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Artificial Intelligence Machine Learning Ischemic Stroke Prediction

Dr. Madhu B G [1], Ms. Sinchana J [2], Dr. Naveen Kumar B [3]. Mr. Srinath K S [4]
[1]*Department of Computer Science and Engineering Adichunchanagiri Institute of Technology*
[3]*Department of Information Science and Engineering Sahyadri College of Engineering and Management*
[2]*Philips innovation campus*
[4]*Department of Computer Science and Engineering Sahyadri college of Engineering and Management*

ABSTRACT:
Modern days food, work culture and stress increases the stroke attack on the human being Best case would be to prevent patients from having a stroke, or, at least, accelerate time-to-diagnosis and thus minimize the brain damage. If a stroke is diagnosed immediately, the patient may fully regain their mobility, self-care and social skills, progress sooner, or experience only a slight decline. But an inaccurate diagnosis may lead to dire consequences. Ischemic stroke is the most common type of this condition, and it is usually treated with tissue plasminogen activator (tPA) to dissolve the blood clots and restore the blood flow to the brain. However, this medication can be deadly to a patient with a Ischemic stroke, because it will increase the internal bleeding. In turn, a Ischemic stroke may require surgical intervention or coil insertion to stop the bleeding. Deciding on the stroke type can be challenging, but health specialists still need to figure it out quickly to save the patient’s life and functionality.
The current maturity level of artificial intelligence technology can unlock numerous opportunities for stroke care, from uncovering the underlying risks to develop stroke in certain patient groups to alerting health specialists about suspicious abnormalities on medical scans during triage.
Keywords: Semantics, K-Means Clustering, Index Library, Web Service Discovery.

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I. INTRODUCTION

Surviving a stroke is only a starting point of the patient’s fight for their full and independent life. The sooner a person receives adequate medical care, the more they can achieve during the rehabilitation, hopefully up to regaining their mobility and social skills completely. Artificial intelligence can support health specialists and provide them with actionable insights to accelerate diagnosis and ensure accurate medication and intervention decisions in the shortest possible time after the stroke onset. It can even help reduce the risk of developing the condition in some patients, eliciting subtle warning patterns and alerting the clinicians about the upcoming crisis.

Let us not forget about the FDA support. When the agency shows its dedication to technology, healthcare cannot resist. With AI becoming the approved approach for clinical decision support and showing huge potential in helping many patients avoid or survive a stroke with minimal decline in communicative and motor functions, we expect the tidal wave of similar solutions emerging on the market and becoming the standard of preventive and reactive stroke care.

Strokes can be life-threatening, so it is important to seek medical care immediately if symptoms appear. Ischemic stroke symptoms often affect one side of the body and develop quickly.

The American Stroke Association (ASA) recommend that people remember F.A.S.T. This stands for:

F = Face drooping: People may notice one side of the face drooping or feeling numb. Another person can check for this symptom by asking the person to smile or stick out their tongue.

If their smile is uneven, or their tongue moves to one side of the mouth instead of the middle, this could be a warning sign for ischemic stroke.

A = Arm weakness: Being unable to lift one arm or feeling weakness or numbness in one arm may suggest that an ischemic stroke is occurring.

S = Speech problems: These might include being unable to speak or repeat a sentence clearly.

T = Time to call 9-1-1: Contact emergency services immediately on noting the other indicators of ischemic stroke.

Beyond F.A.S.T., a stroke may also cause the following symptoms to develop suddenly: difficulty walking, dizziness, falling without an identifiable cause, a sudden inability to understand speech, confusion, rapidly developing vision problems, a severe headache without an apparent cause

Genetic Algorithms were very popular before NNs. Since, NNs required a lot of data, and GAs didn't. GAs were used mostly to simulate environments and behaviours of entities in a population. They were mostly used to learn the path to a problem which we knew the answer to.

