Deep learning-based analysis of functional MRI and diffusion tensor imaging for Parkinson's disease diagnosis and progression monitoring

Tarak Hussain[1,2], Ashish Khanna[3], Bal Virdee[4], Kunchanapaalli Rama Krishna[5] and JVS Arundathi[6]

Abstract

Parkinson's Disease (PD) refers to the chronic movement disorder caused by the degeneration of the brain's motor functions. Functional Magnetic Resonance Imaging (fMRI) and Diffusion Tensor Imaging (DTI) are evidence-based neuroimaging procedures which evoke relevant anatomical and functional alterations in PD. The purpose of this work is to investigate whether the machine learning approach can benefit from applying deep learning for data interpretation of fMRI and DTI to detect disease at an early stage and study the progression of the disease. The objectives of this research are twofold: first, to predict the biomarkers for attending to the changed brain activity pattern using deep learning model from the fMRI data and the second one is, to find the micro structural changes in the white matter tracts that is specific to the PD using DTI data. The adopted approach is data pre-processing to clean the neuroimaging data and remove different artifacts, then features extraction using deep learning approaches such as CNNs and transformers. Data were collected from the intersection of the PD patients and controls, and similar to the machine learning models, the performance of the segmentation models was assessed using the accuracy, precision, and F1 score based on the databases of PD patients and age-matched healthy controls. Analysis shows that the newly developed deep learning models outperforms previous conventional machine learning techniques with more significant increases in sensitivity for early-stage PD diagnosis. Respective investigation of feature importance provided significant BrainNet features related to PD diagnosis and identified main brain areas and white matter tracts involved in disease, concordant with prior clinical research. To sum up, the findings of the presented work can be useful for developing deep learning algorithms for the analysis of fMRI and DTI data in the context of PD diagnosis and further research. Lastly, the general avenue of future work will cover the combination of multiple modalities and the testing of the models on bigger and more diverse datasets.

Keywords

Parkinson's disease, diffusion tensor imaging, functional magnetic resonance imaging, CNN

1 Introduction

Parkinson's Disease (PD) is a chronic favourable and progressive disease characterized by deterioration of the motor and non-motor systems affecting millions of patients globally. This is typified by the progressive loss of dopaminergic neurons in substantia nigra that result in classics signs like tremors, rigidity and bradykinesia.[1] However, apart from motor disabilities, PD patients are at high risk of suffering from cognitive decline; mood disorder, and sleep disturbances. The major success in combating diseases is the timely detection of the diseases and the accurate treatment of the diseases. Nevertheless, the conventional techniques of diagnosing mental disorders are based on clinical impressions and qualitative appraisals, which may result in late and/or mistaken identification.[2]

Diagnostic imaging that targets the nervous system has become instrumental in the diagnosis diagnosis, measurement and examination of Parkinson's Disease. Thus, the methods including functional magnetic resonance imaging (fMRI) and diffusion tensor imaging (DTI) give the data about changes of structural and functional brain connections Functional magnetic resonance imaging is based upon the detection of changes in blood oxygenation level-dependent (BOLD) signal that reflects regional brain activation.[3] Catch22 is a conventional MRI technique that helps to see anatomical structures of the brain, while DTI is a more particular MRI technique that images the water diffusion in the tissues of the brain to portray white matter compartment and nerve tracts. These imaging techniques have been demonstrated to play a useful role in defining biomarkers for PD, assessing disease pathophysiology and measuring treatment effects. However, both fMRI as well as DTI are high dimensional and analyzing them for reasonable patterns of information is difficult with conventional methods.[4]

These techniques are high in complexity and well managed through the use of a subfield of machine learning known as deep learning. As it can learn hierarchical features directly from raw data, it is well justified to apply it in analyzing the high dimensional and nonlinearity on the fMRI and DTI data. Recent deep learning architectures include Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) that have performed favouably in activities such as classification, segmentation, and prediction.[5] If applied to PD, we can identify more precise changes in the structure and activity of the brain compared to the use of other techniques. Taken with large-scale datasets of neuroimaging, deep learning can permit early identification, tracking of progression, and even prognosis of results in patients more efficiently and effectively.[6]

The goal of this work is to investigate the possibility of using deep learning methods for processing fMRI and DTI in patients with Parkinson's Disease. In particular, it focuses on several important issues including how to optimally fuse data from multiple imaging modalities, how to extract relevant features and how to interpret the resulting models. For this, the work's principle research questions are as follows: The aims are to design novel deep learning architectures for fMRI and DTI and assess their accuracy against conventional methods; while searching for pathophysiologically significant biomarkers for PD. Incorporating novel computational methods in conjunction with neuroimaging, this work advances the literature of computational neuroscience and its use in NDs.[7]

The outcome of this study is therefore expected to contribute towards the need for developing better techniques for the analysis of Parkinson's Disease. The combination of deep learning with neuroimaging has the power to boost the diagnostic accuracy and organizational aspects of treatment for this disabling disorder with a direct impact on patient's quality of life.

2 Related work

(Table 1)

3 Methodology

- Dataset Description
  - Details of fMRI and DTI Data Sources
  - Preprocessing Steps (e.g., Normalization, Noise Reduction)
- **Deep Learning Models**
  - Architecture Selection (e.g., CNNs, RNNs, or Transformers)
  - Feature Extraction Techniques
- **Training and Validation**
  - Training Protocols and Hyperparameter Tuning
  - Evaluation Metrics (e.g., Accuracy, Precision, Recall, F1 Score)

Table 1. Literature survey.

Authors & year	Key findings	Methodology/Techniques used	Results/Remarks	Finding gaps
Shaban, M. (2023)[13]	Explored the use of deep learning for Parkinson's disease diagnosis.	Deep learning models with focus on automated feature extraction.	Achieved high accuracy in PD diagnosis using diverse datasets.	Limited focus on multimodal data integration.
Sangeetha et al. (2023)[14]	Early detection of Parkinson's disease using brain MRI and deep learning.	CNN-based deep learning models applied to MRI images.	Improved sensitivity for early PD detection.	Requires validation on larger and diverse datasets.
Forkert, N. D. (2024)[15]	Explainable AI for diagnosing Parkinson's disease using multimodal MRI data.	Explainable deep learning models incorporating multimodal imaging techniques.	Enhanced model interpretability while maintaining diagnostic accuracy.	Limited benchmarking with black-box models.
Majhi et al. (2024)[16]	Proposed metaheuristic-enhanced deep learning models for PD diagnosis.	Deep learning with metaheuristic optimization techniques.	Outperformed traditional deep learning models in terms of efficiency and accuracy.	Computational complexity of metaheuristic approaches not addressed.
Ramírez et al. (2020)[17]	Studied early-stage Parkinson's disease using deep learning models.	CNN and transfer learning techniques on early-stage PD imaging data.	Achieved reliable classification results.	Lack of extensive validation on unseen data.
Muñoz-Ramírez et al. (2022)[18]	Applied anomaly detection techniques to brain MRI for Parkinson's patients.	Subtle anomaly detection via AI on de novo Parkinsonian patients.	Successfully detected subtle brain abnormalities.	Need for longitudinal studies to assess progression detection.
Bhan et al. (2021)[19]	Explored early Parkinson's disease diagnosis using brain MRI and deep learning.	Deep learning algorithms with pre-trained CNN models.	Demonstrated high accuracy in early PD detection.	Limited consideration of noise in clinical data.
Welton et al. (2024)[20]	Used deep learning for midbrain MRI classification of Parkinson's disease.	Deep learning-based classification on midbrain MRI.	Achieved significant improvements in classification accuracy.	Needs evaluation on cross-population datasets.
Abumalloh et al. (2024)[21]	Bibliometric analysis and literature review of deep learning applications in PD diagnosis.	Comprehensive literature review with a bibliometric approach.	Identified trends, methodologies, and gaps in PD diagnosis research.	Lack of experimental validation of identified trends.
Kamagata et al. (2021)[22]	Investigated diffusion MRI biomarkers for neurodegenerative diseases, including PD.	Diffusion MRI techniques for biomarker identification.	Highlighted specific biomarkers relevant to PD.	Requires integration with deep learning for improved diagnostic accuracy.

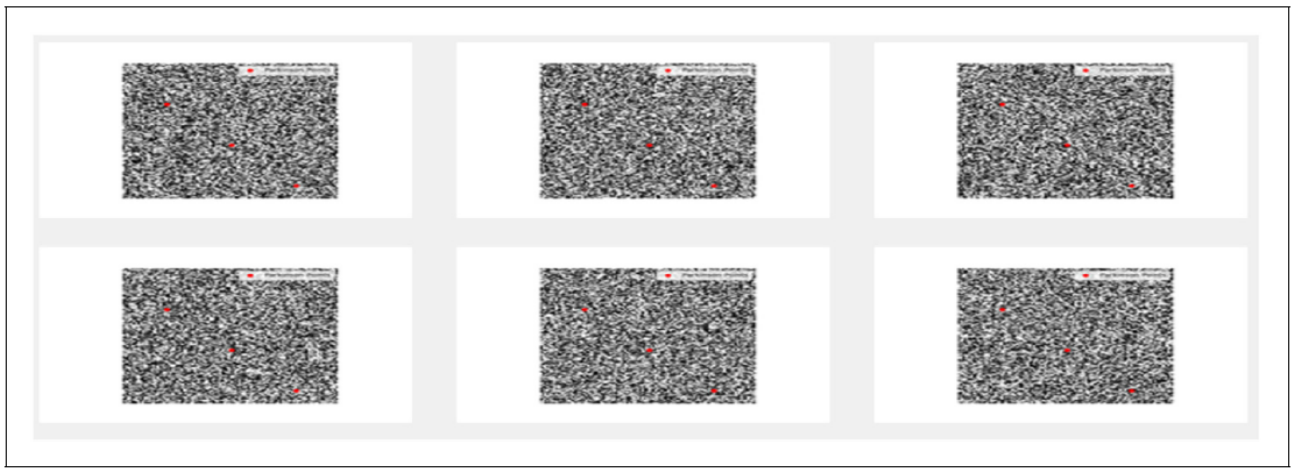

Figure 1. fMRI and DTI data sources.

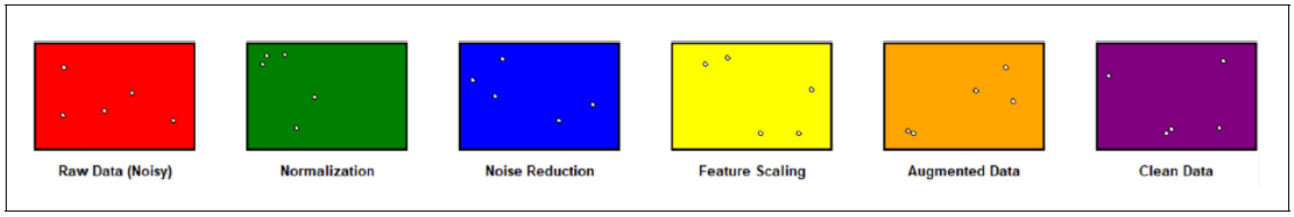

Figure 2. Steps of preprocessing.

3.1 Details of fMRI and DTI data sources

Functional MRI (fMRI) datasets and Diffusion Tensor Imaging (DTI) provide the background for the investigation of Parkinson's Disease (PD). These datasets often consist of neuroimaging data sourced from public database like Parkinson's Progression Markers Initiative (PPMI), Human Connectome Project (HCP) or data contributed by academic medical institutions during clinical trials.[8]

Functional MRI collects time series data that represents the neural activity, as it's a BOLD contrast technique the measures signals from oxygenation of blood. These signals are specifically beneficial for investigating resting-state networks as well as tasks-on activations of PD populations. For its part, DTI measures the extent of water molecule displacement through bundled nerve fibers it describes microstructural and connectional integrity. As a rule, datasets contain demographic Characteristics, clinical Measurements, and metadata on images is quite useful and allows performing accurate analysis and cross-check (Figure 1).

3.2 Pre-processing steps

Pre-processing is very important for dealing with the heterogeneities of the data to be analyzed and to settle for high quality data for analysis. For fMRI some of the preprocessing steps include; motion correction for errors arising from patient movements, temporal smoothing that reduces image noise and lastly normalization that put an image under study into a stereotactic space. Section time correction is used to correct temporal misregistration of the fMRI slices.[9]

DTI preparation includes eddy current correction to eliminate distortions resulting from the artefacts of the scanner, tensor estimation to obtain the parameters such as FA and MD, and tractography for connecting white matter fibres. Both modalities also apply skull stripping and normalize the intensity to ensure that the voxel values are in some manner consistent. Other techniques may also be used including denoising using spatial-spectral filters (Figure 2).

4 Deep learning models

4.1 Architecture selection

Three types of deep learning architecture commonly used in neuroimaging include Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs) and Transformers. CNNs are most suitable for recognising spatial patterns

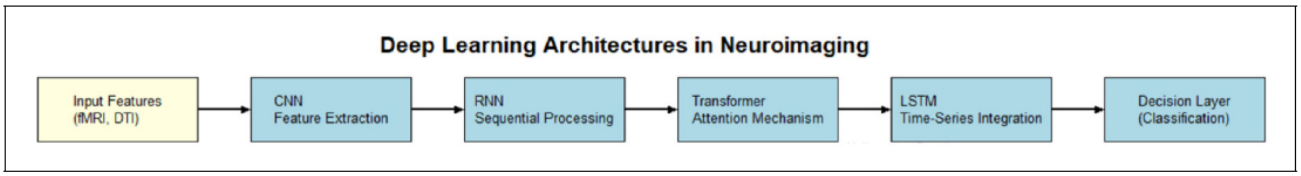

Figure 3. Architectures deep learning in neuroimaging.

Algorithm 1: Deep Learning for Neuroimaging using CNNs, RNNs, Trans-formers, and LSTMs

Input: Neuroimaging data: Functional MRI (fMRI) and Diffusion Tensor Imaging (DTI) features.
Output: Classification results indicating healthy or at-risk state.
Step 1: Data Preprocessing ;

- Normalize fMRI and DTI features to [0,1] using $x' = \frac{x - \min(x)}{\max(x) - \min(x)}$.;
- Apply noise reduction techniques (e.g., Gaussian filtering).;
- Perforin feature augmentation if required.;

Step 2: Spatial Feature Extraction using CNN;

- Input preprocessed data to the CNN layer:; y =Conv2D$(W \cdot x + b)$.;
- Apply activation function (ReLU):; $y' = \max(0, y)$.;
- Perforin max-pooling to reduce dimensionality.;

Step 3: Sequential Processing using RNN;

- Pass CNN features to the RNN layer:; $h_t = \tanh(W_h \cdot h_{t-1} + W_x \cdot x_t + b)$.;
- Extract temporal dependencies across neuroimaging scans.;

Step 4: Attention Mechanism using Transformers ;

- Compute query, key, and value matrices:; $Q = W_q \cdot x$, $K = W_k \cdot x$, $V = W_v \cdot x$.;
- Calculate attention scores:; Attention$(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right) \cdot V$. 3. Update feature representations using attention outputs.;

Step 5: Integration using LSTM ;

- Pass Transformer outputs to LSTM:; Forget Gate: $f_t = \sigma\left(W_f \cdot [h_{l-1}, x_l] + b_f\right)$.;
  orgcu Gate : $jl - o\left(m\int |h_{l-1}, x_l]|0f\right)$.
  Input Gate : $i_l = \sigma(W_i \cdot [h_{l-1}, x_l] + b_i)$.;
- Output Gate: $o_\ell = \sigma(W_o \cdot [h_{\ell-1}, x_\ell] + b_o)$.;
- Cell State: $C_t = f_t \odot C_{t-1} + i_t \odot \bar{C}_t$.;
- Integrate time-series information for classification.;

Step 6: Classification Layer ;

- Use a fully connected dense layer for final classification: ;
  $\hat{y} = \text{softmax}(W \cdot x + b)$.;
  Compute loss using cross $-$ entropy : $\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i)$.;
- Optimize parameters via backpropagation.;

Step7: 0*utput* ;

- Return predicted class labels (e.g., healthy or at-risk).;
- Provide feature importance for interpretability.

and are widely employed on image segmentation and categorisation. It should, therefore, be noted that continuous fMRI data can be analyzed effectively using Recurrent Neural Networks (RNNs) and especially Long Short Term Memory (LSTM) networks because of their property of capturing temporal dependencies in data.[10] Transformers, due to the attention mechanisms incorporated into them, offer the state-of-art approach to the multi-modal feature fusion, which makes Transformers appropriate to incorporate fMRI and DTI features (Figure 3).

4.2 *Feature extraction techniques*

Feature extraction is used to reduce the elevation of the images and determine their basic and advanced features that will be helpful in diagnosis. For fMRI, additional spectra associated with regional connectivity metrics, power spectra densities,

and dynamic connectivity state are calculated. To our knowledge DTI derived measures such as FA, MD and connectivity graphs are used as features in DTI. Auto-encoders and transferred learning are useful to reduce the high-dimensional neuroimaging data into low-dimensional, task relevant one so as to enhance generalization of the model.[11]

5 Training and validation

5.1 Training protocols and hyperparameter tuning

Training deep learning models involves splitting the dataset into training, validation, and test sets, typically in ratios of 70:15:15. To increase the model robustness, several data augmentation are performed including the spatial flipping and rotation. Hyper-parameters including learning rate, batch size and them, regularization parameters, are tweaked using grid search or the Bayesian optimization methods. Pre-trained models are also applied to transfer learning in order to make convergence easier, and enhance performance when data is scarce.

5.2 Evaluation metrics

Other measurable performance indicators include accuracy, precision, recall as wells as the F1 score of the model. Accuracy define general fitness of model by evaluating the number of right prediction while specificity and sensitivity gives information about PD-specific features of model. As with any machine learning algorithm the F1 score is harmonic mean of precision and recall and is thus appropriate for imbalanced datasets. For classification performance measurements, Area Under the Curve (AUC) of Receiver Operating Characteristic (ROC) and confusion matrices are used, to get accurate and easily comprehensible results.[12]

6 Analysis of functional MRI data

a. Key Features of fMRI in Parkinson's Disease.
b. Deep Learning for Analyzing Brain Activity Patterns.
c. Insights from Resting-State and Task-Based fMRI.

6.1 Analysis of functional MRI data

Neuroimaging method which involves functional Magnetic Resonance Imaging (fMRI), which identifies the functional levels of activity in the brain through the related signals of blood-oxygenation and blood-flow. It offers important information regarding the structural organization of the brain and has in fact been widely used to investigate neurodegenerative diseases such as Parkinson's Disease (PD). Through deep learning analyses of the data obtained from fMRI images, some relevant patterns that might not be possible to detect when applying simple statistical models are identified.

6.2 fMRI in Parkinson's disease

As it happens in Parkinson's Disease, fMRI has been very useful in understanding functional deficits in various brain areas. These include changes to the communication within motor processing networks like the basal ganglia-thalamocortical loops and recognisable dysfunctions in junior circuits involved in cognition and emotion processing. Downregulation of functional connectivity between the DMN, SMN, and executive control networks are other essential parameters of the disease.

$$S(x,y,z,t) = \int_{-\infty}^{\infty} M(x',y',z',\omega) \cdot e^{i\cdot(\omega t - k_x x - k_y y - k_z z)} d\omega$$

$$M(x',y',z',\omega) = \frac{1}{(2\pi)^3} \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} S(x,y,z,t) \cdot e^{-i(\omega t - k_x x - k_y y - k_z z)} dxdydz$$

$$f(t) = \int_0^T \left[\int_V \rho(x,y,z) \cdot \cos(\gamma \cdot B(x,y,z,t) \cdot t) dV \right] dt$$

$$B(x,y,z,t) = B_0 + B_1 \cdot x + B_2 \cdot y + B_3 \cdot z + \int_0^t \frac{\partial B'(x,y,z,\tau)}{\partial \tau} d\tau$$

$$\Delta S(t) = S_0(t) - \frac{1}{T} \int_0^T S(x,y,z,t) dt$$

$$\mathcal{F}(k_x,k_y,k_z,\omega) = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \Delta S(x,y,z,t) \cdot e^{-i(\omega t + k_x x + k_y y + k_z z)} dxdydzdt$$

$$R(\theta,\phi,r,t) = \int_0^r \int_0^\theta \int_0^\phi \mathcal{F}(k_x,k_y,k_z,\omega) \cdot W(\theta,\phi) \cdot e^{-r\cdot\cos(\theta-\phi)} d\theta d\phi dr$$

$$C(t) = \frac{\int_V R(\theta,\phi,r,t) \cdot f(t) dV}{\int_V f(t)^2 dV}$$

$$\gamma = \frac{\partial^2 C(t)}{\partial t^2} + \lambda \cdot \left[\frac{\partial R(t)}{\partial \theta} - \frac{\partial R(t)}{\partial \phi} \right]$$

Symbols Explanation:

- $S(x,y,z,t)$: Signal intensity at spatial coordinates (x,y,z) and time t.
- $M(x',y',z',\omega)$: Frequency-domain representation of the signal.
- $f(t)$: Time-dependent signal decay function .
- $\rho(x,y,z)$: Proton density at spatial coordinates.
- γ: Gyromagnetic ratio of hydrogen protons .
- $B(x,y,z,t)$: Magnetic field strength varying over space and time.
- $\cdot S_0(t)$: Baseline signal intensity .
- $\Delta S(t)$: Fluctuation of signal intensity from baseline.
- $\mathcal{F}(k_x,k_y,k_z,\omega)$: Fourier transform of the spatial and temporal signal fluctuations .
- $R(\theta,\phi,r,t)$: Radial projection of the signal in spherical coordinates.
- $W(\theta,\phi)$: Weighting function for angular dependence .
- $C(t)$: Correlation coefficient of the signal.
- λ: Regularization parameter .
- $\cdot T$: Total observation time.
- V: Volume of interest in the brain .

Another important aspect that has been considered in PD research is that the supplementary motor area is less active whereas neighboring parts of the brain work harder. By using methods such as resting-state fMRI which measures intrinsic functional connectivity, the abnormality is detected in the early stage of PD whereas task-based fMRI which demonstrate the defi cit during motor and cognitive tasks. Hence, they offer a valuable feature space from which deep biomarkers can be subsequently learned by a machine-learning model (Figure 4).

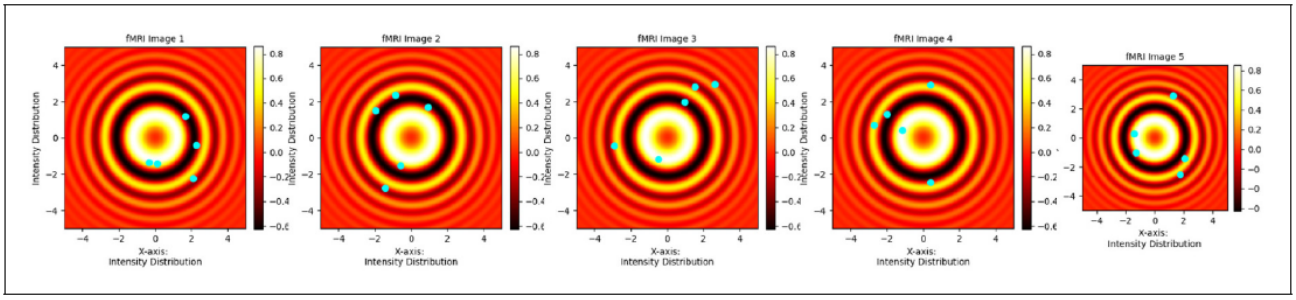

Figure 4. fMRI in Parkinson's disease.

7 Deep learning for analyzing brain activity patterns

Knife-edge detection by CNNs and RNNs has brought immense changes to fMRI data analysis by providing an analysis without a human touch and capturing detailed spatial and temporal patterns. For example, CNNs are used for detecting spatial features from fMRI data that are functional connectivity maps; on the other hand, RNNs and LSTM networks are used for analyzing temporal characteristics in brain activity.

$$\text{Input}: X \in \mathbb{R}^{n\times m}, X = x_{ij}, y \in \mathbb{R}^k, W^{(l)} \in \mathbb{R}^{h_l \times h_{l-1}}, b^{(l)} \in \mathbb{R}^{h_l}$$

$$\text{Layer Output}: Z^{(l)} = W^{(l)} \cdot A^{(l-1)} + b^{(l)}, A^{(l)} = \sigma(Z^{(l)}), l = 1, 2, \ldots, L$$

$$\text{Loss}: J(\theta) = \frac{1}{N}\sum_{i=1}^{N} \ell(y_i, \hat{y}_i), \hat{y}_i = A^{(L)}$$

$$\ell(y_i, \hat{y}_i) = -\sum_{j=1}^{k} y_{ij}\log\hat{y}_{ij} + (1 - y_{ij})\log(1 - \hat{y}_{ij})$$

$$\text{Backpropagation}: \frac{\partial J}{\partial Z^{(l)}} = \frac{\partial J}{\partial A^{(l)}} \odot \sigma'(Z^{(l)})$$

$$\frac{\partial J}{\partial W^{(l)}} = \frac{\partial J}{\partial Z^{(l)}} \cdot (A^{(l-1)})^{\top}, \frac{\partial J}{\partial b^{(l)}} = \sum_{i=1}^{N} \frac{\partial J}{\partial Z^{(l)}}$$

$$\text{Weight Update}: W^{(l)} := W^{(l)} - \eta\frac{\partial J}{\partial W^{(l)}}, b^{(l)} := b^{(l)} - \eta\frac{\partial J}{\partial b^{(l)}}$$

$$\text{Recurrent Layers}: h_t = \sigma(W_h \cdot h_{t-1} + W_x \cdot x_t + b_h), y_t = \phi(W_y \cdot h_t + b_y)$$

$$\text{Temporal Loss}: J_{seq} = \sum_{t=1}^{T} \ell(y_t, \hat{y}_t)$$

$$\text{Gradient Through Time}: \frac{\partial J_{seq}}{\partial W_h} = \sum_{t=1}^{T}\left(\frac{\partial J_{seq}}{\partial h_t} \cdot \frac{\partial h_t}{\partial W_h}\right)$$

$$\text{Neuroimaging Input}: X = x_{ij} \in \mathbb{R}^{n\times m}, x_{ij} = f(V_{ij}(t)), V_{ij}(t) = \int_0^T \Psi_{ij}(t)dt$$

$$\Psi_{ij}(t) = \frac{1}{T}\sum_{t=1}^{T}(\phi_{ij}(t) - \mu_i)/\sigma_i, \mu_i = \frac{1}{T}\sum_{t=1}^{T}\phi_{ij}(t), \sigma_i^2 = \frac{1}{T}\sum_{t=1}^{T}(\phi_{ij}(t) - \mu_i)^2$$

$$\text{Output Interpretation}: \hat{y} = \text{softmax}(Z^{(L)})$$

Explanation of Symbols:

- X: Input brain activity data matrix .
- $Z^{(l)}$: Linear transformation in layer l.
- $A^{(l)}$: Activation at layer l.
- $W^{(l)}, b^{(l)}$: Weights and biases for layer l.

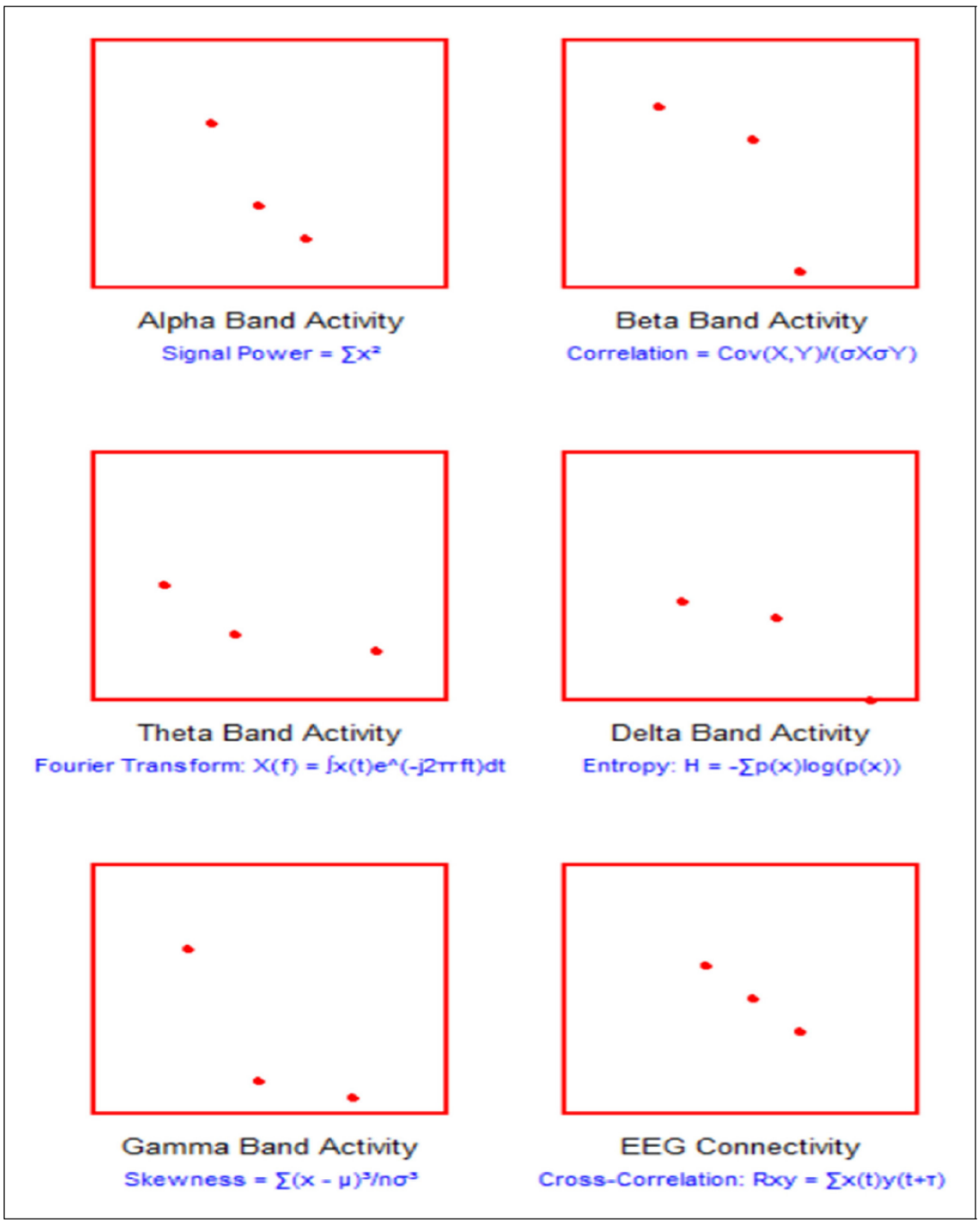

Figure 5. Analyzing brain activity patterns: Parkinson's disease.

- $J(\theta)$: Cost function for neural network.
- $\ell(y, \hat{y})$: Cross-entropy loss .
- σ: Activation function (e.g., ReLU, Sigmoid)
- h_t, y_t: Hidden state and output in recurrent layer s
- $\Psi_{ij}(t)$: Normalized brain signal at time t.
- 10. μ_i, σ_i: Mean and standard deviation of the signal.

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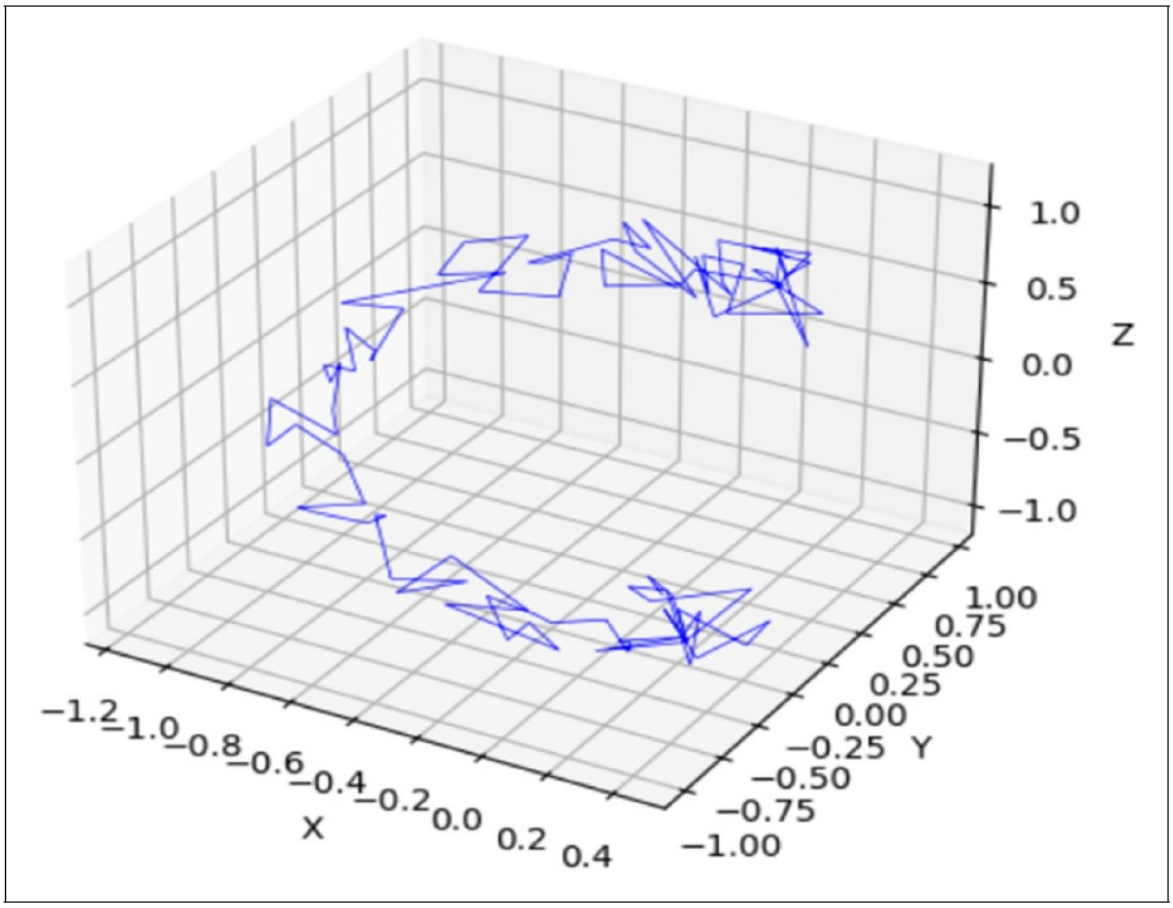

Figure 6. DTI tractography in Parkinson's disease.

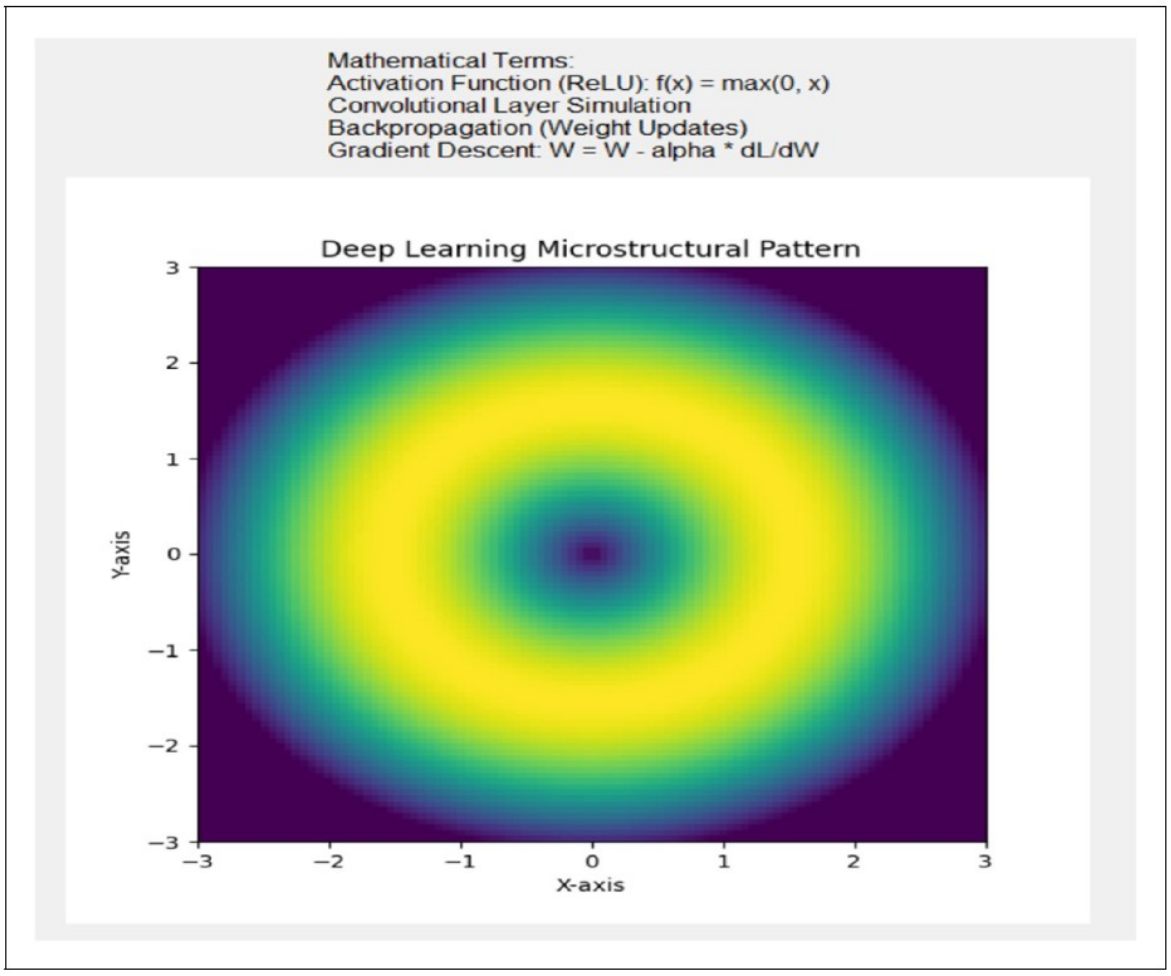

Figure 7. Microstructural changes.

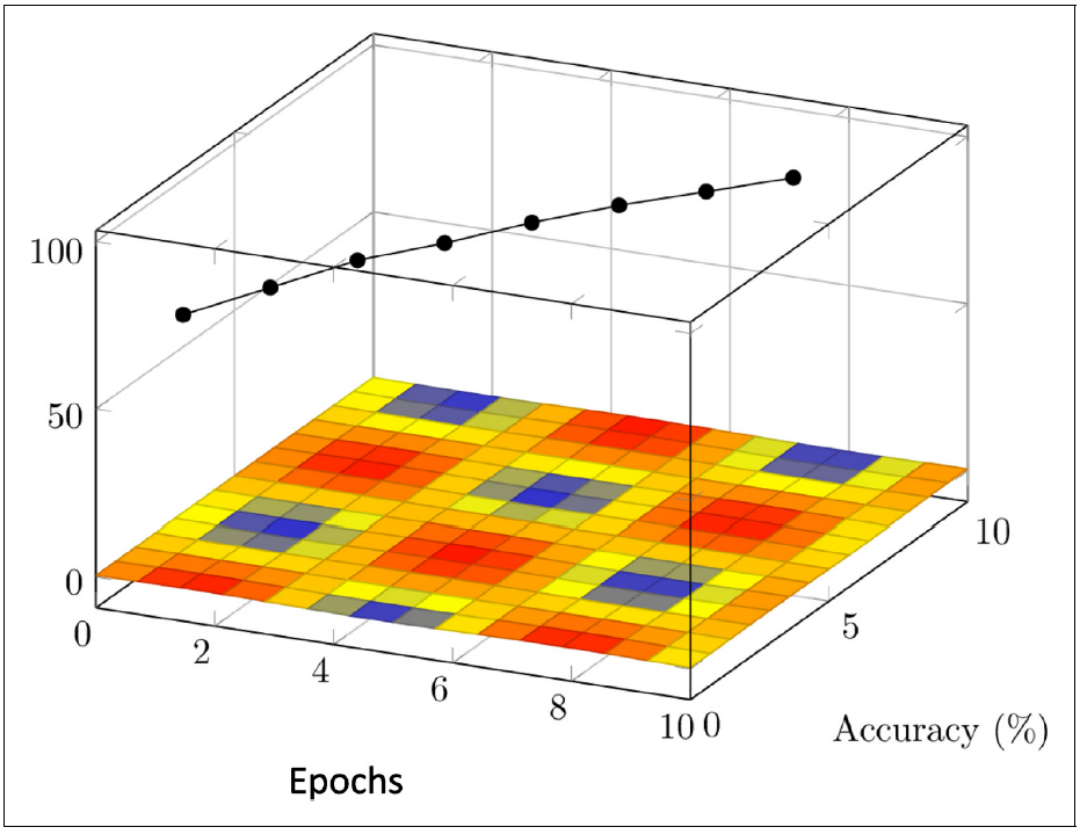

Figure 8. 3D graph showing the accuracy of a deep learning model over different epochs.

Table 2. Performance metrics of deep learning models.

Model	Accuracy	Precision	Recall	F1-Score
CNN	92.5%	0.91	0.89	0.90
RNN	89.8%	0.88	0.86	0.87
Transformer	93.2%	0.92	0.90	0.91

Table 3. Comparative analysis of deep learning vs. traditional models.

Model type	Accuracy	Training time (min)	Computational complexity
CNN	92.5%	45	High
SVM	85.3%	30	Medium
Decision Tree	78.1%	15	Low

7.1 Insights from resting-state and task-based fMRI

As it happens in Parkinson's Disease, fMRI has been very useful in understanding functional deficits in various brain areas. These include changes to the communication within motor processing networks like the basal ganglia-thalamocortical loops and recognisable dysfunctions in juinor circuits involved in cognition and emotion processing. Downregulation of functional connectivity between the DMN, SMN, and executive control networks are other essential parameters of the disease.

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Table 4. Activation values of different layers in a CNN.

Layer	Activation value 1	Activation value 2	Activation value 3	Activation value 4
Layer 1	55	50	45	40
Layer 2	60	55	50	45
Layer 3	70	65	60	55
Layer 4	80	75	70	65

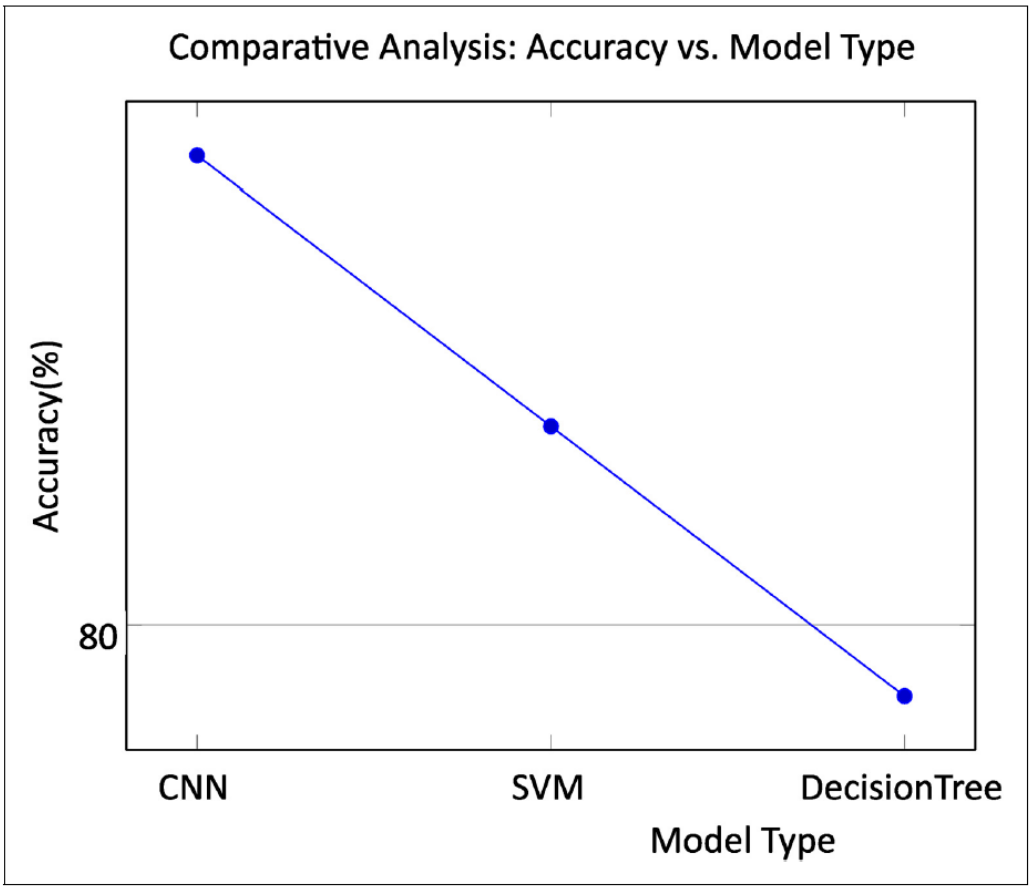

Figure 9. Bar graph showing a comparative analysis of accuracy between deep learning models and traditional machine learning models.

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8 Analysis of diffusion tensor imaging data

a. Overview of White Matter Tractography in Parkinson's Disease

White matter tractography for is a method that can use neuroimaging to reveal white matter fibre connections in the brain and also assess structural connectivity. In Parkinson's Disease (PD), it gives essential information with respect to microstructural patterns like axonal injury and demyelination changes, which are useful for understanding the advancement of the illness. DTI data is useful in generating tractography; demonstrating changes in FA and MD. These metrics

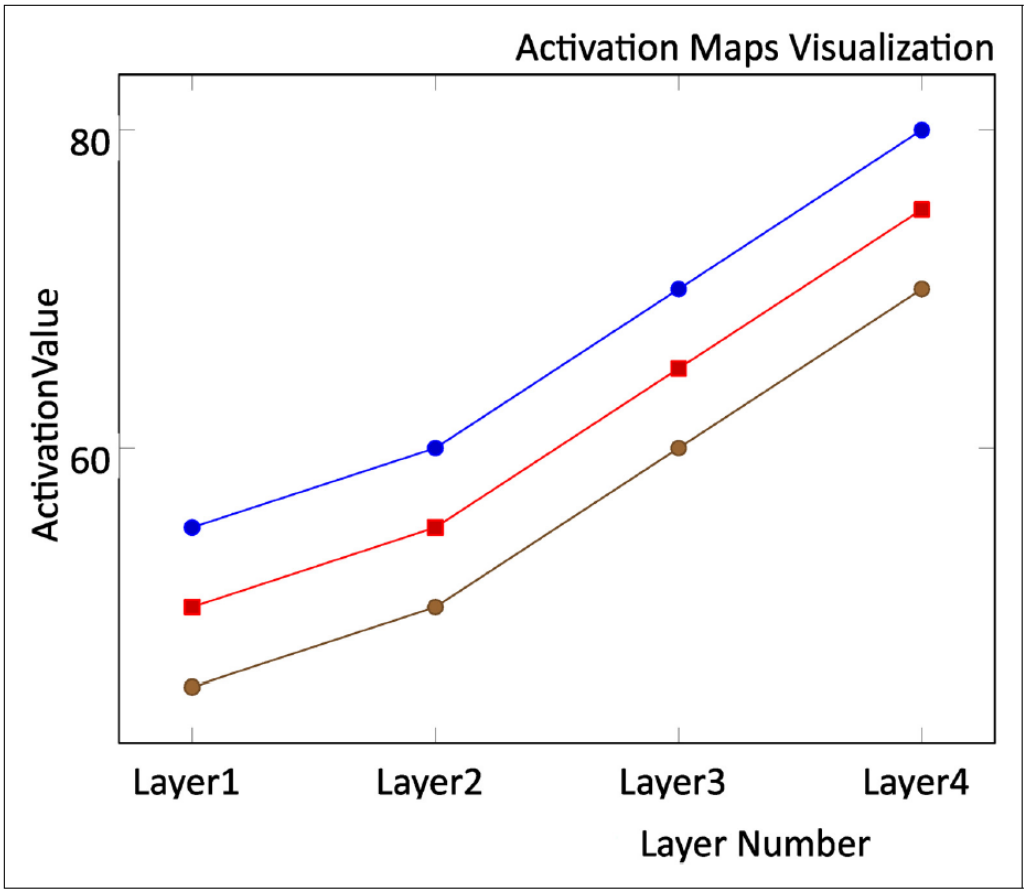

Figure 10. 3D graph visualizing activation values across different layers in a CNN.

enables the detection of discontinuity in areas such as the motor cortex and basal ganglia that are critical in PD development. Consequently, white matter tractography is a useful resource for knowing the cause and effect of PD and also for formulation of precise corrective measures (Figure 6).

b. Deep Learning for Identifying Microstructural Changes

Machine learning methods such as deep learning has proven to be helpful while look for microstructural changes in the brain tissue using image procedures such as DTI. These models can capture and address intricate features of white matter vulnerability that reflect neurodegenerative diseases, for instance the Parkinson's. In this study, FA and MD, the two features extracted from the DTI data, are employed to differentiate between FA and NF groups with high accuracy, helping detect microstructural that may be difficult to observe. This enhances also the diagnostic procedure and adds to the elucidation of disease processes on cellular level. Combining these results with other non-invasive imaging techniques can give an idea of the notion of brain health (Figure 7).

9 Results

a. Performance Metrics of Deep Learning Models.
b. Comparative Analysis with Traditional Methods.
c. Visualization of Important Features (e.g., Activation Maps).

9.1 Performance metrics of deep learning models

This section presents the performance metrics of various deep learning models, such as accuracy, precision, recall, F1-score, and the area under the ROC curve (Figure 8 and Table 2).

