Early Detection of Parkinson's Disease Using SiamDNN: A Dual Deep Neural Network Approach

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Abstract*—Parkinson's disease is the second most common neurological disorder that reduces the quality of life, leads to significant physical disability, and lacks a recognized treatment. As a neurological disorder, it affects individuals disproportionately, resulting in muscle stiffness, speech, and movement changes. About 90% of individuals with Parkinson's disease have speech difficulties. The main application of machine learning algorithms is early detection of diseases to prolong life expectancy and improve the quality of life for individuals with chronic diseases such as Parkinson's disease. This study used a dataset of audio data and proposed an approach consisting of two deep neural networks (DNNs) with a Siamese neural network (SNN) along with ten five machine learning algorithms to predict individuals with Parkinson's disease. This work aims to estimate the performance using a cross-validation technique, rather than a split-train-test strategy. The objective is to guarantee that every sample in this unbalanced audio dataset helps with the training and testing procedures to generate specific evaluations of the classifier's performance on unseen datasets, giving an accurate indication of how well the suggested method works to diagnose Parkinson's disease through voice defects. The next model, SiamDNN, achieved 97.4% and 96.5% accuracy and f1 score, respectively, outperforming the previous models by 2.6%.

Keywords*—*Siamese Neural Network, Parkinson's disease, Machine Learning, Cross Validation, Healthcare.

I. Introduction

The symptoms of Parkinson's disease (PD), a chronic disorder, include speech difficulty, limited movement, muscle rigidity, and tremors. A disproportionate number of middle-aged and older people are impacted. The neurotransmitter dopamine deficiency and the atrophy of the brain's basal ganglia are linked to it. Individuals with Parkinson's disease experience different symptoms. Early disease signs can be minor and undetected [1]. Traditionally, the ability of medical professionals to determine the type of disease or condition based on symptomatology was the basis for diagnosing illnesses. Recent advancements in artificial intelligence (AI) and the Internet of Things have afforded the scientific community and researchers numerous opportunities to develop efficient decision-support systems for diagnosing various diseases in medical fields and healthcare facilities, both locally and remotely. Decision-support systems are now prevalent across multiple medical specialties. They are crucial in analyzing a range of conditions, including breast cancer [2], atherosclerotic diseases [3], brain tumors [4], and their subsequent mental health impacts, such as depression [5] and Parkinson's disease [6], among others.

Supervised learning is a typical machine learning approach wherein the model obtains knowledge about correlations and patterns using labeled training samples. It is extensively utilized across various fields, including fraud detection, sentiment analysis of text, image classification, and medical diagnosis. This is an effective method that employs labeled data to predict and classify forthcoming, unknown events. The train-test split technique is typically employed with huge datasets; however, it is also routinely utilized for training and testing machine learning algorithms or models, irrespective of data size, availability, or unique research goals.

Cross-validation is employed when a more demanding performance evaluation is necessary, particularly in the medical field, or when the dataset is constrained and imbalanced. The dimensions of the train-test partitions, stratification, and random state (shuffling) are the three factors that affect the classifier's performance during the training and evaluation phases utilizing train-test splits. Moreover, as demonstrated in the related work section, other literature research has proposed methodologies that, when applied to imbalanced or limited datasets, may differentiate between individuals with Parkinson's Disease and those in optimal health.

The main contribution of this study is as follows:

- People with biological voice measurements from 31 people, 23 of whom have Parkinson's disease diagnoses, were classified and detected.
- An approach combining two DNNs within a model known as a Siamese neural network was proposed, which outperformed all conventional machine learning algorithms.
- Used a cross-validation technique to ensure that all samples of the data are passed, which ensures the best performance.

This document is structured as follows: Section 2 covers previous studies on this topic, while Section 3 explores the technique, equipment, and resources employed to evaluate the classifiers. Section 4 subsequently defines the results and observations. The paper concludes in Section 5.

II. Related Work

Changes in speech quality occur frequently in Parkinson's patients, which may be the first indicator of the disease. Voice is used in many research studies to diagnose diseases. We will discuss some studies relevant to our research topic.

Sharma and Sundaram [7] showed that the modified grey wolf optimization (MGWO) method is an efficient feature selection technique for Parkinson's disease classification, achieving an accuracy of 93.87% with random forest (RF).

