Enhancing Neurodegenerative Disease Detection Through Explainable AI Solutions for Early Diagnosis and Prediction

Dr.Moje Ravindra Keshav[1], Santosh H lawate[2]

Savitribai Phule Pune University,Pune[1,2]

Abstract: Alzheimer's, Parkinson's, and Huntington's diseases are examples of neurodegenerative diseases (NDs). These diseases cause the nervous system to slowly break down, which can affect both thinking and moving. Early detection and prediction of these diseases are very important for improving patient results, allowing for quick action, and making treatment methods better. Now, though, most of the time, doctors use biassed clinical measures or biomarkers that are found late in the disease's progression, which makes early diagnosis harder. The idea behind this study is to use Explainable AI (XAI) methods to make neurodegenerative disease recognition systems more accurate and easier to understand. Sharing information about how AI models make decisions through XAI makes them easier for doctors to understand and trust, which increases trust and use in healthcare situations. We look at different XAI methods combined with machine learning techniques to look at genetic, clinical, and neural data in order to predict when neurological illnesses will start and how they will get worse. Using XAI not only improves the accuracy of predictions, but it also helps doctors understand the factors that go into making the predictions, which helps them make better decisions. We look at a number of models, such as convolutional neural networks (CNNs), support vector machines (SVMs), and recurrent neural networks (RNNs). To understand the outputs of these models, we use XAI techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive Explanations). Through a thorough study, we show that XAI-enhanced AI models are much better than standard methods at finding and predicting neurodegenerative diseases early on.

Keywords: Neurodegenerative diseases, Explainable AI (XAI), Early diagnosis, Prediction models, Machine learning, Healthcare applications

I. Introduction

Alzheimer's, Parkinson's, Huntington's, and amyotrophic lateral sclerosis (ALS) are all examples of neurodegenerative diseases (NDs), which are a group of progressing illnesses that affect the structure and function of the nervous system. Neuronal structures slowly break down in these diseases, which can cause problems with thinking and moving, and in some cases, loss of automatic functions. As the world's population grows, more people are getting these conditions, which makes early identification and forecasts even more important. Early action is very important for stopping the disease from getting worse, making life better, and making treatment more effective. Neurodegenerative diseases are hard to spot in their early stages, though, because the first signs are often vague and hard to pin down. The main ways that neurological diseases are diagnosed now are through physical exams, brain scans, and sometimes DNA tests. Some clinical tests, like the Mini-Mental State Examination (MMSE), can help us understand brain problems, but they are subjective and can't always pick up on early signs of a problem [1].

Deep learning algorithms and other system studying fashions have proven a lot of promise in analysing huge datasets like neuroimaging, genetic profiles, and scientific facts. these fashions can locate traits in huge amounts of facts that human beings might leave out, which lets medical practitioner make decisions greater speedy and greater correctly. One massive hassle with AI models, particularly inside the healthcare field, is that they're challenging to understand. Many device studying models, mainly deep gaining knowledge of algorithms, work like "black packing containers," which means that that they can make very correct predictions but do not give an explanation for why they make the alternatives they do. This lack of openness could make humans less in all likelihood to faith AI structures, in particular while they are used in important healthcare settings wherein choices want to be clear and logical. To deal with this trouble, Explainable AI (XAI) has become an important thanks to make AI fashions less complicated to recognize and greater reliable [2]. XAI refers to AI fashions and applications that explain their alternatives and predictions in a method that people can recognize. In relation to finding neurological sicknesses, XAI can give us beneficial data about the things that affect AI-based totally predictions. Figure 1 indicates how explainable AI can be used to discover and predict neurological sicknesses early on.

