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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.

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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 PPMI database PhysioNet mPower database Others (1 PPMI + Sheffield Teaching Hospitals NHS Foundation Trust; 1 PPMI + Seoul National University Hospital cohort; 1 UCI + collected from participants	Accuracy Sensitivity (recall) Specificity (TNR) AUC MCC Precision (PPV) NPV F1 score Others (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: Accuracy = 89.4% Sensitivity = 87.0% Specificity = 91.8% Severity assessment with ANN: Accuracy = 95.0% sensitivity = 90.0% 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: HC vs. PD: Accuracy = 0.950	2019	[6]

		validation	F-measure = 0.947 HC + IH vs. PD: Accuracy = 0.917 F-measure = 0.912 HC vs. IH vs. PD: Accuracy = 0.789 F-measure = 0.796		
Diagnosis,Collected from participants	Classification of PD from HC	Deep-MIL-CNN with LOSO or RkF	With LOSO: Precision = 0.987 Sensitivity = 0.9 specificity = 0.993 F1-score = 0.943 With RkF: Precision = 0.955 Sensitivity = 0.828 Specificity = 0.979 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% Precision = 83.5% Recall = 83.4% F1-score = 81% Kappa = 64%	2019	[8]
Diagnosis,Collected from participants	Classification of PD from HC	Naïve Bayes, KNN, SVM with leave-one-out cross validation	SVM: Accuracy = 95% Precision = 0.951 AUC = 0.950	2019	[9]
Diagnosis and differential diagnosis,Collected from participants	Classification of PD, HC and IH	SVM-polynomial, random forest with 5-fold cross validation	HC vs. PD, random forest: Precision = 1.000 Recall = 1.000 Specificity = 1.000 Accuracy = 1.000 F-measure = 1.000 Multiclass classification (HC vs. IH vs. PD), random forest: Precision = 0.930 Recall = 0.911 Specificity = 0.956 Accuracy = 0.911 F-measure = 0.920	2019	[10]
Diagnosis,PhysioNet	Classification of PD from HC and assess the severity of PD	1D-CNN, 2D-CNN, LSTM, 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 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]

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

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			Accuracy = 95.2% AUC = 0.990 HC: Sensitivity = 100.0% Specificity = 97.5% Accuracy = 98.4% AUC = 1.000		
Diagnosis,Collected from participants	Classification of PD from HC	Boosted logistic regression with nested cross-validation	Accuracy = 76.2% Sensitivity = 81% 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: Test accuracy = 80.0% Test sensitivity = 0.86 Test specificity = 0.70 Test AUC = 0.913 PD vs. APS with CNN-DL: Test accuracy = 85.7% Test sensitivity = 1.00 Test specificity = 0.50 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% Sensitivity = 85.00% Specificity = 90.00% AUC = 90.00%	2019	[23]
Diagnosis,PPMI database	Classification of PD and SWEDD from HC	SSAE with 10-fold cross validation	HC vs. PD: Accuracy = 85.24%, 88.14%, and 96.19% for baseline, 12m, and 24m HC vs. SWEDD: 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]

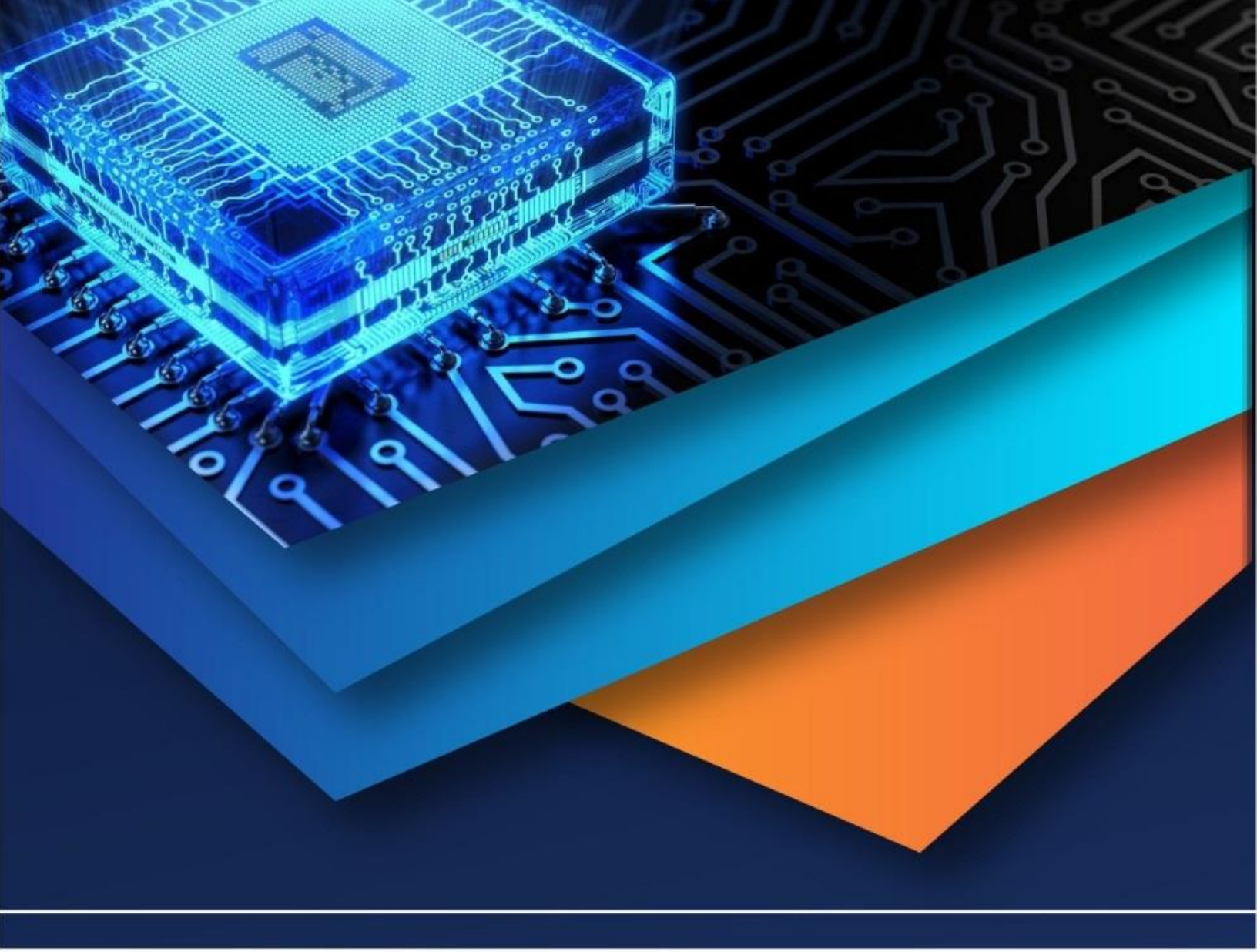
IV. CONCLUSION

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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