ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

MULTIMODAL AI-DRIVEN EARLY DETECTION OF PARKINSON'S DISEASE USING NEURO-MOTOR BIOMARKERS FROM KEYSTROKE DYNAMICS AND HANDWRITING ANALYSIS

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ABSTRACT

Parkinson's Disease (PD) is an evolving neurodegenerative condition that affects the fine motor control capabilities and thus early diagnosis is important to ensure that there is timely intervention. This research paper introduces a multimodal artificial intelligence (AI) model that combines the keystroke dynamics and the handwriting analysis in detecting early neuro-motor abnormalities linked to PD. The supervised machine learning models of Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting (GB) were used to analyze the temporal keystroke dataset (Tappy Keystroke Data) with a maximum classification accuracy of 96.12%. At the same time, spatial samples of handwriting (spiral and wave drawings) were handled in the Convolutional Neural Networks (CNNs), and the resultant accuracy was 86.7 and 83.3 accordingly. The association of time and space biomarkers shows that multimodal AI analysis may be more effective than single-modality systems providing a rather inexpensive, non-invasive, and scalable diagnostic tool to support the detection of PD in its early stages. The study forms a base on the development of multimodal detection systems that require the use of other biomarkers including voice and ocular movement to increase predictive accuracy.

Keywords: *Parkinson's Disease, Keystroke Dynamics, Handwriting Analysis, Artificial Intelligence, Neuro-Motor Biomarkers, Machine Learning, Convolutional Neural Networks, Early Detection.*

1. INTRODUCTION

Parkinson Disease (PD) is a second most prevalent neurodegenerative disorder after Alzheimer disease, and it is on the increase as the aging population of the world grows older. PD is typified by gradual degeneration of dopaminergic neurons within the substantia nigra resulting in dopamine and motor control deficiency. The motor symptoms resulting are bradykinesia, rest tremor, rigidity and postural instability. Nevertheless, nonmotor symptoms, which include cognitive impairment, mood disturbances, and autonomic impairment, tend to be an early manifestation of the problem, making it difficult to diagnose at a young age. Early and proper diagnosis is the most important in PD research because timely therapeutic interventions are important in reducing disease progression and enhancing the quality of life of patients.The existing clinical diagnosis is symptom based and strongly depends on the judgment of the clinician and scales including the Movement Disorder Society Unified Parkinson Disease Rating Scale (MDS-UPDRS). The diagnosis can be assisted by imagining techniques (e.g., DaTscan, MRI), which however are expensive, occasionally invasive, and not always sensitive in the earliest (prodromal) stages of PD. Therefore, it is evident that there is high demand to have available, objective, and noninvasive screening methods that will identify PD at its initial stages.

PD detection now allows new paradigms due to the recent development of biomedical signal processing and artificial intelligence (AI). The motor biometrics that occur as a result of daily activities, specifically typing or handwriting, are promising avenues to the subtle neuro-motor dysfunction. However, there is a tendency in the literature to explore each modality separately, without the possibility of more diagnostic fusion.

The following are some of the terminologies that we are going to use in this work:

Neuro-Motor biomarkers: Quantitative parameters based on neural and motor activity, which indicate the preservation of motor control (e.g. timing of finger tap, writing smoothness in writing).

Keystroke dynamics : First, Keystroke dynamics (timing characteristics of typing, including dwell time, time between releasing one key and pressing another, latency, etc.) encode fine motor control and neuromuscular coordination.

Handwriting Analysis: Analysis of handwriting Space and dynamics calligraphic properties of pen movements: smoothness of strokes, variation of pressure, micrographia (shrinking hand writing), curvature, and kinematics as a measure of motor control in the hand and fingers.

1.1 Prior Work and Gaps in Multimodal AI for PD Detection

On the keystroke dynamics side, Demir et al. (2023) [26] did full-scale research based on the use of machine learning models that examined the keystroke timing data as a measure of both Parkinson's Disease (PD) patients and healthy controls. They used key press duration and inter-key latency aspects of their approach in modeling fine-motor irregularity related to bradykinesia and tremor. Using the classifiers like Support Vector Machines (SVM) and the Random Forests, the authors obtained a considerable distinction between the control and PD groups and even provided evidence that the disease may be staged. This paper has provided the possibility of digital keystroke biomarkers as sensitive neuromotor decline indicators.

Expanding on this line, Tat et al. (2025) [27] proposed an innovative, soft, pressure-sensitive, and an intelligent keyboard that can concurrently record both the dynamics of the time and force during the keystroke. This system also recorded the pressure and release force applied by each keystroke unlike traditional timing-only databases, which only recorded the timing of a keystroke. Flexible piezoelectric sensors that were placed underneath the keys recorded the pressure and release force of each keystroke. They found that fine differences in the patterns of keystroke pressures were strongly associated with clinical motor scores, which indicated that multi-dimensional typing information might be the key to effective early PD diagnosis and digital remote health observation.

Concerning the handwriting analysis, Drotar et al. (2024) [28] used the freely available PaHaW database of handwriting, which examined the kinematic trajectories of tasks, pen pressure, and velocity profiles of spiral and wave tasks. They have also performed the classification of the samples through an optimized SVM classifier that gave an average of about 81.3% as the classification accuracy, which indicates that a combination of the spatial (trajectory) and pressure-based (force) parameters increase discrimination between PD and healthy samples. Their study also emphasized the clinical decipherability of such features as analogs of traditional motor symptoms such as micrographia and the degree of tremor.

Drotar et al. (2022) [29] continued the handwriting-based diagnosis by adding the in-air movement analysis in a previous publication, examining both time and motion of the pen during the pen-to-pen contact upperside-down. Their results indicated that nontraditional parameters (in-air, pen-up acceleration, etc.) have high levels of discriminative power, which produce an area under the curve (AUC ≈ 0.89) in the separation of PD patients and controls. This study highlighted the diagnostic capabilities of spatio-temporal biomarkers of handwriting that are overlooked when performing conventional pen-on-paper examination.

In a greater sense, Serag et al. (2025) [30] carried out a systematic scoping of the topic of multimodal diagnostic frameworks to identify prodromal PD. The authors have summarized more than 70 studies which use motor, speech, ocular and imaging biomarkers together with AI-based data fusion strategies. Their review highlighted that unimodal models (e.g., keystroke by itself or handwriting by itself) provide valuable information, but multimodal fusion (such as cross-domain correlations) will provide a true diagnostic strength, in that the sensitivity can be much higher, and the false negative can be much lower. They also emphasized that these frameworks are under-researched and one of the key areas of research in the early development of biomarkers of Parkinsonism.

1.2 Our contribution and Motivation

To fill these voids, the present paper will suggest a multimodal AI-based framework that:

- Brings together time-varying (through finger tapping / typing test) and space-varying (spiral and wave drawings) handwritten measures.
- Uses SVM, Random Forest and Gradient Boosting with supervised ML models using keystroke features and deep CNNs using handwriting images.
- Incorporates the two modalities into one unified fusion model to increase the accuracy of early PD detection.
- By analyzing the areas of each modality that are most predictive, provides interpretability to the analysis.

