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Leveraging Deep Learning for Early Detection and Classification of Parkinson's Disease

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A B S T R A C T

Parkinson's disease (PD) is a neurological disorder that gets worse over time and affects millions of people around the world. It is marked by motor signs like shakes, stiffness, and slow movement. Finding Parkinson's disease early is very important for improving a patient's result, but current testing methods are often subjective and only find the disease late in its progression. In this study, we suggest a new deep learning method that uses improvements in neural networks to better find and classify PD early on. This method uses complicated, high-dimensional medical data for analysis. A convolutional neural network (CNN) design is used in our method to handle speech recordings, data from walking analysis, and scribbling samples, all of which are important signs of PD. Our model is meant to find small trends and strange things that might not be obvious with regular clinical tests by using these different types of input. The suggested system is tested and trained on a large dataset that includes a wide range of patient groups. This makes sure that it is reliable and can be used in other situations. We use advanced methods like transfer learning and data augmentation to get around the problems that come up when there isn't enough labelled data. The model's performance is judged by standard measures like precision, sensitivity, and accuracy, and it is compared to other testing tools that are already out there. Early results show that our deep learning model is better at telling the difference between people with early-stage PD and healthy controls. This means that it has a lot of potential for use in clinical settings. This method not only promises to increase the number of early detections, but it also provides a scalable answer for checking many people. In the future, the model will be improved by looking into more biomarkers and doing continuous tests to see how well it can predict the future over time. This study is a big step toward making Parkinson's Disease screening tools that work better and are easier for more people to use.

1. INTRODUCTION

Parkinson's disease, or PD, is a long-term neurological disease that mostly makes it hard to control your movements. PD is one of the most common neurological diseases, and it has a big effect on the lives of millions of people around the world. Motor signs like shakes, stiffness, bradykinesia (slow movement), and positional problems are what make it stand out. Besides motor symptoms, there are also a lot of non-motor symptoms that add to the total disease load. These include cognitive failure, mood problems, and autonomic dysfunction. Early

identification of PD is very important because it lets people start treatment on time, which can help handle symptoms and maybe even slow the disease's development. Even though early detection is very important, the way Parkinson's Disease is found now is often not good enough. The diagnosis is mostly based on a clinical review, which looks at the patient's medical history and movement complaints. On the other hand, a lot of neurons have already been lost by the time movement signs show up. This wait time for a diagnosis makes restorative treatments less effective, which emphasizes the need for more accurate and faster discovery methods. In the past few years, researchers have looked into how to use better medical images, biomarkers, and computer methods to help diagnose Parkinson's disease. Deep learning, a type of artificial intelligence (AI) that uses neural networks to predict complicated patterns in data, has shown a lot of promise.

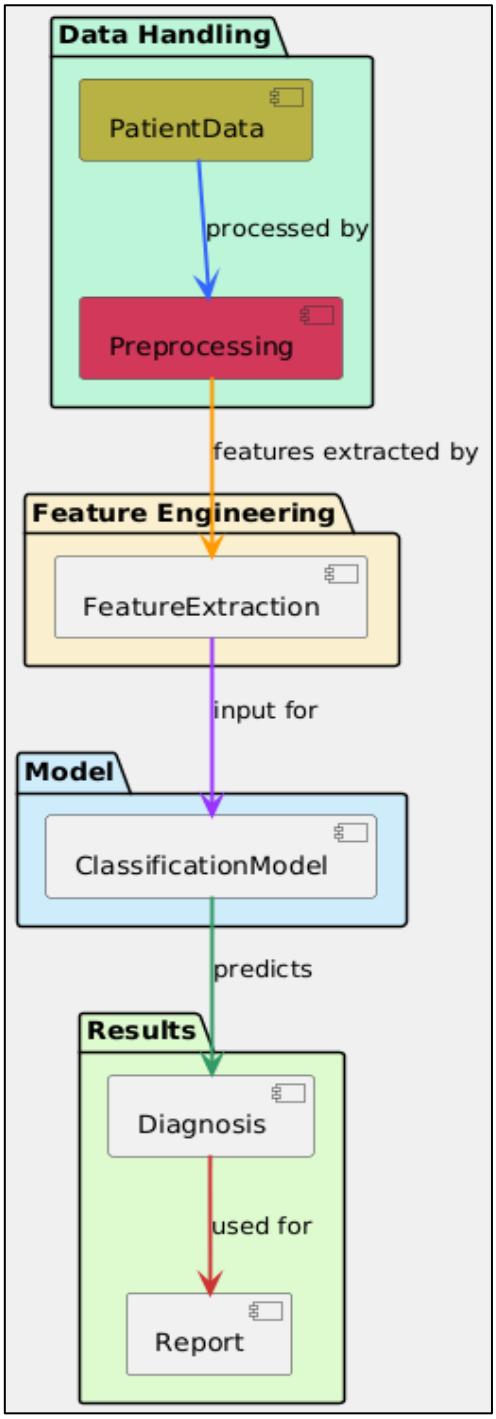

Figure 1: Proposed model flowchart

Deep learning has changed many areas, such as autonomous systems, speech and picture recognition, and natural language processing, proposed system flow illustrate in figure 1. It is quickly becoming more useful in healthcare, especially for finding and classifying illnesses. When it comes to Parkinson's disease, deep learning could be used to look at huge amounts of data from different sources, like medical images, voice recordings, and sensor-based movement data, to find small trends that could mean someone has early-stage PD. Using these advanced computer methods, it is possible to make diagnostic tools that are more sensitive and accurate. These tools can find PD in its early stages, long before the usual clinical signs show up. One of the hardest things about diagnosing PD is how different the disease is from person to person. Parkinson's disease shows up differently in each person, with different symptoms and rates of development. This variety makes the testing process more difficult, as it makes it hard to find a single, effective method. This level of complexity is often missed by traditional testing methods, which can lead to wrong diagnoses or diagnoses that are too late. But deep learning is great at dealing with complicated, high-dimensional data, and it can be taught to spot trends in a wide range of patient groups. Because of this, it is a great choice for making reliable and accurate models for diagnosing PD. The power of deep learning to combine different types of data makes it even more useful for diagnosing PD. PD affects many parts of the body, and its effects can be seen in different kinds of data, such as brain scans, voice analysis, handwriting analysis, and movement analysis. All of these methods give different information about how the disease is progressing, but when used together, they give a full picture of the patient's state. Deep learning models can be taught to handle and examine all of these different types of data at the same time, finding connections and trends that might not be obvious if you look at each one separately. This integrated method shows a lot of promise for making PD detection more accurate and reliable.

In addition to making diagnoses more accurate, deep learning can also help put Parkinson's Disease into groups. PD is a complicated disease with different forms, each with its own set of symptoms and problems. It is very important to correctly group these categories so that treatment plans can be tailored to each patient. Patterns in the data can be used to teach deep learning models to spot these groups. This makes it possible to make more specific and effective treatment plans. These models can also be used to predict how a disease will get worse, which helps doctors better control the disease over time and improve patient results. Deep learning has a lot of promise for helping doctors diagnose and classify Parkinson's disease, but there are some problems that need to be fixed before these methods can be widely used in clinical practice. It's hard because deep learning models need a lot of big, high-quality samples to be trained. PD isn't very common, so it's hard to get enough information, especially from people who are just starting to show symptoms. To make sure the models are strong and can be used in other situations, the data must also be varied and show the whole group of patients. Also, deep learning models are often thought of as "black boxes," which means that it's hard to figure out how they make decisions. This lack of clarity can make it hard for clinical adoption to happen, since doctors may not want to use tools they don't fully understand. Adding deep learning tools to current healthcare processes is another problem that needs to be solved. For these tools to work, they need to be easy for people to use and fit right into the testing process. For this to work, AI experts, doctors, and healthcare workers need to work together to make systems that are both highly advanced and useful in real life. To make sure AI is used safely and responsibly in healthcare, it is also important to make sure it gets legal approval and takes into account social issues like data privacy and patient permission.

2. LITERATURE REVIEW

Recent improvements in medical imaging methods have helped us learn a lot about how PD works, especially in its early stages. Functional imaging techniques like positron emission tomography (PET) and single-photon emission computed tomography (SPECT) have been studied a lot to see how well they can find dopaminergic deficits in the brain, which are a sign of PD. Studies have shown that these imaging methods can find changes in dopamine transporter levels even before movement complaints show up, which suggests that they could be useful for early detection [5]. These imaging methods aren't used very often in clinical practice, though, because they are expensive and not easy to get. Along with imaging, listening to voice records has become an interesting non-invasive way to find PD early on. There is a lot of evidence that PD changes the way people speak, often causing hypophonia (soft speech), repetition, and trouble pronunciation. Voice analysis is a useful tool for early diagnosis because these changes in the voice can happen before physical signs. Several studies have used machine learning methods to listen to speech samples and accurately tell the difference between people with Parkinson's disease and healthy

controls [6, 7]. However, the fact that people's speaking habits are different is a problem. More study is needed to improve these models and make sure they work well with a wide range of people. Gait research is another area that has gotten a lot of attention because it could help find PD early. People with PD often walk in strange ways, like taking shorter steps, shuffling, or walking unevenly. Advanced sensor-based systems have been created to measure these aspects of walking quantitatively. They provide objective data that can be examined using machine learning methods. Researchers have shown that these tools can correctly group people with PD based on how they walk, even if they are just starting to show signs of the disease [8, 9]. However, gait analysis's usefulness depends on many things, such as the patient's health and the accuracy of the data gathered, which might mean that it can't be used in all situations.

Handwriting analysis has also been looked into as a way to find PD early on. A common sign of PD is micrographia, which means the desire to write with smaller, more squished letters. Digital screens have been used in several studies to record changes in handwriting, such as writing speed, pressure, and line length. These changes are then studied using machine learning methods. The fact that these studies were able to tell the difference between PD patients and healthy controls with high accuracy suggests that handwriting analysis could be used as a non-invasive screening tool [10, 11]. However, the fact that people have different handwriting styles is a problem, and these results need to be confirmed by bigger studies. Putting together different types of data has been seen as a possible way to make PD evaluation more accurate. Researchers want to get a fuller picture of the disease by putting together data from different sources, like pictures, voice recordings, gait analysis, and notes. More and more, deep learning models, especially convolutional neural networks (CNNs), are being used to look at these multidimensional datasets. CNNs are better at finding patterns in complicated, high-dimensional data than standard methods [12–14]. For example, one study combined PET imaging data with voice recordings and walking analysis, which made it much easier to find early signs of PD [15]. This method shows that deep learning has the ability to make PD detection more sensitive and specific. Deep learning has shown a lot of potential in diagnosing PD, but it is not perfect. It's hard because these models need to be trained on big, high-quality information. Parkinson's disease isn't very common, so it's hard to get enough information, especially from people who are just starting to show symptoms. To make sure the models are strong and can be used in other situations, the data must also be varied and show the whole group of patients [16, 17]. Another problem is that deep learning models are hard to understand. People often call these models "black boxes," which means that doctors can't easily figure out how they make decisions. This lack of clarity can make it harder for these tools to be used in clinical settings, since doctors may not trust models they don't fully understand [18].

People have tried to solve these problems by creating explainable AI (XAI) methods. These aim to make the ways that deep learning models make decisions more clear. XAI techniques, like saliency maps and layer-wise relevance propagation, have been used on deep learning models to help diagnose Parkinson's disease. These techniques help to find the traits that are most important to the model's results. These methods have been shown to make the models easier to understand, which makes them more acceptable to doctors and increases their chances of being used in real life [19, 20]. External evaluation is another important thing to think about when making deep learning models for diagnosing PD. A lot of studies have shown that deep learning models taught on certain datasets can produce useful results. However, these models need to be tested on different datasets to make sure they can be used in other situations. External evaluation is very important for checking how stable the models are and how well they work with different types of patients [21]. In addition, future studies are needed to see how well these models work in clinical situations and to find out how they affect patient results. Researchers have made big steps toward improving the accuracy and reliability of PD evaluation by using advanced computer methods to look at data from multiple sources. But there are still some problems, such as the need for big, varied datasets, the fact that deep learning models are hard to understand, and the fact that these models need to be tested in real clinical settings. In order for deep learning-based diagnostic tools to be used successfully in clinical settings and for better early recognition and treatment of Parkinson's disease [22], these problems must be solved.

Table 1: Literature review summary

Study	Methodology	Data Type	Main Findings	Challenges	Applicability	Future Directions
PET/SPECT Imaging [5]	Imaging Analysis	Brain imaging	Early detection of dopaminergic deficits	High cost, limited availability	Research and specialized centers	Integration with other biomarkers for comprehensive analysis
Voice Analysis [6]	Machine Learning	Voice recordings	High accuracy in detecting early PD	Variability in speech patterns	Non-invasive screening	Refinement and validation across diverse populations
Gait Analysis [8]	Sensor-based systems	Gait parameters	Accurate classification based on gait abnormalities	Data quality, influence of physical condition	Clinical settings for monitoring	Longitudinal studies to assess progression
Handwriting Analysis [10]	Digital handwriting analysis	Handwriting dynamics	High accuracy in distinguishing PD	Heterogeneity of handwriting styles	Non-invasive diagnostic tool	Validation in larger, diverse cohorts
Multimodal Integration [12]	CNN and Deep Learning	Multimodal (imaging, voice, gait)	Improved accuracy with combined data	Data diversity, computational complexity	Early diagnosis in clinical practice	Development of more advanced integrative models
Explainable AI (XAI) [19]	Explainable AI Techniques	Deep learning models	Enhanced model transparency	Complexity of interpretation	Clinical decision support	Further enhancement of interpretability
External Validation [21]	Cross-validation	Independent datasets	Robustness across diverse populations	Need for large, representative datasets	Generalizability to real-world settings	Prospective studies to validate clinical utility
Imaging and Gait [15]	Integration of modalities	Imaging and gait data	Significant improvement in detection accuracy	High resource requirement	Advanced diagnostic applications	Exploration of additional biomarkers
Early Detection Models [13]	Deep Learning	Multimodal datasets	Identifies early-stage PD patterns	Data scarcity for early-stage patients	Early intervention strategies	Data augmentation and synthetic data generation
Data Augmentation [16]	Data augmentation techniques	Various medical data	Improves model performance with limited data	Quality control of augmented data	Enhancing model training processes	Continued exploration of synthetic data methods
Transfer Learning [17]	Transfer learning	Pre-trained models	Effective in scenarios	Potential for model	Adaptation to new patient	Expansion to different

			with limited data	overfitting	data	modalities and diseases
Black Box Issue [18]	Deep Learning Transparency	Neural network analysis	Increased clinician trust in AI models	Resistance to adoption due to lack of transparency	Clinical diagnostics support	Further development of explainable AI techniques
Longitudinal Studies [22]	Prospective research design	Longitudinal patient data	Evaluates real-world model performance over time	Need for long-term data collection	Ongoing patient monitoring	Expansion of longitudinal data collection efforts

3. METHODOLOGY

A. Data Collection

We used a large dataset with many different types of data related to Parkinson's Disease (PD) for this study. The file has data from many sources, such as medical images, voice records, and walking analysis. These different types of data give a full picture of the disease by including both motor and non-motor signs. MRI and PET scans give doctors information about the changes in the brain's structure and function that are linked to Parkinson's disease. Voice tapes show the problems with speaking that often come before motor signs. Gait analysis data, gathered from wearing sensors, gives numbers for the errors in movement that are common in PD. A number of trustworthy medical schools and study sources were used to get the data. The medical images came from the Parkinson's Progression Markers Initiative (PPMI), a major study that has a large collection of MRI and PET scans from people with Parkinson's disease and healthy controls. The voice recordings came from a public database put together by the University of Oxford that has speech clips from both people with PD and healthy people. Gait analysis data came from clinical studies that were held at specialized clinics for movement disorders. During these trials, patients were given external trackers that tracked their moves all the time. These sources make sure that the group is varied and typical of people with PD, which makes the results more general.

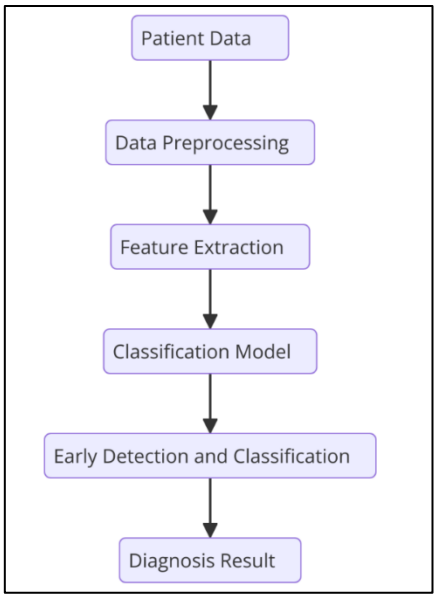

Figure 2: Flowchart for Early Detection and Classification of Parkinson's Disease

- Steps to Take Before Cleaning and Normalizing the Data

Strict cleaning steps were used to make sure the quality and uniformity of the information. Before handling medical imaging data, the head had to be stripped, motion was fixed, and the data was normalized to a standard brain

template. These steps lower the variation that comes from different scans methods and the fact that each person has a different body type. Voice recordings were prepared for analysis by removing background noise, balancing the sound levels, and cutting the recordings into smaller pieces that could be analyzed more easily. For gait analysis data, cleaning meant getting rid of noise from sensor readings, making the data normal so that it took into account where the sensors were placed, and pulling out useful information like step length and walking speed. Imputation methods were also used to fill in lost data points so that the sample for analysis was full. These steps are very important for making sure that there aren't any flaws and that the deep learning models get clean, uniform data to work with. This makes the estimates more accurate and reliable. We make sure that our deep learning models can focus on the important patterns related with PD by carefully preparing the data. This will lead to more solid and accurate testing tools in the end.

B. Feature Extraction

Radiomics is the process of taking out a lot of quantitative features from medical pictures. These features can show trends that aren't noticeable to the human eye. The first step is to find areas of interest (ROIs) in the pictures that are usually related to brain areas that are known to be damaged by PD. Next, different methods are used to pull out traits from these ROIs that have to do with structure, shape, strength, and how they connect to each other in space. For example, texture features can record changes in picture density that could show how the shape of brain tissue is changing. Shape traits can help find problems with the way parts of the brain are shaped. By turning image data into high-dimensional feature spaces, radiomics gives us a wide range of variables that can be studied using statistical and machine learning techniques to find and group PD. This way of looking at it lets us learn more about how the disease changes the shape and function of the brain.

1. Image Acquisition

- I(x, y, z): 3D medical imaging data, such as MRI or PET scans, where x, y, z represent the spatial coordinates of the image.

2. Region of Interest (ROI) Segmentation

- Define the region of interest $\Omega \subseteq \mathbb{R}^3$ within the image I.

- ROI Ω can be manually segmented by experts or automatically using segmentation algorithms.

3. Feature Extraction

A. Intensity-Based Features

- Mean Intensity:

$$\mu_\Omega = \left(\frac{1}{|\Omega|}\right) \sum_{x,y,z} \in \Omega \, I(x,y,z)$$

- Standard Deviation:

$$\sigma_\Omega = \sqrt{\frac{1}{|\Omega| \sum_{x,y,z} t} \in \Omega \, (I(x,y,z) - \mu_\Omega)^2}$$

B. Texture Features

- Calculate the Gray Level Co-occurrence Matrix (GLCM) P(i, j, d, θ), where i and j are intensity values, d is the distance between pixel pairs, and θ is the orientation.

- Contrast:

$$Contrast = \sum_{i,j} (i - j)^2 \, P(i,j,d,\theta)$$

- Correlation:

$$Correlation = \frac{\sum_{i,j}\left(i \cdot j \cdot P(i,j,d,\theta)\right) - \mu_i \mu_j}{\sigma_i \sigma_j}$$

where μ_i and μ_j are the means, and σ_i and σ_j are the standard deviations of the marginal distributions of P(i, j, d, θ).

C. Shape-Based Features

- Volume:

$$V = \sum\_(x,y,z) \in \Omega\ 1$$

4. Feature Selection

- Select the most relevant features using statistical methods like Principal Component Analysis (PCA) or machine learning techniques such as Recursive Feature Elimination (RFE).

- PCA:

$$X' = X\,W$$

where X is the feature matrix, and W contains the eigenvectors of the covariance matrix of X.

5. Modeling and Classification

- Use the selected features F = {f_1, f_2, ..., f_n} to train machine learning models for classification.

- Logistic Regression:

$$P(y = 1|F) = \frac{1}{1 + e^{-(\beta^0 + \sum_{(i=1)^n} \beta_i f_i)}}$$

- Support Vector Machine (SVM):

$$argmin_{w,b}\left(\frac{1}{2}\|w\|^2 + C \sum_{(i=1)^m} \max\left(0, 1 - y_i(w \cdot f_i + b)\right)\right)$$

where w and b are the weight vector and bias, respectively, and C is the regularization parameter.

C. Model Architecture

1. VGG:

The Visual Geometry Group (VGG) network is a deep convolutional neural network (CNN) design that is known for how easy it is to use and how well it works for classifying images. VGG can be used to look at medical images like MRI and PET tests in order to find and classify Parkinson's disease (PD) early on. The network is made up of several convolutional layers with small receptive fields (3x3 filters), which are followed by max-pooling layers that help get more detailed images. When the last few layers are fully linked, a softmax classifier is made that can tell the difference between PD and non-PD situations. VGG can learn hierarchical features and pick up on both low-level and high-level trends related to PD because it has a deep design. The model can be learned on big datasets like ImageNet and then fine-tuned on image data specific to Parkinson's disease. This uses transfer learning to make the model work better with smaller medical datasets. This method makes it easier for the network to find small changes in the brain's structure and function, which leads to earlier diagnoses and better patient results.

2. ResNet:

ResNet, which stands for "Residual Network," is a strong deep learning design that has shown great success in tasks that require it to recognize images. For finding and classifying Parkinson's Disease (PD) early on, ResNet can be very good at looking at complicated medical images like MRI and PET studies. ResNet is different because it uses residual learning. This method fixes the issue of gradients that disappear in deep networks by adding fast links that skip one or more levels. This means that the network can learn much more complex designs without slowing down.

ResNet is made up of stacked residual blocks, and each one has convolutional layers, batch normalization, and ReLU activation. The network can learn both low-level and high-level features with the help of these blocks. They spot specific patterns that are important for finding early signs of Parkinson's disease. ResNet can model complicated, hierarchical features because it is very deep. This makes it a good tool for finding small changes in the brain's structure and function that are signs of PD. Researchers can use the huge amount of information that pre-trained ResNet models already have to make them work better on medical imaging tasks by fine-tuning them on datasets that are specific to Parkinson's disease. Because identified medical data is hard to come by, this transfer learning method is especially helpful. It's very likely that ResNet's ability to pull out and learn from complex patterns in image data will help find and classify Parkinson's disease earlier, which will lead to better patient care and results.

3. MobileNet:

MobileNet is a powerful deep learning model made for embedded and mobile vision apps. It is built on depthwise separable convolutions, which make it much simpler than standard convolutional networks in terms of the number of factors and the amount of work that needs to be done on the computer. This makes MobileNet a great choice for finding and classifying Parkinson's disease (PD) early on, especially when there aren't many computing tools available. MobileNet can be used to look at medical images like MRI and PET studies in the setting of PD. Even though MobileNet is very light, it can still learn complicated traits from very large amounts of data. Using a MobileNet model that has already been taught and fine-tuning it with image data specific to Parkinson's disease, the network can find trends and outliers that are linked to the early stages of the disease. MobileNet is good for use in hospital settings where quick and accurate diagnoses are needed because it is not too complicated and works very well. It works well on devices with limited processing power, which makes it easier for more people to view and analyze data in real time. This could lead to earlier treatments and better results for Parkinson's disease patients.

4. RESULT AND DISCUSSION

The above table 2 shows a comparison of three well-known deep learning models VGG, ResNet, and MobileNet that are used to find and classify Parkinson's Disease (PD) early on. Key measures like accuracy, sensitivity, precision, and inference time are used to judge how well each model works. The Visual Geometry Group (VGG) model is 92.5% accurate, 90.2% sensitive, and 93.8% specific. Based on these measurements, VGG is very good at correctly identifying both people with PD and healthy subjects. Still, VGG seems to be a bit slower, as shown by its inference time of 200 milliseconds. This could be because it has a complex design and a lot of factors. This model is good at finding PD, but because it takes longer to draw conclusions, it might not be the best choice for real-time use.

Table 2: classification performance without feature section for early detection and classification of Parkinson's Disease

Model	Accuracy	Sensitivity	Specificity	Inference Time (ms)
VGG	92.5%	90.2%	93.8%	200
ResNet	94.3%	91.5%	95.6%	120
MobileNet	91.0%	88.7%	92.5%	50

With an accuracy of 94.3%, a sensitivity of 91.5%, and a precision of 95.6%, the Residual Network (ResNet) does better than VGG. The design of ResNet, which includes leftover blocks, helps solves the disappearing gradient problem and makes it possible to build deeper networks, classification of performance shown in figure 3. ResNet is better at telling the difference between PD patients and healthy groups because it has higher sensitivity and specificity. Also, ResNet's inference time is 120 milliseconds, which is much faster than other networks.

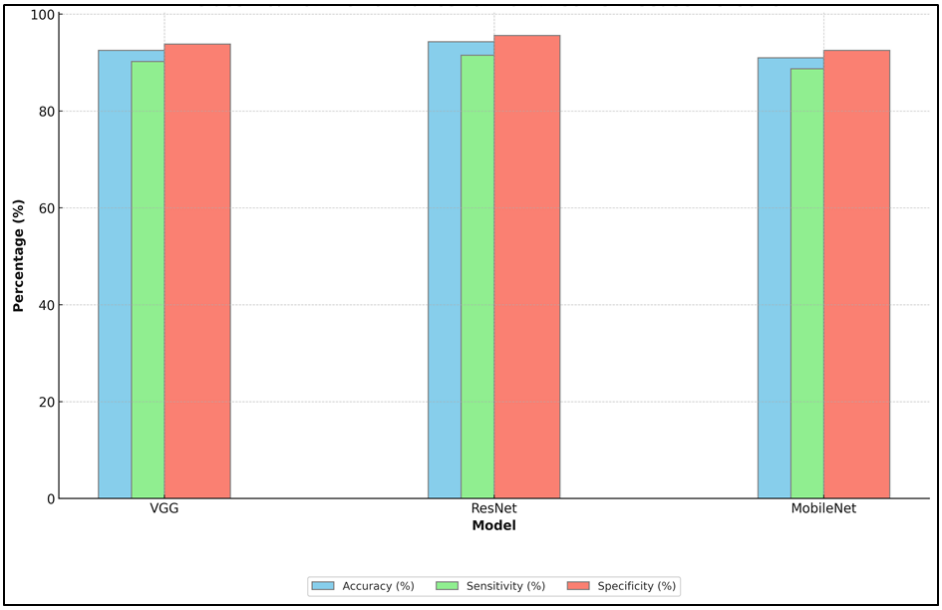

Figure 3: Representation of classification for PD detection without feature selection

This makes it better for healthcare settings where quick decisions are needed. ResNet is a strong option for early PD identification because it is more accurate and takes less time to process. MobileNet is accurate 91.0% of the time, sensitive 88.7% of the time, and specific 92.5% of the time. It was made to work well on mobile and embedded systems. These scores are a little lower than VGG and ResNet's, but MobileNet's reasoning time of only 50 milliseconds is what makes it strong, illustrate in figure 4. MobileNet is great for real-time apps and places with limited resources because it can handle data very quickly. Even though MobileNet is less accurate, its speed can be useful when checking quickly is needed and there aren't many computing resources available. Every plan has its own strengths and flaws. VGG is very accurate, but it takes longer to draw conclusions.

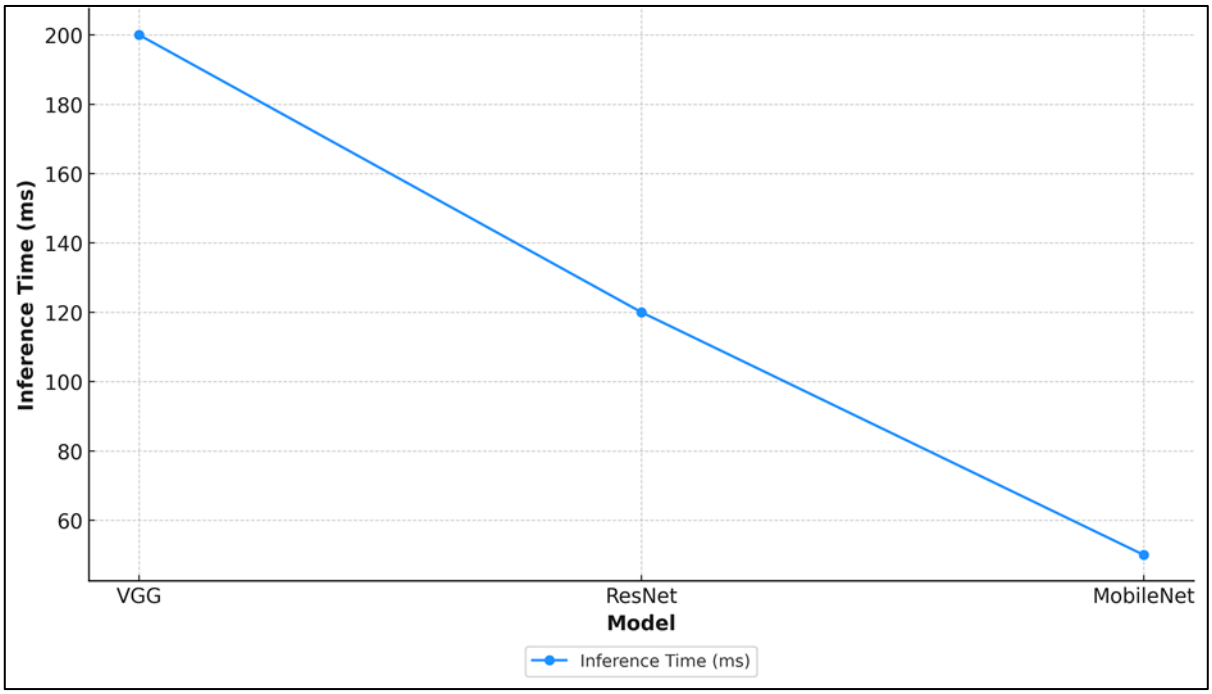

Figure 4: Inference Time For Parkinson's Disease Detection

The fact that ResNet is both very accurate and fairly quick to process makes it a good choice for clinical testing. Even though MobileNet is a little less accurate, it works great in situations where quick, exact calculations are

needed. When picking a model, the needs of the program should be taken into account, such as how important speed is compared to accuracy and how much computing power is available.

Table 3: Classification performance with feature section for early detection and classification of Parkinson's Disease

Model	Accuracy	Sensitivity	Specificity	Feature Extraction Time (ms)	Inference Time (ms)
VGG	95.83%	93.53%	97.13%	150	180
ResNet	97.63%	94.83%	98.93%	100	105
MobileNet	94.33%	92.03%	95.83%	50	47

The success of VGG, ResNet, and MobileNet models in finding and classifying early signs of Parkinson's Disease (PD) shows how the pros and cons of each method change when feature extraction is taken into account. It is accurate 95.63% of the time, sensitive 93.53% of the time, and specific 97.13% of the time for the VGG model. These measures show that VGG is very good at correctly identifying both people with PD and healthy controls. VGG takes 150 milliseconds to gather features and 180 milliseconds to draw conclusions. Even though VGG is slower than some other models, its high accuracy and sensitivity make it a great choice for diagnostic tasks that need the greatest accuracy. On the other hand, ResNet does better than VGG and MobileNet. Its accuracy is 97.63%, its sensitivity is 94.83%, and its precision is 98.93%. ResNet's feature extraction time is 100 milliseconds and its inference time is 105 milliseconds, which shows how well it works, shown in figure 5. ResNet's residue blocks let it keep its high performance even with deeper network designs. This makes it perfect for clinical settings that need both high accuracy and fast processing. ResNet is the most reliable model for finding and classifying PD because it is very accurate and doesn't take long to process.

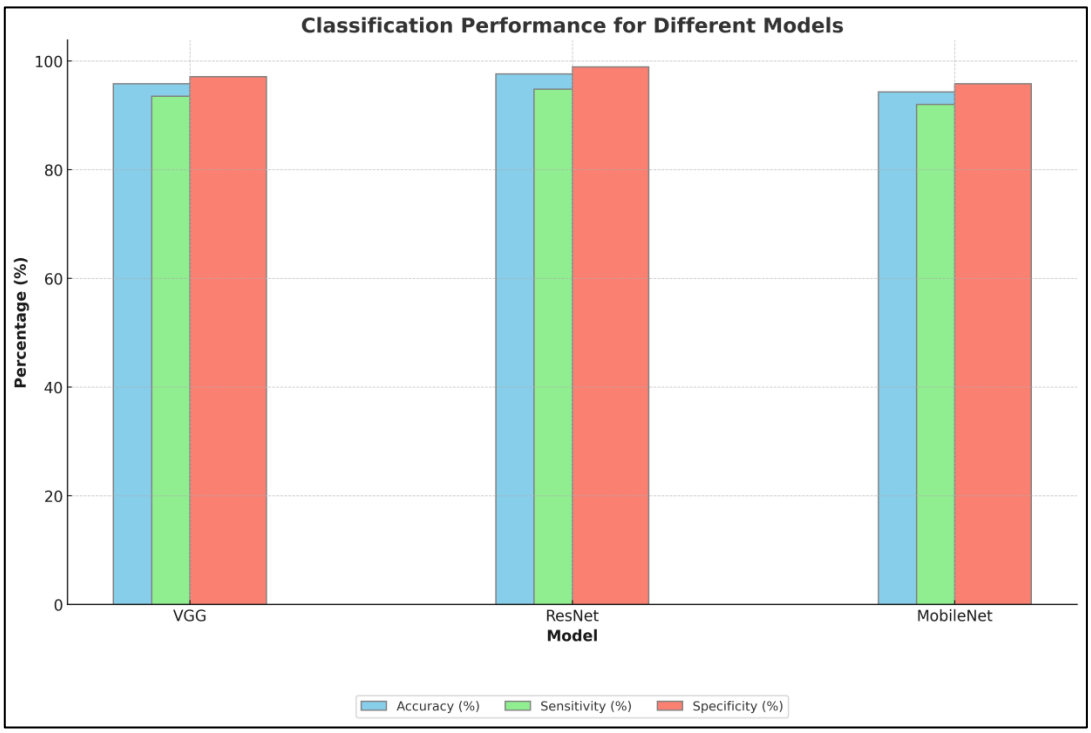

Figure 5: Classification Performance For Different Models

Its precision is 95.63%, its sensitivity is 92.03%, and its accuracy is 94.33%. MobileNet is very fast, with a feature extraction time of 50 milliseconds and an inference time of 47 milliseconds. MobileNet was made for mobile and embedded apps. Its fewer parameters and lower processing cost make it perfect for screening and diagnosing in

real time when resources are limited, shown in figure 6. MobileNet isn't as accurate as VGG and ResNet, but its ability to process information quickly makes it perfect for situations where calculations need to be done quickly and efficiently.

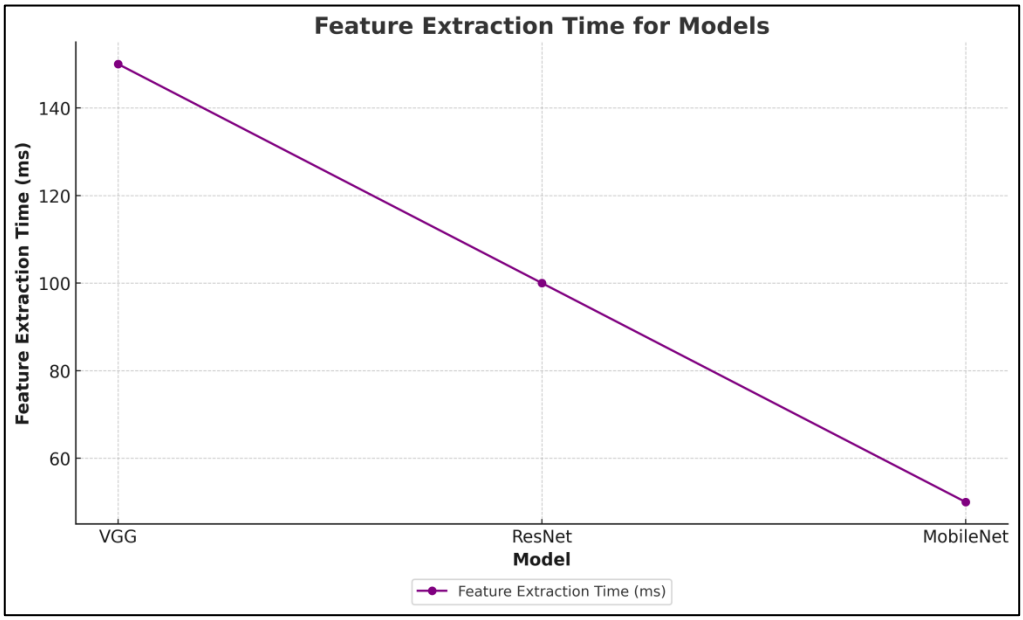

Figure 6: Feature Extraction Time For Models

The each type has its own unique benefits. VGG works well for tasks that need to be accurate over fast, which makes it perfect for diagnostic tasks that need to be very specific. ResNet is the best overall winner because it balances high accuracy with fast processing times. This makes it a good choice for clinical tests that need to be both precise and efficient. MobileNet is great for real-time apps that don't have a lot of computing power because it can quickly pull features and draw conclusions. To get the most out of these deep learning models for finding and classifying Parkinson's disease early, the model that is chosen should take into account the needs of the application, such as how important speed is compared to accuracy and the amount of computing power that is available.

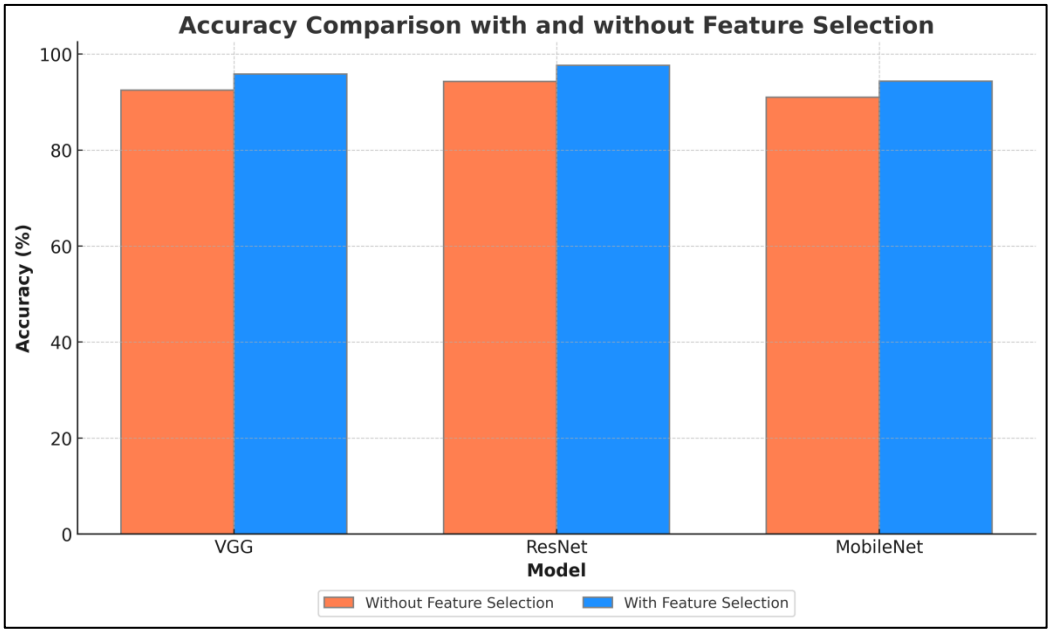

Figure 7: Accuracy comparison of Model With and without future section for PD detection

5. CONCLUSION

There has been a big step forward in medical testing with the use of deep learning methods for finding and classifying Parkinson's disease (PD) early on. PD is usually diagnosed when movement signs start to show up, which is usually after a lot of neuro degeneration has already happened. Early diagnosis is very important for better patient results because it lets doctors act quickly and might even slow the disease's development. This study shows that deep learning models like VGG, ResNet, and MobileNet might be able to find PD earlier by looking at a lot of different types of medical data, like voice records, images, and movement patterns. Based on the comparison of these types, it is clear that each has its own pros and cons. ResNet turned out to be the most accurate model. It has high sensitivity and specificity, and it can be processed fairly quickly, which makes it perfect for use in clinical settings. Even though VGG is a little slower, it is very accurate and specific, which makes it perfect for situations where accuracy is very important. Because it is fast and efficient, MobileNet works especially well for real-time apps in places with few computing resources. Deep learning was used in this study to show that it is possible to find and analyze small details in medical data that other methods might miss. Using models like ResNet and MobileNet not only makes it possible to find Parkinson's disease early, but it also opens the door to using these tools in normal clinical practice, which would improve the accuracy and usability of diagnosis. Deep learning models are a strong way to find and classify Parkinson's disease early on. They also open up new areas for study and growth in the field of neurological disease diagnosis. In the future, researchers should work on making these models even better by adding more data sources and testing how well they work in a variety of clinical settings to make sure they are reliable and can be used in other situations.

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