In [ ]:

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.utils import resample
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)
```

# Step 1: Preprocessing

## Load and View Data

**Drop unnecessary columns pertaining to histogram results, which aren't typically a part of CTG results.**

In [ ]:

```
data = pd.read_csv('/content/drive/MyDrive/DM_Project/fetal_health.csv')
feat = data[['baseline value',
             'accelerations',
             'fetal_movement',
             'uterine_contractions',
             'light_decelerations',
             'severe_decelerations',
             'prolongued_decelerations',
             'abnormal_short_term_variability',
             'mean_value_of_short_term_variability',
             'mean_value_of_long_term_variability',
             'percentage_of_time_with_abnormal_long_term_variability',
             'fetal_health']]
feat = feat.rename(columns={'percentage_of_time_with_abnormal_long_term_variability':'percent_time_abnormal_long_variability'})
data.shape
```

Out[ ]:

```
(2126, 22)
```

In [ ]:

```
X = feat[['baseline value',
          'accelerations',
          'fetal_movement',
          'uterine_contractions',
          'light_decelerations',
          'severe_decelerations',
          'prolongued_decelerations',
          'abnormal_short_term_variability',
          'mean_value_of_short_term_variability',
          'mean_value_of_long_term_variability',
          'percent_time_abnormal_long_variability']]
y = feat[['fetal_health']]
```

In [ ]:

```
feat.describe().T
```

Out[ ]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **baseline value** | 2126.0 | 133.303857 | 9.840844 | 106.0 | 126.000 | 133.000 | 140.000 | 160.000 |
| **accelerations** | 2126.0 | 0.003178 | 0.003866 | 0.0 | 0.000 | 0.002 | 0.006 | 0.019 |

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **fetal_movement** | 2126.0 | 0.009481 | 0.046666 | 0.0 | 0.000 | 0.000 | 0.003 | 0.481 |
| **uterine_contractions** | 2126.0 | 0.004366 | 0.002946 | 0.0 | 0.002 | 0.004 | 0.007 | 0.015 |
| **light_decelerations** | 2126.0 | 0.001889 | 0.002960 | 0.0 | 0.000 | 0.000 | 0.003 | 0.015 |
| **severe_decelerations** | 2126.0 | 0.000003 | 0.000057 | 0.0 | 0.000 | 0.000 | 0.000 | 0.001 |
| **prolongued_decelerations** | 2126.0 | 0.000159 | 0.000590 | 0.0 | 0.000 | 0.000 | 0.000 | 0.005 |
| **abnormal_short_term_variability** | 2126.0 | 46.990122 | 17.192814 | 12.0 | 32.000 | 49.000 | 61.000 | 87.000 |
| **mean_value_of_short_term_variability** | 2126.0 | 1.332785 | 0.883241 | 0.2 | 0.700 | 1.200 | 1.700 | 7.000 |
| **mean_value_of_long_term_variability** | 2126.0 | 8.187629 | 5.628247 | 0.0 | 4.600 | 7.400 | 10.800 | 50.700 |
| **percent_time_abnormal_long_variability** | 2126.0 | 9.846660 | 18.396880 | 0.0 | 0.000 | 0.000 | 11.000 | 91.000 |
| **fetal_health** | 2126.0 | 1.304327 | 0.614377 | 1.0 | 1.000 | 1.000 | 1.000 | 3.000 |

In [ ]:

```
feat.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2126 entries, 0 to 2125
Data columns (total 12 columns):
 #   Column                                  Non-Null Count  Dtype  
---  ------                                  --------------  -----  
 0   baseline value                          2126 non-null   float64
 1   accelerations                           2126 non-null   float64
 2   fetal_movement                          2126 non-null   float64
 3   uterine_contractions                    2126 non-null   float64
 4   light_decelerations                     2126 non-null   float64
 5   severe_decelerations                    2126 non-null   float64
 6   prolongued_decelerations                2126 non-null   float64
 7   abnormal_short_term_variability         2126 non-null   float64
 8   mean_value_of_short_term_variability    2126 non-null   float64
 9   mean_value_of_long_term_variability     2126 non-null   float64
 10  percent_time_abnormal_long_variability  2126 non-null   float64
 11  fetal_health                            2126 non-null   float64
dtypes: float64(12)
memory usage: 199.4 KB
```

## Dimensionality Reduction - Principal Component Analysis

In [ ]:

```
# Scale data with standard scalar
sc = StandardScaler().set_output(transform='pandas')
scaled = sc.fit(X).transform(X)
```

In [ ]:

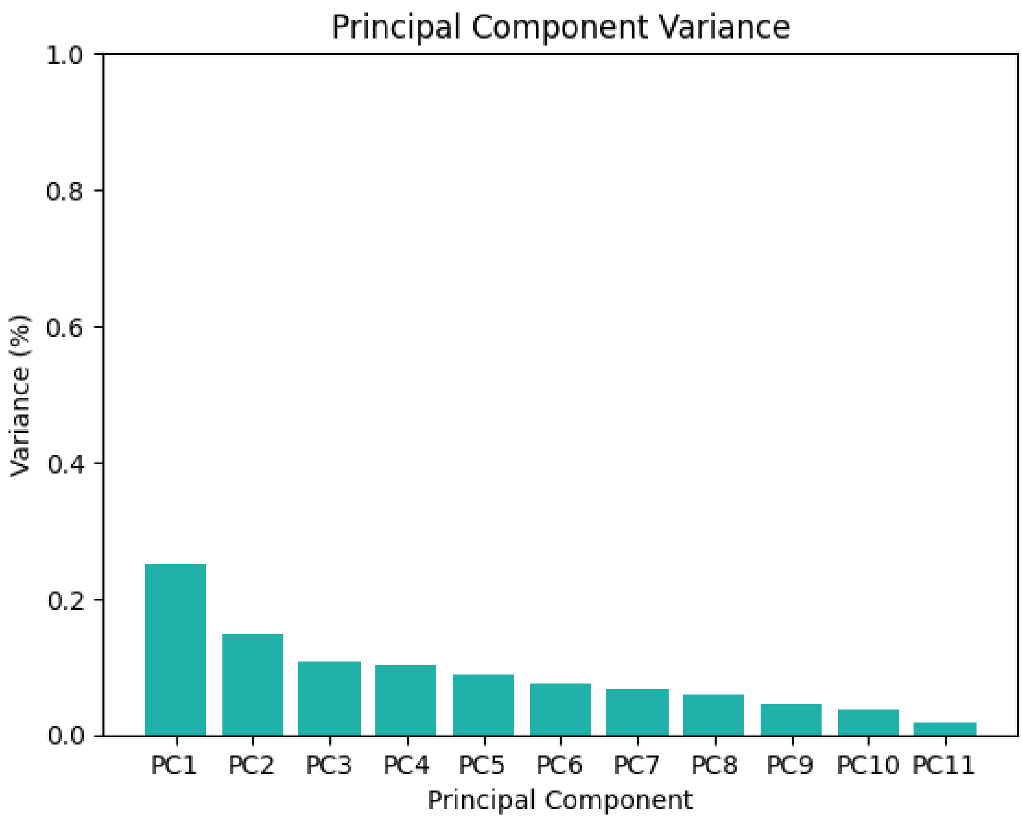
```
pca = PCA()
pca.fit(scaled)
d = {'Feature':scaled.columns.values, 'PCA Variance Ratio':pca.explained_variance_ratio_
}
pca_info = pd.DataFrame(data=d)
l=[]

for z in range(1, len(pca_info['PCA Variance Ratio']) + 1):
  l.append(sum(pca_info['PCA Variance Ratio'].iloc[:z]))

pca_info['Sum PCA Variance'] = l
display(pca_info)
```

| | Feature | PCA Variance Ratio | Sum PCA Variance |
|---|---|---|---|
| **0** | baseline value | 0.250640 | 0.250640 |
| **1** | accelerations | 0.148219 | 0.398859 |

| | Feature | PCA Variance Ratio | Sum PCA Variance |
|---|---|---|---|
| 2 | fetal_movement | 0.107775 | 0.506633 |
| 3 | uterine_contractions | 0.102701 | 0.609334 |
| 4 | light_decelerations | 0.089323 | 0.698657 |
| 5 | severe_decelerations | 0.076052 | 0.774709 |
| 6 | prolongued_decelerations | 0.066112 | 0.840821 |
| 7 | abnormal_short_term_variability | 0.059541 | 0.900362 |
| 8 | mean_value_of_short_term_variability | 0.043945 | 0.944307 |
| 9 | mean_value_of_long_term_variability | 0.036622 | 0.980929 |
| 10 | percent_time_abnormal_long_variability | 0.019071 | 1.000000 |

In [ ]:

```
trained_pca = pca.transform(scaled)
var_ratio = pca_info['PCA Variance Ratio']

x=range(0, len(var_ratio))
plt.bar(x, var_ratio, color='lightseagreen')
plt.ylabel('Variance (%)')
plt.xlabel('Principal Component')
plt.xticks(x, ['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7', 'PC8', 'PC9', 'PC10', 'P
C11'])
plt.ylim([0,1])
plt.title('Principal Component Variance')
plt.show()
```



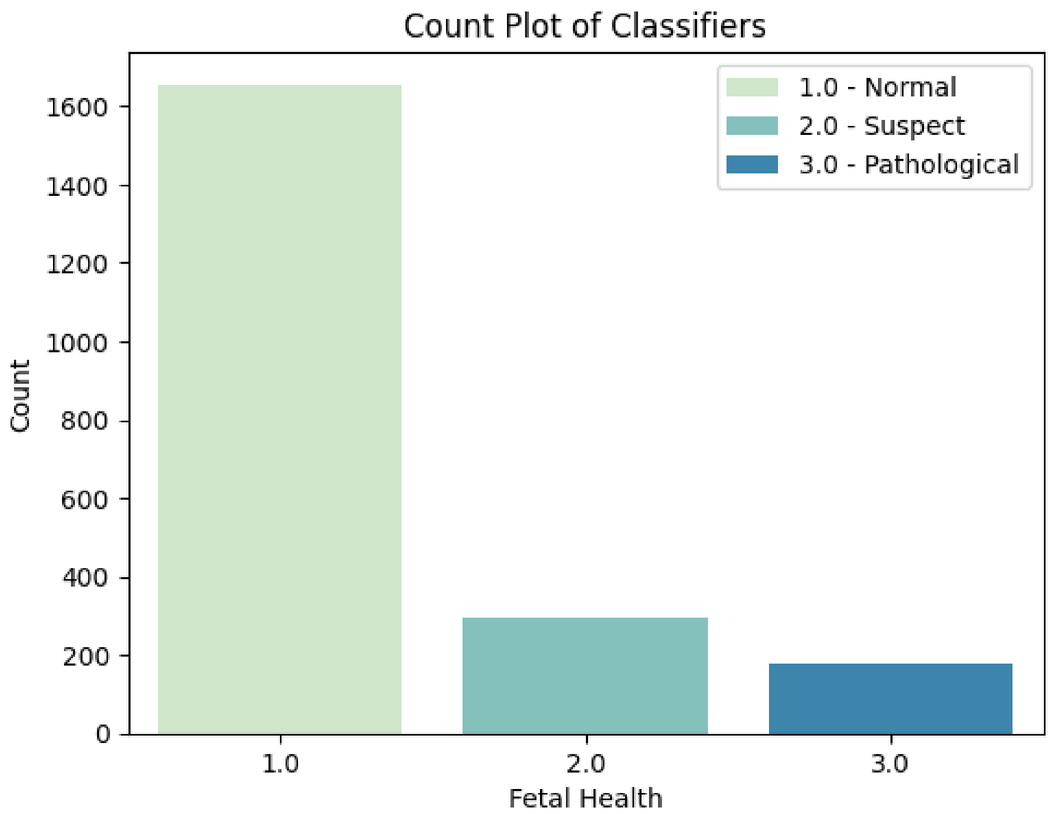

# Step 2: Data Analysis

### Classifier Distribution

In [ ]:

```
labels = ['1.0 - Normal', '2.0 - Suspect', '3.0 - Pathological']
sns.countplot(data, x='fetal_health', palette='GnBu', label=labels)
plt.title('Count Plot of Classifiers')
plt.xlabel('Fetal Health')
plt.ylabel('Count')
```

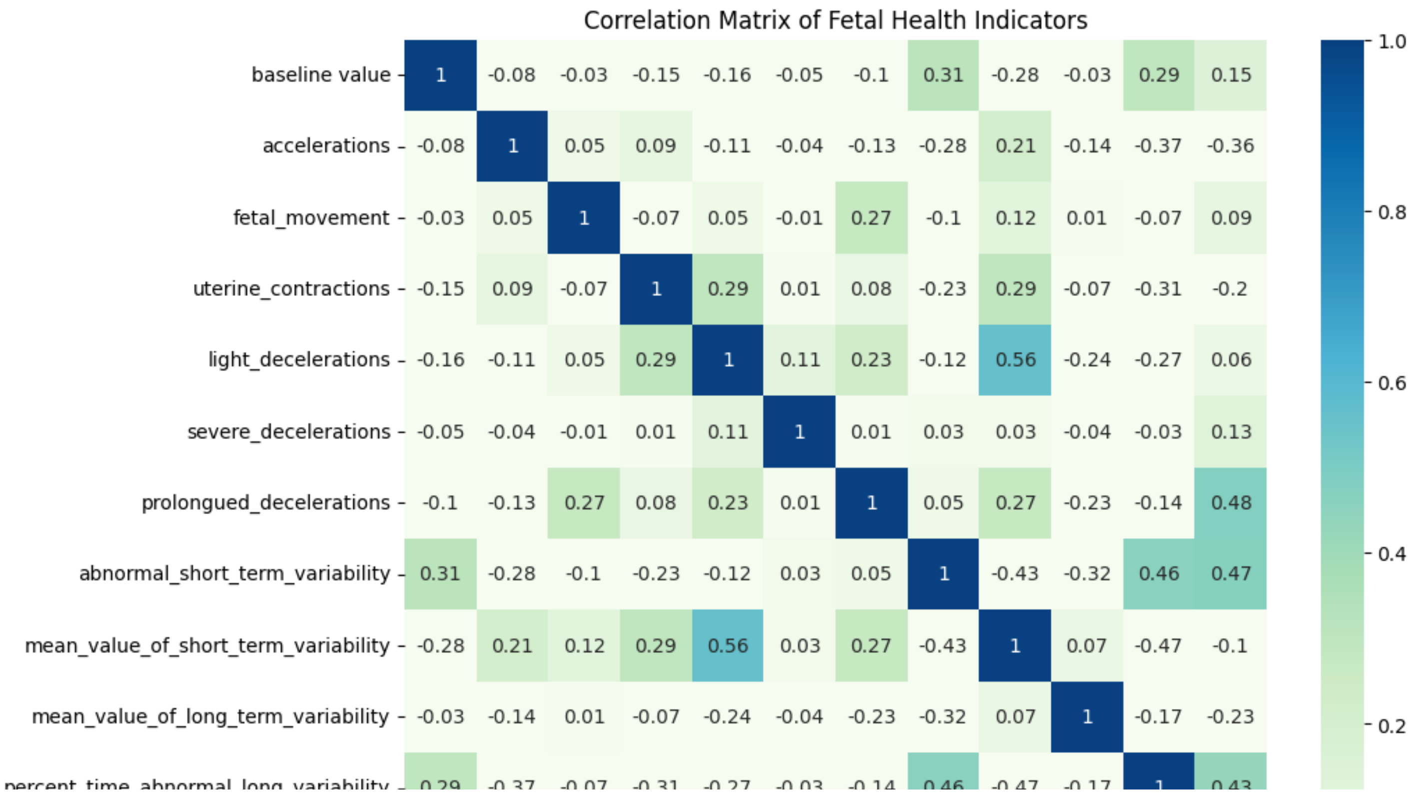
```
plt.legend()
plt.show()
```

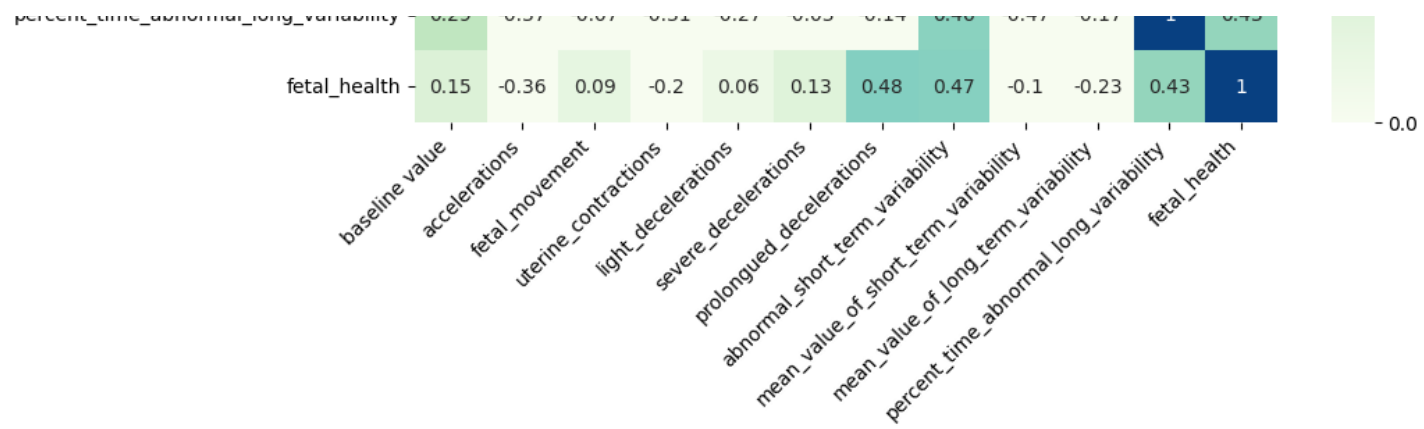



## Correlation Matrix

In [ ]:

```
corr = round(feat.corr(), 2)
fig = plt.figure(figsize=(10,8))
axes = fig.subplots()

sns.heatmap(corr, vmin=0, vmax=1, annot=True, cmap='GnBu')

plt.title('Correlation Matrix of Fetal Health Indicators')
plt.xticks(ha='right', rotation=45)
plt.show()
```

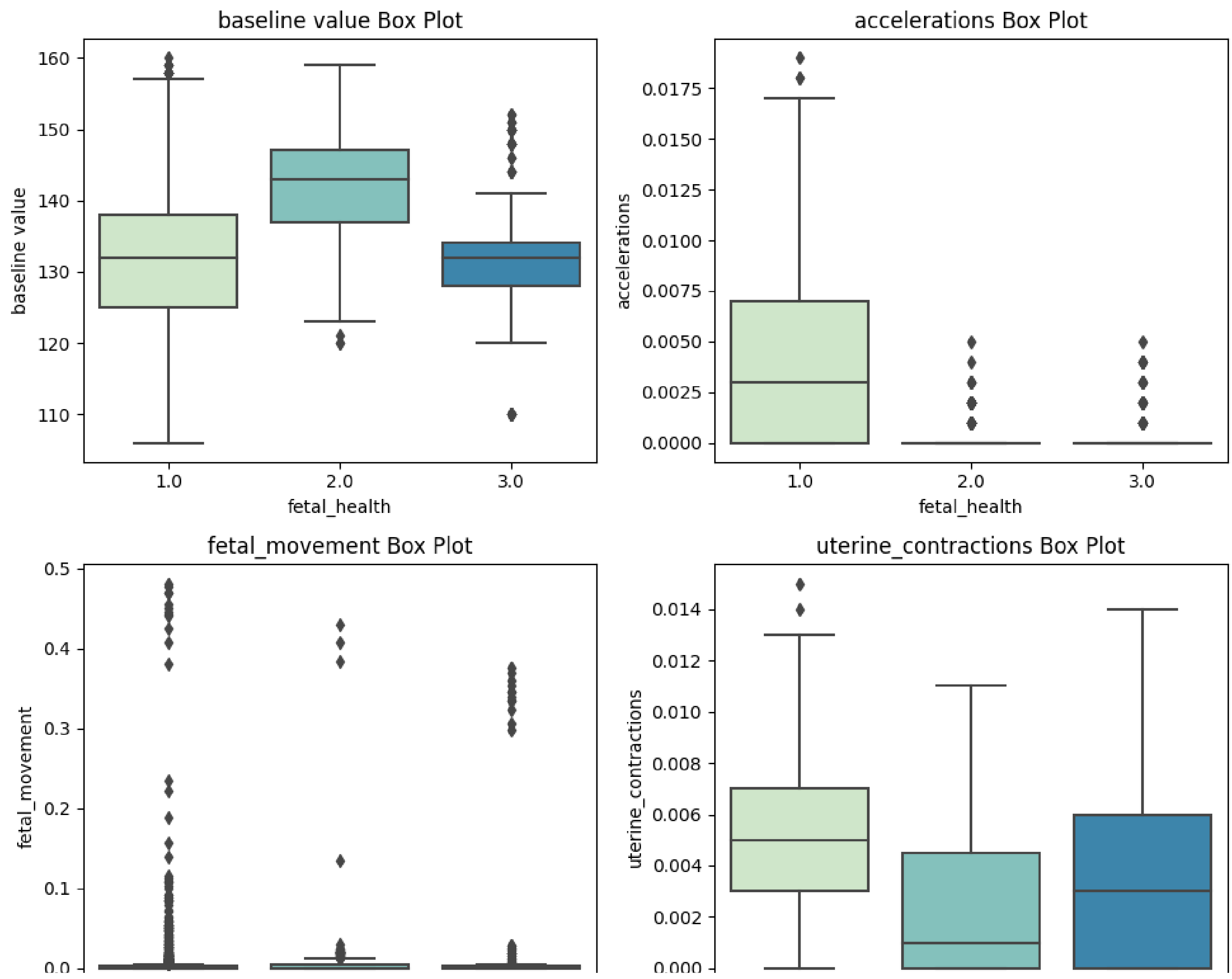


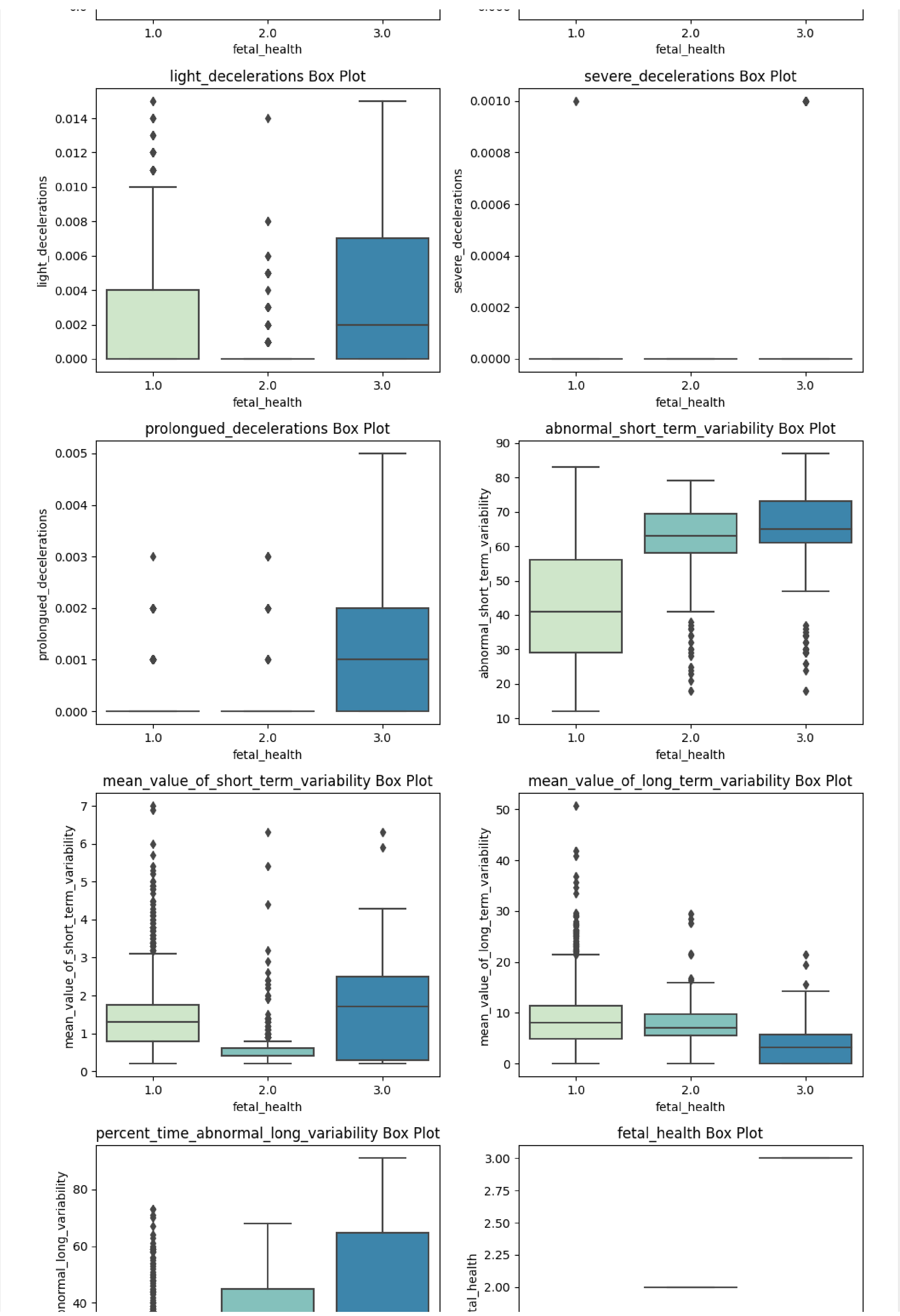



### View Data Distribution - Box Plots

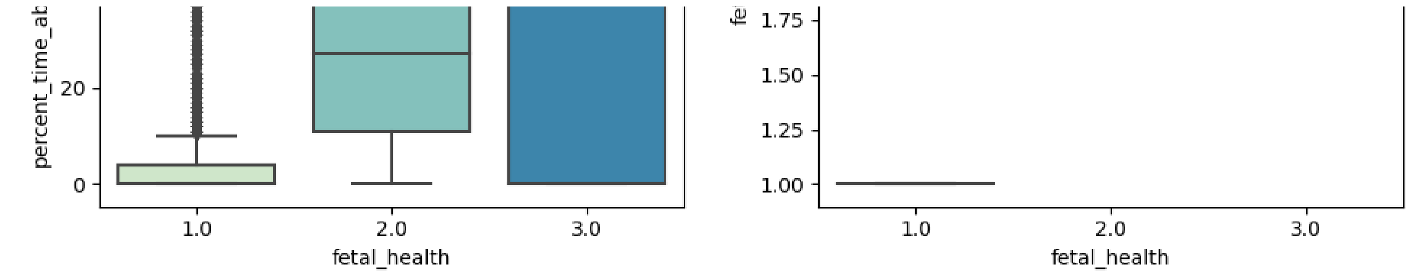
In [ ]:

```
fig = plt.figure(figsize=(10,25)) # W x H
axes = fig.subplots(6,2)
temp = feat.columns.values
i=0
for row in range(6):
  for col in range(2):
    sns.boxplot(x=feat['fetal_health'],
                y = feat[temp[i]],
                data=feat,
                ax=axes[row,col],
                palette='GnBu')
    axes[row,col].set_title(f'{temp[i]} Box Plot')
    i+=1
fig.tight_layout()
plt.show()
```





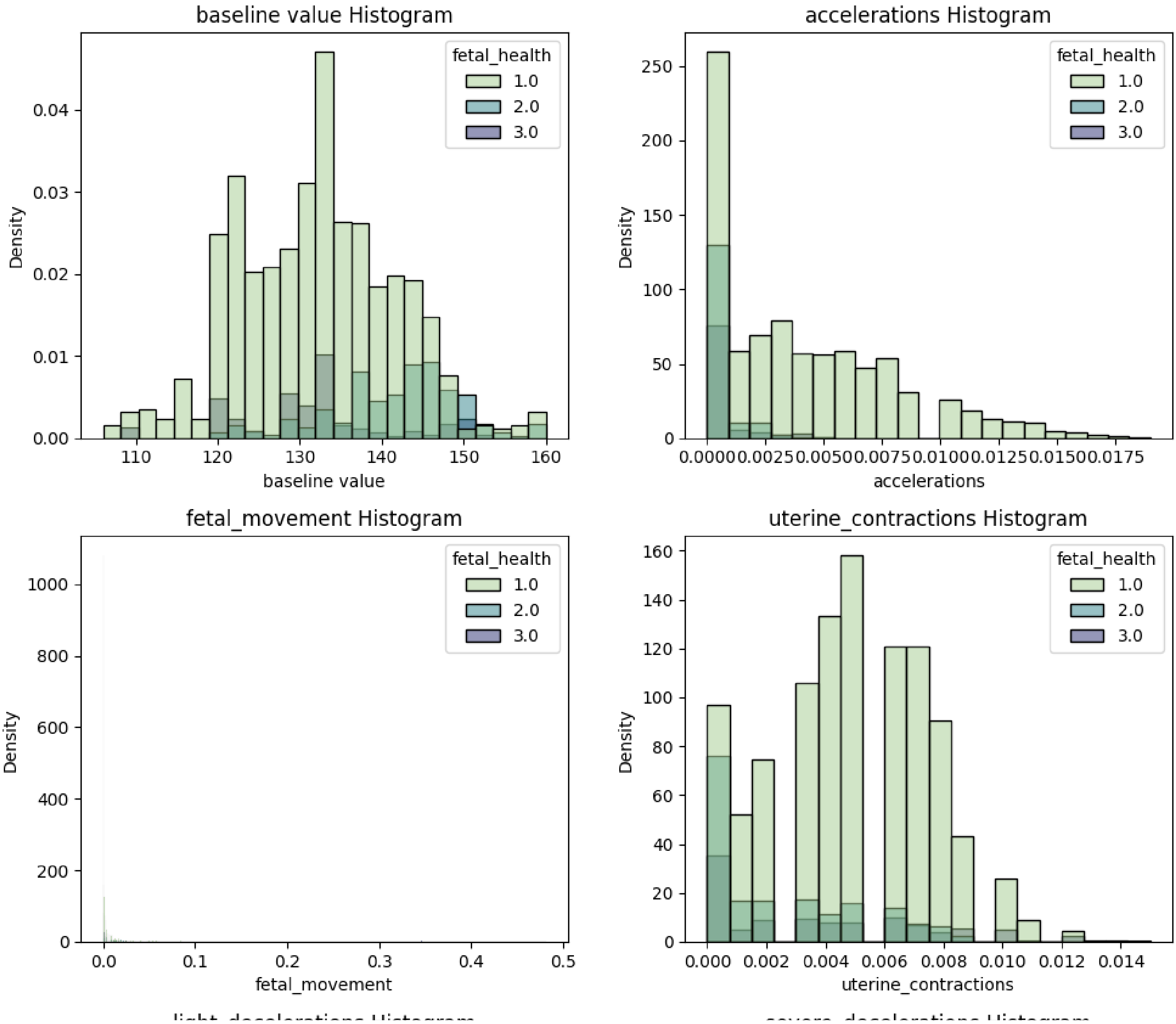
1.0
2.0
3.0
fetal_health
1.0
2.0
3.0
fetal_health
light_decelerations Box Plot
light_decelerations
0.000
0.002
0.004
0.006
0.008
0.010
0.012
0.014
1.0
2.0
3.0
fetal_health
severe_decelerations Box Plot
severe_decelerations
0.0000
0.0002
0.0004
0.0006
0.0008
0.0010
1.0
2.0
3.0
fetal_health
prolongued_decelerations Box Plot
prolongued_decelerations
0.000
0.001
0.002
0.003
0.004
0.005
1.0
2.0
3.0
fetal_health
abnormal_short_term_variability Box Plot
abnormal_short_term_variability
10
20
30
40
50
60
70
80
90
1.0
2.0
3.0
fetal_health
mean_value_of_short_term_variability Box Plot
mean_value_of_short_term_variability
0
1
2
3
4
5
6
7
1.0
2.0
3.0
fetal_health
mean_value_of_long_term_variability Box Plot
mean_value_of_long_term_variability
0
10
20
30
40
50
1.0
2.0
3.0
fetal_health
percent_time_abnormal_long_variability Box Plot
40
60
80
fetal_health Box Plot
2.00
2.25
2.50
2.75
3.00

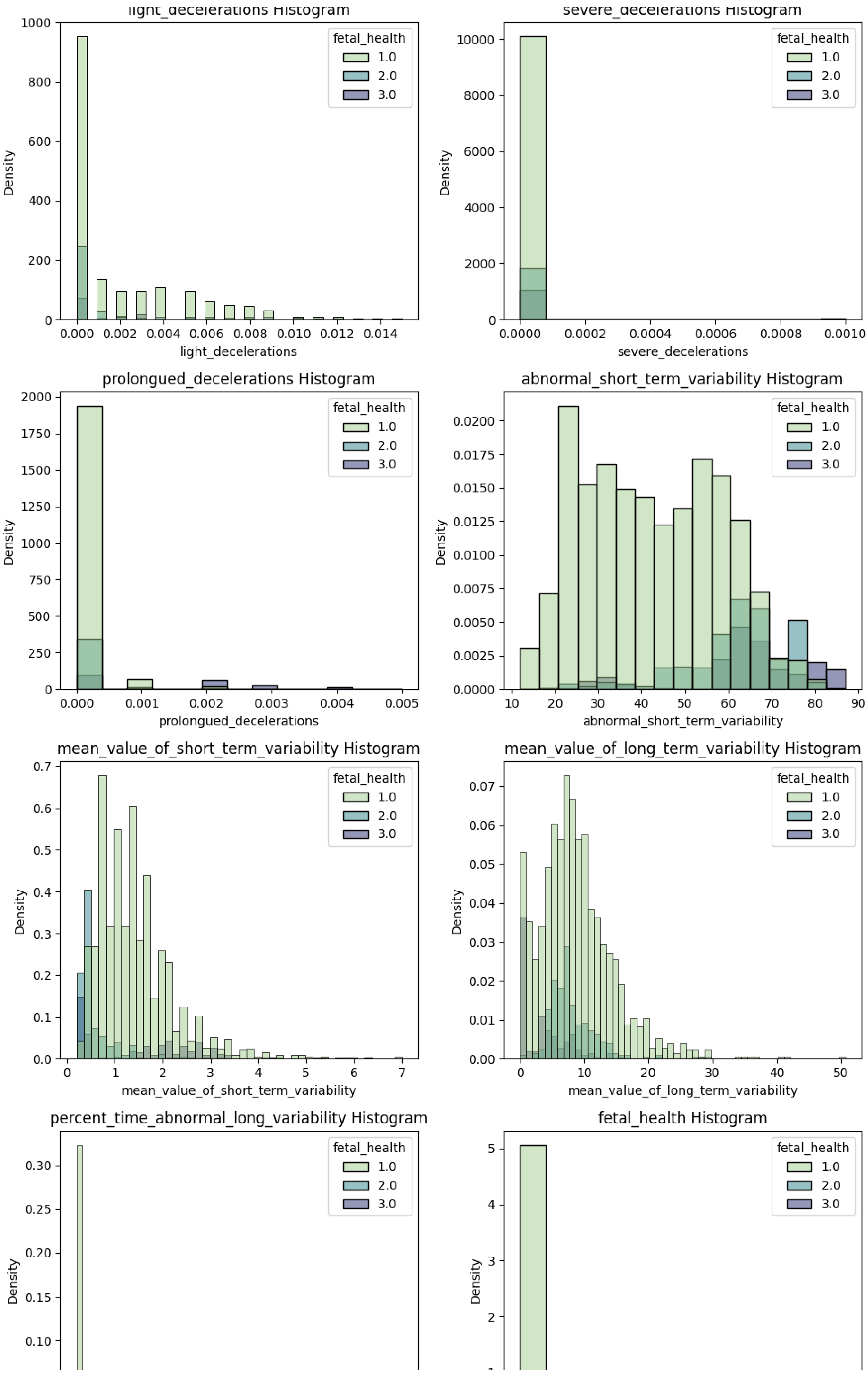


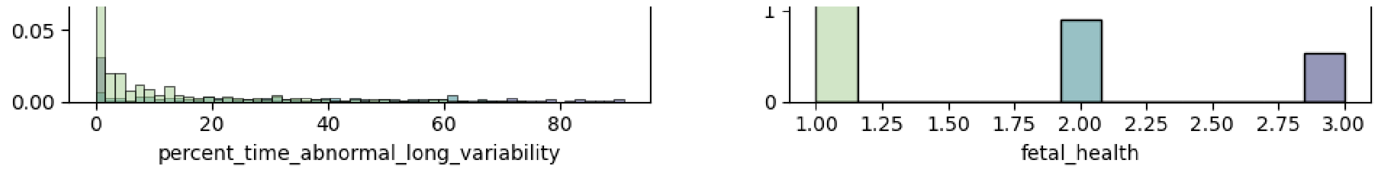

## View Data Distribution - Frequency Histograms

In [ ]:

```
fig = plt.figure(figsize=(10,25)) # W x H
axes = fig.subplots(6,2)
temp = feat.columns.values
i=0
for row in range(6):
  for col in range(2):
    sns.histplot(data=feat,
                 x=feat[temp[i]],
                 hue=feat['fetal_health'],
                 stat='density',
                 palette='crest',
                 ax=axes[row,col],)
    axes[row,col].set_title(f'{temp[i]} Histogram')
    i+=1
fig.tight_layout()
plt.show()
```

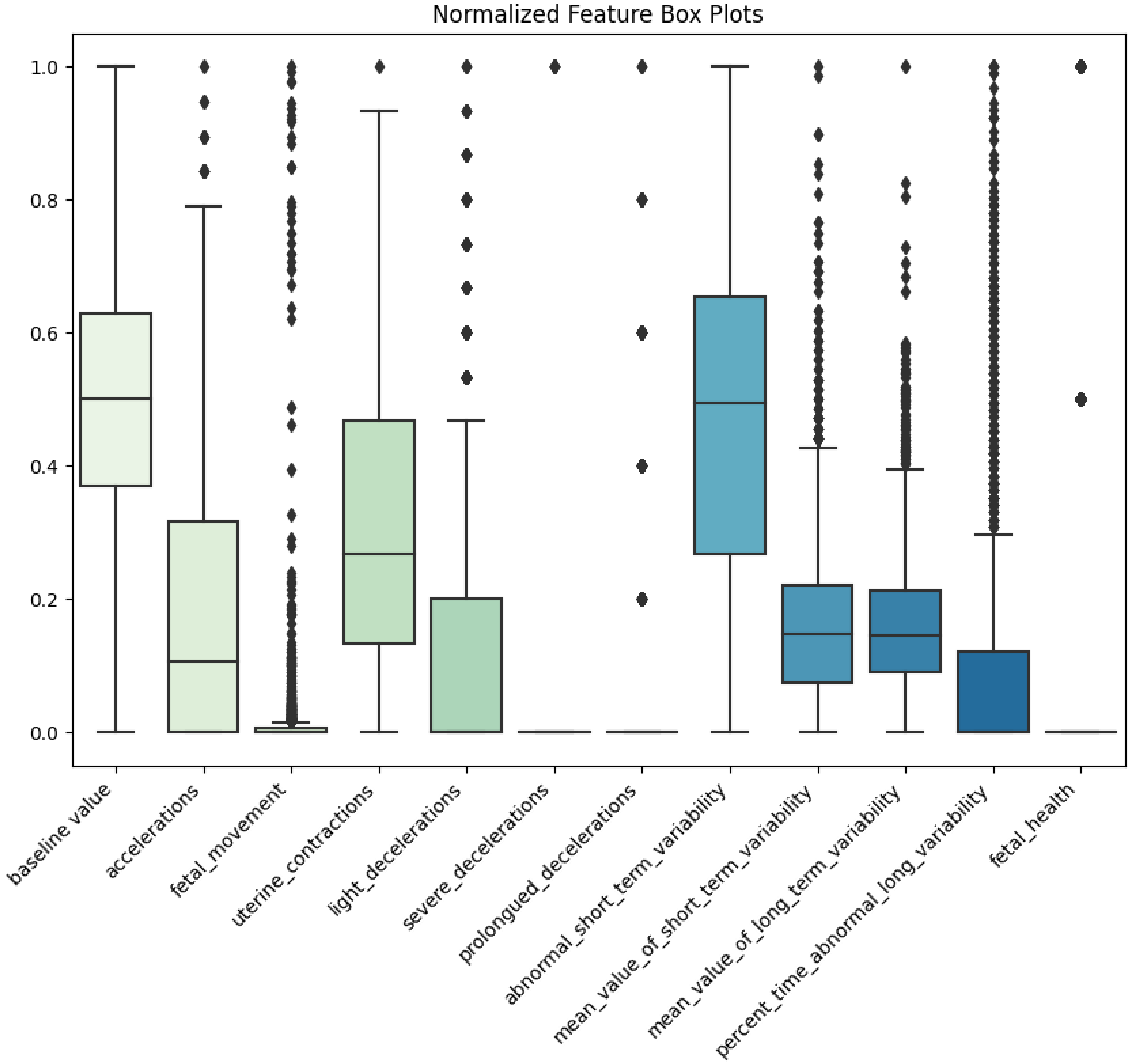



light_decelerations Histogram
Density
light_decelerations
fetal_health
1.0
2.0
3.0
severe_decelerations Histogram
Density
severe_decelerations
fetal_health
1.0
2.0
3.0
prolongued_decelerations Histogram
Density
prolongued_decelerations
fetal_health
1.0
2.0
3.0
abnormal_short_term_variability Histogram
Density
abnormal_short_term_variability
fetal_health
1.0
2.0
3.0
mean_value_of_short_term_variability Histogram
Density
mean_value_of_short_term_variability
fetal_health
1.0
2.0
3.0
mean_value_of_long_term_variability Histogram
Density
mean_value_of_long_term_variability
fetal_health
1.0
2.0
3.0
percent_time_abnormal_long_variability Histogram
Density
fetal_health
1.0
2.0
3.0
fetal_health Histogram
Density
fetal_health
1.0
2.0
3.0




In [ ]:

```
from sklearn.preprocessing import MinMaxScaler
minmax = MinMaxScaler(feature_range=(0,1)).set_output(transform='pandas')
range_scaled = minmax.fit_transform(feat)
fig = plt.figure(figsize=(10,7))
sns.boxplot(range_scaled,
            palette='GnBu')
plt.title('Normalized Feature Box Plots')
plt.xticks(ha='right',rotation=45)
plt.show()
```




## Step 3: Model Evaluation

In [ ]:

```
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import train_test_split
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import ConfusionMatrixDisplay
from sklearn.metrics import classification_report
from sklearn.inspection import DecisionBoundaryDisplay
from sklearn.preprocessing import LabelBinarizer
from sklearn.metrics import RocCurveDisplay
from sklearn.calibration import CalibratedClassifierCV
from sklearn.model_selection import GridSearchCV
from sklearn.svm import SVC
```

In [ ]:

```
sc = StandardScaler().set_output(transform='pandas')
X_temp = feat.iloc[:, :-1]
X = sc.fit(X_temp).transform(X_temp).values
y = feat.iloc[:, -1].values
sss = StratifiedShuffleSplit(n_splits=2,
                             train_size=0.8,
                             test_size=0.2,
                             random_state=1234)

for i, (train_index, test_index) in enumerate(sss.split(X, y)):
  X_train = X[train_index]
  y_train = y[train_index]

  X_test = X[test_index]
  y_test = y[test_index]
print(X_train.shape)

label_binarizer = LabelBinarizer().fit(y_train)
y_onehot_test = label_binarizer.transform(y_test) # for ROC curves
```

```
(1700, 11)
```

In [ ]:

```
def plot_split_results(data, param_dict, model_name):
  data = data.drop(columns=['mean_fit_time', 'std_fit_time', 'mean_score_time', 'std_sco
re_time',
                            'mean_test_score', 'std_test_score', 'std_train_score',
                            'rank_test_score', 'split0_train_score', 'split1_train_score
',
                            'split2_train_score', 'split3_train_score', 'split4_train_sc
ore',
                            'split5_train_score', 'split6_train_score', 'split7_train_sc
ore',
                            'split8_train_score', 'split9_train_score', 'mean_train_scor
e',])

  fig = plt.figure(figsize=(15,5))
  axes = fig.subplots(1, len(param_dict), sharey=True)

  for i, (param_name, param_range) in enumerate(param_dict.items()):
    fig.suptitle(f'10-Fold Cross-Validation Results for {model_name} Hyper-Parameters', f
ontsize=15)
    grouped = data.groupby(by=f'param_{param_name}').agg('mean').T
    grouped.index = np.arange(1, len(grouped) + 1)

    sns.lineplot(grouped, palette='ocean', ax=axes[i])
    axes[i].set(title=param_name,
                xlabel='Fold',
                ylabel='Score',
                visible=True)
    axes[i].set_xticks(grouped.index)
    axes[i].legend()
  plt.show()
```

In [ ]:

```
def plot_ROC_curve(mod, XX_train, yy_train, XX_test):
  fig = plt.figure(figsize=(5,10))
  axes=fig.subplots(2,1)
  ConfusionMatrixDisplay.from_predictions(y_true=y_test,
                                          y_pred=pred,
                                          cmap='GnBu',
                                          ax=axes[0])
  axes[0].set(title=f'{model_names[i]} Confusion Matrix')
  try:
    y_score = mod.fit(XX_train, yy_train).predict_proba(XX_test)
  except:
    m = CalibratedClassifierCV(mod)
    m.fit(XX_train, yy_train)
    y_score = m.predict_proba(XX_test)

  print(classification_report(y_test, pred))
  RocCurveDisplay.from_predictions(y_onehot_test.ravel(),
                                   y_score.ravel(),
                                   name="Micro-Average One-vs-Rest",
                                   color="navy",
                                   ax=axes[1])
  axes[1].set(title=f'{model_names[i]} ROC Curve', xlabel='False Positive Rate', ylabel=
'True Positive Rate')
  axes[1].plot([0, 1], [0, 1], label="chance level (AUC = 0.5)", color='lightgreen', lin
estyle='--')
  plt.legend()
  plt.show()
```

In [ ]:

```
def plot_decision_boundary(mod):
  X_train_corr = X_temp[['abnormal_short_term_variability', 'percent_time_abnormal_long_v
ariability']]

  mod.fit(X_train_corr, y)

  disp = DecisionBoundaryDisplay.from_estimator(mod,
                                                X_train_corr,
                                                response_method="predict",
                                                alpha=0.5,
                                                xlabel='Abnormal Short Term Variability'
,
                                                ylabel='Percent Time Abnormal Long Varia
bility',
                                                cmap='GnBu')

  decision_function = mod.decision_function(X_train_corr)
  support_vector_indices = np.where(np.abs(decision_function) <= 1 + 1e-15)[0]
  support_vectors = X_train_corr.values[support_vector_indices]

  scat = plt.scatter(X_train_corr.iloc[:, 0],
                     X_train_corr.iloc[:, 1],
                     c=y,
                     edgecolors="k",
                     cmap='GnBu')
  plt.title('Decision Boundaries for Support Vector Machine')

  handles, labels = scat.legend_elements()
  labels = ['1.0 - Normal', '2.0 - Suspect', '3.0 - Pathological']
  plt.legend(handles=handles, labels=labels)

  plt.show()
```

In [ ]:

```
model_names = ['Decision Tree',
               'Support Vector Machine',
               'Gradient Boost',
               'k-Nearest Neighbors',
```

```
               'Logistic Regression']

dt = DecisionTreeClassifier(class_weight='balanced')

svm = SVC(class_weight='balanced')

gb = GradientBoostingClassifier()

knn = KNeighborsClassifier()

logreg = LogisticRegression(class_weight='balanced')

models = [dt, svm, gb, knn, logreg]
```

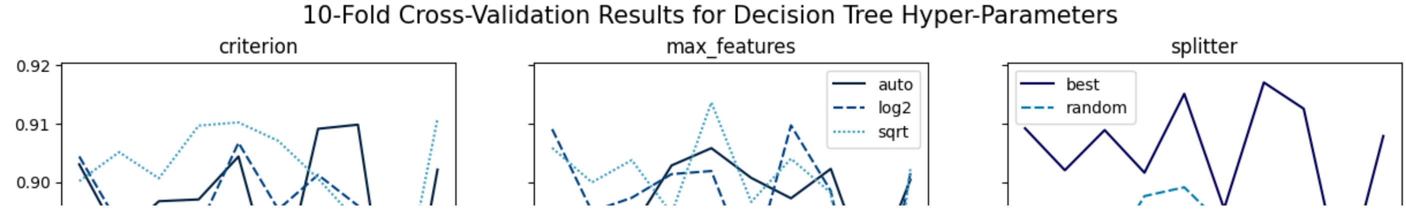
In [ ]:

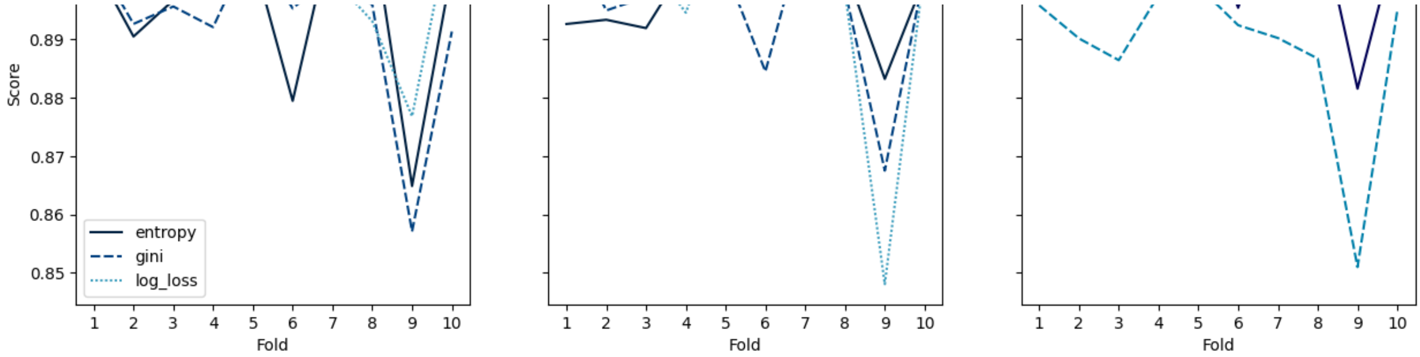
```
dt_params = {'criterion':('gini', 'entropy', 'log_loss'),
             'max_features':('auto', 'sqrt', 'log2'),
             'splitter':('random', 'best')}

svm_params = {'C':(1.0, 1.25, 1.5, 1.75, 2.0),
              'kernel':('linear', 'rbf', 'poly', 'sigmoid'),
              'degree':(1,2,3,4,5)}

gb_params = {'criterion':('friedman_mse', 'squared_error'),
             'loss':('log_loss', 'deviance'),
             'n_estimators':(100, 150, 200, 250)}

knn_params = {'metric':('manhattan','euclidean','cosine'),
              'weights':('uniform', 'distance'),
              'n_neighbors':(3, 5, 7, 9)}

logreg_params = {'C':(1.0, 1.25, 1.5, 1.75, 2.0),
                 'penalty': ('l1', 'l2'),
                 'solver': ['liblinear']}

param_grids = [dt_params, svm_params, gb_params, knn_params, logreg_params]
```

In [ ]:

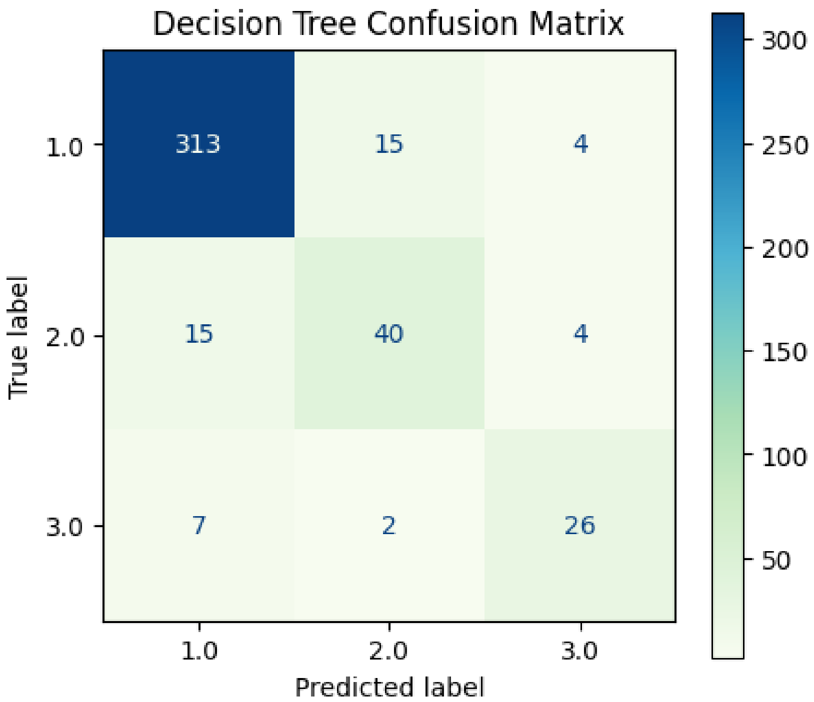
```
for i in range(len(models)):
  grid = GridSearchCV(estimator=models[i],
                      param_grid=param_grids[i],
                      scoring='f1_weighted',
                      return_train_score=True,
                      cv=10)
  grid.fit(X_train, y_train)
  results = pd.DataFrame(grid.cv_results_)#.loc[:,'params':'split9_test_score']
  plot_split_results(results, param_grids[i], model_names[i])

  print(f'\n    -------  {type(models[i]).__name__}  -------  ')
  print(f'  The best estimator: {grid.best_estimator_}')
  print(f'  The best score: {round(grid.best_score_, 4)}')
  print(f'  The best parameters: {grid.best_params_}\n')
  # display(results[['params', 'rank_test_score',
  #                  'mean_test_score', 'std_test_score',
  #                  'mean_train_score', 'std_train_score']])

  model = grid.best_estimator_
  pred = grid.predict(X_test)

  plot_ROC_curve(model, X_train, y_train, X_test)
  if model_names[i] == 'Support Vector Machine':
    plot_decision_boundary(model)
```

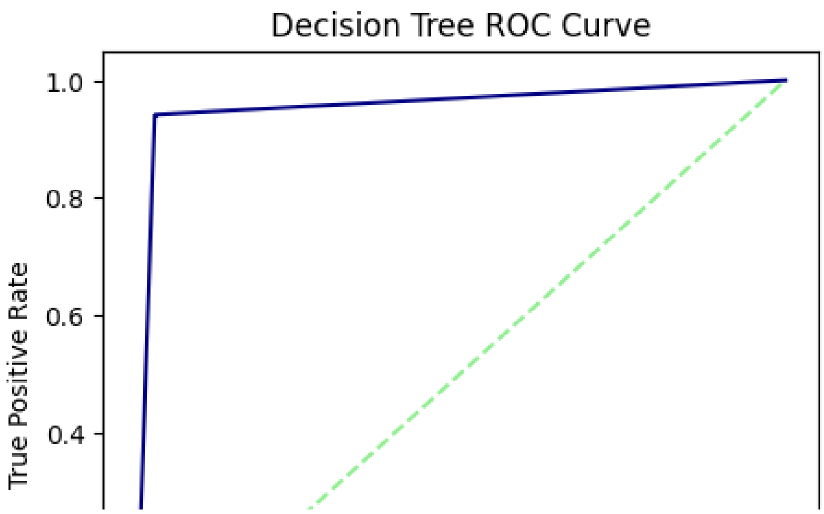
10-Fold Cross-Validation Results for Decision Tree Hyper-Parameters

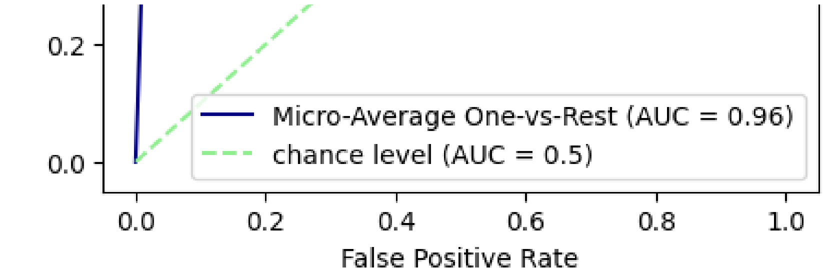


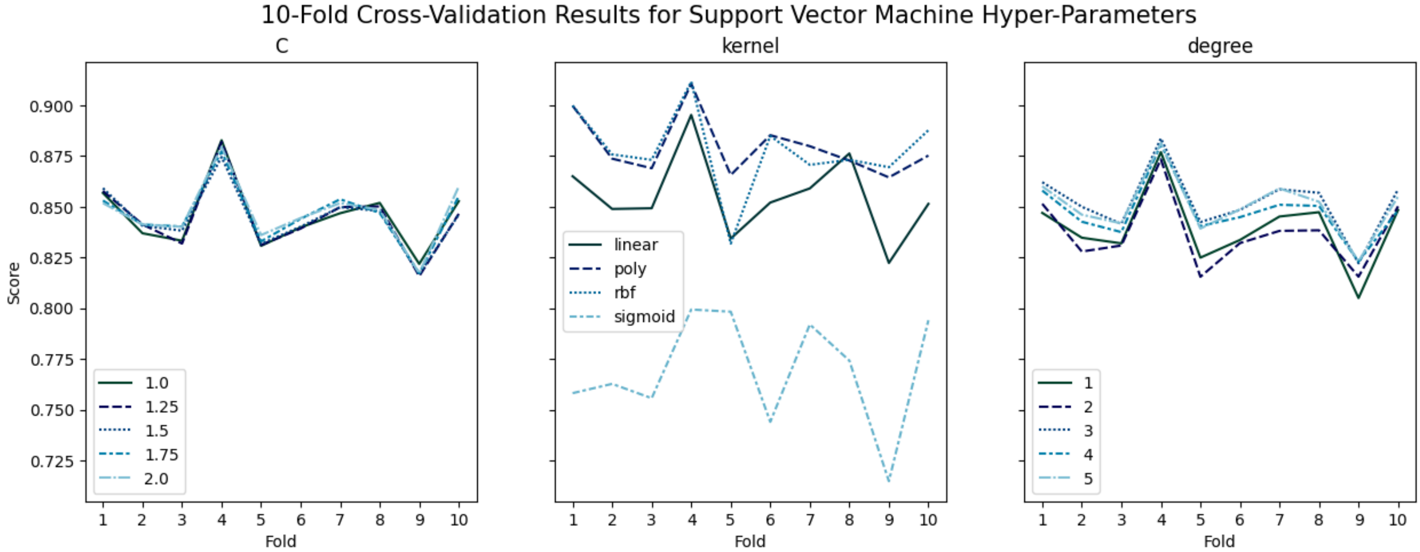



```
    -------  DecisionTreeClassifier  -------
  The best estimator: DecisionTreeClassifier(class_weight='balanced', criterion='log_loss
',
                       max_features='log2')
  The best score: 0.9153
  The best parameters: {'criterion': 'log_loss', 'max_features': 'log2', 'splitter': 'bes
t'}

              precision    recall  f1-score   support

         1.0       0.93      0.94      0.94       332
         2.0       0.70      0.68      0.69        59
         3.0       0.76      0.74      0.75        35

    accuracy                           0.89       426
   macro avg       0.80      0.79      0.79       426
weighted avg       0.89      0.89      0.89       426
```

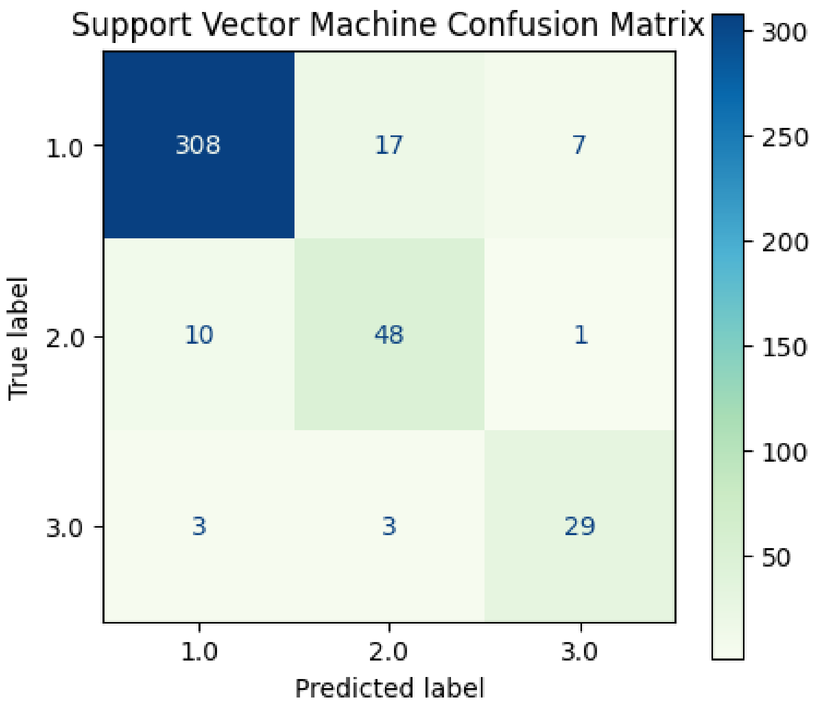


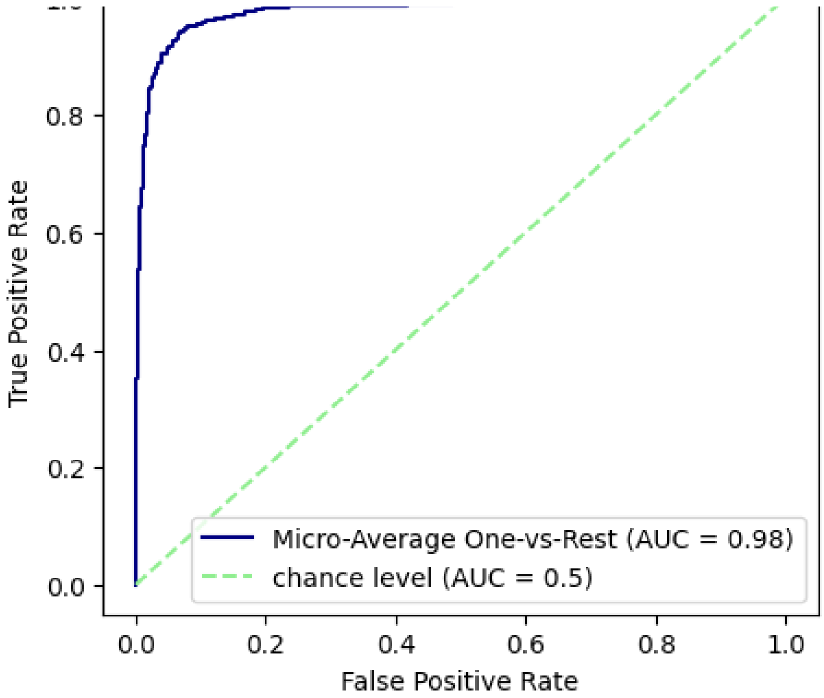



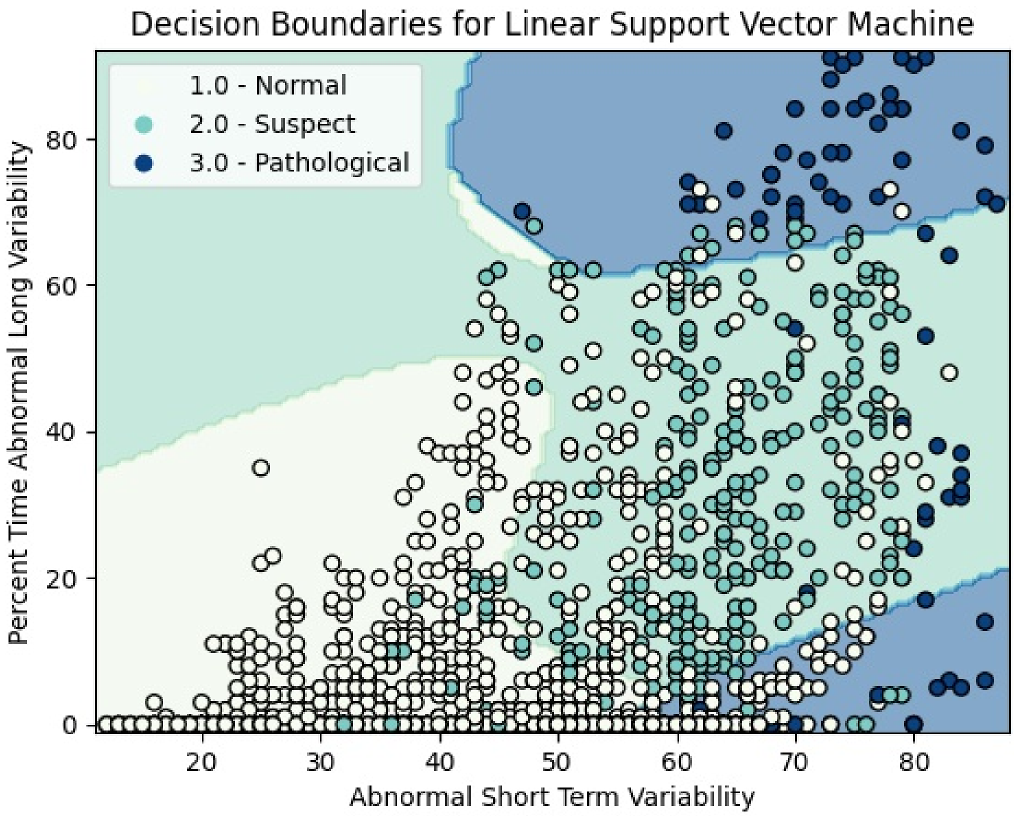


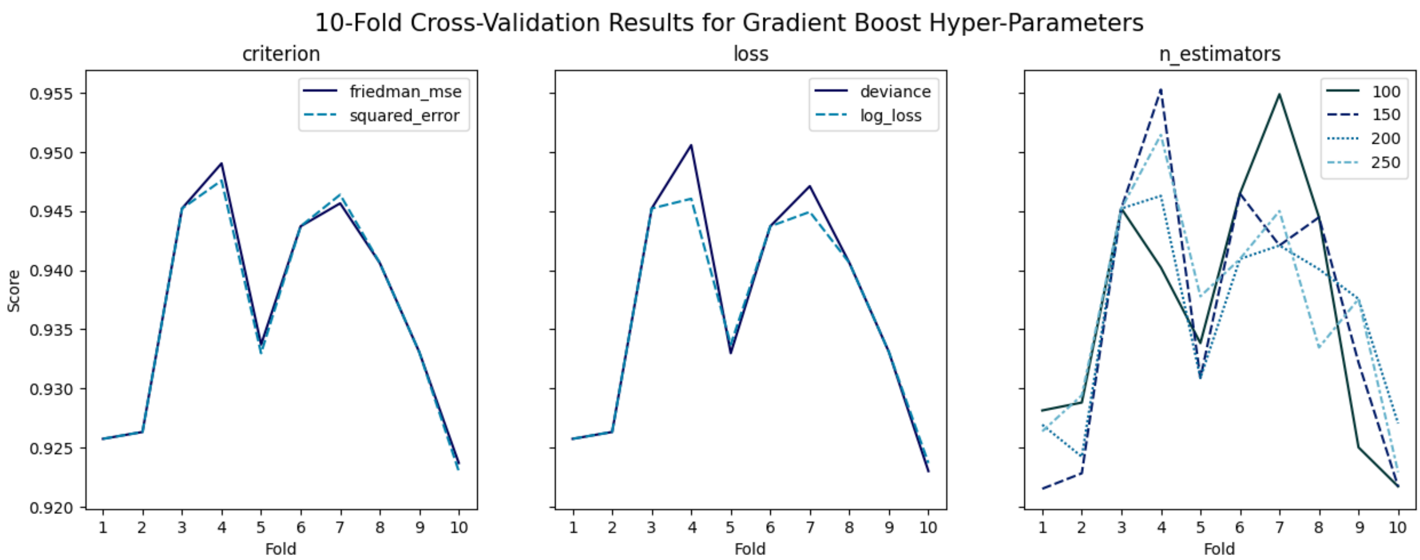




