04_supervised_learning

September 4, 2025

1 04 - Supervised Learning (Classification)

This notebook includes: - Target variable definition pass/fail - Feature engineering and encoding - Multiple classification algorithms - Hyperparameter tuning - Cross-validation - Model interpretation

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.metrics import accuracy_score, precision_score, recall_score,␣
↪f1_score
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV

try:
    from xgboost import XGBClassifier

    print("XGBoost successfully imported!")
except ImportError:
    print("XGBoost not installed. Install with: pip install xgboost")
    XGBClassifier = None
import warnings

warnings.filterwarnings("ignore")
```

```
XGBoost successfully imported!
```

[3]:
```
df = pd.read_pickle(r"../data/processed/cleaned_dataset.pkl")
df.drop(columns=["grade_average"], inplace=True)
```

[4]:

```python
# Handle different data types properly after preprocessing

# Apply encoding
df_encoded = df.copy()

# 1. ORDINAL VARIABLES - Convert ordered categoricals to numeric (preserve␣
↪order)
ordinal_vars = [
    "Medu",
    "Fedu",
    "traveltime",
    "studytime",
    "famrel",
    "freetime",
    "goout",
    "Dalc",
    "Walc",
    "health",
]
for var in ordinal_vars:
    if var in df_encoded.columns:
        df_encoded[var] = df_encoded[
            var
        ].cat.codes  # Converts to 0,1,2,3,4 maintaining order
        print(f"Ordinal encoded {var}")

# 2. BINARY VARIABLES - Convert booleans to 0/1
binary_vars = [
    "schoolsup",
    "famsup",
    "paid",
    "activities",
    "nursery",
    "higher",
    "internet",
    "romantic",
]
for var in binary_vars:
    if var in df_encoded.columns:
        df_encoded[var] = df_encoded[var].astype(int)  # True->1, False->0
        print(f"Boolean to binary: {var}")

# 3. NOMINAL CATEGORICALS - Binary mapping for 2-level, one-hot for multi-level
# Binary mappings for 2-level categoricals
binary_mappings = {
    "school": {"GP": 1, "MS": 0},
    "sex": {"F": 1, "M": 0},
```

```python
    "address": {"U": 1, "R": 0},
    "famsize": {"GT3": 1, "LE3": 0},
    "Pstatus": {"T": 1, "A": 0},
}

# Apply binary encoding
for col, mapping in binary_mappings.items():
    if col in df_encoded.columns:
        df_encoded[col] = df_encoded[col].map(mapping)
        print(f"Binary encoded {col}")

# Multi-level categorical columns for one-hot encoding
categorical_cols = ["Mjob", "Fjob", "reason", "guardian"]

# One-hot encode categorical columns
df_encoded = pd.get_dummies(df_encoded, columns=categorical_cols,␣
 ↪drop_first=True)
print(f"One-hot encoded: {categorical_cols}")
print(f"New shape after encoding: {df_encoded.shape}")

# 4. NUMERIC VARIABLES already handled (age, failures, absences, G1, G2, G3)

# Remove target leakage
features_to_drop = ["G3"]
X = df_encoded.drop(columns=features_to_drop + ["pass_fail"])
y = df_encoded["pass_fail"]

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

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

# Results
print(f"\nFinal results:")
print(f"Training shape: {X_train_scaled.shape}")
print(f"Test shape: {X_test_scaled.shape}")
print(f"Pass rate - Train: {y_train.mean():.1%}, Test: {y_test.mean():.1%}")
print(f"All features are now numeric and scaled.")
```

```
Ordinal encoded Medu
Ordinal encoded Fedu
Ordinal encoded traveltime
Ordinal encoded studytime
```

```
Ordinal encoded famrel
Ordinal encoded freetime
Ordinal encoded goout
Ordinal encoded Dalc
Ordinal encoded Walc
Ordinal encoded health
Boolean to binary: schoolsup
Boolean to binary: famsup
Boolean to binary: paid
Boolean to binary: activities
Boolean to binary: nursery
Boolean to binary: higher
Boolean to binary: internet
Boolean to binary: romantic
Binary encoded school
Binary encoded sex
Binary encoded address
Binary encoded famsize
Binary encoded Pstatus
One-hot encoded: ['Mjob', 'Fjob', 'reason', 'guardian']
New shape after encoding: (649, 44)

Final results:
Training shape: (519, 42)
Test shape: (130, 42)
Pass rate - Train: 84.6%, Test: 84.6%
All features are now numeric and scaled.

Final results:
Training shape: (519, 42)
Test shape: (130, 42)
Pass rate - Train: 84.6%, Test: 84.6%
All features are now numeric and scaled.
```

[5]:

```
# Create two feature sets from the scaled data
print("Available features:", X.columns.tolist())

# Set 1: Keep all current features (includes G1, G2)
X_with_grades = X.copy()
X_train_with_grades = X_train_scaled.copy()
X_test_with_grades = X_test_scaled.copy()

# Set 2: Remove G1 and G2 from the scaled data
grade_columns = ["G1", "G2"]
grade_indices = [X.columns.get_loc(col) for col in grade_columns if col in X.
 ↪columns]
```

```
X_without_grades = X.drop(columns=grade_columns)
X_train_without_grades = np.delete(X_train_scaled, grade_indices, axis=1)
X_test_without_grades = np.delete(X_test_scaled, grade_indices, axis=1)

# Results
print(f"\nFeature sets created:")
print(
    f"WITH G1, G2 - Train: {X_train_with_grades.shape}, Test:␣
 ↪{X_test_with_grades.shape}"
)
print(
    f"WITHOUT G1, G2 - Train: {X_train_without_grades.shape}, Test:␣
 ↪{X_test_without_grades.shape}"
)
print(f"Features removed: {grade_columns}")
```

```
Available features: ['school', 'sex', 'age', 'address', 'famsize', 'Pstatus',
'Medu', 'Fedu', 'traveltime', 'studytime', 'failures', 'schoolsup', 'famsup',
'paid', 'activities', 'nursery', 'higher', 'internet', 'romantic', 'famrel',
'freetime', 'goout', 'Dalc', 'Walc', 'health', 'absences', 'G1', 'G2',
'attendance_proxy', 'Mjob_health', 'Mjob_other', 'Mjob_services',
'Mjob_teacher', 'Fjob_health', 'Fjob_other', 'Fjob_services', 'Fjob_teacher',
'reason_home', 'reason_other', 'reason_reputation', 'guardian_mother',
'guardian_other']

Feature sets created:
WITH G1, G2 - Train: (519, 42), Test: (130, 42)
WITHOUT G1, G2 - Train: (519, 40), Test: (130, 40)
Features removed: ['G1', 'G2']
```

2 Function-Based Model Implementation

2.1 Logistic Regression

[6]:
```
def logistic_regression_base(X_train, X_test, title):
    """Base Logistic Regression Model"""
    print(f"LOGISTIC REGRESSION MODEL {title.upper()}")

    # Initialize and train the model
    log_reg = LogisticRegression(random_state=42)
    log_reg.fit(X_train, y_train)

    # Make predictions on TEST data
    y_pred_lr = log_reg.predict(X_test)

    # Evaluate the model
    print("\nClassification Report:")
```

```python
    print(classification_report(y_test, y_pred_lr))

    # Logistic Regression metrics
    lr_accuracy = accuracy_score(y_test, y_pred_lr)
    lr_precision = precision_score(y_test, y_pred_lr)
    lr_recall = recall_score(y_test, y_pred_lr)
    lr_f1 = f1_score(y_test, y_pred_lr)

    # Confusion Matrix
    print("Confusion Matrix:")
    cm = confusion_matrix(y_test, y_pred_lr)
    plt.figure(figsize=(8, 6))
    lr_color = "#0d47a1"
    sns.heatmap(
        cm,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(lr_color, as_cmap=True),
    )
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Logistic Regression - {title}")
    plt.show()

    return lr_accuracy, lr_precision, lr_recall, lr_f1


def logistic_regression_tuned(X_train, X_test, title):
    """Hyperparameter Tuned Logistic Regression Model"""
    print(f"HYPERPARAMETER TUNED LOGISTIC REGRESSION MODEL {title.upper()}")

    # Define the parameter grid
    param_grid = {
        "C": [0.001, 0.01, 0.1, 1, 10, 100],
        "penalty": ["l1", "l2"],
        "solver": ["liblinear", "saga"],
    }

    # Initialize GridSearchCV
    grid_search = GridSearchCV(
        LogisticRegression(random_state=42, max_iter=1000),
        param_grid,
        cv=5,
        scoring="f1",
        n_jobs=-1,
    )
```

```python
    # Fit the grid search to the data
    grid_search.fit(X_train, y_train)

    # Get the best model
    best_log_reg = grid_search.best_estimator_

    # Print the best parameters
    print("Best Hyperparameters for Logistic Regression:")
    print(grid_search.best_params_)

    # Make predictions with the improved model
    y_pred_lr = best_log_reg.predict(X_test)

    # Evaluate the improved model
    print("\nClassification Report for Improved Logistic Regression:")
    print(classification_report(y_test, y_pred_lr))

    # Tuned Logistic Regression metrics
    lr_tuned_accuracy = accuracy_score(y_test, y_pred_lr)
    lr_tuned_precision = precision_score(y_test, y_pred_lr)
    lr_tuned_recall = recall_score(y_test, y_pred_lr)
    lr_tuned_f1 = f1_score(y_test, y_pred_lr)

    # Confusion Matrix for the improved model
    print("\nConfusion Matrix for Improved Model:")
    cm_improved = confusion_matrix(y_test, y_pred_lr)
    plt.figure(figsize=(8, 6))
    lr_tuned_color = "#42a5f5"
    sns.heatmap(
        cm_improved,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(lr_tuned_color, as_cmap=True),
    )
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Tuned Logistic Regression - {title}")
    plt.show()

    return lr_tuned_accuracy, lr_tuned_precision, lr_tuned_recall, lr_tuned_f1
```

2.2 Random Forest

[7]:
```python
def random_forest_base(X_train, X_test, title):
    """Base Random Forest Model"""
    print(f"RANDOM FOREST MODEL {title.upper()}")
```

```python
    # Initialize and train the model
    rf = RandomForestClassifier(n_estimators=100, random_state=42)
    rf.fit(X_train, y_train)

    # Make predictions
    y_pred_rf = rf.predict(X_test)

    # Evaluate the model
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred_rf))

    # Random Forest metrics
    rf_accuracy = accuracy_score(y_test, y_pred_rf)
    rf_precision = precision_score(y_test, y_pred_rf)
    rf_recall = recall_score(y_test, y_pred_rf)
    rf_f1 = f1_score(y_test, y_pred_rf)

    # Confusion Matrix
    print("Confusion Matrix:")
    cm_rf = confusion_matrix(y_test, y_pred_rf)
    plt.figure(figsize=(8, 6))
    rf_color = "#1b5e20"
    sns.heatmap(
        cm_rf,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(rf_color, as_cmap=True),
    )
    plt.title(f"Random Forest - {title}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return rf_accuracy, rf_precision, rf_recall, rf_f1


def random_forest_tuned(X_train, X_test, title):
    """Hyperparameter Tuned Random Forest Model"""
    print(f"HYPERPARAMETER TUNED RANDOM FOREST MODEL {title.upper()}")

    # Define the parameter distribution for Randomized Search
    param_dist = {
        "n_estimators": [100, 200, 300],
        "max_depth": [10, 20, 30, None],
        "min_samples_split": [2, 5, 10],
        "min_samples_leaf": [1, 2, 4],
        "bootstrap": [True, False],
```

```
}

# Initialize RandomizedSearchCV
random_search = RandomizedSearchCV(
    RandomForestClassifier(random_state=42),
    param_distributions=param_dist,
    n_iter=20,  # Try 20 different combinations
    cv=5,
    scoring="f1",
    n_jobs=-1,
    random_state=42,
)

random_search.fit(X_train, y_train)

# Get the best model
best_rf = random_search.best_estimator_

print("Best Hyperparameters for Random Forest:")
print(random_search.best_params_)

# Make predictions with the tuned model
y_pred_rf = best_rf.predict(X_test)

# Evaluate the tuned model
print("\nClassification Report for Tuned Random Forest:")
print(classification_report(y_test, y_pred_rf))

# Tuned Random Forest metrics
rf_tuned_accuracy = accuracy_score(y_test, y_pred_rf)
rf_tuned_precision = precision_score(y_test, y_pred_rf)
rf_tuned_recall = recall_score(y_test, y_pred_rf)
rf_tuned_f1 = f1_score(y_test, y_pred_rf)

# Confusion Matrix for the tuned model
print("\nConfusion Matrix for Tuned Model:")
cm_rf_tuned = confusion_matrix(y_test, y_pred_rf)
plt.figure(figsize=(8, 6))
rf_tuned_color = "#66bb6a"
sns.heatmap(
    cm_rf_tuned,
    annot=True,
    fmt="d",
    cmap=sns.light_palette(rf_tuned_color, as_cmap=True),
)
plt.xlabel("Predicted")
plt.ylabel("Actual")
```

```
    plt.title(f"Tuned Random Forest - {title}")
    plt.show()

    return rf_tuned_accuracy, rf_tuned_precision, rf_tuned_recall, rf_tuned_f1
```

2.3 Gradient Boosting Machine

[8]:
```
def gradient_boosting_base(X_train, X_test, title):
    """Base Gradient Boosting Model"""
    print(f"GRADIENT BOOSTING MODEL {title.upper()}")

    gbm = GradientBoostingClassifier(random_state=42)
    gbm.fit(X_train, y_train)

    y_pred_gbm = gbm.predict(X_test)

    # Evaluate the model
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred_gbm))

    # Gradient Boosting metrics
    gbm_accuracy = accuracy_score(y_test, y_pred_gbm)
    gbm_precision = precision_score(y_test, y_pred_gbm)
    gbm_recall = recall_score(y_test, y_pred_gbm)
    gbm_f1 = f1_score(y_test, y_pred_gbm)

    # Confusion Matrix
    print("Confusion Matrix:")
    cm_gbm = confusion_matrix(y_test, y_pred_gbm)
    plt.figure(figsize=(8, 6))
    gbm_color = "#4a148c"
    sns.heatmap(
        cm_gbm,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(gbm_color, as_cmap=True),
    )
    plt.title(f"Gradient Boosting - {title}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return gbm_accuracy, gbm_precision, gbm_recall, gbm_f1


def gradient_boosting_tuned(X_train, X_test, title):
    """Hyperparameter Tuned Gradient Boosting Model"""
```

```python
print(f"TUNED GRADIENT BOOSTING MODEL {title.upper()}")

