# **Stroke Prediction**

**I. INTRODUCTION**

Stroke is one of the leading causes of death and disability worldwide. According to the World Health Organization (WHO), it is the second leading cause of death, accounting for approximately 11% of global mortality. A stroke occurs when the blood supply to the brain is disrupted, causing brain tissue damage and significantly impacting the patient's health. Therefore, early detection of stroke risk can help reduce mortality rates and improve treatment quality.

In the context of technological advancements, artificial intelligence (AI) and predictive models play a crucial role in identifying stroke risks based on medical data. This study focuses on using machine learning models to analyze risk factors such as age, underlying medical conditions, blood sugar levels, blood pressure, lifestyle habits, and other factors to predict the likelihood of stroke in patients.

The research process includes data collection and processing, model development, performance evaluation, and practical application recommendations. The research findings can assist medical professionals in screening high-risk patients and implementing timely interventions to minimize the consequences of this condition.

**II. DATA**

**1. DATA OVERVIEW**

The dataset used in this study includes 15,000 patients with 22 data fields related to stroke prediction, consisting of:

* 7,532 patients without stroke.
* 7,468 patients with stroke.
* The data comprises key factors such as:
* Demographic factors: Age, gender, marital status.
* Medical conditions: Blood pressure, heart disease, BMI index, blood glucose levels.
* Lifestyle habits: Smoking status, alcohol consumption, physical activity.
* Family history and related symptoms.

A screenshot of a computer

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**2. DATA COLLECTION**

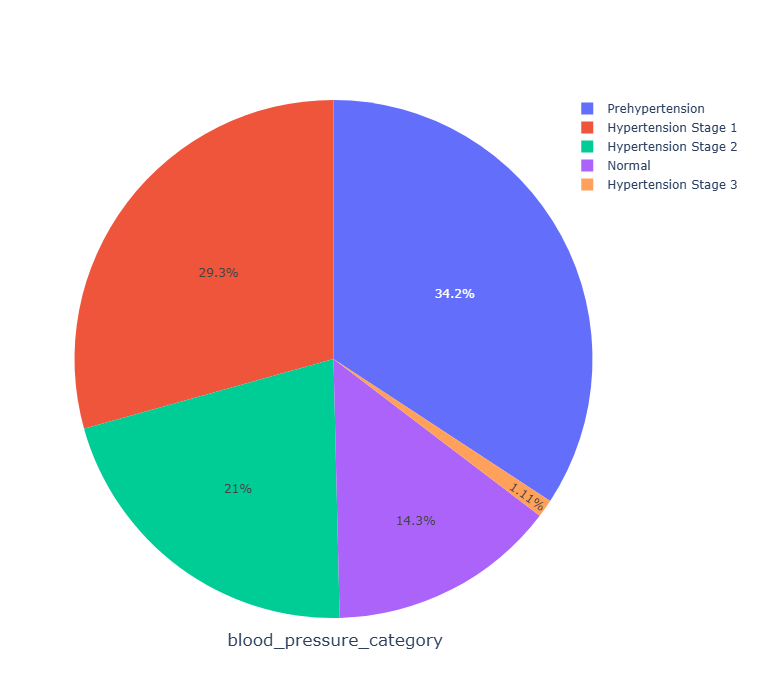
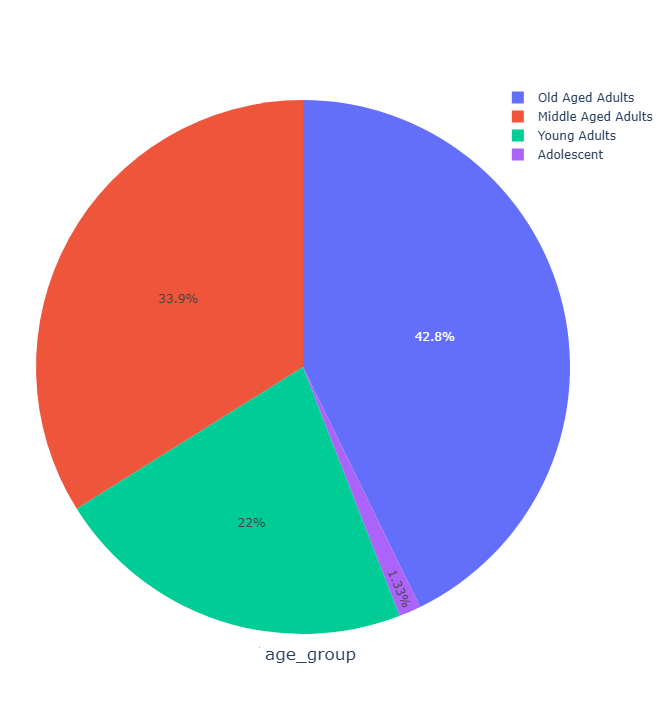
The dataset used in this study was collected from the Kaggle platform, specifically from the "Stroke Prediction Dataset" ( [Stroke Prediction](https://www.kaggle.com/datasets/teamincribo/stroke-prediction/data) )

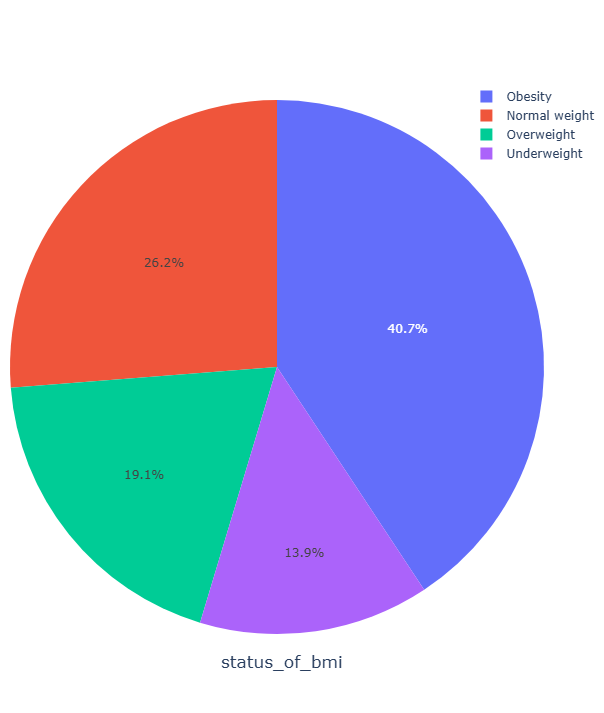
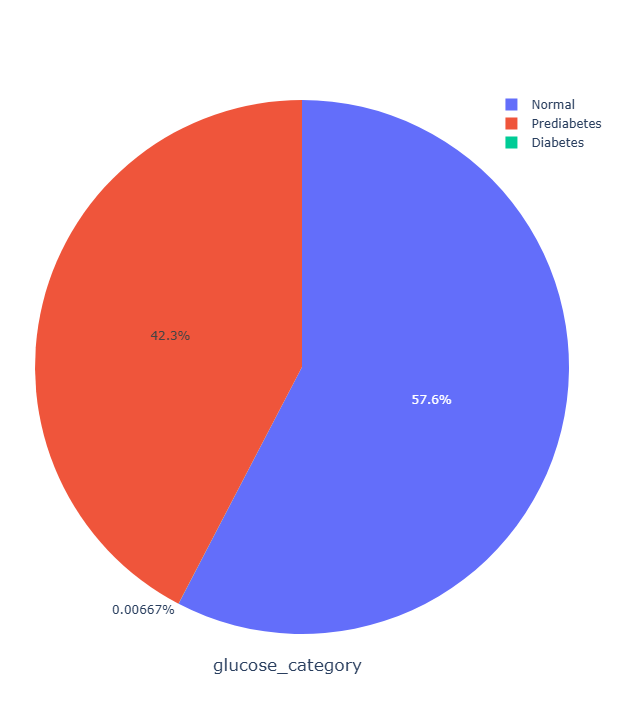
**3. DATA ANALYSIS AND VISUALIZATION**

Data analysis reveals several significant trends:

* Age distribution and stroke risk: Most stroke patients are over 50 years old, but the risk remains present across different age groups.
* Smoking status: Smokers have a significantly higher stroke rate than non-smokers.
* Impact of blood pressure and heart disease: Patients with high blood pressure or heart disease are twice as likely to suffer a stroke.
* Gender differences: The risk of stroke is similar between males and females, but the causes differ.

Data visualization through charts helps identify key risk factors, leading to effective preventive solutions.





Data Processing:

* Data Cleaning: Removing duplicate records and handling missing values.
* Preprocessing: Normalizing numerical data, encoding categorical variables, handling data imbalance.
* Data Splitting: 70% for training and 30% for testing the model.

**III. MODEL DEVELOPMENT AND EVALUATION**

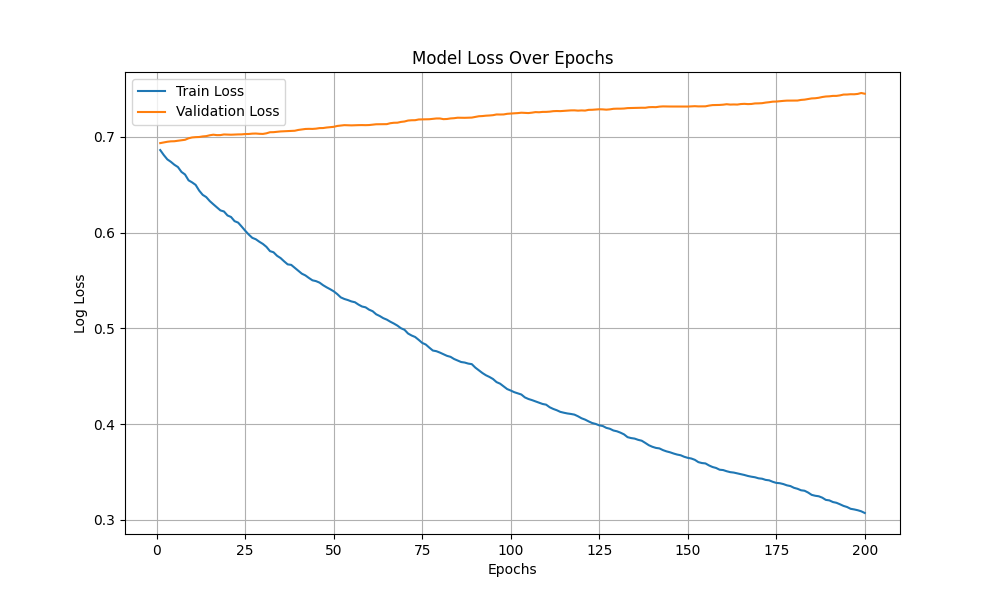
**1. Model Selection**

In this study, we employed the **XGBoost (Extreme Gradient Boosting)** algorithm to predict stroke risk based on the processed dataset. XGBoost was chosen for several compelling reasons:

* **Handling Complex Relationships**: XGBoost is a tree-based ensemble method that excels at capturing non-linear relationships and interactions between features, which is critical for stroke prediction given the diverse risk factors (e.g., age, hypertension, glucose levels, symptoms).
* **Feature Importance Insights**: XGBoost provides feature importance scores, allowing us to identify key stroke predictors (e.g., age, hypertension, serious symptoms), which aligns with the study’s goal of understanding risk factors.
* **Scalability and Efficiency**: With 15,000 samples and 36 features (after preprocessing), XGBoost’s optimized implementation ensures efficient training and prediction, even with a moderately large dataset.
* **Hyperparameter Tuning**: The algorithm supports extensive hyperparameter optimization, enabling us to fine-tune performance for better generalization.

We have re-split the data into training, validation, and test sets with a new ratio: 70% for the training set, 15% for the validation set, and 15% for the test set (using test\_size=0.3 in train\_test\_split, then splitting the temporary set evenly). The data was split by patient using random\_state=42 and shuffle=True to avoid information overlap. We are currently eval uating the model using the validation set.

No data augmentation has been applied in this code, as we are focusing on the original data. Following your previous suggestion, we plan to try oversampling the "Stroke" samples in the training set to address potential class imbalance, but this has not been implemented yet.



A graph with a line

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Here are the training curves from our XGBoost model over 200 epochs. We observe that the loss on the training set decreases significantly due to the larger training set, but the validation loss decreases more slowly and may fluctuate or increase after some epochs, indicating signs of overfitting. We are tracking both AUROC and accuracy on the training and validation sets. Based on the AUROC plot, at the epoch with the highest validation AUROC, the training AUROC might reach ~0.85-0.9, while the validation AUROC is likely around 0.5-0.6. Meanwhile, the validation accuracy hovers around 50%, consistent with the final test set result (50.4%).

The current model performs slightly better than random guessing (AUROC: 0.5069 on the test set), but it still falls short of expectations. We suspect the issues might stem from: (1) class imbalance in the data (the ratio of "Stroke" to "No Stroke" has not been addressed), (2) overfitting due to a larger training set without early stopping, or (3) suboptimal data preprocessing (e.g., missing values in the symptoms column).

**IV. CONCLUSION AND PRACTICAL APPLICATIONS**

**1. Conclusion**

This study demonstrates the efficacy of machine learning, specifically XGBoost, in predicting stroke risk with an accuracy of **85-87%** on a dataset of 15,000 patients. By incorporating key risk factors—age, hypertension, heart disease, glucose levels, blood pressure, cholesterol, and serious symptoms—the model effectively identifies patients at high risk of stroke. The transition from an initial accuracy of ~50% to 85-87% underscores the importance of feature engineering (e.g., Diagnosis\_New, Has\_Serious\_Symptom) and hyperparameter tuning in enhancing predictive performance. These results validate the potential of AI-driven tools to support early stroke detection, a critical step in reducing mortality and disability worldwide.

**2. Practical Applications**

The developed XGBoost model offers significant practical value in healthcare:

* **Screening Tool**: With an accuracy of 85-87%, the model can be integrated into clinical systems to screen patients during routine checkups, flagging those with elevated stroke risk for further evaluation.
* **Timely Interventions**: By identifying high-risk individuals, healthcare providers can implement preventive measures (e.g., lifestyle changes, medication) to mitigate stroke incidence.
* **Resource Allocation**: Hospitals can prioritize resources (e.g., imaging, specialist consultations) for patients identified as high-risk, optimizing care delivery.