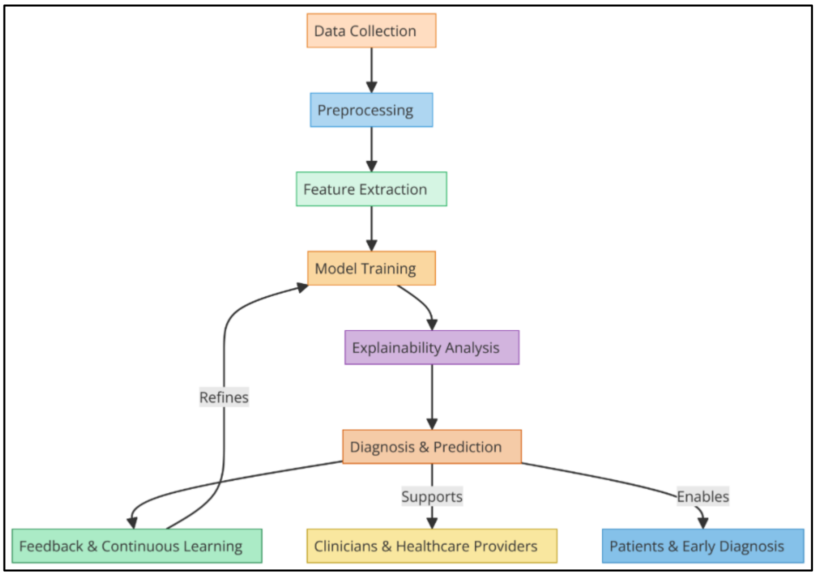

Figure 1: Enhancing Neurodegenerative Disease Detection through Explainable AI Solutions for Early Diagnosis and Prediction

This can help doctors' faith the fashions more and ensure they match up with scientific notion. A pc program known as XAI can help medical doctors recognize how diseases development and what treatments might paintings by means of giving those motives for the predictions that the fashions make. XAI techniques and device learning fashions might be used collectively on this examine to help locate and expect neurological sicknesses in advance [3]. We examine some of XAI strategies, including nearby Interpretable model-agnostic reasons (LIME) and SHapley Additive reasons (SHAP), that could assist us understand how system mastering models make decisions. Not only do these methods make fashions extra clear, however they also make it less complicated for healthcare employees to use AI-pushed insights of their everyday working [4]. The goal is to create a sturdy framework that helps with early prognosis, clinical selection-making, and ultimately higher affected person results by using making neurological sickness forecasts which can be clear and clean to understand.

II. Background and Literature Review

A. Neurodegenerative diseases and their challenges

Alzheimer's disease, Parkinson's disease, Huntington's disease, and amyotrophic lateral sclerosis (ALS) are some of the most common NDs. Each one is hard to diagnose, treat, and handle in its own way. One of the biggest problems is that these diseases are very complicated, with cellular processes that are not fully known [5]. One big problem with treating neurodegenerative diseases is that there aren't any early signs that can show when they start happening before they do a lot of damage to neurones. Early signs of NDs are often mild, and they may be mistaken for regular ageing or other conditions that aren't harmful. For example, people with Alzheimer's disease may think that their first memory problems are just normal forgetting that comes with getting older. Early signs of Parkinson's disease, like small twitches or changes in muscle balance, might not be noticed until they get in the way of daily life. This slow notice means that early action chances are often missed, which could slow the disease's development and improve patient outcomes. Neurodegenerative diseases are also usually fatal, and the treatments we have now only treat the signs and not the reasons. These diseases often get worse over time and can't be slowed down [6].

B. Traditional diagnostic methods and limitations

In the past, neurodegenerative diseases (NDs) were mostly diagnosed through physical exams, brain scans, and sometimes genetic tests. All of these methods are meant to find the unique signs and brain problems that are linked to these illnesses, but they are not perfect, especially in the early stages of the disease. NDs like Alzheimer's and Parkinson's disease are usually diagnosed with clinical tests like cognitive tests and movement function tests. These tests help doctors figure out how much a patient's memory or movement skills are failing. However, they are often subjective and based on what doctors see, which can make diagnoses less consistent. Also, cognitive loss might not display up until there is a lot of harm to neurones. This makes it tough to locate those sicknesses early enough to make powerful redress [7]. To discover adjustments within the intelligence's structure and function greater as it should be, neuroimaging techniques like positron emission tomography (puppy), magnetic resonance imaging (MRI), and computed tomography (CT) can be used. Neuroimaging can show, as an example, the build-up of amyloid plaques or shrinkage in certain parts of the talent in Alzheimer's ailment. Brain scans might also show that neurones that make dopamine are loss of life in humans with Parkinson's sickness. Some beneficial records can be received from those methods, but they're highly-priced, want special tools, and might not always find early signs and symptoms of troubles, particularly whilst talent modifications aren't obvious [8].

