Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Deep Learning Based Classification Of Parkinson's Disease Using Medical Imaging

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Parkinson's Disease (PD) is a progressive neurological disorder characterized by the degeneration of dopamine-producing neurons in the brain, leading to a range of motor and non-motor symptoms. Early and accurate diagnosis is crucial for effective intervention and management of the disease. This project aims to classify PD leveraging spiral and wave datasets, comparing traditional feature extraction methods with Histogram of Oriented Gradients (HoG). Various machine learning and deep learning algorithms, including Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), ResNet, and a hybrid model, are explored for precise PD classification. By examining discriminative features extracted through conventional methods against HoG, this research seeks to discern the optimal model, offering insights into potential advancements in diagnostic accuracy and methodology.

Keywords: Parkinson's Disease, PD classification, feature extraction, machine learning, deep learning, HoG, SVM, Random Forest, CNNs, RNNs, LSTM, ResNet, hybrid model.

1 INTRODUCTION

Parkinson's Disease (PD) presents a formidable challenge in the realm of neurodegenerative disorders, characterized by its progressive nature and diverse array of motor and non-motor symptoms. As the prevalence of PD continues to rise globally, early and accurate diagnosis becomes increasingly imperative for effective disease management and intervention. This project aims to address the pressing need for precise PD prediction through a multifaceted approach that combines advanced data analysis techniques with cutting-edge machine learning and deep learning methodologies[1][2].

The complexities surrounding PD diagnosis underscore the importance of timely detection. The consequences of misdiagnosis or delayed intervention in PD can be profound, leading to exacerbated symptoms and diminished quality of life for affected individuals. Against this backdrop, this project endeavors to enhance the accuracy of PD prediction through the integration of spiral/wave dataset and innovative analytical frameworks[3][5]. Leveraging the spiral and wave dataset, this research aims to extract discriminative features that can aid in the early identification of PD symptoms. Given that tremors are one of the hallmark symptoms of PD and can be detected through drawing patterns, these datasets offer a unique opportunity to capture subtle motor impairments indicative of the disease. In particular, the study seeks to compare the efficacy of traditional feature extraction methods with Histogram of Oriented Gradients (HoG), with the goal of discerning the most informative features for PD classification[4].

Furthermore, the exploration extends to a comprehensive evaluation of machine learning and deep learning algorithms, including Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM), ResNET, DenseNET, AlexNET and hybrid models[6]. By examining the performance of these algorithms across the datasets and feature extraction approaches, this research aims to identify the optimal model architecture for precise PD classification. In doing so, this project hopes to contribute to the advancement of diagnostic accuracy and methodology in the field of PD prediction. By elucidating the most effective techniques for early detection, the study aspires to empower healthcare professionals with tool that can facilitate timely intervention [7].

- Feature Extraction: Extracting informative features from the medical imaging data while preserving relevant information poses a challenge. Determining the most discriminative features for PD classification is crucial.

- Model Selection: Choosing the most appropriate machine learning and deep learning algorithms for PD classification requires careful consideration. Each algorithm has its strengths and weaknesses, and selecting the optimal one is challenging

- Overfitting: Preventing overfitting, especially in complex deep learning models, is essential to ensure generalizability to unseen data. Regularization techniques and proper validation strategies are necessary to mitigate this risk.

- Interpretable Models: Interpreting the predictions of black-box deep learning models like CNNs and RNNs can be challenging. Ensuring model transparency and interpretability is crucial for gaining insights into the underlying mechanisms of PD classification.

- Computational Resources: Deep learning models often require substantial computational resources for training and evaluation. Access to high- performance computing infrastructure posed a challenge.The main objective of this work is to

The project endeavors to tackle the diagnostic complexities entrenched within Parkinson's Disease (PD), a condition where diagnosis heavily leans on subjective clinical evaluations, posing considerable challenges, particularly in the disease's early stages[8][10]. This reliance on subjective assessments often leads to underexploitation of advanced computational techniques, such as deep learning, in the diagnostic process [9].

Compounded by the lack of automated diagnostic tools, this approach further prolongs the identification of PD severity, impeding timely intervention and management. Thus, the project seeks to address these challenges by investigating the efficacy of the Histogram of Oriented Gradients (HoG) feature extraction method in conjunction with an array of deep learning models [11-15].

These models encompass a diverse range, including Support Vector Machines (SVM), random forest, Convolutional Neural Networks (CNN), pretrained CNN models, Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and hybrid architectures. Through the analysis of the Spiral and Wave dataset, this research aims to uncover the most effective combination of feature extraction techniques and deep learning models for accurate PD classification [16][18]. By doing so, the project aims to pave the way for the development of automated diagnostic tools that can enhance the efficiency and precision of PD diagnosis, ultimately improving patient outcomes and facilitating more effective management strategies for this debilitating neurological condition.

- The project seeks to systematically evaluate and identify the most effective deep learning network architecture for diagnosing Parkinson's Disease (PD) using Spiral-Wave data. This involves a comprehensive exploration of various machine learning algorithms, including SVM, Random Forest, KNN, Gradient Boosting, and Ensemble Models [19].

- Additionally, different deep learning models such as various pre-trained Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid model configurations will be investigated, tailored specifically to the unique characteristics of the Spiral/Wave dataset [20].

- By addressing existing gaps in PD research, the project aims to develop innovative solutions and enhancements. This endeavor aims to significantly contribute to bridging the gap between the capabilities of deep learning and their underutilization in Parkinson's research [21][22].

- Ultimately, the project aims to provide a more reliable and efficient platform for PD diagnosis and understanding by leveraging advanced computational techniques [23][24].

The paper aims to identify the optimal deep learning network configuration for precise PD diagnosis, leveraging both traditional machine learning and cutting-edge deep learning methodologies. Additionally, the project seeks to address existing gaps in PD research by developing innovative solutions to enhance diagnostic accuracy and understanding.

2 RELATED WORKS

Parkinson's Disease (PD) poses significant challenges in diagnosis and management due to its complex symptoms and the lack of definitive diagnostic markers. Traditional diagnostic methods often rely on clinical evaluation, which can be subjective and prone to misinterpretation. However, recent advancements in medical imaging and machine learning offer promising avenues for more accurate and timely diagnosis. A plethora of studies have explored the integration of Convolutional Neural Networks (CNNs) and other machine learning algorithms with various imaging modalities and clinical data to improve PD diagnosis. This literature review provides a comprehensive overview of recent research efforts in this domain, highlighting key themes, gaps, and future directions.

One notable research direction involves leveraging MRI data for PD diagnosis. Shah et al. (Year) and Mozhdehfarahbakhsh et al. (Year) demonstrate the potential of CNNs in analyzing MRI scans to detect PD and predict disease stages accurately. These studies underscore the importance of deep learning techniques in extracting meaningful features from MRI data, contributing to more precise diagnostic outcomes. However, both studies acknowledge the need for further validation and exploration of diverse datasets to enhance the robustness and generalizability of their models.

Similarly, Grover et al. (Year) and Gottapu and Dagli (Year) focus on utilizing machine learning algorithms, including CNNs and LSTM networks, for PD severity prediction using

MRI and clinical data. While these studies show promising results in predicting disease severity, they highlight limitations such as dataset exclusivity and the lack of real-world validation. Future research directions could involve incorporating multimodal data sources and exploring alternative deep learning architectures to address these limitations. Furthermore, the integration of non-imaging clinical data with machine learning algorithms offers new opportunities for PD diagnosis. Leung et al. (Year) demonstrate the significance of incorporating both imaging and non-imaging clinical features for predicting motor outcomes in PD patients. Their study emphasizes the importance of larger clinical datasets and explores alternative deep learning approaches to improve prediction accuracy. However, the study overlooks potential biases in clinical data collection and lacks interpretability analysis, which are crucial for clinical decision-making.

Another innovative approach involves analyzing handwriting patterns using machine learning algorithms for PD diagnosis, as explored by Ranjan et al. (Year) and Afandi, Ardhianto, and Lin (Year). These studies highlight the potential of non-invasive and cost-effective diagnostic methods using hand-drawn images and handwriting analysis. However, challenges such as variability in drawing styles and the need for standardized analysis methods pose significant limitations to the feasibility of this approach. Additionally, Horn et al. (Year) investigate the use of functional MRI and machine learning to predict optimal deep brain stimulation parameters for PD patients. While their study offers valuable insights into personalized treatment strategies, limitations such as non-randomized data acquisition and hardware specificity raise questions about the generalizability of their findings.

Standardization of Data Collection: There is a lack of standardized protocols for collecting hand-drawn images for PD diagnosis, leading to variability in the quality and consistency of the dataset.

Limited Diversity in Dataset: Existing datasets of hand-drawn images may lack diversity in terms of demographic characteristics, disease severity, and drawing styles, hindering the generalizability of the diagnostic model.

Validation Across Multiple Settings: Research gaps exist regarding the validation of CNN-based PD diagnosis using hand-drawn images across different clinical settings, including variations in equipment, expertise, and patient populations.

Overall, the literature review underscores the growing interest in leveraging machine learning and advanced imaging techniques for PD diagnosis. However, several gaps and limitations persist, including the need for diverse and standardized datasets, real-world validation, interpretability analysis, and exploration of alternative data sources. Future research directions should focus on addressing these challenges to enhance the accuracy, reliability, and accessibility of PD diagnostic tools. By bridging these gaps, researchers can pave the way for more effective management and treatment of Parkinson's Disease.

3. PROPOSED ARCHITECTURE

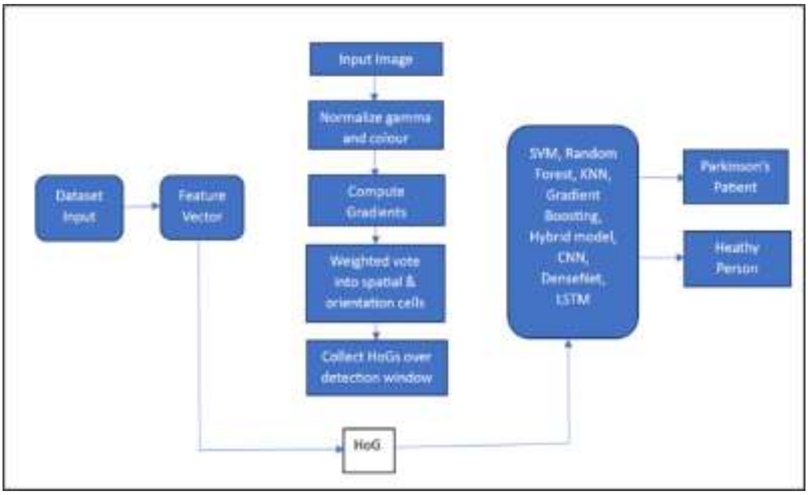
Input Image
Normalize gamma and colour
Compute Gradients
Weighted vote into spatial & orientation cells
Collect HoGs over detection window
Dataset Input
Feature Vector
HoG
SVM, Random Forest, KNN, Gradient Boosting, Hybrid model, CNN, DenseNet, LSTM
Parkinson's Patient
Heathy Person

Figure 1: Flowchart of proposed methodology 1

Figure 1 shows the process flow of the proposed image Parkinson’s Disease prediction system **.** Leveraging PyTorch's DataLoader for efficient data loading and preprocessing. The dataset, consisting of 102 images each of Parkinson's patients and healthy controls, is split into training and testing sets with a 70-30 ratio. Images are resized to 64x64 pixels, converted to grayscale, and transformed into PyTorch tensors. Feature extraction is performed using the Histogram of Oriented Gradients (HoG) technique. A diverse range of classification models, including Random Forest, SVM, KNN, Gradient Boosting, and various deep learning architectures like CNN, denseNet-201, LSTM, ConvLSTM, LSTM over CNN, ConvNet, and AlexNet, are trained and evaluated for their efficacy in Parkinson's disease classification.

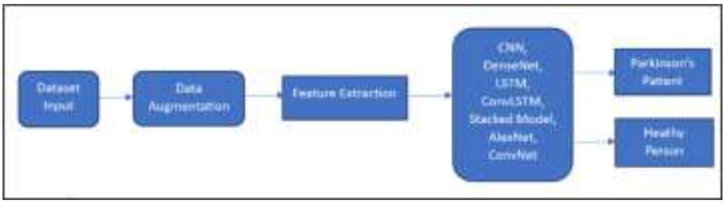

Figure 2: Flowchart of proposed methodology 2

Figure 2 shows the process flow of the proposed image Parkinson’s Disease prediction system**.** The fastai library for data organization, augmentation, and model training. Images are categorized into train and test sets using DataBlock, with augmentation techniques applied to enhance model robustness. Transfer learning is utilized with models such as ResNet34, CNN, denseNET, LSTM, ConvLSTM, stacked models, AlexNET, and ConvNET. The training process is followed by fine-tuning and evaluation phases, where interpretation tools like top losses and confusion matrix visualization are utilized to analyze model performance comprehensively. This proposed system offers a comprehensive approach to deep learning model development for Parkinson's disease classification, encompassing various architectures and evaluation techniques. By advancing the accuracy and efficiency of diagnostic methods, this research aims to contribute to the early detection and management of Parkinson's disease, ultimately aiding in the advancement of medical research in neurodegenerative disorders.

3.1. Data Loading and Pre-processing

- Methodology 1: Utilizes PyTorch's DataLoader for efficient data loading and preprocessing. The dataset is split into training and testing sets with a 70-30 ratio. Images are resized to 64x64 pixels, converted to grayscale, and transformed into PyTorch tensors.
- Methodology 2: Employs the fastai library for data organization, augmentation, and model training. Images are categorized into train and test sets using DataBlock, with augmentation techniques applied to enhance model robustness.

3.2. Data Visualization

Data visualization techniques are employed on the dataset utilizing the grid() function from the matplotlib.pyplot package, aiming to unveil deeper insights into the data. This approach helps reveal hidden relationships between variables, facilitating a clearer understanding of the dataset's underlying patterns. Additionally, to visualize the accuracy derived from the model, the confusion_matrix function from the sklearn package is utilized, providing a comprehensive overview of the model's performance in classification tasks.

3.3. Feature Extraction

Methodology 1 incorporates the Histogram of Oriented Gradients (HoG) technique as a fundamental step in the process of feature extraction. This technique analyzes the gradients or edge orientations within an image, capturing intricate details regarding the distribution of gradient directions. By leveraging HoG, the methodology aims to extract rich and descriptive features from the input data, facilitating subsequent analysis and modeling tasks.

3.4. Model selection and training

- Methodology 1: Trains a diverse range of classification models, including Random Forest, SVM, KNN, Gradient Boosting, and various deep learning architectures like CNN, denseNet-201, LSTM, ConvLSTM, LSTM over CNN, ConvNet, and AlexNet.
- Methodology 2: Employs transfer learning with models such as ResNet34, CNN, denseNET, LSTM, ConvLSTM, stacked models, AlexNET, and ConvNET.

3.5 Proposed Algorithm

As mentioned in architecture section 3 figure 1. proposed recommendation system follows below steps.

Step 1: Mount Google Drive and Import Libraries:

- Mount Google Drive to access the dataset stored in Google Drive.
- Import necessary libraries including torch, torchvision, numpy, and scikit-learn.

Step 2: Prepare Data:

- Define transformations for image preprocessing using torchvision.transforms.Compose().
- Load training and test data using torchvision.datasets.ImageFolder().
- Create DataLoader objects for batch processing.

Step 3: Visualize Data:

- Display sample images from both training and test datasets using matplotlib.

Step 4: Extract HOG Features:

- Define a function to extract Histogram of Oriented Gradient (HOG) features from images using skimage.feature.hog().
- Extract HOG features from both training and test images.

Step 5: Visualize HOG Features:

- Display sample HOG images and features using matplotlib.

Step 6: Train and Evaluate Classifiers:

- Train various classifiers including Random Forest, SVM, Decision Tree, KNN, and Gradient Boosting using extracted HOG features.
- Evaluate the performance of each classifier using accuracy_score from scikit-learn.

Step 7. Meta-Learning:

- Define a neural network model (MetaLearner) using PyTorch.

- Train the meta-learner using predictions from SVM, Random Forest, and Gradient Boosting as features and original labels as targets.
- Evaluate the performance of the meta-learner on the test set.

  Step 8: Display Results:
- Visualize the comparison of different classifiers' accuracies using matplotlib.

As mentioned in architecture section 3 figure 2. proposed recommendation system follows below steps.

Step 1: Installation and Importing Libraries:

- Install the fastai library using pip: `pip install fastai`.
- Import necessary modules:
- import fastai
- from fastai.vision.all import *

  Step 2: Setup for Colab and Mounting Google Drive:
- Set up the Colab environment and mount Google Drive for data storage and retrieval:
- !curl -s https://course-v3.fast.ai/setup/colab | bash
  - from google.colab import drive
  - drive.mount('/content/drive', force_remount=True)

Step 3: Setting up Data and DataLoaders:

- Define transformations and create DataBlock and DataLoader objects for loading and preprocessing image data:
- path = ('/content/drive/My Drive/dataset')
  - data = DataBlock(….)
  - dls = data.dataloaders(path)

Step 4: Model Training:

- Define a convolutional neural network model using a ResNet34 architecture and train it using transfer learning:
- learn=vision_learner(dls,models.resnet34,metrics=accuracy).to_fp16()
- learn.fit_one_cycle(5)

Step 5: Model Evaluation and Interpretation:

- Evaluate the trained model's performance, analyze losses, and visualize the results using interpretation tools provided by fastai:
- interp = ClassificationInterpretation.from_learner(learn)
- interp.plot_top_losses(9, figsize=(12,10))
- interp.plot_confusion_matrix()

Step 6: Additional Training and Evaluation:

- Further fine-tune the model, evaluate performance, and save the trained model:
- learn.unfreeze()
- learn.fit_one_cycle(5, lr_max=slice(1e-03, 1e-05/2))
- learn.save('rn-34-unfreeze')

4. METHODOLOGY

4.1 Dataset

Both methodologies utilize the Spiral/Wave dataset sourced from the UCI Machine Learning repository, which has been carefully curated to ensure balance, comprising 102 images each of Parkinson's patients and healthy controls. This meticulous curation guarantees equitable representation for both classes within the dataset. Employing a systematic partitioning approach, the dataset is meticulously divided into a 70-30 split for training and testing purposes. This strategic division facilitates a comprehensive evaluation of model performance, ensuring that the models are rigorously tested across a diverse set of data samples. By adhering to this systematic approach, not only is fairness in data representation upheld, but it also bolsters the reliability and robustness of the evaluation process. Such meticulous methodologies lay a solid groundwork for advancing research in Parkinson's disease diagnosis through the utilization of machine learning techniques.

4.2 Hyper Parameters Analysis

Optimizing the classification task for Parkinson's disease detection requires a meticulous hyperparameter tuning process. Key hyperparameters play crucial roles in refining the model:

- Learning Rate: This parameter regulates the rate at which the model weights are updated during training. A suitable learning rate facilitates efficient convergence toward the optimal solution without overshooting or diverging. Variations in learning rates significantly influence the training process and model performance.

- Number of Epochs: The number of epochs dictates how many times the entire training dataset is exposed to the model during training. Insufficient epochs may lead to underfitting, while excessive epochs can result in overfitting. Striking the right balance is imperative for achieving high classification accuracy.
- Batch Size: Batch size refers to the number of samples fed into the model before weight updates. It impacts the training process's speed and stability. Larger batch sizes may expedite convergence but could escalate memory requirements and computational complexity. Conversely, smaller batch sizes may promote more stochastic updates and potentially enhance generalization.
- Dropout: Dropout serves as a regularization technique that randomly deactivates a portion of neurons during training. This helps prevent overfitting by enhancing model robustness and generalization. The dropout probability determines the likelihood of neuron deactivation during each training iteration.

To optimize these hyperparameters, the "training model optimizer" technique is employed. This optimizer iteratively adjusts model weights and learning rates to minimize loss and maximize accuracy. The Adam optimizer, renowned for its efficacy in managing noisy or sparse gradients, is commonly employed for this purpose.

Through systematic hyperparameter tuning and leveraging the capabilities of the Adam optimizer, the classification model can be finely tuned to achieve optimal performance in Parkinson's disease detection. This rigorous hyperparameter analysis ensures that the model effectively distinguishes between healthy individuals and those afflicted by Parkinson's disease, thus contributing to the development of more reliable diagnostic tools and advancements in disease management.

4.3. Data Preprocessing

In the initial methodology, preprocessing steps are meticulously applied to the images before analysis. Firstly, the images undergo resizing to a uniform dimension of 64x64 pixels, ensuring consistency across the dataset. Subsequently, a grayscale transformation is employed, converting the images into a single-channel representation, thereby simplifying subsequent analysis while retaining essential features. Finally, the preprocessed images are converted into PyTorch tensors, a format compatible with the analysis framework, facilitating seamless integration into the model pipeline.

In contrast, the second methodology employs advanced data augmentation techniques to enhance model generalization and robustness. These techniques involve applying a variety of transformations to the images, including rotations, flips, and resizing. By exposing the model to diverse variations of the input data, these transformations help mitigate overfitting and improve the model's ability to generalize to unseen data. This augmentation strategy enriches the training dataset with a broader range of image variations, thereby enhancing the model's capacity to accurately classify Parkinson's disease based on the Spiral/Wave dataset.

4.4. Machine Learning Models Formulation

In the first methodology, feature extraction is carried out using Histogram of Oriented Gradients (HoG), a technique renowned for its effectiveness in capturing local gradient information from images. This process involves utilizing the extract_hog_features() function from the skimage.feature.hog() module to extract pertinent features from the preprocessed images. By analyzing gradients in various orientations within localized regions, HoG effectively captures distinctive patterns essential for distinguishing between Parkinson's patients and healthy individuals.

In the second methodology, a sophisticated DataBlock approach is employed for image data preprocessing. This involves a comprehensive pipeline utilizing functions such as get_image_files for efficient file retrieval, GrandparentSplitter for strategic train-test splitting, and parent_label for accurate label extraction from the directory structure. Additionally, images are uniformly resized to 128x128 pixels using the Resize(128) function, ensuring consistency in image dimensions across the dataset. This meticulous preprocessing scheme lays a solid foundation for subsequent model training and evaluation, enhancing the overall effectiveness and reliability of the classification task.

4.4.1 Random Forest

In the first methodology, a diverse array of machine learning algorithms is deployed to classify Parkinson's disease using the Spiral/Wave dataset. The Random Forest (RF) algorithm is a prominent choice, utilizing an ensemble of 100 decision trees to collectively make predictions. This approach leverages the wisdom of crowds, amalgamating the predictions of multiple decision trees to enhance overall accuracy and robustness.

4.4.2 SVM

Next, the Support Vector Machine (SVM) algorithm is employed with a linear kernel. SVMs excel in separating classes in high-dimensional spaces, making them well- suited for tasks like image classification. By maximizing the margin between classes, SVMs strive for optimal separation, achieving high classification performance.

4.4.3 Decision Tree

Additionally, a Decision Tree (DT) classifier is utilized, which partitions the feature space into distinct regions based on learned decision rules. Decision trees are intuitive and easily interpretable, making them valuable for understanding the underlying decision-making process of the model.

4.4.4 KNN

Lastly, the K-Nearest Neighbors (KNN) algorithm is employed, which makes predictions based on the majority class of the k-nearest data points. With k set to 5, the algorithm calculates distances between instances in the feature space to determine the most similar instances, enabling effective classification based on local patterns.

4.5. Hybrid Models Formulation

This meta learner model is designed for Parkinson's disease classification, integrating predictions from Support Vector Machine (SVM), Random Forest, and Gradient Boosting models. It concatenates the probability predictions from these models and feeds them as features to a neural network. The neural network, implemented using PyTorch, comprises two fully connected layers with ReLU activation. It's trained using cross-entropy loss and Adam optimizer, aiming to optimize classification performance. The model demonstrates its effectiveness through improved accuracy on the test dataset, validating its potential for Parkinson's disease classification

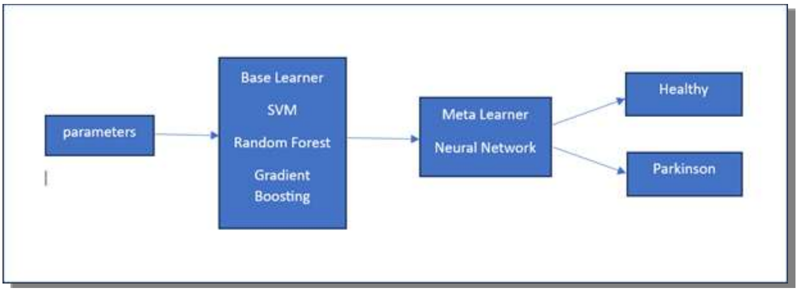

Figure 3: Architecture for meta learner model

4.6. Deep Learning Models Formulation

In the first approach, the methodology employs Histogram of Oriented Gradients (HoG) for feature extraction, a well-established technique renowned for its efficacy in capturing local gradient information from images. This process entails utilizing the extract_hog_features() function available in the skimage.feature.hog() module to extract relevant features from preprocessed images. By scrutinizing gradients across various orientations within localized regions, HoG adeptly captures distinctive patterns crucial for discerning between Parkinson's patients and healthy individuals. This approach offers a robust foundation for subsequent deep learning model training, as it effectively encodes essential image characteristics into feature vectors.

In contrast, the second methodology adopts a sophisticated DataBlock approach for image data preprocessing. This comprehensive pipeline integrates various functions such as get_image_files for streamlined file retrieval, GrandparentSplitter for strategic train-test partitioning, and parent_label for accurate label extraction from the directory structure. Furthermore, images undergo uniform resizing to 128x128 pixels using the Resize(128) function, ensuring uniformity in image dimensions throughout the dataset. This meticulous preprocessing regimen establishes a solid groundwork for subsequent deep learning model training and evaluation, bolstering the overall efficacy and reliability of the classification task by ensuring consistency and coherence in data representation.

4.6.1 CNN WITH 2 CONVOLUTIONAL LAYERS

In the realm of image recognition, Convolutional Neural Networks (CNNs) stand out for their exceptional ability to classify intricate features within images. CNNs typically consist of Conv2D layers, which effectively apply filters to capture distinctive patterns and features, enhanced by Rectified Linear Unit (ReLU) activation functions that introduce non-linearity to the network. Following Conv2D layers, Max Pooling operations are employed for downsampling, reducing computational complexity while preserving essential features. Flattening the output prepares the data for Dense layers, allowing the network to learn complex relationships and hierarchies among features extracted from the input images. The use of ReLU activation addresses the vanishing gradient problem, ensuring stable and efficient training. Ultimately, the network culminates in a binary-classification Dense layer, providing decisive outputs. This architectural design highlights the efficacy of CNNs in the intricate process of feature learning and robust image classification, making them indispensable tools in the realm of computer vision and pattern recognition.

Let (X) represent the input image data, (W_i) represent the weights of the (i)th layer, (b_i) represent the biases of the (i)th layer, (f) represent the activation function (ReLU in this case), and (P) represent the max pooling operation:

For each layer (i) in the CNN:

1. Convolutional Layer (Conv2D):

[Z_i = f(X * W_i + b_i)]

2. Max Pooling Layer (Max Pooling):

[X_{i+1} = P(Z_i)]

3. Flatten Layer:

[X_{flat} = \text{Flatten}(X_{i+1})]

4. Dense Layer:

[Y = f(X_{flat} \cdot W_{dense} + b_{dense})]

Where:

(X) is the input image data.

(W_i) are the weights for the (i)th convolutional layer.

(b_i) are the biases for the (i)th convolutional layer.

(Z_i) is the output of the (i)th convolutional layer.

(X_{i+1}) is the output of the (i)th max pooling layer.

(X_{flat}) is the flattened output.

(W_{dense}) are the weights for the dense layer.

(b_{dense}) are the biases for the dense layer.

(Y) is the final output (binary classification in this case).

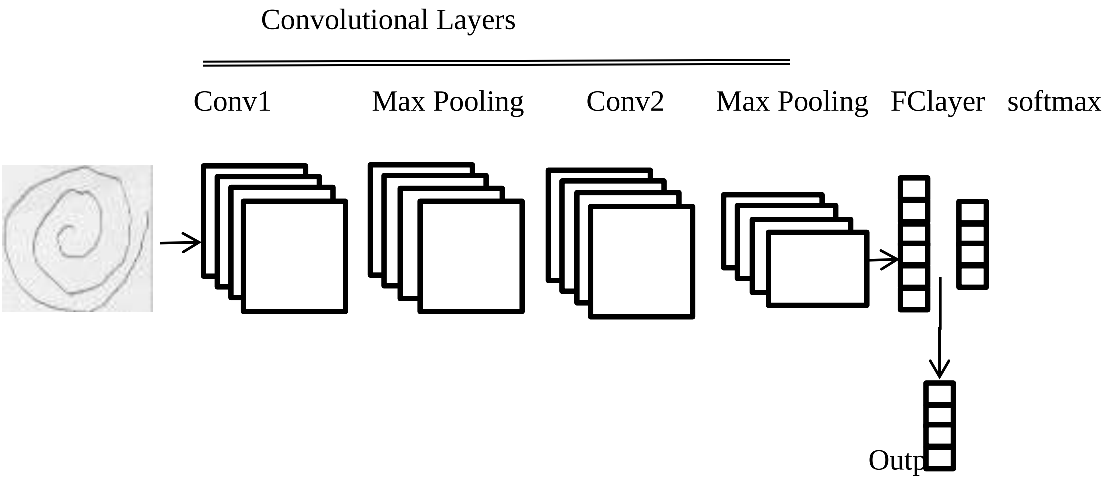

Figure 4: CNN Architecture

Table 1: Hyper parameters used for CNN model

Parameter	**Value**
Optimizer	Adam Optimizer
Epochs	40
Learning rate	0.001
Batch size	32

4.6.2 RESNET-34

In this research, the ResNet (Residual Network) architecture is harnessed, representing a breakthrough in image classification methodologies. Specifically, the ResNet34 variant, comprising 34 layers, is selected for its profound impact on the field. This architecture integrates residual blocks, a pivotal innovation enabling the training of deeper neural networks without succumbing to the vanishing gradient issue. By effectively circumventing this challenge, ResNet34 ensures the efficient propagation of gradients during training, facilitating the exploration of increasingly complex features within the dataset. Due to its inherent robustness and efficiency, ResNet34 emerges as an ideal candidate for medical image classification tasks such as Parkinson's disease detection. Its ability to accurately discern subtle patterns within medical images underscores its significance in advancing diagnostic capabilities and enhancing patient care.

Table 2: Hyper parameters used for RESNET-34

Parameter	**Value**
Optimizer	Adam Optimizer
Epochs	10
Learning rate	0.001
Batch size	32

4.6.3 TRANSFER LEARNING

The DenseNet169 model emerges as a standout performer in the realm of Parkinson's disease detection, boasting an impressive accuracy rate of 86.67% on the Spiral/Wave dataset. Its superiority lies in its adept utilization of efficient feature reuse mechanisms, enabling it to extract and leverage features effectively for classification tasks. Moreover, its lightweight design renders it particularly well-suited for deployment on resource-constrained devices, ensuring accessibility across various platforms. Additionally, by leveraging transfer learning from the ImageNet dataset, the model harnesses pre-existing knowledge to enhance its efficacy, particularly in scenarios with limited labeled data. Thus, the amalgamation of efficient feature reuse, lightweight design, and transfer learning capabilities positions DenseNet169 as a formidable tool in the accurate and efficient diagnosis of Parkinson's disease.

DenseNet (Densely Connected Convolutional Networks) utilizes dense blocks, where each layer is connected to every other layer in a feed-forward fashion, facilitating feature reuse and gradient flow throughout the network. DenseNet169 specifically denotes a variant with 169 layers.

Let (X) represent the input data, (W_i) represent the weights of the (i)th layer, (b_i) represent the biases of the (i)th layer, (f) represent the activation function, and (D) represent the dense block:

For each layer (i) in the DenseNet169:

1. Initial Convolutional Layer:

[Z_1 = f(X * W_1 + b_1)]

2. Dense Blocks:

[Z_{i+1} = D(Z_1, Z_2, ldots, Z_i, W_{i+1})]

3. Transition Layers: Transition layers may be optionally used to reduce spatial dimensions and feature maps before passing to the next dense block or the output layer.

4. Global Average Pooling Layer:

[Z_{text{gap}} = text{GlobalAvgPool}(Z_{text{last}})]

5. Fully Connected Layer:

[Y = f(Z_{text{gap}} * W_{text{last}} + b_{text{last}})]

Where:

(X) is the input data.

(Z_i) represents the output of the (i)th layer.

(W_i) are the weights for the (i)th layer.

(b_i) are the biases for the (i)th layer.

(f) is the activation function (commonly ReLU).

(D) represents the dense block, which consists of several convolutional layers with skip connections from all previous layers.

(Z_{text{last}}) is the output of the last dense block or transition layer.

(Z_{text{gap}}) is the output of the global average pooling layer, which averages the spatial dimensions of the feature maps.

(W_{text{last}}) and (b_{text{last}}) are the weights and biases of the fully connected layer, respectively.

Table 3: Hyper parameters used for Transfer Learning

Parameter	**Value**
Optimizer	Adam Optimizer
Epochs	40
Learning rate	0.001
Batch size	32

4.6.4 LSTM

In this research endeavor, the LSTM (Long Short-Term Memory) model emerges as a pivotal tool for Parkinson's disease classification, capitalizing on its ability to effectively process sequential data through recurrent neural networks. The model architecture is thoughtfully designed, featuring an LSTM layer that captures intricate temporal dependencies, followed by a fully connected layer for robust classification. Trained meticulously on the training dataset, the LSTM model exhibits its prowess during evaluation on the test data, achieving an impressive accuracy rate of 86.67%. This noteworthy performance underscores the efficacy of employing LSTM-based approaches in medical diagnostics, showcasing their capacity to discern subtle patterns within sequential data and accurately classify Parkinson's disease with a high level of precision and reliability.

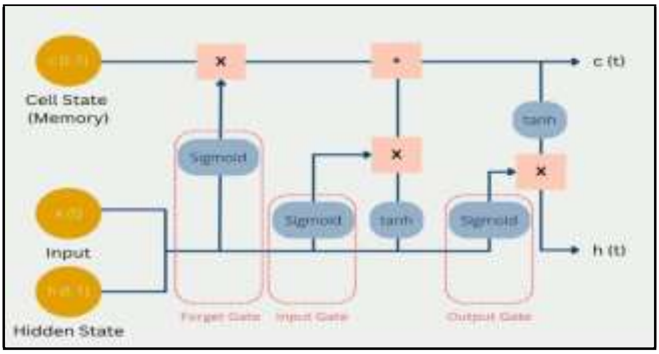

Figure 5: LSTM Architecture

4.6.5 LSTM stacked over CNN

In this research, a stacked model comprising a CNN (Convolutional Neural Network) followed by an LSTM (Long Short-Term Memory) network is utilized for Parkinson's disease classification. The CNN extracts spatial features from input images, which are then fed into the LSTM for sequential modeling. The model is trained and evaluated using training, validation, and test datasets. Training and validation losses are monitored across epochs, and the model's performance is assessed using accuracy and a confusion matrix visualization.

4.6.6 ConvNET

In this research, AlexNet is employed as a feature extractor for Parkinson's disease classification. The pre-trained AlexNet model is utilized to extract features from input images. The extracted features are then flattened and passed through a fully connected layer for classification. The model is trained and evaluated using training, validation, and test datasets. Training and validation losses are monitored across epochs, and the model's performance is assessed using accuracy and a confusion matrix visualization.

4.6.7 AlexNET

In this research, AlexNet is employed as a feature extractor for Parkinson's disease classification. The pre-trained AlexNet model is utilized to extract features from input images. The extracted features are then flattened and passed through a fully connected layer for classification. The model is trained and evaluated using training, validation, and test datasets. Training and validation losses are monitored across epochs, and the model's performance is assessed using accuracy and a confusion matrix visualization.