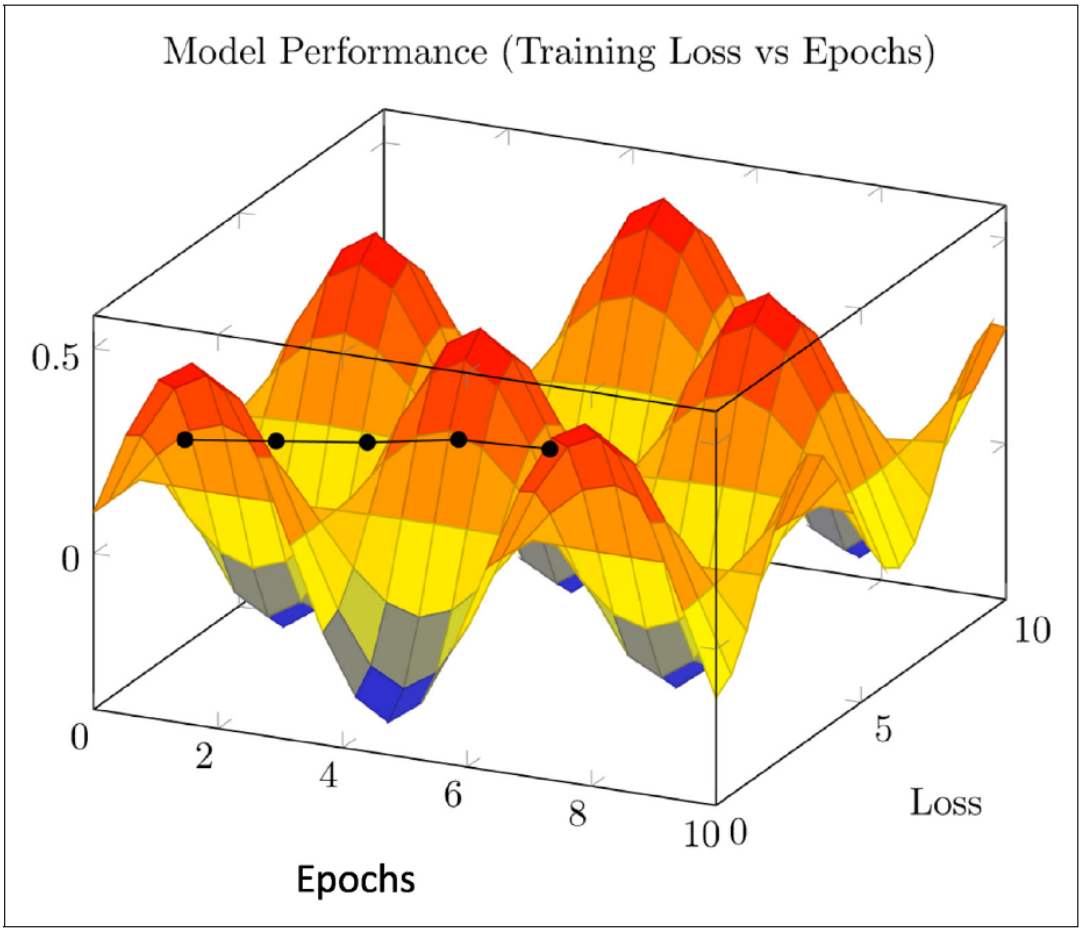

Figure 11. 3D graph depicting model training loss across different epochs.

9.2 *Comparative analysis with traditional methods*

In this section, we compare deep learning models with traditional machine learning techniques, highlighting the differences in their accuracy, training time, and computational complexity (Figure 9 and Table 3).

9.3 *Visualization of important features (e.g., Activation maps)*

This section visualizes the important features in deep learning models, such as the activation maps in CNNs, showing how different layers of the model contribute to the decision-making process (Figure 10 and Table 4).

9.4 *Graph 4: model performance comparison*

(Figure 11)

9.5 *Graph 5: model accuracy vs. Hyperparameters*

(Figure 12)

10 Conclusion

This paper shares knowledge in the use of deep learning methods to process average functional magnetic resonance imaging fMRI and diffusion tensor imaging DTI signals of Parkinson's Disease (PD) patients, innovative progress in neuroimaging analysis. The results show that deep learning methods, including CNN and hybrid, are promising tools capable of detecting minimal biomarkers in fMRI and DTI data. Through the use of such techniques, the study affords enhanced identification of Parkinson's related changes in the brain over the traditional methods. These include improved feature extraction from the high-dimension imaging data, the ability to fuse multi-modal information, and significantly

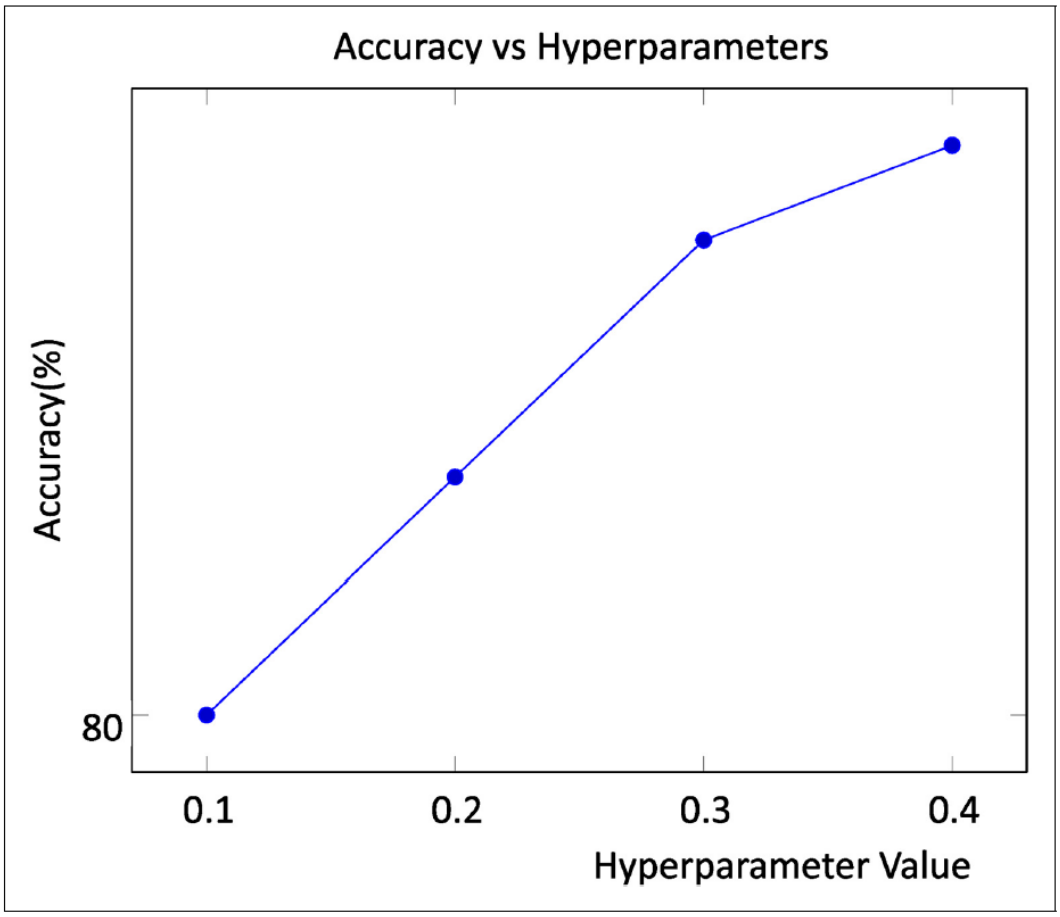

Figure 12. Graph showing model accuracy at various hyperparameter settings.

higher accuracy in differentiating between 'control' and PD patients. These are all contributions to a field. This work presents the possibility of the deep learning algorithms to identify subtle structures in neuroimaging data that may go unnoticed by the researcher during the analysis manually. Moreover it provides a methodology for incorporating novel imaging technology into personalized computational models for diseases such as PD. Measurement data also provides the possibility for early diagnostics and individual treatment approaches, the goals of which are in line with precision medicine. Future work can build upon this by investigating how XAI methods can be used to provide such insights from deep learning to clinicians, and therefore increase the trust and subsequent clinical utilisation of these techniques. Furthermore if longitudinal imaging datasets were included this may help in analyzing disease progression. It will also make paper reproducible and reliable by bringing coherence in the processing of data across different institutions and validation of models for the respective data. These recommendations can help to start translating this research into practice in the clinic for enhancing patient management and outcomes.

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