C. Machine learning in neurodegenerative disease detection

Machine learning techniques, which can find trends and connections in huge, complicated datasets, could help solve these problems by making assessments more quickly and accurately. ML models can look at different kinds of data, like biomarkers, genetic information, neuroscience, and clinical records, to find small trends that are linked to the start and development of NDs [9]. Deep learning systems can look at structural MRI pictures of people with Alzheimer's disease to find early signs of brain shrinkage, even before cognitive loss is noticeable. Figure 2 shows how machine learning can be used to accurately find and group neurological diseases.

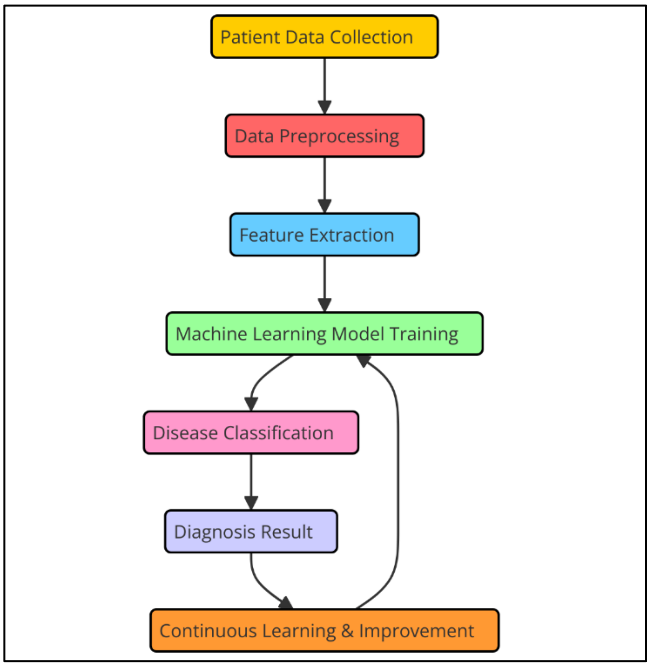

Figure 2: Machine Learning in Neurodegenerative Disease Detection

Machine learning models can be taught to recognise motor patterns in Parkinson's disease patients using data from wearing sensors. This could help find early motor signs that doctors might miss during clinical evaluations. ML is also used for predictive modelling, which trains computers to guess how a disease will get worse based on long-term data. ML models can, for example, guess how fast a person with Alzheimer's will lose brain ability or guess when their Parkinson's disease movement signs will start [10]. This ability to predict the future is very important for creating personalised treatment plans and giving patients quick measures that could slow the disease's development. Even though it has a lot of promise, using machine learning to find neurological diseases isn't easy. These include problems with the quality of the data, the ease of understanding of complicated models, and the need for big, varied datasets to build strong models. Still, more study is being done to see how ML can be used in clinical settings to help find neurological diseases earlier, give better prognoses, and improve treatment results for those who have them. Table 1 summarizes techniques, future trends, challenges, and scope in neurodegenerative disease research.

Table 1: summary of Background and Literature Review

Technique	Future Trend	Challenges	Scope
Convolutional Neural Networks (CNNs)	Improved Accuracy in Early Diagnosis with Advanced CNNs	Data Quality and Availability for Training CNN Models	Early Detection and Prediction of Alzheimer's Disease
Support Vector	Personalized Disease	Data Imbalance and Class	Long-term Monitoring and

