International Journal of Mathematics, Statistics, and Computer Science
Vol 2, 2024
ISSN: 2704-1077 eISSN 2704-1069, DOI: 10.59543/ijmscs.v2i.7821

Hand-Sketchs based Parkinson's disease Screening using Lightweight Deep-Learning with Two-Fold Training and Fused Optimal Features

Venkatesan Rajinikanth[1], Sahar Yassine[2], Syed Ahmad Chan Bukhari[3]

[1]Department of Computer Science and Engineering, Division of Research and Innovation, Saveetha School of Engi-neering, SIMATS, Chennai 602105, India; v.rajinikanth@ieee.org
[2]Department of Applied Data Science, Noroff University College, Kristiansand, Norway; Sahar.Yassine@noroff.no
[3]Division of Computer Science, Mathematics and Science, Collins College of Professional Studies, St John's Univer-sity, USA; bukharis@stjohns.edu

ABSTRACT: Older people experience different Age-Associated Diseases (AAD), and appropriate diagnosis and treatment will help them to lead a peaceful life. Parkinson's disease (PD) is one of the ADD generally found in people aged >60 years. The clinical-level screening of PD is performed using different procedures, including the hand sketches, such as wave/spiral patterns. The proposed research implements Pretrained Lightweight Deep-Learning (PLDL) methods with two-fold training to detect the patterns accurately from hand sketches belonging to the healthy/PD class. The developed system consists of the following stages; (i) Image preprocessing, (ii) Data augmentation, (iii) Two-fold training to improve the detection accuracy, and (iv) Deep features selection with 50% drop-out and binary classification. This work considered the fused features of MobileNets to achieve better detection accuracy. The outcome of this research confirms that this procedure offers a satisfactory result in predicting PD from the considered test images. The K-Nearest Neighbor (KNN) classifier offered a detection accuracy of 100% with the chosen database.

Keywords: Parkinson's disease, Hand sketches, Deep learning, MobileNet, Features selection, Classification.

1. INTRODUCTION

Infectious and acute diseases areradually rising globally due to various causes, and timely detection and handling are necessary [1]. Compared to adults, the elderly group is affected mainly due to various diseases, and these diseases are commonly referred to as Age-Associated Diseases (AAD).

Common AADs such as diabetes, vision-related issues, and other issues in body parts are common, and several clinical protocols exist to treat these diseases. Parkinson's disease (PD) is also a type of AAD, mainly due to the problem linked with the nervous system, and it may cause mild to severe symptoms. PD is a steadily increasing neurology-associated disease in people living in low- and middle-income countries. Further, this causes a substantial global disease burden, and untreated PD will cause various other illnesses [2], [3].

The common symptoms of Parkinson's include tremors in the hand, change in speech, bradykinesia, and change in body position and moving pattern [4]. Accurate detection of Parkinson's can help the individual to get the necessary treatment and support to reduce the effect of the disease. The typical treatment includes medication, physiotherapy, and surgery (in some cases).

The initial level screening of Parkinson's is performed using speech signals collected from the individuals or the hand sketch obtained using a chosen approach. The collected data is then processed to detect the PD and its severity. In the hand-sketch-based approach, the wave or the spiral patterns are collected from the individuals, and it helps to identify the PD and its severity based on the change in image patterns due to the tremor in hand. It is one of the standard procedures, so researchers perform several research workto automatically assess the hand sketches [5].

Recently, machine-learning (ML) and deep learning (DL) based procedures have been widely performed by researchers to automate hand-sketch examination procedures [6-11]. The earlier works confirm that the implemented ML and DL schemes efficiently segregate the considered hand sketches into healthy/PD classes [12,13]. When the patient with PD is identified during this screening process, other clinically recommended procedures are executed to confirm the PD and its severity for planning the appropriate treatment to reduce the impact of the disease.

This research aims to develop and implement a deep-learning approach for detecting PD using wave sketches. The stages of the proposed scheme involve; (i) Image preprocessing, (ii) Deep features mining using a Lightweight deep-learning scheme (LDLS), (iii) Deep features fu-sion, and (iv) Classification using a 3-fold cross-validation. First, image preprocessing is considered to resize the wave image and then convert it to a binary image using bi-level thresholding to achieve better pattern detection. This image is then examined using the chosen LDLS, and the extracted features are then considered to classify the sketches into healthy/PD using a chosen binary classifier.

In this work, a small image database is considered; hence, a two-fold training is implemented using the LDLS to achieve better accuracy. This training is executed by considering 50 epochs in every case. After mining the deep features, a 50% dropout is applied, and the reduced features are then serially concatenated to get a dual-deep feature vector to achieve better classification accuracy. The experimental outcome of the proposed research confirms that this scheme helped to achieve a disease detection accuracy of 100% when the KNN classifier is considered along with the fused deep features. This work also presents the results of LDLS methods, like SqueezeNet, ShuffleNetV1, and NASNet, and the achieved results are presented and discussed.

The main contribution of this research includes:

(i) Implementation of a suitable pre-processing scheme to improve the pattern in wave sketch,

(ii) Performance evaluation of chosen LDLS using two-fold training,

(iii) Implementation of dual-deep features to improve PD detection accuracy.

The other sections of this work are arranged as follows; Section 2 presents the literature re-view, Section 3 depicts the methodology, and Sections 4 and 5 show experimental outcomes and conclusions.

