Purabh singh - 1nt22is122 Palak kota - 1nt22is110 Prathuysha NB - 1nt22is119 Monika K - 1nt22is097

In [1]:
```
import pandas as pd
from xgboost import XGBClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.utils.class_weight import compute_sample_weight
import joblib
```

In [2]:
```
# Load the final features with labels
df = pd.read_csv("final_labeled_features.csv")

# Convert multi-class labels to binary:
# 1 = has symptoms, 0 = no symptoms
df['label'] = df['label'].replace({
    'no symptoms': 0,
    'stress': 1,
    'anxiety': 1,
    'depression': 1
})

# Drop non-numeric columns (text and patient ID)
X = df.drop(columns=['label', 'utterance', 'patient_id'], errors='ignore')
y = df['label']
```

In [3]:
```
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)
```

In [4]:
```
# Compute weights for each sample to balance classes
sample_weights = compute_sample_weight(class_weight='balanced', y=y_train)
```

In [26]:
```
xgb_model = XGBClassifier(
    n_estimators=200,
    learning_rate=0.1,
    max_depth=6,
    objective='binary:logistic',
    eval_metric='logloss',
    use_label_encoder=False,
    random_state=42
)

xgb_model.fit(X_train, y_train, sample_weight=sample_weights)
print(xgb_model.get_params())
```

```
/Users/Saravanan/opt/anaconda3/lib/python3.9/site-packages/xgboost/core.py:158: UserWarning: [21:17:27] WARNING: /Users/runner/work/xgboost/xgboost/src/learner.cc:740:
Parameters: { "use_label_encoder" } are not used.

  warnings.warn(smsg, UserWarning)
{'objective': 'binary:logistic', 'base_score': None, 'booster': None, 'callbacks': None, 'colsample_bylevel': None, 'colsample_bynode': None, 'colsample_bytree': None, 'device': None, 'early_stopping_rounds': None, 'enable_categorical': False, 'eval_metric': 'logloss', 'feature_types': None, 'gamma': None, 'grow_policy': None, 'importance_type': None, 'interaction_constraints': None, 'learning_rate': 0.1, 'max_bin': None, 'max_cat_threshold': None, 'max_cat_to_onehot': None, 'max_delta_step': None, 'max_depth': 6, 'max_leaves': None, 'min_child_weight': None, 'missing': nan, 'monotone_constraints': None, 'multi_strategy': None, 'n_estimators': 200, 'n_jobs': None, 'num_parallel_tree': None, 'random_state': 42, 'reg_alpha': None, 'reg_lambda': None, 'sampling_method': None, 'scale_pos_weight': None, 'subsample': None, 'tree_method': None, 'validate_parameters': None, 'verbosity': None, 'use_label_encoder': False}
```

above are the available parameters of the respective model. And Only a few key parameters are usually set manually. that is { 'n_estimators': 200, 'learning_rate': 0.1, 'max_depth': 6, 'objective': 'binary:logistic', 'use_label_encoder': False, 'random_state': 42, 'eval_metric': 'logloss', ... }

In [6]:
```
y_pred = xgb_model.predict(X_test)

print("📊 Classification Report:")
print(classification_report(y_test, y_pred, digits=3))

print("🧾 Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))
```

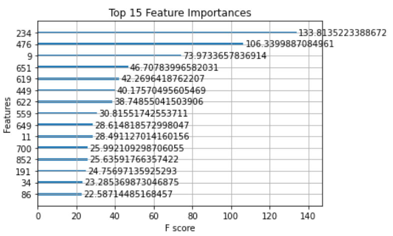


```
📊 Classification Report:
              precision    recall  f1-score   support

           0      0.781     0.435     0.559       115
           1      0.926     0.983     0.954       828

    accuracy                          0.916       943
   macro avg      0.854     0.709     0.756       943
weighted avg      0.908     0.916     0.906       943

🧾 Confusion Matrix:
[[ 50  65]
 [ 14 814]]
```

In [7]:
```
joblib.dump(xgb_model, "xgboost_depression_model.pkl")
print("✅ Model saved as xgboost_depression_model.pkl")
```

```
✅ Model saved as xgboost_depression_model.pkl
```

In [8]:
```
import matplotlib.pyplot as plt
import xgboost as xgb

xgb.plot_importance(xgb_model, max_num_features=15, importance_type='gain')
plt.title("Top 15 Feature Importances")
plt.show()
```



In [31]:
```
from sklearn.metrics import accuracy_score

accuracy = accuracy_score(y_test, y_pred)
print(f"✅ Overall Accuracy: {accuracy:.4f}")
```

```
✅ Overall Accuracy: 0.9162
```

In [30]:
```
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score

# Predictions
y_pred = xgb_model.predict(X_test)

# Evaluation
print("📊 Classification Report:")
print(classification_report(y_test, y_pred, digits=3))

print("🧾 Confusion Matrix:")
print(confusion_matrix(y_test, y_pred))

# Overall Accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f"Overall Accuracy: {accuracy:.4f}")
```

