


```
from google.colab import drive
drive.mount('/content/drive')
%cd /content/drive/MyDrive/Colab Notebooks
```

 Mounted at /content/drive
/content/drive/MyDrive/Colab Notebooks

```
# === 1. Install necessary libraries ===
!pip install xgboost lightgbm scikit-learn matplotlib tensorflow
```

```
# === 2. Imports ===
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.feature_selection import mutual_info_classif
from lightgbm import LGBMClassifier
from sklearn.metrics import accuracy_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
```

```
# Load your CSV from this path
df = pd.read_csv("CBioFiltered_Genes_Subset.csv")
```

```
# === 4. Preprocessing ===
df_cleaned = df.drop(columns=["Unnamed: 0", "batch"])
X = df_cleaned.drop(columns=["group"])
y = df_cleaned["group"].astype(int)
```

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

```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# === 5. Feature selection ===
rfc = RandomForestClassifier(n_estimators=100, random_state=42)
rfc.fit(X_train_scaled, y_train)
rfc_importance = rfc.feature_importances_
```

```
xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_scaled, y_train)
xgb_importance = xgb.feature_importances_
```

```
mi = mutual_info_classif(X_train_scaled, y_train, random_state=42)
```

```
# Combine using voting
rfc_norm = rfc_importance / np.max(rfc_importance)
xgb_norm = xgb_importance / np.max(xgb_importance)
mi_norm = mi / np.max(mi)
combined_score = (rfc_norm + xgb_norm + mi_norm) / 3
```

```
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'RFC': rfc_norm,
    'XGBoost': xgb_norm,
    'MI': mi_norm,
    'MeanScore': combined_score
}).sort_values(by="MeanScore", ascending=False)
```

```
top_features = feature_importance_df.head(30)["Feature"].values
```

```
# Plot top features
plt.figure(figsize=(12, 8))
plt.barh(feature_importance_df.head(30)["Feature"], feature_importance_df.head(30)["MeanScore"], color='skyblue')
plt.xlabel("Importance Score (Normalized Average)")
plt.title("Top 20 Important Features (RFC + XGBoost + MI)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

```
# === 6. Prepare top features for modeling ===
X_train_top = X_train_scaled[:, [X.columns.get_loc(f) for f in top_features]]
X_test_top = X_test_scaled[:, [X.columns.get_loc(f) for f in top_features]]
```

```
# === 7. Evaluate models ===
```

```
# Random Forest
```

```

rfc_model = RandomForestClassifier(random_state=42)
rfc_model.fit(X_train_top, y_train)
rfc_pred = rfc_model.predict(X_test_top)
print('Random Forest Accuracy:', accuracy_score(y_test, rfc_pred))

# XGBoost
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb_model.fit(X_train_top, y_train)
xgb_pred = xgb_model.predict(X_test_top)
print("XGBoost Accuracy:", accuracy_score(y_test, xgb_pred))

# LightGBM
lgbm_model = LGBMClassifier(random_state=42)
lgbm_model.fit(X_train_top, y_train)
lgbm_pred = lgbm_model.predict(X_test_top)
print("LightGBM Accuracy:", accuracy_score(y_test, lgbm_pred))

# ANN (Keras)
model = Sequential()
model.add(Dense(64, input_dim=X_train_top.shape[1], activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid')) # Use '1' output for binary

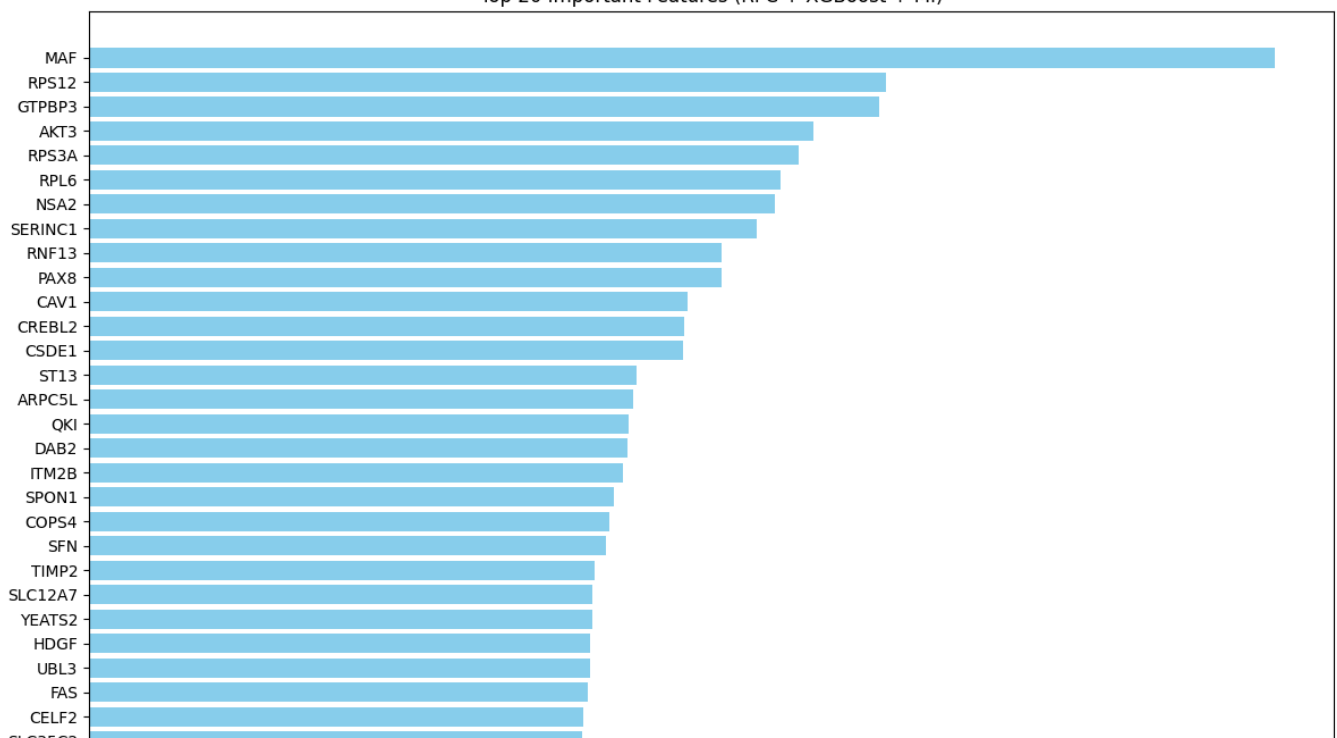
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train_top, y_train, epochs=50, batch_size=16, verbose=0)
ann_loss, ann_acc = model.evaluate(X_test_top, y_test, verbose=0)
print("ANN Accuracy:", ann_acc)

```

Requirement already satisfied: xgboost in /usr/local/lib/python3.11/dist-packages (2.1.4)
Requirement already satisfied: lightgbm in /usr/local/lib/python3.11/dist-packages (4.5.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.11/dist-packages (1.6.1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: tensorflow in /usr/local/lib/python3.11/dist-packages (2.18.0)
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Requirement already satisfied: nvidia-nccl-cu12 in /usr/local/lib/python3.11/dist-packages (from xgboost) (2.21.5)
Requirement already satisfied: scipy in /usr/local/lib/python3.11/dist-packages (from xgboost) (1.15.2)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.11/dist-packages (from scikit-learn) (3.6.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
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Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.4.0)
Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.6.3)
Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (25.2.10)
Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.6.0)
Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.2.0)
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Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.4.0)
Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<6.0.0dev,>=3.20.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.32.3)
Requirement already satisfied: setuptools in /usr/local/lib/python3.11/dist-packages (from tensorflow) (75.2.0)
Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.17.0)
Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.1.0)
Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (4.13.2)
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Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (1.71.0)
Requirement already satisfied: tensorboard<2.19,>=2.18 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (2.18.0)
Requirement already satisfied: keras>=3.5.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (3.8.0)
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Requirement already satisfied: ml-dtypes<0.5.0,>=0.4.0 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.4.1)
Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.11/dist-packages (from tensorflow) (0.37.0)
Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.11/dist-packages (from astunparse>=1.6.0->tensorflow) (0.43.0)
Requirement already satisfied: rich in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (13.9.4)
Requirement already satisfied: namex in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.0.9)
Requirement already satisfied: optree in /usr/local/lib/python3.11/dist-packages (from keras>=3.5.0->tensorflow) (0.15.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (3.10.0)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.11/dist-packages (from requests<3,>=2.21.0->tensorflow) (2025.1.1)
Requirement already satisfied: markdown>=2.6.8 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (3.7.0)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in /usr/local/lib/python3.11/dist-packages (from tensorboard<2.19,>=2.18->tensorflow) (0.7.0)
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Requirement already satisfied: MarkupSafe>=2.1.1 in /usr/local/lib/python3.11/dist-packages (from werkzeug>=1.0.1->tensorboard<2.19,>=2.18->tensorflow) (3.0.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in /usr/local/lib/python3.11/dist-packages (from rich->keras>=3.5.0->tensorflow) (2.18.0)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.11/dist-packages (from markdown-it-py>=2.2.0->rich->keras>=3.5.0->tensorflow) (0.1.2)
/usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [04:41:28] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

warnings.warn(msg, UserWarning)

Top 20 Important Features (RFC + XGBoost + MI)




