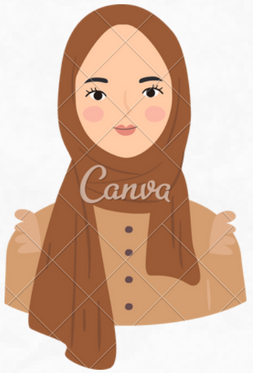
Third Group (Class DS2)

Analyzing Stroke Risk Factors Using Logistic Regression

12 DECEMBER, 2024

OUR TEAMS



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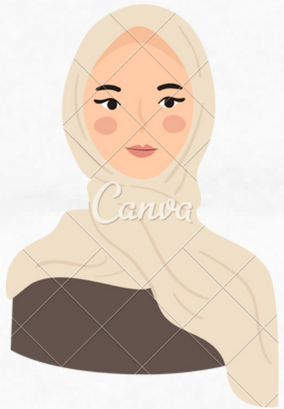

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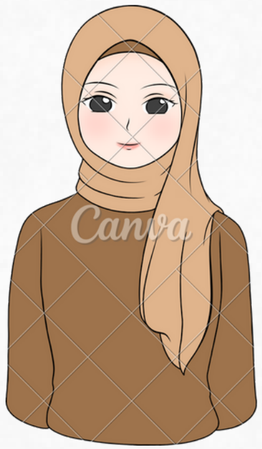

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DATA UNDERSTANDING

The dataset contains information on demographic, health, and lifestyle factors related to stroke. Here's an overview of the data:

Dependent Variable = Stroke (0 = No , 1 = Yes)

Categoric Variable Predictors

1. Gender
2. Hypertension
3. Heart Disease
4. Ever Married
5. Work Type
6. Residence Type
7. Smoking Status

Continous Variable Predictors

1. Age
2. Average Glucose Level
3. BMI (Body Mass Index)

PURPOSES

The purposes of this analysis are

1. Identify which factors associated with the likelihood of having a stroke.
2. Build a logistic regression model to predict the likelihood of a person having a stroke based on relevant factors.
3. Evaluate the impact of these factors on stroke likelihood to provide guidance on prevention.

Pre Processing

In this process,

- We changed the type of a variable.
- We used the mean to impute missing values on BMI variable
- We remove one row with the value 'Other' on gender variabel.

```
   gender          age        hypertension heart_disease ever_married
 Female:2994   Min.   : 0.08   0:4612       0:4834        No :1757
 Male  :2115   1st Qu.:25.00   1: 498       1: 276        Yes:3353
 Other :   1   Median :45.00
               Mean   :43.23
               3rd Qu.:61.00
               Max.   :82.00

        work_type    Residence_type avg_glucose_level      bmi
 children      : 687   Rural:2514     Min.   : 55.12    Min.   :10.30
 Govt_job      : 657   Urban:2596     1st Qu.: 77.25    1st Qu.:23.50
 Never_worked :  22                   Median : 91.89    Median :28.10
 Private       :2925                  Mean   :106.15    Mean   :28.89
 Self-employed: 819                   3rd Qu.:114.09    3rd Qu.:33.10
                                      Max.   :271.74    Max.   :97.60
                                                        NA's   :201

        smoking_status     stroke
 formerly smoked: 885   Min.   :0.00000
 never smoked   :1892   1st Qu.:0.00000
 smokes         : 789   Median :0.00000
 Unknown        :1544   Mean   :0.04873
                        3rd Qu.:0.00000
                        Max.   :1.00000
```

NOISE

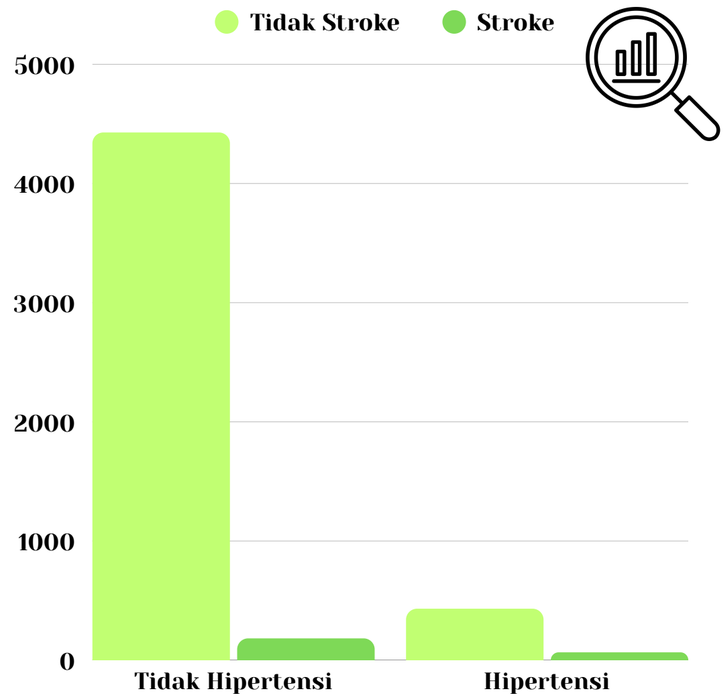
MISSING VAIUE

```
tibble [5,110 × 11] (S3: tbl_df/tbl/data.frame)
 $ gender           : chr [1:5110] "Male" "Female" "Male" "Female" ...
 $ age              : chr [1:5110] "67" "61" "80" "49" ...
 $ hypertension     : num [1:5110] 0 0 0 0 1 0 1 0 0 0 ...
 $ heart_disease    : num [1:5110] 1 0 1 0 0 0 1 0 0 0 ...
 $ ever_married     : chr [1:5110] "Yes" "Yes" "Yes" "Yes" ...
 $ work_type        : chr [1:5110] "Private" "Self-employed" "Private" "Private" ...
 $ Residence_type   : chr [1:5110] "Urban" "Rural" "Rural" "Urban" ...
 $ avg_glucose_level: chr [1:5110] "228.69" "202.21" "105.92" "171.23" ...
 $ bmi              : chr [1:5110] "36.6" "N/A" "32.5" "34.4" ...
 $ smoking_status   : chr [1:5110] "formerly smoked" "never smoked" "never smoked" "smokes" ...
 $ stroke           : num [1:5110] 1 1 1 1 1 1 1 1 1 1 ...
```

MODEL BUILDING

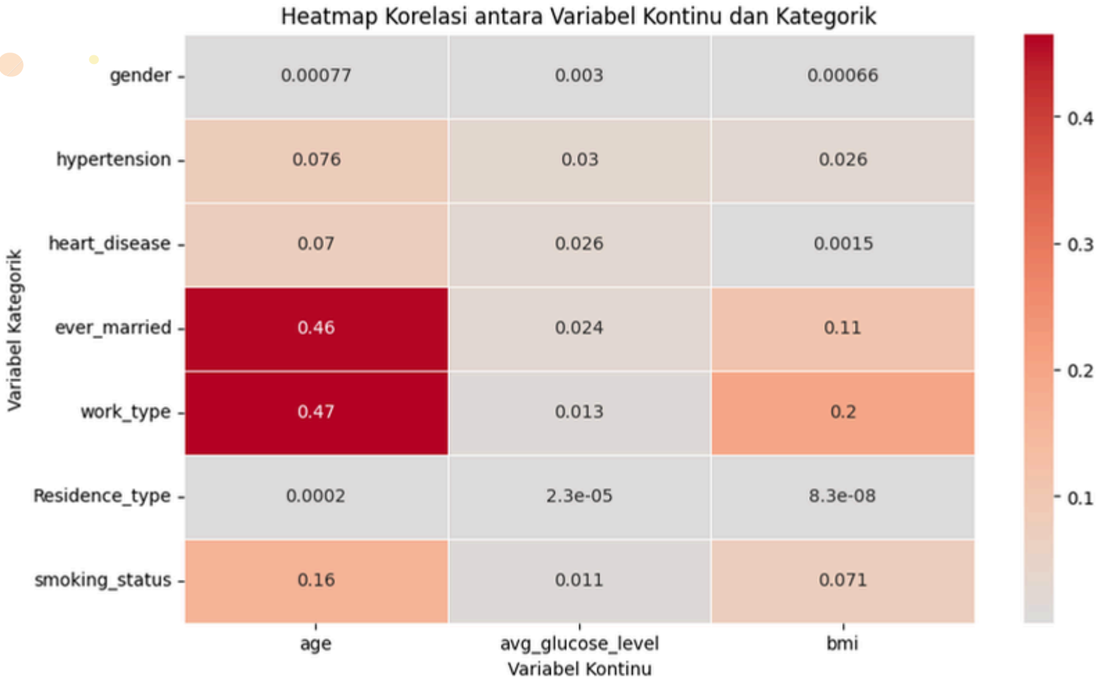
EXPLORATORY DATA ANALYSIS (EDA)

Proportion of Stroke Cases by Hypertension Status



the proportion of stroke cases is relatively higher among individuals with hypertension compared to those without.

Correlation Between Independent variable



Higher correlation represented with darker colors, indicating stronger relationships.

MODEL ASSUMPTION

MODEL ASSUMPTION

```
summary(glm.logit)
```

```
Call:
glm(formula = stroke ~ avg_glucose_level + Residence_type + work_type +
    ever_married + bmi + heart_disease * hypertension + age *
    heart_disease + age * hypertension + smoking_status * gender,
    family = binomial(link = "logit"), data = data)

Coefficients:
                                     Estimate Std. Error z value Pr(>|z|)
(Intercept)                        -6.815132   0.793585  -8.588  < 2e-16
avg_glucose_level                   0.003885   0.001202   3.233  0.00122
Residence_typeUrban                 0.070406   0.138235   0.509  0.61053
work_typeGovt_job                  -1.166791   0.852573  -1.369  0.17114
work_typeNever_worked             -10.349112 309.501676  -0.033  0.97333
work_typePrivate                   -1.031307   0.836513  -1.233  0.21763
work_typeSelf-employed             -1.410105   0.855842  -1.648  0.09943
ever_marriedYes                    -0.203064   0.225201  -0.902  0.36721
bmi                                 0.001710   0.011413   0.150  0.88088
heart_disease1                      2.682193   1.309459   2.048  0.04053
hypertension1                       1.322502   1.011679   1.307  0.19113
age                                 0.079217   0.006563  12.071  < 2e-16
smoking_statusnever smoked         -0.150851   0.232383  -0.649  0.51624
smoking_statussmokes               -0.063148   0.310224  -0.204  0.83870
smoking_statusUnknown              -0.167639   0.286369  -0.585  0.55828
genderMale                         -0.039452   0.264232  -0.149  0.88131
heart_disease1:hypertension1       -0.325321   0.415329  -0.783  0.43346
heart_disease1:age                 -0.032203   0.018322  -1.758  0.07881
hypertension1:age                  -0.012384   0.014592  -0.849  0.39604
smoking_statusnever smoked:genderMale -0.190103   0.361767  -0.525  0.59925
smoking_statussmokes:genderMale     0.333174   0.426240   0.782  0.43442
smoking_statusUnknown:genderMale    0.224330   0.410354   0.547  0.58460

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1990.3  on 5108  degrees of freedom
Residual deviance: 1574.4  on 5087  degrees of freedom
AIC: 1618.4

Number of Fisher Scoring iterations: 14
```

is there multicolinearity?

NO

The picture shows that several variables are significant (with p-values less than 5%), and the difference in deviance indicates that the model has at least one significant variable.

```
> p_value <- 1 - pchisq( 415.9 , 21)
> p_value
[1] 0
```

MULTICOLINEARITY

See that the value of VIF (third column) for all variabel is less than 10. That's indicates there is no multicolinearity on this model assumption.

	GVIF	Df	GVIF^(1/(2*Df))
avg_glucose_level	1.121441	1	1.058981
Residence_type	1.009382	1	1.004680
work_type	1.498642	4	1.051870
ever_married	1.106981	1	1.052132
bmi	1.128648	1	1.062379
heart_disease	52.827435	1	7.268248
hypertension	40.862915	1	6.392411
age	1.769327	1	1.330161
smoking_status	7.075194	3	1.385553
gender	3.637534	1	1.907232
heart_disease:hypertension	1.650024	1	1.284533
heart_disease:age	53.649611	1	7.324589
hypertension:age	42.135591	1	6.491193
smoking_status:gender	14.389092	3	1.559572

MODEL SELECTION

Backward, Forward, and Stepwise Elemination

```
Call:  glm(formula = stroke ~ age + avg_glucose_level + hypertension +
    heart_disease + age:heart_disease, family = binomial(link = "logit"),
    data = data)

Coefficients:
       (Intercept)                 age   avg_glucose_level       hypertension1
         -7.646978            0.071512            0.004033            0.378696
    heart_disease1  age:heart_disease1
          2.745935           -0.033691

Degrees of Freedom: 5108 Total (i.e. Null);  5103 Residual
Null Deviance:      1990
Residual Deviance: 1588     AIC: 1600
```

Backward, forward, and stepwise selection methods all lead to the same result: age, hypertension, heart disease, average glucose levels, and interaction between age &heart disease are associated with an increased likelihood of having a stroke.

log odds of having stroke = β0 + β1(avg_glucose_level) + β2(hypertension) + β3(age) + β4(heart_disease) +β5(age*heart_disease)

Evaluation and Model Checking

Hosmer and Lemeshow goodness of fit (GOF) test

H0 : The model fits the data well

H1 : The model doesn't fits the data well

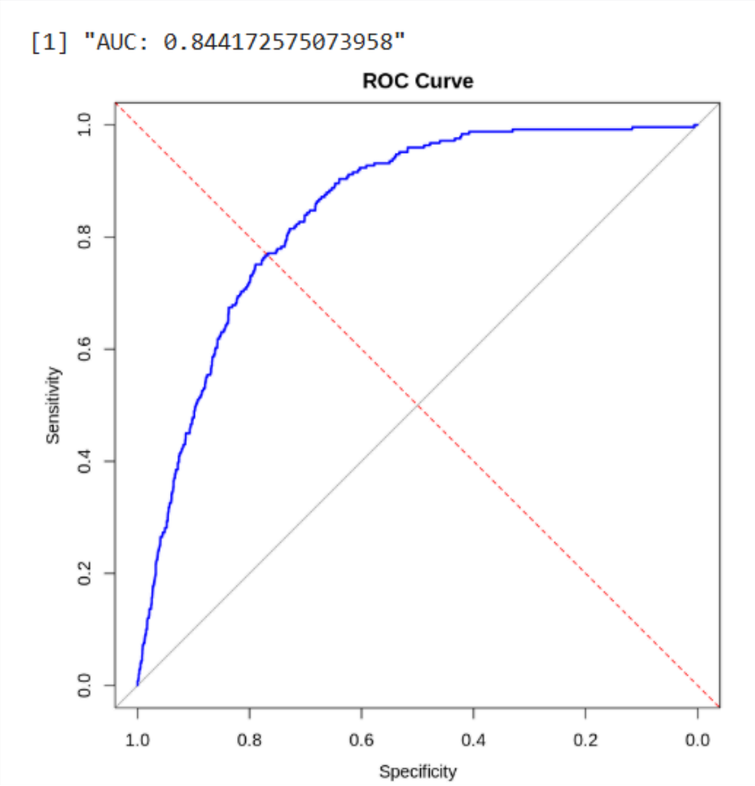
```
ResourceSelection 0.3-6          2023-06-27


        Hosmer and Lemeshow goodness of fit (GOF) test

data:  data$stroke, predicted_probabilities
X-squared = 5.3998, df = 8, p-value = 0.7141
```

Since the p-value is 0.7141, which is greater than 5%, so we accept the null hypothesis and conclude that the logistic regression model fits the data well.

ROC CURVE



The AUC = 0.844 indicates the model has excellent classification ability, so the model can distinguish between people who had a stroke and those who did not have a stroke.

Wald Test for β

H0 : βi=0

H1 :βi≠0

```
Call:
glm(formula = stroke ~ avg_glucose_level + hypertension + age *
    heart_disease, family = binomial(link = "logit"), data = data)

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)        -7.646978   0.376319 -20.320  < 2e-16 ***
avg_glucose_level   0.004033   0.001161   3.474 0.000513 ***
hypertension1       0.378696   0.162217   2.335 0.019569 *
age                 0.071512   0.005430  13.170  < 2e-16 ***
heart_disease1      2.745935   1.293066   2.124 0.033705 *
age:heart_disease1 -0.033691   0.018075  -1.864 0.062329 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1990.3  on 5108  degrees of freedom
Residual deviance: 1588.3  on 5103  degrees of freedom
AIC: 1600.3
```

For β1, β2, β3, and β4 the p-value is less than 5%, so we reject the null hypothesis and conclude that β1, β2, β3, and β4 is not equal to 0. And for β5 the p-value is greater than 5%, so we accept the null hypothesis and conclude that β5 equal to 0.

CLASSIFICATION TABLE

	Actual	
Predicted	0	1
0	1985	4
1	2875	245

Accuracy: 0.4364846
Error: 0.5635154
Sensitivity: 0.9839357
Specificity: 0.4084362

Although the model's accuracy is low (43.64%), its high sensitivity (98.39%) shows it is very effective at detecting people who have had a stroke. This is crucial in stroke detection, where identifying positive cases is more important than avoiding false positives. However, with low specificity (40.84%), the model struggles to correctly classify those without stroke.

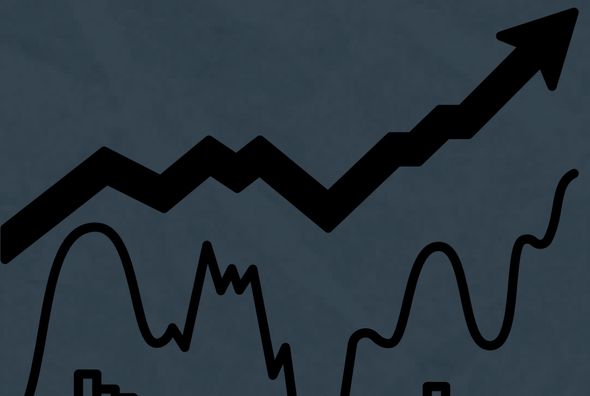
Interpretation and Conclusion

Model Estimate

So, based on Wald Test for β we have estimated model, such as :

- log odds of having stroke = -7.65 + 0.004(avg_glucose_level) + 0.379(hypertension) + 0.071(age) + 2.75(heart_disease) +0(age*heart_disease)

log odds of having stroke = −7.65 + 0.004(avg_glucose_level) + 0.379(hypertension) + 0.071(age) + 2.75(heart_disease)



INTERPRETATION

log odds of having stroke = -7.65 + 0.004(**avg_glucose_level**) + 0.379(**hypertension**) + 0.071(**age**) + 2.75(**heart_disease**)

1. **avg_glucose_level**: For 1 unit increase in glucose level the odds of stroke increases by e^0.004.
2. **hypertension**: The presence of hypertension increases the odds of stroke by e^0.379.
3. **age:** For 1-year increase in age the odds of stroke increases by e^0.071.
4. **heart_disease :** The presence of heart disease increases the odds of stroke by e^2.75.

CONCLUSION

Which factors associated with the likelihood of having a stroke ?

- Age
- Hypertension
- Heart Disease
- Average Glucose Level

How to predict the likelihood of having a stroke ?

Just by inputting variable values into the estimate model. However, the model needs to be updated regularly with the latest data to ensure optimal performance

Recommendations for Stroke Prevention

- Regularly check-up especially for older individuals to manage stroke risk factors
- Manage healthy blood glucose, blood pressure with medication and a healthy lifestyle.
- Do proper treatment for heart disease and cholesterol management to prevent blood clot formation.

WE WANT TO SAY

THANK YOU

FOR YOUR ATTENTION