Maternal Health Risk

1 Maternal Health Risk Evaluation

In this dataset we were given 1013 instances and 7 features.

Dataset link: https://archive.ics.uci.edu/dataset/863/maternal+health+risk

On the basis of 6 features which included:
1. Age
2. SystolicBP
3. DiastolicBP
4. BS (Blood Sugar)
5. BodyTemp
6. HeartRate

We were given the task to analyze and classify RiskLevel (low, mid, high) on the basis of these 6 features. For this task, we proceeded as per the index below:

1.1 Index

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1.1.1 Importing and Initial overview of Dataset

[1]:
```
import pandas as pd

file_path = 'Maternal Health Risk Data Set.csv'
data = pd.read_csv(file_path)

data.head(), data.info()
```

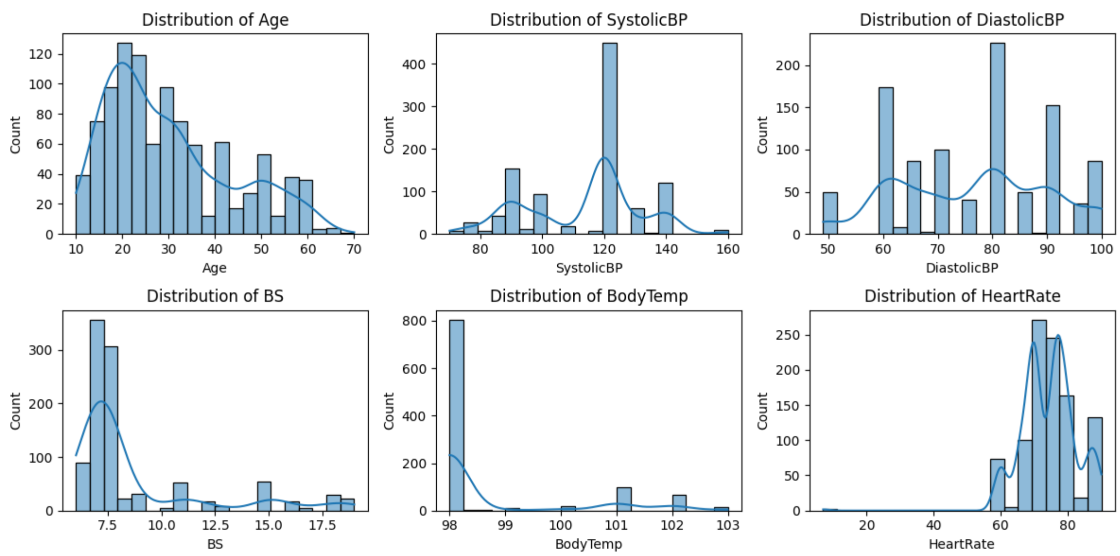
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1014 entries, 0 to 1013
Data columns (total 7 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   Age          1014 non-null   int64
 1   SystolicBP   1014 non-null   int64
 2   DiastolicBP  1014 non-null   int64
 3   BS           1014 non-null   float64
 4   BodyTemp     1014 non-null   float64
 5   HeartRate    1014 non-null   int64
 6   RiskLevel    1014 non-null   object
dtypes: float64(2), int64(4), object(1)
memory usage: 55.6+ KB
```

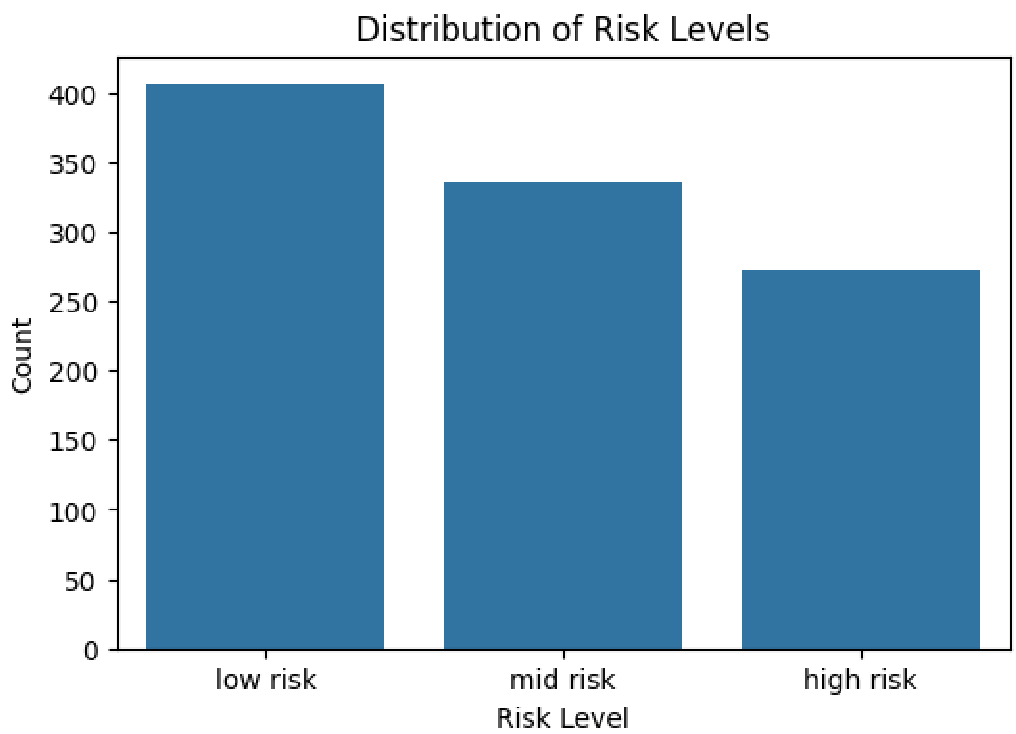
[1]:
```
(   Age  SystolicBP  DiastolicBP    BS  BodyTemp  HeartRate  RiskLevel
 0   25         130           80  15.0      98.0         86  high risk
 1   35         140           90  13.0      98.0         70  high risk
 2   29          90           70   8.0     100.0         80  high risk
 3   30         140           85   7.0      98.0         70  high risk
 4   35         120           60   6.1      98.0         76   low risk,
 None)
```

1.1.2 Exploratory Data Analysis

[2]:
```
import matplotlib.pyplot as plt
import seaborn as sns

summary_stats = data.describe()
risk_level_distribution = data['RiskLevel'].value_counts()