```
from sklearn.metrics import confusion_matrix, roc_curve, auc, ConfusionMatrixDisplay
import seaborn as sns
```

```
# Plotting function for ROC curves
```

```
def plot_roc_curves(models, model_names, X_test, y_test):
    plt.figure(figsize=(10, 7))
    for model, name in zip(models, model_names):
        if hasattr(model, "predict_proba"):
            y_proba = model.predict_proba(X_test)[: , 1]
        else: # ANN model returns probability directly
            y_proba = model.predict(X_test).ravel()
        fpr, tpr, _ = roc_curve(y_test, y_proba)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')

    plt.plot([0, 1], [0, 1], 'k--')
    plt.xlabel("False Positive Rate")
    plt.ylabel("True Positive Rate")
    plt.title("ROC Curves")
    plt.legend(loc="lower right")
    plt.grid(True)
    plt.show()
```

```
# Plotting function for confusion matrices
```

```
def plot_confusion_matrices(models, model_names, X_test, y_test):
    for model, name in zip(models, model_names):
        if name == "ANN":
            y_pred = (model.predict(X_test).ravel() > 0.5).astype(int)
        else:
            y_pred = model.predict(X_test)
        cm = confusion_matrix(y_test, y_pred)
        disp = ConfusionMatrixDisplay(confusion_matrix=cm)
        disp.plot(cmap='Blues')
        plt.title(f"Confusion Matrix - {name}")
        plt.show()
```

```
# List of models and their names
```

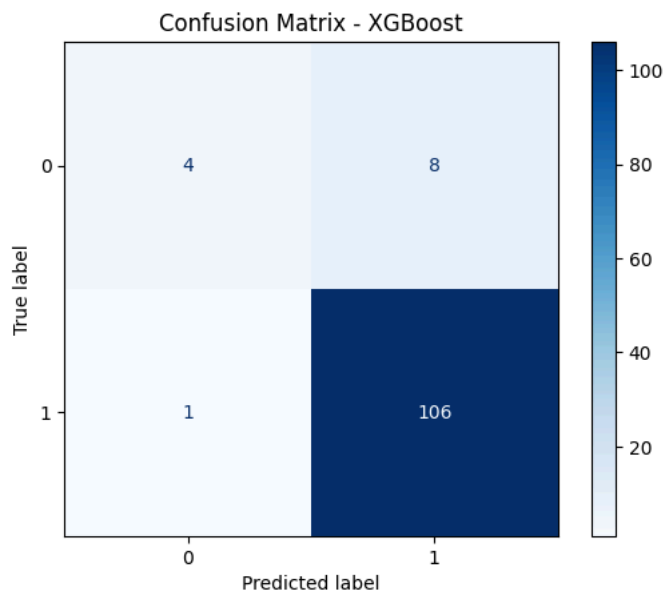
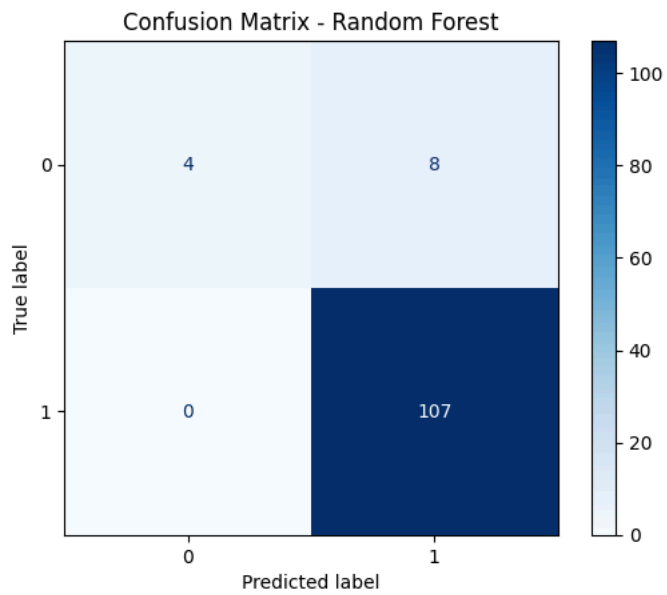
```
models = [rfc_model, xgb_model, lgbm_model, model]
model_names = ["Random Forest", "XGBoost", "LightGBM", "ANN"]
```

