A FIELD PROJECT REPORT

on

"Parkinson's Disease Detection"

Submitted

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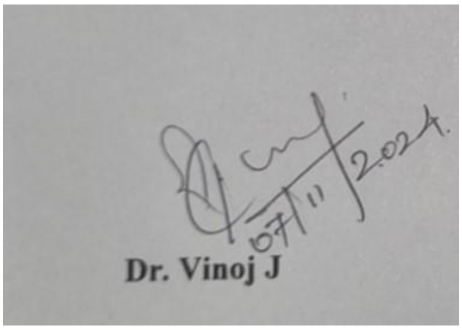
CERTIFICATE

This is to certify that the Field Project entitled **"Parkinson's Disease Detection"** that is being submitted by 221FA04050 (D.Bala Sree), 221FA04134 (V.Keerthana), 221FA04204 (T.Harsha Sri Sai Lakshmi), 221FA04649 (N.Chaitanya Gopinath) for partial fulfilment of Field Project is a bonafide work carried out under the supervision of Dr.Vinoj J, Assistant Professor, Department of CSE.



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DECLARATION

We hereby declare that the Field Project entitled **“Parkinson’s Disease Detection”** is being submitted by 221FA04050 (D. Bala Sree), 221FA04134 (V. Keerthana), 221FA04204 (T. Harsha Sri Sai Lakshmi) and 221FA04649 (N. Chaitanya Gopinath) in partial fulfilment of Field Project course work. This is our original work, and this project has not formed the basis for the award of any degree. We have worked under the supervision of Dr. Vinoj J, Assistant Professor, Department of CSE.

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ABSTRACT:

This study focuses on enhancing the diagnosis of Parkinson's disease (PD) by utilizing Convolutional Neural Networks (CNN) to analyse brain MRI scans. Parkinson's is a neurodegenerative disorder that impacts movement and can be challenging to diagnose accurately in its early stages due to symptoms that overlap with other movement disorders. The main goal of the study is to create CNN models that can effectively distinguish between patients with neurodegenerative diseases, particularly those with movement disorders, and healthy individuals. By differentiating these groups, the model aims to minimize diagnostic errors and improve accuracy, offering a valuable resource for healthcare professionals.

The proposed CNN model will enable automated analysis of MRI scans, resulting in more consistent and reproducible outcomes compared to traditional diagnostic methods. With CNN technology, the model will efficiently process large volumes of MRI data, thereby reducing the time needed for diagnosis and supporting the early detection of PD. Beyond enhancing diagnostic speed, the model's reproducibility of results is a significant advantage. Consistent and accurate outcomes across various MRI tests will help eliminate potential human errors, ensuring a higher level of reliability in diagnoses. This improved diagnostic process could facilitate earlier and more precise treatment decisions for patients, ultimately enhancing their quality of life. Overall, this study contributes to the progress of medical imaging technology and the timely diagnosis of Parkinson's disease through the capabilities of CNNs.

Key Words: Parkinson’s Disease, Deep Learning, Convolutional Neural Network, Classification, Classifiers (SVM, Decision Tree, KNN, ANN).

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INTRODUCTION

1. INTRODUCTION

Parkinson’s disease is a complex neurodegenerative disorder that significantly impacts the quality of life of affected individuals. The underlying mechanism involves the progressive degeneration of dopamine-producing neurons in the substantia nigra, leading to the hallmark symptoms of movement difficulties. These symptoms can severely impair daily activities, making timely diagnosis crucial. However, early-stage Parkinson’s can often mimic other neurological disorders, complicating diagnosis. Traditional methods for diagnosing Parkinson's disease, like clinical assessments and MRI scans, often miss early brain changes. This highlights the need for better diagnostic tools to improve accuracy and ease the workload on healthcare providers. Machine learning advancements, particularly convolutional neural networks (CNNs), are now being used to analyse MRI data more effectively. These models can find patterns in brain images that might go unnoticed, helping to automate the screening process. This automation can reduce human error, speed up diagnosis, and allow for earlier treatment options.

The impact of early diagnosis cannot be overstated; research suggests that timely treatment can slow the progression of symptoms and improve the overall quality of life for patients. Given that Parkinson's disease affects approximately 5.8 million people globally and contributes to a significant number of fatalities each year, the integration of CNNs in neuroimaging represents a transformative advancement in the field. This approach allows for more precise visualization and analysis of brain patterns associated with Parkinson's, providing a clearer picture of disease onset and progression. As CNNs continue to evolve, their use in clinical settings could enable personalized treatment plans tailored to the patient’s unique neurological profile. This technological shift not only enhances the potential for early intervention but also supports ongoing research efforts aimed at unlocking further insights into the complexities of Parkinson's, leading to improved management strategies and outcomes for patients.

CHAPTER-2

LITERATURE SURVEY

2. LITERATURE SURVEY

2.1 Literature Survey

Lub Xya Hli (2015) emphasizes the need for urgent diagnosis of early neuroimaging and cognitive markers as a critical step in addressing Parkinson’s disease [1]. Nalini et al. (2023) advanced medical image analysis through computer vision and IoT, improving diagnostic methodologies [2]. Ali et al. (2022) utilized deep learning for early-stage recognition of Parkinson’s, highlighting neural networks’ role in accurate diagnosis [4]. Rana and Chen (2022) demonstrated SVM classifiers as valuable machine learning tools in diagnostics [5]. Xu et al. (2022) used neural monitoring techniques with deep learning to track disease progression in real-time [6]. Similarly, Naseer et al. (2021) applied advanced AI methods, enhancing reliability in Parkinson’s detection [7]. Rumman et al. (2018) focused on early detection through ANN and image processing [8]. Joy et al. (2023) explored machine learning for voice pathology detection, adding another dimension to Parkinson’s diagnosis [9].

Rana et al. (2022) reviewed key machine learning algorithms for Parkinson’s detection [10]. Ibanez et al. (2019) worked on spatial and temporal neural networks, advancing precision in Parkinson’s imaging [11]. Meijer and Goraj (2014) contributed insights into MRI techniques for disease tracking [13]. Zhang et al. (2019) employed resting-state fMRI to analyze dynamic neural activity in Parkinson’s patients, shedding light on disease effects on brain networks [14]. Rana et al. (2022) examined robotic approaches for automated diagnosis using MRI [15].

Mucha et al. (2018) analyzed dysgraphia in advanced Parkinson’s, illustrating how handwriting analysis detects motor impairments [16]. Alhussein and Muhammad (2018) applied deep learning to vocal analysis for Parkinson’s, expanding diagnostic approaches [17]. Pereira et al. (2016) used predictive learning models for early diagnosis [18]. Way et al. (2005) highlighted speech therapy’s role in improving life quality for patients [19]. Logemann et al. (1978) provided foundational insights on vocal dysfunctions in Parkinson’s, underlining the disease’s impact on communication [20].

2.2 Motivation

The urgency for enhanced diagnostic methods for Parkinson's disease has never been more critical. With the global prevalence of this debilitating neurodegenerative disorder affecting approximately 5.8 million individuals and resulting in 329,000 fatalities annually, the healthcare community faces a pressing challenge. The symptoms of Parkinson's disease, including tremors, bradykinesia, rigidity, and postural instability, not only impair movement and coordination but also severely affect the quality of life of those diagnosed. However, the complexity of accurately diagnosing Parkinson's disease is compounded by its symptomatic overlap with other neurological disorders. Traditional methods, such as clinical examinations and MRI scans, often fail to detect subtle yet significant changes in the brain, leading to misdiagnosis or delayed treatment.

In this context, leveraging the capabilities of machine learning, particularly convolutional neural networks (CNNs), presents a transformative opportunity for the field of neuroimaging. By automating the analysis of MRI scans, CNNs can provide a level of diagnostic precision that is often unattainable through human interpretation alone. This not only reduces the potential for human error but also streamlines the diagnostic process, leading to faster and more reliable results. The proposed study seeks to develop and implement robust CNN models that can effectively differentiate between neurodegenerative patients with movement disorders and healthy individuals, ultimately enhancing diagnostic accuracy. Through early and accurate identification of Parkinson's disease, we can facilitate timely interventions that significantly improve patient outcomes. The integration of CNN technology into the diagnostic workflow is not merely an advancement in imaging but a vital step towards improving the management and treatment of Parkinson's disease, thereby addressing a critical need in the healthcare landscape.

CHAPTER-3

PROPOSED SYSTEM

3. PROPOSED SYSTEM

The proposed system aims to enhance the diagnosis of Parkinson's disease by utilizing convolutional neural networks (CNNs) to analyse MRI scans. The dataset comprises MRI images categorized into five dementia levels, with each level containing 154 validation images, 3,601 training images, and 3 test images. All images are standardized to a resolution of 640x640 pixels to ensure consistency in analysis. The initial step involves data preprocessing, which includes resizing the images to 640x640 pixels and normalizing the pixel values to a range of 0-1. To improve the robustness of the model, various data augmentation techniques, such as rotation, motion, and translation, are employed. This helps increase the diversity of the training dataset. The data is divided into three subsets: training, validation, and testing, with 20% of the total dataset allocated for testing purposes. For feature extraction, the system leverages pre-trained models like VGG16, VGG19, and ResNet50. These models are renowned for their effectiveness with large datasets, such as ImageNet. The VGG models have deeper architectures with simpler convolutional filters, which enhance the extraction of meaningful features from the images. Additionally, ResNet50 utilizes residual learning to address the vanishing gradient problem, enabling the training of deeper networks without significant loss of information.

To evaluate the performance of the classification, several metrics are employed, including accuracy, precision, recall, and F1 score. Accuracy is defined as the ratio of correctly classified data points to the total number of data points in the model. The F1 score balances precision and recall, providing a comprehensive view of the model's effectiveness. The classification algorithms implemented in this system include Support Vector Machine (SVM), Decision Trees, K-Nearest Neighbours (KNN), and Artificial Neural Networks (ANN). Each algorithm is assessed using the aforementioned performance metrics, ensuring the identification of the most effective model for accurately diagnosing Parkinson's disease. This comprehensive approach aims to improve diagnostic accuracy and facilitate earlier intervention for better patient outcomes.

3.1 Input dataset

The dataset utilized in this study is specifically curated to enhance the classification and analysis of Parkinson's Disease Dementia (PDD). It comprises a comprehensive collection of MRI images that are categorized into five distinct classes, representing varying stages of dementia severity. These classes range from Non-Demented to Severe-Demented, allowing for a nuanced understanding of cognitive decline associated with Parkinson's disease.

3.1.1 Detailed Features of the Dataset

The dataset consists of a total of 3,758 images, meticulously prepared to ensure high-quality inputs for machine learning models. The breakdown of the dataset is as follows:

Image Resolution: All images are standardized to a resolution of 640x640 pixels, providing uniformity for analysis and feature extraction.

Training Images: The dataset includes 3,601 labelled training images, which serve as the primary input for training machine learning models. This substantial number allows for effective learning and generalization of the models.

Validation Images: A total of 154 labelled validation images are included to assess the model's performance during training. This validation set helps fine-tune the models and prevent overfitting.

Test Images: The dataset contains 3 labelled test images, which are used to evaluate the final performance of the trained models. This small test set provides a preliminary assessment of the model's effectiveness in real-world applications.

The careful arrangement of the dataset not only supports specific objectives in the classification of dementia severity in PDD but also facilitates an understanding of cognitive decline progression. Moreover, the dataset aims to provide automatic diagnostic tools for early detection and monitoring of dementia in patients with Parkinson's disease, ultimately improving patient outcomes through timely interventions.

3.2 Data Pre-processing

Data pre-processing is the essential process of preparing raw data for analysis and modelling by cleaning, transforming, and structuring it to enhance data quality and utility. It involves tasks like handling missing values, correcting errors, encoding features, and scaling data to ensure it's in an optimal form for further analysis. It encompasses a range of operations and transformations designed to refine raw data, ensuring that it is clean, structured, and amenity subsequent analysis. This process is driven by its manifold significance in data science and analysis.

Through meticulous data cleaning, transformation, feature engineering, dimensionality reduction, outlier handling, scaling, and data splitting, it prepares raw data for more accurate and reliable analysis and modelling. Ultimately, the goal is to obtain more meaningful insights, make informed decisions, and optimize predictive models for a wide range of applications in data science and analysis.

preprocessing techniques applied:

The preprocessing of the dataset involved several key techniques aimed at preparing the data for effective training of machine learning models. These techniques include:

Image Resizing: All images in the dataset were resized to a consistent dimension of 640 × 640 pixels. This uniformity is crucial for ensuring that the model can process the images effectively without discrepancies in size.

Normalization: Pixel values of the images were normalized to a range of 0-1. This was achieved by dividing each pixel value by 255, the maximum value for 8-bit images. Normalization helps improve the convergence of neural networks during training, leading to more stable and faster learning.

Data Augmentation: To enhance the diversity of the training dataset and mitigate the risk of overfitting, several data augmentation techniques were applied, including:

Random Rotation: Images were randomly rotated by up to 20 degrees to introduce variation in orientation.

Horizontal and Vertical Shifts: Images were shifted horizontally and vertically by up to 20%.

This simulates different perspectives and positions of the subject within the frame.

Shearing: This technique involves slanting the image along the x or y-axis, providing additional variability in the dataset.

Zooming: Images were randomly zoomed in and out, allowing the model to learn from different levels of detail.

Horizontal Flipping: Images were flipped horizontally to provide mirrored versions of the original images, increasing dataset diversity.

Dataset Splitting: The entire dataset was divided into three subsets: training, validation, and testing. Typically, the test set constituted 20% of the total dataset. This division ensures that the model is evaluated on unseen data, providing a reliable assessment of its performance and generalization capabilities.

3.3 Model Building

Model building is a critical phase in developing a machine learning solution for the classification of Parkinson's Disease Dementia using MRI images. This phase encompasses the selection of appropriate algorithms, the design of the neural network architecture, and the training of the model using the pre-processed dataset.

The initial step in model building involves selecting suitable machine learning algorithms. In this case, convolutional neural networks (CNNs) are chosen due to their efficacy in image processing tasks. CNNs are particularly adept at capturing spatial hierarchies in images, making them well-suited for classifying MRI scans.

Neural Network Architecture

The architecture of the CNN is designed to optimize feature extraction and classification. The model typically consists of several layers, including:

Convolutional Layers: These layers apply convolutional filters to the input images, enabling the model to learn and extract essential features. Multiple convolutional layers may be stacked to capture increasingly complex features.

Activation Functions: After each convolutional layer, activation functions, such as ReLU (Rectified Linear Unit), are applied to introduce non-linearity into the model. This allows the network to learn more complex patterns.

Pooling Layers: Max pooling layers are incorporated to down-sample the feature maps, reducing their spatial dimensions while retaining the most important information. This helps to decrease computational complexity and mitigate the risk of overfitting.

Fully Connected Layers: After several convolutional and pooling layers, the feature maps are flattened and passed through one or more fully connected layers. These layers are responsible for making the final classification decisions based on the extracted features.

Output Layer: The final layer of the model typically uses a SoftMax activation function, which outputs probabilities for each class. This allows the model to classify the input images into the appropriate dementia severity categories.

Training the Model

Once the architecture is defined, the model is trained using the pre-processed training dataset. During training, the model learns to minimize a loss function, which quantifies the difference between the predicted outputs and the actual labels. Common loss functions for multi-class classification include categorical cross-entropy.

The model is trained for a specified number of epochs, during which the training data is fed into the network in batches. During each epoch, the model's performance is evaluated using the validation dataset to monitor for overfitting and ensure that the model is generalizing well to unseen data.

Performance Evaluation

After training, the model is evaluated on the test dataset to assess its performance using various metrics, including accuracy, precision, recall, and F1 score. These metrics provide insight into the model's ability to correctly classify images of varying dementia severity levels, ultimately determining its effectiveness as a diagnostic tool for Parkinson's Disease Dementia.

This systematic approach to model building ensures the development of a robust and effective model capable of accurately classifying MRI images and aiding in the early detection and monitoring of dementia in patients with Parkinson's disease

3.4 Methodology of the system

Having discussed the foundational elements in the preceding sections, we now venture into the core of our traffic congestion prediction system. In this section, we embark on a journey through the inner workings of our model, unveiling the methodology that drives our system's ability to forecast traffic congestion. Just as a well-orchestrated symphony requires each instrument to play its part harmoniously, our methodology combines data, pre-processing, modelling, and evaluation to create a seamless and efficient prediction system.

proposed architecture

The methodology of the system encompasses a structured approach to developing an automated diagnostic tool for the classification of Parkinson's Disease Dementia (PDD) using convolutional neural networks (CNNs) and MRI image analysis. This methodology can be divided into several key phases:

fig 3.4.1 depicts the stages of evaluation of the model namely:

1. **Dataset Preparation**

   Data Collection: A carefully curated dataset of MRI images is collected, encompassing a range of dementia severity levels. The dataset is organized into five classes: Non-Demented, Mildly Demented, Moderately Demented, Severely Demented, and Very Severely Demented.

   Data Annotation: Each image is labelled according to its corresponding dementia severity level to facilitate supervised learning during model training.

2. **Data Preprocessing**

   Image Resizing: All images are resized to a standard resolution of 640 × 640 pixels to ensure uniform input dimensions for the model.

   Normalization: Pixel values are normalized to the range of 0-1 by dividing by 255, improving the convergence and training stability of the neural network.

   Data Augmentation: Various augmentation techniques, such as random rotation, shifts, shearing, zooming, and flipping, are applied to increase dataset diversity and reduce overfitting.

   Dataset Splitting: The dataset is partitioned into training, validation, and testing sets, with the test set typically comprising 20% of the total data.

3. **Model Development**

   Architecture Design: A convolutional neural network (CNN) architecture is designed, incorporating multiple convolutional layers, activation functions, pooling layers, and fully connected layers. This architecture is optimized for feature extraction and classification of MRI images.

Model Compilation: The model is compiled with an appropriate optimizer (e.g., Adam or SGD), a loss function (categorical cross-entropy for multi-class classification), and performance metrics (such as accuracy).

4. **Model Training**

   Training Process: The CNN model is trained on the pre-processed training dataset for a predetermined number of epochs. During training, the model learns to identify patterns in the MRI images and optimize its parameters to minimize the loss function.

   Validation: The validation dataset is used during training to monitor the model's performance and make adjustments, such as tuning hyperparameters or implementing early stopping to prevent overfitting.

5. **Model Evaluation**

   Testing: After training, the model's performance is evaluated using the test dataset. Various metrics, including accuracy, precision, recall, and F1 score, are calculated to assess the model's ability to classify images accurately across different dementia severity levels.

   Confusion Matrix: A confusion matrix is generated to visualize the model's classification performance and identify areas for improvement.

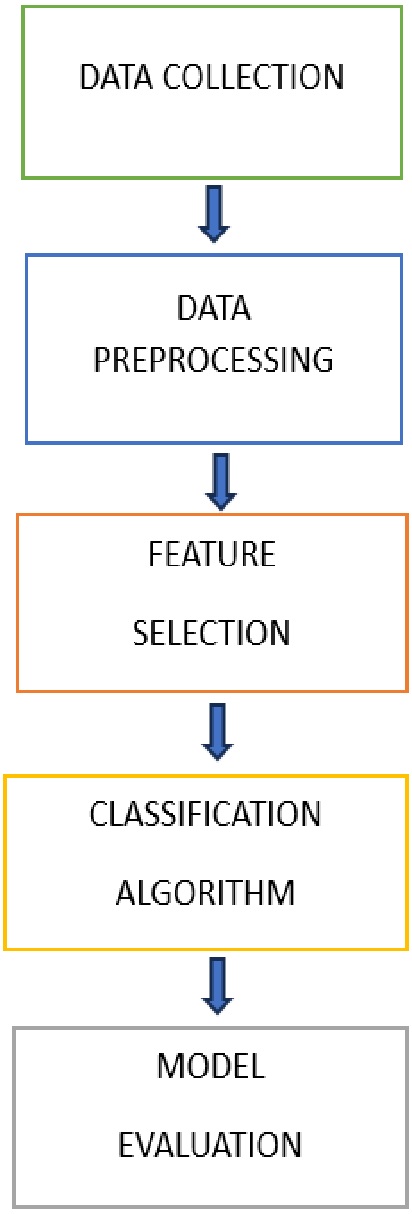


Fig: 3.4.1(proposed architecture)

3.5 Model Evaluation

Model evaluation is a critical aspect of any machine learning project, particularly in the context of diagnosing Parkinson's Disease Dementia (PDD) using MRI images. This phase involves systematically assessing the performance and accuracy of a trained model on new, unseen data. It is essential for several reasons:

1. **Performance Assessment**: Evaluating the model on a separate test dataset allows for a clear understanding of how well the model generalizes to data it has not encountered during training. This helps in identifying its strengths and weaknesses.
2. **Accuracy Measurement**: By calculating metrics such as accuracy, precision, recall, and F1 score, stakeholders can quantify the model's effectiveness in classifying MRI images across different stages of dementia. These metrics provide insights into the model's ability to make correct predictions.
3. **Overfitting Detection**: A thorough evaluation helps in identifying overfitting, where the model performs well on the training data but poorly on unseen data. Monitoring performance metrics on both training and validation datasets aids in making informed decisions about model adjustments and improvements.
4. **Benchmarking**: Comparing the model's performance against baseline methods or other existing models enables researchers and practitioners to gauge its effectiveness. Benchmarking helps in establishing the model's competitive advantage and justifies its deployment in clinical settings.
5. **Error Analysis**: By analysing misclassifications, the evaluation process can highlight specific areas where the model struggles, such as distinguishing between certain severity levels of dementia. This information is invaluable for refining the model and improving its accuracy.
6. **Decision-Making Support**: For healthcare professionals, understanding the model's performance is crucial for integrating the tool into clinical workflows. High accuracy and reliability are necessary for the model to gain acceptance and trust from medical practitioners.
7. **Clinical Relevance**: In the context of Parkinson's Disease Dementia, accurate diagnosis is vital for timely intervention and treatment. Evaluating the model ensures it meets the necessary clinical standards and can significantly impact patient outcomes.
8. **Continuous Improvement**: The evaluation process is not a one-time event; it facilitates ongoing refinement of the model as new data becomes available. This iterative approach

allows the system to adapt to changing patient populations and improve its diagnostic capabilities over time.

