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A HYBRID TWO–STAGE SQUEEZENET AND SUPPORT VECTOR MACHINE SYSTEM FOR PARKINSON'S DISEASE DETECTION BASED ON HANDWRITTEN SPIRAL PATTERNS

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Parkinson's disease (PD) is the second most common neurological disorder in the world. Nowadays, it is estimated that it affects from 2% to 3% of the global population over 65 years old. In clinical environments, a spiral drawing task is performed to help to obtain the disease's diagnosis. The spiral trajectory differs between people with PD and healthy ones. This paper aims to analyze differences between handmade drawings of PD patients and healthy subjects by applying the SqueezeNet convolutional neural network (CNN) model as a feature extractor, and a support vector machine (SVM) as a classifier. The dataset used for training and testing consists of 514 handwritten draws of Archimedes' spiral images derived from heterogeneous sources (digital and paper-based), from which 296 correspond to PD patients and 218 to healthy subjects. To extract features using the proposed CNN, a model is trained and 20% of its data is used for testing. Feature extraction results in 512 features, which are used for SVM training and testing, while the performance is compared with that of other machine learning classifiers such as a Gaussian naive Bayes (GNB) classifier (82.61%) and a random forest (RF) (87.38%). The proposed method displays an accuracy of 91.26%, which represents an improvement when compared to pure CNN-based models such as SqueezeNet (85.29%), VGG11 (87.25%), and ResNet (89.22%).

Keywords: Parkinson's disease, spirography, convolutional neural network, deep learning.

1. Introduction

Parkinson's disease (PD) is a relatively common neural impairment that affects 2–3% of the global population older than 65 years old (Poewe *et al.*, 2017), making it the most widespread neurodegenerative disorder after Alzheimer's disease. PD is a neurodegenerative dysfunction that is present in around 1,000,000 people worldwide (Chen-Plotkin, 2017). The disease affects the human motor system, which may lead to tremors, muscle stiffness, slowness of movement, postural instability (Tysnes and Storstein, 2017) and freezing of gait (Priya *et al.*, 2021). The non-motor symptoms of PD are represented by cognitive problems, neuropsychiatric disturbances, and sensory changes. PD is related to the lack of dopamine; however, what triggers the process is not yet known (Pereira *et al.*, 2018). The motor symptoms

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characteristic of the disease is a result of the degeneration of dopaminergic neuron cells in the nigrostriatal pathway, which originates in a brain region called *Substantia Nigra* (Trist *et al.*, 2019), and sends its signals to the *caudate nuclei* and putamen of the striatum (Crowley *et al.*, 2019). Despite technological advances and healthcare precautions, no diagnostic treatment exists that can slow down nor prevent the disease progression (Oertel, 2017).

There is no specific test capable of diagnosing the PD. The diagnosis of the disease is given by a neurologist based on their past experiences, physical and neurological laboratory tests, and a review of symptoms (Gelb *et al.*, 1999). PD is considered if the patient has one or more characteristic symptoms. The presence of resting tremors makes the diagnosis of PD more propitious, although this symptom manifests in only 80% of the cases (Savitt, 2006). Clinical rating scales such as the Unified PD Rating Scale (UPDRS) are used to evaluate the state of the motor system of the PD patients. However, such observations are costly and time-consuming. Subjective evaluation of the patient should be complemented by objective and affordable motor abilities tests.

Handwriting research has been shown to be helpful in diagnosing and tracking neurodegenerative disorders. Deterioration of handwriting abilities, for example, appears to be linked to Alzheimer's disease (AD) (Garre-Olmo *et al.*, 2017), and some handwriting-related features can be used as markers for diagnosing it, or to distinguish the neurogenerative disease from a mild cognitive dysfunction. Since handwriting problems in PD patients have been known for a long time, the characteristics of handwriting is a good biomarker of the disease (Impedovo and Pirlo, 2019). Handwriting is, in particular, a multifaceted operation that requires fine motor control, eye-hand coordination, and visuo-spatial skills (Tseng and Cermak, 1993).

Currently, the Archimedes spiral handdrawing test, which is part of the Fahn tremor rating scale (FTRS), is a golden standard test for analysing hand tremor (de Ipina *et al.*, 2018). Traditionally, the Archimedes spiral is performed as a simple manual measurement of tremor severity. For example, the Fahn–Tolosa–Marín tremor rating scale (FTM) uses a scale of 0 to 4 to assess hand tremor in spiral drawings. Such tremor rating scales provide subjective assessments of the severity of tremor. A digital version of the Archimedes spiral hand drawing was developed for quantitative analysis, which has the potential to provide increased objectivity and clinical utility, as well as sensitivity in capturing and analyzing tremor severity. Digital spiral analysis is a promising and inexpensive technique that can be used to quantify movement abnormalities in motor function oriented tasks (Luciano *et al.*, 2016). Kinematic analysis of tests using the Archimedes spiral provides sufficient quantitative kinematic parameters (frequency, direction, amplitude, velocity, acceleration, and pressure) to differentiate types of tremors among neurological movement disorders (Hess *et al.*, 2014). The analysis of spirals, drawn either on paper or on a graphics tablet, has been shown to be a sensitive and valid method to quantify tremor in cohorts of patients with essential tremor (ET), which is largely based on the assessment of rhythmical components of tremor within spirals (Haubenberger *et al.*, 2011).

