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PARKINSONNET: CLASSIFICATION PARKINSON'S DISEASE MODEL BASED ON NOVEL DEEP LEARNING STRUCTURE

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Abstract

Neuroimaging, particularly magnetic resonance imaging (MRI), has advanced significantly in recent decades and has played a significant sessional part in studying brain functions and diseases. MRI images, combined with unique ML approaches and developed tools during these years, have opened up new opportunities for diagnosing neurological illnesses. However, due to the apparent symptoms that are similar to each other, brain illnesses are regarded as difficult to precisely detect. This research examines a newly developed algorithm (ParkinsonNet) to classify Parkinson's disorder into two unique classes which are Control (healthy) and Parkinson's (PD), Convolutional neural networks (CNN) are one of the deep learning methodologies used in this procedure. CNN is one way that may be used to classify a range of brain illnesses such as Parkinson's. We employed a freshly constructed CNN technique from scratch, and we got 97.9% accuracy which is considered outstanding compared with recently published articles using the same dataset.

Keywords: Parkinson's Disease, CNN, MRI Image, Deep Learning.

BAŞLIK

Özet

Son birkaç on yılda nörogörüntüleme, özellikle de manyetik rezonans görüntüleme (MRI), beyin fonksiyonları ve hastalıklarının incelenmesinde önemli bir oturumsal rol oynamıştır. Bu yıllarda benzersiz makine öğrenimi yaklaşımları ve geliştirilen araçlarla birleştirilen MRI görüntüleri, nörolojik hastalıkların teşhisinde yeni fırsatlar yarattı. Ancak belirtilerin birbirine benzer olması nedeniyle beyin hastalıklarının kesin olarak tespit edilmesi zor kabul edilmektedir. Bu araştırma, Parkinson hastalığını Kontrol (sağlıklı) ve Parkinson (PD) olmak üzere iki benzersiz sınıfa ayırmak için yeni geliştirilen bir algoritmayı (ParkinsonNet) incelemektedir; bu yöntem, derin öğrenme yaklaşımlarından biri olan Evrişimsel sinir ağları (CNN). CNN, Parkinson gibi çeşitli beyin hastalıklarını sınıflandırmak için kullanılabilecek yollardan biridir. Yeni oluşturulmuş bir CNN tekniğini sıfırdan kullandık ve aynı veri kümesini kullanan yakın zamanda yayınlanan makalelerle karşılaştırıldığında olağanüstü kabul edilen %97,9 doğruluk oranı elde ettik.

Anahtar Kelimeler: Parkinson hastalığı (PD), Evrişimli Sinir Ağı (CNN), MRI Görüntüsü, Derin Öğrenme.

1. Introduction

The human brain may face lots of diseases that affect its control ability and may lead to uncontrol action and judgments. For instance, Alzheimer's disease (AD)(Al-Jumaili et al. 2023), Common neurological illnesses include Parkinson's disease (PD) and schizophrenia (SZ) which cause a disruption in brain function (Tolosa, Wenning, and Poewe 2006; Danielyan and Nasrallah 2009; Al-Jumaili et al. 2023; Al-azzawi et al. 2022). PD is considered a hazardous illness that, if detected in time, can be eradicated or, in the worst situation, slowed (Fontana et al. 2017; Leparulo et al. 2019). In this study, we explore the difficulties in classifing PD and highlight the potential applications of deep learning algorithms. PD is a chronic, progressive neurological disorder characterized by a lack of dopamine in the brain's substantia nigra. Figure 1 depicts the location of the substantia nigra in the brain as well as the substantia in a healthy individual and a Parkinson's disease patient. Our disease is more frequent among the aged people, generating stride and posture alterations that may increase the risk of falling and lead to mobility issues.

So, the result, it interferes with daily activities and reduces the quality of life for patients and their families (Hughes et al. 2002).

