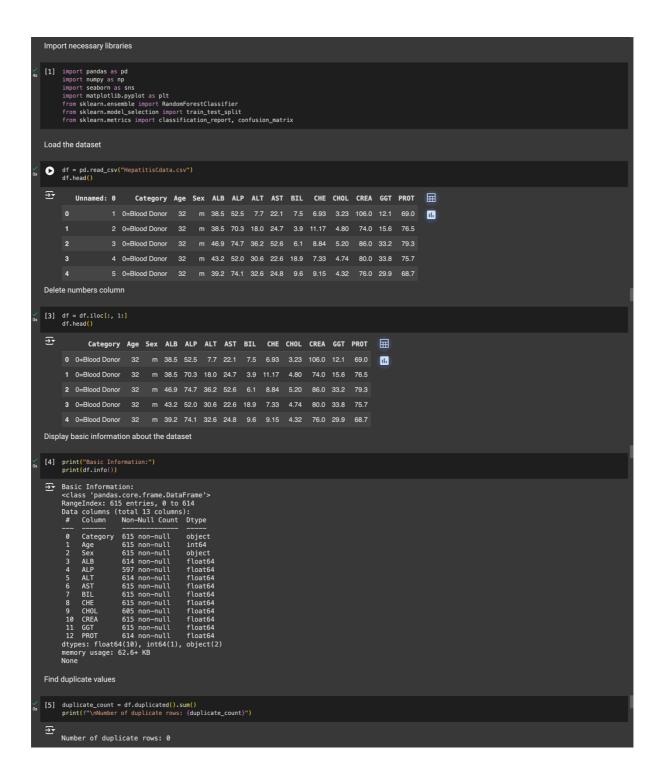
Exploratory Data Analysis Digital Assignment

Submitted by – Ashish Chauhan Reg. No – 21BDS0271



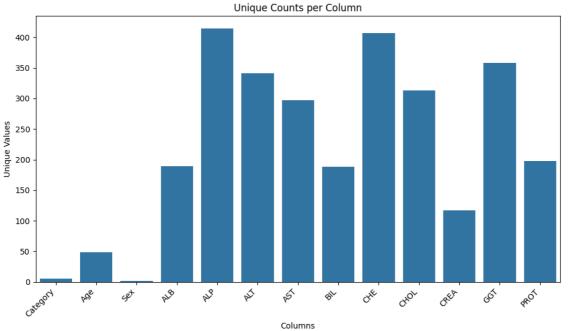
```
No of unique values in each column:

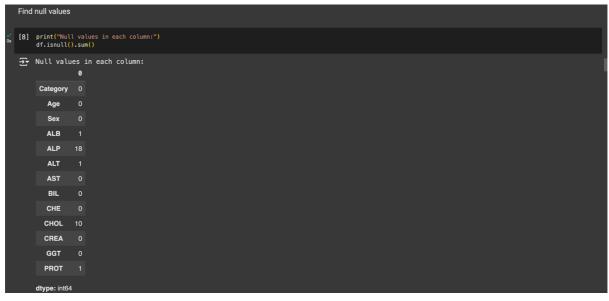
[6] print("\nUnique values in each column:")
for col in dr.columns:
    print(f(cb): (df(cb): (df(cb): nunique())")

[7] Unique values in each column:
    Category: 5
    Age: 49
    Sex: 2
    AllB: 189
    All: 144
    All: 341
    All: 341
    All: 341
    All: 188
    CHE: 407
    CHOL: 313
    CRA: 117
    GGT: 358
    PROT: 198

Visualize unique counts

[7] unique_counts = df.nunique()
    plx.figure(figsize=(18, 6))
    sns.barplot(xunique_counts.index, y=unique_counts.values)
    plx.title("unique Counts per Column")
    plx.title("unique Counts per Column")
    plx.title("columns")
    plx.title("columns")
    plx.titlet("columns")
    plx.titlet("columns")
```





```
Replace null values
   [9] from sklearn.impute import KNNImputer
imputer = KNNImputer(n_neighbors= 5)
numeric_df = df.select_dtypes(include='float64')
imputed_df = imputer.fit_transform(numeric_df)
imputed_df = pd.DataFrame(imputed_df ,columns=numeric_df.columns)
df.numeric_df.columns] = imputed_df
df.isna().sum()
      <u>+</u>
                        Category 0
                             Age 0
                            CHE 0
