In [1]:

```
#Import Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split, GridSearchCV
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix
import xgboost as xgb
```

In [2]:

```
#Load Data
df = pd.read_csv('C:\liver_cirrhosis.csv')
df.head()
```

Out[2]:

	N_Days	Status	Drug	Age	Sex	Ascites	Hepatomegaly	Spiders	Edema	Biliru
0	2221	C	Placebo	18499	F	N	Y	N	N	
1	1230	C	Placebo	19724	M	Y	N	Y	N	
2	4184	C	Placebo	11839	F	N	N	N	N	
3	2090	D	Placebo	16467	F	N	N	N	N	
4	2105	D	Placebo	21699	F	N	Y	N	N	

In [3]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999
Data columns (total 19 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   N_Days         25000 non-null  int64  
 1   Status         25000 non-null  object 
 2   Drug           25000 non-null  object 
 3   Age            25000 non-null  int64  
 4   Sex            25000 non-null  object 
 5   Ascites        25000 non-null  object 
 6   Hepatomegaly   25000 non-null  object 
 7   Spiders        25000 non-null  object 
 8   Edema          25000 non-null  object 
 9   Bilirubin      25000 non-null  float64
 10  Cholesterol    25000 non-null  float64
 11  Albumin        25000 non-null  float64
 12  Copper         25000 non-null  float64
 13  Alk_Phos       25000 non-null  float64
 14  SGOT           25000 non-null  float64
 15  Tryglicerides  25000 non-null  float64
 16  Platelets      25000 non-null  float64
 17  Prothrombin    25000 non-null  float64
 18  Stage          25000 non-null  int64  
dtypes: float64(9), int64(3), object(7)
memory usage: 3.6+ MB
```

In [4]:
```
print(df.describe())
```

```
             N_Days           Age     Bilirubin   Cholesterol       Albumin  \
count  25000.000000  25000.000000  25000.000000  25000.000000  25000.000000   
mean    1887.117040  18495.877080      3.402644    372.331471      3.486578   
std     1091.690918   3737.596616      4.707491    193.668452      0.380488   
min       41.000000   9598.000000      0.300000    120.000000      1.960000   
25%     1080.000000  15694.000000      0.800000    275.000000      3.290000   
50%     1680.000000  18499.000000      1.300000    369.510563      3.510000   
75%     2576.000000  20955.000000      3.400000    369.510563      3.750000   
max     4795.000000  28650.000000     28.000000   1775.000000      4.640000   

             Copper      Alk_Phos          SGOT  Tryglicerides     Platelets  \
count  25000.000000  25000.000000  25000.000000   25000.000000  25000.000000   
mean     100.184663   1995.675597    123.166345     123.822548    256.007337   
std       73.184840   1798.885660     47.747616      52.786350     98.679006   
min        4.000000    289.000000     26.350000      33.000000     62.000000   
25%       52.000000   1032.000000     92.000000      92.000000    189.000000   
50%       97.648387   1828.000000    122.556346     124.702128    251.000000   
75%      107.000000   1982.655769    134.850000     127.000000    311.000000   
max      588.000000  13862.400000    457.250000     598.000000    721.000000   

        Prothrombin        Stage  
count  25000.000000  25000.00000  
mean      10.734549      2.00116  
std        0.904436      0.81387  
min        9.000000      1.00000  
25%       10.000000      1.00000  
50%       10.600000      2.00000  
75%       11.100000      3.00000  
max       18.000000      3.00000  
```

In [5]:
```
print(df.isnull().sum())
```

```
N_Days           0
Status           0
Drug             0
Age              0
Sex              0
Ascites          0
Hepatomegaly     0
Spiders          0
Edema            0
Bilirubin        0
Cholesterol      0
Albumin          0
Copper           0
Alk_Phos         0
SGOT             0
Tryglicerides    0
Platelets        0
Prothrombin      0
Stage            0
dtype: int64
```

In [6]:

```
print("\nClass Distribution:")
print(df['Stage'].value_counts())
```

```
Class Distribution:
Stage
2    8441
3    8294
1    8265
Name: count, dtype: int64
```

In [7]:

```
df = df.drop(columns=['N_Days'], errors='ignore')
df
```

Out[7]:

	Status	Drug	Age	Sex	Ascites	Hepatomegaly	Spiders	Edema	Biliru
0	C	Placebo	18499	F	N	Y	N	N	
1	C	Placebo	19724	M	Y	N	Y	N	
2	C	Placebo	11839	F	N	N	N	N	
3	D	Placebo	16467	F	N	N	N	N	
4	D	Placebo	21699	F	N	Y	N	N	
...	...	...	...	...	...	...	...	...	
24995	D	D-penicillamine	23612	F	N	N	N	N	
24996	D	D-penicillamine	23612	F	N	N	N	N	
24997	D	D-penicillamine	16736	F	N	Y	Y	Y	
24998	C	D-penicillamine	16990	F	N	Y	N	N	
24999	C	D-penicillamine	16990	F	N	Y	N	N	

25000 rows × 18 columns

In [8]:

```
df['Age'].describe()
```

Out[8]:

```
count    25000.000000
mean     18495.877080
std       3737.596616
min       9598.000000
25%      15694.000000
50%      18499.000000
75%      20955.000000
max      28650.000000
Name: Age, dtype: float64
```

In [9]:

```
print(df['Age'].head())
```

```
0    18499
1    19724
2    11839
3    16467
4    21699
Name: Age, dtype: int64
```

In [10]:

```
df['Age'] = df['Age']/365
```

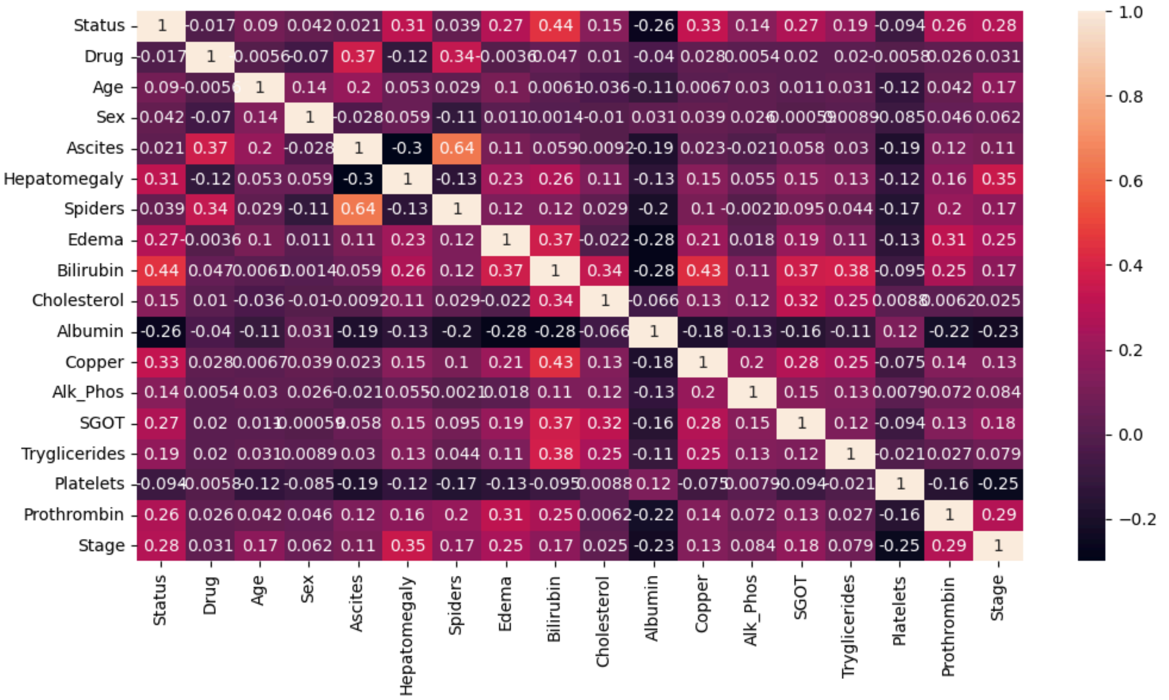
In [11]:
```
#Encode Categorical Features
from sklearn.preprocessing import LabelEncoder