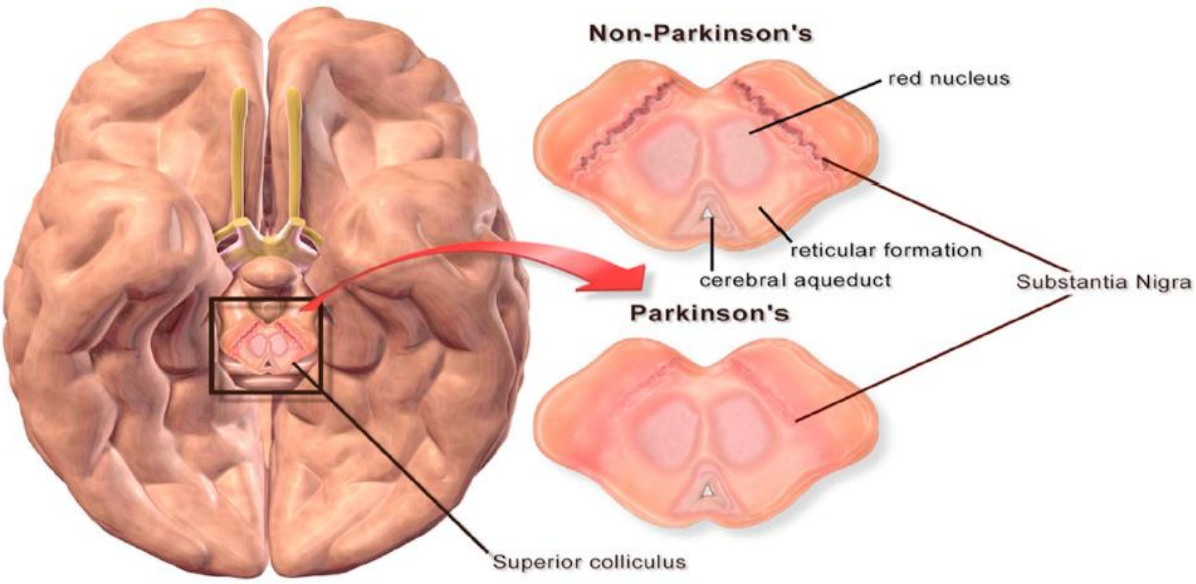

Figure 1. A healthy subject (top right) and a PD (bottom right) have their substantia-nigra images compared.

PD symptoms usually appear gradually over time. Due to the disease's variety, the symptoms of progression differ from one another. This makes detecting the illness in its first phases exceedingly challenging. The current clinical diagnosis of Parkinson's disease is primarily clinical; however, imaging can assist in confirming dopamine degradation and distinguish Atypical parkinsonism is a kind of Parkinson's disease (Stoessl, Lehericy, and Strafella 2014). Furthermore, the severity of the illness is assessed using the Unified Parkinson Illness Rating Scale (UPDRS), This comprises a log of various patient motions taken at regular intervals. UPDRS data and the images are utilized for diagnosis and research allowing us to design tasks that take advantage of deep learning capabilities while reducing the manual work required to analyze this data. Doctors employ a variety of tests and imaging to confirm Parkinson's disease because there is no standardized method. We offer an overview of the many forms of data collected and develop a classification/prediction problem to aid in diagnosis.

Several neuroimaging approaches, including MRI and CT techniques, help to identify these illnesses early identification, deep learning (DL)-based analytic algorithms have been created (Islam and Zhang 2018; Shatte, Hutchinson, and Teague 2019; Salvatore et al. 2014; Mathew, Vivek, and Anurenjan 2018), as well as to develop appropriate treatment plans (Mahmud and Vassanelli 2016, 2019; Poldrack, Gorgolewski, and Varoquaux 2019). In the last era, ML had been the magic wand that applied successfully in various fields and with different needs such as image analysis (Ali, Kaiser, and Mahmud 2019), disease detection (Noor et al. 2019; Miah et al. 2021), data mining (Mahmud et al. 2018; Mahmud et al. 2021), etc. Moreover, DL has a noticeable success when dealing with neurological when researchers attempted to employ DL-based for the diagnosis of brain disorders from MRI scans (Islam and Zhang 2020; Lei et al. 2020; Chand et al. 2020).