Handwritten spiral drawing has become common in evaluating the tremors characteristic of PD (Lin *et al.*, 2018) being also a significant biomarker for the diagnosis process (Stefano *et al.*, 2019). Machine learning approaches to distinguishing between normal and unhealthy subjects based on simple and easy-to-perform handwriting tasks have been shown to be efficient (Rosenblum *et al.*, 2013). Spiral abnormalities including smoothness and drawing speed were proposed to be a useful measure that can be derived from spirals in patients with PD (Saunders-Pullman *et al.*, 2008). Exploiting dynamic aspects of the handwriting process is often used for researching the diagnostic ability of handwriting tasks. This method is based on the study of time series data describing handwriting, which can be obtained using e-tablets and electronic pens. Digital spiral analysis is a fast and inexpensive approach that can be used to evaluate motor abnormalities in functional drawing tasks. Analysis of tests using the Archimedes spiral provides sufficient quantitative kinematic parameters (frequency, direction, amplitude) to distinguish between the types of tremors among neurological movement disorders (Hess *et al.*, 2014). The analysis of spirals, drawn on paper or on a digital tablet, was proven to be a valid method to quantify tremor in patients with essential tremor (ET) (Haubenberger *et al.*, 2011) and in patients with PD (Saunders-Pullman *et al.*, 2008).

The advances of touch screen and tablet/smartphone technologies enables the acquisition of online hand tremor signals, which include both spatial and temporal data, allowing to explore a large variety of temporal, kinematic, and dynamic features, which cannot be studied objectively using a classical paper-and-pen based method. The touch screen devices are able to record the finger-touching movements with great spatial and temporal precision and allow for quantitative characterization of kinematics of upper limb motor performance (Lauraitis *et al.*, 2019; 2020), but their use is mitigated by the natural variability of the tremor (de Ipina *et al.*, 2018). The advance of artificial intelligence (AI) technology allowed automated recognition of many diseases (Chen *et al.*, 2020; Guan *et al.*, 2020; Kowal *et al.*, 2021), including a better comprehension of the characteristics of PD (Espay *et al.*, 2016). Nowadays, many works are developed each year aiming to find a computer aid approach that allows the detection of PD. As an example of such research, some are highlighted in the following section.

This study proposes a new approach based on the use of two powerful computational tools, convolutional neural networks (CNNs) as feature extractors, and a support vector machine (SVM) as a classifier on handwritten spiral draws performed by PD patients and healthy subjects. The novelty and contribution of this paper are the following:

- A new data set of spiral drawings of PD affected subjects and healthy subjects made by combining paper drawings and digitally acquired drawings from multiple public datasets, totalizing 514 drawings.

- A novel hybrid two-stage CNN and SVM system (SqueezeNet + SVM method) for spiral drawing classification and PD diagnostics.

Further, this work is structured as follows. In Section 2, related works are analyzed and discussed. In Section 3, a theoretical base is established for an easier understanding of the proposed solution. Section 4 presents and describes the methods used in this work. In Section 5, the obtained results are displayed, and in Section 6 conclusions are presented and future work is discussed.

2. Related works

Machine learning (ML) bounds a vast range of algorithms and modeling tools used for a vast spectrum of data processing works. The making of predictions is based on input data features previously presented for model training. The learning process can be classified in two groups: supervised learning, when the algorithm is presented with classes to which the presented data belong, and unsupervised learning, when the classes are not informed to the algorithm. The ML algorithms have the potential to improve the efficiency of health care when applied to predict the disease. Clinical data sources allow a fast generation of disease prediction models for many similar clinical questions (Chen and Asch, 2017).

Some of ML methods were proposed in the context of PD recognition. For example, Gupta *et al*. (2018) proposed an improved and optimized version of the crow search algorithm (OCSA). To measure the performance of the proposed method, it was applied on 20 benchmark data sets. The proposed solution was able to find an optimal subset of features for optimizing the accuracy of disease recognition.

In the work of Pereira *et al*. (2018), a CNN was used to learn features from images produced by handwritten dynamics, which captured diversified information during the individual's assessments. The results were compared against raw data and texture-based descriptors, resulting in an accuracy of 95%.

Gupta *et al*. (2019) suggested an optimized cuttlefish algorithm (OCA) to detect PD in its early stages. To accomplish the proposed task, the decision tree (DT) and K-nearest neighbor (KNN) were applied on a data set composed of handwritings and sound records. The proposed model achieved 94% accuracy and showed that a bio-inspired algorithm can find a reduced subset of features, which maximized the accuracy.

A CNN applied to electroencephalogram (EEG) signals was proposed by Oh *et al*. (2018). The data originating from 20 PD patients and 20 healthy individuals was submitted to a 13-layer CNN. The model achieved 88.25% accuracy, 84.71% sensitivity, and 91.77% specificity.

In the work of Almeida *et al*. (2019), 18 feature extraction techniques and four ML methods were applied on voice records in the Lithuanian language through the usage of two microphones from acoustic cardioid and a smartphone. The study showed that the data from the phonation task allowed to achieved a better performance than the data from the speech task. The task showed an accuracy of 94.55% on the AC channel and 92.94% on the SP channel in detection of PD.

