Cerebral Stroke Prediction

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Abstract

We used cerebral stroke data to predict the onset of stroke. One sample of this data was marked with a stroke of 0 or 1, along with 12 types of health-related data that may or may not be related to cerebral stroke. A total of 43,400 of these samples were used. During pretreatment, missing values in bmi level and smoking status were treated and these data were removed because the stroke incidence rate was significantly lower in those under 35 years of age.
ROC auc score and F1 score were used for model evaluation. MLP, logistic regression, random forest classifier, XGB classifier, and Linear SVC were applied to the model. Among them, MLP had the highest model accuracy and ROC auc score, and the results of logistic regression, XGB classifier, and Linear SVC were not bad either. However, in the case of the random forest classifier, the accuracy and f1 score were high, but the ROC auc score was low, so it was judged not suitable.
Therefore, we considered it most appropriate for predicting the onset of MLP stroke, that is, for binary classification.

1. Introduction

A stroke, a cerebrovascular accident (CVA), happens when part of the brain loses its bloo d supply causing the part of the body that the blood-deprived brain cells control to stop working. There are 2 kinds of stroke: ischemic and hemorrhagic. Ischemic stroke happens when a major blood vessel in the brain is blocked, lacking blood flow into the brain. He morrhagic stroke occurs when a blood vessel in the brain bursts and spills bleeding into brain tissue. A stroke is a medical emergency because brain cells begin to die after a few minutes, and this leads to death or permanent disability. There are opportunities to treat ischemic strokes, but that treatment needs to be started in the first few hours after the si gns of a stroke begin.

There are several risk factors for strokes. According to the Global Burden of Diseases, Inju ries, and Risk Factors Study (GBD) 2019([1]), estimated 19 behavioral, environmental, and occupational, and metabolic stroke risk factors. In 2020, the World Health Organization (WHO) and the International Labor Organization (ILO) ([2]) systemically review and meta-a nalyze estimates of the effect of exposure to long working hours on stroke. Recent studi es analyze the effects of risk factors on stroke (three outcomes: prevalence, incidence, an d mortality). In this paper, we explore the effects of risk factors on stroke and build a clas sification model to classify whether the stroke occurs.

2. Background

2.1 Binary Classification

Binary classification is the task of classifying the elements of a set into two groups on th e basis of a classification rule. It is dichotomization applied to a practical situation. In ma ny practical binary classification problems, the two groups are not symmetric, and rather than overall accuracy, the relative proportion of different types of errors is of interest. For example, in medical testing, detecting a disease when it is not present (a false positive) is considered differently from not detecting a disease when it is present (a false negative).

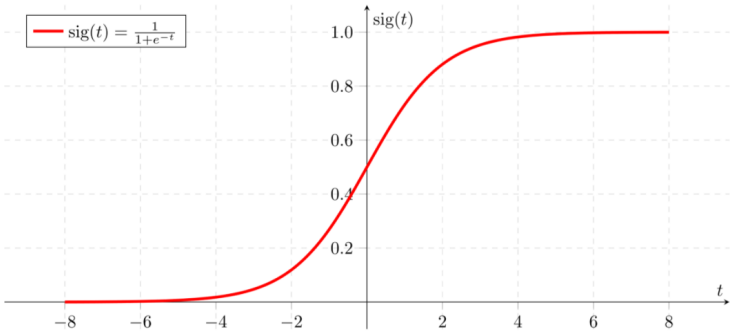
Statistical classification is a problem studied in machine learning. It is a type of supervise d learning, a method of machine learning where the categories are predefined, and is us ed to categorize new probabilistic observations into said categories. When there are only two categories the problem is known as statistical binary classification. Some of the meth ods commonly used for binary classification are decision trees, random forests, bayesian networks, support vector machines, neural networks, logistic regression, probit model. Ea ch classifier is best in only a select domain based upon the number of observations, the dimensionality of the feature vector, the noise in the data and many other factors.

2.2 Logistic Regression

The logistic model (or logit model) is used to model the probability of a certain class or event existing such as pass/fail, win/lose, alive/dead or healthy/sick.

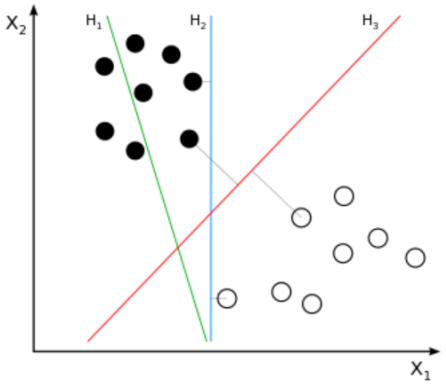
Logistic regression is a statistical model that in its basic form uses a logistic function to model a binary dependent variable, although many more complex extensions exist. In re gression analysis, logistic regression is estimating the parameters of a logistic model (a f orm of binary regression). Mathematically, a binary logistic model has a dependent varia ble with two possible values, such as pass/fail which is represented by an indicator variab le, where the two values are labeled "0" and "1". In the logistic model, the log-odds (the logarithm of the odds) for the value labeled "1" is a linear combination of one or more i ndependent variables ("predictors"); the independent variables can each be a binary varia ble (two classes, coded by an indicator variable) or a continuous variable (any real value). The corresponding probability of the value labeled "1" can vary between 0 (certainly the value "0") and 1 (certainly the value "1"), hence the labeling; the function that converts lo g-odds to probability is the logistic function, hence the name.