                           CHOL 0
                           CREA 0
                            GGT 0
                         PROT 0
                    dtype: int64
     Check data types
  [10] print("\nData types of the columns:")
    print(df.dtypes)
                  Data types of the columns:
Category object
Age int64
Sex object
ALB float64
ALP float64
ALT float64
AST float64
BIL float64
CHE float64
CHE float64
CHG float64
CREA float64
GGT float64
RROT float64
dtype: object
                     GGT fi
PROT fi
dtype: object
      Filter the data
  [11] filtered_data = df[df["Category"] == "1=Hepatitis"]
    print("\nFiltered data (Category = 1=Hepatitis):")
    filtered_data.head()
   [11] Filtered data (Category = 1=Hepatitis):
                                Category Age Sex ALB ALP ALT AST BIL CHE CHOL CREA GGT PROT 🖽

        540
        1=Hepatitis
        38
        m
        45.0
        56.30
        28.02
        33.1
        7.0
        9.58
        6.00
        77.9
        18.9
        63.0
        11.

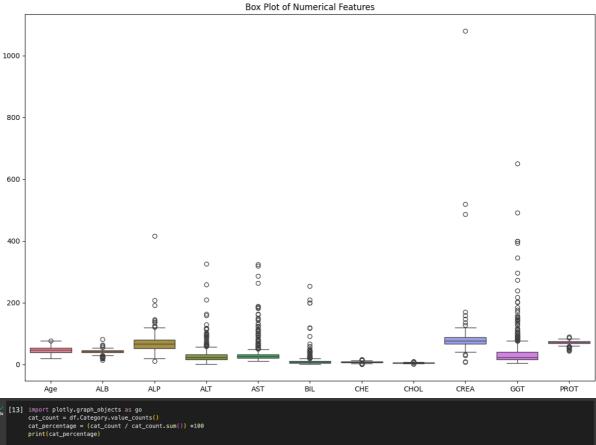
        541
        1=Hepatitis
        19
        m
        41.0
        64.22
        87.00
        67.0
        12.0
        7.55
        3.90
        62.0
        65.0
        75.0

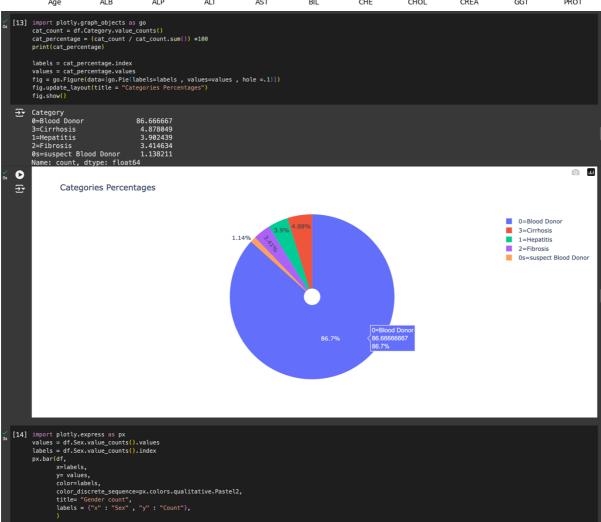
        542
        1=Hepatitis
        23
        m
        47.0
        19.10
        38.90
        164.2
        7.00
        7.09
        3.20
        79.3
        90.4
        70.1

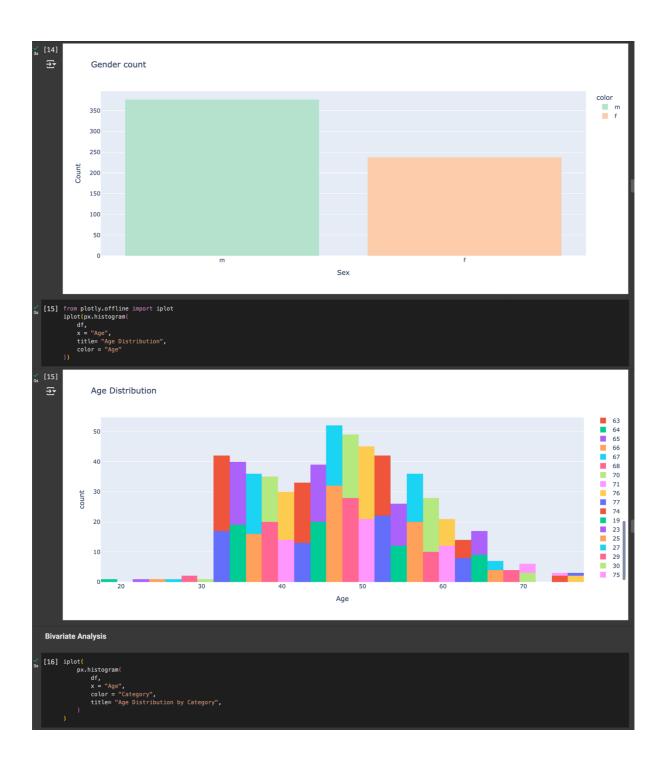
        543
        1=Hepatitis
        25
        m
        42.0
        38.20
        63.30
        187.7
        14.0
        6.00
        4.28
        66.9
        40.2
        70.5

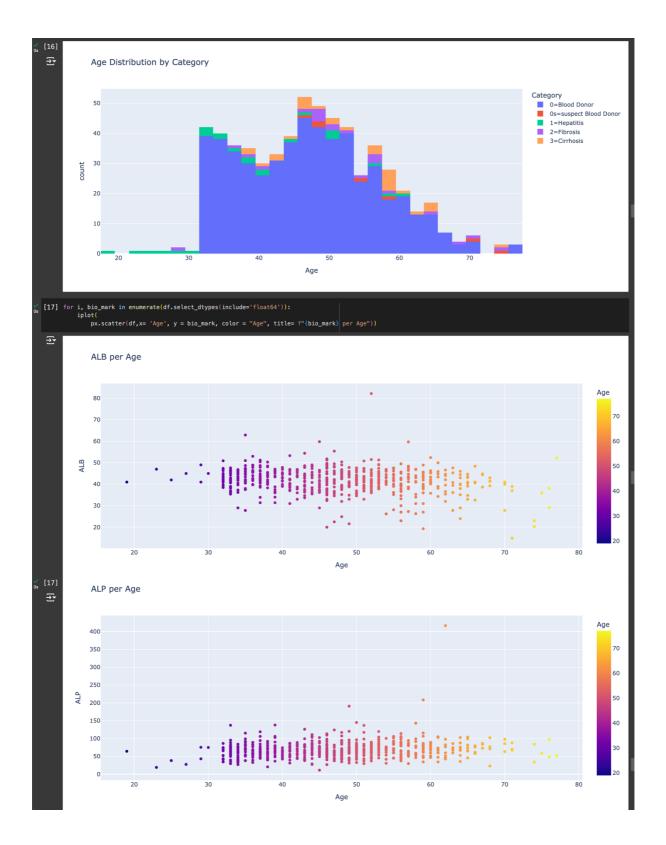
        544
        1=Hepatitis
        27
        m
        42.0
        27.50
        10.50
        37.8
        10.0
        8.77
        3.20
        55.2
        35.9
        74.5

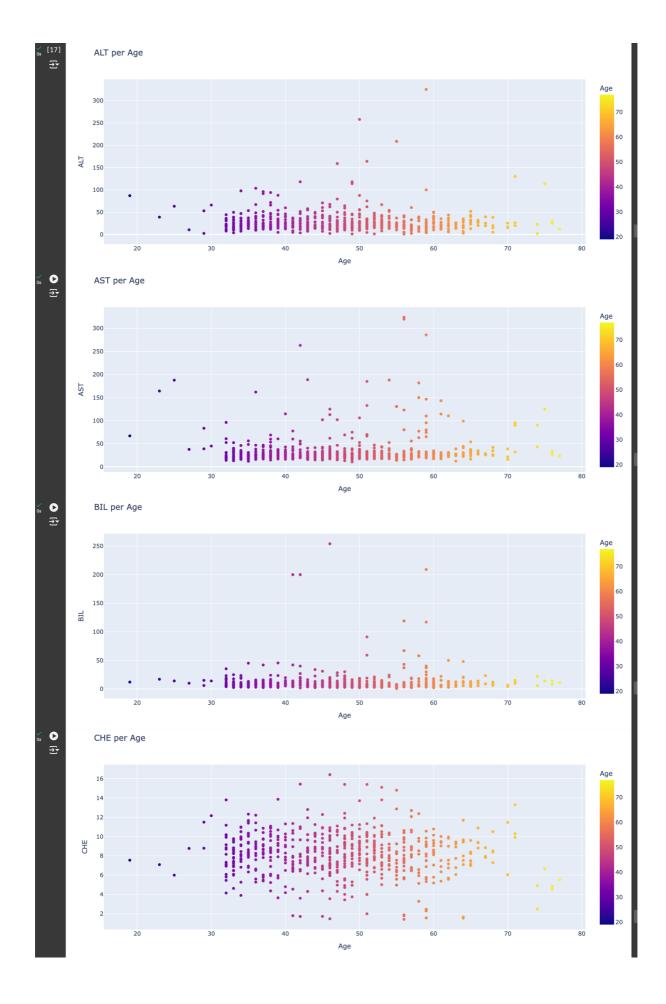
     Univariate Analysis
[12] plt.figure(figsize=(12, 8))
sns.boxplot(data=df.select_dtypes(include=[np.number]))
plt.title("Box Plot of Numerical Features")
plt.tight_layout()
plt.show()
```

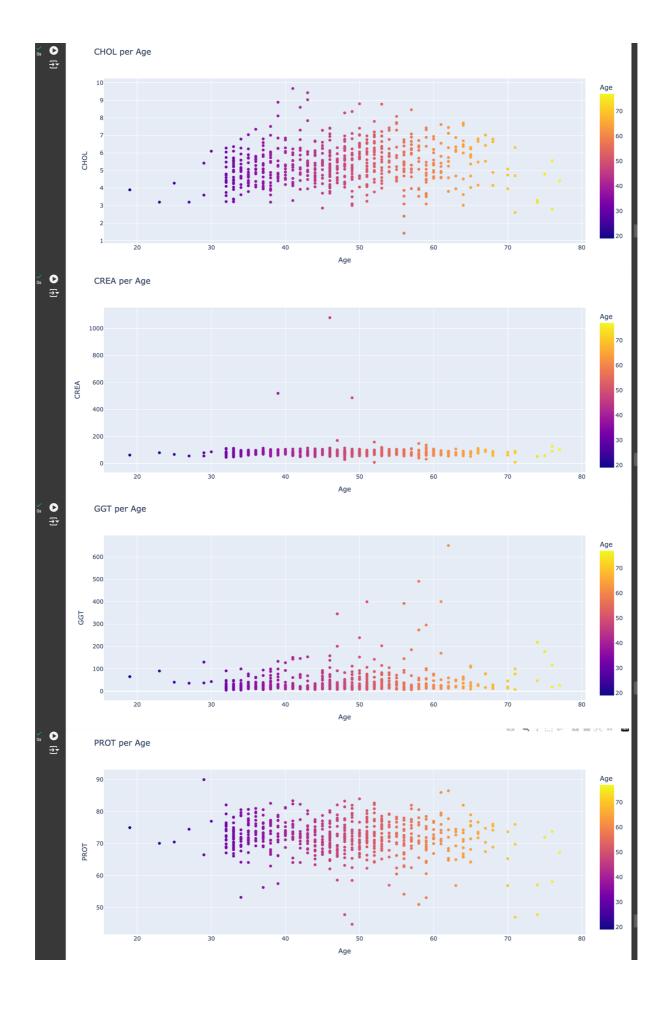




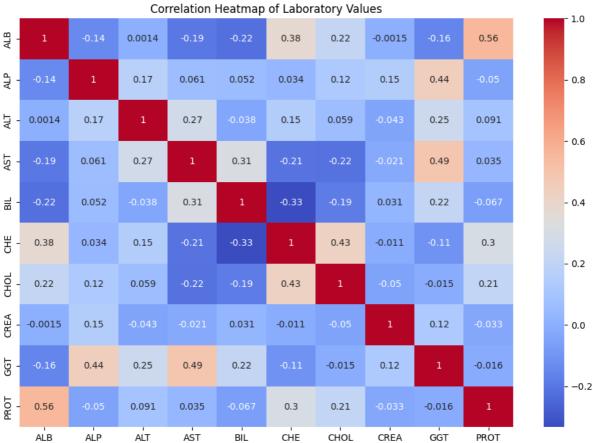












```
PCA Analysis

[19] from sklearn.decomposition import PCA from sklearn.preprocessing import StandardScaler

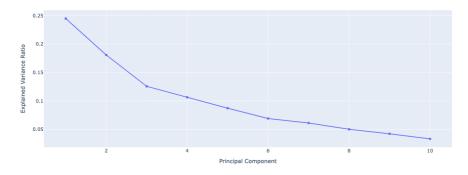
df_numeric = df.select_dtypes(include='float64') scalar = StandardScaler() df.scaled = scalar.fit_transform(df_numeric) pca = PCA() pca_result = pca.fit_transform(df_scaled) fig = go.Figure()

fig.add_trace(go.Scatter(x=list(range(1, len(pca.explained_variance_ratio_) + 1)), y=pca.explained_variance_ratio_, mode='lines+markers', name='Explained Variance Ratio'))