label_cols = ['Sex', 'Ascites', 'Hepatomegaly', 'Spiders', 'Edema', 'Drug', 'Statu
for col in label_cols:
    df[col] = LabelEncoder().fit_transform(df[col])
```

In [12]:
```
print(df.head())
```

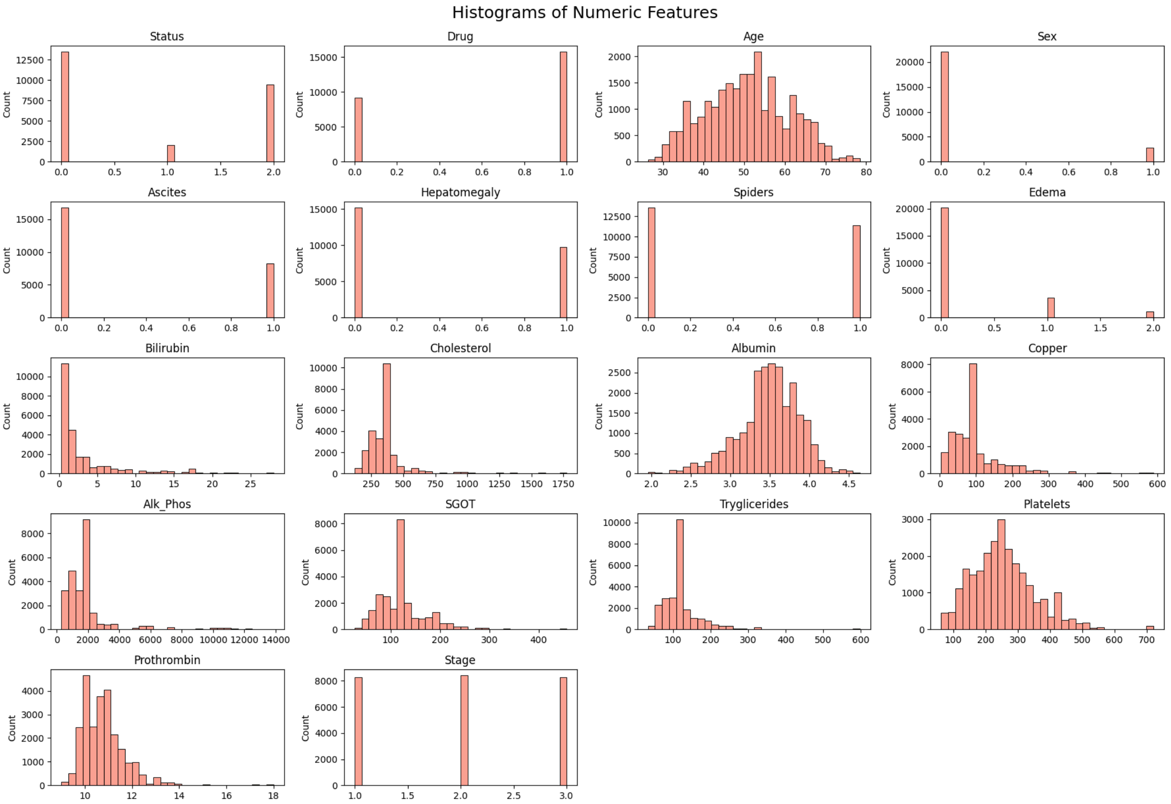
```
   Status  Drug        Age  Sex  Ascites  Hepatomegaly  Spiders  Edema  \
0       0     1  50.682192    0        0             1        0      0   
1       0     1  54.038356    1        1             0        1      0   
2       0     1  32.435616    0        0             0        0      0   
3       2     1  45.115068    0        0             0        0      0   
4       2     1  59.449315    0        0             1        0      0   

   Bilirubin  Cholesterol  Albumin  Copper  Alk_Phos    SGOT  Tryglicerides  \
0        0.5        149.0     4.04   227.0     598.0   52.70           57.0   
1        0.5        219.0     3.93    22.0     663.0   45.00           75.0   
2        0.5        320.0     3.54    51.0    1243.0  122.45           80.0   
3        0.7        255.0     3.74    23.0    1024.0   77.50           58.0   
4        1.9        486.0     3.54    74.0    1052.0  108.50          109.0   

   Platelets  Prothrombin  Stage  
0      256.0          9.9      1  
1      220.0         10.8      2  
2      225.0         10.0      2  
3      151.0         10.2      2  
4      151.0         11.5      1  
```

In [13]:
```
plt.figure(figsize=(12,6))
sns.heatmap(df.corr(), annot=True)
```

Out[13]:
```
<Axes: >
```



In [14]:
```
numeric_columns = df.select_dtypes(include='number').columns
plt.figure(figsize=(18, 12))
for i, col in enumerate(numeric_columns, 1):
    plt.subplot((len(numeric_columns) - 1) // 4 + 1, 4, i)
    sns.histplot(df[col], bins=30, color='salmon', edgecolor='black')
    plt.title(col)
    plt.xlabel('')
    plt.ylabel('Count')
plt.tight_layout()
plt.suptitle("Histograms of Numeric Features", fontsize=18, y=1.02)
plt.show()
```



In [15]:
```
#Recode Target Variable (Stage)
df['Stage'] = df['Stage'].replace({1:0,2:1,3:2})
```

In [16]:
```
df
```

Out[16]:

	Status	Drug	Age	Sex	Ascites	Hepatomegaly	Spiders	Edema	Bilirubir
0	0	1	50.682192	0	0	1	0	0	0.5
1	0	1	54.038356	1	1	0	1	0	0.5
2	0	1	32.435616	0	0	0	0	0	0.5
3	2	1	45.115068	0	0	0	0	0	0.7
4	2	1	59.449315	0	0	1	0	0	1.9
...	...	...	...	...	...	...	...	...	..
24995	2	0	64.690411	0	0	0	0	0	0.8
24996	2	0	64.690411	0	0	0	0	0	0.8
24997	2	0	45.852055	0	0	1	1	2	5.1
24998	0	0	46.547945	0	0	1	0	0	0.8
24999	0	0	46.547945	0	0	1	0	0	0.8

25000 rows × 18 columns

In [17]:

```
df['Stage']
```

Out[17]:

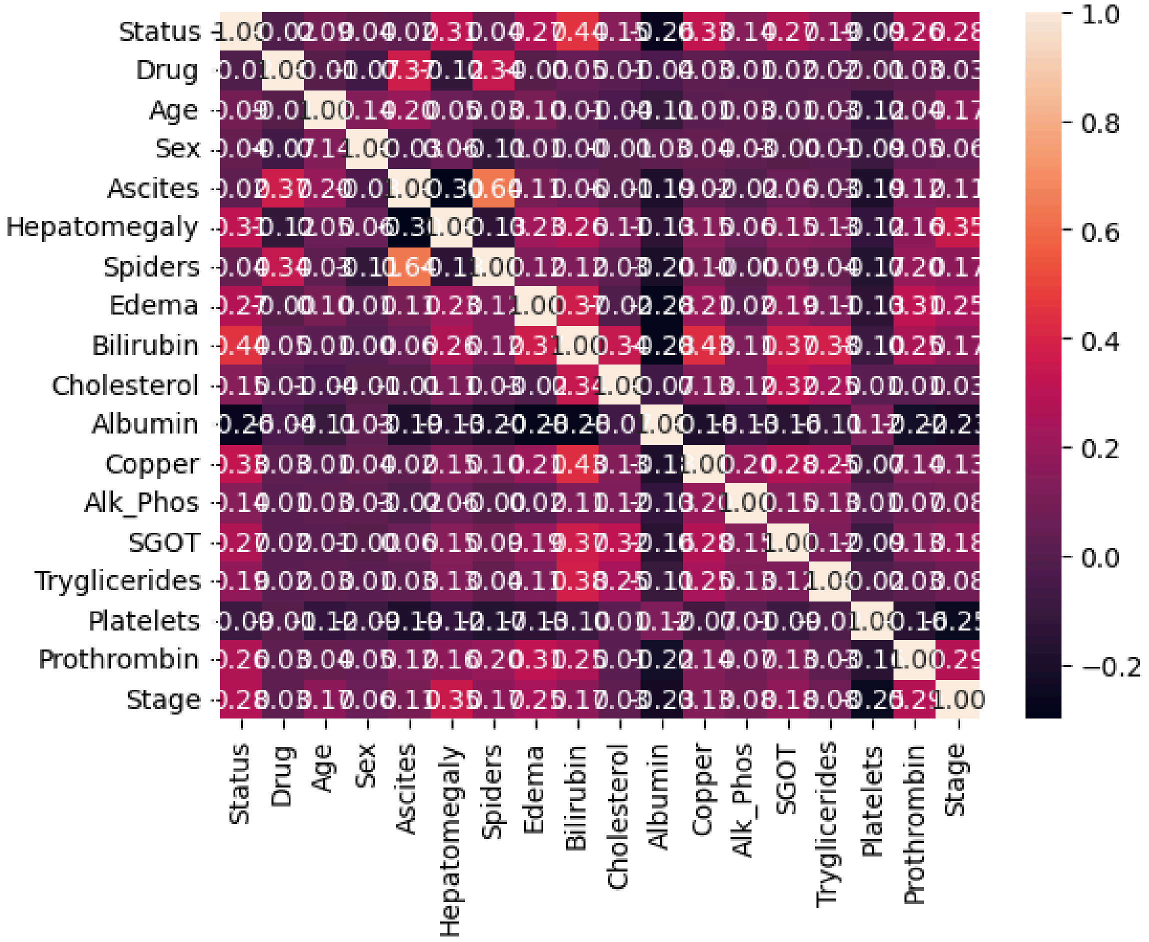
```
0        0
1        1
2        1
3        1
4        0
        ..
24995    1
24996    1
24997    2
24998    1
24999    1
Name: Stage, Length: 25000, dtype: int64
```

In [18]:

```
#Exploratory Data Analysis
sns.countplot(x='Status', data=df)
sns.heatmap(df.corr(), annot=True, fmt='.2f')
```

Out[18]:

```
<Axes: >
```



```
In [19]: # Feature and Target Split
         X = df.drop(columns=['Status'])
         y = df['Status']
```

```
In [20]: #Scale Features
         scaler = StandardScaler()
         X_scaled = scaler.fit_transform(X)
```

```
In [21]: #Train/Test Split
         X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, ra
```

```
In [22]: #Train Multiple Models
         log_reg = LogisticRegression(max_iter=1000)
         log_reg.fit(X_train, y_train)
         y_pred_log_reg = log_reg.predict(X_test)

         print("Logistic Regression Performance")
         print(confusion_matrix(y_test, y_pred_log_reg))
         print(classification_report(y_test, y_pred_log_reg))
```

```
Logistic Regression Performance
[[2381    1  321]
 [ 212   18  176]
 [ 770    7 1114]]
              precision    recall  f1-score   support

           0       0.71      0.88      0.79      2703
           1       0.69      0.04      0.08       406
           2       0.69      0.59      0.64      1891

    accuracy                           0.70      5000
   macro avg       0.70      0.50      0.50      5000
weighted avg       0.70      0.70      0.67      5000
```

In [23]:
```
rf_clf = RandomForestClassifier(class_weight='balanced', random_state=42)
rf_clf.fit(X_train, y_train)
y_pred_rf = rf_clf.predict(X_test)

print("Random Forest Performance")
print(confusion_matrix(y_test, y_pred_rf))
print(classification_report(y_test, y_pred_rf))
```

```
Random Forest Performance
[[2690    2   11]
 [  14  383    9]
 [  28    0 1863]]
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      2703
           1       0.99      0.94      0.97       406
           2       0.99      0.99      0.99      1891

    accuracy                           0.99      5000
   macro avg       0.99      0.97      0.98      5000
weighted avg       0.99      0.99      0.99      5000
```

In [24]:
```
xgb_clf = xgb.XGBClassifier(eval_metric='mlogloss', use_label_encoder=False)
xgb_clf.fit(X_train, y_train)
y_pred_xgb = xgb_clf.predict(X_test)

print("XGBoost Performance")
print(confusion_matrix(y_test, y_pred_xgb))
print(classification_report(y_test, y_pred_xgb))
```

```
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [13:54:15] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
```

```
XGBoost Performance
[[2692    2    9]
 [   9  391    6]
 [  22    0 1869]]
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      2703
           1       0.99      0.96      0.98       406
           2       0.99      0.99      0.99      1891

    accuracy                           0.99      5000
   macro avg       0.99      0.98      0.99      5000
weighted avg       0.99      0.99      0.99      5000
```

In [25]:

```
svm_clf = SVC(class_weight='balanced', kernel='linear', random_state=42)
svm_clf.fit(X_train, y_train)
y_pred_svm = svm_clf.predict(X_test)

print("SVM Performance")
print(confusion_matrix(y_test, y_pred_svm))
print(classification_report(y_test, y_pred_svm))
```

```
SVM Performance
[[2193  198  312]
 [  81  256   69]
 [ 535  320 1036]]
              precision    recall  f1-score   support

           0       0.78      0.81      0.80      2703
           1       0.33      0.63      0.43       406
           2       0.73      0.55      0.63      1891

