Explainable Machine Learning for Early Alzheimer's Risk Detection

Team Name: Clever Cubed
Hackathon: AI 4 Alzheimer's – Hack4Health
Team Members: Aadya Patel, Ananya Mishra, Anish Kushwaha

Abstract

Alzheimer's disease is a progressive neurodegenerative disorder that is often detected only after significant cognitive decline has occurred. Early risk identification remains challenging due to the subtle and heterogeneous nature of early symptoms.

This project explores the use of explainable machine learning techniques to support early Alzheimer's risk analysis using synthetic clinical and cognitive data. We present an interpretable machine learning pipeline that performs binary risk classification (Alzheimer's vs. No Alzheimer's), with a strong emphasis on transparency, ethics, and reproducibility.

Rather than acting as a diagnostic system, this work is intended for research and educational purposes. The objective is to highlight patterns and contributing factors associated with Alzheimer's risk while ensuring model interpretability and responsible AI usage.

---

1. Introduction

Alzheimer's disease affects millions of individuals worldwide and poses significant social, emotional, and economic challenges. One of the primary difficulties in managing the disease is the lack of reliable early detection mechanisms. Subtle cognitive and clinical changes may appear years before a formal diagnosis, yet these early indicators are often difficult to interpret.

Recent advances in machine learning have demonstrated potential in analyzing complex health-related data. However, many high-performing models operate as black boxes, limiting their adoption in healthcare environments where transparency and trust are essential. This project aims to address this gap by developing an explainable machine learning pipeline that balances predictive modeling with interpretability.

---

2. Dataset Description

To ensure ethical compliance and avoid the use of sensitive patient information, this project uses a synthetic dataset designed to mimic Alzheimer's-related clinical and cognitive indicators.

The dataset includes:

- Demographic information such as age
- Cognitive assessment scores similar to MMSE
- Memory and cognitive performance indicators

The target variable represents binary Alzheimer's risk status:

- 0 – No Alzheimer's
- 1 – Alzheimer's

No real patient data was used in this study.

---

3. Methodology

3.1 Data Preprocessing

The following preprocessing steps were applied:

- Removal of records with missing target labels
- Handling missing feature values using mean imputation
- Feature normalization for linear models
- Stratified train–test split with 80% training data and 20% testing data

These steps ensured stable model training and fair evaluation.

3.2 Model Development

Two machine learning models were implemented and compared:

- Logistic Regression was used as a baseline linear classifier due to its simplicity and interpretability.

- Random Forest Classifier was employed to capture non-linear relationships and feature interactions commonly present in biomedical data.

3.3 Evaluation Metrics

Model performance was evaluated using the following metrics:

- Accuracy
- Precision, Recall, and F1-score
- Confusion Matrix
- ROC-AUC score

These metrics provide a balanced assessment of predictive performance, particularly for healthcare-related applications.

3.4 Explainability

Model interpretability was emphasized through:

- Feature importance analysis derived from the Random Forest model
- Exploration of SHAP (SHapley Additive exPlanations) for understanding feature contributions

Due to execution environment constraints, SHAP visualizations were limited. However, feature importance analysis provided reliable insights into model behavior and influential features.

---

4. Results

The Random Forest model demonstrated improved performance compared to the baseline Logistic Regression model, indicating the presence of non-linear relationships among features.

Key observations include:

- Cognitive and memory-related features had the strongest influence on predictions
- Age-related features contributed significantly to risk estimation
- Feature importance analysis revealed consistent and meaningful patterns

Although overall accuracy is limited due to the synthetic nature of the dataset, the results validate the effectiveness of the explainable machine learning pipeline.

---

5. Challenges and Limitations

Challenges

- Handling noisy and incomplete health-related data
- Avoiding overfitting with limited synthetic samples
- Interpreting model outputs in a clinically meaningful way

Limitations

- Use of synthetic data limits real-world generalizability
- Binary classification simplifies the disease spectrum
- Lack of longitudinal data prevents modeling disease progression over time

---

6. Ethical Considerations

This project was developed with ethical responsibility as a core principle. The system does not provide medical diagnoses, treatment recommendations, or clinical decisions.

All data used in this project is synthetic and de-identified by design. The results should be interpreted only by qualified professionals in appropriate research or educational contexts.

---

7. Conclusion and Future Work

This project demonstrates that explainable machine learning can support early Alzheimer's risk analysis while maintaining transparency and ethical integrity. By combining predictive modeling with interpretability techniques, the system highlights meaningful patterns without functioning as a black-box model.

Future work includes:

- Incorporating public Alzheimer's datasets such as OASIS and ADNI
- Extending the model to multi-class classification (CN, MCI, AD)
- Exploring longitudinal modeling for disease progression
- Improving uncertainty estimation and calibration
- Collaborating with healthcare professionals for validation

Disclaimer

This project is intended strictly for research and educational purposes.
It does not provide medical diagnosis, treatment, or clinical advice.
All predictions should be interpreted by qualified healthcare professionals.