Predictive Modeling for Alzheimer's Disease Risk Factors

By Adrian Chavez-Loya

Introduction

Alzheimer's disease is a complex neurodegenerative disorder that affects millions worldwide. Understanding the factors associated with Alzheimer's can aid in early diagnosis and intervention strategies. This study aims to identify significant predictors of Alzheimer's disease using machine learning techniques on a comprehensive dataset.

The dataset includes demographic details, lifestyle factors, medical history, clinical measurements, cognitive assessments, symptoms, and a diagnosis of Alzheimer's Disease. By exploring this rich dataset, we aim to uncover key insights into the interplay of various factors contributing to Alzheimer's risk.

Methodology

Data Preparation and Exploration

The dataset contains extensive information on 2,149 patients, encompassing variables such as age, gender, ethnicity, lifestyle habits, medical history, cognitive assessments, and more.

Data Source

Alzheimer's Disease Dataset

Citation:

- Title: Alzheimer's Disease Dataset
- Author: Rabie El Kharoua

- Publisher: Kaggle
- Year: 2024
- DOI: 10.34740/KAGGLE/DSV/8668279

Analytical Objectives

We aim to:

- Identify the most significant predictors of Alzheimer's disease through correlation analysis and feature importance ranking
- Develop and compare multiple machine learning models for accurate Alzheimer's classification
- Determine which demographic, lifestyle, clinical, and cognitive factors have the strongest association with Alzheimer's diagnosis
- Provide data-driven insights that could inform early detection strategies

Data Preprocessing

In [ ]:

```
import pandas as pd
df = pd.read_csv('alzheimers_disease_data.csv') # Imported Data
df.head()
```

Out[ ]:

	PatientID	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking
0	4751	73	0	0	2	22.927749	0
1	4752	89	0	0	0	26.827681	0
2	4753	73	0	3	1	17.795882	0
3	4754	74	1	0	1	33.800817	1
4	4755	89	0	0	0	20.716974	0

5 rows × 35 columns

In [ ]:

```
print(f"Dataset shape: {df.shape}")
print(f"Missing values: {df.isnull().sum().sum()}")
print(f"Diagnosis distribution: {df['Diagnosis'].value_counts()}"
```

```
Dataset shape: (2149, 35)
Missing values: 0
Diagnosis distribution: Diagnosis
0    1389
1     760
Name: count, dtype: int64
```

Results:

- **Total Records**: 2,149 patients
- **Missing Values**: 0 (Complete dataset - no imputation needed)
- **Class Distribution**:
  - Non-Alzheimer's (0): 1,389 patients (64.6%)
  - Alzheimer's (1): 760 patients (35.4%)

The dataset is clean with no missing values and good class balance! All variables are properly encoded for machine learning analysis.

Dataset Variables Overview

Below is a table explaining the different variables included in our dataset. The dataset is properly encoded and allows us to directly proceed with analysis!

Category	Variable	Description	Encoding/Scale
Demographic	Age	Patient age in years	60-90 years
	Gender	Biological sex	0 = Male, 1 = Female
	Ethnicity	Racial/ethnic background	0 = Caucasian, 1 = African American, 2 = Asian, 3 = Other
	EducationLevel	Education level	0 = None, 1 = High School, 2 = Bachelor's, 3 = Higher
Lifestyle	BMI	Body Mass Index	15-40 kg/m²

Category	Variable	Description	Encoding/Scale
	Smoking	Tobacco use status	0 = No, 1 = Yes
	AlcoholConsumption	Weekly alcohol consumption	0-20 units
	PhysicalActivity	Weekly physical activity	0-10 hours
	DietQuality	Diet quality score	0-10 (Higher = Better)
	SleepQuality	Sleep quality score	4-10 (Higher = Better)
Medical History	FamilyHistoryAlzheimers	Genetic predisposition	0 = No, 1 = Yes
	CardiovascularDisease	Heart/circulatory conditions	0 = No, 1 = Yes
	Diabetes	Blood sugar disorder	0 = No, 1 = Yes
	Depression	Mental health condition	0 = No, 1 = Yes
	HeadInjury	History of head trauma	0 = No, 1 = Yes
	Hypertension	High blood pressure	0 = No, 1 = Yes
Clinical Measurements	SystolicBP	Blood pressure (upper)	90-180 mmHg
	DiastolicBP	Blood pressure (lower)	60-120 mmHg
	CholesterolTotal	Total cholesterol level	150-300 mg/dL
	CholesterolLDL	"Bad" cholesterol	50-200 mg/dL
	CholesterolHDL	"Good" cholesterol	20-100 mg/dL
	CholesterolTriglycerides	Blood fats	50-400 mg/dL
Cognitive Assessments	MMSE	Mini-Mental State Exam	0-30 (Higher = Better

