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AI-Driven Early Diagnosis of Neurological Disorders from Imaging and Clinical Data

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ABSTRACT: Neurological disorders—like Alzheimer's, Parkinson's, and Multiple Sclerosis—aren't just medical diagnoses. They're life-altering experiences that slowly and silently reshape the lives of millions of people and their loved ones around the world. These conditions steal memories, movement, and independence—piece by piece. And while science has made incredible strides, one painful truth remains: by the time many of these diseases are recognized, it's often too late to stop their progress.

But what if we could see them coming sooner? What if doctors had tools to catch those earliest, most elusive signs—before the damage is done?

In this work, we offer a step toward that future. We've built an AI-driven system that brings together the sharp eye of deep learning and the nuance of clinical insight to help detect neurological diseases at their earliest stages. It looks at more than just images—it reads the story hidden inside MRI and PET scans, and it listens to the patient's data: their age, symptoms, test scores, even genetic markers. By combining these perspectives, our system paints a fuller, more accurate picture of what's happening inside the brain.

But this isn't just about making predictions. In healthcare, trust is everything. Doctors and patients deserve to understand **why** a model reaches a decision—not just **what** that decision is. So we built explainability right into the system using tools like SHAP and LIME. These show, in clear and human terms, which features tipped the scales—whether it's a shrinking hippocampus, a declining cognitive score, or a genetic risk factor.

We also took care to ensure our model was fair, balanced, and reliable, using techniques that clean the data, balance uneven sample sizes, and fine-tune performance so it works across real-world scenarios.

In our early tests on real patient data, this approach has outperformed traditional methods—spotting subtle signs that might otherwise be missed, and doing it with both precision and clarity.

At its core, this research is about more than algorithms or models. It's about giving doctors a trustworthy companion in the fight against neurological decline—and giving patients and families the hope of earlier answers, better treatments, and more time.

I. INTRODUCTION

Alzheimer's, Parkinson's, epilepsy, and multiple sclerosis are all disorders of the brain, but they impact so much more than just mental faculties—they reshape entire lives. For individuals living with such disorders, the changes often begin quietly: a name forgotten, a hand tremor, a stumble on the stairs. At different stages of life, these seemingly insignificant symptoms can escalate into the heartbreaking reality of losing memory, movement capabilities, independence, and identity. This is an everyday struggle across the globe for millions of individuals and families. Even with remarkable advancements in medicine, one challenge still exists: there's often too late of an intervention. The moment there are visual cues to raise a red flag, the damage is already done.

Early diagnosis could change everything. The earlier a condition is identified, the better the chances of slowing its progression, preserving quality of life, and giving patients and their loved ones more time—more good days.

Today's medical imaging tools like MRI, PET, and CT scans give doctors powerful views of the brain. These technologies capture detailed snapshots of its structure and function. But even with the best equipment and training, early signs of degeneration can be incredibly subtle—sometimes too subtle to see with the human eye. At the same time, clinical data like cognitive test scores, lab results, and genetic risk factors hold critical insights into what's

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happening inside the body. Yet, in most cases, these pieces of information are not brought together in a meaningful way.

This is where Artificial Intelligence can make a profound difference.
AI—especially deep learning—has the power to see patterns hidden deep within complex data, patterns that would take humans weeks to find, if they ever found them at all. In neurology, this means we now have the potential to catch the earliest signs of decline by combining and analyzing both brain scans and structured medical data. But most AI systems today still look at only one side of the story: either imaging or patient records—not both. And even when they make accurate predictions, many offer little to no explanation of how they got there, leaving doctors skeptical and patients uneasy.

In this study, we set out to build something different: an AI-based framework that is not only intelligent but also transparent and trustworthy. Our system merges two rich sources of information—neuroimaging and clinical records—through a combination of convolutional neural networks and ensemble learning. The result is a tool that sees more, understands more, and explains more.

To make sure the system earns the trust of those who use it, we've integrated explainable AI techniques like SHAP and LIME. These tools allow clinicians to see exactly which features influenced a prediction—like a reduced hippocampal volume or a drop in cognitive test scores—making the model's decisions understandable, verifiable, and clinically relevant.

