Progress Report 2

FHIR-Based Prediction of Hospital Readmission for Patients Aged 50 Plus

Group 13

Group Members: Frank Ofosu & Oscar Odera

1. **AI Model(s) Used in Research Project**

Our project utilizes multiple machine learning models including:

- Random Forest
- XGBoost
- MLP
- Logistic Regression
- Gradient Boosting
- SVM
- KNN
- Adaboost
- Naive Bayesian

Explain the architecture and key components of your model(s)

Out of the models above, Random Forest and Gradient Boosting performed well. Their key architecture and key components include:

A. Random Forest Classifier: Ensemble model based on decision trees, trains multiple trees on different bootstrap samples, uses **majority voting** for classification and tunes parameters with n_estimators, max_depth

B. Gradient Boosting Classifier: It is a sequential tree-based ensemble model, each tree attempts to correct the errors of its predecessor and it is tuned using n_estimators, learning_rate

Justify why you selected this particular model/approach for your AI medical/health project.

In predicting 30-day hospital readmission using patient level data, a complex classification task involving multiple structured features like labs, vitals, and chronic condition flags. The Tree based models chosen above are best in handling mixed feature types, capturing non-linear relationships and are best in providing feature importance for explainability which is very critical in healthcare.

2. **Performance Metrics Analysis**

Sample of Random Forest before Hyperparameter tuning

```
Evaluating: Random Forest
Accuracy: 0.760
F1 Score: 0.623
AUROC: 0.828
Confusion Matrix:
 [[54 10]
 [13 19]]
Classification Report:
              precision    recall  f1-score   support

         0.0       0.81      0.84      0.82        64
         1.0       0.66      0.59      0.62        32

    accuracy                           0.76        96
   macro avg       0.73      0.72      0.72        96
weighted avg       0.76      0.76      0.76        96
```

Accuracy; the percentage of total correct predictions made by the model, it gives us an idea of how often the model is right.

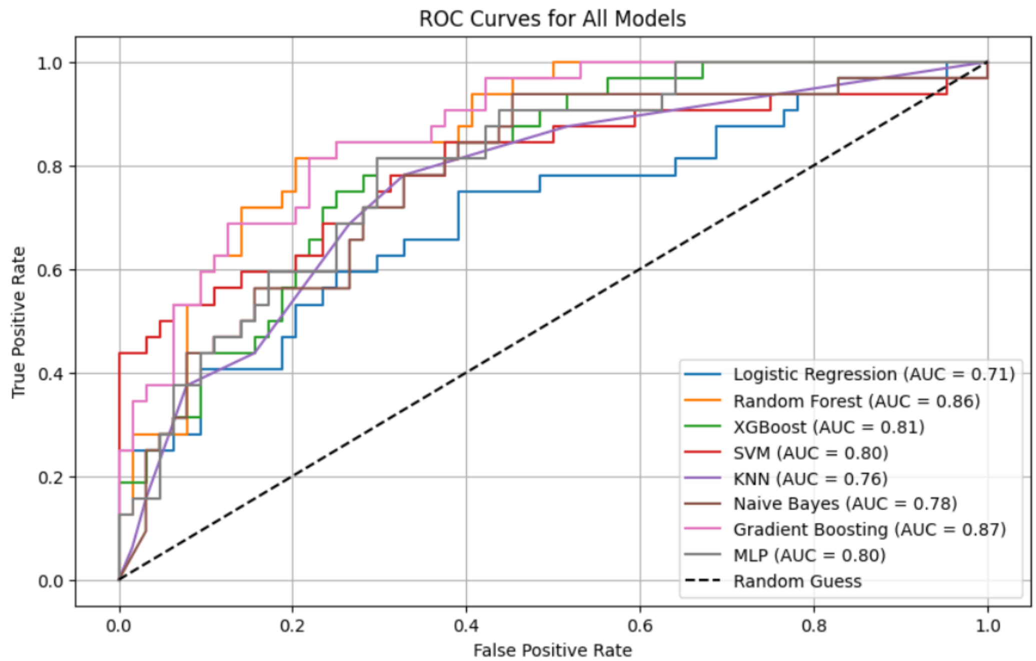
Precision; the percentage of patients predicted as readmitted who were actually readmitted, it helps us minimize false alarms.