fig.update_layout(title='Explained Variance by Principal Components', xaxis_title='Principal Component', yaxis_title='Explained Variance Ratio',)

fig.show()
```

Explained Variance by Principal Components



```
Random Forest Model
 Label Encoding
        Label_pre = LabelEncoder()
data_cols=df.select_dtypes(exclude={'int','float'}).columns
label_col = list(data_cols)
df(label_col)= df(label_col).apply(lambda col:Label_pre.fit_transform(col))
[21] df.head()
         Category Age Sex ALB ALP ALT AST BIL CHE CHOL CREA GGT PROT 🖽
               0 32 1 38.5 52.5 7.7 22.1 7.5 6.93 3.23 106.0 12.1 69.0 ii.
0 32 1 38.5 70.3 18.0 24.7 3.9 11.17 4.80 74.0 15.6 76.5
0 32 1 46.9 74.7 36.2 52.6 6.1 8.84 5.20 86.0 33.2 79.3
                0 32 1 43.2 52.0 30.6 22.6 18.9 7.33 4.74 80.0 33.8 75.7
 Splitting features and target
[22] x = df.drop("Category", axis=1)
y = df["Category"]
 → ((615, 12), (615,))
 Train Test Split
        X_train, X_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
        print("Rows and columns of training data X_train:", X_train.shape)
print("Rows and columns of testing data X_test:", X_test.shape)
 Rows and columns of training data X_train: (492, 12)
Rows and columns of testing data X_test: (123, 12)
 SMOTE to balance data
[26] from imblearn.over_sampling import SMOTE
smote = SMOTE(k_neighbors=2, random_state=42)
X_train_res, y_train_res = smote.fit_resample(X_train, y_train)
         print("Class distribution after SMOTE:")
print(pd.Series(y_train_res).value_counts())
 Class distribution after SMOTE:
Category
0 437
3 437
4 437
2 437
1 437
Name: count of type: int64
         Name: count, dtype: int64
 Model Creation
                                                                                                          + Code + Text
[27] rf_model = RandomForestClassifier(random_state=42)
    rf_model.fit(X_train_res, y_train_res)
 RandomForestClassifier 0 0
         RandomForestClassifier(random state=42)
 Evaluate the model
[28] y_pred = rf_model.predict(X_test)
    print("Classification Report:")
    print(classification_report(y_test, y_pred))
 Classification Report: precision
                                                   recall f1-score support
                                        0.91
1.00
1.00
0.40
1.00
                                                        1.00
0.67
0.44
0.33
0.78
                                                                         0.96
0.80
0.62
0.36
0.88
                                                                          0.90
0.72
0.89
                                                                                            123
123
123
        accuracy
macro avg
weighted avg
```

