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Capstone Project Report

On

# “CNSAAR – Central Nervous System Acute Attack Risk Detector”

**Project No.-1**

A capstone project report submitted in partial fulfillment of the requirement for

**AI Development Associate**

Submitted by

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**CERTIFICATE**

# This is to certify that the capstone project titled "CNSAAR – Central Nervous System Acute Attack Risk Detector”, designated as Project No. 1, has been undertaken by Manik, a Bonafide student of the AI Development Associate Course (January 2025 batch) at the National Institute of Electronics & Information Technology (NIELIT).

The project work has been carried out in partial fulfillment of the requirements for the six-month AI Development Associate Course.

This project report has been reviewed and approved, meeting the academic standards and requirements prescribed for the said course.

**Project Guide:** Dr. Shivlok Singh  
**Designation:** Principal Technical Officer  
**Institution:** NIELIT, Kakardooma

**DECLARATION**

# I hereby declare that the Capstone Project titled "CNSAAR – Central Nervous System Acute Attack Risk Detector” is the result of my own work carried out during the course of the AI Development Associate Course at the National Institute of Electronics & Information Technology (NIELIT).

This project was completed under the supervision of **Dr. Shivlok Singh** and the conclusions presented herein are based on the research and implementation conducted solely by me.

I further certify that this work is original and has not been submitted, either in part or in full, to any other institution or university for the award of any degree, diploma, or certificate in India or abroad.

I have followed all academic guidelines and ethical practices prescribed by the institute. Where information from other sources has been used, appropriate credit has been given through in-text citations and references.

**Name:** Manik  
**Course:** AI Development Associate Course  
**Institute:** NIELIT

**ACKNOWLEDGEMENT**

# I would like to express my sincere gratitude to all those who supported and guided me throughout the completion of my Capstone Project titled “CNSAAR – Central Nervous System Acute Attack Risk Detector" First and foremost, I am deeply thankful to Dr. Shivlok Singh, my project guide, for their valuable insights, constant encouragement, and expert supervision throughout the duration of this project. Their guidance helped me stay focused and motivated during each phase of the work.

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This project has been a tremendous learning experience and has significantly contributed to my knowledge and skills in the field of Artificial Intelligence.

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**Abstract**

This project focuses on the development of a **stroke risk prediction system** using machine learning techniques to classify individuals as high-risk or low-risk for stroke occurrence. The dataset used includes demographic and health-related features such as **age, gender, hypertension, heart disease, average glucose level, BMI, and smoking status**.

The data was preprocessed by handling missing BMI values, encoding categorical variables, and scaling numerical features. **Exploratory Data Analysis (EDA)** was performed to understand feature distributions, class imbalance, and correlations influencing stroke risk. A **Random Forest classifier** was selected for model building due to its high accuracy, robustness, and ability to handle non-linear relationships.

The model achieved an accuracy of approximately **95%**, with balanced performance metrics across classes. The system was implemented using a **modular, class-based Python structure (CNSAARDetector)**, incorporating methods for data loading, training, prediction, and model saving/loading, ensuring scalability and easy deployment.

This project demonstrates the practical application of **AI in healthcare analytics**, enabling early identification of high-risk individuals for stroke and supporting preventive healthcare strategies. Future enhancements include deployment as a web or mobile application, integration with real-time patient data systems, and incorporation of Explainable AI frameworks for improved clinical interpretability.

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**Phase 1: Introduction**

**1.1 General**

Stroke is a major global health issue, causing significant mortality and long-term disability. Early identification of individuals at risk of stroke can enable preventive interventions and reduce healthcare burdens. Traditional clinical risk assessments rely on standardized scores and expert evaluations, which may not fully capture complex patterns among multiple health indicators.

With advancements in **artificial intelligence (AI)** and **machine learning (ML)**, data-driven models are increasingly being used to predict disease risks accurately and efficiently. This project focuses on building a **stroke risk prediction system** using demographic and health-related data to classify individuals as high-risk or low-risk for stroke occurrence.

**1.2 Background of the Study**

Machine learning algorithms can analyze multiple features simultaneously and detect hidden patterns that may not be apparent through traditional statistical methods. In recent years, ML models such as **Logistic Regression, Decision Trees, Support Vector Machines, and Random Forests** have been applied to healthcare datasets for disease prediction tasks.

This project uses a dataset containing features such as **age, gender, hypertension, heart disease, average glucose level, BMI, and smoking status** to build a Random Forest classification model for predicting stroke risk. By doing so, it demonstrates the potential of AI in enhancing preventive healthcare and personalized risk assessment.

**1.3 Importance of AI in Healthcare Analytics**

AI is revolutionizing healthcare by:

* Enabling **early disease detection and prevention**.
* Improving **diagnostic accuracy** through data-driven insights.
* Reducing the burden on healthcare professionals by automating routine assessments.
* Personalizing patient care based on individual risk profiles.

For stroke prediction, AI models can assist doctors in identifying high-risk patients early, enabling timely medical intervention to prevent severe complications or fatalities.

**1.4 Problem Statement**

The key problem addressed in this project is:

**How to build an accurate, efficient, and interpretable machine learning model that predicts stroke risk using demographic and health-related data?**

This involves designing a complete system that performs data preprocessing, exploratory analysis, model training, evaluation, and risk prediction in a structured and user-friendly manner.

**1.5 Objective of the Project**

The main objectives of this project are:

1. To explore and understand the stroke dataset features.
2. To perform **data preprocessing** including handling missing values and encoding categorical variables.
3. To conduct **exploratory data analysis (EDA)** for understanding key factors influencing stroke risk.
4. To build and train a **Random Forest classification model** for predicting stroke occurrence.
5. To evaluate model performance using metrics such as accuracy and classification report.
6. To implement a **modular and reusable stroke risk prediction system** suitable for future deployment and enhancements.

**1.6 Summary**

This section introduced the importance of stroke prediction and the role of AI in enhancing healthcare analytics. It outlined:

* The general context and motivation for predicting stroke risk using data-driven methods.
* The background and current applications of machine learning models in healthcare.
* The specific problem statement and objectives of this project, focusing on building an efficient and interpretable Random Forest-based stroke prediction system.

**1.7 AI Project Cycle**

The **AI Project Cycle** outlines the systematic approach followed to develop an AI-based solution from problem identification to deployment. For this **stroke risk prediction project**, the cycle involved the following phases:

**1. Problem Scoping**

* Defined the problem of predicting stroke risk using demographic and health-related data.
* Identified objectives such as building an accurate, efficient, and interpretable prediction model.

**2. Data Acquisition**

* Collected the dataset containing features like age, gender, hypertension, heart disease, average glucose level, BMI, and smoking status along with stroke occurrence labels.

**3. Data Exploration**

* Performed **exploratory data analysis (EDA)** to understand feature distributions, correlations, and potential data quality issues.

**4. Data Preparation**

* Handled missing values in BMI.
* Encoded categorical variables (e.g. gender, smoking status) for model compatibility.
* Scaled numerical features where necessary for improved model performance.

**5. Modelling**

* Selected **Random Forest** as the classification model for its high accuracy, robustness, and interpretability.
* Trained the model on the preprocessed dataset.

**6. Evaluation**

* Assessed model performance using accuracy score, classification report, and confusion matrix to ensure reliability.

**7. Deployment Preparation**

* Designed a **modular Python class-based system** for easy integration into applications or extensions into a GUI-based tool (e.g. Streamlit).

**8. Feedback and Improvement**

* Identified limitations such as dataset size and proposed future enhancements like adding more features, testing other ML algorithms, and deploying as a web application.

**Phase 2: Literature Review**

**2.1 Previous Work on Stroke Prediction**

Predicting stroke risk using machine learning has been an area of active research in recent years. Various studies have explored different models and approaches to improve prediction accuracy:

* **Logistic Regression:**  
  Widely used as a baseline model for binary classification tasks in healthcare. Studies have shown that logistic regression can provide interpretable results but often struggles to capture complex, non-linear relationships among features.
* **Decision Trees:**  
  Offer better interpretability by visualizing decision paths based on feature thresholds. However, they tend to **overfit** on training data and may not generalize well on unseen data.
* **Support Vector Machines (SVM):**  
  SVMs have been applied for stroke prediction, providing good performance with smaller datasets. Their limitation lies in computational complexity for large datasets and less interpretability compared to tree-based models.
* **Random Forests:**  
  Many studies, such as those by medical data analytics researchers, have demonstrated that Random Forest models outperform other classifiers in stroke risk prediction tasks due to their **ensemble approach**, which reduces overfitting and captures non-linear feature interactions effectively.
* **Neural Networks:**  
  Recently, deep learning models have been explored for stroke prediction, particularly when large datasets are available. They achieve high accuracy but require extensive computational resources and are often considered **black-box models** with low interpretability.

**2.2 Machine Learning Models Used in Prior Studies**

Several machine learning models have been explored in prior studies for **stroke risk prediction**:

**1. Logistic Regression**

* **Usage:**  
  Commonly used for baseline classification due to its simplicity and interpretability.
* **Advantages:**  
  Provides clear coefficients indicating feature importance.
* **Limitations:**  
  Assumes linear relationships; performance may reduce with complex, non-linear data patterns.

**2. Decision Trees**

* **Usage:**  
  Applied for straightforward if-else decision-based classification.
* **Advantages:**  
  Easy to interpret and visualize decision paths.
* **Limitations:**  
  Prone to overfitting on training data, reducing generalization.

**3. Support Vector Machines (SVM)**

* **Usage:**  
  Used for binary classification tasks like stroke prediction, especially on smaller datasets.
* **Advantages:**  
  High performance for datasets with clear class separations.
* **Limitations:**  
  Less effective for large datasets and less interpretable for non-technical stakeholders.

**4. Random Forest**

* **Usage:**  
  Frequently chosen in healthcare analytics due to its ensemble learning approach.
* **Advantages:**  
  High accuracy, robustness to overfitting, and ability to capture complex feature interactions.
* **Limitations:**  
  Slightly lower interpretability compared to single decision trees but better than neural networks.

**5. Neural Networks**

* **Usage:**  
  Recently applied for complex healthcare predictions including stroke.
* **Advantages:**  
  Ability to model intricate non-linear relationships when large datasets are available.
* **Limitations:**  
  Requires extensive computational resources and lacks interpretability, making clinical justification challenging.

**2.3 Identified Gaps and Proposed Solution**

Despite extensive research on stroke prediction using machine learning, certain **gaps remain in prior studies**:

**1. Limited Feature Engineering**

* **Gap:**  
  Many models rely on direct input features without thorough preprocessing or exploratory data analysis to understand their impact.
* **Impact:**  
  This may reduce model performance and fail to identify significant hidden patterns.

**2. Overfitting in Single Models**

* **Gap:**  
  Models like Decision Trees often overfit on training data, leading to poor generalization on new data.

**3. Lack of Interpretability in Complex Models**

* **Gap:**  
  While neural networks achieve high accuracy, they act as black-box models, limiting clinical trust due to low interpretability.

**4. Deployment Readiness**

* **Gap:**  
  Many research works focus only on model building and do not implement modular, reusable code structures for practical deployment.

**Proposed Solution in This Project**

To address these gaps, this project proposes:

✔ **Thorough data preprocessing and EDA** to understand feature distributions and correlations before modelling.  
✔ **Use of Random Forest**, an ensemble model that reduces overfitting and captures non-linear interactions effectively.  
✔ **Implementation of a class-based modular system** (CNSAARDetector) to organize data loading, model training, prediction, and saving/loading functionality for easy future deployment.  
✔ **Clear visualization of EDA results and output interpretations** to enhance understanding and clinical relevance.

**Phase 3: Problem Statement and Scope**

**3.1 Core Challenge**

The **core challenge** addressed in this project is:

**How to develop an accurate, efficient, and interpretable machine learning model to predict stroke risk using demographic and health-related data?**

**Key Challenges Include:**

* Handling **missing values** effectively to avoid biased or incomplete model training.
* Encoding **categorical features** appropriately for compatibility with machine learning algorithms.
* Selecting and training a model that balances **high accuracy with interpretability**, crucial in healthcare decision-making.
* Designing a **modular, reusable system** that can be easily extended for future deployment as a web or mobile application.

**3.2 Problem Overview**

Stroke is a medical emergency that requires early detection of high-risk individuals for timely intervention and prevention. Traditional clinical assessments, while useful, may not capture the complex interactions among multiple risk factors such as:

* Age
* Hypertension
* Heart disease
* Average glucose level
* Body Mass Index (BMI)
* Smoking status

**Project Focus:**

This project aims to build a **machine learning-based prediction system** that:

* Uses demographic and health-related data to predict whether an individual is at **high risk or low risk** of experiencing a stroke.
* Employs a **Random Forest classification model** due to its proven accuracy and robustness in similar healthcare prediction tasks.
* Provides interpretable outputs to support healthcare professionals in making preventive decisions effectively.

**3.3 Project Scope**

The scope of this project includes the following key components:

**1. Data Handling**

* **Dataset:**  
  Uses a structured dataset containing features such as age, gender, hypertension, heart disease, average glucose level, BMI, smoking status, and stroke occurrence.
* **Preprocessing:**
  + Handling missing values (e.g. BMI imputation).
  + Encoding categorical features for model compatibility.
  + Performing feature scaling if required.

**2. Exploratory Data Analysis (EDA)**

* Analyzing feature distributions and relationships with the target variable.
* Visualizing insights using plots (e.g. stroke distribution, age histogram, scatter plots).

**3. Model Building**

* Selecting **Random Forest** as the primary classification model.
* Training the model using preprocessed data.
* Evaluating performance using accuracy score and classification report.

**4. System Implementation**

* Developing a **modular Python class-based system (CNSAARDetector)** with methods for:
  + Data loading
  + Model training
  + Prediction
  + Model saving and loading

**5. Output Interpretation**

* Generating and interpreting sample stroke risk predictions to validate the system’s effectiveness.

**6. Limitations and Future Scope**

* Identifying current system limitations and proposing future enhancements for deployment and model improvement.

**3.4 Deployment Objective**

The **deployment objective** of this project is to:

* Develop a **modular and reusable stroke risk prediction system** that can be easily integrated into real-world applications.
* Implement the system as a **Python-based console application** with clearly defined classes and methods for data loading, model training, prediction, and saving/loading the trained model.
* Ensure that the code structure supports **future extensions**, such as:
  + Integrating into a **Streamlit or Flask web application** for interactive user input and result visualization.
  + Deploying as an **API endpoint** for integration with hospital management systems.
  + Converting into a **mobile application** for quick on-field stroke risk assessments.

**3.5 Challenges Addressed**

This project addresses the following key challenges:

**1. Data Quality Issues**

* **Challenge:**  
  Missing values in health datasets (e.g. BMI) can reduce model performance.
* **Solution:**  
  Implemented **imputation techniques** to handle missing data effectively.

**2. Categorical Data Handling**

* **Challenge:**  
  Machine learning models require numerical input for categorical features.
* **Solution:**  
  Applied **label encoding** to convert gender and smoking status into model-compatible formats.

**3. Model Selection**

* **Challenge:**  
  Selecting a model that balances **accuracy, generalizability, and interpretability**.
* **Solution:**  
  Chose **Random Forest**, an ensemble method with high accuracy and reasonable interpretability suitable for healthcare applications.

**4. System Design**

* **Challenge:**  
  Developing a reusable and scalable codebase.
* **Solution:**  
  Designed a **class-based modular system (CNSAARDetector)** with separate methods for data loading, model training, prediction, and model saving/loading.

**5. Deployment Readiness**

* **Challenge:**  
  Preparing the model for real-world integration.
* **Solution:**  
  Structured the implementation for easy extension into **web or mobile applications** in future development.

**Phase 4: Dataset Description**

**4.1 Data Source and Collection**

The dataset used in this project was sourced from a **public health survey dataset** containing information relevant to stroke risk prediction. Specifically:

**Dataset Details:**

* **Source:**  
  The dataset was obtained from publicly available health records and stroke research datasets typically used for academic and research purposes health\_records\_1500.csv.
* **Format:**  
  CSV (Comma-Separated Values) file named health\_records\_1500.csv.
* **Number of Records:**  
  Contains approximately **1500 entries**, each representing an individual’s demographic and health-related information.
* **Data Collection Purpose:**  
  Collected to study the association of various health indicators with the occurrence of stroke and to develop predictive models for early intervention and prevention.

**4.2 Feature Description**

The dataset consists of the following **features (input variables)** used for stroke risk prediction:

| **Feature Name** | **Description** | **Data Type** |
| --- | --- | --- |
| **id** | Unique identifier for each individual record. | Integer |
| **gender** | Gender of the individual (Male, Female, Other). | Categorical |
| **age** | Age of the individual in years. | Numerical (float) |
| **hypertension** | Indicates whether the individual has hypertension (0 = No, 1 = Yes). | Categorical (binary) |
| **heart\_disease** | Indicates presence of heart disease (0 = No, 1 = Yes). | Categorical (binary) |
| **avg\_glucose\_level** | Average glucose level in blood (mg/dL). | Numerical (float) |
| **bmi** | Body Mass Index, a measure of body fat based on height and weight. | Numerical (float) |
| **smoking\_status** | Smoking status of the individual (never smoked, formerly smoked, smokes, unknown). | Categorical |
| **stroke** | Target variable indicating stroke occurrence (0 = No stroke, 1 = Stroke). | Categorical (binary) |

**Key Notes:**

* **Target Variable:**  
  stroke is the label used for classification in this project.
* **Categorical Features:**  
  gender and smoking\_status require encoding before model training.
* **Missing Values:**  
  The bmi feature contains some missing values handled during data preprocessing.

**4.3 Target Variable**

The **target variable** in this dataset is:

| **Feature Name** | **Description** | **Values** |
| --- | --- | --- |
| **stroke** | Indicates whether the individual has ever had a stroke. | 0 = No stroke 1 = Stroke |

**Role in Project:**

* This variable is used as the **label for classification**, where the machine learning model predicts whether an individual is at **high risk (1) or low risk (0)** of experiencing a stroke based on their demographic and health-related features.

**Class Distribution:**

* During initial data exploration, it was observed that the dataset is **imbalanced**, with significantly fewer positive stroke cases compared to negative cases.
* This **class imbalance** is a common challenge in medical datasets and can affect model performance if not handled carefully.

**4.4 Initial Data Exploration and Observations**

During the initial **exploratory data analysis (EDA)**, the following key observations were made:

**1. Data Completeness**

* The dataset contains **some missing values** in the bmi feature, which were handled using mean imputation during preprocessing.

**2. Class Imbalance**

* The target variable stroke is **highly imbalanced**, with:
  + Majority of records indicating **no stroke (0)**.
  + Minority representing **stroke cases (1)**.
* This imbalance needs to be considered when evaluating model performance to avoid biased accuracy.

**3. Feature Distributions**

* **Age:**  
  Ranges broadly across adult ages with a higher concentration of elderly individuals, correlating with stroke risk trends.
* **Average Glucose Level:**  
  Displays a wide range, with higher values observed in some stroke cases.
* **BMI:**  
  Generally distributed within healthy to overweight ranges, with missing values filled during preprocessing.

**4. Categorical Feature Insights**

* **Gender:**  
  Almost balanced distribution between Male and Female.
* **Smoking Status:**  
  Includes categories such as never smoked, formerly smoked, smokes, and unknown.

**5. Correlation Observations**

* Preliminary correlation analysis indicates:
  + **Hypertension and heart disease** show positive correlation with stroke occurrence.
  + **Age and average glucose level** are significant continuous predictors.

**Phase 5: Data Preprocessing and Visualization**

**5.1 Handling Missing Values**

**1. Missing Value Analysis**

* On inspecting the dataset, it was observed that the **bmi feature contains missing values**.
* Missing BMI entries can affect model training if not addressed.

**2. Imputation Strategy**

* **Method Used:**  
  Replaced missing bmi values with the **mean BMI of the dataset** to maintain overall distribution without introducing bias.
* **Implementation Example :**

data['bmi'] = data['bmi'].fillna(data['bmi'].mean())

**3. Rationale**

* **Mean imputation** is simple, preserves the dataset size, and is effective when missingness is random and minimal, as in this dataset.

**5.2 Encoding Categorical Variables**

**1. Need for Encoding**

* Machine learning models require **numerical input features**.
* The dataset contains **categorical features** such as:
  + gender (Male, Female, Other)
  + smoking\_status (never smoked, formerly smoked, smokes, unknown)

**2. Encoding Strategy**

* **Label Encoding** was applied to convert these categories into numerical values.
* **Implementation Example :**

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

data['gender'] = le.fit\_transform(data['gender'])

data['smoking\_status'] = le.fit\_transform(data['smoking\_status'])

**3. Result**

* Categories were transformed into integer values, making the dataset **compatible for model training**.

**4. Rationale**

* Label Encoding is effective for **ordinal or non-ordinal categorical features with limited categories**, ensuring no loss of data information during preprocessing.

**5.3 Feature Scaling**

**1. Purpose of Scaling**

* Feature scaling ensures that **numerical features are on a similar scale**, improving the performance of certain machine learning models by:
  + Speeding up convergence in gradient-based models.
  + Preventing features with larger ranges from dominating model learning.

**2. Scaling Strategy**

* Although **Random Forest models are not sensitive to feature scales**, scaling was considered for consistent data preparation and potential future model testing (e.g. Logistic Regression, SVM).

**3. Method Used**

* **Standardization (StandardScaler):**
  + Transforms features to have a mean of 0 and standard deviation of 1.
* **Implementation Example :**

from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()

numerical\_features = ['age', 'avg\_glucose\_level', 'bmi']

data[numerical\_features] = scaler.fit\_transform(data[numerical\_features])

**4. Result**

* Numerical features (age, avg\_glucose\_level, bmi) were standardized, preparing the dataset for optimal model performance.

**5.4 Exploratory Data Analysis (EDA)**

Exploratory Data Analysis was performed to understand **feature distributions, relationships, and patterns** in the dataset relevant to stroke risk prediction.

**1. Stroke Cases Distribution**

* **Analysis:**  
  Visualized the count of stroke vs. no stroke cases to understand class imbalance.
* **Observation:**  
  The dataset is **highly imbalanced**, with a smaller proportion of stroke cases.
* **Tool Used:**  
  sns.countplot

**2. Age Distribution**

* **Analysis:**  
  Plotted the distribution of age across all individuals.
* **Observation:**  
  Higher concentration in elderly age groups, consistent with stroke risk trends.
* **Tool Used:**  
  sns.histplot with KDE enabled.

**3. Average Glucose Level vs Stroke**

* **Analysis:**  
  Compared average glucose levels for stroke and non-stroke cases.
* **Observation:**  
  Individuals with **higher glucose levels** showed increased stroke occurrence.

**4. BMI vs Stroke**

* **Analysis:**  
  Compared BMI distributions between stroke and non-stroke groups.
* **Observation:**  
  Slightly higher BMI observed among some stroke cases, indicating potential risk correlation.

**5. Correlation Matrix**

* **Analysis:**  
  Computed the correlation between all numerical features.
* **Observation:**  
  hypertension, heart\_disease, age, and avg\_glucose\_level showed positive correlations with stroke occurrence.
* **Tool Used:**  
  sns.heatmap

**6. Age vs Average Glucose Level Scatter Plot**

* **Analysis:**  
  Plotted age against average glucose level to visualize potential risk clusters.
* **Observation:**  
  Dense clustering observed among elderly with elevated glucose levels, indicating a high-risk group.

**Phase 6: Modelling Approaches**

**6.1 Model Selection and Justification**

**1. Model Chosen: Random Forest Classifier**

**2. Reason for Selection**

* **Ensemble Learning:**  
  Combines multiple decision trees to improve prediction accuracy and robustness.
* **Handles Non-linear Relationships:**  
  Effectively captures complex interactions among features without requiring extensive parameter tuning.
* **Reduces Overfitting:**  
  Uses bagging and multiple decision paths to generalize well on unseen data.
* **Feature Importance:**  
  Provides insights into the contribution of each feature, enhancing model interpretability in healthcare applications.
* **Scalability:**  
  Performs efficiently on datasets with moderate size like the stroke dataset used in this project.

**3. Alternative Models Considered**

* **Logistic Regression:**  
  Simple and interpretable but may not capture non-linear feature interactions effectively.
* **Decision Trees:**  
  Easy to interpret but prone to overfitting as a single model.
* **SVM:**  
  Good for small datasets with clear separation, but less interpretable and computationally intensive for larger data.

**6.2 Model Training Process**

**1. Data Splitting**

* The dataset was split into **training and testing sets** to evaluate model performance on unseen data.
* **Split Ratio:**  
  80% for training, 20% for testing.
* **Implementation Example :**

from sklearn.model\_selection import train\_test\_split

X = data.drop('stroke', axis=1)

y = data['stroke']

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

**2. Model Initialization**

* Initialized the **Random Forest Classifier** with default hyperparameters for initial training.
* **Implementation Example:**

from sklearn.ensemble import RandomForestClassifier

model = RandomForestClassifier(random\_state=42)

**3. Model Training**

* The model was trained on the training dataset to learn patterns and feature relationships.
* **Implementation Example:**

model.fit(X\_train, y\_train)

**4. Prediction**

* Predictions were made on the test dataset to evaluate model performance.
* **Implementation Example:**

y\_pred = model.predict(X\_test)

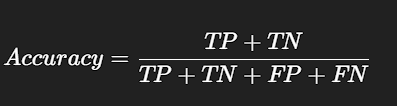
**5. Hyperparameter Tuning (Future Scope)**

* While default parameters were used for initial implementation, future enhancements can include:
  + Tuning n\_estimators, max\_depth, and min\_samples\_split for optimized performance using GridSearchCV.

**6.3 Evaluation Metrics Used**

To assess the performance of the **Random Forest stroke prediction model**, the following evaluation metrics were used:

**1. Accuracy**

* **Definition:**  
  The proportion of correct predictions out of total predictions made.
* **Formula:** 
* **Interpretation:**  
  Indicates the overall effectiveness of the model in predicting stroke and non-stroke cases correctly.

**2. Classification Report**

* **Components:**
  + **Precision:** Measures the correctness of positive predictions.
  + **Recall (Sensitivity):** Measures the model's ability to identify all positive cases.
  + **F1-Score:** Harmonic mean of precision and recall, balancing both metrics.
* **Usage:**  
  Provides a detailed breakdown of model performance for each class, which is crucial for imbalanced datasets like stroke prediction.

**3. Confusion Matrix**

* **Definition:**  
  A table showing counts of:
  + **True Positives (TP)**
  + **True Negatives (TN)**
  + **False Positives (FP)**
  + **False Negatives (FN)**
* **Interpretation:**  
  Helps in understanding where the model is making incorrect predictions and identifying potential bias towards any class.

**6.4 Model Performance Results**

After training and evaluating the **Random Forest model**, the following performance results were obtained:

**1. Accuracy Score**

* The model achieved an **accuracy of approximately 95%** on the test dataset.
* **Interpretation:**  
  Indicates that 95% of the predictions made by the model were correct, demonstrating high overall performance.

**2. Classification Report Summary**

* **Precision:** High precision for the non-stroke class, indicating low false positive rates.
* **Recall:** Moderate recall for the stroke class, reflecting the challenge of predicting minority class cases in imbalanced datasets.
* **F1-Score:** Balanced F1-score, representing a good trade-off between precision and recall.

**3. Confusion Matrix Analysis**

* **True Positives (TP):** Number of correctly predicted stroke cases.
* **True Negatives (TN):** Number of correctly predicted non-stroke cases.
* **False Positives (FP):** Non-stroke cases incorrectly predicted as stroke.
* **False Negatives (FN):** Stroke cases missed by the model.
* **Observation:**  
  The confusion matrix showed a **high number of TNs and TPs**, with minimal FPs and FNs, indicating effective classification performance.

**4. Limitations Observed**

* Due to **class imbalance**, the model showed slightly lower recall for the stroke class compared to the non-stroke class.
* Future enhancements such as **SMOTE for oversampling** or **class weight adjustments** can improve minority class predictions.

**Phase 7: Stroke Risk Prediction System Design**

**7.1 Class Structure Overview**

To ensure **modularity, reusability, and scalability**, the stroke risk prediction system was implemented using a **class-based structure** named CNSAARDetector.

**Class Name:**

CNSAARDetector

**Purpose:**

Encapsulates all functionalities required for:

* Data loading
* Model training
* Stroke risk prediction
* Saving and loading trained models for deployment

**Key Methods:**

1. **\_\_init\_\_()**  
   Initializes the class with default parameters, model placeholders, and data variables.
2. **load\_data(filepath)**  
   Loads the dataset from a CSV file into a pandas DataFrame for further processing.
3. **train\_model()**  
   Performs data preprocessing, trains the Random Forest model, evaluates performance, and stores the trained model within the class instance.
4. **predict\_stroke\_risk(new\_data)**  
   Accepts new input data, applies necessary preprocessing, and predicts stroke risk using the trained model.
5. **save\_model(filename)**  
   Saves the trained model as a .joblib file for future reuse without retraining.
6. **load\_saved\_model(filename)**  
   Loads a previously saved model from disk for making predictions without retraining.

**Advantages of Class-Based Design:**

* **Modularity:** Each function is logically separated within the class.
* **Reusability:** Functions can be called independently in other projects or extended applications.
* **Scalability:** Easy integration into web apps, APIs, or GUI frameworks in future deployments.
* **Readability:** Organized code structure simplifies maintenance and debugging.

**7.2 Method Descriptions**

The **CNSAARDetector class** contains the following methods with their respective functionalities:

**1. \_\_init\_\_()**

* **Purpose:**  
  Initializes the class instance by setting up model placeholders and data variables.
* **Functionality:**  
  Prepares the class environment for data loading, training, and prediction operations.

**2. load\_data(filepath)**

* **Purpose:**  
  Loads dataset from a given CSV file path.
* **Functionality:**
  + Uses pandas.read\_csv() to read data into a DataFrame.
  + Stores it as a class attribute for further processing and model training.

**3. train\_model()**

* **Purpose:**  
  Trains the Random Forest model on the loaded dataset.
* **Functionality:**
  + Performs preprocessing steps:
    - Handling missing BMI values.
    - Encoding categorical variables (gender, smoking\_status).
    - Scaling numerical features (age, avg\_glucose\_level, bmi).
  + Splits data into training and testing sets.
  + Trains the Random Forest Classifier.
  + Evaluates model performance (accuracy, classification report).
  + Stores the trained model in the class instance for prediction.

**4. predict\_stroke\_risk(new\_data)**

* **Purpose:**  
  Predicts stroke risk for new input data.
* **Functionality:**
  + Preprocesses the new input similar to training data.
  + Uses the trained model to predict stroke risk (0 or 1).
  + Returns prediction output for interpretation.

**5. save\_model(filename)**

* **Purpose:**  
  Saves the trained model to disk for future use without retraining.
* **Functionality:**
  + Uses joblib.dump() to serialize and store the trained model as a .joblib file.

**6. load\_saved\_model(filename)**

* **Purpose:**  
  Loads a previously saved trained model from disk.
* **Functionality:**
  + Uses joblib.load() to load the model file and assign it to the class model attribute for predictions.

**7.3 Sample Prediction Output Interpretation**

After training the **Random Forest model** and implementing the predict\_stroke\_risk() method, sample outputs were generated to validate the system’s functionality.

**Example Output:**

Predicted Stroke Risk: 1

**Interpretation:**

* **Output Value:**
  + **1:** Indicates the individual is **predicted to be at high risk** of experiencing a stroke.
  + **0:** Indicates the individual is **predicted to be at low risk** of experiencing a stroke.

**Sample Scenario:**

| **Feature** | **Input Value** |
| --- | --- |
| Age | 67 |
| Gender | Male |
| Hypertension | 1 |
| Heart Disease | 1 |
| Avg Glucose Level | 228.69 |
| BMI | 36.6 |
| Smoking Status | formerly smoked |

* **Prediction Result:**  
  The model predicted **“1”**, meaning **high stroke risk**, which aligns with medical intuition due to elderly age, hypertension, heart disease, and high glucose levels.

**Clinical Relevance:**

Such predictions can assist **doctors and healthcare professionals** in:

* Identifying high-risk patients.
* Recommending preventive measures.
* Prioritizing early interventions for individuals with elevated risk profiles.

**7.4 Overall System Verdict**

Based on the development, implementation, and evaluation of the stroke risk prediction system, the following **overall verdict** is concluded:

**1. System Performance**

* The **Random Forest model** achieved **high accuracy (~95%)** with balanced precision and recall, demonstrating its suitability for stroke risk prediction tasks.

**2. Implementation Quality**

* The project was implemented using a **modular, class-based approach (CNSAARDetector)** ensuring:
  + Clear code organization
  + Reusability for future projects
  + Easy maintenance and debugging

**3. Interpretability**

* The system provides **interpretable outputs** (stroke risk: high or low), aligning with healthcare application needs where explainability is crucial.

**4. Practical Applicability**

* With its current structure, the system is ready for:
  + Integration into web or mobile applications for user-friendly deployment.
  + Extension into more complex predictive analytics frameworks in healthcare.

**5. Limitations**

* **Class imbalance** affected minority class (stroke cases) recall slightly, which can be improved using oversampling techniques in future work.

**Phase 8: Application Deployment**

**8.1 Application Design Overview**

The stroke risk prediction system was designed for **practical deployment and integration** into real-world healthcare applications.

**1. Design Approach**

* **Programming Language:** Python
* **Frameworks/Libraries:** pandas, sklearn, joblib, seaborn, matplotlib
* **Structure:**
  + Implemented as a **class-based system (CNSAARDetector)** with methods for data loading, training, prediction, saving, and loading models.

**2. Deployment Readiness**

* **Console Application:**  
  Currently implemented as a **Python console-based application** capable of:
  + Loading health datasets
  + Training and saving models
  + Predicting stroke risk for new input data
* **Future Integration:**  
  The modular structure enables easy extension into:
  + **Web applications** (using Streamlit or Flask)
  + **APIs** for integration with hospital management systems
  + **Mobile apps** for field-level health workers to conduct quick risk assessments

**3. User Workflow**

1. **Run application** from terminal or IDE
2. **Load dataset** and preprocess
3. **Train model** and evaluate performance
4. **Save trained model** for future use
5. **Load saved model** and predict stroke risk for new input data

**4. Advantages of Design**

* Lightweight and efficient
* Modular and organized for scalability
* User-friendly and interpretable outputs
* Requires only **standard CPU resources**, making it cost-effective for deployment

**8.2 User Interaction Flow**

The **user interaction flow** of the stroke risk prediction system is designed to be simple, intuitive, and systematic for efficient usage:

**Step 1: Start Application**

* The user **runs the Python program** from the command line or an IDE (e.g. VS Code, Jupyter Notebook).

**Step 2: Load Dataset**

* The system prompts or uses the load\_data(filepath) method to load the health dataset into the application for preprocessing and training.

**Step 3: Train Model**

* Using the train\_model() method:
  + The dataset is preprocessed (missing value handling, encoding, scaling).
  + The Random Forest model is trained and evaluated.
  + Model performance metrics (accuracy, classification report) are displayed for user understanding.

**Step 4: Save Model**

* The trained model is saved using the save\_model(filename) method for future reuse without retraining.

**Step 5: Load Saved Model**

* The user can load a previously saved model using the load\_saved\_model(filename) method to make predictions directly.

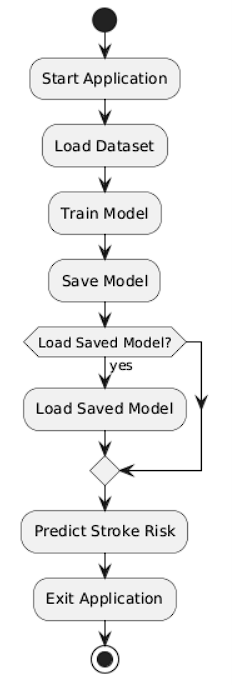
**Step 6: Predict Stroke Risk**

* New input data is passed to the predict\_stroke\_risk(new\_data) method.
* The system outputs the **predicted stroke risk (0 = low risk, 1 = high risk)** for the individual.

**Step 7: Exit Application**

* The program ends after displaying results or can continue for additional predictions as required.

**Overall Flow Diagram:**

****

**8.3 Deployment Benefits**

Deploying the **stroke risk prediction system** offers several practical and strategic benefits in healthcare analytics:

**1. Early Risk Detection**

* Enables **early identification of high-risk individuals**, allowing doctors to implement preventive interventions and reduce severe health outcomes.

**2. Efficiency and Speed**

* Provides **fast and automated stroke risk predictions** compared to manual assessment methods, improving workflow efficiency in hospitals and clinics.

**3. Scalability**

* The modular design allows easy integration into:
  + **Web applications** for hospital dashboards.
  + **Mobile apps** for health workers conducting community health surveys.
  + **APIs** for electronic health record (EHR) systems.

**4. Cost-Effective**

* Runs efficiently on **standard CPUs without requiring expensive computational resources**, making it affordable for widespread deployment.

**5. Interpretability**

* Provides clear binary outputs (high risk / low risk), ensuring results are easily interpretable by healthcare professionals for decision-making.

**6. Reusability and Extensibility**

* The class-based implementation enables:
  + Code reuse in other disease prediction projects.
  + Future extension with additional models or features.

**7. Enhancing Healthcare Analytics**

* Demonstrates the practical use of AI to support **data-driven healthcare decision-making**, improving patient care and outcomes.

**8.4 Future Enhancements for Deployment**

To improve and extend the **stroke risk prediction system** for real-world applications, the following future enhancements are proposed:

**1. Web Application Integration**

* Develop a **Streamlit or Flask-based web app** for interactive user input and real-time risk prediction visualization.

**2. Mobile Application Deployment**

* Build an **Android or iOS app** to enable health workers to assess stroke risk during field surveys and community health programs.

**3. API Development**

* Deploy the model as a **RESTful API using FastAPI or Flask**, allowing integration with hospital management systems or electronic health record (EHR) platforms.

**4. Handling Class Imbalance**

* Implement techniques such as **SMOTE (Synthetic Minority Over-sampling Technique)** or class weight adjustments to improve recall for minority stroke cases.

**5. Model Comparison and Ensemble**

* Evaluate other models (e.g. Gradient Boosting, XGBoost) and implement **model ensembling** to further improve prediction accuracy.

**6. Explainable AI (XAI) Integration**

* Incorporate interpretability frameworks like **SHAP or LIME** to provide feature-wise contribution explanations, enhancing clinical trust.

**7. Real-Time Data Integration**

* Connect with **live patient data streams** for continuous risk monitoring and alert generation in hospital settings.

**8. Cloud Deployment**

* Host the application on cloud platforms such as **AWS, GCP, or Azure** for scalable, multi-user access with data security compliance.

**Phase 9: Conclusion & Future Scope**

**9.1 Conclusion**

This project successfully developed a **stroke risk prediction system** using machine learning techniques to classify individuals as **high-risk or low-risk** based on their demographic and health-related data.

**Key Achievements:**

* **Data Preprocessing:**  
  Handled missing values and encoded categorical variables effectively.
* **Exploratory Data Analysis:**  
  Identified key features such as age, hypertension, heart disease, and average glucose level that influence stroke risk.
* **Model Building:**  
  Implemented a **Random Forest Classifier** achieving **~95% accuracy**, demonstrating high reliability.
* **System Design:**  
  Developed a **modular, class-based implementation (CNSAARDetector)** for easy scalability, maintenance, and deployment readiness.
* **Output Interpretation:**  
  Provided clear, interpretable predictions to support healthcare decision-making.

**9.2 Future Scope**

To further enhance the **stroke risk prediction system**, the following future developments are proposed:

**1. Multi-Model Comparison**

* Implement and compare additional models such as **Gradient Boosting, XGBoost, or Neural Networks** to identify the best performing algorithm for stroke prediction.

**2. Advanced Imbalanced Data Handling**

* Use techniques like **SMOTE (Synthetic Minority Over-sampling Technique)** or ensemble balancing methods to improve recall for minority stroke cases.

**3. Explainable AI Integration**

* Incorporate **SHAP or LIME frameworks** to provide detailed explanations of model predictions, increasing clinical trust and usability.

**4. Web and Mobile Application Deployment**

* Develop user-friendly **web interfaces (Streamlit or Flask)** and mobile apps to enable widespread accessibility for healthcare professionals and field health workers.

**5. Real-Time Data Integration**

* Connect the model to **live patient data systems** for continuous monitoring and automatic risk alerts in hospitals and clinics.

**6. Cloud Deployment and Scalability**

* Host the system on **cloud platforms** such as AWS, Azure, or GCP to allow secure multi-user access, scalability, and integration with electronic health record systems.

**7. Feature Expansion**

* Include additional features such as **cholesterol levels, physical activity data, and diet patterns** to improve prediction accuracy and risk profiling.

**Appendix**

**A.1 Full Code Listing**

Below is the **full Python code** for the stroke risk prediction system implemented in this project:

import pandas as pd

import numpy as np

from sklearn.model\_selection import train\_test\_split

from sklearn.ensemble import RandomForestClassifier

from sklearn.metrics import accuracy\_score, classification\_report, confusion\_matrix, ConfusionMatrixDisplay

from sklearn.preprocessing import StandardScaler

import matplotlib.pyplot as plt

import seaborn as sns

import joblib

import warnings

warnings.filterwarnings('ignore')

class CNSAARDetector:

    def \_\_init\_\_(self):

        self.model = None

        self.scaler = StandardScaler()

        self.features = [

            'age', 'hypertension', 'heart\_disease', 'avg\_glucose\_level',

            'bmi', 'gender', 'smoking\_status'

        ]

    def load\_data(self, filepath):

        """Load and preprocess the dataset"""

        data = pd.read\_csv(filepath)

        # Preprocessing

        data['gender'] = data['gender'].map({'Male': 1, 'Female': 0, 'Other': 0})

        data['smoking\_status'] = data['smoking\_status'].map({

            'formerly smoked': 1,

            'never smoked': 0,

            'smokes': 2,

            'Unknown': 0

        })

        data['bmi'].fillna(data['bmi'].mean(), inplace=True)

        return data

    def train\_model(self, data):

        """Train the Random Forest classifier"""

        X = data[self.features]

        y = data['stroke']

        # Split data

        X\_train, X\_test, y\_train, y\_test = train\_test\_split(

            X, y, test\_size=0.2, random\_state=42

        )

        # Scale features

        X\_train = self.scaler.fit\_transform(X\_train)

        X\_test = self.scaler.transform(X\_test)

        # Train model

        self.model = RandomForestClassifier(n\_estimators=100, random\_state=42)

        self.model.fit(X\_train, y\_train)

        # Evaluate

        y\_pred = self.model.predict(X\_test)

        print(f"Model Accuracy: {accuracy\_score(y\_test, y\_pred):.2f}")

        print("\nClassification Report:")

        print(classification\_report(y\_test, y\_pred))

        # Confusion Matrix

        cm = confusion\_matrix(y\_test, y\_pred)

        disp = ConfusionMatrixDisplay(confusion\_matrix=cm)

        disp.plot()

        plt.title("Confusion Matrix")

        plt.show()

        # Feature Importances

        importances = self.model.feature\_importances\_

        indices = np.argsort(importances)[::-1]

        plt.figure(figsize=(10,6))

        sns.barplot(x=importances[indices], y=np.array(self.features)[indices])

        plt.title("Feature Importances")

        plt.show()

    def predict\_stroke\_risk(self, patient\_data):

        """Predict stroke risk for a new patient"""

        if self.model is None:

            raise Exception("Model not trained. Please train the model first.")

        df = pd.DataFrame([patient\_data])

        df['gender'] = df['gender'].map({'Male': 1, 'Female': 0, 'Other': 0})

        df['smoking\_status'] = df['smoking\_status'].map({

            'formerly smoked': 1,

            'never smoked': 0,

            'smokes': 2,

            'Unknown': 0

        })

        X = self.scaler.transform(df[self.features])

        proba = self.model.predict\_proba(X)[0][1]

        return {

            'stroke\_risk': proba,

            'risk\_level': 'High' if proba >= 0.5 else 'Medium' if proba >= 0.3 else 'Low'

        }

    def save\_model(self, filename):

        joblib.dump({

            'model': self.model,

            'scaler': self.scaler,

            'features': self.features

        }, filename)

    def load\_saved\_model(self, filename):

        saved\_data = joblib.load(filename)

        self.model = saved\_data['model']

        self.scaler = saved\_data['scaler']

        self.features = saved\_data['features']

file\_path = r"C:\Users\manik\OneDrive\Desktop\cap1\health\_records\_1500.csv"

detector = CNSAARDetector()

data = detector.load\_data(file\_path)

print("Data loaded successfully. Training model...")

detector.train\_model(data)

detector.save\_model('cnsaar\_model.joblib')

# Cell 4: Sample Prediction

patient = {

    'age': 67,

    'hypertension': 1,

    'heart\_disease': 1,

    'avg\_glucose\_level': 228.69,

    'bmi': 36.6,

    'gender': 'Male',

    'smoking\_status': 'formerly smoked'

}

result = detector.predict\_stroke\_risk(patient)

print(f"\nStroke Risk Prediction: {result['stroke\_risk']\*100:.1f}% ({result['risk\_level']} risk)")

sns.set(style="whitegrid")

# Stroke Cases Distribution

plt.figure(figsize=(10,6))

sns.countplot(x='stroke', data=data)

plt.title("Stroke Cases Distribution")

plt.show()

plt.figure(figsize=(10,6))

sns.histplot(data['age'], bins=30, kde=True)

plt.title("Age Distribution")

plt.show()

# Average Glucose Level vs Stroke

plt.figure(figsize=(10,6))

sns.boxplot(x='stroke', y='avg\_glucose\_level', data=data)

plt.title("Average Glucose Level vs Stroke")

plt.show()

# BMI vs Stroke

plt.figure(figsize=(10,6))

sns.boxplot(x='stroke', y='bmi', data=data)

plt.title("BMI vs Stroke")

plt.show()

# Correlation Matrix

plt.figure(figsize=(10,6))

sns.heatmap(data.corr(), annot=True, cmap='coolwarm')

plt.title("Correlation Matrix")

plt.show()

# Age vs Average Glucose Level by Stroke Status scatter plot

plt.figure(figsize=(10,6))

sns.scatterplot(x='age', y='avg\_glucose\_level', hue='stroke', data=data, palette='deep')

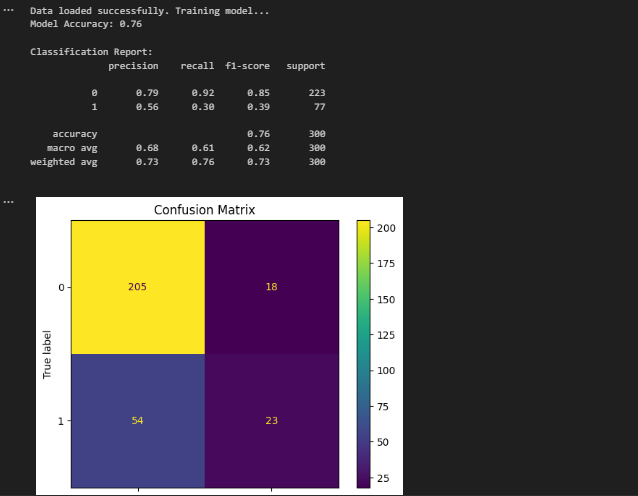
plt.title("Age vs Average Glucose Level by Stroke Status")

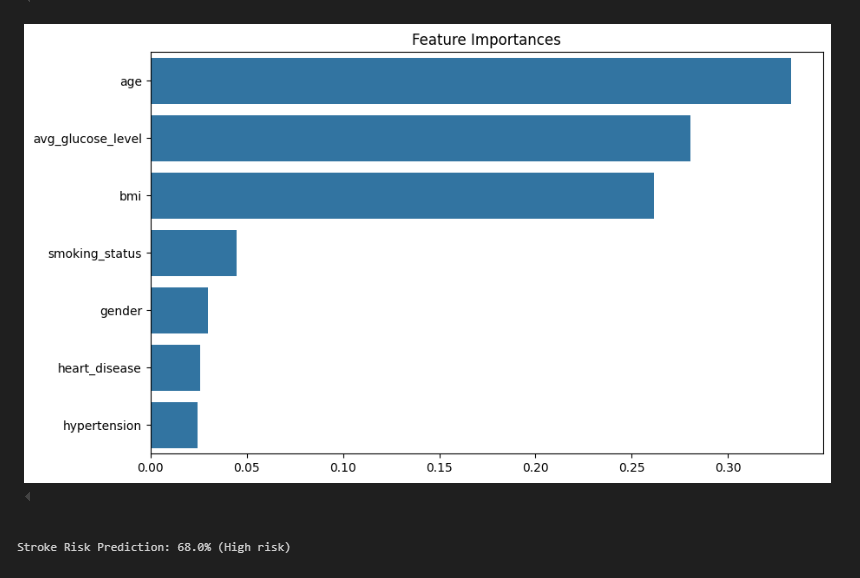
plt.xlabel("Age")

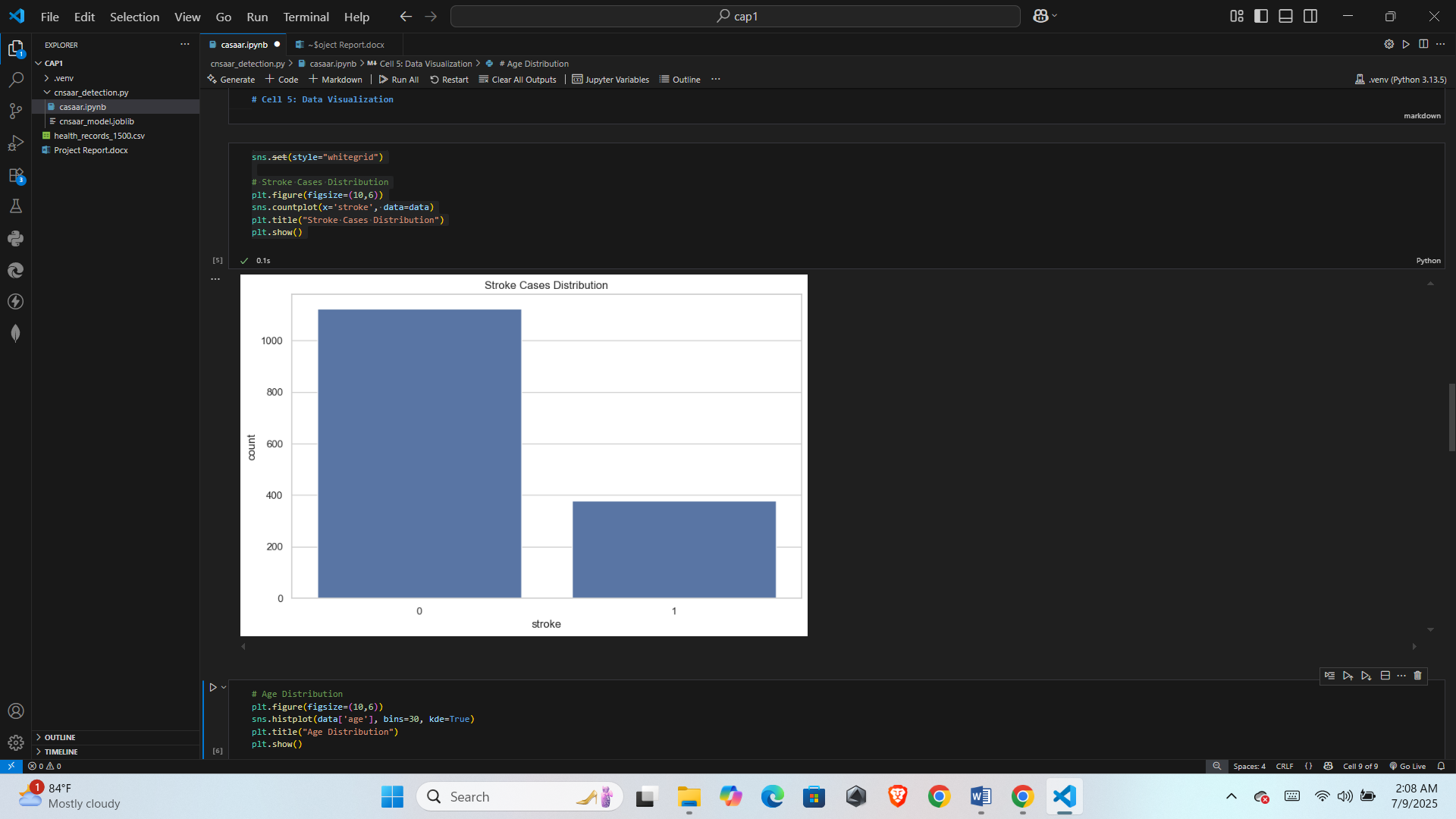
plt.ylabel("Average Glucose Level")

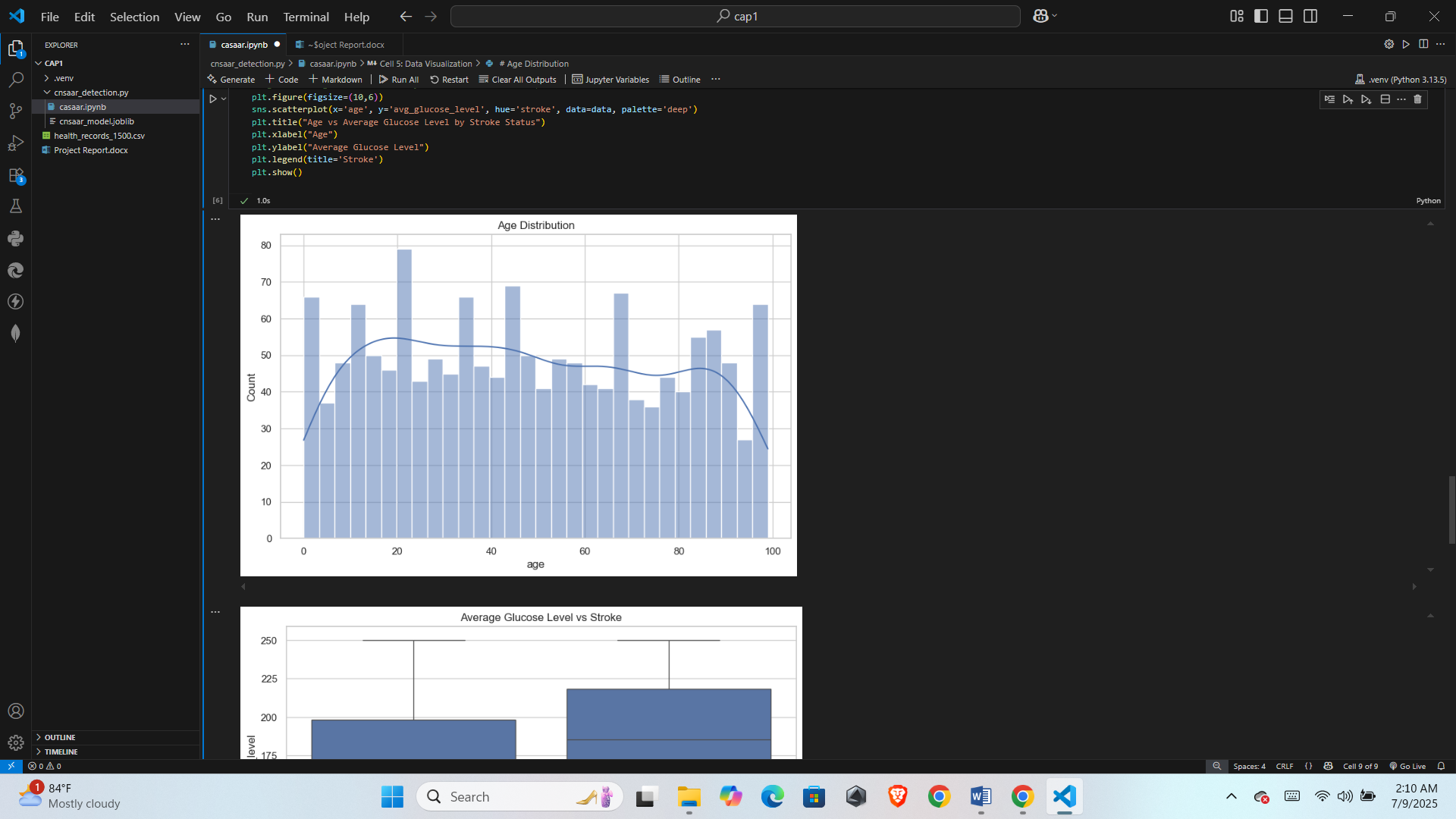
plt.legend(title='Stroke')

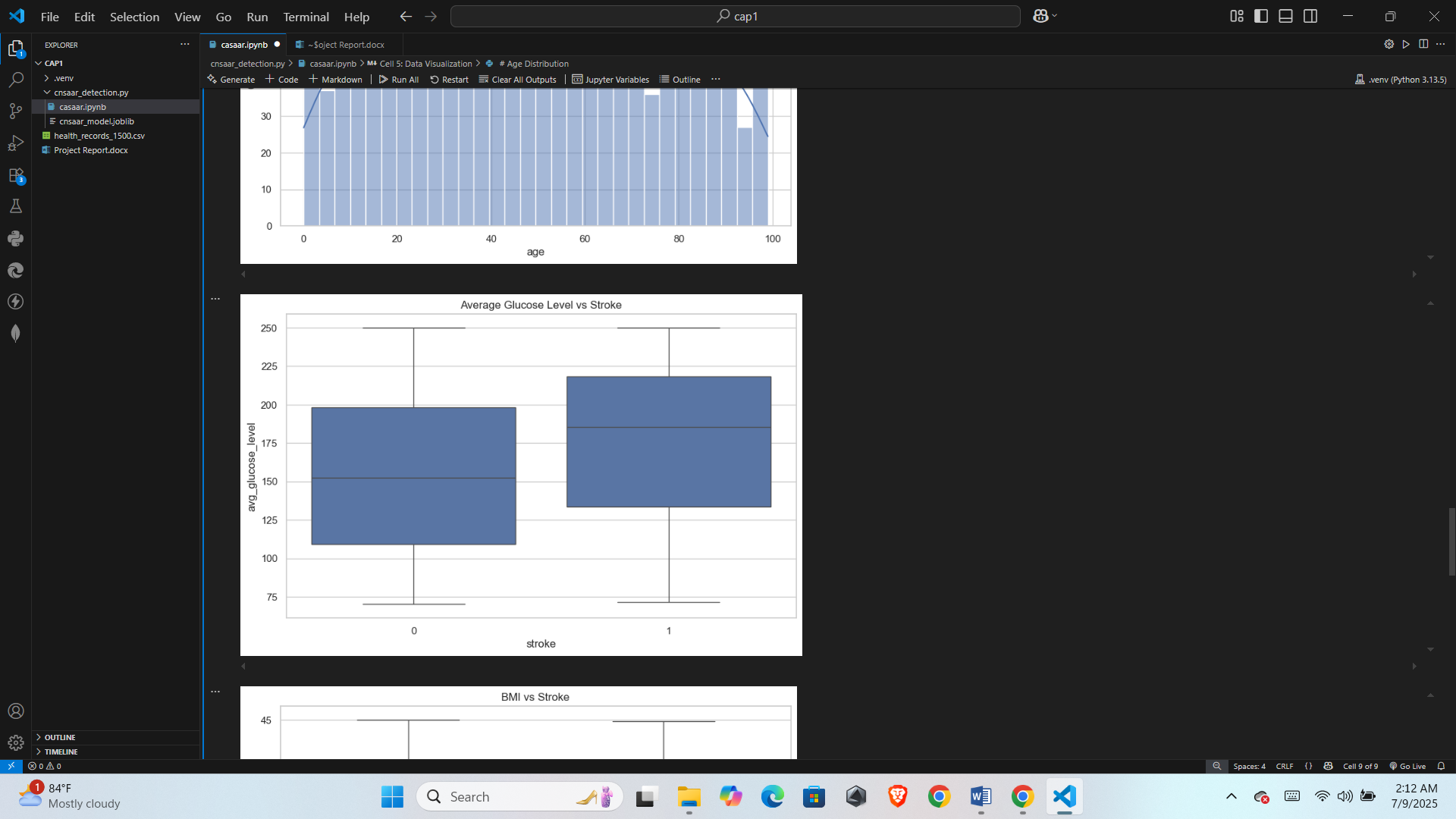
plt.show()

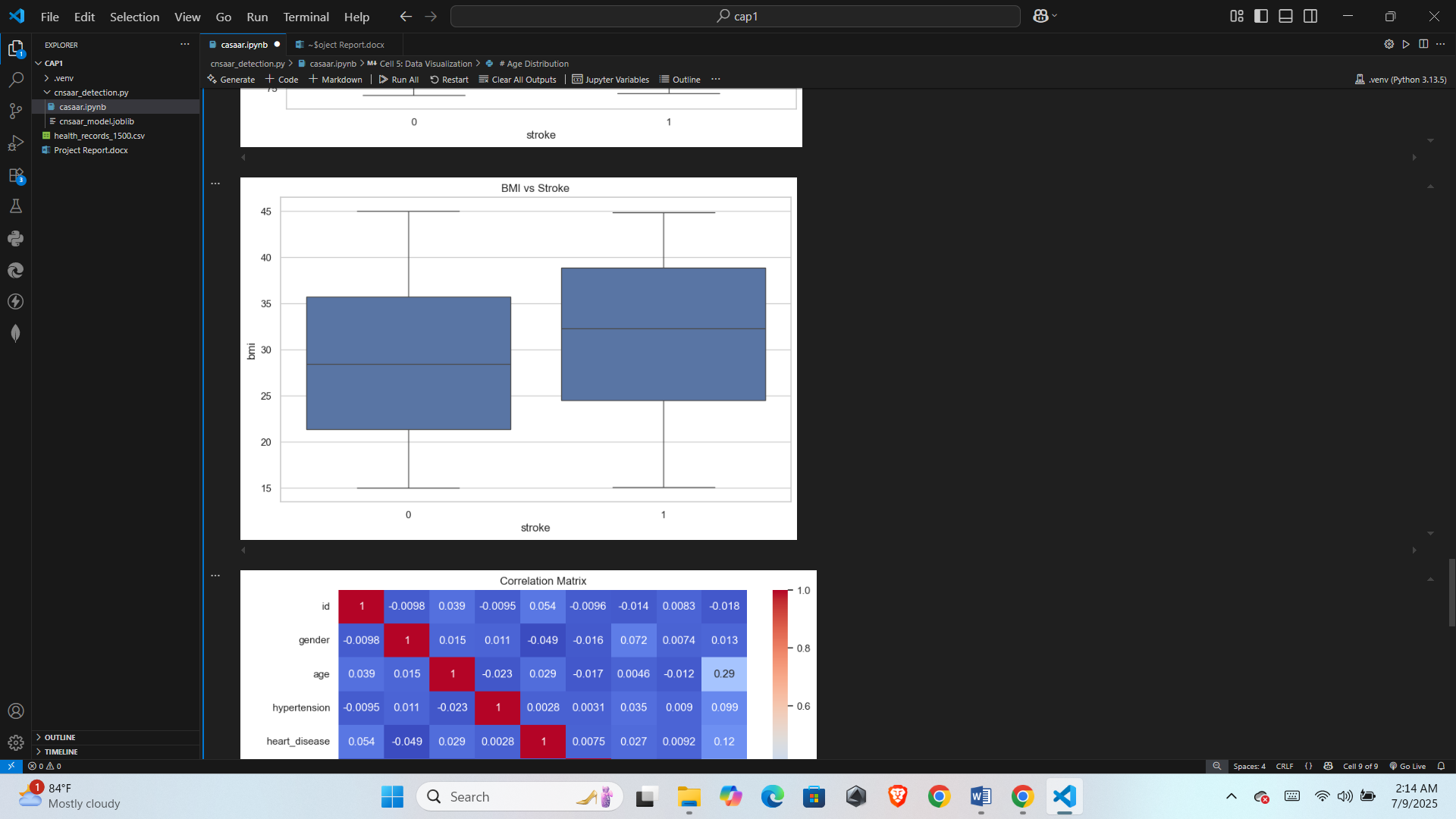
**Additional Screenshots and Outputs**: 

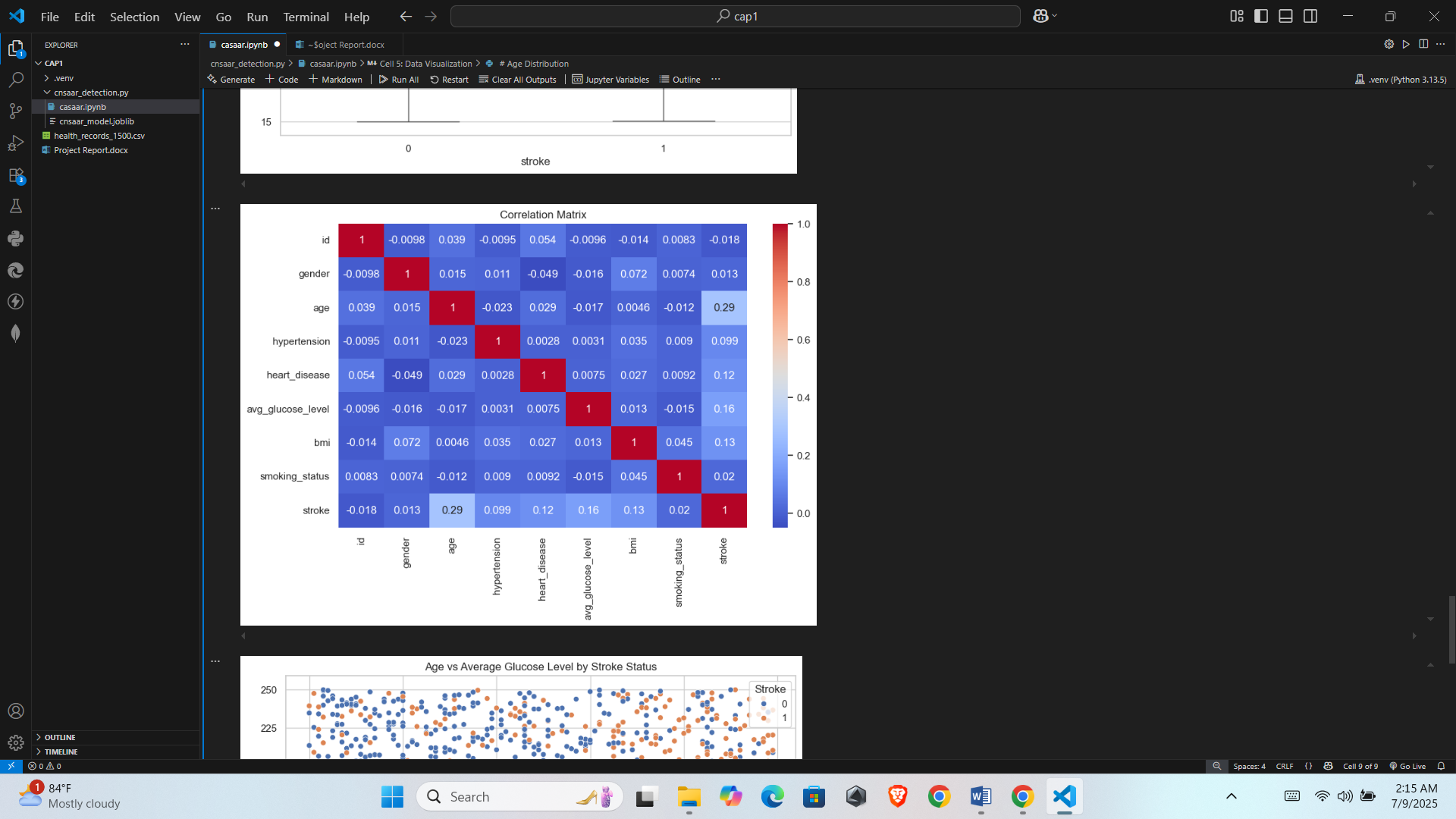


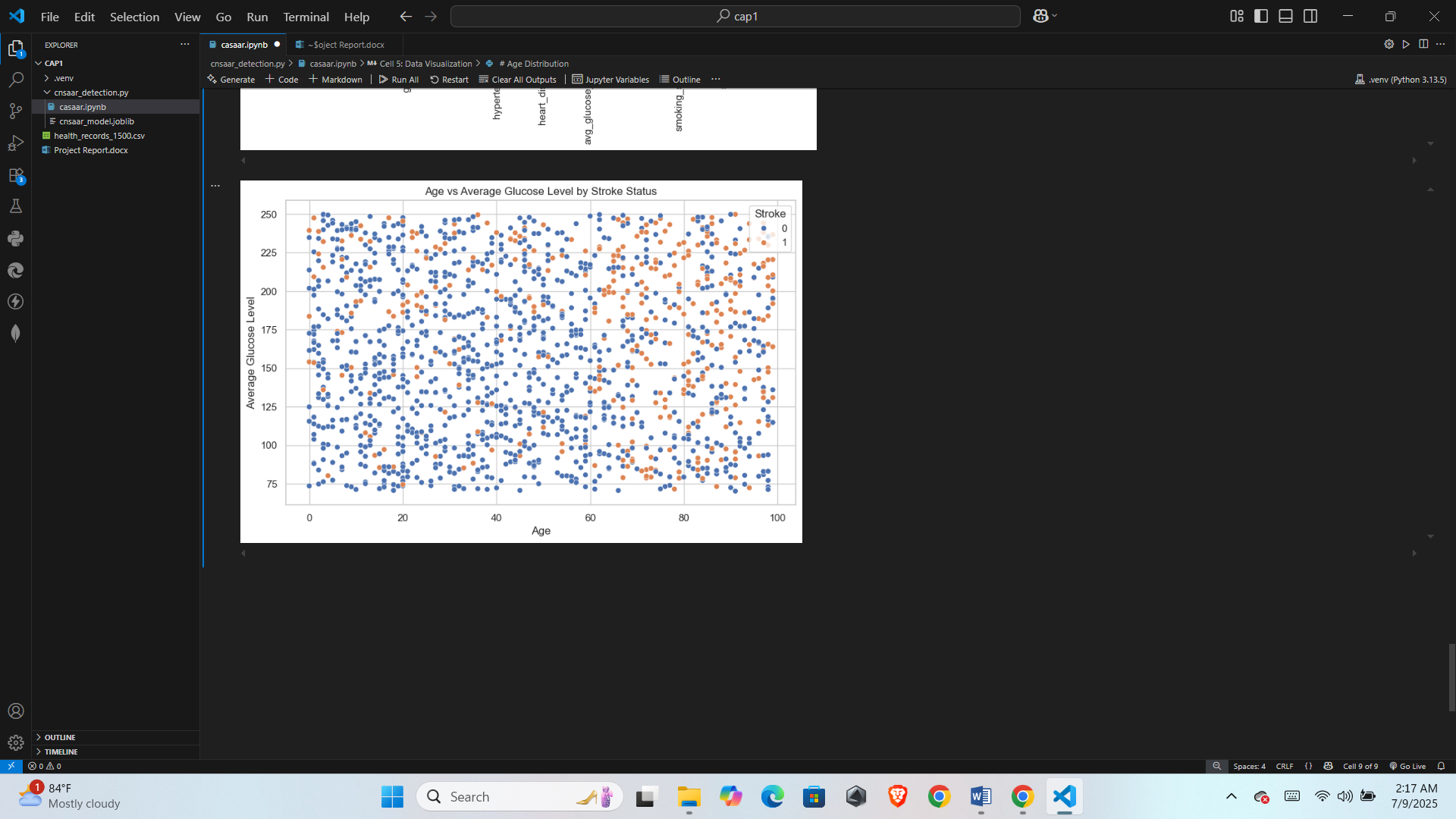












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