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RESEARCH ARTICLE

Parkinson's Disease Detection From Online Handwriting Based on Beta-Elliptical Approach and Fuzzy Perceptual Detector

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ABSTRACT The increasing age of our society is connected to a rising number of people suffering from disorders. One such disorder is Parkinson's disease (PD). Predictions indicate that the number of individuals affected by PD will more, than double in the future. Neurologists and data scientists consider handwriting as one of the motor symptoms of PD and recognize it as a valuable resource for detecting this disorder. Within this framework, we introduce an innovative system for Parkinson's disease detection, which encompasses several key stages. The process commences with data augmentation and preprocessing, subsequently leading to the segmentation of online handwriting into Beta strokes. Following that, feature extraction is carried out utilizing the Beta-elliptical approach and the fuzzy perceptual detector. Finally, we employ bidirectional long short-term memory (BLSTM) for the classification task. To assess the performance of our system, we created a new online Arabic handwriting dataset designed for detecting Parkinson's disease. The results we obtained affirm the efficacy of our proposed system. Through comprehensive evaluations conducted on the PaHaW dataset, we achieved good accuracy, thereby highlighting that our system surpasses the performance of existing systems.

INDEX TERMS Parkinson's disease, online handwriting, PD patients, healthy controls, Beta-elliptical approach, fuzzy perceptual detector.

I. INTRODUCTION

Parkinson's disease (PD) is a complex and chronic neurodegenerative disorder that primarily affects movement. The exact cause of PD is not fully understood, and it likely involves a combination of genetic and environmental factors such as air pollution, solvents and pesticides [1], [2], [3]. PD occurs due to the gradual deterioration of specific neurons in the brain that produce a neurotransmitter called dopamine. Dopamine plays a crucial role in regulating movement and

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coordination [4], [5], [6]. As dopamine levels decrease, individuals with Parkinson's disease experience a wide range of symptoms [7], [8], [9], including:

1) Tremors: Involuntary shaking or trembling of the hands, arms, legs, jaw, or face, usually when at rest.
2) Bradykinesia: Slowness of movement, making everyday tasks more challenging.
3) Muscle Rigidity: Stiffness of muscles, often leading to decreased range of motion and discomfort.
4) Postural Instability: Difficulty maintaining balance and an increased risk of falls.
5) Gait Disturbances: Changes in walking pattern, such as shuffling steps and decreased arm swing.
6) Non-motor symptoms: These can include cognitive changes, mood swings, sleep disturbances, constipation, and more.

Even individuals undergoing dopaminergic treatment or deep brain stimulation experience a decline as they age, and their mortality rate surpasses that of the broader population by a factor of two to three [10]. Moreover, it is expected that the number of people impacted by PD will surpass double going up from 4 million, in 2005 to 9 million, by the year 2030 [11]. The growing occurrence of PD is expected to have an impact, on healthcare systems due to the increased needs and reduced productivity commonly observed in individuals with PD. Consequently, PD has become a burden on society [12].

PD is known for its gradual onset, and symptoms can be subtle in the early stages. It's common for the symptoms of PD to go undetected or be mistaken for other issues until the disease has progressed to a point where they become more noticeable. This delay in detection is one of the challenges in diagnosing PD accurately in its early stages [13]. Indeed, the timely detection of PD in its initial phases holds pivotal importance, enabling the implementation of appropriate interventions to mitigate morbidity and alleviate the healthcare load among the elderly.

The diagnosis and treatment of PD can involve a range of procedures, and not all medical facilities are equipped to offer every procedure. The availability of diagnostic tools and treatment options can vary depending on the level of specialization and resources of the medical facility. Some procedures, especially invasive ones like deep brain stimulation (DBS) surgery, require specialized expertise and equipment that may only be available at certain medical centers or neurology clinics [14]. Considering the costs and complexities involved in some diagnostic methods along, with the risk of incorrect diagnosis, there is a pressing need, for an effective technique that provides reliable accurate detection of PD. Such a method would contribute to enhancing the well-being and quality of life of patients.

Changes in handwriting can be a sign of Parkinson's disease [15]. The act of handwriting involves skills, such as coordinating motor abilities, perception, precise motor control and planning movements. These abilities are notably affected by several neurodegenerative diseases like Parkinson's disease and Alzheimer's Disease that impact the brain's functioning. People, with PD have shown signs of dysgraphia or micrography which can be used as indicators to identify the likelihood or presence of the disease [16]. Therefore, the analysis of handwriting is widely acknowledged as a cost-effective and practical approach to detect PD in real-time.

There are two ways to capture handwriting data; offline and online. In the offline method, handwritten content on paper is captured using a scanner. In the online method, a specialized device like a graphic tablet is used to track sequential data such as pressure [17], [18]. In this present work, we focus on the online method.

Undoubtedly, the detection of PD using online handwriting poses several challenges and difficulties. One of the primary challenges lies in the variability in handwriting impairments [19]. In fact, PD affects individuals differently, and the handwriting impairments seen in PD patients can also vary widely. Some patients may exhibit micrographia (abnormally small handwriting), while others may show changes in the speed, pressure, or fluency of their handwriting. This variability makes it difficult to establish consistent handwriting features for PD detection.

Furthermore, Parkinson's symptoms, especially in its early stages, can be subtle and overlap with other conditions. Online handwriting analysis must distinguish between Parkinson's-induced motor impairments and those caused by other factors, such as cognitive decline, fatigue, stress or depression.

Another difficulty in the detection of PD using online handwriting tasks is the progression over time. In fact, the progression of PD can also be different for each patient, which means that handwriting impairments may change over time. This poses a challenge for the detection system as it needs to account for these changes in handwriting over time.

The small size of available datasets represents another difficulty for the detection of PD. In other words, there are a limited number of large, publicly available datasets of online handwriting from PD patients and healthy controls. This makes it difficult to train and evaluate machine learning models for PD detection.

As a result, the development of a new system becomes imperative to differentiate the online handwriting attributes associated with PD from those observed in the general elderly population.

The main contributions of our present work can be outlined as follows:

- A publicly available online Arabic handwriting dataset has been created, consisting of five tasks contributed by 30 PD patients and 30 healthy controls.
- The Beta strokes segmentation is adopted to segment the online handwriting.
- The Beta-elliptical approach [20], [21] and the fuzzy perceptual detector [22], [23] are adopted for the first time in the features extraction to the PD detection system.

The remainder of the paper is structured as follows. Section II takes notable research works on PD detection. Section III provides a comprehensive presentation of the dataset we have created. In Section IV, we thoroughly explain the methodology employed by our proposed system. Section V shows the experimental setup and performance evaluations. Finally, section VI states the conclusion and future impression of the proposed system.

II. RELATED WORKS

In recent years, there has been increasing interest in the application of biometrics in the medical field. Especially in the task of PD detection using online handwriting. In [24], Nolazco-Flores et al. proposed a novel PD detection using online handwriting. In their system, the authors introduce spectral and cepstral handwriting features alongside the previously utilized temporal, kinematic, and statistical handwriting features. Initially, temporal and kinematic features are computed based on displacement, statistical features (SF) are derived from displacement, horizontal and vertical displacement, while spectral (SDF) and cepstral (CDF) features incorporate displacement, horizontal and vertical displacement, and pressure. Given the limited size of the existing dataset, the authors balance the training set by augmenting the smaller class to match the larger one. Subsequently, both classes are augmented to enhance the training data for patients, with random Gaussian noise introduced in all augmentations. The next step involves selecting the most pertinent features using the modified fast correlation-based filtering method (mFCBF). Finally, autoML techniques are employed to train and evaluate over ten individual and ensemble classifiers. Regarding this work, while data augmentation can help address the limited dataset size, introducing random Gaussian noise may lead to artificially inflated performance metrics or overfitting, particularly if not carefully controlled.