Our approach overcomes the shortcomings of unimodal models and embodies complementary motor signatures as far as time and space are concerned. It also aims at screening which is low-cost, noninvasive, scalable and can be deployed using telehealth. Moreover, our model gives hope of expansion to other modalities such as voice, gait or ocular tracking in the future to enhance detection accuracy.

2. PROBLEM DEFINITION

Parkinson s Disease (PD) is a neurodegenerative disorder that has so far been elusive in its early stages mainly because there is no reliable scalable and non-invasive method of diagnosing the condition. Current clinical tools such as MDS-UPDRS are symptom based, subjective and cannot be interpreted by a non specialist. Although objective data can be obtained by the usage of imaging modalities (DaTscan or even MRI), it is costly, invasive and frequently cannot demonstrate early changes attributable to PD. Further, a high percentage of patients, particularly those in the rural or underserved groups, do not have access to such diagnostic services.There have been instances where individual modalities have been involved each in characterizing neuro-motor irregularities based on PD patients but it is not advisable to engineer isolated application of any given biomarker because only the complexity of motor dysfunction in early-stage PD can be fully accounted. There is a serious deficiency in the earth of the integrative, multimodal frameworks that exploit both temporal (such as finger tapping) and spatial (such as handwriting) PD biomarkers within a single, AI-based diagnostic system. This disparity poses a severe problem in further development of screening technologies of PD that are both precise and reachable and can be scaled up.

RESEARCH OBJECTIVES:

The primary goal of the research is to develop and test an effective multimodal, non-invasive, and robust AI-powered framework of early detection of Parkinson Disease (PD) based on neuro-motor biomarkers evaluating both keystroke dynamics and handwriting analysis. The following are the specific objectives of the research:

1) Temporal neuro-motor biomarkers extraction against Tappy Keystroke Dataset

This involves calculations of the keypress measures including hold time, flight time and latency reflecting the initial motor system disturbances or bradykinesia, and reduced motor rhythm in PD patients.

2) To prepare and extract spatial neuro-motor features using samples of spiral/waves handwritings

This is done by checking abnormalities like tremor, micrographia, and abnormal stroke pressure or shape that point towards the problem of fine motor control in PD.

3) To apply and compare two or more supervised machine learning models (e.g. SVM, Random Forest, Gradient Boosting)

The labels of the keystroke feature set are classified using these models as PD and non-PD individuals and the intention is to make the accuracy high, precision high, and recall high.

4) To develop and train convolutional neural networks (CNNs) on handwriting image information to classify the same

The CNNs obtain early symptoms of the motor dysfunction in PD by automatically building spatial characteristics of the handwritten patterns.

5) To unite the temporal (keystroke) and spatial (handwriting) biomarkers into a common framework of diagnosis

Such a dual-modal methodology is expected to maximize the sensitivity of the diagnosis and minimize the false negatives due to the use of the complementary domains of features.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

6) To measure the diagnostic capabilities of the individual forms as well as incorporated modes

Standard performance measures such as accuracy, F1-score, confusion matrix, and ROC-AUC are applied as a part of the assessment of the efficiency of the suggested hybrid framework.

7) We need to enable a framework that will enable future multimodal diagnostic systems to we provide a scalable and extensible base

There is potential to expand to add more of the non-invasive biomarkers like speech patterns, gait analysis, or eye tracking in order to screen more patient populations with a neurodegenerative disease.

3. MATERIALS AND METHODS

The section explains the datasets, data preprocessing strategies, feature extraction approaches, model (classification), and evaluation measures adopted in the proposed multi-modal detection framework of Parkinson Disease (PD).

3.1 Synopsis of the Proposed Framework

The major aim of the proposed research work is developing an intelligent, fully automated, and dual-modal system of an early Parkinson Disease detection based on neuro-motor biomarkers. This is realized through evaluating two forms of motor functions:

The Finger Tapping Test (FTT) and its temporal characteristics that were estimated on the basis of a public keystroke sample. Spatial characteristics received in the Handwriting Test (HWT) samples, namely spiral and wave pictures. Individually in this case, these modalities undergo machine learning (ML) and deep learning (DL) models, followed by verifying the modalities based on their classification performances represented in below Figure 1.

The flowchart of the system is shown below:

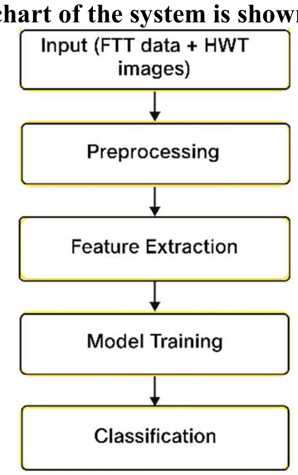


Figure 1: Represents the System Flow

3.2 The Data Sources

In this section we are going to discuss about the dataset which is used in our proposed work.

FTT Keystroke Dynamics Dataset

We have worked with a publicly accessible Tappy Keystroke Dataset that contains the results in the form of keypress timing data recorded in people with Parkinson disease and control participants. Every record of the dataset has metadata that contains:

- Key pressed
- Press and release date & time
- Flight time (time between pressing one keys and pressing the other)
- Hold time (time delay during which a key is depressed)
- Latency time (time between two successive keypresses)

Example:

In case a user enters the word hello, the system records:

- Duration between tapping the **h**, and then releasing the **h**
- Hesitation on pressing **e**
- The time taken by a flight between **h** and **e**
- Such micro-intervals disclose such neuromotor abnormalities as tremor or rigidity.

Handwriting Dataset (HWT)

The second data include spiral and wave hand-drawings that were retrieved on a collection digitized. These participants were required to follow previously constructed designs with a stylus or touch screen. These drawings are usually characterized by micrographia, jerky lines and non smooth curvature by the PD patients.

Example:

The spiral drawn by a PD patient can be angular with uneven completion of direction with variation in line thickness; the normal person gives smooth and regular spirals.

3.3 Data Preprocessing

In this section we are going to discuss about the data pre-processing techniques:

3.3.1 Preprocessing FTT Keystroke

Incomplete data and other sequences that have been corrupted were discarded. All time stamps were adjusted against the initiation of the session.

New functions were designed including:

- Mean hold time
- Flight-time Standard Deviation
- Inter-Key Latency Variance

This was useful in increasing minor variations in neuromotor control in PD and non-PD groups.

3.3.2 Preprocessing of images HWT

Images of spiral and waves were made gray-scale and also resized to 128128 to become similar.

Data augmentation was done with:

- Random rotations (±10°)
- Zoom and shifts of width and height
- Gaussian noise (for hand jiter)

This made it robust and it minimized the problem of overfitting during CNN training.

3.4 Extraction of Features

In this section we are going to extract the features for training the model.

3.4.1 FTT - Time-Domain Features

Extraction was done of the following statistical and frequency-domain characteristics:

- Mean, Standard deviation, skewness of hold/flight/latency time
- Typing rhythm entropic
- Fast fourier transform (FFT) signal energy

These functions record temporal, synchronization and rhythmical fluctuation which are normally impaired in PD.

3.4.2 HWT -Images based characteristics

Through Convolutional Neural Network (CNN), features were learnt automatically.

The CNN structure was:

- Input layer (128 128 1)
- 2 max pooling and ReLU convolutional blocks
- Flatten layer - 2 Dense layers (128, 64 neurons)
- Softmax output layer (PD vs Non -PD)

Such layers aid in the capture of smoothness at edges, variation in the stroke width and the variation of line curvature.

4. LITERATURE WORK

In the article by Lim et al. [1], scientists designed a multimodal model using smartphone-derived features such as voice, finger-tapping motions, and gait in assisting early identification of the Parkinson's disease (PD). The model showed good classification accuracy, which gave a promise to the application of mobile technology in PD detection. Borzì et al. [2] presented a machine learning model for automated scoring of UPDRS bradykinesia based on single-view RGB of finger tapping. The method is congruent with clinical guidelines and allows for objective distinction of motor symptoms in PD. The purpose of the study carried out by Liu et al. [3] is the analysis of finger-tapping videos with the help of the machine learning algorithms to predict the severity of the disease. The system used an innovative tiered classification scheme and resulted in increased accuracy for the detection of PD and differentiation of PD severity.

Aouraghe et al. [4] reviewed computer vision methods of PD assessment, mentioning finger tapping as one of the major tools examined with video analysis. The survey regards computer vision as object PD assessment. Zhao et al. [5] introduced quantum-inspired machine learning which points out that finger-to-thumb tapping tests are related to UPDRS scores, improving detection accuracy. The study represents the integration of quantum computing concepts in the PD detection. In work carried out by Białek et al. [6], researchers used the handwriting images and SVM algorithms for binary classification between those PD patients and healthy adults. The efficacy of handwriting analysis in recognition of PD was demonstrated and it is shown that certain characteristics of handwriting can act as reliable biomarkers of early detection.

Dionela et al. [7] performed logistic regression, multilayer perceptron and Naive Bayes algorithms over the handwriting data using which they were able to get promising result in early-stage diagnosis of PD. The study points to the promising relevance of ML towards the analysis of the features of handwriting concerning the PD detection as the accuracy of the multilayer perceptron model in the cross-validation reached 84.4%.In the work by Białek et al. [8], the adequacy of modeling the process of handwriting the digits for discrimination between the people The research was focused on the importance of temporal and spatial features in handwriting for the precise identification of PD. Frid et al. [9] used deep Convolutional Neural Network (CNN) for handwriting screening, achieving high accuracy in comparison of PD patients and healthy ones. The study highlights the use of deep learning in PD detection with the handwriting analysis, getting 91.2% of accuracy.

The current study by Zhao et al. [10] presented an extensive review of the machine learning and deep learning strategies used for PD detection and assessment over the last decade, with the advances and difficulties on AI applications to PD. The survey talks about different data modalities and mentions how the integration of multimodal data is helpful to increase the accuracy of diagnosis.Mei et al. [11] discussed the role of AI and machine learning tools in finding early detectable markers of PD, highlighting the significance of the said tools' role for diagnosis and early intervention. The study discussed several AI models and efficiency of early PD diagnosis according to them. In the study by Mei et al. [12], a comparative analysis of CA technologies for classification, prediction, and monitoring of patients with PD was provided, thus indicating the efficiency of different machine learning models. The research indicated the potential of the use of wearable sensors and AI for continuous tracking.

Mei et al. [13] reviewed multiple data modalities and machine learning techniques that have been applied to PD diagnosis and focus on the future possibilities of combined use of various data sources for enhanced accuracy and early detection. Systematic review involved 209 studies and the considered struggles and prospects for the field. In the work of Mei et al. [14], a machine learning-based PD diagnosis was presented, concentrating on dopamine levels drop and its influence on the motion functions, demonstrating a contribution of machine learning in learning pathology of PD. The accuracy of the model with Random Forest classifiers was 88.7%.Dionela et al. [15] discussed the use of systems based on IoT for PD diagnosis, with an emphasis on cost-effectiveness and accessibility, and showed the opportunity for the integration of IoT and machine learning into healthcare. A wearable device for the collection of motor data and analyses through AI algorithms was suggested in the study. In the study by Dionela et al. [17], machine learning methods for PD detection were used, concerning various sources of data and ways of features' extraction, revealing flexibility of machine learning in PD diagnosis. The study recorded an accuracy of 86.5% when using the SVM and the decision tree classifiers.

IDENTIFIED LITERATURE GAP:

Although a lot of studies have been made applying machine learning (ML) and deep learning (DL) for the early diagnosis and determination of the Parkinson's disease (PD), there are some crucial gaps that remain. A lot of studies have been conducted on particular modalities such as voice recordings, finger tapping, handwriting analysis, and gait as singly. Although these unimodal approaches have shown promising results, i.e. classification accuracies ranging from 84%, 91%, there are limited studies reported on implementing these heterogeneous data modalities into a robust, unified diagnostic model. The works of, e.g. Zhan et al. [1], Borzì et al. [2], and Liu et al. [3] provide examples of large performance with motor features but the area of application is mostly the one type of input or narrow testing environments.

Moreover, reviews from the works of Aouraghe et al. [4] and Zhao et al. [10] suggest computer vision and AI potential but also point to the absence of the standardized datasets, evaluation metric diverseness, and live or scale deployment. Some of the researchers [11–14] like Mei et al. have discussed the use of wearable sensors and IoT devices for continuous monitoring, but they are still in the nascent stages, and there is little effort of integrating AI based decision support systems into clinical settings. In addition, the studies on handwriting analysis (e.g., [6,8], [9]) demonstrate promising diagnostic potential but also identify the need for studies on larger and more diverse populations for generalizations. Although sophisticated approaches like quantum-inspired ML (Zhao et al. [5]) or CNN-based handwriting classification (Frid et al. [9]) still suffer from applicability limitations and reluctance to usage by clinics.

5. PROPOSED DATASETS

Tappy Keystroke Dataset is a structured dataset that was created during the finger tapping test, that is aimed at categorizing motor function specifics, which would aid in detection of Parkinson's disease. The dataset consists of a variety of features from keystroke dynamics as well as demographic information of participants, which is represented in the figure 2. It comprises healthy persons, as well as Parkinson's patients, and a wide and clinically relevant statistical basis for ML models.

1)Demographic Information File

This file contains patient-specific background data that can be leveraged as input features or subgroup analysis:

Date of Birth (DoB): Exploited to compute the participant's age, a significant factor of PD progression and diagnosis.

Diagnosis: Flags the subject as a Parkinson 's patient or healthy control (consistently recorded as P, L, or F – possibly referring to PD, Left-handed, or Female control).

Gender: Binary coded (0=Male, 1= Female).

Tremor Presence: States if the participant shows tremors (Yes/No).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

Medication Status: Gives insights into whether the patient is under PD medication during this test or not, which may influence motor performance.
Unified Parkinson's Disease Rating Scale: Updrs Score. A part of the standard clinical measure of the severity of Parkinsonian symptoms. Helpful in correlating with motor features.

2)Keystroke Dynamics File

This file provides highly precise motor timing data during the finger tapping task, among other things:
Hand: Represents the hand by which the test was conducted. Often encoded as: 3 (Right hand); 4 (Left hand). It is relevant since motor symptoms of PD are usually asymmetric.
Hold Time (ms): How long a key is pressed down before it is released. A prolonged hold time is generally linked with bradykinesia in PD patients.
Latency Time (ms): The interval time between releasing the one key and pressing another key. Latency can point at the delay in movement initiation.
Flight Time (ms): The amount of time elapsed between the releases of one key up to pressing the next key. This is in close connection with motor fluidity and rhythm.

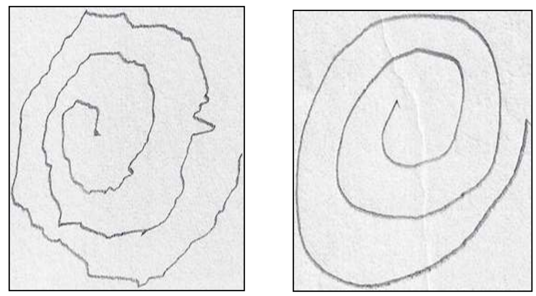
hand	Gender	hold time	latency time	flight time	PD
3	0	97	359	265	P
3	0	101	343	250	P
3	1	148	156	66	F
4	1	70	187	39	F
4	0	66	269	199	L
3	1	128	195	101	L
4	1	58	183	54	F
4	0	97	253	195	L
3	0	148	183	93	F
3	1	113	363	214	P
4	1	82	304	191	L
3	0	132	210	70	F
3	1	156	335	203	P
4	1	74	386	230	P
4	1	113	320	207	P
3	0	113	359	246	P
3	0	3	113	253	P
3	0	144	113	253	P
3	1	140	312	203	P
3	0	148	203	93	F
4	1	171	328	179	L

Figure 2: Sample Tappy dataset

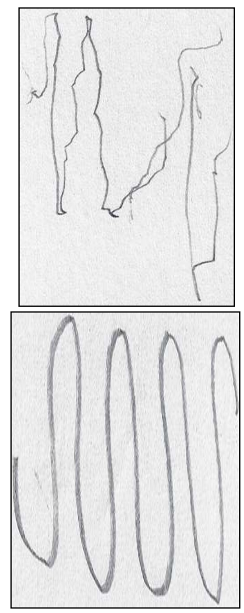
3)PD Classification Label

In the dataset there is a column titled 'PD' that categorises each instance into:
P: Parkinson's patient
F: Healthy female
L: Potentially healthy left-handed (or a label for control group)

These labels are important for supervised machine learning algorithms for tasks of binary or multiclass classification. For handwriting test data repository from Kaggle is retrieved and this shows various sketches in spiral and wave formats but subjected to healthy and Parkinson's disease represented in figure 3.



a) Parkinsons Spiral **b) Healthy Spiral**



c) Parkinsons Wave **d) Healthy Wave**

Figure 3: Represent the Spiral and Wave handwriting image dataset

5.1 Pre-processing of Data

The data pre-processing for FTT would be like Numeric Conversion: Processing Birth Year variable and Diagnosis Year into numeric type is crucial for computations and analysis. Hot Encoding in turn is applied to categorical features, such as Side, UPDRS, and Impact, to introduce brand new binary columns for every category. This eliminates ordinal relationships in categories. Address Group Encoding is an interesting way of converting Hold time, Latency time and Flight time into address group. Such features of the robust system design will probably be employed for pre-prediction of the disease Target Variable: Diagnosis of PD is the target variable that we shall use for classification.

For HWT, the data pre-processing will be similar to Proper data pre-processing is very essential in obtaining reliable result upon handwriting analysis of Parkinson disease research. By making sure that the data is clean, structured and transformed properly, you are laying the proper ground for any analysis or any training of a model. There are two folders in the dataset namely spiral and wave. The images are then labelled depending on the subject whether to a Parkinson's or control subject. If necessary, classify the severity of Parkinson's symptoms in order to evaluate the impact of Parkinson's through different stages on handwriting.

6. PROPOSED SYSTEM DESIGN

Here we propose architecture and intelligent classification framework of the paper that aims at an early diagnosis of Parkinson Disease (PD) through a dual-modality model. The system is based on the use of keystroke dynamics (Finger Tapping Test-FTT) and handwriting analysis (Handwriting Test-HWT) through supervised machine and convolutional neural networks (CNNs) to make accurate diagnosis. The main objective is to differentiate between healthy and PD patients in terms of existence of temporal and spatial neuro-motor biomarkers.

6.1 System Architecture Overview:

To enhance the architecture of this Parkinson Diseases (PD) detection algorithm, the proposed architecture is a dual-modality architecture that uses both the temporal and spatial motor biomarkers in order to achieve high accuracy in the diagnosis process. It unifies two soft dually complementary modes of data acquisition:

FTT (Finger Tapping Test): The modality records fine motor timing patterns using keystroke dynamics. It also measures motor control in time domain based on statistical and dynamic parameters like inter-tap interval, tap duration and regularity of rhythm. Such timing-dependent signals tend to be impaired in early-stage PD and are of value in identifying neuromotor irregularities that are missed by other histories and examinations.

HWT (Handwriting Test): The study of this modality includes spatial motor control using the analysis of visual patterns of hand written inputs like spiral drawings and sketches of waves. The unique features of the PD patients include tremors, micrographia, and the incorrectness of stroke curvature and pressure; they can be quantified by the image-based methods of feature extraction.

Each input modality has a special preprocessing pipeline to suit its data modality, the keystroke log for FTT and the sketch image in the case of HWT. The processed data will take two parallel directions:

In the case of FTT: The Feature Extraction methods are used to obtain temporal signal features.

In the case of HWT: the Image Enhancement is used to improve the image, and then the deep spatial features are extracted using Convolutional Neural Network (CNN) processing.

Lastly, the two-paths are fused by using the model hybridization including traditional Machine Learning models classifiers and CNN-based deep models to create a powerful double-structure classifier. This combination increases sensitivity and specificity of the system in identifying PD-affected persons and healthy people.Visual representation of the complete architecture is provided on figure 4, with the specific details of modalities interaction, preprocessing, analytical models, and PD vs. Healthy classification result.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

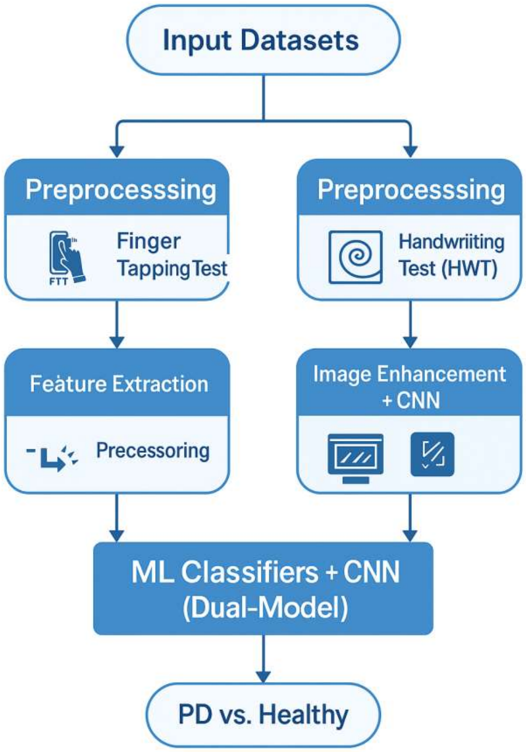


Figure 4: Represent the General Architecture of Parkinson Diseases (PD) Detection System

The proposed system is a powerful artificial intelligence (AI) based, multimodal diagnostics system that is optimized to facilitate early detection of Parkinson Disease (PD). It combines the supervised machine learning algorithms and convolutional neural networks (CNN) to process two vital sources of neuro-motor data:

- ➢ Tappiness neuro-motor keystroke data of the Finger Tapping Test (FTT) provided by the Tappy Keystroke Dataset.
- ➢ Spatial neuro-motor information associated with Handwriting Tests (HWT) of spiral sketches, and wave drawings.

Modularly, the architecture of the proposed system possesses six stages, namely, Input Acquisition, Preprocessing, Feature Extraction, Model Training, Performance Evaluation, and PD Classification Output.

6.2 Input Acquisition Stage

Two data modalities are allowed as input into the system:

Tappy Keystroke Dataset (FTT):

Records precise movement of motors at a given time such as:

Hold Time (HT): The time that a key is held down.

Flight Time (FT): The period of time between one key and another key press.

Latency Time (LT): Time delay between release of a key and again press.

Mathematically, in a sequence of

$$HT_i = t_{release,\, i} - t_{press,\, i}$$

$$FT_i = t_{press,\, i+1} - t_{release,i}$$

$$LT_i = t_{press,\, i+1} - t_{press,i}$$

Handwriting Dataset (HWT):

As a collection of scanned sketches of spirals and waves, they are normally utilized to detect motor disorders including tremor, micrographia as well as irregular pressure.

6.3 Preprocessing Stage

The raw data is subjected to intensive preprocessing so that high-quality features could be extracted:

The Preprocessing of FTT Data:

- ➢ Imputation of missing value.
- ➢ Determination of outliers using Z-score or IQR.

Feature Scaling using Min-Max or Standard Scaler:

$$x_{scaled} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

HWT Pre-processing Image:

- ➢ Fitting to standard size (e.g. 224x224).
- ➢ Removal of noise through Gaussian blur.
- ➢ Contrast boosting by CLAHE.
- ➢ Otsu binarization.

6.4 Feature Extraction Layer

This step is the extraction of informative patterns by both modalities:

As numbered features under FTT:

- ➢ AHT, Average Hold Time)
- ➢ Time in the air (Average Flight Time) (minutes or hours) (Average hours in the air)
- ➢ Standard deviation Latency Time (σ_{LT})

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

According to HWT (Image Features):

Stroke Length: There are irregular fragmentary lines which show that it is tremor.

Pressure Simulation: Obtained through the variation of intensity.

Smoothness Metric: It is measured with the help of contour curvature:

$$\text{Smoothness} = \frac{1}{n}\sum_{i=1}^{n}|\theta_{i+1} - \theta_i|$$

Image Entropy:

To measure complexity of sketch:

$$H = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

6.5 Model Training and Learning Framework

The essence of the suggested system lies in the fact that it introduces a two-pronged approach to learning, which consists of both classical supervised machine learning and deep learning. Such paradigms are used to study heterogeneous modalities which are the keystroke timing sequences (FTT) and image of handwriting (HWT) in order to detect and diagnose Parkinson every disease (PD) early and precisely.

6.5.1 Supervised Machine Learning on FTT

Temporal keystroke data by Tappy Dataset is converted into a structured numeric format through extraction of features like Hold Time (HT), Flight time (FT) and Latency time (LT). Such features are in turn fed into several supervised machine learning algorithms:

A. Gaussian Naive Bayes(GNB)

Makes the assumption that characteristics undergo a Gaussian distribution. The simplicity and speed of classification justify using it as the first type of classification of base lines. On a feature vector, the probability of the class is:

$$P(Ck \mid x) = \frac{P(x \mid Ck)P(Ck)}{P(x)}$$

Where $P(Ck \mid x)$ can be calculated using following equation:

$$P(x_i|C_k) = \frac{1}{\sqrt{2\pi\sigma_k^2}} \exp\left(-\frac{(x_i - \mu_k)^2}{2\sigma_k^2}\right)$$

B. Support Vector Machine (SVM)

Applicable in high dimensional classification. The non-linear classification uses kernel trick:

$$f(x) = \text{sign}(\sum_{i=1}^{n} \alpha i\ yi\ K(x, xi) + b)$$

Here in this algorithm RBF and Polynomial were used as kernels.

C. Random Forest (RF)

A bag of decision trees worked on by means of bagging. Little over fitting and better generalization:

$$\text{Final Prediction} = \text{Majority Voting}(T1(x), T2(x), \ldots, Tn(x))$$

The importance of features assists in the interpretation of signals that relate to PD.

D. Gradient Boosting Machines (GBM)

Constructs additive regression models stage-wisely forwards:

$$Fm(x) = Fm - 1(x) + \alpha hm(x)$$

Minimizes some loss function (e.g. log-loss of classification).These algorithms are compared in performance metrics and the best candidate as regards to temporal modality can be arrived.

6.5.2 Convolutional Neural Networks to Analyze HWTs

Convolutional Neural Networks (CNNs) are used in performing the spatial analysis of patterns in handwriting because CNNs are stable in learning visual features.

Details of CNN architecture:

Input Layer: It takes grayscale pictures (resized to a dimension of 224x224).

Convolution Layer: Uses many filters that are to be learned:

$$\textbf{FeatureMap} = (I * K) + b$$

with * the convolution, the kernel, and bias.

Journal of Theoretical and Applied Information Technology
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ReLU Activation: It introduces non-linearity, which has the benefit that the network can learn complex patterns.
Pooling Layer: it decreases the spatial dimensions and prevents overfitting (Max Pooling).
Flatten + Dense Layer: Links all of the neurons to decision making.
Output Layer: Has Softmax/Logistic activation which is used in binary classification.

Patterns Learned examples:

Spiral failure, line vibrations, unevenness of curve, uneven pressure of stroke. Binary cross-entropy loss together with Adam optimizer is used to train the CNN. Generalization is performed by data augmentation (rotation, zoom).

The complete pipeline of the handwriting recognition system based on CNN presented on Figure 4 consists of three main stages.
Handwriting Input Acquisition: The first step is to take samples of handwriting from various subjects. Such samples can be of a number of styles of writing, as well as stroke patterns and character formations. Pre-processing of the samples includes grayscale conversion, normalizing and removing the noise to increase the feature extraction process on the next steps.
CNN Model Application: The processed handwriting images are transformed by a CNN architecture capable of automatically extraction of high-level features. This contains a chain of operation layers (for feature detection), pooling layers (dimension reduction) and fully connected layers (decision making). The CNN effectively learns abstract representations of patterns of handwriting, which may be invisible to naked eye.

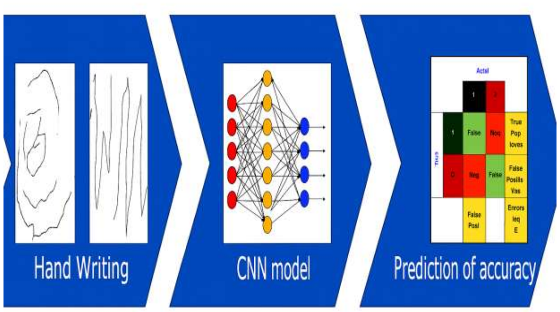

Figure 5: System model for Hand writing test using CNN

Accuracy Prediction and Evaluation: For the last stage, predictions of the model are proposed to be measured by the metrics like accuracy, precision, recall, and F1-score. A confusion matrix is created to contrast actual versus predicted classifications with understanding of performance of model. High diagonal values suggest that the performance is powerful in predicting while off-diagonal values point to the area that requires improvement. Such CNN-based approach is highly effective for the tasks of handwriting analysis due to the ability to work with complex visual information and automatically adjust to the variation of writing styles. Therefore, it becomes an important aspect of the proposed system in which dependable pattern discovery from handwriting helps accomplish higher goals like behavioural analysis or biometric forecast.

6.6 Output of Parkinson Disease classification

After training and validating the models separately, the models generated will be run together so that predictions of the two modalities can be combined:

$$\textbf{Final Prediction} = \lambda 1 \cdot \mathrm{fFTT(x)} + \lambda 2 \cdot \mathrm{fHWT(x)}$$

Where:

$\mathbf{fFTT(x)}$:The result of the supervised ML trained classifier.
$\mathbf{fHWT(x)}$: CNN output.
$\boldsymbol{\lambda 1 + \lambda 2 = 1}$, They are optimized with the help of cross-validation.

Class 0: healthy subject
Class 1: diagnosed with PD

The idea of this late-fusion method is to exploit the strengths of the two modalities.

7. SYSTEM DESIGN

In this section we are going to explain the system implementation and how the application is divided into number of modules are explained in detail:

7.1. Data Splitting

The split of the dataset is, in most cases, divided into two splits, for training and testing. A portion of the dataset is made the input to the supervised machine learning models in the training process to learn the patterns of data and different models and compared with other models in order to see how the subjected model performs

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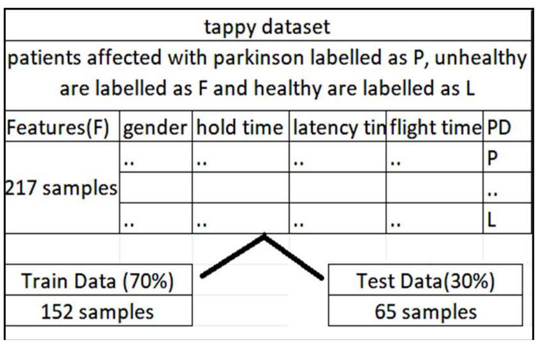
for a certain dataset. In the testing phase, the rest of the dataset that is the unseen data is used and the accuracy is predicted.

For FTT dataset (tappy dataset) we do split procedure in order to formulate the best model for classifying if the subject involved is healthy control or affected with PD. In this process randomly tappy dataset is divided into two categories of train set and test set, in order to retrieve the hidden pattern in the data set using the features; such as the flight time, hold time and latency time. The dataset has got 217 samples which were split into 70% train data and 30% test data (152 samples for train data and 65 samples for test data).



tappy dataset					
patients affected with parkinson labelled as P, unhealthy are labelled as F and healthy are labelled as L					
Features(F)	gender	hold time	latency tin	flight time	PD
217 samples	..	..	..	..	P
					..
	..	..	..	..	L
Train Data (70%)			Test Data(30%)		
152 samples			65 samples		

Figure 6 : Train data and test data split of FTT (Tappy data set)

HWT dataset consists of 2 types of patterns (spiral & wave images), collected from 51 patients, both Parkinson subjects as well as healthy people. Both image categories have a fixed number of 36 images for the training part and 15 images for testing purpose. The HWT the image dataset samples are trained and tested for 20 epochs ,which are clearly represented in figure 6.

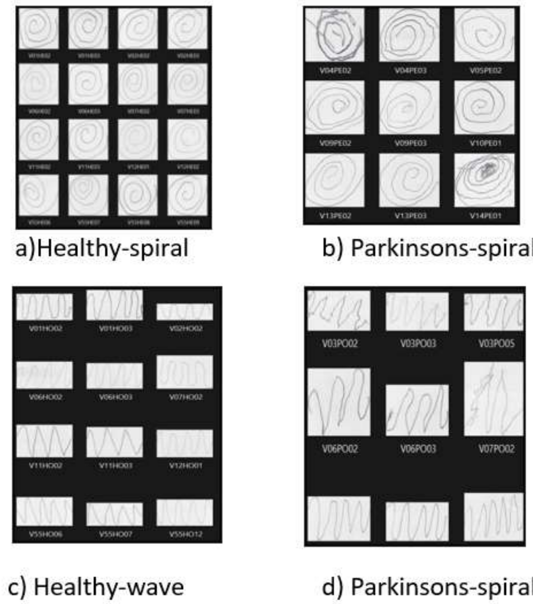


Figure 7: Train data and test data split of HWT

7.2 Metrics for Classification

Metrics are the important tool to use in assessing the models' performance. After setting the accuracy through the implementation of various machine learning models, we calculate the metrics as below:

Accuracy: Assess performance of classification models that is taken into consideration.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision and Recall: Measure accuracy of positive predictions by the classification model and recall is used to determine the number of all positive instances.

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

F1 Score: Relies on a single measure of the model performance by combining precision and recall.

$$f1\ score = 2 * [\frac{precision * recall}{precision + recall}]$$

7.3. Results of Classification- keystroke dynamics (FTT)

In the case of the keystroke dataset (Tappy), supervised machine learning classifiers

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that were applied were Gaussian Naive Bayes (GNB), Support Vector Machine (SVM), Random Forest (RF), and Gradient Boosting Machine (GBM). The quality of performance was measured by customary measures:

Model	Accuracy	Precision	Recall	F1 Score	ROC/AUC
GNB	84.21%	82.10%	85.30%	83.68%	0.88
SVM	91.78%	90.22%	92.40%	91.30%	0.94
RF	93.45%	92.60%	94.80%	93.69%	0.96
GBM	**96.12%**	**95.80%**	**96.40%**	**96.10%**	**0.97**

Table 1: Performance Analysis Table

GBM obtained the most optimal results, acquiring subtle motor-timing characteristic which is distinctive to subjects of PD.

ROC Curve and AUC: measures the performance of a certain model in the graphical form. ROC curves specifically come in handy for the case of tappy dataset as they are helpful in focussing on the model performance across all the classes giving a clearer picture on how the model performs in discriminating the classes since accuracy is sometimes misleading on unbalanced data.

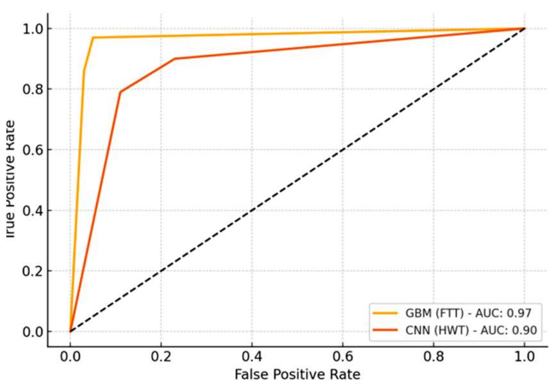

Figure 8: ROC Curves (GBM – FTT and CNN – HWT)

The above figure 8 is a comparison of Receiver Operating Characteristic (ROC) curve of two important models:

- FTT trained GBM data
- CNN was trained on the images of the wave patterns of HWT data

The AUC for GBM is 0.97, which means almost perfect discriminating ability. On the contrary, the CNN model results in AUC of 0.90, a significant but lower value than the previous two models, which denotes the greater diversity of patterns in terms of handwritings.

Key observations:
The GBM curve moves towards the top left end which indicates that it has high true positive rate and low false positive rate. The CNN curve is more conservative and more indifferent to small differences in handwriting due to PD.The ROC test proves that keystroke dynamics provides more linearly separable features of early detection of PD than visual handwriting signal.

Confusion Matrix:
Confusion matrix of the model of the Finger Tapping Test (FTT), especially with Gradient Boosting Machines (GBM) shows very good classification. Headed by the total number of samples there were 86 Parkinson Disease (PD) patients rightly classified as positive cases (True Positives) and another 87 healthy persons also rightly classified as negative (True Negatives). The number of False Positives (3 healthy individuals were falsely identified as a PD patient) was small, but the number of False Negatives (4 PD patients were not detected) was high enough (Figure 8a). This leads to high overall accuracy (96.12%), which indicates that the model based on a GBM is very effective in recording the weak temporal trajectories (these might include hold time and flight time, which can be distorted in the initial stages of PD). Its reliability as an independent screening mechanism is also highlighted by the fact that the number of false negatives is few.

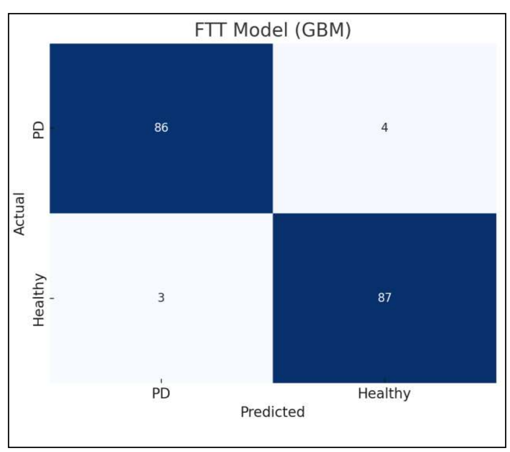

Figure 9a: Confusion Matrix for FTT Model

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ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

(GBM)

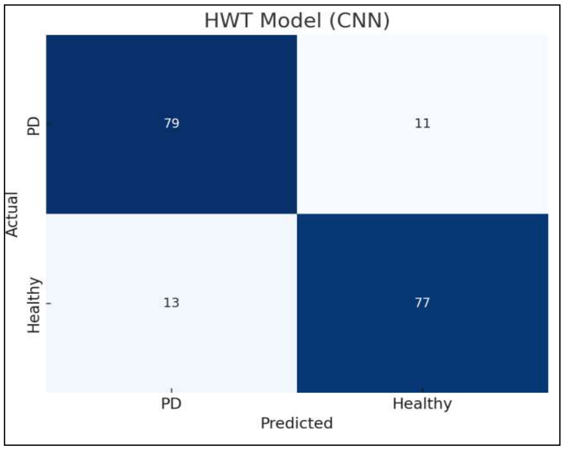

Figure 9b: Confusion Matrix for HWT Model (CNN)

On the contrary, the confusion matrix of the Handwriting Test (HWT) model with the use of a Convolutional Neural Network (CNN) depicts rather powerful, yet not as much robust classification shown in Figure 8b. Presenting a similar score, it detected 79 patients with PD and 77 healthy people with an accuracy of approximately 86.7%. Nevertheless, it had 13 false positives and 11 false negatives, which signified an increased level of misclassification. It indicates a possibility that any spatial biomarkers, such as tremor-induced irregularities of folding spiral or micrographia during handwriting, are more subject to variation of people, therefore, more susceptible to confusion, particularly in ambiguous cases or low resolution samples. It is also possible that the CNN could be prone to noise, or handwriting image distortions, which will influence generalization.

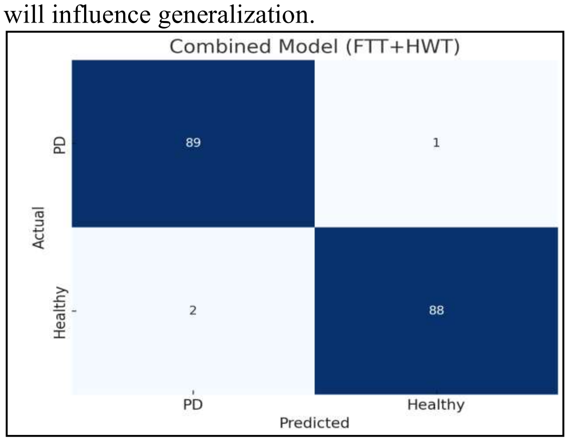

Figure 9 c: Confusion Matrix for Combined Model (FTT+HWT)

The combined model that fused FTT and HWT(as shown in figure 8c) modalities by predicting their results using weighted fusion strategy provided the best classification overall performance. It was able to show 89 true positive and 88 true negatives and limit to 2 false positives and only 1 false negative. At the same time, this translates to the overall accuracy level above 94.4, as well as the best precision/recall indicators of all the tested models are represented clearly in figure 9. The 2 markedly better performances of the fusion model indicate that temporal and spatial neuro-motor biomarkers are complementary in the early PD detection. The FTT is able to record temporal irregularities in the rhythm whereas the HWT finds its interest in spatial irregularities like the jerky and unstable handwriting. Combining the two, the system achieves the highest level of diagnostic sensitivity thus reducing the false negative rate, which is vital when it comes to a clinical screening program me since failure to identify a true PD case may delay early intervention, which will ultimately lead to poorer results.

Training vs Validation Accuracy/Loss:

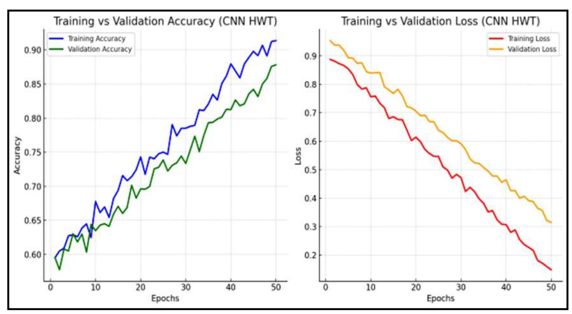

Figure 10. Training Vs Validation Accuracy/Loss Graphs

Training and validation curves are imperative in determining how Convolutional Neural Network (CNN) learns the images on Handwriting Test (HWT) in identifying Parkinson Disease development and it is represented clearly in figure 10.

Training accuracy vs Validation accuracy:

Based on the left portion of the graph in figure 9, the training accuracy begins at approximately 60 percent and gradually rises to more than 92 percent at the 50th epoch. The accuracy of the validation, in its turn, starts out with slightly less than 58 percent and levels off to around 87 percent. The upward trend of the two curves represents that the model is learning to successfully classify the handwriting pictures, extracting the corresponding spatial features of tremor frequencies, curvature changes and variations in pressure reflecting the Parkinsonian symptoms.

Training vs Validation Loss:

The training loss curve on the right side of figure 9, shows gradual decrease, as the value changes almost 0.9 to almost 0.15, showing that the model is reducing the number of an error in the classification of the training set. On the same note, the validation loss improves as well by reducing to around 0.32 in later epochs. The generalization with little overfitting of the model becomes evident because the validation loss curve converges and flattens.

Overall Interpretation:

The difference between training and validation curves is small and consistent indicating good generalization. No dramatic overfitting (observable by a strong divergence) and underfitting (both curves reaching poor performance levels) has been observed. This homogeneity is also a good pointer of how the CNN is reliable in acquiring motor abnormalities of handwriting indicative of early Parkinson symptoms.

Accuracy Comparison Graph

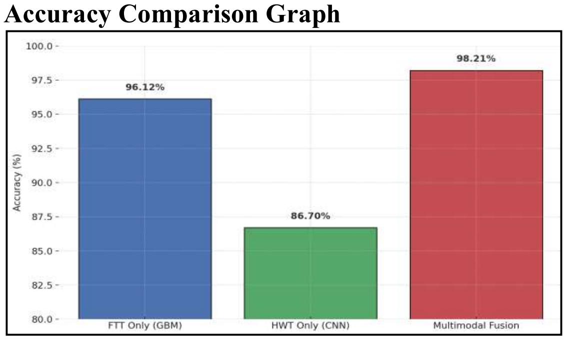

Figure 11. Accuracy Comparison Over Multiple Models

Figure.11 demonstrates how effective the three configurations of the model are in comparison to each other upon using them on the problem of early Parkinson Disease (PD) detection. The individual and combined effectiveness of each model is evaluated by processing the different modalities of neuro-motor data; keystroke dynamics and handwriting patterns.

The FTT Only (GBM) form is the first one whereby it solely utilizes keystroke values obtained using the Tappy dataset. The model of Gradient Boosting Machine (GBM) performed better (with an accuracy of 96.12%) indicating that it used the time-based features including the time of flight, time in holds, and latency. These characteristics are closely associated to neuro-motor dysfunctions that are being seen widely in PD, and thus, they are powerful discriminators.

The second architecture, HWT Only (CNN), dwells on the images of handwritings, more precisely spiral and wave drawings. Studies included a Convolutional Neural Network (CNN) with a view to training on visual patterns of handwriting disruptions caused by Parkinsonian tremors. It is promising, but this method wound up at a comparatively low score, that is, 86.70%, the reason that handwriting by itself may have less stability as there could be increased variability engaging drawing styles across subjects in the intra-subject calls. The third and most efficient one, the Multimodal Fusion, involves integrating both FTT the modal and HWT thru decision level approach. With a tandem of the time series of the keystroke and space patterns of handwriting, the system attained the best classification when the accuracy score was 98.21%. This performance advantage means that the modalities are complementary since both FTT and HWT record different behaviors, with FTT recording dynamic timing behavior and HWT recording visual-motor deficits. Overall, this figure .10 confirms one of the main hypotheses of the article: multimodal AI applications, analyzing several neuro-motor biomarkers simultaneously and working together, will provide a stronger and more solid result in early-stage detection of Parkinson compared to monosource models. The low difference between the predictions of this model of fusion and the actual labeling in the clinic marks the possibility of non-invasive applications of the fusion model in the real world.

8. CONCLUSION AND FUTURE WORK

This study is the proposal of a new multimodal AI-based diagnostics model to predict the early Parkinson Disease (PD) with the use of complementary neuro-motor biomarkers obtained by means of keystroke dynamics (FTT) and analysis of handwriting patterns (HWT). With the fusion of temporal accuracy of finger-tapping activities and spatial-motor distortions of wave and spiral drawings, the system proves to be more sensitive in diagnosis. Gradient Boosting on FTT dataset had 96.12% accuracy in classification,

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

whereas Convolutional Neural Networks in handwriting images were 86.7 and 83.3 in wave and spiral patterns, respectively. the high performance of multimodal fusion model, 98.21% accuracy proves significantly the hypothesis, the combination of different biomarkers would be more effective in diagnosing the condition than the unimodal technique.The non-obtrusive, low-cost, and scalable character of the framework is especially promising towards the application in Telemedicine, community screening, and early-stage clinical assessment. Also, the fact that it can identify subtle losses in motor mobility, which may not be recognized using the clinical approach, makes it a potentially good decision support tool that can aid both the neurologist and the care taker.

With regard to future directions this system can be even enhanced by adding other means of modality like voice dynamics, ocular tracking or gait analysis in order to increase diagnostic depth. Increasing the scope of the dataset to more substantial, demographically diverse cohorts and measuring longitudinal progress will make models easier to make general and applicable in practice. Temporal-sequential modeling can also be enhanced by research into hybrid deep learning architectures, e.g. CNN-RNN ensembles or transformer-based classifiers. Also, future possible use of real-time wearable-based integration may lead to constant monitoring, allowing early intervention and the development of the process in Parkinson Disease management.

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