Functionality of Pre-Prepared CNN Models using Deep Learning Technique for Detection of Parkinson Disease

[1]Rohit Agarwal, [2]Juginder Pal Singh,

[1]Rohit Agarwal, [2]Juginder Pal Singh,
Department of Computer Engineering and Application, GLA University, Mathura
Department of Computer Engineering, GLA University, Mathura.
E-Mail: [1]rohit.agrwal@gla.ac.in, [2]juginder.singh@gla.ac.in

ABSTRACT

Parkinson Disease is one of the most widely recognized neurodegenerative disorders. In the U.S. Parkinson disease prevalence is roughly 20 cases for every 100,000 people per year, with the mean period of beginning near 60 years. Thus, building up an automatic system for detecting parkinson would be gainful for treating the infection without any delay especially in remote areas. Due to the accomplishment of profound learning calculations in breaking down clinical images, Convolution Neural Networks (CNNs) have increased a lot of consideration for medical disease classification. What's more, highlights realized by pre-prepared CNN models on huge scale datasets are a lot of valuable in picture characterization errands. In this work, we evaluate the functionality of pre-prepared CNN models used as highlight extractors followed by different classifiers for the order of anomalous and normal MRI check pictures.

Keywords: CNN, Parkinson disease

Introduction

Symptoms of Parkinson's and the rate of progression differ among individuals. Sometimes individuals excuse early indications of Parkinson's as the impacts of typical aging. In most cases, there are no clinical tests to authoritatively distinguish the sickness, so it can be difficult to analyze accurately. Parkinson illness is a neurodegenerative disease and movement disorder. It is primarily caused by low and falling dopamine levels. The fall in dopamine level is caused by the death of dopaminergic neurons in the substantianigra. X-ray information is utilized to take a gander at the connectivity, or quality of brain networks, in the basal ganglia where dopamine nerves are located. It enables to identify Parkinson's disease in an early stage. In Fig. 1.8 the basal ganglia region is shown.

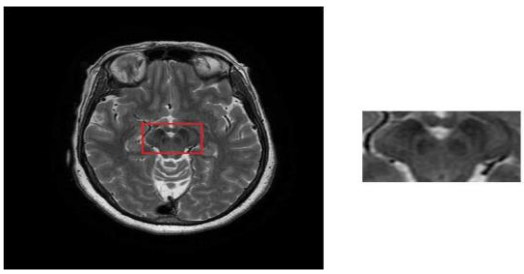


Fig. 1.8: Substantial region in a T2 weighted MRI

Related Work

Parkinson disease (PD) is a predominant neurodegenerative sickness that is regularly analyzed after important pathology and neuronal cell misfortune has happened. Biomarker of PD such as epigenome is utilized for early PD diagnosis [1].During early stages of the sickness; patients are efficiently treated by verbal prescription like levodopa [2]. There has additionally been a fast expansion in the treatment options mutually in the early and in the later phases of the sickness]. Thus early detection of PD is inevitable for the recovery of the patient.

The objectives of this research are to detect whether a patient has parkinson disease or not, based on an MRI scan image of their brain. Thus, automatic early diagnoses not only assist the doctors in accuracy and fast reporting but.it also reduces the death rate. Evaluating Profound Learning models for automated decision making also reduces the cost and time involved in predicting the Parkinson's disease through MRI scan images.

Convolutional Neural Network:

Convolution Neural Network (CNN) is the architecture behind computer vision applications. We will use Tensor Flow to construct a Convolutional Neural Network for recognition of images by extracting main features of the image which include different layers such as Convolution layer, Pooling layer, Flattening layer and Full Connection.

Convolution: The convolution operation is the structure square of a convolution neural organizes as the name proposes it. In the convolution layer, we input both convolution filter and MRI image. At that point, the convolution includes superimposing the channel onto the picture network, including the product of the qualities from the channel and the qualities from the picture grid, which will create a feature map. For example, let's consider the 5x5 lattice beneath as a piece of an image. And the convolution filter will be the 3x3 red matrixes. These two forms a 3x3 output feature Map.

