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USING DEEP LEARNING ALGORITHM TO DIAGNOSE PARKINSON DISEASE WITH HIGH ACCURACY

PARKİNSON HASTALIĞINI YÜKSEK DOĞRULUKLA TESPİT ETMEK İÇİN DERİN ÖĞRENME ALGORİTMASININ KULLANIMI

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ÖZET

Hem motor hem de motor dışı semptomlarda hayati ve kalıcı hasara neden olan Parkinson hastalığının erken teşhisi, hasta durumunun daha da kötüleşmesini önlemek için çok önemlidir. Bu çalışmada, UCI deposundan alınan Parkinson Hastalığı verileri derin öğrenme mimarisi kullanılarak sınıflandırılmıştır. Çalışmadaki derin öğrenme mimarisi, Python Keras tarafından oluşturulan ileri beslemeli bir sinir ağıdır (İBSA). Çalışmadaki mimari, bir girdi katmanı, iki gizli katman ve softmax fonksiyonunu ReLu (Rectified Linear Units) ile bir çıkış katmanı olarak oluşturulmaktadır. Derin öğrenme mimarisi, Parkinson Hastalığı (PH) veri seti iki sınıfa sahip olduğundan dolayı, ikili veri sınıflandırma problemini çözer. PH veri setini sınıflandırmak için test ve eğitim verisi farklı oranlarda bölünerek birçok test yapıldı. PH veri seti sınıflandırması, % 20'sinde test ve kalan veri eğitim verisi olmak üzere, derin öğrenme algoritması kullanılarak % 100 doğrulukta başarılı oldu.

Anahtar Kelimeler: İkili sınıflandırma, derin öğrenme, ileri beslemeli sinir ağı, parkinson hastalığı (PH), tıbbi tanı

ABSTRACT

Early diagnosis of Parkinson's disease, which causes vital and permanent damage to both motor and non-motor symptoms, is very important to prevent further deterioration of the patient condition. In the present study, Parkinson's Disease data set from UCI repository is classified using deep learning architecture. The deep learning architecture in the study is a feed-forward neural network (FFNN) which is builded by Keras of Python. The architecture in the study composes of an input layer, two hidden layers and softmax function with ReLu (Rectified Linear Units) as an output layer. The deep learning architecture solves binary classification problem since PD data set has two classes. In order to classify the Parkinson Disease (PD) data set, many tests were performed by splitting the test and train data in different ratios. The PD data set classification was succeeded with 100% accuracy using deep learning algorithm splitting in 20 % of the data as the test and the remaining as train data in epoch 30.

Keywords: Binary classification, deep learning (DL), feed-forward neural network (FFNN), parkinson disease (PD), medical diagnosis

INTRODUCTION

In age of various diseases, the transformation from medical big data into meaningful and useful information has rose as a new important field to improve disease diagnosis. Parkinson disease (PD) is one of most common neurodegenerative disorders for people over 60 (Sprenger, F., et all., 2013). PD continues to cause disability reasoned by motor and non-motor symptoms in spite of the therapeutic advances for last 20 years (Sprenger, F., et all., 2013). The disease has many negative effects. The most common of these is shivering; there are many motor symptoms such as slowness, balance problems and many other motor symptoms. There are also problems with many non-motor symptoms such as mood, sleep disorder. Majority patients with Parkinson's disease lose their jobs within 5 years

(Sakar, C. O et all., 2019). For these reasons, early diagnosis and treatment of Parkinson's disease is very important. In recent years, PD has been aimed for early diagnosis using telediagnosis and telemonitoring systems (Sakar, C. O et all., 2019; Sakar C.O., et all., 2009; Min, S., Lee, B., et all., 2017).

In the study, it is aimed to perform new PD diagnosis method, due to PD is latter most common neurodegenerative disease after Alzheimer disease and it is waited to increase widespread of PD. PD diagnosis has performed using the deep neural network classifier with 30 different 10-fold cross-validation techniques containing a stacked autoencoder and a softmax with 93.79 accuracy (Caliskan, A., et all., 2017). Around 90 % accuracy in PD diagnosis is obtained using artificial neural network and support vector machine together for 31 patients which 23 of them are with PD (David Gil, A., et all., 2004). In (Das, R., 2010), four classifiers as Regression, Data Mining Neural, Neural Network and Decision Tree is performed to diagnose PD and Neural network with 92.9 % accuracy rate is performed the most successful classification among them. In (Gharehchopogh, F. S., et all., 2013), two classifiers as d Multi-Layer Perceptron (MLP) with back-propagation learning algorithm and a new algorithm which is built Radial Basis Function (RBF) and ANN (Artificial Neural Network) together is used to diagnose PD for 195 samples. MLP with 93.22 % accuracy is more successful PD diagnosis than the new algorithm with RBF and ANN with 86.44 % accuracy. In (Chen, H. L., et all., 2013), fuzzy k-nearest neighbor (FKNN) is performed to diagnose PD with high accuracy rate. FKNN-based method with 96.07 % classification accuracy by a 10-fold cross validation method outperforms methods such as SVM. In the study, features are reduced by Principal Component Analysis (PCA). FKNN with PCA for PD diagnosis outperforms ANN and SVM. In (Srinivasan, S. M., et all., 2017), ANN with three different preprocessing techniques as discretization, resampling, and smote for success of PD diagnosis is tested. The study successes over 95 % using ANN with preprocessing steps as resampling and smote together by splitting as train in 70 % rate and test in 30 % rate. Hence, it is difficult to obtain results above 95% for PD diagnosis using artificial neural network algorithm or any algorithm of other machine learning algorithms without any preprocessing steps. Hence, the neural network classifier need structural changes. in order to increase succes of neural network for all problems such as parkinson diagnosis as performed in [Badem, H.„ 2017]