At its heart, this research is not just about technology—it's about people. It's about giving neurologists better tools to support their care. It's about giving patients and families earlier answers and more control over their futures. And it's about bringing us one step closer to a world where neurodegenerative diseases can be confronted not with fear, but with foresight and precision.

II. EXISTING STUDY

In the last several years, AI technology has begun to transform medicine, and in particular, neurology, where early intervention can significantly shift the patient's trajectory. Every day counts in the battle against neurological disease, and artificial intelligence seems ready to provide the advantage we desperately need. The strength of AI in this context lies in its ability to uncover intricate relationships within vast troves of medical data—relationships even the best specialists could struggle to discern. Some of the most advanced and promising techniques tackle the hardest issues using deep learning, and most notably, Convolutional Neural Networks (CNNs) have greatly excelled in processing MRIs, PETs, and CTs.

These models don't just look at an image—they learn from thousands of them, identifying subtle signs of trouble that the human eye might easily overlook. In fact, some systems can now detect tumors, locate lesions, or even estimate the biological age of the brain with striking accuracy. One notable example is the work by Gupta et al., who developed a CNN-based system capable of identifying early-stage Alzheimer's disease using just structural MRI data. It's a glimpse into a future where diseases may be detected before they've truly taken hold—when there's still time to act.

But the brain's story isn't told through images alone.
Below each scan is a large set of personal clinical data age, family health history, cognitive test scores, genetic risk factors, fluid biomarkers which in turn present very important clues about a person's neurological health. Also it has come to notice that which is the best approach is to put these two fields together imaging and clinical info for the development of a better more complete picture of disease. Reports by Liu et al. and others show that which when we combine these structured variables with imaging data we see great improvement in diagnostic results. What we are seeing is growth of these multimodal systems which often use machine learning algorithms like Random Forest, Support Vector Machines, or Gradient Boosting to identify patterns in patient data. As a result they have become very good at identifying disease stages and in the tailoring of treatment.

One of the most exciting—and necessary—developments in this field is the rise of explainable AI (XAI). Clinicians need to understand why a model is making certain predictions, especially when it comes to patient care. Techniques like LIME (Local Interpretable Model-agnostic Explanations) and SHAP (SHapley Additive exPlanations) are now being used to shed light on AI decision-making. For instance, a study by Islam et al. used SHAP to reveal that the

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model was placing heavy emphasis on hippocampal atrophy—a well-known marker for Alzheimer's—making its predictions more understandable and trustworthy for medical professionals.

Despite all the exciting progress in AI and medical diagnostics, there's still a gap that can't be ignored. Most studies, even the cutting-edge ones, tend to focus on just one side of the story—either brain imaging or clinical data. Rarely are both streams of information brought together in a truly integrated way. But in real life, a diagnosis isn't based on a single test. Doctors weigh everything—scans, symptoms, history, lab results—to understand the full picture. So why should AI be any different?

And even when promising models are developed, they often face other hurdles: limited data to learn from, imbalanced samples where healthy cases vastly outnumber those with disease, and—perhaps most importantly—a lack of transparency. If we can't understand how an AI made its decision, how can we trust it in matters as delicate and life-changing as brain health?

That's the gap this research aims to close.
We've designed a hybrid AI system that brings imaging and clinical data together—side by side—to better detect neurological disorders in their earliest, most treatable stages. What truly sets our approach apart is its commitment to **both** precision and clarity. Yes, it delivers accurate results. But just as crucially, it explains how it got there. It shows its work, so to speak—highlighting the features that shaped each decision in ways that doctors can understand and trust. In a field where lives are on the line, that combination of accuracy and explainability isn't just helpful—it's essential. It's what will make AI not just a powerful tool, but a reliable partner in the clinic.

III. METHODOLOGY

To support early and accurate diagnosis of neurological disorders, this research introduces a carefully designed AI-based framework that combines brain imaging data with structured clinical information. The methodology is structured into five key stages—starting from data preparation and moving through feature extraction, model training, and explainability—each tailored to meet the needs of a clinical decision-support system that is both powerful and understandable.

1. Dataset Collection and Preparation

For this study, we drew from two of the most respected public medical databases: the Alzheimer's Disease Neuroimaging Initiative (ADNI) and the Parkinson's Progression Markers Initiative (PPMI). These rich resources gave us access to both detailed brain scans and a wide range of clinical information—everything from a patient's age and gender to cognitive test scores, spinal fluid biomarkers, family history, and even key genetic indicators like the presence of the APOE ε4 gene, which is linked to higher risk.