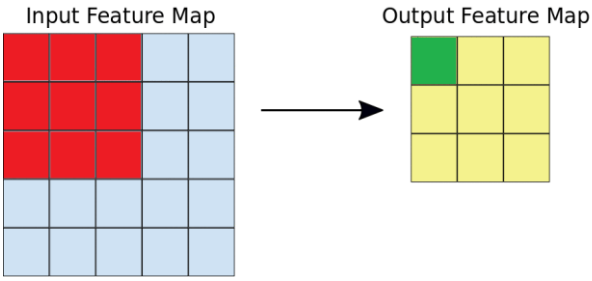


Fig3: Feature Map

ReLu activation function

Our nonlinear activation utility is ReLu(Rectified Linear unit). The ReLu work is f(x) =max(0, x). Accordingly, all negatives are changed over to zeros while all positives remain the same. ReLu is one of the most well known initiation capacities since it lessens the disappearing slope issue and is computationally less expensive to process.

Max Pooling:

Pooling operation is applied to the feature map. Pooling avoids or prevents Overfitting and Spatial Invariance. Here you'll put a 2×2 box at the top-left corner, and move along the line. For each 4 cells your case remains on, you'll find the maximum numerical worth and supplement it into the pooled featured map. In the figure underneath, for example, the container as of now contains a gathering of cells where the maximum esteem is 4.

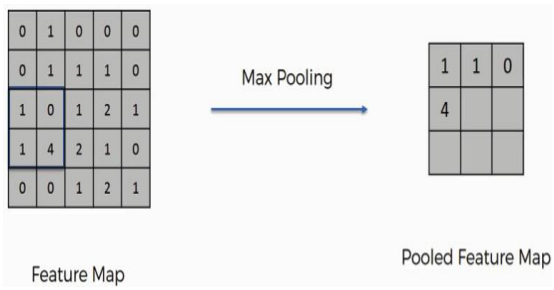


Fig4: Max Pooling

Fully Connected layer:

In the full connection step, we have three layers namely Input layer, Fully-Connected layer and Output layer. The input layer straightens our pooled feature map into a segment as by reducing multi dimension to single dimension. The output layer contains the softmax activation function for finding the classification probabilities from zero to one.

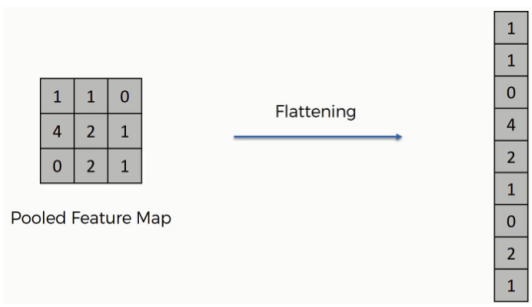


Fig5: Flattening

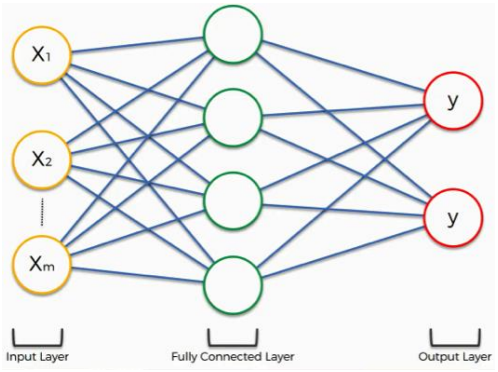


Fig.6: Full Connection

CNN Architecture

The general building of the projected CNN model which comprises of two significant parts: the element extractors and a classifier. Every layer in the component removal layer take its brisk going before layer's yield as data, and its yield is passed as a commitment to the subsequent layers. The proposed design contains the convolution, max-pooling, and order layers solidified mutually