In [25], Lamba et al. proposed a novel PD detection using online handwriting. To release their system, the authors extracted 29 kinematics features from the raw time-series data. Then, they used the genetic algorithm and mutual information gain feature selection methods to select the relevant features. Finally, they used Support Vector Machines, Random Forest, AdaBoost and XGBoost to evaluate the performance of their system. As a critical view of this work, while genetic algorithms and mutual information gain are commonly used feature selection methods, they may not always identify the most relevant features or could overlook important patterns in the data.

In the research study of Diaz et et al. [26], the authors have introduced a novel model that relies on one-dimensional convolutions and employs Bidirectional GRUs to discern unique patterns within the handwriting sequences of individuals with Parkinson's disease (PD) as well as those without the neurodegenerative disorder. Diverse sets of dynamic features, obtained from online graphomotor samples collected from both PD patients and control subjects, serve as the model's input. The convolutional layers, as part of the process, conduct sub-sampling and acquire proficient feature representations before forwarding the sequences to the Bidirectional GRU component of the network. One-dimensional convolution and bidirectional GRUs were used also in the work of Moetesum et al. in [27] for the purpose of detecting unique patterns within the handwriting sequences of Parkinson's disease (PD) patients. The model takes as input a collection of traditional spatio-temporal, pressure, and kinematic characteristics derived from the online graphomotor samples of both PD patients and healthy controls. Subsequently, the convolutional layers perform sub-sampling prior to training a stacked bidirectional GRU model. The convolutional neural networks is used also in the study of Diaz et al. in [28] to extract features from three representations which are raw images, median filter residual images, and edge images. The combined feature vectors extracted by the three CNN models were then fed into traditional machine learning algorithms which are support vector machines, random forest, AdaBoost, and ensemble similar.

Mucha et al. in [29] introduced an approach for identifying Parkinson's disease utilizing fractional derivatives derived from handwriting patterns. The study employed the PaHaW dataset [30] for its analysis. From this dataset, velocity, acceleration, and jerk measurements were extracted, and subsequent calculations were performed for mean, median, standard deviation (std), and maximum (max) values. Feature selection was carried out using Spearman's and Pearson's correlation methods. The classification task was performed with a random forest classifier, resulting in the attainment of the highest accuracy at 89.91%. As a critical view of this work, using a random forest classifier may limit the exploration of alternative classifiers that could potentially yield better performance or provide insights into the underlying data characteristics.

Impedovo et al. in [31] explored the utilization of dynamic handwriting features in the context of PD detection. In this investigation, a portion of the PaHaW dataset [30] was employed. Each feature underwent analysis and ranking through a linear SVM classifier based on its predictive accuracy, with only the features possessing higher-ranking attributes being retained. The classification task was performed using six distinct classifiers, leading to an accuracy of 74.76% achieved by ensemble classifiers.

For differentiating between healthy and Parkinson's disease individuals, Zham et al. in [32] extracted fourteen dynamic features. After that, they used the SPSS statistical tool to make a Spearman correlation coefficient analysis. Feature selection was carried out using the Relief-F method. For classification, they used the Naïve Bayes classifier. To evaluate their system, they created a new dataset containing three handwriting tasks and an Archimedean-guided spiral sketching. The best result is obtained with an accuracy of 93.30% using a spiral sketching task. Regarding this work, using a Naïve Bayes classifier may not fully exploit the complexity of the data or account for potential nonlinear relationships between features, limiting the discriminatory power of the classification model.

Kotsavasiloglou et al. in [33] introduced an automated system for detecting PD. In their proposed system, various features related to normalized velocity variability, velocity's standard deviation, mean, and signal entropy were extracted. Feature selection was carried out using the Weka tool, employing thirteen different feature selection methods. For classification, six classifiers were employed: naive Bayes, AdaBoost (J48), logistic regression, J48, support vector machine, and random forest. Through these classifiers, an average accuracy of 91% was achieved in the classification task using their own dataset, collected from 24 PD patients and 20 healthy controls, containing drawings of ten basic horizontal lines in both left-to-right and right-to-left directions from each participant. In another work, Drotár et al. [30] showed that kinematic and pressure features in online handwriting can be used for the differential diagnosis of PD. For classification, they compared three different classifiers which are K-nearest neighbors (K-NN), ensemble AdaBoost classifier, and support vector machines (SVM).

Detecting Parkinson's disease through online handwriting remains an ongoing challenge, despite the multitude of methods that have been proposed. These methods all share a common goal: the objective discrimination between individuals with Parkinson's disease and those who are healthy. Upon examining the existing literature, we have identified various technical deficiencies and limitations that have prompted the development of our proposed methodology. Specifically, the task of detecting Parkinson's disease entails the analysis of dynamic and continuous hand movements, a process for which current approaches often falter in accommodating the inherent variability in individual handwriting styles and speeds. These methods rely on simplistic feature representations that may fail to capture the subtle intricacies of online handwriting, consequently risking accuracy issues. Our proposed methodology seeks to rectify these technical shortcomings by presenting a more comprehensive solution that effectively addresses the complexities involved in Parkinson's disease detection, thus constituting a significant contribution to this advancing domain. In this research, we explore the utility of the Beta-elliptical approach, and the fuzzy perceptual detector as means of extracting features with the aim of precisely distinguishing between healthy and PD patients.

Indeed, the Beta-elliptical approach and the fuzzy perceptual detector are used for features extraction in various tasks like writer identification [34], [35], signature verification [36], [37] and character recognition [38]. In fact, the Beta-elliptical approach is based on a description combining two aspects: 1) Beta functions that characterize the velocity profile in the dynamic domain. 2) Elliptic arcs which characterize the handwriting trajectory in the static domain. Moreover, the fuzzy perceptual detector represents a common practice for examining handwritten documents by searching for the occurrence of special visual perception. In other words, these techniques are employed to extract features that characterize biometrical, kinematical, and graphical data, demonstrating their versatility in different applications within the realm of biometrics and document examination.

To the best of our knowledge, this is the first time where the Beta-elliptical approach and the fuzzy perceptual detector have been applied to the field of detecting Parkinson's disease. Furthermore, we are interested to use the Recurrent Neural Networks (RNNs), specifically Bidirectional Long Short-Term Memory (BLSTM), in the classification stage. Further details regarding our online Arabic handwriting dataset for analyzing Parkinson's disease and a comprehensive exposition of our proposed system will be presented in forthcoming sections.

III. PROPOSED ONLINE ARABIC HANDWRITING DATASET FOR PARKINSON'S DISEASE DETECTION

While the investigation of Parkinson's disease (PD) has garnered considerable attention from researchers, there are a lack of available databases for the evaluation of handwriting patterns. Additionally, our understanding of PD-related patterns is constrained and biased towards existing datasets [39]. To address this gap, we collected a novel online Arabic handwriting dataset, at the Neurology Department, Habib Bourguiba Hospital, Sfax, Tunisia, designed to detect Parkinson's disease. Through this initiative, we provide researchers with access to this dataset for exploration and study [17].