Gil-Martín *et al*. (2019) used a CNN model on drawing movements to recognize the PD. As input to the CNN, the coefficients of the fast Fourier transform (FFT) in the range of frequencies between 0 Hz and 25 Hz were used. A data set of handmade spirals with data acquired from a tablet was used. The model achieved 96.5% of accuracy, and an F1-score of 97.7%.

Bernardo *et al*. (2019) applied three machine learning algorithms, optimum-path forest, SVM, and naive Bayes (NB), for analysing handwritten patterns, such as spiral, triangle, and cube, collected from 20 PD patients, from which 11 features were extracted, to obtain the PD diagnosis. The system obtained 96% accuracy on a triangle pattern, 100% on cube and 100% on spiral pattern, and 100% sensitivity on all three patterns, but the dataset was very small, so the perfect result may have been due to over-fitting.

The work of Zhang *et al*. (2020) consisted of applying a CNN on speech signals to obtain the diagnosis of PD. Time-series signals were converted into spectrograms to represent the time and frequency features of the signal as an image. The spectrograms were then applied to train the CNN model, which achieved an accuracy of 91%.

Based on the impaired handwritten ability of PD patients, Al-Yousef *et al*. (2020) applied the static spiral test and a dynamic spirals test performed on a digital tablet for the diagnosis of PD. The semi-local edge histogram extracted from the dynamic spiral test, and conveyed to a Gaussian kernel SVM presented a better result than other systems considered in the study, achieving specificity and accuracy of about 90%.

In the work of Awatramani and Gupta (2020), the handwritten examinations from the HandPd data set, which contains images of spirals and Meander template, were used. The images were submitted to a transfer learning deep learning process aiming to detect the disease in its early stage. The solution achieved 98.24% accuracy on the spiral image set, and 98.11% on the Meander set.

Chakraborty *et al.* (2020) proposed a method to distinguish between PD patients and healthy subjects using two CNN models applied to handwritten patterns such as spiral and wave. The solution used data from a total of 55 patients obtaining an accuracy of 93.3%, recall of 94%, precision of 93.5%, and F1-score of 93.04%.

Moshkova *et al.* (2020) used a leap motion device to acquire PD patient hand tremors during motor tasks. The collected data were submitted to a one-dimensional (1D) CNN, trained on a data set of each hand during the performance of three motor tasks: finger tapping, finger opening-closing, pronation-supination of the hands. The features learned by the CNN were used by ML algorithms such as KNN, SVM, DT, and RF for classification. From the tested algorithms, SVM achieved a better performance, obtaining 85.1% accuracy.

The usage of the VGG-19 CNN model, pre-trained on more than a million images from the ImageNet database, for PD diagnosis was proposed by Shaban (2020). To train and test the proposed solution, the Kaggle dataset was used, providing 102 images of handwritten spirals and 102 images of handwritten waves. The patterns were pre-processed by applying image resize and data augmentation based on image rotation aiming to minimize overfitting. The model achieved an accuracy of 88% and 89%, and sensitivity of 89% and 87% on the wave and spiral patterns, respectively.

Another promising approach was published by Moetesum *et al.* (2019), who reached an 83% accuracy by employing CNN models that were used to extract the discriminating visual features from handwriting data transformed into the offline mode.

Summarizing the related research, small data set size, class imbalance, overfitting, high false detection rate, model complexity, and other obstacles have hampered research efforts in the early diagnosis of PD due to comparative rarity of the disease. Using small datasets for model training can lead to very good results due to overfitting, however such models are often unusable with real-world data due to diversity of sources and high variability of subject characteristics. A summary of related works based on the approaches to detect PD can be seen in Table 1.

3. Theoretical foundations

We describe the use of the Archimedean spiral for PD recognition and the methods used in our framework.

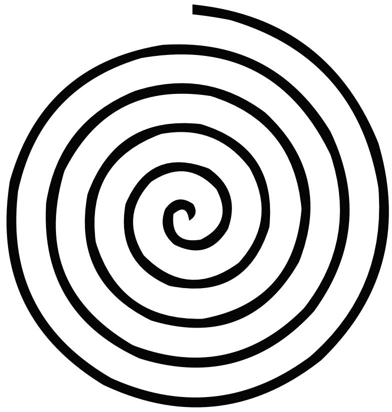

Fig. 1. Graphical representation of the Archimedean spiral.

3.1. Archimedean spiral. The Archimedean spiral, shown in Fig. 1, can be expressed in polar coordinates (r, θ) through

$$r = a + b \times \cos(\theta). \tag{1}$$

The parameter *a* controls the rotation of the spiral, while b establishes the distance between successive rotations. Here, r is the radial distance, a and b are the real number constants. Varying a turns the spiral, whereas varying b controls the distance between successive turns, and θ is the polar angle.

This pattern has been vastly used to help PD diagnosis and disease progression in a clinical environment since it offers a good graphical representation of motor impairment, being a gold standard for PD recognition (Stefano *et al.*, 2019; Impedovo and Pirlo, 2019).