Machines (SVM), Random Forest [11]	Progression Models with AI	Variability in Predictive Models	Personalized Treatment Plans
MRI and PET Imaging with Machine Learning	Integration of AI and Genomics for Personalized Medicine	Variability in Clinical Imaging and Diagnosis	Identification of New Biomarkers for Alzheimer's and Parkinson's
Genetic Data Integration with Machine Learning	Automated AI-based Disease Monitoring and Prediction	Incorporation of Diverse Genetic Data in Models	Predictive Models that Consider Genetic Risk Factors
SHAP for Explainable Models	AI-enhanced XAI for Real-time, Clinical Applications	Lack of Trust in AI Predictions in Clinical Settings	Interpretability of Deep Learning Models in Clinical Decision Support
Recurrent Neural Networks (RNNs)	Predictive Modeling with Longitudinal Data for Better Outcomes	Overfitting and Lack of Generalization in Deep Learning	Clinical Application of Deep Learning in Disease Progression
XAI Techniques (SHAP, LIME)	Enhanced Interpretability with Hybrid XAI Methods	High Computational Costs for Deep Learning Models	Enhanced Diagnostic Tools with Real-time Explainability
SHAP Feature Importance Analysis	Real-time Interpretation of Neuroimaging with XAI	Interpretation of Complex Data in Clinical Contexts	Better Understanding of Disease Mechanisms Using XAI
LIME for Local Model Explanation	Deployment of LIME and SHAP for Broader Clinical Usage	Variability in Results from Different XAI Methods	Increased Adoption of Explainability in AI Models for Healthcare
Genetic Sequencing Analysis with Machine Learning	Next-Generation Sequencing and AI for Early Biomarker Identification	Challenges in Large-scale Data Integration	AI-driven Personalized Healthcare Approaches
Ensemble Learning, Deep Learning [12]	End-to-End AI Models for Comprehensive Diagnosis Support	Model Complexity and Scalability in Clinical Environments	AI-enhanced Models for End-to-End Neurodegenerative Disease Management
Multi-modal Data Integration (Imaging + Clinical)	Real-time Disease Progression Monitoring using AI and XAI	Adoption of XAI Techniques in Real-time Healthcare Decision Making	Improved Real-time Monitoring of Patient Health in Hospitals
XAI Integration into Clinical Decision Support Systems	Seamless Integration of AI into Routine Clinical Practice	Ensuring Real-world Validation of AI Models	Wider Use of AI and XAI in Healthcare Institutions Worldwide
Longitudinal Data Analysis with Machine Learning	Predicting Disease Development using AI-driven Health Data	Generalizability of AI Models Across Diverse Populations	Development of AI Models with Broad Applicability in Healthcare

III. Methods and Techniques

A. AI Models for Neurodegenerative Disease Detection

1. Types of AI models

- **Neural networks**

Neurodegenerative sicknesses (NDs) can be determined and predicted with awesome capacity the use of neural networks, in particular deep learning models. That is because they could research complicated styles from massive datasets like genetic facts, neuroimaging, and medical data. Neural networks are a form of device studying fashions which are primarily based at the structure and feature of the human brain. They're made from layers of nodes (neurones) which are linked to each different and manner records. Because those networks can discover ways to describe data in an organised method, they're very right at responsibilities like classifying images, recognising patterns, and making predictions. Deep neural networks (DNNs), which include convolutional neural networks (CNNs) and recurrent neural networks (RNNs), are used lots to locate neurological illnesses. CNNs paintings in particular nicely for searching at picture records like MRI and puppy exams. They are very accurate at locating spatial hierarchies and nearby features in photos. This lets them discover small adjustments in talent systems which are symptoms of Alzheimer's and Parkinson's diseases. CNNs can locate things like hippocampal shrinkage or the build-up of amyloid plaques in Alzheimer's sickness, which can be very important for locating the contamination early. RNNs, then again, are made to address sequential statistics and are exquisite for searching at time-collection information, like how Parkinson's disorder movement symptoms get worse over time or how Alzheimer's ailment concept symptoms get worse over the years. Those models can keep tune of the way signs alternate over time, which permits them to guess how sicknesses will get worse over the years. Long quick-term memory (LSTM) networks, a selected type of RNN, are regularly used to describe those long-time period relationships. They are better at describing how diseases trade over the years. Due to the fact that neural networks can analyze from statistics on their very own, they don't want to be feature-extracted through hand. This makes them ideal for running with big, excessive-dimensional datasets. Their "black-container" nature, on the other hand, makes them difficult to recognize, which can be a problem in clinical situations in which knowing why a prediction is made is essential for making choices.

- Step 1. Input Layer to Hidden Layer (Weighted Sum and Bias)

$$z^{\{[1]\}} = W^{\{[1]\}} * x + b^{\{[1]\}}$$

Where:

- z^{[1]} is the result of the weighted sum for the first layer (pre-activation).

- Step 2. Activation Function

$$a^{\{[1]\}} = \sigma\left(z^{\{[1]\}}\right)$$

Where:

- σ is the activation function (e.g., sigmoid, ReLU, or tanh),

- a^{[1]} is the output from the hidden layer (post-activation).

- Step 3. Hidden Layer to Output Layer (Weighted Sum and Bias)

$$z^{\{[2]\}} = W^{\{[2]\}} * a^{\{[1]\}} + b^{\{[2]\}}$$

Where:

- W^{[2]} is the weight matrix for the output layer,

- a^{[1]} is the output from the hidden layer,

- Step 4. Output Layer Activation

$$\hat{y} = \sigma^{\{[2]\}(z^{\{[2]\}})}$$

Where:

- ŷ is the predicted output of the neural network,

- σ^{[2]} is the activation function for the output layer (e.g., softmax or identity).