An explanation of logistic regression can begin with an explanation of the standard logist ic function. The logistic function is a sigmoid function, which takes any real input, and ou tputs a value between zero and one. For the logit, this is interpreted as taking input log-odds and having output probability.



2.3 SVM

Classifying data is a common task in machine learning. Suppose some given data points each belong to one of two classes, and the goal is to decide which class a new data poin t will be in. In the case of support-vector machines, a data point is viewed as a p dimensi onal vector (a list of p numbers), and we want to know whether we can separate such p oints with a (p-1)dimensional hyperplane. This is called a linear classifier. There are many hyperplanes that might classify the data. One reasonable choice as the best hyperplane i s the one that represents the largest separation, or margin, between the two classes. So we choose the hyperplane so that the distance from it to the nearest data point on each side is maximized. If such a hyperplane exists, it is known as the maximum-margin hyper plane and the linear classifier it defines is known as a maximum-margin classifier; or equi valently, the perceptron of optimal stability.

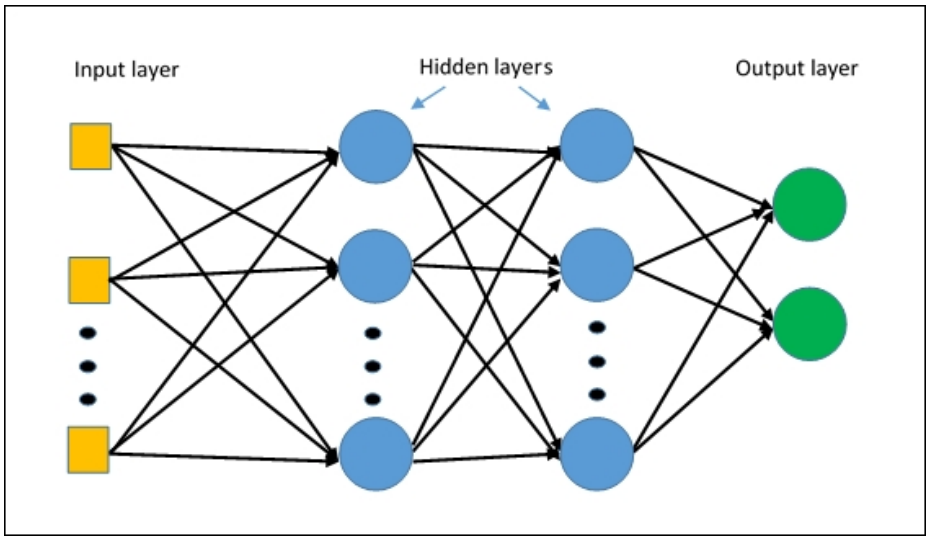


H1 does not separate the classes. H2 does, but only with a small margin. H3 separates th em with the maximal margin.

2.4 MLP

A multilayer perceptron (MLP) is a class of feedforward artificial neural network (ANN). Th e term MLP is used ambiguously, sometimes loosely to mean any feedforward ANN, som etimes strictly to refer to networks composed of multiple layers of perceptrons. Multilaye r perceptrons are sometimes colloquially referred to as "vanilla" neural networks, especial ly when they have a single hidden layer.

An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an o utput layer. Except for the input nodes, each node is a neuron that uses a nonlinear activ ation function. MLP utilizes a supervised learning technique called backpropagation for tr aining. Its multiple layers and non-linear activation distinguish MLP from a linear perceptr on.



2.5 XGB classification

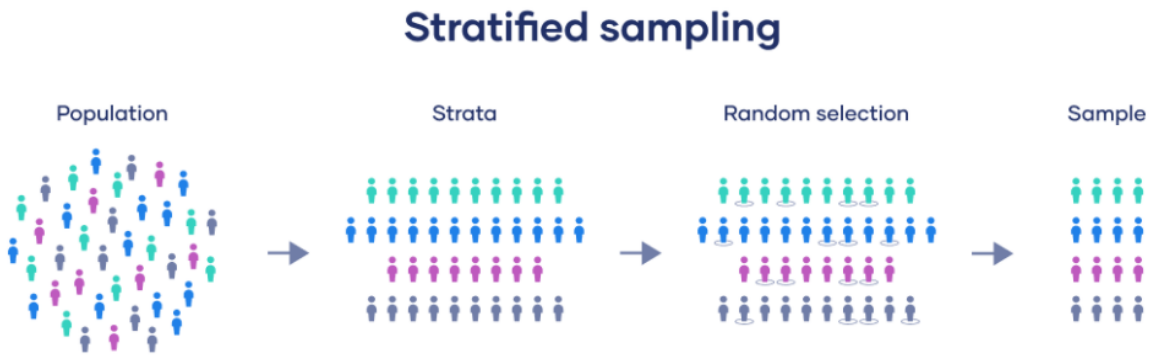
XGBoost stands for eXtreme Gradient Boosting. XGBoost is an implementation of gradien t boosted decision trees designed for speed and performance that is dominative competi

tive machine learning. Although it is based on GBM, it is an algorithm that solves GBM's disadvantages such as slow execution time and overfitting regulations.

3. Methods

3.1 Stratified Sampling

Stratified random sampling is a method of sampling that involves the division of a population into smaller sub-groups. In stratified random sampling, the strata are formed based on members' shared attributes or characteristics. The reason to use stratified sampling is, if measurements within strata have lower standard deviation, stratification gives smaller error in estimation. For example, if the values vary greatly, stratified sampling will ensure that estimates can be made with equal accuracy.



3.2 One-Hot-Encoding

Machine learning algorithms cannot work directly with categorical data and they must be transformed into numeric values before training a model. Most common type of categorical encoding is One Hot Encoding (also known as dummy encoding) where each categorical level becomes a separate feature in the dataset containing binary values (1 or 0). This is ideal for features having categorical data. In other different scenarios other methods of encoding must be used.

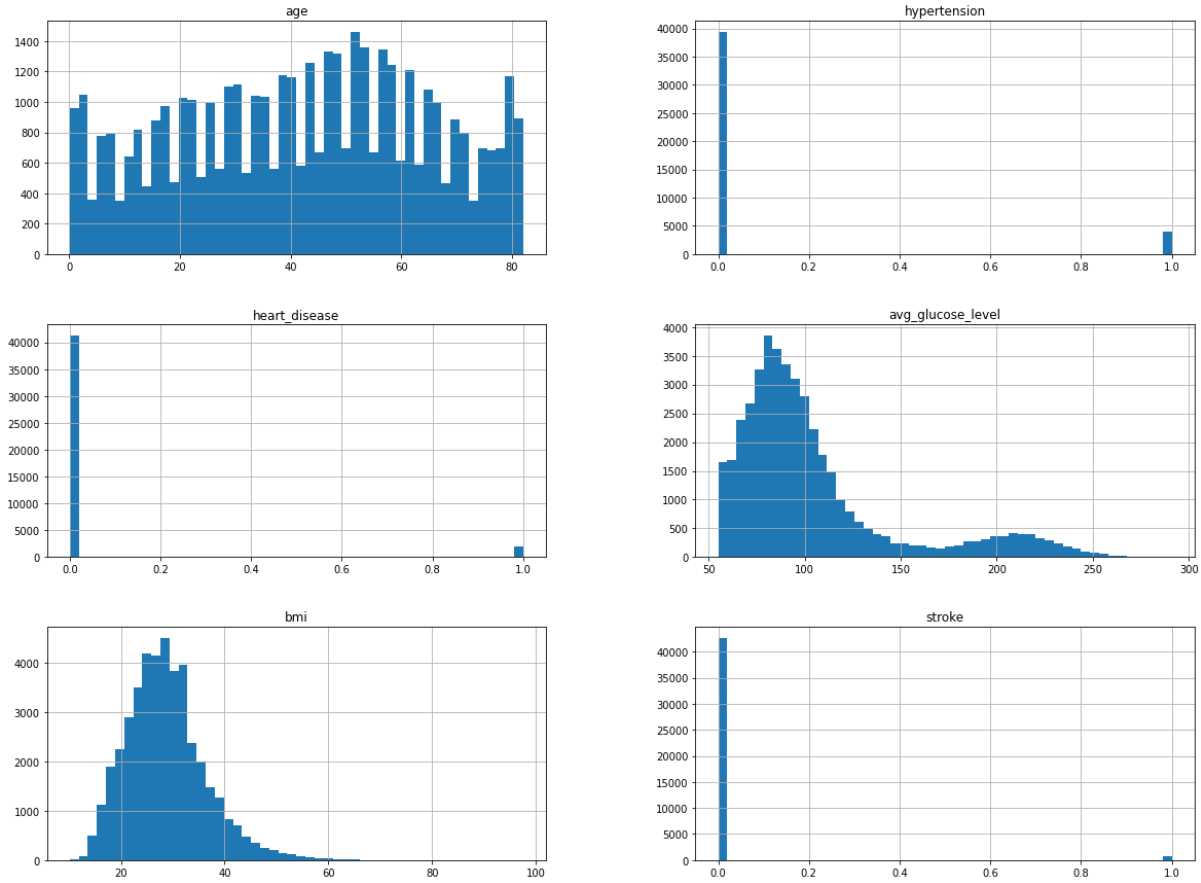
4. Experiments

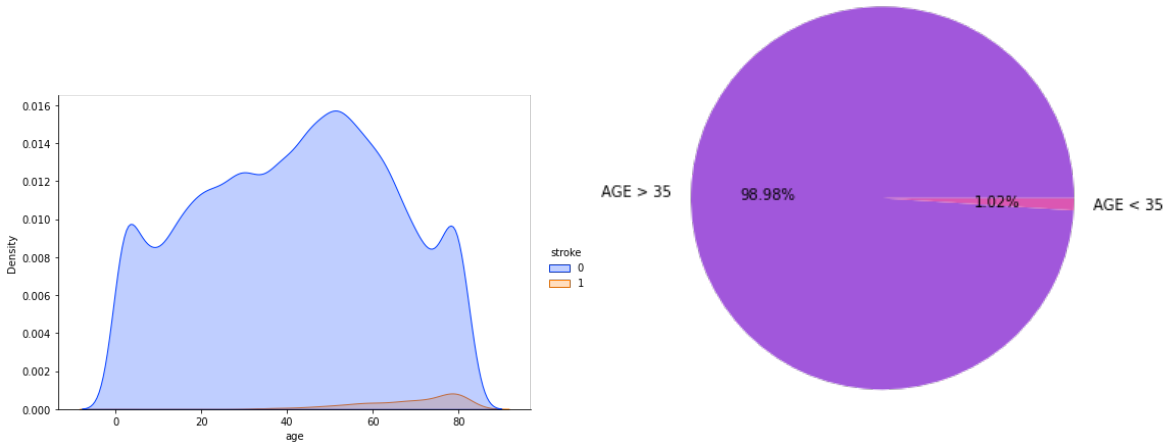
In our experiments, we endeavored to see which factor affects the occurrence of cerebral stroke and predict the probability to have cerebral stroke.

4.1 Data Exploration

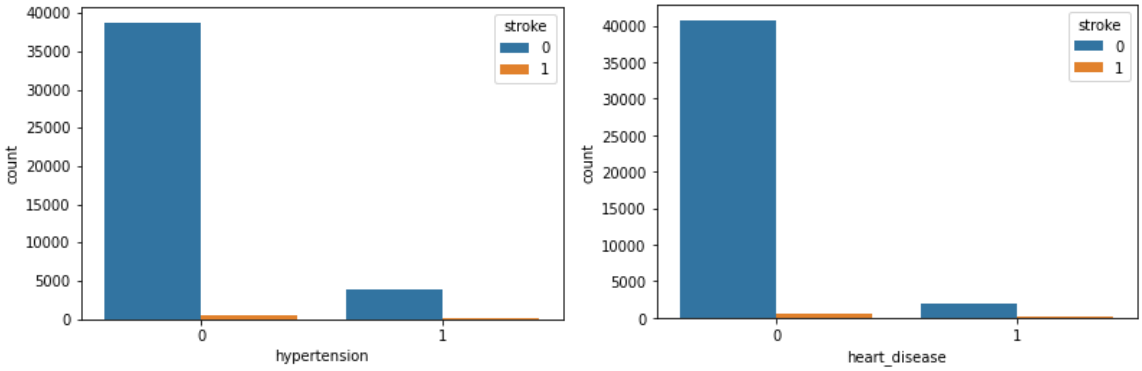
The cerebral stroke dataset consists of 43,400 people's information, which we used to predict cerebral stroke for our experiments. Each sample has 12 classes which are id, gender, age, hypertension, heart disease, ever married, work type, residence type, average glucose level, bmi, smoking status, and whether stroke or not.

	id	gender	age	hypertension	heart_disease	ever_married	work_type	Residence_type	avg_glucose_level	bmi	smoking_status	stroke
0	30669	Male	3.0	0	0	No	children	Rural	95.12	18.0	NaN	0
1	30468	Male	58.0	1	0	Yes	Private	Urban	87.96	39.2	never smoked	0
2	16523	Female	8.0	0	0	No	Private	Urban	110.89	17.6	NaN	0
3	56543	Female	70.0	0	0	Yes	Private	Rural	69.04	35.9	formerly smoked	0
4	46136	Male	14.0	0	0	No	Never_worked	Rural	161.28	19.1	NaN	0





The difference in stroke occurrence is large according to age. Looking at the two graphs above, most strokes occur in people over the age of 35. In addition, the incidence rate of stroke is significantly lower than that of non-stroke cases.



4.1.1 Which factors will have the biggest impact?

In a sample that had a stroke, we calculated the proportion of patients with certain factors among all stroke patients. The probability that patients with hypertension had a stroke was only 10.70%, and patients with heart disease had only a 6.15% chance of having a stroke. Married people were roughly twice as likely to have a stroke than unmarried people, and those who were working were more than 90 percent higher than those who weren't working. In the case of residence, the ratio of urban and rural areas was the same, and the prevalence of stroke was twice as high for obese and smokers, respectively.

4.2 Data Preprocessing

4.2.1 Handling Missing Values

Most machine learning algorithms require numeric input values, and a value to be present for each row and column in a dataset. As such, missing values can cause problems for machine learning algorithms and it is common to identify missing values in a dataset and replace them with a numeric value. Therefore, missing values should be treated before training a machine learning model. When we checked missing values of our dataset, there were missing values in bmi and smoking status.

4.2.1.1 Treating missing value of bmi

First, we checked bmi's correlation with other factors.

	id	age	hypertension	heart_disease	avg_glucose_level	bmi	stroke
id	1.000000	0.012760	0.006571	0.009234	0.024634	0.018839	0.002976
age	0.012760	1.000000	0.272169	0.250188	0.237627	0.358897	0.156049
hypertension	0.006571	0.272169	1.000000	0.119777	0.160211	0.161225	0.075332
heart_disease	0.009234	0.250188	0.119777	1.000000	0.146938	0.057677	0.113763
avg_glucose_level	0.024634	0.237627	0.160211	0.146938	1.000000	0.191295	0.078917
bmi	0.018839	0.358897	0.161225	0.057677	0.191295	1.000000	0.020285
stroke	0.002976	0.156049	0.075332	0.113763	0.078917	0.020285	1.000000

According to the result, we thought that bmi value has a high correlation with age. There fore, from now on we are going to get the average value of bmi by age. Age values rang e from 0 to 82 years. So we split them into the 0's ~ 80's.

And then, we got average values of bmi by age. Finally, we applied these average values to the bmi missing values. After that, we could check null values of bmi are eliminated.

4.2.1.2 Treating missing value of smoking status

When we checked the number of people according to smoking status, those who have n ever smoked have the highest percentage.

```
df["smoking_status"].value_counts()
```

```
never smoked       16053
formerly smoked     7493
smokes              6562
Name: smoking_status, dtype: int64
```

Similar to the previous step which treated the missing values of mbi, we got the distribut ion of smoking by age. According to the results, we know that many children and teenag

ers are non-smokers. Therefore, we filled the missing value of smoking status with 'never smoked'.

After that, the missing value of smoking status decreased from about 30% to about 15%.

To decrease the missing value more, we applied a little information. First, many people w ith heart disease have smoked in the past. So we filled the smoking status's missing valu e of people who have heart disease into 'formerly smoked'.

heart_disease	smoking_status	
0	never smoked	22013
	formerly smoked	6846
	smokes	6135
1	formerly smoked	647
	never smoked	608
	smokes	427

correlation between heart disease and smoking status

Second, we checked the smoking status by age and gender.

Female	아동	formerly smoked	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0	8.0
		never smoked	2228.0	2228.0	2228.0	2228.0	2228.0	2228.0	2228.0	2228.0	2228.0	2228.0
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	10대	formerly smoked	168.0	168.0	168.0	168.0	168.0	168.0	168.0	168.0	168.0	168.0
		never smoked	2071.0	2071.0	2071.0	2071.0	2071.0	2071.0	2071.0	2071.0	2071.0	2071.0
		smokes	156.0	156.0	156.0	156.0	156.0	156.0	156.0	156.0	156.0	156.0
	20대	formerly smoked	476.0	476.0	476.0	476.0	476.0	476.0	476.0	476.0	476.0	476.0
		never smoked	1681.0	1681.0	1681.0	1681.0	1681.0	1681.0	1681.0	1681.0	1681.0	1681.0
		smokes	701.0	701.0	701.0	701.0	701.0	701.0	701.0	701.0	701.0	701.0
	30대	formerly smoked	484.0	484.0	484.0	484.0	484.0	484.0	484.0	484.0	484.0	484.0
		never smoked	1619.0	1619.0	1619.0	1619.0	1619.0	1619.0	1619.0	1619.0	1619.0	1619.0
		smokes	646.0	646.0	646.0	646.0	646.0	646.0	646.0	646.0	646.0	646.0
	40대	formerly smoked	651.0	651.0	651.0	651.0	651.0	651.0	651.0	651.0	651.0	651.0
		never smoked	1754.0	1754.0	1754.0	1754.0	1754.0	1754.0	1754.0	1754.0	1754.0	1754.0
		smokes	775.0	775.0	775.0	775.0	775.0	775.0	775.0	775.0	775.0	775.0
	50대	formerly smoked	796.0	796.0	796.0	796.0	796.0	796.0	796.0	796.0	796.0	796.0
		never smoked	1738.0	1738.0	1738.0	1738.0	1738.0	1738.0	1738.0	1738.0	1738.0	1738.0
		smokes	704.0	704.0	704.0	704.0	704.0	704.0	704.0	704.0	704.0	704.0
	60대	formerly smoked	1322.0	1322.0	1322.0	1322.0	1322.0	1322.0	1322.0	1322.0	1322.0	1322.0
		never smoked	1277.0	1277.0	1277.0	1277.0	1277.0	1277.0	1277.0	1277.0	1277.0	1277.0
		smokes	428.0	428.0	428.0	428.0	428.0	428.0	428.0	428.0	428.0	428.0
	70대	formerly smoked	1178.0	1178.0	1178.0	1178.0	1178.0	1178.0	1178.0	1178.0	1178.0	1178.0
		never smoked	1155.0	1155.0	1155.0	1155.0	1155.0	1155.0	1155.0	1155.0	1155.0	1155.0
		smokes	233.0	233.0	233.0	233.0	233.0	233.0	233.0	233.0	233.0	233.0
	80대	formerly smoked	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0
		never smoked	258.0	258.0	258.0	258.0	258.0	258.0	258.0	258.0	258.0	258.0
		smokes	38.0	38.0	38.0	38.0	38.0	38.0	38.0	38.0	38.0	38.0

Male	아동	formerly smoked	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0	7.0
		never smoked	2353.0	2353.0	2353.0	2353.0	2353.0	2353.0	2353.0	2353.0	2353.0	2353.0
		smokes	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	10대	formerly smoked	124.0	124.0	124.0	124.0	124.0	124.0	124.0	124.0	124.0	124.0
		never smoked	1800.0	1800.0	1800.0	1800.0	1800.0	1800.0	1800.0	1800.0	1800.0	1800.0
		smokes	96.0	96.0	96.0	96.0	96.0	96.0	96.0	96.0	96.0	96.0
	20대	formerly smoked	208.0	208.0	208.0	208.0	208.0	208.0	208.0	208.0	208.0	208.0
		never smoked	675.0	675.0	675.0	675.0	675.0	675.0	675.0	675.0	675.0	675.0
		smokes	414.0	414.0	414.0	414.0	414.0	414.0	414.0	414.0	414.0	414.0
	30대	formerly smoked	322.0	322.0	322.0	322.0	322.0	322.0	322.0	322.0	322.0	322.0
		never smoked	847.0	847.0	847.0	847.0	847.0	847.0	847.0	847.0	847.0	847.0
		smokes	457.0	457.0	457.0	457.0	457.0	457.0	457.0	457.0	457.0	457.0
	40대	formerly smoked	465.0	465.0	465.0	465.0	465.0	465.0	465.0	465.0	465.0	465.0
		never smoked	957.0	957.0	957.0	957.0	957.0	957.0	957.0	957.0	957.0	957.0
		smokes	613.0	613.0	613.0	613.0	613.0	613.0	613.0	613.0	613.0	613.0
	50대	formerly smoked	741.0	741.0	741.0	741.0	741.0	741.0	741.0	741.0	741.0	741.0
		never smoked	942.0	942.0	942.0	942.0	942.0	942.0	942.0	942.0	942.0	942.0
		smokes	603.0	603.0	603.0	603.0	603.0	603.0	603.0	603.0	603.0	603.0
	60대	formerly smoked	1135.0	1135.0	1135.0	1135.0	1135.0	1135.0	1135.0	1135.0	1135.0	1135.0
		never smoked	645.0	645.0	645.0	645.0	645.0	645.0	645.0	645.0	645.0	645.0
		smokes	422.0	422.0	422.0	422.0	422.0	422.0	422.0	422.0	422.0	422.0
	70대	formerly smoked	1061.0	1061.0	1061.0	1061.0	1061.0	1061.0	1061.0	1061.0	1061.0	1061.0
		never smoked	525.0	525.0	525.0	525.0	525.0	525.0	525.0	525.0	525.0	525.0
		smokes	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0	241.0
	80대	formerly smoked	225.0	225.0	225.0	225.0	225.0	225.0	225.0	225.0	225.0	225.0
		never smoked	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0	94.0
		smokes	33.0	33.0	33.0	33.0	33.0	33.0	33.0	33.0	33.0	33.0

Other	아동	formerly smoked	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	10대	formerly smoked	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	20대	formerly smoked	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
	30대	formerly smoked	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	40대	formerly smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		never smoked	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0	2.0
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	50대	formerly smoked	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	60대	formerly smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	70대	formerly smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
	80대	formerly smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		never smoked	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
		smokes	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

According to the results, among men, formerly smoked is the most in their 60s, 70s, and 80s. Therefore we filled the smoking status's missing value of people who are 60s, 70s, a nd 80s men into 'formerly smoked'.

After these two steps, 10% of missing values are still left. Since we do not have correlatio n in data anymore, we decided to fill the remaining missing value into 'never smoked'.

4.2.2 Splitting

The difference in stroke occurrence according to age was large, so we tried to discard sa mples under 35 years of age. And since the ratio of stroke values differs greatly, layered extraction is performed. The ratio of the test set was set to 0.3. Then to proceed with mo del evaluation for model selection, layered extraction is performed once more with valida tion and train set.

4.2.3 Pipeline

First, we seperated the categorical data and the numeric data.

To assemble several steps that can be cross-validated together while setting different par ameters, we used a pipeline in scikit-learn.

We put a standard scaler inside the pipeline, and we didn't give parameter values. And t hen, we converted the data previously divided into numeric and categorical types. We us ed a standard scaler to convert numeric data, and used a one-hot-encoder to convert cat egorical data.

The data we have is markedly different in the number of the two classes. Therefore, we tr ied to solve the problem of unbalanced data and we used an asymmetric data processin g program called SMOTE (synthetic minority oversampling technique). The operation met hod of SMOTE is an oversampling method that takes a sample of a class with a small am ount of data and adds a random value to create a new sample and add it to the data.

5. Model Selections

For evaluation of each model, ROC auc score and f1 score were used.

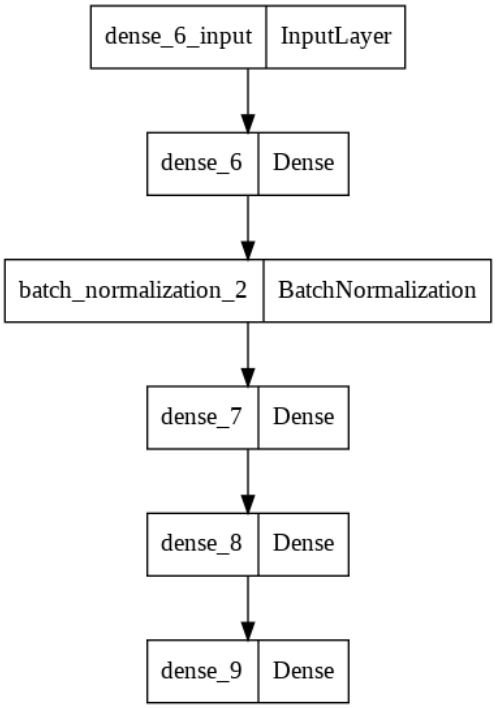
ROC is a probability curve and AUC presents the degree or measure of separability. It tell s how much the model is capable of distinguishing between classes. Higher the AUC, the better the model is at predicting 0 classes as 0 classes as 0 and 1 classes as 1.

The F1 score combines precision and recall. Precision and recall are two building blocks of the F1 score. The goal of the F1 score is to combine the precision and recall metrics in to a single metric. At the same time, the F1 score has been designed to work well on im balanced data.

5.1 MLP

5.1.1 Training

We trained the ML on the 30,380 training data for 15 epochs and batch size for 300 usin g an Adam optimizer with a binary crossentropy loss function.
Initially, we created a model with 4 layers. The first layer using the relu function, the batc h normalization layer, the second layer using the relu function, and the last layer using th e sigmoid function. Then we checked accuracy and ROC auc score.
After that, we tried increasing the number of neurons used and adding one more layer u sing the relu function.



5.1.2 Results

The final training accuracy was 95.58% and the final validation ROC auc score was 0.79. I n general, if the AUC is 0.8 or higher, it is evaluated as a binary classifier with very good performance. Anything between 0.7 and 0.8 is a good binary classifier. If the AUC is 0.5-0 .7, it is helpful to have a binary classifier. Since our MLP has an ROC auc score of 0.79, th is is considered a pretty good result.

5.2 Logistic Regression

5.2.1 Training

We gave class weight 0.93 to training and 0.08 to testing.

5.2.2 Results

The final training accuracy was 78.44%, final validation accuracy was 73.89%, f1 score was 0.80, and ROC auc score was 0.77. Although the ROC auc score is still high, the accuracy is considerably reduced compared to the previously applied MLP.

5.3 Random Forest Classifier

Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dat aset.

5.3.1 Training

We used previously preprocessed data (with samples under 35 years old) for training.

5.3.2 Results

The final training accuracy was 100.00%, final validation accuracy was 92.58%, f1 score w as 1.0, and ROC auc score was 0.57. The accuracy was very high in both the training data and the validation data, and the F1 score also reached its best value. However, the ROC auc score was 0.57, which was significantly lower than the previous two models. If the AU C is less than 0.5, then the binary classifier is useless. Therefore, we think that the rando m forest classifier is not appropriate.

5.4 XGB Classifier

XGB is an algorithm that has recently been dominating applied machine learning and Ka ggle competitions for structured or tabular data. XGB is an implementation of gradient b oosted decision trees designed for speed and performance.

5.4.1 Training

We used previously preprocessed data (with samples under 35 years old) for training.

5.4.2 Results

The final training accuracy was 86.84%, final validation accuracy was 74.71%, f1 score was 0.86, and ROC auc score was 0.75.

5.5 Linear SVC

The objective of a Linear SVC (Support Vector Classifier) is to fit to the data we provided, returning a "best fit" hyperplane that divides, or categorizes, our data. From there, after g etting the hyperplane, we can then feed some features to our classifier to see what the p redicted class is. This makes this specific algorithm rather suitable for our uses, though w e can use this for many situations.

5.5.1 Training

We used previously preprocessed data (with samples under 35 years old) for training.

5.5.2 Results

The final training accuracy was 78.64%, final validation accuracy was 73.28%, f1 score was 0.80, and ROC auc score was 0.77.

6. Model Tuning and Testing

Since the data we have is unbalanced, we thought it would be appropriate to use the da ta oversampling with the SMOTE method. For this oversampling data, the best result was when XGBclassifier was applied. Therefore, in order to finally classify the oversampling da ta with the XGBclassifier, the validation set was also processed with the SMOTE technique .

As a result, the f1 score was 0.82, the accuracy was 79.48%, and the ROC auc score was 0 .80. Although the accuracy was slightly lower than the results confirmed in the model sel ection earlier, the f1 score and the ROC auc score were able to obtain quite good values.

7. Discussion

We used cerebral stroke data to predict the onset of stroke. One sample of this data was marked with a stroke of 0 or 1, along with 12 types of health-related data that may or may not be related to cerebral stroke. A total of 43,400 of these samples were used.
Data exploration found that people who smoke, are obese, and who work are more likely to have a stroke. In the data preprocessing process, it was found that people under the age of 35 had a very low chance of developing a stroke, and this data was excluded in the future modeling process. A total of five models were used to predict the stroke onset probability for various factors (MLP, logistic regression, random forest classifier, XGBclassifier, and linear SVC). As a result, the rest of the models except for the random forest classifier were considered suitable for our binary classification model, and we considered it most appropriate for predicting the onset of MLP stroke.

We wanted to make a model that can calculate the probability of an outbreak by going further from predicting whether or not there is an outbreak with a more diverse and many datasets. In addition, we think that the current model can be improved by using Bayes networks, probit models, and other neural networks that can perform binary classification
.
We first wanted to know which of the factors in each sample had the greatest influence on the occurrence of stroke, as well as predicting the occurrence of stroke. For now, working with data, we computed only one relationship for each factor. However, Previously, when calculating the probability of being a stroke patient for each factor, there were parts that did not match the above facts. This is thought to be due to the small amount of data. Therefore, it is thought that more data is needed. And since stroke is not caused by a single cause, but as a complication of several diseases, creating a model that can broadly understand the relationship between various factors will be more helpful in predicting stroke onset.

8. Conclusion

The brain is damaged when the blood vessels supplying blood to the brain are blocked or burst, and the resulting neurological abnormalities such as hemiparesis, speech disorders, and consciousness disorders are called strokes. Causes of the disease include high blood pressure, diabetes, smoking, heart disease, and obesity.

Various classification models were applied to predict the occurrence of cerebral hemorrhage. The dataset we used was a case of binary classification, and MLP, logistic regression, random forest classifier, XGBclassifier, and linear SVC were applied. As a result, pretty good results were obtained in most models except for the random forest classifier, and the accuracy was the highest when using MLP. Therefore, it was considered that MLP was suitable for binary classification. In addition, the XGBclassifier was evaluated with data oversampling by the SMOTE method. As a result, the accuracy was slightly lower than the results confirmed in the model selection earlier, but the f1 score and the ROC auc score were able to obtain quite good values.

In the case of the random forest classifier, the accuracy was high, but the ROC auc score was low, about 0.5. The reason for this seems to be that if a decision tree is used, the result or performance fluctuates widely. In order to improve this, it is thought that hyper parameter tuning to find an appropriate hyper parameter (ex. class_weight) through trial and error is additionally needed.

If the probability of stroke can be predicted through the relationship between living characteristics or information on current diseases, it is expected that the probability of occurrence can be reduced by paying close attention to stroke.

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