Category	Variable	Description	Encoding/Scale
			cognition)
	FunctionalAssessment	Daily functioning ability	0-10 (Higher = Better function)
	ADL	Activities of Daily Living	0-10 (Higher = More independent)
Behavioral Symptoms	MemoryComplaints	Self-reported memory issues	0 = No, 1 = Yes
	BehavioralProblems	Behavioral changes	0 = No, 1 = Yes
	Confusion	Mental confusion episodes	0 = No, 1 = Yes
	Disorientation	Spatial/temporal confusion	0 = No, 1 = Yes
	PersonalityChanges	Personality alterations	0 = No, 1 = Yes
	DifficultyCompletingTasks	Task execution problems	0 = No, 1 = Yes
	Forgetfulness	Memory lapse frequency	0 = No, 1 = Yes
Target	Diagnosis	Alzheimer's Disease status	0 = Negative, 1 = Positive
Administrative	DoctorInCharge	Confidential doctor information	"XXXConfid" (to be excluded from analysis)

In [ ]:

```
# Drop unnecessary columns permanently
df = df.drop(columns=['DoctorInCharge', 'PatientID'])
df.head()
```

Out[ ]:

	Age	Gender	Ethnicity	EducationLevel	BMI	Smoking	AlcoholC
0	73	0	0	2	22.927749	0	
1	89	0	0	0	26.827681	0	
2	73	0	3	1	17.795882	0	
3	74	1	0	1	33.800817	1	
4	89	0	0	0	20.716974	0	

5 rows × 33 columns

Correlation Matrix

We will use a correlation matrix to find correlations between variables and target variable which is Alzheimer's diagnosis.

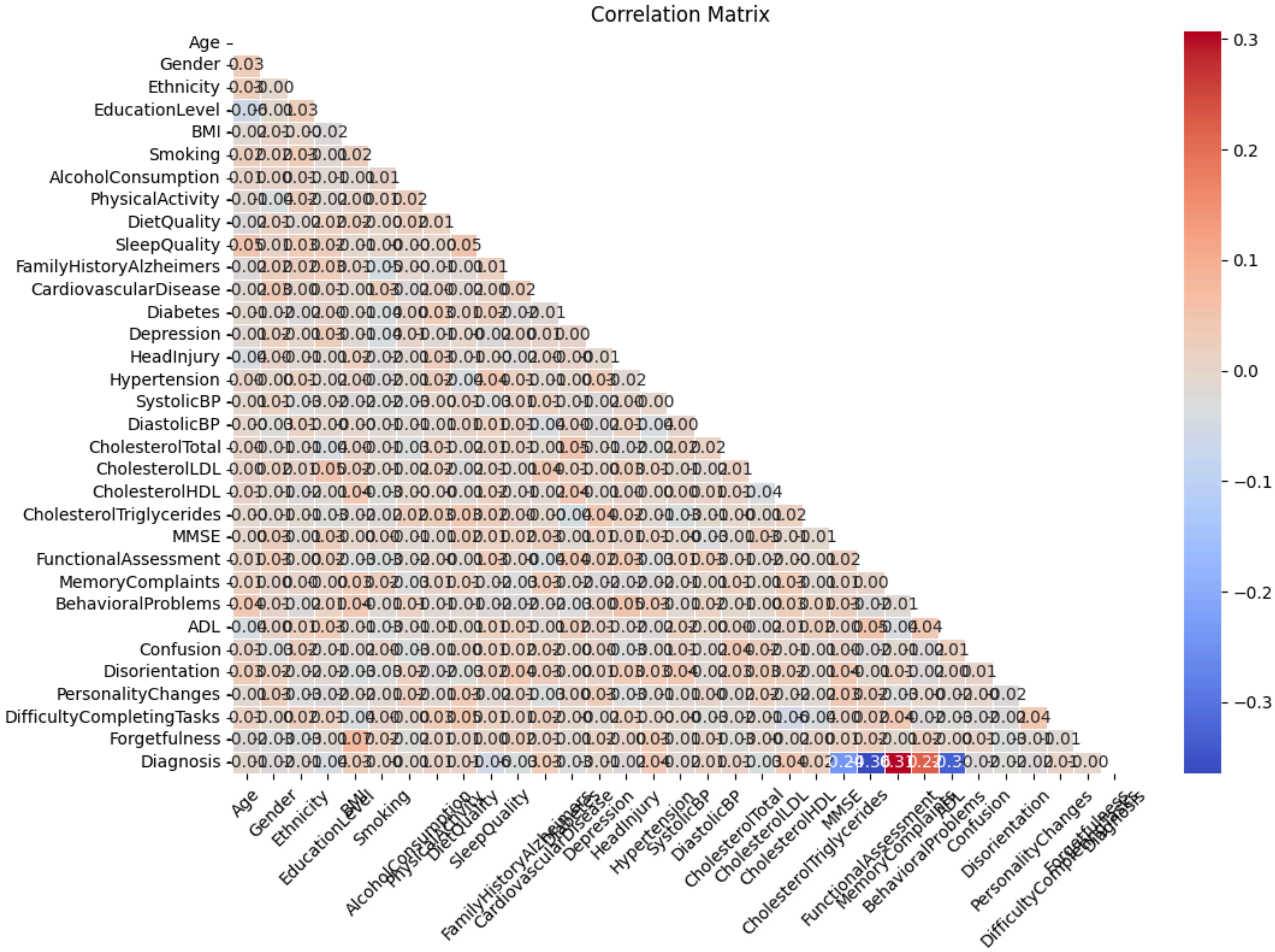
In [ ]:

```
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np

# Calculate correlation matrix
corr_matrix = df.corr()
mask = np.triu(np.ones_like(corr_matrix, dtype=bool)) # Mask for

# Heatplot configuration
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, fmt='.2f', cmap='coolwarm', 
plt.xticks(rotation=45)
plt.yticks(rotation=0)
plt.title('Correlation Matrix')
plt.show()

# Correlations with the target variable (Diagnosis)
corr_with_target = corr_matrix['Diagnosis'].sort_values(ascending
print(corr_with_target)
```


Correlation Matrix
Age
Gender
Ethnicity
EducationLevel
BMI
Smoking
AlcoholConsumption
PhysicalActivity
DietQuality
SleepQuality
FamilyHistoryAlzheimers
CardiovascularDisease
Diabetes
Depression
HeadInjury
Hypertension
SystolicBP
DiastolicBP
CholesterolTotal
CholesterolLDL
CholesterolHDL
CholesterolTriglycerides
MMSE
FunctionalAssessment
MemoryComplaints
BehavioralProblems
ADL
Confusion
Disorientation
PersonalityChanges
DifficultyCompletingTasks
Forgetfulness
Diagnosis
0.3
0.2
0.1
0.0
−0.1
−0.2
−0.3

```
Diagnosis                    1.000000
MemoryComplaints             0.306742
BehavioralProblems           0.224350
CholesterolHDL               0.042584
Hypertension                 0.035080
CardiovascularDisease        0.031490
BMI                          0.026343
CholesterolTriglycerides     0.022672
DifficultyCompletingTasks    0.009069
DietQuality                  0.008506
CholesterolTotal             0.006394
PhysicalActivity             0.005945
DiastolicBP                  0.005293
Forgetfulness               -0.000354
Smoking                     -0.004865
Age                         -0.005488
Depression                  -0.005893
AlcoholConsumption          -0.007618
Ethnicity                   -0.014782
SystolicBP                  -0.015615
Confusion                   -0.019186
PersonalityChanges          -0.020627
Gender                      -0.020975
HeadInjury                  -0.021411
Disorientation              -0.024648
Diabetes                    -0.031508
CholesterolLDL              -0.031976
FamilyHistoryAlzheimers     -0.032900
EducationLevel              -0.043966
SleepQuality                -0.056548
MMSE                        -0.237126
ADL                         -0.332346
FunctionalAssessment        -0.364898
Name: Diagnosis, dtype: float64
```

Correlation Analysis Results

Key Clinical Predictors

Feature	Correlation	Clinical Significance
Functional Assessment	-0.365	Measures daily task performance - decline indicates disease progression
ADL	-0.332	Basic self-care abilities - impairment signals advanced stage

Feature	Correlation	Clinical Significance
MMSE	-0.237	Gold standard cognitive test - lower scores confirm diagnosis
Memory Complaints	0.307	Early patient-reported symptom - often first warning sign
Behavioral Problems	0.224	Personality/mood changes - common in mid-stage disease

Clinical Insights

- **Cognitive/functional tests** strongest predictors (expected - core diagnostic tools)
- **Patient symptoms** valuable for early detection before clinical tests show decline
- **Traditional risk factors** (diet, exercise) show minimal impact in this dataset
- **HDL correlation** (0.043) too weak for clinical relevance

Feature Selection for Modeling

Based on our correlation analysis, we filter the dataset to include only features with meaningful predictive power (|correlation| ≥ 0.05). This removes noise and focuses our models on the strongest predictors.

In [ ]:

```
# Filtered down to features with meaningful correlation (|r| >= 0
significant_features = corr_with_target[abs(corr_with_target) >=
print("Features with meaningful correlation (|r| >= 0.05):")
print(significant_features)

# Filtered dataset with only significant features
df = df[significant_features]
print(f"\nReduced dataset shape: {df.shape}")
print("Final features:", df.columns.tolist())
```

```
Features with meaningful correlation (|r| >= 0.05):
['Diagnosis', 'MemoryComplaints', 'BehavioralProblems', 'SleepQual
ity', 'MMSE', 'ADL', 'FunctionalAssessment']

Reduced dataset shape: (2149, 7)
Final features: ['Diagnosis', 'MemoryComplaints', 'BehavioralProbl
ems', 'SleepQuality', 'MMSE', 'ADL', 'FunctionalAssessment']
```

Model Training with Selected Features

We now train multiple machine learning models using the 6 strongest predictors identified from our correlation analysis. The dataset has been split into training (80%) and testing (20%) sets, and features are standardized for optimal performance.

In [ ]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, precision_score, reca

# Features and target variable
X = df.drop(columns=['Diagnosis'])  # Fixed: PatientID already re
y = df['Diagnosis']

# Data split into train/test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_si

# Features standardized (with standard scaler)
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Logistic Regression with L1 regularization (Lasso)
logreg = LogisticRegression(penalty='l1', solver='liblinear')
logreg.fit(X_train, y_train)

# Display feature importance
importance = abs(logreg.coef_[0])
feature_names = X.columns
feature_importance = pd.DataFrame({'Feature': feature_names, 'Imp
feature_importance = feature_importance.sort_values(by='Importanc
print(feature_importance)
```

```
                Feature  Importance
5  FunctionalAssessment    1.315204
4                   ADL    1.236592
0      MemoryComplaints    1.056284
3                  MMSE    0.858940
1    BehavioralProblems    0.846633
2          SleepQuality    0.082270
```

Logistic Regression Feature Importance

The LASSO logistic regression confirms our correlation analysis, showing the same top predictors with similar ranking:

Feature	Importance Score
Functional Assessment	1.315
ADL	1.237
Memory Complaints	1.056
MMSE	0.859
Behavioral Problems	0.847
Sleep Quality	0.082

Key Validation:

- Same top 6 features identified by both correlation and LASSO
- Sleep Quality has much lower importance (0.082 vs ~1.3 for others)
- Model automatically weighted features according to predictive power

Comprehensive Model Comparison

We now evaluate four different machine learning algorithms to identify the best performing model for Alzheimer's classification using our 6 selected features.

In [ ]:
```
# Model Evaluation Function
def evaluate_model(model, X_train, y_train, X_test, y_test):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    precision = precision_score(y_test, y_pred)
    recall = recall_score(y_test, y_pred)
    f1 = f1_score(y_test, y_pred)
    return accuracy, precision, recall, f1
```

In [ ]:
```
# Logistic Regression with L1 regularization (Lasso)
logreg = LogisticRegression(penalty='l1', solver='liblinear')
logreg_acc, logreg_prec, logreg_rec, logreg_f1 = evaluate_model(l
```

```
# Decision Tree Classifier
dtree = DecisionTreeClassifier(random_state=42)
dtree_acc, dtree_prec, dtree_rec, dtree_f1 = evaluate_model(dtree