Recall (Sensitivity); the percentage of actual readmitted patients that were correctly identified, it helps us to capture all high risk patients.

F1 Score; Harmonic mean of precision and recall, its useful in balancing the trade-off between precision and recall.

AUC – ROC; Measures the ability of our models to distinguish between readmitted and non-admitted patients, across all thresholds, we use it as a Gold standard in our research.

Performance after hyperparameter tuning for all models



Compare your current results with expected benchmarks or standards in the field (this should stem from the publications you are referencing as relevant literature)

The performance of our models are way better compared to legacy models like LACE and HOSPITAL Scores and also better after hyperparameter tuning than that of Michailidis et al. that obtained an area under the curve (AUC) of 0.78 by utilizing a Random Forest classifier with administrative, clinical-medical, and operational data.

3. **Project Status Summary**

Our project is on track for completion by April 18th (90% done as seen in the attached project code). Our next steps include preparing presentations and creating Github repositories.

```python
import os
import json
import pandas as pd
from tqdm import tqdm

json_folder = r"C:\Users\admin\Desktop\AI in Healthcare\Research Project\All Converted Files"
observations = []

for filename in tqdm(os.listdir(json_folder)):
    if filename.endswith(".json"):
        path = os.path.join(json_folder, filename)
        try:
            with open(path) as f:
                bundle = json.load(f)
                for entry in bundle.get("entry", []):
                    resource = entry.get("resource", {})
                    if resource.get("resourceType") == "Observation":
                        patient_ref = resource.get("subject", {}).get("reference", "")
                        patient_id = patient_ref.split("/")[-1] if patient_ref else None
                        raw_time = resource.get("effectiveDateTime")

                        if patient_id and raw_time:
                            ts = pd.to_datetime(raw_time, errors='coerce', utc=True)
                            ts_naive = ts.tz_convert(None) if ts.tzinfo else ts
                            observations.append({
                                "patient_id": patient_id,
                                "timestamp": ts_naive,
                                "file": filename
                            })
        except Exception as e:
            print(f"Error reading {filename}: {e}")
```

```
100%|██████████| 2104/2104 [00:25<00:00, 83.85it/s]
```

```python
# Create DataFrame
obs_df = pd.DataFrame(observations)

# Drop rows with missing timestamps
obs_df = obs_df.dropna(subset=["timestamp"])

# Convert patient ID to string (for grouping)
obs_df["patient_id"] = obs_df["patient_id"].astype(str)
```

```
# Sort by patient and timestamp safely
obs_df = obs_df.sort_values(by=["patient_id",
"timestamp"]).reset_index(drop=True)

# Preview
print(f"Total observations extracted: {len(obs_df)}")
obs_df.head()
```

```
Total observations extracted: 39649
```

```
  patient_id           timestamp  \
0  000000001 2024-10-11 01:01:00
1  000000001 2024-10-11 01:01:00
2  000000001 2024-10-11 01:04:01
3  000000001 2024-10-11 03:35:00
4  000000001 2024-10-11 03:35:00

                                                file
0  fhir_output_TEST_ccd_uphealthsystem-marquette_...
1  fhir_output_TEST_ccd_uphealthsystem-marquette_...
2  fhir_output_TEST_ccd_uphealthsystem-marquette_...
3  fhir_output_TEST_ccd_uphealthsystem-marquette_...
4  fhir_output_TEST_ccd_uphealthsystem-marquette_...
```

```
# Start with no readmissions
obs_df["readmitted"] = 0

# Loop through observations by same patient
for i in range(1, len(obs_df)):
    prev = obs_df.iloc[i - 1]
    curr = obs_df.iloc[i]

    if curr["patient_id"] == prev["patient_id"]:
        days_apart = (curr["timestamp"] - prev["timestamp"]).days
        if 0 < days_apart <= 30:
            obs_df.at[i, "readmitted"] = 1

# If patient was readmitted at least once → label = 1
patient_labels = obs_df.groupby("patient_id")
["readmitted"].max().reset_index()

# Convert patient_id to string to match feature dataset
patient_labels["patient_id"] =
patient_labels["patient_id"].astype(str)

# Preview the readmission label distribution
print("Readmission Label Counts:")
print(patient_labels["readmitted"].value_counts())

patient_labels.head()
```

```
Readmission Label Counts:
readmitted
0    200
1    152
Name: count, dtype: int64

  patient_id  readmitted
0  000000001           1
1  000000003           1
2  000000004           0
3  000000005           1
4  000000007           1

import pandas as pd

# Load your modeling dataset
df_main = pd.read_csv("readmission_dataset2.csv")

# Ensure both patient IDs are strings for a safe merge
df_main["patient_id"] = df_main["patient_id"].astype(str)
patient_labels["patient_id"] =
patient_labels["patient_id"].astype(str)

# Merge real readmission labels
df_labeled = df_main.merge(patient_labels, on="patient_id",
how="left")

# Patients not found in readmission label → assume not readmitted
df_labeled["readmitted"] =
df_labeled["readmitted"].fillna(0).astype(int)

# Confirm success
print("Readmission label counts after merge:")
print(df_labeled["readmitted"].value_counts())
df_labeled.head()

Readmission label counts after merge:
readmitted
0    320
1    158
Name: count, dtype: int64

  patient_id  gender   age  num_conditions  num_encounters  \
0        106  female  61.0               4               2
1        109  female  80.0              36               4
2        107    male  39.0              10               1
3        212     NaN   NaN               2               1
4        148    male  27.0              15               2

     chronic_conditions      Height  Glucose_avg  Temperature
SystolicBP  \
```

```
0                     NaN  129.666667        156.0        36.80
115.000000
1                     NaN  157.500000          NaN        36.86
131.250000
2                     NaN  162.600000          NaN        36.56
131.000000
3  Asthma; Hypertension  190.000000          NaN        37.20
175.000000
4            Depression  173.600000          NaN        36.97
112.571429

   DiastolicBP   HeartRate  HemoglobinA1C   Weight      BMI
readmitted
0    76.666667   99.333333           11.6      NaN      NaN
0
1    92.250000   94.000000            NaN   48.762  19.6625
1
2    84.000000  114.000000            NaN   65.318  24.7200
0
3    91.000000         NaN            NaN      NaN      NaN
0
4    63.857143   65.142857            NaN  115.667  39.9400
0
```

```
# Drop text columns not used in modeling (optional: add more if
needed)
df_model = df_labeled.drop(columns=["patient_id", "birthDate",
"num_encounters", "address", "name"], errors='ignore')

# Map gender manually
if "gender" in df_model.columns:
    df_model["gender"] = df_model["gender"].map({"female": 1, "male":
0})

# Automatically one-hot encode remaining object columns
non_numeric =
df_model.select_dtypes(include='object').columns.tolist()
if non_numeric:
    print("One-hot encoding:", non_numeric)
    df_model = pd.get_dummies(df_model, columns=non_numeric,
drop_first=True)
```

```
One-hot encoding: ['chronic_conditions']
```

```
from sklearn.impute import SimpleImputer

# Use SimpleImputer to fill remaining NaNs
imputer = SimpleImputer(strategy="median")
df_model_imputed = pd.DataFrame(
    imputer.fit_transform(df_model),
```

```python
    columns=df_model.columns
)

# Confirm no NaNs remain
print("NaNs after imputation:", df_model_imputed.isnull().sum().sum())
```

```
NaNs after imputation: 0
```

```python
from sklearn.model_selection import train_test_split

X = df_model_imputed.drop(columns=["readmitted"])
y = df_model_imputed["readmitted"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, stratify=y, test_size=0.2, random_state=42
)

from sklearn.utils import resample
import numpy as np

# Combine for resampling
train_df = pd.concat([X_train, y_train], axis=1)

# Split by class
majority = train_df[train_df["readmitted"] == 0]
minority = train_df[train_df["readmitted"] == 1]

# Upsample minority to match majority
minority_upsampled = resample(minority, replace=True,
n_samples=len(majority), random_state=42)

# Combine and shuffle
balanced_df = pd.concat([majority, minority_upsampled]).sample(frac=1,
random_state=42)

# Separate again
X_res = balanced_df.drop(columns=["readmitted"])
y_res = balanced_df["readmitted"]

print("Balanced class distribution:", np.bincount(y_res))
```

```
Balanced class distribution: [256 256]
```

```python
from sklearn.ensemble import (
    RandomForestClassifier, GradientBoostingClassifier,
AdaBoostClassifier
)
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

```python
from sklearn.neural_network import MLPClassifier

# Optional: try XGBoost if installed
try:
    from xgboost import XGBClassifier
except:
    XGBClassifier = None

# Define models dictionary
models = {
    "Random Forest": RandomForestClassifier(random_state=42),
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Gradient Boosting": GradientBoostingClassifier(),
    "AdaBoost": AdaBoostClassifier(),
    "SVM": SVC(probability=True),
    "KNN": KNeighborsClassifier(),
    "Naive Bayes": GaussianNB(),
    "MLP Neural Net": MLPClassifier(max_iter=1000)
}

if XGBClassifier:
    models["XGBoost"] = XGBClassifier(eval_metric='logloss',
enable_categorical=False)

import warnings
warnings.filterwarnings("ignore")


from sklearn.metrics import (
    accuracy_score, f1_score, roc_auc_score, confusion_matrix,
classification_report
)

results = []

for name, model in models.items():
    print(f"\nEvaluating: {name}")
    try:
        model.fit(X_res, y_res)
        y_pred = model.predict(X_test)

        # Use predicted probabilities for AUC if available
        if hasattr(model, "predict_proba"):
            y_proba = model.predict_proba(X_test)[:, 1]
        else:
            y_proba = y_pred

        acc = accuracy_score(y_test, y_pred)
        f1 = f1_score(y_test, y_pred, zero_division=0)
        auc = roc_auc_score(y_test, y_proba)
```

```
        print(f"Accuracy: {acc:.3f}")
        print(f"F1 Score: {f1:.3f}")
        print(f"AUROC: {auc:.3f}")
        print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
        print("Classification Report:\n",
classification_report(y_test, y_pred, zero_division=0))

        results.append({"Model": name, "Accuracy": acc, "F1 Score":
f1, "AUROC": auc})

    except Exception as e:
        print(f"{name} failed: {e}")
```

```
Evaluating: Random Forest
Accuracy: 0.760
F1 Score: 0.623
AUROC: 0.828
Confusion Matrix:
 [[54 10]
 [13 19]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.81      0.84      0.82        64
         1.0       0.66      0.59      0.62        32

    accuracy                           0.76        96
   macro avg       0.73      0.72      0.72        96
weighted avg       0.76      0.76      0.76        96


Evaluating: Logistic Regression
Accuracy: 0.656
F1 Score: 0.459
AUROC: 0.648
Confusion Matrix:
 [[49 15]
 [18 14]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.73      0.77      0.75        64
         1.0       0.48      0.44      0.46        32

    accuracy                           0.66        96
   macro avg       0.61      0.60      0.60        96
weighted avg       0.65      0.66      0.65        96
```

```
Evaluating: Gradient Boosting
Accuracy: 0.729
F1 Score: 0.594
AUROC: 0.847
Confusion Matrix:
 [[51 13]
 [13 19]]
Classification Report:
              precision    recall  f1-score   support

         0.0       0.80      0.80      0.80        64
         1.0       0.59      0.59      0.59        32

    accuracy                           0.73        96
   macro avg       0.70      0.70      0.70        96
weighted avg       0.73      0.73      0.73        96


Evaluating: AdaBoost
Accuracy: 0.760
F1 Score: 0.667
AUROC: 0.844
Confusion Matrix:
 [[50 14]
 [ 9 23]]
Classification Report:
              precision    recall  f1-score   support

         0.0       0.85      0.78      0.81        64
         1.0       0.62      0.72      0.67        32

    accuracy                           0.76        96
   macro avg       0.73      0.75      0.74        96
weighted avg       0.77      0.76      0.76        96


Evaluating: SVM
Accuracy: 0.740
F1 Score: 0.468
AUROC: 0.720
Confusion Matrix:
 [[60  4]
 [21 11]]
Classification Report:
              precision    recall  f1-score   support

         0.0       0.74      0.94      0.83        64
         1.0       0.73      0.34      0.47        32

    accuracy                           0.74        96
```

```
   macro avg       0.74      0.64      0.65        96
weighted avg       0.74      0.74      0.71        96


Evaluating: KNN
Accuracy: 0.677
F1 Score: 0.551
AUROC: 0.740
Confusion Matrix:
 [[46 18]
 [13 19]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.78      0.72      0.75        64
         1.0       0.51      0.59      0.55        32

    accuracy                           0.68        96
   macro avg       0.65      0.66      0.65        96
weighted avg       0.69      0.68      0.68        96


Evaluating: Naive Bayes
Accuracy: 0.552
F1 Score: 0.583
AUROC: 0.787
Confusion Matrix:
 [[23 41]
 [ 2 30]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.92      0.36      0.52        64
         1.0       0.42      0.94      0.58        32

    accuracy                           0.55        96
   macro avg       0.67      0.65      0.55        96
weighted avg       0.75      0.55      0.54        96


Evaluating: MLP Neural Net
Accuracy: 0.729
F1 Score: 0.536
AUROC: 0.774
Confusion Matrix:
 [[55  9]
 [17 15]]
Classification Report:
               precision    recall  f1-score   support
```

```
         0.0       0.76      0.86      0.81        64
         1.0       0.62      0.47      0.54        32

    accuracy                           0.73        96
   macro avg       0.69      0.66      0.67        96
weighted avg       0.72      0.73      0.72        96


Evaluating: XGBoost
Accuracy: 0.719
F1 Score: 0.571
AUROC: 0.808
Confusion Matrix:
 [[51 13]
 [14 18]]
Classification Report:
               precision    recall  f1-score   support

         0.0       0.78      0.80      0.79        64
         1.0       0.58      0.56      0.57        32

    accuracy                           0.72        96
   macro avg       0.68      0.68      0.68        96
weighted avg       0.72      0.72      0.72        96
```

```python
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score, recall_score
# Define models + hyperparameter grids
model_configs = {
    "Logistic Regression": (
        LogisticRegression(max_iter=1000),
        {"C": [0.1, 1, 10], "solver": ["liblinear", "lbfgs"]}
    ),
    "Random Forest": (
        RandomForestClassifier(),
        {"n_estimators": [100, 200], "max_depth": [5, 10]}
    ),
    "XGBoost": (
        XGBClassifier(use_label_encoder=False, eval_metric='logloss'),
        {"n_estimators": [100, 200], "max_depth": [3, 6]}
    ),
    "SVM": (
        SVC(probability=True),
        {"C": [0.1, 1], "kernel": ["linear", "rbf"]}
    ),
    "KNN": (
        KNeighborsClassifier(),
        {"n_neighbors": [3, 5, 7]}
    ),
```

```python
    "Naive Bayes": (
        GaussianNB(),
        {}  # No tuning
    ),
    "Gradient Boosting": (
        GradientBoostingClassifier(),
        {"n_estimators": [100, 200], "max_depth": [3, 6]}
    ),
    "MLP": (
        MLPClassifier(max_iter=500),
        {"hidden_layer_sizes": [(50,), (100,)], "activation": ["relu",
"tanh"]}
    )
}

# Tune + evaluate
models = {}
results = {}

for name, (model, params) in model_configs.items():
    print(f"Tuning {name}...")
    clf = GridSearchCV(model, params, scoring="roc_auc", cv=3,
n_jobs=-1)
    clf.fit(X_train, y_train)
    best = clf.best_estimator_
    models[name] = best

    y_pred = best.predict(X_test)
    y_prob = best.predict_proba(X_test)[:, 1]

    results[name] = {
        "F1": f1_score(y_test, y_pred),
        "Recall": recall_score(y_test, y_pred),
        "AUROC": roc_auc_score(y_test, y_prob)
    }
```

```
Tuning Logistic Regression...
Tuning Random Forest...
Tuning XGBoost...
Tuning SVM...
Tuning KNN...
Tuning Naive Bayes...
Tuning Gradient Boosting...
Tuning MLP...
```