# Plot the distribution of features
plt.figure(figsize=(12, 6))

for i, column in enumerate(data.columns[:-1], 1):
    plt.subplot(2, 3, i)
    sns.histplot(data[column], kde=True, bins=20)
    plt.title(f"Distribution of {column}")
    plt.xlabel(column)
```

```
plt.tight_layout()
plt.show()

plt.figure(figsize=(6, 4))
sns.countplot(data=data, x='RiskLevel', order=risk_level_distribution.index)
plt.title("Distribution of Risk Levels")
plt.xlabel("Risk Level")
plt.ylabel("Count")
plt.show()

summary_stats, risk_level_distribution
```



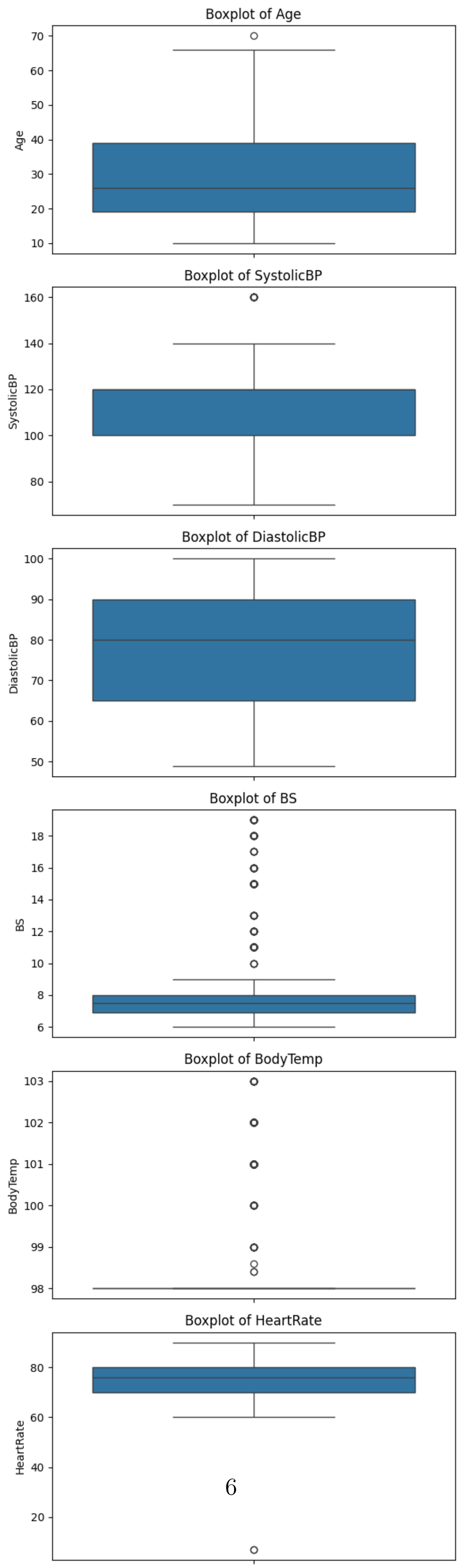


[2]:
```
(                Age   SystolicBP  DiastolicBP           BS     BodyTemp  \
 count  1014.000000  1014.000000  1014.000000  1014.000000  1014.000000
 mean     29.871795   113.198225    76.460552     8.725986    98.665089
 std      13.474386    18.403913    13.885796     3.293532     1.371384
 min      10.000000    70.000000    49.000000     6.000000    98.000000
 25%      19.000000   100.000000    65.000000     6.900000    98.000000
 50%      26.000000   120.000000    80.000000     7.500000    98.000000
 75%      39.000000   120.000000    90.000000     8.000000    98.000000
 max      70.000000   160.000000   100.000000    19.000000   103.000000

          HeartRate
 count  1014.000000
 mean     74.301775
 std       8.088702
 min       7.000000
 25%      70.000000
 50%      76.000000
 75%      80.000000
 max      90.000000  ,
 RiskLevel
 low risk     406
 mid risk     336
 high risk    272
```

```
Name: count, dtype: int64)
```

1.1.3 Identification of Outliers

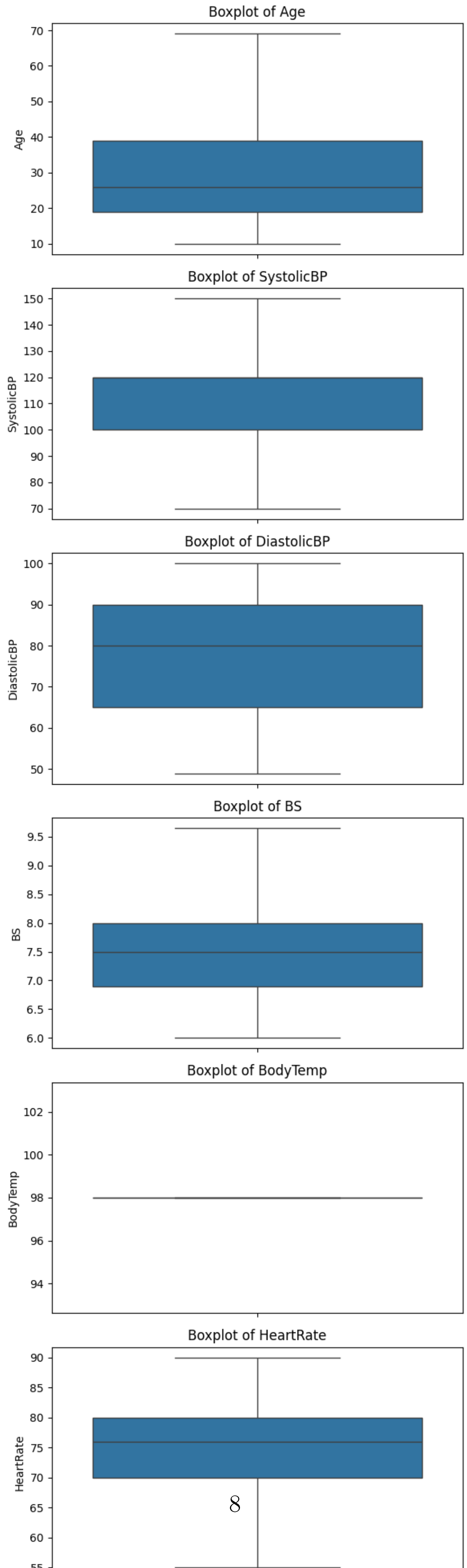
[3]:
```python
import matplotlib.pyplot as plt
import seaborn as sns

