



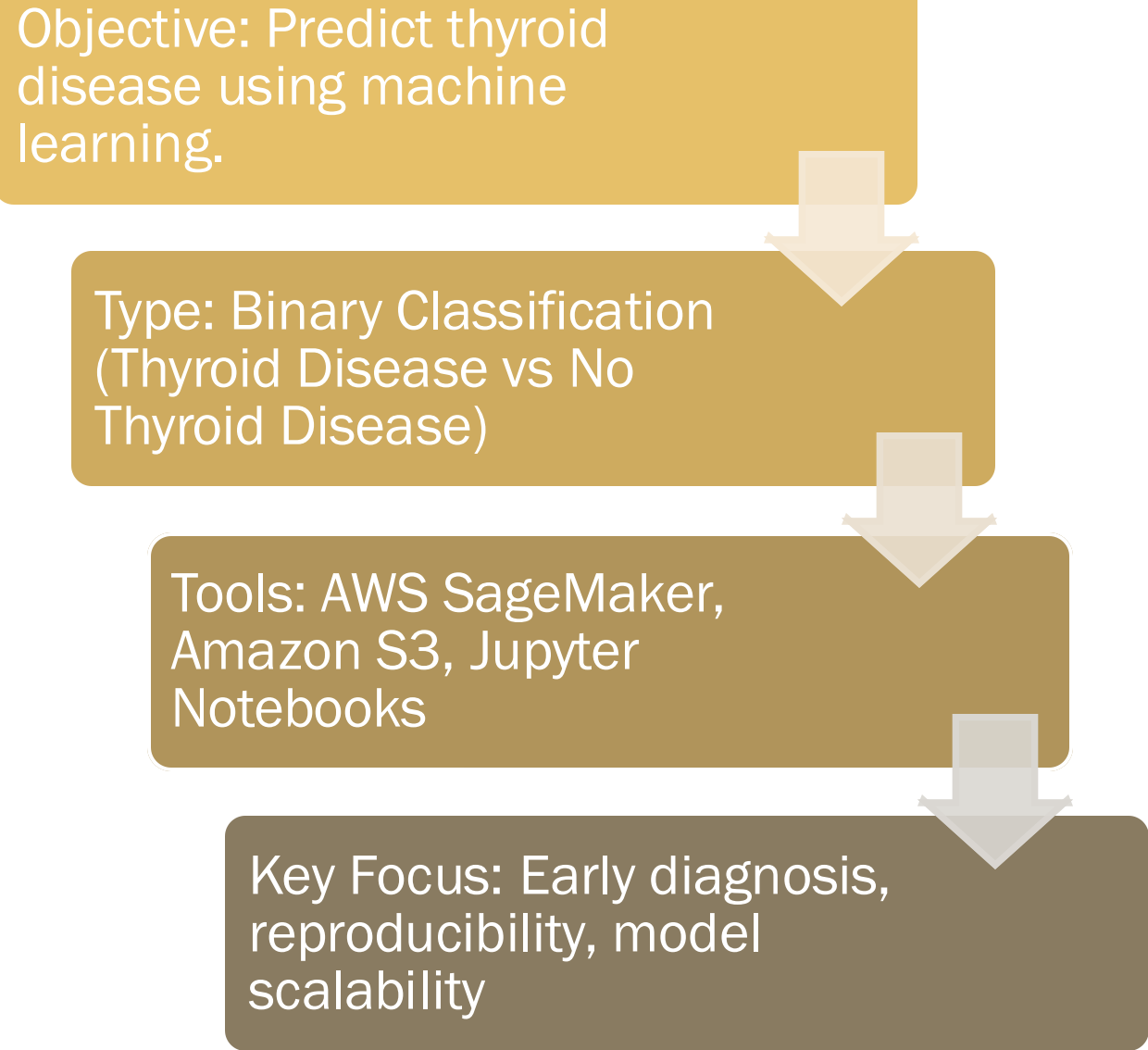
# THYROID DISEASE DETECTION AND PREDICTION

IS597 Final Project Presentation

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# Project Overview

Objective: Predict thyroid disease using machine learning.



```
graph TD; A[Objective: Predict thyroid disease using machine learning.] --> B[Type: Binary Classification (Thyroid Disease vs No Thyroid Disease)]; B --> C[Tools: AWS SageMaker, Amazon S3, Jupyter Notebooks]; C --> D[Key Focus: Early diagnosis, reproducibility, model scalability];
```

Type: Binary Classification (Thyroid Disease vs No Thyroid Disease)

Tools: AWS SageMaker, Amazon S3, Jupyter Notebooks

Key Focus: Early diagnosis, reproducibility, model scalability

# Dataset Summary



Total Records: 9,000+ patients



Features: Hormone levels (TSH, T3, TT4, T4U, FTI), demographic info



Target Variable: Thyroid condition (yes/no)



Challenges: Missing values, slight class imbalance

# Methodology



## Models Implemented:

Decision Tree Classifier  
Random Forest Classifier  
Logistic Regression (Baseline Model)



## Data Handling:

Missing Value Imputation (Median/Mode)  
Stratified Train/Test Split (80/20)



## Feature Engineering:

One-Hot Encoding for categorical variables  
Principal Component Analysis (PCA) for dimensionality reduction

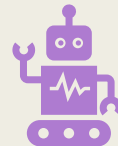
# SageMaker Workflow



Data upload and  
storage on  
Amazon S3



Notebook-based  
Data  
Preprocessing



Model Training  
using SageMaker  
built-in algorithms



Evaluation Metrics  
Calculation



Model Export:  
Models saved as  
Joblib files to S3

# MODEL TRAINING

## 80/20 stratified split

```
Training set shape: (7336, 26)
Testing set shape: (1835, 26)
Class distribution in y_train:
0      0.738
1      0.262
```

## Data Loading and Preprocessing

```
One-hot encoding complete.
X_train shape: (7336, 26)
X_test shape: (1835, 26)
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score

# Define baseline models
models = {
    "Decision Tree": DecisionTreeClassifier(random_state=42),
    "Random Forest": RandomForestClassifier(random_state=42),
    "Logistic Regression": LogisticRegression(max_iter=2000, solver='lbfgs', random_state=42)
```

# Model Results

===== Decision Tree =====

Accuracy: 0.937

	precision	recall	f1-score	support
0	0.96	0.96	0.96	1355
1	0.88	0.88	0.88	480
accuracy			0.94	1835
macro avg	0.92	0.92	0.92	1835
weighted avg	0.94	0.94	0.94	1835

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===== Random Forest =====

Accuracy: 0.942

	precision	recall	f1-score	support
0	0.97	0.95	0.96	1355
1	0.86	0.93	0.89	480
accuracy			0.94	1835
macro avg	0.92	0.94	0.93	1835
weighted avg	0.94	0.94	0.94	1835

===== Logistic Regression =====

Accuracy: 0.837

	precision	recall	f1-score	support
0	0.83	0.98	0.90	1355
1	0.87	0.44	0.59	480
accuracy			0.84	1835
macro avg	0.85	0.71	0.74	1835
weighted avg	0.84	0.84	0.82	1835

# Model Performance Evaluation

Model	Accuracy	Precision (Class 1)	Recall (Class 1)	F1-Score (Class 1)	AUC-ROC
Decision Tree	93.7%	0.88	0.88	0.88	0.933
Random Forest	94.2%	0.86	0.93	0.89	0.947
Logistic Regression	83.7%	0.87	0.44	0.59	0.850

## Random Forest Classifier

- **High recall** is critical to minimize false negatives.
- Strongly **recommended** for healthcare predictions needing reliability.

## Decision Tree Classifier

- **Slightly weaker** generalization compared to Random Forest.
- Prone to overfitting on noisy or redundant data.

## Logistic Regression

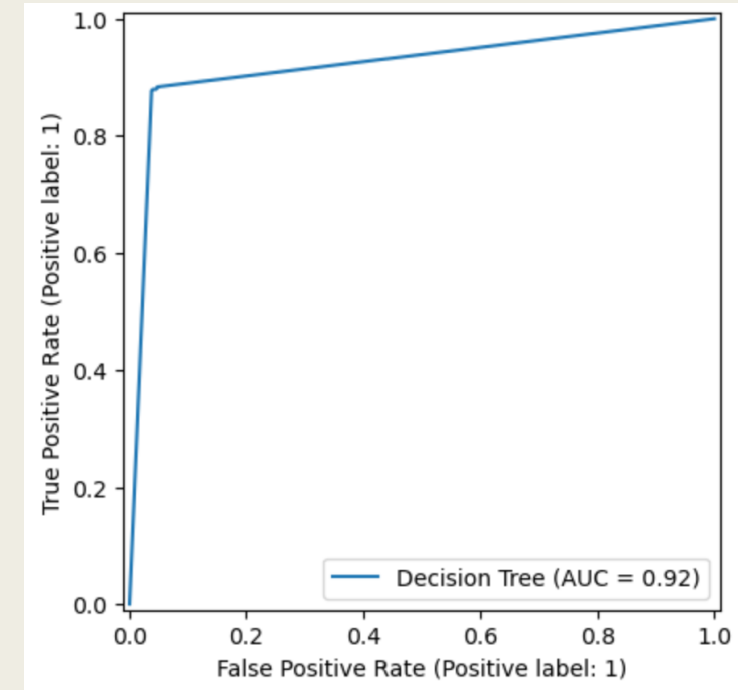
- Underperformed
- **Low recall** — missed many true thyroid disease cases.



# ROC CURVE

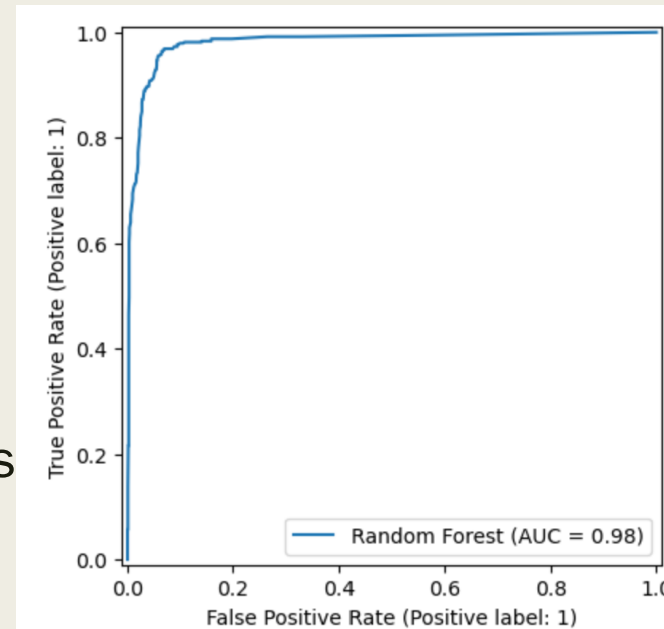
## Decision Tree

- AUC of 0.92
- balancing accuracy and model interpretability.



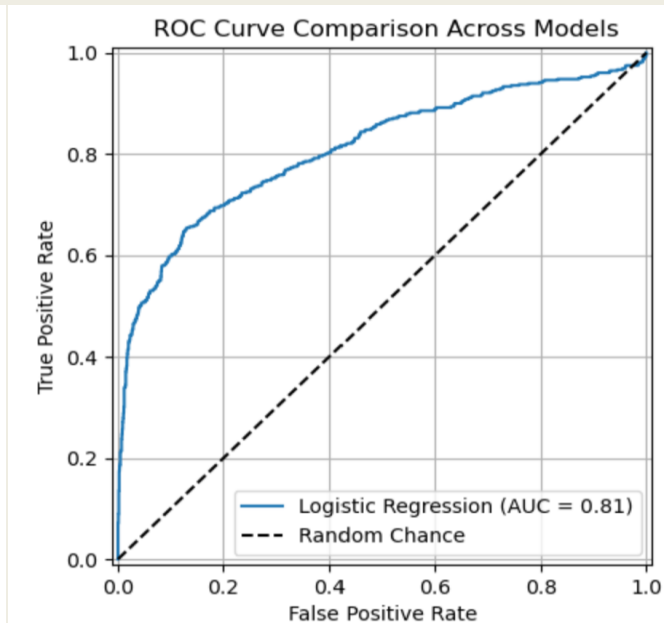
## Random Forest :

- best performance
- AUC of 0.98
- high sensitivity
- low false positive rates



## Logistic Regression

- AUC of 0.81
- struggling to detect positive thyroid cases



# Confusion Matrix

## Decision Tree Classifier

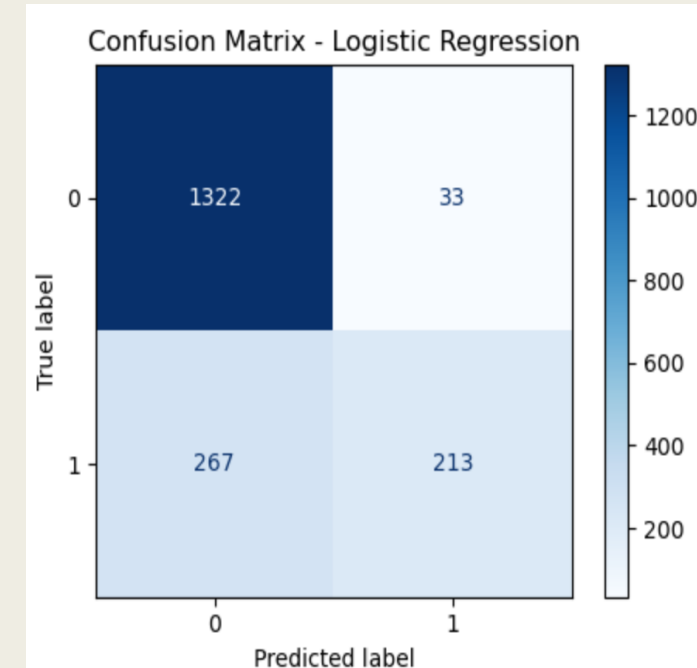
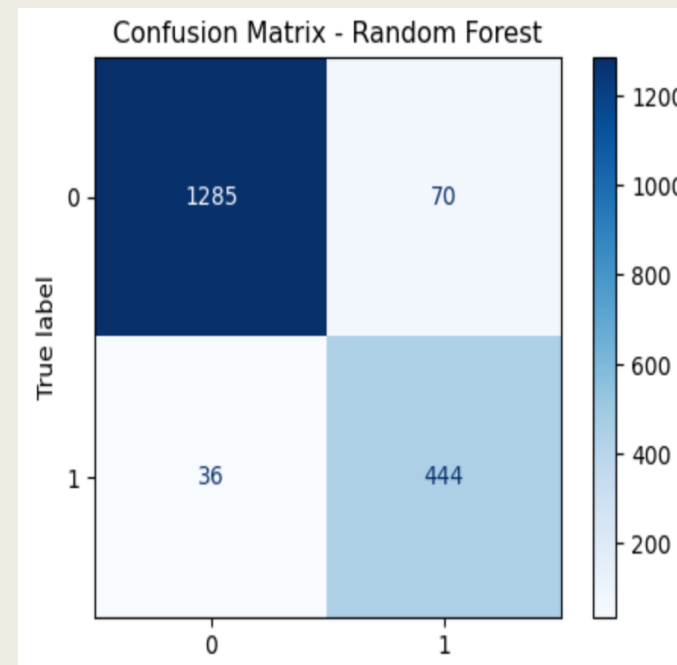
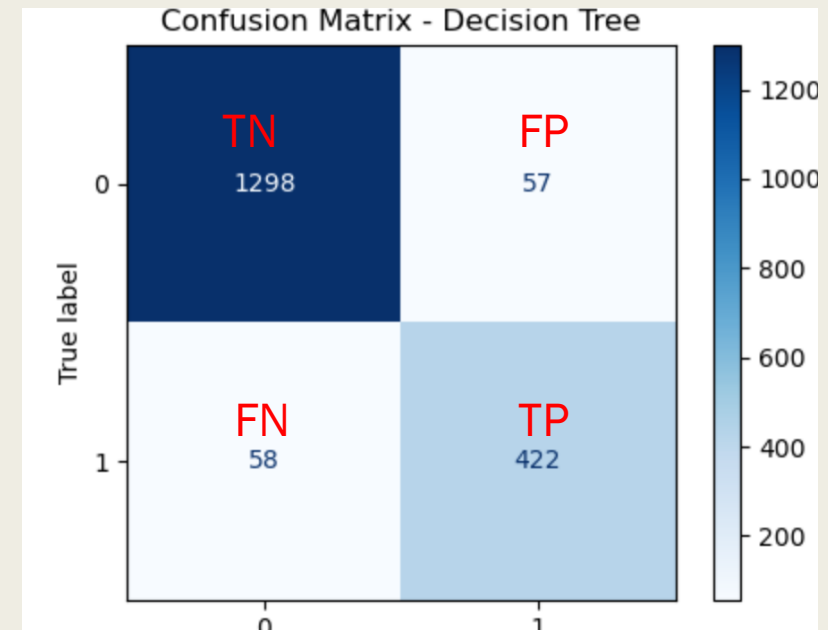
- Balanced performance
- moderate FN :58.

## Random Forest Classifier

- **Best recall** , Low FN: 36 .
- Stronger at detecting thyroid disease
- Trade-off in FP.

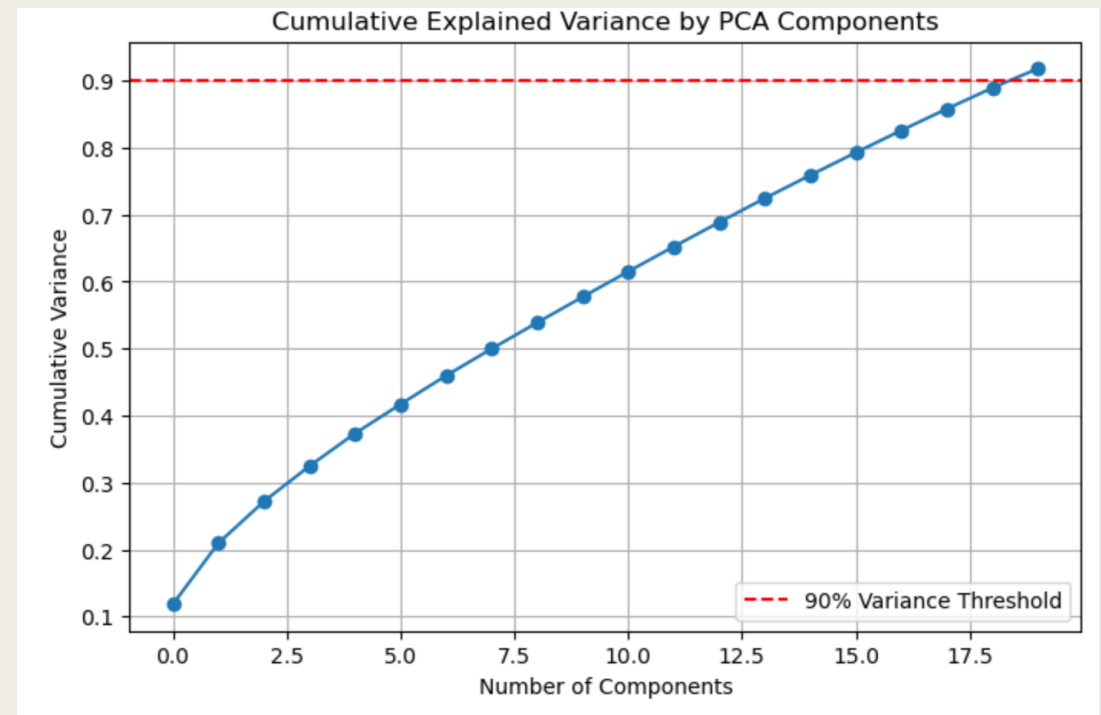
## Logistic Regression

- High TN, **high FN: 267**
- **Poor recall**: misses many thyroid cases.



==== Random Forest on PCA-Reduced Features (20 Components) ====

	precision	recall	f1-score	support
0	0.88	0.93	0.90	1355
1	0.75	0.63	0.68	480
accuracy			0.85	1835
macro avg	0.81	0.78	0.79	1835
weighted avg	0.84	0.85	0.84	1835



# Impact of PCA

- **Accuracy:** 85% on the test set (compared to ~94% without PCA).
- **Recall (for class 1 - thyroid cases):** Dropped to 0.63, indicating reduced sensitivity.
- **F1-score (for class 1):** Reduced to 0.68.



# Strengths & Challenges

## ☐ Strengths:

- Cloud-native and scalable pipeline
- Effective preprocessing for noisy healthcare data
- Strong model generalization

## ■ Challenges:

- PCA improved efficiency but slightly reduced thyroid detection sensitivity.
- Dataset demographic bias (Mostly adult patients)
- Minor class imbalance affected logistic regression performance

# Future Enhancements



Automate full SageMaker pipeline using AWS Step Functions



Integrate XGBoost and LightGBM for potentially higher accuracy



Deploy REST API for real-time thyroid prediction



Utilize SHAP or LIME for model explainability in healthcare compliance

# Conclusion



ACHIEVED 94.2% ACCURACY  
USING RANDOM FOREST



DEMONSTRATED FEASIBILITY OF  
ML-ASSISTED THYROID  
DIAGNOSIS



READY FOR SCALING WITH  
MORE DIVERSE DATASETS AND  
REAL-WORLD INTEGRATION

# Team Contributions



**Pranav Rajesh Charakondala:**

Model Training using SageMaker built-in algorithms  
Evaluation Metrics Calculation



**Danni Wu and Arundhati Raj:**

Choosing final dataset and uploading it on S3  
Notebook-based Data Preprocessing



Thank You!