For much over a decade, medical issues have been solved using neural networks. However, as processing power has increased in the last few years,

, CNN has found its way into the medical profession due to its high sensitivity in identifying tumors and other abnormalities (Thaha et al. 2019; Mahmoudi et al. 2022; Kumari and Barpanda 2023; Moujahid, Cherradi, and Bahatti 2020). In PD case, medical imaging entails the use of various scans such as MRI, PET, and DAT-scan, each of which should be equipped with its own trained model to be relevant in PD diagnosis. The next reviews summarize various perspectives. For instance, one of them tries to combine the uses of machine learning and big data to investigate mental health (Shatte, Hutchinson, and Teague 2019). Moreover, several ML-based tasks have been investigated using connectome data from MRI in order to improve the diagnosis of neurological diseases (Neromyliotis et al. 2022). In addition, researchers in (Litjens et al. 2017), analyzed various medical images such as neuro, pulmonary, and pathology and applied them to DL. The authors of (Gottapu and Dagli 2018) investigated the use of DL to improve understanding and diagnosis of Parkinson's illness. In the same matter, researchers in (Lee et al. 2018), used Voxel-based morphometry which is an automatic volume method, used mainly to compare differences in brain volume between healthy and patient people. Huang et al. (Huang et al. 2021), suggested an unsupervised feature selection strategy for manifold learning based on longitudinal multimodal data. The method's fundamental idea is to compute the similarity matrix and discriminant features adaptively using joint embedding and sparse regression. Additionally, Cigdem et al. (Cigdem and Demirel 2018), They created 3D montages for GM (grey matter) and WM (white matter) tissues by combining various variables and GM, WM, and a two-sample t-test procedure to classify Parkinson. Kollias et al. (Kollias et al. 2018), They suggested a DNN architecture that included CNN for deriving rich internal representations from input data and a bidirectional-LSTM/gated recurrent units (GRU RNNs)-based RNN for analyzing the temporal progression of the inputs and giving final predictions. The ResNet and ReLU architectures were used to create a hybrid supervised and unsupervised learning approach. They helped to create a new database that was utilized for training, testing, and verifying the suggested systems. Norwitz et al. (Norwitz et al. 2020), They compared the effects of immediate administration of a ketone ester drink and a taste-matched, carbohydrate-based control drink on endurance exercise performance in 14 participants with Parkinson's disease (40). Within 30 minutes of intake, the ketone ester drink increased participants' -HB levels to a mean of 3.5 mmol/L. When compared to the isocaloric placebo drink, consumption of the ketone ester drink was related to a 24% increase in exercise endurance capacity, suggesting that ketone ester supplementation has the potential to alter motor function in Parkinson's disease. However, authors face throughout the diagnosing of the disease it involves multiple features such as motor functions, dopamine concentration, and many other clinical tests so it is considered a Challenge. Therefore, examining only one attribute to Understand the condition is insufficient as there are several brain-related disorders with comparable symptoms. Based on the previous accuracy values obtained from the different types of studies. Thus, we propose a novel convolutional neural network to increase the accuracy further. And to provide a tool that can help the health sector classify Parkinson's diseases. Our paper Sections are structured like this: Section 2 uses strategies, while Section 3 offers the work results. Finally, the conclusion is listed in Section 4.

2. Methodology

2.1. Brain MRI Dataset

The primary motivation for this project was to provide an ensembled framework for Parkinson's disease classification; the MRI dataset used came from Kaggle's public databases (Kabir 2022). This dataset contains 6477 MRI pictures, including 3010 MRI slices for healthy people, 906 MRI slices for Parkinson's disease, and 2561 MRI slices for Alzheimer's illness. The full set of MRI slices is in PNG format, and their size was changed to 224 X 224 pixels throughout the work. We used here just two classes: the PD and the healthy condition as presented in Figure 2.