plt.figure(figsize=(6, 20))

data_cleaned = data.copy()

for i, column in enumerate(data_cleaned[['Age', 'SystolicBP', 'DiastolicBP',␣
 ↪'BS', 'BodyTemp', 'HeartRate']], 1):
    plt.subplot(6, 1, i)
    sns.boxplot(data=data_cleaned, y=column)
    plt.title(f"Boxplot of {column}")

plt.tight_layout()
plt.show()
```


Boxplot of Age
Age
Boxplot of SystolicBP
SystolicBP
Boxplot of DiastolicBP
DiastolicBP
Boxplot of BS
BS
Boxplot of BodyTemp
BodyTemp
Boxplot of HeartRate
HeartRate

1.1.4 Removal of Outliers

[4]:
```
def remove_outliers(data):
  for col in data.columns:
    if col not in ['RiskLevel']:
      data[col] = data[col].astype(float)
      Q1 = data[col].quantile(0.25)
      Q3 = data[col].quantile(0.75)
      IQR = Q3 - Q1
      data[col] = data[col].clip(lower=Q1 - 1.5*IQR , upper = Q3 + 1.5*IQR)

remove_outliers(data_cleaned)
```

[5]:
```
plt.figure(figsize=(6, 20))

for i, column in enumerate(data_cleaned[['Age', 'SystolicBP', 'DiastolicBP',␣
 ↪'BS', 'BodyTemp', 'HeartRate']], 1):
    plt.subplot(6, 1, i)
    sns.boxplot(data=data_cleaned, y=column)
    plt.title(f"Boxplot of {column}")

plt.tight_layout()
plt.show()
```

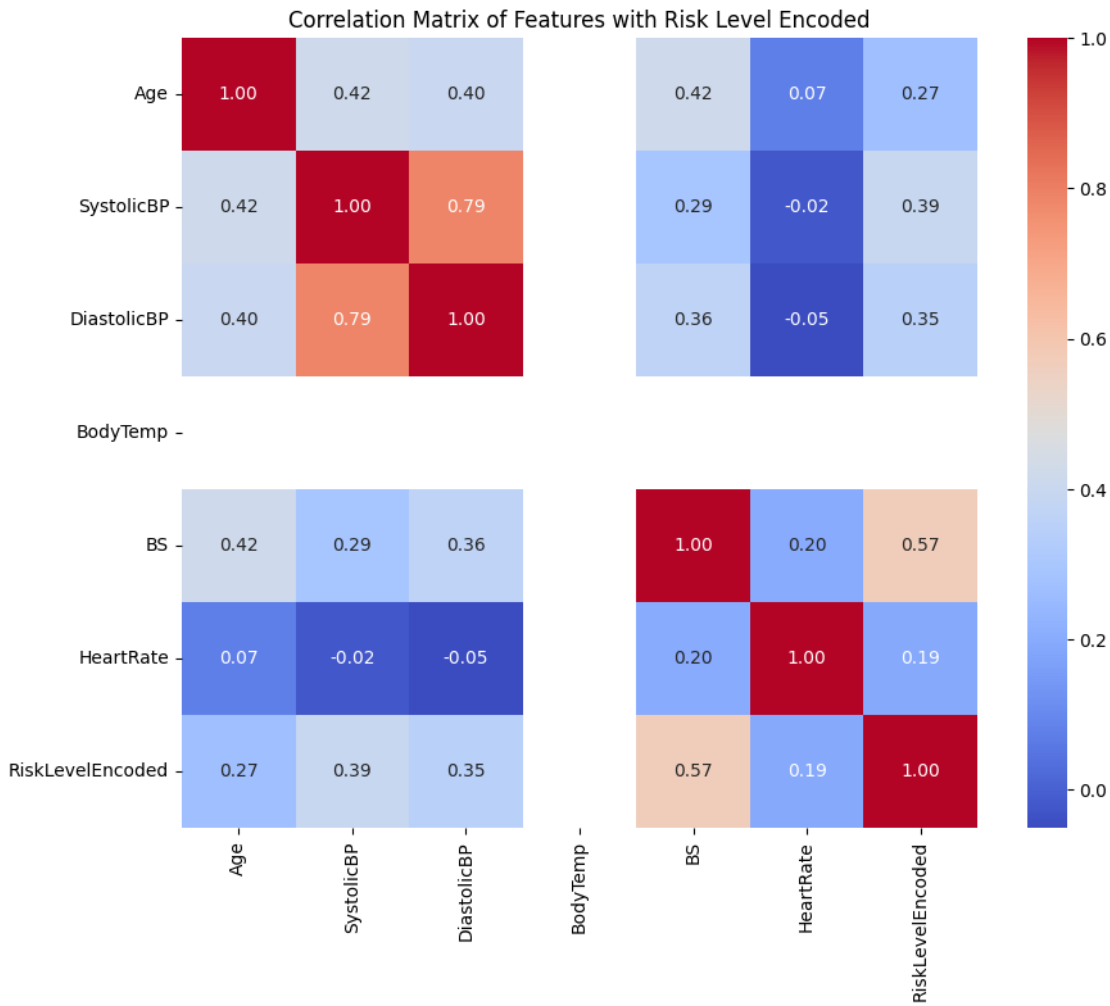

Boxplot of Age
Age
10 20 30 40 50 60 70
Boxplot of SystolicBP
SystolicBP
70 80 90 100 110 120 130 140 150
Boxplot of DiastolicBP
DiastolicBP
50 60 70 80 90 100
Boxplot of BS
BS
6.0 6.5 7.0 7.5 8.0 8.5 9.0 9.5
Boxplot of BodyTemp
BodyTemp
94 96 98 100 102
Boxplot of HeartRate
HeartRate
55 60 65 70 75 80 85 90

[6]:
```
from sklearn.preprocessing import LabelEncoder
data_cleaned = data_cleaned[(data_cleaned['HeartRate'] > 40) &␣
↪(data_cleaned['HeartRate'] <= 90)]

# Custom mapping for RiskLevel encoding
risk_level_mapping = {'low risk': 0, 'mid risk': 1, 'high risk': 2}

data_cleaned['RiskLevelEncoded'] = data_cleaned['RiskLevel'].
↪map(risk_level_mapping)

cleaned_summary_stats = data_cleaned.describe()

# The risk_level_encoded_classes is now derived from the mapping
risk_level_encoded_classes = risk_level_mapping

cleaned_summary_stats, risk_level_encoded_classes
```

[6]:
```
(                Age   SystolicBP  DiastolicBP           BS  BodyTemp  \
 count  1014.000000  1014.000000  1014.000000  1014.000000    1014.0
 mean     29.870809   113.099606    76.460552     7.714645      98.0
 std      13.471482    18.178042    13.885796     1.138902       0.0
 min      10.000000    70.000000    49.000000     6.000000      98.0
 25%      19.000000   100.000000    65.000000     6.900000      98.0
 50%      26.000000   120.000000    80.000000     7.500000      98.0
 75%      39.000000   120.000000    90.000000     8.000000      98.0
 max      69.000000   150.000000   100.000000     9.650000      98.0

          HeartRate  RiskLevelEncoded
 count  1014.000000       1014.000000
 mean     74.396450          0.867850
 std       7.563788          0.807353
 min      55.000000          0.000000
 25%      70.000000          0.000000
 50%      76.000000          1.000000
 75%      80.000000          2.000000
 max      90.000000          2.000000  ,
 {'low risk': 0, 'mid risk': 1, 'high risk': 2})
```

[7]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

correlation_matrix = data_cleaned[['Age', 'SystolicBP',␣
↪'DiastolicBP','BodyTemp', 'BS', 'HeartRate', 'RiskLevelEncoded']].corr()
```

```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f" ,cbar =␣
 ↪True)
plt.title('Correlation Matrix of Features with Risk Level Encoded')
plt.show()
```



1.1.5 Feature Selection: Removal of BodyTemp

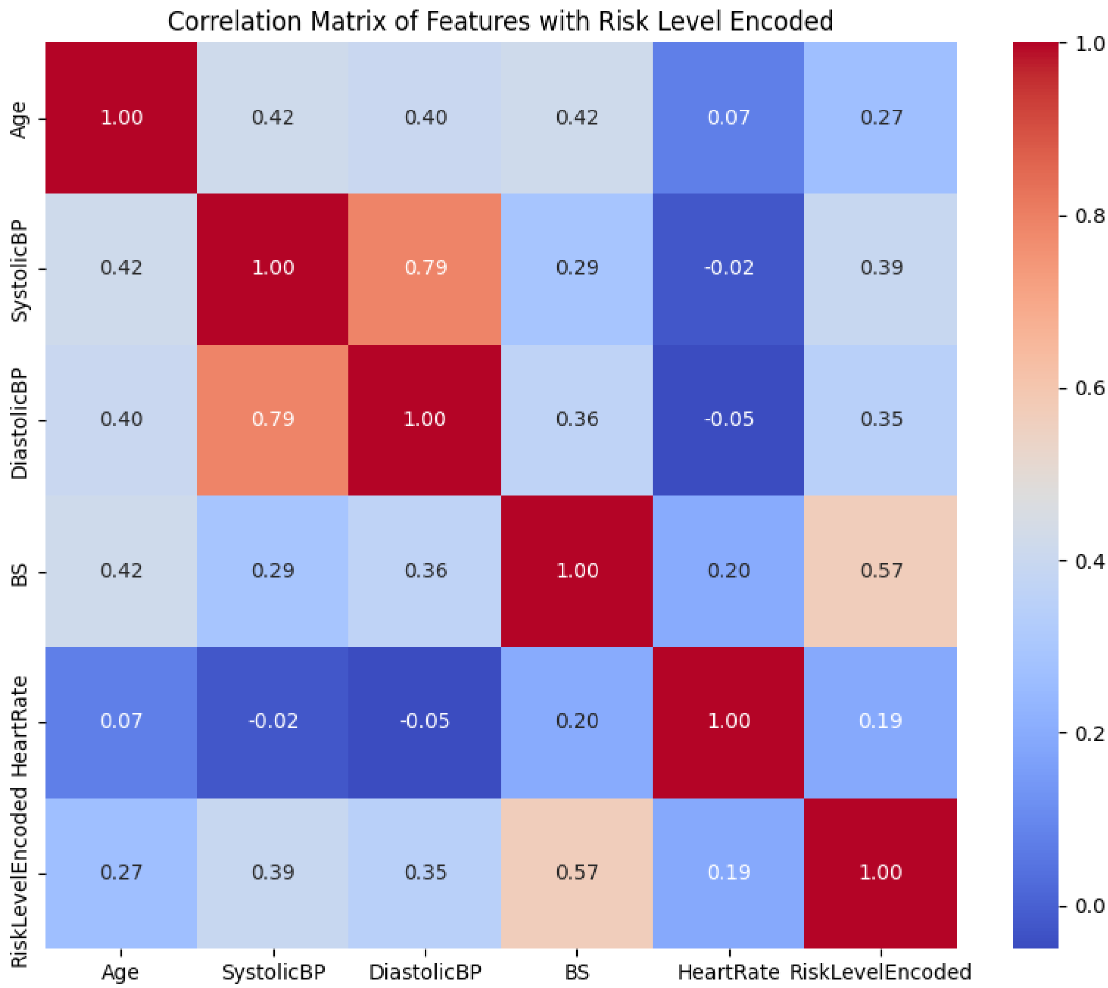
As observed from the correlation matrix above, the feature **BodyTemp** does not have any significant effect on the target variable **RiskLevelEncoded**. Therefore, the feature **BodyTemp** has been removed as part of the feature selection process.

[8]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X = data_cleaned[['Age', 'SystolicBP', 'DiastolicBP', 'BS', 'HeartRate']]
```

```
y = data_cleaned['RiskLevelEncoded']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
↪random_state=42, stratify=y)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[8]:
```
((811, 5), (203, 5), (811,), (203,))
```

[9]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

correlation_matrix = data_cleaned[['Age', 'SystolicBP', 'DiastolicBP', 'BS',␣
↪'HeartRate', 'RiskLevelEncoded']].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f" ,cbar =␣
↪True)
plt.title('Correlation Matrix of Features with Risk Level Encoded')
plt.show()
```



1.1.6 Data Preprocessing

Preparing data so that it can be trained on Classification Models

[10]:
```
from sklearn.preprocessing import LabelEncoder

data_cleaned = data_cleaned[(data_cleaned['HeartRate'] > 40) &
↪(data_cleaned['HeartRate'] <= 90)]

encoder = LabelEncoder()
data_cleaned['RiskLevelEncoded'] = encoder.
↪fit_transform(data_cleaned['RiskLevel'])

cleaned_summary_stats = data_cleaned.describe()
risk_level_encoded_classes = dict(zip(encoder.classes_, range(len(encoder.
↪classes_))))
```

```
cleaned_summary_stats, risk_level_encoded_classes
```

[10]:
```
(                 Age    SystolicBP   DiastolicBP            BS   BodyTemp  \
 count  1014.000000   1014.000000   1014.000000   1014.000000     1014.0
 mean     29.870809    113.099606     76.460552      7.714645       98.0
 std      13.471482     18.178042     13.885796      1.138902        0.0
 min      10.000000     70.000000     49.000000      6.000000       98.0
 25%      19.000000    100.000000     65.000000      6.900000       98.0
 50%      26.000000    120.000000     80.000000      7.500000       98.0
 75%      39.000000    120.000000     90.000000      8.000000       98.0
 max      69.000000    150.000000    100.000000      9.650000       98.0

          HeartRate  RiskLevelEncoded
 count  1014.000000       1014.000000
 mean     74.396450          1.063116
 std       7.563788          0.772146
 min      55.000000          0.000000
 25%      70.000000          0.000000
 50%      76.000000          1.000000
 75%      80.000000          2.000000
 max      90.000000          2.000000  ,
 {'high risk': 0, 'low risk': 1, 'mid risk': 2})
```

[11]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

X = data_cleaned[['Age', 'SystolicBP', 'DiastolicBP', 'BS', 'BodyTemp',␣
 ↪'HeartRate']]
y = data_cleaned['RiskLevelEncoded']

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2,␣
 ↪random_state=42, stratify=y)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

[11]:
```
((811, 6), (203, 6), (811,), (203,))
```

1.1.7 Model Training on Selected Machine Learning Classification Algorithms

The model is now being trained using a set of selected machine learning classification algorithms.

Logistic Regression

[12]:
```python
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

logreg = LogisticRegression(n_jobs=-1)
logreg.fit(X_train, y_train)

y_pred_logreg = logreg.predict(X_test)

accuracy_logreg = accuracy_score(y_test, y_pred_logreg)
conf_matrix_logreg = confusion_matrix(y_test, y_pred_logreg)

print("Logistic Regression Results:")
print(f"Accuracy: {accuracy_logreg}")
print("Confusion Matrix:")
print(conf_matrix_logreg)
print("Classification Report:")
print(classification_report(y_test, y_pred_logreg))
```

```
Logistic Regression Results:
Accuracy: 0.6157635467980296
Confusion Matrix:
[[43  5  7]
 [ 3 59 19]
 [ 8 36 23]]
Classification Report:
              precision    recall  f1-score   support

           0       0.80      0.78      0.79        55
           1       0.59      0.73      0.65        81
           2       0.47      0.34      0.40        67

    accuracy                           0.62       203
   macro avg       0.62      0.62      0.61       203
weighted avg       0.61      0.62      0.60       203
```

Random Forest

[13]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)

y_pred_rf = rf_model.predict(X_test)
```

```python
accuracy_rf = accuracy_score(y_test, y_pred_rf)
conf_matrix_rf = confusion_matrix(y_test, y_pred_rf)
class_report_rf = classification_report(y_test, y_pred_rf)

print("Random Forest Results:")
print(f"Accuracy: {accuracy_rf}")
print("Confusion Matrix:")
print(conf_matrix_rf)
print("Classification Report:")
print(class_report_rf)
```

```
Random Forest Results:
Accuracy: 0.8571428571428571
Confusion Matrix:
[[50  1  4]
 [ 0 66 15]
 [ 2  7 58]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.91      0.93        55
           1       0.89      0.81      0.85        81
           2       0.75      0.87      0.81        67

    accuracy                           0.86       203
   macro avg       0.87      0.86      0.86       203
weighted avg       0.87      0.86      0.86       203
```

