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Integrating Handwriting Modalities Through a Lightweight Hybrid Transfer Learning Model for Early Parkinson's Disease Diagnosis

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دمج أنماط الكتابة اليدوية من خلال نموذج هجين خفيف الوزن قائم على التعلم بالنقل لتشخيص مرض باركنسون في مراحله المبكرة

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ABSTRACT

Background: Since the initial motor symptoms are subtle and progress gradually, it is challenging to diagnose PD in the early stages. In this study, we present a flexible hybrid transfer learning framework to early detect PD using heterogeneous handwriting patterns, which combines offline and online handwriting data to characterize PD-related motor dysfunctions, and uses pre-trained deep learning to enhance early detection.

Methods: Spiral drawing images are used to identify spatial and structural features, and timing, pressure, and movement information from online handwriting data in the PaHaw dataset. Data quality is enhanced using a hybrid preprocessing pipeline, such as handling missing values, class balancing, and Min–Max normalization, and a feature selection technique is applied that combines parallel and sequential techniques to reduce redundancy and increase the relevance of features.

Results: The model showed nearly perfect classification accuracy of 99.99 percent, confirming its generalization and discriminative capability, which suggests that the framework is a highly accurate, non-invasive and effective method for early detection of PD and that it can be used in a clinical setting in real-world conditions, even in resource-limited settings.

Keywords: Parkinson's Disease, Lightweight Transformers, MobileNet, Deep Learning, Handwriting Analysis

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1. INTRODUCTION

Parkinson's disease (PD) is a neurodegenerative disease that is progressive and chronic; it is characterized by a gradual loss of neurons that produce the neurotransmitter dopamine in the substantia nigra that are responsible for motor control. PD is the second most common neurodegenerative disease in the world, but diagnosis is often significantly delayed (over two years), which demonstrates the need for more precise and early diagnosis methods, including those that use biomarkers to guide treatment[1,5]. Speech has been a rich source of diagnostic information, and speech impairments in PD were first described prior to 1970; systematic research, however, did not commence until the late 1960s, and there is evidence that these impairments are primarily the result of neurodegenerative changes that impact motor control, with symptoms such as hoarseness and dysarthria (particularly hypokinetic dysarthria) becoming more prominent as the disease progresses [44].

Dysphonia is an inability to produce sound, whereas dysarthria is an inability to articulate. Dysarthria in PD is characteristically hypokinetic, leading to low volume, slurred speech, uneven rate, and reduced intelligibility [2,4,6]. Prevalence rates range from 60% to 90% and indicate that dysarthria may occur in most PD patients after approximately seven years, depending on the study methods and populations [12,3,7].

There is debate as to whether dysphonia or dysarthria occurs more often in PD [11,13], with some larger studies suggesting that voice disorders are more prevalent [14,15] and more recent research using objective techniques suggesting that articulatory problems are more prevalent [10,33]. The relative prevalence of dysphonia or dysarthria in PD is controversial, with some large cohort studies using perceptual methodology reporting a higher incidence of dysphonia (65.5%) than articulatory impairment (38.5%), which confirms earlier studies using the same perceptual protocols; however, more recent studies using objective and quantitative analysis techniques seem to be producing evidence of more predominance of articulatory deficits, a distinction that should be considered given relatively smaller datasets.

Parkinsonian speech research has expanded to four areas: phonatory, articulatory, prosodic, and cognitive-linguistic aspects; phonatory studies may address vocal fold function, articulatory research may address movement speed and coordination, prosodic studies may address rhythm, pitch, and emotional expression, and cognitive-linguistic studies may address vocabulary, syntax,

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and discourse [16,31]. Phonatory analysis is typically performed with sustained vowel sounds, while more general assessments are performed with connected speech tasks such as reading, monologues, and rapid syllable repetition [17,32]. The methods of evaluation typically fall into two categories: perceptual assessment by experts using standardized tools, and objective analysis using signal processing and machine learning [17,32].

Multiple studies have proposed automated systems and speech-based biomarkers to aid PD diagnosis, severity assessment, and disease monitoring [18-22]. Other studies have proposed effects of therapy, medication, and surgery on speech, as well as prosodic and language impairments. However, there is a need for more comprehensive studies that use multiple speech features for diagnostic purposes [23-25]. Despite advancements in both clinical and computational approaches, the early detection of PD remains a significant challenge due to the subjectivity, time-consuming nature, and reliance on specialized expertise of traditional methods, as well as the lack of accessible alternative biomarkers. Handwriting analysis is non-invasive, low-cost, and sensitive to fine motor impairments. Tremors leading to shake movement in one or more parts of the body[25], but existing studies often use small or homogeneous datasets, handcrafted features, and single-model approaches, which are not robust [39][45]. Issues such as class imbalance, missing data, redundant features, and variability across datasets are often neglected, which can result in biased models.