3.6 Constraints

While developing and implementing a machine learning model for the diagnosis of Parkinson's Disease Dementia (PDD) using MRI images, several constraints must be considered. These constraints can affect the model's performance, applicability, and overall effectiveness:

1.Data Quality and Availability: The accuracy of the model heavily relies on the quality and quantity of the training dataset. Limited availability of high-quality, labeled MRI images can hinder the model's ability to learn effectively and generalize well to new data.

2.Imbalance in Classes: If the dataset contains an uneven distribution of images across different dementia severity levels, the model may become biased toward the majority class, leading to poor performance in classifying less frequent categories.

3.Variability in MRI Scans: Differences in MRI acquisition protocols, machine settings, and patient characteristics can introduce variability in the images, complicating the model's ability to learn consistent patterns across different datasets.

4. Overfitting: A complex model may perform exceptionally well on training data but struggle with unseen data due to overfitting. This necessitates careful selection of model architecture and hyperparameter tuning to achieve a balance between complexity and generalization.

5.Interpretability: Deep learning models, particularly convolutional neural networks, are often viewed as "black boxes," making it challenging to interpret how the model arrives at specific classifications. This lack of transparency can hinder clinician trust and acceptance of the automated diagnostic tool.

6.Computational Resources: Training deep learning models requires substantial computational resources, including powerful GPUs and significant memory. Limited access to these resources can constrain the model's development and deployment.

7.Real-time Performance: In clinical settings, the need for real-time analysis can be a constraint. If the model requires excessive processing time, it may not be practical for integration into diagnostic workflows where prompt results are essential.

8.Regulatory and Ethical Considerations: The deployment of a diagnostic tool in healthcare is subject to regulatory scrutiny. Compliance with healthcare regulations, ethical standards, and patient privacy laws can impose additional constraints on model development and usage.

9.Generalizability: Models trained on specific datasets may not generalize well to different populations or clinical environments. Variability in patient demographics, comorbidities, and imaging techniques can affect the model's applicability across diverse settings.

10.User Training and Acceptance: Successful implementation of the model requires adequate training for healthcare professionals who will use the tool. Resistance to adopting new technologies can limit the tool's effectiveness, emphasizing the need for comprehensive training and support.

11.Longitudinal Variability: Parkinson's Disease Dementia is a progressive condition, and changes in the disease's manifestation over time can affect the model's performance. Ensuring that the model adapts to longitudinal changes is crucial for maintaining its diagnostic accuracy.

3.7 Cost and sustainability Impact

1.Computational Resources: Training deep learning models often requires high-performance computing resources, including GPUs and cloud-based services. These infrastructure costs can be substantial, especially for extensive training periods or large datasets.

2.Data Acquisition: Obtaining high-quality, annotated MRI images can be costly. This may involve partnerships with hospitals or research institutions, and there may be fees associated with accessing proprietary datasets.

3.Maintenance and Updates: Continuous monitoring and updating of the model are necessary to ensure its performance remains optimal as new data becomes available. This requires ongoing investment in terms of time and resources, including periodic retraining of the model.

4.Regulatory Compliance: The cost of meeting regulatory standards in healthcare, such as obtaining necessary approvals and conducting clinical validations, can be significant. This includes legal fees, documentation, and potentially extensive testing to meet healthcare regulations.

5.Training and Integration: Implementing the model in clinical settings necessitates training healthcare professionals, which incurs costs related to developing training materials, conducting workshops, and providing ongoing support.

Sustainability Impact

1.Environmental Considerations: The computational resources required for training machine learning models can lead to a considerable carbon footprint due to energy consumption. Sustainable practices, such as utilizing energy-efficient hardware or renewable energy sources for data canters, can mitigate this impact.

Long-term Health Benefits: Early and accurate diagnosis of Parkinson's Disease Dementia can lead to timely interventions, improving patient quality of life and potentially reducing healthcare costs associated with advanced stages of the disease. This can result in significant long-term benefits for both individuals and healthcare systems.

Resource Efficiency: Automating the diagnostic process through machine learning can streamline healthcare workflows, reducing the time and resources spent on manual assessments. This efficiency can contribute to better resource allocation in healthcare settings.

2.Community Engagement: Involving patients and communities in the development process can enhance the model's relevance and acceptance. This fosters a sense of ownership and can lead to more sustainable adoption of the technology within healthcare systems.

3.Public Health Outcomes: By improving diagnostic accuracy and reducing the time to diagnosis, the project can contribute to better public health outcomes. This aligns with sustainability goals related to health equity and access to care for individuals affected by Parkinson's Disease Dementia.

CHAPTER-4

IMPLEMENTATION

4.1 Environment Setup for Running the Model

To execute the code for feature extraction using VGG 16, VGG19 and ResNet50 and training multiple classifiers (SVM, Decision Tree, and KNN), certain libraries and tools need to installed.

1. **Operating System**
   Ubuntu 20.04 or Windows 10/11 are recommended.
2. **Python Version**
   Python 3.8 or higher is required.
3. **Hardware Requirements**
   CPU: Intel i5 or above is recommended.
   GPU: CUDA-enabled NVIDIA GPU (optional but recommended for faster training and feature extraction).
   RAM: 16GB (minimum).
   Storage: At least 100GB of free space (for dataset storage and feature files).
4. **Python Libraries and Dependencies**
   TensorFlow: For deep learning and the use of VGG19.
   Keras: For high-level neural network APIs and integration with TensorFlow.
   NumPy: For numerical operations and array manipulations.
   scikit-learn: For machine learning algorithms like SVM, Decision Tree, KNN, and evaluation metrics.
   OpenCV: For image processing (optional but useful for additional image manipulation tasks).
   Pillow: For handling image files.