2. LITERATURE REVIEW

Automatic detection of the disease using a clinical data is a common procedure to reduce the disease screening burden. This work proposes a LDLS to detect the PD using the wave-sketch collected from the volunteers. The earlier works on hand-sketch assessment using the wave- and spiral-pattern confirms that the PD in an individual can be effectively confirmed with this test and it identifies the changes in the pattern due to tremor in hand. This section presents few chosen earlier works on ML and DL supported PD detection using the hand-sketches [12,13].

Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects the motor system, resulting in tremors, rigidity, and bradykinesia. Early detection of PD is essential for effective treatment, but it can be challenging as symptoms can be subtle and varied. Recently, researchers have explored the use of wave sketches to aid in the detection of PD. This literature review will summarize and analyze the existing research on Parkinson's disease detection using wave sketches.

One study conducted by Akter (2020) investigated the use of wave sketches to detect PD in patients. The results showed that the wave sketches were able to detect significant differences in motor activity between the two groups, indicating that wave sketches may be a useful tool for detecting PD [6].

In a more recent study, Chakraborty et al. (2020) used wave sketches and a convolutional neural network (CNN) to detect PD from accelerometer data. The researchers collected data from 32 PD patients and 22 control subjects and used wave sketches to extract features from the data. They then trained a CNN to classify the data as either PD or control. The results showed that the CNN achieved a classification accuracy of 90.6%, indicating that wave sketches may be a useful tool for PD detection [7].

A study by Shaban (2020) used wave sketches to analyze electroencephalogram (EEG) data for PD detection. The researchers collected EEG data from 13 PD patients and 13 control subjects and used wave sketches to extract features from the data. They then trained a machine learning model to classify the data as either PD or control [8]. The results showed that the machine learning model achieved an accuracy of 85%, indicating that wave sketches may be a useful tool for PD detection using EEG data.

Few similar studies on PD detection from the real patient information can be found in [9][10][11][12][13]. In conclusion, the existing research suggests that wave sketches may be a useful tool for Parkinson's disease detection in various types of data, including accelerometer, voice, and EEG data. While the studies reviewed here are promising, more research is needed to validate the effectiveness of wave sketches in detecting PD in larger and more diverse populations.

3. METHODOLOGY

This work aims to develop an LDLS to effectively classify the wave sketch into healthy/PD classes. In order to achieve better accuracy, this work implements a series of image processing schemes and achieves a better accuracy using a chosen binary classifier using 3-fold cross-validation.

Figure 1 depicts the framework developed to detect the PD screening scheme. The collected wave sketch is initially resized and pre-processed to get the binary image. The obtained image is then considered to extract the deep features using the chosen LDLS, and the extracted features are then reduced using 50% dropout. The reduced features are then serially concatenated to get a single feature vector with a dimension of $1 \times 1 \times 1000$ features. This feature vector is then considered for the binary classification with 3-fold cross-validation. The achieved results are considered to verify the merit of the proposed scheme.

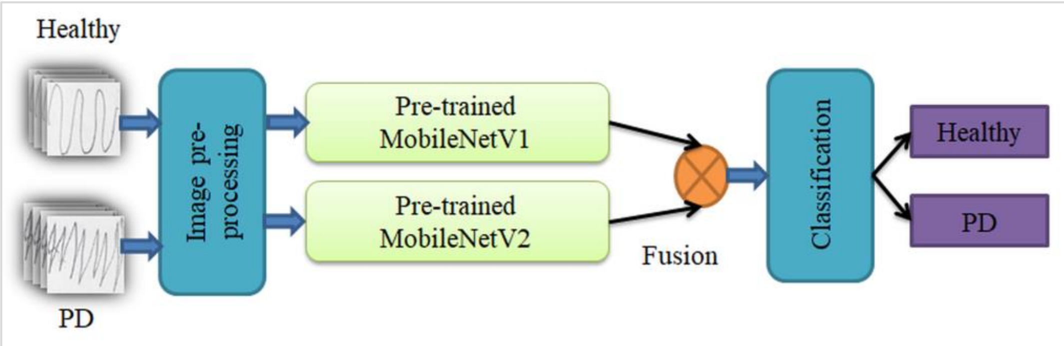


Figure 1. Proposed scheme to detect PD using hand sketch

3.1 Wave-sketch database

In the literature, wave and spiral sketches are widely used to detect PD using the ML, and DL approaches. In this research, the wave sketches of [14]. This database consists of 51 healthy and 51 PD class images (102). The earlier works with this database can be found in [11][12], and chosen sample images for demonstration can be found in Figure 2. In this work, the standard image augmentation procedures, such as vertical flip, horizontal flip, zoom, and angle-based rotation, are considered to increase the image dimension to a more significant value (1080 images). Furthermore, 80% of the images are chosen for training (864 images), and 20% are considered for validation (216 images). Finally, 30 images (15 healthy and 15 PD) are considered for testing the performance of the developed scheme.