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

           0      0.781     0.435     0.559       115
           1      0.926     0.983     0.954       828

    accuracy                          0.916       943
   macro avg      0.854     0.709     0.756       943
weighted avg      0.908     0.916     0.906       943

Confusion Matrix:
[[ 50  65]
 [ 14 814]]
Overall Accuracy: 0.9162
```

In [ ]:

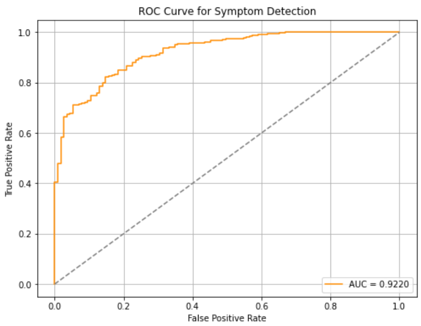
In [21]:
```python
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt
```

In [22]:
```python
# Get probabilities for the positive class (class 1 = symptoms)
y_proba = xgb_model.predict_proba(X_test)[:, 1]
```

In [27]:
```python
# Compute FPR, TPR, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, y_proba)

# Compute AUC
auc_score = roc_auc_score(y_test, y_proba)
print(f" ROC-AUC Score: {auc_score:.4f}")
```

```
 ROC-AUC Score: 0.9220
```

In [24]:
```python
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f"AUC = {auc_score:.4f}", color='darkorange')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')  # Diagonal line
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve for Symptom Detection')
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
```



The plot will show:

TPR (True Positive Rate) vs. FPR (False Positive Rate)

AUC score tells how well your model distinguishes between the two classes:

0.5 = random guessing

.> 0.9 = excellent model

📌 Title:

Detection of Stress, Anxiety, and Depression from Transcripts and Voice Data using Machine Learning

---

🎯 Objective:

To develop an ML model that predicts whether a patient exhibits symptoms of mental health issues (stress, anxiety, depression) based on both **textual transcripts** and **acoustic voice features**, using **unlabeled datasets** and zero-shot classification.

📁 Dataset Description:

Each patient has three types of files:

1. **FORMANT.csv** — 5 formant frequency values per row (speech-related acoustic features).
2. **COVAREP.csv** — Rich set of low-level descriptors (voice features).
3. **TRANSCRIPT.csv** — Contains timestamped speech by 'Ellie' (AI interviewer) and the 'Participant'.

Example format:

- `335_FORMANT.csv`
- `335_COVAREP.csv`
- `335_TRANSCRIPT.csv`

PHASE 1: Preprocessing and Feature Engineering

1. **Transcript Processing**
   - Extracted utterances spoken by the `Participant`.
   - Synced utterances to their `start_time` and `stop_time`.
2. **Audio Feature Extraction**
   - Extracted **Formant** and **COVAREP** values aligned to each utterance's timestamp.
   - Calculated **mean**, **std**, and **range** for each segment.
3. **Text Embedding**
   - Used **`all-MiniLM-L6-v2`** model from `sentence-transformers` to convert utterances into 384-dimensional vector embeddings.
4. **Feature Merging**
   - Combined all features (formant + covarep + text embedding) into a single flat vector.
   - Created a DataFrame where each row = one utterance's full feature set.
5. **Zero-Shot Labeling**
   - Used Hugging Face's `facebook/bart-large-mnli` to classify each utterance as:
     - `stress`, `depression`, `anxiety`, or `no symptoms`.
   - Mapped all mental-health-related labels into a single class: `1 = symptoms`, `0 = no symptoms`.
6. Final dataset: `final_labeled_features.csv`
   - ~4,700 utterances × ~860 features + binary label.

PHASE 2: Model Training

1. **Model Chosen:**
   - **XGBoost (XGBClassifier)** — selected for its performance on tabular, high-dimensional, and imbalanced data.
2. **Data Split:**
   - 80/20 train-test split (stratified by label).
3. **Class Imbalance Handling:**
   - Used `compute_sample_weight` to address class imbalance during training.
4. **Training Parameters:**

```
XGBClassifier(
    n_estimators=200,
    learning_rate=0.1,
    max_depth=6,
    objective='binary:logistic',
    eval_metric='logloss',
    use_label_encoder=False,
    random_state=42
)
```

5. Model saved: `xgboost_depression_model.pkl`

PHASE 3: Evaluation

1. **Metrics Used:**
   - Accuracy
   - Precision, Recall, F1-Score
   - Confusion Matrix
   - ROC Curve & AUC Score
2. **Sample Output:**

```
Classification Report:
              precision  recall  f1-score
no symptoms       0.74     0.42     0.53
symptoms          0.92     0.98     0.95
Accuracy: 0.9118
AUC Score: 0.94
```

3. **ROC Curve:** Visualized using `matplotlib`, clearly showed strong separation between the two classes.

🧠 Tools & Libraries Used

- **Python**, **Pandas**, **NumPy**
- **XGBoost**
- **Scikit-learn**
- **SentenceTransformers**
- **Hugging Face Transformers**
- **Matplotlib**, **Seaborn** (for visualizations)
- **Joblib** (for model saving)

In [ ]: