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Bankruptcy Project

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from lightgbm import LGBMClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
```

In [2]:
```
bankruptcy_df = pd.read_csv(r"C:\Users\chris\Documents\Bellevue University\10 - Applied Data Science\Proj
```

In [3]:

```
bankruptcy_df.head(20)
```

Out[3]:

	company_name	status_label	year	X1	X2	X3	X4	X5	X6	X7	...	X9	X10	
0	C_1	alive	1999	511.267	833.107	18.373	89.031	336.018	35.163	128.348	...	1024.333	740.998	1
1	C_1	alive	2000	485.856	713.811	18.577	64.367	320.590	18.531	115.187	...	874.255	701.854	1
2	C_1	alive	2001	436.656	526.477	22.496	27.207	286.588	-58.939	77.528	...	638.721	710.199	2
3	C_1	alive	2002	396.412	496.747	27.172	30.745	259.954	-12.410	66.322	...	606.337	686.621	1
4	C_1	alive	2003	432.204	523.302	26.680	47.491	247.245	3.504	104.661	...	651.958	709.292	2
5	C_1	alive	2004	474.542	598.172	27.950	61.774	255.477	15.453	127.121	...	747.848	732.230	2
6	C_1	alive	2005	624.454	704.081	29.222	91.877	323.592	35.163	136.272	...	897.284	978.819	3
7	C_1	alive	2006	645.721	837.171	32.199	118.907	342.593	58.660	181.691	...	1061.169	1067.633	2
8	C_1	alive	2007	783.431	1080.895	39.952	168.522	435.608	75.144	202.472	...	1384.919	1362.010	5
9	C_1	alive	2008	851.312	1110.677	40.551	166.080	477.424	78.651	227.300	...	1423.976	1377.511	3
10	C_1	alive	2009	863.429	1065.902	38.930	134.345	496.904	44.628	238.466	...	1352.151	1501.042	3
11	C_1	alive	2010	913.985	1408.071	59.296	196.312	507.274	69.826	296.489	...	1775.782	1703.727	3
12	C_1	alive	2011	1063.272	1662.408	80.333	222.693	599.752	67.723	324.879	...	2074.498	2195.653	6
13	C_1	alive	2012	1033.700	1714.500	108.600	245.200	582.900	55.000	315.400	...	2167.100	2136.900	6
14	C_1	alive	2013	1116.900	1581.400	113.400	256.000	632.900	72.900	297.900	...	2035.000	2199.500	5
15	C_1	alive	2014	954.100	1342.700	92.300	83.700	566.700	10.200	231.100	...	1594.300	1515.000	
16	C_1	alive	2015	873.100	1354.900	70.800	136.900	563.700	47.700	242.700	...	1662.600	1442.100	1
17	C_1	alive	2016	888.500	1422.700	71.000	148.200	601.100	56.500	251.400	...	1767.600	1504.100	1
18	C_1	alive	2017	942.700	1413.200	40.500	126.500	547.900	15.600	203.000	...	1748.300	1524.700	1
19	C_2	alive	1999	1029.438	930.142	102.090	413.739	243.882	87.635	436.751	...	1926.947	1672.529	

20 rows × 21 columns

In [4]:

```
# Removes columns "company_name" and "year"
bankruptcy_df1 = bankruptcy_df.drop(columns=["company_name", "year"])

# Converts "alive" to 0 and "failed" to 1 in the "status_label" column
bankruptcy_df1["status_label"] = bankruptcy_df1["status_label"].replace({"alive": 0, "failed": 1})