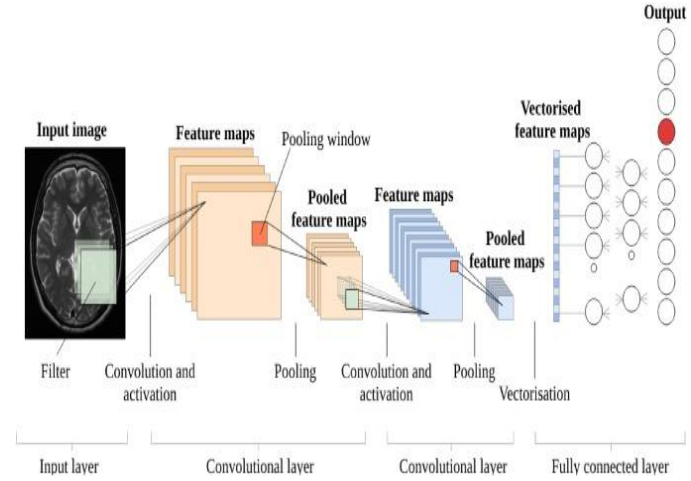


Fig 9: Architecture of CNN

Proposed Work

Dataset Description

The test is performed by means of the dataset of the Parkinsons Progression Markers Initiative (PPMI) database. In this tentatively planned investigation, 60 patients with PD (26 women, 34 men) 26 healthy subjects (11 men, 15 women) are in use as manage gathering. The 30 irregular data consists of 10 mellow, 10 reasonable and superior. The mean age of the tolerant gathering is 66.7 ± 8.5 and of the benchmark group is 57.19 ± 9.46 PD patients had a mean ailment length of 6.25 ± 3.31 years.

Imaging Protocol: The basic T2-weighted polarization prepared fast gradient reverberation pictures are non-heritable on a 1.5-T Vision scanner during an imaging phase. Image parameters: TR is 9.7 msec, TE is 4.0 millisecond, Flip angle is 10, TI is 20millisecond, TD is 200 unit of time, 128 mesial 1.25 millimeter slices

whereas no holes and pixels resolution of 256×256.

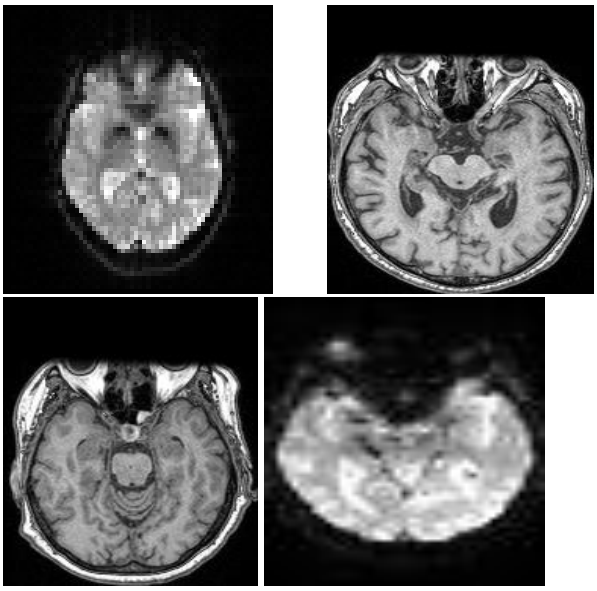


Fig. 1 Brain MRI scan images of a person suffering with parkinson disease

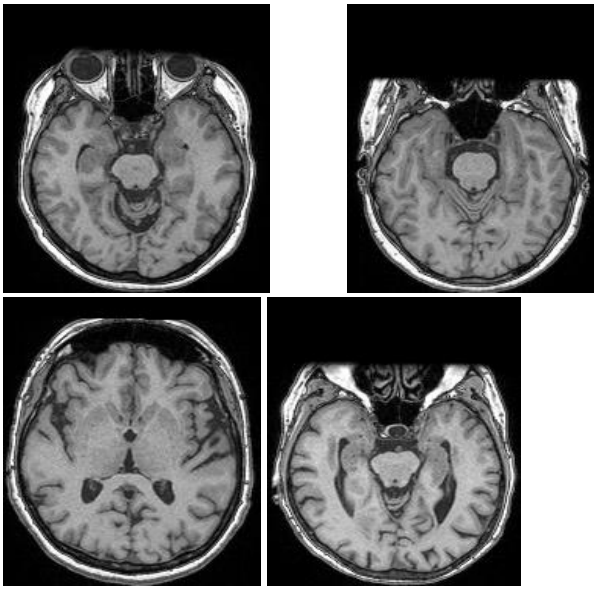


Fig. 1 Brain MRI scan images of normal person

Tools Utilized

As in implementation, we have created CNN Sequential model by calling the constructor in python .First errand is to peruse the dataset and perform perceptions on it to get a few experiences about the data. We utilize the cv2 library in python for the perusing the dataset. The corrupted pictures are not perused they are skipped. In general 80% of the data is utilized for training and 20% is used for Testing. Second is to rescale or normalize our data by multiplying the pixel values by 1/255, we can condense each pixel value to a value between 0-1.This is much easier for our model to process. After Data Exploration, as of now the data is split into training and testing sets and standardized, the information presently is appropriate for Convolution neural systems.