A. SUBJECTS

We recruited a total of 40 individuals diagnosed with Parkinson's disease for this study. However, only 30 of these PD patients were able to actively participate, as the remaining 10 were unable to complete the required tasks and were consequently excluded from the study. In summary, our online Arabic handwriting dataset for the analysis of Parkinson's disease comprised 30 individuals diagnosed with PD (16 women and 14 men) with an average age of 58 years, alongside 30 healthy controls (10 women and 20 men) with an average age of 60 years. Written informed consent was obtained from each participant.

All the individuals involved in this study are native Arabic speakers, right-handed, and have received a minimum of 6 years of education. None of the participants exhibited any psychiatric symptoms or had a history of illnesses that impact the central nervous system, except for Parkinson's disease. The healthy controls were selected based on rigorous criteria: none of them had Parkinson's disease or essential tremor, and they had no history of intracranial diseases or neurological symptoms or signs. Additionally, none of the participants had a history of alcohol or drug abuse, and none of the healthy controls had a family history of Parkinson's disease.

Table 1 presents the demographic information of the study participants.

During the data collection process, the neurologists at the Neurology Department, Habib Bourguiba Hospital, Sfax conducted various clinical assessments, including the Movement

TABLE 1. Demographic information of the study participants.

	PD patients	Healthy controls
Number (N)	30	30
Age (years, mean ± SD)	58±11.09	60±6.92
Range of age (min years -max years)	36-84	50-73
Men (N)	14	20
Women (N)	16	10

TABLE 2. Clinical data of PD patients.

MDS-UPDRS off (mean ± SD)		21.00±10.03
MDS-UPDRS on (mean ± SD)		10.73 ±7.84
Phenotypes (N, %)	TD	13/30 (43.33)
	PIGD	17/30 (56.67)
Disease duration (years, mean ± SD)		4.57 ±3.34
Hoehn-Yahr stage (N, %)	Stage 1	6/30 (20)
	Stage 1.5	10/30 (33.33)
	Stage 2	14/30 (46.66)

Disorders Society Unified Parkinson's disease Rating Scale (MDS-UPDRS), both during off and on periods [40]. Additionally, the neurologists identified the specific phenotypes of Parkinson's disease (PD) patients, categorizing them as either tremor-dominant (TD) or postural instability/gait difficulty (PIGD) subtypes [41]. Furthermore, crucial information such as the age of disease onset, disease duration, and the daily dosage of levodopa equivalent (LED) was meticulously recorded. The severity of PD was assessed using the Hoehn and Yahr (H-Y) stage, and PD patients underwent examinations in both "Off" and "On" periods, with assessments conducted one hour after their regular dopaminergic medication intake. At the time of the study, their symptoms were effectively managed, and they were not receiving any analgesic treatment. Additional details regarding the clinical data of PD patients can be found in Table 2.

B. DATA ACQUISITION SYSTEM

Our novel online Arabic handwriting dataset for the detection of Parkinson's disease was created by employing a Wacom digitizing tablet (Intuos Pro, model PTH-660). A custom-built software program, developed within the C# platform, was utilized for data capture, recording various signals which are x-position, y-position, and pressure. The output data from this tool is stored in a CSV file, containing these signals. Furthermore, the signals generated by the pen were converted into PNG images.

C. TASKS

During the data collection process, participants were seated in a comfortable chair with a seat height fixed at 45 cm. They were instructed to maintain contact between their elbows and a table positioned at a height of 80 cm. Notably, the chair and table heights were not adjustable. The concept involves requiring individuals to complete tasks that are anticipated to be challenging for PD patients. Participants were instructed to replicate five distinct handwriting tasks displayed on the right side of the digitizing tablet. The initial task involved manually tracing an ellipse repeatedly for thirty seconds. The second task entailed drawing a spiral. Task three involved writing the digit 8 five times. The fourth task required writing the Arabic word "لولو" two times. Lastly, the fifth task involved tracing the Latin character 'l' continuously eight times. Each participant completed the tasks at their own pace, with their handwriting speed and size being consistent with their individual preferences.

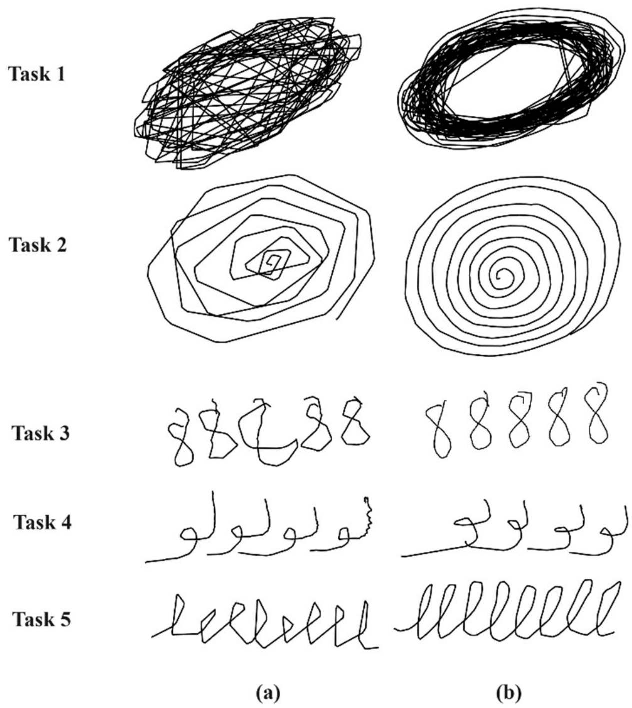

FIGURE 1. Examples of sample tasks executed by (a): PD patients during their "Off" periods, and (b): Healthy control participants.

Figure 1 showcases sample tasks executed by both PD patients during their "Off" periods and by healthy control participants.

IV. PROPOSED PARKINSON'S DISEASE DETECTION SYSTEM

The methodology addressed in this work consists of five main stages: data augmentation, preprocessing, segmentation, feature extraction, and classification. This methodology is summarized in Figure 2. Details of each stage are presented in the following subsections.

A. DATA AUGMENTATION

In general, the training dataset available for Parkinson's disease detection tasks does not adequately encompass the variations in hand movements. To overcome this problem, numerous researchers in many fields of research have resorted to the use of the data augmentation method to

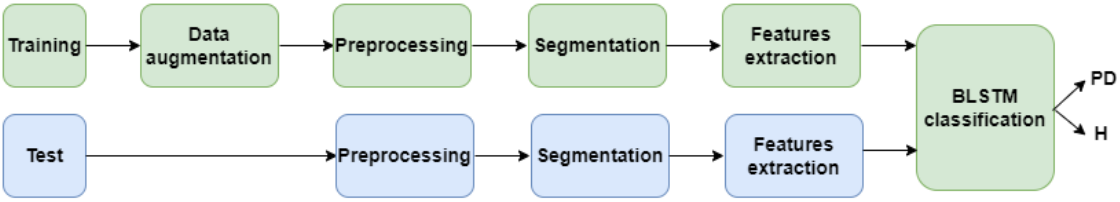

FIGURE 2. **The proposed Parkinson's disease detection system from online handwriting.**

develop more training samples and model the variation of a given person [42].

In the data augmentation phase of our work, we employed the approach described by Hamdi et al. in [43]. More specifically, we applied geometric techniques, encompassing the italicity angle, magnitude ratio variation, and baseline inclination angle. Figure 3 demonstrates the application of data augmentation on a spiral example extracted from our dataset.

B. PREPROCESSING

The pretreatment step involves the application of a low-pass filter to the input path. This is done to reduce the impact of noise and errors introduced by the acquisition system's temporal and spatial quantification. Specifically, we employ a Chebyshev type II filter with a cut-off frequency of $f_{cut} =$ 12Hz, which is aligned with the frequency ripple observed in handwriting. Next, a procedure of normalization is implemented to standardize the size of the handwriting by adjusting its height to a constant value of $h = 128$, while maintaining the same aspect ratio of length to height. To normalize each point along the hand movement trajectory, we calculate the normalized values (x_norm and y_norm) using the following equations:

$$x_{norm} = h.\frac{x - x\_min}{m} \quad (1)$$

$$y_{norm} = h.\frac{y - y\_min}{m} \quad (2)$$

where

$$m = max(max_x - min_x, max_y - min_y) \quad (3)$$

In these equations, (x, y) denote the original point coordinates, while (x_norm, y_norm) represent the coordinates after the normalization process. Figure 4 illustrates the preprocessing applied to an example of spiral extracted from our dataset.

C. SEGMENTATION

To segment the online handwriting, the initial step entails representing the curvilinear velocity using (4).

$$V_\sigma(t) = \sqrt{\left(\frac{dx(t)}{dt}\right)^2 + \left(\frac{dy(t)}{dt}\right)^2} \quad (4)$$

Following that, we distinguish between two types of points within $V\sigma(t)$:

- The double inflection point, denoting a speed change and signaling the shift from one neuromuscular subsystem to another or from one neurophysiologic impulse to the next.

- The local minimum, indicating the curvilinear velocity's local minima.

Afterward, the curvilinear velocity is partitioned into smaller segments referred to as Beta strokes. These strokes are defined by the presence of two consecutive local minima or double inflection points in the velocity profile. Following this division, the handwriting trajectory is further subdivided into strokes based on the corresponding points derived from the curvilinear velocity. Figure 5 illustrates an application of segmenting a spiral example taken from our dataset.

D. FEATURES EXTRACTION

We are keen on integrating the Beta-elliptical approach into our Parkinson's disease detection system. This choice is justified by the fact that the Beta-elliptical approach has the capability to effectively model hand movements by integrating both its constituent elements: the elliptic arcs and the Beta impulses [44], [45]. Consequently, the alignment between these two profiles enables a more precise characterization of online handwriting compared to alternative methods like the oscillatory and geometric approaches. As a result, we are able to derive numerous parameters that capture both the geometric and kinematic aspects, encompassing attributes representing smoothness, regularity, speed, fluidity, precision, and coordination. This allows for a more accurate representation of the intricate dynamics of handwriting, which can reveal subtle deviations associated with Parkinson's disease. Moreover, the Beta-elliptical approach lies in its ability to offer a comprehensive and nuanced analysis of hand movements, which can be indicative of motor impairments associated with Parkinson's disease. Furthermore, by leveraging the Beta-elliptical approach, your system can analyze hand movements in real-time. This capability is crucial for detecting immediate changes or fluctuations in motor performance, which may not be captured by methods relying on static or pre-recorded data.

Additionally, our goal is to incorporate the fuzzy perceptual detector to precisely depict the handwriting trajectory [22], [23]. The justification for utilizing the fuzzy perceptual detector in features extraction for a Parkinson's disease detection system stems from their

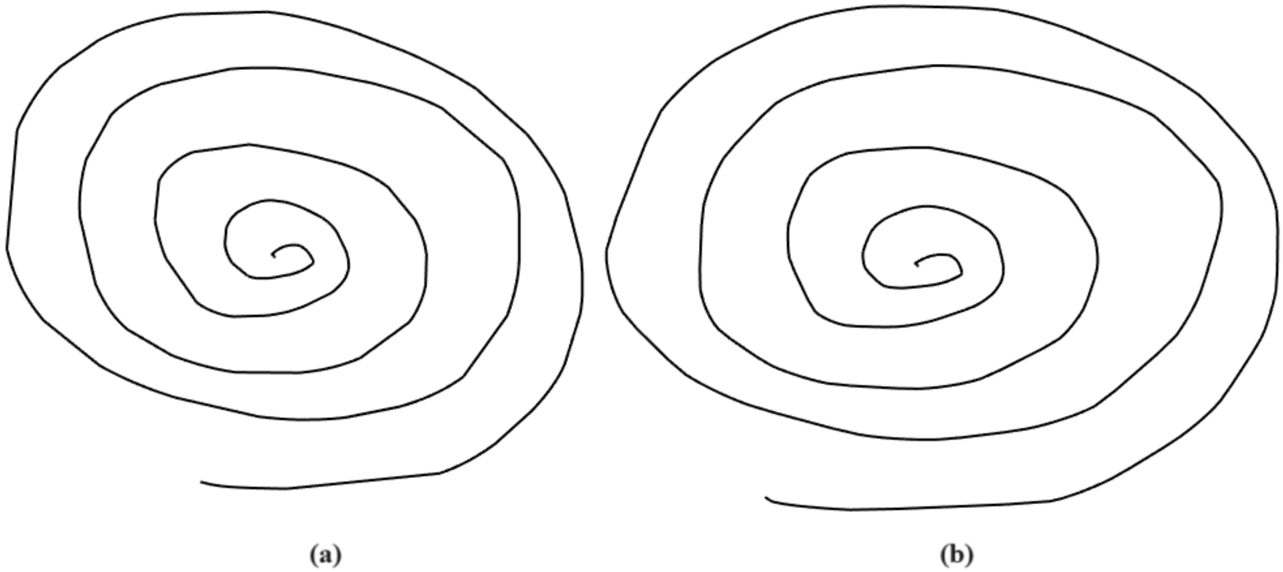

FIGURE 3. Application of data augmentation on an example of spiral extracted from our dataset. (a): original sample, (b) after applying the data augmentation method.

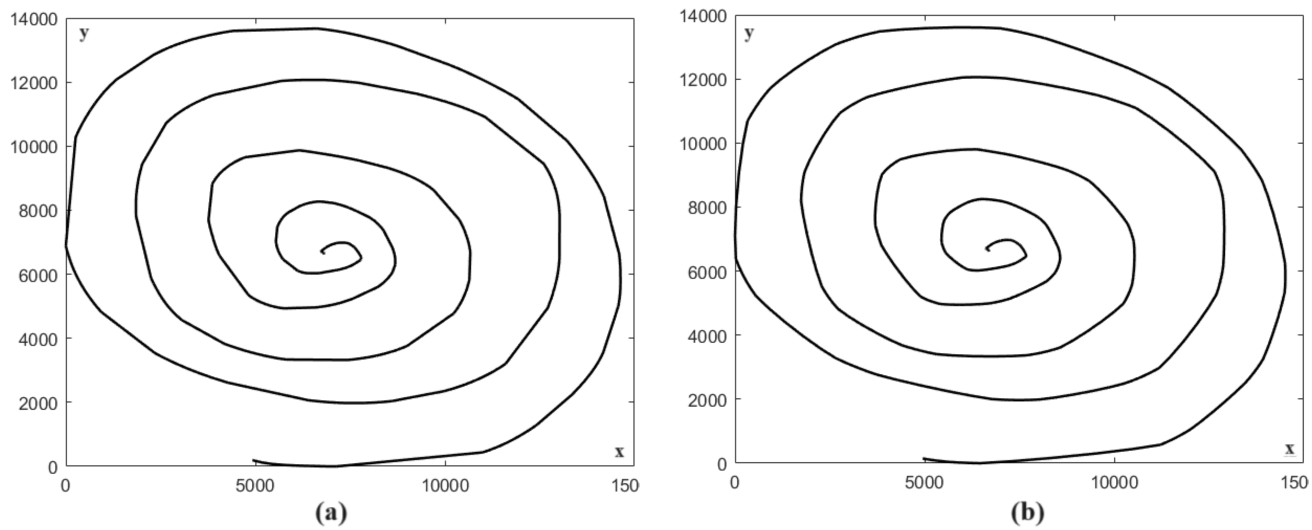

FIGURE 4. Application of preprocessing on an example of spiral extracted from our dataset. (a): original sample, (b) after applying the preprocessing method.

effectiveness in enhancing the discriminative power of the system. In fact, by incorporating fuzzy elementary perceptual codes, systems can benefit from advanced feature extraction methods that improve the accuracy of PD detection.

Indeed, handwriting emerges as a consequence of the activation of N neuromuscular subsystems. This activation begins within the neuronal system and is subsequently transmitted via motor nerves to engage the muscles in the hand and arm. Considerable research has been dedicated to exploring the impact of these neuromuscular subsystems on the dynamic profile, often referred to as the velocity profile. The results of these studies indicate that each subsystem produces an impulsive signal that can be approximated using a Beta function [46], depicted as follows:

$$pulse\beta(K,t,q,p,t_0,t_1) = \left\{ \begin{array}{ll} K.\left(\frac{t-t_0}{t_c-t_0}\right)^p.\left(\frac{t_1-t}{t_1-t_c}\right)^q & if\ t\in[t_0,t_1] \\ 0, \quad elsewhere & \end{array} \right\} \tag{5}$$

The generated impulse possesses a clearly defined initiation time t_0 and termination time t_1, signifying the duration of the impulse. At time t_c, the impulse reaches its peak amplitude K, with intermediate parameters p and q. Formula 6 offers a means to compute the velocity profile.

$$\begin{aligned} V(t) &= \sum\nolimits_{i=1}^{n} V_i(t-t_{0i}) \\ &= \sum\nolimits_{i=1}^{n} pulse\beta_i(K_i,t,q_i,p_i,t_{0i},t_{1i}) \end{aligned} \tag{6}$$

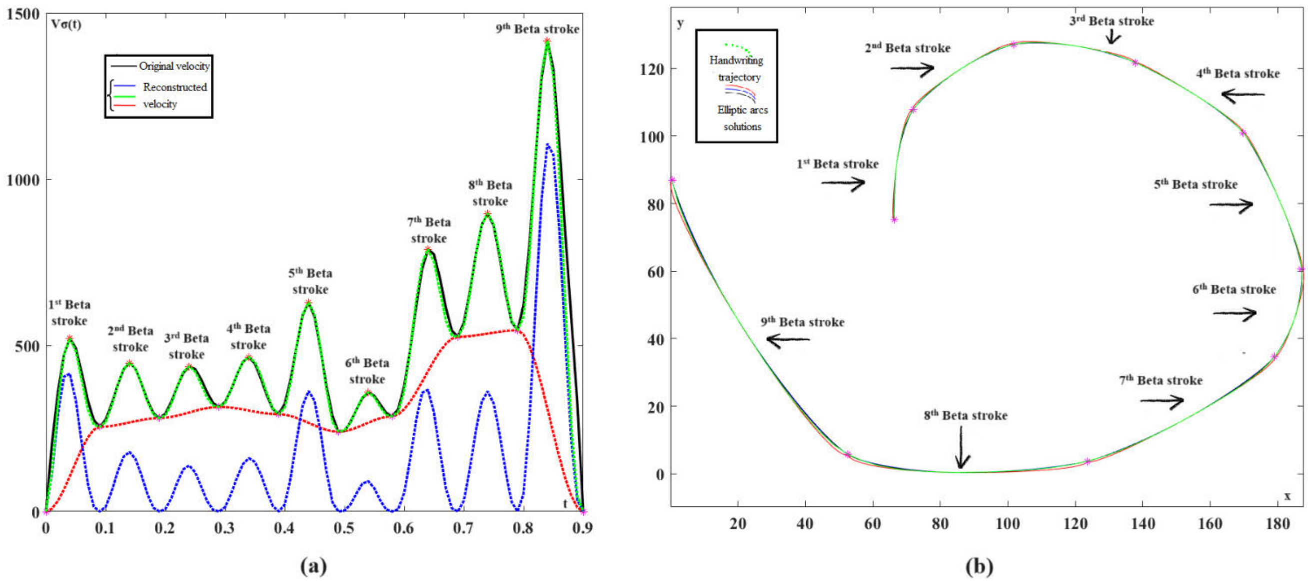

FIGURE 5. Application of segmenting a spiral example extracted from our dataset (a): Velocity profile modeling, (b) Geometric profile modeling.

In their research paper [21], Boubaker et al. present an innovative method for modeling the velocity profile. They introduce the simplified Beta-Elliptic model, which includes a continuous training component. In our study, we have utilized this model. Within this technique, the curvilinear velocity during the time interval $[t_0, t_1]$ can be partitioned into two components:

1) An impulsive element as expressed in (7).

$$V_{Imp}(t) = K \cdot \left(\frac{t - t_0}{t_C - t_0}\right)^p \cdot \left(\frac{t_1 - t}{t_1 - t_C}\right)^q \tag{7}$$

In this context: t_0 and t_1 indicate the initial and final times of the constructed impulse, t_c represents the moment when the impulse achieves its maximum amplitude, denoted as K. P and q are intermediary parameters.

2) A continuous training element computed using (8).

$$V_{Tra}(t) = A \cdot \left[\frac{(t - t_0)^3}{3} - \frac{(t_1 - t_0) \cdot (t - t_0)^2}{2}\right] + V_i \tag{8}$$

where:

$$A = -6 \cdot \frac{V_f - V_i}{(t_1 - t_0)^3} \tag{9}$$

where: t_0 and t_1 indicate the initial and final times of the constructed impulse, V_i and V_f represent the velocities at the initial and final times of the constructed impulse.

Ultimately, the curvilinear velocity is established by combining the impulsive element and the continuous training element. This fusion is accomplished by adding the two components together, as outlined in (10).

$$V_R(t) = V_{Imp}(t) + V_{Tra}(t) \tag{10}$$

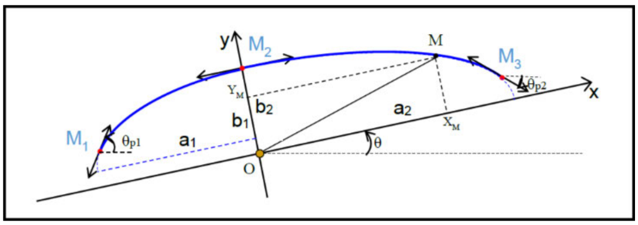

FIGURE 6. Parameters of the geometric profile.

