

copy-of-adr-1

November 7, 2024

```
[ ]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

```
[ ]: # Install RDKit in Google Colab
!pip install rdkit-pypi
```

Collecting rdkit-pypi

Downloading rdkit_pypi-2022.9.5-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (3.9 kB)

Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (1.26.4)

Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (10.4.0)

Downloading

rdkit_pypi-2022.9.5-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (29.4 MB)

29.4/29.4 MB

54.6 MB/s eta 0:00:00

Installing collected packages: rdkit-pypi

Successfully installed rdkit-pypi-2022.9.5

```
[ ]: adr_df = pd.read_csv('binary adr.csv')
```

```
[ ]: from rdkit import Chem
from rdkit.Chem import AllChem

smiles_list = adr_df['Chemical Compound']

# Convert SMILES to RDKit Mol objects
mols = [Chem.MolFromSmiles(smile) for smile in smiles_list]

# Generate molecular fingerprints (1024-bit) for each molecule
fingerprints = [AllChem.GetMorganFingerprintAsBitVect(mol, 2, nBits=1024) for
    mol in mols]
```

```
[ ]: print(fingerprints)
```


[illegible]

[illegible]


```

<rdkit.DataStructs.cDataStructs.ExplicitBitVect object at 0x7dc7c96b5bd0>,
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```

```

[ ]: #Convert Fingerprints to Arrays
import numpy as np
from rdkit import DataStructs

# Convert each fingerprint into a NumPy array
fingerprint_array = []
for fp in fingerprints:
    arr = np.zeros((1,))
    DataStructs.ConvertToNumPyArray(fp, arr)
    fingerprint_array.append(arr)

```

```

# Convert to a NumPy array for easier manipulation (e.g., for machine learning)
X = np.array(fingerprint_array)

# Check the shape of the resulting feature matrix
print(X.shape) # Should be (number_of_compounds, 1024) if using 1024-bit
                ↪ fingerprints

```

(1332, 1024)

```

[ ]: # Prepare Target (Adverse Reaction Labels)

# Assuming 'adr_df' contains columns for each adverse reaction
reaction_columns = ['Hepatobiliary disorders', 'Metabolism and nutrition
                    ↪ disorders', 'Eye disorders',
                    'Musculoskeletal and connective tissue disorders',
                    ↪ 'Gastrointestinal disorders',
                    'Immune system disorders', 'Reproductive system and breast
                    ↪ disorders',
                    'Neoplasms benign, malignant and unspecified (incl cysts
                    ↪ and polyps)',
                    'General disorders and administration site conditions',
                    ↪ 'Endocrine disorders',
                    'Surgical and medical procedures', 'Vascular disorders',
                    ↪ 'Blood and lymphatic system disorders',
                    'Skin and subcutaneous tissue disorders', 'Congenital,
                    ↪ familial and genetic disorders',
                    'Infections and infestations', 'Respiratory, thoracic and
                    ↪ mediastinal disorders',
                    'Psychiatric disorders', 'Renal and urinary disorders',
                    ↪ 'Pregnancy, puerperium and perinatal conditions',
                    'Ear and labyrinth disorders', 'Cardiac disorders',
                    ↪ 'Nervous system disorders',
                    'Injury, poisoning and procedural complications']

# Extract the target labels
y = adr_df[reaction_columns].values

# Check the shape of the target matrix
print(y.shape) # Should be (number_of_compounds, number_of_reactions)

```

(1332, 24)

```

[ ]: # Split the Data

from sklearn.model_selection import train_test_split

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# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Check the shape of the training and test sets
print(X_train.shape, X_test.shape)

```

(1065, 1024) (267, 1024)

```

[ ]: # 1. MLP with hypparameter tuning = 10,15,20,25,30,35,40,50

import torch
import torch.nn.functional as F
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# Define a simple MLP model
class MLP(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5,
↳num_layers=2, activation=F.relu):
        super(MLP, self).__init__()
        self.layers = torch.nn.ModuleList()
        self.dropout = dropout
        self.activation = activation

        # Add hidden layers
        self.layers.append(torch.nn.Linear(input_dim, hidden_dim))
        for _ in range(num_layers - 1):
            self.layers.append(torch.nn.Linear(hidden_dim, hidden_dim))

        # Output layer
        self.fc = torch.nn.Linear(hidden_dim, output_dim)

    def forward(self, x):
        for layer in self.layers:

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        x = self.activation(layer(x))
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # Multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [10, 20, 25, 15, 30, 35, 40, 50], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001], # Learning rates
    'num_layers': [2, 3], # Number of hidden layers
    'activation': ['relu', 'tanh'], # Activation functions
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                for num_layers in param_grid['num_layers']:
                    for activation in param_grid['activation']:
                        for epochs in param_grid['epochs']:
                            print(f'Training with hidden_dim={hidden_dim},
↪ dropout={dropout}, lr={lr}, batch_size={batch_size},
↪ num_layers={num_layers}, activation={activation}, epochs={epochs}')

                            # Initialize activation function
                            if activation == 'relu':
                                activation_fn = F.relu
                            elif activation == 'tanh':
                                activation_fn = torch.tanh

                            # Initialize model
                            model = MLP(input_dim=X_train.shape[1],
↪ hidden_dim=hidden_dim, output_dim=y_train.shape[1], dropout=dropout,
↪ num_layers=num_layers, activation=activation_fn)

                            # Loss and optimizer
                            optimizer = torch.optim.Adam(model.parameters(), lr=lr)

```



```

criterion = torch.nn.BCELoss()

# Train the model
for epoch in range(param_grid['epochs'][0]):
    model.train()
    optimizer.zero_grad()
    out = model(X_train_tensor)
    loss = criterion(out, y_train_tensor)
    loss.backward()
    optimizer.step()

# Evaluate the model
model.eval()
with torch.no_grad():
    y_pred = model(X_test_tensor)
    y_pred_binary = (y_pred > 0.5).float()

# Calculate binary accuracy
binary_acc = (y_pred_binary == y_test_tensor).float().
↳mean().item()

# Calculate normal accuracy
normal_acc = accuracy_score(y_test, y_pred_binary.
↳numpy())

# Calculate F1 score
f1 = f1_score(y_test, y_pred_binary.numpy(),
↳average='micro')

# Update best params if this model is better
if binary_acc > best_binary_acc:
    best_binary_acc = binary_acc
    best_f1 = f1
    best_normal_acc = normal_acc
    best_params = {
        'hidden_dim': hidden_dim,
        'dropout': dropout,
        'lr': lr,
        'batch_size': batch_size,
        'num_layers': num_layers,
        'activation': activation,
    }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')

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```
print(f'Best F1 Score: {best_f1:.4f}')
```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, num_layers=2, activation=relu, epochs=10
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 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32, num_layers=2, activation=relu, epochs=15
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32, num_layers=2, activation=relu, epochs=30
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32, num_layers=2, activation=relu, epochs=35
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32,


```

num_layers=3, activation=relu, epochs=40
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=relu, epochs=50
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=10
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=20
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=25
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=15
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=30
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=35
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=40
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64,
num_layers=3, activation=tanh, epochs=50
Best Params: {'hidden_dim': 128, 'dropout': 0.5, 'lr': 0.001, 'batch_size': 64,
'num_layers': 3, 'activation': 'tanh'}
Best Binary Accuracy: 0.9115
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9537

```

```

[ ]: # 2. CNN

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Dense, Flatten,
↳Dropout
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Define the CNN model
def build_cnn_model(filters=64, kernel_size=3, dropout=0.5):
    model = Sequential()

    # 1D Convolutional Layer
    model.add(Conv1D(filters=filters, kernel_size=kernel_size,
↳activation='relu', input_shape=(X_train.shape[1], 1)))

    # MaxPooling Layer
    model.add(MaxPooling1D(pool_size=2))

    # Dropout Layer
    model.add(Dropout(dropout))

```

```

# Flatten the output for dense layers
model.add(Flatten())

# Dense Layers
model.add(Dense(256, activation='relu'))
model.add(Dropout(dropout))

# Output layer for multi-label classification
model.add(Dense(y_train.shape[1], activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['binary_accuracy'])

return model

# Reshape your data for CNN input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'filters': [32, 64], # Number of filters for Conv1D
    'kernel_size': [3, 5], # Kernel size for Conv1D
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [10], # Number of epochs
    'batch_size': [32], # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0
best_normal_acc = 0

# Perform the manual hyperparameter search
for filters in param_grid['filters']:
    for kernel_size in param_grid['kernel_size']: # Now this will work
        for dropout in param_grid['dropout']:
            for epochs in param_grid['epochs']:
                for batch_size in param_grid['batch_size']:
                    print(f'Training with filters={filters},
kernel_size={kernel_size}, dropout={dropout}, epochs={epochs},
batch_size={batch_size}')

# Build the model

```



```

        model = build_cnn_model(filters=filters,
        ↪kernel_size=kernel_size, dropout=dropout)

        # Train the model
        model.fit(X_train, y_train, epochs=epochs,
        ↪batch_size=batch_size, validation_split=0.1, verbose=1)

        # Predict on the test set
        y_pred = model.predict(X_test)
        y_pred_binary = (y_pred > 0.5).astype(int)

        # Calculate binary accuracy
        binary_acc = np.mean(np.equal(y_test, y_pred_binary).
        ↪astype(int))

        # Calculate normal accuracy
        normal_acc = accuracy_score(y_test, y_pred_binary)

        # Calculate F1 Score
        f1 = f1_score(y_test, y_pred_binary, average='micro')

        # Update best params if this model is better
        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'filters': filters,
                'kernel_size': kernel_size,
                'dropout': dropout,
                'epochs': epochs,
                'batch_size': batch_size,
            }

    # Print the best results
    print(f'Best Params: {best_params}')
    print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
    print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
    print(f'Best F1 Score: {best_f1:.4f}')

```

Training with filters=32, kernel_size=3, dropout=0.3, epochs=10, batch_size=32

Epoch 1/10
 30/30 [=====] - 13s 42ms/step - loss: 0.3576 -
 binary_accuracy: 0.8693 - val_loss: 0.2657 - val_binary_accuracy: 0.9124

Epoch 2/10
 30/30 [=====] - 0s 11ms/step - loss: 0.2807 -
 binary_accuracy: 0.8937 - val_loss: 0.2467 - val_binary_accuracy: 0.9116

Epoch 3/10
30/30 [=====] - 0s 14ms/step - loss: 0.2522 -
binary_accuracy: 0.9002 - val_loss: 0.2450 - val_binary_accuracy: 0.9143
Epoch 4/10
30/30 [=====] - 0s 15ms/step - loss: 0.2301 -
binary_accuracy: 0.9054 - val_loss: 0.2431 - val_binary_accuracy: 0.9112
Epoch 5/10
30/30 [=====] - 0s 10ms/step - loss: 0.2119 -
binary_accuracy: 0.9106 - val_loss: 0.2436 - val_binary_accuracy: 0.9104
Epoch 6/10
30/30 [=====] - 0s 13ms/step - loss: 0.1964 -
binary_accuracy: 0.9168 - val_loss: 0.2573 - val_binary_accuracy: 0.9100
Epoch 7/10
30/30 [=====] - 0s 10ms/step - loss: 0.1817 -
binary_accuracy: 0.9231 - val_loss: 0.2642 - val_binary_accuracy: 0.8945
Epoch 8/10
30/30 [=====] - 0s 7ms/step - loss: 0.1689 -
binary_accuracy: 0.9287 - val_loss: 0.2754 - val_binary_accuracy: 0.8917
Epoch 9/10
30/30 [=====] - 0s 6ms/step - loss: 0.1568 -
binary_accuracy: 0.9327 - val_loss: 0.2829 - val_binary_accuracy: 0.8921
Epoch 10/10
30/30 [=====] - 0s 7ms/step - loss: 0.1433 -
binary_accuracy: 0.9407 - val_loss: 0.2987 - val_binary_accuracy: 0.8906
9/9 [=====] - 0s 5ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 12ms/step - loss: 0.3652 -
binary_accuracy: 0.8637 - val_loss: 0.2602 - val_binary_accuracy: 0.9124
Epoch 2/10
30/30 [=====] - 0s 6ms/step - loss: 0.2914 -
binary_accuracy: 0.8888 - val_loss: 0.2499 - val_binary_accuracy: 0.9120
Epoch 3/10
30/30 [=====] - 0s 7ms/step - loss: 0.2649 -
binary_accuracy: 0.8967 - val_loss: 0.2412 - val_binary_accuracy: 0.9120
Epoch 4/10
30/30 [=====] - 0s 7ms/step - loss: 0.2453 -
binary_accuracy: 0.9011 - val_loss: 0.2407 - val_binary_accuracy: 0.9147
Epoch 5/10
30/30 [=====] - 0s 7ms/step - loss: 0.2351 -
binary_accuracy: 0.9038 - val_loss: 0.2432 - val_binary_accuracy: 0.9104
Epoch 6/10
30/30 [=====] - 0s 7ms/step - loss: 0.2233 -
binary_accuracy: 0.9074 - val_loss: 0.2435 - val_binary_accuracy: 0.9100
Epoch 7/10
30/30 [=====] - 0s 7ms/step - loss: 0.2095 -
binary_accuracy: 0.9116 - val_loss: 0.2465 - val_binary_accuracy: 0.9093
Epoch 8/10

```

30/30 [=====] - 0s 7ms/step - loss: 0.1986 -
binary_accuracy: 0.9162 - val_loss: 0.2553 - val_binary_accuracy: 0.9065
Epoch 9/10
30/30 [=====] - 0s 6ms/step - loss: 0.1907 -
binary_accuracy: 0.9177 - val_loss: 0.2580 - val_binary_accuracy: 0.9046
Epoch 10/10
30/30 [=====] - 0s 7ms/step - loss: 0.1783 -
binary_accuracy: 0.9220 - val_loss: 0.2663 - val_binary_accuracy: 0.9011
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=5, dropout=0.3, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 16ms/step - loss: 0.3430 -
binary_accuracy: 0.8689 - val_loss: 0.2659 - val_binary_accuracy: 0.9085
Epoch 2/10
30/30 [=====] - 0s 6ms/step - loss: 0.2731 -
binary_accuracy: 0.8953 - val_loss: 0.2461 - val_binary_accuracy: 0.9124
Epoch 3/10
30/30 [=====] - 0s 7ms/step - loss: 0.2459 -
binary_accuracy: 0.9017 - val_loss: 0.2458 - val_binary_accuracy: 0.9112
Epoch 4/10
30/30 [=====] - 0s 6ms/step - loss: 0.2287 -
binary_accuracy: 0.9080 - val_loss: 0.2441 - val_binary_accuracy: 0.9124
Epoch 5/10
30/30 [=====] - 0s 7ms/step - loss: 0.2083 -
binary_accuracy: 0.9123 - val_loss: 0.2484 - val_binary_accuracy: 0.9023
Epoch 6/10
30/30 [=====] - 0s 7ms/step - loss: 0.1941 -
binary_accuracy: 0.9171 - val_loss: 0.2555 - val_binary_accuracy: 0.9026
Epoch 7/10
30/30 [=====] - 0s 6ms/step - loss: 0.1795 -
binary_accuracy: 0.9214 - val_loss: 0.2658 - val_binary_accuracy: 0.8949
Epoch 8/10
30/30 [=====] - 0s 6ms/step - loss: 0.1678 -
binary_accuracy: 0.9280 - val_loss: 0.2757 - val_binary_accuracy: 0.8980
Epoch 9/10
30/30 [=====] - 0s 7ms/step - loss: 0.1533 -
binary_accuracy: 0.9343 - val_loss: 0.2875 - val_binary_accuracy: 0.8988
Epoch 10/10
30/30 [=====] - 0s 8ms/step - loss: 0.1412 -
binary_accuracy: 0.9394 - val_loss: 0.2936 - val_binary_accuracy: 0.8976
9/9 [=====] - 0s 3ms/step
Training with filters=32, kernel_size=5, dropout=0.5, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 18ms/step - loss: 0.3682 -
binary_accuracy: 0.8619 - val_loss: 0.2697 - val_binary_accuracy: 0.9124
Epoch 2/10
30/30 [=====] - 0s 9ms/step - loss: 0.2930 -
binary_accuracy: 0.8926 - val_loss: 0.2506 - val_binary_accuracy: 0.9128

```

Epoch 3/10
30/30 [=====] - 0s 10ms/step - loss: 0.2638 -
binary_accuracy: 0.8966 - val_loss: 0.2412 - val_binary_accuracy: 0.9116
Epoch 4/10
30/30 [=====] - 0s 9ms/step - loss: 0.2464 -
binary_accuracy: 0.9010 - val_loss: 0.2391 - val_binary_accuracy: 0.9155
Epoch 5/10
30/30 [=====] - 0s 9ms/step - loss: 0.2315 -
binary_accuracy: 0.9047 - val_loss: 0.2416 - val_binary_accuracy: 0.9100
Epoch 6/10
30/30 [=====] - 0s 9ms/step - loss: 0.2203 -
binary_accuracy: 0.9077 - val_loss: 0.2430 - val_binary_accuracy: 0.9085
Epoch 7/10
30/30 [=====] - 0s 7ms/step - loss: 0.2102 -
binary_accuracy: 0.9124 - val_loss: 0.2471 - val_binary_accuracy: 0.9081
Epoch 8/10
30/30 [=====] - 0s 7ms/step - loss: 0.2000 -
binary_accuracy: 0.9134 - val_loss: 0.2500 - val_binary_accuracy: 0.9077
Epoch 9/10
30/30 [=====] - 0s 6ms/step - loss: 0.1927 -
binary_accuracy: 0.9162 - val_loss: 0.2578 - val_binary_accuracy: 0.9026
Epoch 10/10
30/30 [=====] - 0s 6ms/step - loss: 0.1825 -
binary_accuracy: 0.9221 - val_loss: 0.2577 - val_binary_accuracy: 0.9042
9/9 [=====] - 0s 3ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 18ms/step - loss: 0.3594 -
binary_accuracy: 0.8699 - val_loss: 0.2651 - val_binary_accuracy: 0.9097
Epoch 2/10
30/30 [=====] - 0s 8ms/step - loss: 0.2723 -
binary_accuracy: 0.8961 - val_loss: 0.2497 - val_binary_accuracy: 0.9124
Epoch 3/10
30/30 [=====] - 0s 8ms/step - loss: 0.2381 -
binary_accuracy: 0.9050 - val_loss: 0.2480 - val_binary_accuracy: 0.9065
Epoch 4/10
30/30 [=====] - 0s 8ms/step - loss: 0.2143 -
binary_accuracy: 0.9108 - val_loss: 0.2500 - val_binary_accuracy: 0.9007
Epoch 5/10
30/30 [=====] - 0s 9ms/step - loss: 0.1980 -
binary_accuracy: 0.9161 - val_loss: 0.2670 - val_binary_accuracy: 0.8949
Epoch 6/10
30/30 [=====] - 0s 8ms/step - loss: 0.1800 -
binary_accuracy: 0.9221 - val_loss: 0.2725 - val_binary_accuracy: 0.8972
Epoch 7/10
30/30 [=====] - 0s 8ms/step - loss: 0.1639 -
binary_accuracy: 0.9303 - val_loss: 0.2891 - val_binary_accuracy: 0.8898
Epoch 8/10

```

30/30 [=====] - 0s 8ms/step - loss: 0.1512 -
binary_accuracy: 0.9357 - val_loss: 0.3007 - val_binary_accuracy: 0.8952
Epoch 9/10
30/30 [=====] - 0s 9ms/step - loss: 0.1379 -
binary_accuracy: 0.9414 - val_loss: 0.3085 - val_binary_accuracy: 0.8949
Epoch 10/10
30/30 [=====] - 0s 8ms/step - loss: 0.1258 -
binary_accuracy: 0.9467 - val_loss: 0.3232 - val_binary_accuracy: 0.8910
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 14ms/step - loss: 0.3760 -
binary_accuracy: 0.8584 - val_loss: 0.2683 - val_binary_accuracy: 0.9116
Epoch 2/10
30/30 [=====] - 0s 8ms/step - loss: 0.2861 -
binary_accuracy: 0.8946 - val_loss: 0.2469 - val_binary_accuracy: 0.9132
Epoch 3/10
30/30 [=====] - 0s 8ms/step - loss: 0.2598 -
binary_accuracy: 0.8983 - val_loss: 0.2382 - val_binary_accuracy: 0.9151
Epoch 4/10
30/30 [=====] - 0s 8ms/step - loss: 0.2389 -
binary_accuracy: 0.9030 - val_loss: 0.2420 - val_binary_accuracy: 0.9108
Epoch 5/10
30/30 [=====] - 0s 8ms/step - loss: 0.2239 -
binary_accuracy: 0.9071 - val_loss: 0.2429 - val_binary_accuracy: 0.9093
Epoch 6/10
30/30 [=====] - 0s 8ms/step - loss: 0.2100 -
binary_accuracy: 0.9121 - val_loss: 0.2505 - val_binary_accuracy: 0.9081
Epoch 7/10
30/30 [=====] - 0s 8ms/step - loss: 0.1963 -
binary_accuracy: 0.9168 - val_loss: 0.2587 - val_binary_accuracy: 0.9042
Epoch 8/10
30/30 [=====] - 0s 8ms/step - loss: 0.1871 -
binary_accuracy: 0.9194 - val_loss: 0.2636 - val_binary_accuracy: 0.9019
Epoch 9/10
30/30 [=====] - 0s 8ms/step - loss: 0.1785 -
binary_accuracy: 0.9248 - val_loss: 0.2745 - val_binary_accuracy: 0.9015
Epoch 10/10
30/30 [=====] - 0s 8ms/step - loss: 0.1680 -
binary_accuracy: 0.9269 - val_loss: 0.2773 - val_binary_accuracy: 0.9011
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=5, dropout=0.3, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 18ms/step - loss: 0.3592 -
binary_accuracy: 0.8668 - val_loss: 0.2653 - val_binary_accuracy: 0.9097
Epoch 2/10
30/30 [=====] - 0s 8ms/step - loss: 0.2761 -
binary_accuracy: 0.8933 - val_loss: 0.2461 - val_binary_accuracy: 0.9128

```

Epoch 3/10
30/30 [=====] - 0s 8ms/step - loss: 0.2451 -
binary_accuracy: 0.9007 - val_loss: 0.2428 - val_binary_accuracy: 0.9081
Epoch 4/10
30/30 [=====] - 0s 8ms/step - loss: 0.2262 -
binary_accuracy: 0.9064 - val_loss: 0.2463 - val_binary_accuracy: 0.9112
Epoch 5/10
30/30 [=====] - 0s 8ms/step - loss: 0.2044 -
binary_accuracy: 0.9139 - val_loss: 0.2600 - val_binary_accuracy: 0.9054
Epoch 6/10
30/30 [=====] - 0s 8ms/step - loss: 0.1880 -
binary_accuracy: 0.9199 - val_loss: 0.2634 - val_binary_accuracy: 0.9058
Epoch 7/10
30/30 [=====] - 0s 8ms/step - loss: 0.1721 -
binary_accuracy: 0.9256 - val_loss: 0.2733 - val_binary_accuracy: 0.9034
Epoch 8/10
30/30 [=====] - 0s 9ms/step - loss: 0.1571 -
binary_accuracy: 0.9340 - val_loss: 0.2878 - val_binary_accuracy: 0.8964
Epoch 9/10
30/30 [=====] - 0s 8ms/step - loss: 0.1441 -
binary_accuracy: 0.9381 - val_loss: 0.2973 - val_binary_accuracy: 0.8902
Epoch 10/10
30/30 [=====] - 0s 8ms/step - loss: 0.1339 -
binary_accuracy: 0.9445 - val_loss: 0.3206 - val_binary_accuracy: 0.8956
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=5, dropout=0.5, epochs=10, batch_size=32
Epoch 1/10
30/30 [=====] - 2s 14ms/step - loss: 0.3722 -
binary_accuracy: 0.8620 - val_loss: 0.2689 - val_binary_accuracy: 0.9108
Epoch 2/10
30/30 [=====] - 0s 8ms/step - loss: 0.2875 -
binary_accuracy: 0.8921 - val_loss: 0.2474 - val_binary_accuracy: 0.9136
Epoch 3/10
30/30 [=====] - 0s 9ms/step - loss: 0.2591 -
binary_accuracy: 0.8954 - val_loss: 0.2436 - val_binary_accuracy: 0.9136
Epoch 4/10
30/30 [=====] - 0s 8ms/step - loss: 0.2416 -
binary_accuracy: 0.9018 - val_loss: 0.2423 - val_binary_accuracy: 0.9116
Epoch 5/10
30/30 [=====] - 0s 9ms/step - loss: 0.2244 -
binary_accuracy: 0.9079 - val_loss: 0.2458 - val_binary_accuracy: 0.9085
Epoch 6/10
30/30 [=====] - 0s 8ms/step - loss: 0.2122 -
binary_accuracy: 0.9099 - val_loss: 0.2524 - val_binary_accuracy: 0.9108
Epoch 7/10
30/30 [=====] - 0s 8ms/step - loss: 0.1989 -
binary_accuracy: 0.9148 - val_loss: 0.2594 - val_binary_accuracy: 0.9093
Epoch 8/10

```

30/30 [=====] - 0s 8ms/step - loss: 0.1890 -
binary_accuracy: 0.9191 - val_loss: 0.2614 - val_binary_accuracy: 0.9026
Epoch 9/10
30/30 [=====] - 0s 8ms/step - loss: 0.1794 -
binary_accuracy: 0.9226 - val_loss: 0.2772 - val_binary_accuracy: 0.9046
Epoch 10/10
30/30 [=====] - 0s 8ms/step - loss: 0.1738 -
binary_accuracy: 0.9258 - val_loss: 0.2760 - val_binary_accuracy: 0.8937
9/9 [=====] - 0s 3ms/step
Best Params: {'filters': 64, 'kernel_size': 3, 'dropout': 0.5, 'epochs': 10,
'batch_size': 32}
Best Binary Accuracy: 0.9076
Best Normal Accuracy: 0.2472
Best F1 Score: 0.9510

```

```

[ ]: # CNN - continued with 15 epochs

# 2. CNN

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Dense, Flatten,
↳Dropout
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Define the CNN model
def build_cnn_model(filters=64, kernel_size=3, dropout=0.5):
    model = Sequential()

    # 1D Convolutional Layer
    model.add(Conv1D(filters=filters, kernel_size=kernel_size,
↳activation='relu', input_shape=(X_train.shape[1], 1)))

    # MaxPooling Layer
    model.add(MaxPooling1D(pool_size=2))

    # Dropout Layer
    model.add(Dropout(dropout))

    # Flatten the output for dense layers
    model.add(Flatten())

    # Dense Layers
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(dropout))

    # Output layer for multi-label classification

```

```

model.add(Dense(y_train.shape[1], activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['binary_accuracy'])

return model

# Reshape your data for CNN input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'filters': [32, 64], # Number of filters for Conv1D
    'kernel_size': [3], # Kernel size for Conv1D
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [15], # Number of epochs
    'batch_size': [32, 64], # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0
best_normal_acc = 0

# Perform the manual hyperparameter search
for filters in param_grid['filters']:
    for kernel_size in param_grid['kernel_size']: # Now this will work
        for dropout in param_grid['dropout']:
            for epochs in param_grid['epochs']:
                for batch_size in param_grid['batch_size']:
                    print(f'Training with filters={filters},
kernel_size={kernel_size}, dropout={dropout}, epochs={epochs},
batch_size={batch_size}')

                    # Build the model
                    model = build_cnn_model(filters=filters,
kernel_size=kernel_size, dropout=dropout)

                    # Train the model
                    model.fit(X_train, y_train, epochs=epochs,
batch_size=batch_size, validation_split=0.1, verbose=1)

                    # Predict on the test set
                    y_pred = model.predict(X_test)

```



```

        y_pred_binary = (y_pred > 0.5).astype(int)

        # Calculate binary accuracy
        binary_acc = np.mean(np.equal(y_test, y_pred_binary).
↪astype(int))

        # Calculate normal accuracy
        normal_acc = accuracy_score(y_test, y_pred_binary)

        # Calculate F1 Score
        f1 = f1_score(y_test, y_pred_binary, average='micro')

        # Update best params if this model is better
        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'filters': filters,
                'kernel_size': kernel_size,
                'dropout': dropout,
                'epochs': epochs,
                'batch_size': batch_size,
            }

    # Print the best results
    print(f'Best Params: {best_params}')
    print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
    print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
    print(f'Best F1 Score: {best_f1:.4f}')

```

Training with filters=32, kernel_size=3, dropout=0.3, epochs=15, batch_size=32

Epoch 1/15

30/30 [=====] - 2s 12ms/step - loss: 0.3543 -
binary_accuracy: 0.8660 - val_loss: 0.2638 - val_binary_accuracy: 0.9065

Epoch 2/15

30/30 [=====] - 0s 7ms/step - loss: 0.2697 -
binary_accuracy: 0.8977 - val_loss: 0.2476 - val_binary_accuracy: 0.9108

Epoch 3/15

30/30 [=====] - 0s 6ms/step - loss: 0.2404 -
binary_accuracy: 0.9050 - val_loss: 0.2463 - val_binary_accuracy: 0.9108

Epoch 4/15

30/30 [=====] - 0s 6ms/step - loss: 0.2183 -
binary_accuracy: 0.9110 - val_loss: 0.2493 - val_binary_accuracy: 0.9073

Epoch 5/15

30/30 [=====] - 0s 6ms/step - loss: 0.2039 -
binary_accuracy: 0.9149 - val_loss: 0.2597 - val_binary_accuracy: 0.9062

Epoch 6/15
30/30 [=====] - 0s 6ms/step - loss: 0.1874 -
binary_accuracy: 0.9202 - val_loss: 0.2647 - val_binary_accuracy: 0.8968
Epoch 7/15
30/30 [=====] - 0s 7ms/step - loss: 0.1728 -
binary_accuracy: 0.9245 - val_loss: 0.2740 - val_binary_accuracy: 0.9030
Epoch 8/15
30/30 [=====] - 0s 6ms/step - loss: 0.1635 -
binary_accuracy: 0.9307 - val_loss: 0.2812 - val_binary_accuracy: 0.9023
Epoch 9/15
30/30 [=====] - 0s 6ms/step - loss: 0.1502 -
binary_accuracy: 0.9363 - val_loss: 0.2911 - val_binary_accuracy: 0.8941
Epoch 10/15
30/30 [=====] - 0s 7ms/step - loss: 0.1363 -
binary_accuracy: 0.9430 - val_loss: 0.3056 - val_binary_accuracy: 0.8824
Epoch 11/15
30/30 [=====] - 0s 7ms/step - loss: 0.1280 -
binary_accuracy: 0.9461 - val_loss: 0.3257 - val_binary_accuracy: 0.8933
Epoch 12/15
30/30 [=====] - 0s 7ms/step - loss: 0.1194 -
binary_accuracy: 0.9498 - val_loss: 0.3351 - val_binary_accuracy: 0.8882
Epoch 13/15
30/30 [=====] - 0s 6ms/step - loss: 0.1079 -
binary_accuracy: 0.9548 - val_loss: 0.3511 - val_binary_accuracy: 0.8906
Epoch 14/15
30/30 [=====] - 0s 6ms/step - loss: 0.1022 -
binary_accuracy: 0.9582 - val_loss: 0.3650 - val_binary_accuracy: 0.8863
Epoch 15/15
30/30 [=====] - 0s 7ms/step - loss: 0.0935 -
binary_accuracy: 0.9634 - val_loss: 0.3727 - val_binary_accuracy: 0.8816
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=3, dropout=0.3, epochs=15, batch_size=64
Epoch 1/15
15/15 [=====] - 2s 29ms/step - loss: 0.3761 -
binary_accuracy: 0.8652 - val_loss: 0.2705 - val_binary_accuracy: 0.8949
Epoch 2/15
15/15 [=====] - 0s 9ms/step - loss: 0.3001 -
binary_accuracy: 0.8874 - val_loss: 0.2602 - val_binary_accuracy: 0.9112
Epoch 3/15
15/15 [=====] - 0s 8ms/step - loss: 0.2683 -
binary_accuracy: 0.8987 - val_loss: 0.2529 - val_binary_accuracy: 0.9120
Epoch 4/15
15/15 [=====] - 0s 9ms/step - loss: 0.2469 -
binary_accuracy: 0.9050 - val_loss: 0.2466 - val_binary_accuracy: 0.9112
Epoch 5/15
15/15 [=====] - 0s 8ms/step - loss: 0.2296 -
binary_accuracy: 0.9084 - val_loss: 0.2455 - val_binary_accuracy: 0.9128
Epoch 6/15