KNN Classifier

[14]:
```python
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

knn = KNeighborsClassifier(n_neighbors=5)
knn.fit(X_train, y_train)

y_pred_knn = knn.predict(X_test)

accuracy_knn = accuracy_score(y_test, y_pred_knn)
conf_matrix_knn = confusion_matrix(y_test, y_pred_knn)

print("K-Nearest Neighbors Results:")
print(f"Accuracy: {accuracy_knn}")
print("Confusion Matrix:")
print(conf_matrix_knn)
```

```
print("Classification Report:")
print(classification_report(y_test, y_pred_knn))
```

```
K-Nearest Neighbors Results:
Accuracy: 0.7192118226600985
Confusion Matrix:
[[42  6  7]
 [ 1 60 20]
 [ 2 21 44]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.76      0.84        55
           1       0.69      0.74      0.71        81
           2       0.62      0.66      0.64        67

    accuracy                           0.72       203
   macro avg       0.75      0.72      0.73       203
weighted avg       0.73      0.72      0.72       203
```

XGBoost Classifier

[15]:
```
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score, confusion_matrix,␣
 ↪classification_report

# Initialize and train an XGBoost model
xgb_model = XGBClassifier(eval_metric='mlogloss', random_state=42)
xgb_model.fit(X_train, y_train)

y_pred_xgb = xgb_model.predict(X_test)

accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
conf_matrix_xgb = confusion_matrix(y_test, y_pred_xgb)
class_report_xgb = classification_report(y_test, y_pred_xgb)

print("XGBoost Results:")
print(f"Accuracy: {accuracy_xgb}")
print("Confusion Matrix:")
print(conf_matrix_xgb)
print("Classification Report:")
print(class_report_xgb)
```

```
XGBoost Results:
Accuracy: 0.8669950738916257
Confusion Matrix:
[[50  0  5]
 [ 2 67 12]
```

```
 [ 2  6 59]]
Classification Report:
              precision    recall  f1-score   support

           0       0.93      0.91      0.92        55
           1       0.92      0.83      0.87        81
           2       0.78      0.88      0.83        67

    accuracy                           0.87       203
   macro avg       0.87      0.87      0.87       203
weighted avg       0.87      0.87      0.87       203
```

Decision Tree Classifier

[16]:
```python
from sklearn.tree import DecisionTreeClassifier

dt_model = DecisionTreeClassifier(random_state=42)
dt_model.fit(X_train, y_train)

y_pred_dt = dt_model.predict(X_test)

accuracy_dt = accuracy_score(y_test, y_pred_dt)
conf_matrix_dt = confusion_matrix(y_test, y_pred_dt)
class_report_dt = classification_report(y_test, y_pred_dt)

# Print the results
print("Decision Tree Results:")
print(f"Accuracy: {accuracy_dt}")
print("Confusion Matrix:")
print(conf_matrix_dt)
print("Classification Report:")
print(class_report_dt)
```

```
Decision Tree Results:
Accuracy: 0.8522167487684729
Confusion Matrix:
[[52  1  2]
 [ 3 62 16]
 [ 2  6 59]]
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.95      0.93        55
           1       0.90      0.77      0.83        81
           2       0.77      0.88      0.82        67

    accuracy                           0.85       203
   macro avg       0.86      0.86      0.86       203
```

```
weighted avg       0.86      0.85      0.85       203
```

Support Vector Classifier (SVC)

[17]:
```
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

svc = SVC(kernel='rbf', probability=True, random_state=42)
svc.fit(X_train, y_train)

y_pred_svc = svc.predict(X_test)

accuracy_svc = accuracy_score(y_test, y_pred_svc)
conf_matrix_svc = confusion_matrix(y_test, y_pred_svc)

print("Support Vector Classifier Results:")
print(f"Accuracy: {accuracy_svc}")
print("Confusion Matrix:")
print(conf_matrix_svc)
print("Classification Report:")
print(classification_report(y_test, y_pred_svc))
```

```
Support Vector Classifier Results:
Accuracy: 0.6798029556650246
Confusion Matrix:
[[45  7  3]
 [ 0 76  5]
 [ 3 47 17]]
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.82      0.87        55
           1       0.58      0.94      0.72        81
           2       0.68      0.25      0.37        67

    accuracy                           0.68       203
   macro avg       0.73      0.67      0.65       203
weighted avg       0.71      0.68      0.65       203
```

Voting Classiifer (Soft Voting)

[18]:
```
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
```

```python
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix
from sklearn.ensemble import StackingClassifier

voting_model = VotingClassifier(
    estimators=[
        ('svm', SVC(probability=True, kernel='rbf', random_state=42)),
        ('rf', RandomForestClassifier(n_estimators=300, random_state=42)),
        ('logreg', LogisticRegression(max_iter=1000)),
        ('dt', DecisionTreeClassifier(random_state=42))
    ],
    voting='soft'
)

voting_model.fit(X_train, y_train)

y_pred_voting = voting_model.predict(X_test)

accuracy_voting = accuracy_score(y_test, y_pred_voting)
conf_matrix_voting = confusion_matrix(y_test, y_pred_voting)
class_report_voting = classification_report(y_test, y_pred_voting)

print("Voting Model with Decision Tree Results:")
print(f"Accuracy: {accuracy_voting}")
print("-------------------------")
print("Confusion Matrix:")
print(conf_matrix_voting)
print("-------------------------")
print("Classification Report:")
print(class_report_voting)
```

```
Voting Model with Decision Tree Results:
Accuracy: 0.8817733990147784
-------------------------
Confusion Matrix:
[[53  1  1]
 [ 0 67 14]
 [ 2  6 59]]
-------------------------
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.96      0.96        55
           1       0.91      0.83      0.86        81
           2       0.80      0.88      0.84        67

    accuracy                           0.88       203
   macro avg       0.89      0.89      0.89       203
```

```
weighted avg       0.89      0.88      0.88       203
```