Lahmiri and Dawson evaluated the radial basis function neural network (RBFNN), support vector machines (SVM), and various other machine learning methodologies [8]. Their PD detection experiment revealed that the SVM outperformed all other methods, whereas the RBFNN required a large dataset to achieve superior results. Khan and Mendes [9] proposed a method to detect Parkinson's disease (PD) with an accuracy of 90.13% by employing cartesian genetic programming (CGP) to create a multi-dimensional wavelet neural network.

The authors of the research [10] employed four classification algorithms and the UCI ML repository dataset. The decision tree classifier showed an accuracy of 73.0%, the SVM achieved an accuracy of 81.0%, the logistic regression achieved an accuracy of 75.0%, and the additional tree classifier showed an accuracy of 77.0%. The authors of the publication [11] employed the UCI dataset to forecast Parkinson's disease utilizing an Artificial Neural Network (ANN) model and a Random Forest Classifier (RFC). Subsequently, they employed Principal Component Analysis (PCA) to evaluate the accuracy of the Artificial Neural Network (ANN) model in comparison to the Random Forest (RF) Classifier. Applying PCA enhances the accuracy of the ANN model from 79.47% to 97.354%, enabling the observation of a significant difference. Nonetheless, the use of the feature reduction technique resulted in a decline in RFC's accuracy from 89.534 to 76.65. The study [12] also evaluates machine learning methods for the remote tracking and monitoring of Parkinson's disease development. The researchers utilized an audio dataset for Parkinson's disease to investigate, evaluate, and compare nine machine-learning methods. They achieved a 97.22% accuracy rate, aligning with the KNN classifier. Furthermore, in [13], both CNN and ANN models were employed to differentiate Parkinson's disease patients from healthy persons based on acoustic characteristics. The CNN model obtained an accuracy rating of 93.10%.

From the previous studies, we proposed a new approach to achieving high results that outperform the previous studies. We achieved the highest results based on the related work and reached 97.4 accuracy for the proposed approach (SiamDNN).

III. Methodology

In this section, the proposed approach to detect and classify Parkinson's disease will be explained. As shown in Fig. 1, several stages starting from data processing through several techniques, then dividing the data into 80% for training and 20% for testing, and to ensure that there is no overfitting, K fold cross-validation was used to prepare the data for the training stage and pass it to the proposed approach (SiamDNN) which will be explained more in Subsection C.

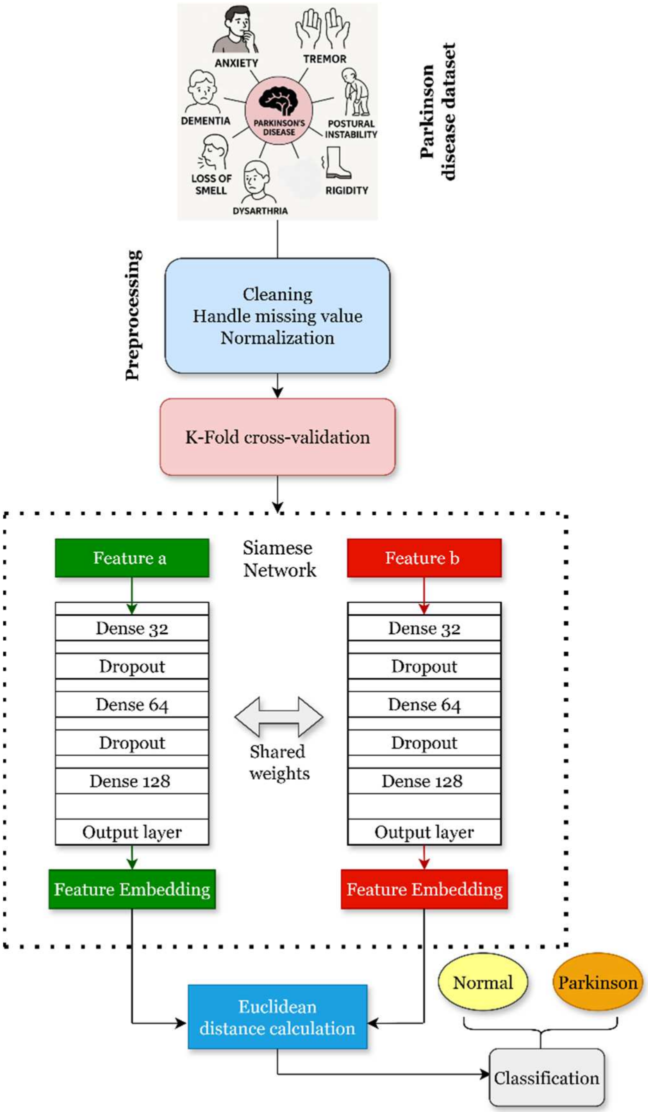

Fig. 1. DNN-based Siamese neural network for Parkinson's disease detection.

A. Dataset Description

This dataset contains biological voice measurements from 31 people, 23 of whom have Parkinson's disease diagnoses. Each participant contributed 195 sound samples, averaging six recordings per individual. According to this study [14], the dataset was centered on feature extraction methods for voice and general speech problems. For patient acoustic sound recordings, there are 22 distinct feature types along with descriptions. A head-mounted microphone was used to record sound in the sound processing cabinet. The Computerized Speech Laboratory (CSL) recorded audio signals directly to a computer at a sampling rate of 44.1 kHz and a bit depth of 16 bits. To correct the differences caused by speaking pressure, the amplitude of the audio samples was digitally adjusted. MDVP (Kay Pentax) denotes the Multidimensional Voice Program.

B. Preprocessing

This study applies dataset preprocessing to transform categorical data into numerical formats, handle missing values by restoration or removal, and delete duplicates to prevent bias. In machine learning, data normalization, or feature scaling or standardization, is a crucial preprocessing technique. Features characterized by different scales or measurement units typically employ it. This strategy aims to prevent any feature from dominating the learning process due to its larger scale by uniformly treating all characteristics with machine learning algorithms. This study employed the Min-Max Scaling method, as defined in Eqs. 1 and 2, to normalize all numerical features of the dataset to the range of [0, 1].

$$y = \frac{x - x_{Min}}{x_{Max} - x_{Min}} \quad (1)$$

$$\hat{x} = y * (Max - Min) + Min \quad (2)$$

The original value is represented by X, the target value by X̂, the maximum and minimum values in the dataset by Xmax and Xmin, respectively, and the desired range is indicated by Max and Min.

C. The Proposed Approach Siamese Neural Network (SiamDNN)

The proposed model can address the challenges in predicting Parkinson's disease. In contrast to other models, the Siamese Convolutional Neural Network [15] computes the distance between input samples by leveraging advanced feature representations. The Siamese Convolutional Neural Network uses CNN to learn new classes to avoid the challenge of learning with a few shots. In our study, we modified the model to a Deep Neural Network (DNN) for its strength in handling clinical data, unlike CNN which is superior in handling images. Fig. 1 shows that two conjugate neural networks process two data samples in parallel: one from the support set and the other from the query set. To ensure that both networks have similar representations for similar inputs, weights, and parameters are shared throughout the training process. The Euclidean distance between the two retrieved features is used to validate the class of the input samples during the testing phase.

D. Machine Learning Algorithms

- In 1967, Cover and Hart created the k-NN method, utilizing distance measurement techniques such as Euclidean, Manhattan, Minkowski, Chebyshev, Hellinger, and Angular distances. The nearest learning instances in the feature space are used to categorize objects, and the most common class is assigned to new vectors. The Euclidean distance is the most employed calculation. K=3 was employed in several experiments to achieve optimal outcomes [16].
- Random Forest: This technique combines the decisions of several decision trees, each trained on a unique dataset. Therefore, the method effectively tackles classification problems with a high success rate.
- Support vector machines are designed to address various categorization problems. A hyperplane is consequently created to optimally separate the classes. Class labels $\{-1, +1\}$ are usually employed to denote classification. The information requiring categorization can be classified as either linearly separable ("AND" and "OR" problems) or non-linearly separable (XOR problems). It is widely recognized that real-world classification challenges often require multiple classes beyond two. A multi-class SVM classifier is necessary to resolve these challenges. The integration of various classifiers facilitates multiple classifications [17].
- The XGBoost Classifier uses an ensemble method with tree-based gradient-boosting approaches to enhance model efficiency. The XGBoost method evaluates a feature's significance by calculating the frequency with which it is employed to partition the data across all trees in the model. Following normalizing the significance of each feature, the total feature importance equals one. As a result, all relevant features have been found, and irrelevant features in the dataset may be removed to simplify the model, enhance its efficacy, and decrease its computational cost [18].
- The fundamental principle of deep learning is the addition of more hidden layers to extract relevant features and get more accurate results. A deep neural network (DNN) has an input layer, an output layer, and one or more hidden layers as its essential components. Each layer of the DNN includes one or more artificial neurons, which are fully interconnected between layers. Furthermore, data is processed in DNN feedforward mode, which involves passing data from the input layer to the output layer through the hidden layer.

IV. RESULTS AND DISCUSSION

The results of six trained models are evaluated to determine the better model. Metrics including the confusion matrix, accuracy, precision, recall, and F1 score were chosen for comparison. Eqs. 3 to 6 demonstrate formulae for different metrics, where TP means True Positives, FP denotes False Positives, TN represents True Negatives, and FN represents False Negatives.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$Precision = \frac{T_p}{T_p+F_p} \quad (4)$$

$$Recall = \frac{T_p}{T_P+F_N} \quad (5)$$

$$F_1 - Score = 2 \times \frac{precision \times Recall}{Precision+Rrecall} \quad (6)$$

The dataset was divided into two divisions: 80% for training and 20% for testing, with 20% of the training data assigned for validation purposes. The exact data partitioning, along with the unique Siamese Neural Network and Deep Neural Network (SiamDNN) architecture, significantly enhanced the model's outstanding capacity to differentiate between Parkinson's disease and normal cases. The proposed model employed the Nadam optimizer and the sigmoid activation function, both of which are optimal for binary classification tasks, to guarantee effective convergence and accurate decision boundaries. A significant benefit of the SNN is its ability to share weights during training, reducing computational complexity and enhancing generalization through the collection of robust, transferable features from paired data comparisons.

The proposed SiamDNN model outperformed all other evaluated models in accuracy, achieving a score of 97.4%. It achieved outstanding precision, recall, and F1 scores of 99% in both Parkinson's (1) and Normal (0) classes, showing its robustness and efficiency as shown in Fig. 2 and Table I. Traditional models, including Support Vector Machine (SVM), achieved 87% accuracy but revealed lower precision, recall, and F1 scores. Both K-Nearest Neighbors (KNN) and XGBoost models achieved 93% accuracy; however, KNN showed worse precision (78% for class 0), while XGBoost showed decreased recall (96% for class 1). The Random Forest (RF) model achieved 90% accuracy, although there were recall inconsistencies, with class 1 at 71%. The independent DNN model, which achieved an accuracy of 94.8% and exceeded previous methodologies, came short of the suggested model in all metrics.

All experiments were conducted on a Jupyter notebook environment with an NVIDIA GeForce GTX 1660 Ti GPU and an Intel Core i5 CPU. GPU acceleration enabled the more efficient training of deep learning models. Table 1 demonstrates the performance of the proposed approach compared to other models.

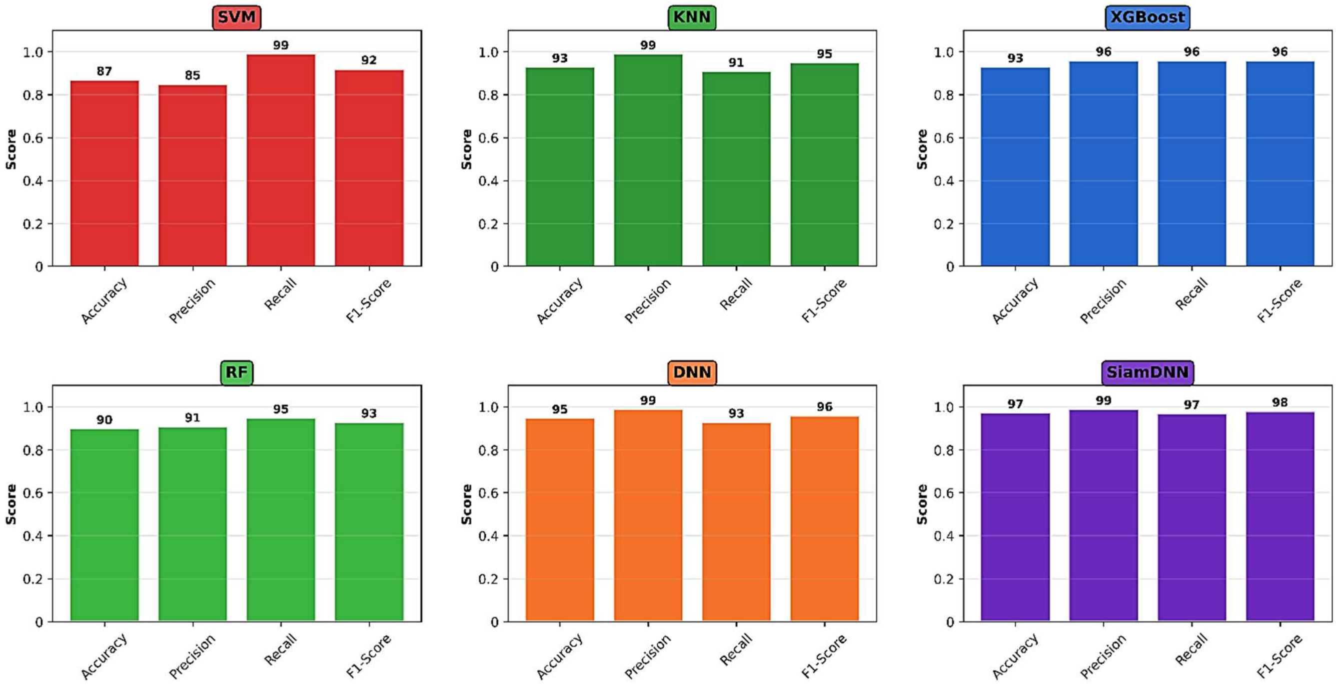

Fig. 2. The Chart Plot of the Performance for the Proposed Approach and Other Models.

TABLE I. THE PERFORMANCE OF THE PROPOSED APPROACH COMPARISION WITH THE OTHER MODELS

Model	Accuracy (%)	Precision (%)		Recall (%)		F1-score (%)	
		0	*1*	*0*	*1*	*0*	*1*
SVM	87	99	85	43	99	60	92
KNN	93	78	99	99	91	87	95
XGBoost	93	86	96	86	96	86	96
RF	90	83	91	71	95	76	93
DNN	94.8	83	99	99	93	91	96
SiamDNN	97.4	91	99	99	97	95	98

The classification efficiency of the proposed SiamDNN approach in discriminating between Parkinson's disease cases (Class 1) and normal cases (Class 0) is shown in the confusion matrix in Fig. 3. The SiamDNN approach misclassified only one instance of a Parkinson's case mistakenly classified as normal while accurately identifying 10 normal cases and 28 Parkinson's cases. This indicates the model's capability to detect Parkinson's disease with few mistakes and high accuracy and reliability.

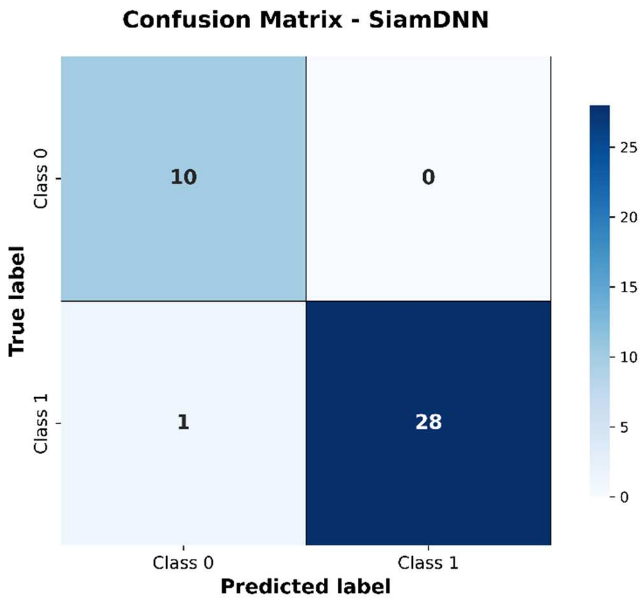

Fig. 3. The Confusion Matrix of SiamDNN Approach.

V. Conclusion

This study evaluated speech abnormalities as an indicator of Parkinson's disease. For this work, we used 5 classifiers and a dataset containing 195 samples with 23 features. The effectiveness of these classifiers was evaluated using metrics such as accuracy, precision, recall, f1-score, K-fold cross-validation, and confusion matrix. We developed a novel approach called SiamDNN that combines two DNNs to classify patients with Parkinson's disease based on speech abnormalities, to enhance prediction accuracy. We achieved 97.4% accuracy using the proposed model, outperforming other models. In future work, we hope to generalize the validity of our proposed approach by evaluating it on a large and diverse dataset of different ages and other factors.

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