3.2. Convolutional neural network. The CNN is a type of artificial neural network (ANN) used in image recognition and processing. It is specifically used to process the data encoded as pixels of an image, and having characteristics such as texture and colour. A typical CNN model has two basic parts: (i) a feature extraction part, consisting of a set of convolutional layers accompanied by max-pooling and an activation function, and (ii) a classifier part, usually consisting of fully connected layers (Khoshdeli *et al.*, 2017). A deep layered architecture of CNN allows the extraction of a large set of discriminating features at many levels of abstraction (Tajbakhsh *et al.*, 2016).

3.3. SqueezeNet. SqueezeNet, shown in Fig. 2, is an 18-layer deep neural network developed with a lower number of parameters, but it still maintains a high accuracy (Islam *et al.*, 2020). The use of SqueezeNet helps us to decrease the memory consumption as well as the processing time for classification as compared with other multi-layered deep learning models (Nguyen

Table 1. Related works on Parkinson's disease diagnosis based on computer-aided approaches.

Reference	Approach	Algorithms	Best accuracy
Gupta *et al.*, 2018	Handwritten draws	OCSA	100%
Pereira *et al.*, 2018	Handwritten draws	CNN	95%
Gupta *et al.*, 2019	Not specified	Optimized cuttlefish, DT, KNN	94%
Oh *et al.*, 2018	EEG	CNN	88.25%
Mucha *et al.*, 2018	Hand writings	Fractional derivatives, RF, SVM	72.38%
Impedovo *et al.*, 2018	Hand writings	RF, SVM, K-NN, NB, LDA, ADA	74.76%
Zham *et al.*, 2018	Handwritten draws (spiral)	Naive Bayes	93.3%
Gallicchio *et al.*, 2018	Handwritten draws (spiral)	Deep echo state networks	89.3%
Khatamino *et al.*, 2018	Handwriting drawings	CNN	72.5%
Almeida *et al.*, 2019	Voice records	ML	94.55%
Gil-Martín *et al.*, 2019	Drawing movements	CNN	96.5%
Bernardo *et al.*, 2019	Handwritten draws	OPF, SVM, naive Bayes	100%
Moetesum *et al.*, 2019	HAndwritings	Differential analysis, CNN, SVM	83%
Zhang *et al.*, 2020	Speech	CNN	91%
Sivaranjini and Sujatha, 2019	MRI	CNN	88.9%
Al-Yousef *et al.*, 2020	Handwritten draws	SVM	90%
Awatramani and Gupta, 2020	Handwritten draws	Deep learning	98.24%
Chakraborty *et al.*, 2020	Handwritten draws	CNN	93.3%
Moshkova *et al.*, 2020	Handwritten draws	CNN, SVM	85.1%
Shaban, 2020	Hand tremours	VGG-19	88%

et al., 2018). We have chosen the SqueezeNet model due to its lightweight architecture, a smaller number of parameters and faster training times. SqueezeNet has been recently released (2016) and is increasingly used by researchers for various applications (see, e.g., Kriti *et al.*, 2020; Jin *et al.*, 2021).

The main advantage of the SqueezeNet network is a 50 times performance improvement over AlexNet, a benchmark deep CNN model, while maintaining a comparable classification accuracy (Iandola *et al.*, 2016). To ensure computational efficiency, the size of the convolution filters has been reduced from 3×3 to 1×1. In consequence, the number of trained parameters has been reduced by 9 times.

Thus, the SqueezeNet network is built from modules of the same type, called "Fire module" (Fig. 2). A Fire module consists of a squeeze convolution layer (which has only 1×1 filters) that feeds into an expand layer, which has a mix of 1×1 and 3×3 convolution filters. SqueezeNet begins with a single convolution layer (*conv1*), succeeded by 8 Fire modules (*fire2–fire9*), ending with a final convolution layer (*conv10*). Max-pooling with a stride of 2 is performed after the *conv1*, *fire4*, *fire8*, and *conv10* layers. Downsampling is done late in the network, so that the convolution layers have large activation maps, which can increase the classification accuracy.

3.4. Support vector machine. SVM is a widely used method for pattern classification, whose accuracy is highly influenced by feature selection and kernel parameter settings (Wang and Chen, 2020). SVM finds a linear hyperplane in a higher dimensional feature space, which results in providing a nonlinear decision boundary in the original input space. This algorithm has shown good performances when applied to the classification of a wide variety of medical problems as presented, e.g., by Wang *et al.* (2018).

The set of mathematical functions used by SVM are called kernels (Cristianini and Ricci, 2008), which are functions responsible for receiving the input data and transforming them into the desired form. Kernel functions can be of different types such as linear

$$k(x_i, x_j) = x_i \cdot x_j, \tag{2}$$

where $x_i \cdot x_j$ represents the linear product of data points x_i and x_j, radial basis functions (RBFs)

$$k(x_i, x_j) = \exp\left(-\frac{||x_i - x_j||^2}{2\sigma^2}\right), \tag{3}$$

where $||x_i - x_j||$ is the Euclidean distance between two data points, while σ represents the variance, and polynomial

$$k(x_i, x_j) = (x_i \cdot x_j + c)^d, \tag{4}$$

where d represents the polynomial order of the kernel, and c is the constant that allows to control the influence of high and low order terms.