bankruptcy_df1.head(20)
```

Out[4]:

	status_label	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	X11	X12
0	0	511.267	833.107	18.373	89.031	336.018	35.163	128.348	372.7519	1024.333	740.998	180.447	70.658
1	0	485.856	713.811	18.577	64.367	320.590	18.531	115.187	377.1180	874.255	701.854	179.987	45.790
2	0	436.656	526.477	22.496	27.207	286.588	-58.939	77.528	364.5928	638.721	710.199	217.699	4.711
3	0	396.412	496.747	27.172	30.745	259.954	-12.410	66.322	143.3295	606.337	686.621	164.658	3.573
4	0	432.204	523.302	26.680	47.491	247.245	3.504	104.661	308.9071	651.958	709.292	248.666	20.811
5	0	474.542	598.172	27.950	61.774	255.477	15.453	127.121	522.6794	747.848	732.230	227.159	33.824
6	0	624.454	704.081	29.222	91.877	323.592	35.163	136.272	882.6283	897.284	978.819	318.576	62.655
7	0	645.721	837.171	32.199	118.907	342.593	58.660	181.691	1226.1925	1061.169	1067.633	253.611	86.708
8	0	783.431	1080.895	39.952	168.522	435.608	75.144	202.472	747.5434	1384.919	1362.010	507.918	128.570
9	0	851.312	1110.677	40.551	166.080	477.424	78.651	227.300	571.5948	1423.976	1377.511	392.984	125.529
10	0	863.429	1065.902	38.930	134.345	496.904	44.628	238.466	777.8348	1352.151	1501.042	336.191	95.415
11	0	913.985	1408.071	59.296	196.312	507.274	69.826	296.489	1049.8206	1775.782	1703.727	329.802	137.016
12	0	1063.272	1662.408	80.333	222.693	599.752	67.723	324.879	485.2897	2074.498	2195.653	669.489	142.360
13	0	1033.700	1714.500	108.600	245.200	582.900	55.000	315.400	790.0029	2167.100	2136.900	622.200	136.600
14	0	1116.900	1581.400	113.400	256.000	632.900	72.900	297.900	961.3080	2035.000	2199.500	564.300	142.600
15	0	954.100	1342.700	92.300	83.700	566.700	10.200	231.100	1046.3954	1594.300	1515.000	85.000	-8.600
16	0	873.100	1354.900	70.800	136.900	563.700	47.700	242.700	842.5112	1662.600	1442.100	136.100	66.100
17	0	888.500	1422.700	71.000	148.200	601.100	56.500	251.400	1200.3288	1767.600	1504.100	155.300	77.200
18	0	942.700	1413.200	40.500	126.500	547.900	15.600	203.000	1551.4580	1748.300	1524.700	177.200	86.000
19	0	1029.438	930.142	102.090	413.739	243.882	87.635	436.751	7161.3749	1926.947	1672.529	11.024	311.649

Training, testing and evaluating the model

In [5]:
```
# Splits the data into features (X) and target (y)
X = bankruptcy_df1.drop(columns=["status_label"])
y = bankruptcy_df1["status_label"]

# Splits the dataset into training and testing sets (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Initializes and trains the LightGBM classifier
lgbm_model = LGBMClassifier()
lgbm_model.fit(X_train, y_train)
```

```
[LightGBM] [Info] Number of positive: 4152, number of negative: 58793
[LightGBM] [Info] Auto-choosing col-wise multi-threading, the overhead of testing was 0.004222 seconds.
You can set `force_col_wise=true` to remove the overhead.
[LightGBM] [Info] Total Bins 4590
[LightGBM] [Info] Number of data points in the train set: 62945, number of used features: 18
[LightGBM] [Info] [binary:BoostFromScore]: pavg=0.065962 -> initscore=-2.650433
[LightGBM] [Info] Start training from score -2.650433
```

Out[5]:
```
LGBMClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [6]:
```
# Predicts the target on the test set
y_pred = lgbm_model.predict(X_test)
```

In [7]:
```
# Evaluates the model's performance
accuracy = accuracy_score(y_test, y_pred)
conf_matrix = confusion_matrix(y_test, y_pred)
classification_rep = classification_report(y_test, y_pred)
```