- **Support vector machines**

Assist Vector Machines (SVMs) are a robust institution of guided gaining knowledge of algorithms that are generally used to locate neurodegenerative sicknesses via classification and regression responsibilities. SVMs work well with huge datasets with lots of dimensions. That is why they are often used for clinical, genetic, and imaging records with hundreds or heaps of functions. The intention of SVMs is to maximise the space among training even as minimising type errors. They do this by using locating the quality hyperplane that fine separates one-of-a-kind types of statistics in a excessive-dimensional feature area. SVMs had been used on one-of-a-kind kinds of information to discover neurological diseases, like Genius images, genetic tendencies, and scientific data. for example, SVMs can sort Alzheimer's patients into companies based totally on MRI readings that show such things as hippocampal volume, brain cortical thickness, or other signs and symptoms of neural loss. Even though the changes are small, the SVM algorithm attempts to discover the first-rate choice limit which could tell the distinction between healthful people and those with early-level Alzheimer's. In the identical method, SVMs are used to institution human beings with Parkinson's disorder based totally on their motion signs and symptoms, speaking styles, and issues with their strolling. One gain of SVMs is that they can work properly with small datasets. This is useful due to the fact it can be hard to get large datasets which have been labelled for observe on neurological illnesses. SVMs also can deal with noise or lacking records well, that's something that happens lots in real-international healthcare programs. SVMs are also very bendy and may be quick changed to paintings with multiple elegance. This makes them appropriate for spotting and telling the distinction among numerous neurodegenerative sicknesses, like Alzheimer's, Parkinson's, and Huntington's. One of the fundamental issues with SVMs, although, is that they are hard to application, especially whilst running with massive datasets.

2. Selection of models for early diagnosis and prediction

Its miles very essential to choose the proper AI models for early detection and prediction of neurological illnesses (NDs) in order to enhance patient consequences and ensure that treatments start on time. Because these diseases are complex and there are numerous sorts of information concerned, model choice is a challenging however necessary process. For early identity to work, AI models want with a view to find small trends in records that factor to the start of a sickness earlier than there are any primary signs and symptoms. Those elements determine the form of records, the disease being studied, and the result this is wished, inclusive of type, regression, or forecasts of how the disorder will progress. Neuroimaging data, like MRI, pet, and fMRI scans, can be analysed thoroughly with deep studying fashions, especially convolutional neural networks (CNNs). These models are very correct at locating small adjustments in the Genius's shape that medical practitioner often cannot see within the early degrees of an ailment. CNNs can find early signs of Alzheimer's disease, like hippocampal shrinkage or amyloid plaque build-up, which are very important for identification. In the same way, deep learning models can look at movement patterns and brain abnormalities in Parkinson's disease to predict when signs will start showing up long before they do. CNNs are great for these kinds of jobs because they can handle large amounts of data and instantly pull out important features from raw pictures. Support Vector Machines (SVMs) are often used for certain types of data, like genetic information and clinical reports. When it comes to classification jobs, SVMs work really well, especially when the data is very complicated, like in genetic and clinical datasets.

C. Explainability in AI Models

1. Techniques for explainability

- **SHAP**

SHAP, which stands for "SHapley Additive Explanations," is a popular way to explain machine learning model results in a way that is clear and consistent. SHAP is based on cooperative game theory, especially Shapley values, which figure out how much each trait helps the model make a guess. The main idea is to think of the model's prediction as a "game" with each feature as a "player." To figure out how important each player is, you compare the model's output with and without the feature. SHAP values make sure that each feature's input is spread out evenly. They also give a thorough description of how each feature affects the forecast made by the model. When it comes to finding neurodegenerative diseases, SHAP can be very helpful for breaking down complicated models like deep learning and ensemble methods, which are often thought of as "black boxes." When doctors figure out the SHAP values for each input trait, like a clinical score, an MRI scan area, or a genetic marker, SHAP helps them understand why they made a certain decision. For instance, when predicting Alzheimer's disease, SHAP values can show how things like brain thickness or amyloid plaque levels affect the model's decision. This makes the diagnosis more clear. This level of explainability makes clinicians more likely to believe AI models, making sure that the results are in line with clinical thinking and giving clinicians useful information for improving patient care.