In the geometric profile, it's feasible to model each Beta stroke by employing two adjacent elliptic arcs, specifically E_1 $(a_1, b_1, \theta_1, \theta_{p1})$ and E_2 $(a_2, b_2, \theta_2, \theta_{p2})$, as depicted in Figure 6. These arcs share identical inclination angles ($\theta 1 = \theta 2 = \theta$). To ensure a seamless transition of curvature when transitioning from the first elliptic arc to the second, the relationship between the lengths of their minor and major axes must adhere to the condition specified in (11).

$$a_2 = a_1 \cdot \sqrt{\frac{b_2}{b_1}} \tag{11}$$

where:

-a_1 corresponds to half of the major axis length of the ellipse linked with the first arc.

-a_2 corresponds to half of the major axis length of the ellipse associated with the second arc.

-b_1 signifies half of the minor axis length of the ellipse supporting the first arc.

-b_2 signifies half of the minor axis length of the ellipse supporting the second arc.

Moreover, as part of the features extraction process, we integrate the coefficient representing the logarithmic relationship between curvilinear velocity and curvature radius,

TABLE 3. Form of EPC.

EPC	Designation	Shape
EPC_1	Valley	—
EPC_2	Left oblique shaft	/
EPC_3	Shaft	$\vert$
EPC_4	Right oblique shaft	$\backslash$

denoted as λ and commonly known as the two-thirds power law. To determine this parameter, we compute the mean absolute gradient of the parametric curve representing the variation in the logarithm of curvilinear velocity concerning the logarithm of curvature radius, as defined in (12).

$$\lambda = \frac{1}{N} \times \sum_{n=1}^{N} \left| \frac{\ln(\mathrm{V}_\sigma(\mathrm{t}_{n+1})) - \ln(\mathrm{V}_\sigma(\mathrm{t}_n))}{\ln(\mathrm{R}_c(\mathrm{t}_{n+1})) - \ln(\mathrm{R}_c(\mathrm{t}_n))} \right| \tag{12}$$

where:

- N stands for the total number of points in the current stroke.

- n stands for the current index of points in the trajectory, and t_n denotes the corresponding execution time.

Additionally, we compute the normalized Jerk which represents the change of acceleration with time per stroke for a fixed average velocity. In fact, when we normalize Jerk in relation to the average speed of the executed trajectory stroke, we effectively eliminate the component associated with the speed gain while emphasizing the component associated with undulation. It's worth noting that the movement optimization approach developed by Flash and Hogan [47] aims to minimize a criterion function referred to as 'Jerk'. This criterion function involves calculating the integral over the time interval $[t_i, t_f]$ of the sum of the squares of the third derivatives of hand displacement along the cartesian plane axes (O, X, Y) with respect to time, specifically, in the x and y directions.

$$C_{Jerk} = \frac{1}{2} \int_{t=t_1}^{t_2} \left[\left(\frac{d^3x(t)}{d^3t} \right)^2 + \left(\frac{d^3y(t)}{d^3t} \right)^2 \right] dt \tag{13}$$

$$Normalized\_Jerk = \frac{C_{Jerk}}{Average\ velocity} \tag{14}$$

Furthermore, taking inspiration from the Perceptual Theory for On-line Handwriting Segmentation (PerTOHS) theory as outlined in references [21] and [22], we propose to use the fuzzy perceptual detector into our PD detection system.

This approach involves utilizing the inclination angle of the major axis of the ellipse θ to associate each Beta stroke with one of the four distinct types of Elementary Perceptual Codes (EPC) described in Table 3.

We divide the trigonometric circle into eight segments, aligning each segment with the Elementary Perceptual Codes (EPC), as demonstrated in Figure 7.

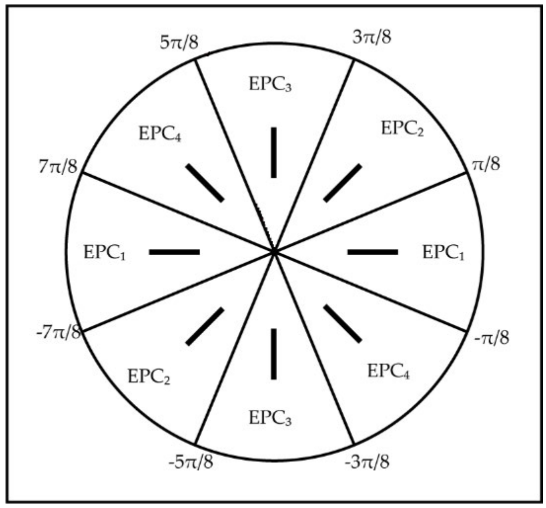

FIGURE 7. Presentation of EPCs on the trigonometric circle.

EPCs may display uncertainty and hesitation, influenced by factors like hand disorders. In response to this challenge, we integrated fuzzy logic theory to allocate a membership degree to each EPC. As a result, we derived four distinct features: $FEPC_1$, $FEPC_2$, $FEPC_3$, and $FEPC_4$, each representing the membership degree of EPC_1, EPC_2, EPC_3, and EPC_4, respectively.

In brief, every Beta stroke is defined by a comprehensive set of 27 features, as detailed in Table 4. The first nine features capture the modified neuromuscular excitations evident during hand movements, while the following fourteen features elucidate the geometric characteristics of the handwriting trajectory. The λ parameter furnishes an elaborate account of the fluctuations in the curvature radius along the path traced during online handwriting. The last three parameters present the pen pressure at the different position point of stroke.

E. CLASSIFICATION BASED ON BLSTM

Recurrent Neural Networks (RNNs) are commonly used for sequential modeling. However, they encounter the challenge of vanishing gradients, which hampers their ability to effectively learn from extended sequences of data [48]. Long Short-Term Memory (LSTM) was specifically designed to address this issue. LSTM is tailored for modeling time series data with prolonged dependencies, offering a solution to the vanishing gradient problem [49]. Compared to RNNs, LSTM replaces conventional hidden units with memory blocks. These memory blocks comprise one or more memory cells. Each memory cell includes a self-connected memory cell (referred to as c_t), which aids in preserving the cell's current state from one moment to the next. Additionally, LSTM incorporates three multiplicative gate units, which are:

1) The forget gate, denoted as f_t, regulates the amount of information from prior sequences that should be forgotten.

TABLE 4. Extracted features based on the Beta-elliptical approach and the fuzzy perceptual detector.