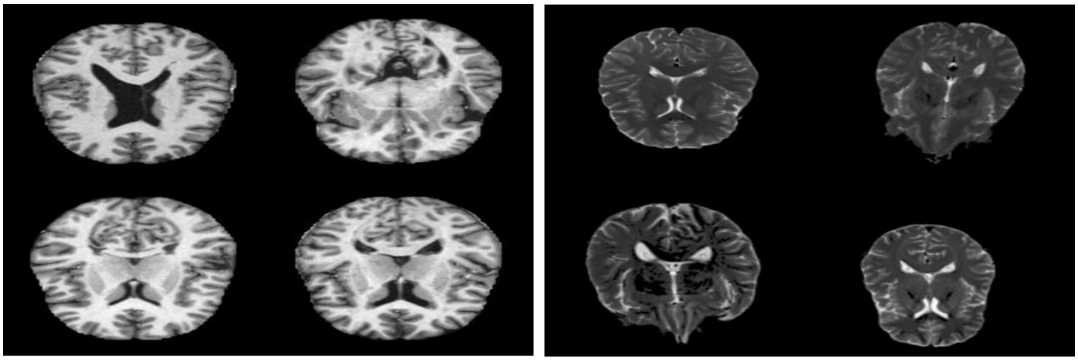

Figure 1. MRI images of the two classes of the dataset used, (A) the healthy, and (B) for PD.

2.2. Design Convolutional Neural Network (CNN)

CNN is a deep learning approach, are designed particularly for image analysis with two-dimensional data (Al-Jumaili et al. 2022). CNN is built on layers, each with its own learning process and outputs that are fed into the following levels. CNN is a learning algorithm that employs a raw input picture as its foundation. The standard structure of CNN is often divided into two basic components: feature extraction and classification. To collect characteristics, several types of layers are used to extract hidden data from MRI images, which play an important role since they have a major influence on the precision of classification results. Following that, the classifier will take all of the features extracted from it and split them into the right classifications. Convolution is the most important stage in CNN approaches since it is responsible for detecting traits and applying filters. Strides and the number of filters are two extremely important elements that have a substantial influence on the output of the convolutional operation, with stride defined as the space that separates two pixels and a number of filters defined as the number of features in the feature map (Haq et al. 2022). Two functions, f, and G, are mathematically merged to produce H(t), where H represents the entire amount of overlap of only one function, f(T), as it moves over the other criterion, G (Yamashita et al. 2018). This is demonstrated in the equation outlined below.

$$H(t) = \int_{-\infty}^{\infty} f(T)G(t-T)dT$$

Whenever used, H = f * G

10	37	1	5	40
4	2	16	55	20
28	17	2	0	47
9	0	19	25	13
8	30	41	6	31

a

X

0	0	1
0	0	0
1	0	0

b

=

29	22	42
25	55	39
10	30	88

c

Figure 3. (a) Input Matrix (b) Kernel Matrix (c) Outcome Matrix.

As shown in Figure 4 below, each of the six blocks of the convolution layer used in our proposed approach for deriving characteristics from MRI images has a (convolution Layer, batch Normalisation Layer, clipped Relu Layer, and MaxPooling Layer). The technique normally starts in the upper left corner, where the kernel matrix we utilized was 3x3 fixed for all Convolution layers yielding a result comparable to that seen in Figure 3. The kernel matrix 3x3 is then used again, but this time it is moved one column to the right owing to the Stride set (1x1), encompassing the full picture input. The activation function is critical in transforming linear input data to nonlinear output in order to speed up training and reduce network sensitivity. Despite the fact that ReLU cannot simultaneously activate all of the neurons in a cell, it is one of the most extensively used activation methods. To keep the final output from growing too large, we employed a Clipped Rectified Linear Unit (clipped Relu Layer) with a limit approach. All input less than zero is converted to zero, and any value more than the ceiling is made to match the clipping ceiling, which is equal to 10. Furthermore, utilizing Max Pooling boosted the precision ratio by pooling the map's convolutional features to reach the highest feasible average value. Furthermore, in the classification portion, input characteristics were sent to three sets of fully connected layers, each of which was preceded by a dropout layer that was (0.5) to prevent overfitting that happened in the model and followed by all features retrieved by convolution layers. The last block consisted of the Fully Connected Layer, SoftMax Layer, and Classification Layer.

