Optimization Sprint Report

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1. Data Exploration and Process Flow

The dataset is used for optimization sprint derived from NACC (National Alzheimer's Coordinating Center). It was the purpose of building a model that predicts whether the patient is at risk of having dementia or not using demographic, lifecycle, social and functional factors as of non-medical inputs.

Key Benefits:

- Contained multiple variables for demographic and lifestyle.
- The dataset which contains patient identifiers as NACCID and visits years as VISITYR suggesting a potential longitudinal structure. However, the implementation is focused on cross sectional risk prediction using baseline than longitudinal analysis.
- Some Patients had multiple visits by enabling assessment of patterns.
- The target variable was DIMENTIA_RISK.

Flow of the Process

- Dataset is loaded directly from Google Drive through direct download and start working on Google Colab.
- Inspection of non-medical fields.
- Selection of target variables.

Exploratory Data Analysis on:

- Risk Distribution.
- Age-risk
- Education, tobacco and marital status impacts.
- Feature Engineering selection for non-medical dementia risk prediction model.

Data Preprocessing:

- Finding missing value and handling it.
- Encoding and Feature scaling.
- Class Balancing

Model and Multiple ML models build and comparison.

Hyperparameter tuning for best performance model.

Final Evaluation with results.

2. Feature Engineering

- Features that have been selected as non-medical factors.
  - ✓ **Demographic:** SEX, RACE, HISPANIC, EDUC, MARISTAT, NACCAGE.
  - ✓ **Lifestyle:** TOBAC30, TOBAC100, SMOKYRS, ALCFREQ, HEIGHT, WEIGHT.
  - ✓ **Social:** RESIDENC, NACCLIVS, INDEPEND.
  - ✓ **Functional:** BILLS, SHOPPING, TRAVEL
- Feature reduction.
  - ✓ Same value for all patients was removed and kept constant.
  - ✓ SelectKBest with ANOVA F-test – used to choose top k significant statistics factors or predictors and where k is determined as dynamically between 15 and available features.
- Feature creation.

  When there is no label available, I chose DEMENTIA_RISK variables and created using these:
  - ✓ Age
  - ✓ Education
  - ✓ Tobacco
  - ✓ Combined a logistic approximation to get top 30% classified as high risk.

- Finalized features after performing feature engineering and preprocessing (each step should be justified).

After feature selection:

- ✓ NACCAGE (Age)
- ✓ EDUC
- ✓ SEX
- ✓ MARISTAT
- ✓ TOBAC30
- ✓ ALCFREQ
- ✓ RESIDENC
- ✓ NACCLIVS
- ✓ INDEPEND
- ✓ BILLS
- ✓ SHOPPING
- ✓ HEIGHT
- ✓ WEIGHT

Justification: These features enhanced strong statistical relationship with dementia risk while avoiding medical information or data to preserve ethical and research constraints.

3. Data Preprocessing

Date Preprocessing Steps:

1. **Missing Value Handling**
   - ✓ Numerical: median
   - ✓ Categorical: mode
   - ✓ **Justification:** Prevents data loss and preserve characteristics.
2. **Label Encoding**
   - ✓ Applied to categorical variables to convert into numerical way.
   - ✓ **Justification:** Most ML requires numerical input only.
3. **Constant Feature Removal**
   - ✓ Dropped features with single unique value.
   - ✓ **Justification:** Add predictive power and reduces model noise.
4. **Train-Test Split**
   - ✓ 80% training and 20% testing.
   - ✓ Stratified sampling.
   - ✓ **Justification:** Proportional risk classes.
5. **Feature Scaling**
   - ✓ Standard Scaler
   - ✓ **Justification:** Improves models like logistic regression and XGBoost.
6. **Handling Class Imbalance**
   - ✓ SMOTE oversampling used.
   - ✓ **Justification:** Compare high risk and low risk, preventing bias.

4. Model Building

1. Logistic Regression

Justification: Baseline interpretable model.

2. Random Forest

Justification: Handles mixed data types, reduces to noise and captures nonlinear relationships.

3. Gradient Boosting

Justification: Strong predictive performance through sequential learning.

4. XGBoost

Justification: It is used for structured data analysis.

Hyperparameter Tuning

Only best performing model was tuned:

- ✓ For GridSearchCV – AUC ROC scoring with algorithm specified parameter grids for XGBoost and Random Forest.

5. Model Evaluation

- Evaluation metrics that have been used, with justifications.
  - ✓ Accuracy
  - ✓ Precision
  - ✓ Recall
  - ✓ F1-Score
  - ✓ AUC-ROC
  - ✓ Cross-Validation Mean AUC

Justification: Dementia risk is a high impact clinical prediction so AUC, Recall and F1 score are used as essential to measure the power and true high-risk identification.

- Comparison of each model that you have built.

Model	Accuracy	Precision	Recall	F1-Score	AUC
Logistic Regression	~0.78	~0.73	~0.70	~0.71	~0.79
Random Forest	~0.82	~0.81	~0.79	~0.80	~0.85
Gradient Boosting	~0.83	~0.82	~0.80	~0.81	~0.86
XGBoost	~0.85	~0.84	~0.82	~0.83	~0.88

These are random values, but actual values may change based on the dataset provided.

- A brief description of your final model, along with justifications

Final Model is: XGBoost

Justification:

- ✓ Highest AUC-ROC score.
- ✓ Most balanced recall.
- ✓ Handles nonlinearities extremely well.
- ✓ Robust with imbalanced and noisy structured data.

6. Explainability & Model Interpretability

- Explainability Techniques Used
    - ✓ Feature Importance (XGBoost built-in)
    - ✓ Correlation analysis
    - ✓ EDA Analysis with non-medical variables.
- Insights Gained from Explainability
    - ✓ Age was the strongest non-medical predictor.
    - ✓ Education level correlated with dementia risk.
    - ✓ Tobacco significantly increased risk as identified.
    - ✓ Functional such as BILLS, SHOPPING had high predictive values.
    - ✓ Social like Living situation and residence type may be strong influenced support dementia risk.
- Tools Used
    - ✓ Python (Google Colab).
    - ✓ Pandas and NumPy.
    - ✓ Scikit-learn.
    - ✓ XGBoost.
    - ✓ Matplotlib and Seaborn.
    - ✓ SMOTE (imbalance learn).
    - ✓ Joblib (model saving).
    - ✓ Gdown (data download automation)
    - ✓ GitHub (Version control).

Summary

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===DEMENTIA RISK PREDICTION FINAL SUMMARY ===

DEMENTIA RISK PREDICTION MODEL - FINAL SUMMARY

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MODEL PURPOSE

Predicts future dementia risk based on non-medical factors only.

MODEL PERFORMANCE

Model: XGBoost

Number of Non-Medical Features: 15

Metrics:

- Accuracy: 0.9268
- Precision: 0.8715 (correct high-risk predictions)
- Recall: 0.8819 (proportion of actual high-risk identified)
- F1-Score: 0.8767 (balance of precision & recall)
- AUC-ROC: 0.9727 (discrimination between high/low risk)
- CV Mean AUC: 0.9834

TOP 5 RISK FACTORS

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1. INDEPEND (importance: 0.4805) - Independence Level
2. SHOPPING (importance: 0.1756) - Shopping Ability
3. BILLS (importance: 0.1044) - Bill Management
4. TRAVEL (importance: 0.0869) - TRAVEL
5. TAXES (importance: 0.0508) - TAXES

RISK STRATIFICATION

- Low Risk (<30%): Routine monitoring
- Medium Risk (30-60%): Enhanced screening
- High Risk (≥60%): Comprehensive evaluation recommended

CLINICAL NOTES

- Predicts FUTURE dementia risk, not current diagnosis
- Uses non-medical factors only

- Serves as preventive screening tool
- High-risk individuals should receive medical evaluation

MODEL READY FOR DEPLOYMENT!

Model saved as 'dementia_risk_prediction_model.pkl'

Performance summary saved as 'model_performance_summary.csv'

Feature importance saved as 'feature_importance_analysis.csv'

MODEL DEPLOYMENT READY!

You can reload the model using: joblib.load('dementia_risk_prediction_model.pkl')

Note: And, before the summary model will predict status of the patient about dementia risk with non-medical variables.

7. GitHub Repo Link

- ✓ https://github.com/SAJIDMIM/Dementia_Analysis