    accuracy                           0.70      5000
   macro avg       0.61      0.66      0.62      5000
weighted avg       0.73      0.70      0.70      5000
```

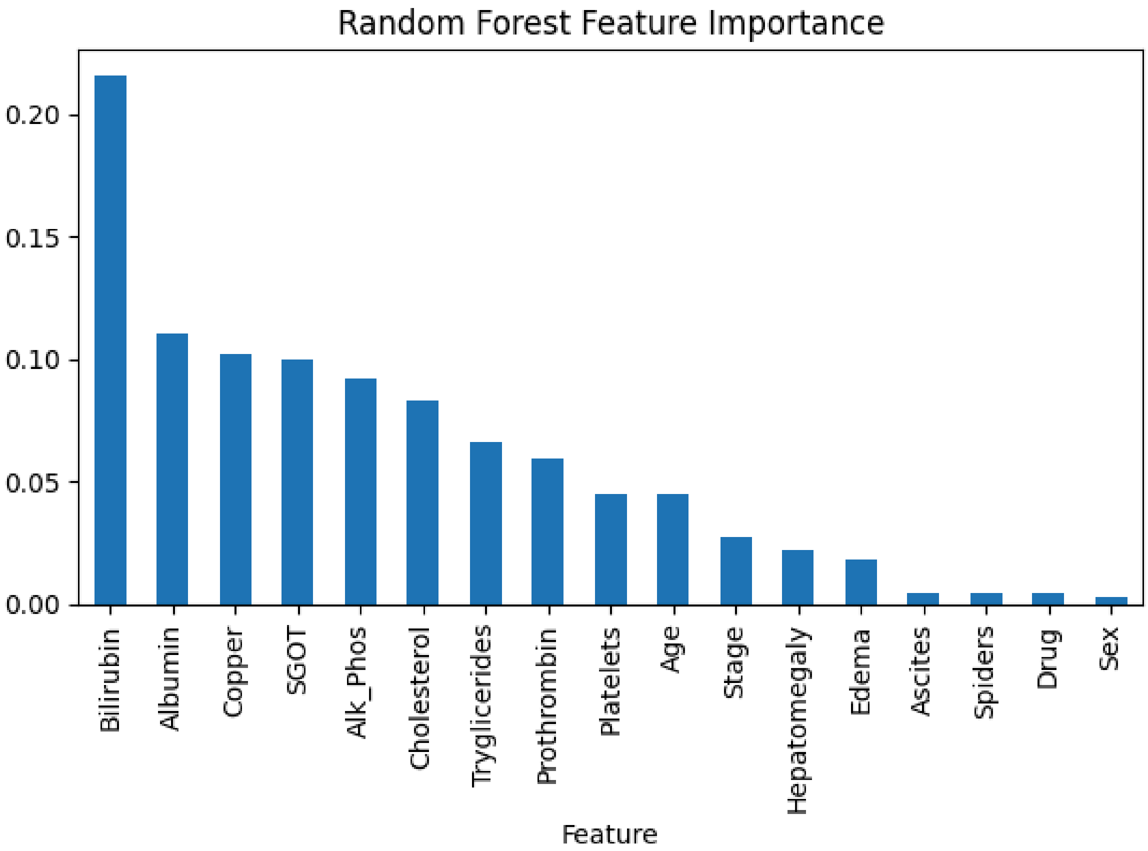
In [26]:

```
#Evaluate Model Performance
models = ['Logistic Regression', 'Random Forest', 'XGBoost', 'SVM']
predictions = [y_pred_log_reg, y_pred_rf, y_pred_xgb, y_pred_svm]

for model, pred in zip(models, predictions):
    print(f"\n{model} Classification Report:")
    print(classification_report(y_test, pred))
    print(confusion_matrix(y_test, pred))
```

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

           0       0.71      0.88      0.79      2703
           1       0.69      0.04      0.08       406
           2       0.69      0.59      0.64      1891

    accuracy                           0.70      5000
   macro avg       0.70      0.50      0.50      5000
weighted avg       0.70      0.70      0.67      5000

[[2381    1  321]
 [ 212   18  176]
 [ 770    7 1114]]

Random Forest Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99      2703
           1       0.99      0.94      0.97       406
           2       0.99      0.99      0.99      1891

    accuracy                           0.99      5000
   macro avg       0.99      0.97      0.98      5000
weighted avg       0.99      0.99      0.99      5000

[[2690    2   11]
 [  14  383    9]
 [  28    0 1863]]

XGBoost Classification Report:
              precision    recall  f1-score   support

           0       0.99      1.00      0.99      2703
           1       0.99      0.96      0.98       406
           2       0.99      0.99      0.99      1891

    accuracy                           0.99      5000
   macro avg       0.99      0.98      0.99      5000
weighted avg       0.99      0.99      0.99      5000

[[2692    2    9]
 [   9  391    6]
 [  22    0 1869]]

SVM Classification Report:
              precision    recall  f1-score   support

           0       0.78      0.81      0.80      2703
           1       0.33      0.63      0.43       406
           2       0.73      0.55      0.63      1891

    accuracy                           0.70      5000
   macro avg       0.61      0.66      0.62      5000
weighted avg       0.73      0.70      0.70      5000

[[2193  198  312]
 [  81  256   69]
 [ 535  320 1036]]
```