# Define the parameter distribution for Randomized Search for GBM
param_dist_gbm = {
    "n_estimators": [100, 200, 300],
    "learning_rate": [0.01, 0.1, 0.2],
    "max_depth": [3, 5, 7],
    "min_samples_split": [2, 5, 10],
    "min_samples_leaf": [1, 2, 4],
    "subsample": [0.8, 0.9, 1.0],
}

# Initialize RandomizedSearchCV for GBM
random_search_gbm = RandomizedSearchCV(
    GradientBoostingClassifier(random_state=42),
    param_distributions=param_dist_gbm,
    n_iter=20,  # Try 20 different combinations
    cv=5,
    scoring="f1",
    n_jobs=-1,
    random_state=42,
)

# Fit the random search to the data
random_search_gbm.fit(X_train, y_train)

# Get the best model
best_gbm = random_search_gbm.best_estimator_

# Print the best parameters
print("Best Hyperparameters for Gradient Boosting:")
print(random_search_gbm.best_params_)

# Make predictions with the tuned model
y_pred_gbm = best_gbm.predict(X_test)

# Evaluate the tuned model
print("\nClassification Report for Tuned Gradient Boosting:")
print(classification_report(y_test, y_pred_gbm))

# Tuned Gradient Boosting metrics
gbm_tuned_accuracy = accuracy_score(y_test, y_pred_gbm)
gbm_tuned_precision = precision_score(y_test, y_pred_gbm)
gbm_tuned_recall = recall_score(y_test, y_pred_gbm)
gbm_tuned_f1 = f1_score(y_test, y_pred_gbm)

# Confusion Matrix for the tuned model
```

```
    print("\nConfusion Matrix for Tuned GBM:")
    cm_gbm_tuned = confusion_matrix(y_test, y_pred_gbm)
    plt.figure(figsize=(8, 6))
    gbm_tuned_color = "#9575cd"
    sns.heatmap(
        cm_gbm_tuned,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(gbm_tuned_color, as_cmap=True),
    )
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Tuned Gradient Boosting - {title}")
    plt.show()

    return gbm_tuned_accuracy, gbm_tuned_precision, gbm_tuned_recall,␣
↪gbm_tuned_f1
```

2.4 Support Vector Machine (SVM)

[9]:
```
def svm_base(X_train, X_test, title):
    """Base SVM Model"""
    from sklearn.svm import SVC

    print(f"SVM MODEL {title.upper()}")

    # Initialize and train the model
    svm = SVC(
        random_state=42, probability=True
    )  # probability=True for better integration
    svm.fit(X_train, y_train)

    # Make predictions
    y_pred_svm = svm.predict(X_test)

    # Evaluate the model
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred_svm))

    # SVM metrics
    svm_accuracy = accuracy_score(y_test, y_pred_svm)
    svm_precision = precision_score(y_test, y_pred_svm)
    svm_recall = recall_score(y_test, y_pred_svm)
    svm_f1 = f1_score(y_test, y_pred_svm)

    # Confusion Matrix
    print("Confusion Matrix:")
```

```python
    cm_svm = confusion_matrix(y_test, y_pred_svm)
    plt.figure(figsize=(8, 6))
    svm_color = "#d32f2f"  # Red color
    sns.heatmap(
        cm_svm,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(svm_color, as_cmap=True),
    )
    plt.title(f"SVM - {title}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return svm_accuracy, svm_precision, svm_recall, svm_f1


def svm_tuned(X_train, X_test, title):
    """Hyperparameter Tuned SVM Model"""
    from sklearn.svm import SVC

    print(f"TUNED SVM MODEL {title.upper()}")

    # Define the parameter distribution for Randomized Search
    param_dist_svm = {
        "C": [0.1, 1, 10, 100, 1000],
        "gamma": ["scale", "auto", 0.001, 0.01, 0.1, 1],
        "kernel": ["rbf", "poly", "sigmoid"],
        "degree": [2, 3, 4],  # Only for poly kernel
    }

    # Initialize RandomizedSearchCV for SVM
    random_search_svm = RandomizedSearchCV(
        SVC(random_state=42, probability=True),
        param_distributions=param_dist_svm,
        n_iter=20,  # Try 20 different combinations
        cv=5,
        scoring="f1",
        n_jobs=-1,
        random_state=42,
    )

    # Fit the random search to the data
    random_search_svm.fit(X_train, y_train)

    # Get the best model
    best_svm = random_search_svm.best_estimator_
```

```
    # Print the best parameters
    print("Best Hyperparameters for SVM:")
    print(random_search_svm.best_params_)

    # Make predictions with the tuned model
    y_pred_svm = best_svm.predict(X_test)

    # Evaluate the tuned model
    print("\nClassification Report for Tuned SVM:")
    print(classification_report(y_test, y_pred_svm))

    # Tuned SVM metrics
    svm_tuned_accuracy = accuracy_score(y_test, y_pred_svm)
    svm_tuned_precision = precision_score(y_test, y_pred_svm)
    svm_tuned_recall = recall_score(y_test, y_pred_svm)
    svm_tuned_f1 = f1_score(y_test, y_pred_svm)

    # Confusion Matrix for the tuned model
    print("\nConfusion Matrix for Tuned SVM:")
    cm_svm_tuned = confusion_matrix(y_test, y_pred_svm)
    plt.figure(figsize=(8, 6))
    svm_tuned_color = "#f44336"  # Light red
    sns.heatmap(
        cm_svm_tuned,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(svm_tuned_color, as_cmap=True),
    )
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Tuned SVM - {title}")
    plt.show()

    return svm_tuned_accuracy, svm_tuned_precision, svm_tuned_recall,␣
↪svm_tuned_f1
```

2.5 XGBoost (eXtreme Gradient Boosting)

```
[10]: def xgboost_base(X_train, X_test, title):
    """Base XGBoost Model"""
    if XGBClassifier is None:
        print("XGBoost not available. Please install with: pip install xgboost")
        return 0, 0, 0, 0

    print(f"XGBOOST MODEL {title.upper()}")
```

```python
    # Initialize and train the model
    xgb = XGBClassifier(
        random_state=42,
        eval_metric="logloss",  # Suppress warning
        verbosity=0,  # Reduce output
    )
    xgb.fit(X_train, y_train)

    # Make predictions
    y_pred_xgb = xgb.predict(X_test)

    # Evaluate the model
    print("\nClassification Report:")
    print(classification_report(y_test, y_pred_xgb))

    # XGBoost metrics
    xgb_accuracy = accuracy_score(y_test, y_pred_xgb)
    xgb_precision = precision_score(y_test, y_pred_xgb)
    xgb_recall = recall_score(y_test, y_pred_xgb)
    xgb_f1 = f1_score(y_test, y_pred_xgb)

    # Confusion Matrix
    print("Confusion Matrix:")
    cm_xgb = confusion_matrix(y_test, y_pred_xgb)
    plt.figure(figsize=(8, 6))
    xgb_color = "#e65100"  # Orange color
    sns.heatmap(
        cm_xgb,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(xgb_color, as_cmap=True),
    )
    plt.title(f"XGBoost - {title}")
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.show()

    return xgb_accuracy, xgb_precision, xgb_recall, xgb_f1


def xgboost_tuned(X_train, X_test, title):
    """Hyperparameter Tuned XGBoost Model"""
    if XGBClassifier is None:
        print("XGBoost not available. Please install with: pip install xgboost")
        return 0, 0, 0, 0

    print(f"TUNED XGBOOST MODEL {title.upper()}")
```

```python
# Define the parameter distribution for Randomized Search
param_dist_xgb = {
    "n_estimators": [100, 200, 300],
    "learning_rate": [0.01, 0.1, 0.2],
    "max_depth": [3, 5, 7],
    "min_child_weight": [1, 3, 5],
    "subsample": [0.8, 0.9, 1.0],
    "colsample_bytree": [0.8, 0.9, 1.0],
    "reg_alpha": [0, 0.1, 0.5],  # L1 regularization
    "reg_lambda": [1, 1.5, 2],  # L2 regularization
}

# Initialize RandomizedSearchCV for XGBoost
random_search_xgb = RandomizedSearchCV(
    XGBClassifier(random_state=42, eval_metric="logloss", verbosity=0),
    param_distributions=param_dist_xgb,
    n_iter=20,  # Try 20 different combinations
    cv=5,
    scoring="f1",
    n_jobs=-1,
    random_state=42,
)

# Fit the random search to the data
random_search_xgb.fit(X_train, y_train)

# Get the best model
best_xgb = random_search_xgb.best_estimator_

# Print the best parameters
print("Best Hyperparameters for XGBoost:")
print(random_search_xgb.best_params_)

# Make predictions with the tuned model
y_pred_xgb = best_xgb.predict(X_test)

# Evaluate the tuned model
print("\nClassification Report for Tuned XGBoost:")
print(classification_report(y_test, y_pred_xgb))

# Tuned XGBoost metrics
xgb_tuned_accuracy = accuracy_score(y_test, y_pred_xgb)
xgb_tuned_precision = precision_score(y_test, y_pred_xgb)
xgb_tuned_recall = recall_score(y_test, y_pred_xgb)
xgb_tuned_f1 = f1_score(y_test, y_pred_xgb)
```

```
    # Confusion Matrix for the tuned model
    print("\nConfusion Matrix for Tuned XGBoost:")
    cm_xgb_tuned = confusion_matrix(y_test, y_pred_xgb)
    plt.figure(figsize=(8, 6))
    xgb_tuned_color = "#ff9800"  # Light orange
    sns.heatmap(
        cm_xgb_tuned,
        annot=True,
        fmt="d",
        cmap=sns.light_palette(xgb_tuned_color, as_cmap=True),
    )
    plt.xlabel("Predicted")
    plt.ylabel("Actual")
    plt.title(f"Tuned XGBoost - {title}")
    plt.show()

    return xgb_tuned_accuracy, xgb_tuned_precision, xgb_tuned_recall,␣
↪xgb_tuned_f1
```

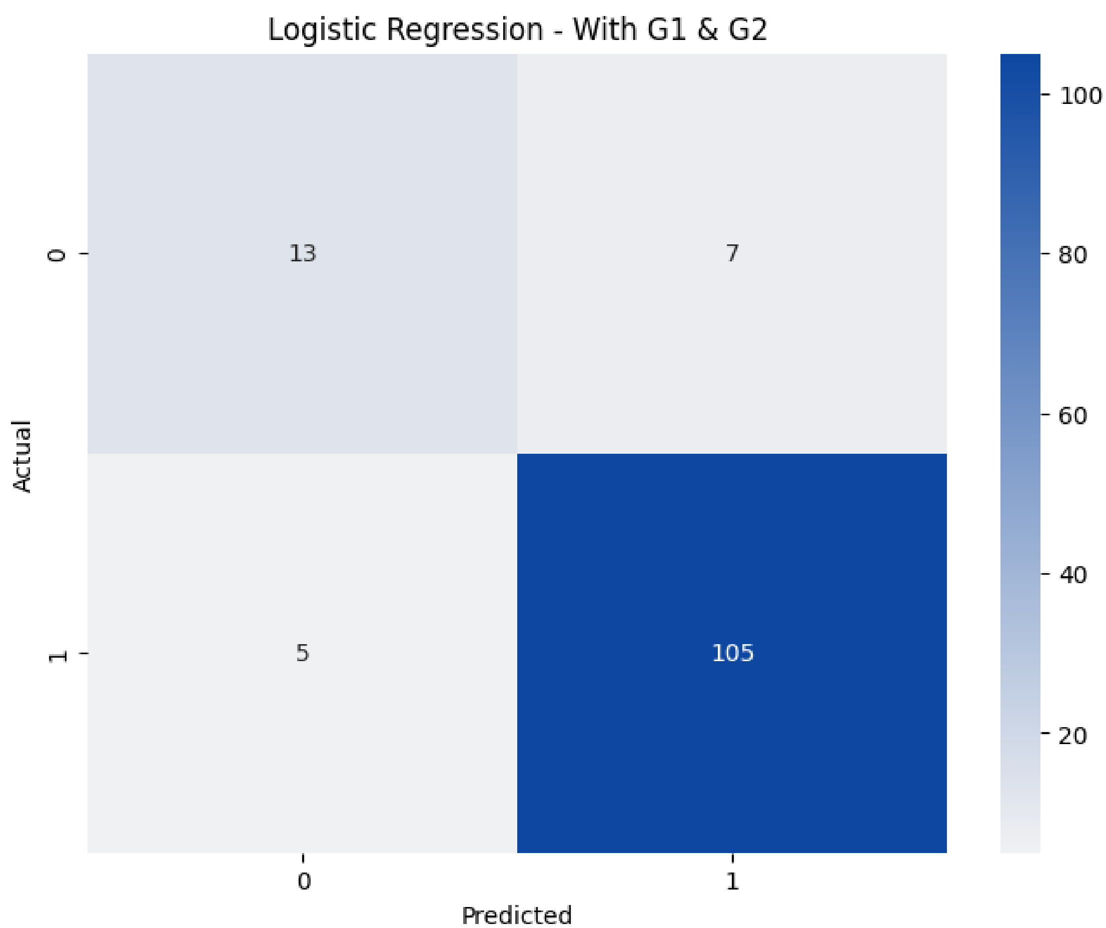
2.6 Model Execution and Comparison

[11]:
```
# Initialize results dictionary for comparison
results = {}

# Run all models WITH G1 & G2
print("=" * 60)
print("MODELS WITH G1 & G2 FEATURES")
print("=" * 60)

# Logistic Regression - Base & Tuned
lr_base_acc, lr_base_prec, lr_base_rec, lr_base_f1 = logistic_regression_base(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

lr_tuned_acc, lr_tuned_prec, lr_tuned_rec, lr_tuned_f1 =␣
↪logistic_regression_tuned(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