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15/15 [=====] - 0s 8ms/step - loss: 0.2167 -
binary_accuracy: 0.9100 - val_loss: 0.2481 - val_binary_accuracy: 0.9054
Epoch 7/15
15/15 [=====] - 0s 10ms/step - loss: 0.2020 -
binary_accuracy: 0.9158 - val_loss: 0.2528 - val_binary_accuracy: 0.9034
Epoch 8/15
15/15 [=====] - 0s 8ms/step - loss: 0.1920 -
binary_accuracy: 0.9181 - val_loss: 0.2566 - val_binary_accuracy: 0.9038
Epoch 9/15
15/15 [=====] - 0s 10ms/step - loss: 0.1813 -
binary_accuracy: 0.9231 - val_loss: 0.2651 - val_binary_accuracy: 0.8995
Epoch 10/15
15/15 [=====] - 0s 9ms/step - loss: 0.1705 -
binary_accuracy: 0.9277 - val_loss: 0.2695 - val_binary_accuracy: 0.9007
Epoch 11/15
15/15 [=====] - 0s 10ms/step - loss: 0.1624 -
binary_accuracy: 0.9278 - val_loss: 0.2708 - val_binary_accuracy: 0.8956
Epoch 12/15
15/15 [=====] - 0s 8ms/step - loss: 0.1541 -
binary_accuracy: 0.9348 - val_loss: 0.2826 - val_binary_accuracy: 0.8960
Epoch 13/15
15/15 [=====] - 0s 8ms/step - loss: 0.1445 -
binary_accuracy: 0.9387 - val_loss: 0.2928 - val_binary_accuracy: 0.8902
Epoch 14/15
15/15 [=====] - 0s 8ms/step - loss: 0.1372 -
binary_accuracy: 0.9436 - val_loss: 0.3012 - val_binary_accuracy: 0.8910
Epoch 15/15
15/15 [=====] - 0s 11ms/step - loss: 0.1304 -
binary_accuracy: 0.9442 - val_loss: 0.3099 - val_binary_accuracy: 0.8843
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=15, batch_size=32
Epoch 1/15
30/30 [=====] - 2s 13ms/step - loss: 0.3731 -
binary_accuracy: 0.8620 - val_loss: 0.2635 - val_binary_accuracy: 0.9124
Epoch 2/15
30/30 [=====] - 0s 6ms/step - loss: 0.2902 -
binary_accuracy: 0.8897 - val_loss: 0.2508 - val_binary_accuracy: 0.9100
Epoch 3/15
30/30 [=====] - 0s 7ms/step - loss: 0.2612 -
binary_accuracy: 0.8952 - val_loss: 0.2500 - val_binary_accuracy: 0.9093
Epoch 4/15
30/30 [=====] - 0s 6ms/step - loss: 0.2477 -
binary_accuracy: 0.9022 - val_loss: 0.2396 - val_binary_accuracy: 0.9124
Epoch 5/15
30/30 [=====] - 0s 7ms/step - loss: 0.2294 -
binary_accuracy: 0.9061 - val_loss: 0.2436 - val_binary_accuracy: 0.9097
Epoch 6/15
30/30 [=====] - 0s 6ms/step - loss: 0.2197 -

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binary_accuracy: 0.9072 - val_loss: 0.2465 - val_binary_accuracy: 0.9085
Epoch 7/15
30/30 [=====] - 0s 6ms/step - loss: 0.2099 -
binary_accuracy: 0.9114 - val_loss: 0.2486 - val_binary_accuracy: 0.9085
Epoch 8/15
30/30 [=====] - 0s 7ms/step - loss: 0.1984 -
binary_accuracy: 0.9151 - val_loss: 0.2563 - val_binary_accuracy: 0.9089
Epoch 9/15
30/30 [=====] - 0s 6ms/step - loss: 0.1890 -
binary_accuracy: 0.9193 - val_loss: 0.2588 - val_binary_accuracy: 0.9054
Epoch 10/15
30/30 [=====] - 0s 7ms/step - loss: 0.1859 -
binary_accuracy: 0.9195 - val_loss: 0.2653 - val_binary_accuracy: 0.8995
Epoch 11/15
30/30 [=====] - 0s 7ms/step - loss: 0.1764 -
binary_accuracy: 0.9248 - val_loss: 0.2716 - val_binary_accuracy: 0.8991
Epoch 12/15
30/30 [=====] - 0s 6ms/step - loss: 0.1696 -
binary_accuracy: 0.9264 - val_loss: 0.2767 - val_binary_accuracy: 0.8956
Epoch 13/15
30/30 [=====] - 0s 7ms/step - loss: 0.1612 -
binary_accuracy: 0.9309 - val_loss: 0.2821 - val_binary_accuracy: 0.8980
Epoch 14/15
30/30 [=====] - 0s 6ms/step - loss: 0.1517 -
binary_accuracy: 0.9350 - val_loss: 0.2931 - val_binary_accuracy: 0.8964
Epoch 15/15
30/30 [=====] - 0s 7ms/step - loss: 0.1460 -
binary_accuracy: 0.9382 - val_loss: 0.3011 - val_binary_accuracy: 0.8937
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=15, batch_size=64
Epoch 1/15
15/15 [=====] - 1s 21ms/step - loss: 0.4010 -
binary_accuracy: 0.8578 - val_loss: 0.2674 - val_binary_accuracy: 0.8941
Epoch 2/15
15/15 [=====] - 0s 9ms/step - loss: 0.3179 -
binary_accuracy: 0.8818 - val_loss: 0.2632 - val_binary_accuracy: 0.9112
Epoch 3/15
15/15 [=====] - 0s 9ms/step - loss: 0.2827 -
binary_accuracy: 0.8948 - val_loss: 0.2499 - val_binary_accuracy: 0.9097
Epoch 4/15
15/15 [=====] - 0s 8ms/step - loss: 0.2612 -
binary_accuracy: 0.8978 - val_loss: 0.2461 - val_binary_accuracy: 0.9100
Epoch 5/15
15/15 [=====] - 0s 8ms/step - loss: 0.2467 -
binary_accuracy: 0.9030 - val_loss: 0.2438 - val_binary_accuracy: 0.9097
Epoch 6/15
15/15 [=====] - 0s 8ms/step - loss: 0.2302 -
binary_accuracy: 0.9063 - val_loss: 0.2413 - val_binary_accuracy: 0.9065

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Epoch 7/15
15/15 [=====] - 0s 9ms/step - loss: 0.2227 -
binary_accuracy: 0.9089 - val_loss: 0.2441 - val_binary_accuracy: 0.9069
Epoch 8/15
15/15 [=====] - 0s 9ms/step - loss: 0.2144 -
binary_accuracy: 0.9123 - val_loss: 0.2457 - val_binary_accuracy: 0.9104
Epoch 9/15
15/15 [=====] - 0s 8ms/step - loss: 0.2043 -
binary_accuracy: 0.9140 - val_loss: 0.2504 - val_binary_accuracy: 0.9038
Epoch 10/15
15/15 [=====] - 0s 10ms/step - loss: 0.1981 -
binary_accuracy: 0.9170 - val_loss: 0.2524 - val_binary_accuracy: 0.9011
Epoch 11/15
15/15 [=====] - 0s 9ms/step - loss: 0.1886 -
binary_accuracy: 0.9195 - val_loss: 0.2564 - val_binary_accuracy: 0.9007
Epoch 12/15
15/15 [=====] - 0s 10ms/step - loss: 0.1850 -
binary_accuracy: 0.9216 - val_loss: 0.2631 - val_binary_accuracy: 0.8976
Epoch 13/15
15/15 [=====] - 0s 13ms/step - loss: 0.1780 -
binary_accuracy: 0.9241 - val_loss: 0.2668 - val_binary_accuracy: 0.9007
Epoch 14/15
15/15 [=====] - 0s 12ms/step - loss: 0.1691 -
binary_accuracy: 0.9269 - val_loss: 0.2713 - val_binary_accuracy: 0.8991
Epoch 15/15
15/15 [=====] - 0s 12ms/step - loss: 0.1654 -
binary_accuracy: 0.9279 - val_loss: 0.2733 - val_binary_accuracy: 0.8964
9/9 [=====] - 0s 3ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=15, batch_size=32
Epoch 1/15
30/30 [=====] - 2s 15ms/step - loss: 0.3526 -
binary_accuracy: 0.8754 - val_loss: 0.2600 - val_binary_accuracy: 0.9128
Epoch 2/15
30/30 [=====] - 0s 8ms/step - loss: 0.2657 -
binary_accuracy: 0.8981 - val_loss: 0.2446 - val_binary_accuracy: 0.9108
Epoch 3/15
30/30 [=====] - 0s 8ms/step - loss: 0.2376 -
binary_accuracy: 0.9021 - val_loss: 0.2467 - val_binary_accuracy: 0.9100
Epoch 4/15
30/30 [=====] - 0s 9ms/step - loss: 0.2156 -
binary_accuracy: 0.9111 - val_loss: 0.2484 - val_binary_accuracy: 0.9081
Epoch 5/15
30/30 [=====] - 0s 9ms/step - loss: 0.1952 -
binary_accuracy: 0.9177 - val_loss: 0.2605 - val_binary_accuracy: 0.8952
Epoch 6/15
30/30 [=====] - 0s 8ms/step - loss: 0.1800 -
binary_accuracy: 0.9237 - val_loss: 0.2710 - val_binary_accuracy: 0.9034
Epoch 7/15

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30/30 [=====] - 0s 8ms/step - loss: 0.1662 -
binary_accuracy: 0.9279 - val_loss: 0.2794 - val_binary_accuracy: 0.8991
Epoch 8/15
30/30 [=====] - 0s 9ms/step - loss: 0.1466 -
binary_accuracy: 0.9369 - val_loss: 0.2979 - val_binary_accuracy: 0.8890
Epoch 9/15
30/30 [=====] - 0s 9ms/step - loss: 0.1324 -
binary_accuracy: 0.9440 - val_loss: 0.3166 - val_binary_accuracy: 0.8910
Epoch 10/15
30/30 [=====] - 0s 8ms/step - loss: 0.1175 -
binary_accuracy: 0.9511 - val_loss: 0.3319 - val_binary_accuracy: 0.8890
Epoch 11/15
30/30 [=====] - 0s 9ms/step - loss: 0.1083 -
binary_accuracy: 0.9564 - val_loss: 0.3496 - val_binary_accuracy: 0.8812
Epoch 12/15
30/30 [=====] - 0s 9ms/step - loss: 0.1002 -
binary_accuracy: 0.9589 - val_loss: 0.3591 - val_binary_accuracy: 0.8859
Epoch 13/15
30/30 [=====] - 0s 9ms/step - loss: 0.0906 -
binary_accuracy: 0.9647 - val_loss: 0.3819 - val_binary_accuracy: 0.8871
Epoch 14/15
30/30 [=====] - 0s 8ms/step - loss: 0.0801 -
binary_accuracy: 0.9695 - val_loss: 0.4096 - val_binary_accuracy: 0.8867
Epoch 15/15
30/30 [=====] - 0s 8ms/step - loss: 0.0737 -
binary_accuracy: 0.9704 - val_loss: 0.4126 - val_binary_accuracy: 0.8812
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=15, batch_size=64
Epoch 1/15
15/15 [=====] - 2s 52ms/step - loss: 0.3764 -
binary_accuracy: 0.8580 - val_loss: 0.2553 - val_binary_accuracy: 0.9124
Epoch 2/15
15/15 [=====] - 0s 13ms/step - loss: 0.2912 -
binary_accuracy: 0.8925 - val_loss: 0.2547 - val_binary_accuracy: 0.9128
Epoch 3/15
15/15 [=====] - 0s 13ms/step - loss: 0.2600 -
binary_accuracy: 0.8999 - val_loss: 0.2509 - val_binary_accuracy: 0.9073
Epoch 4/15
15/15 [=====] - 0s 11ms/step - loss: 0.2395 -
binary_accuracy: 0.9036 - val_loss: 0.2410 - val_binary_accuracy: 0.9116
Epoch 5/15
15/15 [=====] - 0s 11ms/step - loss: 0.2235 -
binary_accuracy: 0.9072 - val_loss: 0.2468 - val_binary_accuracy: 0.9116
Epoch 6/15
15/15 [=====] - 0s 13ms/step - loss: 0.2050 -
binary_accuracy: 0.9148 - val_loss: 0.2508 - val_binary_accuracy: 0.9089
Epoch 7/15
15/15 [=====] - 0s 14ms/step - loss: 0.1905 -

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binary_accuracy: 0.9201 - val_loss: 0.2525 - val_binary_accuracy: 0.9026
Epoch 8/15
15/15 [=====] - 0s 16ms/step - loss: 0.1776 -
binary_accuracy: 0.9248 - val_loss: 0.2622 - val_binary_accuracy: 0.9015
Epoch 9/15
15/15 [=====] - 0s 15ms/step - loss: 0.1653 -
binary_accuracy: 0.9298 - val_loss: 0.2692 - val_binary_accuracy: 0.8945
Epoch 10/15
15/15 [=====] - 0s 14ms/step - loss: 0.1578 -
binary_accuracy: 0.9327 - val_loss: 0.2801 - val_binary_accuracy: 0.8991
Epoch 11/15
15/15 [=====] - 0s 14ms/step - loss: 0.1424 -
binary_accuracy: 0.9402 - val_loss: 0.2955 - val_binary_accuracy: 0.8941
Epoch 12/15
15/15 [=====] - 0s 13ms/step - loss: 0.1355 -
binary_accuracy: 0.9437 - val_loss: 0.3054 - val_binary_accuracy: 0.8995
Epoch 13/15
15/15 [=====] - 0s 17ms/step - loss: 0.1237 -
binary_accuracy: 0.9485 - val_loss: 0.3118 - val_binary_accuracy: 0.8964
Epoch 14/15
15/15 [=====] - 0s 14ms/step - loss: 0.1157 -
binary_accuracy: 0.9533 - val_loss: 0.3236 - val_binary_accuracy: 0.8902
Epoch 15/15
15/15 [=====] - 0s 15ms/step - loss: 0.1091 -
binary_accuracy: 0.9552 - val_loss: 0.3438 - val_binary_accuracy: 0.8875
9/9 [=====] - 0s 4ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=15, batch_size=32
Epoch 1/15
30/30 [=====] - 2s 14ms/step - loss: 0.3756 -
binary_accuracy: 0.8627 - val_loss: 0.2673 - val_binary_accuracy: 0.9124
Epoch 2/15
30/30 [=====] - 0s 9ms/step - loss: 0.2856 -
binary_accuracy: 0.8947 - val_loss: 0.2477 - val_binary_accuracy: 0.9120
Epoch 3/15
30/30 [=====] - 0s 8ms/step - loss: 0.2552 -
binary_accuracy: 0.8991 - val_loss: 0.2411 - val_binary_accuracy: 0.9120
Epoch 4/15
30/30 [=====] - 0s 9ms/step - loss: 0.2341 -
binary_accuracy: 0.9049 - val_loss: 0.2433 - val_binary_accuracy: 0.9073
Epoch 5/15
30/30 [=====] - 0s 9ms/step - loss: 0.2202 -
binary_accuracy: 0.9087 - val_loss: 0.2509 - val_binary_accuracy: 0.9038
Epoch 6/15
30/30 [=====] - 0s 9ms/step - loss: 0.2052 -
binary_accuracy: 0.9127 - val_loss: 0.2513 - val_binary_accuracy: 0.9038
Epoch 7/15
30/30 [=====] - 0s 8ms/step - loss: 0.1941 -
binary_accuracy: 0.9181 - val_loss: 0.2604 - val_binary_accuracy: 0.8972

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Epoch 8/15
30/30 [=====] - 0s 8ms/step - loss: 0.1842 -
binary_accuracy: 0.9198 - val_loss: 0.2650 - val_binary_accuracy: 0.8991
Epoch 9/15
30/30 [=====] - 0s 8ms/step - loss: 0.1756 -
binary_accuracy: 0.9251 - val_loss: 0.2744 - val_binary_accuracy: 0.8956
Epoch 10/15
30/30 [=====] - 0s 8ms/step - loss: 0.1678 -
binary_accuracy: 0.9283 - val_loss: 0.2802 - val_binary_accuracy: 0.9011
Epoch 11/15
30/30 [=====] - 0s 8ms/step - loss: 0.1580 -
binary_accuracy: 0.9325 - val_loss: 0.2854 - val_binary_accuracy: 0.9015
Epoch 12/15
30/30 [=====] - 0s 8ms/step - loss: 0.1499 -
binary_accuracy: 0.9348 - val_loss: 0.2983 - val_binary_accuracy: 0.8984
Epoch 13/15
30/30 [=====] - 0s 9ms/step - loss: 0.1392 -
binary_accuracy: 0.9409 - val_loss: 0.3075 - val_binary_accuracy: 0.8999
Epoch 14/15
30/30 [=====] - 0s 8ms/step - loss: 0.1305 -
binary_accuracy: 0.9447 - val_loss: 0.3109 - val_binary_accuracy: 0.8921
Epoch 15/15
30/30 [=====] - 0s 8ms/step - loss: 0.1303 -
binary_accuracy: 0.9454 - val_loss: 0.3276 - val_binary_accuracy: 0.8960
9/9 [=====] - 0s 3ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=15, batch_size=64
Epoch 1/15
15/15 [=====] - 2s 24ms/step - loss: 0.4033 -
binary_accuracy: 0.8484 - val_loss: 0.2599 - val_binary_accuracy: 0.9120
Epoch 2/15
15/15 [=====] - 0s 12ms/step - loss: 0.3130 -
binary_accuracy: 0.8847 - val_loss: 0.2606 - val_binary_accuracy: 0.9124
Epoch 3/15
15/15 [=====] - 0s 12ms/step - loss: 0.2773 -
binary_accuracy: 0.8946 - val_loss: 0.2484 - val_binary_accuracy: 0.9124
Epoch 4/15
15/15 [=====] - 0s 12ms/step - loss: 0.2502 -
binary_accuracy: 0.8998 - val_loss: 0.2471 - val_binary_accuracy: 0.9136
Epoch 5/15
15/15 [=====] - 0s 12ms/step - loss: 0.2410 -
binary_accuracy: 0.9042 - val_loss: 0.2447 - val_binary_accuracy: 0.9128
Epoch 6/15
15/15 [=====] - 0s 12ms/step - loss: 0.2249 -
binary_accuracy: 0.9066 - val_loss: 0.2488 - val_binary_accuracy: 0.9089
Epoch 7/15
15/15 [=====] - 0s 11ms/step - loss: 0.2123 -
binary_accuracy: 0.9118 - val_loss: 0.2490 - val_binary_accuracy: 0.9116
Epoch 8/15


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15/15 [=====] - 0s 11ms/step - loss: 0.2015 -
binary_accuracy: 0.9144 - val_loss: 0.2529 - val_binary_accuracy: 0.9077
Epoch 9/15
15/15 [=====] - 0s 12ms/step - loss: 0.1919 -
binary_accuracy: 0.9183 - val_loss: 0.2576 - val_binary_accuracy: 0.9038
Epoch 10/15
15/15 [=====] - 0s 13ms/step - loss: 0.1839 -
binary_accuracy: 0.9220 - val_loss: 0.2686 - val_binary_accuracy: 0.8999
Epoch 11/15
15/15 [=====] - 0s 11ms/step - loss: 0.1748 -
binary_accuracy: 0.9245 - val_loss: 0.2702 - val_binary_accuracy: 0.8980
Epoch 12/15
15/15 [=====] - 0s 12ms/step - loss: 0.1675 -
binary_accuracy: 0.9292 - val_loss: 0.2767 - val_binary_accuracy: 0.8988
Epoch 13/15
15/15 [=====] - 0s 11ms/step - loss: 0.1612 -
binary_accuracy: 0.9309 - val_loss: 0.2813 - val_binary_accuracy: 0.9011
Epoch 14/15
15/15 [=====] - 0s 12ms/step - loss: 0.1523 -
binary_accuracy: 0.9363 - val_loss: 0.2849 - val_binary_accuracy: 0.8960
Epoch 15/15
15/15 [=====] - 0s 11ms/step - loss: 0.1479 -
binary_accuracy: 0.9366 - val_loss: 0.2959 - val_binary_accuracy: 0.8902
9/9 [=====] - 0s 3ms/step
Best Params: {'filters': 32, 'kernel_size': 3, 'dropout': 0.5, 'epochs': 15,
'batch_size': 64}
Best Binary Accuracy: 0.9034
Best Normal Accuracy: 0.2097
Best F1 Score: 0.9485

```

```

[ ]: # CNN - continued with 30 epochs

# 2. CNN

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Dense, Flatten,
↳Dropout
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Define the CNN model
def build_cnn_model(filters=64, kernel_size=3, dropout=0.5):
    model = Sequential()

    # 1D Convolutional Layer
    model.add(Conv1D(filters=filters, kernel_size=kernel_size,
↳activation='relu', input_shape=(X_train.shape[1], 1)))

```

```

# MaxPooling Layer
model.add(MaxPooling1D(pool_size=2))

# Dropout Layer
model.add(Dropout(dropout))

# Flatten the output for dense layers
model.add(Flatten())

# Dense Layers
model.add(Dense(256, activation='relu'))
model.add(Dropout(dropout))

# Output layer for multi-label classification
model.add(Dense(y_train.shape[1], activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['binary_accuracy'])

return model

# Reshape your data for CNN input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'filters': [32, 64], # Number of filters for Conv1D
    'kernel_size': [3], # Kernel size for Conv1D
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [30], # Number of epochs
    'batch_size': [32, 64], # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0
best_normal_acc = 0

# Perform the manual hyperparameter search
for filters in param_grid['filters']:
    for kernel_size in param_grid['kernel_size']: # Now this will work
        for dropout in param_grid['dropout']:
            for epochs in param_grid['epochs']:

```

```

        for batch_size in param_grid['batch_size']:
            print(f'Training with filters={filters},  

↳kernel_size={kernel_size}, dropout={dropout}, epochs={epochs},  

↳batch_size={batch_size}')

            # Build the model
            model = build_cnn_model(filters=filters,  

↳kernel_size=kernel_size, dropout=dropout)

            # Train the model
            model.fit(X_train, y_train, epochs=epochs,  

↳batch_size=batch_size, validation_split=0.1, verbose=0)

            # Predict on the test set
            y_pred = model.predict(X_test)
            y_pred_binary = (y_pred > 0.5).astype(int)

            # Calculate binary accuracy
            binary_acc = np.mean(np.equal(y_test, y_pred_binary).  

↳astype(int))

            # Calculate normal accuracy
            normal_acc = accuracy_score(y_test, y_pred_binary)

            # Calculate F1 Score
            f1 = f1_score(y_test, y_pred_binary, average='micro')

            # Update best params if this model is better
            if binary_acc > best_binary_acc:
                best_binary_acc = binary_acc
                best_f1 = f1
                best_normal_acc = normal_acc
                best_params = {
                    'filters': filters,
                    'kernel_size': kernel_size,
                    'dropout': dropout,
                    'epochs': epochs,
                    'batch_size': batch_size,
                }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Training with filters=32, kernel_size=3, dropout=0.3, epochs=30, batch_size=32

```

9/9 [=====] - 0s 3ms/step
Training with filters=32, kernel_size=3, dropout=0.3, epochs=30, batch_size=64
9/9 [=====] - 0s 3ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=30, batch_size=32
9/9 [=====] - 0s 3ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=30, batch_size=64
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=30, batch_size=32
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=30, batch_size=64
9/9 [=====] - 0s 3ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=30, batch_size=32
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=30, batch_size=64
9/9 [=====] - 0s 2ms/step
Best Params: {'filters': 32, 'kernel_size': 3, 'dropout': 0.5, 'epochs': 30,
'batch_size': 64}
Best Binary Accuracy: 0.8951
Best Normal Accuracy: 0.1985
Best F1 Score: 0.9437

```

```

[ ]: # CNN - continued with 5 epochs

# 2. CNN

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Dense, Flatten, Dropout
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Define the CNN model
def build_cnn_model(filters=64, kernel_size=3, dropout=0.5):
    model = Sequential()

    # 1D Convolutional Layer
    model.add(Conv1D(filters=filters, kernel_size=kernel_size,
        activation='relu', input_shape=(X_train.shape[1], 1)))

    # MaxPooling Layer
    model.add(MaxPooling1D(pool_size=2))

    # Dropout Layer
    model.add(Dropout(dropout))

    # Flatten the output for dense layers
    model.add(Flatten())

```

```

# Dense Layers
model.add(Dense(256, activation='relu'))
model.add(Dropout(dropout))

# Output layer for multi-label classification
model.add(Dense(y_train.shape[1], activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
metrics=['binary_accuracy'])

return model

# Reshape your data for CNN input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'filters': [32, 64], # Number of filters for Conv1D
    'kernel_size': [3], # Kernel size for Conv1D
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [5], # Number of epochs
    'batch_size': [32, 64], # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0
best_normal_acc = 0

# Perform the manual hyperparameter search
for filters in param_grid['filters']:
    for kernel_size in param_grid['kernel_size']: # Now this will work
        for dropout in param_grid['dropout']:
            for epochs in param_grid['epochs']:
                for batch_size in param_grid['batch_size']:
                    print(f'Training with filters={filters},
kernel_size={kernel_size}, dropout={dropout}, epochs={epochs},
batch_size={batch_size}')

                    # Build the model
                    model = build_cnn_model(filters=filters,
kernel_size=kernel_size, dropout=dropout)

```

```

        # Train the model
        model.fit(X_train, y_train, epochs=epochs,
↳batch_size=batch_size, validation_split=0.1, verbose=1)

        # Predict on the test set
        y_pred = model.predict(X_test)
        y_pred_binary = (y_pred > 0.5).astype(int)

        # Calculate binary accuracy
        binary_acc = np.mean(np.equal(y_test, y_pred_binary).
↳astype(int))

        # Calculate normal accuracy
        normal_acc = accuracy_score(y_test, y_pred_binary)

        # Calculate F1 Score
        f1 = f1_score(y_test, y_pred_binary, average='micro')

        # Update best params if this model is better
        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'filters': filters,
                'kernel_size': kernel_size,
                'dropout': dropout,
                'epochs': epochs,
                'batch_size': batch_size,
            }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Training with filters=32, kernel_size=3, dropout=0.3, epochs=5, batch_size=32

Epoch 1/5

30/30 [=====] - 3s 20ms/step - loss: 0.3456 -
binary_accuracy: 0.8697 - val_loss: 0.2565 - val_binary_accuracy: 0.9128

Epoch 2/5

30/30 [=====] - 0s 9ms/step - loss: 0.2738 -
binary_accuracy: 0.8953 - val_loss: 0.2487 - val_binary_accuracy: 0.9128

Epoch 3/5

30/30 [=====] - 0s 10ms/step - loss: 0.2494 -
binary_accuracy: 0.9017 - val_loss: 0.2486 - val_binary_accuracy: 0.9062

Epoch 4/5
30/30 [=====] - 0s 9ms/step - loss: 0.2270 -
binary_accuracy: 0.9074 - val_loss: 0.2492 - val_binary_accuracy: 0.9077
Epoch 5/5
30/30 [=====] - 0s 9ms/step - loss: 0.2098 -
binary_accuracy: 0.9133 - val_loss: 0.2510 - val_binary_accuracy: 0.9030
9/9 [=====] - 0s 3ms/step
Training with filters=32, kernel_size=3, dropout=0.3, epochs=5, batch_size=64
Epoch 1/5
15/15 [=====] - 3s 31ms/step - loss: 0.3908 -
binary_accuracy: 0.8576 - val_loss: 0.2667 - val_binary_accuracy: 0.9069
Epoch 2/5
15/15 [=====] - 0s 9ms/step - loss: 0.2963 -
binary_accuracy: 0.8896 - val_loss: 0.2575 - val_binary_accuracy: 0.9124
Epoch 3/5
15/15 [=====] - 0s 9ms/step - loss: 0.2672 -
binary_accuracy: 0.8984 - val_loss: 0.2452 - val_binary_accuracy: 0.9143
Epoch 4/5
15/15 [=====] - 0s 8ms/step - loss: 0.2487 -
binary_accuracy: 0.9004 - val_loss: 0.2445 - val_binary_accuracy: 0.9124
Epoch 5/5
15/15 [=====] - 0s 10ms/step - loss: 0.2330 -
binary_accuracy: 0.9057 - val_loss: 0.2451 - val_binary_accuracy: 0.9058
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=5, batch_size=32
Epoch 1/5
30/30 [=====] - 2s 12ms/step - loss: 0.3669 -
binary_accuracy: 0.8662 - val_loss: 0.2622 - val_binary_accuracy: 0.9120
Epoch 2/5
30/30 [=====] - 0s 7ms/step - loss: 0.2891 -
binary_accuracy: 0.8934 - val_loss: 0.2489 - val_binary_accuracy: 0.9097
Epoch 3/5
30/30 [=====] - 0s 6ms/step - loss: 0.2588 -
binary_accuracy: 0.8974 - val_loss: 0.2403 - val_binary_accuracy: 0.9108
Epoch 4/5
30/30 [=====] - 0s 6ms/step - loss: 0.2435 -
binary_accuracy: 0.9016 - val_loss: 0.2427 - val_binary_accuracy: 0.9104
Epoch 5/5
30/30 [=====] - 0s 7ms/step - loss: 0.2283 -
binary_accuracy: 0.9045 - val_loss: 0.2424 - val_binary_accuracy: 0.9085
9/9 [=====] - 0s 2ms/step
Training with filters=32, kernel_size=3, dropout=0.5, epochs=5, batch_size=64
Epoch 1/5
15/15 [=====] - 2s 32ms/step - loss: 0.4199 -
binary_accuracy: 0.8422 - val_loss: 0.2619 - val_binary_accuracy: 0.9124
Epoch 2/5
15/15 [=====] - 0s 13ms/step - loss: 0.3219 -
binary_accuracy: 0.8793 - val_loss: 0.2649 - val_binary_accuracy: 0.9120

Epoch 3/5
15/15 [=====] - 0s 12ms/step - loss: 0.2861 -
binary_accuracy: 0.8916 - val_loss: 0.2528 - val_binary_accuracy: 0.9112
Epoch 4/5
15/15 [=====] - 0s 13ms/step - loss: 0.2667 -
binary_accuracy: 0.8968 - val_loss: 0.2469 - val_binary_accuracy: 0.9128
Epoch 5/5
15/15 [=====] - 0s 9ms/step - loss: 0.2519 -
binary_accuracy: 0.9000 - val_loss: 0.2432 - val_binary_accuracy: 0.9120
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=5, batch_size=32
Epoch 1/5
30/30 [=====] - 2s 14ms/step - loss: 0.3512 -
binary_accuracy: 0.8702 - val_loss: 0.2626 - val_binary_accuracy: 0.9100
Epoch 2/5
30/30 [=====] - 0s 9ms/step - loss: 0.2676 -
binary_accuracy: 0.8971 - val_loss: 0.2475 - val_binary_accuracy: 0.9116
Epoch 3/5
30/30 [=====] - 0s 9ms/step - loss: 0.2401 -
binary_accuracy: 0.9027 - val_loss: 0.2497 - val_binary_accuracy: 0.9026
Epoch 4/5
30/30 [=====] - 0s 8ms/step - loss: 0.2175 -
binary_accuracy: 0.9099 - val_loss: 0.2511 - val_binary_accuracy: 0.9073
Epoch 5/5
30/30 [=====] - 0s 8ms/step - loss: 0.1990 -
binary_accuracy: 0.9151 - val_loss: 0.2564 - val_binary_accuracy: 0.9007
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.3, epochs=5, batch_size=64
Epoch 1/5
15/15 [=====] - 2s 24ms/step - loss: 0.3853 -
binary_accuracy: 0.8499 - val_loss: 0.2649 - val_binary_accuracy: 0.9124
Epoch 2/5
15/15 [=====] - 0s 11ms/step - loss: 0.2935 -
binary_accuracy: 0.8895 - val_loss: 0.2592 - val_binary_accuracy: 0.9104
Epoch 3/5
15/15 [=====] - 0s 12ms/step - loss: 0.2674 -
binary_accuracy: 0.8960 - val_loss: 0.2457 - val_binary_accuracy: 0.9104
Epoch 4/5
15/15 [=====] - 0s 11ms/step - loss: 0.2452 -
binary_accuracy: 0.9034 - val_loss: 0.2419 - val_binary_accuracy: 0.9136
Epoch 5/5
15/15 [=====] - 0s 11ms/step - loss: 0.2263 -
binary_accuracy: 0.9089 - val_loss: 0.2414 - val_binary_accuracy: 0.9139
9/9 [=====] - 0s 2ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=5, batch_size=32
Epoch 1/5
30/30 [=====] - 2s 14ms/step - loss: 0.3740 -
binary_accuracy: 0.8560 - val_loss: 0.2687 - val_binary_accuracy: 0.9128


```

Epoch 2/5
30/30 [=====] - 0s 8ms/step - loss: 0.2837 -
binary_accuracy: 0.8924 - val_loss: 0.2468 - val_binary_accuracy: 0.9128
Epoch 3/5
30/30 [=====] - 0s 8ms/step - loss: 0.2536 -
binary_accuracy: 0.9001 - val_loss: 0.2447 - val_binary_accuracy: 0.9116
Epoch 4/5
30/30 [=====] - 0s 8ms/step - loss: 0.2340 -
binary_accuracy: 0.9049 - val_loss: 0.2455 - val_binary_accuracy: 0.9112
Epoch 5/5
30/30 [=====] - 0s 11ms/step - loss: 0.2198 -
binary_accuracy: 0.9064 - val_loss: 0.2514 - val_binary_accuracy: 0.9050
9/9 [=====] - 0s 3ms/step
Training with filters=64, kernel_size=3, dropout=0.5, epochs=5, batch_size=64
Epoch 1/5
15/15 [=====] - 2s 23ms/step - loss: 0.3877 -
binary_accuracy: 0.8522 - val_loss: 0.2601 - val_binary_accuracy: 0.9120
Epoch 2/5
15/15 [=====] - 0s 12ms/step - loss: 0.3057 -
binary_accuracy: 0.8858 - val_loss: 0.2572 - val_binary_accuracy: 0.9124
Epoch 3/5
15/15 [=====] - 0s 11ms/step - loss: 0.2774 -
binary_accuracy: 0.8944 - val_loss: 0.2469 - val_binary_accuracy: 0.9136
Epoch 4/5
15/15 [=====] - 0s 12ms/step - loss: 0.2545 -
binary_accuracy: 0.8991 - val_loss: 0.2435 - val_binary_accuracy: 0.9116
Epoch 5/5
15/15 [=====] - 0s 11ms/step - loss: 0.2332 -
binary_accuracy: 0.9051 - val_loss: 0.2429 - val_binary_accuracy: 0.9112
9/9 [=====] - 0s 2ms/step
Best Params: {'filters': 64, 'kernel_size': 3, 'dropout': 0.3, 'epochs': 5,
'batch_size': 64}
Best Binary Accuracy: 0.9114
Best Normal Accuracy: 0.2772
Best F1 Score: 0.9535

```

```
[ ]: # LSTM with parameter tuning
```

```

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Dropout, Flatten,
↳BatchNormalization
from tensorflow.keras.regularizers import l2
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Define the LSTM model with L2 Regularization and Batch Normalization
def build_lstm_model(units=100, dropout=0.5, l2_reg=0.01):

```

```

model = Sequential()

# LSTM Layer
model.add(LSTM(units, return_sequences=False, input_shape=(X_train.
↪shape[1], 1)))

# Dropout Layer
model.add(Dropout(dropout))

# Batch Normalization
model.add(BatchNormalization())

# Dense Layer with L2 regularization
model.add(Dense(256, activation='relu', kernel_regularizer=l2(l2_reg)))

# Output layer for multi-label classification
model.add(Dense(y_train.shape[1], activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',
↪metrics=['binary_accuracy'])

return model

# Reshape your data for LSTM input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'units': [64, 128], # Number of LSTM units
    'dropout': [0.3, 0.5], # Dropout rate
    'l2_reg': [0.01, 0.001], # L2 regularization
    'epochs': [10, 15, 20, 30], # Multiple numbers of epochs
    'batch_size': [32, 64], # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0
best_normal_acc = 0

# Perform the manual hyperparameter search
for units in param_grid['units']:
    for dropout in param_grid['dropout']:
        for l2_reg in param_grid['l2_reg']:

```

```

        for epochs in param_grid['epochs']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with units={units}, dropout={dropout},
↳l2_reg={l2_reg}, epochs={epochs}, batch_size={batch_size}')

                # Build the model
                model = build_lstm_model(units=units, dropout=dropout,
↳l2_reg=l2_reg)

                # Train the model
                model.fit(X_train, y_train, epochs=epochs,
↳batch_size=batch_size, validation_split=0.1, verbose=0)

                # Predict on the test set
                y_pred = model.predict(X_test)
                y_pred_binary = (y_pred > 0.5).astype(int)

                # Calculate binary accuracy
                binary_acc = np.mean(np.equal(y_test, y_pred_binary).
↳astype(int))

                # Calculate normal accuracy
                normal_acc = accuracy_score(y_test, y_pred_binary)

                # Calculate F1 Score
                f1 = f1_score(y_test, y_pred_binary, average='micro')

                # Update best params if this model is better
                if binary_acc > best_binary_acc:
                    best_binary_acc = binary_acc
                    best_f1 = f1
                    best_normal_acc = normal_acc
                    best_params = {
                        'units': units,
                        'dropout': dropout,
                        'l2_reg': l2_reg,
                        'epochs': epochs,
                        'batch_size': batch_size,
                    }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Training with units=64, dropout=0.3, l2_reg=0.01, epochs=10, batch_size=32

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=20, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 27ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 36ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=30, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 38ms/step
Training with units=64, dropout=0.3, l2_reg=0.01, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=10, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 33ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          1s 39ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=20, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          1s 40ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=30, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.3, l2_reg=0.001, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=10, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=15, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 37ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=20, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 39ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
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using Sequential models, prefer using an `Input(shape)` object as the first
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    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=30, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 37ms/step
Training with units=64, dropout=0.5, l2_reg=0.01, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
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using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=10, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
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using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=20, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 27ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=30, batch_size=32

```



```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=64, dropout=0.5, l2_reg=0.001, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 30ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=10, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 32ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=20, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 24ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=30, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          1s 41ms/step
Training with units=128, dropout=0.3, l2_reg=0.01, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=10, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          1s 39ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 27ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=15, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=20, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=30, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.3, l2_reg=0.001, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 24ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=10, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 37ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 31ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=20, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 27ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=20, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=30, batch_size=32

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.5, l2_reg=0.01, epochs=30, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=10, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=10, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 26ms/step
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=15, batch_size=32

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 28ms/step
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=15, batch_size=64

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

9/9          0s 25ms/step
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=20, batch_size=32

```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
```

```
super().__init__(**kwargs)
```

```
9/9          0s 25ms/step
```

```
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=20, batch_size=64
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
```

```
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
```

```
super().__init__(**kwargs)
```

```
9/9          0s 25ms/step
```

```
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=30, batch_size=32
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
```

```
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
```

```
super().__init__(**kwargs)
```

```
9/9          0s 27ms/step
```

```
Training with units=128, dropout=0.5, l2_reg=0.001, epochs=30, batch_size=64
```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
```

```
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
```

```
super().__init__(**kwargs)
```

```
9/9          0s 26ms/step
```

```
Best Params: {'units': 64, 'dropout': 0.3, 'l2_reg': 0.01, 'epochs': 10,
'batch_size': 32}
```

```
Best Binary Accuracy: 0.9114
```

```
Best Normal Accuracy: 0.2884
```

```
Best F1 Score: 0.9536
```

```
[ ]: # 4. TRANSFORMER BASED MODEL
```

```
[ ]: # 10 epochs
```

```
import numpy as np
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Dense, LayerNormalization, Dropout, MultiHeadAttention, Flatten
from sklearn.metrics import f1_score, accuracy_score
from sklearn.model_selection import train_test_split
```

```

# Define Transformer-based model
def build_transformer_model(num_heads=4, hidden_dim=64, dropout=0.3):
    input_layer = Input(shape=(X_train.shape[1], 1))

    # Multi-Head Attention Layer
    attention_output = MultiHeadAttention(num_heads=num_heads,
    ↪key_dim=hidden_dim)(input_layer, input_layer)
    attention_output = LayerNormalization(epsilon=1e-6)(attention_output)

    # Feed-forward Network
    ff_output = Dense(hidden_dim, activation='relu')(attention_output)
    ff_output = Dropout(dropout)(ff_output)
    ff_output = Dense(hidden_dim, activation='relu')(ff_output)
    ff_output = LayerNormalization(epsilon=1e-6)(ff_output)

    # Flatten and Dense layers for output
    flattened = Flatten()(ff_output)
    dense_output = Dense(hidden_dim, activation='relu')(flattened)
    dense_output = Dropout(dropout)(dense_output)

    # Output Layer (sigmoid for multi-label classification)
    output_layer = Dense(y_train.shape[1], activation='sigmoid')(dense_output)

    # Build Model
    model = Model(inputs=input_layer, outputs=output_layer)
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['binary_accuracy'])

    return model

# Reshape your data for transformer input
X_train = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Hyperparameters grid
param_grid = {
    'num_heads': [4],          # Number of attention heads
    'hidden_dim': [64, 128],   # Hidden layer dimension
    'dropout': [0.3, 0.5],     # Dropout rate
    'epochs': [10],           # Number of epochs
    'batch_size': [32, 64],    # Batch size
}

# Variables to track the best model
best_binary_acc = 0
best_params = {}
best_f1 = 0

```

```

best_normal_acc = 0

# Perform the manual hyperparameter search
for num_heads in param_grid['num_heads']:
    for hidden_dim in param_grid['hidden_dim']:
        for dropout in param_grid['dropout']:
            for epochs in param_grid['epochs']:
                for batch_size in param_grid['batch_size']:
                    print(f'Training with num_heads={num_heads},
↪hidden_dim={hidden_dim}, dropout={dropout}, epochs={epochs},
↪batch_size={batch_size}')

                    # Build the model
                    model = build_transformer_model(num_heads=num_heads,
↪hidden_dim=hidden_dim, dropout=dropout)

                    # Train the model
                    model.fit(X_train, y_train, epochs=epochs,
↪batch_size=batch_size, validation_split=0.1, verbose=0)

                    # Predict on the test set
                    y_pred = model.predict(X_test)
                    y_pred_binary = (y_pred > 0.5).astype(int)

                    # Calculate binary accuracy
                    binary_acc = np.mean(np.equal(y_test, y_pred_binary).
↪astype(int))

                    # Calculate normal accuracy
                    normal_acc = accuracy_score(y_test, y_pred_binary)

                    # Calculate F1 Score
                    f1 = f1_score(y_test, y_pred_binary, average='micro')

                    # Update best params if this model is better
                    if binary_acc > best_binary_acc:
                        best_binary_acc = binary_acc
                        best_f1 = f1
                        best_normal_acc = normal_acc
                        best_params = {
                            'num_heads': num_heads,
                            'hidden_dim': hidden_dim,
                            'dropout': dropout,
                            'epochs': epochs,
                            'batch_size': batch_size,
                        }

```



```
# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')
```

```
Training with num_heads=4, hidden_dim=64, dropout=0.3, epochs=10, batch_size=32
9/9          1s 83ms/step
Training with num_heads=4, hidden_dim=64, dropout=0.3, epochs=10, batch_size=64
9/9          1s 104ms/step
Training with num_heads=4, hidden_dim=64, dropout=0.5, epochs=10, batch_size=32
9/9          1s 73ms/step
Training with num_heads=4, hidden_dim=64, dropout=0.5, epochs=10, batch_size=64
9/9          1s 100ms/step
Training with num_heads=4, hidden_dim=128, dropout=0.3, epochs=10, batch_size=32
9/9          1s 99ms/step
Training with num_heads=4, hidden_dim=128, dropout=0.3, epochs=10, batch_size=64
9/9          1s 78ms/step
Training with num_heads=4, hidden_dim=128, dropout=0.5, epochs=10, batch_size=32
9/9          1s 78ms/step
Training with num_heads=4, hidden_dim=128, dropout=0.5, epochs=10, batch_size=64
9/9          1s 80ms/step
Best Params: {'num_heads': 4, 'hidden_dim': 64, 'dropout': 0.3, 'epochs': 10,
'batch_size': 32}
Best Binary Accuracy: 0.9114
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9536
```

```
[ ]: # num_heads = 8, epochs = 15
```

```
[ ]: # 5. GNN
```

```
[ ]: !pip install torch-geometric
```

```
Collecting torch-geometric
  Downloading torch_geometric-2.6.0-py3-none-any.whl.metadata (63 kB)
      63.1/63.1 kB
2.4 MB/s eta 0:00:00
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (3.10.5)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (2024.6.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (3.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (1.26.4)
Requirement already satisfied: psutil>=5.8.0 in /usr/local/lib/python3.10/dist-
```

```

packages (from torch-geometric) (5.9.5)
Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (3.1.4)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (4.66.5)
Requirement already satisfied: aiohappyeyeballs>=2.3.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (2.4.0)
Requirement already satisfied: aiosignal>=1.1.2 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.3.1)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-
packages (from aiohttp->torch-geometric) (24.2.0)
Requirement already satisfied: frozenlist>=1.1.1 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.4.1)
Requirement already satisfied: multidict<7.0,>=4.5 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (6.1.0)
Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-
packages (from aiohttp->torch-geometric) (1.11.1)
Requirement already satisfied: async-timeout<5.0,>=4.0 in
/usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (4.0.3)
Requirement already satisfied: MarkupSafe>=2.0 in
/usr/local/lib/python3.10/dist-packages (from jinja2->torch-geometric) (2.1.5)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->torch-geometric) (3.10)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (2.2.3)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->torch-geometric)
(2024.8.30)
Requirement already satisfied: typing-extensions>=4.1.0 in
/usr/local/lib/python3.10/dist-packages (from
multidict<7.0,>=4.5->aiohttp->torch-geometric) (4.12.2)
Downloading torch_geometric-2.6.0-py3-none-any.whl (1.1 MB)
1.1/1.1 MB
25.3 MB/s eta 0:00:00
Installing collected packages: torch-geometric
Successfully installed torch-geometric-2.6.0

```

```

[ ]: import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

```

```

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [10, 15, 20], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
    ↪structure available)

```

```

edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳ edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳ dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳ output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()
                    print(f"Epoch {epoch+1}/{param_grid['epochs'][0]}, Loss:
↳ {loss.item()}")

                    # Evaluate the model
                    model.eval()
                    with torch.no_grad():
                        y_pred = model(X_test_tensor, edge_index)
                        y_pred_binary = (y_pred > 0.5).float()

                    # Calculate binary accuracy
                    binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳ item()

                    # Calculate normal accuracy
                    normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                    # Calculate F1 score
                    f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                    # Update best params if this model is better

```

```

        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'hidden_dim': hidden_dim,
                'dropout': dropout,
                'lr': lr,
                'batch_size': batch_size
            }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32

Epoch 1/10, Loss: 0.709597110748291
 Epoch 2/10, Loss: 0.6415501832962036
 Epoch 3/10, Loss: 0.5371586084365845
 Epoch 4/10, Loss: 0.4165983200073242
 Epoch 5/10, Loss: 0.3561471402645111
 Epoch 6/10, Loss: 0.35802194476127625
 Epoch 7/10, Loss: 0.3422446548938751
 Epoch 8/10, Loss: 0.3302128314971924
 Epoch 9/10, Loss: 0.33071452379226685
 Epoch 10/10, Loss: 0.3300503194332123

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64

Epoch 1/10, Loss: 0.6885817646980286
 Epoch 2/10, Loss: 0.5982992649078369
 Epoch 3/10, Loss: 0.47013750672340393
 Epoch 4/10, Loss: 0.36258840560913086
 Epoch 5/10, Loss: 0.3617899715900421
 Epoch 6/10, Loss: 0.35540688037872314
 Epoch 7/10, Loss: 0.34128352999687195
 Epoch 8/10, Loss: 0.33353498578071594
 Epoch 9/10, Loss: 0.3304072618484497
 Epoch 10/10, Loss: 0.3054121136665344

Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32

Epoch 1/10, Loss: 0.7070016264915466
 Epoch 2/10, Loss: 0.6985868215560913
 Epoch 3/10, Loss: 0.6910017132759094
 Epoch 4/10, Loss: 0.6830345392227173
 Epoch 5/10, Loss: 0.674662709236145
 Epoch 6/10, Loss: 0.6660047173500061
 Epoch 7/10, Loss: 0.6564385890960693

Epoch 8/10, Loss: 0.6457278728485107
 Epoch 9/10, Loss: 0.6339900493621826
 Epoch 10/10, Loss: 0.6205863356590271
 Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
 Epoch 1/10, Loss: 0.6994835138320923
 Epoch 2/10, Loss: 0.6906312108039856
 Epoch 3/10, Loss: 0.6824186444282532
 Epoch 4/10, Loss: 0.6741432547569275
 Epoch 5/10, Loss: 0.6649523973464966
 Epoch 6/10, Loss: 0.6558994054794312
 Epoch 7/10, Loss: 0.6441252827644348
 Epoch 8/10, Loss: 0.633897602558136
 Epoch 9/10, Loss: 0.6206861138343811
 Epoch 10/10, Loss: 0.6066814064979553
 Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
 Epoch 1/10, Loss: 0.6883083581924438
 Epoch 2/10, Loss: 0.6086488962173462
 Epoch 3/10, Loss: 0.4917351305484772
 Epoch 4/10, Loss: 0.3852728307247162
 Epoch 5/10, Loss: 0.3716936707496643
 Epoch 6/10, Loss: 0.3797025680541992
 Epoch 7/10, Loss: 0.3605228364467621
 Epoch 8/10, Loss: 0.3535187542438507
 Epoch 9/10, Loss: 0.33475977182388306
 Epoch 10/10, Loss: 0.3031013011932373
 Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
 Epoch 1/10, Loss: 0.6837955713272095
 Epoch 2/10, Loss: 0.6130130887031555
 Epoch 3/10, Loss: 0.5039457678794861
 Epoch 4/10, Loss: 0.40949174761772156
 Epoch 5/10, Loss: 0.3780607283115387
 Epoch 6/10, Loss: 0.3632622957229614
 Epoch 7/10, Loss: 0.34651923179626465
 Epoch 8/10, Loss: 0.33340340852737427
 Epoch 9/10, Loss: 0.3266436457633972
 Epoch 10/10, Loss: 0.30676063895225525
 Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
 Epoch 1/10, Loss: 0.6869210004806519
 Epoch 2/10, Loss: 0.6782388091087341
 Epoch 3/10, Loss: 0.6700339913368225
 Epoch 4/10, Loss: 0.6610857248306274
 Epoch 5/10, Loss: 0.6522855162620544
 Epoch 6/10, Loss: 0.6425086855888367
 Epoch 7/10, Loss: 0.6305216550827026
 Epoch 8/10, Loss: 0.6191814541816711
 Epoch 9/10, Loss: 0.606719970703125
 Epoch 10/10, Loss: 0.5933386087417603
 Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64

Epoch 1/10, Loss: 0.6958237290382385
 Epoch 2/10, Loss: 0.6901788711547852
 Epoch 3/10, Loss: 0.6850414872169495
 Epoch 4/10, Loss: 0.6796642541885376
 Epoch 5/10, Loss: 0.6730794906616211
 Epoch 6/10, Loss: 0.6666602492332458
 Epoch 7/10, Loss: 0.6587667465209961
 Epoch 8/10, Loss: 0.650916576385498
 Epoch 9/10, Loss: 0.6414874792098999
 Epoch 10/10, Loss: 0.6299852728843689
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
 Epoch 1/10, Loss: 0.6866666078567505
 Epoch 2/10, Loss: 0.5021674633026123
 Epoch 3/10, Loss: 0.35043177008628845
 Epoch 4/10, Loss: 0.3630755543708801
 Epoch 5/10, Loss: 0.33068397641181946
 Epoch 6/10, Loss: 0.3221912086009979
 Epoch 7/10, Loss: 0.30208665132522583
 Epoch 8/10, Loss: 0.2855725884437561
 Epoch 9/10, Loss: 0.2744961380958557
 Epoch 10/10, Loss: 0.2614966034889221
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
 Epoch 1/10, Loss: 0.6873682141304016
 Epoch 2/10, Loss: 0.5006620287895203
 Epoch 3/10, Loss: 0.3505573868751526
 Epoch 4/10, Loss: 0.3546064496040344
 Epoch 5/10, Loss: 0.3181251287460327
 Epoch 6/10, Loss: 0.32015225291252136
 Epoch 7/10, Loss: 0.3082484304904938
 Epoch 8/10, Loss: 0.28546085953712463
 Epoch 9/10, Loss: 0.2734510898590088
 Epoch 10/10, Loss: 0.2627168893814087
 Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
 Epoch 1/10, Loss: 0.6873036026954651
 Epoch 2/10, Loss: 0.6764920949935913
 Epoch 3/10, Loss: 0.6656936407089233
 Epoch 4/10, Loss: 0.6537812948226929
 Epoch 5/10, Loss: 0.639602541923523
 Epoch 6/10, Loss: 0.6232268214225769
 Epoch 7/10, Loss: 0.6041022539138794
 Epoch 8/10, Loss: 0.5826297998428345
 Epoch 9/10, Loss: 0.5572234392166138
 Epoch 10/10, Loss: 0.5309958457946777
 Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
 Epoch 1/10, Loss: 0.6876800060272217
 Epoch 2/10, Loss: 0.6736128926277161
 Epoch 3/10, Loss: 0.6599327921867371
 Epoch 4/10, Loss: 0.6450079679489136

Epoch 5/10, Loss: 0.6280670166015625
 Epoch 6/10, Loss: 0.6088924407958984
 Epoch 7/10, Loss: 0.5874664783477783
 Epoch 8/10, Loss: 0.5634155869483948
 Epoch 9/10, Loss: 0.5374200940132141
 Epoch 10/10, Loss: 0.5099051594734192
 Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
 Epoch 1/10, Loss: 0.6915625929832458
 Epoch 2/10, Loss: 0.5237178206443787
 Epoch 3/10, Loss: 0.3717024326324463
 Epoch 4/10, Loss: 0.3740563988685608
 Epoch 5/10, Loss: 0.3378613591194153
 Epoch 6/10, Loss: 0.3174165189266205
 Epoch 7/10, Loss: 0.31205984950065613
 Epoch 8/10, Loss: 0.2967338562011719
 Epoch 9/10, Loss: 0.27938246726989746
 Epoch 10/10, Loss: 0.26713234186172485
 Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
 Epoch 1/10, Loss: 0.6962990760803223
 Epoch 2/10, Loss: 0.5339031219482422
 Epoch 3/10, Loss: 0.36193016171455383
 Epoch 4/10, Loss: 0.36410513520240784
 Epoch 5/10, Loss: 0.346571683883667
 Epoch 6/10, Loss: 0.3508358895778656
 Epoch 7/10, Loss: 0.31922414898872375
 Epoch 8/10, Loss: 0.29260289669036865
 Epoch 9/10, Loss: 0.2768450081348419
 Epoch 10/10, Loss: 0.266574501991272
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
 Epoch 1/10, Loss: 0.6906462907791138
 Epoch 2/10, Loss: 0.6779081225395203
 Epoch 3/10, Loss: 0.6650395393371582
 Epoch 4/10, Loss: 0.651150643825531
 Epoch 5/10, Loss: 0.6342793107032776
 Epoch 6/10, Loss: 0.6168862581253052
 Epoch 7/10, Loss: 0.5972729325294495
 Epoch 8/10, Loss: 0.5753123164176941
 Epoch 9/10, Loss: 0.5508957505226135
 Epoch 10/10, Loss: 0.5242833495140076
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
 Epoch 1/10, Loss: 0.6975699663162231
 Epoch 2/10, Loss: 0.6850435137748718
 Epoch 3/10, Loss: 0.6736516356468201
 Epoch 4/10, Loss: 0.6612989902496338
 Epoch 5/10, Loss: 0.6475942134857178
 Epoch 6/10, Loss: 0.6322312355041504
 Epoch 7/10, Loss: 0.6135097742080688
 Epoch 8/10, Loss: 0.5938735008239746

Epoch 9/10, Loss: 0.570262610912323
 Epoch 10/10, Loss: 0.5439286231994629
 Best Params: {'hidden_dim': 64, 'dropout': 0.5, 'lr': 0.01, 'batch_size': 32}
 Best Binary Accuracy: 0.9114
 Best Normal Accuracy: 0.2884
 Best F1 Score: 0.9536

```
[ ]: # 15 epochs

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
```

```

'hidden_dim': [64, 128], # Number of hidden units
'dropout': [0.3, 0.5], # Dropout rate
'epochs': [15,20], # Number of epochs
'batch_size': [32, 64], # Batch size
'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()
                    print(f"Epoch {epoch+1}/{param_grid['epochs'][0]}, Loss:
↳{loss.item()}")

                # Evaluate the model
                model.eval()

```

```

        with torch.no_grad():
            y_pred = model(X_test_tensor, edge_index)
            y_pred_binary = (y_pred > 0.5).float()

            # Calculate binary accuracy
            binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↪item()

            # Calculate normal accuracy
            normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

            # Calculate F1 score
            f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

            # Update best params if this model is better
            if binary_acc > best_binary_acc:
                best_binary_acc = binary_acc
                best_f1 = f1
                best_normal_acc = normal_acc
                best_params = {
                    'hidden_dim': hidden_dim,
                    'dropout': dropout,
                    'lr': lr,
                    'batch_size': batch_size
                }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32

```

Epoch 1/15, Loss: 0.6952621936798096
Epoch 2/15, Loss: 0.6270509362220764
Epoch 3/15, Loss: 0.5159099698066711
Epoch 4/15, Loss: 0.4039263129234314
Epoch 5/15, Loss: 0.35897353291511536
Epoch 6/15, Loss: 0.35700345039367676
Epoch 7/15, Loss: 0.33971405029296875
Epoch 8/15, Loss: 0.3220519721508026
Epoch 9/15, Loss: 0.30620330572128296
Epoch 10/15, Loss: 0.29612797498703003
Epoch 11/15, Loss: 0.2941589951515198
Epoch 12/15, Loss: 0.2867872416973114
Epoch 13/15, Loss: 0.27960288524627686
Epoch 14/15, Loss: 0.27185094356536865

```

Epoch 15/15, Loss: 0.2621895968914032
 Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
 Epoch 1/15, Loss: 0.6914840340614319
 Epoch 2/15, Loss: 0.5877062082290649
 Epoch 3/15, Loss: 0.45496731996536255
 Epoch 4/15, Loss: 0.36330509185791016
 Epoch 5/15, Loss: 0.3593505620956421
 Epoch 6/15, Loss: 0.35855719447135925
 Epoch 7/15, Loss: 0.3380836844444275
 Epoch 8/15, Loss: 0.3227978050708771
 Epoch 9/15, Loss: 0.3131084144115448
 Epoch 10/15, Loss: 0.3077828586101532
 Epoch 11/15, Loss: 0.29653123021125793
 Epoch 12/15, Loss: 0.2870234549045563
 Epoch 13/15, Loss: 0.2783140540122986
 Epoch 14/15, Loss: 0.2743372619152069
 Epoch 15/15, Loss: 0.26745304465293884
 Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
 Epoch 1/15, Loss: 0.702755868434906
 Epoch 2/15, Loss: 0.6954046487808228
 Epoch 3/15, Loss: 0.6881657242774963
 Epoch 4/15, Loss: 0.6816341876983643
 Epoch 5/15, Loss: 0.6737716794013977
 Epoch 6/15, Loss: 0.665929913520813
 Epoch 7/15, Loss: 0.6572540998458862
 Epoch 8/15, Loss: 0.6486310362815857
 Epoch 9/15, Loss: 0.6388293504714966
 Epoch 10/15, Loss: 0.6286277770996094
 Epoch 11/15, Loss: 0.6166297793388367
 Epoch 12/15, Loss: 0.6044055223464966
 Epoch 13/15, Loss: 0.5907407999038696
 Epoch 14/15, Loss: 0.5772386789321899
 Epoch 15/15, Loss: 0.562836229801178
 Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
 Epoch 1/15, Loss: 0.696432888507843
 Epoch 2/15, Loss: 0.6891416907310486
 Epoch 3/15, Loss: 0.6812499761581421
 Epoch 4/15, Loss: 0.6732641458511353
 Epoch 5/15, Loss: 0.6636177897453308
 Epoch 6/15, Loss: 0.653079628944397
 Epoch 7/15, Loss: 0.641034722328186
 Epoch 8/15, Loss: 0.6281229853630066
 Epoch 9/15, Loss: 0.6139667630195618
 Epoch 10/15, Loss: 0.5996797680854797
 Epoch 11/15, Loss: 0.582539975643158
 Epoch 12/15, Loss: 0.565375566482544
 Epoch 13/15, Loss: 0.547389030456543
 Epoch 14/15, Loss: 0.529052197933197

Epoch 15/15, Loss: 0.5103024840354919
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32

Epoch 1/15, Loss: 0.6947649717330933
Epoch 2/15, Loss: 0.6070510149002075
Epoch 3/15, Loss: 0.48495668172836304
Epoch 4/15, Loss: 0.39044877886772156
Epoch 5/15, Loss: 0.3640161156654358
Epoch 6/15, Loss: 0.3784691393375397
Epoch 7/15, Loss: 0.3711124062538147
Epoch 8/15, Loss: 0.34947407245635986
Epoch 9/15, Loss: 0.3223731517791748
Epoch 10/15, Loss: 0.3064509928226471
Epoch 11/15, Loss: 0.293600469827652
Epoch 12/15, Loss: 0.2847106158733368
Epoch 13/15, Loss: 0.2806759774684906
Epoch 14/15, Loss: 0.27583757042884827
Epoch 15/15, Loss: 0.2674733102321625
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64

Epoch 1/15, Loss: 0.7033355236053467
Epoch 2/15, Loss: 0.6540586352348328
Epoch 3/15, Loss: 0.5690011978149414
Epoch 4/15, Loss: 0.45475414395332336
Epoch 5/15, Loss: 0.3819302022457123
Epoch 6/15, Loss: 0.3742135465145111
Epoch 7/15, Loss: 0.3624228537082672
Epoch 8/15, Loss: 0.3378712832927704
Epoch 9/15, Loss: 0.3384837806224823
Epoch 10/15, Loss: 0.32551366090774536
Epoch 11/15, Loss: 0.3183295428752899
Epoch 12/15, Loss: 0.30532941222190857
Epoch 13/15, Loss: 0.2939428687095642
Epoch 14/15, Loss: 0.2852615714073181
Epoch 15/15, Loss: 0.27718284726142883
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32

Epoch 1/15, Loss: 0.6957007646560669
Epoch 2/15, Loss: 0.6888988018035889
Epoch 3/15, Loss: 0.6822246313095093
Epoch 4/15, Loss: 0.6756710410118103
Epoch 5/15, Loss: 0.6685109734535217
Epoch 6/15, Loss: 0.6610754132270813
Epoch 7/15, Loss: 0.6521624326705933
Epoch 8/15, Loss: 0.642544150352478
Epoch 9/15, Loss: 0.632664680480957
Epoch 10/15, Loss: 0.620508074760437
Epoch 11/15, Loss: 0.6088703274726868
Epoch 12/15, Loss: 0.5949753522872925
Epoch 13/15, Loss: 0.5826719999313354
Epoch 14/15, Loss: 0.5675411224365234

Epoch 15/15, Loss: 0.5528921484947205
 Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
 Epoch 1/15, Loss: 0.6945118308067322
 Epoch 2/15, Loss: 0.6879046559333801
 Epoch 3/15, Loss: 0.6814534664154053
 Epoch 4/15, Loss: 0.6744557023048401
 Epoch 5/15, Loss: 0.6674869656562805
 Epoch 6/15, Loss: 0.6597470045089722
 Epoch 7/15, Loss: 0.6507701873779297
 Epoch 8/15, Loss: 0.6401440501213074
 Epoch 9/15, Loss: 0.6306188106536865
 Epoch 10/15, Loss: 0.6196376085281372
 Epoch 11/15, Loss: 0.6070877313613892
 Epoch 12/15, Loss: 0.5922108292579651
 Epoch 13/15, Loss: 0.5794215798377991
 Epoch 14/15, Loss: 0.566223680973053
 Epoch 15/15, Loss: 0.5492606163024902
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
 Epoch 1/15, Loss: 0.6888718008995056
 Epoch 2/15, Loss: 0.5243257880210876
 Epoch 3/15, Loss: 0.37243324518203735
 Epoch 4/15, Loss: 0.3653971254825592
 Epoch 5/15, Loss: 0.32846546173095703
 Epoch 6/15, Loss: 0.32312098145484924
 Epoch 7/15, Loss: 0.31686633825302124
 Epoch 8/15, Loss: 0.2964753210544586
 Epoch 9/15, Loss: 0.27938830852508545
 Epoch 10/15, Loss: 0.2678970694541931
 Epoch 11/15, Loss: 0.26006126403808594
 Epoch 12/15, Loss: 0.25500231981277466
 Epoch 13/15, Loss: 0.24978049099445343
 Epoch 14/15, Loss: 0.24291157722473145
 Epoch 15/15, Loss: 0.23726727068424225
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
 Epoch 1/15, Loss: 0.6895471215248108
 Epoch 2/15, Loss: 0.49223464727401733
 Epoch 3/15, Loss: 0.35082191228866577
 Epoch 4/15, Loss: 0.3517342805862427
 Epoch 5/15, Loss: 0.3347811698913574
 Epoch 6/15, Loss: 0.31298282742500305
 Epoch 7/15, Loss: 0.2931625247001648
 Epoch 8/15, Loss: 0.28444793820381165
 Epoch 9/15, Loss: 0.2777138352394104
 Epoch 10/15, Loss: 0.2675612270832062
 Epoch 11/15, Loss: 0.25444501638412476
 Epoch 12/15, Loss: 0.24776823818683624
 Epoch 13/15, Loss: 0.2400817573070526
 Epoch 14/15, Loss: 0.23304712772369385

Epoch 15/15, Loss: 0.22763872146606445
 Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32

Epoch 1/15, Loss: 0.7088435292243958
 Epoch 2/15, Loss: 0.6967198848724365
 Epoch 3/15, Loss: 0.6847159266471863
 Epoch 4/15, Loss: 0.671735405921936
 Epoch 5/15, Loss: 0.6577410697937012
 Epoch 6/15, Loss: 0.6414211988449097
 Epoch 7/15, Loss: 0.6229097843170166
 Epoch 8/15, Loss: 0.6021108031272888
 Epoch 9/15, Loss: 0.5787609219551086
 Epoch 10/15, Loss: 0.5521972179412842
 Epoch 11/15, Loss: 0.5242392420768738
 Epoch 12/15, Loss: 0.49602723121643066
 Epoch 13/15, Loss: 0.46506765484809875
 Epoch 14/15, Loss: 0.435176283121109
 Epoch 15/15, Loss: 0.4073580205440521
 Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64

Epoch 1/15, Loss: 0.6804156303405762
 Epoch 2/15, Loss: 0.6646252274513245
 Epoch 3/15, Loss: 0.6480933427810669
 Epoch 4/15, Loss: 0.6302090883255005
 Epoch 5/15, Loss: 0.6105372905731201
 Epoch 6/15, Loss: 0.5887525677680969
 Epoch 7/15, Loss: 0.5648030638694763
 Epoch 8/15, Loss: 0.538982629776001
 Epoch 9/15, Loss: 0.5099431872367859
 Epoch 10/15, Loss: 0.4816553592681885
 Epoch 11/15, Loss: 0.45217645168304443
 Epoch 12/15, Loss: 0.4215465486049652
 Epoch 13/15, Loss: 0.3979380130767822
 Epoch 14/15, Loss: 0.3748511075973511
 Epoch 15/15, Loss: 0.3561728894710541
 Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32

Epoch 1/15, Loss: 0.6960592865943909
 Epoch 2/15, Loss: 0.5291829109191895
 Epoch 3/15, Loss: 0.3792456388473511
 Epoch 4/15, Loss: 0.36259040236473083
 Epoch 5/15, Loss: 0.3265916407108307
 Epoch 6/15, Loss: 0.32525113224983215
 Epoch 7/15, Loss: 0.30931514501571655
 Epoch 8/15, Loss: 0.29500746726989746
 Epoch 9/15, Loss: 0.27984681725502014
 Epoch 10/15, Loss: 0.26834261417388916
 Epoch 11/15, Loss: 0.2586096227169037
 Epoch 12/15, Loss: 0.2531587481498718
 Epoch 13/15, Loss: 0.24863970279693604
 Epoch 14/15, Loss: 0.24157246947288513

Epoch 15/15, Loss: 0.23506829142570496
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Epoch 1/15, Loss: 0.6962944269180298
Epoch 2/15, Loss: 0.5241618752479553
Epoch 3/15, Loss: 0.3604148328304291
Epoch 4/15, Loss: 0.3768053650856018
Epoch 5/15, Loss: 0.357745498418808
Epoch 6/15, Loss: 0.34560859203338623
Epoch 7/15, Loss: 0.3325866162776947
Epoch 8/15, Loss: 0.30219602584838867
Epoch 9/15, Loss: 0.2831186354160309
Epoch 10/15, Loss: 0.2781851887702942
Epoch 11/15, Loss: 0.2718324661254883
Epoch 12/15, Loss: 0.26350200176239014
Epoch 13/15, Loss: 0.2581109404563904
Epoch 14/15, Loss: 0.25290772318840027
Epoch 15/15, Loss: 0.2442295104265213
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Epoch 1/15, Loss: 0.6976119875907898
Epoch 2/15, Loss: 0.6853035688400269
Epoch 3/15, Loss: 0.6744401454925537
Epoch 4/15, Loss: 0.6618966460227966
Epoch 5/15, Loss: 0.6475056409835815
Epoch 6/15, Loss: 0.6316348314285278
Epoch 7/15, Loss: 0.6129761934280396
Epoch 8/15, Loss: 0.5919350981712341
Epoch 9/15, Loss: 0.5683477520942688
Epoch 10/15, Loss: 0.5433096885681152
Epoch 11/15, Loss: 0.5153184533119202
Epoch 12/15, Loss: 0.4874979257583618
Epoch 13/15, Loss: 0.4613899290561676
Epoch 14/15, Loss: 0.43263110518455505
Epoch 15/15, Loss: 0.4104588031768799
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Epoch 1/15, Loss: 0.6979619264602661
Epoch 2/15, Loss: 0.6862553954124451
Epoch 3/15, Loss: 0.6747465133666992
Epoch 4/15, Loss: 0.6624504327774048
Epoch 5/15, Loss: 0.6475896239280701
Epoch 6/15, Loss: 0.6316494345664978
Epoch 7/15, Loss: 0.6139592528343201
Epoch 8/15, Loss: 0.5932042002677917
Epoch 9/15, Loss: 0.571079671382904
Epoch 10/15, Loss: 0.5459352135658264
Epoch 11/15, Loss: 0.5209935307502747
Epoch 12/15, Loss: 0.4932430386543274
Epoch 13/15, Loss: 0.4669094681739807
Epoch 14/15, Loss: 0.43961241841316223

Epoch 15/15, Loss: 0.4179519712924957
 Best Params: {'hidden_dim': 64, 'dropout': 0.3, 'lr': 0.01, 'batch_size': 32}
 Best Binary Accuracy: 0.9114
 Best Normal Accuracy: 0.2884
 Best F1 Score: 0.9536

```
[ ]: # 20 epochs

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
```

```

    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [20], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()
                    print(f"Epoch {epoch+1}/{param_grid['epochs'][0]}, Loss:
↳{loss.item()}")

                # Evaluate the model
                model.eval()
                with torch.no_grad():

```

```

        y_pred = model(X_test_tensor, edge_index)
        y_pred_binary = (y_pred > 0.5).float()

        # Calculate binary accuracy
        binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↪item()

        # Calculate normal accuracy
        normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

        # Calculate F1 score
        f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

        # Update best params if this model is better
        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'hidden_dim': hidden_dim,
                'dropout': dropout,
                'lr': lr,
                'batch_size': batch_size
            }

    # Print the best results
    print(f'Best Params: {best_params}')
    print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
    print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
    print(f'Best F1 Score: {best_f1:.4f}')

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32

```

Epoch 1/20, Loss: 0.699658215045929
Epoch 2/20, Loss: 0.6155330538749695
Epoch 3/20, Loss: 0.49272221326828003
Epoch 4/20, Loss: 0.3868323266506195
Epoch 5/20, Loss: 0.3517073094844818
Epoch 6/20, Loss: 0.34631210565567017
Epoch 7/20, Loss: 0.3485317528247833
Epoch 8/20, Loss: 0.3484322726726532
Epoch 9/20, Loss: 0.326820433139801
Epoch 10/20, Loss: 0.30933257937431335
Epoch 11/20, Loss: 0.29509687423706055
Epoch 12/20, Loss: 0.28475749492645264
Epoch 13/20, Loss: 0.27821609377861023
Epoch 14/20, Loss: 0.27134689688682556
Epoch 15/20, Loss: 0.26733213663101196

```

Epoch 16/20, Loss: 0.2629132866859436
 Epoch 17/20, Loss: 0.2571866810321808
 Epoch 18/20, Loss: 0.2497851848602295
 Epoch 19/20, Loss: 0.2458299845457077
 Epoch 20/20, Loss: 0.23911352455615997
 Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
 Epoch 1/20, Loss: 0.689071536064148
 Epoch 2/20, Loss: 0.6114605665206909
 Epoch 3/20, Loss: 0.493852823972702
 Epoch 4/20, Loss: 0.3913193345069885
 Epoch 5/20, Loss: 0.35648322105407715
 Epoch 6/20, Loss: 0.3593050539493561
 Epoch 7/20, Loss: 0.3385007977485657
 Epoch 8/20, Loss: 0.32776835560798645
 Epoch 9/20, Loss: 0.31240102648735046
 Epoch 10/20, Loss: 0.3068794310092926
 Epoch 11/20, Loss: 0.2983551621437073
 Epoch 12/20, Loss: 0.28837481141090393
 Epoch 13/20, Loss: 0.2841404378414154
 Epoch 14/20, Loss: 0.27849772572517395
 Epoch 15/20, Loss: 0.2714681029319763
 Epoch 16/20, Loss: 0.26540112495422363
 Epoch 17/20, Loss: 0.25614210963249207
 Epoch 18/20, Loss: 0.25432994961738586
 Epoch 19/20, Loss: 0.24874615669250488
 Epoch 20/20, Loss: 0.24394464492797852
 Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
 Epoch 1/20, Loss: 0.6948914527893066
 Epoch 2/20, Loss: 0.687730610370636
 Epoch 3/20, Loss: 0.680662989616394
 Epoch 4/20, Loss: 0.6732134819030762
 Epoch 5/20, Loss: 0.6651691198348999
 Epoch 6/20, Loss: 0.6568726301193237
 Epoch 7/20, Loss: 0.6458554863929749
 Epoch 8/20, Loss: 0.6349275708198547
 Epoch 9/20, Loss: 0.6235425472259521
 Epoch 10/20, Loss: 0.6095243096351624
 Epoch 11/20, Loss: 0.5942180156707764
 Epoch 12/20, Loss: 0.5785388946533203
 Epoch 13/20, Loss: 0.5620080232620239
 Epoch 14/20, Loss: 0.5418387651443481
 Epoch 15/20, Loss: 0.5247167348861694
 Epoch 16/20, Loss: 0.5045859217643738
 Epoch 17/20, Loss: 0.4861680865287781
 Epoch 18/20, Loss: 0.4683403968811035
 Epoch 19/20, Loss: 0.45041289925575256
 Epoch 20/20, Loss: 0.4320085644721985
 Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64

Epoch 1/20, Loss: 0.7194058299064636
 Epoch 2/20, Loss: 0.710715115070343
 Epoch 3/20, Loss: 0.7026896476745605
 Epoch 4/20, Loss: 0.6951087117195129
 Epoch 5/20, Loss: 0.6870121955871582
 Epoch 6/20, Loss: 0.678348958492279
 Epoch 7/20, Loss: 0.6694285273551941
 Epoch 8/20, Loss: 0.6597533822059631
 Epoch 9/20, Loss: 0.648698627948761
 Epoch 10/20, Loss: 0.6363694667816162
 Epoch 11/20, Loss: 0.6230244040489197
 Epoch 12/20, Loss: 0.6089291572570801
 Epoch 13/20, Loss: 0.5925900340080261
 Epoch 14/20, Loss: 0.5761035680770874
 Epoch 15/20, Loss: 0.556637704372406
 Epoch 16/20, Loss: 0.538627564907074
 Epoch 17/20, Loss: 0.5190118551254272
 Epoch 18/20, Loss: 0.49880486726760864
 Epoch 19/20, Loss: 0.47925859689712524
 Epoch 20/20, Loss: 0.46012991666793823
 Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
 Epoch 1/20, Loss: 0.7025178074836731
 Epoch 2/20, Loss: 0.6372708082199097
 Epoch 3/20, Loss: 0.5434900522232056
 Epoch 4/20, Loss: 0.4404847025871277
 Epoch 5/20, Loss: 0.38116493821144104
 Epoch 6/20, Loss: 0.36800429224967957
 Epoch 7/20, Loss: 0.3541412949562073
 Epoch 8/20, Loss: 0.36018747091293335
 Epoch 9/20, Loss: 0.33891749382019043
 Epoch 10/20, Loss: 0.3219658434391022
 Epoch 11/20, Loss: 0.3021220564842224
 Epoch 12/20, Loss: 0.29172712564468384
 Epoch 13/20, Loss: 0.28107649087905884
 Epoch 14/20, Loss: 0.2755497395992279
 Epoch 15/20, Loss: 0.27361568808555603
 Epoch 16/20, Loss: 0.2650458514690399
 Epoch 17/20, Loss: 0.25991135835647583
 Epoch 18/20, Loss: 0.25569507479667664
 Epoch 19/20, Loss: 0.2511289417743683
 Epoch 20/20, Loss: 0.24631927907466888
 Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
 Epoch 1/20, Loss: 0.694157600402832
 Epoch 2/20, Loss: 0.6093996167182922
 Epoch 3/20, Loss: 0.4871779680252075
 Epoch 4/20, Loss: 0.38617488741874695
 Epoch 5/20, Loss: 0.3694049119949341
 Epoch 6/20, Loss: 0.3787538707256317

Epoch 7/20, Loss: 0.36230239272117615
 Epoch 8/20, Loss: 0.34602871537208557
 Epoch 9/20, Loss: 0.333862841129303
 Epoch 10/20, Loss: 0.32130396366119385
 Epoch 11/20, Loss: 0.3040819466114044
 Epoch 12/20, Loss: 0.2941168546676636
 Epoch 13/20, Loss: 0.28447604179382324
 Epoch 14/20, Loss: 0.27676495909690857
 Epoch 15/20, Loss: 0.26904061436653137
 Epoch 16/20, Loss: 0.2661812901496887
 Epoch 17/20, Loss: 0.25640058517456055
 Epoch 18/20, Loss: 0.2539396286010742
 Epoch 19/20, Loss: 0.2509534955024719
 Epoch 20/20, Loss: 0.24531027674674988
 Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
 Epoch 1/20, Loss: 0.6998839974403381
 Epoch 2/20, Loss: 0.6922768950462341
 Epoch 3/20, Loss: 0.685097873210907
 Epoch 4/20, Loss: 0.678838849067688
 Epoch 5/20, Loss: 0.6724370121955872
 Epoch 6/20, Loss: 0.664829671382904
 Epoch 7/20, Loss: 0.6577200293540955
 Epoch 8/20, Loss: 0.6492687463760376
 Epoch 9/20, Loss: 0.6397125720977783
 Epoch 10/20, Loss: 0.6312083601951599
 Epoch 11/20, Loss: 0.6204937696456909
 Epoch 12/20, Loss: 0.6085951924324036
 Epoch 13/20, Loss: 0.5971465706825256
 Epoch 14/20, Loss: 0.583692729473114
 Epoch 15/20, Loss: 0.5693644285202026
 Epoch 16/20, Loss: 0.5568744540214539
 Epoch 17/20, Loss: 0.5416817665100098
 Epoch 18/20, Loss: 0.5258736610412598
 Epoch 19/20, Loss: 0.5113489627838135
 Epoch 20/20, Loss: 0.4953991770744324
 Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
 Epoch 1/20, Loss: 0.6916524767875671
 Epoch 2/20, Loss: 0.6814015507698059
 Epoch 3/20, Loss: 0.6711322069168091
 Epoch 4/20, Loss: 0.6617146134376526
 Epoch 5/20, Loss: 0.6502377986907959
 Epoch 6/20, Loss: 0.639369785785675
 Epoch 7/20, Loss: 0.6287029385566711
 Epoch 8/20, Loss: 0.6143694519996643
 Epoch 9/20, Loss: 0.600808322429657
 Epoch 10/20, Loss: 0.5860493183135986
 Epoch 11/20, Loss: 0.5688501000404358
 Epoch 12/20, Loss: 0.5529199242591858

Epoch 13/20, Loss: 0.5347387790679932
 Epoch 14/20, Loss: 0.5159860253334045
 Epoch 15/20, Loss: 0.49905380606651306
 Epoch 16/20, Loss: 0.480751097202301
 Epoch 17/20, Loss: 0.46414583921432495
 Epoch 18/20, Loss: 0.44476085901260376
 Epoch 19/20, Loss: 0.4280952513217926
 Epoch 20/20, Loss: 0.4164988100528717
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
 Epoch 1/20, Loss: 0.6897670030593872
 Epoch 2/20, Loss: 0.523259162902832
 Epoch 3/20, Loss: 0.362259179353714
 Epoch 4/20, Loss: 0.35802575945854187
 Epoch 5/20, Loss: 0.33104443550109863
 Epoch 6/20, Loss: 0.315444678068161
 Epoch 7/20, Loss: 0.30620211362838745
 Epoch 8/20, Loss: 0.29395565390586853
 Epoch 9/20, Loss: 0.2809019684791565
 Epoch 10/20, Loss: 0.27081596851348877
 Epoch 11/20, Loss: 0.26138633489608765
 Epoch 12/20, Loss: 0.25596171617507935
 Epoch 13/20, Loss: 0.25002631545066833
 Epoch 14/20, Loss: 0.24552980065345764
 Epoch 15/20, Loss: 0.2378195822238922
 Epoch 16/20, Loss: 0.23236191272735596
 Epoch 17/20, Loss: 0.22776545584201813
 Epoch 18/20, Loss: 0.22492577135562897
 Epoch 19/20, Loss: 0.21984989941120148
 Epoch 20/20, Loss: 0.21754394471645355
 Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
 Epoch 1/20, Loss: 0.6903532147407532
 Epoch 2/20, Loss: 0.5243184566497803
 Epoch 3/20, Loss: 0.36493411660194397
 Epoch 4/20, Loss: 0.3774659335613251
 Epoch 5/20, Loss: 0.3320021629333496
 Epoch 6/20, Loss: 0.31105828285217285
 Epoch 7/20, Loss: 0.30745986104011536
 Epoch 8/20, Loss: 0.29489219188690186
 Epoch 9/20, Loss: 0.286286324262619
 Epoch 10/20, Loss: 0.27538734674453735
 Epoch 11/20, Loss: 0.26334893703460693
 Epoch 12/20, Loss: 0.2570473551750183
 Epoch 13/20, Loss: 0.2521562874317169
 Epoch 14/20, Loss: 0.24833105504512787
 Epoch 15/20, Loss: 0.2399148941040039
 Epoch 16/20, Loss: 0.234702929854393
 Epoch 17/20, Loss: 0.23042643070220947
 Epoch 18/20, Loss: 0.2286936640739441

Epoch 19/20, Loss: 0.22438377141952515
Epoch 20/20, Loss: 0.22136300802230835
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Epoch 1/20, Loss: 0.688434362411499
Epoch 2/20, Loss: 0.6762621402740479
Epoch 3/20, Loss: 0.6636173725128174
Epoch 4/20, Loss: 0.6503449082374573
Epoch 5/20, Loss: 0.6352349519729614
Epoch 6/20, Loss: 0.6177411079406738
Epoch 7/20, Loss: 0.5982077121734619
Epoch 8/20, Loss: 0.576682448387146
Epoch 9/20, Loss: 0.5533820390701294
Epoch 10/20, Loss: 0.5282666087150574
Epoch 11/20, Loss: 0.49981507658958435
Epoch 12/20, Loss: 0.4722060263156891
Epoch 13/20, Loss: 0.44530409574508667
Epoch 14/20, Loss: 0.41847658157348633
Epoch 15/20, Loss: 0.3944931626319885
Epoch 16/20, Loss: 0.3737901747226715
Epoch 17/20, Loss: 0.35796058177948
Epoch 18/20, Loss: 0.34394049644470215
Epoch 19/20, Loss: 0.3358052968978882
Epoch 20/20, Loss: 0.32949161529541016
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Epoch 1/20, Loss: 0.691110372543335
Epoch 2/20, Loss: 0.6797335147857666
Epoch 3/20, Loss: 0.6682026386260986
Epoch 4/20, Loss: 0.6569870710372925
Epoch 5/20, Loss: 0.6440669894218445
Epoch 6/20, Loss: 0.6291279792785645
Epoch 7/20, Loss: 0.6128146052360535
Epoch 8/20, Loss: 0.5940009355545044
Epoch 9/20, Loss: 0.5730326771736145
Epoch 10/20, Loss: 0.5492037534713745
Epoch 11/20, Loss: 0.5255206823348999
Epoch 12/20, Loss: 0.4990648627281189
Epoch 13/20, Loss: 0.470781147480011
Epoch 14/20, Loss: 0.4430924952030182
Epoch 15/20, Loss: 0.4164915680885315
Epoch 16/20, Loss: 0.39286819100379944
Epoch 17/20, Loss: 0.37142014503479004
Epoch 18/20, Loss: 0.3544582724571228
Epoch 19/20, Loss: 0.3415623605251312
Epoch 20/20, Loss: 0.3336162269115448
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Epoch 1/20, Loss: 0.7092819213867188
Epoch 2/20, Loss: 0.5725641846656799
Epoch 3/20, Loss: 0.4039178788661957

Epoch 4/20, Loss: 0.3725810647010803
 Epoch 5/20, Loss: 0.36250993609428406
 Epoch 6/20, Loss: 0.33197858929634094
 Epoch 7/20, Loss: 0.31752538681030273
 Epoch 8/20, Loss: 0.3088107705116272
 Epoch 9/20, Loss: 0.2950946092605591
 Epoch 10/20, Loss: 0.285712331533432
 Epoch 11/20, Loss: 0.27566009759902954
 Epoch 12/20, Loss: 0.26707518100738525
 Epoch 13/20, Loss: 0.2612447440624237
 Epoch 14/20, Loss: 0.255196213722229
 Epoch 15/20, Loss: 0.24966809153556824
 Epoch 16/20, Loss: 0.24377015233039856
 Epoch 17/20, Loss: 0.2388983815908432
 Epoch 18/20, Loss: 0.23604774475097656
 Epoch 19/20, Loss: 0.23312272131443024
 Epoch 20/20, Loss: 0.228593647480011
 Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
 Epoch 1/20, Loss: 0.7010146975517273
 Epoch 2/20, Loss: 0.5799434185028076
 Epoch 3/20, Loss: 0.40602782368659973
 Epoch 4/20, Loss: 0.369476318359375
 Epoch 5/20, Loss: 0.35787224769592285
 Epoch 6/20, Loss: 0.33343306183815
 Epoch 7/20, Loss: 0.3145439326763153
 Epoch 8/20, Loss: 0.30883821845054626
 Epoch 9/20, Loss: 0.3034120798110962
 Epoch 10/20, Loss: 0.29011261463165283
 Epoch 11/20, Loss: 0.27633577585220337
 Epoch 12/20, Loss: 0.2643585205078125
 Epoch 13/20, Loss: 0.2587999701499939
 Epoch 14/20, Loss: 0.2566339671611786
 Epoch 15/20, Loss: 0.24680820107460022
 Epoch 16/20, Loss: 0.24079933762550354
 Epoch 17/20, Loss: 0.2369673252105713
 Epoch 18/20, Loss: 0.23411229252815247
 Epoch 19/20, Loss: 0.22890222072601318
 Epoch 20/20, Loss: 0.22622136771678925
 Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
 Epoch 1/20, Loss: 0.6892096996307373
 Epoch 2/20, Loss: 0.6777986884117126
 Epoch 3/20, Loss: 0.6656076312065125
 Epoch 4/20, Loss: 0.6524375081062317
 Epoch 5/20, Loss: 0.6380916833877563
 Epoch 6/20, Loss: 0.6220588684082031
 Epoch 7/20, Loss: 0.6038244366645813
 Epoch 8/20, Loss: 0.5831056833267212
 Epoch 9/20, Loss: 0.5596638917922974

```

Epoch 10/20, Loss: 0.5336142182350159
Epoch 11/20, Loss: 0.5063611268997192
Epoch 12/20, Loss: 0.4779794216156006
Epoch 13/20, Loss: 0.4496092200279236
Epoch 14/20, Loss: 0.4231898784637451
Epoch 15/20, Loss: 0.39845648407936096
Epoch 16/20, Loss: 0.37828829884529114
Epoch 17/20, Loss: 0.36275947093963623
Epoch 18/20, Loss: 0.35127347707748413
Epoch 19/20, Loss: 0.342928946018219
Epoch 20/20, Loss: 0.33968785405158997
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Epoch 1/20, Loss: 0.6854851245880127
Epoch 2/20, Loss: 0.6727800369262695
Epoch 3/20, Loss: 0.6594692468643188
Epoch 4/20, Loss: 0.6460111737251282
Epoch 5/20, Loss: 0.629231333732605
Epoch 6/20, Loss: 0.6117150187492371
Epoch 7/20, Loss: 0.5924291610717773
Epoch 8/20, Loss: 0.5726961493492126
Epoch 9/20, Loss: 0.5484854578971863
Epoch 10/20, Loss: 0.5237650275230408
Epoch 11/20, Loss: 0.4974948763847351
Epoch 12/20, Loss: 0.47382792830467224
Epoch 13/20, Loss: 0.44789350032806396
Epoch 14/20, Loss: 0.42338332533836365
Epoch 15/20, Loss: 0.40014541149139404
Epoch 16/20, Loss: 0.3826206624507904
Epoch 17/20, Loss: 0.3689213991165161
Epoch 18/20, Loss: 0.3575296103954315
Epoch 19/20, Loss: 0.3470417857170105
Epoch 20/20, Loss: 0.33902236819267273
Best Params: {'hidden_dim': 128, 'dropout': 0.3, 'lr': 0.01, 'batch_size': 64}
Best Binary Accuracy: 0.9118
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9539

```

```
[ ]: # 50 epochs (same in 35)
```

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

```

```

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [50], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
    ↪structure available)

```

```

edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳ edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳ dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳ output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()
                    #print(f"Epoch {epoch+1}/{param_grid['epochs'][0]}, Loss:
↳ {loss.item()}")

                    # Evaluate the model
                    model.eval()
                    with torch.no_grad():
                        y_pred = model(X_test_tensor, edge_index)
                        y_pred_binary = (y_pred > 0.5).float()

                    # Calculate binary accuracy
                    binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳ item()

                    # Calculate normal accuracy
                    normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                    # Calculate F1 score
                    f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                    # Update best params if this model is better

```

```

        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'hidden_dim': hidden_dim,
                'dropout': dropout,
                'lr': lr,
                'batch_size': batch_size
            }

```

Print the best results

```

print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Best Params: {'hidden_dim': 128, 'dropout': 0.5, 'lr': 0.001, 'batch_size': 32}
Best Binary Accuracy: 0.9115
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9537

```

[]: *# 100 epochs*

20 epochs

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split

```

```

import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [100], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

```

```

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()

                # Evaluate the model
                model.eval()
                with torch.no_grad():
                    y_pred = model(X_test_tensor, edge_index)
                    y_pred_binary = (y_pred > 0.5).float()

                # Calculate binary accuracy
                binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳item()

                # Calculate normal accuracy
                normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                # Calculate F1 score
                f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                # Update best params if this model is better

```

```

        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'hidden_dim': hidden_dim,
                'dropout': dropout,
                'lr': lr,
                'batch_size': batch_size
            }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Best Params: {'hidden_dim': 64, 'dropout': 0.5, 'lr': 0.001, 'batch_size': 32}
Best Binary Accuracy: 0.9115
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9537

```

[]: # 25 epochs

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

```



```

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [20], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)

```

```

edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳ edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳ dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳ output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()

                # Evaluate the model
                model.eval()
                with torch.no_grad():
                    y_pred = model(X_test_tensor, edge_index)
                    y_pred_binary = (y_pred > 0.5).float()

                # Calculate binary accuracy
                binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳ item()

                # Calculate normal accuracy
                normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                # Calculate F1 score
                f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                # Update best params if this model is better
                if binary_acc > best_binary_acc:
                    best_binary_acc = binary_acc

```

```

        best_f1 = f1
        best_normal_acc = normal_acc
        best_params = {
            'hidden_dim': hidden_dim,
            'dropout': dropout,
            'lr': lr,
            'batch_size': batch_size
        }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Best Params: {'hidden_dim': 128, 'dropout': 0.3, 'lr': 0.01, 'batch_size': 64}
Best Binary Accuracy: 0.9120
Best Normal Accuracy: 0.2921
Best F1 Score: 0.9539

```

[]: *# 30 epochs*

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels

```

```

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

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [30], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳edge connections for GCN

```

```

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳ dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳ output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()

                # Evaluate the model
                model.eval()
                with torch.no_grad():
                    y_pred = model(X_test_tensor, edge_index)
                    y_pred_binary = (y_pred > 0.5).float()

                # Calculate binary accuracy
                binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳ item()

                # Calculate normal accuracy
                normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                # Calculate F1 score
                f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                # Update best params if this model is better
                if binary_acc > best_binary_acc:
                    best_binary_acc = binary_acc
                    best_f1 = f1
                    best_normal_acc = normal_acc
                    best_params = {

```

```

        'hidden_dim': hidden_dim,
        'dropout': dropout,
        'lr': lr,
        'batch_size': batch_size
    }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Best Params: {'hidden_dim': 64, 'dropout': 0.5, 'lr': 0.01, 'batch_size': 32}
Best Binary Accuracy: 0.9132
Best Normal Accuracy: 0.2921
Best F1 Score: 0.9545

```

```

[ ]: # 33 epochs

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

# Use your fingerprint array `X` from your previous code
# X represents the features, and y represents the labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    ↪random_state=42)

```

```

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [30], # Number of epochs
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001], # Learning rates
    'weight_decay': [0, 1e-4, 1e-5], # L2 regularization
    'activation': ['relu', 'leaky_relu', 'tanh'], # Activation functions
    'num_layers': [2, 3], # Number of GCNConv layers
    'lr_decay': [0.95, 0.99], # Learning rate decay
    'batch_norm': [True, False], # Batch normalization
    'aggregation': ['mean', 'sum', 'max'], # Aggregation method
    'residual': [True, False] # Residual connections
}

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

```

```

# Simulate edge connections for GCN (simplified for fingerprints, no real graph
↳structure available)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long) # Placeholder
↳edge connections for GCN

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                print(f'Training with hidden_dim={hidden_dim},
↳dropout={dropout}, lr={lr}, batch_size={batch_size}')

                # Initialize model
                model = GCN(input_dim=X_train.shape[1], hidden_dim=hidden_dim,
↳output_dim=y_train.shape[1], dropout=dropout)

                # Loss and optimizer
                optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                criterion = torch.nn.BCELoss()

                # Train the model
                for epoch in range(param_grid['epochs'][0]):
                    model.train()
                    optimizer.zero_grad()
                    out = model(X_train_tensor, edge_index)
                    loss = criterion(out, y_train_tensor)
                    loss.backward()
                    optimizer.step()

                # Evaluate the model
                model.eval()
                with torch.no_grad():
                    y_pred = model(X_test_tensor, edge_index)
                    y_pred_binary = (y_pred > 0.5).float()

                # Calculate binary accuracy
                binary_acc = (y_pred_binary == y_test_tensor).float().mean().
↳item()

                # Calculate normal accuracy
                normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                # Calculate F1 score
                f1 = f1_score(y_test, y_pred_binary.numpy(), average='micro')

                # Update best params if this model is better

```



```

        if binary_acc > best_binary_acc:
            best_binary_acc = binary_acc
            best_f1 = f1
            best_normal_acc = normal_acc
            best_params = {
                'hidden_dim': hidden_dim,
                'dropout': dropout,
                'lr': lr,
                'batch_size': batch_size
            }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=64, dropout=0.5, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.3, lr=0.001, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.01, batch_size=64
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=32
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64
Best Params: {'hidden_dim': 128, 'dropout': 0.5, 'lr': 0.01, 'batch_size': 64}
Best Binary Accuracy: 0.9129
Best Normal Accuracy: 0.2959
Best F1 Score: 0.9544

```

[]: *# Full GNN code with hyperparameter tuning and self-loop edge_index*

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
import numpy as np

```

```

# Assuming X and y are defined as molecular fingerprints (X) and labels (y)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Convert X_train and y_train to PyTorch tensors
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GNN model definition
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x) # For multi-label classification

# Hyperparameter grid
param_grid = {
    'hidden_dim': [64, 128], # Number of hidden units
    'dropout': [0.3, 0.5], # Dropout rate
    'epochs': [10,15, 20,25, 30,35,50,100], # Different epoch values
    'batch_size': [32, 64], # Batch size
    'learning_rate': [0.01, 0.001] # Learning rates
}

# Create a self-loop graph (each node connected to itself)
num_nodes = X_train_tensor.size(0)
edge_index = torch.arange(0, num_nodes, dtype=torch.long).unsqueeze(0).
↳repeat(2, 1)

# Variables to track the best model
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_params = {}

```

```

# Perform hyperparameter tuning
for hidden_dim in param_grid['hidden_dim']:
    for dropout in param_grid['dropout']:
        for lr in param_grid['learning_rate']:
            for batch_size in param_grid['batch_size']:
                for epochs in param_grid['epochs']: # Loop for different epochs
                    ↪values

                    print(f'Training with hidden_dim={hidden_dim}, ↪
                    ↪dropout={dropout}, lr={lr}, batch_size={batch_size}, epochs={epochs}')

                    # Initialize model
                    model = GCN(input_dim=X_train.shape[1], ↪
                    ↪hidden_dim=hidden_dim, output_dim=y_train.shape[1], dropout=dropout)

                    # Loss and optimizer
                    optimizer = torch.optim.Adam(model.parameters(), lr=lr)
                    criterion = torch.nn.BCELoss()

                    # Train the model
                    for epoch in range(epochs):
                        model.train()
                        optimizer.zero_grad()
                        out = model(X_train_tensor, edge_index)
                        loss = criterion(out, y_train_tensor)
                        loss.backward()
                        optimizer.step()

                    # Evaluate the model
                    model.eval()
                    with torch.no_grad():
                        y_pred = model(X_test_tensor, edge_index)
                        y_pred_binary = (y_pred > 0.5).float()

                    # Calculate binary accuracy
                    binary_acc = (y_pred_binary == y_test_tensor).float().
                    ↪mean().item()

                    # Calculate normal accuracy
                    normal_acc = accuracy_score(y_test, y_pred_binary.numpy())

                    # Calculate F1 score
                    f1 = f1_score(y_test, y_pred_binary.numpy(), ↪
                    ↪average='micro')

                    # Update best params if this model is better
                    if binary_acc > best_binary_acc:

```

```

        best_binary_acc = binary_acc
        best_f1 = f1
        best_normal_acc = normal_acc
        best_params = {
            'hidden_dim': hidden_dim,
            'dropout': dropout,
            'lr': lr,
            'batch_size': batch_size,
            'epochs': epochs
        }

# Print the best results
print(f'Best Params: {best_params}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

```

Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=10
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=15
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=20
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=25
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=30
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=35
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=50
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=32, epochs=100
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=10
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=15
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=20
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=25
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=30
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=35
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=50
Training with hidden_dim=64, dropout=0.3, lr=0.01, batch_size=64, epochs=100
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=10
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=15
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=20
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=25
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=30
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=35
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=50
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=32, epochs=100
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=10
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=15
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=20
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=25
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=30
Training with hidden_dim=64, dropout=0.3, lr=0.001, batch_size=64, epochs=35

```



```

Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64, epochs=50
Training with hidden_dim=128, dropout=0.5, lr=0.001, batch_size=64, epochs=100
Best Params: {'hidden_dim': 64, 'dropout': 0.3, 'lr': 0.01, 'batch_size': 64,
'epochs': 35}
Best Binary Accuracy: 0.9126
Best Normal Accuracy: 0.2884
Best F1 Score: 0.9541

```

```
[ ]: # OPTIMIZATION APPROACHES
```

```
[ ]: # 1. SOFT VOTING
```

```

# Import necessary libraries
import numpy as np
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv1D, MaxPooling1D, Dense, Flatten,
↳Dropout, LSTM
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.regularizers import l2

# Assuming you already have X and y prepared
# X represents molecular fingerprints, y represents the reaction labels
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Convert data to PyTorch tensors for GNN
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)

# Simulate edge connections for GNN (as a placeholder)
edge_index = torch.tensor([[0, 1], [1, 0]], dtype=torch.long)

#####
# CNN Model Definition and Training
#####
def build_cnn_model():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu',
↳input_shape=(X_train.shape[1], 1)))
    model.add(MaxPooling1D(pool_size=2))
    model.add(Dropout(0.5))

```

```

        model.add(Flatten())
        model.add(Dense(256, activation='relu'))
        model.add(Dropout(0.5))
        model.add(Dense(y_train.shape[1], activation='sigmoid')) # Multi-label
        ↪classification
        model.compile(optimizer=Adam(), loss='binary_crossentropy',
        ↪metrics=['binary_accuracy'])
        return model

# Reshape data for CNN input
X_train_cnn = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_cnn = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train CNN model
cnn_model = build_cnn_model()
cnn_model.fit(X_train_cnn, y_train, epochs=10, batch_size=64,
        ↪validation_split=0.1)
cnn_pred = cnn_model.predict(X_test_cnn)

#####
# LSTM Model Definition and Training
#####
def build_lstm_model():
    model = Sequential()
    model.add(LSTM(64, return_sequences=False, input_shape=(X_train.shape[1],
        ↪1), kernel_regularizer=l2(0.01)))
    model.add(Dropout(0.3))
    model.add(Dense(256, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid')) # Multi-label
        ↪classification
    model.compile(optimizer=Adam(), loss='binary_crossentropy',
        ↪metrics=['binary_accuracy'])
    return model

# Reshape data for LSTM input
X_train_lstm = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_lstm = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train LSTM model
lstm_model = build_lstm_model()
lstm_model.fit(X_train_lstm, y_train, epochs=10, batch_size=32,
        ↪validation_split=0.1)
lstm_pred = lstm_model.predict(X_test_lstm)

#####
# GNN Model Definition and Training

```



```
#####
class GCN(torch.nn.Module):
    def __init__(self, input_dim, hidden_dim, output_dim, dropout=0.5):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(input_dim, hidden_dim)
        self.conv2 = GCNConv(hidden_dim, hidden_dim)
        self.fc = torch.nn.Linear(hidden_dim, output_dim)
        self.dropout = dropout

    def forward(self, x, edge_index):
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = F.dropout(x, p=self.dropout, training=self.training)
        x = self.fc(x)
        return torch.sigmoid(x)

# Initialize GNN model
gnn_model = GCN(input_dim=X_train.shape[1], hidden_dim=128, output_dim=y_train.
    ↪shape[1], dropout=0.5)
optimizer = torch.optim.Adam(gnn_model.parameters(), lr=0.01)
criterion = torch.nn.BCELoss()

# Train GNN model
for epoch in range(30):
    gnn_model.train()
    optimizer.zero_grad()
    out = gnn_model(X_train_tensor, edge_index)
    loss = criterion(out, y_train_tensor)
    loss.backward()
    optimizer.step()

# Get GNN predictions
gnn_model.eval()
with torch.no_grad():
    gnn_pred = gnn_model(X_test_tensor, edge_index).numpy()

#####
# Soft Voting (Combining Predictions)
#####
# Perform Soft Voting
combined_pred = (cnn_pred + lstm_pred + gnn_pred) / 3

# Convert to binary predictions
combined_pred_binary = (combined_pred > 0.5).astype(int)
```

```

# Evaluate the combined predictions
binary_acc = np.mean(np.equal(y_test, combined_pred_binary).astype(int))
f1 = f1_score(y_test, combined_pred_binary, average='micro')
normal_acc = accuracy_score(y_test, combined_pred_binary)

# Print the results
print(f'Soft Voting Binary Accuracy: {binary_acc:.4f}')
print(f'Soft Voting F1 Score: {f1:.4f}')
print(f'Soft Voting Normal Accuracy: {normal_acc:.4f}')

```

Epoch 1/10

```

/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.

```

```

super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```

```

15/15          7s 194ms/step -
binary_accuracy: 0.7868 - loss: 0.4658 - val_binary_accuracy: 0.9124 - val_loss:
0.2611

```

Epoch 2/10

```

15/15          4s 16ms/step -
binary_accuracy: 0.8816 - loss: 0.3234 - val_binary_accuracy: 0.9108 - val_loss:
0.2626

```

Epoch 3/10

```

15/15          0s 15ms/step -
binary_accuracy: 0.8891 - loss: 0.2858 - val_binary_accuracy: 0.9116 - val_loss:
0.2499

```

Epoch 4/10

```

15/15          0s 11ms/step -
binary_accuracy: 0.9004 - loss: 0.2517 - val_binary_accuracy: 0.9116 - val_loss:
0.2447

```

Epoch 5/10

```

15/15          0s 12ms/step -
binary_accuracy: 0.9049 - loss: 0.2353 - val_binary_accuracy: 0.9065 - val_loss:
0.2464

```

Epoch 6/10

```

15/15          0s 12ms/step -
binary_accuracy: 0.9114 - loss: 0.2159 - val_binary_accuracy: 0.9054 - val_loss:
0.2493

```

Epoch 7/10

```

15/15          0s 11ms/step -
binary_accuracy: 0.9154 - loss: 0.2037 - val_binary_accuracy: 0.9065 - val_loss:
0.2514

```

Epoch 8/10

```

15/15          0s 11ms/step -

```

```

binary_accuracy: 0.9179 - loss: 0.1963 - val_binary_accuracy: 0.9054 - val_loss:
0.2558
Epoch 9/10
15/15          0s 10ms/step -
binary_accuracy: 0.9148 - loss: 0.1965 - val_binary_accuracy: 0.9003 - val_loss:
0.2634
Epoch 10/10
15/15          0s 11ms/step -
binary_accuracy: 0.9225 - loss: 0.1788 - val_binary_accuracy: 0.9034 - val_loss:
0.2724
9/9            1s 39ms/step

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
  super().__init__(**kwargs)

Epoch 1/10
30/30          6s 50ms/step -
binary_accuracy: 0.8266 - loss: 0.6305 - val_binary_accuracy: 0.9124 - val_loss:
0.2562
Epoch 2/10
30/30          1s 40ms/step -
binary_accuracy: 0.8949 - loss: 0.2823 - val_binary_accuracy: 0.9124 - val_loss:
0.2429
Epoch 3/10
30/30          1s 40ms/step -
binary_accuracy: 0.8965 - loss: 0.2745 - val_binary_accuracy: 0.9124 - val_loss:
0.2383
Epoch 4/10
30/30          1s 31ms/step -
binary_accuracy: 0.8962 - loss: 0.2688 - val_binary_accuracy: 0.9124 - val_loss:
0.2377
Epoch 5/10
30/30          1s 32ms/step -
binary_accuracy: 0.9044 - loss: 0.2522 - val_binary_accuracy: 0.9124 - val_loss:
0.2395
Epoch 6/10
30/30          1s 32ms/step -
binary_accuracy: 0.9011 - loss: 0.2591 - val_binary_accuracy: 0.9124 - val_loss:
0.2436
Epoch 7/10
30/30          1s 32ms/step -
binary_accuracy: 0.8990 - loss: 0.2669 - val_binary_accuracy: 0.9124 - val_loss:
0.2365
Epoch 8/10
30/30          1s 32ms/step -
binary_accuracy: 0.9030 - loss: 0.2561 - val_binary_accuracy: 0.9124 - val_loss:

```

```

0.2387
Epoch 9/10
30/30          1s 32ms/step -
binary_accuracy: 0.9026 - loss: 0.2528 - val_binary_accuracy: 0.9124 - val_loss:
0.2394
Epoch 10/10
30/30          1s 31ms/step -
binary_accuracy: 0.9013 - loss: 0.2542 - val_binary_accuracy: 0.9124 - val_loss:
0.2378
9/9            0s 22ms/step
Soft Voting Binary Accuracy: 0.9131
Soft Voting F1 Score: 0.9544
Soft Voting Normal Accuracy: 0.2884

```

```

[ ]: # WEIGHTED SOFT VOTING

from sklearn.metrics import accuracy_score, f1_score
from itertools import product
import numpy as np

# Define ranges for the weights (can fine-tune these ranges based on your
↳ preference)
weight_range = np.arange(0.1, 1.1, 0.1)

# Initialize variables to track the best performance
best_binary_acc = 0
best_f1 = 0
best_normal_acc = 0
best_weights = None

# Perform grid search for weights w1 (CNN), w2 (LSTM), w3 (GNN)
for w1, w2, w3 in product(weight_range, repeat=3):
    # Weighted soft voting
    combined_pred = (w1 * cnn_pred + w2 * lstm_pred + w3 * gnn_pred) / (w1 + w2
↳ + w3)

    # Convert to binary predictions
    combined_pred_binary = (combined_pred > 0.5).astype(int)

    # Calculate binary accuracy
    binary_acc = np.mean(np.equal(y_test, combined_pred_binary).astype(int))

    # Calculate normal accuracy
    normal_acc = accuracy_score(y_test, combined_pred_binary)

    # Calculate F1 score
    f1 = f1_score(y_test, combined_pred_binary, average='micro')

```

```

# Update the best weights if this configuration performs better
if binary_acc > best_binary_acc:
    best_binary_acc = binary_acc
    best_f1 = f1
    best_normal_acc = normal_acc
    best_weights = (w1, w2, w3)

# Print the best results
print(f'Best Weights: CNN={best_weights[0]}, LSTM={best_weights[1]}, GNN={best_weights[2]}')
print(f'Best Binary Accuracy: {best_binary_acc:.4f}')
print(f'Best Normal Accuracy: {best_normal_acc:.4f}')
print(f'Best F1 Score: {best_f1:.4f}')

```

Best Weights: CNN=0.4, LSTM=0.30000000000000004, GNN=0.5
 Best Binary Accuracy: 0.9137
 Best Normal Accuracy: 0.2921
 Best F1 Score: 0.9547

```
[ ]: # NEW START
```

```
[ ]: # 1. ResNet CNN - with hyperparameter tuning
```

```
[ ]: !pip install keras-tuner tensorflow
```

Collecting keras-tuner

Downloading keras_tuner-1.4.7-py3-none-any.whl.metadata (5.4 kB)

Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-packages (2.17.0)

Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (3.4.1)

Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (24.1)

Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from keras-tuner) (2.32.3)

Collecting kt-legacy (from keras-tuner)

Downloading kt_legacy-1.0.5-py3-none-any.whl.metadata (221 bytes)

Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)

Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)

Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)

Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.6.0)

Requirement already satisfied: google-pasta>=0.1.1 in

/usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)
 Requirement already satisfied: h5py>=3.10.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.11.0)
 Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (18.1.1)
 Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.4.0)
 Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.3.0)
 Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.20.3)
 Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (71.0.4)
 Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)
 Requirement already satisfied: termcolor>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.4.0)
 Requirement already satisfied: typing-extensions>=3.6.6 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (4.12.2)
 Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)
 Requirement already satisfied: grpcio<2.0,>=1.24.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.64.1)
 Requirement already satisfied: tensorboard<2.18,>=2.17 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.17.0)
 Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.37.1)
 Requirement already satisfied: numpy<2.0.0,>=1.23.5 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.26.4)
 Requirement already satisfied: wheel<1.0,>=0.23.0 in /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow) (0.44.0)
 Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (13.8.1)
 Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (0.0.8)
 Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages (from keras->keras-tuner) (0.12.1)
 Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.3.2)
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.8)
 Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2.0.7)
 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2024.8.30)
 Requirement already satisfied: markdown>=2.6.8 in

```

/usr/local/lib/python3.10/dist-packages (from
tensorboard<2.18,>=2.17->tensorflow) (3.7)
Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
/usr/local/lib/python3.10/dist-packages (from
tensorboard<2.18,>=2.17->tensorflow) (0.7.2)
Requirement already satisfied: werkzeug>=1.0.1 in
/usr/local/lib/python3.10/dist-packages (from
tensorboard<2.18,>=2.17->tensorflow) (3.0.4)
Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.10/dist-packages (from
werkzeug>=1.0.1->tensorboard<2.18,>=2.17->tensorflow) (2.1.5)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (2.16.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-
packages (from markdown-it-py>=2.2.0->rich->keras->keras-tuner) (0.1.2)
Downloading keras_tuner-1.4.7-py3-none-any.whl (129 kB)
129.1/129.1 kB
4.1 MB/s eta 0:00:00
Downloading kt_legacy-1.0.5-py3-none-any.whl (9.6 kB)
Installing collected packages: kt-legacy, keras-tuner
Successfully installed keras-tuner-1.4.7 kt-legacy-1.0.5

```

```

[ ]: import tensorflow as tf
from tensorflow.keras.layers import Conv1D, MaxPooling1D,
    GlobalAveragePooling1D, Dense, Dropout, BatchNormalization
from keras_tuner import RandomSearch
from sklearn.metrics import accuracy_score, f1_score

# Custom ResNet-inspired 1D architecture
def build_resnet_1d_model(hp):
    model = tf.keras.Sequential()

    # First convolution block
    model.add(Conv1D(filters=hp.Int('filters', min_value=32, max_value=128,
    step=32),
                    kernel_size=hp.Int('kernel_size', min_value=3,
    max_value=7, step=2),
                    activation='relu', input_shape=(X_train.shape[1], 1)))
    model.add(BatchNormalization())
    model.add(MaxPooling1D(pool_size=2))

    # Second convolution block
    model.add(Conv1D(filters=hp.Int('filters_2', min_value=32, max_value=128,
    step=32),

```

```

        kernel_size=hp.Int('kernel_size_2', min_value=3,
↪max_value=7, step=2),
        activation='relu'))
    model.add(BatchNormalization())
    model.add(MaxPooling1D(pool_size=2))

    # Global Average Pooling and Dense layers
    model.add(GlobalAveragePooling1D())
    model.add(Dense(units=hp.Int('units', min_value=128, max_value=512,
↪step=64), activation='relu'))
    model.add(Dropout(rate=hp.Float('dropout', min_value=0.1, max_value=0.5,
↪step=0.1)))

    # Output layer
    model.add(Dense(y_train.shape[1], activation='sigmoid')) # Multi-label
↪classification

    # Compile the model
    model.compile(optimizer=tf.keras.optimizers.Adam(
        hp.Choice('learning_rate', values=[1e-2, 1e-3, 1e-4])),
        loss='binary_crossentropy',
        metrics=['binary_accuracy'])

    return model

# Reshape the data for Conv1D input
X_train_resnet = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_resnet = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Set up Keras Tuner for hyperparameter tuning
tuner_resnet_1d = RandomSearch(
    build_resnet_1d_model,
    objective='val_binary_accuracy',
    max_trials=10, # Increase this for more extensive tuning
    executions_per_trial=1,
    directory='resnet_1d_tuner',
    project_name='adr_resnet_1d')

# Search for the best hyperparameters
tuner_resnet_1d.search(X_train_resnet, y_train, epochs=10, validation_split=0.2)

# Get the best hyperparameters and model
best_resnet_1d_model = tuner_resnet_1d.get_best_models(num_models=1)[0]

# Train the best model further on the dataset
best_resnet_1d_model.fit(X_train_resnet, y_train, epochs=10,
↪validation_data=(X_test_resnet, y_test))

```



```

# Evaluate ResNet 1D
resnet_1d_pred = best_resnet_1d_model.predict(X_test_resnet)
resnet_1d_pred_binary = (resnet_1d_pred > 0.5).astype(int)

resnet_1d_binary_acc = np.mean(np.equal(y_test, resnet_1d_pred_binary)).
    ↳astype(int))
resnet_1d_f1 = f1_score(y_test, resnet_1d_pred_binary, average='micro')
resnet_1d_normal_acc = accuracy_score(y_test, resnet_1d_pred_binary)

print(f'ResNet 1D Binary Accuracy: {resnet_1d_binary_acc:.4f}')
print(f'ResNet 1D Normal Accuracy: {resnet_1d_normal_acc:.4f}')
print(f'ResNet 1D F1 Score: {resnet_1d_f1:.4f}')

```

Trial 10 Complete [00h 01m 47s]

val_binary_accuracy: 0.9021908640861511

Best val_binary_accuracy So Far: 0.9021908640861511

Total elapsed time: 00h 15m 01s

Epoch 1/10

/usr/local/lib/python3.10/dist-packages/keras/src/saving/saving_lib.py:576:

UserWarning: Skipping variable loading for optimizer 'adam', because it has 2 variables whereas the saved optimizer has 26 variables.

saveable.load_own_variables(weights_store.get(inner_path))

34/34 20s 511ms/step -

binary_accuracy: 0.8987 - loss: 0.2773 - val_binary_accuracy: 0.8830 - val_loss: 0.6108

Epoch 2/10

34/34 25s 639ms/step -

binary_accuracy: 0.8993 - loss: 0.2641 - val_binary_accuracy: 0.8407 - val_loss: 0.6043

Epoch 3/10

34/34 31s 355ms/step -

binary_accuracy: 0.8932 - loss: 0.2692 - val_binary_accuracy: 0.8366 - val_loss: 0.5691

Epoch 4/10

34/34 21s 358ms/step -

binary_accuracy: 0.8924 - loss: 0.2755 - val_binary_accuracy: 0.8258 - val_loss: 0.5258

Epoch 5/10

34/34 10s 309ms/step -

binary_accuracy: 0.8983 - loss: 0.2617 - val_binary_accuracy: 0.8204 - val_loss: 0.4950

Epoch 6/10

34/34 22s 368ms/step -

binary_accuracy: 0.9032 - loss: 0.2546 - val_binary_accuracy: 0.8297 - val_loss:

```

0.4888
Epoch 7/10
34/34          12s 357ms/step -
binary_accuracy: 0.8948 - loss: 0.2657 - val_binary_accuracy: 0.8407 - val_loss:
0.4485
Epoch 8/10
34/34          20s 336ms/step -
binary_accuracy: 0.9030 - loss: 0.2571 - val_binary_accuracy: 0.8641 - val_loss:
0.4398
Epoch 9/10
34/34          12s 352ms/step -
binary_accuracy: 0.9039 - loss: 0.2531 - val_binary_accuracy: 0.8628 - val_loss:
0.4327
Epoch 10/10
34/34          20s 330ms/step -
binary_accuracy: 0.8957 - loss: 0.2718 - val_binary_accuracy: 0.8619 - val_loss:
0.4446
9/9            1s 123ms/step
ResNet 1D Binary Accuracy: 0.8619
ResNet 1D Normal Accuracy: 0.0037
ResNet 1D F1 Score: 0.9240

```

```
[ ]: # 2. GCN, GRAPHSAGE AND GAT
```

```
!pip install torch-scatter torch-sparse torch-geometric rdkit scikit-optimize
```

```

Collecting torch-scatter
  Using cached torch_scatter-2.1.2.tar.gz (108 kB)
  Preparing metadata (setup.py) ... done
Collecting torch-sparse
  Using cached torch_sparse-0.6.18.tar.gz (209 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: torch-geometric in
/usr/local/lib/python3.10/dist-packages (2.6.0)
Collecting rdkit
  Downloading rdkit-2024.3.5-cp310-cp310-manylinux_2_28_x86_64.whl.metadata (3.9
kB)
Collecting scikit-optimize
  Downloading scikit_optimize-0.10.2-py2.py3-none-any.whl.metadata (9.7 kB)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from torch-sparse) (1.13.1)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (3.10.5)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (2024.6.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (3.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (1.26.4)

```

Requirement already satisfied: psutil>=5.8.0 in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (5.9.5)

Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (3.1.4)

Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (2.32.3)

Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (4.66.5)

Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit) (9.4.0)

Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.4.2)

Collecting pyaml>=16.9 (from scikit-optimize)

 Downloading pyaml-24.7.0-py3-none-any.whl.metadata (11 kB)

Requirement already satisfied: scikit-learn>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-optimize) (1.3.2)

Requirement already satisfied: packaging>=21.3 in /usr/local/lib/python3.10/dist-packages (from scikit-optimize) (24.1)

Requirement already satisfied: PyYAML in /usr/local/lib/python3.10/dist-packages (from pyaml>=16.9->scikit-optimize) (6.0.2)

Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.0.0->scikit-optimize) (3.5.0)

Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (2.4.0)

Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.3.1)

Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (24.2.0)

Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.4.1)

Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (6.1.0)

Requirement already satisfied: yarll<2.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.11.1)

Requirement already satisfied: async-timeout<5.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (4.0.3)

Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch-geometric) (2.1.5)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (3.3.2)

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (3.8)

Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (2.0.7)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (2024.8.30)

```
Requirement already satisfied: typing-extensions>=4.1.0 in
/usr/local/lib/python3.10/dist-packages (from
multidict<7.0,>=4.5->aioshttp->torch-geometric) (4.12.2)
Downloading rdkit-2024.3.5-cp310-cp310-manylinux_2_28_x86_64.whl (33.1 MB)
33.1/33.1 MB
43.6 MB/s eta 0:00:00
Downloading scikit_optimize-0.10.2-py2.py3-none-any.whl (107 kB)
107.8/107.8 kB
5.7 MB/s eta 0:00:00
Downloading pyaml-24.7.0-py3-none-any.whl (24 kB)
Building wheels for collected packages: torch-scatter, torch-sparse
Building wheel for torch-scatter (setup.py) ... canceled
ERROR: Operation cancelled by user
```

```
[ ]: #2.1 GCN
import torch
import torch.nn.functional as F
from torch_geometric.data import Data
from torch_geometric.loader import DataLoader # Corrected loader import
from torch_geometric.nn import GCNConv, global_mean_pool
from rdkit import Chem
from rdkit.Chem import rdmolops
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, accuracy_score
import numpy as np

# Function to convert SMILES to a PyTorch Geometric graph with labels
def smiles_to_graph(smiles, labels):
    mol = Chem.MolFromSmiles(smiles)
    adj = rdmolops.GetAdjacencyMatrix(mol)
    atoms = [atom.GetAtomicNum() for atom in mol.GetAtoms()]
    edge_index = torch.tensor(np.array(adj.nonzero()), dtype=torch.long) #
    ↳Converted to NumPy array first
    x = torch.tensor(atoms, dtype=torch.float).view(-1, 1)

    # Add labels to the graph as a 2D tensor (batch_size, num_classes)
    data = Data(x=x, edge_index=edge_index)
    data.y = torch.tensor(labels, dtype=torch.float).view(1, -1) # Convert
    ↳labels into a 2D tensor
    return data

# Convert SMILES to graphs with correct labels
graphs = [smiles_to_graph(smile, label) for smile, label in zip(smiles_list, y)]

# Prepare train/test split
```

```

train_graphs, test_graphs = train_test_split(graphs, test_size=0.2,
↳random_state=42)

# Create PyTorch Geometric DataLoaders
train_loader = DataLoader(train_graphs, batch_size=32, shuffle=True)
test_loader = DataLoader(test_graphs, batch_size=32, shuffle=False)

# Define the GCN Model
class GCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, 128)
        self.conv2 = GCNConv(128, 64)
        self.fc = torch.nn.Linear(64, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, data.batch) # Global mean pooling
        x = self.fc(x)
        return torch.sigmoid(x)

# Train the GCN Model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=100):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y.view(output.size())) # Ensure both
↳target and output have the same shape
            loss.backward()
            optimizer.step()
            total_loss += loss.item()

# Initialize and Train the Model
gcn_model = GCN(num_node_features=1, num_classes=y.shape[1]) # num_classes set
↳to the number of reactions (24)
optimizer = torch.optim.Adam(gcn_model.parameters(), lr=0.001)
criterion = torch.nn.BCELoss()
train_gnn_model(gcn_model, train_loader, optimizer, criterion)

# Evaluate the GCN Model

```

```

def evaluate_gnn_model(model, test_loader):
    model.eval()
    total_acc = 0
    total_f1 = 0
    total_normal_acc = 0 # To track normal accuracy
    num_batches = len(test_loader)

    for data in test_loader:
        with torch.no_grad():
            output = model(data)
            preds = (output > 0.5).float()

            # Binary Accuracy (Micro-average of true/false classifications)
            total_acc += (preds == data.y).sum().item() / data.y.numel()

            # F1 Score (Micro-average)
            total_f1 += f1_score(data.y.cpu(), preds.cpu(), average='micro')

            # Normal Accuracy (Per-sample average accuracy)
            total_normal_acc += accuracy_score(data.y.cpu(), preds.cpu())

    print(f'Binary Accuracy: {total_acc / num_batches:.4f}')
    print(f'F1 Score: {total_f1 / num_batches:.4f}')
    print(f'Normal Accuracy: {total_normal_acc / num_batches:.4f}') # Print_
    ↪ normal accuracy

evaluate_gnn_model(gcn_model, test_loader)

```

Binary Accuracy: 0.9101

F1 Score: 0.9529

Normal Accuracy: 0.2872

[]: *# 2.1.1 bayesian optimization with skopts for GCN*

```

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from torch_geometric.data import DataLoader
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, accuracy_score
from skopt import gp_minimize
from skopt.space import Integer, Real
from skopt.utils import use_named_args

# GCN Model Definition
class GCN(torch.nn.Module):

```

```

    def __init__(self, hidden_dim1, hidden_dim2, num_node_features,
↳ num_classes):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, hidden_dim1)
        self.conv2 = GCNConv(hidden_dim1, hidden_dim2)
        self.fc = torch.nn.Linear(hidden_dim2, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, data.batch)
        x = self.fc(x)
        return torch.sigmoid(x)

# Function to train the GCN model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
↳ len(train_loader)}')

# Function to evaluate the GCN model
def evaluate_gnn_model(model, test_loader):
    model.eval()
    total_acc, total_f1, total_normal_acc = 0, 0, 0
    num_batches = len(test_loader)

    for data in test_loader:
        with torch.no_grad():
            output = model(data)
            preds = (output > 0.5).float()
            total_acc += (preds == data.y).sum().item() / data.y.numel()
            total_f1 += f1_score(data.y.cpu(), preds.cpu(), average='micro')
            total_normal_acc += accuracy_score(data.y.cpu(), preds.cpu())

```

```

    return total_acc / num_batches, total_f1 / num_batches, total_normal_acc /
    ↪ num_batches

# Define the search space for hyperparameters
space = [
    Integer(64, 256, name='hidden_dim1'), # First GCN hidden layer
    Integer(64, 256, name='hidden_dim2'), # Second GCN hidden layer
    Real(0.0001, 0.01, name='learning_rate', prior='log-uniform'),
    Real(0.2, 0.6, name='dropout_rate'),
    Integer(32, 128, name='batch_size'),
    Integer(30, 100, name='epochs')
]

# Objective function to minimize (we want to maximize accuracy, so return
↪ negative accuracy)
@use_named_args(space)
def objective(hidden_dim1, hidden_dim2, learning_rate, dropout_rate,
↪ batch_size, epochs):
    model = GCN(hidden_dim1, hidden_dim2, num_node_features=1,
    ↪ num_classes=y_train.shape[1])
    optimizer = torch.optim.Adam(model.parameters(), lr=learning_rate)
    criterion = torch.nn.BCELoss()

    # Train the model with current hyperparameters
    train_gnn_model(model, train_loader, optimizer, criterion,
    ↪ num_epochs=epochs)

    # Evaluate the model
    acc, f1, normal_acc = evaluate_gnn_model(model, test_loader)

    # We want to maximize accuracy, so we return the negative of accuracy
    return -acc

# Run the Bayesian optimization
res = gp_minimize(objective, space, n_calls=20, random_state=42)

# Print the best hyperparameters found
print("Best hyperparameters: ", res.x)

# Train the final model with the best parameters found
best_hidden_dim1 = res.x[0]
best_hidden_dim2 = res.x[1]
best_learning_rate = res.x[2]
best_dropout_rate = res.x[3]
best_batch_size = res.x[4]
best_epochs = res.x[5]

```



```

# Build and train the final model
best_model = GCN(best_hidden_dim1, best_hidden_dim2, num_node_features=1,
    ↪ num_classes=y_train.shape[1])
optimizer = torch.optim.Adam(best_model.parameters(), lr=best_learning_rate)
criterion = torch.nn.BCELoss()

# Train the best model
train_gnn_model(best_model, train_loader, optimizer, criterion,
    ↪ num_epochs=best_epochs)

# Evaluate the final model
final_acc, final_f1, final_normal_acc = evaluate_gnn_model(best_model,
    ↪ test_loader)

# Print the final results
print(f'Best Binary Accuracy: {final_acc:.4f}')
print(f'Best Normal Accuracy: {final_normal_acc:.4f}')
print(f'Best F1 Score: {final_f1:.4f}')

```

```

Epoch 1/37, Loss: 0.3430831204442417
Epoch 2/37, Loss: 0.2868456257616772
Epoch 3/37, Loss: 0.27612609503900304
Epoch 4/37, Loss: 0.2812717219485956
Epoch 5/37, Loss: 0.2717820778489113
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Epoch 80/98, Loss: 0.2561750376925749
Epoch 81/98, Loss: 0.2569317664293682
Epoch 82/98, Loss: 0.25714873128077564
Epoch 83/98, Loss: 0.2570611115764169
Epoch 84/98, Loss: 0.2575600835330346
Epoch 85/98, Loss: 0.2567279295009725
Epoch 86/98, Loss: 0.25768261227537603
Epoch 87/98, Loss: 0.2564363343750729
Epoch 88/98, Loss: 0.25798164833994475
Epoch 89/98, Loss: 0.2562793659813264
Epoch 90/98, Loss: 0.25630495609606013
Epoch 91/98, Loss: 0.25698640898746605
Epoch 92/98, Loss: 0.2575920268016703
Epoch 93/98, Loss: 0.2564646286122939
Epoch 94/98, Loss: 0.25625433071571235
Epoch 95/98, Loss: 0.25771833561799107
Epoch 96/98, Loss: 0.2583060970201212
Epoch 97/98, Loss: 0.25553521250977235
Epoch 98/98, Loss: 0.2551121847594486
Epoch 1/30, Loss: 0.38987260048880296
Epoch 2/30, Loss: 0.28644001440090294
Epoch 3/30, Loss: 0.2840774572070907
Epoch 4/30, Loss: 0.2800211152609657
Epoch 5/30, Loss: 0.2862597007085295
Epoch 6/30, Loss: 0.278452023425523
Epoch 7/30, Loss: 0.279772063388544
Epoch 8/30, Loss: 0.27927649152629513
Epoch 9/30, Loss: 0.28119754309163375
Epoch 10/30, Loss: 0.2671806435374653
Epoch 11/30, Loss: 0.28517599009415684
Epoch 12/30, Loss: 0.2685929230030845

Epoch 13/30, Loss: 0.2674425533589195
Epoch 14/30, Loss: 0.2682940951165031
Epoch 15/30, Loss: 0.2684032299062785
Epoch 16/30, Loss: 0.27120276496690865
Epoch 17/30, Loss: 0.2670919724247035
Epoch 18/30, Loss: 0.266064113992102
Epoch 19/30, Loss: 0.2638118218849687
Epoch 20/30, Loss: 0.2636488527059555
Epoch 21/30, Loss: 0.26156008287387733
Epoch 22/30, Loss: 0.2607739913989516
Epoch 23/30, Loss: 0.26210372588213754
Epoch 24/30, Loss: 0.26190361818846536
Epoch 25/30, Loss: 0.25767629812745485
Epoch 26/30, Loss: 0.25860946493990283
Epoch 27/30, Loss: 0.2582666764364523
Epoch 28/30, Loss: 0.2591743903125034
Epoch 29/30, Loss: 0.2595633680329603
Epoch 30/30, Loss: 0.25665098823168697
Best hyperparameters: [152, 128, 0.0001930783753654713, 0.46035538917954116, 37, 81]
Epoch 1/81, Loss: 0.6438096253310933
Epoch 2/81, Loss: 0.5118430958074682
Epoch 3/81, Loss: 0.39146261180148406
Epoch 4/81, Loss: 0.32357874293537703
Epoch 5/81, Loss: 0.286073270966025
Epoch 6/81, Loss: 0.2777792416951236
Epoch 7/81, Loss: 0.2789551650776583
Epoch 8/81, Loss: 0.27718352263464646
Epoch 9/81, Loss: 0.28259100502028184
Epoch 10/81, Loss: 0.2855961287722868
Epoch 11/81, Loss: 0.28486348250333
Epoch 12/81, Loss: 0.28271739710779753
Epoch 13/81, Loss: 0.28143367916345596
Epoch 14/81, Loss: 0.2812917101032594
Epoch 15/81, Loss: 0.2819855725940536
Epoch 16/81, Loss: 0.2820233934942414
Epoch 17/81, Loss: 0.2925506221020923
Epoch 18/81, Loss: 0.2934553123572293
Epoch 19/81, Loss: 0.28385331437868233
Epoch 20/81, Loss: 0.27930624783039093
Epoch 21/81, Loss: 0.28466113043182034
Epoch 22/81, Loss: 0.28003669091883826
Epoch 23/81, Loss: 0.2782539659563233
Epoch 24/81, Loss: 0.2771615495576578
Epoch 25/81, Loss: 0.2793461141340873
Epoch 26/81, Loss: 0.2795071119771284
Epoch 27/81, Loss: 0.27829935270197254
Epoch 28/81, Loss: 0.28061799924163255

Epoch 29/81, Loss: 0.27705031107453737
Epoch 30/81, Loss: 0.278854980626527
Epoch 31/81, Loss: 0.2766479481669033
Epoch 32/81, Loss: 0.2778523586252156
Epoch 33/81, Loss: 0.27913130907451406
Epoch 34/81, Loss: 0.2779468582833515
Epoch 35/81, Loss: 0.275718839291264
Epoch 36/81, Loss: 0.27598927170038223
Epoch 37/81, Loss: 0.28753337307887916
Epoch 38/81, Loss: 0.2730820003677817
Epoch 39/81, Loss: 0.27398384932209463
Epoch 40/81, Loss: 0.273350320318166
Epoch 41/81, Loss: 0.27520616001942577
Epoch 42/81, Loss: 0.27479635924100876
Epoch 43/81, Loss: 0.27370432501330094
Epoch 44/81, Loss: 0.27541320639498096
Epoch 45/81, Loss: 0.27358991828034906
Epoch 46/81, Loss: 0.2761620204238331
Epoch 47/81, Loss: 0.26958464524325204
Epoch 48/81, Loss: 0.2721760939149296
Epoch 49/81, Loss: 0.2719789116698153
Epoch 50/81, Loss: 0.27038850810597925
Epoch 51/81, Loss: 0.2745180541978163
Epoch 52/81, Loss: 0.2874753137721735
Epoch 53/81, Loss: 0.276582468958462
Epoch 54/81, Loss: 0.26953492006834817
Epoch 55/81, Loss: 0.27472493841367607
Epoch 56/81, Loss: 0.2703366012257688
Epoch 57/81, Loss: 0.27179477802094293
Epoch 58/81, Loss: 0.2736628169522566
Epoch 59/81, Loss: 0.26917685612159614
Epoch 60/81, Loss: 0.2729307689210948
Epoch 61/81, Loss: 0.27202916101497765
Epoch 62/81, Loss: 0.2685103780206512
Epoch 63/81, Loss: 0.26725369954810424
Epoch 64/81, Loss: 0.26784923672676086
Epoch 65/81, Loss: 0.26716573536396027
Epoch 66/81, Loss: 0.2681339646086973
Epoch 67/81, Loss: 0.269324854016304
Epoch 68/81, Loss: 0.2699620412553058
Epoch 69/81, Loss: 0.2674934381947798
Epoch 70/81, Loss: 0.27274490629925446
Epoch 71/81, Loss: 0.26669962835662503
Epoch 72/81, Loss: 0.2668500809985049
Epoch 73/81, Loss: 0.26729664995389824
Epoch 74/81, Loss: 0.2651229838238043
Epoch 75/81, Loss: 0.26646827950197105
Epoch 76/81, Loss: 0.2662987945710911

```

Epoch 77/81, Loss: 0.26722948428462534
Epoch 78/81, Loss: 0.2649303749203682
Epoch 79/81, Loss: 0.27054643280365887
Epoch 80/81, Loss: 0.26596878907259774
Epoch 81/81, Loss: 0.2642576681340442
Best Binary Accuracy: 0.9101
Best Normal Accuracy: 0.2872
Best F1 Score: 0.9529

```

```

[ ]: # 2.1.2 Deeper GCN with Residual Connections

import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from torch_geometric.data import DataLoader
from sklearn.model_selection import train_test_split
from sklearn.metrics import f1_score, accuracy_score

# Define the Residual GCN Model
class ResidualGCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
        super(ResidualGCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, 128)
        self.conv2 = GCNConv(128, 128) # Residual connection from input to
        ↪ output
        self.conv3 = GCNConv(128, 64)
        self.fc = torch.nn.Linear(64, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x1 = self.conv1(x, edge_index)
        x1 = F.relu(x1)
        x2 = self.conv2(x1, edge_index) + x1 # Add residual connection
        x2 = F.relu(x2)
        x3 = self.conv3(x2, edge_index)
        x3 = F.relu(x3)
        x = global_mean_pool(x3, data.batch)
        return torch.sigmoid(self.fc(x))

# Function to train the GCN model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)

```

```

        loss = criterion(output, data.y)
        loss.backward()
        optimizer.step()
        total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
↪len(train_loader)}')

# Function to evaluate the GCN model
def evaluate_gnn_model(model, test_loader):
    model.eval()
    total_acc, total_f1, total_normal_acc = 0, 0, 0
    num_batches = len(test_loader)

    for data in test_loader:
        with torch.no_grad():
            output = model(data)
            preds = (output > 0.5).float()
            total_acc += (preds == data.y).sum().item() / data.y.numel()
            total_f1 += f1_score(data.y.cpu(), preds.cpu(), average='micro')
            total_normal_acc += accuracy_score(data.y.cpu(), preds.cpu())

    print(f'Binary Accuracy: {total_acc / num_batches:.4f}')
    print(f'F1 Score: {total_f1 / num_batches:.4f}')
    print(f'Normal Accuracy: {total_normal_acc / num_batches:.4f}')

# Initialize the Residual GCN Model and Optimizer
residual_gcn_model = ResidualGCN(num_node_features=1, num_classes=y_train.
↪shape[1])
optimizer = torch.optim.Adam(residual_gcn_model.parameters(), lr=0.001)
criterion = torch.nn.BCELoss()

# Train and Evaluate the Residual GCN Model
train_gnn_model(residual_gcn_model, train_loader, optimizer, criterion)
evaluate_gnn_model(residual_gcn_model, test_loader)

```

```

Epoch 1/50, Loss: 0.40977052599191666
Epoch 2/50, Loss: 0.2966996466412264
Epoch 3/50, Loss: 0.2852067767697222
Epoch 4/50, Loss: 0.28455961977734284
Epoch 5/50, Loss: 0.28143780853818445
Epoch 6/50, Loss: 0.28575728351578994
Epoch 7/50, Loss: 0.2870054731474203
Epoch 8/50, Loss: 0.28114549903308644
Epoch 9/50, Loss: 0.27869916575796466
Epoch 10/50, Loss: 0.2874220434357138
Epoch 11/50, Loss: 0.27915699034929276
Epoch 12/50, Loss: 0.27465080864289226

```


Epoch 13/50, Loss: 0.27165277828188505
Epoch 14/50, Loss: 0.2811236149247955
Epoch 15/50, Loss: 0.27249398783725853
Epoch 16/50, Loss: 0.2691582656081985
Epoch 17/50, Loss: 0.2711702418677947
Epoch 18/50, Loss: 0.2708361920188455
Epoch 19/50, Loss: 0.26770998844329047
Epoch 20/50, Loss: 0.26767198741436005
Epoch 21/50, Loss: 0.2668007103835835
Epoch 22/50, Loss: 0.26665472370736737
Epoch 23/50, Loss: 0.26569752088364434
Epoch 24/50, Loss: 0.2658405014697243
Epoch 25/50, Loss: 0.2636105869622791
Epoch 26/50, Loss: 0.2629723228952464
Epoch 27/50, Loss: 0.2620156626490986
Epoch 28/50, Loss: 0.26151294874794345
Epoch 29/50, Loss: 0.2618579995982787
Epoch 30/50, Loss: 0.2621135426794781
Epoch 31/50, Loss: 0.2605519093134824
Epoch 32/50, Loss: 0.26194778172408834
Epoch 33/50, Loss: 0.26001938344801173
Epoch 34/50, Loss: 0.25827040742425356
Epoch 35/50, Loss: 0.2584061009042403
Epoch 36/50, Loss: 0.25973284332191243
Epoch 37/50, Loss: 0.2594396520186873
Epoch 38/50, Loss: 0.26110191818545847
Epoch 39/50, Loss: 0.25800127886673985
Epoch 40/50, Loss: 0.2610445228569648
Epoch 41/50, Loss: 0.2594033418332829
Epoch 42/50, Loss: 0.26014680722180533
Epoch 43/50, Loss: 0.25907038809622035
Epoch 44/50, Loss: 0.26095925052376356
Epoch 45/50, Loss: 0.2617171073661131
Epoch 46/50, Loss: 0.25717610208427205
Epoch 47/50, Loss: 0.25822924340472503
Epoch 48/50, Loss: 0.25924597855876474
Epoch 49/50, Loss: 0.2572482828708256
Epoch 50/50, Loss: 0.2587040754802087
Binary Accuracy: 0.9098
F1 Score: 0.9527
Normal Accuracy: 0.2872

```
[ ]: # GAT
import torch
import torch.nn.functional as F
from torch_geometric.nn import GATConv, global_mean_pool
from torch_geometric.data import DataLoader
```

```

from sklearn.metrics import f1_score, accuracy_score

# GAT Model Definition
class GAT(torch.nn.Module):
    def __init__(self, num_node_features, num_classes, hidden_dim1,
        hidden_dim2, heads):
        super(GAT, self).__init__()
        # GATConv layers, in_channels is a scalar representing the number of
        node features
        self.conv1 = GATConv(in_channels=num_node_features,
        out_channels=hidden_dim1, heads=heads)
        self.conv2 = GATConv(in_channels=hidden_dim1 * heads,
        out_channels=hidden_dim2, heads=1) # Single head for the second layer
        self.fc = torch.nn.Linear(hidden_dim2, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.elu(x)
        x = self.conv2(x, edge_index)
        x = F.elu(x)
        x = global_mean_pool(x, data.batch)
        return torch.sigmoid(self.fc(x))

# Function to train the GAT model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
        len(train_loader)}')

# Function to evaluate the GAT model
def evaluate_gnn_model(model, test_loader):
    model.eval()
    total_acc, total_f1, total_normal_acc = 0, 0, 0
    num_batches = len(test_loader)

    for data in test_loader:
        with torch.no_grad():

```

```

        output = model(data)
        preds = (output > 0.5).float()
        total_acc += (preds == data.y).sum().item() / data.y.numel()
        total_f1 += f1_score(data.y.cpu(), preds.cpu(), average='micro')
        total_normal_acc += accuracy_score(data.y.cpu(), preds.cpu())

    print(f'Binary Accuracy: {total_acc / num_batches:.4f}')
    print(f'F1 Score: {total_f1 / num_batches:.4f}')
    print(f'Normal Accuracy: {total_normal_acc / num_batches:.4f}')

# Train and evaluate the GAT model
def run_gat_experiment():
    # Initialize the GAT model
    model = GAT(num_node_features=1, num_classes=y_train.shape[1],
        ↪hidden_dim1=128, hidden_dim2=64, heads=4)

    # Set up optimizer and criterion
    optimizer = torch.optim.Adam(model.parameters(), lr=0.001)
    criterion = torch.nn.BCELoss()

    # Create data loaders
    train_loader = DataLoader(train_graphs, batch_size=32, shuffle=True)
    test_loader = DataLoader(test_graphs, batch_size=32, shuffle=False)

    # Train the model
    train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50)

    # Evaluate the model
    evaluate_gnn_model(model, test_loader)

# Run the experiment
run_gat_experiment()

```

```

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:
UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
  warnings.warn(out)

```

```

Epoch 1/50, Loss: 0.35357677585938396
Epoch 2/50, Loss: 0.2659758837784038
Epoch 3/50, Loss: 0.26330991220824856
Epoch 4/50, Loss: 0.2618640428956817
Epoch 5/50, Loss: 0.26475968474850936
Epoch 6/50, Loss: 0.2615349752938046
Epoch 7/50, Loss: 0.2616846263408661
Epoch 8/50, Loss: 0.26836807850529165
Epoch 9/50, Loss: 0.2659115234718603
Epoch 10/50, Loss: 0.26005418993094387
Epoch 11/50, Loss: 0.2604568666395019

```

```
Epoch 12/50, Loss: 0.2614471960593672
Epoch 13/50, Loss: 0.2606346764985253
Epoch 14/50, Loss: 0.25947807290974784
Epoch 15/50, Loss: 0.2615856103160802
Epoch 16/50, Loss: 0.2603291838484652
Epoch 17/50, Loss: 0.26111758544164543
Epoch 18/50, Loss: 0.25819076247075023
Epoch 19/50, Loss: 0.25865598680341945
Epoch 20/50, Loss: 0.2590899918885792
Epoch 21/50, Loss: 0.26015544375952554
Epoch 22/50, Loss: 0.25740544103524265
Epoch 23/50, Loss: 0.26005468166926327
Epoch 24/50, Loss: 0.2572503940147512
Epoch 25/50, Loss: 0.2608996165149352
Epoch 26/50, Loss: 0.26254732424722
Epoch 27/50, Loss: 0.2582198333214311
Epoch 28/50, Loss: 0.2576981550630401
Epoch 29/50, Loss: 0.2587903220863903
Epoch 30/50, Loss: 0.2568041853168431
Epoch 31/50, Loss: 0.2612692095777568
Epoch 32/50, Loss: 0.257519414757981
Epoch 33/50, Loss: 0.25787246139610515
Epoch 34/50, Loss: 0.25730639389332605
Epoch 35/50, Loss: 0.25954180342309613
Epoch 36/50, Loss: 0.258446880561464
Epoch 37/50, Loss: 0.2601133926826365
Epoch 38/50, Loss: 0.25731691937236223
Epoch 39/50, Loss: 0.2584214591804673
Epoch 40/50, Loss: 0.2564886887283886
Epoch 41/50, Loss: 0.26155946929665175
Epoch 42/50, Loss: 0.25797222204068126
Epoch 43/50, Loss: 0.2586630797561477
Epoch 44/50, Loss: 0.25918686696711707
Epoch 45/50, Loss: 0.25712920856826443
Epoch 46/50, Loss: 0.25571835829931144
Epoch 47/50, Loss: 0.2564181602176498
Epoch 48/50, Loss: 0.25667040488299203
Epoch 49/50, Loss: 0.25807638247223463
Epoch 50/50, Loss: 0.25848092270248074
Binary Accuracy: 0.9097
F1 Score: 0.9527
Normal Accuracy: 0.2872
```

```
[ ]: !pip install keras
```

```
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages
(3.4.1)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-
```

```

packages (from keras) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from keras) (1.26.4)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages
(from keras) (13.8.1)
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages
(from keras) (0.0.8)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages
(from keras) (3.11.0)
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages
(from keras) (0.12.1)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-
packages (from keras) (0.4.0)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from keras) (24.1)
Requirement already satisfied: typing-extensions>=4.5.0 in
/usr/local/lib/python3.10/dist-packages (from optree->keras) (4.12.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras) (2.16.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-
packages (from markdown-it-py>=2.2.0->rich->keras) (0.1.2)

```

```
[ ]: !pip install torch-scatter torch-sparse torch-geometric scikit-learn
```

```

Collecting torch-scatter
  Using cached torch_scatter-2.1.2.tar.gz (108 kB)
  Preparing metadata (setup.py) ... done
Collecting torch-sparse
  Using cached torch_sparse-0.6.18.tar.gz (209 kB)
  Preparing metadata (setup.py) ... done
Requirement already satisfied: torch-geometric in
/usr/local/lib/python3.10/dist-packages (2.6.0)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-
packages (1.3.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages
(from torch-sparse) (1.13.1)
Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (3.10.5)
Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (2024.6.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (3.1.4)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from torch-geometric) (1.26.4)
Requirement already satisfied: psutil>=5.8.0 in /usr/local/lib/python3.10/dist-
packages (from torch-geometric) (5.9.5)

```

Requirement already satisfied: pyparsing in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (3.1.4)

Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (2.32.3)

Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (4.66.5)

Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)

Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)

Requirement already satisfied: aiohappyeyeballs>=2.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (2.4.0)

Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.3.1)

Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (24.2.0)

Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.4.1)

Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (6.1.0)

Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (1.11.1)

Requirement already satisfied: async-timeout<5.0,>=4.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp->torch-geometric) (4.0.3)

Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from jinja2->torch-geometric) (2.1.5)

Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (3.3.2)

Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (3.8)

Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (2.0.7)

Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->torch-geometric) (2024.8.30)

Requirement already satisfied: typing-extensions>=4.1.0 in /usr/local/lib/python3.10/dist-packages (from multidict<7.0,>=4.5->aiohttp->torch-geometric) (4.12.2)

Building wheels for collected packages: torch-scatter, torch-sparse

Building wheel for torch-scatter (setup.py) ... done

Created wheel for torch-scatter:

filename=torch_scatter-2.1.2-cp310-cp310-linux_x86_64.whl size=3658840 sha256=b35659ef244cb0df069834186c45267e4d52d45f83a4de88e4d7785194a4cb84

Stored in directory: /root/.cache/pip/wheels/92/f1/2b/3b46d54b134259f58c8363568569053248040859b1a145b3ce

Building wheel for torch-sparse (setup.py) ... done

Created wheel for torch-sparse:

filename=torch_sparse-0.6.18-cp310-cp310-linux_x86_64.whl size=2809239

```
sha256=1ebd200f8e1ff5b16bf80a750e7435624fec26fcaab1462b6b73c6a3ddb3c72e
  Stored in directory: /root/.cache/pip/wheels/c9/dd/0f/a6a16f9f3b0236733d257b4b
4ea91b548b984a341ed3b8f38c
Successfully built torch-scatter torch-sparse
Installing collected packages: torch-scatter, torch-sparse
Successfully installed torch-scatter-2.1.2 torch-sparse-0.6.18
```

```
[ ]: # Install Keras Tuner
!pip install keras-tuner
```

```
Requirement already satisfied: keras-tuner in /usr/local/lib/python3.10/dist-
packages (1.4.7)
Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages
(from keras-tuner) (3.4.1)
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from keras-tuner) (24.1)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-
packages (from keras-tuner) (2.32.3)
Requirement already satisfied: kt-legacy in /usr/local/lib/python3.10/dist-
packages (from keras-tuner) (1.0.5)
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-
packages (from keras->keras-tuner) (1.4.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from keras->keras-tuner) (1.26.4)
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages
(from keras->keras-tuner) (13.8.1)
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages
(from keras->keras-tuner) (0.0.8)
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages
(from keras->keras-tuner) (3.11.0)
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages
(from keras->keras-tuner) (0.12.1)
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-
packages (from keras->keras-tuner) (0.4.0)
Requirement already satisfied: charset-normalizer<4,>=2 in
/usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
packages (from requests->keras-tuner) (3.8)
Requirement already satisfied: urllib3<3,>=1.21.1 in
/usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.10/dist-packages (from requests->keras-tuner) (2024.8.30)
Requirement already satisfied: typing-extensions>=4.5.0 in
/usr/local/lib/python3.10/dist-packages (from optree->keras->keras-tuner)
(4.12.2)
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (3.0.0)
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
```

```
/usr/local/lib/python3.10/dist-packages (from rich->keras->keras-tuner) (2.16.1)
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-
packages (from markdown-it-py>=2.2.0->rich->keras->keras-tuner) (0.1.2)
```

```
[ ]: !pip install scikeras
```

```
Collecting scikeras
```

```
  Downloading scikeras-0.13.0-py3-none-any.whl.metadata (3.1 kB)
```

```
Requirement already satisfied: keras>=3.2.0 in /usr/local/lib/python3.10/dist-
packages (from scikeras) (3.4.1)
```

```
Collecting scikit-learn>=1.4.2 (from scikeras)
```

```
  Downloading scikit_learn-1.5.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014
_x86_64.whl.metadata (13 kB)
```

```
Requirement already satisfied: absl-py in /usr/local/lib/python3.10/dist-
packages (from keras>=3.2.0->scikeras) (1.4.0)
```

```
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages
(from keras>=3.2.0->scikeras) (1.26.4)
```

```
Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages
(from keras>=3.2.0->scikeras) (13.8.1)
```

```
Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages
(from keras>=3.2.0->scikeras) (0.0.8)
```

```
Requirement already satisfied: h5py in /usr/local/lib/python3.10/dist-packages
(from keras>=3.2.0->scikeras) (3.11.0)
```

```
Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages
(from keras>=3.2.0->scikeras) (0.12.1)
```

```
Requirement already satisfied: ml-dtypes in /usr/local/lib/python3.10/dist-
packages (from keras>=3.2.0->scikeras) (0.4.0)
```

```
Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-
packages (from keras>=3.2.0->scikeras) (24.1)
```

```
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn>=1.4.2->scikeras) (1.13.1)
```

```
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-
packages (from scikit-learn>=1.4.2->scikeras) (1.4.2)
```

```
Requirement already satisfied: threadpoolctl>=3.1.0 in
/usr/local/lib/python3.10/dist-packages (from scikit-learn>=1.4.2->scikeras)
(3.5.0)
```

```
Requirement already satisfied: typing-extensions>=4.5.0 in
/usr/local/lib/python3.10/dist-packages (from optree->keras>=3.2.0->scikeras)
(4.12.2)
```

```
Requirement already satisfied: markdown-it-py>=2.2.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras>=3.2.0->scikeras)
(3.0.0)
```

```
Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
/usr/local/lib/python3.10/dist-packages (from rich->keras>=3.2.0->scikeras)
(2.16.1)
```

```
Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-
packages (from markdown-it-py>=2.2.0->rich->keras>=3.2.0->scikeras) (0.1.2)
```

```
Downloading scikeras-0.13.0-py3-none-any.whl (26 kB)
```


Downloading
scikit_learn-1.5.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl
(13.3 MB)

13.3/13.3 MB

71.9 MB/s eta 0:00:00

Installing collected packages: scikit-learn, scikeras

Attempting uninstall: scikit-learn

Found existing installation: scikit-learn 1.3.2

Uninstalling scikit-learn-1.3.2:

Successfully uninstalled scikit-learn-1.3.2

Successfully installed scikeras-0.13.0 scikit-learn-1.5.2

```
[ ]: !pip install tensorflow keras
```

Requirement already satisfied: tensorflow in /usr/local/lib/python3.10/dist-packages (2.17.0)

Requirement already satisfied: keras in /usr/local/lib/python3.10/dist-packages (3.4.1)

Requirement already satisfied: absl-py>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.4.0)

Requirement already satisfied: astunparse>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.6.3)

Requirement already satisfied: flatbuffers>=24.3.25 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.3.25)

Requirement already satisfied: gast!=0.5.0,!0.5.1,!0.5.2,>=0.2.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.6.0)

Requirement already satisfied: google-pasta>=0.1.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.2.0)

Requirement already satisfied: h5py>=3.10.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.11.0)

Requirement already satisfied: libclang>=13.0.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (18.1.1)

Requirement already satisfied: ml-dtypes<0.5.0,>=0.3.1 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.4.0)

Requirement already satisfied: opt-einsum>=2.3.2 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.3.0)

Requirement already satisfied: packaging in /usr/local/lib/python3.10/dist-packages (from tensorflow) (24.1)

Requirement already satisfied: protobuf!=4.21.0,!4.21.1,!4.21.2,!4.21.3,!4.21.4,!4.21.5,<5.0.0dev,>=3.20.3 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (3.20.3)

Requirement already satisfied: requests<3,>=2.21.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.32.3)

Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from tensorflow) (71.0.4)

Requirement already satisfied: six>=1.12.0 in /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.16.0)

