from participants | Classification of PD, APS (MSA, PSP) and HC | CNN-DL, CR-ML, RA-ML with 5-fold cross-validation | PD vs. HC with CNN-DL:<br>Test accuracy = 80.0%<br>Test sensitivity = 0.86<br>Test specificity = 0.70<br>Test AUC = 0.913<br>PD vs. APS with CNN-DL:<br>Test accuracy = 85.7%<br>Test sensitivity = 1.00<br>Test specificity = 0.50<br>Test AUC = 0.911 | 2019 | [21] |
| Diagnosis,PPMI database | Classification of PD from HC | RFS-LDA with 10-fold cross validation | Accuracy = 79.8% | 2019 | [22] |
| Diagnosis,PPMI database | Classification of PD from HC | Naïve Bayes, SVM-RBF with 10-fold cross validation | SVM: Accuracy = 87.50%<br>Sensitivity = 85.00%<br>Specificity = 90.00%<br>AUC = 90.00% | 2019 | [23] |
| Diagnosis,PPMI database | Classification of PD and SWEDD from HC | SSAE with 10-fold cross validation | HC vs. PD:<br>Accuracy = 85.24%, 88.14%, and 96.19% for baseline, 12m, and 24m<br>HC vs. SWEDD:<br>Accuracy = 89.67%, 95.24%, and 93.10% for baseline, 12m, and 24m | 2019 | [24] |
| Diagnosis,PPMI database | Classification of PD from HC | CNN (VGG and ResNet) | ResNet50 accuracy = 88.6% | 2019 | [25] |

## IV. CONCLUSION

We presented included studies in a high-level summary, providing a literature review of studies that used machine learning models to diagnose Parkinson's disease published in 2019, using the PubMed and IEEE Xplore databases, to provide a comprehensive overview of data modalities and machine learning methods that have been used in the diagnosis and differential diagnosis of Parkinson's disease.We evaluated their aims, data sources, data types, machine learning approaches, and associated outcomes in this study.The implementation of machine learning-assisted Parkinson's disease diagnosis has a great potential for a more systematic clinical decision-making system, while the adaption of novel biomarkers may lead to simpler access to PD diagnosis at an earlier stage.

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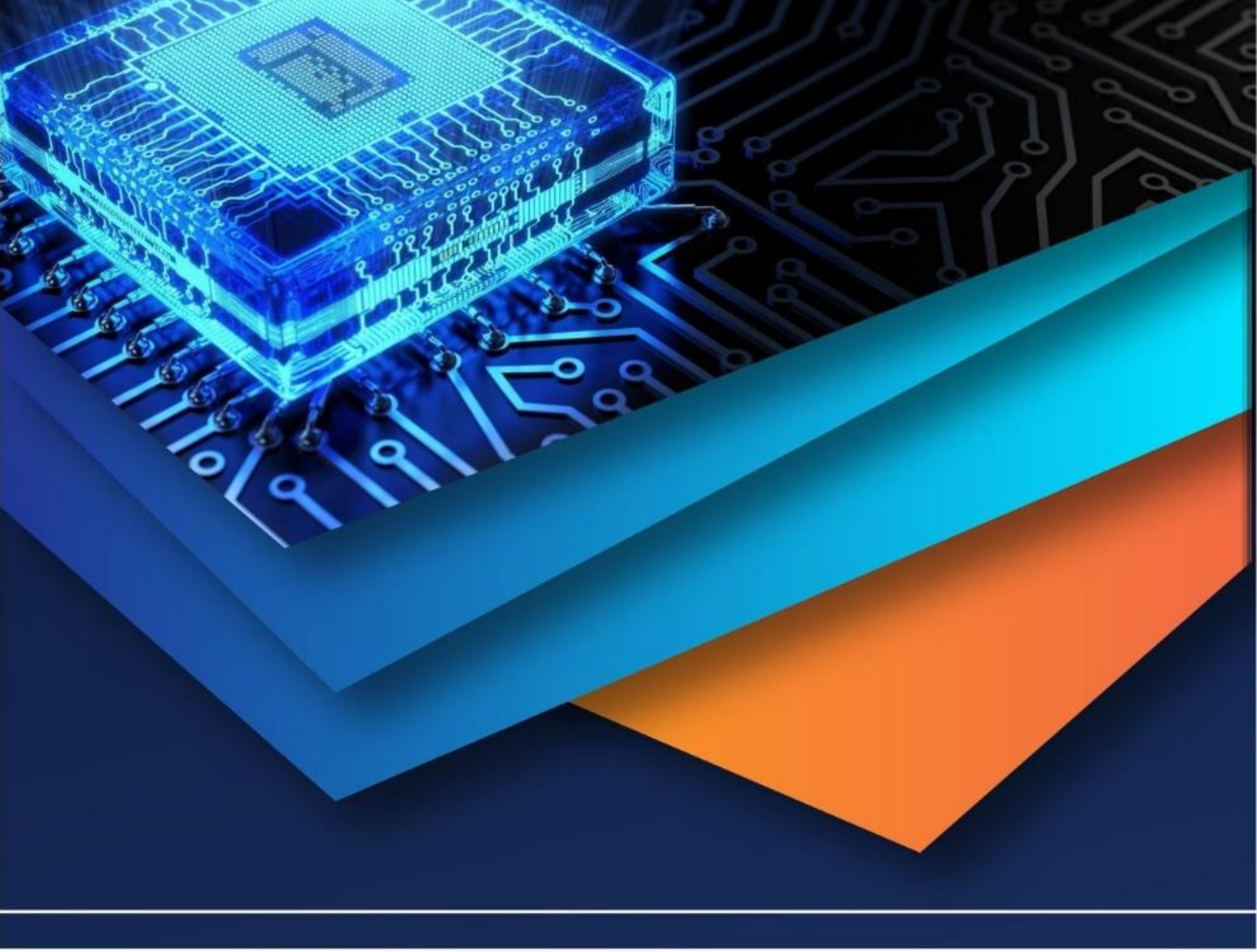

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