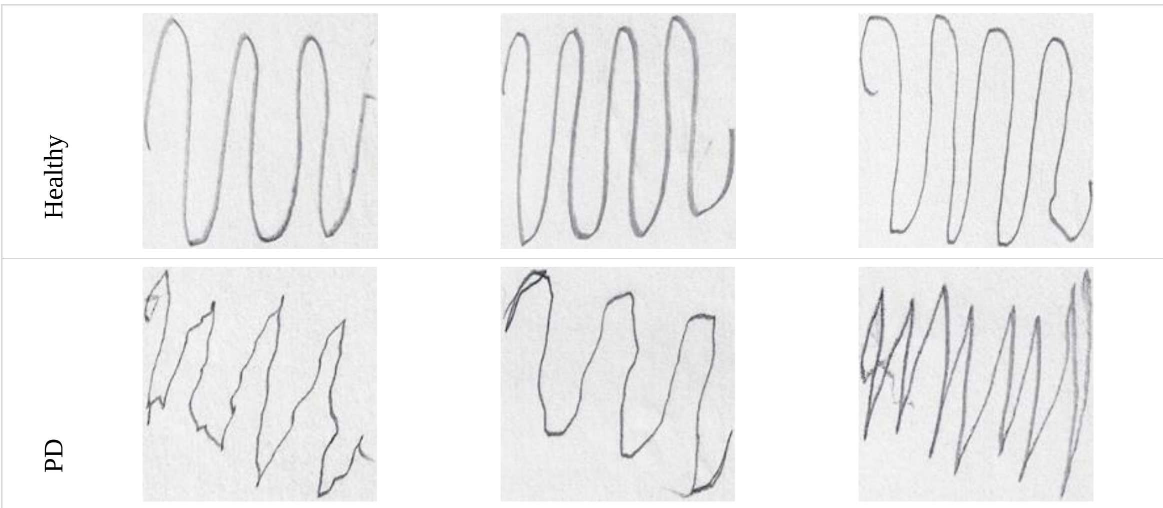
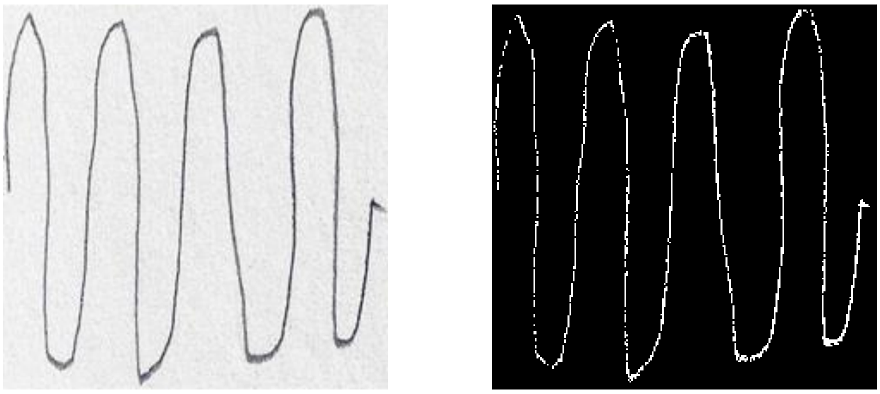


Figure 2. Sample images and the associated GT

3.2 Image pre-processing

Image pre-processing is essential for converting the raw images into the usable form. In this work, the wave-sketch image is a pencil sketch created on a paper and the digital form of this image is in RGB form and hence it is quite complex to trace its wave patterns. To reduce the complexity, this work implemented the following procedure to convert the RGB scale sketch into a binary image, which is easily analysed using a chosen ML and DL approach. The image pre-processing implemented in this scheme involves in; RGB to grey scale conversion, Otsu's based bi-level thresholding, implementing image complement and grey to binary conversion.

Figure 3 presents the outcome of the proposed pre-processing scheme. Figure 3(a) shows the raw wave-sketch and Figure 3(b) presents the processed wave-sketch considered in this research. It is a binary image and helps to achieve a better classification accuracy compared to the raw RGB scale image.



(a) Original (b) Pre-processed

Figure 3. Pre-processed wave-sketch considered in this research

3.3 Lightweight deep-learning

Even though the conventional DL schemes offers a better result on a variety of data examination tasks, its implementation and execution is quite complex and it will not work efficiently on a low processing devices, such as mobile phones and workstation with very lesser RAM. To overcome this issue, LDLS are developed and implemented by the researchers to process a variety of data and achieved a better detection accuracy, which is close to the conventional DL approach. The proposed research considered the LDLS, like SqueezeNet, MobileNetV1, MobileNetV2, ShuffleNetV1 and NASNet to examine the wave-sketch and the necessary information regarding these schemes can be found in [15][16][17][18].

Compared to other conventional DL approaches, the implementation and execution of LDLS is simple and it also supports the mobile supported diagnosis of the chosen medical data. In this work, the performance of these schemes is verified using the individual features and fused dual-deep features. The initial parameters for LDLS are assigned as follows; initial weights =ImageNet, pooling = average, optimizer =ADAM and number of epochs =50. This work implements a two-fold training to achieve better detection accuracy. The best model from the first training is considered as the initial value for the second phase training.

