stroke_risk_analysis

June 23, 2024

[ ]:
```
import pandas as pd
import numpy as np
from scipy import stats
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
import joblib
from stroke_risk_utils import *
from IPython.display import Image
```

[ ]:
```
stroke_df = pd.read_csv("stroke_dataset.csv")
stroke_df.head()
```

[ ]:

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	9046	Male	67.0	0	1	Yes	Private	Urban	228.69	36.6	formerly smoked	1
1	51676	Female	61.0	0	0	Yes	Self-employed	Rural	202.21	NaN	never smoked	1
2	31112	Male	80.0	0	1	Yes	Private	Rural	105.92	32.5	never smoked	1
3	60182	Female	49.0	0	0	Yes	Private	Urban	171.23	34.4	smokes	1
4	1665	Female	79.0	1	0	Yes	Self-employed	Rural	174.12	24.0	never smoked	1

[ ]:
```
stroke_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5110 entries, 0 to 5109
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5110 non-null   int64
 1   gender             5110 non-null   object
 2   age                5110 non-null   float64
 3   hypertension       5110 non-null   int64
 4   heart_disease      5110 non-null   int64
 5   ever_married       5110 non-null   object
 6   work_type          5110 non-null   object
 7   Residence_type     5110 non-null   object
 8   avg_glucose_level  5110 non-null   float64
 9   bmi                4909 non-null   float64
 10  smoking_status     5110 non-null   object
 11  stroke             5110 non-null   int64
dtypes: float64(3), int64(4), object(5)
memory usage: 479.2+ KB
```

[ ]:
```
print(stroke_df.isnull().sum())
```

```
id                   0
gender               0
age                  0
hypertension         0
heart_disease        0
ever_married         0
work_type            0
Residence_type       0
avg_glucose_level    0
bmi                201
smoking_status       0
stroke               0
dtype: int64
```

This dataset contains 5110 entries and 12 columns related to potential stroke risk factors.

Observations:

- **Data Types:** Includes numerical (int64, float64) and categorical (object) features.
- **Missing Values:** The `bmi` column has 201 missing values.
- **Potential Features:** Age, health conditions (hypertension, heart disease), lifestyle factors (smoking, marriage, work type, residence), and glucose/BMI levels could be predictive.
- **Target Variable:** The `stroke` column (likely binary: 0 or 1) is the target for prediction.

Next Steps:

1. **Data Cleaning:**
   - Rename columns for consistency (using lowercase and underscores).

- Address missing values in `bmi` (dropping rows for simplicity in this case as it only contains 4% of the dataset).

[ ]:
```
stroke_df = stroke_df.rename(columns={'Residence_type': 'residence_type'})
```

[ ]:
```
stroke_df = stroke_df.dropna(subset=['bmi'])
stroke_df.head()
```

[ ]:
```
      id  gender   age  hypertension  heart_disease ever_married  \
0   9046    Male  67.0             0              1          Yes
2  31112    Male  80.0             0              1          Yes
3  60182  Female  49.0             0              0          Yes
4   1665  Female  79.0             1              0          Yes
5  56669    Male  81.0             0              0          Yes

        work_type residence_type  avg_glucose_level   bmi   smoking_status  \
0         Private          Urban             228.69  36.6  formerly smoked
2         Private          Rural             105.92  32.5     never smoked
3         Private          Urban             171.23  34.4           smokes
4   Self-employed          Rural             174.12  24.0     never smoked
5         Private          Urban             186.21  29.0  formerly smoked

   stroke
0       1
2       1
3       1
4       1
5       1
```

With missing values in `bmi` handled and features renamed, let's examine the dataset structure.

[ ]:
```
print(stroke_df.describe().T)
```

```
                    count          mean           std    min       25%  \
id                 4909.0  37064.313506  20995.098457  77.00  18605.00
age                4909.0     42.865374     22.555115   0.08     25.00
hypertension       4909.0      0.091872      0.288875   0.00      0.00
heart_disease      4909.0      0.049501      0.216934   0.00      0.00
avg_glucose_level  4909.0    105.305150     44.424341  55.12     77.07
bmi                4909.0     28.893237      7.854067  10.30     23.50
stroke             4909.0      0.042575      0.201917   0.00      0.00

                       50%       75%       max
id                37608.00  55220.00  72940.00
age                  44.00     60.00     82.00
hypertension          0.00      0.00      1.00
heart_disease         0.00      0.00      1.00
avg_glucose_level    91.68    113.57    271.74
bmi                  28.10     33.10     97.60
```

```
stroke                 0.00       0.00       1.00
```

Observations:

- **Numerical Features:**
  - `age`: The average age is approximately 42.87 years, with a wide range (0.08 to 82).
  - `avg_glucose_level`: The average glucose level is 105.31, with a large standard deviation (44.42), indicating a wide spread of values.
  - `bmi`: The average BMI is 28.89, also with a considerable range (10.30 to 97.60).
- **Binary Features:**
  - `hypertension`, `heart_disease`, and `stroke` are binary features (0 or 1).
  - The prevalence of hypertension and heart disease is relatively low in this dataset.
  - The target variable `stroke` has a low prevalence (around 4%), indicating a class imbalance.

Next Steps:

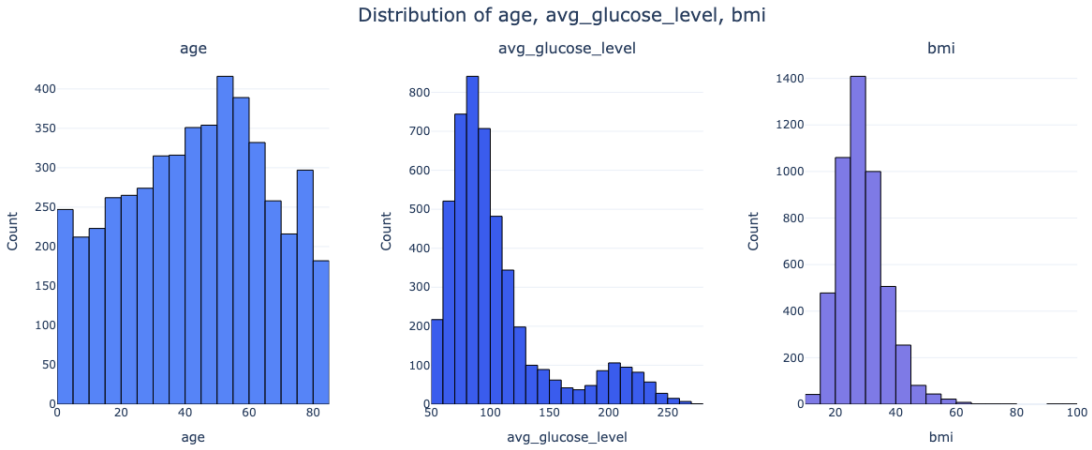
- **Further investigate distributions:** Use histograms and box plots to visualize the distributions of numerical features and identify potential outliers.

[ ]:
```
numerical_features = ['age', 'avg_glucose_level', 'bmi']
categorical_features = ['gender', 'hypertension', 'heart_disease',␣
 ↪'ever_married', 'work_type', 'residence_type', 'smoking_status']
```

[ ]:
```
plot_combined_histograms(stroke_df, numerical_features, nbins=30,␣
 ↪save_path="images/numerical_distributions.png")
```

[ ]:
```
Image(filename="images/numerical_distributions.png")
```

[ ]:



The histograms reveal the following about `age`, `avg_glucose_level`, and `bmi`:

- **Age:** Shows a bimodal distribution, suggesting potential differences in stroke risk across age groups.
- **Average Glucose Level:** Right-skewed, indicating a higher concentration of lower values and a need to consider median or data transformations.

- **BMI:** Approximately normally distributed with a slight right skew. Outliers with very high BMIs warrant further investigation.

Next up, we can move on to the categorical features.

[ ]:
```
%run -i stroke_risk_utils.py
```

[ ]:
```

```