N°	Feature	Description
1	t_1-t_0	Duration of the Beta signal
2	$\frac{t_c - t_0}{t_1 - t_0}$	Report of the Beta signal asymmetry
3	P	Parameter of the Beta signal
4	K	Amplitude of the Beta signal
5	V_i	Velocity at the starting instant of the Beta signal
6	V_f	Velocity at the ending instant of the Beta signal
7	Average curvilinear velocity	Average curvilinear velocity of the current stroke
8	Normalized _Jerk	Normalized Jerk of the current stroke for a fixed average velocity
9	$\frac{k_i}{training}$	Report of the amplitude of Beta signal with respect to the medium value of the training component
10	a_1	Major axis half-length of the ellipse concerning the first arc
11	b_1	Small axis half-length of the ellipse concerning the first arc
12	b_2	Small axis half-length of the ellipse concerning the second arc
13	θp1	Inclination angle of the tangents at the endpoint M1
14	θ	Inclination angle of the ellipse major axis
15	FEPC1	EPC1 with membership degree value
16	FEPC2	EPC2 with membership degree value
17	FEPC3	EPC3 with membership degree value
18	$FEPC_4$	EPC_4 with membership degree value
19	θ_{p2}	Inclination angle of the tangents at the endpoint M3
20	Stroke position	Position of the Beta stroke in the trajectory
21	$\theta_{departure}$	Inclination angle of departure
22	$\theta_{arrival}$	Inclination angle of arrival
23	$\sum \triangle \theta$	Curvature angle of path stroke
24	λ	Coefficient of logarithmic proportionality between the curvilinear velocity and the curvature radius
25	P_departure	Pen pressure at the point of departure of stroke
26	P_arrival	Pen pressure at the point of arrival of stroke
27	P_max	Pen pressure at the maximum local speed

2) The input gate, labeled as i_t, governs the extent to which information from preceding sequences should be inputted.
3) The output gate, represented as o_t, manages the extent to which information from prior sequences should be outputted.

Figure 8 provides a visual representation of an LSTM network, with a single input, a single output, and a single memory block.

$$\text{Input Gate}: i_t = sigm(W_i x_t + U_i h_{t-1} + b_i) \quad (15)$$

$$\text{Forget Gate}: f_t = sigm(W_f x_t + U_f h_{t-1} + b_f) \quad (16)$$

$$\text{Output Gate}: o_t = sigm(W_o x_t + U_o h_{t-1} + b_o) \quad (17)$$

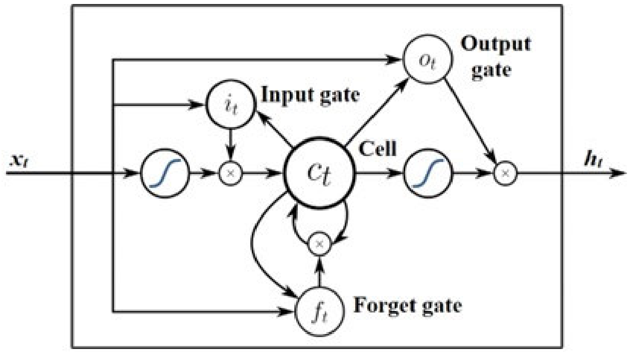

FIGURE 8. Visualization of an LSTM network.

$$\text{Input Modulation}: \tilde{c}_t = tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (18)$$

$$\text{Memory cell Update}: c_t = i_t \odot \tilde{c}_t + f_t \odot c_{t-1} \quad (19)$$

$$\text{Output}: h_t = o_t \odot tanh(c_t) \quad (20)$$

where:

- x_t represents the input data at time t that contains the features vector for t^{th} Beta stroke of the trajectory.
- W and U denote the weight matrices.
- b represents the bias vector parameter.
- *sigm* represents the sigmoid function.
- *tanh* represents the hyperbolic tangent function.
- $\odot$ denotes the element-wise multiplication operation.

LSTM networks can only access the past context for each individual time step. To address this limitation, the utilization of Bidirectional LSTM networks is recommended [50]. In practice, BLSTM networks leverage both past and future context information by processing data in both the forward and backward directions, employing two distinct hidden layers.

Hence, the output of the forward layer, denoted as h_t, and the output of the backward layer, denoted as h'_t, are computed. Subsequently, the ultimate output is produced by combining h_t and h'_t, as elucidated in the subsequent equations.

$$\text{Forward layer}: h_t = LSTM\,(x_t, h_{t-1}) \quad (21)$$

$$\text{Backward layer}: h'_t = LSTM\,\left(x_t, h'_{t+1}\right) \quad (22)$$

$$\text{Final output layer}: y_t = W_{hy} h_t + W_{h'y} h'_t + b_y \quad (23)$$

where:

- *LSTM(.)* represents the LSTM updating.
- W_{hy} and $W_{h'y}$ designate the weights of forward and backward layers respectively.
- b_y denotes the bias of the final output layer.

In our study, the BLSTM is constructed using two multi-layer LSTM networks, coupled with a fully connected layer followed by a Softmax layer, as illustrated in Figure 9.

To elaborate further, the forward multi-layer LSTM network processes the input vectors $S = \{s(1), s(2), \ldots, s(z)\}$ where $s(t)$ represents the feature vector for the t^{th} Beta stroke in the trajectory. This operation results in a hidden state sequence denoted as $[h_1, h_2, \ldots, h_z]$.

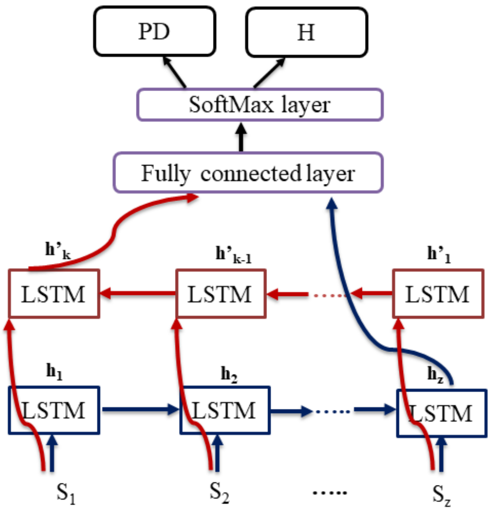

FIGURE 9. The BLSTM for PD detection.

Simultaneously, the backward multi-layer LSTM network handles the input vectors in the reverse order, given by $S = \{s(z), s(z-1), \ldots, s(2), s(1)\}$. This operation yields another hidden state sequence, $[h'_1, h'_2, \ldots, h'_z]$. Consequently, the outputs of the forward and backward layers, h_z and h'_z, are fed into the fully connected layer, followed by a Softmax layer for the ultimate classification process.

V. EXPERIMENTS AND DISCUSSION

In this study, we showcase the effectiveness of our Parkinson's disease detection system by evaluating it with both our own dataset and the publicly available Parkinson's disease handwriting database established by Drotár et al. in [30].

A. EXPERIMENTS AND RESULTS USING OUR OWN DATASET

In the evaluation, we utilized stratified 10-fold cross-validation. The database was divided into ten distinct and complete subsets of equal size. Each subset was treated as a test set, while the combination of the remaining subsets served as the training data. To enhance the dataset's diversity, we applied data augmentation, creating 30 new variations for each original training sample. The entire procedure was iterated 10 times, until each fold was used once as test set. The accuracy for each subset was computed and then averaged to determine the overall accuracy.

Table 5 displays the classification accuracies achieved on our dataset.

Looking at Table 5, it's clear that the results of our suggested system, show considerable promise in Parkinson's disease detection from online handwriting. The accuracy of the first task, which was tracing an ellipse repeatedly for thirty seconds, reached the best value of 93.33%. This can be explained by the fact that PD often involves

TABLE 5. Results obtained using our dataset.

Task	Accuracy
1) repetitive ellipse	93.33%
2) spiral	89.99%
3) 8 8 8 8 8	86.66%
4) لولو لولو	80.00%
5) l in a continuous trace eight times	89.99%

impaired coordination and difficulties in controlling fine motor movements. Tracing an ellipse requires precise hand-eye coordination, and individuals with Parkinson's disease may struggle with maintaining the smooth and controlled movements necessary for accurate tracing compared with healthy controls. The worst accuracy result was 80.00% for the fourth task which was writing the Arabic word "لولو" two times. This may be explained by task complexity. In other words, the complexity of writing the specific Arabic word involving a combination of fine motor skills, coordination, and cognitive processes may not be sufficient to highlight the subtle motor control differences often seen in Parkinson's disease. The accuracy results achieved for the rest of the tasks indicate the efficacity of using the Beta-elliptical approach and the fuzzy perceptual detector for feature extraction, in combination with BLSTM for classification in early detection of Parkinson's Disease.

B. EXPERIMENTS AND RESULTS USING PARKINSON'S DISEASE HANDWRITING DATABASE

To test the robustness and to evaluate the effectiveness of our system, we conducted the experiments also using Parkinson's disease Handwriting Database (PaHaW) [30]. The Parkinson's disease handwriting database consists of multiple handwriting/drawing samples of 37 PD patients and 38 healthy controls (HC).

Participants were requested to complete eight handwriting tasks in accordance with a pre-filled template: 1. Drawing an Archimedes spiral; 2. Writing in cursive the letter l; 3. The bigram le; 4. The trigram les; 5. Writing in cursive the word lektorka ("female teacher" in Czech); 6. porovnat ("to compare"); 7. nepopadnout ("to not catch"); 8. Writing in cursive the sentence Tramvaj dnes už nepojede ("The tram won't go today"). All the tasks are displayed in figure 10.

In the evaluation process, we employed stratified 10-fold cross-validation. The dataset was divided into ten equal-sized, mutually exclusive subsets. For each subset, we used the union of the remaining subsets as the training data. In addition, we applied data augmentation, generating 30 new variations for each original training data sample. The entire procedure was iterated 10 times, until each fold was used once as test set. We then averaged the accuracies of the different subsets to compute the overall accuracy.

Table 6 presents an overview of the results obtained using PaHaW database.

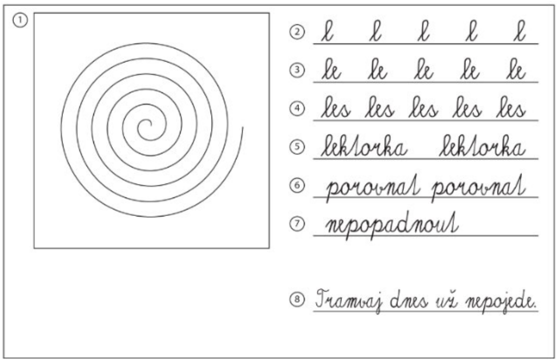

FIGURE 10. Illustration of PaHaW database tasks [30].

TABLE 6. Results obtained using PaHaW database.

Task	Proposed System	Drotár et al., [30]	Diaz et al., [28]	Moetesum et al., [27]	Diaz et al., [26]
1) spiral	**95.00**	62.80	75.00	89.64	93.75
2) l l l	**96.25**	72.30	58.33	75.00	96.25
3) le le le	**90.00**	71.00	53.75	73.75	88.75
4) les les les	**91.25**	66.40	57.08	72.32	90.00
5) lektorka	**95.00**	65.20	75.41	79.46	93.75
6) porovnat	90.00	73.30	63.75	74.46	**91.25**
7) nepopadnout	91.25	67.60	57.50	79.28	**92.50**
8) Sentence	**93.75**	76.50	67.08	81.42	92.50

It can be seen from the results presented in Table 6 that our proposed system using the Beta-elliptical approach and the fuzzy perceptual detector in features extraction and BLSTM in classification achieves a good accuracy compared to the existing systems.

The comprehensive outcomes of our proposed system, evaluated on the PaHaW database using a similar experimental setup, demonstrate notable enhancements in classification performance for the tasks 1, 2, 3, 4, 5 and 8 compared to the findings of Drotár et al., [30], Diaz et al., [28], Moetesum et al., [27], Diaz et al., [26]. our approach exhibits superior results specifically in classifying spiral patterns. However, when classifying the two words porovnat and nepopadnout, our method performs comparably to Diaz et al., [26].

This confirms the effectiveness of the proposed system to detect PD from online handwriting and to serve as a candidate solution for real use in a clinical setting.

C. DVANTAGES AND LIMITATIONS OF OUR PROPOSED WORK

1) ADVANTAGES

The advantages of this innovative system for Parkinson's disease detection include its comprehensive approach, starting from data augmentation and preprocessing to the segmentation of handwriting into Beta strokes. Feature extraction employs advanced methods, such as the Beta-elliptical approach and fuzzy perceptual detection, ensuring robustness. The utilization of bidirectional long short-term memory (BLSTM) enhances classification accuracy. Additionally, the creation of a new online Arabic handwriting dataset tailored for Parkinson's disease detection demonstrates the system's adaptability to different languages and cultural contexts. The obtained results confirm the effectiveness of the proposed system, showcasing superior performance compared to existing systems through thorough evaluations on the PaHaW dataset.

2) LIMITATIONS

The limitations of this innovative system for Parkinson's disease detection include its reliance on online handwriting data, which may limit applicability to patients with limited motor control. Additionally, the effectiveness of the system may vary depending on the quality and consistency of handwriting samples. Further research is needed to validate its performance across diverse populations and languages, as well as to explore its scalability and real-world implementation challenges.

VI. CONCLUSION

We present in this paper an innovative system designed for the detection of Parkinson's disease. This system encompasses several crucial stages, beginning with data augmentation and preprocessing, followed by the segmentation of Beta strokes. Subsequently, we perform feature extraction using the Beta-elliptical approach and the fuzzy perceptual detector. Ultimately, our classification task employs bidirectional long short-term memory (BLSTM). To evaluate the effectiveness of our system, we created a new online Arabic handwriting dataset specifically tailored for Parkinson's disease detection. The results we obtained underscore the efficacy of our proposed system. Through comprehensive assessments conducted on the PaHaW dataset, we achieved a high level of accuracy, clearly demonstrating that our system outperforms existing systems in this context.

In future works, we plan to give attention to, among others, studying the effectiveness of different parameters in order to give a high weight for some parameters that can enhance the variation between PD patients and healthy controls. Furthermore, we intend to employ Hamilton-Jacobi-Bellman (HJB) equation-based learning for neural networks in forthcoming research endeavors [51], [52]. This approach serves as a versatile and potent method for tackling optimal control challenges across a broad spectrum of application domains. Moreover, we plan to evaluate the performance of the medication on off and on periods.

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DECLARATION

Financial Interests: The authors declare they have no financial interests.

Non-Financial Interests: None.

Conflict of Interest: The authors declare that they have no conflict of interest.

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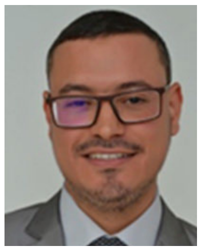

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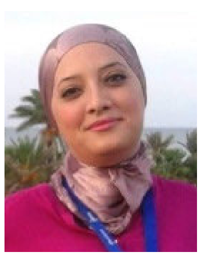

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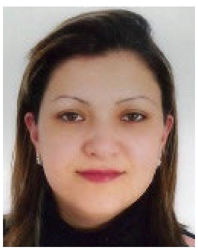

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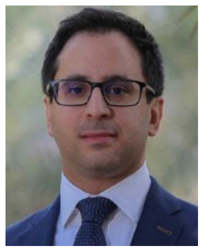

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