The feature vector of this scheme is depicted in Eqns. (1) to (4), Eqn. (1) presents the common feature vector when the LDLS is considered and Eqns. (2) and (3) shows the feature vector after a 50% dropout and Eqn. (4) presents the fused feature vector.

$$\mathrm{Features}_{(1\times1\times1000)} = \mathrm{DF}_{(1,1)}, \mathrm{DF}_{(1,2)}, \dots, \mathrm{DF}_{(1,1000)} \tag{1}$$

$$\mathrm{DF1}_{(1\times1\times500)} = \mathrm{DF1}_{(1,1)}, \mathrm{DF1}_{(1,2)}, \dots, \mathrm{DF1}_{(1,500)} \tag{2}$$

$$\mathrm{DF2}_{(1\times1\times500)} = \mathrm{DF2}_{(1,1)}, \mathrm{DF2}_{(1,2)}, \dots, \mathrm{DF2}_{(1,500)} \tag{3}$$

$$\mathrm{Fused}_{(1\times1\times1000)} = \mathrm{DF1}_{(1\times1\times500)} + \mathrm{DF2}_{(1\times1\times500)} \tag{4}$$

3.4 Performance evaluation and validation

The merit of the developed computer algorithm needs to be verified to confirm its performance towards the real clinical data. To achieve this, the necessary metrics, such as accuracy (AC) precision (PR), sensitivity (SE), specificity (SP) and F1-Score (FS) needs to be computed. In this work, the confusion-matrix (CM) initially provides the measures, like true-positive (TP), true-negative (TN), false-positive (FP) and false-negative (FN) for the chosen healthy (0) and PD (1) class images. The mathematical expression for these measures can be found in the earlier research works [19][20].

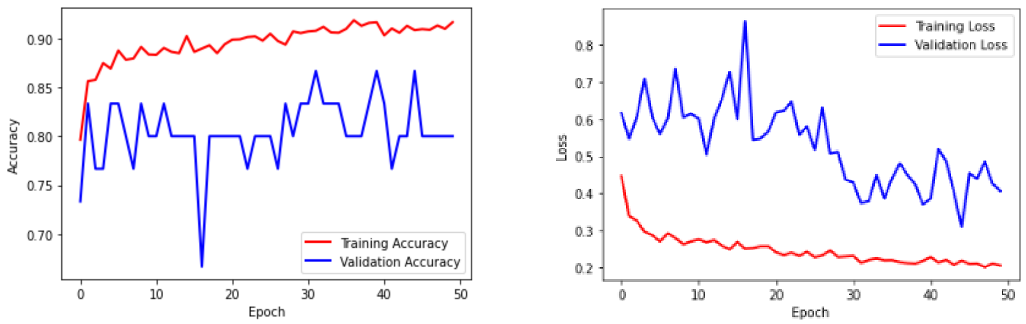
4. RESULTS AND DISCUSSION

This division of the research shows the experimental outcome obtained using the LDLS, and this investigation is implemented using a workstation having; Intel i5 processor, 12 GB of RAM, and 4 GB of VRAM.

Initially, every test image is pre-processed to get a binary image with dimension of $224 \times 224 \times 1$pixels and then image augmentation is implemented to increase 72 image into 1080 images in which 80% is chosen for the training and remaining 20% of data is considered for the validation. This work implements a two-fold training procedure to improve the PD detection accuracy and the achieved outcomes for fold1 and fold2 are depicted in Figure Figure 4 and Figure 5, respectively for MobileNetV2 scheme.

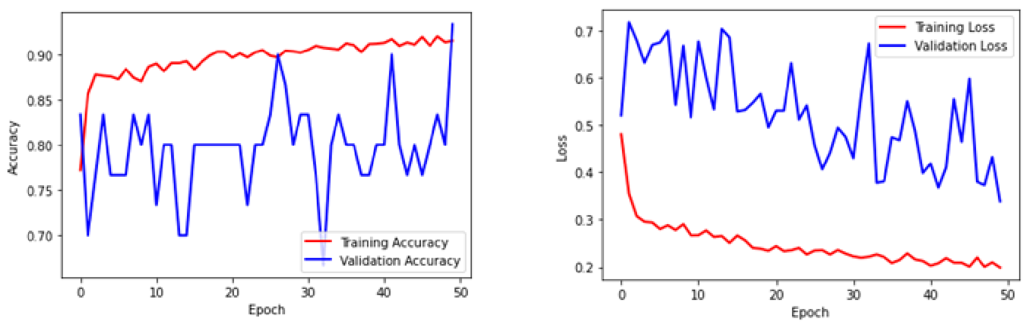
Figure 4 (a) shows the accuracy and Figure 4 (b) presents the loss value achieve with the proposed approach. Firm Figure 4 (a), it can be noted that the validation accuracy of the 1st fold training is around 80% and needs to be improved to achieve a better result.

Figure 5 (a) and (b) shows the accuracy and loss value achieved during the 2nd fold training process and this confirms that the validation accuracy of the chosen LDLS gradually improved towards a higher value and this scheme helped to achieve an accuracy of 93%. Figure 6 presents the intermediate results achieved during the pooling task in which Figure 6 (a) to (d) demonstrates the Convolutional layer outcomes for Conv1 to 4. This confirms that, the considered image is transformed in to features when the information moves through the layers of the LDLS and finally it presents a one-dimensional feature vector with size $1 \times 1 \times 1000$ which is then considered to classify the chosen images into healthy/PD (or 0/1) class. During the classification, the necessary information, such as CM and Receiver operating Characteristic (RoC) curve also obtained as shown in Figure 7. Figure 7(a) shows the CM and Figure 7(b) presents the RoC.