# Random Forest - Base & Tuned
rf_base_acc, rf_base_prec, rf_base_rec, rf_base_f1 = random_forest_base(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)
```

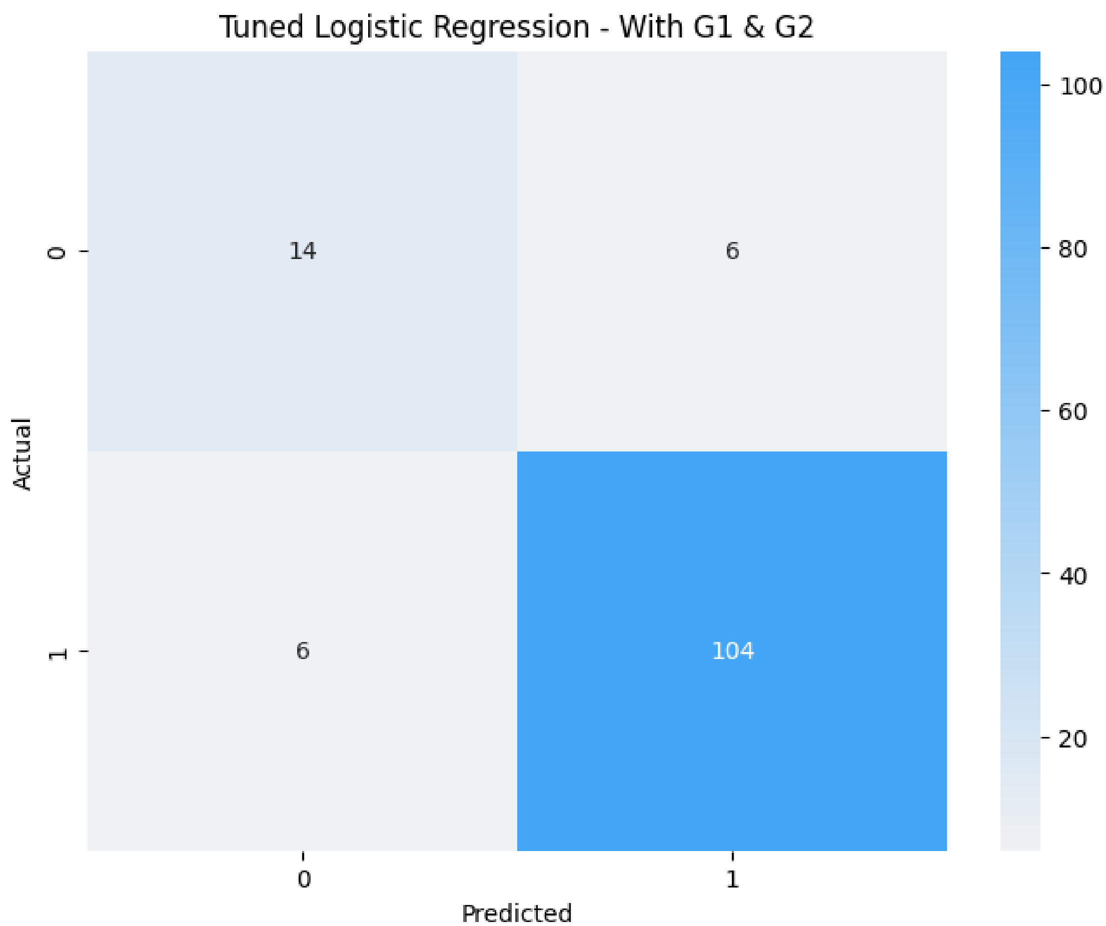
```
rf_tuned_acc, rf_tuned_prec, rf_tuned_rec, rf_tuned_f1 = random_forest_tuned(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

# Gradient Boosting - Base & Tuned
gbm_base_acc, gbm_base_prec, gbm_base_rec, gbm_base_f1 = gradient_boosting_base(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

gbm_tuned_acc, gbm_tuned_prec, gbm_tuned_rec, gbm_tuned_f1 =␣
 ↪gradient_boosting_tuned(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

# XGBoost - Base & Tuned
xgb_base_acc, xgb_base_prec, xgb_base_rec, xgb_base_f1 = xgboost_base(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

xgb_tuned_acc, xgb_tuned_prec, xgb_tuned_rec, xgb_tuned_f1 = xgboost_tuned(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

# SVM - Base & Tuned
svm_base_acc, svm_base_prec, svm_base_rec, svm_base_f1 = svm_base(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)
print("_" * 50)

svm_tuned_acc, svm_tuned_prec, svm_tuned_rec, svm_tuned_f1 = svm_tuned(
    X_train_with_grades, X_test_with_grades, "With G1 & G2"
)

# Store results WITH grades
results["with_grades"] = {
    "LR_Base": [lr_base_acc, lr_base_prec, lr_base_rec, lr_base_f1],
    "LR_Tuned": [lr_tuned_acc, lr_tuned_prec, lr_tuned_rec, lr_tuned_f1],
    "RF_Base": [rf_base_acc, rf_base_prec, rf_base_rec, rf_base_f1],
    "RF_Tuned": [rf_tuned_acc, rf_tuned_prec, rf_tuned_rec, rf_tuned_f1],
    "GBM_Base": [gbm_base_acc, gbm_base_prec, gbm_base_rec, gbm_base_f1],
    "GBM_Tuned": [gbm_tuned_acc, gbm_tuned_prec, gbm_tuned_rec, gbm_tuned_f1],
    "XGB_Base": [xgb_base_acc, xgb_base_prec, xgb_base_rec, xgb_base_f1],
```

```
    "XGB_Tuned": [xgb_tuned_acc, xgb_tuned_prec, xgb_tuned_rec, xgb_tuned_f1],
    "SVM_Base": [svm_base_acc, svm_base_prec, svm_base_rec, svm_base_f1],
    "SVM_Tuned": [svm_tuned_acc, svm_tuned_prec, svm_tuned_rec, svm_tuned_f1],
}
```

```
============================================================
MODELS WITH G1 & G2 FEATURES
============================================================
LOGISTIC REGRESSION MODEL WITH G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.72      0.65      0.68        20
           1       0.94      0.95      0.95       110

    accuracy                           0.91       130
   macro avg       0.83      0.80      0.82       130
weighted avg       0.90      0.91      0.91       130

Confusion Matrix:
```



```
--------------------------------------------------
HYPERPARAMETER TUNED LOGISTIC REGRESSION MODEL WITH G1 & G2
Best Hyperparameters for Logistic Regression:
{'C': 1, 'penalty': 'l1', 'solver': 'liblinear'}

Classification Report for Improved Logistic Regression:
              precision    recall  f1-score   support

           0       0.70      0.70      0.70        20
           1       0.95      0.95      0.95       110

    accuracy                           0.91       130
   macro avg       0.82      0.82      0.82       130
weighted avg       0.91      0.91      0.91       130


Confusion Matrix for Improved Model:
```

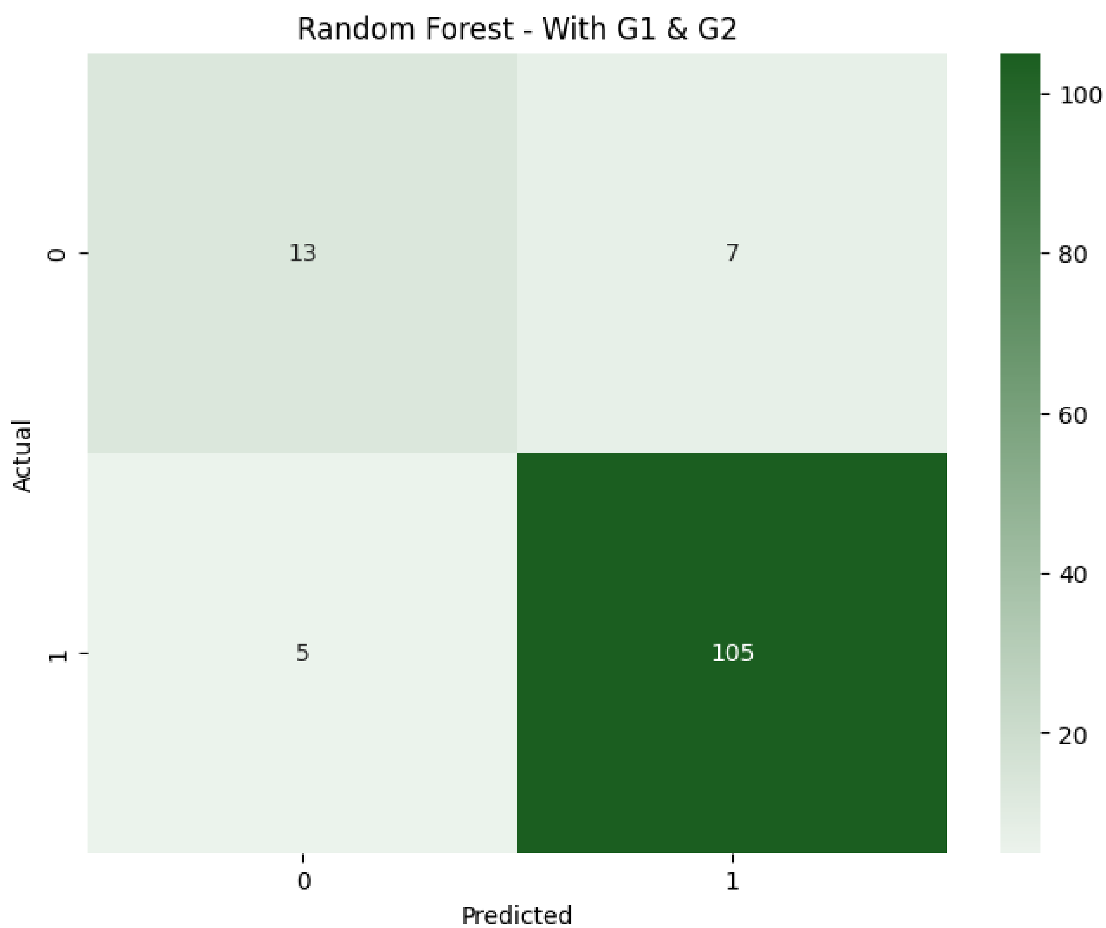


RANDOM FOREST MODEL WITH G1 & G2

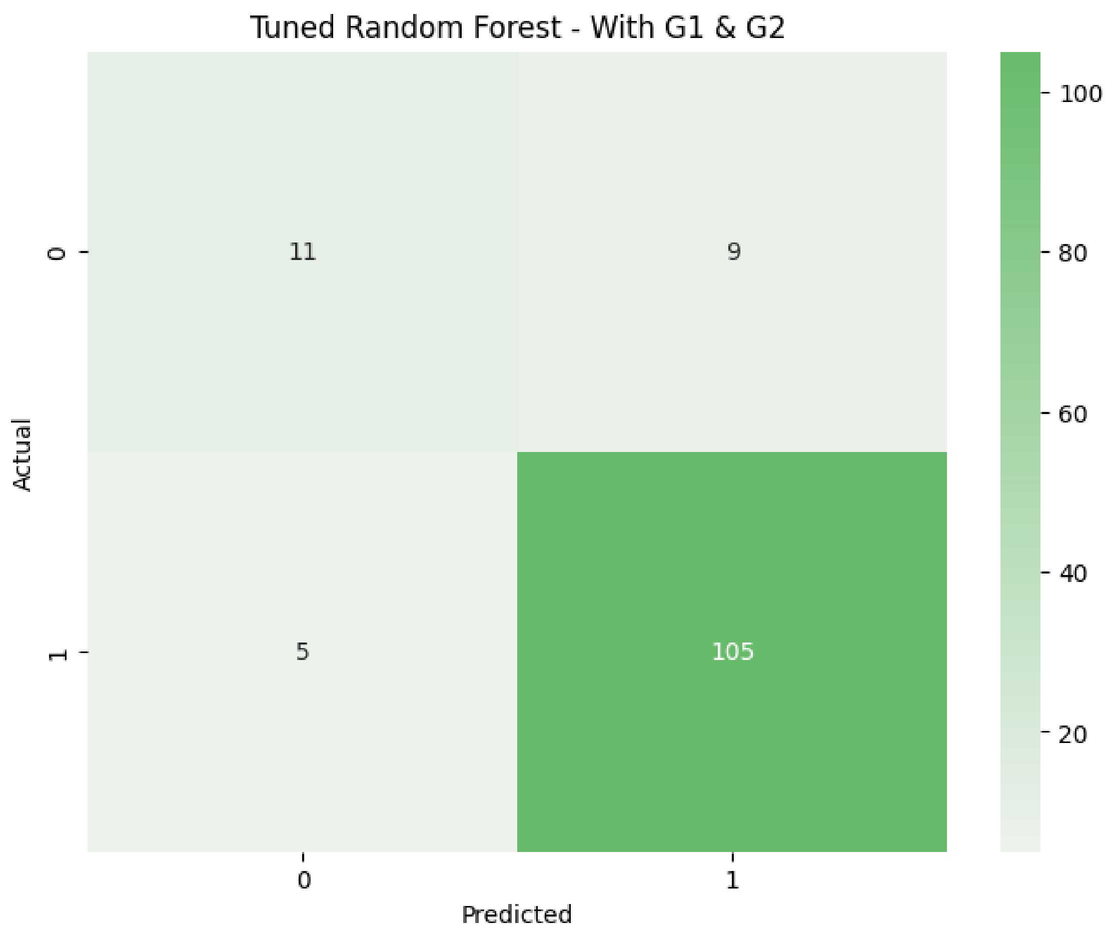
Classification Report:

	precision	recall	f1-score	support
0	0.72	0.65	0.68	20
1	0.94	0.95	0.95	110
accuracy			0.91	130
macro avg	0.83	0.80	0.82	130
weighted avg	0.90	0.91	0.91	130

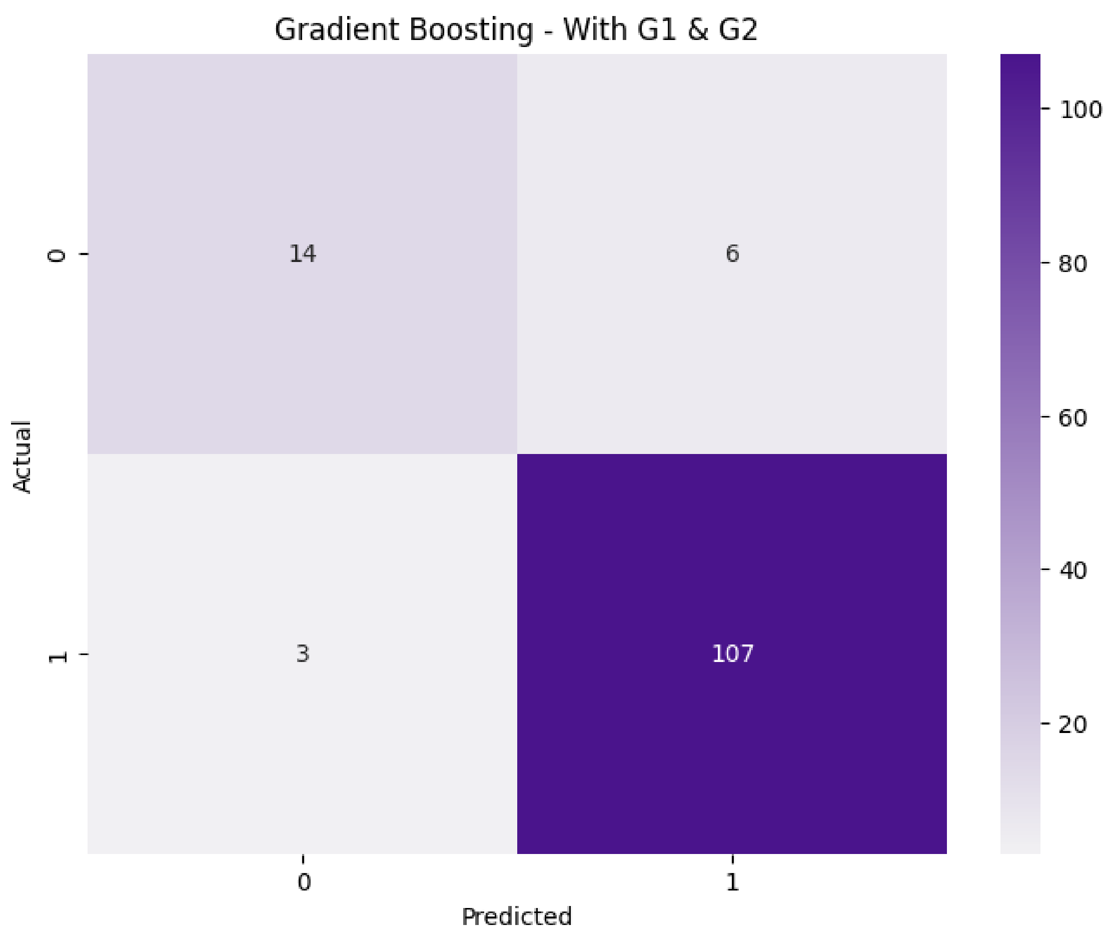
Confusion Matrix:



```
HYPERPARAMETER TUNED RANDOM FOREST MODEL WITH G1 & G2
Best Hyperparameters for Random Forest:
{'n_estimators': 100, 'min_samples_split': 2, 'min_samples_leaf': 4,
'max_depth': 10, 'bootstrap': True}

Classification Report for Tuned Random Forest:
              precision    recall  f1-score   support

           0       0.69      0.55      0.61        20
           1       0.92      0.95      0.94       110

    accuracy                           0.89       130
   macro avg       0.80      0.75      0.77       130
weighted avg       0.89      0.89      0.89       130


Confusion Matrix for Tuned Model:
```

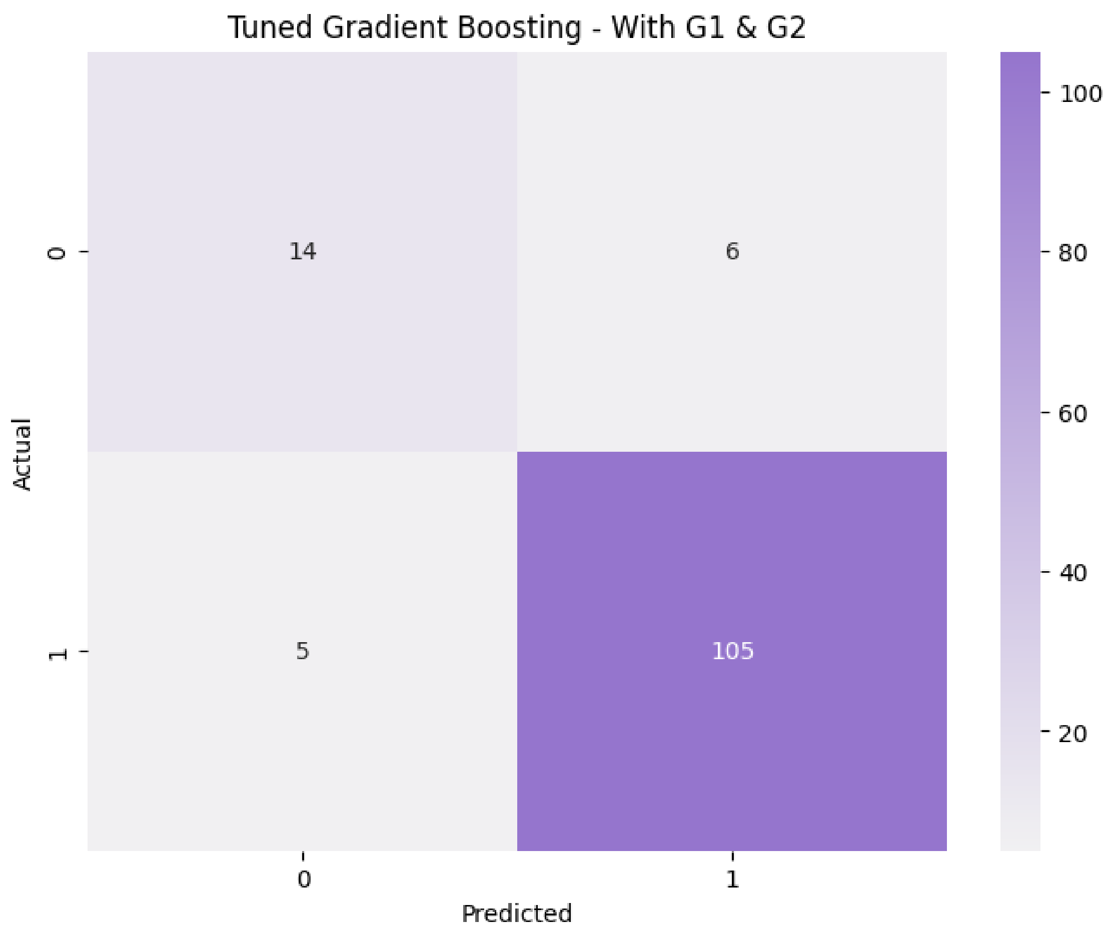


```
--------------------------------------------------
GRADIENT BOOSTING MODEL WITH G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.82      0.70      0.76        20
           1       0.95      0.97      0.96       110

    accuracy                           0.93       130
   macro avg       0.89      0.84      0.86       130
weighted avg       0.93      0.93      0.93       130

Confusion Matrix:
```



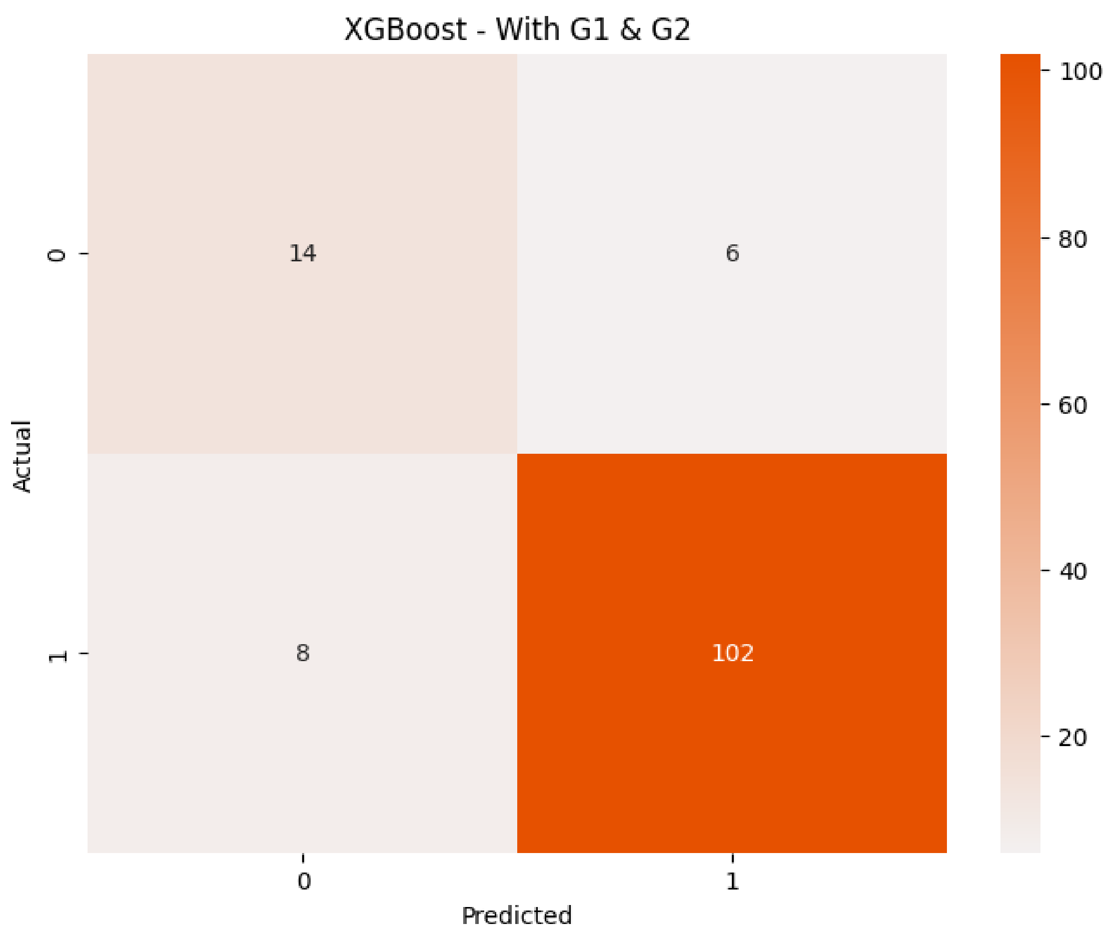

```
--------------------------------------------------
TUNED GRADIENT BOOSTING MODEL WITH G1 & G2
Best Hyperparameters for Gradient Boosting:
```

```
{'subsample': 1.0, 'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 4, 'max_depth': 7, 'learning_rate': 0.1}

Classification Report for Tuned Gradient Boosting:
              precision    recall  f1-score   support

           0       0.74      0.70      0.72        20
           1       0.95      0.95      0.95       110

    accuracy                           0.92       130
   macro avg       0.84      0.83      0.83       130
weighted avg       0.91      0.92      0.91       130


Confusion Matrix for Tuned GBM:
```



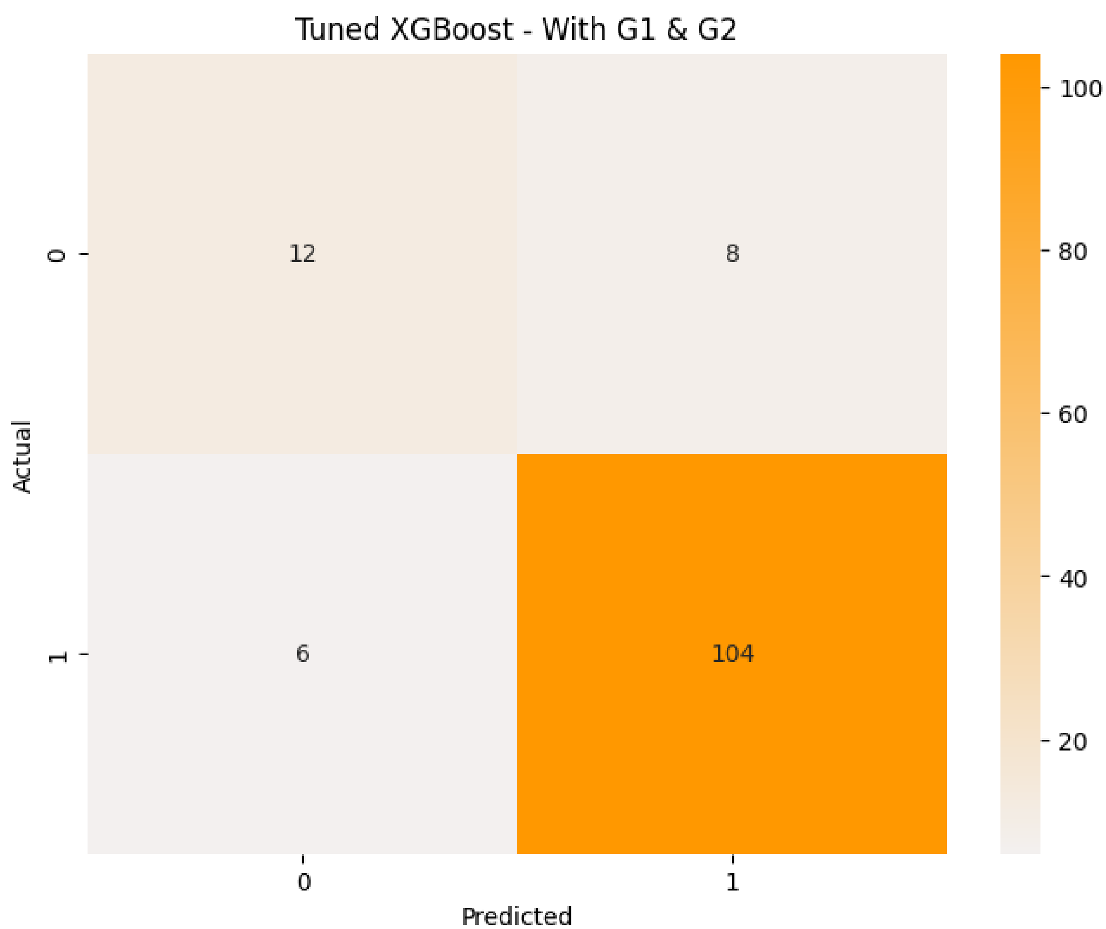

```
--------------------------------------------------
XGBOOST MODEL WITH G1 & G2
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.64      0.70      0.67        20
           1       0.94      0.93      0.94       110

    accuracy                           0.89       130
   macro avg       0.79      0.81      0.80       130
weighted avg       0.90      0.89      0.89       130

Confusion Matrix:
```




```
--------------------------------------------------
TUNED XGBOOST MODEL WITH G1 & G2
Best Hyperparameters for XGBoost:
{'subsample': 0.8, 'reg_lambda': 1.5, 'reg_alpha': 0, 'n_estimators': 100,
'min_child_weight': 1, 'max_depth': 3, 'learning_rate': 0.1, 'colsample_bytree':
```

```
0.9}

Classification Report for Tuned XGBoost:
              precision    recall  f1-score   support

           0       0.67      0.60      0.63        20
           1       0.93      0.95      0.94       110

    accuracy                           0.89       130
   macro avg       0.80      0.77      0.78       130
weighted avg       0.89      0.89      0.89       130


