

PARKINSON'S DISEASE DETECTION USING KEYSTROKE DYNAMICS AND WITH CONVOLUTIONAL NEURAL NETWORKS

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ABSTRACT

Parkinson's Disease is a progressive neurological disorder. It poses major challenges for early diagnosis because its initial symptoms are subtle and depend on subjective clinical evaluations. However, an early diagnosis becomes even more challenging because traditional methods have relied so much on costly medical tests and subjective clinical assessments that often fail to detect PD at its earliest stages when symptoms are minimal. In this respect, this study develops a deep learning-based framework for the automatic detection of Parkinson's Disease using keystroke dynamics collected from typing interactions. Keystroke timing features such as hold time and latency are excellent digital biomarkers for early PD identification since they carry fine-grained motor-control information. The paper proposes a deep learning system using Convolutional Neural Networks (CNNs) model that identifies users as PD or Non-PD based on real-world typing behaviours. The effectiveness of the suggested Pure 1D CNN model in identifying discriminative temporal patterns from keystroke data for Parkinson's disease detection is demonstrated by its 95.21% accuracy and 99% ACC value. Besides the deep learning model, machine learning algorithms were also implemented in order to compare the performance and confirm the robustness of the proposed system. This system aims to improve diagnostic accuracy by reducing dependency on expensive clinical procedures and enabling continuous remote monitoring.



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I. INTRODUCTION

Parkinson's Disease (PD) is a chronic, progressive neurological disorder which disturbs muscle control, movement and balance. In simple terms, PD is a brain disorder. The disease was first described in 1817 by British physician James Parkinson in his Essay on the Shaking Palsy [1]. More than 10 million [1] people worldwide are living with PD. Early identification is important for effective treatment and a better quality of life. Conventional identification relies on clinical observation, which can be time consuming and subjective. Recent work has shown that keystroke dynamics, combined with machine or deep learning models, can provide a non-invasive, inexpensive, and real-time method of detecting early signs of PD. This study focuses on investigating keyboard dynamics for typing patterns from users with and without PD using advanced deep learning techniques to improve accuracy and generalizability compared with and without the use of deep learning techniques.

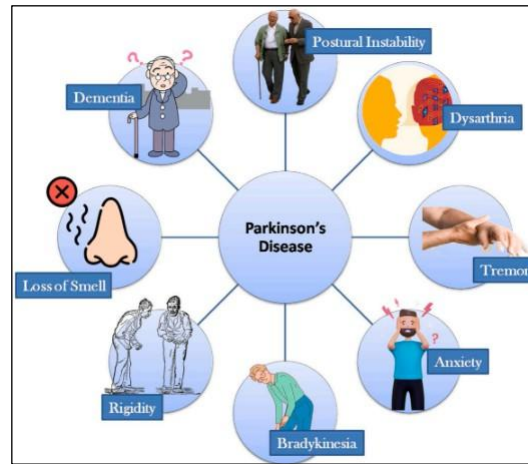


Figure 1: Parkinson's disease (PD) manifests itself in significant ways, both motor and non-motor.
Source: [1].

Parkinson's Disease happens mainly because of the gradual loss of dopamine- producing neurons in the substantia nigra, a part of the midbrain that help control movement. Normally, the amino acid tyrosine gets converted into L- DOPA, [2] which then turn into dopamine. This Dopamine is stored in synaptic vesicles of nerve cells and later released into the striatum to help manage smooth, coordinated muscle movements. In PD, these dopamine producing neurons slowly break down, leading to lower dopamine levels. As a result, communication between the substantia nigra and the striatum is affected, causing symptoms like tremors, stiffness, slow movements, and balance issues.

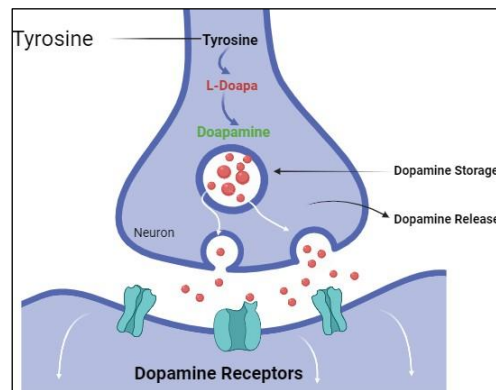


Figure 2: Process of Dopamine.
Source: Authors, (2026).

Effective and accurate detection of PD is key to improving potentially beneficial outcomes for the patient because early treatment can delay disease progression, improve quality of life, and improve symptom management. The typical approach to diagnosis still primarily relies on clinical evaluations and somewhat subjective measures, resulting in delays and uncertainty in diagnosis. Recent advances in technology have provided a novel opportunity for non- invasively and data-driven detection of PD. These techniques include voice signal analysis, handwriting assessments, computer vision, and typing pattern and keystroke dynamics, all of which have shown evidence of identifying prodromal signs of PD. These approaches have incorporated machine-learning or deep-learning models to extract patterns and features related to the physical and cognitive impairments associated with PD. Keystroke dynamics and typing pattern analysis have received particular attention for their relatively low cost, accessibility, and ability to monitor patients in the real world without specialized equipment. Similarly, voice signal analysis provides the ability to assess cues in vocal and speech production, while handwriting and touch-screen-based assessment can provide information on fine motor skills. The structure of this paper is as follows: In Section 2, there is a thorough survey of the related literature, presenting research and methods that are relevant to this particular task. Section 3 discusses and explains the experimental results and analysis of their performance. Section 4 presents the conclusion and future research that could further improve this particular proposed work. Section 5 concludes this research with a comprehensive list of related references cited throughout this particular research paper.

II. RELATED WORK

Recent investigations into the identification of Parkinson's disease have employed diverse data modalities to assess the motor and cognitive deficits characteristic of the condition. Existing research, depending on the data type employed, can be generally divided into three primary categories: datasets derived from typing patterns, detection methods utilizing voice signals, and handwriting-based detection techniques. This section will examine representative studies from each of these categories, emphasizing their respective contributions and inherent limitations.

II.1 TYPING PATTERNS

Keystroke dynamics, a non-invasive and economically viable approach, has garnered considerable interest. These techniques examine temporal characteristics, including key hold time, flight time, and latency, to detect atypical motor activity. Numerous investigations have leveraged publicly accessible datasets, such as the Tappy Keystroke Dataset, which captures typing behaviour during routine smartphone use. Machine learning and deep learning models, encompassing support vector machines, random forests, and convolutional neural networks, have been utilized to extract distinguishing temporal patterns from keystroke sequences. Despite the continuous monitoring and high user convenience offered by keystroke-based methods, challenges persist in managing noisy data, inter-user variability, and the constraints of limited dataset sizes. Iakovakis et al. (2018) sought to identify declines in fine motor skills in early Parkinson's disease (PD) by looking at natural typing patterns on touchscreen smartphones [3]. This effort was based on the need to observe subtle differences in motor function in an unobtrusive and frequent way, before other clinical motor symptoms are recognizable. They established a pipeline that analysed typing features based on keystroke timing values (hold time, flight time) and normalized pressure from short typing periods. Their classification method consisted of a two-stage multi-model fusion process: first separate models (for each keystroke variable) produced probability estimates, before fusing using a logistic regression meta-classifier to produce a final subject classification (PD vs control). They tested their method on a dataset from 33 subjects (18 early PD patients, 15 healthy controls), in which each subject typed on a smartphone for several short typing sessions. Their method resulted in AUC = 0.92, with a sensitivity ≥ 0.82 and a specificity ≥ 0.81 . They concluded that enriched keystroke dynamics (timing + pressure) combined through a multi-model fusion can discriminate between early PD patients and controls with strong performance and offer possibilities for passive screening through interaction with smartphones in everyday life.