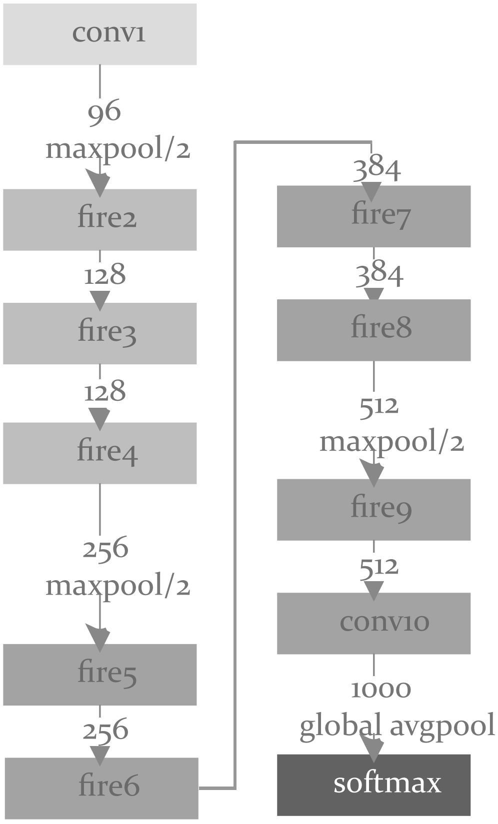

Fig. 2. Architecture of SqueezeNet with main blocks shown (four bypass convolutional 1×1 blocks are not presented) (Nguyen *et al.*, 2018).

4. Methods

In this section, the computational, experimental, and mathematical approaches used for the development of this work are presented. The workflow of the proposed hybrid SqueezeNet + SVM method is presented in Fig. 3 and explained in more detail in Sections 4.2–4.6. The main steps are as follows:

1. image preprocessing and random partitioning of the data set into training (80%) and testing (20%) parts (Section 4.2);

2. augmentation of the training data set using geometrical image transformations of resize and rotation (Section 4.2);

3. training of SqueezeNet model; this step includes multiple iterations of training with different values of model hyperparameters, while optimisation is performed using the Bayesian search (Section 4.3);

4. extraction of deep features for the second stage (SVM) classifier (Section 4.4);

5. training of the SVM classifier; this step includes multiple iterations of training with different values of model hyperparameters, while optimization is performed using the Nelder–Mead method (Section 4.5);

6. classification using unseen data and performance evaluation (Section 4.6).

4.1. Data set. The data set used for this work consists of 514 images of handmade spirals. The images, collected from several public data sets (Parkinson Disease Spiral Drawings Using Digitized Graphics Tablet data set (Isenkul *et al.*, 2014), HandPD data set (Pereira *et al.*, 2016), and Parkinson's Drawings data set (Zham *et al.*, 2017)), were merged into a single data set composed by 218 healthy subjects and 296 Parkinson's patients.

4.2. Image preprocessing. We used the digitized images, see Fig. 4, aiming to collect data from multiple diverse sources such as digital table drawers, tablets, paper scans and others, which allows us to develop a more flexible model while avoiding overfitting. The images were pre-processed for denoising, because the paper scan images of spiral drawings have some noise introduced by the paper scanning process and physical paper texture captured by the scanner. We had the paper texture removed and converted to a black-and-white image, whereas the images from digital media had colors inverted to have white background as in paper-based images. Prior to the training process, the data passed through a data augmentation step, where two operations (rotation and resize) were made, while aiming to avoid overfitting during the training process.

4.3. SqueezeNet model optimization. For the selection of an optimal CNN architecture and its meta-parameters, we used the method described by Kalliola *et al.* (2021). The optimization was performed with respect to the optimization functions, loss functions, batch sizes, learning rates, dropouts, and validation splits (see Table 2). The goal of the hyper-parameter optimization method is to get a wide range of outcomes and to look for relationships between those results and hyper-parameter value combinations. The Bayesian search methods were utilized. The top 10% of the runs are examined for correlations between results and hyper-parameters. The mean square error (MSE) measure was utilized by the Bayesian search method to determine the best performing hyper-parameter values. On the testing set, MSE was computed as the difference between predicted and target values.

Table 2. Hyperparameter value ranges and categories in the optimization step.

Dropout	Batch size	Validation split	Learning rate	Optimizer	Activation function	Search
0–0.5	10–1000	0.05–0.2	0.0007–0.0011	Adam, SGD, RMSProp, NAdam	reLU, elu, selu, sigmoid, tanh	Bayesian

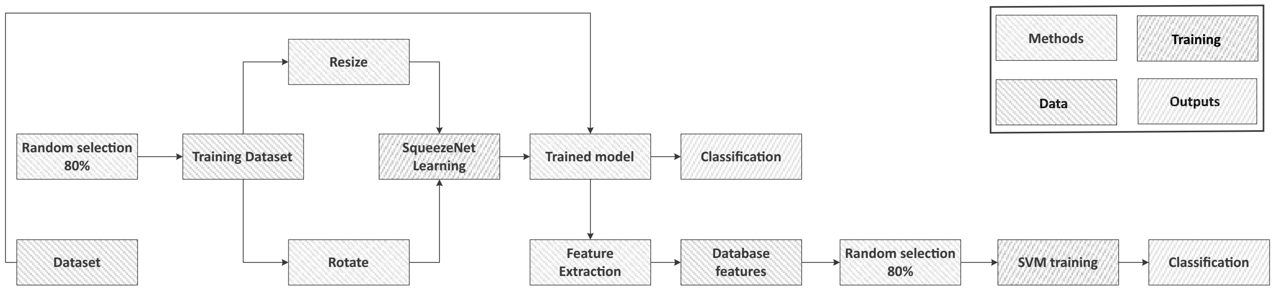

Fig. 3. Diagram description of development steps for the solution.

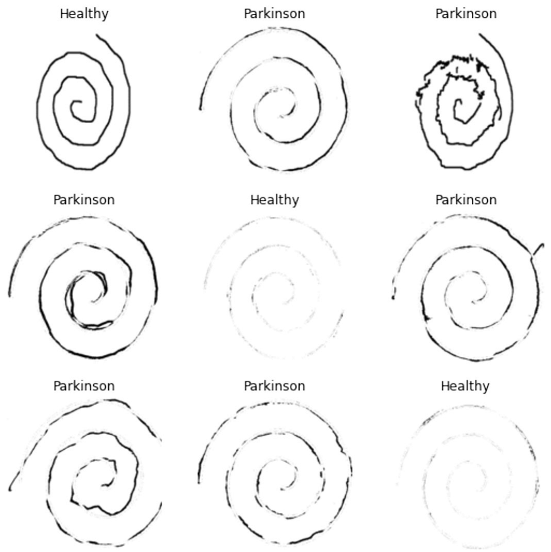

Fig. 4. Example of handwritten spiral images in the dataset (blurriness is due to conversion from color to grayscale).

4.4. Feature extraction. In order to be used the SqueezeNet model as a feature extractor, the output values from the *fire9* module of the neural network need to be captured. To achieve it, we developed a method named *Hook*, which can capture 512 features generated at the output of the *fire9* module of SqueezeNet, which is illustrated in Fig. 5. It allows the capture of the output values from this module and makes it possible to create a new data set (matrix) of deep features with class labels corresponding to the PD patient or health subject, for supervised training. After the extraction of the features from each image present in the data set, the vectors are stored into a matrix of vectors $M(n, 512)$, where n represents the number of images in the data set. The values in the matrix were then used for supervised SVM training.

4.5. SVM training and classification. For the supervised training of SVM, the features created during the extraction phase were divided into two data sets, training and testing. For the training process 80% of the stored data were used, and 20% for testing.

The extracted features, for PD patient and Healthy subject classes, were then used for SVM training with linear, RBF and polynomial kernels. The performance values were then compared with the performance of other CNN classifiers, such as ResNet, VGG11 and SqueezeNet, and with other ML algorithms applied to classify the extracted features to establish the performance of the proposed system in comparison with other methods.

For the selection of SVM hyperparameter values, we have used the method described by Damaševičius (2010), which uses the Nelder–Mead (or downhill simplex) nonlinear optimization algorithm. The optimized SVM hyperparameters were C (a trade-off between training error and margin), Q (a maximum size of quadratic programming sub-problems for SVM optimization), and J (a cost-factor by which training errors on positive examples outweigh errors on negative examples).

4.6. Performance evaluation. In order to evaluate classification performance, we use accuracy, recall, precision and F-score metrics. The metrics are commonly used to evaluate classifier performance by many authors, including multiple studies regarding Parkinson's disease recognition (Pereira *et al.*, 2015; Ali *et al.*, 2019).

Accuracy is the ratio of correctly classified data:

$$accuracy = \frac{tp + tn}{tp + fp + tn + fn}. \tag{5}$$

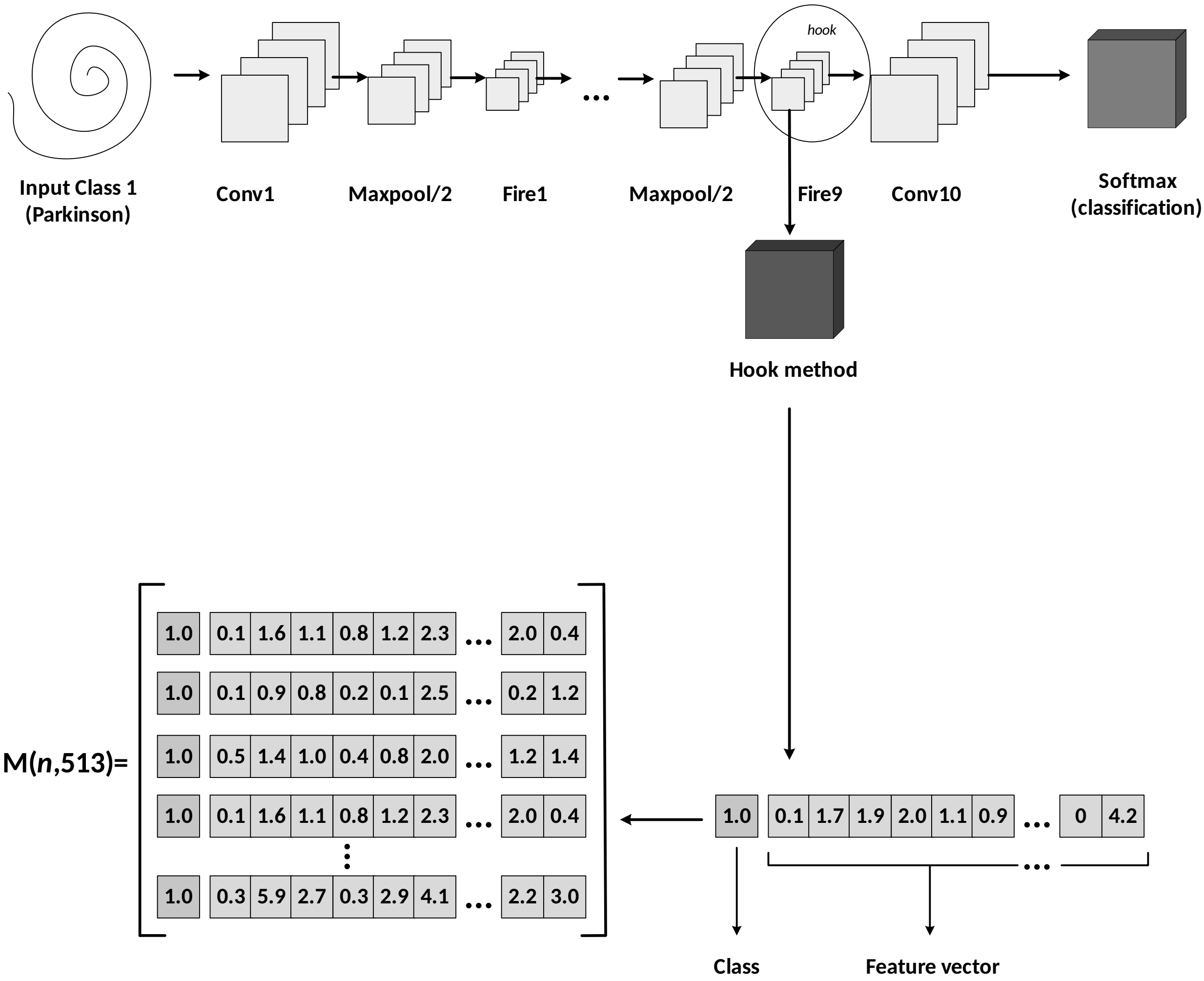

Fig. 5. Illustration of feature extraction from the SqueezeNet deep learning model trained on the collected handwritten spiral data set. Matrix *M* was created from extracting the vector features from the *fire9* module.

Here tp is the number of true positives, tn is the number of true negatives, fp is the number of false positives, and fn is the number of false negatives.

Recall reveals the ratio of data correctly classified as belonging to a class, from all data that truly belong to it,

$$recall = \frac{tp}{tp + fn}. \tag{6}$$

The precision value measures the amount of data that were classified as belonging to a class, in relation to all elements of the class,

$$precision = \frac{tp}{tp + fp}. \tag{7}$$

The performance measure that relates precision and recall is called F-score, which is defined as follows:

$$F = \frac{2 \times recall \times precision}{recall + precision} \tag{8}$$

5. Results

For implementation, we used Colab GPU, with 13 GB RAM on a computer with Ubuntu 18.04.3 LTS. Code was implemented in Python 3.

The collected data set was used to obtain the trained model. The training process of the SqueezeNet model was performed for 12 epochs, until no improvement in the model's accuracy was observed. The learning rate of a CNN has high importance to obtain a maximum performance from the network (Raghavendra *et al.*, 2018). Aiming to establish the best learning rate of the CNN, the data set was submitted for CNN training, and training was interrupted when the smallest loss value was achieved, from where the best learning rate was selected to be from 10^{-7} to 10^{-6}.

To establish the performance of the proposed system, it was compared with three other deep learning classifiers: SqueezeNet (used as a standalone model without any

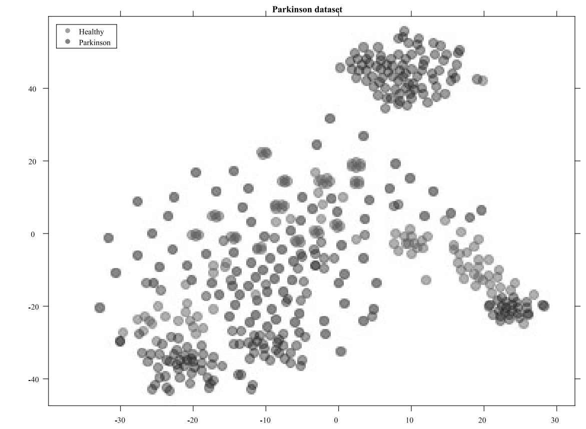

Fig. 6. Distribution of healthy and Parkinson's spiral features in the data set extracted by SqueezeNet after feature dimensionality reduction using t-SNE.

modifications), ResNet, and VGG11. Two characteristics were used to compare the deep learning models: the accuracy on the testing data set, and the time performance of the training process (see Table 3). We used the 'early stopping' criterion to stop the training after the performance starts declining during training. Although all tested deep learning models achieved similar values of accuracy, the time performance of the SqueezeNet model was better. The extracted features from the *Fire9* module of SqueezeNet were plotted in the two-dimensional space by applying the t-distributed stochastic neighbor embedding (t-SNE) (van der Maaten and Hinton, 2008) in order to have a visual representation of how the features of each class were distributed (see Figure 6). To explore the performance of SVM, kernel functions were applied to obtain maximum performance from the SVM model that was initialised with a random state of 109. For SVM kernels, we used the following values of regularization factor C (all kernels), variance σ (only RBF kernel) and degree d (only polynomial kernel), which are important in selecting an optimal hyperplane: $C = 1$, $\sigma = 3$, and degree $d = 3$.

To validate the results obtained from the testing process of SVM, the 10-fold cross validation was applied. For each model the accuracy, precision and F-score metrics were calculated. From the three kernels applied, the linear kernel presented better performance as shown in Table 4.

To compare the efficiency of SVM to perform classification on deep features learned by the SqueezeNet deep learning network, the features extracted from SqueezeNet were submitted to two other ML classifiers: RF and GNB, and 10-fold cross validation was used to evaluate the efficiency of the proposed method. To establish the best algorithm for the considered problem, three supervised models (SqueezeNet + GNB, SqueezeNet + RF and SqueezeNet + SVM (proposed)) were trained, and performance measures (F-score, precision, accuracy and recall) were calculated and presented in Table 5, where SVM had achieved the best performance.

The proposed hybrid method had a better accuracy in comparison with other deep learning methods (standalone SqueezeNet, ResNet and VGG1), achieving 91.26% accuracy, being followed by ResNet, which shows an accuracy of 89.22%, achieving the closest performance to the proposed method (see Table 6).

6. Conclusions and future work

The hybrid SqueezeNet and SVM classification method presented in this paper shows how powerful deep learning and machine learning tools can be used together aiming to help on the diagnosis of a disease that affects millions of people worldwide, being a valuable solution for future works that also aim at the diagnosis of Parkinson's disease (PD). Based on the achieved results, the proposed system can serve as a viable solution to assist the process of diagnosis of the PD, offering an accurate (we achieved an accuracy of 91.26%) and fast result in the process of handwritten spiral image classification, being able to process the provided data in seconds.

Moreover, our proposed system was evaluated on a heterogeneous data set of handwritten spiral images obtained from different sources (digital, paper-based) which offers flexibility in the disease recognition, while other works use homogeneous image data sets for evaluation, leading to overfitting. Despite this advantage, a limitation of the work is that the data set used for training the models is still small compared with the data sets used for other biomedical applications. Collecting more own data and adding externally derived data sets to increase our data set and re-evaluate the models on the larger data set will be a subject of our future work. Despite the advances in understanding the PD and the appearance of more precise computer techniques aiming at its diagnosis, the studies in this field are still in the early stages to provide a definitive computer aid tool to achieve an accurate diagnostics of the PD. However, new techniques based on deep learning offer a light to guide future works and development of tools that in the future will offer a definitive solution to the automated PD diagnosis process.

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Table 3. Results of deep learning model training process: classification accuracy and training time.

ResNet			SqueezeNet (part of our system)			VGG11		
Epoch	Accuracy	Time (sec)	Epoch	Accuracy	Time (sec)	Epoch	Accuracy	Time (sec)
0	0.6568	62	0	0.6862	15	0	0.6470	109
1	0.7156	62	1	0.8235	15	1	0.8333	107
2	0.6568	62	2	0.8823	15	2	0.8725	106
3	0.6862	62	3	0.8823	15	3	0.8529	106
4	0.6470	62	4	0.8921	14	4	0.8823	106
5	0.6764	61	5	0.8921	14	5	0.8823	105
6	0.7156	61	6	0.8823	14	6	0.8921	105
7	0.7843	62	7	0.8823	14	7	0.8921	106
8	0.8235	62	8	0.8627	14	8	0.8921	106
9	0.8921	61	9	0.8627	14	9	0.8921	106
10	0.8921	61	10	0.8627	14	10	0.8921	107
11	0.8921	61	11	0.8529	14	11	0.8725	106

Table 4. Classification results using various SVM kernels.

SVM				
Kernel	Accuracy	Precision	Recall	F-Score
Linear	0.9126	0.9200	0.8985	0.9067
Polynomial	0.8741	0.8950	0.8455	0.8695
RBF	0.8832	0.9058	0.8561	0.8788

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Table 5. Comparison of hybrid classifier performance. Best results are shown in bold.

Algorithm	Accuracy	Precision	Recall	F-score (with std. dev.)
SqueezeNet + GNB	0.8252	0.8261	0.8053	0.8123 (+/- 0.17)
SqueezeNet + SVM (proposed)	**0.9126**	**0.9200**	**0.8985**	**0.9067 (+/- 0.13)**
SqueezeNet + RF	0.8738	0.8728	0.8621	0.8665 (+/- 0.17)

Table 6. Comparison of performance values of the proposed hybrid method and other deep network models. Best results are shown in bold.

Method	Accuracy	Precision	Recall	F-Score (with std. dev.)
SqueezeNet+SVM	**91.26%**	**92.00%**	89.85%	**90.67% (+/- 13.07%)**
SqueezeNet	85.29%	87.27%	85.71%	86.49% (+/- 14.26%)
ResNet	89.22%	86.89%	**94.64%**	90.60% (+/- 11.82%)
VGG11	87.25%	86.44%	91.07%	88.70% (+/- 13.84%)

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