Naive Bayes Classifier

[19]:
```
from sklearn.naive_bayes import GaussianNB

nb_model = GaussianNB()
nb_model.fit(X_train, y_train)

y_pred_nb = nb_model.predict(X_test)

accuracy_nb = accuracy_score(y_test, y_pred_nb)
conf_matrix_nb = confusion_matrix(y_test, y_pred_nb)
class_report_nb = classification_report(y_test, y_pred_nb)

print("Naive Bayes Results:")
print(f"Accuracy: {accuracy_nb}")
print("-------------------------")
print("Confusion Matrix:")
print(conf_matrix_nb)
print("-------------------------")
print("Classification Report:")
print(class_report_nb)
```

```
Naive Bayes Results:
Accuracy: 0.6059113300492611
-------------------------
Confusion Matrix:
[[42  5  8]
 [ 0 59 22]
 [ 4 41 22]]
-------------------------
Classification Report:
              precision    recall  f1-score   support

           0       0.91      0.76      0.83        55
           1       0.56      0.73      0.63        81
           2       0.42      0.33      0.37        67

    accuracy                           0.61       203
   macro avg       0.63      0.61      0.61       203
weighted avg       0.61      0.61      0.60       203
```

Stacking Classifier

[20]:
```
from sklearn.ensemble import StackingClassifier
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,␣
↪confusion_matrix

# Define base learners
base_learners = [
    ('svm', SVC(probability=True, kernel='rbf', random_state=42)),
    ('rf', RandomForestClassifier(n_estimators=100, random_state=42))
]

meta_learner = LogisticRegression(max_iter=1000)

stack_model = StackingClassifier(estimators=base_learners,␣
↪final_estimator=meta_learner, cv=5)

stack_model.fit(X_train, y_train)


y_pred_stack = stack_model.predict(X_test)

accuracy_stack = accuracy_score(y_test, y_pred_stack)
conf_matrix_stack = confusion_matrix(y_test, y_pred_stack)
class_report_stack = classification_report(y_test, y_pred_stack)

print("Stacking Model Results:")
print(f"Accuracy: {accuracy_stack}")
print("Confusion Matrix:")
print(conf_matrix_stack)
print("Classification Report:")
print(class_report_stack)
```

```
Stacking Model Results:
Accuracy: 0.8374384236453202
Confusion Matrix:
[[50  1  4]
 [ 0 67 14]
 [ 2 12 53]]
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.91      0.93        55
           1       0.84      0.83      0.83        81
           2       0.75      0.79      0.77        67

    accuracy                           0.84       203
   macro avg       0.85      0.84      0.84       203
```

```
weighted avg       0.84      0.84      0.84       203
```

Stacking with Naive Bayes

[21]:
```python
base_learners = [
    ('svm', SVC(probability=True, kernel='rbf', random_state=42)),
    ('rf', RandomForestClassifier(n_estimators=100, random_state=42)),
    ('dt', DecisionTreeClassifier(random_state=42)),
    ('nb', GaussianNB())
]

stack_model = StackingClassifier(estimators=base_learners,␣
 ↪final_estimator=LogisticRegression(max_iter=1000), cv=5)
stack_model.fit(X_train, y_train)

y_pred_stack = stack_model.predict(X_test)
accuracy_stack = accuracy_score(y_test, y_pred_stack)
print(f"Stacking Accuracy (with Naive Bayes): {accuracy_stack}")
```

```
Stacking Accuracy (with Naive Bayes): 0.8620689655172413
```

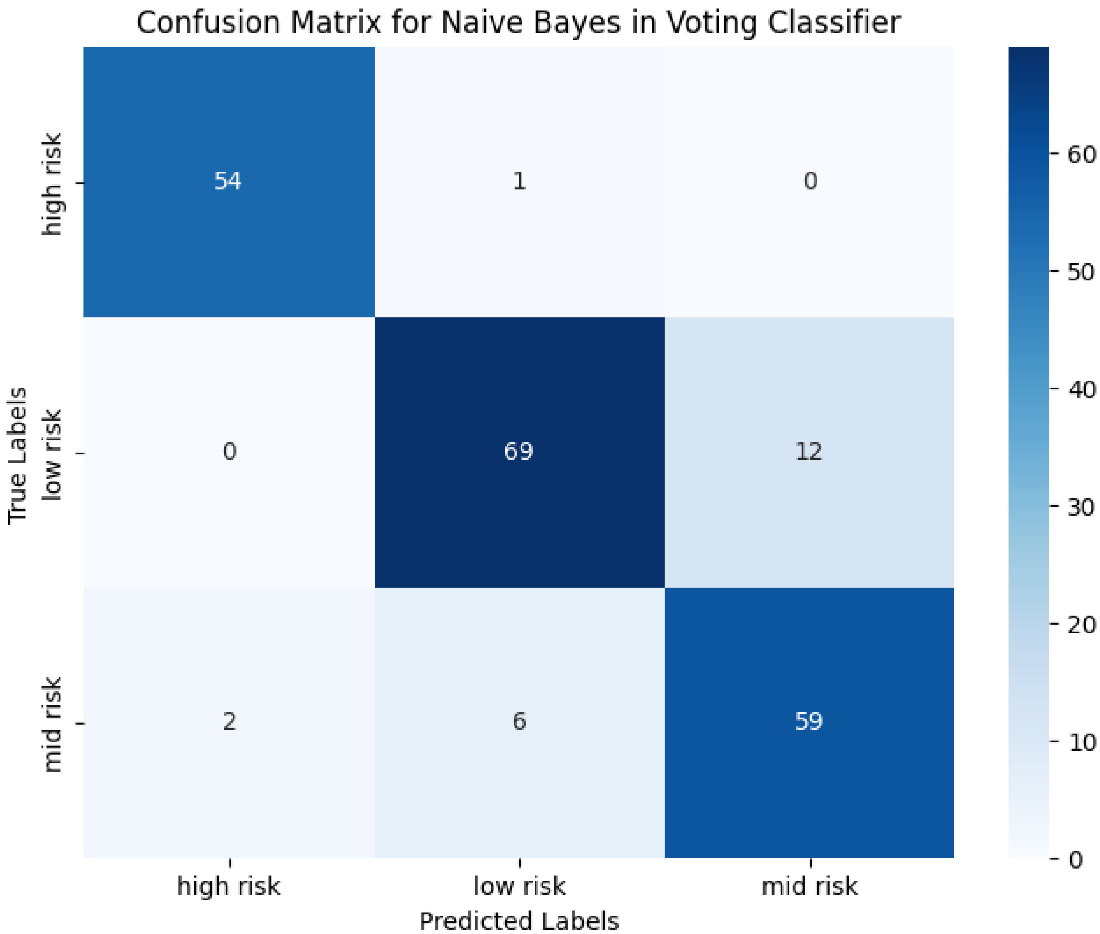
Voting Ensemble of SVM, RandomForest, Decision Tree, Naive Bayes Classifiers Final Model

