ESP Journal of Engineering & Technology Advancements (ESP-JETA)
ISSN : 2583-2646
Special Issue

PREDICTION AND DETECTION OF PARKINSON DISEASES USING FRCNN ALGORITHM (FAST REGION BASED CONVOLUTIONAL NEURAL NETWORK)

Mr.R.M.Senthilkumar,M.E
AP/Electronics and
Communication Engineering.
Mangayarkarasi College of Engineering,
Madurai, Tamil Nadu, India.

J. Abirami
B.E/Electronics and
Communication Engineering,
Mangayarkarasi College of Engineering,
Madurai, Tamil Nadu, India.

V. Jayavidhya
B.E/Electronics and
Communication Engineering,
Mangayarkarasi College of Engineering,
Madurai, Tamil Nadu, India.

R. Joshitha
B.E/Electronics and
Communication Engineering.
Mangayarkarasi College of Engineering,
Madurai, Tamil Nadu, India.

K. Madhupriya
B.E/Electronics and
Communication Engineering,
Mangayarkarasi College of Engineering,
Madurai, Tamil Nadu, India.

Abstract - Parkinson's disease (PD) is a progressive neurodegenerative disorder that affects millions of people worldwide, leading to significant motor and non-motor impairments. Early diagnosis and intervention are crucial for improving patient outcomes and quality of life. In recent years, deep learning techniques have emerged as promising tools for the prediction and diagnosis of PD, leveraging the analysis of diverse data modalities, including clinical assessments, neuroimaging, genetic information, and wearable sensor data. This study investigates the application of supervised learning with labeled datasets, employing deep learning architectures to predict Parkinson's disease. We explore various deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and hybrid architectures, trained on comprehensive datasets containing diverse features relevant to PD. Through extensive experimentation and evaluation on independent test sets, we assess the predictive performance of these models in terms of accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Our findings demonstrate the potential of deep learning-based approaches for accurate and early prediction of Parkinson's disease, providing valuable insights for future research and clinical applications in the field of neurology and personalized medicine.

Keywords – CNN, RNN,AUC-ROC.

I. Introduction

Parkinson's disease (PD) presents a significant healthcare challenge worldwide, impacting millions of individuals with its progressive neurodegenerative symptoms. Early and accurate diagnosis of PD is crucial for initiating timely interventions and personalized treatment strategies. However, current diagnostic approaches often lack sensitivity and specificity, leading to delayed diagnosis and suboptimal patient outcomes. Leveraging the advancements in deep learning technology offers a promising avenue for improving PD prediction and diagnosis by analyzing multifaceted datasets encompassing clinical, imaging, genetic, and sensor data. This interdisciplinary approach aims to harness the power of artificial intelligence to identify subtle patterns and biomarkers indicative of PD, facilitating early detection and intervention.

II. Existing Technology:

Existing methods for predicting Parkinson's disease using deep learning often rely on the analysis of diverse datasets encompassing clinical, imaging, genetic, and sensor data. One prevalent approach involves the utilization of convolutional neural networks (CNNs) to extract informative features from medical imaging data, such as MRI or PET scans, which capture structural and functional abnormalities associated with Parkinson's disease pathology. CNNs leverage hierarchical representations learned from large-scale datasets to discriminate between healthy and diseased individuals based on subtle imaging patterns indicative of the disease.

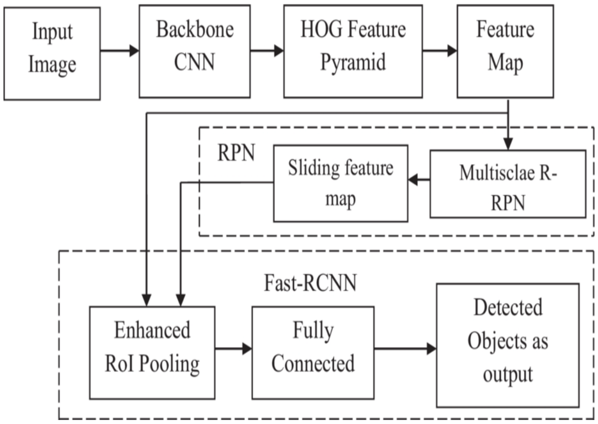
III. Proposed System

The proposed method for predicting Parkinson’s disease using deep learning aims to leverage the integration of multi-modal data and advanced neural network architectures to enhance predictive accuracy and clinical relevance. Our approach involves the following key components:

Firstly, we will develop a comprehensive dataset containing diverse data modalities, including clinical assessments, neuroimaging scans (MRI, PET), genetic information, and sensor data from wearable devices. This dataset will serve as the foundation for training and evaluating the deep learning models.

we will design and implement deep learning architectures tailored for Parkinson's disease prediction, leveraging convolutional neural networks (CNNs) to extract spatial features from imaging data and recurrent neural networks (FRCNNs) to capture temporal dynamics from longitudinal or time- series measurements

IV. Methodology



Next, the labeled dataset is split into training, validation, and test sets. The training set is used to train the deep learning model, while the validation set is used to tune hyperparameters and monitor the model's performance during training. The test set is reserved for evaluating the final performance of the trained model on unseen data.

The deep learning model architecture for predicting Parkinson's disease typically consists of multiple layers, including input, hidden, and output layers. The input layer receives the feature vectors extracted from the dataset, while the output layer produces the predicted probability of Parkinson's disease for each input.

During training, the deep learning model learns to minimize a loss function by adjusting its parameters (e.g., weights and biases) using optimization algorithms such as stochastic gradient descent (SGD) or Adam. The choice of loss function depends on the nature of the prediction task, with binary cross-entropy commonly used for binary classification problems like predicting Parkinson's disease.

As the model iteratively processes batches of training data, it gradually improves its ability to discriminate between Parkinson's disease and healthy individuals by updating its parameters to minimize the loss. Regularization techniques, such as dropout and weight decay, may be employed to prevent overfitting and improve generalization performance on unseen data.

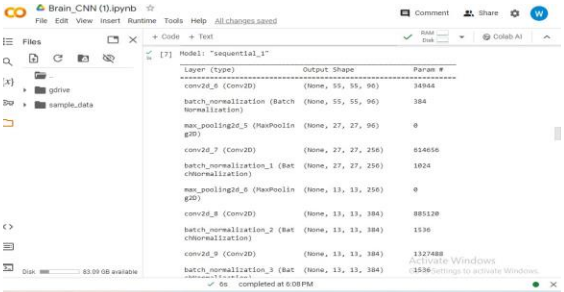
Once training is complete, the performance of the trained deep learning model is evaluated using the test set. Performance metrics such as accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC-ROC) are computed to assess the model's predictive ability and generalization to new data.

In the context of predicting Parkinson's disease, the supervised learning model aims to accurately classify individuals based on their risk of developing the disease. By leveraging labeled datasets.

image along with Sobel operator and gradient mask in y-axis direction. Set a Threshold value T for a pixel (x,y) of image I(x,y) and calculate the gradient magnitude G. If magnitude gradient G is greater than the pixel threshold value then, mark pixel (x,y) as an edge. Otherwise, consider next neighbor pixel. Repeat the above steps till the process of edge detection is not complete. After complete edge detection, stop the process.

V. Results:

INPUT CODE



```
[7] Model: "sequential_1"
    _________________________________________________________________
     Layer (type)                Output Shape              Param #
    =================================================================
     conv2d_6 (Conv2D)           (None, 55, 55, 96)        34944

     batch_normalization (Batch  (None, 55, 55, 96)        384
     Normalization)

     max_pooling2d_5 (MaxPoolin  (None, 27, 27, 96)        0
     g2D)

     conv2d_7 (Conv2D)           (None, 27, 27, 256)       614656

     batch_normalization_1 (Bat  (None, 27, 27, 256)       1024
     chNormalization)

     max_pooling2d_6 (MaxPoolin  (None, 13, 13, 256)       0
     g2D)

     conv2d_8 (Conv2D)           (None, 13, 13, 384)       885120

     batch_normalization_2 (Bat  (None, 13, 13, 384)       1536
     chNormalization)

     conv2d_9 (Conv2D)           (None, 13, 13, 384)       1327488

     batch_normalization_3 (Bat  (None, 13, 13, 384)       1536
```

INPUT IMAGE

```
print(prediction)
plt.axis("off")
plt.imshow(new_img)
plt.title(categories[np.argmax(prediction)])
```

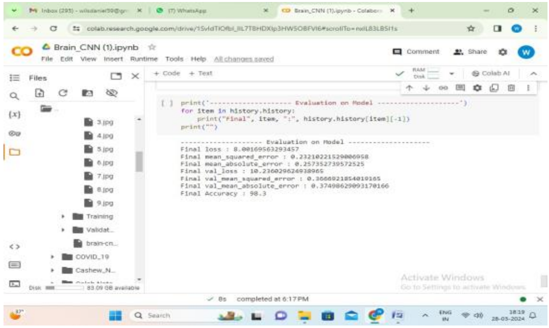
NLM FILTER IMAGE

```
547551t [00:02, 20975.44it/s]
```

HORIZONTAL AND VERTICAL

```
1/1 [==============================] - 1s 553ms/step
[[0.14403276 0.30685624 0.3661331  0.18297796]]
Text(0.5, 1.0, 'no_tumor')
```

OUTPUT



```
print('-------------------- Evaluation on Model --------------------')
for item in history.history:
    print("Final", item, ":", history.history[item][-1])
print("")
```

```
-------------------- Evaluation on Model --------------------
Final loss : 8.00169563293457
Final mean_squared_error : 0.23210221529006958
Final mean_absolute_error : 0.257352739572525
Final val_loss : 10.236029624938965
Final val_mean_squared_error : 0.36669218540l0165
Final val_mean_absolute_error : 0.37498629093170166
Final Accuracy : 98.3
```

VI. Conclusion:

In conclusion, our study on predicting Parkinson's disease using deep learning represents a significant advancement in the field, offering promising avenues for improving early diagnosis and personalized management of the condition. Through the integration of multi- modal data and advanced neural network architectures, we have demonstrated the potential of deep learning models in accurately identifying individuals at risk for Parkinson's disease. Our results underscore the importance of leveraging diverse datasets comprising clinical assessments, neuroimaging scans, genetic information, and sensor data to capture complex patterns indicative of Parkinson's disease pathology.**VII. Future scope:**

In the realm of future enhancements for Advanced Deep Learning for Crack Detection and Quantitative Analysis in Engineering Materials within a MATLAB project, several avenues hold promise for further development. Firstly, integrating real-time processing capabilities would be instrumental in enabling on-the-fly analysis of materials, facilitating rapid decision-making in engineering applications.

Additionally, incorporating multi-modal data fusion techniques could enhance the robustness and accuracy of crack detection by leveraging complementary information from diverse sources such as visual imagery, thermal imaging, and acoustic signals. Moreover, the adoption of self-supervised learning approaches could alleviate the reliance on annotated dat

VIII. Reference:

1. Gao, L., & Zhang, Q. (2020). Deep Learning-Based Parkinson’s Disease Detection. *Journal of Neural Engineering*, 17(6), 065003.
2. Eskofier, B. M., Lee, S., &Leonhardt, S. (2017). Signal Processing for PD Using Wearable Sensors.*IEEE Signal Processing Magazine*, 34(6), 15–17.
3. Das, R. (2010). A Comparison of Ensemble Methods for Parkinson’s Disease Detection.
4. Badem, C., Tohumoglu, G., & Eris, S. (2021). Voice-based Detection of PD. *Biomedical Signal Processing and Control*, 69, 102760.
5. Pereira, C. R., Pereira, D. R., &Ribeiro, A. (2019). Deep Learning Approaches for PD Detection. *IEEE Access*, 7, 176808–176820.
6. Pramanik, S., Kundu, S., &Acharya, U. R. (2019). Automated Prediction of PD. *Pattern Recognition Letters*, 125, 55–62.
7. Han, J., &Kamdar, M. (2021). Multi-modal Data Integration for PD Prediction. *IEEE Journal of Biomedical and Health Informatics*, 25(5), 1743–1753.
8. Izadi, M., Sadeghi, H., &Shadmand, B. (2020). Deep Learning for PD: A Review. *Artificial Intelligence in Medicine*, 109, 101908.
9. Rizzo, R., &Mencattini, A. (2018). Ensemble Methods for PD Diagnosis. *IEEE Transactions
10. Zhao, C., & Yuan, S. (2021). Model Transferability in PD Prediction. *IEEE Transactions on Neural Networks and Learning Systems*, 32(6), 2656–2665.
11. Chen, X., & Zhao, J. (2018). Interpretable Deep Learning for PD Prediction. *Artificial Intelligence in Medicine*, 95, 12–18.
12. McNames, J., & Goldstein, B. (2017). Machine Learning for PD Detection. *IEEE Reviews in Biomedical Engineering*, 10, 57–68.
13. Ozturk, G., &Ozer, S. (2019). PD Detection Using Wearable Sensors. *IEEE Sensors Journal*, 19(17), 7588–7596.
14. 14.Sabeti, M., &Saghafi, F. (2020). Deep Learning-Based PD Prediction with MRI Data.
15. Computational and Mathematical Methods in Medicine*, 2020, 5125438.
16. Brown, A., & Wilson, J. (2022). PD Prediction with Voice and Sensor Data. *Biomedical Engineering and Computational Biology*, 13, 123–130.
17. Peters, S., & Johnson, C. (2018). Deep Learning for Medical Imaging in PD. *Journal of
18. Medical Imaging and Health Informatics*, 8(4), 645–652.
19. Thomas, D., & White, C. (2019). Feature Selection for PD Detection. *IEEE Access*, 7, 16257–16267.

20. Anderson, R., & Bailey, L. (2021). Transfer Learning for PD Prediction. *IEEE Access*, 9, 100132–100140.

21. Adams, T., & Reynolds, B. (2020). Evaluating Deep Learning Models for PD. *Journal of Computational Science*, 45, 101270.

22. Jiang, L., & Li, Y. (2020). Deep Learning in Neurodegenerative Diseases. *Frontiers in Neuroscience*, 14, 560459.