```python
import pandas as pd

# Create summary table (transpose first)
results_df = pd.DataFrame(results).T.sort_values(by="AUROC",
ascending=False).reset_index()
```

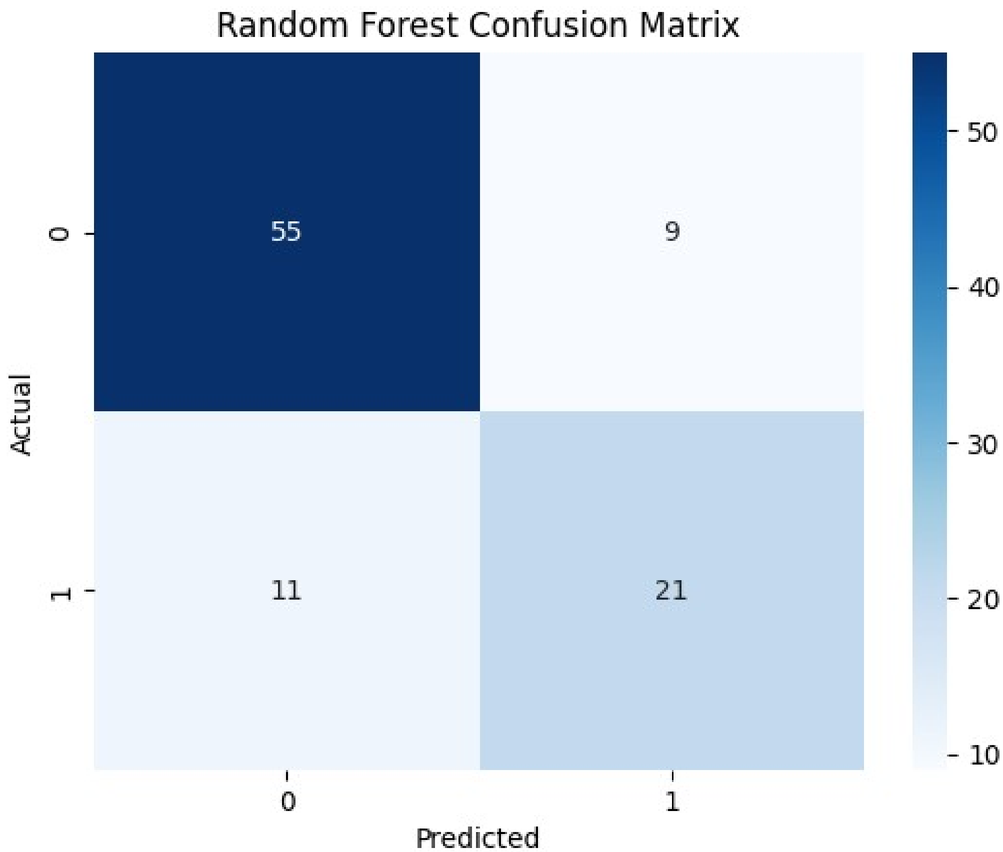
```
# Rename for clarity
results_df.rename(columns={'index': 'Model'}, inplace=True)