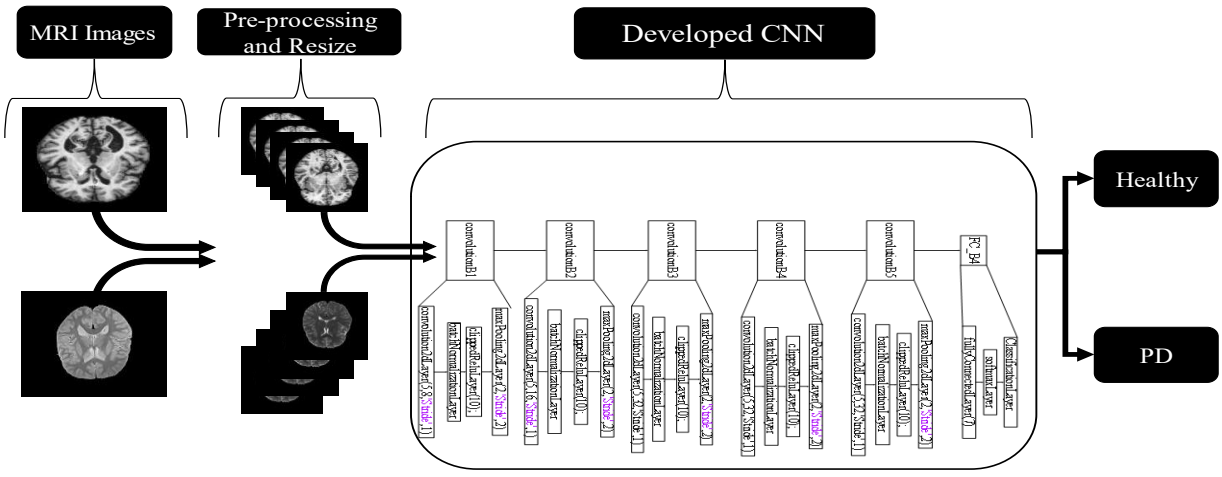

Figure 4. An outline of out technique

2.3. Evaluation Metrics

In accordance with the results that confusion matrix have and illustrated in Table 1, we used a number of assessment metrics to evaluate the efficacy of our proposed model. Table 1 summarises the accurate and wrong values assigned by the classifier for the predictions. These metrics are used to analyze and test the model's efficacy, such as accuracy.

Table 1. confusion matrix outcome.

Classes Name		**Predicted Class**	
Actual Class	Control	130	1
	PD	2	11

Generally, Confusion matrices are extensively used since they offer a more exact image of a model's efficiency than classification accuracy. Moreover, precision, sensitivity, and specificity were evaluated using the means as equations shown in Table 2. Accuracy was defined by the proportion of forecasts in the overall dataset that were correct. The total number of correct positive predictions from each positive prediction is used to calculate recall or sensitivity. While, precision, also known as confidence, is the probability that an actual number will be larger than the total of anticipated positives. Furthermore, the balance of precision and memory is represented by a harmonic, sometimes known as the F1-Score, the combination of precision and recall is represented. Using F1-Score is a secure technique to get a clear sense of the results we received.

Table 2. The equations used to calculate the results.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN}$$
$$Recall = Sensitivity = \frac{TP}{TP + FN}$$
$$Precision = Confidence = \frac{TP}{TP + Fp}$$
$$F1 - score = \frac{2 * TP}{2 * TP + FP + FN}$$

3. Results

The fundamental concept behind this work is to use MRI scans to classify two different forms of the brain disease Parkinson's: control and PD. Our suggested model was built on a convolutional neural network. The suggested model comprises five blocks for obtaining distinguishing information from MRI images and 1 block for identifying the most significant features of the 4 phases. We trained and evaluated our model to guarantee that the outcomes of the suggested technique are accurate, adequate, and efficient. Based on these findings, it was discovered that the suggested model produced improved outcomes when employing the MRI dataset with 97.9% accuracy. Latter, Table 4 below illustrates the equations that have been calculated which are: precision, recall, and F1-Score that have been evaluated for our approach using our constructed CNN architecture.

Table 3. Evaluation metries results.

Class	Precision	Recall	F1 Score	Accuracy
Control (Healthy)	99	98	99	97.9
PD	98	92	88	97.9

There are many methods used to classify Parkinson's disease, each with its own characteristics, but in the end, all of them try to reach the highest accuracy. Thus, in this paper, we develop a new model that has a novel convolutional neural network structure applied to classify PD with superior precision. Our developed algorithm has three main advantages: 1The capacity to extract characteristics from images better than traditional methods 2) The possibility of achieving a classification with high accuracy compared to the method used by many other studies 3) The ability to diagnose time with a shorter time difference than the methods used, based on the structure used in the model's architecture, which led to achieving a high time difference.

There are many types of problems when compared with different datasets due to the gathering of datasets having several factors that affect the dataset, such as 1) the device used to collect the dataset; 2) the resolution of the image produced; and many additional aspects that play a critical role in the diagnosis of diseases. With all the challenges, our model achieved high-accuracy results compared to the other methods. As shown in Table 4, the model we developed clearly outperformed all prior research.

Table 4. The suggested architecture compares the same MRI dataset with various studies.

Ref.	Data Source	Subjects Number	Method	Acc
(Aich et al. 2019)	UCI	31;8HC + 23PD	SVM	97.57
(Al-Fatlawi, Jabardi, and Ling 2016)	UCI	31;8HC + 23PD	Deep Belief Network	94
(Al Sayaydeha and Mohammad 2019)	UCI	31;8HC + 23PD	Enhanced Fuzzy Min-Max Neural Network and OneR	94.21
(Ali, Khan, et al. 2019)	UCI	40; 20HC+20PD	SVM	70
(Ali, Zhu, et al. 2019)	UCI	40; 20HC+20PD	LDA	95
(Alqahtani et al. 2018)	UCI	31;8HC + 23 PD	AdaBoost	96.30
(Anand et al. 2018)	UCI	31;8HC + 23PD	KNN,	95.51
(Cai et al. 2018)	UCI	31;8HC + 23PD	Fuzzy-KNN	97.89
(Celik and Omurca 2019)	UCI	40;20HC+20PD	Logistic Regression	76.03
(Dinesh and He 2017)	UCI	31;8HC+23PD	Boosted Decision Tree	91.21
(Erdogdu Sakar, Serbes, and Sakar 2017)	UCI	50;8HC+42PD	SVM	96.43
(Gunduz 2019)	UCI	252;64HC+188 PD	CNN	869
(Islam et al. 2014)	UCI	31;8HC+23PD	SVM, Random Tree	97.37
(Senturk 2020)	UCI	31;8HC+23PD	SVM	93.84
(Khan, Mendes, and Chalup 2018)	UCI	31;8HC+23PD	Evolutionary Wavelet Neural Networks	92.9
(Kuresan, Samiappan, and Masunda 2019)	UCI	40;20HC+20PD	HMM	95.16
(Marar et al. 2018)	UCI	31;8HC+23PD	ANN	94.87
(Moharkan et al. 2017)	UCI	31;8HC+23PD	KNN	90
(Sheibani, Nikookar, and Alavi 2019)	UCI	31;8HC+23PD	Ensemble	90.6
(Yaman, Ertam, and Tuncer 2020)	UCI	80;40HC+40PD	SVM	91.25
(Montaña, Campos-Roca, and Pérez 2018)	Private	54;27HC+27PD	SVM	94.4
(Sztahó et al. 2017)	Private	88;33HC+55PD	SVM-RBF	89.3
(Wodzinski et al. 2019)	PC-GITA	50PD+50HC	ResNet	91.7
(Buongiorno et al. 2019)	Private	30;14HC+16PD	ANN	89.4
(Xiao et al. 2019)	Private	87PD; 53HC	CNN	89.0
(Yasaka et al. 2021)	Private	115HC+ 115PD	CNN	81.0
(Chakraborty, Aich, and Kim 2020)	PPMI	203HC +203PD	CNN	95.3

(Tremblay, Mei, and Frasnelli 2020)	Private	15HC+15PD	CNN	88.3
(Shinde et al. 2019)	Private	35 HC+45PD	CNN	80.0
(Piccardo et al. 2021)	Private	55HC+43PD	CNN	93.0
(Shen et al. 2018)	Private	225HC+125PD	Group Lasso Sparse Deep Belief Network	90.0
(Dai, Tang, and Wang 2019)	PPMI	127HC+214PD	CNN	84.2
(Magesh, Myloth, and Tom 2020)	PPMI	212HC+ 430PD	CNN	95.2
(Chien et al. 2020)	Private	145HC+234PD	CNN	86.0
(Hsu et al. 2020)	Private	6HC+196PD	CNN	85.0
(Ortiz et al. 2019)	PPMI	111HC+158PD	CNN	95.1
(Martinez-Murcia et al. 2018)	PPMI	194HC+448PD	CNN	94.1
(Oh et al. 2020)	Private	20HC+20PD	1D-CNN	88.3
(Zhang et al. 2020)	Public	2148HC+656PD	CNN	86.0
(Alharthi, Casson, and Ozanyan 2020)	Public	73 HC +93PD	CNN	95.5
(Butt et al. 2020)	Private	50 HC+64PD	LSTM	82.4
(Cantürk 2021)	N.A.	15HC +25PD	CNN	94.0
(Gil-Martín, Montero, and San-Segundo 2019)	N.A.	15HC+62PD	CNN	96.5
(Gazda, Hireš, and Drotár 2021)	N.A.	NA	CNN	94.7
(Pereira et al. 2018)	N.A.	18HC +74PC	CNN	95.0
(Ribeiro, Afonso, and Papa 2019)	N.A.	21HC+14PD	RNN	97.0
(Diaz et al. 2019)	PaHaW	38HC+37PD	CNN	86.67
(Diaz et al. 2021)	NewHandPD	NA	CNN-RNN	90.0
(Nõmm et al. 2020)	N.A.	17HC+17PD;	CNN	93
(Prince and De Vos 2018)	N.A.	866HC+949PD	CNN	62.1
OURs	**Public**	**82HC+100PD**	**CNN**	**97.9**

4. Conclusion

Certain systems inside healthcare may become crucial tools for clinicians to obtain an accurate classification for various diseases such as Parkinson's disease. Consequently, deep learning algorithms have recently been introduced to the medical profession and have proven to be effective for a variety of detection and prediction tasks. These applications have demonstrated that good collaboration between the

healthcare section and deep learning researchers can build a system for illness detection that is easier, simpler, and faster.

This article used public MRI images that were available on Kaggle as a dataset for the classification of two types of health subject conditions: control and Parkinson's disease (PD). Some techniques may require specific data properties, our work approach needed the dataset to be re-sized to 224x224 as a pre-processing phase before applying our developed CNN.

The top results evaluated by constructed CNN models had an accuracy of 97.9%. As a result, the deep learning system provided here can help clinicians diagnose Parkinson's disease more effectively. Finally, we contrasted our findings to other recent cutting-edge studies, and our proposed technique outscored them all.

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