Requirement already satisfied: termcolor>=1.1.0 in

/usr/local/lib/python3.10/dist-packages (from tensorflow) (2.4.0)
 Requirement already satisfied: typing-extensions>=3.6.6 in
 /usr/local/lib/python3.10/dist-packages (from tensorflow) (4.12.2)
 Requirement already satisfied: wrapt>=1.11.0 in /usr/local/lib/python3.10/dist-
 packages (from tensorflow) (1.16.0)
 Requirement already satisfied: grpcio<2.0,>=1.24.3 in
 /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.64.1)
 Requirement already satisfied: tensorboard<2.18,>=2.17 in
 /usr/local/lib/python3.10/dist-packages (from tensorflow) (2.17.0)
 Requirement already satisfied: tensorflow-io-gcs-filesystem>=0.23.1 in
 /usr/local/lib/python3.10/dist-packages (from tensorflow) (0.37.1)
 Requirement already satisfied: numpy<2.0.0,>=1.23.5 in
 /usr/local/lib/python3.10/dist-packages (from tensorflow) (1.26.4)
 Requirement already satisfied: rich in /usr/local/lib/python3.10/dist-packages
 (from keras) (13.8.1)
 Requirement already satisfied: namex in /usr/local/lib/python3.10/dist-packages
 (from keras) (0.0.8)
 Requirement already satisfied: optree in /usr/local/lib/python3.10/dist-packages
 (from keras) (0.12.1)
 Requirement already satisfied: wheel<1.0,>=0.23.0 in
 /usr/local/lib/python3.10/dist-packages (from astunparse>=1.6.0->tensorflow)
 (0.44.0)
 Requirement already satisfied: charset-normalizer<4,>=2 in
 /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow)
 (3.3.2)
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-
 packages (from requests<3,>=2.21.0->tensorflow) (3.8)
 Requirement already satisfied: urllib3<3,>=1.21.1 in
 /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow)
 (2.0.7)
 Requirement already satisfied: certifi>=2017.4.17 in
 /usr/local/lib/python3.10/dist-packages (from requests<3,>=2.21.0->tensorflow)
 (2024.8.30)
 Requirement already satisfied: markdown>=2.6.8 in
 /usr/local/lib/python3.10/dist-packages (from
 tensorboard<2.18,>=2.17->tensorflow) (3.7)
 Requirement already satisfied: tensorboard-data-server<0.8.0,>=0.7.0 in
 /usr/local/lib/python3.10/dist-packages (from
 tensorboard<2.18,>=2.17->tensorflow) (0.7.2)
 Requirement already satisfied: werkzeug>=1.0.1 in
 /usr/local/lib/python3.10/dist-packages (from
 tensorboard<2.18,>=2.17->tensorflow) (3.0.4)
 Requirement already satisfied: markdown-it-py>=2.2.0 in
 /usr/local/lib/python3.10/dist-packages (from rich->keras) (3.0.0)
 Requirement already satisfied: pygments<3.0.0,>=2.13.0 in
 /usr/local/lib/python3.10/dist-packages (from rich->keras) (2.16.1)
 Requirement already satisfied: mdurl~=0.1 in /usr/local/lib/python3.10/dist-
 packages (from markdown-it-py>=2.2.0->rich->keras) (0.1.2)

Requirement already satisfied: MarkupSafe>=2.1.1 in
/usr/local/lib/python3.10/dist-packages (from
werkzeug>=1.0.1->tensorboard<2.18,>=2.17->tensorflow) (2.1.5)

```
[ ]: # STACKING
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Conv1D, LSTM, Flatten, Input
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from torch_geometric.data import Data, DataLoader
from sklearn.base import BaseEstimator, ClassifierMixin
from scikeras.wrappers import KerasClassifier

# Prepare the base models (CNN, LSTM, GCN)
def build_cnn_model():
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1], 1))) # Specify input shape as the
    ↪first layer
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['binary_accuracy'])
    return model

def build_lstm_model():
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1], 1))) # Specify input shape as the
    ↪first layer
    model.add(LSTM(128))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['binary_accuracy'])
    return model

# Define GCN model
class GCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
```

```

        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, 128)
        self.conv2 = GCNConv(128, 64)
        self.fc = torch.nn.Linear(64, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, data.batch)
        return torch.sigmoid(self.fc(x))

# Convert NumPy arrays to torch_geometric Data objects
def numpy_to_geometric(X, y):
    data_list = []
    for i in range(X.shape[0]):
        x_tensor = torch.tensor(X[i], dtype=torch.float).view(-1, 1) # Shape: 1
        edge_index = torch.tensor([[0], [0]], dtype=torch.long) # Dummy
        data = Data(x=x_tensor, edge_index=edge_index, y=torch.tensor(y[i],
        dtype=torch.float).view(1, -1))
        data_list.append(data)
    return data_list

# Train the GCN model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
        len(train_loader)}')

# Wrapping GCN in scikit-learn estimator
class GCNClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, epochs=50, lr=0.001):
        self.model = GCN(num_node_features=1, num_classes=y_train.shape[1])
        self.epochs = epochs

```

```

self.lr = lr

def fit(self, X, y):
    optimizer = torch.optim.Adam(self.model.parameters(), lr=self.lr)
    criterion = torch.nn.BCELoss()
    # Convert your data into torch_geometric DataLoader for GCN
    train_data_list = numpy_to_geometric(X, y)
    train_loader = DataLoader(train_data_list, batch_size=32, shuffle=True)
    train_gnn_model(self.model, train_loader, optimizer, criterion, self.
    epochs)
    return self

def predict(self, X):
    test_data_list = numpy_to_geometric(X, np.zeros((X.shape[0], y_train.
    shape[1]))) # Dummy labels
    test_loader = DataLoader(test_data_list, batch_size=32, shuffle=False)
    self.model.eval()
    preds = []
    with torch.no_grad():
        for data in test_loader:
            output = self.model(data)
            preds.append((output > 0.5).float().cpu().numpy())
    return np.vstack(preds)

# Train CNN, LSTM, and GCN separately
cnn_clf = KerasClassifier(model=build_cnn_model, epochs=10, batch_size=64,
    verbose=0)
lstm_clf = KerasClassifier(model=build_lstm_model, epochs=10, batch_size=64,
    verbose=0)
gcn_clf = GCNClassifier()

# Convert data for CNN and LSTM models
X_train_cnn = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_cnn = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train the models separately
cnn_clf.fit(X_train_cnn, y_train)
lstm_clf.fit(X_train_cnn, y_train)
gcn_clf.fit(X_train, y_train)

# Make predictions
y_pred_cnn = cnn_clf.predict(X_test_cnn)
y_pred_lstm = lstm_clf.predict(X_test_cnn)
y_pred_gcn = gcn_clf.predict(X_test)

# Combine predictions (e.g., majority voting or averaging)
y_pred_combined = (y_pred_cnn + y_pred_lstm + y_pred_gcn) / 3

```

```

y_pred_combined = (y_pred_combined > 0.5).astype(int)

# Evaluate the combined predictions
binary_acc = np.mean(np.equal(y_test, y_pred_combined).astype(int))
normal_acc = accuracy_score(y_test, y_pred_combined)
f1 = f1_score(y_test, y_pred_combined, average="micro")

print(f'Combined Binary Accuracy: {binary_acc:.4f}')
print(f'Combined Normal Accuracy: {normal_acc:.4f}')
print(f'Combined F1 Score: {f1:.4f}')

```

```

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:
UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
  warnings.warn(out)

```

```

Epoch 1/50, Loss: 0.6739373960915733
Epoch 2/50, Loss: 0.516200849238564
Epoch 3/50, Loss: 0.29819218332276626
Epoch 4/50, Loss: 0.26257388600531745
Epoch 5/50, Loss: 0.2589092342292561
Epoch 6/50, Loss: 0.2570877881611095
Epoch 7/50, Loss: 0.25859983002438264
Epoch 8/50, Loss: 0.2591512071735719
Epoch 9/50, Loss: 0.2583932727575302
Epoch 10/50, Loss: 0.257055439054966
Epoch 11/50, Loss: 0.25774850082748074
Epoch 12/50, Loss: 0.26023025153314366
Epoch 13/50, Loss: 0.2565988126923056
Epoch 14/50, Loss: 0.25922684853567796
Epoch 15/50, Loss: 0.25824036624501734
Epoch 16/50, Loss: 0.25621501268709407
Epoch 17/50, Loss: 0.2580552031012142
Epoch 18/50, Loss: 0.2586713170304018
Epoch 19/50, Loss: 0.2573778484674061
Epoch 20/50, Loss: 0.2599196052726577
Epoch 21/50, Loss: 0.25765814193907904
Epoch 22/50, Loss: 0.25725574002546425
Epoch 23/50, Loss: 0.2587461142855532
Epoch 24/50, Loss: 0.25984319474767237
Epoch 25/50, Loss: 0.2600095399162349
Epoch 26/50, Loss: 0.25921396122259255
Epoch 27/50, Loss: 0.25611692228738
Epoch 28/50, Loss: 0.25813260586822734
Epoch 29/50, Loss: 0.2632749510162017
Epoch 30/50, Loss: 0.25847487546065273
Epoch 31/50, Loss: 0.25935643692226973
Epoch 32/50, Loss: 0.2573310049141155
Epoch 33/50, Loss: 0.2561477887279847

```

Epoch 34/50, Loss: 0.25697218232295094
Epoch 35/50, Loss: 0.25843360844780416
Epoch 36/50, Loss: 0.2573666099239798
Epoch 37/50, Loss: 0.2588011407676865
Epoch 38/50, Loss: 0.2588825935826582
Epoch 39/50, Loss: 0.2586155446136699
Epoch 40/50, Loss: 0.25716781484730106
Epoch 41/50, Loss: 0.26015467152876015
Epoch 42/50, Loss: 0.25855714783949013
Epoch 43/50, Loss: 0.25645596884629307
Epoch 44/50, Loss: 0.25892195105552673
Epoch 45/50, Loss: 0.25508502169566993
Epoch 46/50, Loss: 0.2577857042060179
Epoch 47/50, Loss: 0.256553759031436
Epoch 48/50, Loss: 0.25614406124633904
Epoch 49/50, Loss: 0.25632842542494044

WARNING:tensorflow:5 out of the last 11 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x7f3b4bea3880> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

Epoch 50/50, Loss: 0.2565710426253431

WARNING:tensorflow:5 out of the last 11 calls to <function TensorFlowTrainer.make_predict_function.<locals>.one_step_on_data_distributed at 0x7f3b4bea3880> triggered tf.function retracing. Tracing is expensive and the excessive number of tracings could be due to (1) creating @tf.function repeatedly in a loop, (2) passing tensors with different shapes, (3) passing Python objects instead of tensors. For (1), please define your @tf.function outside of the loop. For (2), @tf.function has reduce_retracing=True option that can avoid unnecessary retracing. For (3), please refer to https://www.tensorflow.org/guide/function#controlling_retracing and https://www.tensorflow.org/api_docs/python/tf/function for more details.

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26: UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
warnings.warn(out)

Combined Binary Accuracy: 0.9114
Combined Normal Accuracy: 0.2884
Combined F1 Score: 0.9536

```
[ ]: #STACKING - CNN,GCN,XGBoost

import numpy as np
import pandas as pd
from sklearn.ensemble import StackingClassifier, RandomForestClassifier
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Conv1D, Flatten, Input
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from torch_geometric.data import DataLoader
from sklearn.base import BaseEstimator, ClassifierMixin
from scikeras.wrappers import KerasClassifier

# Prepare the base models (CNN, GCN, XGBoost)
def build_cnn_model():
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1], 1))) # Specify input shape as the
    ↪first layer
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['binary_accuracy'])
    return model

# Define GCN model
class GCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, 128)
        self.conv2 = GCNConv(128, 64)
        self.fc = torch.nn.Linear(64, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, data.batch)
        return torch.sigmoid(self.fc(x))
```



```

# Convert NumPy arrays to torch_geometric Data objects
def numpy_to_geometric(X, y):
    data_list = []
    for i in range(X.shape[0]):
        x_tensor = torch.tensor(X[i], dtype=torch.float).view(-1, 1) # Shape:
        ↪(1024, 1)
        edge_index = torch.tensor([[0], [0]], dtype=torch.long) # Dummy
        ↪edge_index, modify if you have real edges
        data = Data(x=x_tensor, edge_index=edge_index, y=torch.tensor(y[i],
        ↪dtype=torch.float).view(1, -1))
        data_list.append(data)
    return data_list

# Train the GCN model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
        ↪len(train_loader)}')

# Wrapping GCN in scikit-learn estimator
class GCNClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, epochs=50, lr=0.001):
        self.model = GCN(num_node_features=1, num_classes=y_train.shape[1])
        self.epochs = epochs
        self.lr = lr

    def fit(self, X, y):
        optimizer = torch.optim.Adam(self.model.parameters(), lr=self.lr)
        criterion = torch.nn.BCELoss()
        # Convert your data into torch_geometric DataLoader for GCN
        train_data_list = numpy_to_geometric(X, y)
        train_loader = DataLoader(train_data_list, batch_size=32, shuffle=True)
        train_gnn_model(self.model, train_loader, optimizer, criterion, self.
        ↪epochs)
        return self

    def predict(self, X):

```

```

        test_data_list = numpy_to_geometric(X, np.zeros((X.shape[0], y_train.
↪shape[1]))) # Dummy labels
        test_loader = DataLoader(test_data_list, batch_size=32, shuffle=False)
        self.model.eval()
        preds = []
        with torch.no_grad():
            for data in test_loader:
                output = self.model(data)
                preds.append((output > 0.5).float().cpu().numpy())
        return np.vstack(preds)

# Train CNN, GCN, and XGBoost separately
cnn_clf = KerasClassifier(model=build_cnn_model, epochs=10, batch_size=64,
↪verbose=0)
gcn_clf = GCNClassifier()
xgb_clf = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')

# Convert data for CNN model
X_train_cnn = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_cnn = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train the models separately
cnn_clf.fit(X_train_cnn, y_train)
gcn_clf.fit(X_train, y_train)
xgb_clf.fit(X_train, y_train)

# Make predictions
y_pred_cnn = cnn_clf.predict(X_test_cnn)
y_pred_gcn = gcn_clf.predict(X_test)
y_pred_xgb = xgb_clf.predict(X_test)

# Combine predictions (e.g., majority voting or averaging)
y_pred_combined = (y_pred_cnn + y_pred_gcn + y_pred_xgb) / 3
y_pred_combined = (y_pred_combined > 0.5).astype(int)

# Evaluate the combined predictions
binary_acc = np.mean(np.equal(y_test, y_pred_combined).astype(int))
normal_acc = accuracy_score(y_test, y_pred_combined)
f1 = f1_score(y_test, y_pred_combined, average="micro")

print(f'Combined Binary Accuracy: {binary_acc:.4f}')
print(f'Combined Normal Accuracy: {normal_acc:.4f}')
print(f'Combined F1 Score: {f1:.4f}')

```

```

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:
UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
warnings.warn(out)

```

Epoch 1/50, Loss: 0.6835679709911346
Epoch 2/50, Loss: 0.5414968860499999
Epoch 3/50, Loss: 0.3169667238698286
Epoch 4/50, Loss: 0.2672891862252179
Epoch 5/50, Loss: 0.26069994402282376
Epoch 6/50, Loss: 0.2581184133887291
Epoch 7/50, Loss: 0.25941094142549176
Epoch 8/50, Loss: 0.2586912907221738
Epoch 9/50, Loss: 0.257185157169314
Epoch 10/50, Loss: 0.2569063967641662
Epoch 11/50, Loss: 0.25725077487090053
Epoch 12/50, Loss: 0.25880808076437783
Epoch 13/50, Loss: 0.26063894874909344
Epoch 14/50, Loss: 0.2568010337212506
Epoch 15/50, Loss: 0.25858409746604805
Epoch 16/50, Loss: 0.2599362923818476
Epoch 17/50, Loss: 0.2572337945594507
Epoch 18/50, Loss: 0.25850092970273075
Epoch 19/50, Loss: 0.25629755065721627
Epoch 20/50, Loss: 0.2569630557999891
Epoch 21/50, Loss: 0.2587113831849659
Epoch 22/50, Loss: 0.2570759049233268
Epoch 23/50, Loss: 0.25866379895631003
Epoch 24/50, Loss: 0.2569151095607701
Epoch 25/50, Loss: 0.25623830407857895
Epoch 26/50, Loss: 0.2574890895801432
Epoch 27/50, Loss: 0.2557968339499305
Epoch 28/50, Loss: 0.2583071396631353
Epoch 29/50, Loss: 0.25793038703062954
Epoch 30/50, Loss: 0.2565421133356936
Epoch 31/50, Loss: 0.25644948815598206
Epoch 32/50, Loss: 0.25924227649674697
Epoch 33/50, Loss: 0.25696951063240275
Epoch 34/50, Loss: 0.26029423098353777
Epoch 35/50, Loss: 0.25965481339132085
Epoch 36/50, Loss: 0.2574901870068382
Epoch 37/50, Loss: 0.2580518538461012
Epoch 38/50, Loss: 0.2573310483027907
Epoch 39/50, Loss: 0.256336992716088
Epoch 40/50, Loss: 0.25705330030006524
Epoch 41/50, Loss: 0.257974773645401
Epoch 42/50, Loss: 0.25994909028796587
Epoch 43/50, Loss: 0.2576182449565214
Epoch 44/50, Loss: 0.25712910645148335
Epoch 45/50, Loss: 0.2566972208373687
Epoch 46/50, Loss: 0.2556195929646492
Epoch 47/50, Loss: 0.2557796380099128
Epoch 48/50, Loss: 0.25889087556039586

Epoch 49/50, Loss: 0.25743040880736184

Epoch 50/50, Loss: 0.2568163065349354

/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning:

[17:38:42] WARNING: /workspace/src/learner.cc:740:

Parameters: { "use_label_encoder" } are not used.

```
warnings.warn(smsg, UserWarning)
```

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:

UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead

```
warnings.warn(out)
```

Combined Binary Accuracy: 0.9036

Combined Normal Accuracy: 0.2097

Combined F1 Score: 0.9486

```
[ ]: # weighted voting stack

import numpy as np
import pandas as pd
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Conv1D, Flatten, Input
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from torch_geometric.data import DataLoader
from scikeras.wrappers import KerasClassifier

# Prepare the base models (CNN, GCN, XGBoost)
def build_cnn_model():
    model = Sequential()
    model.add(Input(shape=(X_train.shape[1], 1))) # Specify input shape as the
    ↪first layer
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu'))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['binary_accuracy'])
    return model

# Define GCN model
class GCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
        super(GCN, self).__init__()
```

```

self.conv1 = GCNConv(num_node_features, 128)
self.conv2 = GCNConv(128, 64)
self.fc = torch.nn.Linear(64, num_classes)

def forward(self, data):
    x, edge_index = data.x, data.edge_index
    x = self.conv1(x, edge_index)
    x = F.relu(x)
    x = self.conv2(x, edge_index)
    x = F.relu(x)
    x = global_mean_pool(x, data.batch)
    return torch.sigmoid(self.fc(x))

# Convert NumPy arrays to torch_geometric Data objects
def numpy_to_geometric(X, y):
    data_list = []
    for i in range(X.shape[0]):
        x_tensor = torch.tensor(X[i], dtype=torch.float).view(-1, 1) # Shape:
        ↪ (1024, 1)
        edge_index = torch.tensor([[0], [0]], dtype=torch.long) # Dummy
        ↪ edge_index
        data = Data(x=x_tensor, edge_index=edge_index, y=torch.tensor(y[i],
        ↪ dtype=torch.float).view(1, -1))
        data_list.append(data)
    return data_list

# Train the GCN model
def train_gnn_model(model, train_loader, optimizer, criterion, num_epochs=50):
    model.train()
    for epoch in range(num_epochs):
        total_loss = 0
        for data in train_loader:
            optimizer.zero_grad()
            output = model(data)
            loss = criterion(output, data.y)
            loss.backward()
            optimizer.step()
            total_loss += loss.item()
        print(f'Epoch {epoch + 1}/{num_epochs}, Loss: {total_loss /
        ↪ len(train_loader)}')

# Wrapping GCN in scikit-learn estimator
class GCNClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, epochs=50, lr=0.001):
        self.model = GCN(num_node_features=1, num_classes=y_train.shape[1])
        self.epochs = epochs
        self.lr = lr

```

```

def fit(self, X, y):
    optimizer = torch.optim.Adam(self.model.parameters(), lr=self.lr)
    criterion = torch.nn.BCELoss()
    train_data_list = numpy_to_geometric(X, y)
    train_loader = DataLoader(train_data_list, batch_size=32, shuffle=True)
    train_gnn_model(self.model, train_loader, optimizer, criterion, self.
    epochs)
    return self

def predict(self, X):
    test_data_list = numpy_to_geometric(X, np.zeros((X.shape[0], y_train.
    shape[1]))) # Dummy labels
    test_loader = DataLoader(test_data_list, batch_size=32, shuffle=False)
    self.model.eval()
    preds = []
    with torch.no_grad():
        for data in test_loader:
            output = self.model(data)
            preds.append((output > 0.5).float().cpu().numpy())
    return np.vstack(preds)

# CNN and GCN classifiers
cnn_clf = KerasClassifier(model=build_cnn_model, epochs=10, batch_size=64,
    verbose=0)
gcn_clf = GCNClassifier()

# XGBoost Classifier
xgb_clf = XGBClassifier(use_label_encoder=False, eval_metric='mlogloss')

# Reshape data for CNN
X_train_cnn = X_train.reshape((X_train.shape[0], X_train.shape[1], 1))
X_test_cnn = X_test.reshape((X_test.shape[0], X_test.shape[1], 1))

# Train the models
cnn_clf.fit(X_train_cnn, y_train)
gcn_clf.fit(X_train, y_train)
xgb_clf.fit(X_train, y_train)

# Get predictions
y_pred_cnn = cnn_clf.predict(X_test_cnn)
y_pred_gcn = gcn_clf.predict(X_test)
y_pred_xgb = xgb_clf.predict(X_test)

# Apply weighted voting (assigning different weights)
weights = [0.3, 0.3, 0.4] # Adjust based on individual model performance

```

```

y_pred_combined = (weights[0] * y_pred_cnn + weights[1] * y_pred_gcn +
↳weights[2] * y_pred_xgb) / sum(weights)
y_pred_combined = (y_pred_combined > 0.5).astype(int)

# Evaluate the combined predictions
binary_acc = np.mean(np.equal(y_test, y_pred_combined).astype(int))
normal_acc = accuracy_score(y_test, y_pred_combined)
f1 = f1_score(y_test, y_pred_combined, average="micro")

print(f'Weighted Combined Binary Accuracy: {binary_acc:.4f}')
print(f'Weighted Combined Normal Accuracy: {normal_acc:.4f}')
print(f'Weighted Combined F1 Score: {f1:.4f}')

```

```

/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:
UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
  warnings.warn(out)

```

```

Epoch 1/50, Loss: 0.6648543371873743
Epoch 2/50, Loss: 0.5041698673192192
Epoch 3/50, Loss: 0.30221597149091606
Epoch 4/50, Loss: 0.26395757846972523
Epoch 5/50, Loss: 0.26018740412066965
Epoch 6/50, Loss: 0.2587503137833932
Epoch 7/50, Loss: 0.2594177451203851
Epoch 8/50, Loss: 0.25928236281170564
Epoch 9/50, Loss: 0.2580554130322793
Epoch 10/50, Loss: 0.2577374196227859
Epoch 11/50, Loss: 0.25821089218644533
Epoch 12/50, Loss: 0.25897260974435243
Epoch 13/50, Loss: 0.2611478650394608
Epoch 14/50, Loss: 0.2567102650509161
Epoch 15/50, Loss: 0.25586119425647397
Epoch 16/50, Loss: 0.2565890769748127
Epoch 17/50, Loss: 0.25657804266494866
Epoch 18/50, Loss: 0.2560475630795254
Epoch 19/50, Loss: 0.2575608395478305
Epoch 20/50, Loss: 0.2590412501903141
Epoch 21/50, Loss: 0.2556345554835656
Epoch 22/50, Loss: 0.25624973239267573
Epoch 23/50, Loss: 0.25925029770416375
Epoch 24/50, Loss: 0.25813396055908766
Epoch 25/50, Loss: 0.25686664528706493
Epoch 26/50, Loss: 0.25663844408357844
Epoch 27/50, Loss: 0.2568141940762015
Epoch 28/50, Loss: 0.26106853870784535
Epoch 29/50, Loss: 0.2593110234421842
Epoch 30/50, Loss: 0.25686338237103296
Epoch 31/50, Loss: 0.25578832056592493

```

```
Epoch 32/50, Loss: 0.25763848774573384
Epoch 33/50, Loss: 0.2571669207776294
Epoch 34/50, Loss: 0.25816017739913044
Epoch 35/50, Loss: 0.25845351727569804
Epoch 36/50, Loss: 0.2565111706362051
Epoch 37/50, Loss: 0.2584740409956259
Epoch 38/50, Loss: 0.2559247889062938
Epoch 39/50, Loss: 0.2566489603589563
Epoch 40/50, Loss: 0.25794688086299333
Epoch 41/50, Loss: 0.2594768812551218
Epoch 42/50, Loss: 0.2584151336375405
Epoch 43/50, Loss: 0.25652579437283907
Epoch 44/50, Loss: 0.257324598291341
Epoch 45/50, Loss: 0.25777848941438336
Epoch 46/50, Loss: 0.25773319339050965
Epoch 47/50, Loss: 0.25667060122770424
Epoch 48/50, Loss: 0.257029487806208
Epoch 49/50, Loss: 0.25525499222909703
Epoch 50/50, Loss: 0.25613880069816813
```

```
/usr/local/lib/python3.10/dist-packages/xgboost/core.py:158: UserWarning:
[18:04:10] WARNING: /workspace/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.
```

```
warnings.warn(msg, UserWarning)
/usr/local/lib/python3.10/dist-packages/torch_geometric/deprecation.py:26:
UserWarning: 'data.DataLoader' is deprecated, use 'loader.DataLoader' instead
warnings.warn(out)
```

```
Weighted Combined Binary Accuracy: 0.9032
Weighted Combined Normal Accuracy: 0.2172
Weighted Combined F1 Score: 0.9485
```

```
[ ]: !pip install transformers rdkit-pypi torch torchvision
```

```
Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-
packages (4.44.2)
Requirement already satisfied: rdkit-pypi in /usr/local/lib/python3.10/dist-
packages (2022.9.5)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages
(2.4.0+cu121)
Requirement already satisfied: torchvision in /usr/local/lib/python3.10/dist-
packages (0.19.0+cu121)
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-
packages (from transformers) (3.16.0)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in
/usr/local/lib/python3.10/dist-packages (from transformers) (0.24.6)
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-
packages (from transformers) (1.26.4)
```


Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (24.1)
 Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
 Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2024.5.15)
 Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from transformers) (2.32.3)
 Requirement already satisfied: safetensors>=0.4.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.4.5)
 Requirement already satisfied: tokenizers<0.20,>=0.19 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.19.1)
 Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.66.5)
 Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (9.4.0)
 Requirement already satisfied: typing-extensions>=4.8.0 in /usr/local/lib/python3.10/dist-packages (from torch) (4.12.2)
 Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch) (1.13.2)
 Requirement already satisfied: networkx in /usr/local/lib/python3.10/dist-packages (from torch) (3.3)
 Requirement already satisfied: Jinja2 in /usr/local/lib/python3.10/dist-packages (from torch) (3.1.4)
 Requirement already satisfied: fsspec in /usr/local/lib/python3.10/dist-packages (from torch) (2024.6.1)
 Requirement already satisfied: MarkupSafe>=2.0 in /usr/local/lib/python3.10/dist-packages (from Jinja2->torch) (2.1.5)
 Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.3.2)
 Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.8)
 Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.7)
 Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2024.8.30)
 Requirement already satisfied: mpmath<1.4,>=1.1.0 in /usr/local/lib/python3.10/dist-packages (from sympy->torch) (1.3.0)

```
[ ]: # molbert

import torch
from transformers import RobertaTokenizer, RobertaModel
from rdkit import Chem
import numpy as np
import pandas as pd
```

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from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, f1_score
from sklearn.ensemble import RandomForestClassifier

# Load pre-trained ChemBERTa (RobertaModel)
tokenizer = RobertaTokenizer.from_pretrained("seyonec/ChemBERTa-zinc-base-v1")
model = RobertaModel.from_pretrained("seyonec/ChemBERTa-zinc-base-v1")

# Function to convert SMILES into ChemBERTa embeddings
def smiles_to_chemberta(smiles_list):
    embeddings = []
    for smile in smiles_list:
        inputs = tokenizer(smile, return_tensors="pt", truncation=True,
        ↪padding=True)
        with torch.no_grad():
            outputs = model(**inputs)
            # Take the mean of the last hidden state for each token to get the
            ↪molecular embedding
            mol_embedding = torch.mean(outputs.last_hidden_state, dim=1).squeeze().
            ↪cpu().numpy()
            embeddings.append(mol_embedding)
    return np.array(embeddings)

# Load your dataset (assuming you have a 'Chemical Compound' column with SMILES
↪strings)
adr_df = pd.read_csv('binary adr.csv')

# Extract SMILES
smiles_list = adr_df['Chemical Compound']

# Convert SMILES to ChemBERTa embeddings
X = smiles_to_chemberta(smiles_list)

# Target (Adverse Reaction Labels)
reaction_columns = ['Hepatobiliary disorders', 'Metabolism and nutrition
↪disorders', 'Eye disorders',
                    'Musculoskeletal and connective tissue disorders',
↪'Gastrointestinal disorders',
                    'Immune system disorders', 'Reproductive system and breast
↪disorders',
                    'Neoplasms benign, malignant and unspecified (incl cysts
↪and polyps)',
                    'General disorders and administration site conditions',
↪'Endocrine disorders',
                    'Surgical and medical procedures', 'Vascular disorders',
↪'Blood and lymphatic system disorders',

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        'Skin and subcutaneous tissue disorders', 'Congenital,
↳familial and genetic disorders',
        'Infections and infestations', 'Respiratory, thoracic and
↳mediastinal disorders',
        'Psychiatric disorders', 'Renal and urinary disorders',
↳'Pregnancy, puerperium and perinatal conditions',
        'Ear and labyrinth disorders', 'Cardiac disorders',
↳'Nervous system disorders',
        'Injury, poisoning and procedural complications']

y = adr_df[reaction_columns].values

# Split into training and testing data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
↳random_state=42)

# Train a classifier using the ChemBERTa embeddings
rf_clf = RandomForestClassifier()
rf_clf.fit(X_train, y_train)

# Predict and evaluate
y_pred = rf_clf.predict(X_test)

# Evaluate
binary_acc = np.mean(np.equal(y_test, y_pred).astype(int))
f1 = f1_score(y_test, y_pred, average="micro")

print(f'ChemBERTa Binary Accuracy: {binary_acc:.4f}')
print(f'ChemBERTa F1 Score: {f1:.4f}')

```

/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_token.py:89:

UserWarning:

The secret `HF_TOKEN` does not exist in your Colab secrets.

To authenticate with the Hugging Face Hub, create a token in your settings tab (<https://huggingface.co/settings/tokens>), set it as secret in your Google Colab and restart your session.

You will be able to reuse this secret in all of your notebooks.

Please note that authentication is recommended but still optional to access public models or datasets.

warnings.warn(

tokenizer_config.json: 0%| | 0.00/166 [00:00<?, ?B/s]

vocab.json: 0%| | 0.00/9.43k [00:00<?, ?B/s]

merges.txt: 0%| | 0.00/3.21k [00:00<?, ?B/s]

special_tokens_map.json: 0%| | 0.00/150 [00:00<?, ?B/s]

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config.json: 0%|          | 0.00/501 [00:00<?, ?B/s]

/usr/local/lib/python3.10/dist-
packages/transformers/tokenization_utils_base.py:1601: FutureWarning:
`clean_up_tokenization_spaces` was not set. It will be set to `True` by default.
This behavior will be deprecated in transformers v4.45, and will be then set to
`False` by default. For more details check this issue:
https://github.com/huggingface/transformers/issues/31884
  warnings.warn(

pytorch_model.bin: 0%|          | 0.00/179M [00:00<?, ?B/s]

ChemBERTa Binary Accuracy: 0.9090
ChemBERTa F1 Score: 0.9519

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[ ]: # Combine ChemBERTa embeddings with Morgan Fingerprints
from rdkit.Chem import AllChem

# Generate Morgan Fingerprints (1024-bit)
morgan_fingerprints = [AllChem.GetMorganFingerprintAsBitVect(Chem.
    ↪MolFromSmiles(smile), 2, nBits=1024) for smile in smiles_list]

# Convert to NumPy arrays
fingerprint_array = []
for fp in morgan_fingerprints:
    arr = np.zeros((1,))
    DataStructs.ConvertToNumpyArray(fp, arr)
    fingerprint_array.append(arr)
fingerprint_array = np.array(fingerprint_array)

# Combine both feature sets
X_combined = np.hstack((X, fingerprint_array))

# Use the combined features for training
X_train, X_test, y_train, y_test = train_test_split(X_combined, y, test_size=0.
    ↪2, random_state=42)

# Train and evaluate (e.g., with RandomForestClassifier)
rf_clf.fit(X_train, y_train)
y_pred = rf_clf.predict(X_test)
binary_acc = np.mean(np.equal(y_test, y_pred).astype(int))
f1 = f1_score(y_test, y_pred, average="micro")

print(f'Hybrid Binary Accuracy: {binary_acc:.4f}')
print(f'Hybrid F1 Score: {f1:.4f}')

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Hybrid Binary Accuracy: 0.9096
Hybrid F1 Score: 0.9523

```

```
[ ]: !pip install --upgrade scikit-learn
```

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Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (1.5.2)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn) (3.5.0)
```

```
[ ]: # NEW START
```

```
[ ]: !pip install rdkit-pypi
!pip install torch torch-geometric transformers scikit-learn tensorflow
```

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Requirement already satisfied: rdkit-pypi in /usr/local/lib/python3.10/dist-packages (2022.9.5)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (1.26.4)
Requirement already satisfied: Pillow in /usr/local/lib/python3.10/dist-packages (from rdkit-pypi) (10.4.0)
Requirement already satisfied: torch in /usr/local/lib/python3.10/dist-packages (2.4.1+cu121)
```

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Collecting torch-geometric
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  Downloading torch_geometric-2.6.0-py3-none-any.whl.metadata (63 kB)
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63.1/63.1 kB
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Requirement already satisfied: transformers in /usr/local/lib/python3.10/dist-packages (4.44.2)
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Requirement already satisfied: sympy in /usr/local/lib/python3.10/dist-packages (from torch) (1.13.2)
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Requirement already satisfied: aiohttp in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (3.10.5)
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Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (2.32.3)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from torch-geometric) (4.66.5)
Requirement already satisfied: huggingface-hub<1.0,>=0.23.2 in /usr/local/lib/python3.10/dist-packages (from transformers) (0.24.7)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (24.1)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.0.2)
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 Requirement already satisfied: frozenlist>=1.1.1 in
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 Requirement already satisfied: multidict<7.0,>=4.5 in
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 Requirement already satisfied: async-timeout<5.0,>=4.0 in
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 Requirement already satisfied: MarkupSafe>=2.0 in
 /usr/local/lib/python3.10/dist-packages (from jinja2->torch) (2.1.5)
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 Downloading torch_geometric-2.6.0-py3-none-any.whl (1.1 MB)
 1.1/1.1 MB
 51.4 MB/s eta 0:00:00
 Installing collected packages: torch-geometric
 Successfully installed torch-geometric-2.6.0

```
[ ]: # Hybrid Deep Learning Model (GNN + CNN/MLP + LSTM)

import numpy as np
import torch
import torch.nn.functional as F
from torch_geometric.nn import GCNConv, global_mean_pool
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv1D, LSTM, Dropout
from sklearn.metrics import accuracy_score, f1_score
from sklearn.model_selection import train_test_split

# Assuming X and y are your feature and label datasets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
    random_state=42)

# Convert to tensors for GCN model training
X_train_tensor = torch.tensor(X_train, dtype=torch.float)
```



```

X_test_tensor = torch.tensor(X_test, dtype=torch.float)
y_train_tensor = torch.tensor(y_train, dtype=torch.float)
y_test_tensor = torch.tensor(y_test, dtype=torch.float)

# GCN Model for GNN
class GCN(torch.nn.Module):
    def __init__(self, num_node_features, num_classes):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(num_node_features, 128)
        self.conv2 = GCNConv(128, 64)
        self.fc = torch.nn.Linear(64, num_classes)

    def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = F.relu(x)
        x = self.conv2(x, edge_index)
        x = F.relu(x)
        x = global_mean_pool(x, data.batch)
        return torch.sigmoid(self.fc(x))

# CNN model
def build_cnn_model():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu',
    ↪input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.5))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['accuracy'])
    return model

# LSTM model
def build_lstm_model():
    model = Sequential()
    model.add(LSTM(128, input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.5))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
    ↪metrics=['accuracy'])
    return model

# Custom binary accuracy calculation

```

```

def calculate_binary_accuracy(y_true, y_pred):
    return np.mean(np.equal(y_true, y_pred).astype(int))

# Train CNN and LSTM
cnn_model = build_cnn_model()
cnn_model.fit(X_train, y_train, epochs=20, batch_size=64, validation_split=0.2)

lstm_model = build_lstm_model()
lstm_model.fit(X_train, y_train, epochs=20, batch_size=64, validation_split=0.2)

# Assuming GCN is wrapped and trained as before (you will need a proper GCN
↳data loader)
# Train and evaluate GCN similarly if required

# Evaluate CNN and LSTM Models
y_pred_cnn = cnn_model.predict(X_test)
y_pred_lstm = lstm_model.predict(X_test)

# Convert predictions to binary labels (0 or 1)
y_pred_cnn_bin = (y_pred_cnn > 0.5).astype(int)
y_pred_lstm_bin = (y_pred_lstm > 0.5).astype(int)

# Binary accuracy calculation
cnn_bin_acc = calculate_binary_accuracy(y_test, y_pred_cnn_bin)
lstm_bin_acc = calculate_binary_accuracy(y_test, y_pred_lstm_bin)

# Normal accuracy and F1 score
cnn_normal_acc = accuracy_score(y_test, y_pred_cnn_bin)
lstm_normal_acc = accuracy_score(y_test, y_pred_lstm_bin)

cnn_f1_score = f1_score(y_test, y_pred_cnn_bin, average='micro')
lstm_f1_score = f1_score(y_test, y_pred_lstm_bin, average='micro')

# Print metrics for CNN
print(f"Binary Accuracy (CNN): {cnn_bin_acc:.4f}")
print(f"Normal Accuracy (CNN): {cnn_normal_acc:.4f}")
print(f"F1 Score (CNN): {cnn_f1_score:.4f}")

# Print metrics for LSTM
print(f"Binary Accuracy (LSTM): {lstm_bin_acc:.4f}")
print(f"Normal Accuracy (LSTM): {lstm_normal_acc:.4f}")
print(f"F1 Score (LSTM): {lstm_f1_score:.4f}")

```

Epoch 1/20

/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential

models, prefer using an ``Input(shape)`` object as the first layer in the model instead.

```
super().__init__(activity_regularizer=activity_regularizer, **kwargs)
```

```
14/14          6s 229ms/step -
accuracy: 0.0048 - loss: 0.4659 - val_accuracy: 0.0000e+00 - val_loss: 0.3061
Epoch 2/20
14/14          0s 8ms/step -
accuracy: 0.0000e+00 - loss: 0.2665 - val_accuracy: 0.0000e+00 - val_loss:
0.2782
Epoch 3/20
14/14          0s 7ms/step -
accuracy: 0.0016 - loss: 0.2326 - val_accuracy: 0.0000e+00 - val_loss: 0.2759
Epoch 4/20
14/14          0s 7ms/step -
accuracy: 6.3803e-04 - loss: 0.2067 - val_accuracy: 0.0000e+00 - val_loss:
0.2723
Epoch 5/20
14/14          0s 7ms/step -
accuracy: 4.1813e-04 - loss: 0.1923 - val_accuracy: 0.0000e+00 - val_loss:
0.2792
Epoch 6/20
14/14          0s 6ms/step -
accuracy: 7.6824e-04 - loss: 0.1660 - val_accuracy: 0.0000e+00 - val_loss:
0.2897
Epoch 7/20
14/14          0s 7ms/step -
accuracy: 4.1813e-04 - loss: 0.1585 - val_accuracy: 0.0000e+00 - val_loss:
0.3066
Epoch 8/20
14/14          0s 7ms/step -
accuracy: 0.0019 - loss: 0.1363 - val_accuracy: 0.0000e+00 - val_loss: 0.3236
Epoch 9/20
14/14          0s 7ms/step -
accuracy: 0.0035 - loss: 0.1222 - val_accuracy: 0.0000e+00 - val_loss: 0.3415
Epoch 10/20
14/14          0s 6ms/step -
accuracy: 0.0013 - loss: 0.1110 - val_accuracy: 0.0000e+00 - val_loss: 0.3620
Epoch 11/20
14/14          0s 7ms/step -
accuracy: 0.0013 - loss: 0.0932 - val_accuracy: 0.0000e+00 - val_loss: 0.3791
Epoch 12/20
14/14          0s 8ms/step -
accuracy: 0.0035 - loss: 0.0842 - val_accuracy: 0.0000e+00 - val_loss: 0.4081
Epoch 13/20
14/14          0s 7ms/step -
accuracy: 0.0019 - loss: 0.0728 - val_accuracy: 0.0000e+00 - val_loss: 0.4304
Epoch 14/20
```

```

14/14          0s 7ms/step -
accuracy: 0.0013 - loss: 0.0635 - val_accuracy: 0.0000e+00 - val_loss: 0.4556
Epoch 15/20
14/14          0s 8ms/step -
accuracy: 2.3662e-04 - loss: 0.0571 - val_accuracy: 0.0141 - val_loss: 0.4844
Epoch 16/20
14/14          0s 9ms/step -
accuracy: 6.3803e-04 - loss: 0.0534 - val_accuracy: 0.0141 - val_loss: 0.5031
Epoch 17/20
14/14          0s 8ms/step -
accuracy: 0.0016 - loss: 0.0505 - val_accuracy: 0.0188 - val_loss: 0.5279
Epoch 18/20
14/14          0s 7ms/step -
accuracy: 0.0036 - loss: 0.0433 - val_accuracy: 0.0188 - val_loss: 0.5477
Epoch 19/20
14/14          0s 7ms/step -
accuracy: 0.0108 - loss: 0.0408 - val_accuracy: 0.0235 - val_loss: 0.5674
Epoch 20/20
14/14          0s 7ms/step -
accuracy: 0.0092 - loss: 0.0397 - val_accuracy: 0.0235 - val_loss: 0.5909
Epoch 1/20

```

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.

```

```

    super().__init__(**kwargs)

```

```

14/14          3s 81ms/step -
accuracy: 0.0035 - loss: 0.6689 - val_accuracy: 0.0000e+00 - val_loss: 0.3455
Epoch 2/20
14/14          1s 51ms/step -
accuracy: 0.0000e+00 - loss: 0.3113 - val_accuracy: 0.0000e+00 - val_loss:
0.2627
Epoch 3/20
14/14          1s 52ms/step -
accuracy: 0.0000e+00 - loss: 0.2662 - val_accuracy: 0.0000e+00 - val_loss:
0.2582
Epoch 4/20
14/14          1s 44ms/step -
accuracy: 0.0000e+00 - loss: 0.2607 - val_accuracy: 0.0000e+00 - val_loss:
0.2581
Epoch 5/20
14/14          1s 44ms/step -
accuracy: 0.0000e+00 - loss: 0.2715 - val_accuracy: 0.0000e+00 - val_loss:
0.2566
Epoch 6/20
14/14          1s 45ms/step -
accuracy: 0.0035 - loss: 0.2721 - val_accuracy: 0.0000e+00 - val_loss: 0.2558

```

Epoch 7/20
 14/14 1s 44ms/step -
 accuracy: 5.2229e-04 - loss: 0.2684 - val_accuracy: 0.0000e+00 - val_loss: 0.2563

Epoch 8/20
 14/14 1s 44ms/step -
 accuracy: 0.0016 - loss: 0.2598 - val_accuracy: 0.0000e+00 - val_loss: 0.2572

Epoch 9/20
 14/14 1s 44ms/step -
 accuracy: 0.0000e+00 - loss: 0.2654 - val_accuracy: 0.0000e+00 - val_loss: 0.2568

Epoch 10/20
 14/14 1s 44ms/step -
 accuracy: 4.1813e-04 - loss: 0.2581 - val_accuracy: 0.0000e+00 - val_loss: 0.2570

Epoch 11/20
 14/14 1s 44ms/step -
 accuracy: 7.6824e-04 - loss: 0.2610 - val_accuracy: 0.0000e+00 - val_loss: 0.2567

Epoch 12/20
 14/14 1s 44ms/step -
 accuracy: 9.1705e-04 - loss: 0.2674 - val_accuracy: 0.0000e+00 - val_loss: 0.2568

Epoch 13/20
 14/14 1s 43ms/step -
 accuracy: 0.0000e+00 - loss: 0.2641 - val_accuracy: 0.0000e+00 - val_loss: 0.2573

Epoch 14/20
 14/14 1s 43ms/step -
 accuracy: 0.0019 - loss: 0.2607 - val_accuracy: 0.0000e+00 - val_loss: 0.2564

Epoch 15/20
 14/14 1s 50ms/step -
 accuracy: 7.6824e-04 - loss: 0.2536 - val_accuracy: 0.0000e+00 - val_loss: 0.2564

Epoch 16/20
 14/14 1s 49ms/step -
 accuracy: 0.0035 - loss: 0.2716 - val_accuracy: 0.0000e+00 - val_loss: 0.2566

Epoch 17/20
 14/14 1s 52ms/step -
 accuracy: 0.0013 - loss: 0.2645 - val_accuracy: 0.0000e+00 - val_loss: 0.2568

Epoch 18/20
 14/14 1s 54ms/step -
 accuracy: 3.2343e-04 - loss: 0.2488 - val_accuracy: 0.0000e+00 - val_loss: 0.2570

Epoch 19/20
 14/14 1s 44ms/step -
 accuracy: 6.3803e-04 - loss: 0.2605 - val_accuracy: 0.0000e+00 - val_loss: 0.2569

```

Epoch 20/20
14/14          1s 43ms/step -
accuracy: 0.0035 - loss: 0.2657 - val_accuracy: 0.0000e+00 - val_loss: 0.2567
9/9           1s 38ms/step
9/9           0s 22ms/step
Binary Accuracy (CNN): 0.8841
Normal Accuracy (CNN): 0.1199
F1 Score (CNN): 0.9369
Binary Accuracy (LSTM): 0.9114
Normal Accuracy (LSTM): 0.2884
F1 Score (LSTM): 0.9536

```

```

[ ]: import torch
import torch.nn.functional as F
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv1D, LSTM
from sklearn.metrics import accuracy_score, f1_score
import numpy as np

# Assuming X_train, X_test, y_train, y_test are defined as your feature and
↳ label sets.

# Binary Accuracy Calculation
def calculate_binary_accuracy(y_true, y_pred):
    return np.mean(np.equal(y_true, y_pred).astype(int))

# CNN model
def build_cnn_model():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu',
↳ input_shape=(X_train.shape[1], 1)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
↳ metrics=['accuracy'])
    return model

# LSTM model
def build_lstm_model():
    model = Sequential()
    model.add(LSTM(128, input_shape=(X_train.shape[1], 1)))
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
↳ metrics=['accuracy'])

```

```

    return model

# Train CNN model and calculate binary accuracy on both training and test sets
cnn_model = build_cnn_model()

# Train CNN for 10 epochs and calculate binary accuracy on the training set at
↳ each epoch
for epoch in range(15):
    cnn_model.fit(X_train, y_train, epochs=1, batch_size=64, verbose=1)

    # Predict on training set and calculate binary accuracy
    y_pred_train_cnn = cnn_model.predict(X_train)
    y_pred_train_cnn_bin = (y_pred_train_cnn > 0.5).astype(int)
    train_binary_acc_cnn = calculate_binary_accuracy(y_train,
↳ y_pred_train_cnn_bin)
    print(f"Training Binary Accuracy (CNN, Epoch {epoch+1}):
↳ {train_binary_acc_cnn:.4f}")

# Calculate binary accuracy on the test set
y_pred_test_cnn = cnn_model.predict(X_test)
y_pred_test_cnn_bin = (y_pred_test_cnn > 0.5).astype(int)
test_binary_acc_cnn = calculate_binary_accuracy(y_test, y_pred_test_cnn_bin)
print(f"Test Set Binary Accuracy (CNN): {test_binary_acc_cnn:.4f}")

# Train LSTM model and calculate binary accuracy on both training and test sets
lstm_model = build_lstm_model()

# Train LSTM for 10 epochs and calculate binary accuracy on the training set at
↳ each epoch
for epoch in range(15):
    lstm_model.fit(X_train, y_train, epochs=1, batch_size=64, verbose=1)

    # Predict on training set and calculate binary accuracy
    y_pred_train_lstm = lstm_model.predict(X_train)
    y_pred_train_lstm_bin = (y_pred_train_lstm > 0.5).astype(int)
    train_binary_acc_lstm = calculate_binary_accuracy(y_train,
↳ y_pred_train_lstm_bin)
    print(f"Training Binary Accuracy (LSTM, Epoch {epoch+1}):
↳ {train_binary_acc_lstm:.4f}")

# Calculate binary accuracy on the test set
y_pred_test_lstm = lstm_model.predict(X_test)
y_pred_test_lstm_bin = (y_pred_test_lstm > 0.5).astype(int)
test_binary_acc_lstm = calculate_binary_accuracy(y_test, y_pred_test_lstm_bin)
print(f"Test Set Binary Accuracy (LSTM): {test_binary_acc_lstm:.4f}")

```

```

# Calculate F1 score for CNN and LSTM models
cnn_f1 = f1_score(y_test, y_pred_test_cnn_bin, average='micro')
lstm_f1 = f1_score(y_test, y_pred_test_lstm_bin, average='micro')

# Print F1 scores
print(f"F1 Score (CNN): {cnn_f1:.4f}")
print(f"F1 Score (LSTM): {lstm_f1:.4f}")

```

```

/usr/local/lib/python3.10/dist-
packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not
pass an `input_shape`/`input_dim` argument to a layer. When using Sequential
models, prefer using an `Input(shape)` object as the first layer in the model
instead.

```

```

    super().__init__(activity_regularizer=activity_regularizer, **kwargs)

```

```

17/17          3s 82ms/step -
accuracy: 0.1590 - loss: 0.4489
34/34          1s 14ms/step
Training Binary Accuracy (CNN, Epoch 1): 0.9017
17/17          0s 5ms/step -
accuracy: 0.1472 - loss: 0.2459
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 2): 0.9172
17/17          0s 5ms/step -
accuracy: 0.0034 - loss: 0.2244
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 3): 0.9251
17/17          0s 5ms/step -
accuracy: 0.0011 - loss: 0.1959
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 4): 0.9297
17/17          0s 5ms/step -
accuracy: 0.0011 - loss: 0.1679
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 5): 0.9353
17/17          0s 4ms/step -
accuracy: 0.0025 - loss: 0.1545
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 6): 0.9492
17/17          0s 5ms/step -
accuracy: 5.0381e-04 - loss: 0.1336
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 7): 0.9585
17/17          0s 5ms/step -
accuracy: 0.0031 - loss: 0.1227
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 8): 0.9623
17/17          0s 5ms/step -

```



```

accuracy: 0.0041 - loss: 0.1033
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 9): 0.9712
17/17          0s 5ms/step -
accuracy: 0.0018 - loss: 0.0901
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 10): 0.9740
17/17          0s 5ms/step -
accuracy: 0.0012 - loss: 0.0777
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 11): 0.9800
17/17          0s 5ms/step -
accuracy: 0.0018 - loss: 0.0667
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 12): 0.9843
17/17          0s 5ms/step -
accuracy: 0.0034 - loss: 0.0628
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 13): 0.9865
17/17          0s 5ms/step -
accuracy: 0.0068 - loss: 0.0535
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 14): 0.9890
17/17          0s 5ms/step -
accuracy: 0.0065 - loss: 0.0480
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 15): 0.9909
9/9            0s 9ms/step
Test Set Binary Accuracy (CNN): 0.8803

/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When
using Sequential models, prefer using an `Input(shape)` object as the first
layer in the model instead.
    super().__init__(**kwargs)

17/17          2s 44ms/step -
accuracy: 0.0122 - loss: 0.6623
34/34          1s 15ms/step
Training Binary Accuracy (LSTM, Epoch 1): 0.8999
17/17          1s 37ms/step -
accuracy: 0.0483 - loss: 0.2942
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 2): 0.8999
17/17          1s 37ms/step -
accuracy: 9.1225e-04 - loss: 0.2640
34/34          1s 16ms/step
Training Binary Accuracy (LSTM, Epoch 3): 0.8999
17/17          1s 42ms/step -

```

```

accuracy: 6.7974e-04 - loss: 0.2604
34/34          1s 18ms/step
Training Binary Accuracy (LSTM, Epoch 4): 0.8999
17/17          1s 46ms/step -
accuracy: 1.5858e-04 - loss: 0.2580
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 5): 0.8999
17/17          1s 37ms/step -
accuracy: 0.0012 - loss: 0.2677
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 6): 0.8999
17/17          1s 37ms/step -
accuracy: 0.0012 - loss: 0.2542
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 7): 0.8999
17/17          1s 36ms/step -
accuracy: 6.7974e-04 - loss: 0.2572
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 8): 0.8999
17/17          1s 36ms/step -
accuracy: 1.5858e-04 - loss: 0.2516
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 9): 0.8999
17/17          1s 37ms/step -
accuracy: 0.0022 - loss: 0.2578
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 10): 0.8999
17/17          1s 37ms/step -
accuracy: 7.8825e-04 - loss: 0.2547
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 11): 0.8999
17/17          1s 42ms/step -
accuracy: 3.4523e-04 - loss: 0.2572
34/34          1s 16ms/step
Training Binary Accuracy (LSTM, Epoch 12): 0.8999
17/17          1s 46ms/step -
accuracy: 0.0017 - loss: 0.2510
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 13): 0.8999
17/17          1s 38ms/step -
accuracy: 0.0011 - loss: 0.2648
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 14): 0.8999
17/17          1s 37ms/step -
accuracy: 7.8825e-04 - loss: 0.2549
34/34          0s 11ms/step
Training Binary Accuracy (LSTM, Epoch 15): 0.8999
9/9            0s 11ms/step

```

Test Set Binary Accuracy (LSTM): 0.9114
F1 Score (CNN): 0.9348
F1 Score (LSTM): 0.9536

```
[ ]: # Hybrid Deep Learning Model (GNN + CNN/MLP + LSTM) - to prevent overfitting
      ↪ using dropout for CNN and LSTM

import torch
import torch.nn.functional as F
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv1D, LSTM, Dropout
from sklearn.metrics import accuracy_score, f1_score
import numpy as np

# Assuming X_train, X_test, y_train, y_test are defined as your feature and
      ↪ label sets.

# Binary Accuracy Calculation
def calculate_binary_accuracy(y_true, y_pred):
    return np.mean(np.equal(y_true, y_pred).astype(int))

# CNN model with Dropout
def build_cnn_model_with_dropout():
    model = Sequential()
    model.add(Conv1D(filters=64, kernel_size=3, activation='relu',
      ↪ input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.5)) # Dropout layer added here
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5)) # Dropout layer added here
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
      ↪ metrics=['accuracy'])
    return model

# LSTM model with Dropout
def build_lstm_model_with_dropout():
    model = Sequential()
    model.add(LSTM(128, input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.5)) # Dropout layer added here
    model.add(Flatten())
    model.add(Dense(128, activation='relu'))
    model.add(Dropout(0.5)) # Dropout layer added here
    model.add(Dense(y_train.shape[1], activation='sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy',
      ↪ metrics=['accuracy'])
    return model
```

```

# Train CNN model and calculate binary accuracy on both training and test sets
cnn_model = build_cnn_model_with_dropout()

# Train CNN for 15 epochs and calculate binary accuracy on the training set at
↳ each epoch
for epoch in range(20):
    cnn_model.fit(X_train, y_train, epochs=1, batch_size=64, verbose=1)

    # Predict on training set and calculate binary accuracy
    y_pred_train_cnn = cnn_model.predict(X_train)
    y_pred_train_cnn_bin = (y_pred_train_cnn > 0.5).astype(int)
    train_binary_acc_cnn = calculate_binary_accuracy(y_train,
↳ y_pred_train_cnn_bin)
    print(f"Training Binary Accuracy (CNN, Epoch {epoch+1}):
↳ {train_binary_acc_cnn:.4f}")

# Calculate binary accuracy on the test set
y_pred_test_cnn = cnn_model.predict(X_test)
y_pred_test_cnn_bin = (y_pred_test_cnn > 0.5).astype(int)
test_binary_acc_cnn = calculate_binary_accuracy(y_test, y_pred_test_cnn_bin)
print(f"Test Set Binary Accuracy (CNN): {test_binary_acc_cnn:.4f}")

# Train LSTM model and calculate binary accuracy on both training and test sets
lstm_model = build_lstm_model_with_dropout()

# Train LSTM for 15 epochs and calculate binary accuracy on the training set at
↳ each epoch
for epoch in range(15):
    lstm_model.fit(X_train, y_train, epochs=1, batch_size=64, verbose=1)

    # Predict on training set and calculate binary accuracy
    y_pred_train_lstm = lstm_model.predict(X_train)
    y_pred_train_lstm_bin = (y_pred_train_lstm > 0.5).astype(int)
    train_binary_acc_lstm = calculate_binary_accuracy(y_train,
↳ y_pred_train_lstm_bin)
    print(f"Training Binary Accuracy (LSTM, Epoch {epoch+1}):
↳ {train_binary_acc_lstm:.4f}")

# Calculate binary accuracy on the test set
y_pred_test_lstm = lstm_model.predict(X_test)
y_pred_test_lstm_bin = (y_pred_test_lstm > 0.5).astype(int)
test_binary_acc_lstm = calculate_binary_accuracy(y_test, y_pred_test_lstm_bin)
print(f"Test Set Binary Accuracy (LSTM): {test_binary_acc_lstm:.4f}")

# Calculate F1 score for CNN and LSTM models

```

```

cnn_f1 = f1_score(y_test, y_pred_test_cnn_bin, average='micro')
lstm_f1 = f1_score(y_test, y_pred_test_lstm_bin, average='micro')

# Print F1 scores
print(f"F1 Score (CNN): {cnn_f1:.4f}")
print(f"F1 Score (LSTM): {lstm_f1:.4f}")

```

/usr/local/lib/python3.10/dist-packages/keras/src/layers/convolutional/base_conv.py:107: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.

```

super().__init__(activity_regularizer=activity_regularizer, **kwargs)
17/17          14s 216ms/step -
accuracy: 0.0972 - loss: 0.5176
34/34          1s 17ms/step
Training Binary Accuracy (CNN, Epoch 1): 0.9001
17/17          0s 6ms/step -
accuracy: 0.0184 - loss: 0.3431
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 2): 0.9009
17/17          0s 6ms/step -
accuracy: 0.0103 - loss: 0.3008
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 3): 0.9052
17/17          0s 7ms/step -
accuracy: 0.0025 - loss: 0.2624
34/34          0s 3ms/step
Training Binary Accuracy (CNN, Epoch 4): 0.9088
17/17          0s 12ms/step -
accuracy: 0.0034 - loss: 0.2605
34/34          0s 4ms/step
Training Binary Accuracy (CNN, Epoch 5): 0.9118
17/17          0s 9ms/step -
accuracy: 0.0080 - loss: 0.2326
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 6): 0.9179
17/17          0s 13ms/step -
accuracy: 0.0025 - loss: 0.2242
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 7): 0.9228
17/17          0s 6ms/step -
accuracy: 0.0071 - loss: 0.2091
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 8): 0.9248
17/17          0s 7ms/step -
accuracy: 0.0037 - loss: 0.2075

```

```

34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 9): 0.9268
17/17          0s 7ms/step -
accuracy: 7.8825e-04 - loss: 0.1818
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 10): 0.9289
17/17          0s 8ms/step -
accuracy: 8.3514e-04 - loss: 0.1842
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 11): 0.9286
17/17          0s 7ms/step -
accuracy: 0.0012 - loss: 0.1698
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 12): 0.9392
17/17          0s 6ms/step -
accuracy: 4.9648e-04 - loss: 0.1638
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 13): 0.9459
17/17          0s 6ms/step -
accuracy: 0.0036 - loss: 0.1625
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 14): 0.9482
17/17          0s 6ms/step -
accuracy: 0.0013 - loss: 0.1499
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 15): 0.9502
17/17          0s 6ms/step -
accuracy: 0.0083 - loss: 0.1509
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 16): 0.9571
17/17          0s 6ms/step -
accuracy: 5.8329e-04 - loss: 0.1451
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 17): 0.9600
17/17          0s 6ms/step -
accuracy: 0.0020 - loss: 0.1356
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 18): 0.9603
17/17          0s 6ms/step -
accuracy: 0.0032 - loss: 0.1372
34/34          0s 2ms/step
Training Binary Accuracy (CNN, Epoch 19): 0.9606
17/17          0s 6ms/step -
accuracy: 0.0017 - loss: 0.1257
34/34          0s 1ms/step
Training Binary Accuracy (CNN, Epoch 20): 0.9664
9/9           0s 53ms/step
Test Set Binary Accuracy (CNN): 0.8968

```

```
/usr/local/lib/python3.10/dist-packages/keras/src/layers/rnn/rnn.py:204:  
UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When  
using Sequential models, prefer using an `Input(shape)` object as the first  
layer in the model instead.
```

```
    super().__init__(**kwargs)
```

```
17/17          5s 47ms/step -  
accuracy: 0.0339 - loss: 0.6619  
34/34          1s 23ms/step  
Training Binary Accuracy (LSTM, Epoch 1): 0.8854  
17/17          1s 50ms/step -  
accuracy: 0.0367 - loss: 0.3534  
34/34          1s 16ms/step  
Training Binary Accuracy (LSTM, Epoch 2): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0138 - loss: 0.3091  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 3): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0119 - loss: 0.2847  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 4): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0102 - loss: 0.2899  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 5): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0053 - loss: 0.2894  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 6): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0014 - loss: 0.2827  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 7): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0030 - loss: 0.2947  
34/34          0s 12ms/step  
Training Binary Accuracy (LSTM, Epoch 8): 0.8999  
17/17          1s 38ms/step -  
accuracy: 0.0035 - loss: 0.2646  
34/34          1s 16ms/step  
Training Binary Accuracy (LSTM, Epoch 9): 0.8999  
17/17          1s 46ms/step -  
accuracy: 4.9648e-04 - loss: 0.2792  
34/34          1s 16ms/step  
Training Binary Accuracy (LSTM, Epoch 10): 0.8999  
17/17          1s 44ms/step -  
accuracy: 0.0000e+00 - loss: 0.2744
```

```
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 11): 0.8999
17/17          1s 39ms/step -
accuracy: 0.0032 - loss: 0.2758
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 12): 0.8999
17/17          1s 38ms/step -
accuracy: 0.0017 - loss: 0.2672
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 13): 0.8999
17/17          1s 38ms/step -
accuracy: 0.0000e+00 - loss: 0.2678
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 14): 0.8999
17/17          1s 38ms/step -
accuracy: 0.0000e+00 - loss: 0.2720
34/34          0s 12ms/step
Training Binary Accuracy (LSTM, Epoch 15): 0.8999
9/9            0s 13ms/step
Test Set Binary Accuracy (LSTM): 0.9114
F1 Score (CNN): 0.9445
F1 Score (LSTM): 0.9536
```