4.6.8 ConvLSTM

ConvLSTM (Convolutional Long Short-Term Memory) is employed for Parkinson's disease classification in this project. The architecture comprises convolutional layers for feature extraction and LSTM layers for sequential modeling. The model processes input images through convolutional layers, followed by flattening and feeding into fully connected layers for classification. Adam optimizer and cross-entropy loss are utilized for training. Training and validation losses are monitored across epochs, and the model's performance is evaluated using a test dataset, with accuracy and a confusion matrix visualization classification results.

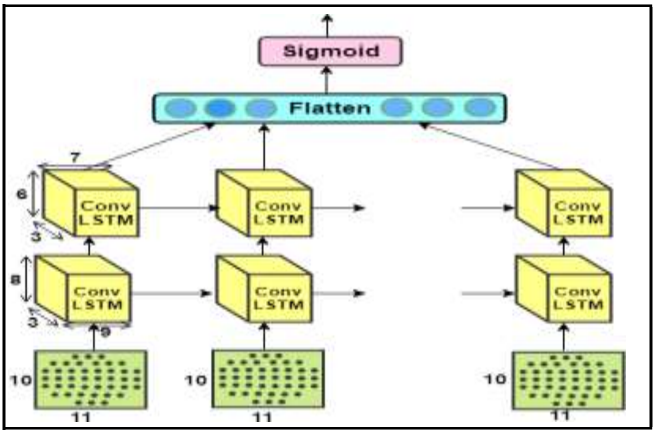

Figure 6: ConvLSTM Architecture

5. RESULTS AND DISCUSSION

The investigation into Parkinson's disease classification from spiral/wave data unveils significant disparities in model accuracy between two distinct methodologies, each employing distinct feature extraction techniques and classification algorithms.

In Methodology 1, which harnesses Histogram of Oriented Gradients (HoG) features, Convolutional Neural Networks (CNNs) emerge as the top-performing model with an impressive accuracy of 88.33%. Following closely are the Support Vector Machine (SVM) and

Long Short-Term Memory (LSTM) models, both achieving an accuracy of 86.67%. Random Forest (RF) and K-Nearest Neighbors (KNN) demonstrate respectable performances, with accuracies of 80% and 78%, respectively. However, Decision Tree and Gradient Boosting models lag behind with accuracies of 58% and 66%, indicating their limited effectiveness in this context.

Contrastingly, Methodology 2 showcases ResNet34's exceptional accuracy, reaching a remarkable 95%. DenseNET and LSTM models also exhibit strong performances, achieving accuracies of 86.67% and 83.33%, respectively. Despite these successes, Convolutional LSTM (ConvLSTM) and Stacked models yield lower accuracies of 68% and 66%, suggesting that their architectures may not be optimally suited for this particular classification task.

The ratio of the number of correctly identified positive pixel samples to total number of identify pixel is precision.

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

$$precision = \frac{TP}{TP+FP}$$

$$recall = \frac{TP}{TP+FN}$$

These findings underscore the efficacy of CNNs and ResNet34 in accurately classifying Parkinson's disease from spiral/wave data. The superior performance of these deep learning models suggests their potential diagnostic utility in clinical settings. By effectively leveraging complex patterns and hierarchical representations within the data, CNNs and ResNet34 demonstrate their ability to discern subtle differences indicative of Parkinson's disease. Furthermore, the notable accuracy discrepancies between Methodology 1 and Methodology 2 highlight the importance of feature extraction techniques and model architectures in the classification process. While HoG-based methods coupled with traditional machine learning algorithms offer respectable performances, the utilization of deep learning models, particularly CNNs and ResNet34, significantly enhances classification accuracy, underscoring the importance of leveraging advanced neural network architectures for complex medical classification tasks.

5.1 Accuracy for Methodology 1

Table 4: Accuracy for Methodology 1

Model	Accuracy
RF	80
SVM	86.67
Decision Tree	58
KNN	78
Gradient Boosting	66
Meta learner 1	86.67
Meta learner 2	81.67
CNN	88.33
DenseNET	71.67
LSTM	86.67

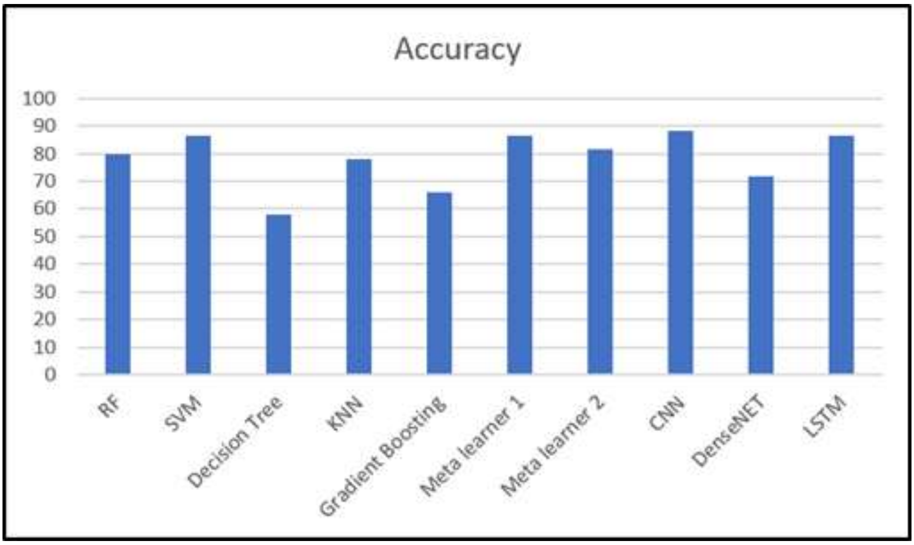

Figure 7: Performance **c**omparison of various models

Fig. 7 shows the accuracy values for the dataset using methdology 1 are presented. Among the various models evaluated, CNN emerges with the highest classification accuracy of 88.33%

Table 5: Evaluation of loss for CNN with increase in number of epochs

Epochs	Loss
1	0.6957
2	0.6987
3	0.6929
4	0.6916
5	0.6848
6	0.6711
7	0.6556
8	0.6083
9	0.5841
10	0.3512

5.2 Accuracy for Methodology 2

In Table 6, the accuracy values for the dataset using methdology 2 are presented. Among the various models evaluated, ResNET emerges with the highest classification accuracy of 95%.

Table 6: Accuracy for Methodology 2

Model	Accuracy
ResNet34	95
DenseNET	86.67
LSTM	83.33
ConvLSTM	68
Stacked Model	66
ConvNET	55
AlexNET	50
DenseNET	71.67

LSTM	86.67

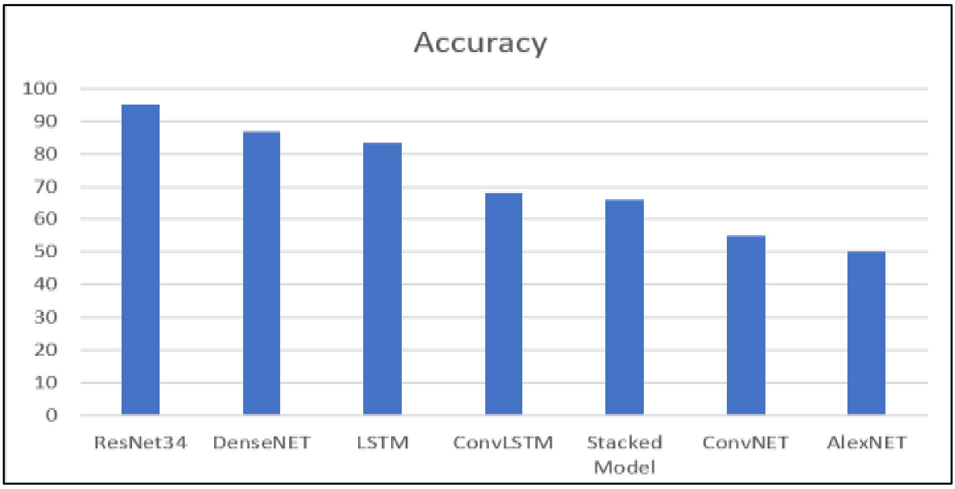

Figure 8: Performance **c**omparison of various models – methodology 2

Table 7: Evaluation of loss for RESNET 34 with increase in number of epochs

Epochs	Training loss	Validation loss	Accuracy
1	0.3616	0.3758	0.8667
2	0.3931	0.3984	0.9000
3	0.3751	0.4091	0.9167
4	0.3410	0.3808	0.9167
5	0.3316	0.3578	0.9500

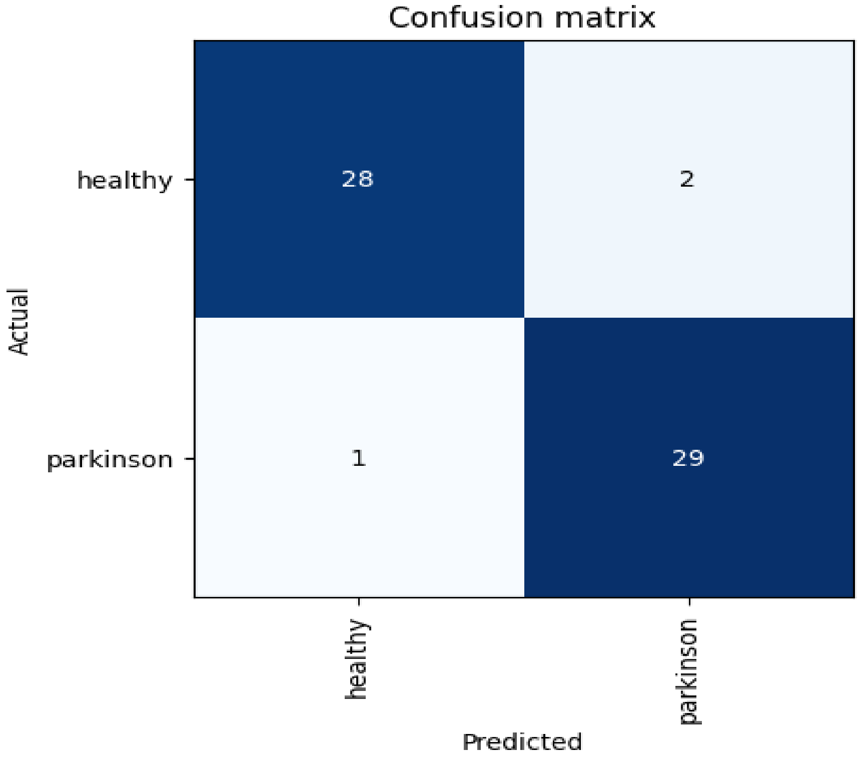

Figure 9: Confusion metrix of RESnet

6 CONCLUSION AND FUTURE WORKS

In conclusion, the study underscores the superior performance of deep learning architectures, particularly CNN and ResNet34, in accurately classifying Parkinson's disease from spiral/wave data. Methodology 2, leveraging ResNet34, demonstrates higher accuracy compared to Methodology 1 using HoG, highlighting the efficacy of deep learning approaches in medical image analysis. These findings emphasize the potential of advanced machine learning techniques in improving disease diagnosis and patient care.

Future research endeavors should focus on exploring ensemble methods to further enhance classification accuracy and robustness. By combining multiple models, researchers can leverage the strengths of different algorithms to achieve superior performance. Additionally, integrating clinical data, such as patient demographics and disease progression metrics, with imaging features could provide more comprehensive diagnostic insights. This multidimensional approach may enhance disease characterization and prognosis, ultimately leading to more personalized treatment strategies. Furthermore, the adoption of explainable AI techniques is crucial for enhancing model interpretability and facilitating clinical decision-making processes. By providing clinicians with insights into how the models arrive at their predictions, explainable AI methods can increase trust and confidence in AI-based diagnostic systems.

Moreover, investigating the scalability and generalizability of the proposed models across diverse patient cohorts and imaging modalities is essential for real-world deployment and broader clinical impact. By validating the models on large and diverse datasets, researchers can ensure their effectiveness across different populations and clinical settings, thereby maximizing their utility in clinical practice. Overall, continued research in these directions holds the potential to revolutionize Parkinson's disease diagnosis and management, ultimately benefiting patients and healthcare providers alike.

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