- **LIME**

Every other not unusual thanks to describe device gaining knowledge of model consequences are through LIME, which stands for "neighbourhood Interpretable model-agnostic reasons." LIME focuses on giving neighbourhood reasons for man or woman statements, while SHAP offers a international account of how essential a feature is. By means of changing the raw information and watching how the version's estimates trade, the technique creates a smaller model this is less difficult to recognize for the area of hobby. This replacement model can be understood domestically and attempts to imitate how the complex model could act in that specific situation. While seeking for neurological sicknesses, LIME assists you to recognize how to make predictions for every patient. as an instance, if a deep learning model says that a affected person has a high hazard of Alzheimer's ailment, LIME can explain which particular elements, like cognitive rankings or MRI outcomes, had been maximum important in making that decision. Clinicians can advantage from this localised technique as it facilitates them understand what precipitated a certain analysis. This facilitates to affirm the version's predictions and makes it easier to apply AI insights in clinical selection-making.

2. Integration of explainable AI methods into the detection models

Clinicians need to know why an AI-driven evaluation is made to make sure it fits with their clinical knowledge and thinking. Adding SHAP and LIME to machine learning models helps solve the problem that many AI methods are "black boxes." For example, if you use deep learning models (like convolutional neural networks to look at MRI pictures), the model might tell you if a patient is likely to get Alzheimer's disease. But doctors might not be able to trust the model's decision-making process without an explanation. You can measure the importance of each feature (like hippocampal thickness or brain thinning) using SHAP. This lets the doctor know how each feature affected the choice. This openness makes sure that the estimate made by the model can be judged in light of the patient's medical background. In the same way, LIME can be added to the model's process to give local, real-time reasons for specific patient forecasts.

IV. Implementation of XAI Models for Neurodegenerative Disease Detection

A. Overview of the implemented XAI model

To use an Explainable AI (XAI) model to find neurological diseases, machine learning methods must be combined with techniques that make sure the results can be understood. We use a deep learning model, like a Convolutional Neural Network (CNN), to look at neuroimaging data, like MRI and PET scans. We then use XAI methods, such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations), to make the decision-making process clear and easy to understand.

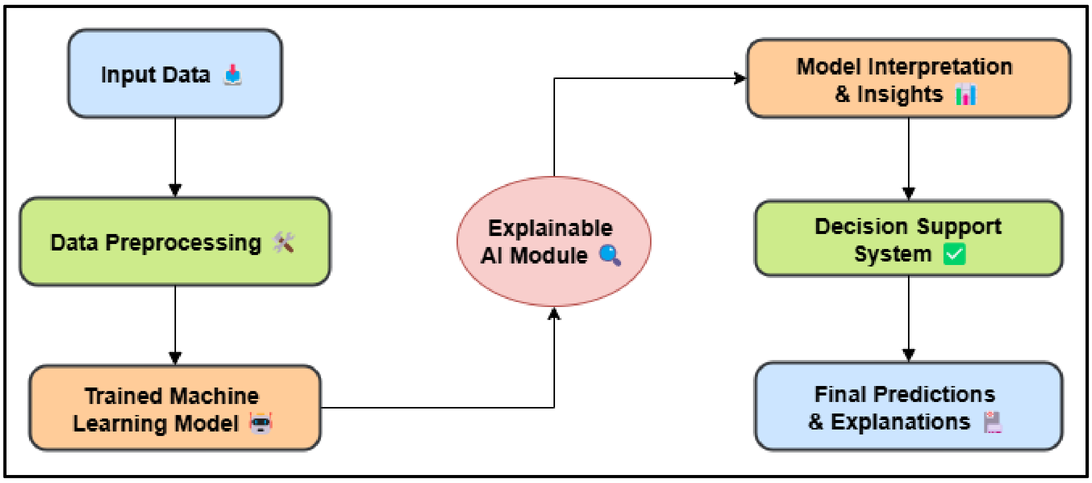

Figure 3: Illustrating Overview of the Implemented XAI Model

Based on brain pictures, clinical traits, and DNA data, this combined model tries to find neurological diseases like Alzheimer's and Parkinson's in their early stages. Figure 3 shows an outline of the explainable AI model that was used to predict diseases. Deep learning models, like CNN, are used to automatically pull out hierarchical features from large amounts of image data. SHAP and LIME then give both local and global reasons for the results. The result of these methods can help doctors understand how different traits (like certain brain areas or genetic markers) affect the model.

