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Early Alzheimer's Disease Detection Using EEG Brain Signals

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Abstract: *Alzheimer's Disease (AD) is a progressive neurodegenerative disease, and early detection is essential for meaningful interventions to improve patient outcomes. While there are diagnostic modalities such as PET scans that can be effective in detecting AD, they tend to be expensive, invasive, or impractical, illustrating the need for more usable alternatives to monitor the progression of AD.*

Electroencephalography (EEG) is a non-invasive and inexpensive way to monitor brain activity, and it has the potential of being a useful way to identify early markers of AD before significant cognitive decline as well. However, a reliable EEG detection model still must overcome the two significant challenges of a lack of large- scale labelled datasets sufficient for training, and considerable variability in EEG signals across individuals, which can ultimately greatly affect the generalizability of EEG models for helpful detection of AD through these differences. In this paper, we propose a novel deep learning framework to address these challenges with self-supervised learning. Our framework consists of a pre- training phase from a large, unlabelled corpus of general EEG data to extract the universal features of brain signals without needing to depend on scarce AD-specific labels. We then use a fine-tuning phase to adapt the model to the classification problem using a smaller, labelled AD dataset. The model architecture can acquire both spatial and temporal features from EEG signals, which EADDs to a more comprehensive method of analysis. The experimental results clearly indicate that this approach offers a substantial improvement in AD detecting performance and that there was an increase in F1 scores at both the sample and the subject level over the current state f-the-art methods. This research outlines the ability of self- supervised contrastive learning to mitigate the problems of data scarcity and inter-subject variability and can contribute towards more accurate and scalable AD diagnostic tools.

Keywords: *Alzheimer's Disease, neurodegenerative, Electroencephalography, non- invasive, deep learning, self-supervised learning.*

I. INTRODUCTION

Framework that leverages both sample-level and subject-level contrastive learning to pretrain EEG feature extractors, which are then fine-tuned for subject-level AD classification. The system will be trained on multiple public AD datasets (ADNI, AIBL, OASIS) and will undergo standardized preprocessing, including artifact removal, filtering, and epoching. The features from both temporal and spatial branches will be fused and fine-tuned using available labelled data to perform binary classification (AD vs. Normal Control), with final subject-level predictions derived through majority voting over multiple EEG epochs. The system's performance will be evaluated using cross-validation across subjects and datasets, with metrics including accuracy, precision, recall, and AUC, to improve the accuracy, cross-dataset generalization, and clinical applicability of EEG-based AD detection.

II. LITERATURE SURVEY

Alzheimer's disease (AD) is a progressive neurodegenerative disorder that severely affects memory, cognition, and daily functioning. [1] Early detection is critical for timely intervention, improved patient care, and slowing disease progression.[2] Traditional diagnostic methods. such as neuroimaging and cerebrospinal fluid analysis are often invasive, expensive, and not widely accessible, particularly in low-resource settings. In this context encephalography (EEG) has emerged as a promising non-invasive, cost-effective, and portable tool for assessing brain activity and identifying neurological abnormalities associated with AD. This literature survey explores various recent research studies that utilize EEG signals the early diagnosis of Alzheimer's disease. [3] It provides a comparative analysis of efferent methods including machine learning algorithms, deep learning models, EEG signal processing techniques, and feature extraction frameworks. [4] Each study is evaluated based its methodological contributions, classification accuracy, dataset size, and practical applicability. [5] The survey aims to highlight the current advancements, advantages, and limitations in this growing field, thereby providing a strong foundation for developing an efficient and accurate Alzheimer's detection system using EEG signals. learning models, EEG signal processing techniques, and feature extraction

frameworks.[4] Each study is evaluated based its methodological contributions, classification accuracy, dataset size, and practical applicability. [5] The survey aims to highlight the current advancements, advantages, and limitations in this growing field, thereby providing a strong foundation for developing an efficient and accurate Alzheimer’s detection system using EEG signal.

III. PROPOSED METHODOLOGY

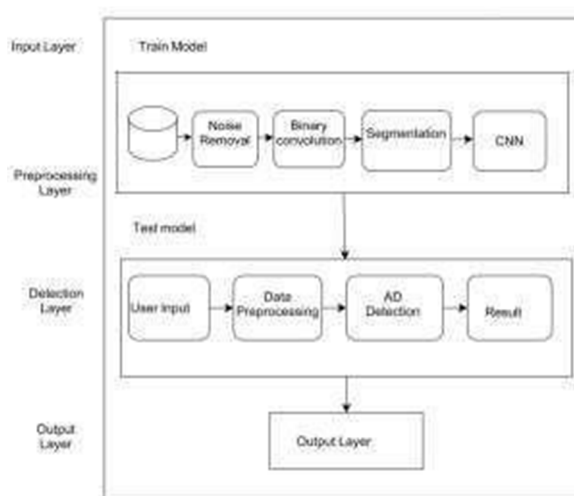


Fig. 2. Proposed System

The EEG-based Alzheimer's disease detection system follows a layered architecture. It begins with EEG signal acquisition from medical datasets or real-time devices, followed by preprocessing steps such as filtering, artifact removal, and normalization to ensure clean input data. Relevant features are then extracted from time, frequency, and wavelet domains and fed into machine learning or deep learning models such as Support vector machine (SVM), Random forest, Convolutional neural network (CNN), or Long short-term memory (LSTM) to classify signals into Normal, Mild Cognitive Impairment (MCI), or Alzheimer’s categories. The system securely stores patient data and results in a database and provides a user-friendly interface that visualizes EEG signals, displays classification probabilities, and generates reports for clinicians and researchers.

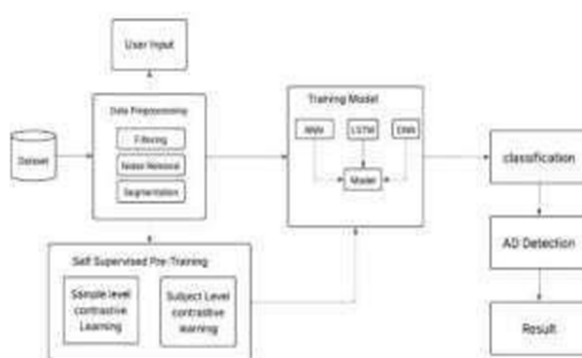


Fig 1. System Architecture

The proposed EEG-based Alzheimer's disease detection system collects brain signals from clinical datasets and wearable devices, then cleans and standardizes them through preprocessing steps such as filtering and artifact removal. Important features are extracted from multiple signal domains and analysed using machine learning and deep learning models, including Convolutional neural network, Long short-term memory, Support vector machine, and Random Forest to categorize cases as Normal, Mild Cognitive Impairment, or Alzheimer’s. The system securely stores patient information and results while providing a user-friendly interface that visualizes EEG data, presents prediction probabilities, and generates reports to support early diagnosis and ongoing clinical assessment.

A. Dataset

The dataset contains multi-channel EEG recordings collected from clinically diagnosed Alzheimer's disease patients and healthy control participants under controlled experimental conditions. These signals capture detailed brain activity patterns across multiple channels, supporting the identification of features relevant for early Alzheimer's detection.

B. Data Split (Train and Test Data)

The dataset is divided into training and testing subsets. The training dataset is used to learn EEG signal patterns associated with Alzheimer's disease, while the testing dataset is used to evaluate the model's performance on unseen EEG samples. This ensures unbiased evaluation and better generalization of the model.

C. Input Data

The input data consists of raw EEG brain signals obtained from EEG devices. These signals may be directly taken from the dataset during training or from real-time EEG recordings during testing. Each EEG sample contains multi-channel time-series data representing electrical brain activity.

D. Preprocessing

Preprocessing prepares the EEG signals for accurate feature learning and classification.

- Noise Removal: EEG signals are filtered using band-passfilters to remove noise such as power-line interference, muscle artifacts, and eye-blink artifacts.
- Signal Normalization: The EEG signals are normalized to maintain consistent amplitude ranges, improving model stability and convergence during training.
- Segmentation: The continuous EEG signals are segmented into fixed-length time windows to ensure uniform input size and effective temporal feature extraction.

E. Model Training

This stage focuses on learning discriminative patterns from EEG signals that differentiate Alzheimer's patients from healthy individuals.

- CNN: CNNs are used to automatically extract spatial and temporal features from EEG signal representations, capturing hidden patterns related to cognitive decline.
- LSTM: LSTM networks capture long-term temporal dependencies in EEG signals, making them effective for modeling sequential brain activity.
- Hybrid CNN-LSTM Model: A combined CNN-LSTM architecture enhances performance by extracting spatial features using CNN and temporal dependencies using LSTM.
- Backbone Architecture: ADformer Ancoder-only Transformer architecture designed for EEG-based AD detection, it captures temporal and spatial features in parallel via multi-head self-attention.

F. Testing Model

The trained model is evaluated using the test dataset or real-time EEG input. Performance metrics such as accuracy, precision, recall, F1- score, and ROC-AUC are calculated to assess the model's effectiveness in early Alzheimer's detection.

G. Detection Result (Alzheimer's Normal)

Based on learned EEG patterns, the system classifies the input as Alzheimer's Disease or Normal (Healthy Control). The final prediction is displayed to the user through the interface, providing a clear and interpretable diagnostic outcome.

IV. SCOPE

The project focuses on the development of an EEG-based diagnostic system for Alzheimer's Disease using multi-dataset EEG recordings (e.g., ADNI, AIBL, OASIS). EEG signals will undergo standardized preprocessing, including artifact removal, filtering, and epoching, to ensure data quality and consistency across datasets. The system employs self-supervised contrastive learning at both the sample level (to enforce augmentation robustness) and the subject level (to enhance subject-level consistency), enabling effective learning from unlabelled data.

Features from both branches will be fused and fine-tuned using available labelled data to perform binary classification: Alzheimer's Disease (AD) vs. Normal Control (NC). Final subject-level predictions will be derived through majority voting over multiple EEG epochs to improve robustness and clinical reliability. The system will be evaluated using cross-validation across subjects and datasets, with metrics including accuracy, precision, recall, and AUC.

V. EVALUATION CRITERIA

The proposed EEG-based model for Alzheimer's disease detection is evaluated using standard metrics such as Accuracy, Precision, Recall, and F1-score derived from TP, TN, FP, and FN values. Results show strong and stable performance, achieving 90.47% accuracy on ADFTD, 89.98% on BrainLat, and 100% on CNBPM, along with notable improvements on Cognision-ERP and Cognision-rsEEG datasets. Overall, the findings demonstrate that the model effectively captures discriminative EEG features and generalizes well across different datasets.

A. Evaluation Matrix

There are two types of Evaluation Matrix are given Below:

1) Subject Level

EADD Achieved in Subject Level F1 increase:

Up to 9.31% over SOTA

Table 1. Subject Level Evaluation Matrix -

Dataset	Best Baseline	EADD Vanilla	EADD DSup	EADD- Base
ADFTD	84.44%	81.65 %	91.3 4%	90.47%
BrainLat	84.26%	79.25 %	85.2 4%	89.98%
CNBPM	96.15%	92.31 %	100. 00%	100.00 %
Cognision-ERP	76.61%	69.83 %	81.1 6%	84.42%
Cognision-rsEEG	80.70%	69.60 %	82.9 0%	91.86%

The table compares different models for subject-level Alzheimer's disease classification across several datasets. It shows that EADD Sup performs the best overall, achieving the highest accuracy on most datasets and even reaching 100% on CNBPM. Base also performs consistently well and usually ranks second, while both outperform the traditional baseline. In contrast, EADD Vanilla generally performs worse than the baseline, indicating it needs improvements. Overall, the results highlight that the EADD framework, especially its supervised version, significantly improves classification performance across different datasets.

2) Sample Level

The table shows how different models perform for sample-level Alzheimer's disease classification across several datasets. Overall, EADD Sup achieves the best results on most datasets, showing clear improvement over the baseline. EADD Base also performs strongly and even gives the highest score on some datasets like BrainLat and Cognision-rsEEG. The baseline model performs moderately well, while EADD Vanilla generally has the lowest accuracy, indicating weaker performance without enhancements. Additionally, CNBPM appears to be the easiest dataset with higher scores across all models, whereas datasets like Cognision-ERP and Cognision-rsEEG are more challenging. In summary, the EADD-based methods, especially the supervised version, provide better and more consistent performance at the sample level.

EADD achieved: Sample-level F1 increase: Up to 9.86% over SOTA.

Table 2. Sample Level Evaluation Matrix

Dataset	Best Baseline	EADD Vanilla	EADD -Sup	EADD -Base
ADFTD	62.77%	60.14%	71.04%	69.17%
BrainLat	67.81%	66.84%	69.94%	71.36%
CNBPM	84.42%	81.33%	91.54%	88.08%
Cognisio n-ERP	61.34%	56.54%	66.21%	71.19%
Cognisio n-rsEEG	64.91%	54.12%	66.14%	74.52%

VI. RESULT AND DISCUSSION

The proposed EEG-based Alzheimer's detection system combines a deep learning-based EEG analysis model with a secure and user-friendly web application to support early diagnosis. Users can register and log in securely before uploading EEG files in .edf or .bdf formats for automated processing. The trained model, implemented on a CUDA-enabled GPU, achieved a subject-level accuracy of approximately 85.7%, with balanced precision, recall, and F1-scores of around 85%, indicating effective differentiation between healthy individuals and patients with Alzheimer's disease. High AUROC and AUPRC values further demonstrate the robustness and reliability of the classification performance. Overall, the system offers an accessible AI driven solution that can assist clinicians in early detection and informed decision-making for neurological disorders.

A. Signup Page

A login screen for the EEG-based Alzheimer's detection App, virtually identical to the first, but the Sign-Up option is selected in the sidebar menu instead of Login. This screen is designed for secure User Authentication to ensure only authorized personnel can access the diagnostic prediction tool. Input Fields: Two standard, clean, light-gray input fields are provided for credentials: Username and Password. Security Feature: The Password field includes a small eye icon on the right side, a common feature that allows the user to temporarily reveal the hidden password text for verification.

B. Login Page

This screen is designed for secure User Authentication to ensure only authorized personnel can access the diagnostic prediction tool. This displays the dedicated Login page for the EEG-based Alzheimer's detection App, serving as the essential security gateway to the prediction tool. The clean, minimalist interface features the EEG-based Alzheimer's detection App and a corresponding brain icon, clearly linking the access point to the application's neurological diagnostic function. The primary prompt, "Login to Access Prediction Tool," sets the expectation for the user. The main body of the screen contains standard input fields for the user's Username and Password, with the latter including a toggle eye icon for secure visibility. The session is initiated by clicking the simple "Log In" button, ensuring that only authenticated individuals can proceed to upload sensitive EEG data and utilize the diagnostic model.

C. Input Dashboard Page

This image displays the main user input dashboard for the EEG-based Alzheimer's detection App, which is the core operational interface after successful authentication. The dashboard is designed to facilitate the first step of the diagnostic process: data submission. It clearly confirms the active user session with "User: Dhruv" and provides an immediate Logout option.

1. Upload Patient Raw EEG Data," instructs the user to submit EEG files in specific medical formats (.edf, .bdf). A large, cloud-themed area supports both drag-and-drop functionality and a traditional "Browse files" button, while explicitly noting the data constraint: a 200MB limit per file. This streamlined interface is optimized for efficiently loading the raw data required for the backend diagnostic analysis.

D. Output Dashboard Page

1) Alzheimer's Positive Patient

The image shows a EADD Clinical Dashboard, which appears to be a medical software interface used for analyzing brain activity data from an EEG (electroencephalogram) file. On the left side of the dashboard, there is a panel



Fig. 3. AD positive Output

displaying the provider name and an option for Secure Logout, indicating that the system is used by a healthcare professional. In the main section, the dashboard allows the user to upload a patient's raw EEG file (supported formats include EDF, BDF, and SET) for automated spatio-temporal analysis. The uploaded file shown in the interface is being processed, and ----analysing the EEG data. Below the processing section, the Diagnostic Results are displayed. The analysis took 824 seconds to complete. The results show a Healthy Control Confidence of 7.0% and an Alzheimer's Confidence of 93.0%, suggesting that the system's algorithm detected patterns strongly associated with Alzheimer's disease. A red warning message labelled "FLAG: ALZHEIMER'S DISEASE" appears at the bottom, indicating a high probability of neurodegenerative markers. The dashboard also recommends further action, advising that the case be forwarded to a specialist for clinical review and confirmation. Overall, the interface represents an AI-assisted clinical tool designed to help doctors interpret EEG data and identify possible neurological conditions.

2) Non-Alzheimer's Patient

In this Project this output image shows a L-EAD Clinical Dashboard, which is a medical analysis interface used for examining a patient's EEG (Electroencephalography) data

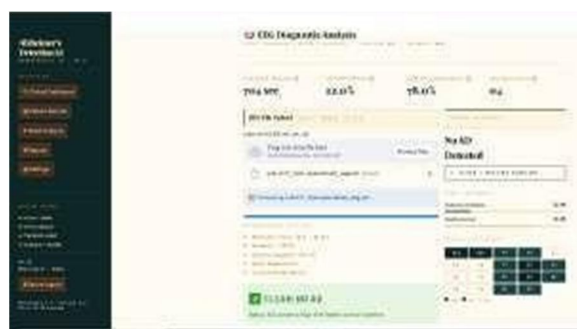


Fig 4. Non-AD output

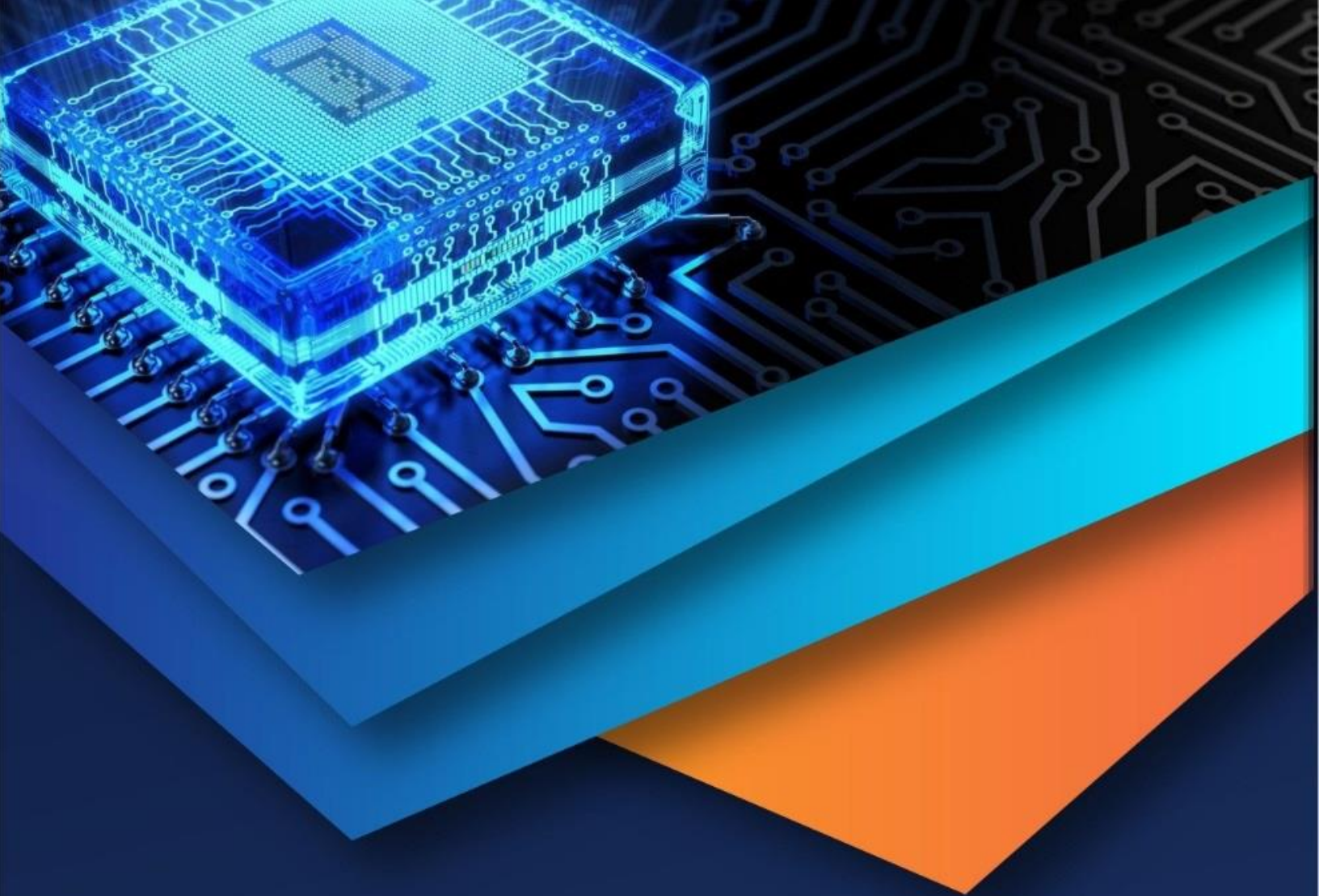
to detect possible neurological conditions. At the top of the dashboard, there is an option to upload a patient's raw EEG file for automated spatiotemporal analysis. The interface allows users to drag and drop EEG files in formats such as EDF, BDF, or SET, with a file size limit of 200 MB. In this example, an EEG file named sub002_task- eyesclosed_eeg.set has been uploaded and processed. A progress bar indicates that the system is analysing the data. Below this, the Diagnostic Results section summarizes the analysis: the system analysed 793 seconds of EEG data, showing 95.0% confidence for a healthy control pattern and only 5.0% confidence for Alzheimer's disease indicators. Based on this analysis, the result displayed in green states "CLEAR: NO AD," meaning the EEG patterns strongly match those of healthy individuals and do not show significant signs associated with Alzheimer's disease. The dashboard also includes a side panel with provider information and a secure logout option, indicating that it is designed for clinical or healthcare professionals to securely review patient diagnostic results.

VII. CONCLUSION

The EEG-based Alzheimer's detection system provides an efficient and accurate method for early diagnosis of Alzheimer's disease. By acquiring and preprocessing EEG signals, the system ensures clean and reliable data for analysis. Feature extraction in time, frequency, and wavelet domains captures essential patterns indicative of cognitive decline. Advanced machine learning and deep learning models, including CNN, LSTM, SVM, and Random Forest, enable precise classification of Normal, MCI, and Alzheimer's cases. Secure storage of patient data and EEG records allows for longitudinal monitoring and research. The intuitive user interface presents results, probability scores, and reports for clinicians and researchers. The system reduces diagnostic time and supports timely intervention. It also provides a scalable framework for integrating new datasets and models. This project demonstrates the potential of combining EEG analysis with AI for neurological disease detection. Overall, it contributes significantly to improving healthcare outcomes through technology-driven solutions.

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