# Random Forest Classifier
rf = RandomForestClassifier(random_state=42)
rf_acc, rf_prec, rf_rec, rf_f1 = evaluate_model(rf, X_train, y_tr

# Support Vector Machine Classifier
svm = SVC(random_state=42)
svm_acc, svm_prec, svm_rec, svm_f1 = evaluate_model(svm, X_train,


# Model Performance
print("Logistic Regression - Accuracy: {:.4f}, Precision: {:.4f},
print("Decision Tree - Accuracy: {:.4f}, Precision: {:.4f}, Recal
print("Random Forest - Accuracy: {:.4f}, Precision: {:.4f}, Recal
print("SVM - Accuracy: {:.4f}, Precision: {:.4f}, Recall: {:.4f},
```

```
Logistic Regression - Accuracy: 0.8326, Precision: 0.7914, Recall:
0.7190, F1-score: 0.7534
Decision Tree - Accuracy: 0.9233, Precision: 0.8947, Recall: 0.888
9, F1-score: 0.8918
Random Forest - Accuracy: 0.9558, Precision: 0.9653, Recall: 0.908
5, F1-score: 0.9360
SVM - Accuracy: 0.9070, Precision: 0.9065, Recall: 0.8235, F1-scor
e: 0.8630
```

Model Performance Results

Model	Accuracy	Precision	Recall	F1-Score
Random Forest	**95.6%**	**96.5%**	90.9%	**93.6%**
Decision Tree	92.3%	89.5%	**88.9%**	89.2%
SVM	90.7%	90.7%	82.4%	86.3%
Logistic Regression	83.3%	79.1%	71.9%	75.3%

Key Findings:

- **Random Forest is the best performer across all metrics**
- **95.6% accuracy** demonstrates strong predictive powerwith very few false positives
- All models perform well, confirming our feature selection was effective!!

The selected 6 features provide excellent predictive capability for Alzheimer's classification.

Random Forest Feature Importance Analysis

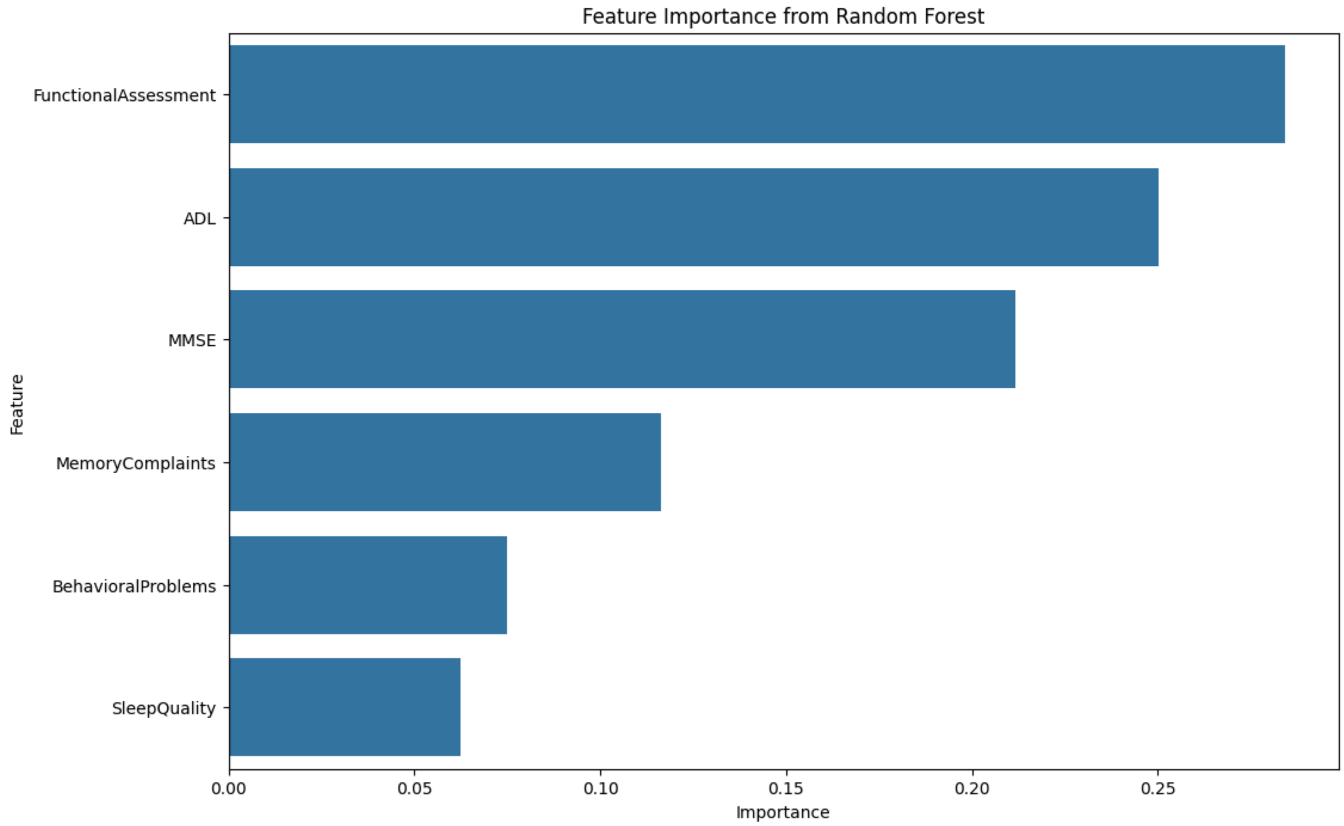
In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

# Random Forest model
rf = RandomForestClassifier(n_estimators=100, random_state=42)
rf.fit(X_train, y_train)

# Feature Importance Ranking
importance = rf.feature_importances_
feature_importance_rf = pd.DataFrame({'Feature': X.columns, 'Impo
feature_importance_rf = feature_importance_rf.sort_values(by='Imp
print(feature_importance_rf)

plt.figure(figsize=(12, 8)) # Feature Importance Plot
sns.barplot(x='Importance', y='Feature', data=feature_importance_
plt.title('Feature Importance from Random Forest')
plt.show()
```

```
                Feature  Importance
5  FunctionalAssessment    0.284297
4                   ADL    0.250254
3                  MMSE    0.211606
0      MemoryComplaints    0.116211
1    BehavioralProblems    0.075095
2          SleepQuality    0.062537
```



Feature Importance Analysis

Feature	Importance
FunctionalAssessment	28.4%
ADL	25.0%
MMSE	21.2%
MemoryComplaints	11.6%
BehavioralProblems	7.5%
SleepQuality	6.3%

Key Findings

Clinical assessments are 3x more predictive than symptoms

- Top 3 tests (FunctionalAssessment, ADL, MMSE): 74.6% of predictive power
- All symptoms combined: 25.4% of predictive power

Standardized testing is essential

- Objective measures vastly outperform subjective complaints
- Symptoms should trigger testing but not replace it

Surprising Insights

- **Memory complaints are the most important symptom** by a significant margin
- **Behavioral problems are a meaningful secondary indicator**
- Sleep quality has minimal predictive value on its own
- **Traditional risk factors** (family history, diabetes, head injuries) show very weak correlation with diagnosis!! However,

Actionable Insight: *Prioritize formal assessments over symptom monitoring for accurate evaluation.* While symptoms like memory issues and behavioral changes should prompt clinical evaluation, they cannot replace standardized testing for reliable diagnosis!!

Evidence-Based Prevention Strategies

While our analysis focuses on diagnosis, prevention remains crucial. Based on broader Alzheimer's research I will like to share the following!:

Lifestyle & Cardiovascular Health

- **Physical Exercise**: Regular aerobic activity shows strong protective effects
- **Heart-Healthy Diet**: Mediterranean or MIND diets correlate with reduced risk
- **Blood Pressure Management**: Controlling hypertension in midlife reduces late-life dementia risk

Cognitive Engagement

- **Lifelong Learning**: Continued education and cognitive stimulation build resilience
- **Social Engagement**: Maintaining strong social connections appears protective

Risk Factor Management

- **Diabetes Control**: Managing blood sugar reduces associated dementia risk
- **Hearing Protection**: Addressing hearing loss may help maintain cognitive function
- **Sleep Quality**: Treating sleep disorders like apnea can reduce risk accumulation

Important Note: These prevention strategies address long-term risk reduction in the general population, while our analysis focused on diagnostic accuracy in symptomatic individuals. Both approaches are complementary for comprehensive brain health management.