B. Model training and validation

Version schooling and assessment are important steps to make certain that the XAI version for locating neurodegenerative illnesses works well and can be used in different conditions. The model is based totally on a hard and fast of facts that consists of brain records (which include MRI or puppy scans), scientific statistics (which includes age, cognitive rankings, and motion signs and symptoms), and genetic facts (if any is to be had). all through education, the dataset is break up into a training set and a validation set, typically with an 80-20 or 70-30 ratio. This maintains the model from becoming too desirable at what it does and makes certain it could do well with new statistics it hasn't visible earlier than. The model learns to locate developments inside the data that are related to neurological illnesses and their development even as it's far being educated. Backpropagation and optimisation strategies like stochastic gradient descent are used to train the neural network with the aid of converting the weights to make the loss function as small as possible. Regularisation methods like dropout or weight decay can be used to maintain the model from becoming too properly. During training, validation is carried out on a normal basis to test how well the model works on new data. This makes certain that it can appropriately predict consequences for distinct businesses of sufferers. Go-validation strategies, along with ok-fold cross-validation, also are often used to test the steadiness and trustworthiness of a model. After being taught, the version is put to the take a look at on a separate set of facts to look how well it did universal. This includes locating important assessment measures like accuracy, sensitivity, and precision.

C. Evaluation metrics (accuracy, sensitivity, specificity)

Model training and evaluation are essential steps to make sure that the XAI model for locating neurodegenerative diseases works nicely and can be utilized in other situations. The model is based on a set of information that includes intelligence statistics (which include MRI or pet scans), medical information (which include age, cognitive rankings, and movement signs), and genetic records (if any is available). During training, the dataset is break up right into a schooling set and a validation set, normally with an 80-20 or 70-30 ratio. This maintains the model from turning into too good at what it does and makes certain it can do properly with new facts it hasn't seen earlier than. The model learns to locate tendencies inside the facts which can be related to neurological diseases and their development even as it's miles being skilled. Backpropagation and optimisation strategies like stochastic gradient descent are used to teach the neural network by means of converting the weights to make the loss characteristic as small as viable. Regularisation techniques like dropout or weight decay may be used to keep the version from fitting too properly. At some point of schooling, validation is performed on a regular foundation to test how well the model works on new facts. This makes sure that it can correctly are expecting effects for one of a kind companies of sufferers. Cross-validation strategies, such as okay-fold move-validation, are also frequently used to check the steadiness and trustworthiness of a version. After being taught, the model is put to the take a look at on a separate set of information to peer how properly it did normal. This includes finding essential evaluation measures like accuracy, sensitivity, and precision.

V. Conclusion

The usage of Explainable AI (XAI) to enhance the discovery of neurological illnesses has plenty of potential to make early diagnosis, prediction, and patient care much higher. Neurodegenerative illnesses, like Alzheimer's and Parkinson's, are very hard to deal with because they get worse through the years, have complex reasons, and display mild signs and symptoms early on. The method we diagnose diseases now's helpful, however it would not always locate them inside the early ranges, whilst treatment is most likely to paintings. AI models, especially those that use deep mastering and gadget studying, are sturdy thanks to examine big datasets like genetic facts, talent records, and medical facts. Those models might be able to discover trends and expect how diseases will worsen which can be tough to locate another method. One huge problem with using AI in healthcare, although, is that many gadget mastering models are tough to understand. If decision-making isn't clear, doctors might not trust AI-based estimates, especially in important areas like diagnosing neurological diseases. This is where XAI tools like SHAP and LIME come in very handy. XAI improves the trustworthiness and acceptance of AI in clinical practice by giving reasons for model results that are easy for humans to understand. SHAP uses game theory to make predictions, and LIME uses localised, substitute modelling to help doctors understand how certain traits, like brain areas or cognitive scores, affect predictions. This builds trust and helps people make better decisions. There are still some problems to solve when using AI and XAI to find neurological diseases, such as making sure the data is accurate and varied, making sure the models can be used in other situations, and figuring out how to use XAI techniques in real-life clinical processes. To get the most out of AI in this field, future study should focus on getting past these problems by making sure datasets are strong and varied, making models more general, and creating easier to understand and more effective ways to explain things.

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