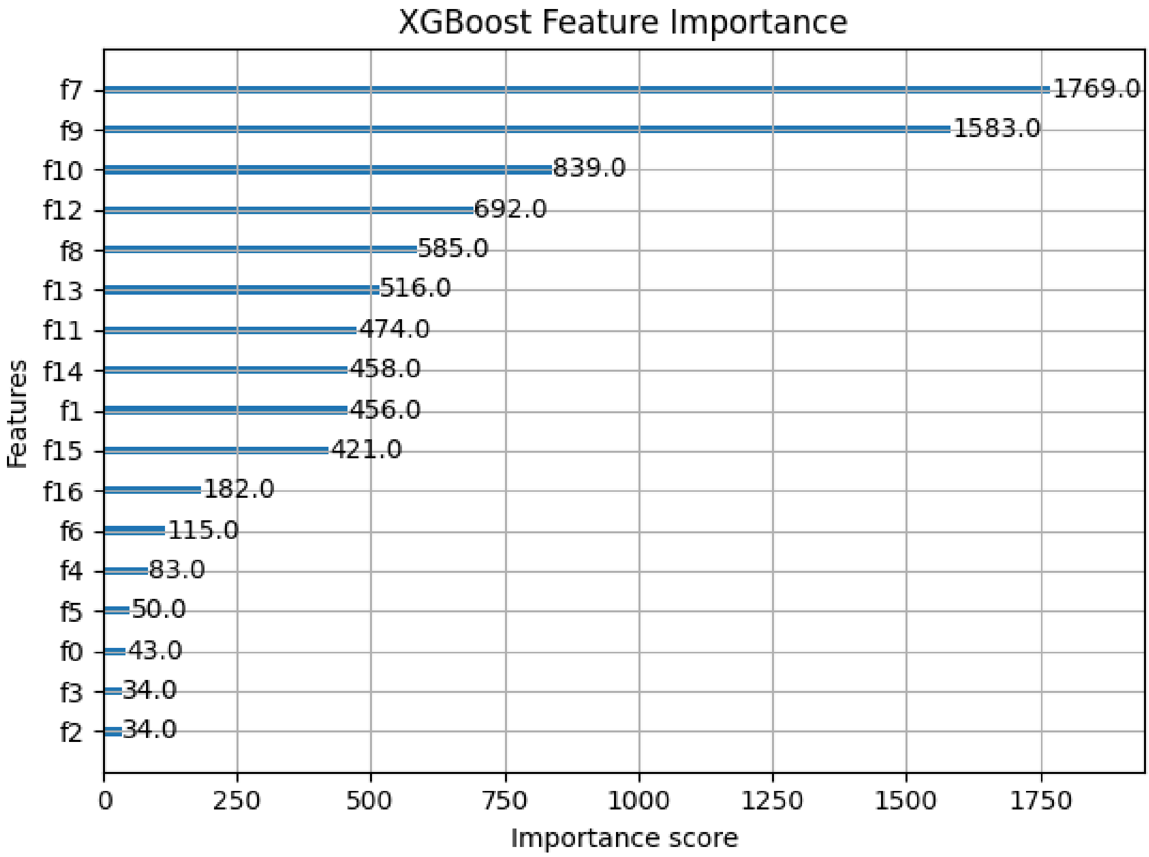
In [27]:

```
#Feature Importance
importances_rf = rf_clf.feature_importances_
feat_df_rf = pd.DataFrame({'Feature': X.columns, 'Importance': importances_rf})
feat_df_rf = feat_df_rf.sort_values(by='Importance', ascending=False)
feat_df_rf.plot(kind='bar', x='Feature', y='Importance', legend=False)
plt.title('Random Forest Feature Importance')
plt.tight_layout()
plt.show()
```



In [28]:

```
xgb.plot_importance(xgb_clf)
plt.title('XGBoost Feature Importance')
plt.tight_layout()
plt.show()
```



In [29]:

```
#Save Best Model
import pickle
```

In [30]:

```
with open('rf_model.pkl', 'wb') as f:
    pickle.dump(rf_clf, f)
```

In [31]:

```
with open('xgb_model.pkl', 'wb') as f:
    pickle.dump(xgb_clf, f)
```

In [32]:

```
#Cross-Validation
from sklearn.model_selection import cross_val_score
```