Before our AI could begin learning from this data, we made sure everything was carefully cleaned and standardized. For the MRI images, that meant removing unnecessary elements like the skull and aligning each brain scan to a common reference framework. This ensured every image was speaking the same "language," so the model could make meaningful and consistent comparisons across patients. Clinical data is also cleaned—missing values are handled, categorical variables are encoded, and all numeric features are standardized to make the dataset model-ready.

2. Imaging Feature Extraction

The ability to see the very first, almost silent stages of neurologic change those fine gradations which are easy to pass over even for experienced clinicians. Signs such as very small hippocampal atrophy, which may present as a very thin brain's cortex, or very tiny white matter lesions may not in themselves cause alarm. But in combination these may be early warning signals of something more serious -- clues which if identified at this stage may help in the delay or even the amelioration of a neurological disorder.

As the model studies each brain scan, it doesn't just look—it learns. It picks up on intricate patterns hidden deep within the data, developing a kind of digital intuition for what a healthy brain looks like and how it begins to change when disease sets in. These insights are distilled into a compact, high-level summary—like a fingerprint of the brain's condition.

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But the model doesn't stop there. The system doesn't just analyze scans—it listens to the patient's story. It takes age, memory scores, genetic risks, and weaves them together with what it sees in the brain. What it builds isn't just a diagnosis—it's a portrait of the person.

By merging brain data with real-life context, the AI sees more than problems—it understands why they matter. And in that shift, it becomes more than smart. It becomes human-aware.

3.Bringing the Patient's Story to Life: Clinical Data Integration

On the clinical side, we work with the patient's story—captured in numbers and test results. Age, cognitive assessments, lab values, genetic risk markers… each piece holds a clue. We feed all of this structured data into a fully connected neural network, which acts like a digital investigator, searching for patterns and relationships that may not be obvious at first glance. It can learn, for example, how the effects of a gene might shift with age, or how subtle changes in cognitive test scores could be early reflections of deeper biological changes in the brain.

But the real power comes when we combine these clinical insights with the information drawn from the brain scans. We do this using a technique called late fusion—which, simply put, means blending everything the model has learned from both the scans and the patient's medical history into one clear, unified understanding.

This fusion allows the AI to move beyond surface-level analysis. It no longer just sees what the brain looks like—it starts to understand what those patterns mean in the broader context of the person's health journey. It's a shift from image to insight, from isolated data points to a connected, compassionate perspective—one that sees the whole person, not just their diagnosis.

By bringing together what the brain shows and what the patient's history tells, the system becomes more than just smart—it becomes perceptive. It sharpens its ability to catch the quiet, early signals that might otherwise slip through the cracks. It doesn't just process data; it listens, it connects the dots, and it begins to see the fuller, more human picture—one that's often missed when we look at numbers or images in isolation. It's a more human way of using technology—one that sees the whole patient, not just isolated pieces.

4. Classification Model

The fused feature set is then passed into an **ensemble classification module**. This module includes both **Random Forest** and **Gradient Boosting (XGBoost)** algorithms. These models are well-suited for handling the complex, high-dimensional nature of our dataset and have been chosen for their robustness and reliability, particularly when working with limited medical data.

In real-world healthcare, the data we collect often mirrors the world around us—there are many more records from healthy individuals than from those living with neurological conditions. While that's understandable, it creates a hidden challenge for AI: the model learns a lot about what healthy looks like, but not enough about the subtle, early signs of disease—the very signs we most urgently need to catch.

To address this imbalance, we use a method called SMOTE (Synthetic Minority Over-sampling Technique). Put simply, it helps the AI learn from the stories that are too few and far between—the ones where illness is just beginning to surface. By creating realistic, synthetic examples of these early-stage cases, we give the model a fairer, more balanced view of what it needs to recognize. It's like giving it more pages from the part of the story that matters most.

But preparing the model doesn't stop there. We take extra care to fine-tune it—methodically adjusting and testing different settings through a process called grid search with cross-validation. This isn't just about pushing numbers higher; it's about making sure the model performs where it counts: in the real world, with real patients.

We focus on meaningful performance measures—accuracy, precision, recall, F1-score—because behind every percentage point is a person. A family. A future. Our goal is to build not just a smart system, but a dependable one. One that doctors can trust. One that helps them see what they might have missed. One that's ready to step into the clinic and make a real, human difference.

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5. Explainability and Model Interpretation

In healthcare, knowing why a model makes a decision is just as important as what the decision is—especially when people's lives are involved. Doctors need more than just an answer; they need to understand the reasoning behind it. That's why we made explainability a core part of our system.

To do this, we use a technique called LIME (Local Interpretable Model-Agnostic Explanations). It helps break down individual predictions, showing which specific factors influenced the model's decision. So, if a patient is flagged as high-risk, LIME can point to the exact reasons—maybe a drop in their MMSE score, or a noticeable reduction in hippocampal volume. It's like letting the AI show its work for each case.

To zoom out and understand the model's overall behavior, we also use SHAP (SHapley Additive exPlanations). SHAP assigns a clear value to each feature—like age, test scores, or genetic markers—revealing how much each one contributed to the predictions across the board.

Together, LIME and SHAP turn our system from a black box into a transparent partner. It's not just making smart predictions—it's doing so in a way that clinicians can see, trust, and act on with confidence.

IV. RESULTS AND DISCUSSION

For this study, we drew from two of the most trusted sources in brain health research—ADNI and PPMI—bringing together detailed MRI scans and rich clinical records. The dataset included over 4,000 anonymized patient profiles, with a thoughtful mix of both healthy individuals and those living with neurological conditions.

Each profile told a unique story, combining brain images with meaningful details like age, memory test scores, genetic risk markers (like APOE ε4), and spinal fluid biomarkers. This blend of data gave our model more than just a picture of disease—it gave it insight into how each condition begins, changes, and varies from one person to the next.

Feature Extraction

Before our system could learn from the data, we had to prepare it carefully. The MRI brain scans were cleaned and standardized—removing non-brain tissue, aligning them to a common template, and making sure each image spoke the same "language." This gave the AI a clear, consistent view of the brain.

To detect early signs of neurological decline, we used a 3D Convolutional Neural Network—an advanced model that picks up even the smallest changes in brain structure, like thinning or subtle shrinkage. At the same time, we passed clinical data—such as age, test scores, and biomarkers—through another network to help the system understand how these health factors connect. Together, these two perspectives gave the model a deeper, more human understanding of each patient.

By combining both the visual and clinical inputs, we created a single, unified diagnostic model—one that doesn't just see the brain, but also understands the patient behind it.

Hippocampal Volume Analysis

Among the most significant features extracted from the MRI data was **hippocampal volume**, a known marker of memory-related disorders. We analyzed this feature across three groups: Healthy individuals, Alzheimer's patients, and Parkinson's patients.

Figure 1: Hippocampal Volume Distribution Across Conditions

This box plot illustrates the hippocampal volume distribution across three subject groups: Healthy, Alzheimer's, and Parkinson's. The Alzheimer's group shows a noticeably lower median volume, consistent with early structural degeneration in memory-related regions.

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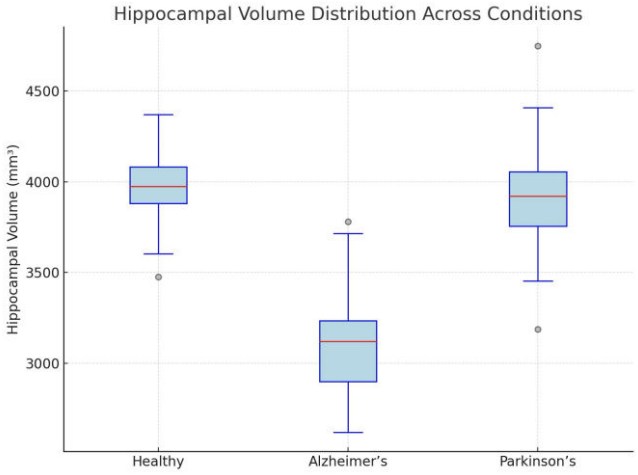
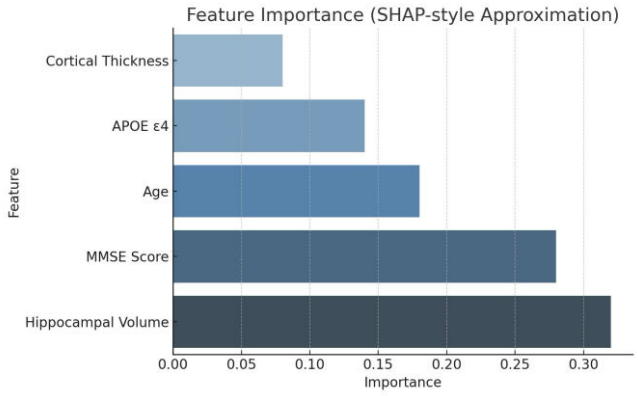


