Predictive Modeling of Stroke Occurrence among Patients using Machine Learning

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Abstract

Stroke is a global public health concern with severe consequences. Early detection and accurate prediction of stroke occurrence are crucial for effective prevention and targeted interventions. This study proposes a machine learning-based approach to predict the likelihood of stroke among patients. A comprehensive dataset encompassing demographic, clinical, and lifestyle factors of a large patient cohort was employed. Variables such as age, gender, hypertension, diabetes, smoking status, BMI, and medical history were considered. Advanced machine learning algorithms, including logistic regression, decision trees, random forests, and support vector machines, were utilized to analyses the dataset and develop a predictive model. The results demonstrate that the machine learning-based approach achieved high predictive accuracy in identifying individuals at risk of stroke. The model exhibited excellent sensitivity and specificity, enabling effective stratification of patients based on their stroke likelihood. Developing an accurate stroke prediction model using machine learning holds immense potential for proactive healthcare strategies and personalized patient care. Early identification of high-risk patients enables timely intervention and implementation of preventive measures, potentially reducing the burden of stroke-related complications. This study showed that the supervised K-Nearest Neighbors Algorithm (K-NN) model outperforms the other methods, with an accuracy of 95% compared with other models.

Keywords

Stroke prediction, Machine learning, Risk Predictive modelling, Healthcare interventions

Introduction

Stroke represents a significant global health challenge, accounting for a substantial proportion of morbidity and mortality worldwide. A stroke, also referred to as a brain attack, happens when a blood artery in the brain bursts or when blood flows to a certain area of the brain is restricted. Specific areas of the brain are damaged or lose function in both cases (National Heart, Lung, and Blood Institute, 2022). According to the latest data published by the World Health Organization (WHO), stroke deaths in Malaysia alone reached 21,592 in 2020, accounting for approximately 12.85% of total deaths (World Health Organization, 2022). These figures demonstrate the critical need for efficient stroke prevention measures and precise stroke risk prediction in patients.

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This emphasizes the significance of using more thorough and advanced techniques for stroke prediction. For instance, Dev et al.'s work from 2022 used machine learning and neural network to predict the occurrence of strokes among patients. With the help of a variety of factors age, heart disease, average glucose level, and hypertension, the researchers were able to identify those at risk of stroke with an astonishing 78% accuracy rate. This demonstrates how machine learning approaches can improve the estimation of the risk of stroke.

The purpose of this study is to investigate how machine learning techniques are used to forecast the likelihood that patients may experience a stroke. Our goal is to create a stroke predictive model that can accurately identify patience at high risk of stroke by utilizing their historical data. Furthermore, we will evaluate the performance of our developed model using evaluation metrics, such as accuracy and precision using modelling software tools in this case we use RapidMiner.

Methodology

The process involved a step-to-step process which starts from data collection, data understanding, selecting desired attributes, data preparation, data cleansing, choosing suitable data analytic dan predictive tools, data model developments and choosing the right visualization for data analysis. All the data for this study was obtained from https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset?resource=download which contains 5110 patient database with 14 attributes. For this study we only use age, hypertension, heart disease, average glucose level and BMI (Table 2). We started with data preparation and data understanding. Once we understand the data, we filtered the unnecessary database for patients that are under 10 years old because none of the patience in the database under 10 years have chronic diseases or stroke. The missing values were replaced with the average of each attribute value (Table 1). All the data cleansing was performed using rapid miner tool 10.0.

| gender | 101 | hpertension | heat doesor | ever_married | work_type | | and glazzie jewi put | who | KING WELLIN | smoking_status |
|---------------|----------------|-----------------|-------------|--------------|---------------|---------|----------------------|------|-------------|----------------------|
| 9040 Male | 0 | Carl Contractor | 8 | 1 Yes | Phate | Utar | 229.09 | 366 | 116 | 1.78 formerly smoked |
| 55678 Fernale | - 61 | | 8 | 0 Yes | Self-employed | Rutal | 202.21 NA | | 85 | t 68 never smoked |
| 31112 Male | 80 | | 8 | 1 Yes | Prute | Rutal | 105.KZ | 32.6 | 92 | 1.68 never smoked |
| 60182 Female | 80 40 75 | | | 0 Yes | Private | Utan | 171.25 | 345 | 60 | 1.55 smokes |
| 1865 Female | 79 | | 1. | 0 Yes | Self-employed | Ratal | 174.12 | 24 | 43 | 1 62 never smoked |
| 50000 Male | 81 | | 8 | 0 Yes | Prute | Uthan | 186.21 | 29 | 95 | 1.81 tomerly smoked |
| 53882 Male | 74 | | 1 | 1 Yes | Phate | Rutal | 70.09 | 27.4 | 54 | 1.75 never smoked |
| 10434 Female | 69 | | | 0.140 | Private | Uttan | 94.39 | 72.9 | 64 | 1.87 never smaked |
| 27419 Female | 10 | | 8 | 0 Yes | Photo | Rati | 78.15 NA | | 85 | 1.53 Unicount |
| (0401 Female | 78 | | 8 | 0.Yes | Private | Uthan | 58.57 | 242 | 62 | 1.6 Unknown |
| 12109 Female | 81 | | 1 | 0 Yes | Phate | Ratal | 80.43 | 29.7 | 88 | 1.72 never smoked |
| 13095 Female | - 61 | | | 1.Yes | God_att | Rati | 120.46 | 36.7 | 95 | 1.52 smokes |
| 12175 Female | 54 | | 8 | 0 Yes | Photo | Utan | 104.St | 27.5 | 69 | 1.59 smokes |
| 8213 Male | 78 | | 8 | 1 Yes | Phate | Uther | 219.84 NA | | 65 | 1.82 Unknown |
| 5317 Female | 79 | | 0 | 1 Yes | Phate | Uttan | 214.09 | 28.3 | 79 | 1.87 never smaked |
| 58202 Female | . 50 | | 1 | 0 Yes | Sel-employed | Real | 167.41 | 30.9 | 60 | 1.64 never smaked |
| 50112 Male | 64 | | 8 | 1 Yes | Phate | Utan | 191-81 | 37.6 | 110 | t 71 smokes |
| 34120 Male | 25 | | 1 | 0 Yes | Private | Uthan | 221.29 | 25.7 | 18 | 1.85 smokes |
| 27458 Female | 60 | | 8 | 0 No | Phate | (attail | 89.72 | 37.9 | 102 | 1.64 never smalled |
| 25225 Wate | 57 | | | 1.145 | God_att | Utan | 217.00 N.A. | | 102 | 1.81 Unknown |
| 70630 Female | 71 | | 8 | 0 Yes | Gost alb | Ratil | 193.94 | 22.5 | 63 | 1.68 smokes |
| 13801 Female | -12 | | 1 | 0.Yes | Sel-employed | Uther | 233.25 | 32.5 | 79 | 1.56 never struked |
| 68794 Female | - 2 79 | | 8 | 0 Yes | Self-employed | Uttan | 229.7 | 25.6 | 77 | 1.7 never smoked |
| 64778 Male | 82 | | | 1.Yes | Private | Ratal | 208.3 | 32.4 | 117 | 1.9 Uninown |
| 4219 Male | | | 8 | 0 Yes | Phate | Urban | 102.67 | 27.4 | 40 | 1.71 formerly anoked |

Table 1. Raw data of stroke patients

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The dataset is a mixture of clustered and un clustered data. Hence, as a researcher we decided to work on both data types to find a suitable model. The next step was, we choose the desired attribute and clustered the linguistic variables as recommended by Yasa et al., 2022 in her study on classification of stroke using K-means and deep learning methods. The age was classified into two groups with age above 46 as senior and below or equal to 45 as under mature category. While those with hypertension, heart disease glucose level and BMI were also categorized according to Table 2 as refer to previous reported studies.

| Attribute | Linguistic Variable | Value Random | | |
|--------------------|---------------------------|------------------------------|--|--|
| Age | Mature | Age ≤ 45 | | |
| | Seniors | 46 ≤ a <i>ge</i> | | |
| Hypertension | Low Risk of Suffering | 0 ≤ Hypertension < 0,1 | | |
| | High Risk of Suffering | $0,1 \leq Hypertension$ | | |
| Heart Disease | Low Risk of Suffering | 0 ≤ Heart Disease < 0,1 | | |
| | High Risk of Suffering | 0,1 ≤ Heart Disease | | |
| Avg. Glucose Level | Normal | 0 ≤ Avg. Glucose Level ≤ 140 | | |
| | Diabetes | 141 ≤ Avg. Glucose Level | | |
| BMI | Mild Excess Weight | 25,1 ≤ BMI < 30,0 | | |
| | Overweight Look at Weight | 30,1 ≤ <i>BMI</i> | | |
| | | | | |

| Ta | ble 2. Classification table | of 5 selected attributes |
|----|-----------------------------|--------------------------|
| | Linguistic Variable | Value Random |

The filtered and clean data has a dataset of 3577 patients with 5 attributes. The additional attribute whereby patient with stroke history will be valued at 1 and patient with no stroke history will be given value 0. After the data cleaning and cleansing process, we progressed to model development and compared the performance of each model by using the accuracy level of each model. We compared 6 data models in the study ranging from decision tree, K-NN, decision tree, Logistic regression, Nave Bayer, K-Means centroid and K-Means Distance. Furthermore, each model has different steps and preparation methods because the data types were sometimes not supported by certain models. The key step that we cannot skip is the SMOTE Up sampling step that must be used for uneven dataset (Figure 1 and Figure 2).

Results and Discussion

The studies' main objective was to develop a good stroke predicting model using patient's history data. The result obtains have an accuracy level range from 12 - 95%. Supervised cluster K-NN value has the highest value compared with supervised unclustered KNN value. Supervised unclustered Naïve Bayer model close in second with 79% accuracy level (Figure 4).

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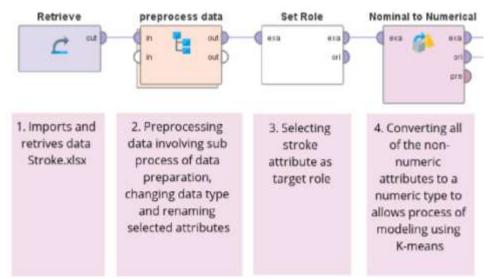


Figure 1: The data preparation.

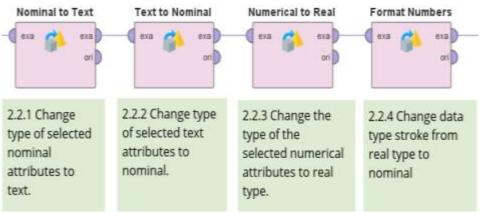


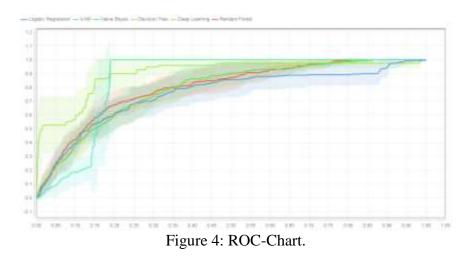
Figure 2: Data converting steps.



Figure 3: Accuracy level of the stroke predicting models.

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Moreover, the ROC-Chart that used to evaluate the performance of a supervised learning model also shows that KNN model has performed better compared with other models (Figure 5). In ROC-Chart the more that the ROC curve hugs the top left corner of the plot, the better the model does at classifying the data into categories; as in this case to categories stroke patience.



The finding is also supported by the finding by Dritsas & Trigka, 2022 where their KNN model have an accuracy of 92% accuracy level in stroke risk prediction study.

Conclusions

A stroke is a potentially fatal illness that must be prevented and/or treated to minimize unforeseen consequences. Now that the models are in place, clinical practitioners, medical specialists, and decision-makers can utilize them to identify the most relevant factors associated with the incidence of strokes and assess the associated likelihood or risk. High performance was showed by the suggested predictive model in terms of accuracy. We provide insights into the underlying mechanisms backing stroke prediction by identifying significant risk factors. From the model we develop using supervised clustered K-NN model, it produces high accuracy in predicting the occurrence of stroke among patience with 95% accuracy level. Yet, this model has some limitation Whereby attributes were narrowed to BMI, age glucose level, hypertension and heart disease. Therefore, we would suggest to study other factors such as living style, workload, family history of patience to get high accuracy level and build better model.

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