4.2: Sample implementation of VGG16 model:

```python
import numpy as np
import os
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.applications import VGG16
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, confusion_matrix

# Set the path to your dataset directory
dataset_dir = '/content/drive/MyDrive/parkinson/Dataset'

# Image dimensions and batch size
img_width, img_height = 224, 224  # Image size compatible with VGG16
batch_size = 32

# Data augmentation and rescaling
train_datagen = ImageDataGenerator(rescale=1./255, validation_split=0.2)

# Load training and validation datasets
train_generator = train_datagen.flow_from_directory(
    dataset_dir,
    target_size=(img_width, img_height),
    batch_size=batch_size,
    class_mode='binary',
    subset='training'
)

validation_generator = train_datagen.flow_from_directory(
    dataset_dir,
    target_size=(img_width, img_height),
    batch_size=batch_size,
    class_mode='binary',
    subset='validation'
)

# Feature Extraction using VGG19
vgg19_model = VGG19(weights='imagenet', include_top=False, input_shape=(img_width, img_height, 3))

# Extract features and flatten them
def extract_features(generator, model, batch_size):
    features = []
    labels = []
    for inputs_batch, labels_batch in generator:
        features_batch = model.predict(inputs_batch)
        features.append(features_batch)
        labels.append(labels_batch)
        if len(features) * batch_size >= generator.samples:
            break
    features = np.vstack(features)
    labels = np.hstack(labels)
    return features, labels

# Extract features for training and validation data
train_features, train_labels = extract_features(train_generator, vgg19_model, batch_size)
validation_features, validation_labels = extract_features(validation_generator, vgg19_model, batch_size)

# Reshape the features to fit classifiers (flattening)
train_features = train_features.reshape(train_features.shape[0], -1)
validation_features = validation_features.reshape(validation_features.shape[0], -1)

# Split training data for train-test split
X_train, X_test, y_train, y_test = train_test_split(train_features, train_labels, test_size=0.2, random_state=42)

# Train SVM Classifier
svm_clf = SVC(kernel='linear', C=1)  # You can experiment with different kernels
svm_clf.fit(X_train, y_train)

# Predict and evaluate SVM
y_pred_svm = svm_clf.predict(X_test)
svm_accuracy = accuracy_score(y_test, y_pred_svm)
svm_cm = confusion_matrix(y_test, y_pred_svm)
```

Fig:4.2.1(Sample implementation)

From fig 4.2.1 shows the sample implementation of the code that extracts image features using VGG16, trains SVM, Decision Tree, and KNN classifiers, and evaluates their performance with accuracy and confusion matrices.

Chapter 5
Experimentation and Result Analysis

The experimental results obtained from applying various classification algorithms on features extracted using different deep learning models demonstrate notable performance differences. For VGG16, the accuracies achieved were as follows: SVM at 93.19%, Decision Tree at 92.86%, KNN at 96.51%, and ANN at 94.19%. In the case of VGG19, the results showed a slight improvement with SVM achieving 94.85%, Decision Tree at 92.36%, KNN at 96.35%, and ANN remaining consistent at 94.19%. However, the ResNet50 model exhibited the highest overall performance, with SVM reaching 94.35%, Decision Tree at 93.19%, KNN achieving 96.68%, and ANN showing an impressive accuracy of 96.35%. These results indicate that ResNet50 not only maintains high accuracy across different classification algorithms but also outperforms VGG16 and VGG19 in terms of KNN and ANN accuracy. This underscores the effectiveness of ResNet50 as a feature extractor, demonstrating its superior ability to learn complex patterns in the data.

VGG16:

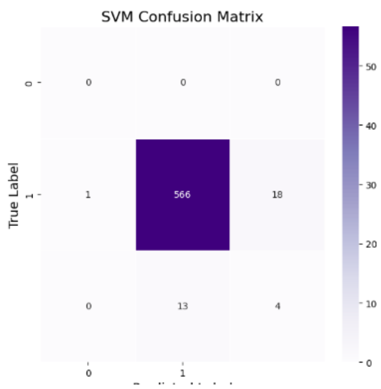


Fig 5.1: SVM Confusion Matrix

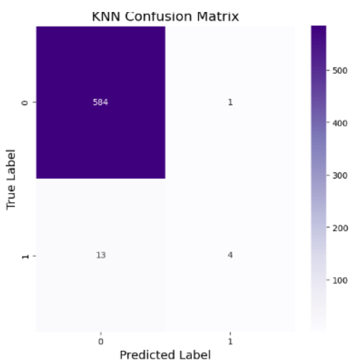
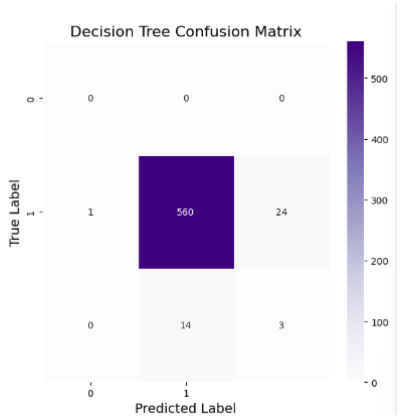


Fig 5.2: KNN Confusion Matrix



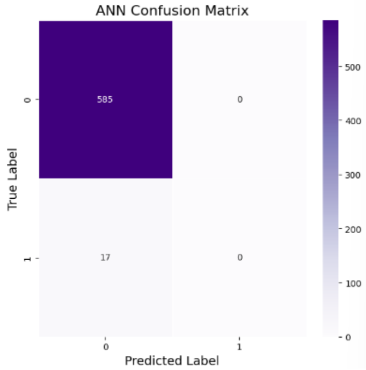


Fig 5.3: Decision Tree Confusion Matrix **Fig 5.4: ANN Confusion Matrix**

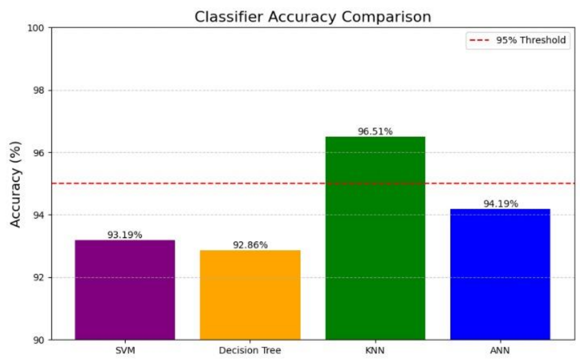


Fig 5.5: Classifier Accuracy Comparison (VGG16)

From fig 5.1 ,from the confusion matrix it is depicted that SVM model predicted 566 instances correctly for class 1 (center of the matrix) and from fig 5.2 KNN model predicted 504 instances correctly for class 0 ,from fig 5.3 Decision Tree model predicted 560 instances correctly for class 1,from fig 5.4 ANN model predicted 585 instances correctly for class 0.

From fig 5.5 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.51% by using (VGG16) as feature extraction model.

VGG19:

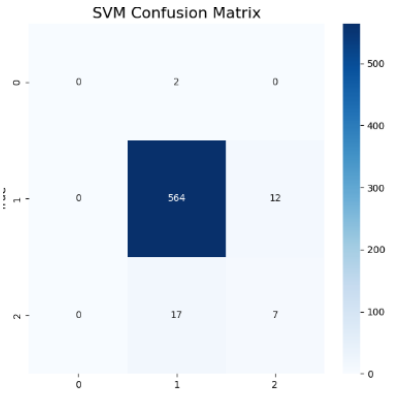


Fig 5.6: SVM Confusion Matrix

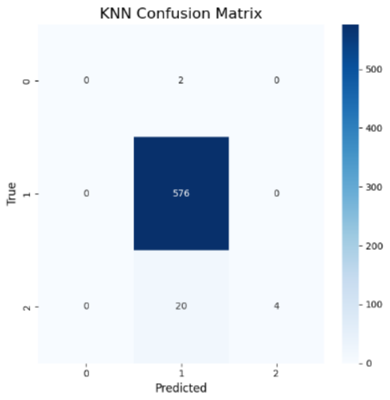


Fig 5.7: KNN Confusion Matrix

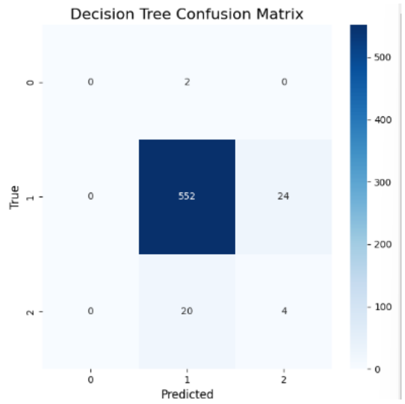


Fig 5.8: Decision Tree Confusion Matrix

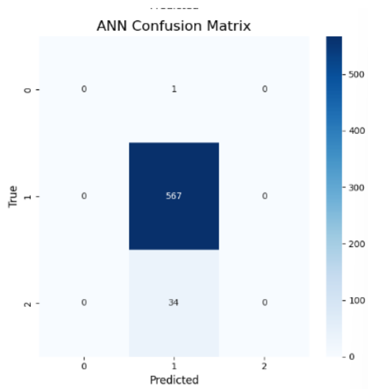


Fig 5.9: ANN Confusion Matrix

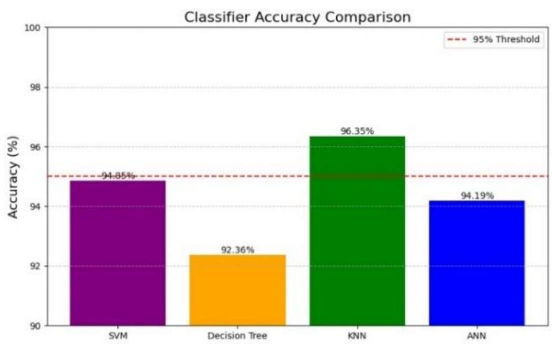


Fig 5.10: Classifier Accuracy Comparison (VGG19)

From fig 5.6, from the confusion matrix it can be depicted that SVM model predicted 564 instances correctly for class 1, fig 5.7 KNN model predicted 576 instances correctly for class 1, fig 5.8 Decision Tree model predicted 552 instances correctly for class1,fig 5.9 ANN model predicted 567 instances correctly for class 1.

From fig 5.10 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.31% by using (VGG19) as feature extraction model.

ResNet50:

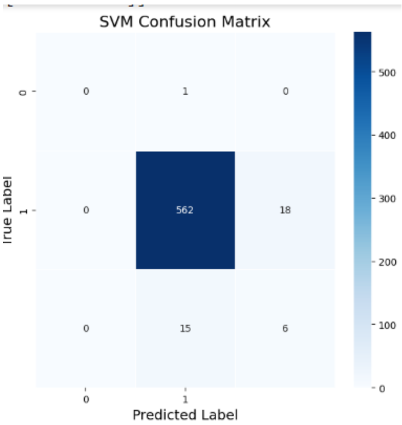


Fig 5.11: SVM Confusion Matrix

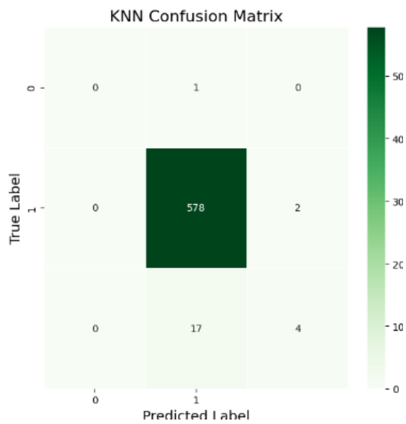
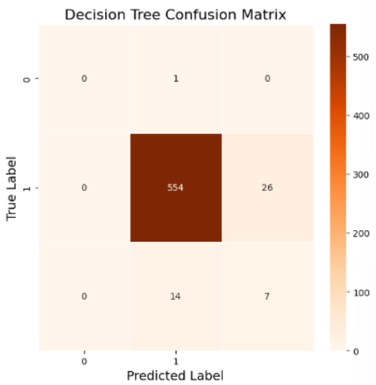


Fig 5.12: KNN Confusion Matrix



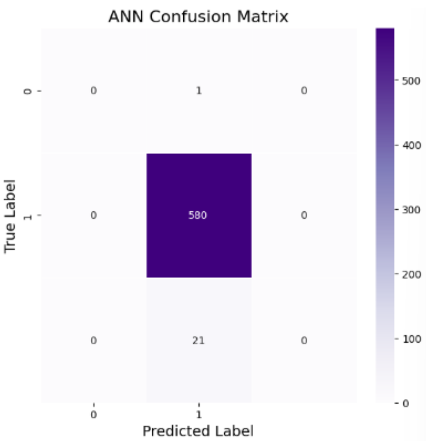


Fig 5.13: Decision Tree Confusion Matrix

Fig 5.14: ANN Confusion Matrix

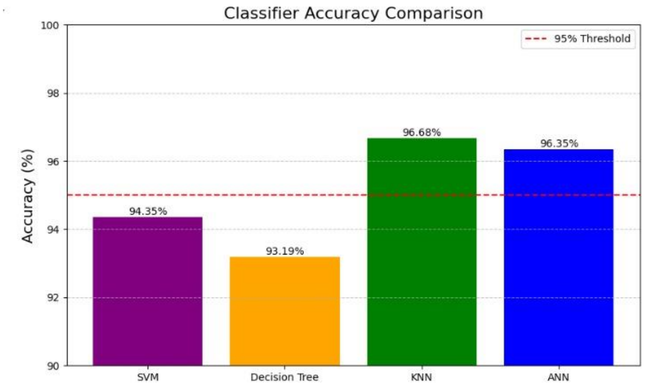


Fig 5.15: Classifier Accuracy Comparison (ResNet50)

From fig 5.11, from the confusion matrix it can be depicted that SVM model predicted 562 instances correctly for class 1, fig 5.12 KNN model predicted 578 instances correctly for class 1,fig 5.13 Decision Tree model predicted 554 instances correctly for class1,fig 5.14 ANN model predicted 580 instances correctly for class 1.

From fig 5.15 it can be observed that among the classifiers used i.e. SVM, KNN, ANN, Decision Tree, KNN shows the highest accuracy of 96.68% by using (ResNet50) as feature extraction model.

SVM

	precision	recall	f1-score	support
1.0	0.98	0.97	0.97	580
2.0	0.32	0.36	0.34	22
accuracy			0.95	602
macro avg	0.65	0.67	0.66	602
weighted avg	0.95	0.95	0.95	602

Fig 5.16 Classification Report(svm)

Decision Tree

	precision	recall	f1-score	support
1.0	0.97	0.96	0.96	580
2.0	0.11	0.14	0.12	22
accuracy			0.93	602
macro avg	0.54	0.55	0.54	602
weighted avg	0.94	0.93	0.93	602

Fig 5.17 Classification Report(Decision Tree)

KNN

	precision	recall	f1-score	support
1.0	0.97	1.00	0.98	580
2.0	0.75	0.14	0.23	22
accuracy			0.97	602
macro avg	0.86	0.57	0.61	602
weighted avg	0.96	0.97	0.96	602

Fig 5.18 Classification Report(KNN)

ANN

	precision	recall	f1-score	support
1.0	0.96	1.00	0.98	580
2.0	0.00	0.00	0.00	22
accuracy			0.96	602
macro avg	0.48	0.50	0.49	602
weighted avg	0.93	0.96	0.95	602

Fig 5.19 Classification Report(ANN)

From figures 5.16,5.17,5.18,5.19 we can depict the precision, recall, f1-score of the different classifiers i.e. SVM, KNN, ANN, Decision Tree for the ResNet50 feature extraction model.
From fig :6,11,14 there can be demonstration that ResNet50 ensured high accuracies in respect to different classification algorithms and even could gain more accuracy than VGG16 and VGG19 with regard to KNN and ANN accuracy. It even reflects the effectiveness of feature extractor like ResNet50 in learning complex patterns within the data, making it an ideal choice for classifying the severity of dementia in Parkinson's Disease. The network Ion, ResNet50 ensured to gain high accuracy toward different classification algorithms and even managed to obtain more accuracy than VGG16 and VGG19 related to KNN and ANN accuracy. It even reflects the efficiency of feature extractor like ResNet50 in learning the complexity of patterns within data, so it is an excellent choice for classifying the seriousness of dementia among Parkinson's Disease.

Chapter 6
Conclusion

CONCLUSION

Early diagnosis of Parkinson's disease is crucial for improving patient outcomes, as timely interventions can significantly slow disease progression and enhance quality of life. In the recent study, researchers explored the use of CNN architectures, specifically ResNet50, in combination with KNN for the detection of Parkinson's Disease (PD) from MRI images. ResNet50, known for its deep feature extraction capabilities, was coupled with KNN's simple yet effective classification approach, resulting in an impressive accuracy of 96.68%. This high accuracy rate positions the hybrid approach as a strong candidate for practical clinical applications. Furthermore, the implementation of explainable AI techniques is also a focus of future development. By enhancing model transparency, the researchers aim to facilitate trust and adoption by medical professionals. Explainable AI can provide insights into the decision-making process of the model, allowing medical professionals to better understand and interpret the results. This transparency is crucial in fostering confidence in the diagnostic process.

Chapter 7
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