ALZHEIMER'S PREDICTION

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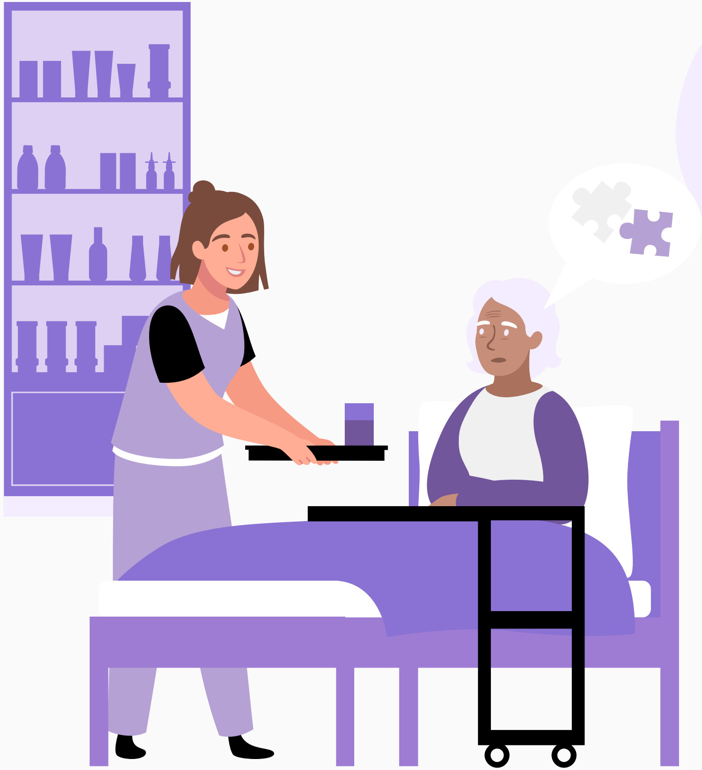


01. Business Understanding

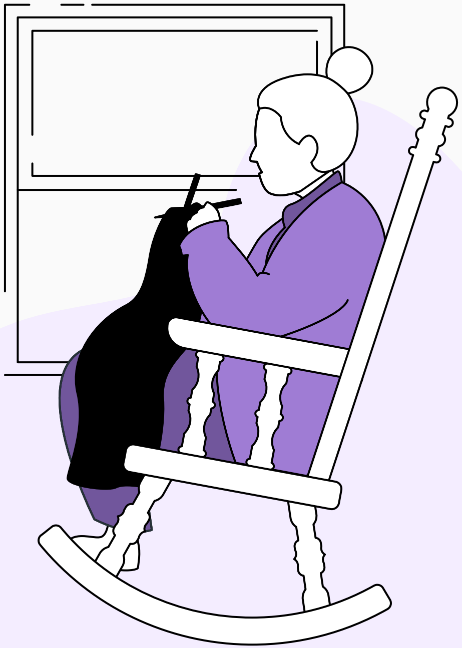
WHY DO WE NEED IT?

Business Problem

- Alzheimer's disease causes progressive cognitive decline and loss of independence
- Traditional diagnosis methods are:
  - Expensive (MRI, PET scans)
  - Time-consuming
  - Dependent on specialist availability
- Delayed diagnosis reduces treatment effectiveness

Business Value

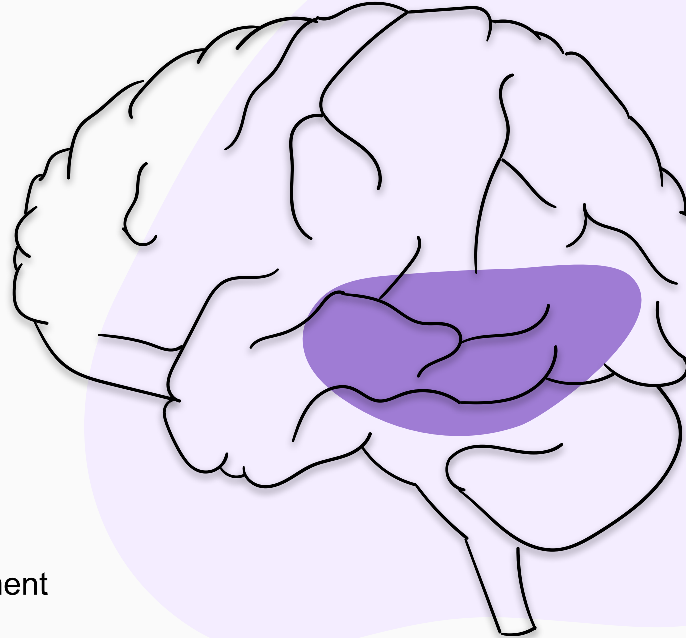
- Early detection enables timely intervention
- Cost-effective screening compared to imaging tests
- Scalable solution for hospitals and telemedicine platforms



CHALLENGES AND SOLUTIONS IMPLEMENTED

Challenges

- Class imbalance between Alzheimer’s and non-Alzheimer’s cases
- Identifying the most relevant clinical features
- Limited interpretability of complex models (XGBoost)
- Risk of false negatives and ethical concerns in healthcare predictions

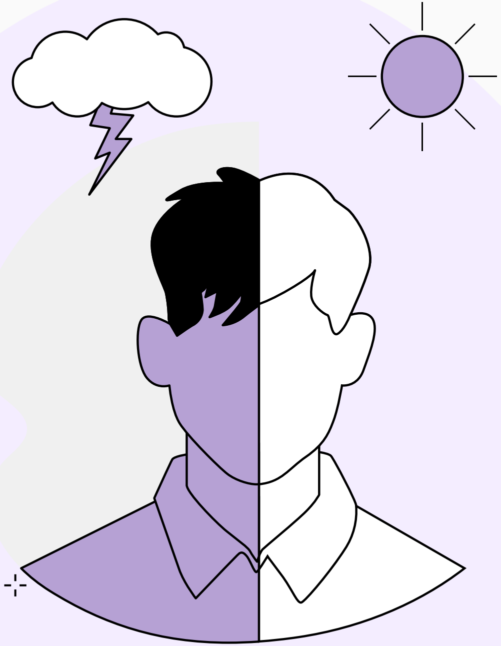


Solutions & Future Scope

- Used XGBoost for robust and accurate predictions
- Evaluated model using recall and confusion matrix, not just accuracy
- Positioned model as a decision-support tool, not a diagnostic replacement
- **Unsolved challenges:** need for clinical validation, bias reduction, and improved model explainability

02.
Data Understanding

DATASET AND CHALLENGES

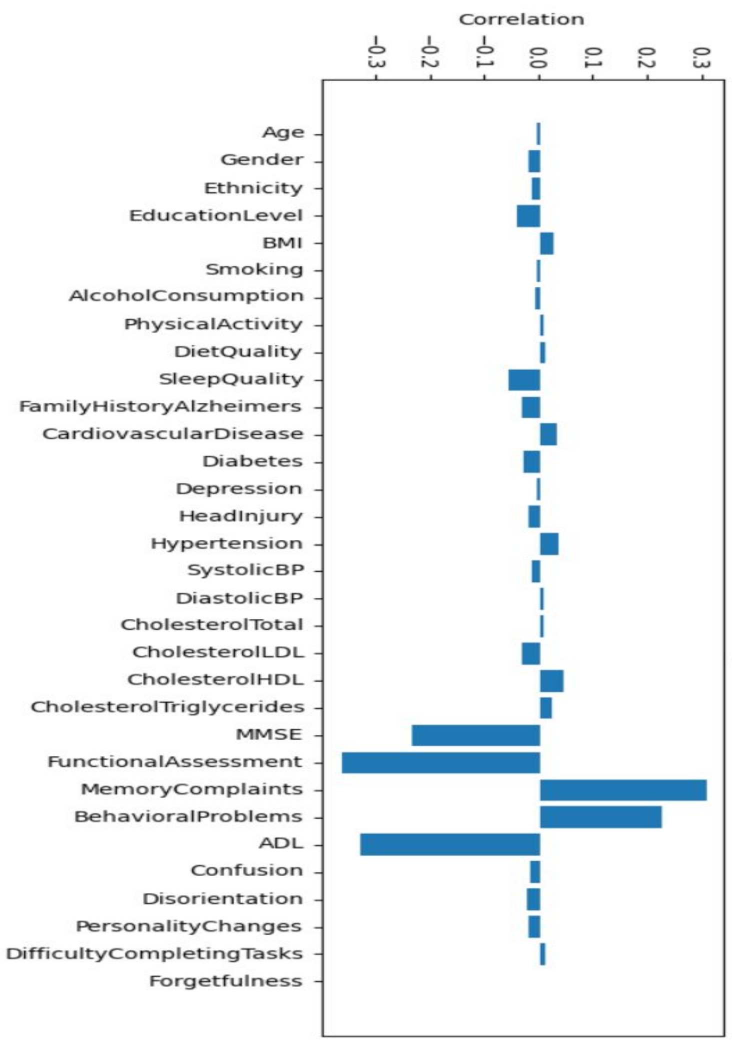


Data Description

- Dataset contains demographic and clinical features (Dataset source: https://www.kaggle.com/datasets/rabieelkharoua/alzheimers-disease-dataset)
- Key columns:
    - Age, Gender, EducationLevel
    - Cognitive scores: MMSE, CDR, MemoryScore
- Target variable: Diagnosis (Alzheimer’s / Non-Alzheimer’s)

Challenges Identified

- Missing values in MMSE and cognitive score fields
- Mixed data types (Gender categorical, scores numerical)
- Class imbalance in Diagnosis
- No clinical metadata explaining feature collection



DATA INSIGHTS AND LIMITATIONS

Key Data Insights

- Pearson correlation analysis shows:
  - MMSE, FunctionalAssessment, and ADL are negatively correlated with Diagnosis
  - MemoryComplaints and BehavioralProblems are positively correlated with Diagnosis

Solutions & Open Issues

- Applied data cleaning and encoding for categorical variables
- Used correlation analysis to guide feature selection
- Unsolved challenges: demographic bias, limited real-world validation, and dependency on dataset quality

03.

Data Preparation

CHALLENGES AND SOLUTIONS IMPLEMENTED

Feature Engineering

- Removed irrelevant attributes to reduce noise and missing diagnostic records
- Encoded categorical diagnosis labels using Label Encoding
- Prepared dataset optimized for tree-based models (XGBoost)

Challenges & Solutions

- Missing clinical values → Applied median imputation
- Limited feature availability → Adapted model to use available, medically relevant features
- Non-numeric diagnosis labels → Converted using label encoding
- Risk of overfitting → Used feature selection and train–test split

04.

Modeling

MODEL SELECTION

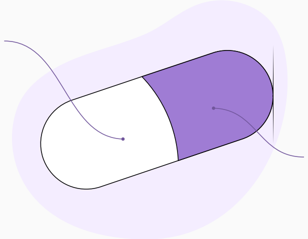
MODEL	ACCURACY	RECALL(0)	RECALL(1)	CONFUSION MATRIX
RANDOM FOREST	94.42%	0.97	0.89	[270, 8] [16,136]
XG BOOST	**95.35%**	**0.98**	**0.91**	**[271, 6] [14,139]**
LOGISTIC REGRESSION	83.02%	0.89	0.73	[246,31] [42 ,111]
SVM	83.26%	0.90	0.71	[250,27] [45,108]

Models Evaluated

- Logistic Regression
- Support Vector Machine (SVM)
- Random Forest
- XGBoost Classifier

Model Selection Rationale

- Models were compared using accuracy, recall, and confusion matrix
- Recall was prioritized to minimize missed Alzheimer’s cases
- XGBoost demonstrated:
    - Higher recall
    - Better class separation in the confusion matrix
    - Strong overall accuracy



05.

Evaluation

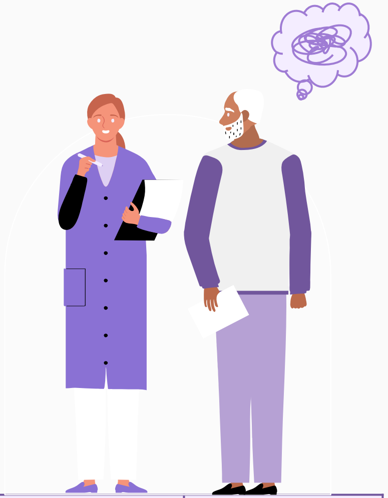
INTERPRETATION AND CHALLENGES

Performance Interpretation

- Recall of 91% shows the model successfully identifies most Alzheimer’s cases
- Low false negatives (14 cases) reduces missed diagnoses
- Balanced precision and recall ensure reliable predictions

Challenges & Solutions

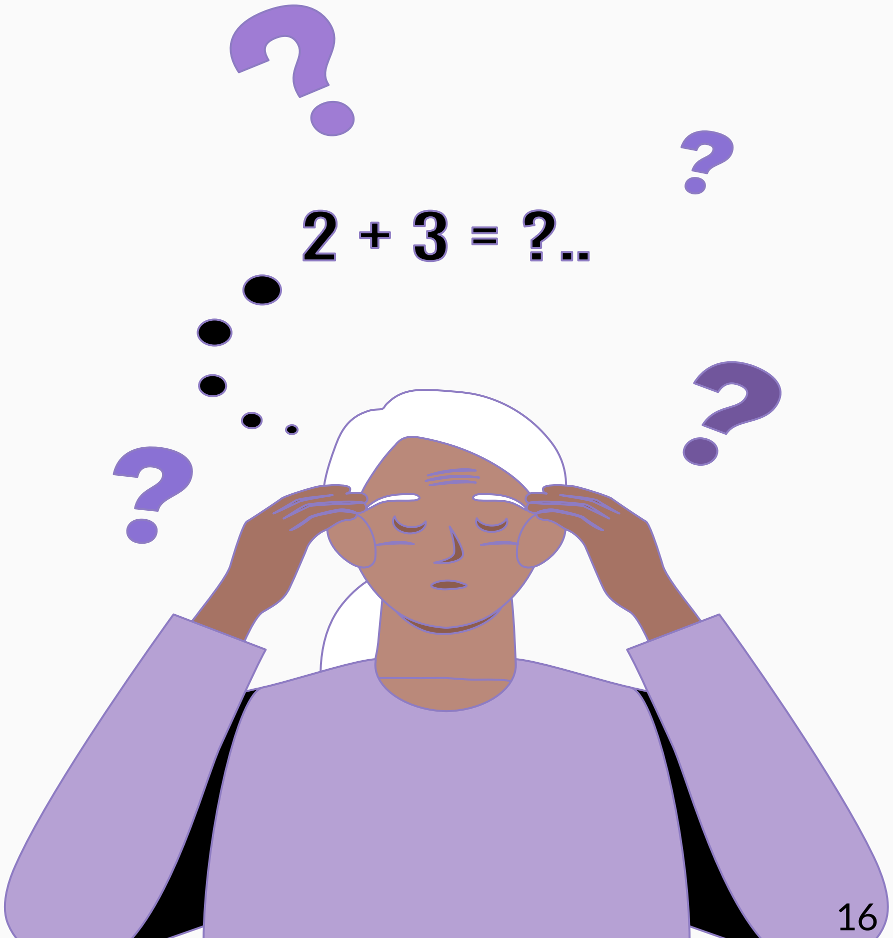
- Class imbalance in dataset → Used stratified 80/20 train–test split
- Risk of false negatives in medical prediction → Prioritized recall over accuracy
- Metric misinterpretation risk → Used confusion matrix and F1-score for validation



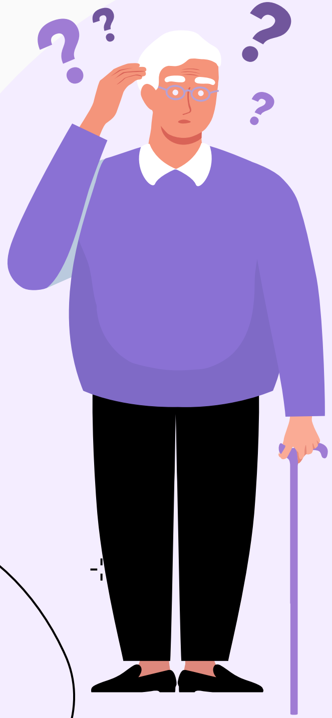
TN: 271	FP: 6
FN: 14	TP: 139

06.

Deployment



DEPLOYMENT- JUPYTER NOTEBOOK



Deployment Approach

- Trained XGBoost Alzheimer's prediction model
- Enabled deployment through an interactive Python-based prediction system
- Binary classification:
  - Alzheimer's
  - Not Alzheimer's

Deployment Challenges & Solutions

- Consistent feature ordering → Stored feature list with model
- Handling missing input values → Median-based preprocessing
- Model reuse across environments → Serialized model using Joblib
- User interpretation of results → Clear label mapping and confidence score

OUTPUT

INPUT

```
========== INPUT SCALE ==========
MMSE (Mini-Mental State Examination): 0-30
Functional Assessment: 0-5
Memory Complaints: 0 = No, 1 = Yes
Behavioral Problems: 0 = No, 1 = Yes
ADL (Activities of Daily Living): 0-6
=================================

Enter the following values:
MMSE score:  23
Functional Assessment score:  4
Memory Complaints (0 = No, 1 = Yes):  ↑↓ for history. Search history with c-↑/c-
```

```
========== INPUT SCALE ==========
MMSE (Mini-Mental State Examination): 0-30
Functional Assessment: 0-5 or according to your dataset scale
Memory Complaints: 0 = No, 1 = Yes
Behavioral Problems: 0 = No, 1 = Yes
ADL (Activities of Daily Living): 0-6 or according to your dataset
=================================

Enter the following values:
MMSE score:  23
Functional Assessment score:  3
Memory Complaints (0 = No, 1 = Yes):  1
Behavioral Problems (0 = No, 1 = Yes):  0
ADL score:  2

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Prediction: Alzheimer's
Confidence: 1.00
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```

07.

Conclusion

CONCLUSION

- Successfully applied XGBOOST to create an Alzheimer’s Prediction model with 95% accuracy and 91% recall effectively minimizing missed diagnoses.
- Key features such as MMSE, Functional Assessment, Memory Complaints, Behavioral Problems, and ADL were used to capture cognitive and functional impairment patterns.
- The trained model was deployed as an interactive prediction tool, providing real-time risk assessment with confidence scores.
- Suitable as a decision-support tool, not a diagnostic replacement

THANK YOU