Keras provides an easy front-end layer to build deep neural network utilizing Tensor Flow or Theano at the back-end. It enables quick experimentation with profound neural networks.

CNN Modelling

We create our model using the “Sequential” model from Keras. This model is a straight heap of layers, meaning that we will create our model layer-by-layer. Sequential model with convolution layer, max pooling layer, flattening layer, hidden layer, and output layer is built. In this model convolution layers are used with filters 32x32, 64x64 and activation as “relu”, padding as “same”, and max pooling layers are used with pool size 2x2, flatten layer to avoid over fitting. Fully connected layer has activation function as “softmax”.

Results and Discussion

The main aim of our relocating learning approach was to properly diagnose Parkinson disease amongst normal MRI scan images. For that we arrange all of the representations as exposed over and qualified them independently. We execute training and testing by means of a system.

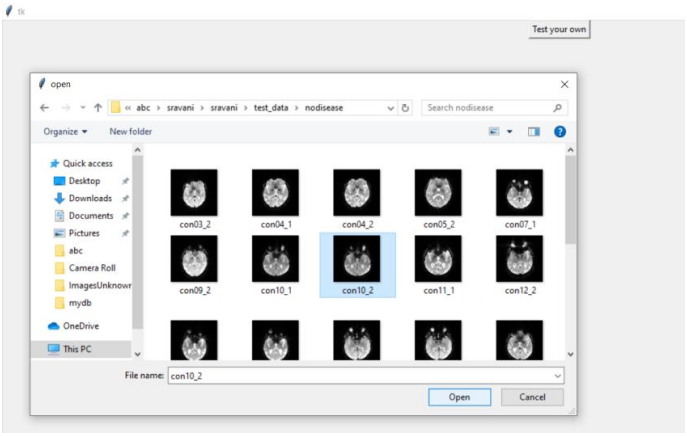


Fig. 1 Brain MRI scan images is seleceted for prediction

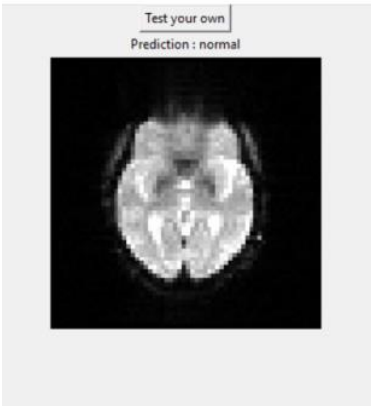


Fig. 1 Brain MRI scan images is predicted as Normal

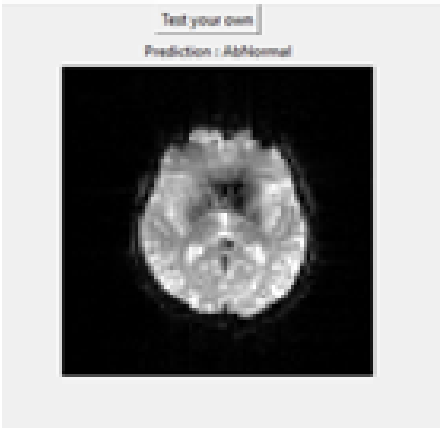
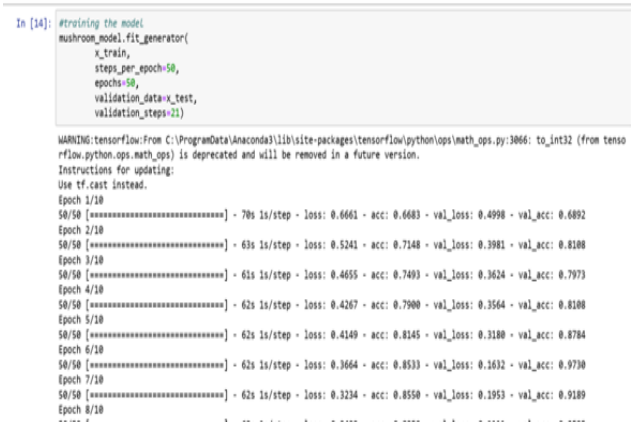


Fig. 1 Brain MRI scan images is predicted as Abnormal

We train our model with images with the frontal view of brain MRI images of a normal person and a person suffering with parkinson's disease. Our model, convolution neural network that inputs a brain MRI images and outputs the prediction of whether the brain consisting of parkinson's disease or not.We use dense connections and normalization to make the optimization. We label images that are normal and abnormal.



```
In [14]: #training the model
mushroom_model.fit_generator(
        x_train,
        steps_per_epoch=50,
        epochs=50,
        validation_data=x_test,
        validation_steps=21)

WARNING:tensorflow:From C:\ProgramData\Anaconda3\lib\site-packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from tenso
rflow.python.ops.math_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Epoch 1/10
50/50 [==============================] - 70s 1s/step - loss: 0.6661 - acc: 0.6683 - val_loss: 0.4998 - val_acc: 0.6892
Epoch 2/10
50/50 [==============================] - 63s 1s/step - loss: 0.5241 - acc: 0.7148 - val_loss: 0.3981 - val_acc: 0.8108
Epoch 3/10
50/50 [==============================] - 61s 1s/step - loss: 0.4655 - acc: 0.7493 - val_loss: 0.3624 - val_acc: 0.7973
Epoch 4/10
50/50 [==============================] - 62s 1s/step - loss: 0.4267 - acc: 0.7900 - val_loss: 0.3564 - val_acc: 0.8108
Epoch 5/10
50/50 [==============================] - 62s 1s/step - loss: 0.4149 - acc: 0.8145 - val_loss: 0.3180 - val_acc: 0.8784
Epoch 6/10
50/50 [==============================] - 62s 1s/step - loss: 0.3664 - acc: 0.8533 - val_loss: 0.1632 - val_acc: 0.9730
Epoch 7/10
50/50 [==============================] - 62s 1s/step - loss: 0.3234 - acc: 0.8550 - val_loss: 0.1953 - val_acc: 0.9189
Epoch 8/10
```

Fig. 1 Automated CNN based MRI system execution epoch output

Conclusion

We introduce a copy to distinguish and categorize parkinson's disease from mind MRI pictures. The calculation starts by changing cerebrum MRI pictures into sizes littler than the first. The following stage includes the recognizable proof and arrangement of pictures by the convolution neural organizes structure, which concentrates highlights from the pictures and orders them. suitable to the adequacy of the prepared CNN model for recognizing Parkinson's illness from cerebrum MRI pictures, the approval exactness of our model was essentially higher when contrasted and different methodologies. To attest the presentation of the representation, we rehashed the preparation procedure of the representation several times, each time acquiring similar outcomes. To approve the resonation of the trained representation on dissimilar brain MRI picture sizes, we fluctuated the spans of the preparation and validation dataset and still got moderately comparable outcomes.

References

1. Epigenetic Biomarkers for Parkinson's Disease: From Diagnostics to Therapeutics Jakubowski, Jennifer L.a | Labrie, Vivianea; b; *,vol. 7, 10.3233/JPD-160914
2. Deep Brain Stimulation for Parkinson's Disease with Early Motor Complications: A UK Cost-Effectiveness Analysis", Tomasz Fundament1 , Paul R. Eldridge2 , Alexander L. Green3 *, Alan L. Whone4 , Rod S. Taylor5 , Adrian C. Williams6 , W. M. Michael Schuepbach7, | DOI:10.1371/journal.pone.0159340
3. Developing and validating Parkinson's disease subtypes and their motor and cognitive progression", Michael Lawton,[1] Yoav Ben-Shlomo,[1] Margaret T May,[1] Fahd Baig,[2,3] Thomas R Barber,[2,3] Johannes C Klein,[2,3] Diane M A Swallow,[4] Naveed Malek,[5] Katherine A Grosset,[5] Nin Bajaj,[6] Roger A Barker,[7] Nigel Williams,[8] David J Burn,[9] Thomas Foltynie,[10] Huw R Morris,[11] Nicholas W Wood,[12] Donald G Grosset,[#5] and Michele T M Hu[#2,3,] doi: 10.1136/jnnp-2018-318337
4. Introducing a new journal on Parkinson's disease", Sulzer, D., Chaudhuri, K. & Fahn, https://doi.org/10.1038/npjparkd.2015.6
5. A review of Parkinson's disease", C. A. Davie, DOI:10.1093/bmb/ldn013
6. Current treatment of behavioral and cognitive symptoms of Parkinson's disease", IrenaRektorova, https://doi.org/10.1016/j.parkreldis.2019.02.042\
7. Rehabilitation for Parkinson's disease: Current outlook and future challenges", GiovanniAbbruzzese, RobertaMarchese, LauraAvanzino, ElisaPelosin, https://doi.org/10.1016/j.parkreldis.2015.09.005
8. Caloric vestibular stimulation for the management of motor and non-motor symptoms in Parkinson's disease", DavidWilkinson, AleksandraPodlewska, Sarah E.Banducci, Tracy Pellat-Higgins, Martin Slade, Mayur Bodani, Mohamed Sakel, LantySmith, PeterLeWitt, Kristen K.Ade, https://doi.org/10.1016/j.parkreldis.2019.05.031
9. Gut microbiota: Implications in Parkinson's disease", Arun Parashar, Malairaman Udayabanu, https://doi.org/10.1016/j.parkreldis.2017.02.002
10. Kumar, Manoj, and Ashish Sharma. "Mining of data stream using "DDenStream" clustering algorithm." 2013 IEEE International Conference in MOOC, Innovation and Technology in Education (MITE). IEEE, 2013.
11. Sharma, Ashish, Anant Ram, and Archit Bansal. "Feature Extraction Mining for Student Performance Analysis." Proceedings of ICETIT 2019. Springer, Cham, 2020. 785-797.
12. Sharma, Ashish, and Dhara Upadhyay. "VDBSCAN Clustering with Map-Reduce

Technique." Recent Findings in Intelligent Computing Techniques. Springer, Singapore, 2018. 305-314.
13. Sharma, Ashish, Ashish Sharma, and Anand Singh Jalal. "Distance-based facility location problem for fuzzy demand with simultaneous opening of two facilities." International Journal of Computing Science and Mathematics 9.6 (2018): 590-601.
14. Ram, Anant, et al. "A density based algorithm for discovering density varied clusters in large spatial databases." International Journal of Computer Applications 3.6 (2010): 1-4.
15. Kulshrestha, Jagrati, and Anant Ram. "An Analytical Study of the Chain Based Data Collection Approaches." 2019 4th International Conference on Information Systems and Computer Networks (ISCON). IEEE, 2019.
16. Agarwal, Rohit, A. S. Jalal, and K. V. Arya. "A review on presentation attack detection system for fake fingerprint." Modern Physics Letters B 34.05 (2020): 2030001.
17. Mishra, Ayushi, et al. "A robust approach for palmprint biometric recognition." International Journal of Biometrics 11.4 (2019): 389-408.
18. Singh, Anshy, Shashi Shekhar, and Anand Singh Jalal. "Semantic based image retrieval using multi-agent model by searching and filtering replicated web images." 2012 World Congress on Information and Communication Technologies. IEEE, 2012.
19. Shekhar, Shashi, et al. "A WEBIR crawling framework for retrieving highly relevant web documents: evaluation based on rank aggregation and result merging algorithms." 2011 International Conference on Computational Intelligence and Communication Networks. IEEE, 2011.
20. Varun K L Srivastava, N. Chandra Sekhar Reddy, Dr. Anubha Shrivastava, "An Effective Code Metrics for Evaluation of Protected Parameters in Database Applications", International Journal of Advanced Trends in Computer Science and Engineering, Volume 8, No.1.3, 2019. doi.org/10.30534/ijatcse/2019/1681.32019
21. N Chandra Sekhar Reddy, Dr. Purna Chandra Rao Vemuri, Dr. A Govardhan, Ch. Vijay, "An Empirical Study On Feature Extraction Techniques For Intrusion Detection System", Journal of Advanced Research in Dynamical and Control Systems, Vol. 9. Sp– 12 / 2017.