Based on these results, the deep learning algorithm is tried, which it is thought it could obtain the most accurate and high results without any preprocessing steps, in the diagnosis of PD in this study. In section 2, PD classification data set is used to classify, deep learning algorithm which are used to classify are introduced. The experimental results of the study such as classification accuracy and preferred epoch number are given in section 3. Conclusion and future work are provided in section 4.

METHOD

Parkinson's Disease Classification Data Set

Parkinson's Disease Classification Data Set used in the study is obtained from UCI Repository (Sakar, C. O., et all., 2019). The data set was collected total 756 samples from 252 people which 188 patients are PD patient and rest of them are healthy. The data set is a binary classification problem since it is composed of two classes as healthy and PD patient. The data set composes of total 754 features which are based on Baseline features, time frequency, mel frequency cepstral coefficients, wavelet transform based features, vocal fold features and the tunable Q-factor wavelet transform (TWQT) features in Table 1 (Sakar, C. O., et all., 2019).

Table 1. Distribution of features of parkinson's disease classification data Set

Feature set	Measure	Number of features
Baseline features	Jitter variants	5
	Shimmer variants	6
	Fundamental frequency parameters	5
	Harmonicity parameters	2
	Recurrence Period Density Entropy (RPDE)	1
	Detrended Fluctuation Analysis (DFA)	1
	Pitch Period Entropy (PPE)	1
Time frequency features	Intensity Parameters	3
	Formant Frequencies	4
	Bandwidth	4
Mel Frequency Cepstral Coefficients (MFCCs)	MFCCs	84
Wavelet Transform based Features	Wavelet transform (WT) features related with F0	182
Vocal fold features	Glottis Quotient (GQ)	3
	Glottal to Noise Excitation (GNE)	6
	Vocal Fold Excitation Ratio (VFER)	7
	Empirical Mode Decomposition (EMD)	6
TWQT features		

Deep Learning

Deep learning has used successfully in many fields such as speech recognition, visual object recognition, object detection, natural language understanding, topic classification, sentiment analysis (LeCun, Y., 2015). Deep learning endeavors to learn data representations with multiple abstraction levels using machine learning techniques with multiple processing layers (LeCun, Y., 2015; Chen, X. W., 2014). Since the data features are extracted from the own data without engineers, deep learning differentiates from other algorithms. Deep learning successfully overcomes complex calculations that artificial intelligence cannot solve in high-dimensional data. It uses the backpropagation algorithm to discover these complex structures. The backpropagation algorithm is used to show the change of parameters which represent information transferred from each previous layer to each subsequent layer (LeCun, Y., 2015). In general, ReLu for deep learning is used as activation function of the hidden layers in deep learning. ReLu takes the penultimate layer activation to learn the classification layer weight parameters using backpropagation. ReLu is used usually with softmax function. When deep learning is used for classification, the softmax function is usually used as the last layer. The softmax function in this last layer assumes the classification task. The softmax function defines a discrete probability distribution according to the number of classes in the problem (Agarap, A. F., 2018). Adam optimization algorithm for deep learning is used to learn weight parameters and the sparse_categorical_crossentrop loss function for deep learning is used in the study.

Feed-forward neural network (FFNN)

FFNN takes substitute for ANN whose neurons between units do not create a directed cycle. As in the human brain, ANN also provides interconnected neurons to exchange messages. FFNN composes of an input layer, an output layer and at least a hidden layer. The hidden layer composes of sigmoid neurons and the output layer composes linear neurons. All relationships between all vectors are extracted with neurons in multiple layers. The values are required the ranging from –1 and +1 are extracted using the network linear output layer. Though, a network outputs extract values ranging from 0 and 1 are fabricated. Therefore, a sigmoid transfer function is used acquiring expected values in the output layer. Log-sigmoid transfer threshold function is calculated to optimize status for FFFN as shown in Figure 1 (Ben-Bright, B., 2017; Beale, M. H., 2010).

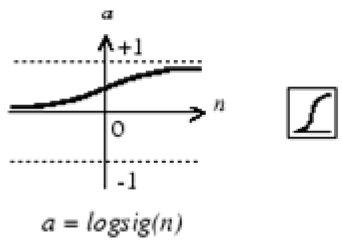


Figure 1. Log-sigmoid Function

EXPERIMENTAL RESULTS

Early diagnosis of Parkinson's disease, which causes vital and permanent damage to both motor and non-motor symptoms, is very important to prevent further deterioration of the patient condition. In the present study, Parkinson's Disease data set from UCI repository is classified using deep learning architecture. The deep learning architecture in the study is a FFNN which is builded by Keras in Tensorflow library of Python. The architecture in the study composes of an input layer, two hidden layers and softmax function with ReLu as an output layer. The deep learning architecture in the study composes of 1 input layer, 2 hidden layers and 1 output layer, ReLu as an activation function, a softmax as a classification function. In addition to four layers, adam function is used as an optimization algorithm and the sparse_categorical_crossentrop is used as a loss function. The deep learning architecture solves binary classification problem since PD data set has two classes. In order to classify the PD data set, many tests were performed by splitting the test and train data in different ratios as shown in Table 2. The highest accuracies of Table 2 are selected as 0.05, 0.20, 0.28, 0.30 and 0.33 test ratios and they are tested again with different epoch numbers as shown in Table 3 and Table 4. PD diagnosis loss and accuracy curves by splitting as 30 % test-70 % train, 20 % test-80 % train, and 10 % test-70 % train are shown in Figure 1, Figure 2 and Figure 3, respectively. The highest performance is obtained by selecting of 0.2 test ratio and 30 epoch number without preprocessing step except for test and train separation and epoch number selection as shown in Table 3 and Figure 2.

Table 2. PD diagnosis classification results using deep learning according to test-train partition.

Rate of Test Data	Rate of Train Data	Percent of Accuracy	Percent of Validation Accuracy
0.05	0.95	100 %	88.30 %
0.10	0.90	100 %	89.89 %
0.15	0.85	100 %	83.33 %
0.20	0.80	100 %	89.87 %
0.27	0.73	99.79 %	91.67 %
0.28	0.72	100 %	85.92 %
0.29	0.71	99.79 %	92.86 %
0.30	0.70	100 %	89.86 %
0.33	0.67	100 %	86.36 %
0.50	0.50	99.39 %	82.00 %
0.66	0.34	98.65 %	85.29 %
0.80	0.20	97.71 %	80.00 %

Table 3. PD diagnosis classification results using deep learning according to epoch number

Rate of Test Data	Rate of Train Data	Epoch Number	Percent of Accuracy	Percent of Validation Accuracy
0.05	0.95	12	100 %	88.30 %
0.05	0.95	20	100 %	89.36 %
0.05	0.95	30	100 %	87.23 %
0.05	0.95	40	100 %	89.36 %
0.05	0.95	45	100 %	90.43 %
0.20	0.80	12	100 %	84.81 %
0.20	0.80	20	100 %	88.61 %
0.20	0.80	30	100 %	93.67 %
0.20	0.80	40	100 %	83.54 %
0.20	0.80	45	100 %	88.61 %
0.28	0.72	12	100 %	84.51 %
0.28	0.72	20	100 %	90.14 %
0.28	0.72	30	100 %	90.14 %
0.28	0.72	40	100 %	90.14 %
0.28	0.72	45	97.71 %	85.92 %
0.30	0.70	12	100 %	88.41 %
0.30	0.70	20	98.70 %	86.96 %
0.30	0.70	30	100 %	91.30 %
0.30	0.70	40	100 %	91.30 %
0.30	0.70	45	100 %	88.41 %
0.33	0.67	12	100 %	86.36 %
0.33	0.67	20	100 %	87.88 %
0.33	0.67	30	100 %	87.88 %
0.33	0.67	40	100 %	90.91 %
0.33	0.67	45	100 %	89.39 %

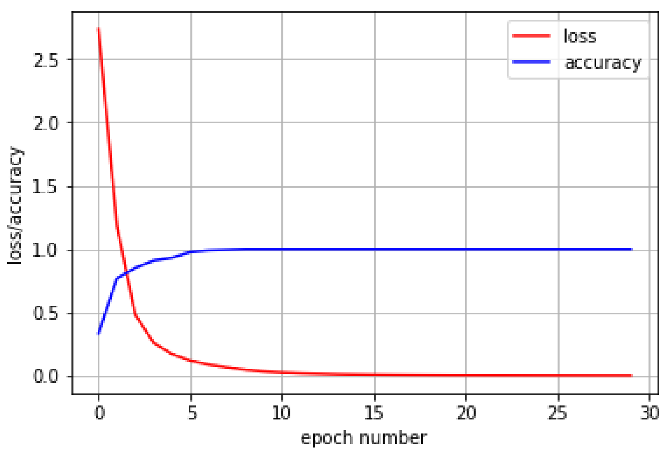


Figure 2. Loss and accuracy curves for PD diagnosis by splitting 30 % test.

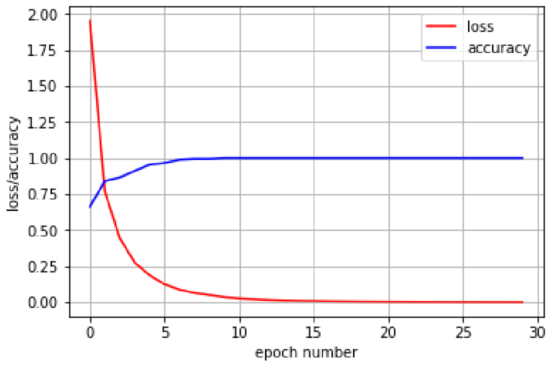


Figure 3. Loss and accuracy curves for PD diagnosis by splitting 20 % test.

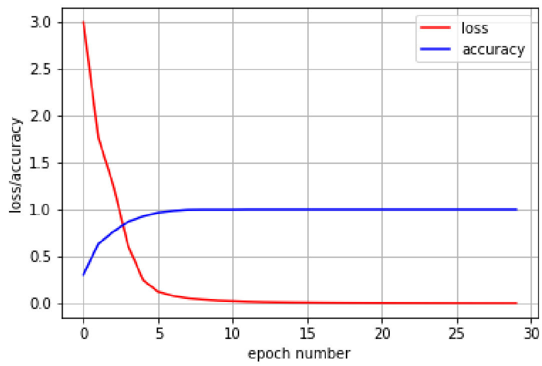
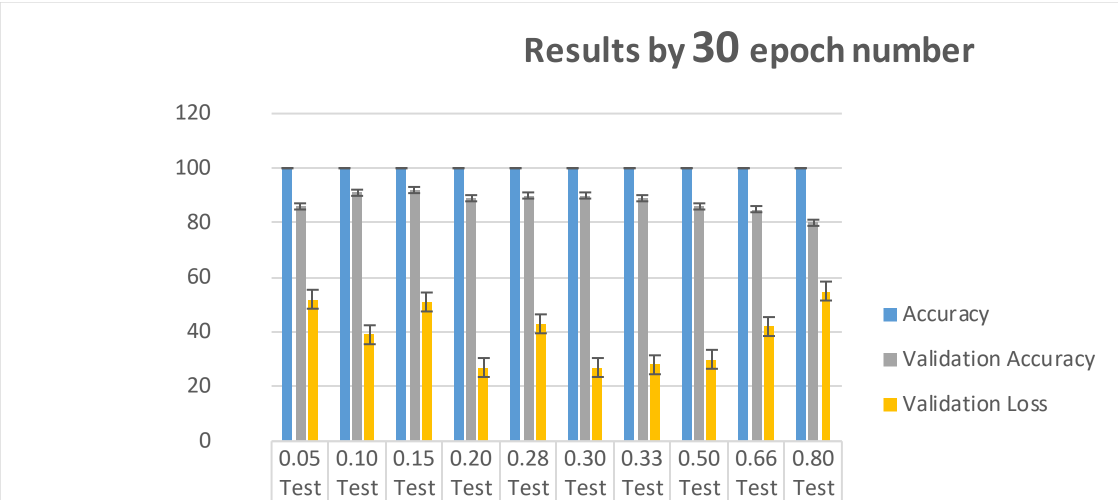


Figure 4. Loss and accuracy curves for PD diagnosis by splitting 10 % test.

Table 4. PD diagnosis classification results using deep learning



	0.05 Test	0.10 Test	0.15 Test	0.20 Test	0.28 Test	0.30 Test	0.33 Test	0.50 Test	0.66 Test	0.80 Test
Accuracy	100	100	100	100	100	100	100	100	100	100
Validation Accuracy	86	91	92	89	90	90	89	86	85	80
Validation Loss	52	39	51	27	43	27	28	30	42	55

CONCLUSIONS

The proposed method in the study is PD diagnosis using deep learning which is not performed in the literature in Python. Parkinson's Disease data set is classified with 100 % accuracy by 80–20 % train-test data partition and 30 epoch number using Keras API in Tensorflow deep learning library of Python programming language. The method performs PD diagnosis as a binary classification problem, healthy and Parkinson patients. The study for PD diagnosis outperforms previous studies which are performed by ANN and other methods for PD diagnosis, although without any preprocessing steps was performed. In the future works, train-test partition and epoch number selection set for PD diagnosis will be proposed.

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