```
# Plot Confusion Matrices
```

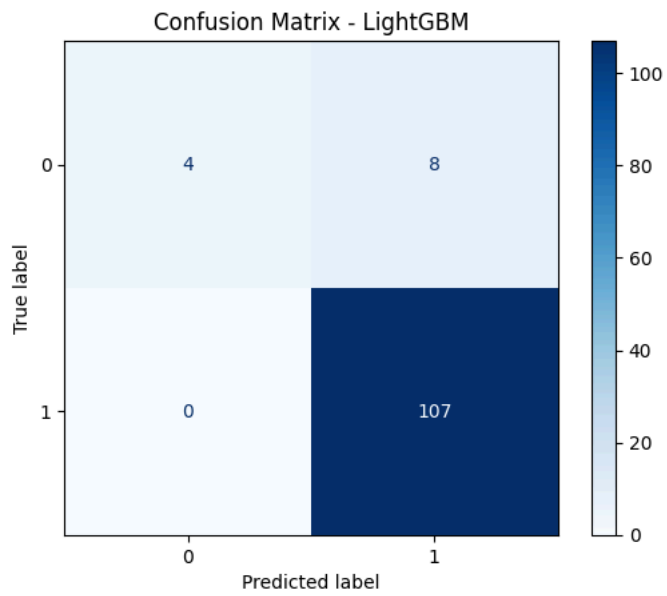
```
plot_confusion_matrices(models, model_names, X_test_top, y_test)
```

```
# Plot ROC Curves
```

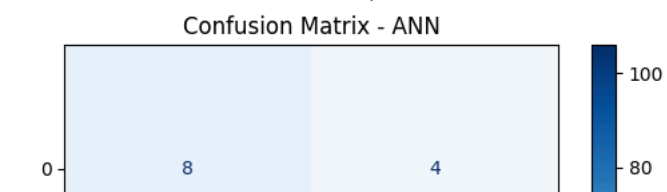
```
plot_roc_curves(models, model_names, X_test_top, y_test)
```

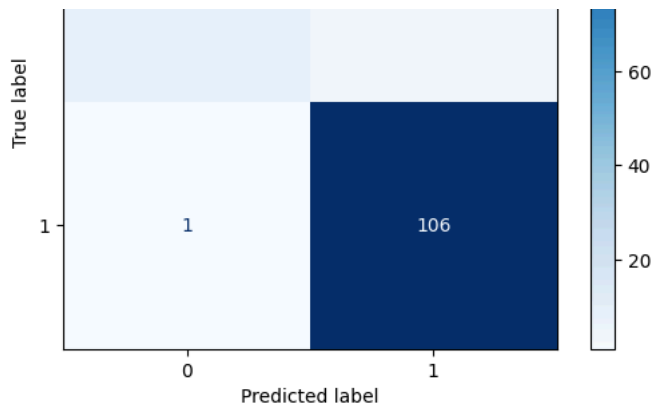


/usr/local/lib/python3.11/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_finite' in 1.2. Please use 'ensure_finite' instead of 'force_all_finite'. warnings.warn()



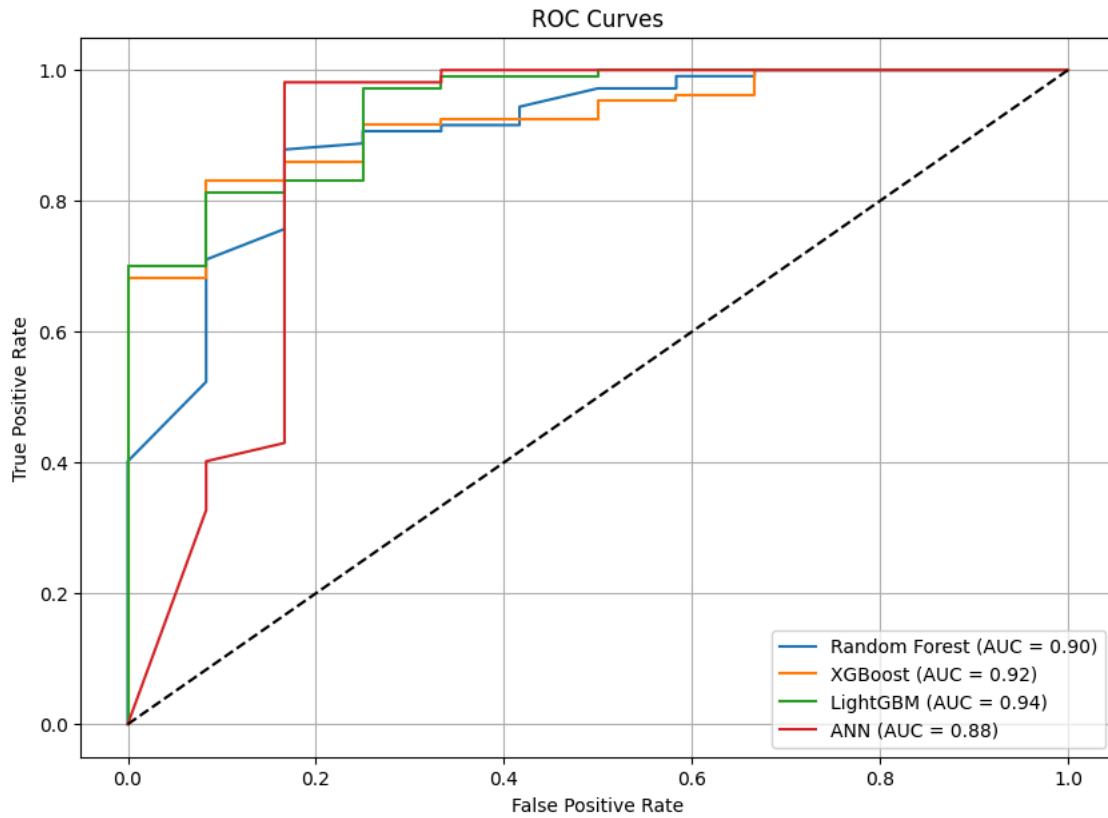
4/4 — 0s 29ms/step





/usr/local/lib/python3.11/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_all_finite' in 1.2. Please use 'ensure_all_finite' instead.
warnings.warn()

4/4 — 0s 24ms/step




```
top_features = feature_importance_df.head(30)["Feature"].values
```

```
print("Top 20 features based on ensemble importance voting:")
for i, feature in enumerate(top_features, 1):
    print(f"{i}. {feature}")
```

```
➦ Top 20 features based on ensemble importance voting:
```

1. MAF
2. RPS12
3. GTPBP3
4. AKT3
5. RPS3A
6. RPL6
7. NSA2
8. SERINC1
9. RNF13
10. PAX8
11. CAV1
12. CREBL2
13. CSDE1
14. ST13
15. ARPC5L
16. QKI
17. DAB2
18. ITM2B
19. SPON1
20. COPS4
21. SFN
22. TIMP2
23. SLC12A7
24. YEATS2
25. HDGF
26. UBL3
27. FAS
28. CELF2
29. SLC35C2
30. BNC2

```
import seaborn as sns
```

```
# Select top 20 features from the original (unscaled) data for interpretability
```

```
X_top_20 = X[top_features]
```

```
X_top_20["group"] = y.values # Add target label back
```

```
# Set up the plot
```

```
plt.figure(figsize=(16, 10))
```

```
sns.heatmap(X_top_20.groupby("group").mean(), cmap="viridis", annot=True, fmt=".2f", cbar=True)
```

```
plt.title("Mean Feature Expression Heatmap by Group (Top 20 Features)")
```

```
plt.xlabel("Feature")
```

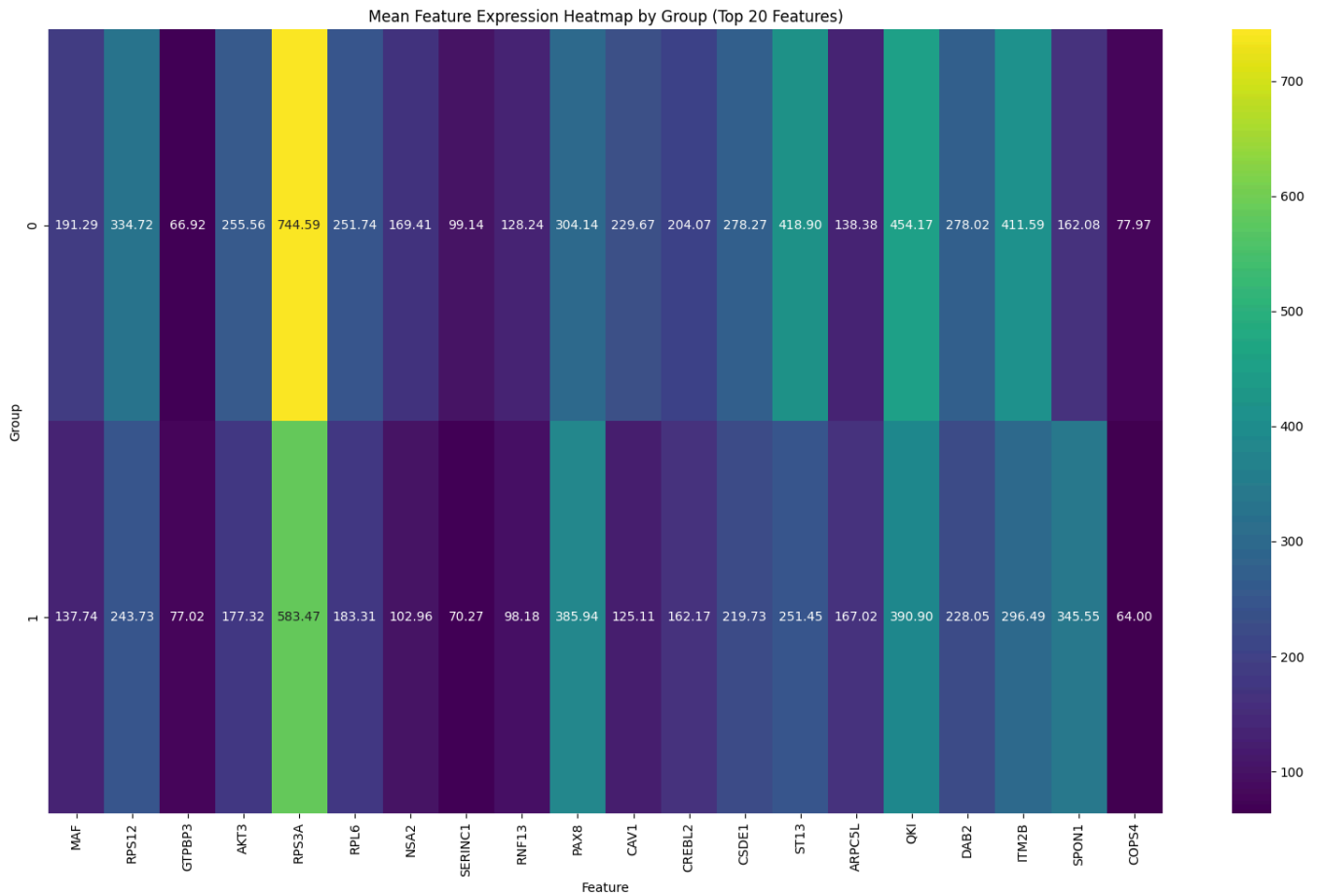
```
plt.ylabel("Group")
```

```
plt.tight_layout()
```

```
plt.show()
```

```
<ipython-input-9-e210cb42eea1>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus
X_top_20["group"] = y.values # Add target label back




```
import seaborn as sns

# Select and prepare top features
X_top_20 = X[top_features]
X_top_20["group"] = y.values

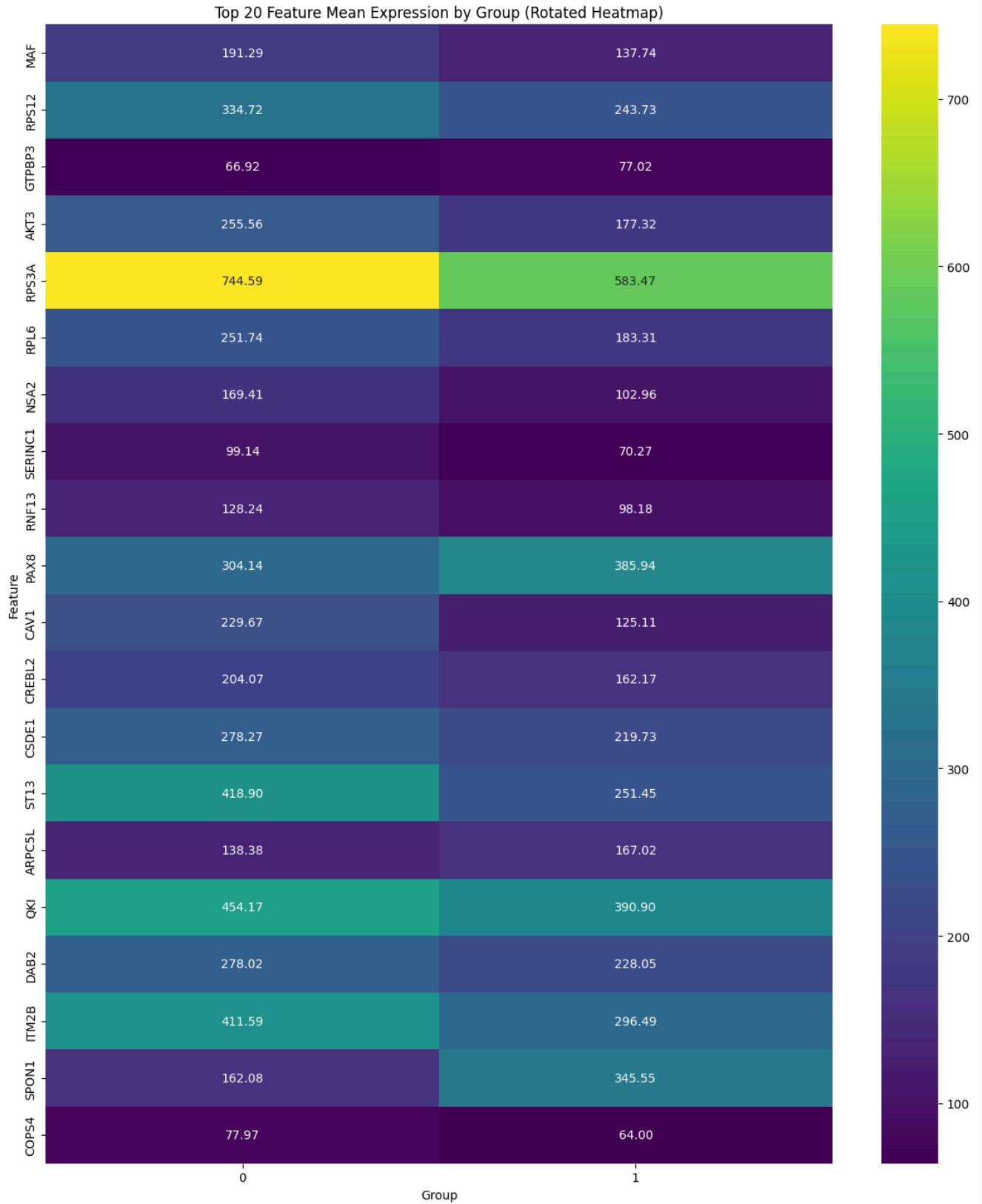
# Transpose the grouped mean for rotated heatmap
heatmap_data = X_top_20.groupby("group").mean().T

# Plot
plt.figure(figsize=(12, 14))
sns.heatmap(heatmap_data, cmap="viridis", annot=True, fmt=".2f", cbar=True)

plt.title("Top 20 Feature Mean Expression by Group (Rotated Heatmap)")
plt.xlabel("Group")
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```

 <ipython-input-10-67781f504875>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-vers
X_top_20["group"] = y.values



```

# === 2. Imports ===
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from sklearn.feature_selection import mutual_info_classif
from lightgbm import LGBMClassifier
from sklearn.metrics import accuracy_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

# === 3. Load Dataset ===
df = pd.read_csv("Predicted_OC_subset_with_labels.csv")

# === 4. Preprocessing ===
df_cleaned = df.drop(columns=["Unnamed: 0"], errors='ignore') # Drop index col if exists
X = df_cleaned.drop(columns=["predicted_group"]) # Features
y = df_cleaned["predicted_group"].astype(int) # Labels

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

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# === 5. Feature selection via ensemble ===
rfc = RandomForestClassifier(n_estimators=100, random_state=42)
rfc.fit(X_train_scaled, y_train)
rfc_importance = rfc.feature_importances_

xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_scaled, y_train)
xgb_importance = xgb.feature_importances_

mi = mutual_info_classif(X_train_scaled, y_train, random_state=42)

# Normalize and vote
rfc_norm = rfc_importance / np.max(rfc_importance)
xgb_norm = xgb_importance / np.max(xgb_importance)
mi_norm = mi / np.max(mi)
combined_score = (rfc_norm + xgb_norm + mi_norm) / 3

feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'RFC': rfc_norm,
    'XGBoost': xgb_norm,
    'MI': mi_norm,
    'MeanScore': combined_score
}).sort_values(by="MeanScore", ascending=False)

top_features = feature_importance_df.head(30)["Feature"].values

# === 6. Visualize top features ===
plt.figure(figsize=(12, 8))
plt.barh(feature_importance_df.head(30)["Feature"], feature_importance_df.head(20)["MeanScore"], color='skyblue')
plt.xlabel("Importance Score (Normalized Average)")
plt.title("Top 20 Important Features (RFC + XGBoost + MI)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# === 7. Prepare top features for modeling ===
X_train_top = X_train_scaled[:, [X.columns.get_loc(f) for f in top_features]]
X_test_top = X_test_scaled[:, [X.columns.get_loc(f) for f in top_features]]

# === 8. Model Evaluations ===

# Random Forest
rfc_model = RandomForestClassifier(random_state=42)
rfc_model.fit(X_train_top, y_train)
rfc_pred = rfc_model.predict(X_test_top)
print("Random Forest Accuracy:", accuracy_score(y_test, rfc_pred))

# XGBoost
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb_model.fit(X_train_top, y_train)
xgb_pred = xgb_model.predict(X_test_top)


```

```
print("XGBoost Accuracy:", accuracy_score(y_test, xgb_pred))

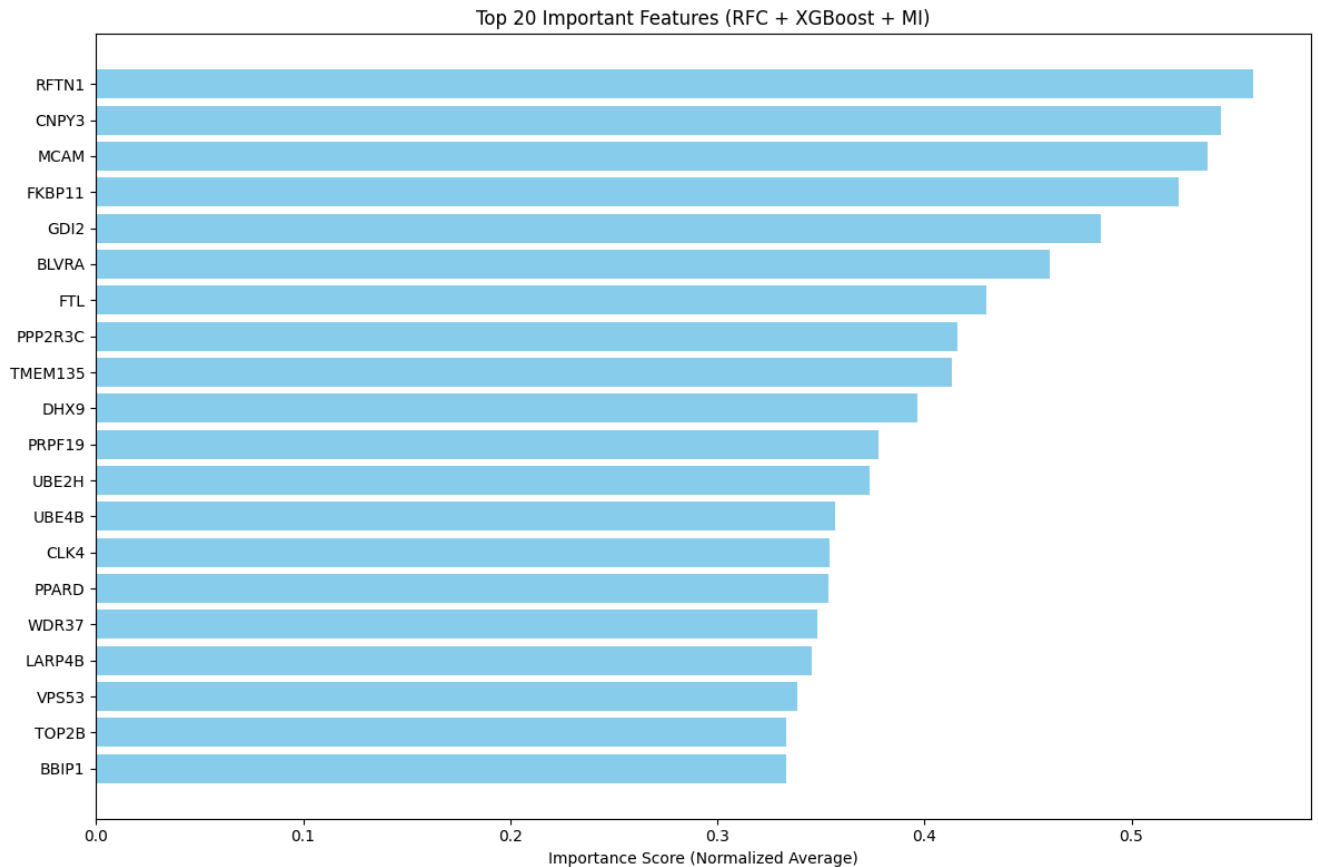
# LightGBM
lgbm_model = LGBMClassifier(random_state=42)
lgbm_model.fit(X_train_top, y_train)
lgbm_pred = lgbm_model.predict(X_test_top)
print("LightGBM Accuracy:", accuracy_score(y_test, lgbm_pred))

# ANN using Keras
model = Sequential()
model.add(Dense(64, input_dim=X_train_top.shape[1], activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid')) # Binary classification

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])
model.fit(X_train_top, y_train, epochs=50, batch_size=16, verbose=0)
ann_loss, ann_acc = model.evaluate(X_test_top, y_test, verbose=0)
print("ANN Accuracy:", ann_acc)
```

 /usr/local/lib/python3.11/dist-packages/xgboost/core.py:158: UserWarning: [04:28:52] WARNING: /workspace/src/learner.cc:740: Parameters: { "use_label_encoder" } are not used.

warnings.warn(msg, UserWarning)



Random Forest Accuracy: 0.4864864864864865

XGBoost Accuracy: 0.4594594594594595

[LightGBM] [Info] Number of positive: 72, number of negative: 74

[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.000137 seconds.

You can set 'force_col_wise=true' to remove the overhead.

[LightGBM] [Info] Total Bins 1508

[LightGBM] [Info] Number of data points in the train set: 146, number of used features: 30

[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.493151 -> initscore=-0.027399

[LightGBM] [Info] Start training from score -0.027399

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

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[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf


```

# === 2. Imports ===
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from xgboost import XGBClassifier
from sklearn.feature_selection import mutual_info_classif
from lightgbm import LGBMClassifier
from sklearn.metrics import accuracy_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout
from tensorflow.keras.callbacks import EarlyStopping

# === 3. Load Dataset ===
df = pd.read_csv("Predicted_OC_subset_with_labels.csv")

# === 4. Preprocessing ===
df_cleaned = df.drop(columns=["Unnamed: 0"], errors='ignore') # Drop index col if exists
X = df_cleaned.drop(columns=["predicted_group"]) # Features
y = df_cleaned["predicted_group"].astype(int) # Labels

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

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# === 5. Feature selection via ensemble voting ===
rfc = RandomForestClassifier(n_estimators=100, random_state=42)
rfc.fit(X_train_scaled, y_train)
rfc_importance = rfc.feature_importances_

xgb = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb.fit(X_train_scaled, y_train)
xgb_importance = xgb.feature_importances_

mi = mutual_info_classif(X_train_scaled, y_train, random_state=42)

# Normalize and combine
rfc_norm = rfc_importance / np.max(rfc_importance)
xgb_norm = xgb_importance / np.max(xgb_importance)
mi_norm = mi / np.max(mi)
combined_score = (rfc_norm + xgb_norm + mi_norm) / 3

feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'RFC': rfc_norm,
    'XGBoost': xgb_norm,
    'MI': mi_norm,
    'MeanScore': combined_score
}).sort_values(by="MeanScore", ascending=False)

top_features = feature_importance_df.head(30)["Feature"].values

# === 6. Visualize top features ===
plt.figure(figsize=(12, 8))
plt.barh(feature_importance_df.head(30)["Feature"], feature_importance_df.head(30)["MeanScore"], color='skyblue')
plt.xlabel("Importance Score (Normalized Average)")
plt.title("Top 30 Important Features (RFC + XGBoost + MI)")
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()

# === 7. Prepare data with selected features ===
X_train_top = X_train_scaled[:, [X.columns.get_loc(f) for f in top_features]]
X_test_top = X_test_scaled[:, [X.columns.get_loc(f) for f in top_features]]

# === 8. Hyperparameter Tuning for RF ===
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [None, 10, 20],
    'min_samples_split': [2, 5]
}

grid_search = GridSearchCV(RandomForestClassifier(random_state=42), param_grid, cv=3, scoring='accuracy', n_jobs=-1)
grid_search.fit(X_train_top, y_train)
best_rf = grid_search.best_estimator_

```



```

# === 9. Train XGBoost and LightGBM ===
xgb_model = XGBClassifier(use_label_encoder=False, eval_metric='logloss', random_state=42)
xgb_model.fit(X_train_top, y_train)

lgbm_model = LGBMClassifier(random_state=42)
lgbm_model.fit(X_train_top, y_train)

# === 10. Voting Classifier Ensemble ===
voting_model = VotingClassifier(estimators=[
    ('rf', best_rf),
    ('xgb', xgb_model),
    ('lgbm', lgbm_model)
], voting='soft')

voting_model.fit(X_train_top, y_train)
voting_pred = voting_model.predict(X_test_top)
print("Voting Classifier Accuracy:", accuracy_score(y_test, voting_pred))

# === 11. Improved ANN ===
model = Sequential()
model.add(Dense(128, input_dim=X_train_top.shape[1], activation='relu'))
model.add(Dropout(0.4))
model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))
model.add(Dense(32, activation='relu'))
model.add(Dense(1, activation='sigmoid')) # Binary output

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

early_stop = EarlyStopping(monitor='val_loss', patience=5, restore_best_weights=True)
model.fit(X_train_top, y_train, validation_split=0.2, epochs=100, batch_size=16, verbose=0, callbacks=[early_stop])

ann_loss, ann_acc = model.evaluate(X_test_top, y_test, verbose=0)
print("Improved ANN Accuracy:", ann_acc)

```


[illegible]

[illegible]

[LightGBM] [Warning] No further splits with positive gain, best gain: -inf
Voting Classifier Accuracy: 0.4594594594594595
Improved ANN Accuracy: 0.5945945978164673

```
# === Print Top 30 Features with Importances ===
print("\n=== Top 30 Features by Ensemble Importance ===")
print(feature_importance_df.head(30).to_string(index=False))
```



```
=== Top 30 Features by Ensemble Importance ===
Feature      RFC  XGBoost      MI  MeanScore
RFTN1 0.583471 0.417042 0.675741 0.558752
CNPY3 0.951109 0.117479 0.560896 0.543161
MCAM 0.428714 1.000000 0.180788 0.536501
FKBP11 0.505867 0.763407 0.299585 0.522953
GDI2 1.000000 0.082486 0.372769 0.485085
BLVRA 0.646419 0.467693 0.267867 0.460660
FTL 0.464914 0.000000 0.825350 0.430088
PPP2R3C 0.585084 0.000000 0.662829 0.415971
TMEM135 0.515351 0.000000 0.723869 0.413073
DHX9 0.000000 0.657232 0.533063 0.396765
PRPF19 0.000000 0.676384 0.457683 0.378022
UBE2H 0.248739 0.000000 0.872064 0.373601
UBE4B 0.319527 0.158539 0.592147 0.356738
CLK4 0.561675 0.021279 0.479266 0.354074
PPARD 0.375995 0.000000 0.685518 0.353837
WDR37 0.516124 0.000000 0.529543 0.348556
LARP4B 0.202867 0.209571 0.624410 0.345616
VPS53 0.619001 0.013702 0.382622 0.338442
TOP2B 0.000000 0.000000 1.000000 0.333333
BBIP1 0.840277 0.158752 0.000000 0.333009
RAB3GAP1 0.163612 0.000000 0.825869 0.329827
DYNLT3 0.223822 0.077134 0.682958 0.327971
RPL31 0.000000 0.000000 0.971875 0.323958
CAND2 0.348786 0.229128 0.389635 0.322516
SNX27 0.252671 0.000000 0.704502 0.319058
ITGB4 0.430054 0.000000 0.524527 0.318194
XRCC6 0.000000 0.000000 0.950620 0.316873
PIGG 0.307097 0.000000 0.639732 0.315610
NDUFB4 0.000000 0.586018 0.351224 0.312414
NCOR1 0.374605 0.043673 0.517302 0.311860
```

```
from sklearn.metrics import classification_report, confusion_matrix
```

```
# === Helper function to evaluate a model ===
```

```
def evaluate_model(name, model, X_test, y_test):
    preds = model.predict(X_test)
    print(f"\n=== {name} ===")
    print("Accuracy:", accuracy_score(y_test, preds))
    print("Classification Report:")
    print(classification_report(y_test, preds))
    print("Confusion Matrix:")
    print(confusion_matrix(y_test, preds))
```

```
# Evaluate Random Forest (best_rf from GridSearch)
evaluate_model("Tuned Random Forest", best_rf, X_test_top, y_test)
```

```
# Evaluate XGBoost
evaluate_model("XGBoost", xgb_model, X_test_top, y_test)
```

```
# Evaluate LightGBM
evaluate_model("LightGBM", lgbm_model, X_test_top, y_test)
```

```
# Evaluate Voting Classifier
evaluate_model("Voting Classifier (Ensemble)", voting_model, X_test_top, y_test)
```

```
# Evaluate ANN separately (sigmoid output thresholded)
ann_pred_prob = model.predict(X_test_top).flatten()
ann_pred = (ann_pred_prob > 0.5).astype(int)
print("\n=== ANN (Keras) ===")
print("Accuracy:", accuracy_score(y_test, ann_pred))
print("Classification Report:")
print(classification_report(y_test, ann_pred))
print("Confusion Matrix:")
print(confusion_matrix(y_test, ann_pred))
```



```
=== Tuned Random Forest ===
Accuracy: 0.4864864864864865
Classification Report:
              precision    recall  f1-score   support

     0       0.33         0.36         0.34         14
     1       0.59         0.57         0.58         23

   accuracy          0.48
  macro avg          0.46         0.46         0.46         37
```

```
weighted avg      0.49      0.49      0.49      37
```

Confusion Matrix:

```
[[ 5  9]
 [10 13]]
```

=== XGBoost ===

Accuracy: 0.4594594594594595

Classification Report:

	precision	recall	f1-score	support
0	0.35	0.50	0.41	14
1	0.59	0.43	0.50	23
accuracy			0.46	37
macro avg	0.47	0.47	0.46	37
weighted avg	0.50	0.46	0.47	37

Confusion Matrix:

```
[[ 7  7]
 [13 10]]
```

=== LightGBM ===

Accuracy: 0.5675675675675675

Classification Report:

	precision	recall	f1-score	support
0	0.42	0.36	0.38	14
1	0.64	0.70	0.67	23
accuracy			0.57	37
macro avg	0.53	0.53	0.53	37
weighted avg	0.56	0.57	0.56	37

Confusion Matrix:

```
[[ 5  9]
 [ 7 16]]
```

=== Voting Classifier (Ensemble) ===

Accuracy: 0.4594594594594595

Classification Report:

	precision	recall	f1-score	support
0	0.31	0.36	0.33	14
1	0.57	0.52	0.55	23

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

=== Function to plot ROC ===

```
def plot_roc_curves(models, model_names, X_test, y_test):
    plt.figure(figsize=(10, 8))
```

```
    for model, name in zip(models, model_names):
        if name == "ANN":
            y_scores = model.predict(X_test).flatten()
        else:
            try:
                y_scores = model.predict_proba(X_test)[:, 1]
            except:
                y_scores = model.decision_function(X_test)

        fpr, tpr, _ = roc_curve(y_test, y_scores)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.2f})')
```

```
    # Plot base line
    plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curves for All Models')
    plt.legend(loc='lower right')
    plt.grid(True)
    plt.tight_layout()
    plt.show()
```

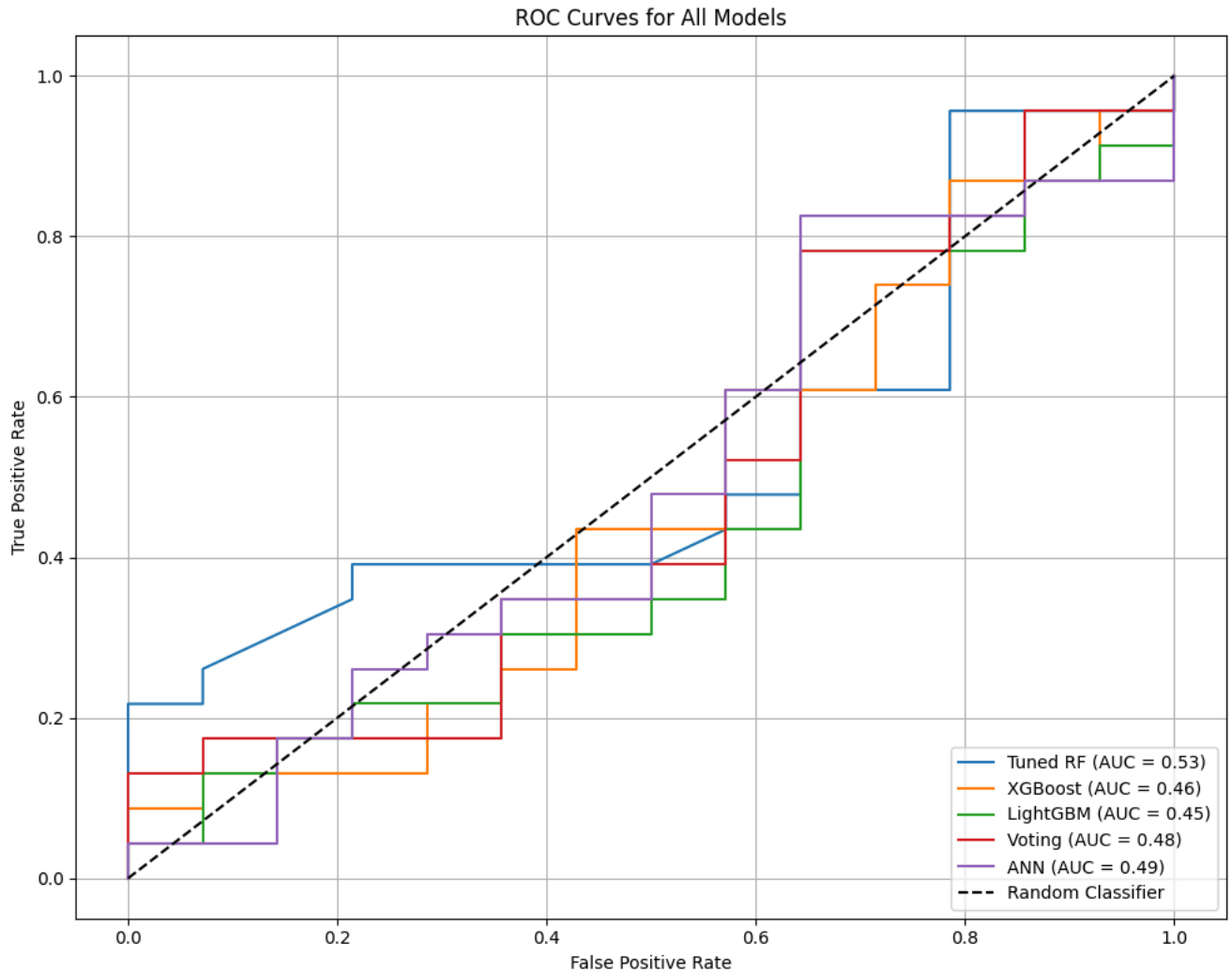
=== Plot all ROC curves ===

```
plot_roc_curves(
    models=[best_rf, xgb_model, lgbm_model, voting_model, model],
    model_names=["Tuned RF", "XGBoost", "LightGBM", "Voting", "ANN"],
    X_test=X_test_top,
    y_test=y_test
)
```

```

/usr/local/lib/python3.11/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_
warnings.warn(
/usr/local/lib/python3.11/dist-packages/sklearn/utils/deprecation.py:151: FutureWarning: 'force_all_finite' was renamed to 'ensure_
warnings.warn(
2/2 ————— 0s 59ms/step

```



```

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

# === Function to plot ROC ===
def plot_roc_curves(models, model_names, X_test, y_test):
    plt.figure(figsize=(10, 8))

    for model, name in zip(models, model_names):
        if name == "ANN":
            y_scores = model.predict(X_test).flatten()
        else:
            try:
                y_scores = model.predict_proba(X_test)[:, 1]
            except:
                y_scores = model.decision_function(X_test)

        fpr, tpr, _ = roc_curve(y_test, y_scores)
        roc_auc = auc(fpr, tpr)
        plt.plot(fpr, tpr, label=f'{name} (AUC = {roc_auc:.3f})')

    plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('ROC Curves for All Models (No Voting)')
    plt.legend(loc='lower right')
    plt.grid(True)
    plt.tight_layout()
    plt.show()

# === Use the function for your trained models ===
plot_roc_curves(
    models=[best_rf, xgb_model, lgbm_model, model],
    model_names=["Tuned RF", "XGBoost", "LightGBM", "ANN"],
    X_test=X_test_top,

```