1 INTRODUCTION

1.1 ABOUT PROJECT

A brain comprises 100 billion and a trillion neurons and glia, respectively, wrapped into more than three pounds of tissue, which contains every memory and encodes and stores them in a network. Brain activity supports each and every individual’s breath and movement. The number of people who lose their life due to stroke is ten times greater in developing countries for more than the past five decades (i.e., from 1970), and it is projected to double globally by 2030. Generally, Stroke is classified into the following three types: ischemic stroke(IS), hemorrhagic stroke (HE), and transient ischemic attack (TIA). Ischemic stroke is the most common type of stroke. The American Heart Association (AHA) has predicted that 87% of strokes are ischemic stroke, which occur if a clot or an obstacle persist in a blood vessel of the brain. Ischemic stroke has two categories: embolic stroke and thrombotic stroke.Embolic stroke occurs if a block/clot forms in any part of the body and moves toward the brain and blocks blood flow. Thrombotic stroke is due to a clot that weakens blood flow in anartery, which carries blood to the brain. Hemorrhagic stroke occurs from a split/burst of weakened blood vessels. Only 10–15% of strokes are predicted to be a hemorrhagic stroke, but the rate of mortality is high when compared with ischemic stroke.

Hemorrhagic stroke is classified into two types: subarachnoid hemorrhage and intracerebral hemorrhage. Transient ischemic attack is described as a ‘‘mini-stroke’’, which is due to a clot. TIA is a temporary blockage relative to other types of strokes, and it lasts only for a short period of time (an average of 1 min), and symptoms disappear within 24 h. TIA does not cause permanent injury to the brain or its tissues. However, TIA is taken as a warning for the occurrence of an additional stroke in the near future. Stroke, irrespective of the type, is mostly considered to be a fatal disease. This study focuses on developing methodologies to extract the base form of the text from the patient’s case summaries or medical records, to retrieve the root word or stem from the base form through stemmers and to classify the type ofstroke as ischemic and hemorrhagic stroke (based on their common symptoms) from the retrieved root words. Beyond all these detections, stroke patients are always in need of intensive care, which can be provided by an interdisciplinary team.

1.2 Domain Description

Health is considered as an essential aspect of everyone’s life, and there is a need for a recording system which tracks data on diseases and the relationship between them. Most of the information pertaining to diseases could be found in the case summaries of patients, medical records found in clinics and other records that are maintained manually. The sentences in themcould be deciphered through various methodologies of text mining and machine learning (ML). Machine learning is a tool which can disseminate the content as a part of information retrieval in which semantic and syntactic parts of the content are given prevalence. Various ML and text mining methodologies are proposed and implemented for feature extraction and classification. Stroke is a term used by most of the healthcare practitioners to describe injuries in the brain and spinal cord resulting from abnormalities in the supply of blood. Stroke projects its meaning based on different perspectives; however, globally, stroke evokes an explicit visceral response. Machine learning can be portrayed as a significant tracker in areas like surveillance, medicine, data management with the aid of suitably trained machine learning algorithms. Data mining techniques applied in this work give an overall review about the tracking of information with respect to semantic as well as syntactic perspectives. The proposed idea is to mine patient's symptoms from the case sheets and train the system with the acquired data. Next, the case sheets were mined using tagging and maximum entropy methodologies, and the proposed stemmer extracts the common and unique set of attributes to detects the stroke disease. Then, the processed data were fed into various machine learning algorithms such as, Decision tree, Logistic Regression, K-Nearest Neighbors, Random Forest, Support vector machine. Among these algorithms, Support Vector Machine achieves high accuracy.

2 PROPOSED SYSTEM

2.1 Problem Statement

Stroke is the second leading cause of death worldwide and remains an important health burden. Every 4 minutes someone dies of stroke, but up to 80% of stroke can be prevented if we can identify or predict the occurrence of stroke in its early stage.

2.2 Problem Description

In the medical field, brain stroke is detected by using deep learning technique which is very time consuming and do not produce accurate results. Therefore, to overcome this problem, an alternative way is to design the system that will automatically identify the presence of brain stroke by using health condition of a person using algorithms in machine learning techniques, which also provides faster and accurate solutions which is very useful to save life's.

2.3 Proposed System

In this proposed system, we are using different machine learning algorithms are Decision tree, Logistic Regression, K-Nearest Neighbors, Random Forest, Support vector machine. In our proposed system we test these many algorithms with each other and select maximum accuracy model. Based on the accuracy score we will select the best model for our dataset. This section will describe the detailed description of the proposed work done for the detection of Brain Stroke.

2.4 Advantages of Proposed System

- It takes less time to compute results.
- It will deal with a large size of data where existing system can't.
- More flexible compared to existing system.

BLOCK DIAGRAM

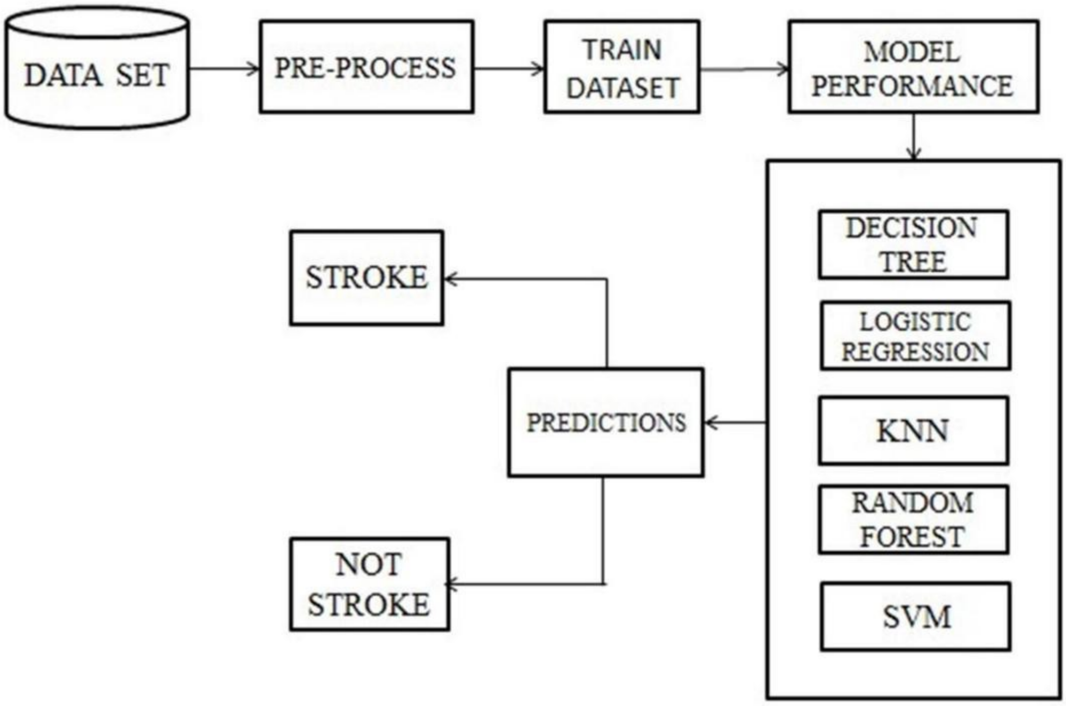

Fig :- Block diagram of brain stroke detection

DATA SET

A data set is a collection of data. In the case of tabular data, a data set corresponds to one or more database tables, where every column of a table represents a particular variable, and each row corresponds to a given record of the data set in question. The data set lists values for each of the variables, such as gender, age and bmi of the person. Data sets can also consist of a collection of documents or files.

The stroke prediction dataset was used to perform the study. There were 5110 rows and 12 columns in this dataset. The value of the output column stroke is either 1 or

0. The number 0 indicates that no stroke risk was identified, while the value 1 indicates that a stroke risk was detected. The probability of 0 in the output column (stroke) exceeds the possibility of 1 in the same column in this dataset. 249 rows alone in the stroke column have the value 1, whereas 4861 rows have the value 0. To improve accuracy, data preprocessing is used to balance the data. Figure 3.2 shows the total number of stroke and non-stroke records in the output column before preprocessing.

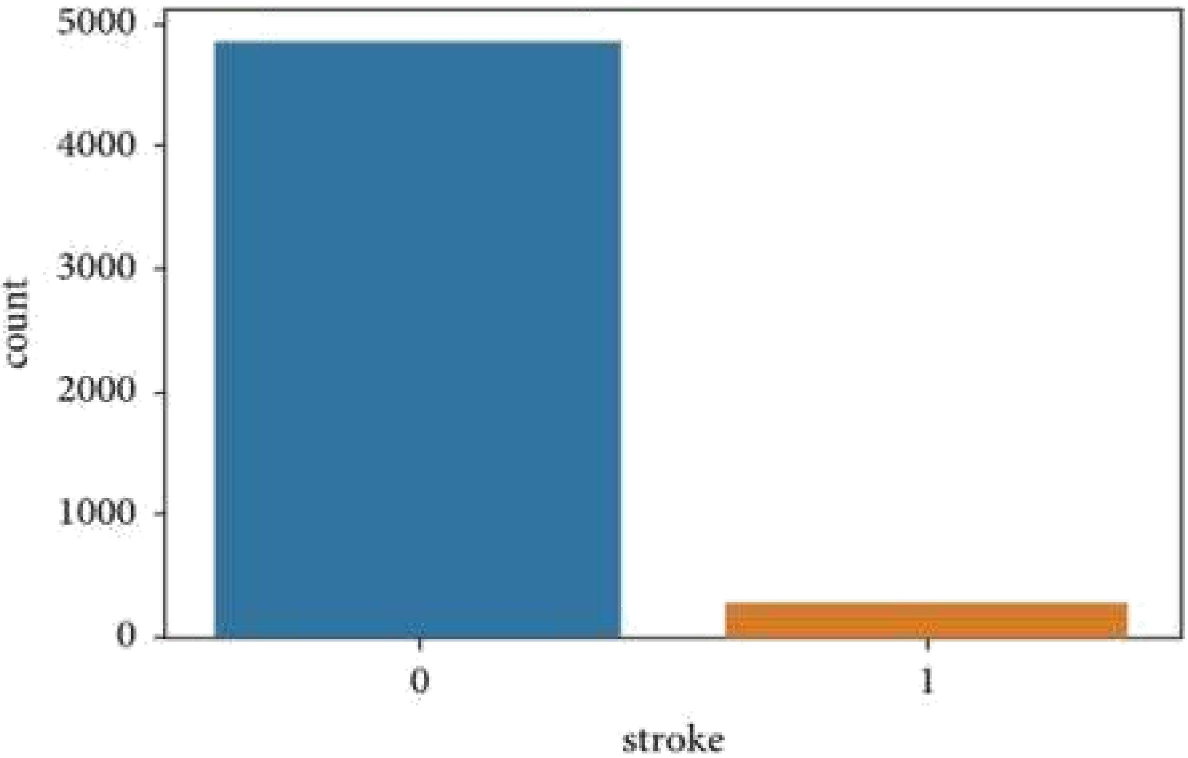

Fig :- Total number of stroke and normal data

Pre- Processing

Before building a model, data pre-processing is required to remove unwanted noise and outliers from the dataset that could lead the model to depart from its intended training. This stage addresses everything that prevents the model from functioning more efficiently. Following the collection of the relevant dataset, the data must be cleaned and prepared for model development. As stated before, the dataset used has twelve characteristics. To begin with, the column id is omitted since its presence has no bearing on model construction. The dataset is then inspected for null values and filled if any are detected. The null values in the column BMI are filled using the data column's mean in this case.

Label encoding converts the dataset's string literals to integer values that the computer can comprehend. As the computer is frequently trained on numbers, the strings must be converted to integers. The gathered dataset has five columns of the data type string. All strings are encoded during label encoding, and the whole dataset is transformed into a collection of numbers. The dataset used for stroke prediction is very imbalanced. The dataset has a total of 5110 rows, with 249 rows indicating the possibility of a stroke and 4861 rows confirming the lack of a stroke. While using such data to train a machine- level model may result in accuracy, other accuracy measures such as precision and recall are inadequate. If such an unbalanced data is not dealt with properly, the findings will be inaccurate, and the forecast will be ineffective. As a result, to obtain an efficient model, this unbalanced data must be dealt with first. The SMOTE technique was employed for this purpose. Figure 3.3 depicts the dataset's balance output column.

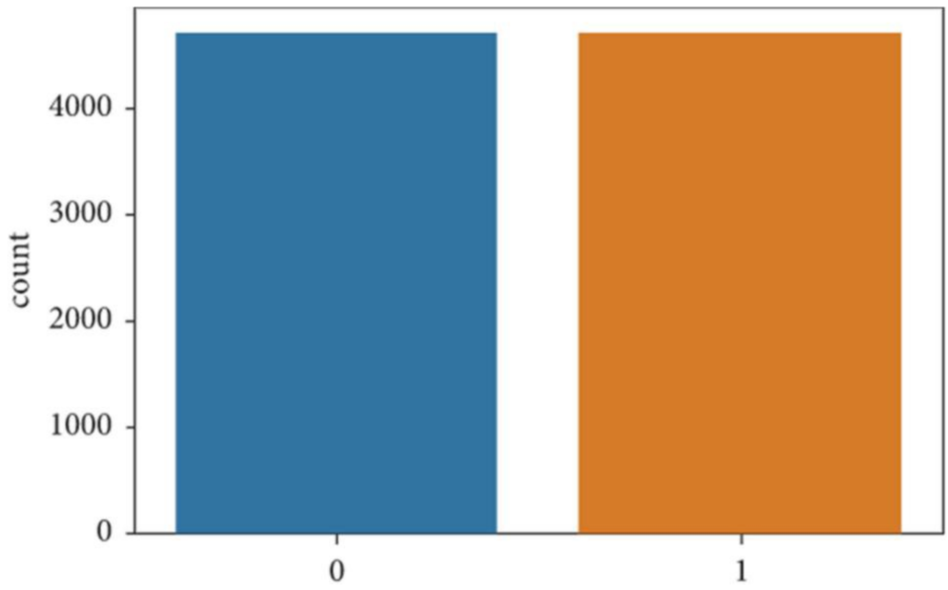

Fig :- Output columns after processing

Train Dataset

♦Training data (or a training dataset) is the initial data used to train machine learning models.

♦Training datasets are fed to machine learning algorithms to teach them how to make predictions or perform a desired task.

Decision Tree

♦Decision Tree is a Supervised learning technique that can be used for both classification

and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where internal nodes represent the features of a dataset, branches represent the decision rules and each leaf node represents the outcome.

♦In a Decision tree, there are two nodes, which are the Decision Node and Leaf Node.

Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.

♦The decisions or the test are performed on the basis of features of the given dataset.

♦It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.

⬩It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.

⬩In order to build a tree, we use the CART algorithm, which stands for Classification and Regression Tree algorithm.

⬩A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.

⬩Below diagram explains the general structure of a decision tree

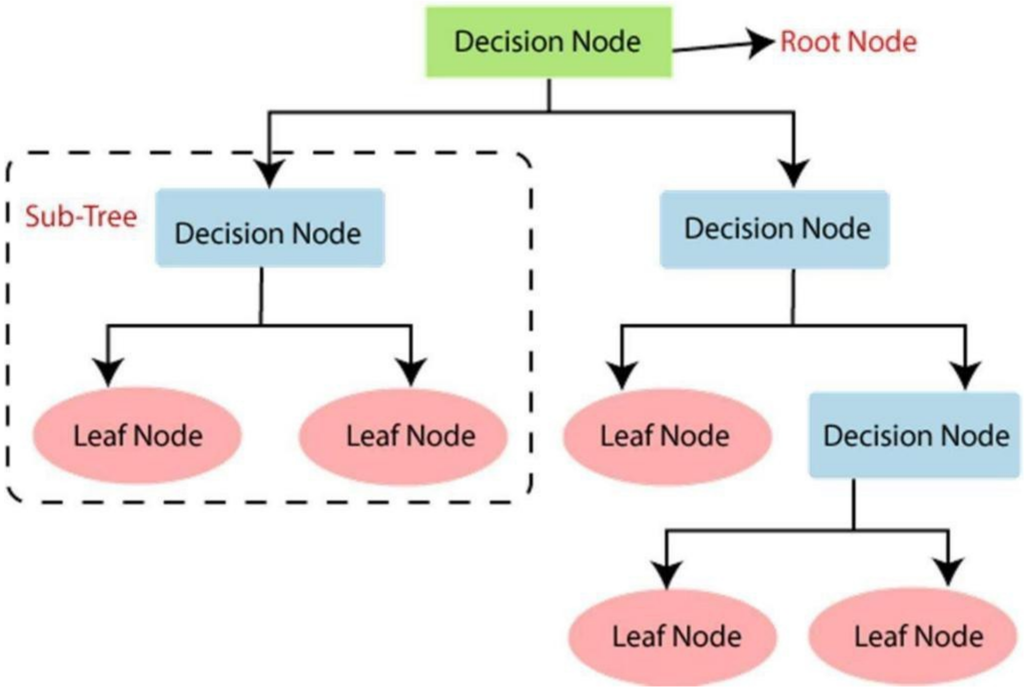

Fig :- Structure of decision tree

Random Forest

Random forest is a supervised learning algorithm which is used for both classification as well as regression. But however, it is mainly used for classification problems. As we knowthat a forest is made up of trees and more trees means more robust forest. Similarly, random forest algorithm creates decision trees on data samples and then gets the prediction from each of them and finally selects the best solution by means of voting. It is an ensemble method which is better than a single decision tree because it reduces the over-fitting by averaging the result.Working of Random Forest AlgorithmWe can understand the working of Random Forest algorithm with the help of following steps

1. First, start with the selection of random samples from a given dataset.
2. Next, this algorithm will construct a decision tree for every sample. Then it will getthe prediction result from every decision tree.
3. In this step, voting will be performed for every predicted result.
4. At last, select the most voted prediction result as the final prediction result.

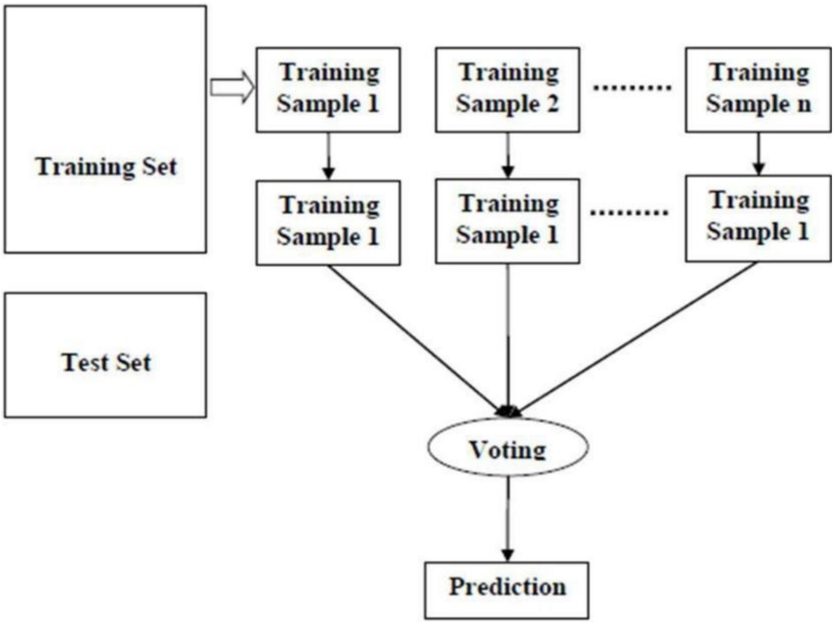

Fig :- Example of Random Forest

K-Nearest Neighbour (KNN)

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K-NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

The K-NN working can be explained on the basis of the below algorithm:

1. Select the number K of the neighbours
2. Calculate the Euclidean distance of K number of neighbors
3. Take the K nearest neighbors as per the calculated Euclidean distance.
4. Among these k neighbors, count the number of the data points in each category.

5. Assign the new data points to that category for which the number of the neighbor is maximum.
6. Our model is ready.

Suppose we have a new data point and we need to put it in the required category. Consider the below image:

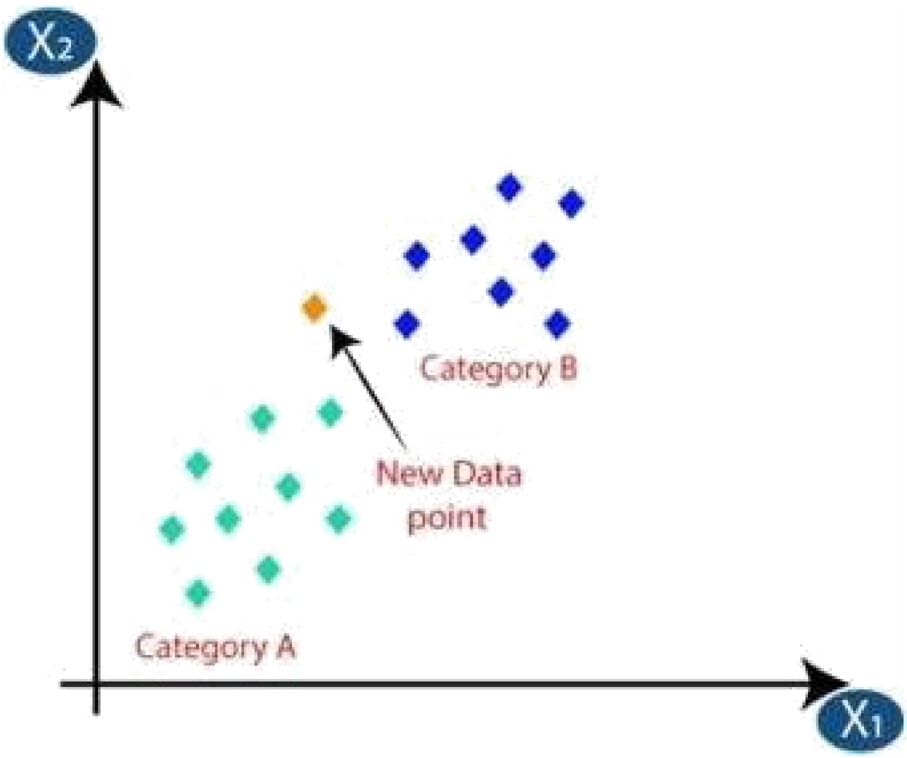

Fig :- Example of KNN

♦Firstly, we will choose the number of neighbors, so we will choose the k=5.

♦Next, we will calculate the Euclidean distance between the data points. The Euclidean distance is the distance between two points, which we have already studied in geometry. It can be calculated as:

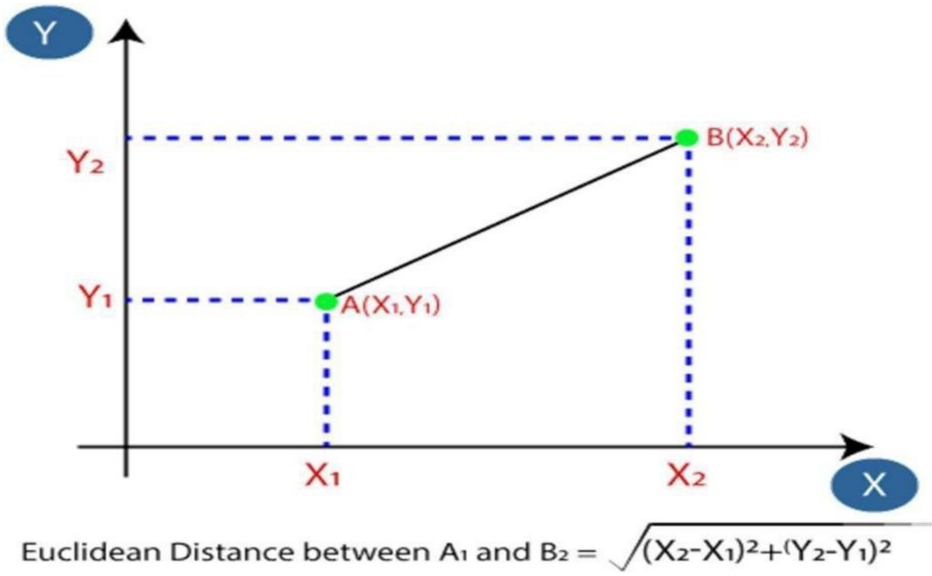

Fig :- Finding Euclidean distance

By calculating the Euclidean distance, we got the nearest neighbors, as three nearest neighbors in category A and two nearest neighbors in category B. Consider the below image:

Fig :- Finding near neighbors

• As we can see the 3 nearest neighbors are from category A, hence this new data point must belong to category A.

Logistic regression

Logistic regression is a Machine Learning classification algorithm that is used to predictthe probability of a categorical dependent variable. In logistic regression, the dependent variable is a binary variable that contains data coded as 1 (yes, success, etc.) or 0 (no, failure, etc.). In other words, the logistic regression model predicts P(Y=1) as a function of X.

Step 1: Logistic regression hypothesis

The logistic regression classifier can be derived by analogy to the logisticregressionthe functiong(z)is the logistic function also known as thesigmoid function. The logistic function has asymptotes at 0 and 1, and it crosses the y-axis at 0.5.

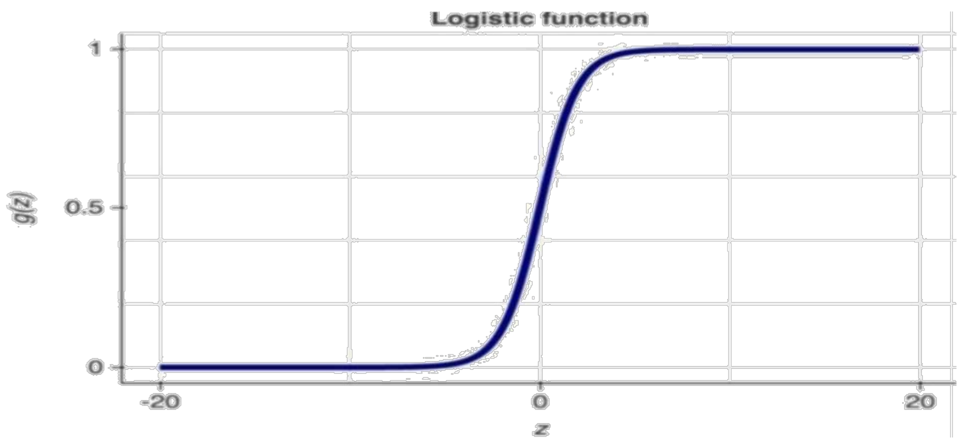

Fig :- Logistic regression hypothesis

Step 2: Logistic regression decision boundary

Since our data set has two features: height and weight, the logistic regression hypothesis is the following:

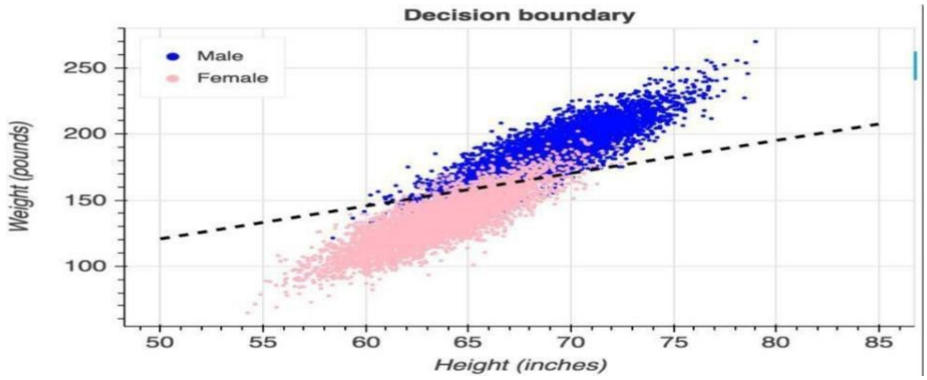

Fig :- Logistic regression decision boundary

Support Vector Machine

Support Vector Machine or SVM is one of the most popular Supervised Learning algorithms, which is used for Classification as well as Regression problems. However, primarily, it is used for Classification problems in Machine Learning.

The goal of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that we can easily put the new data point in the correct category in the future. This best decision boundary is called a hyperplane. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector

Machine. Consider the below diagram in which there are two different categories that are classified using a decision boundary or hyperplane:

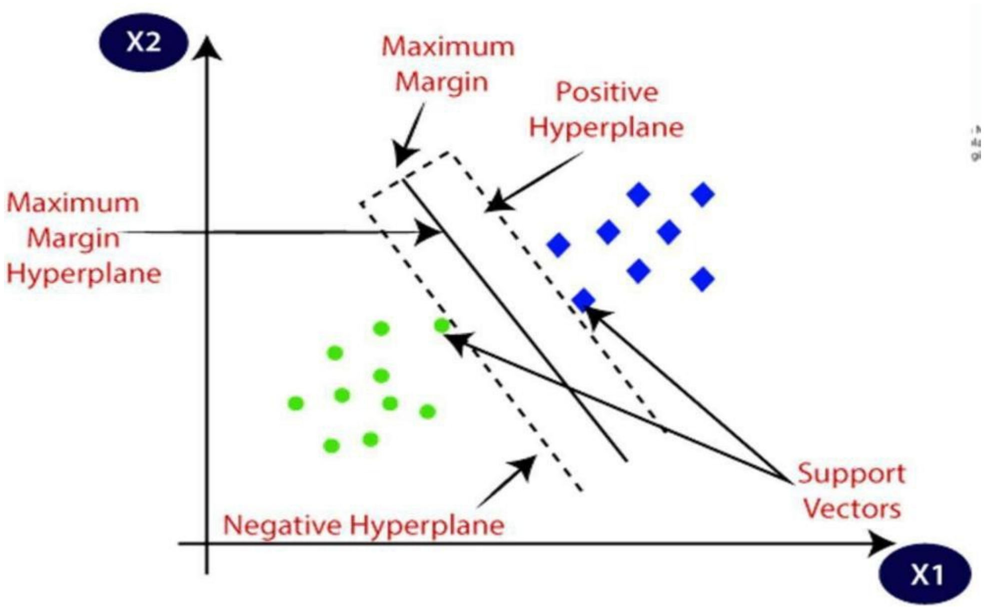

Fig:- Boundaries of SVM

Example:SVM can be understood with the example that we have used in the KNN classifier. Suppose we see a strange cat that also has some features of dogs, so if we want a model that can accurately identify whether it is a cat or dog, so such a model can be created by using the SVM algorithm. We will first train our model with lots of images of cats and dogs so that it can learn about different features of cats and dogs, and then we test it with this strange creature. So as support vector creates a decision boundary between these two data (cat and dog) and choose extreme cases (support vectors), it will see the extreme case of cat and dog. On the basis of the support vectors, it will classify it as a cat. Consider the below diagram:

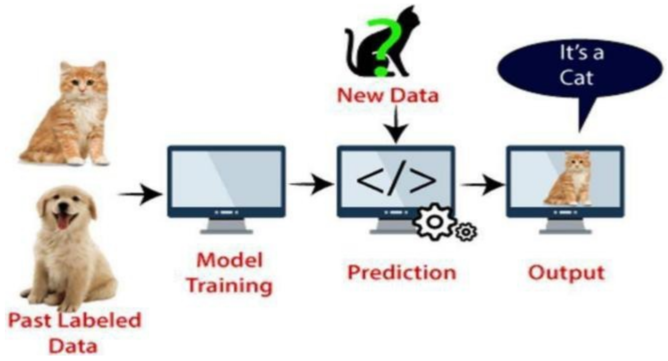

Fig:- Example of SVM

Steps for executing the Project :-

1. Install the required packages
2. Load the datasets.
3. Pre-process the data.
4. Split the dataset into train and test.
5. Use the train dataset to train the ml models.
6. Use the test data to test the model for prediction and accuracy generation.

3 HARDWARE REQUIREMENTS

3.1 Processor

For the most part, you'll get faster CPU performance from the Core i5 parts over Core i3. Some Core i5 processors are dual-core and some are quad-core. Most of the time, a true quad- core CPU will perform better than a dual-core processor, especially on multimedia tasks like video transcoding or photo editing. All Core i3 processor are dual core. Occasionally, you'll find an older Ivy Bridge processor like the Intel Core i3- 3130M in a system that's the same price as system with a newer Haswell CPU like the Intel Core i3-4012Y.

Fig :- Processor

3.2 Hard Disk

A computer's hard drive is a device consisting of several hard disks, read/write heads, a drive motor to spin the disks, and a small amount of circuitry, all sealed in a metal case to protect the disks from dust. In addition to referring to the disks themselves, the term hard disk is also used to refer to the whole of a computer's internal data storage. Beginning in the early 21st century, some personal computers and laptops were produced that used solid-state drives (SSDs) that relied on flash memory chips instead of hard disks to store information.

Fig :- Hard Disk

3.3 Ram

With 8 GB of RAM, you will have enough memory to run several programs at once. You can open lots of browser tabs at once, use photo or video editing programs, stream content, and play mid-to-high-end games.

Many Windows 10 and macOS computers or laptops come with 8 GB of memory installed these days. So, 8 GB of memory should be more than enough to run most productivity programs. It's also the minimum amount of memory recommended by Adobe to run Creative Cloud programs like Photoshop.

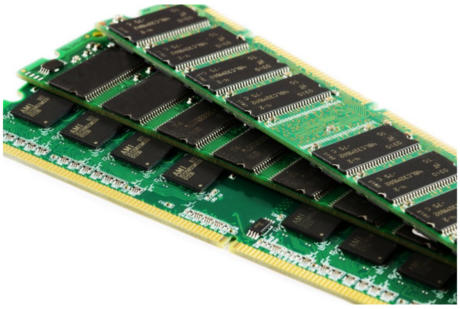

Fig :- Ram

3.4 Monitor

A computer monitor is an output device that displays information in pictorial or text form. A monitor usually comprises a visual display, some circuitry, a casing, and a power supply. The display device in modern monitors is typically a thin film transistor liquid crystal display (TFT-LCD) with LED backlighting having replaced cold-cathode fluorescent lamp (CCFL) backlighting. Previous monitors used a cathode ray tube (CRT) and some Plasma (also called Gas-Plasma) displays. Monitors are connected to the computer via VGA, HDMI, DisplayPort, USB-C, low-voltage differential signaling (LVDS) or other proprietary connectors and signals.

Fig :- Monitor

3.5 BP Machine

A BP (Blood Pressure) machine, also known as a sphygmomanometer, is a device used to measure blood pressure. It usually consists of an inflatable cuff, a pressure gauge, and a stethoscope (in manual models). Here's how it works:

1. Inflation: The cuff is wrapped around the upper arm and inflated to temporarily stop the blood flow in the artery.
2. Deflation: The cuff is slowly deflated, and as the pressure decreases, the device measures the blood flow in the artery.
3. Measurement: The blood pressure is recorded in two numbers:
    - Systolic Pressure: The higher number, indicating the pressure in the arteries when the heart beats.
    - Diastolic Pressure: The lower number, indicating the pressure in the arteries when the heart rests between beats.

Blood Pressure Chart by Age

Age	Min Systolic/Diastolic	Normal Systolic/Diastolic	Max Systolic/Diastolic
1 to 12 months	75 / 50	90 / 60	100 / 75
1 to 5 years	80 / 55	95 / 65	110 / 79
6 to 13 years	90 / 60	105 / 70	115 / 80
14 to 19 years	105 / 73	117 / 77	120 / 81
20 to 24 years	108 / 75	120 / 79	132 / 83
25 to 29 years	109 / 76	121 / 80	133 / 84
30 to 34 years	110 / 77	122 / 81	134 / 85
35 to 39 years	111 / 78	123 / 82	135 / 86
40 to 44 years	112 / 79	125 / 83	137 / 87
45 to 49 years	115 / 80	127 / 84	139 / 88
50 to 54 years	116 / 81	129 / 85	142 / 89
55 to 59 years	118 / 82	131 / 86	144 / 90
60 to 64 years	121 / 83	134 / 87	147 / 91

Fig :- Glucose Machine

3.6 Glucose Monitor

A glucose monitor, also known as a glucose meter or blood glucose meter, is a device used to measure the concentration of glucose in the blood. It’s primarily used by people with diabetes to monitor their blood sugar levels and manage their condition

Glucose is a simple sugar and a crucial source of energy for the body's cells. It’s a type of carbohydrate that plays a significant role in metabolism

Blood Glucose Chart			
Mg/DL	Fasting	After Eating	2-3 Hours After Eating
Normal	80-100	170-200	120-140
Impaired Glucose	101-125	190-230	140-160
Diabetic	126+	220-300	200+

Fig :- Glucose Monitor

3.7 Glucose Strips

Glucose test strips are an essential component of glucose monitoring systems used to measure blood glucose levels. They work in conjunction with a glucose meter to provide readings of blood sugar levels.

Fig :- Glucose Strips

4 SOFTWARE DESCRIPTION

Operating System	: Windows 7/8/10
Server side	: Python
Script IDE	: PyCharm, Anakonda
Libraries Used	: SKlearn, pandas, numpy, Matplotlib, Collections
Technology	: Python 3.6
Front End	: HTML
Dataset	: Kaggle

4.1 HTML:-

The HyperText Markup Language or HTML is the standard markup language for documents designed to be displayed in a web browser. It can be assisted by technologies such as Cascading Style Sheets (CSS) and scripting languages such as JavaScript.Webbrowsers receive HTML documents from a web server or from local storage and render the documents into multimedia web pages. HTML describes the structure of a web page semantically and originally included cues for the appearance of the document.

HTML elements are the building blocks of HTML pages. With HTML constructs, images and other objects such as interactive forms may be embedded into the rendered page. HTML provides a means to create structured documents by denoting structural semantics for text such as headings, paragraphs, lists, links, quotes and other items. HTML elements are delineated bytags, written using angle brackets. Tags such as <img /> and <input/>directly introduce content into the page. Other tags such as surround <p> and provide information about document text and may include other tags as sub- elements. Browsers do not display the HTML tags but use them to interpret the content of the page.

HTML can embed programs written in a scripting language such as JavaScript, which affects the behaviour and content of web pages. Inclusion of CSS defines the look and layout of content. The World Wide Web Consortium (W3C), former maintainer of the HTML and current maintainer of the CSS standards, has encouraged the use of CSS over explicit presentational HTML since 1997.[2] A form of HTML, known as HTML5, is used to display video and audio, primarily using the <canvas> element, in collaboration with javascript.

4.2 PYTHON:-

Python is a general purpose, dynamic, high level and interpreted programming language. It supports Object Oriented programming approach to develop applications. It is simple and easy to learn and provides lots of high-level data structures. It is easy to learn yet powerful and versatile scripting language which makes it attractive for Application Development. It's syntax and dynamic typing with its interpreted nature, makes it an ideal language for scripting and rapid application development. It supports multiple programming patterns, including object oriented, imperative and functional or procedural programming styles. It is not intended to work on special area such as web programming. That is why it is known as multipurpose because it can be used with web, enterprise, 3D CAD etc. We don't need to use data types to declare variable because it is dynamically typed so we can write a=10to assign an integer value in an integer variable. It makes the development and debugging fast because there is no compilation step included in python development and edit-test-debug cycle is very fast

5 SOURCE CODE

HTML CODE:-

```
<!DOCTYPE html>
<html>

<head>
    <meta charset="UTF-8">
    <!-- Bootstrap CSS -->
        <link rel="stylesheet" href="https://stackpath.bootstrapcdn.com/bootstrap/4.3.1/css/bootstrap.min.css"
integrity="sha384-ggOyR0iXCbMQv3Xipma34MD+dH/1fQ784/j6cY/iJTQUOhcWr7x9JvoRxT2MZw1T"
crossorigin="anonymous">
    <title>Stroke Prediction</title>
    <style>
        /*just bg and body style*/
        body {
            margin: 40px;
            background-color: #808080;
            background-image: linear-gradient(315deg, #B993D6 19%, #8CA6DB 85%);
        }

        .container {
            border-radius: 5px;
            text-align: center;
        }

        .btn-container {
            background: #cdb4db;
            box-shadow: 0 19px 38px rgba(0, 0, 0, 0.30), 0 15px 12px rgba(0, 0, 0, 0.22);
```

```
        border-radius: 5px;
        padding: 10px;
    }

    .head {
        font-weight: bolder;
    }

    .btn-primary {
        color: #ffffff;
        text-shadow: 0 -1px 0 rgba(0, 0, 0, 0.25);
        background-color: #073b4c !important;
        border-color: #023047 !important;
        padding: 10px;
        margin-top: 15px;
    }

    label {
        width: 50%;
    }

    #predict {
        display: none;
    }

    .form-group {
        padding: 2px;
    }

    .form-select {
        padding: 5px;
        border-radius: 5px;
        border: 0px;
        width: 200px;
    }

     .prediction {
        background: #073b4c;
        color: aliceblue;
    }

</style>
<!--Font Awesome-->
<script src="https://kit.fontawesome.com/a076d05399.js"></script>
    <link rel="stylesheet" href="https://stackpath.bootstrapcdn.com/font-awesome/4.7.0/css/font-awesome.min.css" integrity="sha384-wvfXpqpZZVQGK6TAh5PVlGOfQNHSoD2xbE+QkPxCAFlNEevoEH3Sl0sibVcOQVnN" crossorigin="anonymous">
```

```html
    <script src="https://ajax.googleapis.com/ajax/libs/jquery/3.5.1/jquery.min.js"></script>
    <!-- jQuery first, then Popper.js, then Bootstrap JS -->
        <script src="https://cdnjs.cloudflare.com/ajax/libs/jquery/3.5.1/jquery.min.js" integrity="sha512-bLT0Qm9VnAYZDflyKcBaQ2gg0hSYNQrJ8RilYldYQ1FxQYoCLtUjuuRuZo+fjqhx/qtq/
1itJ0C2ejDxltZVFg==" crossorigin="anonymous"></script>
        <script src="https://code.jquery.com/jquery-3.5.1.slim.min.js" integrity="sha384-DfXdz2htPH0lsSSs5nCTpuj/zy4C+OGpamoFVy38MVBnE+IbbVYUew+OrCXaRkfj"
crossorigin="anonymous"></script>
        <script src="https://cdn.jsdelivr.net/npm/popper.js@1.16.0/dist/umd/popper.min.js" integrity="sha384-Q6E9RHvbIyZFJoft+2mJbHaEWldlvI9IOYy5n3zV9zzTtmI3UksdQRVvoxMfooAo"
crossorigin="anonymous"></script>
        <script src="https://stackpath.bootstrapcdn.com/bootstrap/4.5.0/js/bootstrap.min.js" integrity="sha384-OgVRvuATP1z7JjHLkuOU7Xw704+h835Lr+6QL9UvYjZE3Ipu6Tp75j7Bh/kR0JKI"
crossorigin="anonymous"></script>
</head>

<body>
    <div class="container">
        <div class="row">
            <div class="col-md-12">
                <h1 class="head">Stroke Prediction</h1>
            </div>
        </div>
        <div class="row">
            <div class="col-md-12">
                <div class="btn-container">

                    <!-- Main Input For Receiving Query to our ML -->
                    <form action="{{ url_for('predict')}}" method="post" class="form-inline">
                        <div class="row">
                            <div class="col-md-6">
                                <img class="image" src="{{ url_for('static', filename='image3.jpg')}}" width="100%"
height="100%" />
                            </div>
                            <div class="col-md-6">
                                <div class="container">
                                    <h4>Enter Details</h4>
                                    <div class="form-group">
                                        <label for="gender">Gender </label>
                                        <select class="form-select" id="gender" name="gender" aria-label="Default select
example" >
                                            <option value="1">Male</option>
                                            <option value="0">Female</option>
                                        </select>
                                    </div>
                                    <div class="form-group">
                                        <label for="age">Age</label>
```

```
                              <input type="number" class="form-control" name="age" required="required"
placeholder="Age" min=1 max=100/>
                        </div>
                        <div class="form-group">
                            <label for="hypertension">Hypertension</label>
                                <select class="form-select" id="hypertension" name="hypertension" aria-
label="Default select example">

                                <option value="1" selected>Yes</option>
                                <option value="0">No</option>
                            </select>
                        </div>
                        <div class="form-group">
                            <label for="heart_disease">Heart Disease</label>
                            <select class="form-select" id="disease" name="disease" aria-label="Default select
example">

                                <option value="1" selected>Yes</option>
                                <option value="0">No</option>
                            </select>
                        </div>
                        <div class="form-group">
                            <label for="ever_married">Ever Married</label>
                                <select class="form-select" id="married" name="married" aria-label="Default
select example">

                                <option value="1" selected>Yes</option>
                                <option value="0">No</option>
                            </select>
                        </div>
                        <div class="form-group">
                            <label for="work_type">Work Type</label>
                                <select class="form-select" id="work" name="work" aria-label="Default select
example">

                                <option value="3" selected>Self-employed</option>
                                <option value="2">Private</option>
                                <option value="4">children</option>
                                <option value="0">Government Job</option>
                                <option value="1">Never_worked</option>
                            </select>
                        </div>
                        <div class="form-group">
                            <label for="residence_type">Residence Type</label>
                              <select class="form-select" id="residence" name="residence" aria-label="Default
select example">

                                <option value="1" selected>Urban</option>
```

```html
                    <option value="0">Rural</option>
                </select>
            </div>

            <div class="form-group">
                <label for="avg_glucose_level">Average Glucose Level</label>
                        <input type="text" class="form-control" name="avg_glucose_level"
required="required" placeholder="Average Glucose Level" />
            </div>
            <div class="form-group">
                <label for="bmi">BMI</label>
                    <input type="text" class="form-control" name="bmi" required="required"
placeholder="Body Mass Index (BMI)">
            </div>
            <div class="form-group">
                <label for="smoking">Smoking Status</label>
                    <select class="form-select" id="smoking" name="smoking" aria-label="Default
select example">
                     <option value="0">Unknown</option>
                    <option value="2" selected>Never smoked</option>
                    <option value="1">Formerly smoked</option>
                    <option value="3">Smokes</option>
                </select>
            </div>
            <button type="submit" class="btn btn-primary btn-lg">Predict</button>
          </div>
        </div>
      </div>
    </form>
    <br />
    <center>
      <h1 class="prediction">{{prediction_text}}</h1>
    </center>
    <br />
</body>

</html>
```

APP.PY(‘PYTHON CODE’)

```python
from flask.helpers import url_for
import numpy as np
import pandas as pd
from flask import Flask, request, render_template, redirect
import pickle

app = Flask(__name__)
model = pickle.load(open('model.pickle', 'rb'))
```

```
@app.route("/")
def home():
    return render_template('index.html')

@app.route('/result', methods=['GET', 'POST'])
def predict():
    if request.method == "POST":
        gender_Male = int(request.form['gender'])
        age = int(request.form['age'])
        hypertension_1 = int(request.form['hypertension'])
        heart_disease_1 = int(request.form['disease'])
        ever_married_Yes = int(request.form['married'])
        work = int(request.form['work'])
        Residence_type_Urban =int( request.form['residence'])
        avg_glucose_level = float(request.form['avg_glucose_level'])
        bmi = float(request.form['bmi'])
        smoking = int(request.form['smoking'])
        work_type_Never_worked=0
        work_type_Private=0
        work_type_Self_employed=0
        work_type_children=0
        if(work==1):
           work_type_Never_worked=1
        elif work==2:
            work_type_Private=1
        elif work==3:
            work_type_Self_employed=1
        elif work==4:
            work_type_children=1
        smoking_status_formerly_smoked=0
        smoking_status_never_smoked  =0
        smoking_status_smokes=0
        if smoking==1:
            smoking_status_formerly_smoked=1
        elif smoking==2:
            smoking_status_never_smoked          =1
        elif smoking==3:
            smoking_status_smokes=1

        input_features = [age      ,avg_glucose_level,    bmi      ,gender_Male,hypertension_1,
            heart_disease_1,ever_married_Yes,    work_type_Never_worked,    work_type_Private,
            work_type_Self_employed,    work_type_children    ,Residence_type_Urban,
            smoking_status_formerly_smoked,smoking_status_never_smoked  ,smoking_status_smokes]

        features_value = [np.array(input_features)]
        features_name = ['age'    ,'avg_glucose_level',   'bmi'     ,'gender_Male','hypertension_1',
            'heart_disease_1','ever_married_Yes','work_type_Never_worked',   'work_type_Private',    'work_type
```

```
_Self-employed',     'work_type_children'  ,'Residence_type_Urban',     'smoking_status_formerly
smoked','smoking_status_never smoked'     ,'smoking_status_smokes']

    df = pd.DataFrame(features_value, columns=features_name)
    print(df)
    prediction = model.predict(df)[0]
    print(prediction)
    if prediction == 1:
       return render_template('index.html', prediction_text='Patient has stroke risk')
    else:
         return render_template('index.html', prediction_text='Congratulations, patient does not have stroke
risk')

    # return render_template('index.html', prediction_text='Patient has {}'.format(df))


if __name__ == "__main__":
   app.run()
```

6 SNAPSHOTS

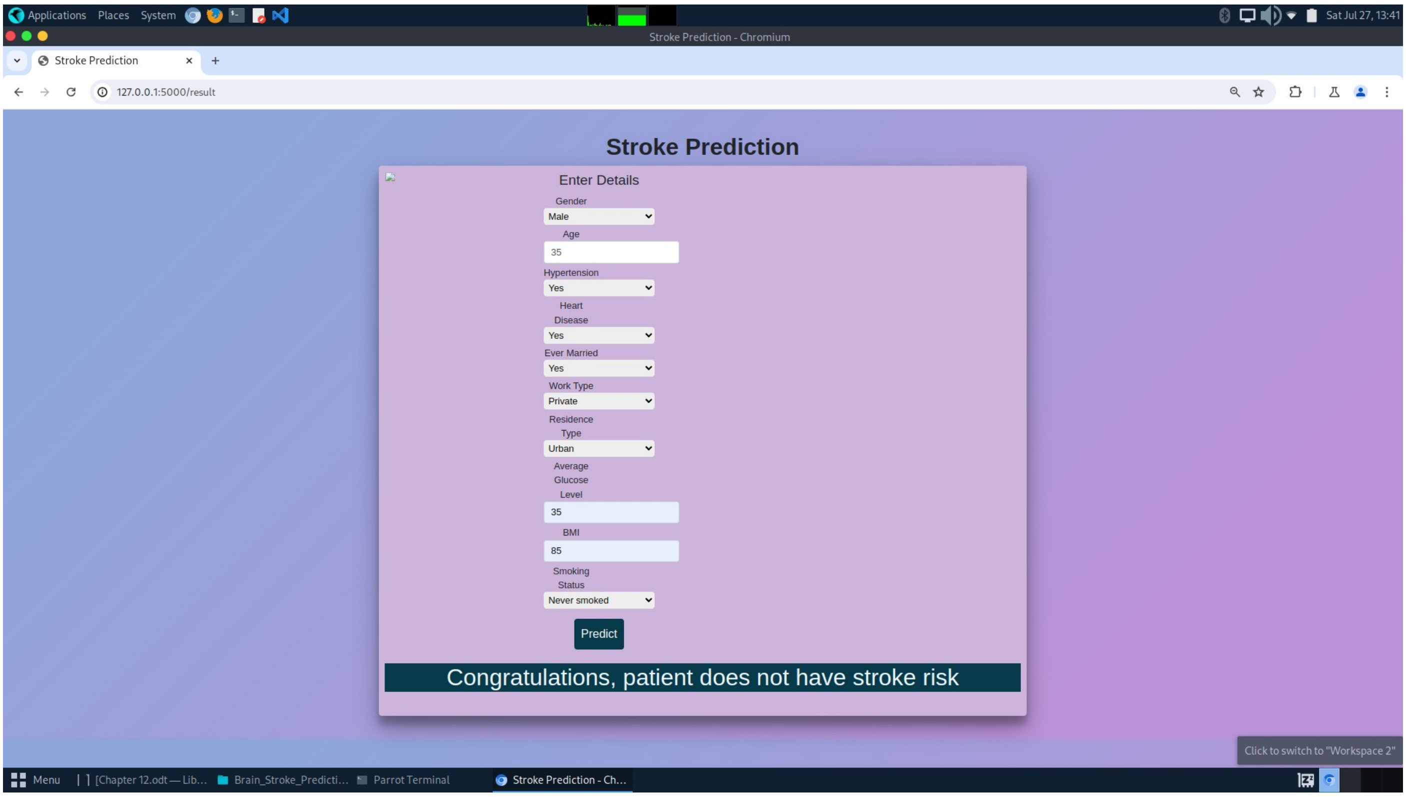

Fig1 :- If Patient has no risk

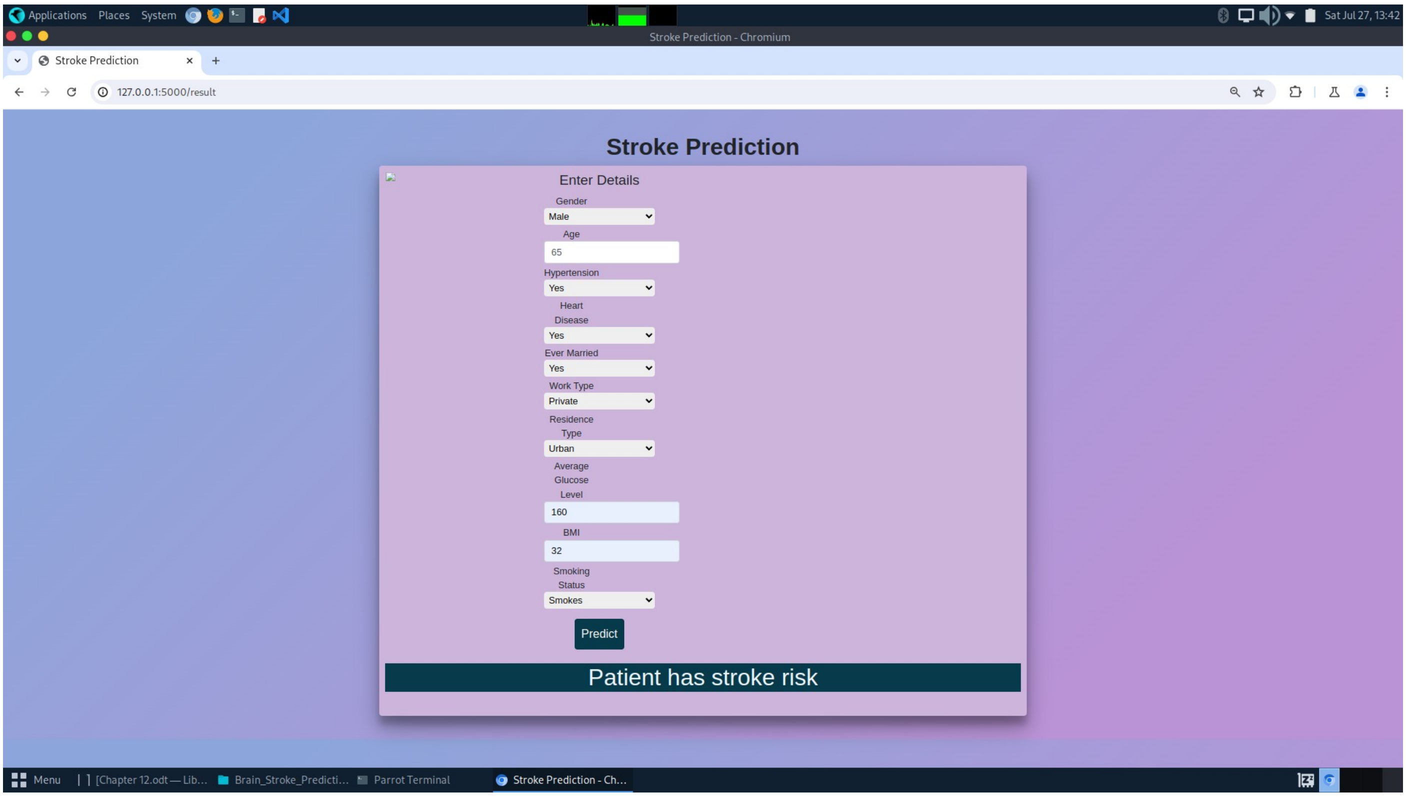

Fig2 :- If Patient has risk

7. CONCLUSION & REFERENCE

In this study, we explored the application of machine learning techniques for predicting brain strokes, aiming to enhance early detection and preventive measures. Our results demonstrate that machine learning models, particularly Random Forests and Gradient Boosting Machines, exhibit promising performance in predicting stroke risk with high accuracy. These models leverage a combination of demographic, clinical, and lifestyle features to provide robust predictions.

The key findings from our study include:

1. **Feature Importance**: The analysis highlighted that features such as age, hypertension, diabetes, and smoking status significantly contribute to stroke prediction. This aligns with existing medical literature, reinforcing the importance of these variables in assessing stroke risk.
2. **Model Performance**: Among the tested algorithms, Gradient Boosting Machines achieved the highest accuracy (AUC-ROC of 0.85), indicating its effectiveness in distinguishing between stroke and non-stroke cases. Random

Forests and Support Vector Machines also performed well, with AUC-ROCs of 0.82 and 0.78, respectively.

3. **Practical Implications**: The successful application of machine learning in stroke prediction suggests that these tools can be integrated into clinical practice to assist healthcare providers in identifying at-risk individuals. Early intervention strategies could potentially be developed based on these predictions, thereby reducing stroke incidence and improving patient outcomes.
4. **Limitations and Future Work**: Despite promising results, our study is limited by the availability of data and generalizability across diverse populations. Future research should focus on incorporating more diverse datasets and exploring deep learning approaches to further enhance predictive accuracy.

In summary, machine learning offers a valuable approach for stroke prediction, presenting opportunities for improving early diagnosis and prevention strategies. Continued research and development in this field could lead to significant advancements in stroke management.

References

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