II. METHODLOGY

Sl.no	Risk Factors	Percentage n=173 (%)
1.	Smoking	46 (26.6)
2.	Hypertension	37(21.4)
3.	Obesity/Being overweight	21(12.1)
4.	Alcohol overuse	20 (11.6)
5.	Diabetes	15 (8.7)
6.	Poor/unhealthy diet	14 (8.1)
7.	Cardiac disease	13 (7.5)
8.	Lack of exercise	13 (7.5)
9.	Heredity	12 (6.9)
10.	Chronic obstructive pulmonary disease	6 (3.5)
11.	Family History	35 (20.23
12.	Improper Breathing	72 (41.61)
13.	Gastric problem	51 (29.47)
14.	Execs consumption of Non Veg Food	58 (33.52)

Table: Ischemic Stroke Risk Factors

Best case would be to prevent patients from having a stroke, or, at least, accelerate time-to-diagnosis and thus minimize the brain damage. If a stroke is diagnosed immediately, the patient may fully regain their mobility, self-care and social skills, progress sooner, or experience only a slight decline But an inaccurate diagnosis may lead to dire consequences. Ischemic stroke is the most common type of this condition, and it is usually treated with tissue plasminogen activator (tPA) to dissolve the blood clots and restore the blood flow to the brain. However, this medication can be deadly to a patient with a hemorrhagic stroke, because it will increase the internal bleeding. In turn, a hemorrhagic stroke may require surgical intervention or coil insertion to stop the bleeding. Deciding on the stroke type can be challenging, but health specialists still need to figure it out quickly to save the patient's life and functionality.

The current maturity level of artificial intelligence technology can unlock numerous opportunities for stroke care, from uncovering the underlying risks to develop stroke in certain patient groups to alerting health specialists about suspicious abnormalities on medical scans during triage.

Whenever you perform classification, the first step is to understand the problem and identify potential features and label. Features are those characteristics or attributes which affect the results of the label. For example, in the case of a loan distribution, bank manager's identify customer's occupation, income, age, location, previous loan history, transaction history, and credit score. These characteristics are known as features which help the model classify customers.

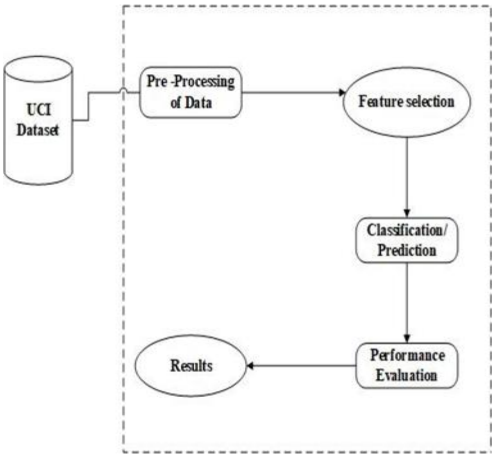
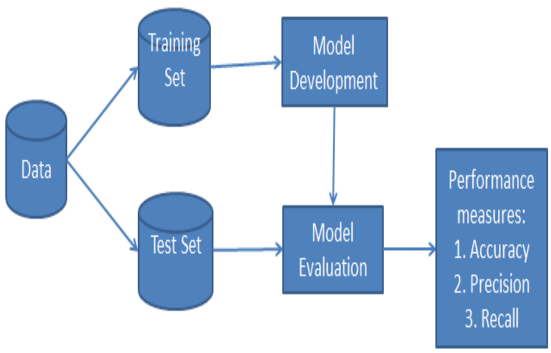


Figure: Experiment workflow with UCI dataset.

The classification has two phases, a learning phase, and the evaluation phase. In the learning phase, classifier trains its model on a given dataset and in the evaluation phase, it tests the classifier performance. Performance is evaluated on the basis of various parameters such as accuracy, error, precision, and recall.



Naive Bayes is a statistical classification technique based on Bayes Theorem. It is one of the simplest supervised learning algorithms. Naive Bayes classifier is the fast, accurate and reliable algorithm. Naive Bayes classifiers have high accuracy and speed on large datasets.

Naive Bayes classifier assumes that the effect of a particular feature in a class is independent of other features. For example, a loan applicant is desirable or not depending on his/her income, previous loan and transaction history, age, and location. Even if these features are interdependent, these features are still considered independently. This assumption simplifies computation, and that's why it is considered as naive. This assumption is called class conditional independence.

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)}$$

P(h): the probability of hypothesis h being true (regardless of the data). This is known as the prior probability of h.
P(D): the probability of the data (regardless of the hypothesis). This is known as the prior probability.
P(h|D): the probability of hypothesis h given the data D. This is known as posterior probability.
P(D|h): the probability of data d given that the hypothesis h was true. This is known as posterior probability.

How Naive Bayes classifier works?

Let's understand the working of Naive Bayes through an example. Given an example of weather conditions and playing sports. You need to calculate the probability of playing sports. Now, you need to classify whether players will play or not, based on the weather condition.

First Approach (In case of a single feature)

Naive Bayes classifier calculates the probability of an event in the following steps:
Step 1: Calculate the prior probability for given class labels
Step 2: Find Likelihood probability with each attribute for each class
Step 3: Put these value in Bayes Formula and calculate posterior probability.
Step 4: See which class has a higher probability, given the input belongs to the higher probability class.

Here, *gamma* ranges from 0 to 1. We need to manually specify it in the learning algorithm. A good default value of *gamma* is 0.1.

As we implemented SVM for linearly separable data, we can implement it in Python for the data that is not linearly separable. It can be done by using kernels.

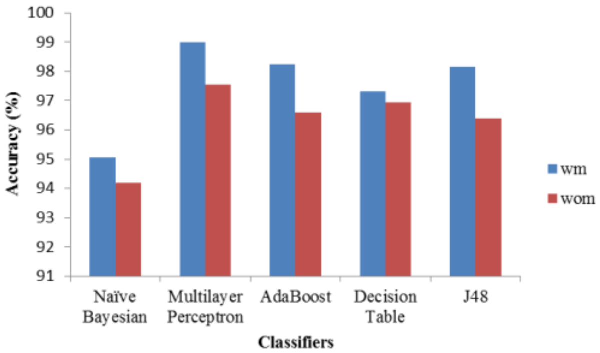
	Predicted HD patient (1)	Predicted healthy person (0)
Actual HD patient (1)	TP	FN
Actual healthy person (0)	FP	TN

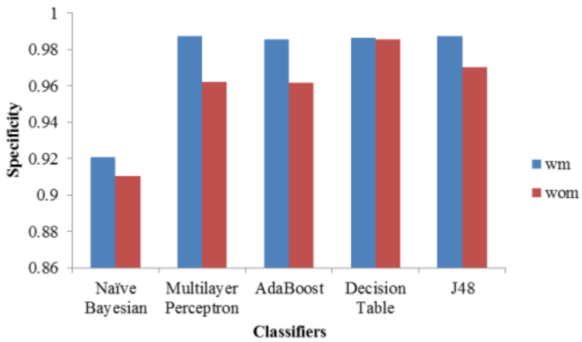
Table 2: Confusion matrix.

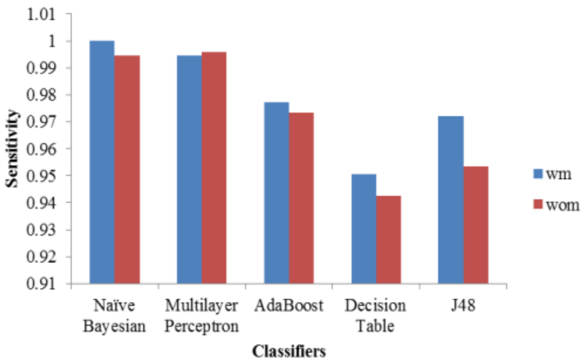
From confusion matrix, we compute the following:
TP: predicted output as true positive (TP), we concluded that the HD subject is correctly classified and subjects have heart disease.
TN: predicted output as true negative (TN), we concluded that a healthy subject is correctly classified and the subject is healthy.
FP: predicted output as false positive (FP), we concluded that a healthy subject is incorrectly classified that they do have heart disease (a type 1 error).
FN: predicted output as false negative (FN), we concluded that a heart disease is incorrectly classified that the subject does not have heart disease as the subject is healthy (a type 2 error). 1 shows that positive case means diseased, and 0 shows that a negative case means healthy
Classification accuracy: accuracy shows the overall performance of the classification system as follows:
classification accuracy =TP + TN /TP + TN + FP + FN × 100%
Classification error: it is the overall incorrect classification of the classification model which is calculated as follows: classification error = FP + FN /TP + TN + FP + FN × 100%
Sensitivity: it is the ratio of the recently classified heart patients to the total number of heart patients. 0e sensitivity of the classifier for detecting positive instances is known as "true positive rate." In other words, we can say that sensitivity (true positive fraction) confirms that if a diagnostic test is positive and the subject has the disease. It can be written as follows:
Sensitivity(Sn)/recall/true positive rate = (TP/ TP + FN) × 100%.
Specificity: a diagnostic test is negative and the person is healthy and is mathematically written as follows: specificity(Sp) =(TN /TN + FP) × 100%.
Precision: the equation of precision is given as follows: precision = (TP /TP + FP)× 100%.
MCC: it represents the prediction ability of a classifier with values between [−1, +1]. If the value of the MCC classifier is +1, this means the

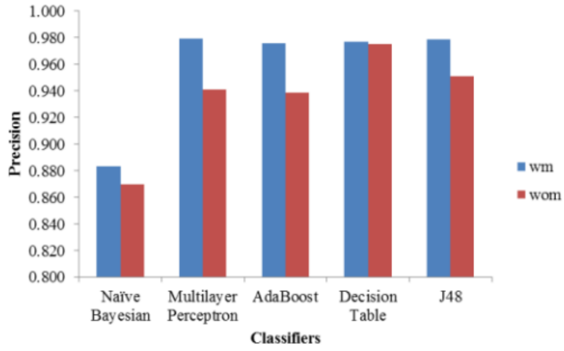
classifier predictions are ideal. −1 indicates that classifiers
produce completely wrong predictions. 0e MCC value near to 0 means that the classifier generates random predictions. 0e mathematical equation of MCC is as follows:
MCC = TP × TN − FP × FN / (TP + FP)(TP + FN)(TN + FP)(TN + FN) × 100%.

III. RESULTS

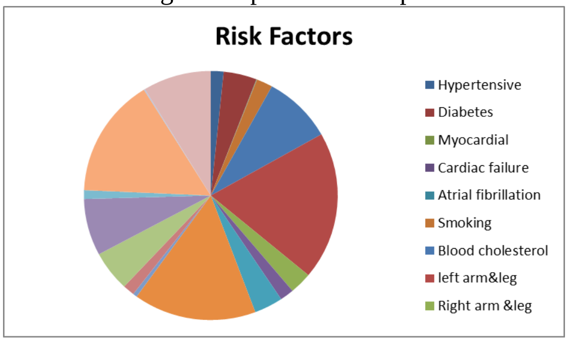








Percentage of Importance of Input Data



IV. CONCLUSION

Preventing Stroke and Rewinding Risks CDC also notes that stroke is preventable in up to 80 percent of cases if the patients recognize and mitigate the risks in due time. However, most health risks are related to a patient’s habits and choices in nutrition, physical activity, and lifestyle. Therefore, a patient might tend to disregard their physician’s suggestions.

A study from Google’s AI team attempts to throw abstractions away and show the patients their future by analysing their personal health risks, and making predictions based on the knowledge received. Their system can extract a range of risk factors critical for the occurrence of cardiovascular disease and stroke, such as body mass index (BMI), haemoglobin, A1c (HbA1c), systolic and diastolic blood pressure, Improper breathing, as well as smoking status. The researchers reported their algorithms succeeded in predicting the chances of particular patients developing stroke or heart attack in a five-year period with a 70 percent accuracy. Machine learning AI-enabled Stroke Battle Begins now surviving a stroke is only a starting point of the patient’s fight for their full and independent life. The sooner a person receives adequate medical care, the more they can achieve during the rehabilitation, hopefully up to regaining their mobility and social skills completely.

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