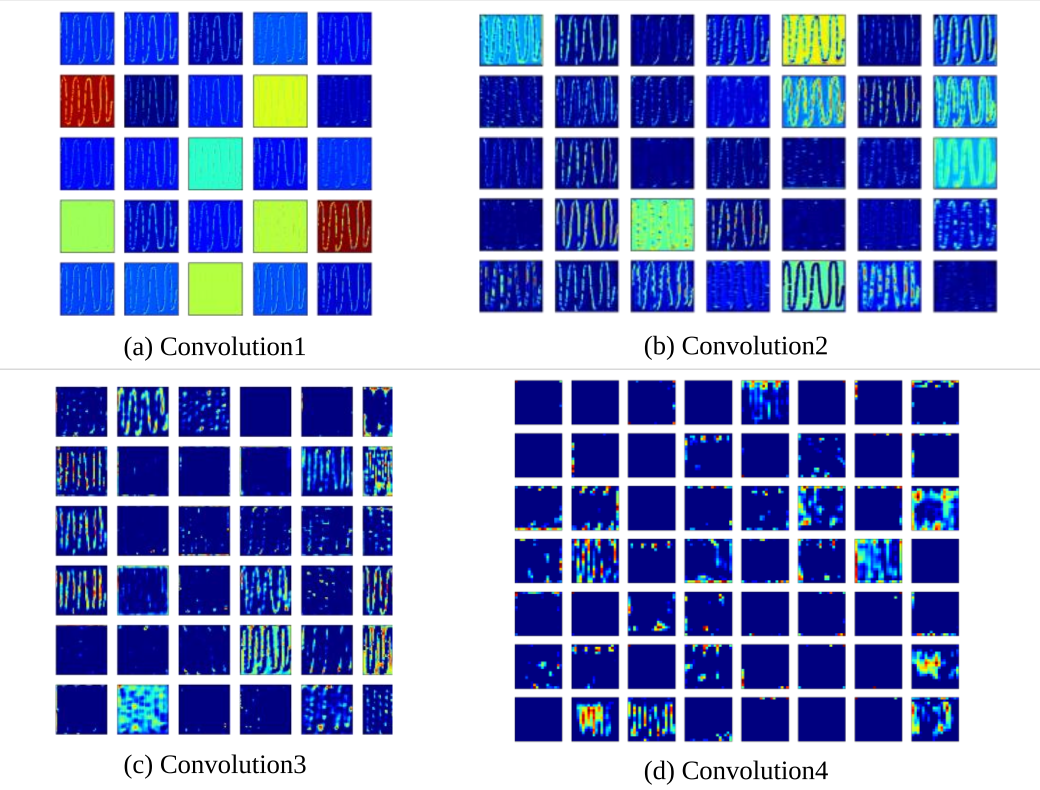
(a) Accuracy (b) Loss

Figure 4. Experimental outcome during fold1 training



(a) Accuracy (b) Loss

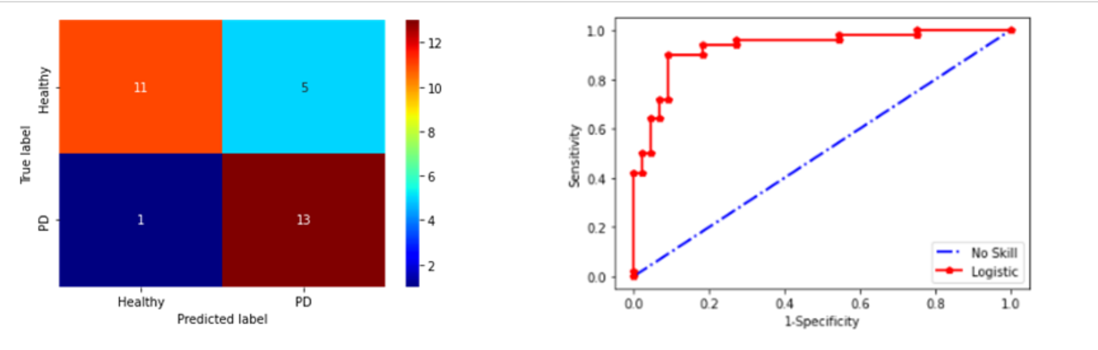
Figure 5. Experimental outcome during fold2 training



(a) Convolution1 (b) Convolution2

(c) Convolution3 (d) Convolution4

Figure 6. Various convolutional layer outcomes for MobileNetV2



(a) CM (b) RoC

Figure 7. The final result obtained using MobileNetV2

Similar procedure is repeated with other LDLS and the achieved CM is shown in Figure 8. Figure 8(a) presents outcome for SqueezeNet, Figure 8(b) shows the CM of MobileNetV1, and Figure 8(c) and (d) presents the CMs for ShuffleNet V1 and NASNet. The necessary TP, TN, FP and FN values for each case is then collected from the respective CM and the necessary metrics are then computed using these values.