[22]:
```python
voting_model = VotingClassifier(
    estimators=[
        ('svm', SVC(probability=True, kernel='rbf', random_state=42)),
        ('rf', RandomForestClassifier(n_estimators=300, random_state=42)),
        ('dt', DecisionTreeClassifier(random_state=42)),
        ('nb', GaussianNB())
    ],
    voting='soft'
)

voting_model.fit(X_train, y_train)

y_pred_voting = voting_model.predict(X_test)
accuracy_voting = accuracy_score(y_test, y_pred_voting)
print(f"Voting Accuracy (with Naive Bayes): {accuracy_voting}")

conf_matrix_voting = confusion_matrix(y_test, y_pred_voting)
class_report_voting = classification_report(y_test, y_pred_voting)
print("-------------------------")
print("Confusion Matrix:")
print(conf_matrix_voting)
print("-------------------------")
print("Classification Report:")
print(class_report_voting)
```

```
Voting Accuracy (with Naive Bayes): 0.896551724137931
-------------------------
Confusion Matrix:
[[54  1  0]
 [ 0 69 12]
 [ 2  6 59]]
-------------------------
Classification Report:
              precision    recall  f1-score   support

           0       0.96      0.98      0.97        55
           1       0.91      0.85      0.88        81
           2       0.83      0.88      0.86        67

    accuracy                           0.90       203
   macro avg       0.90      0.90      0.90       203
weighted avg       0.90      0.90      0.90       203
```

[23]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix


conf_matrix_voting_nb = confusion_matrix(y_test, y_pred_voting)

plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix_voting_nb, annot=True, fmt='d', cmap='Blues',␣
 ↪xticklabels=encoder.classes_, yticklabels=encoder.classes_)
plt.title('Confusion Matrix for Naive Bayes in Voting Classifier')
plt.xlabel('Predicted Labels')
plt.ylabel('True Labels')
plt.show()
```



1.1.8 Performance Summary of the Models Applied

Below is a summary of the performance of various machine learning models applied to the dataset. Each model's accuracy is presented, and it is clear that the **Voting Classifier with Naive Bayes** achieved the highest accuracy of **89.69%**, showcasing the strength of ensemble methods in combining the predictive power of multiple algorithms.

Model	Accuracy
Logistic Regression	61.57
Random Forest	85.71
KNN Classifier	71.92
XGBoost Classifier	86.69
Decision Tree Classifier	85.22
Support Vector Classifier	67.98
Voting Classifier - Soft Voting (SVM, Random Forest, Logistic Regression, Decision Tree)	88.17
Naive Bayes	60.59

Model	Accuracy
Stacking Classifier	83.74
Stacking Classifier with Naive Bayes	86.20
Voting with Naive Bayes	89.65

The model that achieved the highest performance is the **Voting Classifier with Naive Bayes**, which attained an impressive accuracy of **89.65%**. This demonstrates its effectiveness in combining the strengths of multiple classifiers.

1.1.9 Inferences Drawn from the Analysis

1. **Feature Impact on Maternal Health Risk**:
   - **Age**: Older individuals tend to have higher maternal health risks, as indicated by patterns in the dataset.
   - **SystolicBP and DiastolicBP**: Elevated blood pressure levels are strongly associated with higher risk levels.
   - **Blood Sugar (BS)**: High blood sugar is a significant indicator of increased risk, especially for the "High Risk" category.
   - **Body Temperature**: This feature have minimal correlation with RiskLevel and were less impactful for prediction.
2. **Effectiveness of Data Preprocessing**:
   - Removing outliers improved the quality of the dataset, enhancing model reliability and reducing potential biases caused by extreme values.
   - Feature selection (removing BodyTemp) streamlined the dataset without compromising predictive performance.
3. **Modeling Insights**:
   - The analysis highlighted the importance of feature engineering and careful selection of predictors for improving classification accuracy.
   - Models performed better with refined data, showcasing the impact of robust preprocessing steps.
   - With the use of Voting Ensemble the overall efficiency of the model increased better than any other models we used.
4. **Correlation and Predictive Relationships**:
   - Strong correlations between certain features (e.g., blood pressure and blood sugar) and RiskLevel underscore their importance in identifying maternal health risks.
5. **Healthcare Implications**:
   - The analysis reaffirms that regular monitoring of critical health parameters like blood pressure and blood sugar is essential for early risk detection and intervention in maternal health.

1.2 References

1. **Scikit-learn Documentation**
   Scikit-learn: Machine Learning in Python. https://scikit-learn.org

2. **Matplotlib Documentation**
   Matplotlib: Visualization with Python. https://matplotlib.org

3. **Seaborn Documentation**
Seaborn: Statistical Data Visualization. https://seaborn.pydata.org

4. **Pandas Documentation**
Pandas: Python Data Analysis Library. https://pandas.pydata.org

5. **CampusX YouTube Channel**
CampusX: Educational videos on machine learning and data science. CampusX YouTube Channel

6. **Dataset Source**
https://archive.ics.uci.edu/dataset/863/maternal+health+risk