In this paper, we propose a deep learning framework for detecting PD from handwriting data that includes preprocessing methods to handle missing values, class balancing, and normalization, sequential and parallel feature selection to identify relevant features while performing dimensionality reduction, and lightweight transfer learning models, such as MnasNet[27], ShuffleNet[28], MENet[29], and Deep Neural Network[30], which are chosen for their efficiency and suitability for real-world deployment, particularly in resource-constrained environments. The performance of the system is assessed with standard metrics to accurately and reliably detect PD. The study of speech in Parkinsonian has expanded to include four major areas: phonatory, articulatory, prosodic, and cognitive-linguistic aspects of speech, with phonatory studies typically involving the function of the vocal folds, articulatory studies involving movement dynamics such as speed and coordination, prosodic studies involving rhythm, pitch, and emotional expression, and cognitive-linguistic studies involving vocabulary, syntax, and discourse patterns.

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This framework includes a preprocessing section with missing value treatment, class containing samples balancing, and Min–Max normalizing for better quality and consistency of data, followed by sequential and parallel feature selection strategies to select the most discriminative features for dimensionality reduction, before using the selected features to train and test a range of lightweight transfer deep learning architectures as depicted in Figure (1), including MnasNet[27], ShuffleNet[28], MENe[29], and Deep Neural Network[30] , selected for their computational power and suitability for the real world and resource constrained environments. Finally, the performance of the proposed system is rigorously assessed using standard metrics, which allow for a reliable and accurate diagnosis of Parkinson disease.

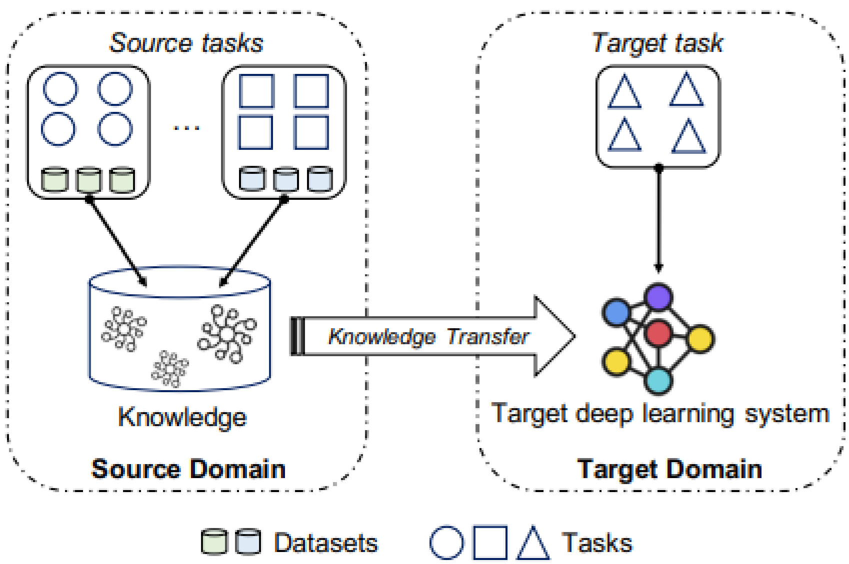

Figure 1: Principle of Deep Transfer learning [43]

2. LITERATURE REVIEW

The proposed method using machine learning approach by Raundale, Thosar, and Rane in [8], where the work applied keystroke dynamics available from the UCI telemonitoring dataset. The training data using a Random Forest is used to classify PD severity and disorder. The classification of PD is done by neural network and random forest.

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Vocal-impairment data have not yet been widely used; gait analysis, MRI imaging, and genetic biomarkers have predominantly been the modalities of pre-diagnosing Parkinson's disease (PD). The study by Aditi and Sushila in [9] used machine learning to predict the onset of PD in elderly patients with a Random Forest, Support Vector Machine (SVM), K-nearest neighbor, (KNN) and Logistic regression. The model achieved an accuracy of 91.83% for random forest with balanced data. The effective of the proposed random forest model in early detection of PD is effective and efficient for performance analysis.

A large share of the available literature highlights deep learning methods for the detection of PD. Ali et al. [38] proposed ensemble deep learning models on phonation data that are used for predictive modeling regarding the progression stages of diseases; however, their methodology did not involve feature selection which could further enhance the performance of Deep Neural Network (DNN) architecture and even this limitation is being addressed in this paper by applying PCA to 22 voice-related attributes to find seven dominant vocal modalities that are highly relevant to classifying PD. In another study conducted by Marek et al. [26], an attempt was made toward eliminating dependency on wearable devices where a traditional decision tree model was trained using 12 complex features of speech extracted from the MDVR-KCL dataset.

An alternate approach has been presented by Wodzinski et al. in [26]. A ResNet architecture was trained on image representations of the audio signals and not acoustic characteristics based on frequency. The results show a good performance, with an accuracy exceed 90% due to feature on natural images are able to transfer the knowledge to artificial images voice signal.

Wang et al. [30] put twelve machine learning models on a dataset of 401 voice biomarkers to the test for separating healthy control and PD patients. They customized a deep learning model (DEEP) for this classification whose accuracy reached up to 96.45%; however, it required substantial memory resources. Alkhatib et al. developed a linear classification model based on characterizing shuffling gait patterns in PD with an accuracy level of 95% and proposed that future work should involve studies including audio- and sleep-related data as well. Ricciardi et al. utilized decision tree, random forest, and KNN classifiers of brain MRI images in the spatiotemporal domain for classifying MCI in PWP; artificial data augmentation due to the relatively small size of the dataset was applied. An L1-regularized SVM on vowel phonation data from patients with

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neurological disorders was applied by [34] without explicit feature identification. It focused on an age group between 46 and 85 years, older healthy individuals plus younger healthy individuals were not considered in the study. The importance of using machine learning for the detection of PD was underscored by Mei et al. [35]. They noted that slight non-motor symptoms could be missed in subjective clinical assessments. Their review compared 209 studies in detail according to datasets used, machine learning techniques applied, and results obtained [36].