Confusion Matrix for Tuned XGBoost:
```

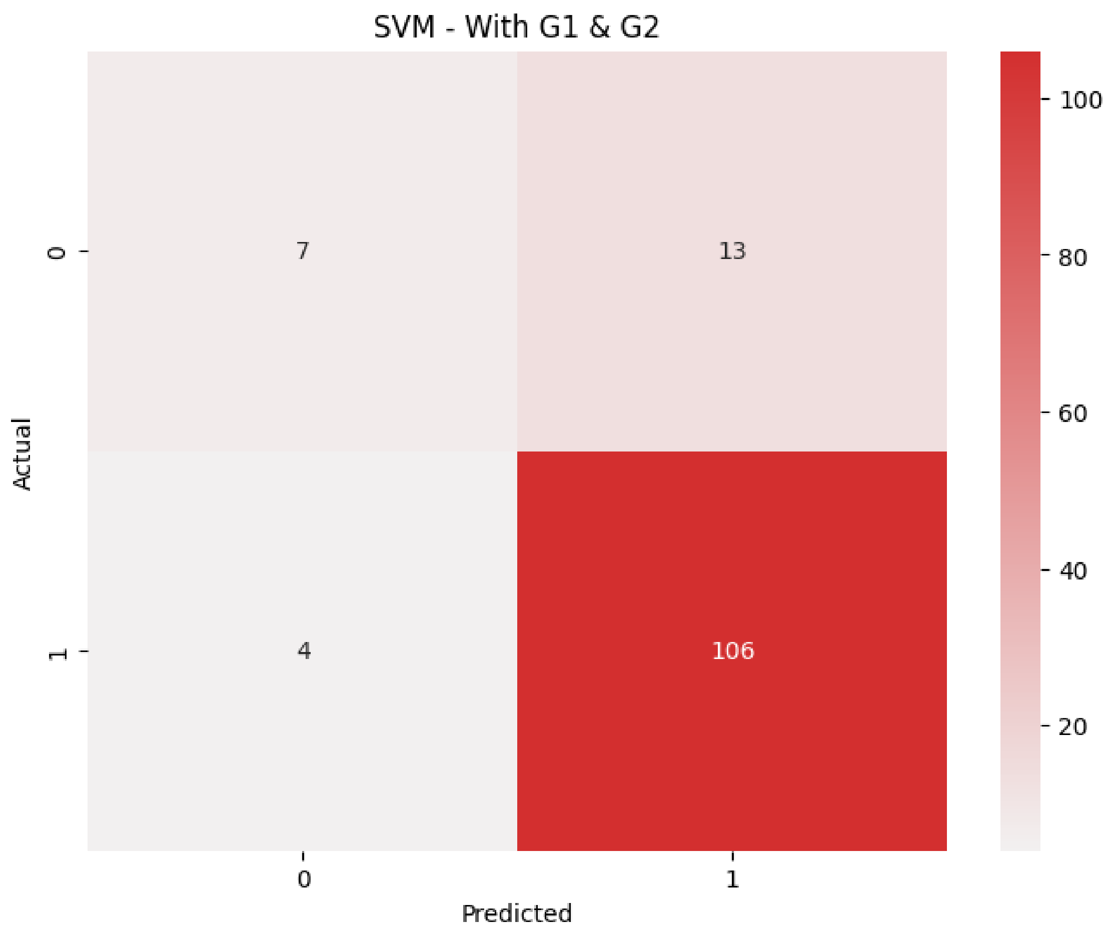



```
--------------------------------------------------
SVM MODEL WITH G1 & G2
```

Classification Report:

	precision	recall	f1-score	support
0	0.64	0.35	0.45	20
1	0.89	0.96	0.93	110
accuracy			0.87	130
macro avg	0.76	0.66	0.69	130
weighted avg	0.85	0.87	0.85	130

Confusion Matrix:

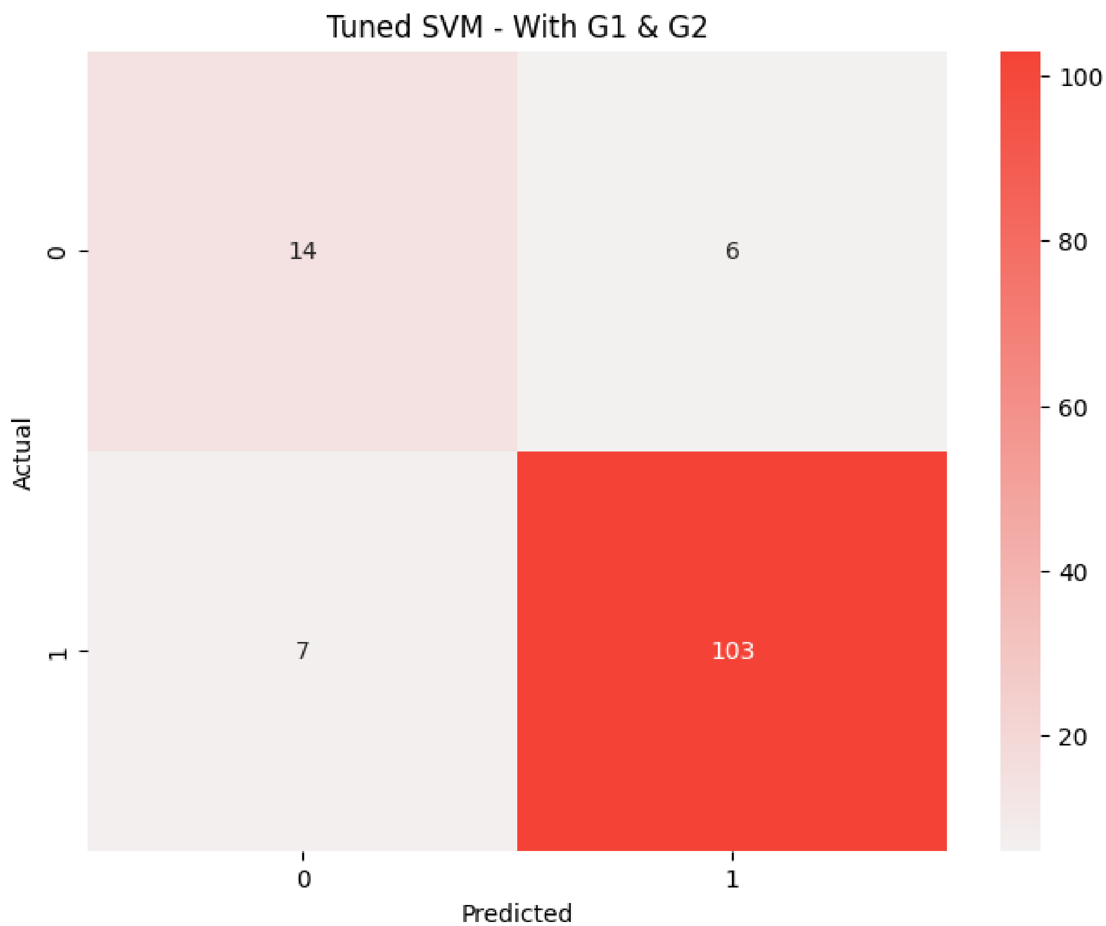


TUNED SVM MODEL WITH G1 & G2
Best Hyperparameters for SVM:
{'kernel': 'sigmoid', 'gamma': 0.01, 'degree': 3, 'C': 10}

Classification Report for Tuned SVM:

```
              precision    recall  f1-score   support

           0       0.67      0.70      0.68        20
           1       0.94      0.94      0.94       110

    accuracy                           0.90       130
   macro avg       0.81      0.82      0.81       130
weighted avg       0.90      0.90      0.90       130
```

```
Confusion Matrix for Tuned SVM:
```



[12]:

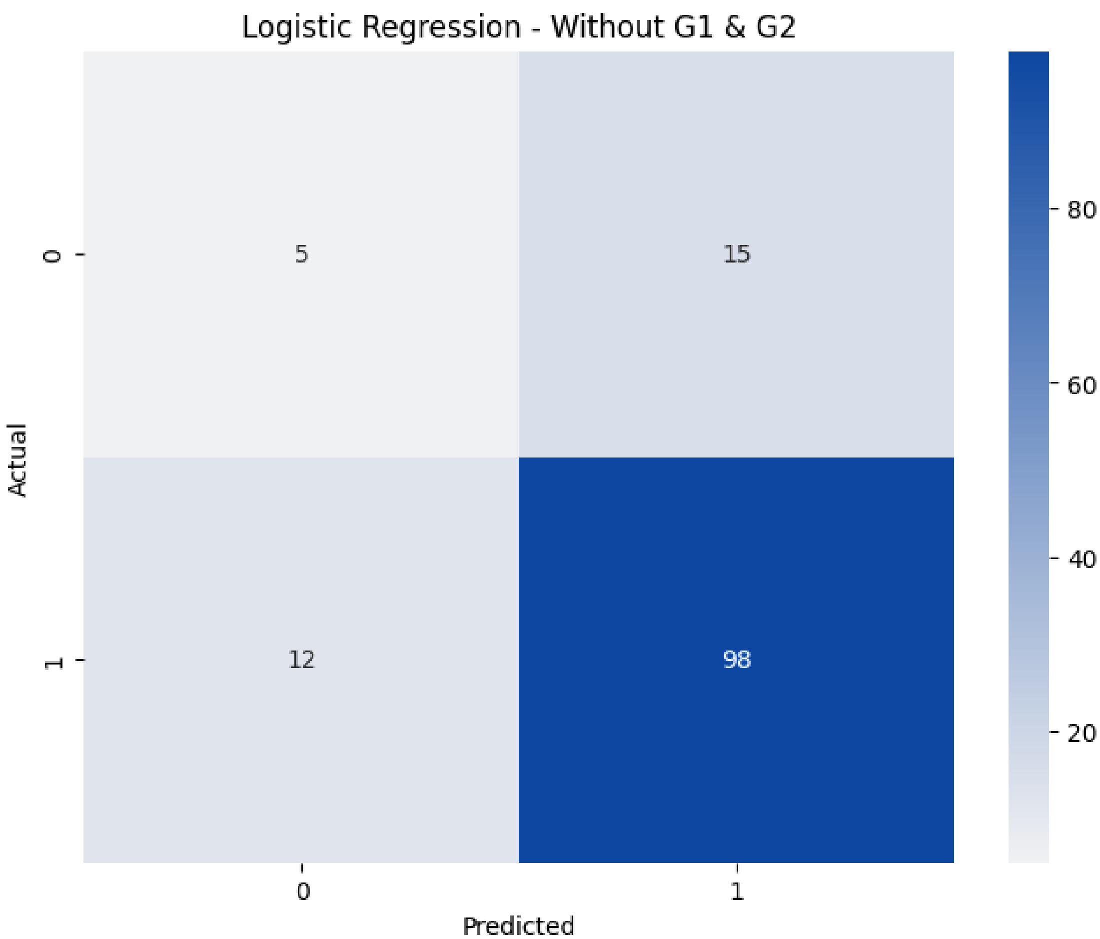
```python
# Run all models WITHOUT G1 & G2
print("\n" + "=" * 60)
print("MODELS WITHOUT G1 & G2 FEATURES")
print("=" * 60)

# Logistic Regression - Base & Tuned
```

```
lr_base_acc_no, lr_base_prec_no, lr_base_rec_no, lr_base_f1_no = (
    logistic_regression_base(
        X_train_without_grades, X_test_without_grades, "Without G1 & G2"
    )
)
print("_" * 50)

lr_tuned_acc_no, lr_tuned_prec_no, lr_tuned_rec_no, lr_tuned_f1_no = (
    logistic_regression_tuned(
        X_train_without_grades, X_test_without_grades, "Without G1 & G2"
    )
)
print("_" * 50)

# Random Forest - Base & Tuned
rf_base_acc_no, rf_base_prec_no, rf_base_rec_no, rf_base_f1_no = random_forest_base(
    X_train_without_grades, X_test_without_grades, "Without G1 & G2"
)
print("_" * 50)

rf_tuned_acc_no, rf_tuned_prec_no, rf_tuned_rec_no, rf_tuned_f1_no = (
    random_forest_tuned(
        X_train_without_grades, X_test_without_grades, "Without G1 & G2"
    )
)
print("_" * 50)

# Gradient Boosting - Base & Tuned
gbm_base_acc_no, gbm_base_prec_no, gbm_base_rec_no, gbm_base_f1_no = (
    gradient_boosting_base(
        X_train_without_grades, X_test_without_grades, "Without G1 & G2"
    )
)
print("_" * 50)

gbm_tuned_acc_no, gbm_tuned_prec_no, gbm_tuned_rec_no, gbm_tuned_f1_no = (
    gradient_boosting_tuned(
        X_train_without_grades, X_test_without_grades, "Without G1 & G2"
    )
)
print("_" * 50)

# XGBoost - Base & Tuned
xgb_base_acc_no, xgb_base_prec_no, xgb_base_rec_no, xgb_base_f1_no = xgboost_base(
    X_train_without_grades, X_test_without_grades, "Without G1 & G2"
```

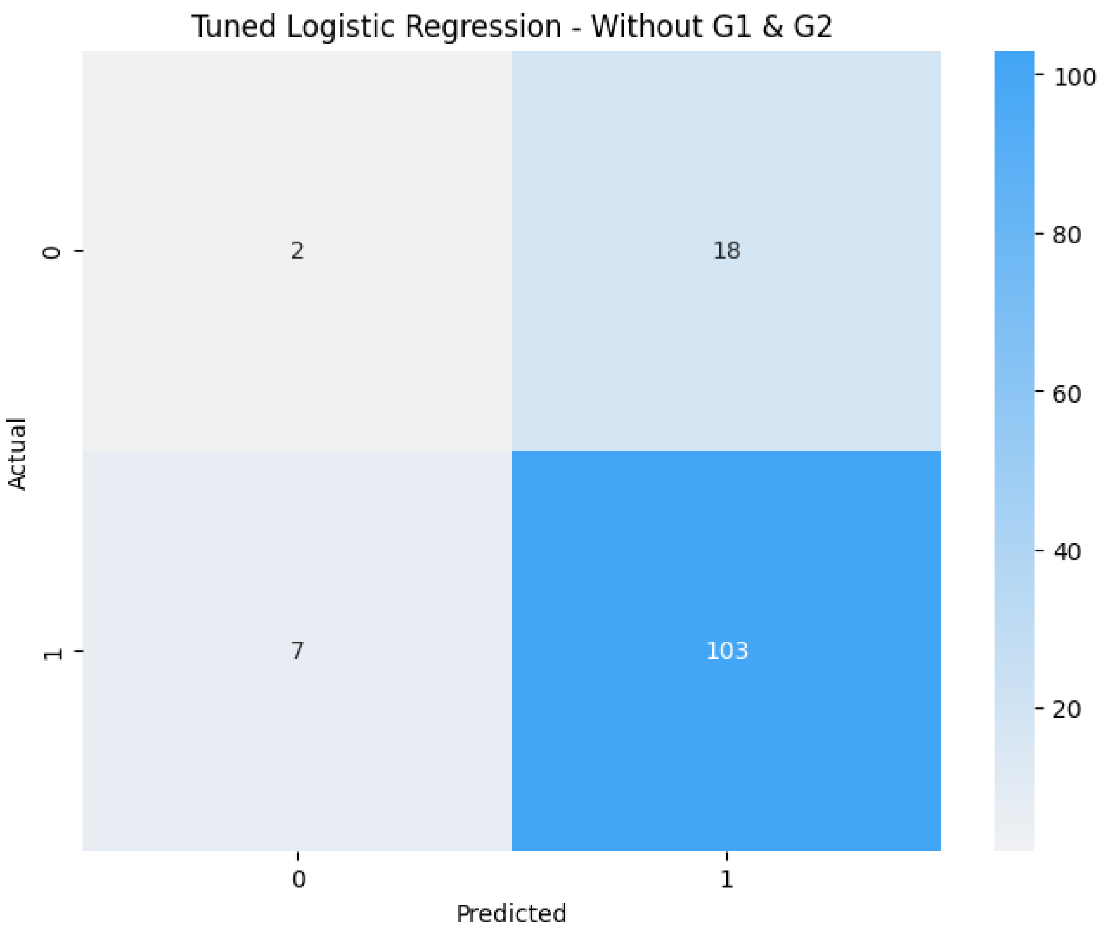
```
)
print("_" * 50)

xgb_tuned_acc_no, xgb_tuned_prec_no, xgb_tuned_rec_no, xgb_tuned_f1_no =␣
↪xgboost_tuned(
    X_train_without_grades, X_test_without_grades, "Without G1 & G2"
)
print("_" * 50)

# SVM - Base & Tuned
svm_base_acc_no, svm_base_prec_no, svm_base_rec_no, svm_base_f1_no = svm_base(
    X_train_without_grades, X_test_without_grades, "Without G1 & G2"
)
print("_" * 50)

svm_tuned_acc_no, svm_tuned_prec_no, svm_tuned_rec_no, svm_tuned_f1_no =␣
↪svm_tuned(
    X_train_without_grades, X_test_without_grades, "Without G1 & G2"
)

# Store results WITHOUT grades
results["without_grades"] = {
    "LR_Base": [lr_base_acc_no, lr_base_prec_no, lr_base_rec_no, lr_base_f1_no],
    "LR_Tuned": [lr_tuned_acc_no, lr_tuned_prec_no, lr_tuned_rec_no,␣
↪lr_tuned_f1_no],
    "RF_Base": [rf_base_acc_no, rf_base_prec_no, rf_base_rec_no, rf_base_f1_no],
    "RF_Tuned": [rf_tuned_acc_no, rf_tuned_prec_no, rf_tuned_rec_no,␣
↪rf_tuned_f1_no],
    "GBM_Base": [gbm_base_acc_no, gbm_base_prec_no, gbm_base_rec_no,␣
↪gbm_base_f1_no],
    "GBM_Tuned": [
        gbm_tuned_acc_no,
        gbm_tuned_prec_no,
        gbm_tuned_rec_no,
        gbm_tuned_f1_no,
    ],
    "XGB_Base": [xgb_base_acc_no, xgb_base_prec_no, xgb_base_rec_no,␣
↪xgb_base_f1_no],
    "XGB_Tuned": [
        xgb_tuned_acc_no,
        xgb_tuned_prec_no,
        xgb_tuned_rec_no,
        xgb_tuned_f1_no,
    ],
    "SVM_Base": [svm_base_acc_no, svm_base_prec_no, svm_base_rec_no,␣
↪svm_base_f1_no],
```

```
    "SVM_Tuned": [
        svm_tuned_acc_no,
        svm_tuned_prec_no,
        svm_tuned_rec_no,
        svm_tuned_f1_no,
    ],
}
```

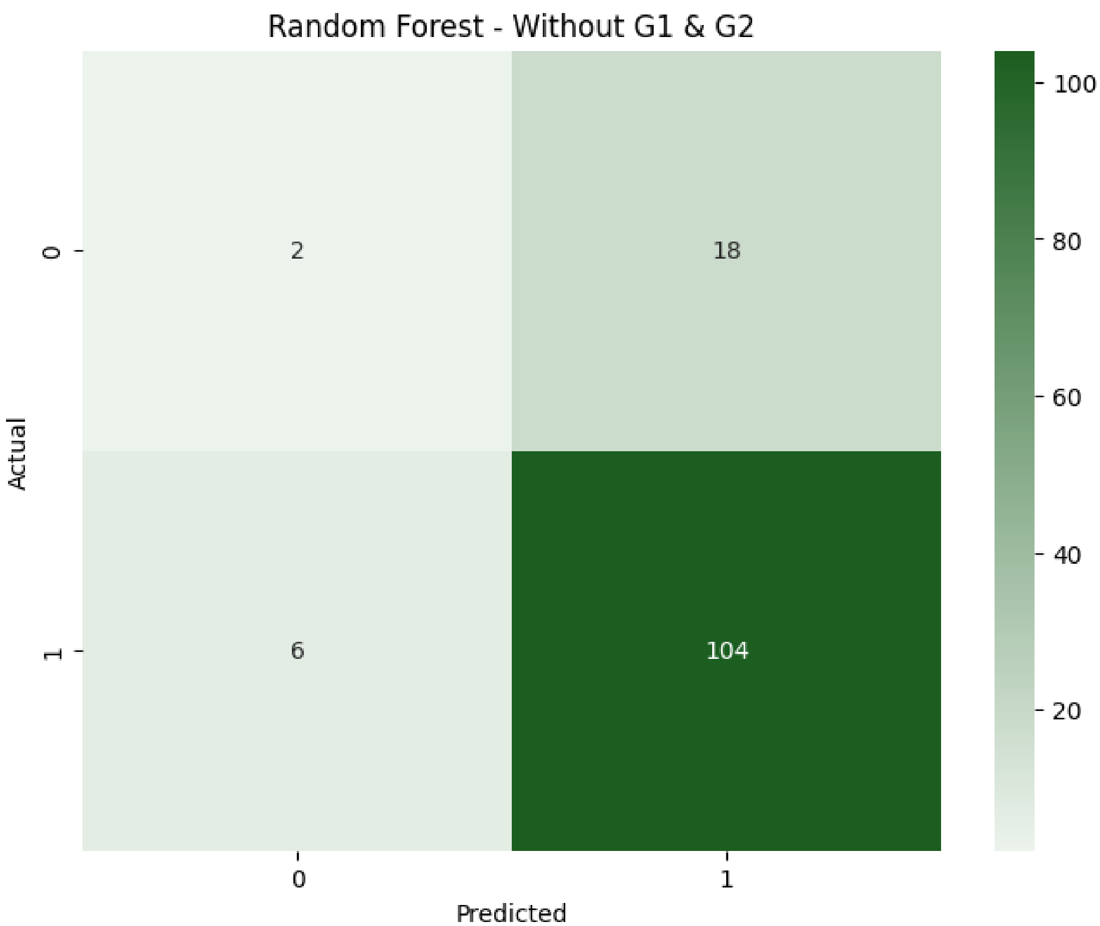
```
============================================================
MODELS WITHOUT G1 & G2 FEATURES
============================================================
LOGISTIC REGRESSION MODEL WITHOUT G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.29      0.25      0.27        20
           1       0.87      0.89      0.88       110

    accuracy                           0.79       130
   macro avg       0.58      0.57      0.57       130
weighted avg       0.78      0.79      0.79       130

Confusion Matrix:
```



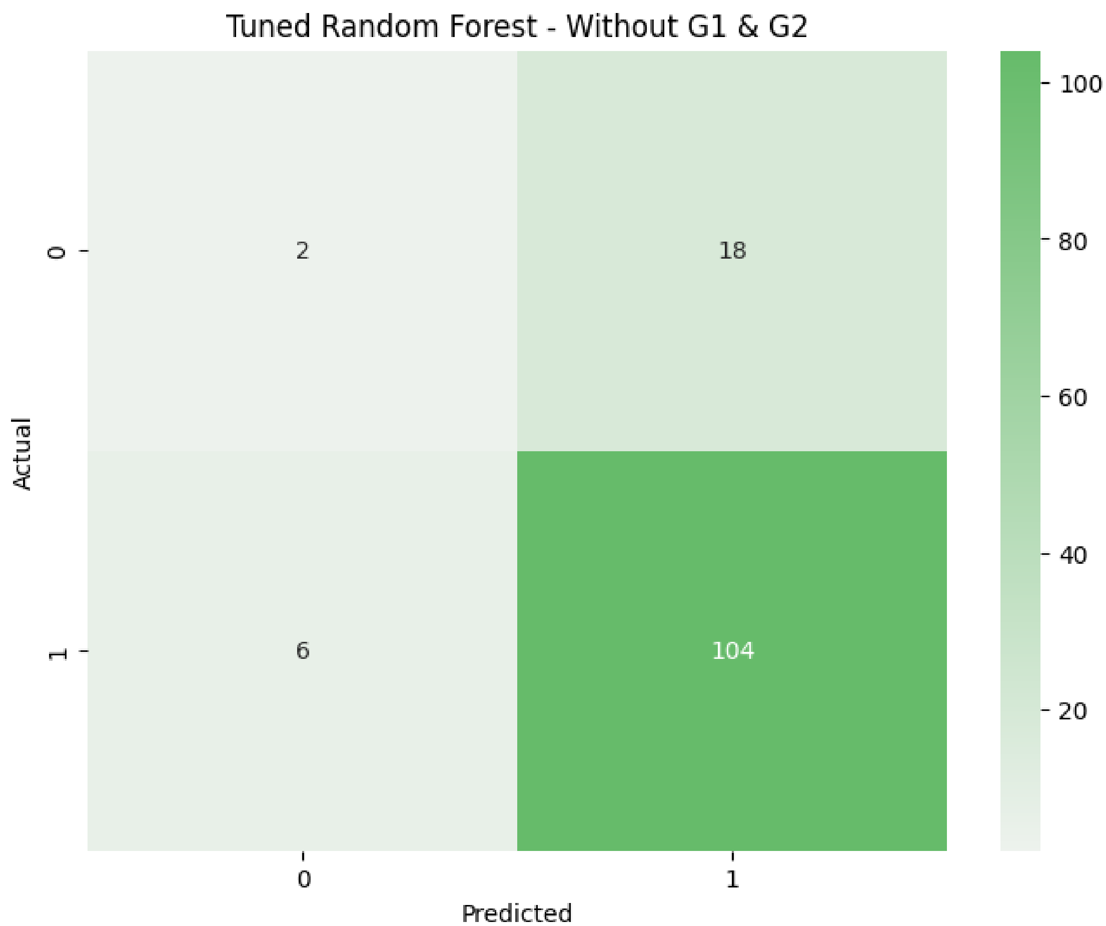

```
----------------------------------------------------
HYPERPARAMETER TUNED LOGISTIC REGRESSION MODEL WITHOUT G1 & G2
Best Hyperparameters for Logistic Regression:
{'C': 0.1, 'penalty': 'l1', 'solver': 'saga'}

Classification Report for Improved Logistic Regression:
              precision    recall  f1-score   support

           0       0.22      0.10      0.14        20
           1       0.85      0.94      0.89       110

    accuracy                           0.81       130
   macro avg       0.54      0.52      0.51       130
weighted avg       0.75      0.81      0.78       130


Confusion Matrix for Improved Model:
```



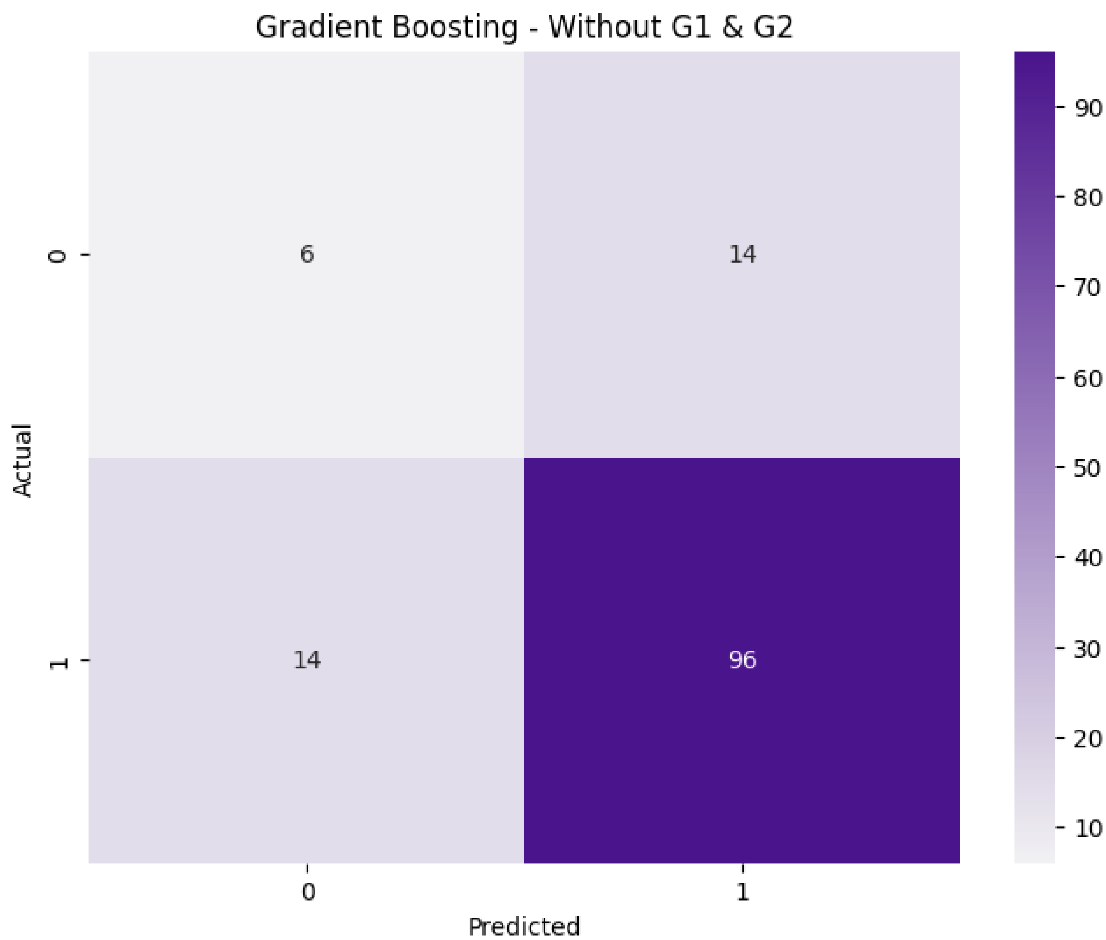

```
--------------------------------------------------
RANDOM FOREST MODEL WITHOUT G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.25      0.10      0.14        20
           1       0.85      0.95      0.90       110

    accuracy                           0.82       130
   macro avg       0.55      0.52      0.52       130
weighted avg       0.76      0.82      0.78       130

Confusion Matrix:
```



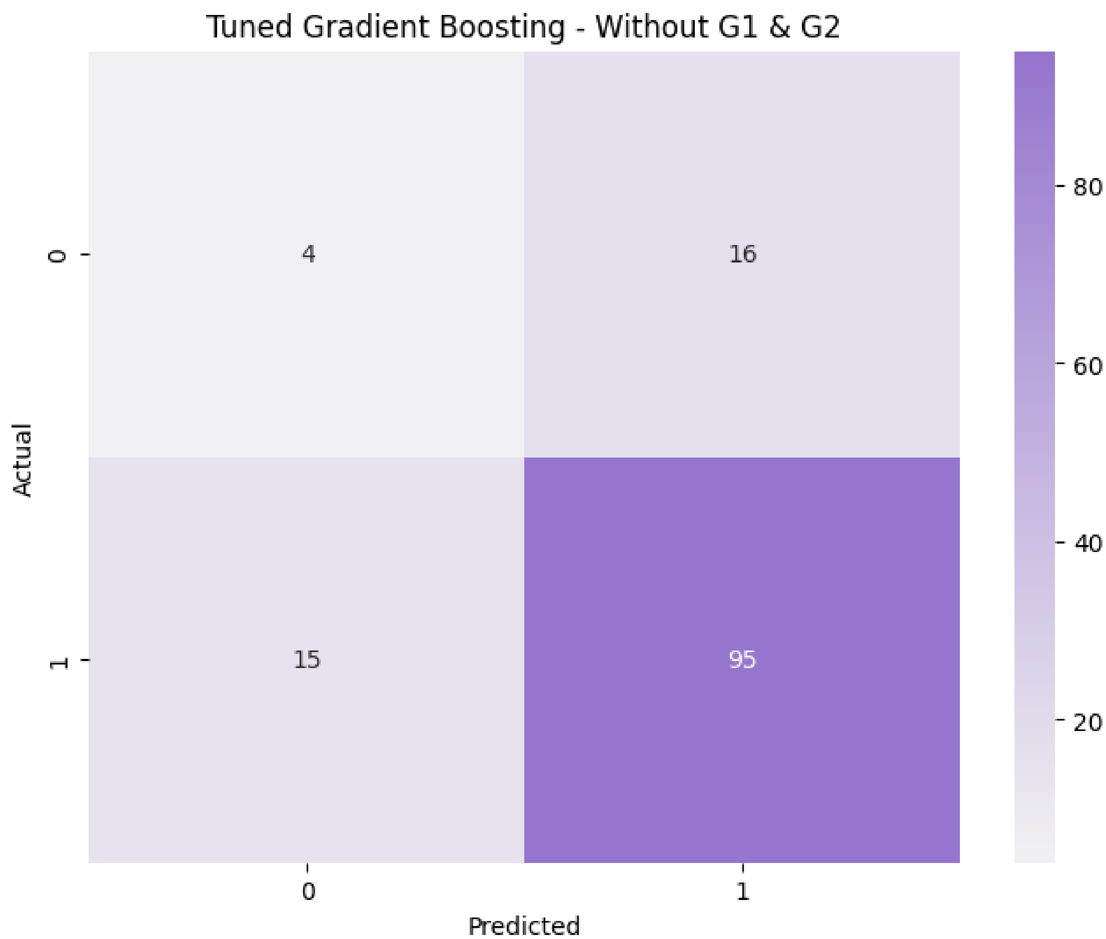

```
--------------------------------------------------
HYPERPARAMETER TUNED RANDOM FOREST MODEL WITHOUT G1 & G2
Best Hyperparameters for Random Forest:
{'n_estimators': 200, 'min_samples_split': 5, 'min_samples_leaf': 2,
'max_depth': 30, 'bootstrap': True}

Classification Report for Tuned Random Forest:
              precision    recall  f1-score   support

           0       0.25      0.10      0.14        20
           1       0.85      0.95      0.90       110

    accuracy                           0.82       130
   macro avg       0.55      0.52      0.52       130
weighted avg       0.76      0.82      0.78       130


Confusion Matrix for Tuned Model:
```




```
--------------------------------------------------
GRADIENT BOOSTING MODEL WITHOUT G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.30      0.30      0.30        20
           1       0.87      0.87      0.87       110

    accuracy                           0.78       130
   macro avg       0.59      0.59      0.59       130
weighted avg       0.78      0.78      0.78       130

Confusion Matrix:
```




```
--------------------------------------------------
TUNED GRADIENT BOOSTING MODEL WITHOUT G1 & G2
Best Hyperparameters for Gradient Boosting:
{'subsample': 1.0, 'n_estimators': 200, 'min_samples_split': 2,
'min_samples_leaf': 4, 'max_depth': 7, 'learning_rate': 0.1}

Classification Report for Tuned Gradient Boosting:
              precision    recall  f1-score   support

           0       0.21      0.20      0.21        20
           1       0.86      0.86      0.86       110

    accuracy                           0.76       130
   macro avg       0.53      0.53      0.53       130
weighted avg       0.76      0.76      0.76       130


Confusion Matrix for Tuned GBM:
```

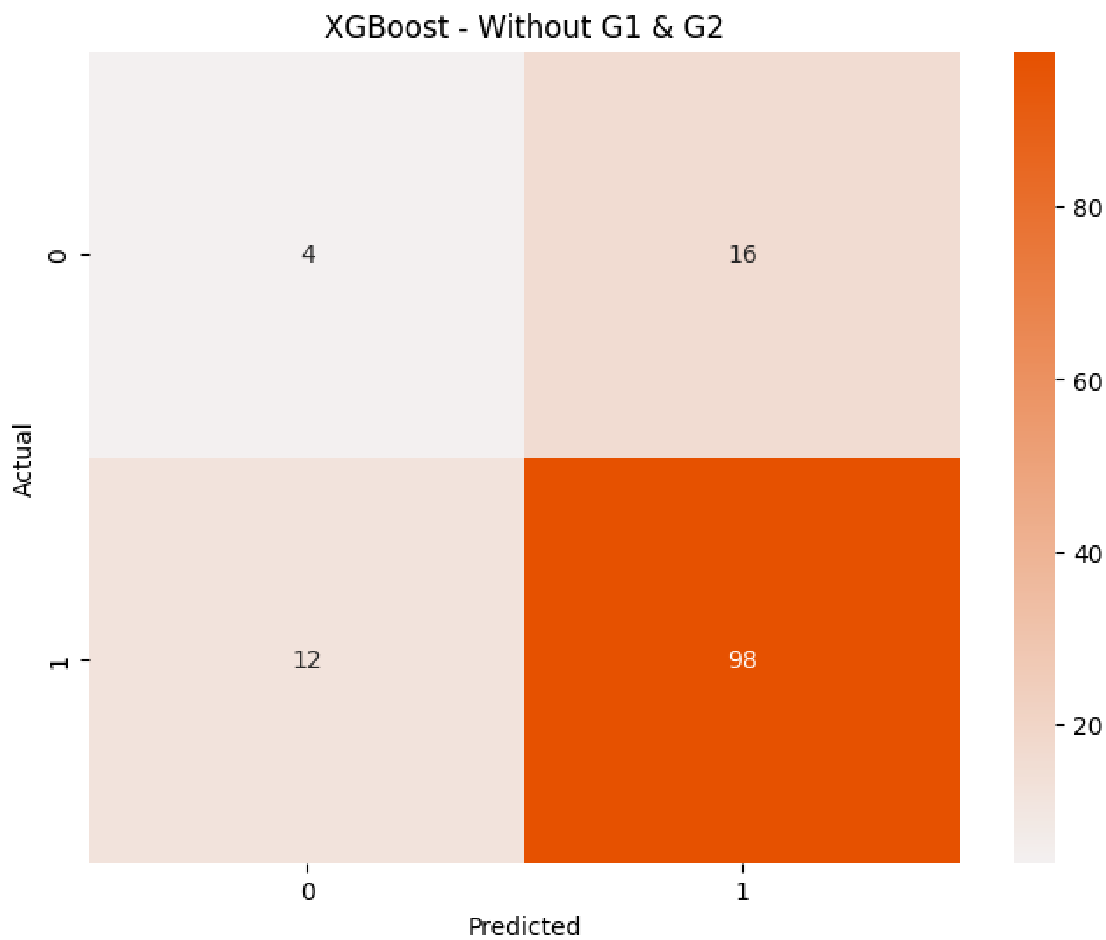


XGBOOST MODEL WITHOUT G1 & G2

Classification Report:

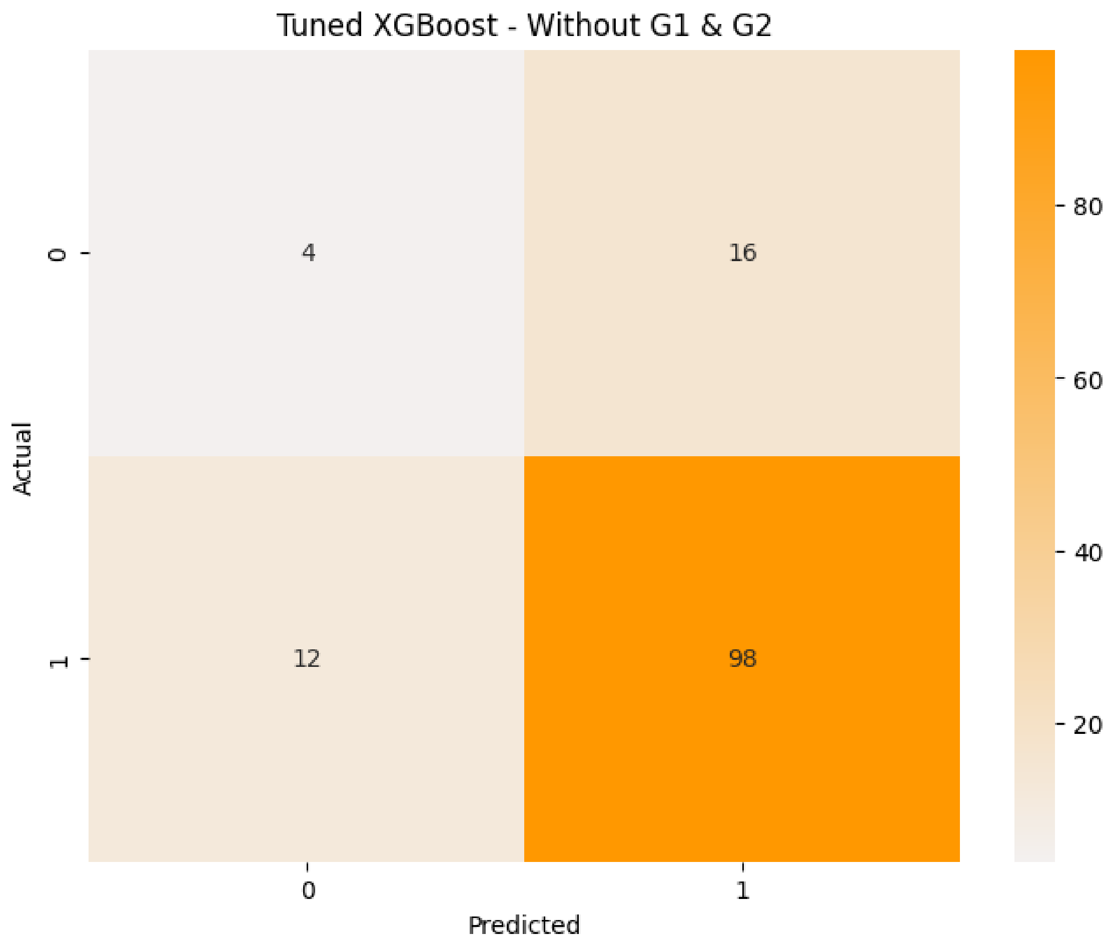
	precision	recall	f1-score	support
0	0.25	0.20	0.22	20
1	0.86	0.89	0.88	110
accuracy			0.78	130
macro avg	0.55	0.55	0.55	130
weighted avg	0.77	0.78	0.77	130

Confusion Matrix:

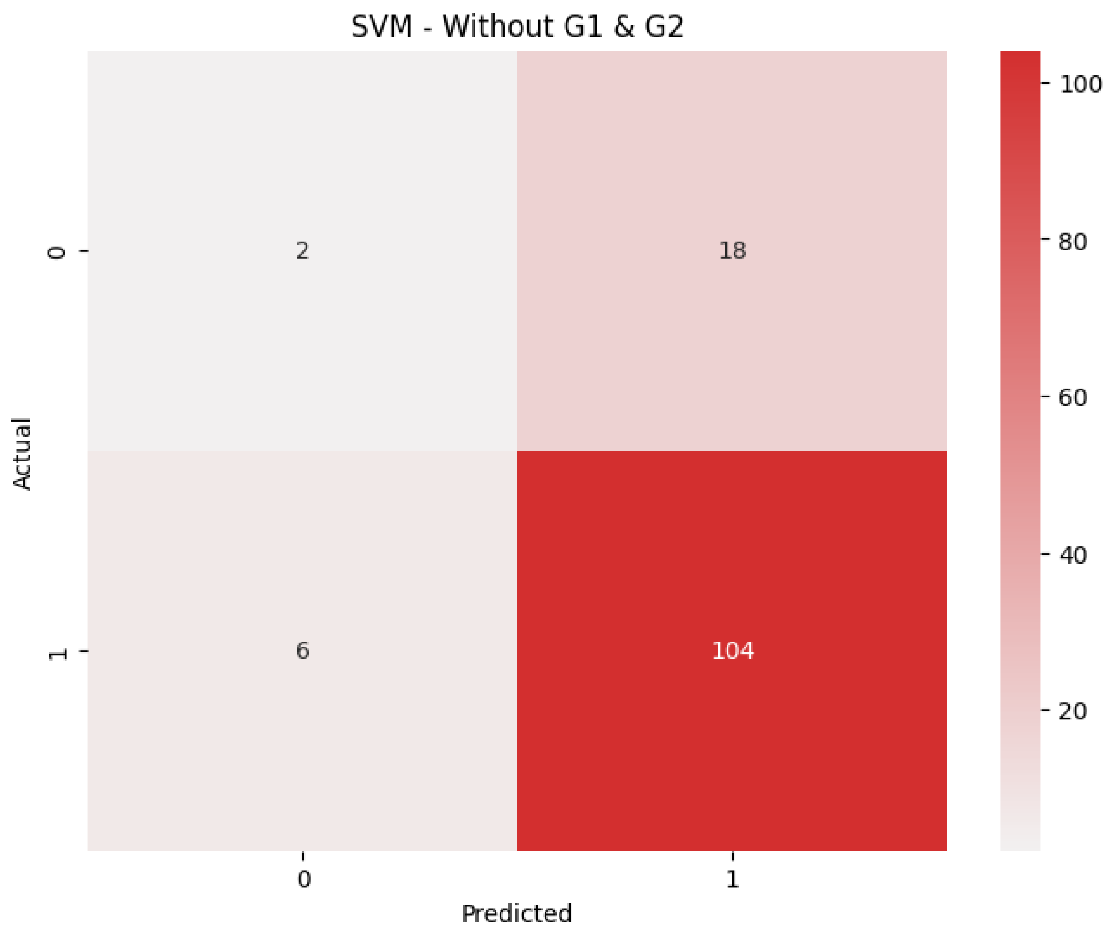



```
----------------------------------------------------
TUNED XGBOOST MODEL WITHOUT G1 & G2
Best Hyperparameters for XGBoost:
{'subsample': 1.0, 'reg_lambda': 2, 'reg_alpha': 0.1, 'n_estimators': 200,
'min_child_weight': 1, 'max_depth': 5, 'learning_rate': 0.1, 'colsample_bytree':
1.0}

Classification Report for Tuned XGBoost:
              precision    recall  f1-score   support

           0       0.25      0.20      0.22        20
           1       0.86      0.89      0.88       110

    accuracy                           0.78       130
   macro avg       0.55      0.55      0.55       130
weighted avg       0.77      0.78      0.77       130
```

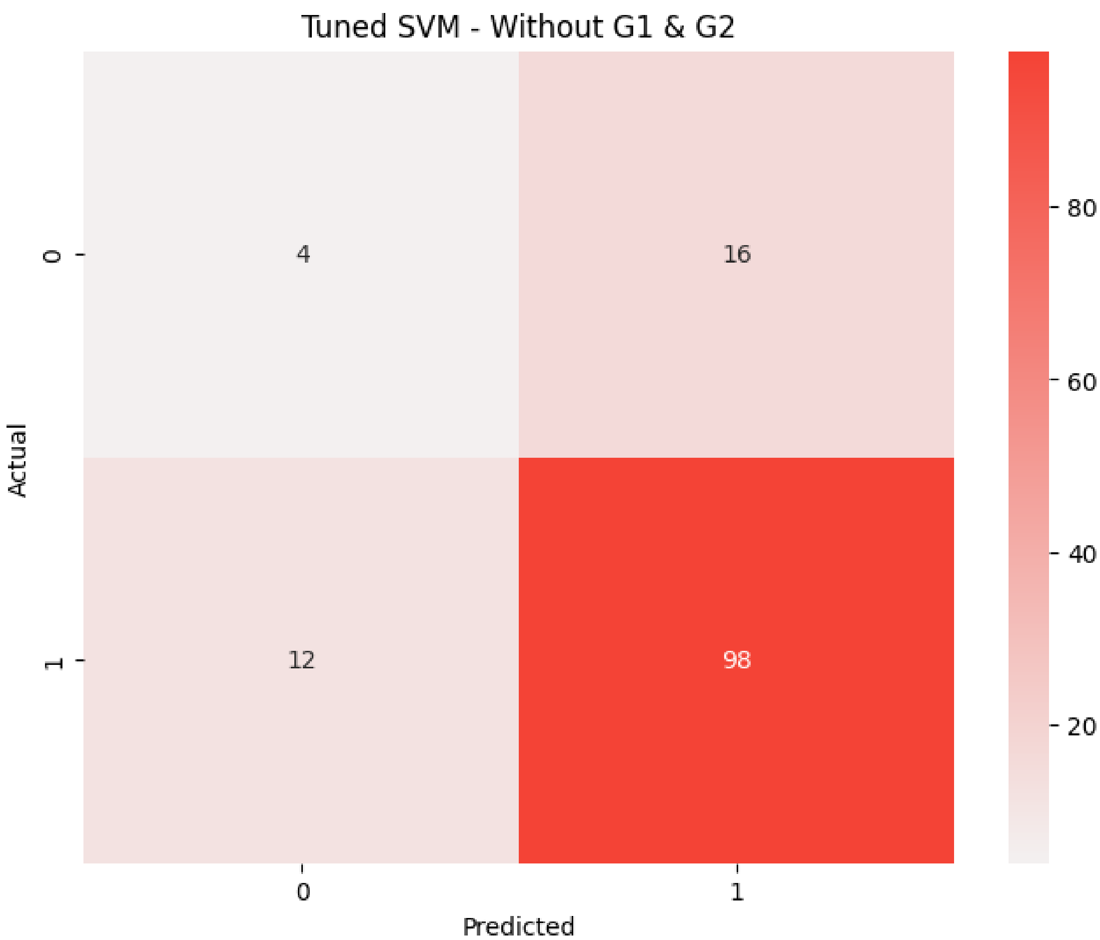
```
Confusion Matrix for Tuned XGBoost:
```




```
--------------------------------------------------
SVM MODEL WITHOUT G1 & G2

Classification Report:
              precision    recall  f1-score   support

           0       0.25      0.10      0.14        20
           1       0.85      0.95      0.90       110

    accuracy                           0.82       130
   macro avg       0.55      0.52      0.52       130
weighted avg       0.76      0.82      0.78       130

Confusion Matrix:
```




```
--------------------------------------------------
TUNED SVM MODEL WITHOUT G1 & G2
Best Hyperparameters for SVM:
{'kernel': 'sigmoid', 'gamma': 0.01, 'degree': 3, 'C': 10}

Classification Report for Tuned SVM:
              precision    recall  f1-score   support

           0       0.25      0.20      0.22        20
           1       0.86      0.89      0.88       110

    accuracy                           0.78       130
   macro avg       0.55      0.55      0.55       130
weighted avg       0.77      0.78      0.77       130


Confusion Matrix for Tuned SVM:
```



[13]:
```python
# Create comprehensive comparison DataFrame
print("\n" + "=" * 80)
print("COMPREHENSIVE MODEL COMPARISON")
print("=" * 80)

# Create comparison dataframes
metrics = ["Accuracy", "Precision", "Recall", "F1-Score"]

# WITH G1 & G2 DataFrame
df_with_grades = pd.DataFrame(results["with_grades"], index=metrics).T
df_with_grades.columns = [f"{col}_WITH_GRADES" for col in df_with_grades.
 ↪columns]

# WITHOUT G1 & G2 DataFrame
df_without_grades = pd.DataFrame(results["without_grades"], index=metrics).T
df_without_grades.columns = [
    f"{col}_WITHOUT_GRADES" for col in df_without_grades.columns
```

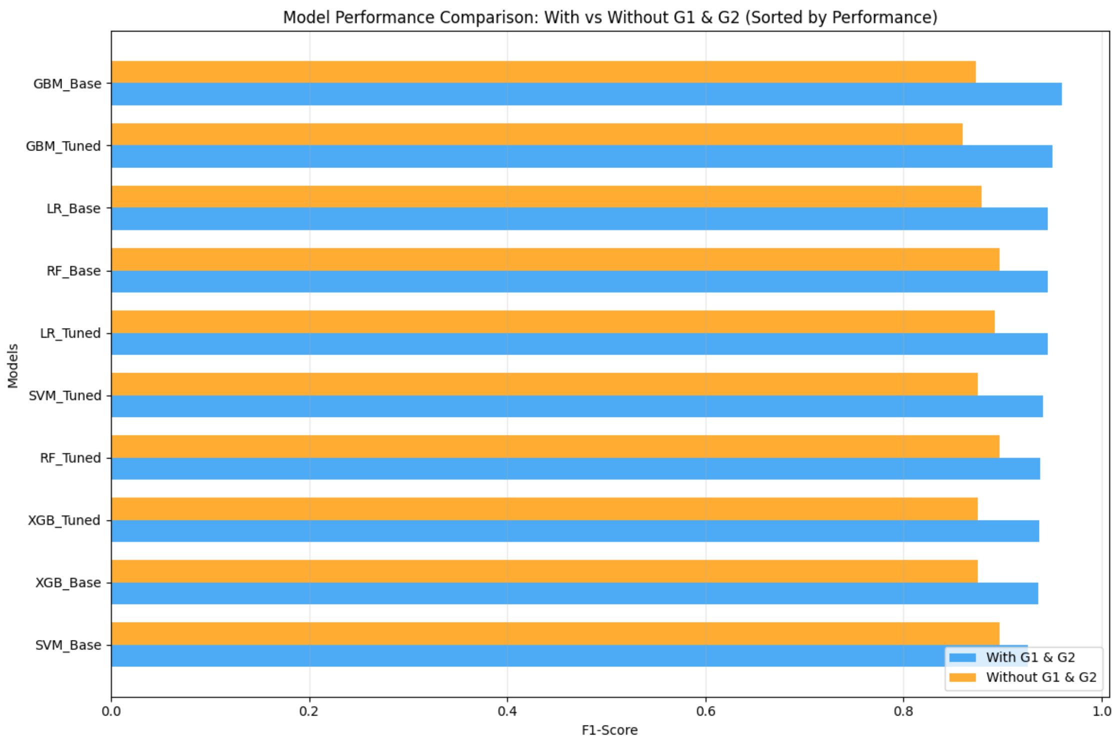
```
]

# Combine both dataframes
comparison_df = pd.concat([df_with_grades, df_without_grades], axis=1)

# Round to 4 decimal places for better readability
comparison_df = comparison_df.round(4)

print("Full Model Comparison Table:")
print(comparison_df)

# Create a focused comparison (F1-Score only)
f1_comparison = pd.DataFrame(
    {
        "With G1 & G2": [
            results["with_grades"][model][3] for model in␣
 ↪results["with_grades"].keys()
        ],
        "Without G1 & G2": [
            results["without_grades"][model][3]
            for model in results["without_grades"].keys()
        ],
    },
    index=list(results["with_grades"].keys()),
)

print("\nF1-Score Comparison:")
print(f1_comparison.round(4))

# Visualize F1-Score comparison with horizontal bars (sorted)
# Sort by "With G1 & G2" performance (descending)
f1_comparison_sorted = f1_comparison.sort_values(
    "With G1 & G2", ascending=True
)  # ascending=True for horizontal bars

plt.figure(figsize=(12, 8))
y_pos = np.arange(len(f1_comparison_sorted.index))
bar_height = 0.35

plt.barh(
    y_pos - bar_height / 2,
    f1_comparison_sorted["With G1 & G2"],
    bar_height,
    label="With G1 & G2",
    alpha=0.8,
    color="#2196f3",
)
```

```python
plt.barh(
    y_pos + bar_height / 2,
    f1_comparison_sorted["Without G1 & G2"],
    bar_height,
    label="Without G1 & G2",
    alpha=0.8,
    color="#ff9800",
)

plt.ylabel("Models")
plt.xlabel("F1-Score")
plt.title(
    "Model Performance Comparison: With vs Without G1 & G2 (Sorted by␣
 ↪Performance)"
)
plt.yticks(y_pos, f1_comparison_sorted.index)
plt.legend(loc="lower right")
plt.grid(True, alpha=0.3, axis="x")
plt.tight_layout()
plt.show()

# Find best performing models
print("\nBest Performing Models:")
print(
    f"WITH G1 & G2: {f1_comparison['With G1 & G2'].idxmax()} "
    f"(F1: {f1_comparison['With G1 & G2'].max():.4f})"
)
print(
    f"WITHOUT G1 & G2: {f1_comparison['Without G1 & G2'].idxmax()} "
    f"(F1: {f1_comparison['Without G1 & G2'].max():.4f})"
)

# Calculate improvement from G1 & G2
print("\nImprovement from including G1 & G2:")
improvements = f1_comparison["With G1 & G2"] - f1_comparison["Without G1 & G2"]
for model in improvements.index:
    improvement = improvements[model]
    pct_improvement = (improvement / f1_comparison.loc[model, "Without G1 &␣
 ↪G2"]) * 100
    print(f"{model}: +{improvement:.4f} ({pct_improvement:.1f}% improvement)")
```

```
================================================================================
COMPREHENSIVE MODEL COMPARISON
================================================================================
Full Model Comparison Table:
           Accuracy_WITH_GRADES  Precision_WITH_GRADES  Recall_WITH_GRADES  \
```

```
LR_Base                   0.9077                  0.9375                0.9545
LR_Tuned                  0.9077                  0.9455                0.9455
RF_Base                   0.9077                  0.9375                0.9545
RF_Tuned                  0.8923                  0.9211                0.9545
GBM_Base                  0.9308                  0.9469                0.9727
GBM_Tuned                 0.9154                  0.9459                0.9545
XGB_Base                  0.8923                  0.9444                0.9273
XGB_Tuned                 0.8923                  0.9286                0.9455
SVM_Base                  0.8692                  0.8908                0.9636
SVM_Tuned                 0.9000                  0.9450                0.9364

           F1-Score_WITH_GRADES  Accuracy_WITHOUT_GRADES  \
LR_Base                  0.9459                   0.7923
LR_Tuned                 0.9455                   0.8077
RF_Base                  0.9459                   0.8154
RF_Tuned                 0.9375                   0.8154
GBM_Base                 0.9596                   0.7846
GBM_Tuned                0.9502                   0.7615
XGB_Base                 0.9358                   0.7846
XGB_Tuned                0.9369                   0.7846
SVM_Base                 0.9258                   0.8154
SVM_Tuned                0.9406                   0.7846

           Precision_WITHOUT_GRADES  Recall_WITHOUT_GRADES  \
LR_Base                      0.8673                 0.8909
LR_Tuned                     0.8512                 0.9364
RF_Base                      0.8525                 0.9455
RF_Tuned                     0.8525                 0.9455
GBM_Base                     0.8727                 0.8727
GBM_Tuned                    0.8559                 0.8636
XGB_Base                     0.8596                 0.8909
XGB_Tuned                    0.8596                 0.8909
SVM_Base                     0.8525                 0.9455
SVM_Tuned                    0.8596                 0.8909

           F1-Score_WITHOUT_GRADES
LR_Base                     0.8789
LR_Tuned                    0.8918
RF_Base                     0.8966
RF_Tuned                    0.8966
GBM_Base                    0.8727
GBM_Tuned                   0.8597
XGB_Base                    0.8750
XGB_Tuned                   0.8750
SVM_Base                    0.8966
SVM_Tuned                   0.8750

F1-Score Comparison:
```

	With G1 & G2	Without G1 & G2
LR_Base	0.9459	0.8789
LR_Tuned	0.9455	0.8918
RF_Base	0.9459	0.8966
RF_Tuned	0.9375	0.8966
GBM_Base	0.9596	0.8727
GBM_Tuned	0.9502	0.8597
XGB_Base	0.9358	0.8750
XGB_Tuned	0.9369	0.8750
SVM_Base	0.9258	0.8966
SVM_Tuned	0.9406	0.8750



Best Performing Models:
WITH G1 & G2: GBM_Base (F1: 0.9596)
WITHOUT G1 & G2: RF_Base (F1: 0.8966)

Improvement from including G1 & G2:
LR_Base: +0.0670 (7.6% improvement)
LR_Tuned: +0.0537 (6.0% improvement)
RF_Base: +0.0494 (5.5% improvement)
RF_Tuned: +0.0409 (4.6% improvement)
GBM_Base: +0.0869 (10.0% improvement)
GBM_Tuned: +0.0905 (10.5% improvement)

```
XGB_Base: +0.0608 (6.9% improvement)
XGB_Tuned: +0.0619 (7.1% improvement)
SVM_Base: +0.0292 (3.3% improvement)
SVM_Tuned: +0.0656 (7.5% improvement)
```