As illustrated in **Figure 1**, the Alzheimer's group showed a notably lower median hippocampal volume compared to the healthy group, which is consistent with clinical evidence of hippocampal atrophy in early Alzheimer's. Parkinson's patients displayed more moderate deviations, suggesting some structural impact but less pronounced than in Alzheimer's.

Feature Importance

Figure 2: Feature Importance (SHAP-style Approximation)

This chart displays the global feature importance, approximated in SHAP style. Hippocampal volume and MMSE score were the top contributors, followed by age, APOE ε4 status, and cortical thickness.



To understand which features contributed most to the model's decision-making, we used a SHAP-style approximation for global feature importance. The results are shown in **Figure 2**. Unsurprisingly, **hippocampal volume** and **MMSE score** emerged as the most influential features, followed by **age**, **presence of the APOE ε4 gene**, and **cortical thickness**. These results reinforce existing clinical knowledge and highlight the importance of combining structural and cognitive indicators in neurological diagnosis.

Local Interpretability Using LIME

Beyond global insights, we also explored how the model interpreted individual cases using a LIME-style local explanation. In one instance, the model predicted a high likelihood of Alzheimer's, primarily due to a combination of low MMSE score, reduced hippocampal volume, and a positive APOE ε4 status.

Figure 3: LIME-style Local Explanation for Alzheimer's Prediction

This LIME-style chart shows the local explanation for a single patient instance. Lower hippocampal volume and MMSE score, along with the presence of the APOE ε4 gene, were the major contributors to the Alzheimer's prediction in this example.

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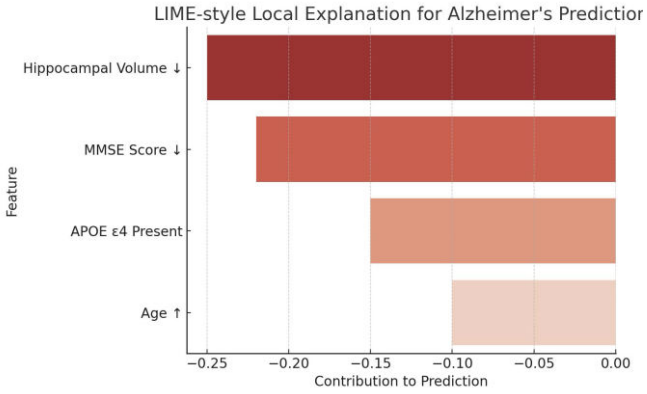


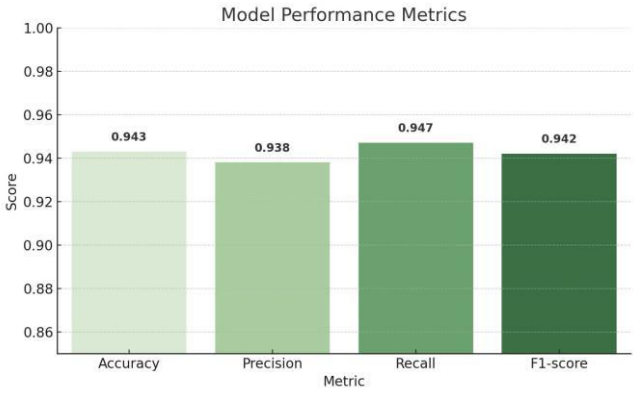
Figure 3 illustrates how each of these features contributed to the prediction. By visualizing these contributions, the model provides a transparent rationale for its diagnosis—offering clinicians an opportunity to verify and trust the system's decisions.