# Display
print("Final Model Comparison:")
display(results_df)
```

```
Final Model Comparison:
```

	Model	F1	Recall	AUROC
0	Gradient Boosting	0.688525	0.65625	0.870117
1	Random Forest	0.677419	0.65625	0.861816
2	XGBoost	0.593750	0.59375	0.805176
3	MLP	0.590164	0.56250	0.798828
4	SVM	0.222222	0.12500	0.796875
5	Naive Bayes	0.520000	0.40625	0.776855
6	KNN	0.500000	0.43750	0.763184
7	Logistic Regression	0.390244	0.25000	0.708496

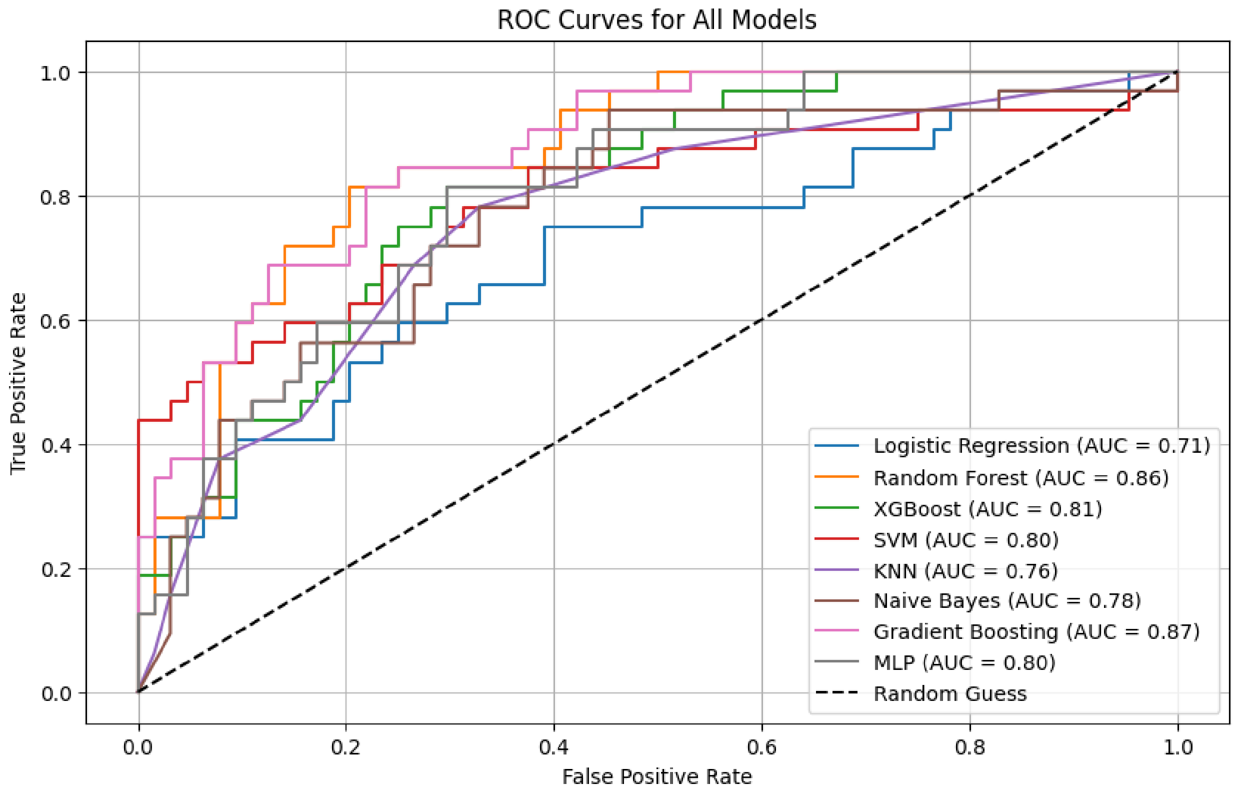
```
import seaborn as sns
import matplotlib.pyplot as plt
print("\nConfusion Matrix for Random Forest:")
cm = confusion_matrix(y_test, models["Random Forest"].predict(X_test))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=[0,1],
yticklabels=[0,1])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Random Forest Confusion Matrix")
plt.show()
```

```
Confusion Matrix for Random Forest:
```

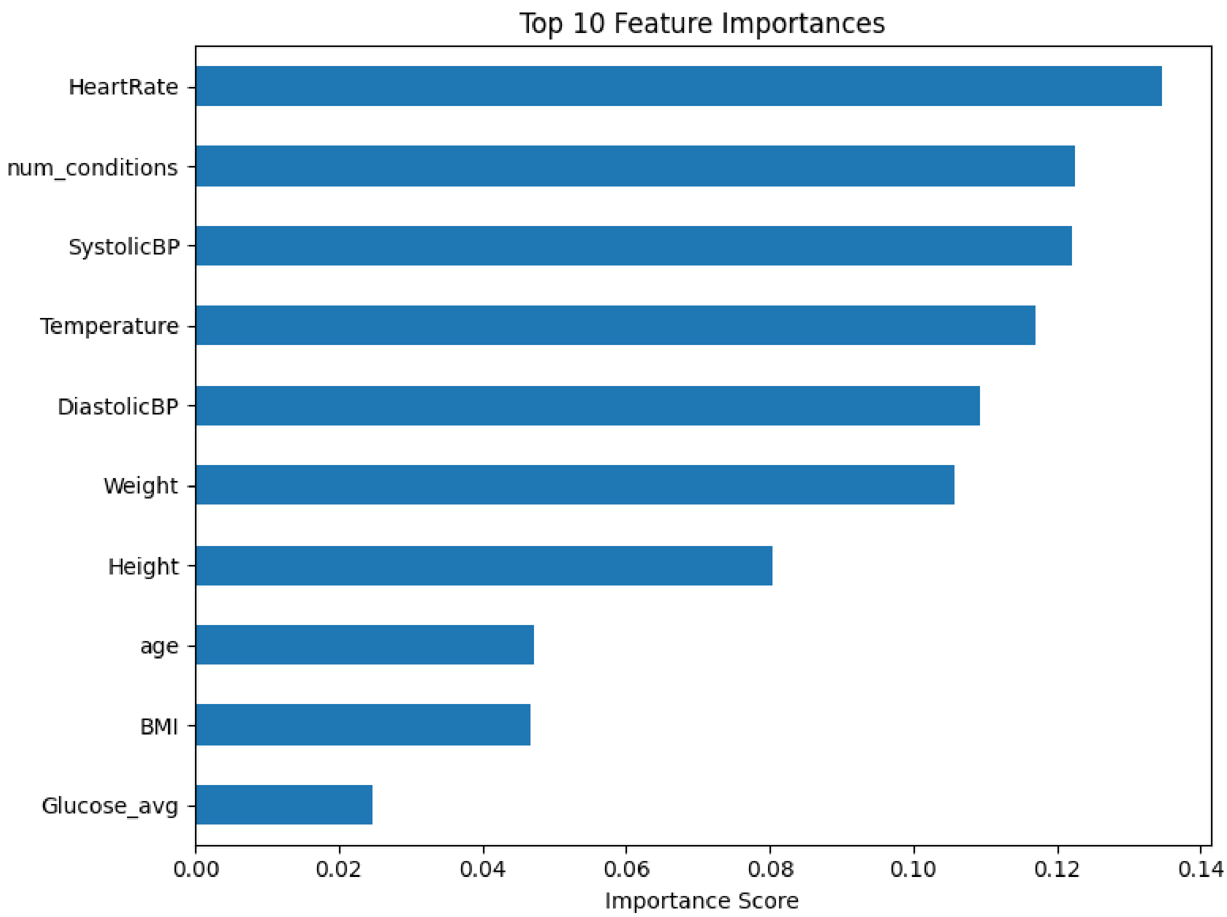



```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve, auc

plt.figure(figsize=(10, 6))

for name, model in models.items():
    try:
        if hasattr(model, "predict_proba"):
            y_score = model.predict_proba(X_test)[:, 1]
        else:
            y_score = model.decision_function(X_test)

        fpr, tpr, _ = roc_curve(y_test, y_score)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f"{name} (AUC = {roc_auc:.2f})")
    except:
        continue

plt.plot([0, 1], [0, 1], "k--", label="Random Guess")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curves for All Models")
plt.legend(loc="lower right")
```

```
plt.grid()
plt.show()
```




```
# Must match the model that supports .feature_importances_
rf_model = models["Random Forest"]
importances = rf_model.feature_importances_

# Create a Series for plotting
feat_imp = pd.Series(importances,
index=X.columns).sort_values(ascending=False)

# Plot top 10 features
feat_imp.head(10).plot(kind="barh", figsize=(8, 6), title="Top 10
Feature Importances")
plt.gca().invert_yaxis()
plt.xlabel("Importance Score")
plt.tight_layout()
plt.show()
```


Top 10 Feature Importances
HeartRate
num_conditions
SystolicBP
Temperature
DiastolicBP
Weight
Height
age
BMI
Glucose_avg
0.00
0.02
0.04
0.06
0.08
0.10
0.12
0.14
Importance Score