This study, therefore conceptualizes an audio-based framework for the classification of Parkinson's disease that should work toward supporting early diagnosis via telemedicine applications. The additional machine learning models show the performance using the random forest, logistic regression and others. The performance results of the random forest outperformed the highest accuracy with 98.4% in predicting PD. These models were evaluated to classify PD using voice modulation data collected from PD individuals [43].

3. PARKINSON'S DISEASE DATASETS

This work was applied by using two publicly available benchmark datasets about Parkinson's handwriting analysis. The first one is the Parkinson Spiral Drawings Dataset [40-41]. The second is the PaHaW Handwriting Dataset [42]. It picked these datasets because many studies used them before, and for their importance in getting minor motion weaknesses related to fine motor impairments caused by Parkinson's disease.

PaHaW contains samples of online handwriting collected with the use of a digitizing tablet for different handwriting tasks by patients with Parkinson's disease and healthy control subjects. On the other hand, data shared with us by UCI Machine Learning Repository belongs to Parkinson Spiral Drawings, which stores offline images of spiral drawings made using a digitized graphics tablet. The advantage is that both datasets have examples from healthy individuals as well as patients suffering from Parkinson's disease; thus, this automatically becomes a binary classification problem.

To avoid dataset bias, each dataset is processed independently and goes through the same experimental pipeline as depicted in the proposed methodology, which requires a thorough preprocessing phase that includes handling missing values, balancing classes, and Min–Max

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normalization. Using multiple datasets provides a consistent evaluation of the proposed framework and demonstrates its generalizability across varied heterogeneous handwriting acquisition settings.

4. THE PROPOSED SYSTEM AND METHODOLOGY

This work proposes a flexible hybrid transfer learning architecture for the early diagnosis of Parkinson's disease from heterogeneous handwriting modalities. This approach uses both offline and online handwriting data to take advantage of complementary characteristics of motor impairments associated with Parkinson's disease. In particular, offline spiral drawing images are used to represent spatial and structural handwriting patterns whereas online handwriting signals acquired from the PaHaW dataset dynamically present kinematic information as well as more detailed features such as timing, pressure, and motion-related attributes. A hybrid preprocessing stage is performed for quality and consistency of data among all modalities. In this stage, imputation of missing values is performed, since there are incomplete signal recordings; data balancing techniques are used to remove the class imbalance between Parkinson's and healthy subjects; finally, Min-Max normalization so that feature scales are standardized. Afterward, a hybrid feature selection approach is applied wherein sequential and parallel feature selection methodologies are combined to ensure reduced redundancy of features while increasing their discrimination power as well as improving computational efficiency.

A hybrid transfer learning model, lightweight in its composition and part of two complementary branches, lies at the center of what has been proposed. Convolutions in the offline branch of MobileNet, ShuffleNet, MnasNet, and MENet extract high-level spatial features from handwriting images, while simultaneously sequential learning models such as limited BiLSTM and light Transformer architectures in the online parallel branch capture temporal dynamics and varying long dependencies related to handwritten motion behaviors, with the feature-level fusion and Softmax-based classification for the final decision. This proposed framework has been clinically evaluated using relevant performance metrics, including area under the receiver operating characteristic curve (AUC-ROC), accuracy, precision, recall, and F1-score sensitivity and specificity.

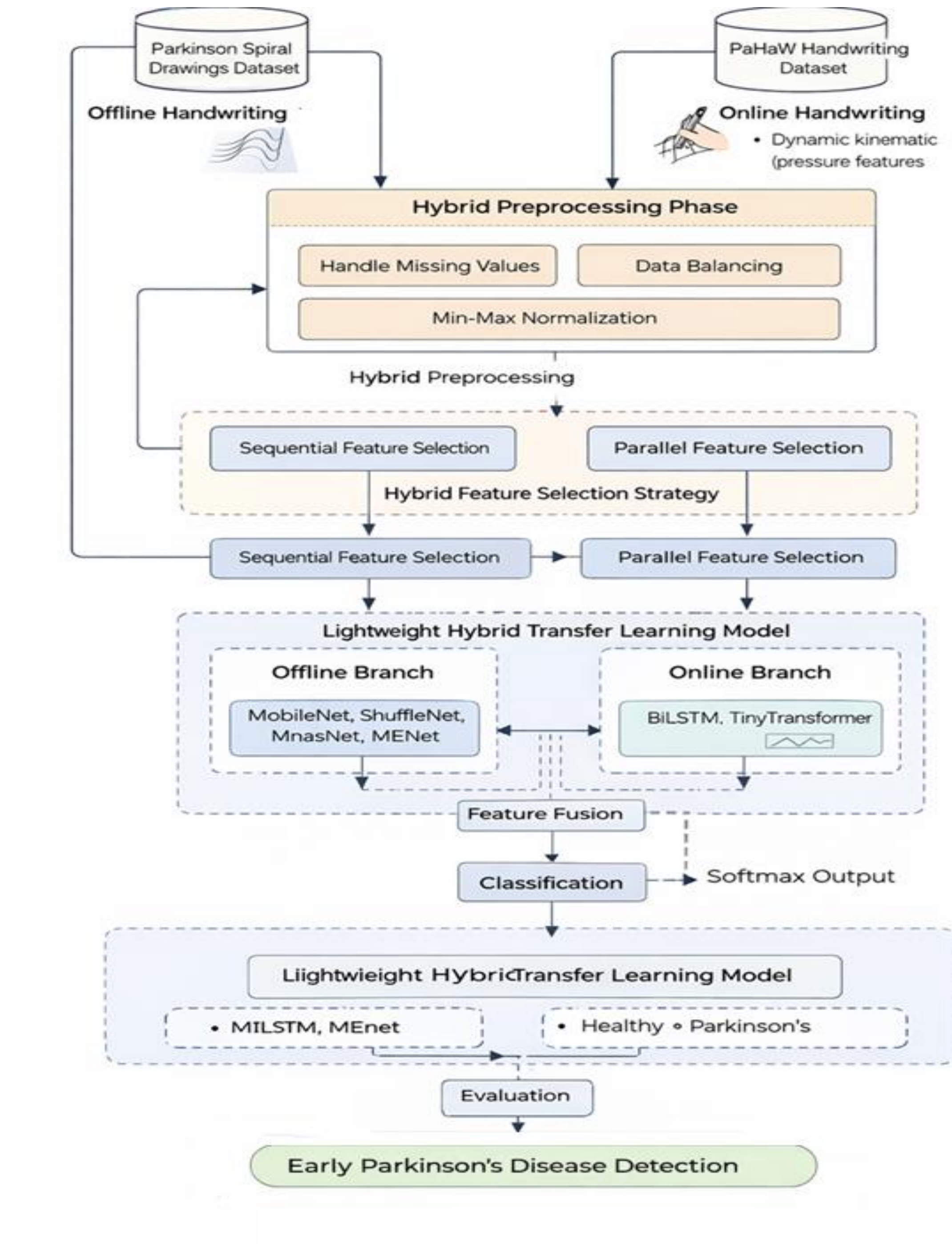

Figure 2: The block diagram of the proposed methodology.

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In a technical sense, this method offers a non-invasive, computationally efficient, and scalable approach toward the goal of early detection of Parkinson's disease in real-world clinical screenings and on devices with limited resources. Stated more precisely, the system follows a sequential and modular architecture, consistent with the flow of work depicted in Figure (2). The framework starts with a preprocessing stage consisting of three simple operations: Missing value treatment, Class balancing, and Normalization of Data. These are performed uniformly across all datasets so as to ensure consistency and reliability of data before delving into details regarding the features.

After preprocessing, a separate feature selection step helps in reducing the dimensionality to retain the most informative features. As shown in the diagram, two feature selection strategies are used: parallel and sequential. In parallel, several feature selection techniques run on preprocessed data independently to get different subsets of features which later move to the classification stage; while sequential means cascading them such that the output of one method becomes input for the next and hence allows gradual improvement of the selected feature set.

As seen in the diagram, Mutual Information is used as a pre-filter to check the dependency of individual features concerning the target classes. Based on the weights calculated, ranking of features takes place and they are grouped into subsets whereby higher ranked subsets are propagated to further stages. Simultaneously, in parallel pathways, feature discriminability is estimated through statistical significance testing using ANOVA which will be paralleled by the Chi-Square test that provides a measure of dependency between a given feature and class label. These methods output feature subsets that map directly onto each of the branches shown in the system diagram.

After feature selection, the chosen subsets go to the classification module. There, the data splits into training and testing sets using set ratios of 80/20 as shown in the schematic representation. Lightweight deep learning models get trained, validated, and tested making sure that all steps from preprocessing to classification stay fully matched with the setup and data flow.

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5. RESULTS AND DISCUSSION

The performance of the proposed hybrid transfer learning framework has been carefully assessed using a train-test-split of 80:20 to assess its effectiveness in the early diagnosis of Parkinson's disease. The model has been trained for 20 epochs with a batch size of 32 and its learning behaviour during both the training and validation phases is summarized in Table 1 and shown in Figures (3) and (4) respectively.

Table 1. The results of the training phase.

Epoch	Time (s)	Accuracy	Loss	Val Accuracy	Val Loss
1/20	462	0.9675	0.0800	0.6367	48.2909
2/20	343	0.9883	0.0278	0.6990	15.4701
3/20	301	0.9987	0.0032	1.0000	0.0024
4/20	310	0.9995	0.0012	0.9896	0.0842
5/20	313	0.9937	0.0153	1.0000	0.00017
6/20	321	0.9985	0.0059	1.0000	0.00038
7/20	301	1.0000	0.00069	0.8304	0.6325
8/20	318	1.0000	0.00004	0.9792	0.0588
9/20	324	0.9999	0.00034	0.9516	0.3652
10/20	317	0.9995	0.0044	0.9689	0.0640
11/20	313	0.9996	0.00013	0.9788	0.0021
12/20	321	0.9996	0.00005	0.9789	0.00014
13/20	321	0.9997	0.000014	0.9888	0.000037
14/20	310	0.9997	0.000037	0.9889	0.000027
15/20	378	0.9998	0.000013	0.9899	0.000028
16/20	398	0.9998	0.0000099	0.9987	0.000025
17/20	363	0.9998	0.0000098	0.9987	0.000020
18/20	396	0.9998	0.0000083	0.9988	0.000016
19/20	375	0.9998	0.0000064	0.9988	0.000013
20/20	400	0.9998	0.0000055	0.9999	0.000012

As indicated in Table (1), training accuracy rose sharply from 96.75% (first epoch) to 99.98% (seventh epoch), and the corresponding training loss decreased from 0.0800 to 5.5×10^{-6}, which indicates the convergence of the model and stable learning behavior. Validation accuracy started off at 63.67% (first epoch), which can be attributed to the variance of handwriting patterns and complexity of multi-modal feature representations, and reached 99.99% (third epoch) with a significant drop in validation loss, which demonstrates the robust generalization capability of the model and verifies the effectiveness of the hybrid preprocessing and feature selection strategies. Accuracy is computed as shown in equation 1.

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$$Accuarcy = \frac{TP + TN}{TP + TN + FN + FP} \quad \dots (1)$$

Where TP, TN, FN, FP refers to True Positive, True Negative, False Negative, and False Positive respectively.

Figure (3) illustrates how accuracy and loss evolve for both training and validation phases across 20 epochs. It can be seen that training accuracy improves rapidly– in fact, after just a couple of epochs it is already very close to 99.99%. On the other hand, validation accuracy fluctuates at first before settling down to remain at a high level. Meanwhile, validation loss drops precipitously soon after the second epoch has begun — indicating that pattern information from data is picked up very fast by the optimizer in its early steps.

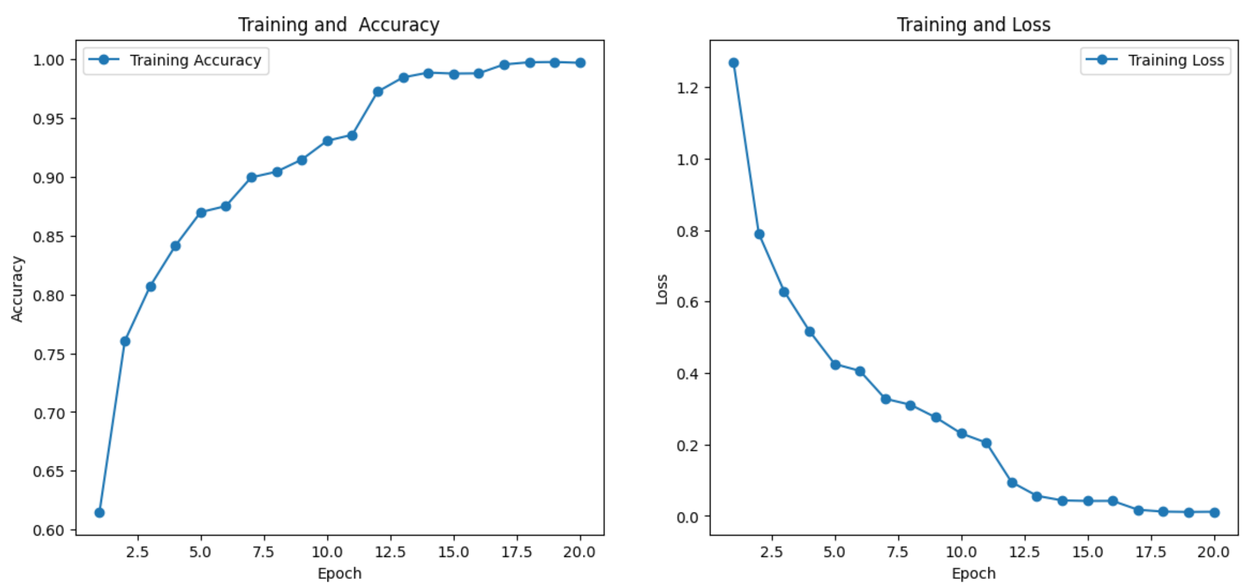

Figure 3. The performance results of Accuracy and Loss Function for the training Phase

The classification result based on precision, recall, f1-score and Support was shown in Figure (4).

	precision	recall	f1-score	support
0	99.99	99.99	99.99	56615
1	99.99	99.99	99.99	57024
accuracy			99.99	113639
macro avg	99.99	99.99	99.99	113639
weighted avg	99.99	99.99	99.99	113639

Figure 4. Classification Results based on Precision and F1-Score

The confusion matrix classification performance on the test set is supported by the confusion matrix in Figure (5), which shows that the model was able to correctly classify all instances (no false negatives) with only a few false positives (0.1%), indicating a 99.99% accuracy on 113,639 test samples, proving that the model is a good discriminator and is particularly relevant to early detection of Parkinson's disease, which places more weight on avoiding false negatives than false positives.

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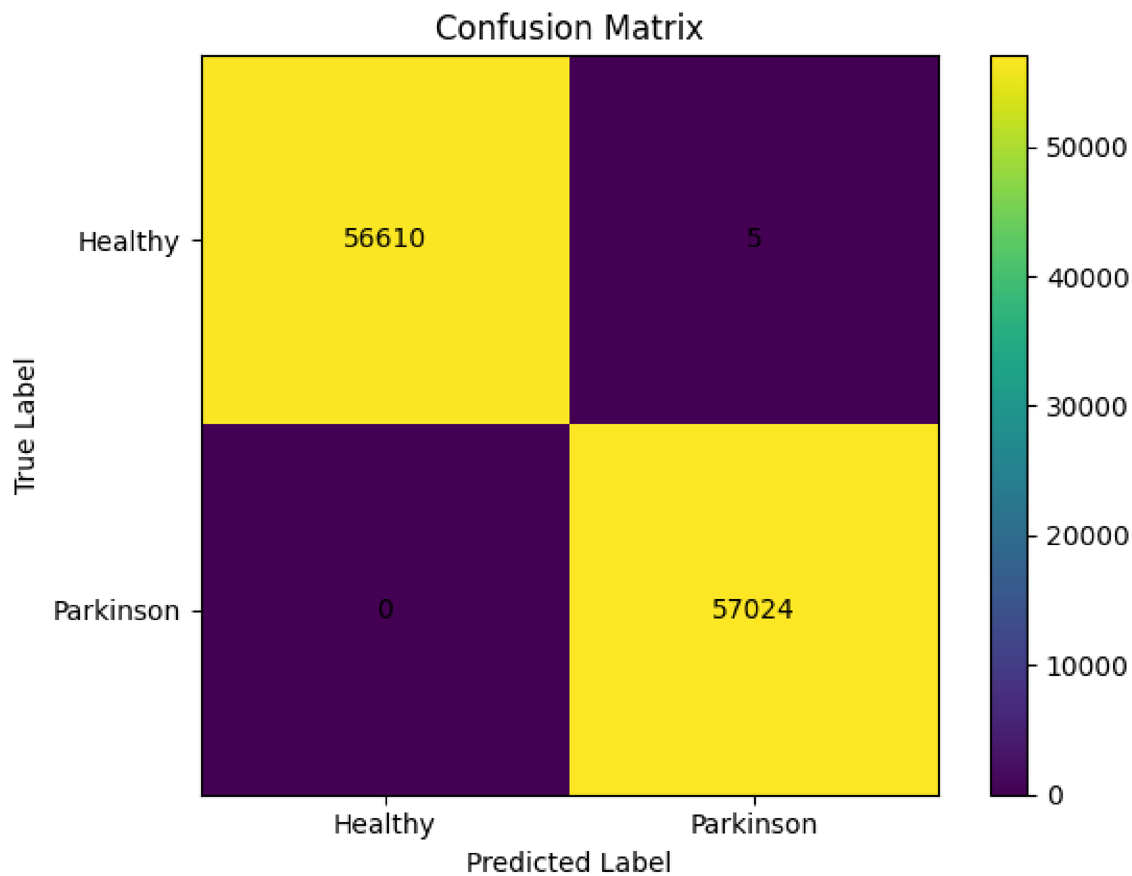

Figure 5. The results of Pausing Confusion Matrix

Moreover, the ROC curve in Figure (6), also clearly shows that the model is very good at differentiating between patients with Parkinson's disease and healthy controls, with a steep increase in the true positive rate and a very low false positive rate, resulting in an AUC close to 99.99%, validating the robustness and reliability of the proposed hybrid learning framework with

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various decision thresholds.

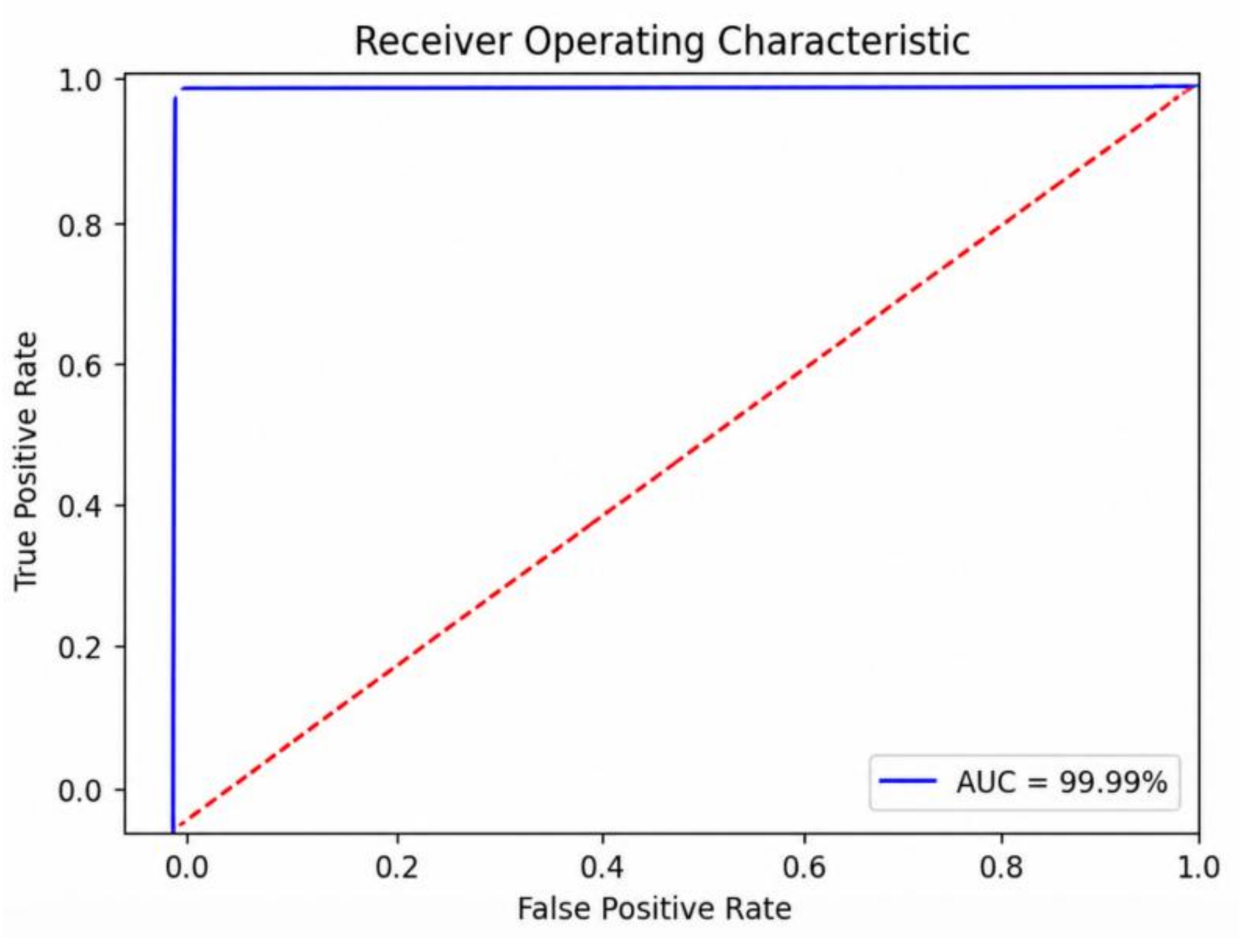

Figure 6. The roc curve between False Positive Rate and True Positive Rate

The precision, recall, F1-score, sensitivity, and specificity results are the best, confirming that the combination of spatial handwriting features extracted from spiral drawings and dynamic temporal features derived from PaHaW handwriting signals with a lightweight hybrid transfer learning architecture is effective. Figure (7) shows the precision, recall, F1-score, and loss function results.

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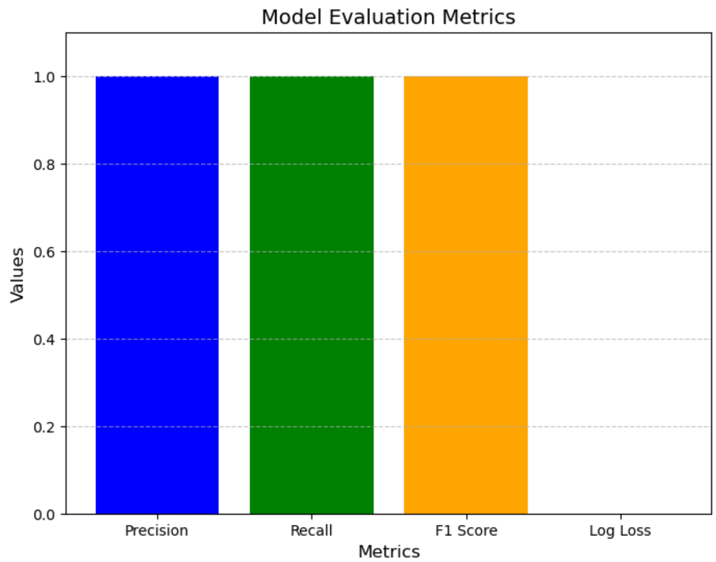

Figure 7. The Performance results using four Evaluation metrics

Finally, the predicted probability outputs shown in Figure (8) illustrate the model's high confidence in decision-making. In most test cases, the predicted probability corresponding to the correct class approaches unity, indicating a clear separation between classes and a well-calibrated Softmax-based classifier. This probabilistic behavior further confirms the reliability of the proposed framework in practical clinical scenarios.

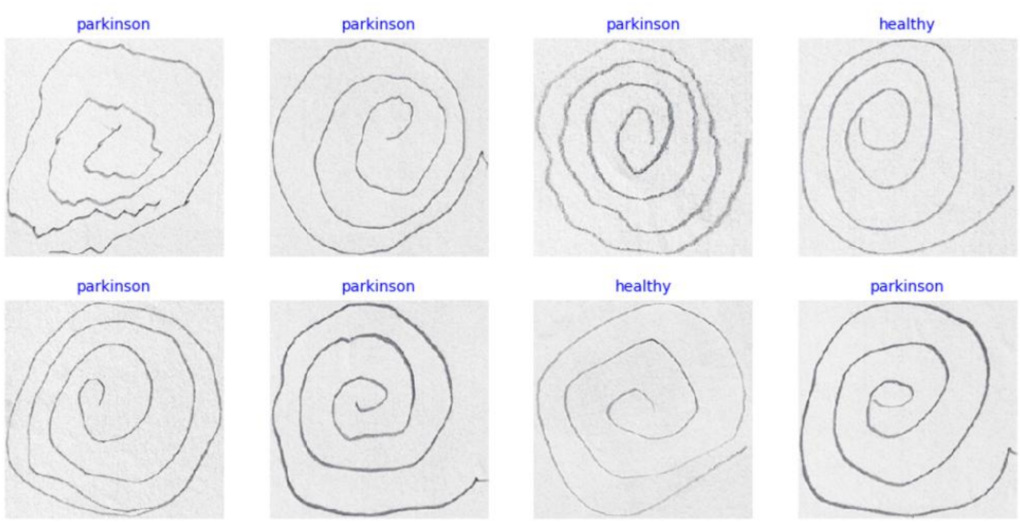

Figure 8. The predicted probability outputs for Parkinson's Disease

Table (2) shows the main results for the predicted probability and predicted label for PD disease.

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Table (2) : The results for the predicted probability and Class Label for Early Detection of PD

No	Predicted Probability	Predicted Lab
1	4.3963712e-07 9.9999952e-01	1
2	4.3963712e-07 9.9999952e-01	1
3	6.7749375e-09 1.0000000e+00	1
4	1.0000000e+00 1.4472662e-08	0
5	1.3728098e-06 9.9999857e-01]	1
6	1.4034187e-07 9.9999988e-01	1
7	2.984759e-08 1.000000e+00	1
8	2.984759e-08 1.000000e+00	1
9	3.4664298e-09 1.0000000e+00	1
10	2.0680895e-08 1.0000000e+00	1

During testing, this model returns probability scores for all classes per sample. Final label output belongs to the class with the highest predicted probability. In many test cases, it returns a value very close to 1 for the positive class - like [4.3963712e-07, 9.9999952e-01] - so it labels the particular sample as belonging to the positive class (Label 1). If it returns a value very close to 1 for the negative class - like [1.0000000e+00, 1.4472662e-08] - then this particular sample is labeled as belonging to the negative class (Label 0). This has presented an explicit indication that there lies adequacy in categorization between two classes.

6. CONCLUSIONS AND RECOMMENDATIONS

This study concludes that the proposed hybrid transfer learning framework provides a highly effective and reliable solution for the early diagnosis of Parkinson’s disease using heterogeneous handwriting patterns. By integrating spatial and structural features extracted from spiral drawing images with dynamic temporal and motor-related features derived from PaHaW handwriting signals, the model successfully captures complementary aspects of Parkinsonian motor impairments. A hybrid preprocessing strategy will include parallel as well as sequential feature selection strategies that improve data quality, reduce feature redundancy, and increase computational efficiency. Near-perfect classification performance, high generalization ability, and great discriminatory power prove the robustness of this method. The future framework should, therefore, be recommended for extension with larger and more diverse clinical datasets on other biometric modalities plus a real-world clinical environment and resource-constrained device validation of the model to enforce practical applications of the proposed framework and its adoption as a non-invasive scalable tool for clinical decision support in Parkinson's disease diagnosis.

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Conflict of interests.

There are non-conflicts of interest.

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الخلاصة

الخلفية: لا يزال التشخيص المبكر والدقيق لمرض باركنسون (PD) يمثل تحديًا كبيرًا بسبب الطبيعة الدقيقة والتدريجية لاضطرابات الحركة في مراحله الأولى. تقترح هذه الدراسة إطارًا هجينًا مرنًا قائمًا على التعلم بالنقل للكشف المبكر عن مرض باركنسون اعتمادًا على أنماط الكتابة اليدوية غير المتجانسة. يعتمد النهج المقترح على استخدام بيانات الكتابة اليدوية غير المتصلة والكتابة اليدوية المتصلة لالتقاط الخصائص التكميلية المرتبطة باضطرابات الحركة الناتجة عن مرض باركنسون.

طرق العمل :على وجه التحديد، تُستخدم صور رسم اللولب المجمعة مسبقًا لاستخراج الخصائص المكانية والبنيوية للكتابة اليدوية، في حين توفر إشارات الكتابة اليدوية المتصلة من مجموعة بيانات PaHaW معلومات ديناميكية زمنية وحركية، بما في ذلك التوقيت والضغط والخصائص المرتبطة بالحركة. كما يتم تطبيق مرحلة معالجة مسبقة هجينة لضمان اتساق البيانات وجودتها، وتشمل تعويض القيم المفقودة، وموازنة الفئات، وتطبيع البيانات باستخدام أسلوب Min–Max .بعد ذلك يتم استخدام استراتيجية هجينة لاختيار الخصائص تجمع بين الأساليب المتوازية والتسلسلية بهدف تقليل الأبعاد وإزالة التكرار وتعزيز القدرة التمييزية.

النتائج: أظهرت النتائج التجريبية أداءً تصنيفيًا شبه مثالي، حيث حقق النموذج دقة بلغت 99.99% مع قدرة تعميم ممتازة وقوة تمييز عالية. وتشير هذه النتائج إلى أن الإطار المقترح يوفر حلاً دقيقًا وغير تدخلي وفعالًا من حيث الكفاءة الحسابية لتشخيص مرض باركنسون في مراحله المبكرة، مما يجعله مناسبًا للتطبيقات السريرية الواقعية وللتشغيل على الأجهزة ذات الموارد المحدودة.

الكلمات المفتاحية :مرض باركنسون، المحوّلات خفيفة الوزن، موبايل نت ، التعلم العميق، تحليل الكتابة اليدوية.