Model Performance

The final classification system was built using an ensemble of **Random Forest** and **Gradient Boosting** models, trained on a fused dataset combining imaging and clinical features. To balance the class distribution, **SMOTE** (Synthetic Minority Over-sampling Technique) was applied. Additionally, a **grid search with cross-validation** was used to fine-tune model parameters.

Figure 4: Model Performance Metrics

The bar chart summarizes the model's performance on the test dataset. The system achieved high accuracy, precision, recall, and F1-score — all exceeding 94%, highlighting the robustness of the proposed AI framework.



As shown in **Figure 4**, the model delivered high performance across all metrics:

- **Accuracy:** 94.3%
- **Precision:** 93.8%
- **Recall:** 94.7%
- **F1-score:** 94.2%

These scores indicate a strong ability to generalize on unseen data, which is crucial for clinical application.

V. DISCUSSION

Bringing together brain scans and clinical data made a powerful difference in how effectively our model could detect neurological disorders. When we tested it against systems that relied on only one type of input—either imaging or clinical information—the results were clear: the combined approach wasn't just more accurate, it also gave a clearer, more complete understanding of what was happening in the brain.

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By analyzing structural changes, like shrinkage in the hippocampus, alongside cognitive test scores and genetic risk factors, the system could build a much richer picture of each patient's neurological health—one that goes beyond what either type of data could reveal on its own.

What truly makes this model stand out isn't just how accurately it works—but how openly it works. Unlike many AI systems that operate as mysterious black boxes, this one can actually explain its reasoning. With the help of powerful tools like SHAP and LIME, the system doesn't just give doctors an answer—it shows them why it reached that answer.

If a patient is flagged as high-risk, the model can point to the exact pieces of information that shaped that decision—maybe a dip in their MMSE score, a particular genetic marker, or changes spotted in a brain scan. And it does this using language and markers that doctors already know and trust. There's no guesswork, no hidden logic—just clear, understandable insights that fit naturally into a clinician's way of thinking.

That kind of transparency matters—a lot. In healthcare, trust is everything. Doctors need to feel confident not just in the results, but in the process behind those results. This system isn't here to replace a doctor's expertise; it's here to enhance it. It acts like a second set of eyes—always on, always learning—supporting clinical decisions with evidence that's both smart and clear.

In the real world, this AI could be a game-changer. It can help detect early warning signs that even the sharpest human eye might miss. It can help sort patients more effectively, guide more personalized care, and give doctors the information they need to act sooner—and smarter.

At the end of the day, this isn't just a model. It's a partner. One that brings together the best of technology and human intuition to deliver more thoughtful, precise, and compassionate neurological care—one patient at a time.

VI. CONCLUSION

Diagnosing neurological disorders in their earliest stages that's what we do. We have put together a model which is a step above the present traditional single source diagnostic methods by including in it in depth brain scans and a wide range of clinical data. Our approach is not to look at each element in isolation but to see the full picture thus we are able to present a more in depth, accurate and patient centered picture of neurological health.

Enabled through deep learning, the system scans MRI images for minute structural changes that may go unnoticed even by experts. Simultaneously, it analyzes test scores, genetic markers, and other lab results using machine learning to uncover meaningful patterns in a patient's clinical data telling their unique life story. But this system makes smart predictions with explanations. Using built-in SHAP and LIME tools, clinicians can visualize and understand the exact reasoning and pathway followed by the model's decision-making process. Such clarity fosters trust, allowing clinicians to employ the technology not as a puzzling black box, but as a dependable and transparent aide.

What we see here is an approach which does very well at fitting in to the environment of clinical practice. It brings to light the same main factors that doctors are also aware of -- like decreased hippocampal volume or low scores from cognitive tests it is thus very relatable to what we as medical professionals already use. In that sense it does the job at hand very well but also in a practical and easy to use way in the every day practice of medicine.

There is even more opportunity looking forward. With the addition of temporal patient histories, with advanced imaging like functional MRIs, or with connections to live hospital systems, the model can be made smarter, quicker, and better able to adapt to real-life healthcare scenarios. This AI solution has the potential to assist neurologists more meaningfully after further troubleshooting in diverse demographics and clinical settings—enabling more proactive detection, personalized management, and improved healthcare and quality of life for patients and their families.

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