Stroke Prediction

Dataset description:

The data set used was the stroke prediction dataset which can be found at Kaggle.

The attributes of patients that contributed to the data collection are as follows:

Feature	Description
1. id	Unique patient identifier
2. gender	Values include “male”, “female” and “other”
3. age	The age of the patient
4. hypertension	0 if the patient doesn’t have hypertension and 1 if the patient does
5. heart_disease	0 if the patient doesn’t have heart disease and 1 if the patient does
6. ever_married	Accepted values are “Yes” or “No”
7. work_type	Values include “children”, “Govt_jov”, “Never_worked”, “Private” and “Self-employed”
8. Residence_type	Accepted values are “Rural” or “Urban”
9. avg_glucose_level	Average glucose level in patient’s blood
10. smoking_status	Values include “formerly smoked”, “never smoked”, “smokes”, and “Unknown”
11. bmi	Body Mass Index of patient
12. stroke	The target variable. 1 if the patient had stroke and 0 if they didn’t

Main Objective of Analysis:

The objective here is to train a model that best predicts the likelihood of a patient getting stroke considering the afore mentioned features.

More emphasis will be placed in getting as many right guesses for stroke patients even at the cost of a few false alarms.

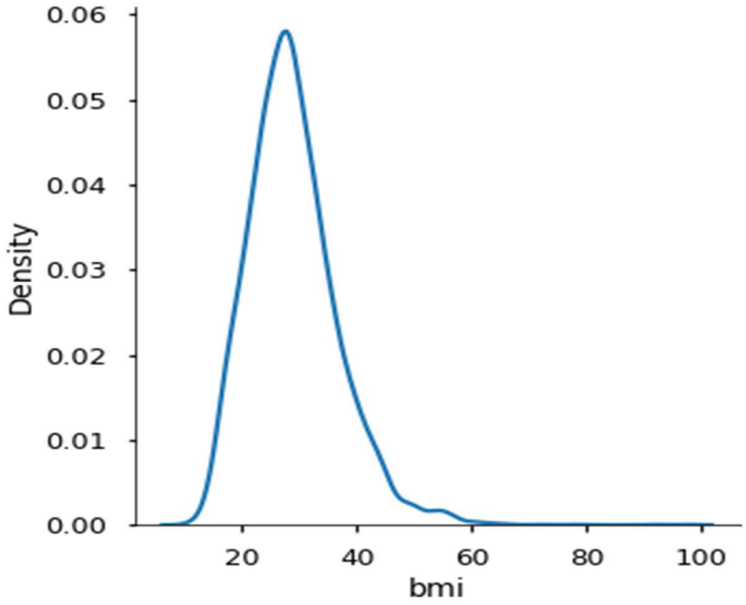
But we would like to minimize the number of false alarms as much as possible.

Summary of EDA:

1. Handling of missing data:
   All features but “bmi” (which had 201 missing) had no missing values for any patient.

Missing data was therefore filled with the mean bmi after a careful inspection of the distribution. Since the bmi data followed a normal distribution (meaning most of the patient's bmi were around the mean bmi), and the mean of both patient's with stroke and those without were very close, the mean bmi proved to be the best estimate.

a. Distribution of BMI of patients



b. Distribution of BMI for patients with stroke and those without

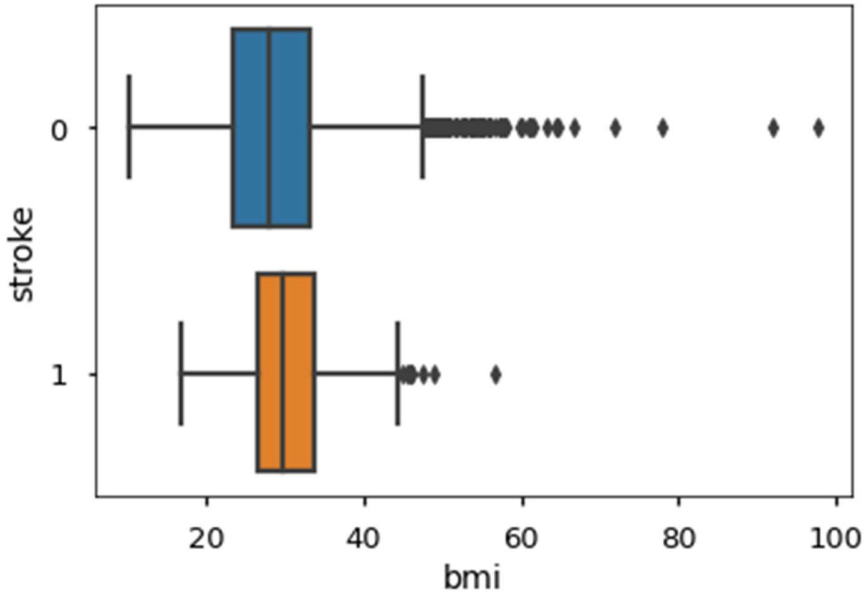


Figure 1 a) figure showing that the distribution of the bmi of the patients is normal. It can be seen that most of the patients have BMI around the mean value.

b) figure showing distribution of bmi of patients with and without stroke. It can be seen that the mean values of both boxplots (the middle line in both the orange and blue box) are very close to each other.

1. Removing unnecessary features:
   Since the "id" feature is unique to each patient, it will not help in our prediction, therefore, it was removed from the dataset.

2. Checking normality of continuous features:
   After a careful inspection of the distribution of all the continuous data (age, average_glucose_level, bmi) it was observed that most of them had roughly normal distribution hence no transformation was needed in that respect.

3. Checking scale of continuous features:
   After an inspection of the standard deviation of the continuous features, it was observed that the features were measured on different scales.
   Hence sklearn's **StandardScaler** was used to normalize the features so that each had a standard deviation of 1.

4. Visualizing categorical features:
   Because the data was unbalanced, that is a '**95:4'** ratio for '**no stroke : stroke'**, observing the frequency of various features among patients with stroke and those without stroke will not give much insight into which categorical features play more important roles in the stroke status of a patient.

5. Resampling of data:
   New datasets were created with both **over sampling** and **under sampling** for the models to be trained on.
   Four new datasets were created with the training split of the data. Each new different dataset was created with a different type of resampling technique;
   a. Random Over Sampling
   b. SMOTE
   c. ADASYN
   d. Random Under Sampling

Training Models:

Six different models were trained with and without resampled training data.

The results are as shown in the table below:

Model	Sampling	AUC	Accuracy	Recall	Precision	F -score
Logistic Regression	Without resampling	0.510	0.952	0.020	1.00	0.039
	Class Weighting	0.673	0.846	0.480	0.155	0.234
	Random Oversampling	0.693	0.792	0.620	0.120	0.201

	SMOTE	0.657	0.764	0.540	0.110	0.183
	ADASYN	0.675	0.761	0.580	0.115	0.192
	Under sampling	0.717	0.732	0.700	0.119	0.204
Random Forest	Without resampling	0.500	0.951	0.000	0.000	0.000
	Class Weighting	0.700	0.736	0.660	0.115	0.196
	Random Oversampling	0.703	0.743	0.660	0.118	0.201
	SMOTE	0.701	0.755	0.640	0.121	0.204
	ADASYN	0.704	0.743	0.660	0.119	0.201
	Under sampling	0.722	0.706	0.740	0.114	0.198
Gradient Boosting Classifier	Without resampling	0.508	0.949	0.02	0.250	0.037
	Random Oversampling	0.504	0.942	0.02	0.091	0.033
	SMOTE	0.542	0.940	0.100	0.238	0.141
	ADASYN	0.530	0.936	0.080	0.174	0.110
	Under sampling	0.702	0.704	0.700	0.109	0.188
XGBClassifier	Without resampling	0.499	0.949	0.000	0.000	0.000
	Random Oversampling	0.566	0.932	0.160	0.222	0.186
	SMOTE	0.556	0.932	0.140	0.206	0.167
	ADASYN	0.533	0.923	0.100	0.128	0.112
	Under sampling	0.720	0.719	0.720	0.117	0.201
SVC	Without resampling	0.500	0.951	0.000	0.000	0.000
	Class Weighting	0.704	0.690	0.720	0.106	0.185
	Random Oversampling	0.657	0.798	0.5	0.121	0.195
	SMOTE	0.602	0.803	0.380	0.101	0.159
	ADASYN	0.592	0.801	0.360	0.095	0.151
	Under sampling	0.699	0.716	0.68	0.110	0.190
KNN	Without resampling	0.498	0.948	0.000	0.000	0.000
	Random Oversampling	0.525	0.889	0.120	0.080	0.096
	SMOTE	0.619	0.781	0.440	0.101	0.164
	ADASYN	0.579	0.812	0.32	0.092	0.143
	Under sampling	0.725	0.712	0.740	0.116	0.201
Voting Classifier	Under sampling	0.736	0.732	0.740	0.123	0.212

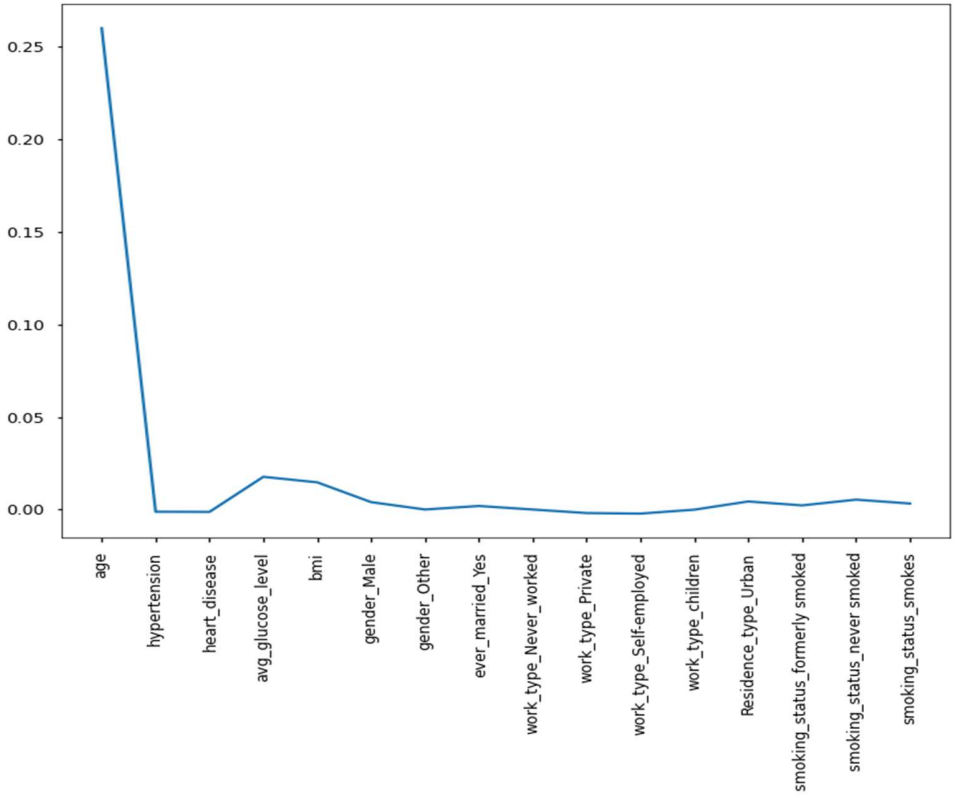
Observation:

The ideal model for prediction would be one with high **recall**, **precision** and consequently a high **f1 score**. And one that maintains a relatively high accuracy.

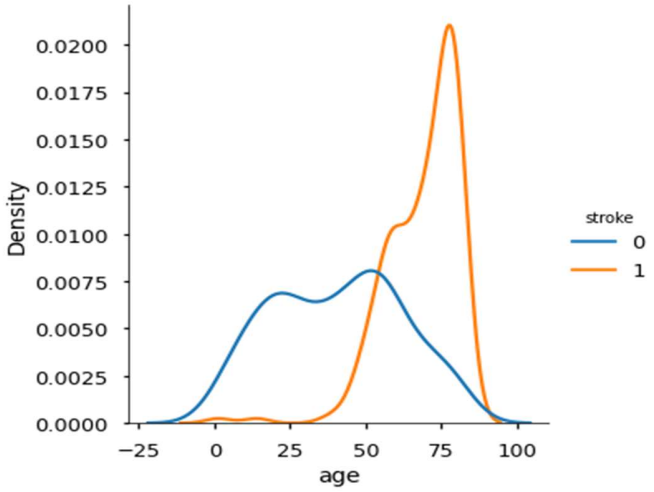
From the table above, it can be observed that the Voting Classifier model trained (using the following models: logistic regression, xgbclassifier, knn, svc) on the under sampled data meets the criteria best.

Observing relevant features in model:

a) Importance of features



b) Distribution of age for patients with and without stroke



From figure **a** above, it can be observed that age plays a major role in determining the likelihood of an individual getting stroke.

The figure below, figure **b** affirms that and shows that **the older a person, the more likely they are to get stroke**.

Suggestions for making better predictions:

The major issue faced here was lack of sufficient data. More specifically data on patients who have had stroke before. Therefore, to be able to improve upon the model's accuracy and precision, getting more data, about patients that have had stroke before, that can be augmented into our current dataset, would prove very useful.