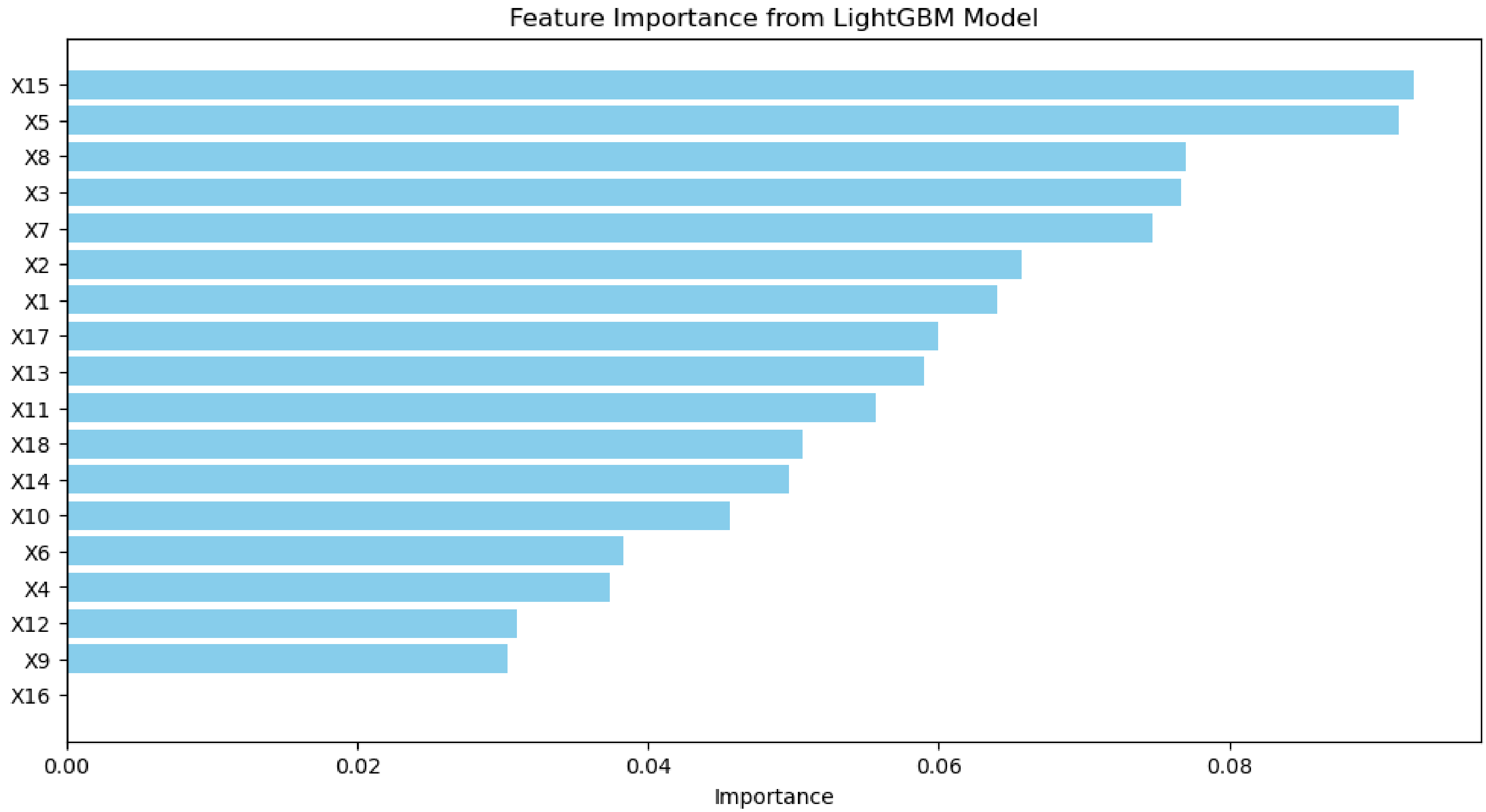
In [8]:
```
# Prints the evaluation metrics
print(f"Accuracy: {accuracy}")
print("Confusion Matrix:")
print(conf_matrix)
print("Classification Report:")
print(classification_rep)
```

```
Accuracy: 0.9343585181419585
Confusion Matrix:
[[14658    11]
 [ 1022    46]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      1.00      0.97     14669
           1       0.81      0.04      0.08      1068

    accuracy                           0.93     15737
   macro avg       0.87      0.52      0.52     15737
weighted avg       0.93      0.93      0.91     15737
```

Feature importance

In [9]:

```
# Gets feature importance from the trained model
importance = lgbm_model.feature_importances_

# Creates a DataFrame for feature importance
feature_importance_df = pd.DataFrame({
    'Feature': X.columns,
    'Importance': importance
})

# Normalizes the importance values to be between 0 and 1
feature_importance_df['Importance'] = feature_importance_df['Importance'] / feature_importance_df['Import

# Sorts the DataFrame by importance
feature_importance_df = feature_importance_df.sort_values(by='Importance', ascending=False)

# Plotting the feature importance as a bar chart
plt.figure(figsize=(12, 6))
plt.barh(feature_importance_df['Feature'], feature_importance_df['Importance'], color='skyblue')
plt.xlabel('Importance')
plt.title('Feature Importance from LightGBM Model')
plt.gca().invert_yaxis()  # Invert y-axis for better readability
plt.show()

# Display the ranked table of feature importance
print(feature_importance_df)
```


Feature Importance from LightGBM Model
X15
X5
X8
X3
X7
X2
X1
X17
X13
X11
X18
X14
X10
X6
X4
X12
X9
X16
0.00
0.02
0.04
0.06
0.08
Importance

```
    Feature  Importance
14      X15    0.092667
4        X5    0.091667
7        X8    0.077000
2        X3    0.076667
6        X7    0.074667
1        X2    0.065667
0        X1    0.064000
16      X17    0.060000
12      X13    0.059000
10      X11    0.055667
17      X18    0.050667
13      X14    0.049667
9       X10    0.045667
5        X6    0.038333
3        X4    0.037333
11      X12    0.031000
8        X9    0.030333
15      X16    0.000000
```

In [ ]: