**THE GEORGE WASHINGTON UNIVERSITY**DATS6103 - Summary Report  
Professor Divya Pandove Narula

**STROKE PREDICTION  
TEAM 6 -** Aswin Balaji Thippa Ramesh, Barathkumar Anantharaj,   
Gowri Sriram Lakshmanan, Rahul Aravind

**INTRODUCTION**

Stroke remains a leading cause of mortality and long-term disability worldwide, with its occurrence significantly influenced by a combination of medical, demographic, and lifestyle factors. According to the World Health Organization (WHO), approximately 15 million people suffer from strokes annually, with nearly 5 million fatalities and 5 million survivors facing permanent disabilities. Early identification of individuals at higher risk of stroke is critical for prevention and timely intervention.

This project analyzes stroke occurrence using the Stroke Prediction Dataset sourced from Kaggle, which comprises over 5,000 observations and various attributes like age, gender, medical history (hypertension, heart disease), and lifestyle factors (BMI, smoking status). While physical health factors like glucose levels and BMI are known to contribute to stroke risk, other variables such as work type, marital status, and residence type may also provide insights into identifying high-risk groups.

Through Exploratory Data Analysis and machine learning models like Logistic Regression and Random Forest, we aim to uncover the key predictors of stroke, assess their significance, and evaluate model accuracy. This study also explores trends in stroke occurrences across age groups and demographic segments, providing actionable insights to guide public health strategies and clinical practices.

**INFORMATION ABOUT THE DATASET**

We utilized the Stroke Prediction Dataset from [Kaggle](https://www.kaggle.com/datasets/fedesoriano/stroke-prediction-dataset), which contains 5,110 observations and 11 key variables. These variables encompass multiple dimensions:

**Demographic Factors:** Age, gender, residence type, work type

**Medical History:** Hypertension, heart disease, BMI, average glucose level

**Lifestyle Factors:** Smoking status

**Target Variable:** Stroke occurrence (binary: 1 for stroke, 0 for no stroke)

The dataset presents a significant class imbalance, with stroke occurrences accounting for only about 5% of the total cases. This imbalance poses challenges for model training, as traditional algorithms may become biased toward the majority class. To address this, we plan to employ resampling techniques like SMOTE to create a balanced class representation, improve model performance, and ensure the minority class (stroke cases) is appropriately represented during training. By carefully preprocessing the data and addressing these challenges, we aim to build a robust predictive model that accurately identifies stroke risks

**THE SMART QUESTIONS**

With the intention of addressing critical aspects of stroke prediction using the Stroke Prediction Dataset, our project explores the following key questions:

1. What are the key factors most strongly associated with the occurrence of strokes?
2. How does each predictor's distribution differ between stroke and non-stroke cases?
3. Can we determine statistically significant correlations or patterns in stroke occurrence based on categorical variables?
4. Can we identify trends or variations in stroke risk based on time-related factors like age?
5. How accurate is it to build a machine learning model to predict stroke occurrence based on the dataset?

**DATA PREPARATION**

The data preparation stage involves essential steps to ensure the dataset is clean, well-structured, and ready for analysis or model training.

1. **Data Loading & Structure :**

* We loaded the dataset using **Pandas** and confirmed successful loading by viewing the first few rows.
* The dataset contained **5,110** observations and **11** columns, as verified using the shape function.

**A screenshot of a computer code

Description automatically generatedA screenshot of a computer

Description automatically generated**

**A close up of a text

Description automatically generated**

1. **Handling missing & unwanted values :**

* We checked for missing values across all columns using the isnull().sum() method.
* The **BMI** column had missing values, with approximately **4.5%** of its entries missing. To retain data integrity and avoid loss of observations, we performed **mean imputation** for the **BMI** column.
* During the inspection of the **gender** column, we identified an **unwanted value** (e.g., "Other") that was inconsistent with the valid categories ("Male" and "Female"). This value was removed to ensure consistency in the data

A close-up of numbers

Description automatically generatedA screenshot of a computer program

Description automatically generated

1. **Outliers Check :**

* Outliers in our dataset were identified using **boxplots**. These outliers were considered **useful** as they reflect real-world variations, such as high BMI or glucose levels, which are critical indicators of stroke risk.

A graph of a boxplot

Description automatically generatedA graph of a box plot

Description automatically generated

1. **Encoding Variables:**

* Categorical variables such as **gender**, **work\_type**, **Residence\_type**, and **smoking\_status** were transformed using **Label Encoding** to prepare them for modeling. Label Encoding was chosen over one-hot encoding to keep the dataset compact and avoid increasing dimensionality.

A screen shot of a computer code

Description automatically generated

A screenshot of a computer

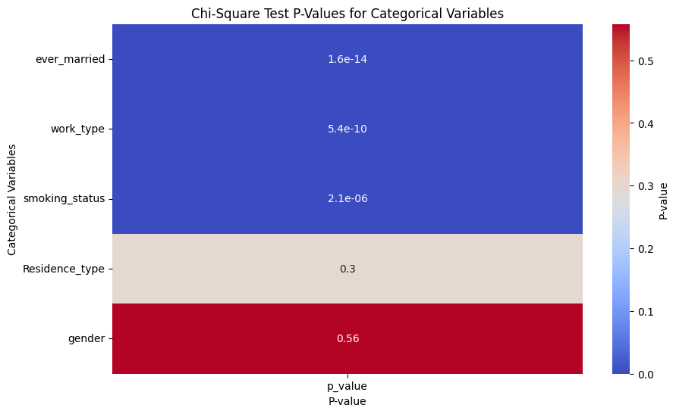
Description automatically generated

**EXPLORATORY DATA ANALYSIS**

Exploratory Data Analysis (EDA) was conducted to gain a deeper understanding of the dataset, uncover patterns, and answer the SMART questions related to stroke risk. We explored the distributions, relationships, and correlations between variables, with a focus on identifying factors that contribute to stroke occurrence.

1. **Can we determine statistically significant correlations or patterns in stroke occurrence based on categorical variables?**

* **Objective**: We performed the **Chi-Square Test of Independence** to identify significant associations between categorical variables and the target variable (**stroke**).
* **Significance Threshold**: Variables with p-values **< 0.05** were considered statistically significant.

****

From the graph, variables like **ever\_married**, **work\_type**, and **smoking\_status** **(dark blue)** are important for predicting stroke, while **Residence\_type** **(light shade)** and **gender (red)** are less relevant. This highlights where the focus should be during feature selection for modeling.

1. **Can we identify trends or variations in stroke risk based on time-related factors like age?**

* We grouped ages into predefined bins (e.g., 0-18, 19-30, 31-40, etc.) to better analyze stroke occurrences by age range.
* A **Density Plot** was created to show the distribution of stroke occurrences across age.
* A **Bar Chart** was plotted to display stroke counts for each age group, making trends across age ranges easier to interpret.

A graph of a number of stroke occurrence

Description automatically generatedA graph of stroke occurrence

Description automatically generated

From both visualizations, it is evident that stroke occurrences are heavily concentrated among older individuals, particularly those aged **71–80 years**, with a notable increase starting from age **50**. 

1. **How does each predictor's distribution differ between different stroke cases ?**

* These insights provide a foundation for identifying significant variables and understanding patterns that contribute to stroke risk.
* Examined the proportions of stroke occurrences across categories (e.g., work type, smoking status, marital status) using bar charts and stacked plots.
* Observed clear differences in distributions, such as older individuals, higher BMI, and glucose levels being more common among stroke cases.

* **Marital Status**: Individuals who were **ever married** experienced significantly more stroke cases compared to those who were not, indicating marital status may be linked to lifestyle or age-related factors contributing to stroke risk.
* **Gender**: Stroke cases were **higher among females** compared to males overall, suggesting gender could play a role in stroke susceptibility.

Among stroke cases, females who were **ever married** represented the largest group, indicating that marital status and gender together may amplify stroke risk.

A graph of different colored squares

Description automatically generated

A graph showing different types of cases

Description automatically generatedA graph of a function

Description automatically generated with medium confidence

A graph showing a number of stroke occurrences

Description automatically generatedA graph with a rectangular bar

Description automatically generated with medium confidenceA graph with different colored squares

Description automatically generated

* **Work Type:** Stroke cases are most common among individuals in the private sector, followed by the self-employed, while occurrences are much lower for government workers and children.
* **BMI:** The BMI distribution shows that stroke cases are concentrated in the overweight to moderately obese range (BMI 25–35)
* **Residence Type:** Stroke cases are almost uniformly distributed between urban and rural areas, indicating that residence type has minimal impact on stroke occurrences.

A graph of a graph showing a green and a blue rectangular bar

Description automatically generated

The analysis reveals that while hypertension is a known risk factor for stroke, the majority of stroke cases occur in individuals **without hypertension**.

A graph of smoking status

Description automatically generatedA graph of a patient's level

Description automatically generated

* **Average Glucose Level**: Stroke cases are associated with a **wide range of glucose levels**, with many individuals having elevated glucose levels above **100 mg/dL**, indicating that hyperglycemia could be a contributing factor.
* **Smoking Status**: Stroke cases are more prevalent among individuals who **never smoked** and those who were **formerly smokers**, followed by lower counts in current smokers and those with **unknown smoking status**.

1. **What are the key factors most strongly associated with the occurrence of strokes?**

* We applied **Recursive Feature Elimination (RFE)** using a **linear model (lm)** on the imbalanced dataset to identify and rank the most important features associated with stroke occurrence. This method iteratively eliminated less important features to highlight the strongest predictors.

A screenshot of a computer

Description automatically generated

The top predictors include age, average glucose level, BMI, work type, and smoking status, with age being the most significant. These findings emphasize that age-related factors, metabolic indicators (like glucose and BMI), and lifestyle attributes are crucial in understanding and predicting stroke risk.

**MULTICOLLINEARITY CHECK**

To detect and address multicollinearity among predictors, we created a **correlation heatmap** to visualize and identify highly correlated numerical predictors and calculated **Variance Inflation Factor (VIF)** values, using a threshold of **5** to detect and remove predictors with high multicollinearity.

A screenshot of a computer screen

Description automatically generated

A screenshot of a computer

Description automatically generated

The multicollinearity check, conducted using the **correlation matrix** and **Variance Inflation Factor (VIF)**, confirms that there is no significant multicollinearity among the predictors:

* The **correlation heatmap** shows no strong correlations between features, with correlation coefficients remaining well below the critical threshold of **0.8**.
* The **VIF values** for all predictors are below the threshold of **5**, with the highest being **2.3** for the age variable. This indicates that none of the predictors are highly correlated with others, ensuring the dataset does not suffer from multicollinearity.

The results confirm that the predictors are independent and can be safely included in the modeling process.

**MODEL BUILDING**

We implemented various **machine learning models** on both the **imbalanced** and **balanced datasets** to evaluate their performance. The balanced dataset was created using techniques like **SMOTE** to address class imbalance. The analysis yielded **surprising results**, highlighting differences in model performance based on data balance and the significance of certain predictors in stroke prediction.

1. **Logistic Regression on Imbalanced data:**

A graph with a blue square

Description automatically generated

* The model achieved 0% accuracy for stroke predictions (True Positives = 0).
* It achieved 100% accuracy for non-stroke predictions, as it classified all instances as "No Stroke" due to the dominance of the majority class.

**Balancing the data:**

To address the severe class imbalance in the dataset (4861 non-stroke cases vs. 249 stroke cases), we applied **SMOTE** (Synthetic Minority Oversampling Technique) to generate synthetic samples for the minority class.

A number on a white background

Description automatically generatedA number with black text

Description automatically generated with medium confidence

This resulted in a balanced dataset with **4861 stroke cases** and **4861 non-stroke cases**, ensuring equal class representation. Balancing the data improves model performance by enabling the model to learn patterns for both classes effectively, reducing bias toward the majority class.

1. **Logistic Regression on balanced data:**

A screenshot of a graph

Description automatically generatedWe built a classification model on the **balanced dataset** to predict stroke occurrences. The model's performance was evaluated using the following metrics:

A blue squares with white text

Description automatically generated

A graph with a line

Description automatically generated

A blue squares with white text

Description automatically generated

* **ROC-AUC Score**: The model achieved an **AUC of 0.81**, indicating good predictive performance.
* **Confusion Matrix**: Correctly predicted **1134 No-Stroke** cases and **1221 Stroke** cases.  
  Misclassified **325 No-Stroke** cases and **237 Stroke** cases.
* **Classification Report:** Precision, recall, and F1-score were balanced for both classes, with an overall **accuracy of 81%**.

The balanced dataset significantly improved the model's ability to predict both stroke and non-stroke cases. With an **AUC of 0.81** and strong precision-recall scores, the model demonstrates reliable performance, successfully overcoming the limitations observed with the imbalanced data.

1. **Random Forest Model on balanced data:**

We implemented a Random Forest model on the balanced dataset to predict stroke occurrences. To evaluate its performance, we assessed key metrics that we used previously. This approach allowed us to measure the model’s ability to classify stroke and non-stroke cases effectively.

A blue squares with white squares

Description automatically generated

A graph with a line

Description automatically generated

* **ROC-AUC Score**: The Random Forest model achieved an impressive **AUC of 0.99**, significantly improving from the previous model's **AUC of 0.81**, demonstrating stronger discriminative ability.
* **Confusion Matrix**: The Random Forest model correctly predicted **895 No-Stroke** and **939 Stroke** cases, reducing misclassifications (**78 No-Stroke** and **33 Stroke**) compared to the previous model's higher misclassification rates (**325 No-Stroke** and **237 Stroke**).
* **Classification Report:** Precision, recall, and F1-score improved to **94%** for both classes, up from **80-81%** in the previous model. Overall **accuracy** increased to **94%**, compared to the previous model's **81%**.

The **Random Forest model** outperformed the previous model across all metrics, achieving higher accuracy, precision, recall, and AUC scores. This significant improvement highlights the Random Forest’s ability to better capture patterns in the balanced dataset, making it a superior choice for stroke prediction.

A screenshot of a computer screen

Description automatically generated **CONCLUSION**

We evaluated three models for stroke prediction: **Logistic Regression**, **a prior balanced model**, and **Random Forest**. Logistic Regression on the imbalanced dataset failed to predict stroke cases, achieving **0% accuracy** for strokes due to class bias. The second model on balanced data improved performance significantly, achieving an **AUC of 0.81** and an accuracy of **81%**. Finally, the **Random Forest model** on the balanced dataset outperformed all, with an **AUC of 0.99** and **94% accuracy**, demonstrating exceptional precision, recall, and minimal misclassifications. The results confirm that addressing class imbalance and using ensemble methods like Random Forest significantly enhance model performance for stroke prediction.

**LIMITATIONS**

* The dataset suffers from **class imbalance** (only 5% stroke cases), leading to bias toward the majority class. Additionally, **population bias** exists, with females showing higher stroke occurrences, which may reflect sampling issues rather than actual trends, limiting generalizability across different demographics.
* Based on general stroke case study, critical medical predictors like **cholesterol levels, blood pressure trends**, and **family medical history** are missing, while contextual factors such as **treatment history, environmental influences**, and socioeconomic status are not included. This reduces the dataset’s depth and predictive power.
* The data is **cross-sectional** and does not track risk progression over time. Measurement errors in self-reported values (e.g., BMI, glucose) may reduce reliability, and synthetic balancing methods like **SMOTE** can introduce overfitting risks, making cautious interpretation necessary.

**REFERENCES**

A predictive analytics approach for stroke prediction using machine learning and neural networks  
<https://www.sciencedirect.com/science/article/pii/S2772442522000090>

Predicting stroke occurrences: a stacked machine learning approach with feature selection and data preprocessing   
<https://bmcbioinformatics.biomedcentral.com/articles/10.1186/s12859-024-05866-8>

Stroke Risk Factors, Genetics, and Prevention  
<https://pmc.ncbi.nlm.nih.gov/articles/PMC5321635/#:~:text=The%20Framingham%20Stroke%20Risk%20Profile,the%20presence%20of%20cardiovascular%20disease%20(>

The most efficient machine learning algorithms in stroke prediction: A systematic review  
<https://pmc.ncbi.nlm.nih.gov/articles/PMC11443322/>

Stroke Prediction and Contributing Factors Using Machine Learning  
<https://www.researchgate.net/publication/380424935_Stroke_Prediction_and_Contributing_Factors_Using_Machine_Learning>