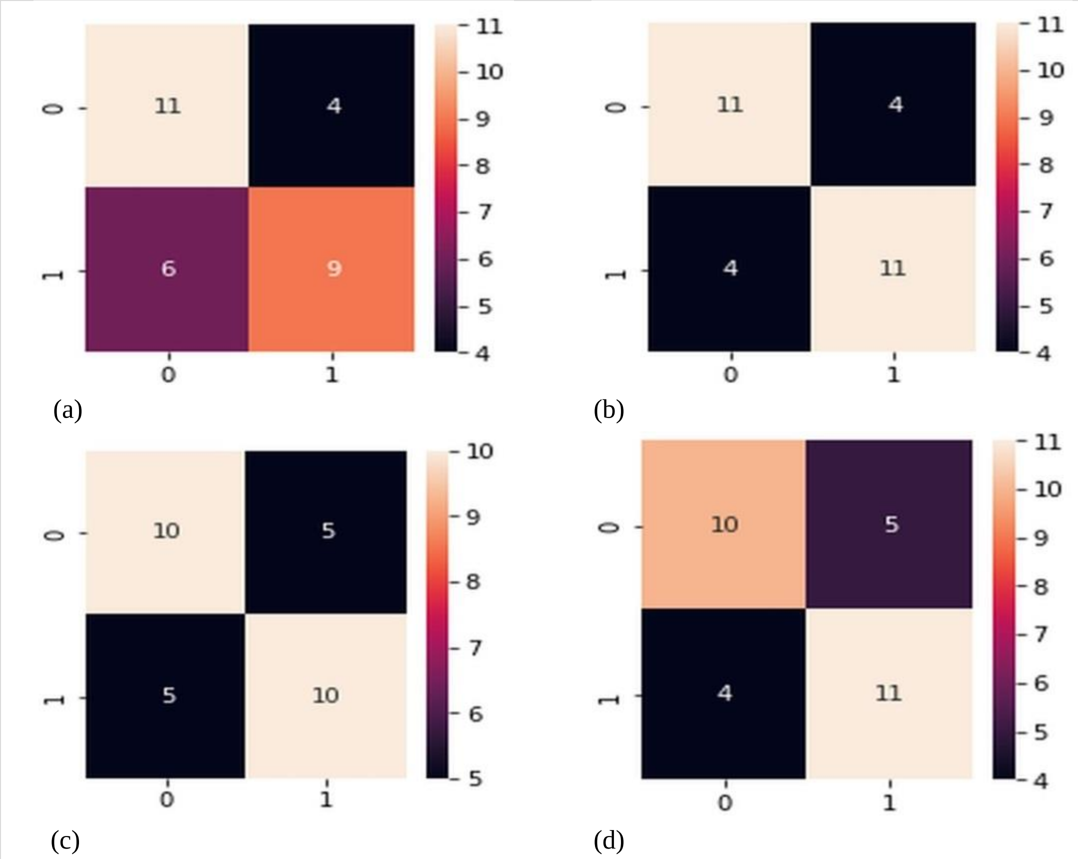


Figure 8. Results achieved with the chosen LDLS

For each scheme, the default SoftMax classifier is considered to get the necessary result as presented in Figures Figure 7 and Figure 8. By using the CM values, the performance metrics are then computed as shown in Table 1. This table confirms that the results of MobileNetV1 and V2 are better compared to other approaches and the Glyph plot in Figure 9 also confirms the merit. Hence, the dual-deep feature is then generated using the above said features using a 50% dropout after ranking. The new feature vector is then considered for the classification and the achieved result with various binary classifiers are shown in Table 2. The outcome of this research confirms that the MobileNetV1 and V2 helps to achieve a better detection accuracy (93.33%) compared to other methods and the Glyph plot shown in Figure 10 confirms that the overall performance also better with the MobileNet scheme.

Table 1. Experimental outcome for the chosen LDLS during fold1 training

Scheme	TP	FN	TN	FP	AC	PR	SE	SP	FS
SqueezeNet	9	6	11	4	66.67	69.23	60.00	73.33	64.28
MobileNetV1	11	4	11	4	73.33	73.33	73.33	73.33	73.33
MobileNetV2	13	1	11	5	80	72.22	92.86	68.75	81.25
ShuffleNetV1	10	5	10	5	66.67	66.67	66.67	66.67	66.67
NASNet	11	4	10	5	70.00	68.75	73.33	66.67	70.97

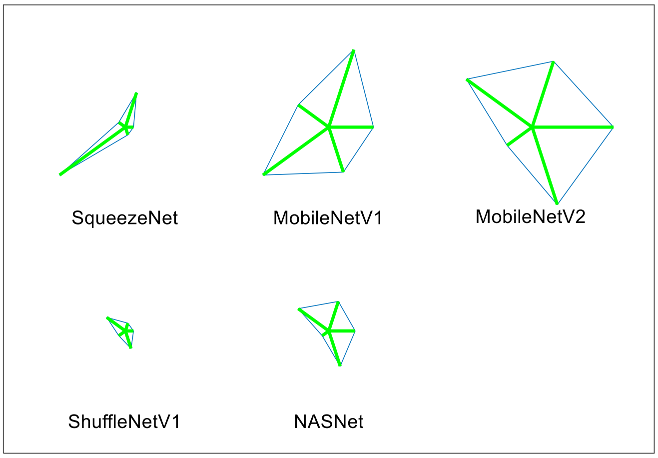


Figure 9. Glyph plot for the fold1 training data

Table 2. Experimental outcome for the chosen LDLS during fold2 training

Scheme	TP	FN	TN	FP	AC	PR	SE	SP	FS
SqueezeNet	12	2	14	2	86.67	85.71	85.71	87.50	85.71
MobileNetV1	14	2	14	0	93.33	100	87.50	100	93.33
MobileNetV2	13	1	15	1	93.33	92.86	92.86	93.75	92.88
ShuffleNetV1	13	2	14	1	90.00	92.86	86.67	93.33	89.65
NASNet	13	1	13	3	86.67	81.25	92.86	81.25	86.67

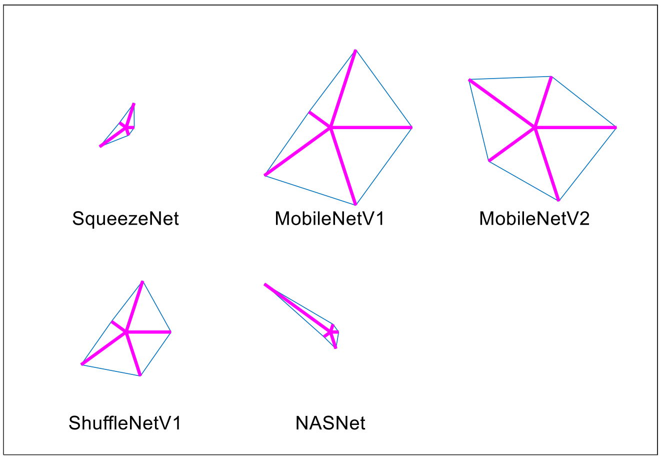


Figure 10. Glyph plot for the fold2 training data

The achieved result from Table 1 and Table 2 confirms that the classification achieved with MobileNetV1 and V2 is better and then a 50% dropout is implemented and a features fusion is executed to get a new features vector. This feature set is then considered to verify the merit of the proposed scheme and the achieved results for various binary classifiers is presented in Table 3. This confirms that the KNN classifier helps in achieving a detection accuracy of 100% on the chosen database. The Glyph plot shown in Figure 11 also confirms that the overall performance of the KNN is better compared to the alternatives.

Table 3. Classification result obtained using fused features

Scheme	TP	FN	TN	FP	AC	PR	SE	SP	FS
SqueezeNet	14	2	14	0	93.33	100	87.50	100	93.33
MobileNetV1	14	1	14	1	93.33	93.33	93.33	93.33	93.33
MobileNetV2	15	0	14	1	96.67	93.75	100	93.333	96.77
ShuffleNetV1	15	0	15	0	100	100	100	100	100
NASNet	14	0	15	1	96.67	93.33	100	93.75	96.55

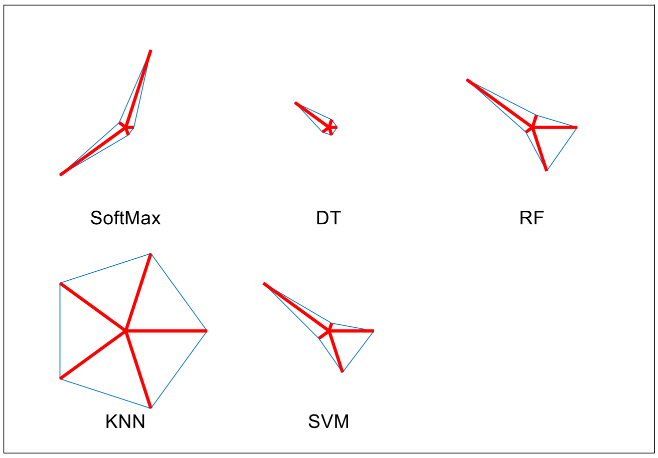


Figure 11. Glyph plot constructed with the fused features results

This research work proposed a methodology to examine the hand sketches using the pretrained LDLS and achieved better detection accuracy. In future, this scheme can be considered to classify the wave hand sketch data collected from the clinics.

5. CONCLUSION

Parkinson's disease (PD) is a complex neurodegenerative disorder that can be difficult to di-agnose in its early stages. Wave sketches have emerged as a potential tool for PD detection, as they can provide a detailed analysis of motor, vocal, and cognitive symptoms associated with the disease. The achieved result by this research suggests that wave sketches can be a useful tool for PD detection, especially when combined with LDLS method. Studies have demonstrat-ed that wave sketches can successfully detect PD with a better accuracy and when individual and fused MobileNet features are considered, it can help to achieve better detection accuracy. The KNN classifier along with the fused features helped to achieve 100% detection accuracy. Further research is needed to validate these findings and to explore the potential of wave sketches and deep learning techniques in detecting early stages of PD. Overall, wave sketches show promise as a useful tool for improving the early detection and diagnosis of Parkinson's disease, which can ultimately lead to more effective treatment and better patient outcomes.

REFERENCES

[1] N. Razmjooy and V. Rajinikanth, *Frontiers of Artificial Intelligence in Medical Imaging*. in 2053-2563. IOP Publishing, 2022. doi: 10.1088/978-0-7503-4012-0.

[2] A. Govindu and S. Palwe, "Early detection of Parkinson's disease using machine learning," *Procedia Comput Sci*, vol. 218, pp. 249–261, 2023, doi: https://doi.org/10.1016/j.procs.2023.01.007.

[3] M. Funayama, K. Nishioka, Y. Li, and N. Hattori, "Molecular genetics of Parkinson's disease: Contributions and global trends," *J Hum Genet*, vol. 68, no. 3, pp. 125–130, 2023, doi: 10.1038/s10038-022-01058-5.

[4] M. Thakur, S. Dhanalakshmi, H. Kuresan, R. Senthil, R. Narayanamoorthi, and K. W. Lai, "Automated restricted Boltzmann machine classifier for early diagnosis of Parkinson's disease using digitized spiral drawings," *J Ambient Intell Humaniz Comput*, vol. 14, no. 1, pp. 175–189, 2023, doi: 10.1007/s12652-022-04361-3.

[5] S. Dixit *et al.*, "A Comprehensive Review on AI-Enabled Models for Parkinson’s Disease Diagnosis," *Electronics (Basel)*, vol. 12, no. 4, 2023, doi: 10.3390/electronics12040783.

[6] Ferdib-Al-Islam and L. Akter, "Early Identification of Parkinson's Disease from Hand-drawn Images using Histogram of Oriented Gradients and Machine Learning Techniques," in *2020 Emerging Technology in Computing, Communication and Electronics (ETCCE)*, 2020, pp. 1–6. doi: 10.1109/ETCCE51779.2020.9350870.

[7] S. Chakraborty, S. Aich, Jong-Seong-Sim, E. Han, J. Park, and H.-C. Kim, "Parkinson's Disease Detection from Spiral and Wave Drawings using Convolutional Neural Networks: A Multistage Classifier Approach," in *2020 22nd International Conference on Advanced Communication Technology (ICACT)*, 2020, pp. 298–303. doi: 10.23919/ICACT48636.2020.9061497.

[8] M. Shaban, "Deep Convolutional Neural Network for Parkinson's Disease Based Handwriting Screening," in *2020 IEEE 17th International Symposium on Biomedical Imaging Workshops (ISBI Workshops)*, 2020, pp. 1–4. doi: 10.1109/ISBIWorkshops50223.2020.9153407.

[9] M. Aghzal and A. Mourhir, "Early Diagnosis of Parkinson's Disease based on Handwritten Patterns using Deep Learning," in *2020 Fourth International Conference On Intelligent Computing in Data Sciences (ICDS)*, 2020, pp. 1–6. doi: 10.1109/ICDS50568.2020.9268738.

[10] L. S. Bernardo, R. Damaševičius, V. H. C. De Albuquerque, and R. Maskeliūnas, "A hybrid two-stage SqueezeNet and support vector machine system for Parkinson's disease detection based on handwritten spiral patterns," *International Journal of Applied Mathematics and Computer Science*, vol. 31, no. 4, pp. 549–561, 2021, doi: doi:10.34768/amcs-2021-0037.

[11] A. Shrivastava, M. Chakkaravarthy, and M. Asif Shah, "A Novel Approach Using Learning Algorithm for Parkinson's Disease Detection with Handwritten Sketches'," *Cybern Syst*, pp. 1–17, Jan. 2023, doi: 10.1080/01969722.2022.2157599.

[12] K.-M. Giannakopoulou, I. Roussaki, and K. Demestichas, "Internet of Things Technologies and Machine Learning Methods for Parkinson’s Disease Diagnosis, Monitoring and Management: A Systematic Review," *Sensors*, vol. 22, no. 5, 2022, doi: 10.3390/s22051799.

[13] M. Alissa *et al.*, "Parkinson's disease diagnosis using convolutional neural networks and figure-copying tasks," *Neural Comput Appl*, vol. 34, no. 2, pp. 1433–1453, 2022, doi: 10.1007/s00521-021-06469-7.

[14] Kaggle, "https://www.kaggle.com/datasets/kmader/parkinsons-drawings." https://www.kaggle.com/datasets/kmader/parkinsons-drawings (accessed Jun. 16, 2023).

[15] F. N. Iandola, S. Han, M. W. Moskewicz, K. Ashraf, W. J. Dally, and K. Keutzer, "SqueezeNet: AlexNet-level accuracy with 50x fewer parameters and <0.5MB model size." 2016.

[16] T.-J. Yang *et al.*, "NetAdapt: Platform-Aware Neural Network Adaptation for Mobile Applications," in *Proceedings of the European Conference on Computer Vision (ECCV)*, Sep. 2018.

[17] Y. Li, H. Huang, Q. Xie, L. Yao, and Q. Chen, "Research on a Surface Defect Detection Algorithm Based on MobileNet-SSD," *Applied Sciences*, vol. 8, no. 9, 2018, doi: 10.3390/app8091678.

[18] F. Saxen, P. Werner, S. Handrich, E. Othman, L. Dinges, and A. Al-Hamadi, "Face Attribute Detection with MobileNetV2 and NasNet-Mobile," in *2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA)*, 2019, pp. 176–180. doi: 10.1109/ISPA.2019.8868585.

[19] V. Rajinikanth, P. M. D. R. Vincent, K. Srinivasan, G. A. Prabhu, and C.-Y. Chang, "A framework to distinguish healthy/cancer renal CT images using the fused deep features," *Front Public Health*, vol. 11, 2023.

[20] K. S. Manic, V. Rajinikanth, A. S. Al-Bimani, D. Taniar, and S. Kadry, "Framework to Detect Schizophrenia in Brain MRI Slices with Mayfly Algorithm-Selected Deep and Handcrafted Features," *Sensors*, vol. 23, no. 1, 2023, doi: 10.3390/s23010280.