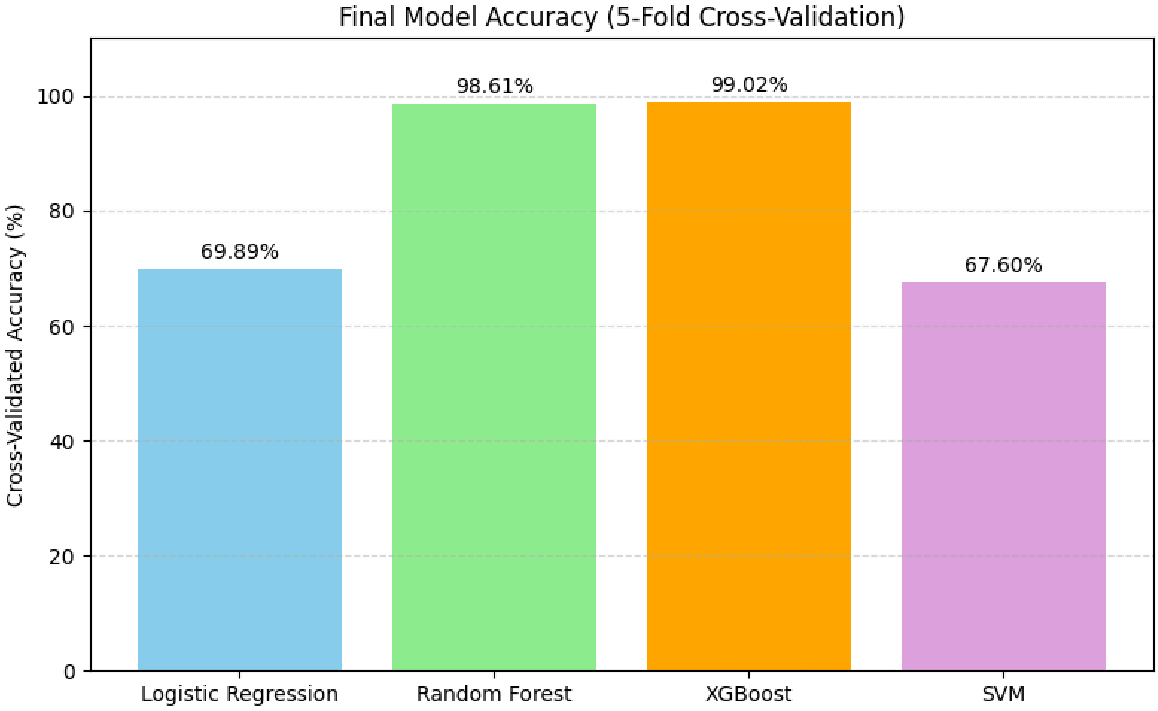
In [33]:

```
log_reg_scores = cross_val_score(log_reg, X_scaled, y, cv=5, scoring='accuracy')
rf_scores = cross_val_score(rf_clf, X_scaled, y, cv=5, scoring='accuracy')
xgb_scores = cross_val_score(xgb_clf, X_scaled, y, cv=5, scoring='accuracy')
svm_scores = cross_val_score(svm_clf, X_scaled, y, cv=5, scoring='accuracy')

print("Logistic Regression CV Accuracy: ", log_reg_scores.mean())
print("Random Forest CV Accuracy: ", rf_scores.mean())
print("XGBoost CV Accuracy: ", xgb_scores.mean())
print("SVM CV Accuracy: ", svm_scores.mean())
```

```
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [13:59:53] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [13:59:55] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [13:59:56] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [13:59:58] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
C:\Users\sakshi\AppData\Roaming\Python\Python311\site-packages\xgboost\training.py:
183: UserWarning: [14:00:00] WARNING: C:\actions-runner\_work\xgboost\xgboost\src\l
earner.cc:738:
Parameters: { "use_label_encoder" } are not used.

  bst.update(dtrain, iteration=i, fobj=obj)
Logistic Regression CV Accuracy:  0.69892
Random Forest CV Accuracy:  0.98612
XGBoost CV Accuracy:  0.99024
SVM CV Accuracy:  0.6759600000000001
```

In [34]:

```python
models = ['Logistic Regression', 'Random Forest', 'XGBoost', 'SVM']
cv_accuracies = [
    log_reg_scores.mean()*100,
    rf_scores.mean()*100,
    xgb_scores.mean()*100,
    svm_scores.mean()*100
]

plt.figure(figsize=(8, 5))
bars = plt.bar(models, cv_accuracies, color=['skyblue', 'lightgreen', 'orange', 'p

for bar, acc in zip(bars, cv_accuracies):
    plt.text(bar.get_x() + bar.get_width()/2, bar.get_height() + 1,
             f'{acc:.2f}%', ha='center', va='bottom')

plt.ylim(0, 110)
plt.ylabel('Cross-Validated Accuracy (%)')
plt.title('Final Model Accuracy (5-Fold Cross-Validation)')
plt.grid(axis='y', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```


Final Model Accuracy (5-Fold Cross-Validation)
Cross-Validated Accuracy (%)
0
20
40
60
80
100
69.89%
98.61%
99.02%
67.60%
Logistic Regression
Random Forest
XGBoost
SVM

```
In [ ]:
```