Proposed a home-based, non-invasive screening tool for Parkinson's disease (PD) relying on keystroke dynamics [4]. They presented a set of features obtained from the time spent pressing and releasing keys on a keyboard while typing, and subsequently used these features to detect PD in an ecologically valid data acquisition context in the participant's home and no pre-defined task was required. The authors proposed a model that combines a new form of representation of keystroke dynamics signal using hold time and flight time series as an interactive function of type of key pressed and asymmetry in the hold and flight time series using a convolutional neural network. The results of their model indicated an Area Under the Receiving Operating Characteristic ranging from 0.80 to 0.83 on a dataset of subjects that interacted actively with their computer for 5 months. This approach has a positive comparison against state-of-the-art approaches previously tested with other forms of keystroke dynamics data captured with mechanical keyboard. Potekhin et al. (2023) conducted a study [2] to evaluate the ability to detect Parkinson's Disease (PD) from keystroke dynamics using machine learning algorithms. The authors used raw keystroke data from participants and extracted 378 features that represented typing behaviours. They built new models with Support Vector Machines (SVM), k-Nearest Neighbors (kNN), and Random Forest (RF) algorithms. They also used alternative feature selection approaches such as Minimum Redundancy Maximum Relevance (mRmR), RELIEF, and sequential forward selection (SFS) to improve feature selection.

They concluded that ensemble models using the most important features from each of the feature selection methods had accuracies anywhere from 81.08% to 100% with the greatest accuracies coming from models using the same selected features. In conclusion, the authors' research provides a clear indication of the promise for using keystroke dynamics as a non-invasive and straightforward approach for the detection of early PD. In a study by Liu et al. (2023), researchers examined the feasibility of using keystroke biometrics for early detection and clinical evaluation of Parkinson's disease (PD) [5]. Researchers gathered keystroke data from natural typing tasks using two datasets from PhysioNet, focusing particularly on alternating-finger tapping (afTap) as well as standard deviations of interkey latencies (IL SD) and release latencies (RL SD). They identified statistically significant differences for those parameters for de novo Parkinson's disease patients compared to controls, with sensitivity rates of afTap = 83%, IL SD = 88%, and RL SD = 96%. They also noted statistically significant negative correlations with typing speed and UPDRSIII (a Parkinson's disease clinical measure) in early PD patients for the number of words typed. Overall, the authors concluded that simple algorithms utilizing keystroke biometric parameters can be utilized as screening tests and reliable clinical status assessment tools. Tripathi et al. (2024), introduced a self-supervised learning based approach to identify Parkinson's disease (PD) using keystroke dynamics. [6]. This approach was motivated by the lack of labelled clinical datasets and the need for PD detection models that generalize to uncontrolled real-world environments. The authors proposed a new training objective that integrated Barlow Twins loss (to minimize redundancy of features within the same subject) and Dissimilarity loss (to decorrelate features across distinct subjects), teaching the encoder on unlabelled typing data, then fine-tuning the model on clinically validated samples.

The results indicated that the proposed approach demonstrated improved generalization compared to traditional supervised models, feature-engineering or pre-trained deep learning methods. Moreover, the authors concluded that self-supervised learning could utilize large volumes of unlabelled typing data to develop effective models for detecting PD without relying heavily on explicit labelled datasets. Roy et al. (2025) introduced a new way [7], to do ensemble classification to identify Parkinson's disease (PD) and the associated neural stress based on keystroke dynamics from modern active devices, prompted from a desire to provide serviceable early detection of PD in a non-invasive and easily accessible manner. The authors extracted features including the hold time for each key press and the latency between key presses and releases, and which they state are characteristics of motor control and cognitive processing. The authors' ensemble model is bootstrapped-based and homogeneous, allowing for improved predictability and addressing classes' imbalance. The authors utilized the NeuroQWERTY MIT-CSXPD dataset, a public set, and achieved noticeably better performance: for the full dataset AUC 0.86 (sensitivity 74.46%, specificity 82.13%), for de novo PD detection AUC 0.79, and while detecting early stage PD AUC 0.84. Overall, this ensemble classification approach shows comparable performance to other considering models, and highlights keystroke detection metrics as a potential scalable tool to assess PD in a naturalistic environment. Tat et al. (2025) introduced a novel approach to diagnosing Parkinson's disease (PD) by analysing keystroke dynamics through a soft, portable intelligent keyboard that leverages magneto elasticity to detect subtle pressure variations during typing. By [8] this method aims to provide an early and accurate diagnosis of PD, which is crucial for therapeutic interventions but remains a substantial challenge.

The intelligent keyboard converts continuous keystrokes into high-fidelity electrical signals, enabling the quantitative analysis of PD motor symptoms using machine learning. The system demonstrates high sensitivity, intrinsic waterproofing, and biocompatibility, with successful demonstration in a pilot study on patients with PD. Additionally, a customized cell phone application was developed to integrate the intelligent keyboard into a wireless platform, facilitating continuous monitoring of PD. This intelligent keyboard system's compelling properties position it as a promising tool for advancing early diagnosis and facilitating personalized, predictive, preventative, and participatory approaches to PD healthcare. Bagher et al. (2025) presented an innovative data-driven solution for the detection of Parkinson's disease (PD) via keystroke dynamics, addressing shortcomings of traditional rule-based approaches in managing large datasets and complex feature extraction [9]. In their paper, they examined two diagnoses pipelines procedure 1 used traditional machine learning models paired with features derived with Discrete Wavelet Transform (DWT) and Dynamic Time Warping (DTW) models, while procedure 2 used an end-to-end model with a real-time model where self-attention is built into the pipeline of processing. Their results demonstrate improved performance from both data-driven procedures, with the approach using DYTW and Extreme Gradient Boosting (XGB) reporting state-of-the-art outcomes, with ROC-AUC scores of 0.86 and 0.91 on the De-novo and Early-PD subsets of the neuroQWERTY dataset, respectively, exceeding the previously reported best scores of 0.85 and 0.80 between the two studies. In their recent study, Yang et al. (2024) presented MELPD-detector, a new method for Parkinson's disease (PD) detection using free-text keystroke dynamics (free-KD). By [10] the method is based on a multi-level ensemble learning (EL) architecture with adaptive data augmentation to mitigate class imbalance in PD ethnicity datasets. The EL architecture combines three base models that were augmented in three different ways in order to enhance generalization.

The overall method achieved a max of 99.8% accuracy across both free composition and transcription tasks, indicating very high robustness and generalization in different typing contexts. MELPD-detector was applied to the neuroQWERTY dataset that incorporates free-text keystroke data that is obtained from individuals, with and without PD. Overall, this manuscript illustrates the utility of free-KD as a potential non-invasive, and scalable detection mechanism for early diagnosis of PD. Sun et al. (2024) published a thorough review examining the role of digital biomarkers in the precision diagnosis and monitoring of Parkinson's disease (PD)[11]. This publication notes the increasing importance of digital biomarkers for the detection of early symptoms of PD, assessment of treatment effects, and guiding clinical medication. The review takes into consideration the different areas of digital biomarkers, focusing on assessment of motor function, responsiveness, and sleep quality. In addition, the review notes the advancements in digital health technology which have shifted the role of digital biomarkers in the management of PD. However, the authors did not identify specific algorithms, datasets, or accuracy metrics, as the authors were limited to what they already reviewed. The study conducted by Bahar et al. (2023) focused on utilizing machine learning models to identify Parkinson's disease (PD) through keystroke dynamics in a non-invasive and accessible way [12]. Fourteen sub-datasets were created according to the patients based on their current drug usage, disease severity, and gender. In total, 378 features were extracted from the keystroke data. There were several machine learning algorithms, including Support Vector Machines (SVM), kNearest Neighbors (kNN), and Random Forest (RF) were used to classify the data into four different sub-datasets.

To assess the feature importance in distinguishing PD, several feature selection techniques were used, including Minimum Redundancy Maximum Relevance (mRmR), RELIEF, and sequential forward selection (SFS). In addition, they used feature ensemble (FE) and model ensemble (ME) strategies in order to improve classification performance. The FE models produced accuracy ranges from 91.73% - 100% and the ME models produced accuracy (81.08% - 100%) built over the fourteen datasets. Roy et al. (2023) moved forward with a new subtheory to detect Parkinson's disease (PD) using keystroke dynamics while also addressing challenges associated with class imbalance in medical datasets [13]. The authors used homogeneous ensemble learning to balance training sets through the use of bootstrapping methods from the neuroQWERTY MITCSXPD dataset, which had both fixed-text typing and free-text typing data. In this study, conventional keystroke features (e.g. key hold time, inter-key latencies) were extracted and used to train classifiers. The ensemble learning model achieved an area under the curve (AUC) of 0.86 with sensitivity and specificity rates of 74.46% and 82.13%, respectively. Also noteworthy, there were higher AUCs for identifying early stage PD (83.81) than for de novo patients (79.83), indicating the potential for early diagnosis capability. Overall, this method is a robust, easy-to-use, and quick diagnostic tool for eHealth applications that can detect and manage PD at home environments, allowing for early detection and consequently better management of PD. In their 2024 article, Hazar et al. examine the feasibility of an early diagnosis of Parkinson's disease (PD) from non-invasive keyboard interaction data [14]. Their work explores data from the NeuroQWERTY MIT-CSXPD data, which contains the typing data from 85 individuals while they were typing sentences.

Using machine learning techniques, more specifically the Random Forest classifier, the study's authors identified a number of features, including keypress duration, key release time and pressed key, and found these features to significantly distinguish PD from healthy participants. Their model achieved an impressive 99.86% accuracy, demonstrating that typing data obtained during computer use can be used for early diagnosis of PD. The paper by Bernardo et al. (2022) presents a new version of SqueezeNet to detect Parkinson's disease (PD) using data generated from keypresses [15]. It addresses the growing body of literature demonstrating that unique non-invasive, efficient, & low-cost methods exist to conduct early-stage diagnosis for PD. A deep learning approach is applied, leveraging keypress data which is both easily collected & readily available. The authors used SqueezeNet convolutional neural network (CNN) and modified it for keypress patterns. Keypress patterns were transformed into spectrograms using Continuous Wavelet Transform (CWT). Using this data transformation, they have allowed the model to capture parameters associated with temporal and frequency dynamics intrinsic to typing. The dataset represents experiences of those with and without PD collected with a web app. Pre-processing for this data included standardization and synthetic balancing (SMOTE) of class imbalance. The modified SqueezeNet model attained 90% accuracy distinguishing PD patients from healthy controls according to typing patterns. The study conducted by Khaoucha et al. in 2024, titled Predicting Parkinson's Disease [16] from Typing Patterns Using Shapley Additive Explanations and Machine Learning, addresses the need for early and accurate detection of Parkinson's disease (PD) using non-invasive ways to improve diagnosis.

Current diagnostic methods are often made via clinical assessments, which can be subjective and lead to time lapses to disease diagnosis. The authors suggested an advanced predictive model to examine typing patterns to predict PD. They applied three sophisticated machine learning models: XGBoost, Random Forest, and Support Vector Machine (SVM). The authors tested model performance by evaluating metrics such as F1-score, accuracy, recall, and ROC AUC. All three machine learning models returned encouraging results, with accuracies over 80% in the testing set. XGBoost had the highest accuracy at 87% followed by Random Forest at 85% and SVM at 81.8%. XGBoost outperformed the other two machine learning models on all metrics in both testing and validating sets confirming its performance. With regard to feature importance, SHAP (SHapley Additive exPlanations) was utilized to understand the features used in the models. The "Hold" feature was particularly important with regard to the three models predictions. The study illustrates there is promise from using typing patterns along with advanced machine learning techniques and explainable AI methods such as SHAP with early and accurate diagnosis of PD. In their 2018 manuscript, Milne et al. introduce a new method to detect early Parkinson's disease (PD) from typing behaviour [17] using keystroke dynamics. Diagnosis of PD typically relies on complex models with large amounts of data, which require considerable resources to implement. The researchers sought to demonstrate that a simpler form of model could be valuable for detection of early PD using a few keystroke dynamics measures reflecting typing behaviour. The researchers developed a feature to capture the dynamic variation between subsequent keystrokes and then applied it to a univariate modelling approach which performed classification using $AUC = 0.85$ from only a few hundred keystrokes during typing behaviour. The authors ascertained that the approach was simpler and more effective than existing models, which typically rely on complex models and several continuous measures, capturing dynamic variation measures. The authors claim the simpler model approach reflects a balance of elegance, transparency and effectiveness, whereas existing approaches are based on significantly more complicated models.

The study conducted by Warwick R. Adams in 2017, named High-accuracy detection of early Parkinson's Disease using multiple characteristics of finger movement while typing, provides a unique opportunity to detect early Parkinson's Disease (PD) among individuals who have not yet received a diagnosis of PD, or to identify decrement of motor and mental function in patients with existing PD, without having to rely on subjective clinical assessments to make that determination [18]. In a conventional clinical setting, many factors can influence the detection of diminished motor or cognitive scale, including physical examination findings, family members' or the patient's perceptual biases, clinicians' potential biases, and so forth, which can lead to more uncertainties or delays in ordering testing or definitive diagnosis of early PD. The authors therefore sought to develop first-stage predictive model using typing data to assess for early PD using a novel composite measure of keystroke patterns. To do this, the authors utilized multiple constituent keystroke features, including key press and release durations, inter-key press intervals, and keystroke rhythms, all of which was processed through an ensemble of several supervised machine learning classification models (e.g., support vector machine, random forest, neural network model). The authors compiled and used keystroke data from 103 individuals, of whom only 32 were subjects with mild severity of PD, while the remaining subjects were considered "non-PD" controls. The results indicated high levels of accuracy, yielding 96% sensitivity, 97% specificity, and AUC of 0.98, therefore, this systematic review study was able to demonstrate the potential for early PD detection without the need for specialized medical equipment or supervision.

II.2 VOICE SIGNAL-BASED DETECTION

Voice-based Parkinson's disease detection methods focus on analyzing speech impairments such as reduced loudness, monotonic pitch, and articulation difficulties. Numerous studies have used sustained vowel phonations and continuous speech recordings to extract acoustic features, including jitter, shimmer, and Mel-frequency cepstral coefficients (MFCCs). These features are then classified using machine learning models such as k-nearest neighbors, support vector machines, and deep neural networks. Voice-based detection techniques have demonstrated promising accuracy; however, their performance can be affected by environmental noise, recording conditions, and language dependency, which may limit their generalizability in real-world scenarios. In their 2023 study, [19] tackled the challenge of detecting Parkinson's Disease (PD) early, affordably, and noninvasively by focusing on voice signal characteristics, as vocal issues often appear before noticeable motor symptoms. They developed their model using the UCI Parkinson's voice dataset, which includes 195 voice recordings (147 from PD patients and 48 from healthy individuals), and employed both machine learning and deep learning techniques: K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Multi-Layer Perceptron (MLP). To enhance performance and address class imbalance, they utilized SMOTE (Synthetic Minority Over-sampling Technique), GridSearchCV for hyper parameter optimization, and SelectKBest for feature selection, although ultimately all features were used.

Their most successful outcomes were 98.31% accuracy with MLP and 95% accuracy with a tuned SVM. When compared to previous studies using the same dataset, their method surpassed many earlier models, some of which achieved accuracies between 90-93%. Their work is noteworthy as it demonstrates that integrating voice features with strong ML/DL techniques, along with oversampling and hyperparameter tuning, can significantly boost classification performance beyond many prior efforts on the same dataset. Suppa et al. (2022) sought [20] to examine if voice characteristics could distinguish Parkinson's disease (PD) patients from healthy subjects across different stages of the disease and treatment regimens, in order to support voice as a potentially non-invasive PD biomarker. They recorded the voices of 115 PD patients (including untreated early PD and mid-to-advanced PD patients treated with L-Dopa) and 108 healthy controls. They extracted the acoustic voice features of jitter, shimmer, and harmonic-to-noise ratio from the recordings, and used the Support Vector Machine (SVM) algorithm for classification and ROC curves for diagnostic accuracy. Their results showed high accuracy in the differentiation of healthy subjects from PD subjects, and in the differentiation of OFF L-Dopa from ON L-Dopa therapies. This work showed that voice abnormalities show up early and worsen with disease progression, and that L-Dopa improves but does not fully restore voice changes. They also described a novel "LR value" (from model output) that correlated with clinical severity to monitor disease progression. This work was important in supporting the potential for voice measures and machine learning.

Ahmed et al. (2022) sought to develop a machine-learning [21] algorithm to classify Parkinson's Disease (PD) from voice signal features, especially since speech and voice features are often affected in PD and represent a non-invasive diagnostic tool. The authors extracted multiple acoustic and spectral features from recordings of PD patients' voice samples (pitch frequency measures noise-harmonic ratios) and evaluated six different ML algorithms: Stochastic Gradient Descent (SGD) Classifier, Extreme Gradient Boosting (XGB), Logistic Regression, Random Forest, K-Nearest Neighbors (KNN) and Decision Tree. For training and testing, they used a voice dataset consisting of 147 PD and 48 healthy control samples, with an 80% train / 20% test split. In the results, Random Forest achieved the highest accuracy (97%) while XGB, KNN and Decision Tree achieved around 95% accuracy, different classifiers showed about 91% accuracy (SGD and Logistic Regression). Their work illustrated that among six classifiers tested, ensemble/forest methods (Random Forest) showed the strongest performance for PD based on voice, and demonstrated that applying rich features and strong classifiers can lead to excellent diagnostic accuracy.

II.3 HANDWRITING-BASED DETECTION

Digital tablets and smart pens are frequently used to record dynamic handwriting features, such as pressure, velocity, acceleration, and pen trajectory. Several studies have applied statistical analysis and deep learning models to distinguish Parkinson's patients from healthy individuals based on these features. While handwriting-based approaches provide detailed motor insights, they frequently require specialized hardware and controlled data collection environments, which may reduce their scalability and ease of deployment. nKasemsap et al. (2025) introduced a method using computer vision to evaluate Parkinson's disease (PD) through the assessment of the presence of bradykinesia (slowness of movement) from a finger tapping test [22]. This method uses an automated, non-contact assessment of motion as opposed to the traditional subjective visual inspection. Using a smartphone, they recorded 10-second videos of bilateral finger tapping, which they then analysed with the Google Media Pipe Hands software to extract hand/landmark features (e.g. amplitude, decrement, and differences between hands). Additionally, they trained six machine learning algorithms (Logistic Regression, Support Vector Machine, Random Forest, Decision Tree, LightGBM, and K-Nearest Neighbors) through a nested cross-validation process (5-fold outer, 3-fold inner) in an effort to rigorously tune the hyper parameters and evaluate the models.

Of the machine learning algorithms, Support Vector Machine (SVM) had the best model performance, achieving an average accuracy of approximately 0.84 to classify bradykinesia features between individuals with PD vs individuals in a control group. The main takeaway of this study is that the authors found that a computer-vision pipeline applied to videos with finger tapping exercises can fairly accurately assess the existence of PD in a person via bradykinesia, and therefore can produce a potentially scalable and contactless-bradykinesia screening tool that could be used as an adjunct to clinical assessment. Zhao and Li (2023) propose an original hybrid neural network model to evaluate handwriting [23] irregularities for detecting Parkinson's disease (PD). The model uses a three-layer Convolutional Neural Network (CNN) and a Bidirectional Gated Recurrent Unit (BiGRU) module to capture temporal and spatial features from handwriting tasks. The authors used samples from the NewHandPD dataset that contained drawings of spiral, meander, and circle tasks completed by PD patients and healthy controls. The proposed model reached accuracy scores of 92.91%, 85.71%, and 90.55% for the spiral, meander, and circle drawings, respectively, which is better than a variety of standard methods. Writing analysis with hybrid neural network architectures holds promise for a cost-effective and non-invasive way to assess and detect, as well as diagnose PD.

Table 1: Multi-Modal Dataset and Method Comparison for PD Detection.

Author	Dataset	Records	Attributes	Proposed Method	ML	DL	CNN	Depth wise CNN	Limitations
Iakovakis et al. [3]	Collected via custom Android app from smartphone	Not stated	Motor features	RF, SVM, GB, LR	Yes	No	No	No	Device variability
Tripathi et al. [4]	NeuroQWERTY	281	HT, FT features	CNN-based GEMASYMET	Yes	Yes	Yes	No	Population Bias
Potekhin et al. [2]	Tappy Keystroke, NeuroQWERTY MIT-CSXPD	47+	Timing stats	RF, CatBoost	Yes	No	No	No	Typing variability
Liu et al. [5]	Custom keystroke	281	HT, FT	RF, SVM, GB, LR	Yes	No	No	No	Device dependency
Tripathi et al. [6]	Multidataset KD	Varies	HT, FT	SSL-CNN (self supervised)	Yes	Yes	Yes	No	Domain shift
Roy et al. [7]	Tappy + MITCSXPD	Not fixed	HT, FT, Pressure	XGBoost Ensemble, SVM, Regression	Yes	No	No	No	Device heterogeneity

Tat et al. [8]	Custom IKS dataset	16	Timing + pressure	DT, RF, CNN with transfer learning	Yes	Yes	Yes	No	Very small PD sample
Bagher et al. [9]	neuroQWERTY	85	HT, FT	XGB, SVM, Linear, MLP	Yes	Yes	No	No	Small dataset
Yang et al. [10]	Multi-keystroke	Variable	Statistical + entropy	MELPD ensemble + CNN	Yes	Yes	Yes	No	Dataset heterogeneity
Sun et al. [11]	Multiple digital biomarkers	Large-scale	Multi-sensor	ML, DL	Yes	Yes	Yes	-	Lack of standardization
Bahar et al. [12]	PhysioNet – Tappy Keystroke	200+	HT, latency, FT	SVM, kNN, RF, Ensemble	Yes	No	No	No	Dataset Imbalance
Roy et al. [13]	neuroQWERTY + Colin Bannard	Not fixed	HT, FT, Pressure	XGBoost Ensemble	Yes	No	No	No	Device heterogeneity
Hazar et al. [14]	NeuroQWERTY	85	Pressed, HT, Release	RF, Bagging, KNN, XGB	Yes	No	No	No	Possible overfitting
Bernardo et al. [15]	Tappy Keystroke	200+	HT, FT, latency	Modified SqueezeNet, AlexNet, SqueezeNet, MobileNet V3	No	Yes	Yes	No	Small sample size
Khaoucha et al. [16]	Tappy Keystroke	200+	HT, FT, latency	RF, XGB, LGBM, SVM	Yes	No	No	No	Possible overfitting
Milne et al. [17]	Tappy Keystroke	200+	HT, FT, latency	Logistic Regression	Yes	No	No	No	Limited generalizability
Warwick R. Adams [18]	Tappy Keystroke	200+	HT, latency	LDA, SVM, Decision Tree, KNN, Ensemble	Yes	No	No	No	Only keystroke timing considered
Alshammri et al. [19]	UCI Parkinson's voice	195	22	SVM, RF, DT, KNN	Yes	No	No	No	Small, imbalanced dataset
Suppa et al. [20]	UCI Parkinson's voice	195	22	SVM, RF, KNN, DT, LR, NB, GB	Yes	No	No	No	Small sample, class imbalance
Ahmed et al. [21]	UCI Parkinson's voice	195	Acoustic features	RF, KNN, LR, XGB, DT	Yes	No	No	No	Limited dataset size
Kasemsap et al. [22]	Finger-tapping	100	Motion features	SVM, RF, etc	Yes	No	No	No	Motion blur, small dataset
Zhao and Li. [23]	NewHandPD	195	biomedical voice measure	SGD, XGB, LR, RF, KNN, DT	Yes	No	No	No	Limited dataset size

Source: Authors, (2026).

III. PROPOSED METHODOLOGY

In order to improve early diagnostic efficiency and lessen reliance on expert evaluation, this paper suggests a pure convolutional neural network-based method for automated Parkinson's disease detection using keystroke dynamics. The proposed system starts by gathering raw keystroke dynamics data from the Tappy Keystroke Dataset, which records users' precise typing habits. User metadata and keystroke log data are extracted independently and transformed into a structured Data Frame format for additional processing during the extraction and integration stage. After pre-processing, which includes data cleaning and noise reduction, the data is feature-selected to preserve the most pertinent keystroke characteristics.

The chosen features are normalized using feature scaling, and continuous typing sequences are converted into CNN-compatible input representations using fixed-length keystroke windowing. Subsets for testing, validation, and training are then created from the processed dataset. Next, using the training data, a pure convolutional neural network (CNN) model is created to automatically extract discriminative temporal patterns from the keystroke sequences. Standard performance metrics are used to evaluate the efficacy of the trained model. Lastly, the system classifies users as either Parkinson's disease (PD) users or non-PD users based on the learned features. Show Figure 3.

III.1 DATASET DESCRIPTION

This keystroke dataset supports a study on the detection of early Parkinson's Disease using multiple characteristics of finger movement while typing Figure 4. The dataset contains keystroke logs collected from over 200 subjects, with and without Parkinson's Disease (PD), as they typed normally on their own computer (without any supervision) over a period of weeks or months (having initially installed a custom keystroke recording app, Tappy). This dataset has been collected and analyzed in order to indicate that the routine interaction with computer keyboards can be used to detect changes in the characteristics of finger movement in the early stages of PD. Along with this Tappy dataset, several public datasets are also available, where the best reported model accuracy reaches up to 72.79%.

III.2 DATA HANDLING – DATA COLLECTION

The Tappy Keystroke Dataset is used to gather raw keystroke dynamics data at the start of the process. In order to identify neurological patterns associated with Parkinson's disease, this dataset captures users' typing behaviour, including key press and release events.

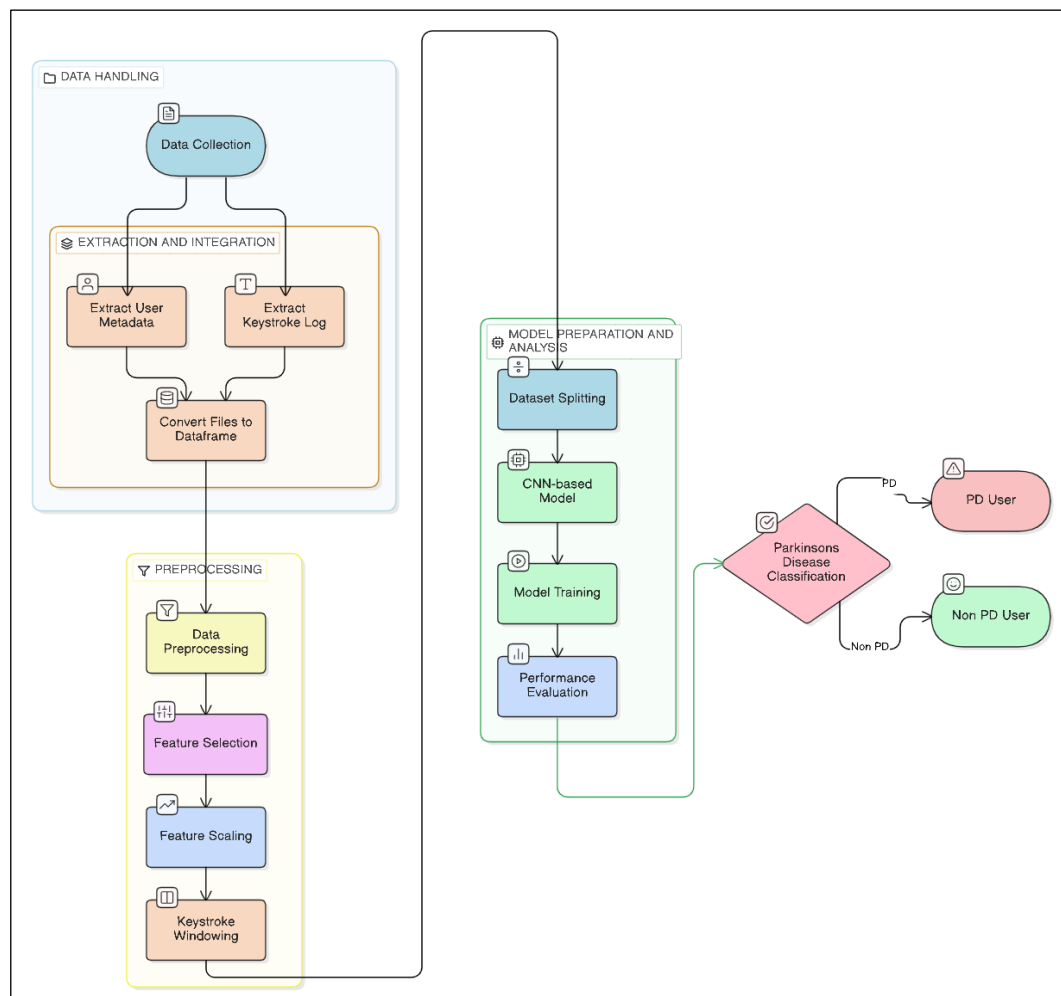


Figure 3: Proposed CNN Model Architecture for Parkinson's Disease Detection.
Source: Authors, (2026).

III.3 EXTRACTION AND INTEGRATION

In this stage, the raw keystroke data collected from the dataset is organized into structured components suitable for analysis. In order to link typing behavior to specific users, user metadata such as subject identification, age, gender, and class labels (Parkinson's disease or healthy control) are first extracted. The raw typing logs are then processed to extract keystroke log data that includes temporal typing characteristics like key hold time and inter-key latency. The fine-grained motor behaviour necessary for neurological analysis is captured by these timing features. Lastly, as in the suggested system, both metadata and keystroke logs are transformed into a DataFrame format, allowing for effective data manipulation, filtering, and feature extraction using Python libraries.

Extract User Metadata: The dataset is used to extract user-specific data, including subject ID, age, gender, and class label (PD/Healthy). As used in the proposed system's data loading phase, this metadata permits subject-wise grouping and guarantees that every keystroke sequence is accurately linked to its corresponding user and diagnosis label.

Extract Keystroke Log: Raw typing logs are used to extract keystroke timing characteristics, such as key hold time and inter-key latency. Fine-grained temporal motor patterns that are extremely sensitive to neurological conditions like Parkinson's disease are captured by these features.

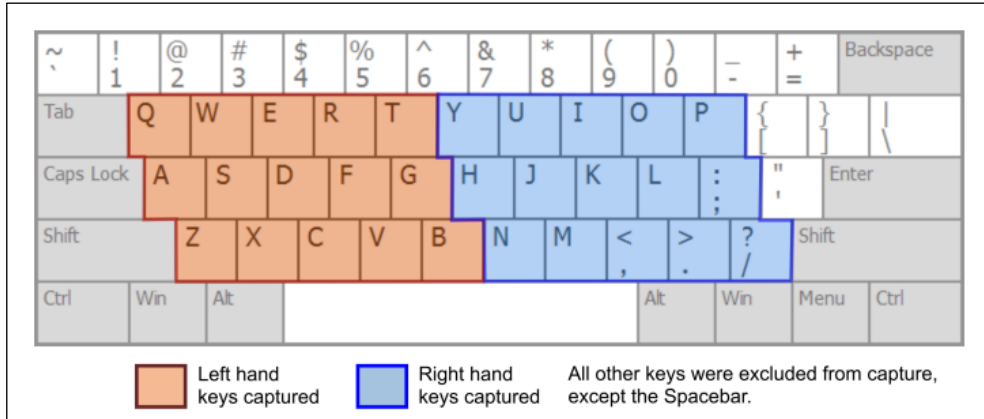


Figure 4: The areas of the keyboard included in keystroke capture.

Source: [18].

Convert Files to DataFrame: Keystroke timing logs and metadata are both transformed into a structured DataFrame format. The implemented code reflects how this representation makes it easier to use Python-based data processing libraries for effective filtering, aggregation, window construction, and feature manipulation.

III.4 PREPROCESSING

Several preprocessing steps are used to guarantee data consistency and enhance model reliability. Initially, data preprocessing is performed to remove noisy and incomplete records, handle missing values, and filter irrelevant keystroke events that could negatively impact model training. Feature selection is then used to reduce dimensionality and computational complexity by keeping only the most informative keystroke characteristics that aid in the detection of Parkinson's disease. The chosen features are then normalized into a common numerical range using feature scaling, which enhances CNN convergence and stabilizes gradient updates. Lastly, continuous typing streams are divided into fixed-length sequences for keystroke windowing. In this step, raw keystroke data is transformed into structured temporal inputs that are compatible with the proposed model's Pure 1D CNN architecture.

Data Preprocessing: To guarantee consistency and dependability of the input data, the raw keystroke dataset is refined during preprocessing. To avoid distorted temporal patterns impacting the learning process, records with incomplete, invalid, or missing keystroke events are eliminated. Furthermore, irrelevant keystroke entries that don't help identify Parkinson's disease are eliminated. Only high-quality keystroke sequences are sent to later stages thanks to this cleaning procedure. The suggested method lowers variance in the training data and enhances the CNN model's stability and generalization capacity by removing noisy samples early on.

Feature Selection: Then, the task of feature selection is employed to preserve informative keystroke attributes for Parkinson's disease. From the collected keystroke reads, we extract temporal typing dimensions like key hold time and inter-key latency as well as demographic information. Non-movement related features are removed. This focused selection constrains the dimensionality of the feature space, reduces redundancy, and avoids computational burden. Consequently, the CNN model is thus capable of learning beneficial discriminative temporal patterns rather than irrelevant variations, which helps better training efficiency and performance.

Feature Scaling: The chosen features are normalized to a common scale in order to guarantee numerical stability during CNN training. Feature scaling keeps attributes with larger magnitudes from controlling the learning process because keystroke features like latency and hold time may vary across different numerical ranges. By applying normalization prior to window construction, the suggested implementation enables the CNN to learn temporal dependencies consistently across all features. This stage contributes to quicker and more dependable training, stabilizes gradient updates, and speeds up the Pure 1D CNN model's convergence.

Normalization

$$X_{\text{normalized}} = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

Keystroke Windowing: It is not possible to feed the cleaned and normalised keystroke data straight into a CNN because it is a continuous stream of typing events. As a result, the keystroke stream is divided into fixed-length temporal windows using a windowing technique. Each window captures localised temporal typing behaviour by displaying a brief series of consecutive keystroke events. To maintain unique typing characteristics, these windows are built subject-wise. The resulting windowed sequences are transformed into a three-dimensional tensor format that satisfies the Pure 1D CNN architecture's input specifications.

As shown in the suggested methodology diagram, this transformation makes it possible for the CNN to efficiently learn temporal patterns linked to Parkinson's disease.

III.5 MODEL PREPARATION AND ANALYSIS

As shown in the suggested methodology diagram, the prepared keystroke sequences are sent to the model learning and evaluation stage after preprocessing and window construction are finished.

Dataset Splitting: Following keystroke windowing, the produced fixed-length keystroke sequences are arranged into a three-dimensional input tensor of shape (number of windows $\times$ window length $\times$ number of features), with matching class labels designating either Parkinson's disease or a healthy control. The dataset is divided at the subject level rather than at random at the sample level to guarantee objective and trustworthy model evaluation. This stops the same user's keystroke windows from showing up in both training and testing sets, which could otherwise result in data leakage and inflated performance outcomes. First, a training set and a temporary set are created from the entire dataset. CNN parameters, such as convolutional filters and dense layer weights, are learned from the training set. The temporary set is further divided into testing and validation sets. During model training, the validation set is used to adjust hyperparameters, track convergence, and stop early to avoid overfitting. The testing set is only used once to assess the performance of the final model and is kept entirely hidden during training. By ensuring that the CNN model is trained, validated, and tested on mutually exclusive data, this three-way splitting technique offers a fair evaluation of the model's capacity for generalization.

CNN-based Model: The suggested system uses keystroke dynamics data to automatically learn discriminative temporal patterns using a Pure One-Dimensional Convolutional Neural Network (1D-CNN). Each input sample is represented as a fixed-length sequence of keystroke events following preprocessing and windowing, maintaining the temporal order of characteristics like latency and key hold time. 1D convolution is especially appropriate because of this structured representation, which enables the model to capture both short-term and long-term variations in typing rhythm linked to Parkinson's disease by sliding convolutional filters across the time dimension.

$$y(t) = \sum_{i=0}^{k-1} x(t+i)w(i) + b \quad (2)$$

Several Conv1D layers make up the CNN architecture, which uses learnable kernels to extract local temporal features from keystroke sequences. Pooling layers, which lower dimensionality and improve robustness to slight timing variations in typing behavior, come after these layers. The model can learn intricate patterns by using non-linear activation functions. The learned temporal features are integrated and high-level representation learning is carried out by fully connected (dense) layers after the extracted feature maps have been flattened. Ultimately, an output layer with an appropriate activation function generates the class prediction, differentiating users with Parkinson's disease from those without. The model is effective and efficient for keystroke-based Parkinson's disease detection because its pure CNN design allows for end-to-end learning without the need for manual feature engineering.

Model Training: The suggested Pure 1D CNN model is trained using the prepared keystroke windows from the training set following dataset splitting. The Adam optimiser, which adaptively modifies the learning rate for each parameter based on first- and second-order moment estimates, is used in the implemented code to optimise the network parameters. This promotes stable learning and quicker convergence. During training, the CNN uses backpropagation to iteratively update convolutional and fully connected layer weights in order to minimise a classification loss function (binary cross-entropy). The model learns discriminative temporal patterns linked to Parkinson's disease by processing batches of windowed keystroke sequences during each training epoch. As shown in the suggested methodology diagram, training proceeds until convergence while validation performance is tracked to guarantee trustworthy generalisation.

$$L = -\frac{1}{N} \sum_{i=1}^N y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i) \quad (3)$$

III.6 CLASSIFICATION

A CNN-based classifier uses the extracted features to determine whether a subject is healthy or shows symptoms of Parkinson's disease. By enabling early and precise Parkinson's disease detection, this automated classification lessens the need for human clinical evaluation.

IV. RESULTS AND DISCUSSION

This part shows the experimental results from the proposed pure CNN-based system for finding Parkinson's disease and talks about how well it works. After preprocessing, feature selection, feature scaling, and fixed-length windowing, the model was tested using keystroke dynamics data. The dataset was divided into training, validation, and testing subsets to ensure unbiased evaluation.

Evaluation Metrix: Several common classification performance metrics are used to quantitatively evaluate the effectiveness and dependability of the suggested 1D Convolutional Neural Network (CNN) model for typing-pattern-based neurological condition detection. These metrics are widely accepted in medical and behavioural signal analysis and provide a comprehensive evaluation of the model's diagnostic capability.

Accuracy: By calculating the ratio of correctly classified samples to all samples, accuracy assesses how accurate the model is overall. It gives a broad idea of how well the model can differentiate between subjects who are afflicted and those who are healthy.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (4)$$

Precision: The ability of the model to accurately identify positive cases among all predicted positive samples is reflected in precision. When it comes to typingbased neurological disorder detection, high precision means that the model reduces false alarms, which lowers the possibility of misclassifying healthy people as afflicted.

$$\text{Precision} = \frac{TP}{TP + FP} \quad (5)$$

Recall: Recall (Sensitivity) evaluates the model's capability to correctly detect actual affected cases. In medical and health-related applications, a high recall value is especially crucial because it guarantees that the majority of true cases are successfully identified with few false negatives.

$$\text{Recall} = \frac{TP}{TP + FN} \quad (6)$$

F1-Score: When the dataset shows class imbalance, the F1-Score—the harmonic mean of precision and recall—is utilized to balance both metrics. It guarantees that the evaluation is not dominated by false positives or false negatives.

$$\text{F1 - Score} = 2 * \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (7)$$

ROC-AUC (Receiver Operating Characteristic-Area Under Curve): Additionally, the model's discriminative ability across various classification thresholds is examined using the ROC-AUC (Receiver Operating Characteristic – Area Under Curve) metric. A higher AUC value closer to 1 indicates strong separation between affected and non-affected classes.

$$\text{TRP} = \frac{TP}{TP + FN} \quad (8)$$

$$\text{FPR} = \frac{FP}{FP + TN} \quad (9)$$

The proposed 1D Convolutional Neural Network (CNN) was trained on keystroke dynamics data using five features: RightKey, Latency, Hold time, Age, and Gender. The model processes temporal sequences of length 200 using three convolutional blocks with batch normalization and max-pooling, followed by global average pooling and fully connected layers. The final architecture contains 45,057 parameters, of which 44,609 are trainable, making the model computationally efficient while maintaining high representational capacity. Training was conducted using class-weighted binary cross-entropy to address minor class imbalance. A learning rate scheduler progressively reduced the learning rate, enabling stable convergence and preventing overfitting.

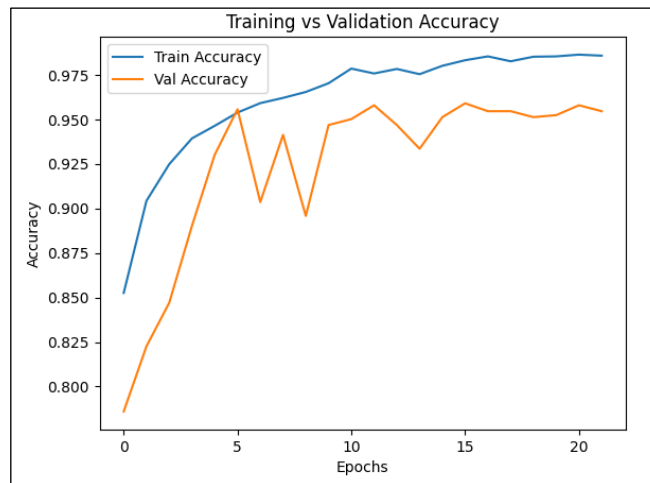


Figure 5: Accuracy Comparison of Training and Validation.
Source: Authors, (2026).

Training vs. validation accuracy and AUC figures show quick convergence in the first ten epochs. Strong generalization ability was demonstrated by training accuracy rising from 85.26% to 98.63% and validation accuracy stabilizing around 95–96%. In a similar vein, the Area Under the ROC Curve (AUC) reached 0.992 on validation data and continuously exceeded 0.99 for training. The inclusion of batch normalization and dropout layers further supports the close alignment between the training and validation curves, which indicates little overfitting. Minor fluctuations observed in validation accuracy during intermediate epochs can be attributed to the stochastic nature of mini-batch optimization and the temporal variability inherent in keystroke dynamics. The suggested model demonstrated exceptional discriminative performance with an overall accuracy of 95.21% and an AUC of 0.9928 on the independent test set of 1,503 sliding windows.

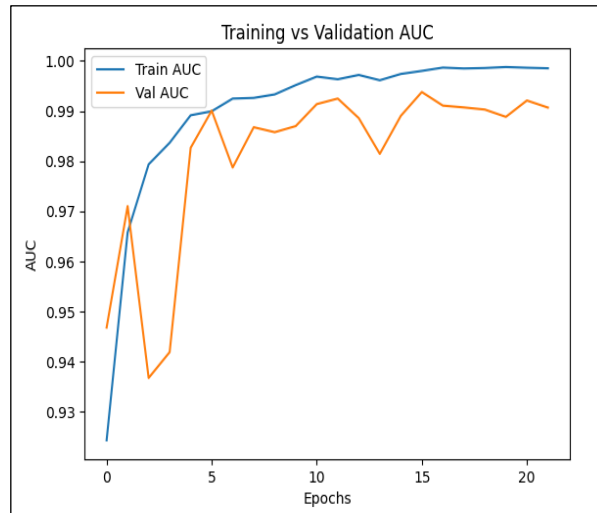


Figure 6: AUC Comparison of Training and Validation.
Source: Authors, (2026).

The detailed classification report shows balanced precision and recall for both classes:

Class 0 (Healthy): F1-score = 0.9512, Recall = 0.9683, and Precision = 0.9348

Class 1 (Parkinson's): F1-score = 0.9529, recall = 0.9370, and precision = 0.9694

These findings show that the model successfully reduces false positives and false negatives, which is important for applications involving clinical screening. There are only 23 false positives and 49 false negatives in the confusion matrix, which shows 702 true negatives and 729 true positives. The slightly higher number of false negatives highlights the intrinsic overlap in motor behaviour at early stages of the disease and suggests that a small subset of Parkinson's samples display keystroke patterns similar to those of healthy users.

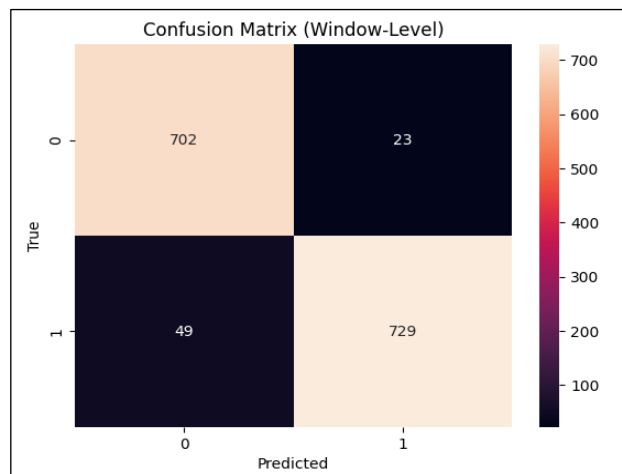


Figure 7: Confusion Matrix of CNN for Parkinson Decisise Detection.
Source: Authors, (2026).

However, the model exhibits strong robustness across a variety of typing behaviours, and the overall error rate is still low.

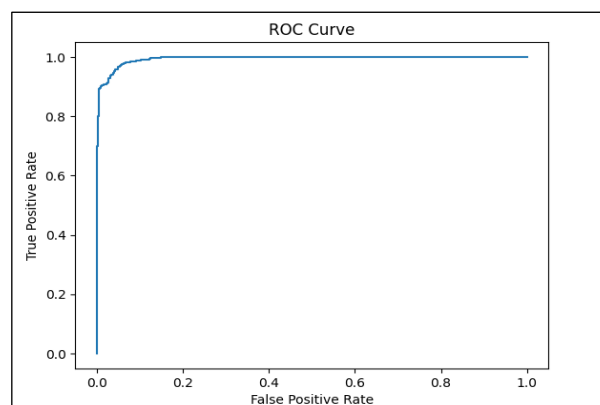


Figure 8: Roc curve for CNN model.
Source: Authors, (2026).

The ROC curve, which closely follows the plot's upper-left boundary, provides additional evidence of the model's efficacy. This indicates a high true positive rate even at low false positive rates, reinforcing the suitability of the proposed CNN model for early Parkinson's disease detection using keystroke dynamics.

Table 2: Summary of Keystroke Dataset Studies with Methods and Accuracy.

Author	Proposed Method	Accuracy
Potekhin et al.[2]	RF, CatBoost	76%
Roy et al.[7]	XGBoost Ensemble, SVM, Regression	79%
Yang et al.[10]	MELPD ensemble + CNN	93%
Bahar et al. [12]	SVM, kNN, RF, Ensemble	-
Bernardo et al.[15]	Modified SqueezeNet, AlexNet, SqueezeNet, MobileNet V3	90%
Khaoucha et al. [16]	RF, XGB, LGBM, SVM	85%
Milne et al. [17]	Logistic Regression	81%
Warwick R. Adams [18]	LDA, SVM, Decision Tree, KNN, Ensemble	-

Source: Authors, (2026).

V. CONCLUSIONS

I have complete careful and detailed analysis of various research papers for my area and literature, the appropriate dataset and approach for the detection of Parkinson's disease have determine. The Tappy keystroke datasets has been selected for implementation based on the study, and a deep learning technique using Convolutional Neural Network has been used for the disease categorization and key press dynamic modeling. The suggested strategy has undergone thorough testing and implementation. The applied CNN based model demonstrates a strong capacity to distinguish between normal typing behavior and patterns associated with Parkinson's disease, with an accuracy of 95.21% and an ACC value of 99%. The experimental study unequivocally shows that 99% accuracy been attained by the suggested method. The implementation process has specifically involved experimentation with various already-available techniques, which have helped draw key insights into the pre-processing, feature selection, and optimization of the proposed technique, resulting in its high efficacy and efficiency level.

VI. AUTHOR'S CONTRIBUTION

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