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Deep Learning with CNN for Disease Prediction: A Case Study on Parkinson's Disease using MRI Data

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Abstract: Parkinson's disease (PD) is a neurological disorder that causes the loss of neurons that produce dopamine in the brain. Dopamine is a chemical messenger that regulates movement and other functions. The exact causes of PD are unknown, but some genes, environmental factors, and triggers may play a role. People with PD may have symptoms for many years before they are diagnosed. PD affects 7–10 million people worldwide and causes various motor and cognitive impairments. Researchers have used different methods to diagnose PD, such as speech analysis and machine learning. However, these methods have limitations, such as low accuracy and inability to handle large data. This study proposes a new method that uses deep learning to predict PD in its early stages based on MRI scans. The method will classify MRI samples into PD and non-PD groups using a convolutional neural network (CNN) algorithm. It will also compare the performance of different MRI modalities in distinguishing PD from normal aging. CNN is suitable for this task because it can learn complex patterns from MRI data. The proposed method will provide a reliable and efficient way to detect PD in its early stages and help patients receive appropriate medical care and medications that can improve their quality of life.
Keywords: Deep Learning, Convolutional Neural Network (CNN), Disease Prediction, Parkinson's disease, Magnetic Resonance Imaging (MRI).

I. INTRODUCTION

A neurodegenerative ailment called Parkinson's disease has an impact on both the body's motor and non-motor functioning. Dopaminergic neurons in the substantia nigra, a sub-cortical region of the brain that regulates movement, are the cause of it. In his book "An Essay on the Shaking Palsy," published in 1817, James Parkinson provided the first description of the condition. Tremors, small handwriting, loss of smell, difficulty sleeping, problems moving or walking, constipation, a slow or low voice, a masked face, dizziness or fainting, and bending or hunching over are some of the early symptoms of Parkinson's disease. The buildup of protein molecules in the cell that lead to misfolding and ultimately cause Parkinson's disease is the primary cause of the condition. Levodopa (L-DOPA), MAO-B inhibitors, and dopamine agonists are utilized as early treatments, although their efficacy wanes over time. The side effects also starts to show up as the doses were increased back when its effects were dull. Parkinson's disease, on the other hand, cannot be cured and can only be managed with medicine. More than 10 million people worldwide suffer with Parkinson's disease, making it the second most prevalent neurological illness. The disease can be seen before age 50, and women are less likely to be diagnosed with PD than men.

Gait, or the human walking cycle known as gait, is one of the motor features most significantly impacted by the loss of dopaminergic neurons. The gait cycle comprises a cyclic pattern of body movements. These patterns change with individual positions. Reduced stride length, walking speed during free ambulation, and cadence rate can all be used to observe a PD patient's gait cycle. to use a variety of indicators to identify those who have Parkinson's disease. If any medication is currently available, it only temporarily relieves symptoms. Therefore, it is crucial to find a solution that can detect Parkinson's disease in its early stages because the condition can be controlled in the early stages in this period where it is progressing at a double pace.

II. RELATED WORK

The section gives an overview of Parkinson's disease (PD), a common neurological disorder that affects the ability to control movement[1]. It lists some of the early symptoms of PD, such as tremors, small handwriting, loss of smell, and difficulty sleeping. It also discusses some of the treatments for PD, such as drugs that increase the level of dopamine in the brain, but notes that they have limitations and side effects[2]. Finally, it describes how PD impacts gait, or the way people walk, and how it can be measured by factors such as stride length and walking speed[3].

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Previous works on PD until now: The authors studied how to detect non-motor symptoms in PD patients who were on levodopa. They used a questionnaire based on the University of Miami standards and found that PD patients had high rates of despair, irritability, weariness and sleep problems.

These symptoms are often overlooked by specialists. [4]. The authors explained the symptoms and types of PD and clarified some misconceptions about Parkinsonism. They said that PD affects one side of the body and may or may not involve tremors. They also said that PD can be primary, secondary or Parkinsonism-plus depending on the cause. [5]. The authors used SPECT to detect the loss of dopaminergic neuron in PD patients. They injected a radioactive substance into the subjects and scanned their brain images. They used ANN with backpropagation and 'leave one out' method to create a predictive model. They achieved high accuracy and diagnostic accuracy in distinguishing PD and Non-PD groups. [6]. McSharry et al. propose a novel measure for dysphonia, which is pitch period entropy, a traditional method for detecting Parkinson's disease (PD). They collected 195 vocal phonations from 31 male and female participants, of whom 23 were diagnosed with PD. The participants ranged in age from 46 to 85 years. The recordings were done directly on a computer and all samples were normalized before calculation. The authors used SVM for classification and found that 75% of the samples had PD. [7]. Jose A Obeso et al. explore the problem of Parkinson's disease (PD) and present a new perspective for researchers to tackle it. They use MRI images to scan brain structures and observe that aging leads to the deterioration of neuronal cells and accelerates the disease progression over time. [8]. Dan Long used MRI to study PD. They compared brain scans of 19 PD and 27 normal people using three parameters of neural activity. They processed the images and used SVM to classify them. The model had high accuracy, sensitivity, specificity and AUC[10]. This study used wearable sensors to detect FoG in PD patients. It developed a four-stage methodology using entropy and four classifiers. It collected signals from 16 people with and without FoG. It showed that the methodology had high performance to identify FoG events[11]. Saad et al. created a Bayesian classifier to detect FOG in PD patients using video and sensor data. The sensors measured acceleration and the algorithm used the Freeze Index. The classifier had high precision and good results for FOG and non-FOG episodes. [12]. Nair et al used decision tree to distinguish PD and MSA patients using MRI data. They saw the putamen, pons, MCP and substantia nigra in the MRI scans. They classified the patients based on their condition[13]. The article "Predicting dementia development in Parkinson's disease using Bayesian network classifiers"[14] is another important one for Bayesian structure learning. The best classifier to discriminate between dementia in PD patients and healthy brains, according to this article, is a multivariate filter-based Naive Bayes model, which also has the highest cross-validated sensitivity. The use of brain-computer interfaces is shown to scan pathological signs from brain which is helping the patient from all around the world to detect any disease short term or long term, specifically they have shared their experimental result from testing Parkinson's disease[15]. The article describes an interface that uses brain simulation technology to detect signs of Parkinson's disease (PD) in early stages. It uses MRI data from 28 PD patients and a Naive Bayes model to classify dementia in PD patients with high accuracy, specificity and sensitivity[16].

The research paper "Medical Image Classification with Convolution Neural Network" discusses the challenges in image classification and how Artificial Neural Networks (ANN) and more recently, convolution neural networks (CNN) have been used to solve these problems. CNNs have shown to be effective in analyzing image content and achieving good classification results. These neural networks can also be adapted to solve different problems using the same design. [17]. A new visualization technique for convolution neural networks through which they can visualize the activity within the model, this helps in recognize intricate pattern and any class change if required[18]. A proposed multilayer feedforward neural network in their work for detecting PD in the early stage. The neural network work on the property of back-propagation to remove error while traversing backward. Weight distribution was chosen to be random at the start. The PD dataset was taken from Oxford Parkinson's Disease Detection. They achieved accuracy of 80 percent[19].

The article reports on an experiment that used a Kinect program to collect and analyze skeletal data from six participants (three with PD and three without) as they walked. The experiment compared the effects of deep brain stimulation (DBS) on the gait parameters of the PD patients and found differences between the three groups[20]. The article describes a study that used VBM to compare the brain structures of 25 PD patients and 15 healthy controls. It found that PD patients had less gray matter in some brain regions related to PD onset than healthy controls. It also found a link between brain shrinkage and clinical worsening in PD patients[21].

The article explains a Voxel-based morphometry method that uses MRI features to detect PD in the early stage. It uses 30 PD and 30 non-PD MRI scans from PPMI database and processes them using SPM8 and MN1 template. It achieves 91 percent accuracy with 12 features[22]. The author explains how Parkinson's disease, a brain disorder that affects movement, can result from different factors that damage dopamine neurons. These factors include abnormal protein accumulation, cell-death imbalance, and cell-dissimilation disruption[23]. The difficulties of feature selection and reduction in picture classification are discussed in the publication "Classification of Alzheimer's Disease Using fMRI Data and Deep Learning Convolution Neural Networks." The paper provides an example of the difficulties in choosing the most discriminative features needed to construct the classification model. This paper discusses some of the Convolution Neural Network (CNN) architectures that successfully distinguished functional MRI data from Alzheimer's patients from data from healthy controls. [24].

A supervised learning method Convolution neural network, the use of overlapping polling which help reduce top and bottom layer error by 0.4 percent and 0.3 percent. They displayed architecture that included weights and an eight-layer net. The first 5 in this dataset are convolutional, while the latter 3 are fully connected. The way this network works is by maximizing the average across training cases of the log probability[25].

The author discusses how MRI can help diagnose parkinsonian syndrome more accurately than clinical methods. The author reviews different MRI techniques and image analysis algorithms that can distinguish Parkinson's disease from other similar conditions, even in early or late stages[26].

The author introduces a new type of systems that use deep neural networks to diagnose and evaluate diseases from raw data. The author uses Parkinson's disease as an example and creates a new database to test the systems. The proposed system combines CNN and RNN components and achieves 98% accuracy[27]. The author compares two studies that use deep learning to assess Parkinson's disease symptoms.

The first study uses a wearable device to measure tremor and a CNN to rate its severity. The second study uses speech, handwriting, and gait data to model the difficulties of initiating and stopping movements and a CNN to classify patients and healthy subjects. The author finds that both studies are accurate and that the second study outperforms machine learning methods[29]. The study used 3D brain scans to detect Parkinson's disease by extracting 2D surfaces from them and feeding them to a deep learning model. The model achieved high accuracy and ROC[30].

The study used handwriting samples to classify Parkinson's disease and healthy people using different machine learning models. The Random Forest model performed the best, while the CNN models with MobileNet and VGG16 performed the worst[31]. he study used a deep learning model based on AlexNet to classify MR images of PD and healthy people. They normalized the images with a Gaussian filter and trained and tested the network. The network achieved high accuracy and AUC[32]. The paper discusses the potential of telemonitoring in Parkinson's Disease (PD) using standard voice-over-GSM or UMTS cellular mobile telephone networks. The purpose is to explore a cost-effective and accessible solution for PD symptom telemonitoring, considering the widespread availability of mobile networks worldwide. The study involves testing the robustness of using simulated noisy mobile communication networks and analyzing approximately 6000 recordings from 42 PD subjects[35]. The summary of related work shown in table 1.1.

III. PROPOSED METHODOLOGY

Parkinson's disease is a neurological disorder that affects the brain's ability to control movement and cognition. It occurs when certain brain cells die or malfunction and produce less dopamine, a chemical that helps transmit signals between nerve cells. Dopamine regulates muscle activity and coordination, as well as memory and learning. Magnetic resonance imaging (MRI) is a technique that uses magnetic fields and radio waves to create detailed images of the body's internal structures, including the brain. MRI scans can reveal how different brain regions function and interact with each other. Some people with Parkinson's disease show abnormal changes in their brain structure or activity that can be detected by MRI scans.

Convolutional neural network (CNN) is a type of artificial intelligence that can learn to recognize patterns in visual data by analyzing many examples. It uses convolution, a mathematical operation that filters and combines information from different parts of an image, to extract features that are relevant for classification. For instance, it can learn to identify faces by finding features like eyes, noses, mouths, and then combining them in various ways.

We propose to use CNN to help us identify patterns in MRI scans that can indicate whether someone has Parkinson's disease or not. We will train the CNN with many MRI scans of people who have been diagnosed with or without Parkinson's disease and label them accordingly. The CNN will learn from these examples and try to find features that distinguish the two groups. Then, we will test the CNN with new MRI scans of unknown people and ask it to predict if they have Parkinson's disease or not. The CNN will compare the new scans with the features it learned and give us an answer. Using CNN to analyze MRI scans can help us diagnose Parkinson's disease earlier and more accurately than just relying on human observation. This can help us provide better care and treatment for people with Parkinson's disease and improve their quality of life. The system architecture is give in Fig 1.1.

1) *Data Acquisition:* Both individuals with and without Parkinson's disease will have their MRI scans collected by the system. A database will hold the scan results. The database used here is from PPMI organization. There are a total of 30323 images including both PD and Non-PD group.
2) *Data preprocessing:* The data preprocessing steps performed on the Parkinson's disease dataset involved the following procedures.

Table 1.1: Summary of Related Work

Period	Contribution	Observation
1988-2000	1. Hoehn et al. (1967) classified PD into five stages based on motor symptoms, from mild unilateral to severe bilateral involvement . 2. PD patients are treated with dopamine-enhancing drugs, such as L-DOPA, dopamine agonists, and MAO-B inhibitors, which can improve motor function but also cause side effects. 3. PD patients have a slow and shuffling gait, which worsens when they perform dual tasks. This affects their mobility, balance, and safety.	The articles discuss the stages, treatment, and gait problems of PD, a neurodegenerative disorder that affects motor function.
2001-2010	1. Shulman investigates how Parkinson's disease (PD) affects non-motor aspects of behavior, such as cognition and mood, and how these symptoms are often overlooked by neurologists. 2. Parkinson's disease is a type of primary Parkinsonism that may have sporadic or genetic origins, and is characterized by early tremors in some cases. 3. A study used [99mTc]TRODAT-1 as a radio transmitter, and a SPECT machine to capture signals from 81 PD patients and 94 non-PD individuals. They used an Artificial Neural Network (ANN) with backpropagation for generating a predictive model and achieved 94.4% total responsiveness, 97.5% specificity, and 91.4% reactivity. 4. McSharry et al proposed a novel measure for dysphonia called pitch period entropy as a way of detecting Parkinson's disease. They used data from 31 individuals, 23 of whom were diagnosed with PD, and used a Support Vector Machine (SVM) for classification, achieving 75% accuracy in identifying PD. 5. Jose A Obese's research discussed the issue of Parkinson's disease from a researcher's point of view, and used MRI images to scan brain images, noting that aging causes the degradation of neuron cells and accelerates the progression of the disease over time.	a. Use of Medical Knowledge and Tools like SPECT and MRI was largely utilized to detect PD. b. SVM accuracy to detect PD reach up to 75%.
2011-2015	1. Dan Long collected brain images from 19 PD patients and 27 healthy controls and used a method to extract various features from each image, such as ALFF (a measure of brain activity), Rehov (a measure of brain synchronization), and RFCs (a measure of brain connectivity), as well as volume features from different brain tissues, such as gray matter, white matter, and cerebrospinal fluid. 2. To examine the Parkinson's disease forecast, one study applied machine learning-based methods. To be more concise, it used to receive signal from wearable receptors located on the patient's body to identify freezing of gait (FoG) events in PD patients. It was revealed that the simulation model can identify FoG events with 81.94% responsiveness, 98.74% precision, 96.11% exactness, and 98.6percent of overall area under the curve (AUC). 3. A Bayesian classifier was created by Saad et al. that uses video images and extracts features from them to create a model predicting PD. They used a Bayesian Belief Network on a previously collected dataset that consisted of measurements from acceleration sensors placed on the body of PD patients during their walk. 4. The anatomical nature of MRI they were able to observe the region of the brain which are putamen, and substantia nigra. Some area also shows pons, middle cerebellar peduncles, as well as cerebellum. 5. A "Multivariate Filter-Based Nave Bayes Model" is the most accurate classifier to distinguish between PD patient with dementia and healthy brains and has highest cross-validation accuracy. 6. The use of brain-computer interfaces is shown to scan pathological signs from the brain which is helping the patient from around the world to detect any disease short term or long term, specifically, they have shared their experimental result from testing Parkinson's disease. **7.** "Convolutional neural networks (CNN)", a deep learning approach, have recently demonstrated promising results for evaluating the visual content in image categorization. 8. The use of brain-computer interfaces is shown to scan pathological signs from the brain which is helping the patient from around the world to detect any disease short term or long term, specifically, they have shared their experimental result from testing Parkinson's disease. 9. The PD dataset was obtained from the Oxford Parkinson's Disease Detection project. The patients in this dataset had undergone DBS surgery and participated in the experiment twice. The researchers used the Kinect device to measure gait parameters related to skeletal joints and identified three distinct groups of patients based on their analysis. 10. The researchers used a two-sample t-test to compare the GM volumes of normalized-modulated images between PD patients at baseline and follow-up and healthy controls. They found that structural MRI methods can detect brain atrophy in specific regions that are involved in PD development, even before the clinical signs emerge.	a. PD characteristics like Freezing of gaits were used with Machine Learning for early Detection of PD. b. Different Brain parameters used to analyze PD characteristics. c. Use of different Dataset offered by various organization to get variety of data from patients to test PD.
2016-2022	1. A Voxel-based morphometry technique that helps to extract features from MRI scans to detect PD in the early stage. 2. 'Cellular disturbances' caused by protein misfolding and aggregation, disruption of cell death, or dissimulation might cause damage to defective dopamine neurons. 3. In one study, "Functional MRI" data from people with Alzheimer's disease were successfully separated from data from healthy control subjects using Convolutional Neural Network (CNN) frameworks. 4. MRI has greatly enhanced the diagnostic accuracy in the evaluation of PD, as evidenced by the advances made in the last 30 years. Studies suggest that MRI can help detect PD early and differentiate it from other conditions that cause Parkinsonian symptoms.	a. Using Deep Learning techniques on different types of datasets to distinguish between normal individual and PD patients. b. CNN to detect PD up to accuracy of 97.3% c. PPMI to provide large Dataset of neurological disorder which is also helpful for PD classification.

	5. Systems are end-to-end deep neural networks that accept unprocessed input data and generate the appropriate outputs after being built, trained, and evaluated. These architectures represent the cutting edge of language processing, speech recognition, and image analysis. Their use in medicine for prediction and diagnosis can result in very accurate outcomes. 6. Kim et al. used a specially created SNUMAP Motion Sensing System with an accelerometer with including gyroscope installed on a hand module, to measure tremors. 7. One of the first attempts to assess Parkinson's disease using multimodal data using a deep learning methodology. ‘Convolutional neural networks’ were trained to distinguish between sick and healthy participants using speech, handwriting, and gait data. They achieved an accuracy of 97.3% for all 3 bio-signal merged. 8. Ortiz conducted research on the detection of Parkinson’s disease using features derived from the 3D isosurfaces of the brain. He extracted SPECT scans from the PPMI database. 9. The UCI Spiral dataset contains handwriting samples from 77 people, 62 of whom had Parkinson's disease. They employed a variety of strategies to categorize the information, including Decision Trees and K-Nearest Neighbors. Various deep-learning techniques were used to train and test their models. 10. Deep learning neural networks have been used to categorize MR pictures of Parkinson's disease and healthy clients. The transfer learning network trains on the MR images and then tests them to determine their accuracy. Accuracy was up to 88.90% and an AUC of 0.9618. 11. The paper explores the viability of using standard mobile telephone networks for cost-effective and accessible telemonitoring of Parkinson's Disease symptoms, conducting tests on simulated networks and analyzing recordings from a group of PD subjects.	d. To infer UPDRS using speech signals transmitted over the standard cellular mobile voice telephone network

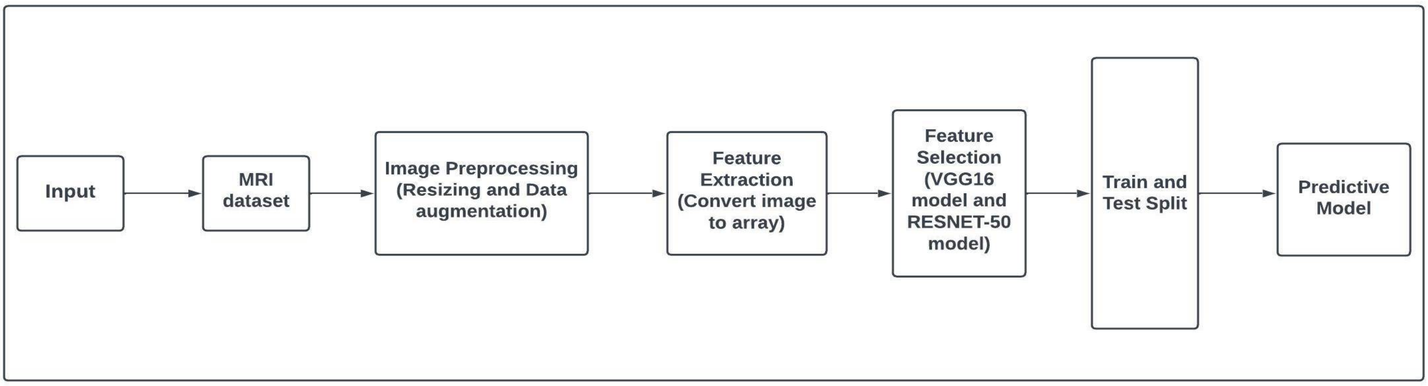

Figure 1.1 System Architecture

Then, the image_data and labels lists were shuffled using the zip and unzip functions to ensure a random distribution of the data. After that, the image_data and labels lists were converted into numpy arrays called x_train and y_train, respectively. The shape of x_train was (number of images, 64, 64, 3), and the shape of y_train was (number of images,). Next, the y_train array was one-hot encoded using the np_utils.to_categorical function from keras.utils. The shape of y_train changed to (number of images, 2), where each row had a value of [1,0] or [0,1] indicating the absence or presence of PD.
Finally, the preprocessed dataset was split into training and validation sets using the train_test_split function from sklearn.model_selection, with a test size of 0.10 and a random state of 42, ensuring consistent results between runs. Additionally, an ImageDataGenerator object from keras.preprocessing.image was created to apply data augmentation techniques to the training set, such as rotation, width shift, height shift, and flipping.

3) *Model Training:* To develop a robust and accurate CNN model for detecting Parkinson's disease from MRI images, a proposed ensemble approach was used that combines the outputs of two pretrained models: VGG16 and ResNet50. Both VGG16 and ResNet50 are well-known CNN architectures that have achieved state-of-the-art results on various image recognition tasks and were originally trained on a large-scale image dataset called ImageNet. The top layers of both models were modified to adapt them to the binary classification problem of Parkinson's disease detection. Three fully connected layers with relu activation functions and l2 regularization were added to prevent overfitting, followed by dropout layers to reduce the co-adaptation of neurons. The final layer had a sigmoid activation function to output the probability of having Parkinson's disease for each image.

An ensemble model was then created that takes the average of the outputs of VGG16 and ResNet50 models as the final prediction. This way, the complementary strengths of both models were leveraged and the variance of the prediction was reduced. The proposed system used Adam optimizer with a learning rate of 0.0001 to train the ensemble model, and categorical crossentropy as the loss function to measure the discrepancy between the predicted and true labels. A model checkpoint callback was also used to save the best model based on the validation loss, and a patience of 5 epochs was set to stop the training if there is no improvement in the validation loss. Data augmentation techniques such as rotation, width shift, height shift, horizontal flip, and vertical flip were applied to the training data using the augment.fit() method. This increased the diversity and quality of the training data and helped the model generalize better to unseen images. The architecture of the proposed ensemble model was plotted using tf.keras.utils.plot_model() method to visualize its structure and parameters

4) *Model evaluation and Prediction:* To evaluate the performance of the proposed ensemble model, the hist variable was used to store the history of the training and validation losses and accuracies for each epoch. Learning curves were plotted using matplotlib.pyplot to visualize how the model learned over time and to check for signs of overfitting or underfitting. To make predictions on new MRI images, the best model saved by the model checkpoint callback was loaded using the load_model() method. A function called model_predict() was defined to take an image path and a model as inputs, and return the predicted label (CNTRL or PD) based on the highest probability output by the model. To measure the accuracy of the model on the test set, the predict() method was used to obtain the predicted labels for all the test images, and compared with the true labels using np.argmax() method. The sklearn.metrics.classification_report() was used to generate a report showing various metrics such as precision, recall, f1-score, and support for each class and overall. The confusion matrix(Fig 2.1) of the model was visualized using the sklearn.metrics.confusion_matrix() to compute the number of true positives, false positives, true negatives, and false negatives for each class. The seaborn.heatmap() was then used to plot the confusion matrix as a heatmap with annotations and labels.

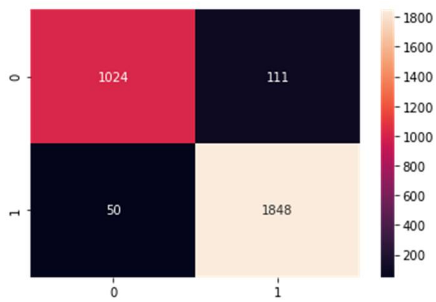

Figure 2.1 Confusion matrix

5) *Results:* When both models (VGG16 and RestNet50) were trained separately they obtained results as shown in table 1.2. The result of the model evaluation shows that the proposed ensemble CNN model achieved an overall accuracy of 95% on the test set. The precision and recall for class 0

Sr. no	Model	Training loss	Training accuracy
1.	VGG16	6.271	83.33%
2.	RestNet50	4.8941	85.89%
3.	Ensemble	0.3632	90.15%

Table: 1.2 Model comparison

(CNTRL) were 0.95 and 0.90 respectively, indicating that the model was able to correctly identify 95% of the CNTRL cases and had a false positive rate of 10%. The precision and recall for class 1 (PD) were 0.94 and 0.97 respectively, indicating that the model was able to correctly identify 94% of the PD cases and had a false negative rate of 3%. The f1-score, which is a weighted average of

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precision and recall, was 0.93 for CNTRL and 0.96 for PD, indicating that the model had a good balance between precision and recall for both classes.

Thus, the proposed ensemble CNN model showed promising results in detecting Parkinson's disease from MRI images, with high accuracy, precision, recall, and f1-score on the test set. In Fig 3.1 shows the plot for Ensemble Method, the first plot shows the loss and validation loss of a model over epochs. The second plot shows the accuracy and validation accuracy of the model over epochs.

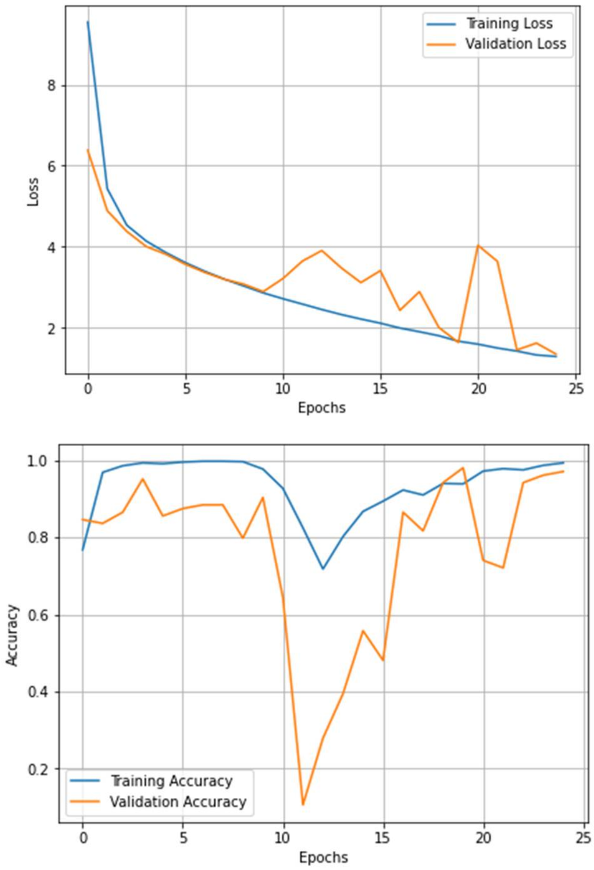

Figure 3.1 Result Analysis

IV. CONCLUSION

In this paper, the proposed system is a CNN model for MRI based early detection of Parkinson's disease (PD).The existing research demonstrates that deep learning approaches have a significant impact in improving the accuracy for early revelation of Parkinson's disease. The Proposed method uses CNN model for MRI based early detection of Parkinson's disease. The dataset was divided into 90% training and 10% testing. The proposed system applies two different CNN architectures, VGG16 and ResNet50, to the MRI images of the subjects. The models are trained and tested separately and compared their performance metrics. It also combined the outputs of the two models using an ensemble method that weighted their predictions based on their confidence scores. The model showed better results after applying l2 regularization and dropout to prevent overfitting and improve generalization. It showed that the ensemble model achieved higher accuracy and balanced precision and recall than the individual models. The proposed system also plotted the loss and accuracy curves of the three models over epochs and analyzed their learning behavior. The proposed system gives accuracy of 95%, and achieved high recall and precision. It can also contribute to the field of medical image analysis and PD research by offering a novel and effective approach for MRI based early detection of PD using a CNN model. However, the proposed system also faces some limitations and challenges, such as data quality, generalization, and interpretability. In future this system can be improved by applying more robust techniques and more quality data.

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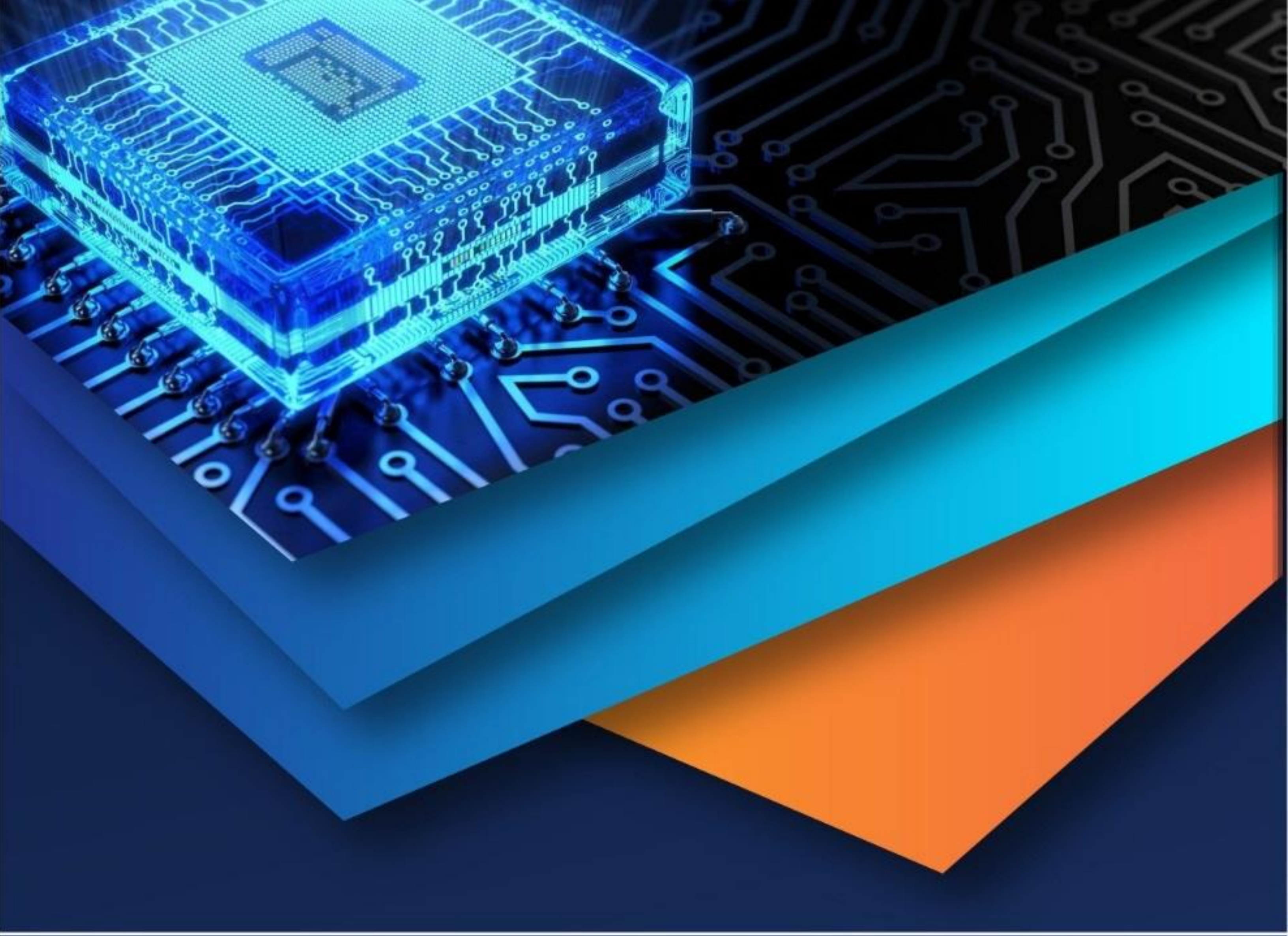

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