```
 -------  SVC  -------
The best estimator: SVC(class_weight='balanced', kernel='poly')
The best score: 0.9091
The best parameters: {'C': 1.0, 'degree': 3, 'kernel': 'poly'}

              precision    recall  f1-score   support

         1.0       0.96      0.93      0.94       332
         2.0       0.71      0.81      0.76        59
         3.0       0.78      0.83      0.81        35

    accuracy                           0.90       426
   macro avg       0.82      0.86      0.83       426
weighted avg       0.91      0.90      0.91       426
```



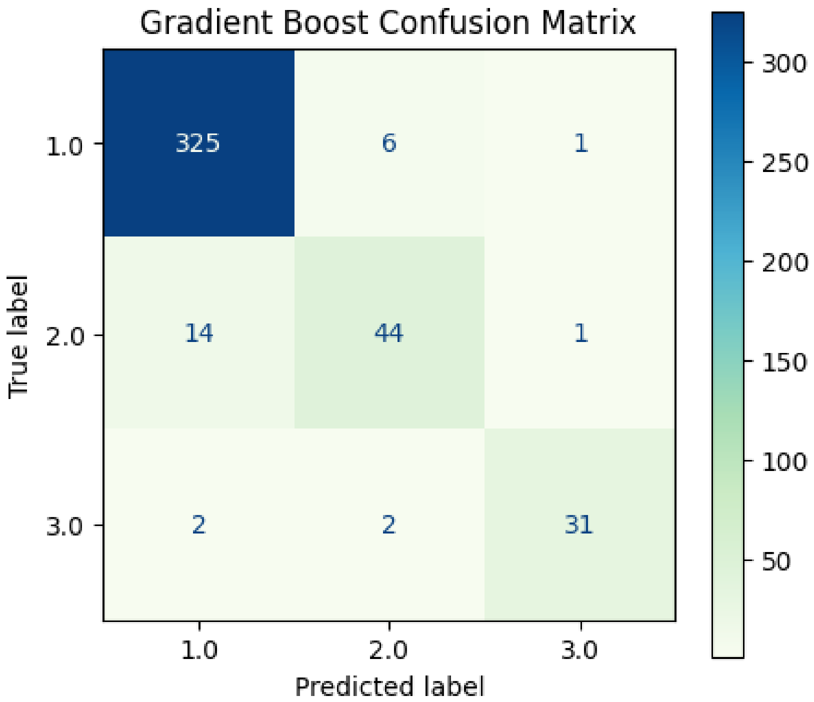



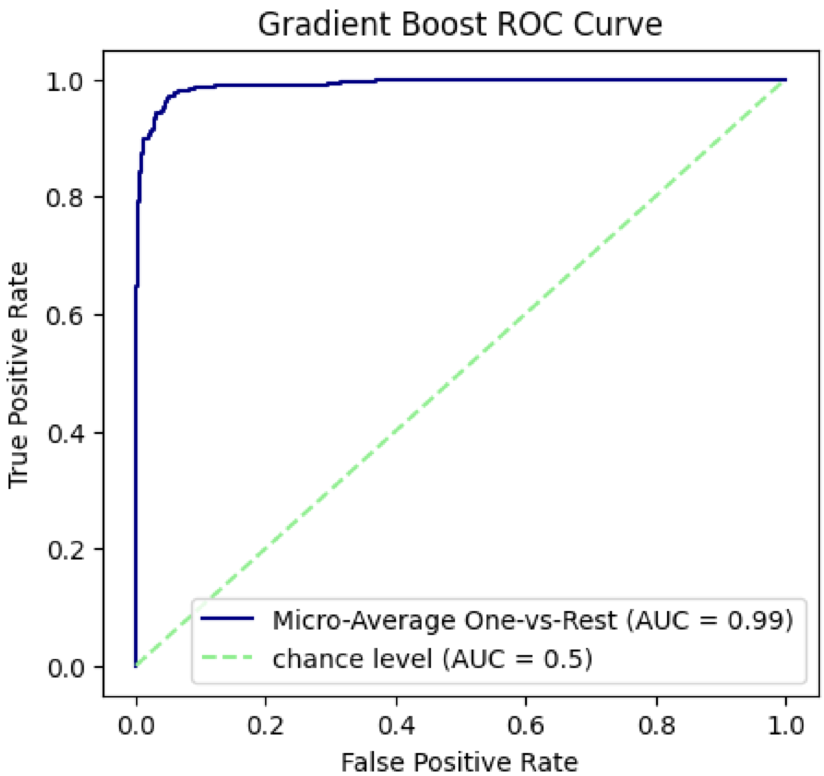



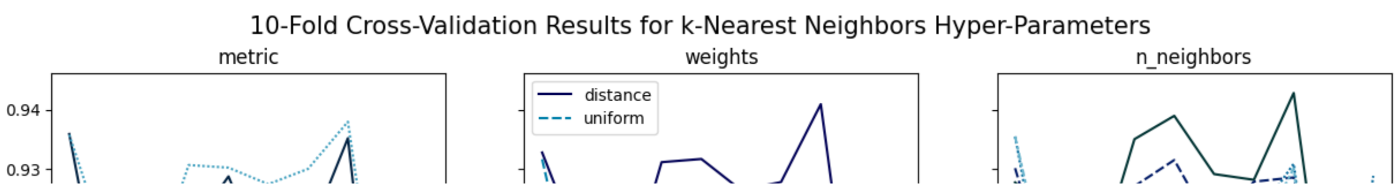



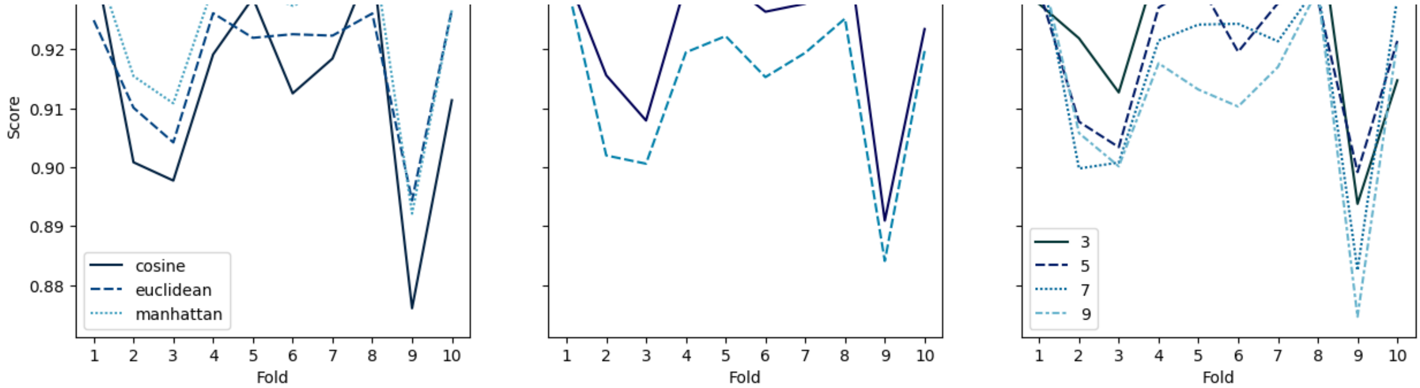

```
-------   GradientBoostingClassifier   -------
```

```
  The best estimator: GradientBoostingClassifier(loss='deviance')
  The best score: 0.9376
  The best parameters: {'criterion': 'friedman_mse', 'loss': 'deviance', 'n_estimators':
100}

              precision    recall  f1-score   support

         1.0       0.95      0.98      0.97       332
         2.0       0.85      0.75      0.79        59
         3.0       0.94      0.89      0.91        35

    accuracy                           0.94       426
   macro avg       0.91      0.87      0.89       426
weighted avg       0.94      0.94      0.94       426
```

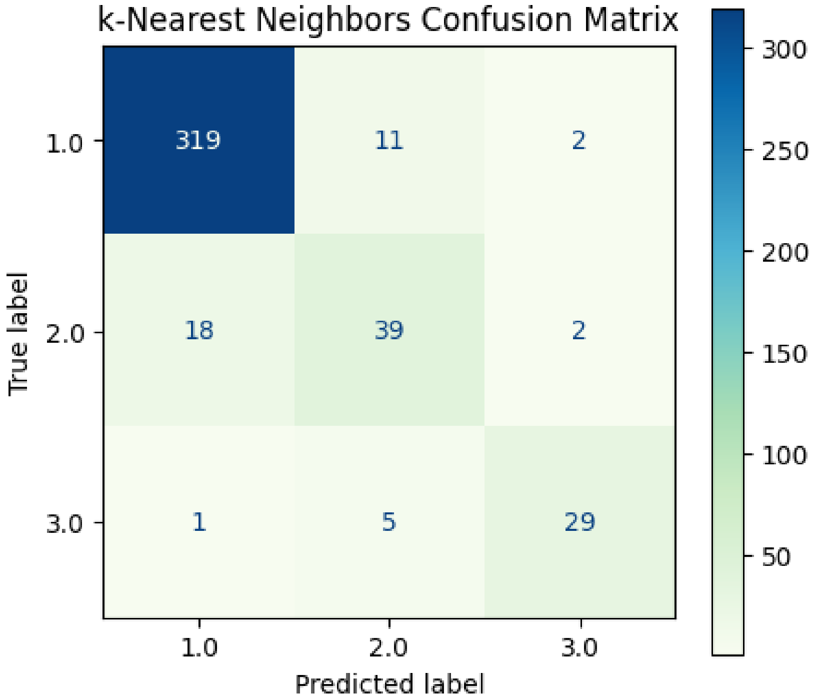


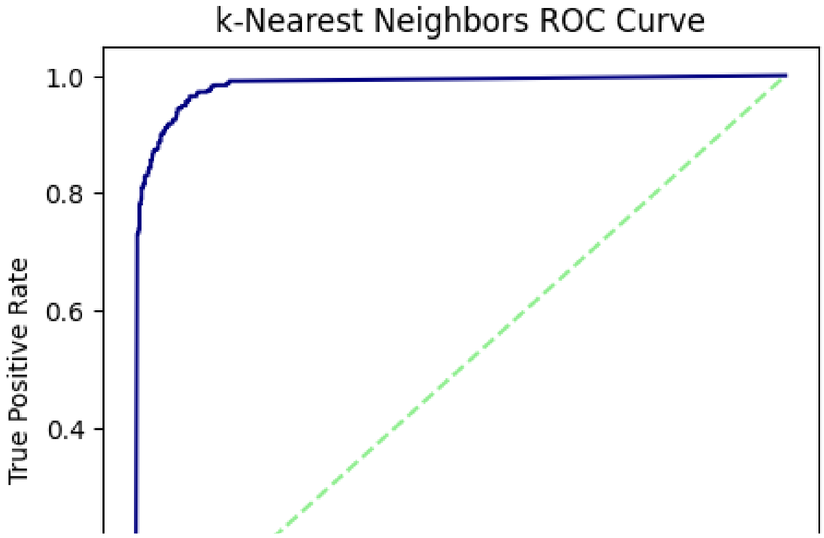



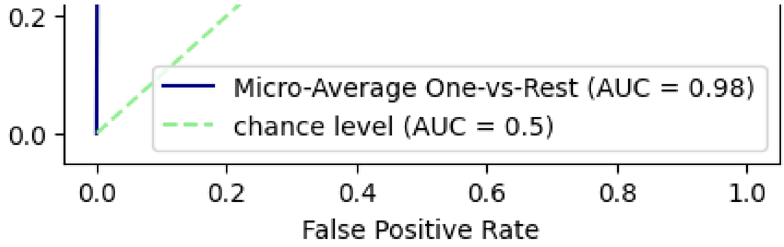



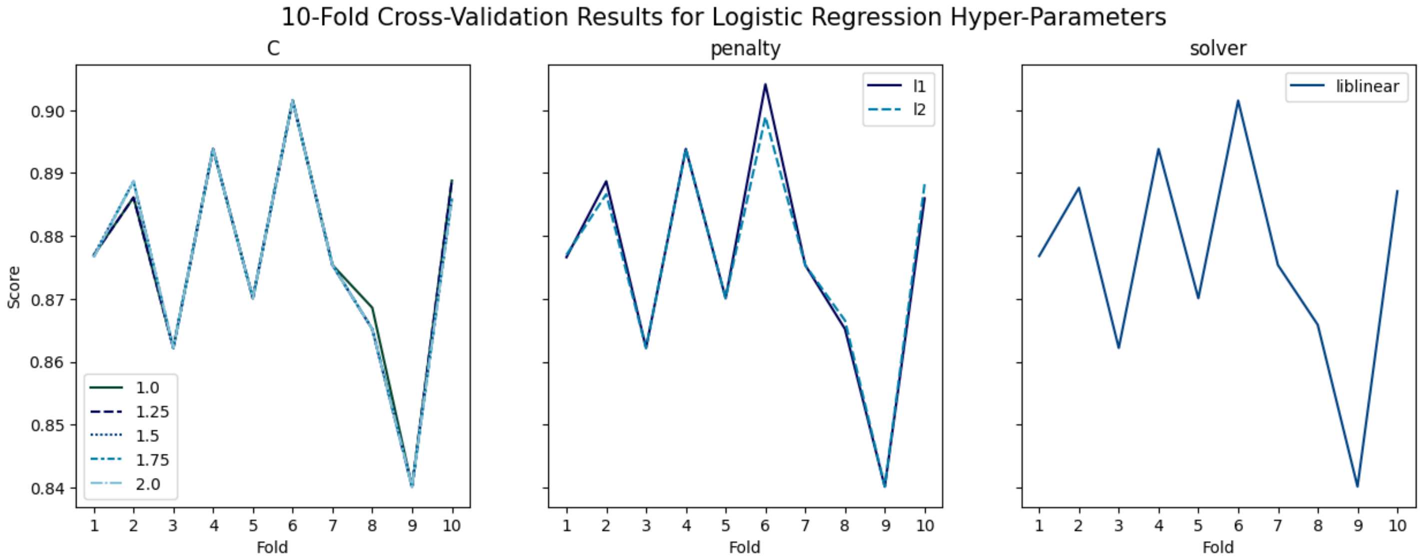



```
    -------  KNeighborsClassifier  -------
  The best estimator: KNeighborsClassifier(metric='manhattan', n_neighbors=7, weights='di
stance')
  The best score: 0.9293
  The best parameters: {'metric': 'manhattan', 'n_neighbors': 7, 'weights': 'distance'}

              precision    recall  f1-score   support

         1.0       0.94      0.96      0.95       332
         2.0       0.71      0.66      0.68        59
         3.0       0.88      0.83      0.85        35

    accuracy                           0.91       426
   macro avg       0.84      0.82      0.83       426
weighted avg       0.91      0.91      0.91       426
```

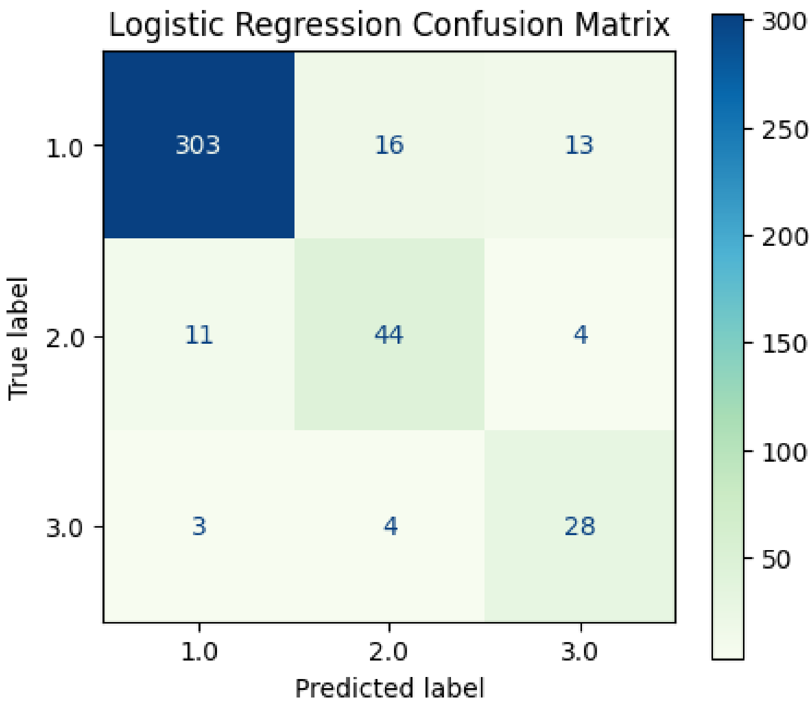


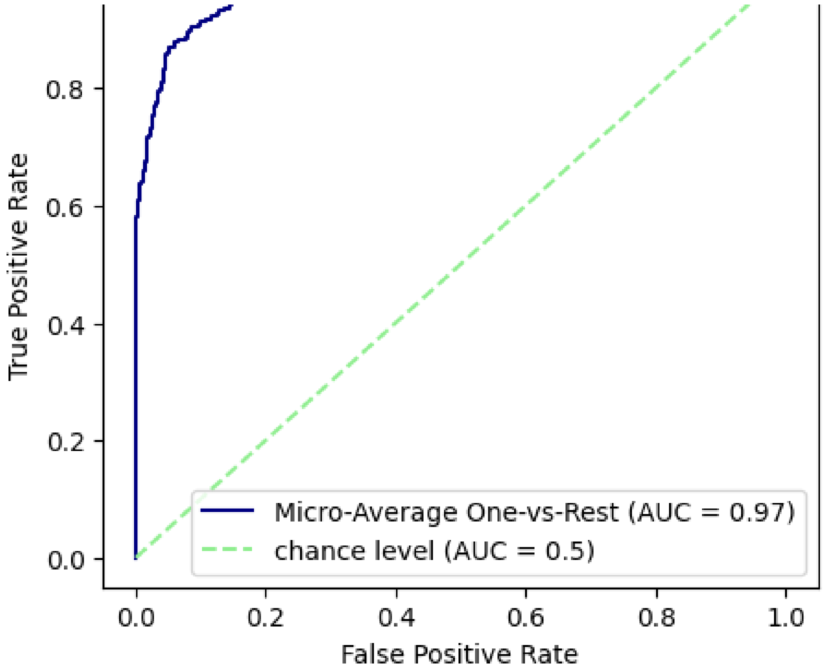






```
   -------  LogisticRegression  -------
 The best estimator: LogisticRegression(class_weight='balanced', solver='liblinear')
 The best score: 0.8765
 The best parameters: {'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}

               precision    recall  f1-score   support

          1.0       0.96      0.91      0.93       332
          2.0       0.69      0.75      0.72        59
          3.0       0.62      0.80      0.70        35

     accuracy                           0.88       426
    macro avg       0.76      0.82      0.78       426
 weighted avg       0.89      0.88      0.88       426
```



0.8
0.6
0.4
0.2
0.0
True Positive Rate
Micro-Average One-vs-Rest (AUC = 0.97)
chance level (AUC = 0.5)
0.0
0.2
0.4
0.6
0.8
1.0
False Positive Rate


In [ ]: