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# AN ARTIFICIAL INTELLIGENCE ENABLED FRAMEWORK WITH HYBRID FEATURE SELECTION METHOD FOR EFFICIENT EARLY DETECTION OF STROKE

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**ABSTRACT**

Healthcare is the domain which is indispensable for leveraging human health and also minimize mortality rate caused by different diseases. One such disease is brain stroke. Medically brain stroke is the condition that occurs due to poor blood flow to brain causing cell death and it is causing millions of deaths all over the world. According to WHO in 2019, stroke caused more than 6 million deaths across the globe. There are many machine learning methods used for stroke detection using data driven approach. However, their performance is deteriorated when the training data quality is mediocre. To overcome this problem, some feature selection methods came into existence. Those methods could improve performance of prediction models. Nevertheless, there is still need for leveraging prediction performance. In this paper, we proposed a hybrid feature selection method to enhance accuracy of prediction of stroke from the given benchmark dataset. Different prediction models are used along with the proposed hybrid feature selection method along with other existing feature selection methods. The experimental results revealed many useful insights. First, all brain stroke prediction models could perform well with feature selection methods when compared with the models without feature selection. Second, the stroke prediction models exhibited highest performance with the proposed hybrid feature selection model. Thus the proposed stroke detection framework can be used in Clinical Decision Support Systems (CDSSs).

**Keywords –** *Stroke Detection, Feature Selection, Machine Learning, Hybrid Feature Selection*

## 1. INTRODUCTION

According to WHO in 2019, the 7 out of top 10 diseases that caused more deaths were communicable diseases. They accounted to 44% while all top 10 diseases caused 80% of deaths.

Non communicable diseases on the other hand caused 74% of deaths globally. Particularly stroke caused more than 6 million deaths in 2019. This indicates that the death rate caused by stroke is alarming and needs substantial efforts to minimize the same. In the recent past machine learning (ML) has grown rapidly catering to the needs of various problems associated with different domains. ML can process massive amounts of data and thus for the contemporary era, for data analytics, ML has become very essential.Different machine learning techniques are widely used to solve classification problems in the real world. Out of them most widely used models that are used in the empirical study of this paper include Naïve Bayes, Logistic Regression, Random Forest, KNearest Neighbour and Decision Tree.

In this paper, each of the aforementioned models is observed with and without feature selection method. The feature selection methods that are existing such as Step Forward Feature Selection (SFFS), Step Backward Feature Selection (SBFS), Exhaustive Feature Selection (EFS) and Recursive Feature Selection (RFS) are used in the experiments. In addition to this, a hybrid feature selection method is proposed and used along with stroke prediction models. The experimental results revealed many useful insights. First, all brain stroke prediction models could perform well with feature selection methods when compared with the models without feature selection. Second, the stroke prediction models exhibited highest performance with the proposed hybrid feature selection model.Our contributions are as follows.

1. We proposed a brain stroke detection framework that is based on machine

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learning models using data driven approach.

2. We proposed a feature selection method known as Hybrid Feature Selection (HFS) which leverages stroke detection performance of machine learning models.
3. A prototype is built using Python data science platform for evaluating the stroke prediction models with the proposed feature selection method. Empirical results revealed that the proposed feature selection method could improve prediction performance of machinelearning based stroke prediction models.

The remainder of the paper is structured as follows. Section 2 reviews literature on different existing stroke detection models. Section 3 presents the proposed AI enabled framework for stroke detection including the proposed hybrid feature selection algorithm. Section 4 presents experimental setup and methodology for performance evaluation. Section 5 presents results of stroke prediction models with and without feature selection algorithms. Section 6 concludes the paper and provides directions for future scope of the research.

## 3. PROPOSED STROKE DETECTION FRAMEWORK

We proposed a stroke detection framework using data driven approach. It takes benchmark dataset as input and performs prediction. Figure 1 shows modus operandi of the framework. It takes stroke dataset as input and divides that into 80% training and 20% testing data. The training data is subjected to the proposed hybrid feature selection method prior to detection of stroke in test samples. Without feature selection method, the stroke prediction models used in this paper such as Naïve Bayes, Logistic Regression, Random Forest, KNearest Neighbour and Decision Tree lead to mediocre performance.

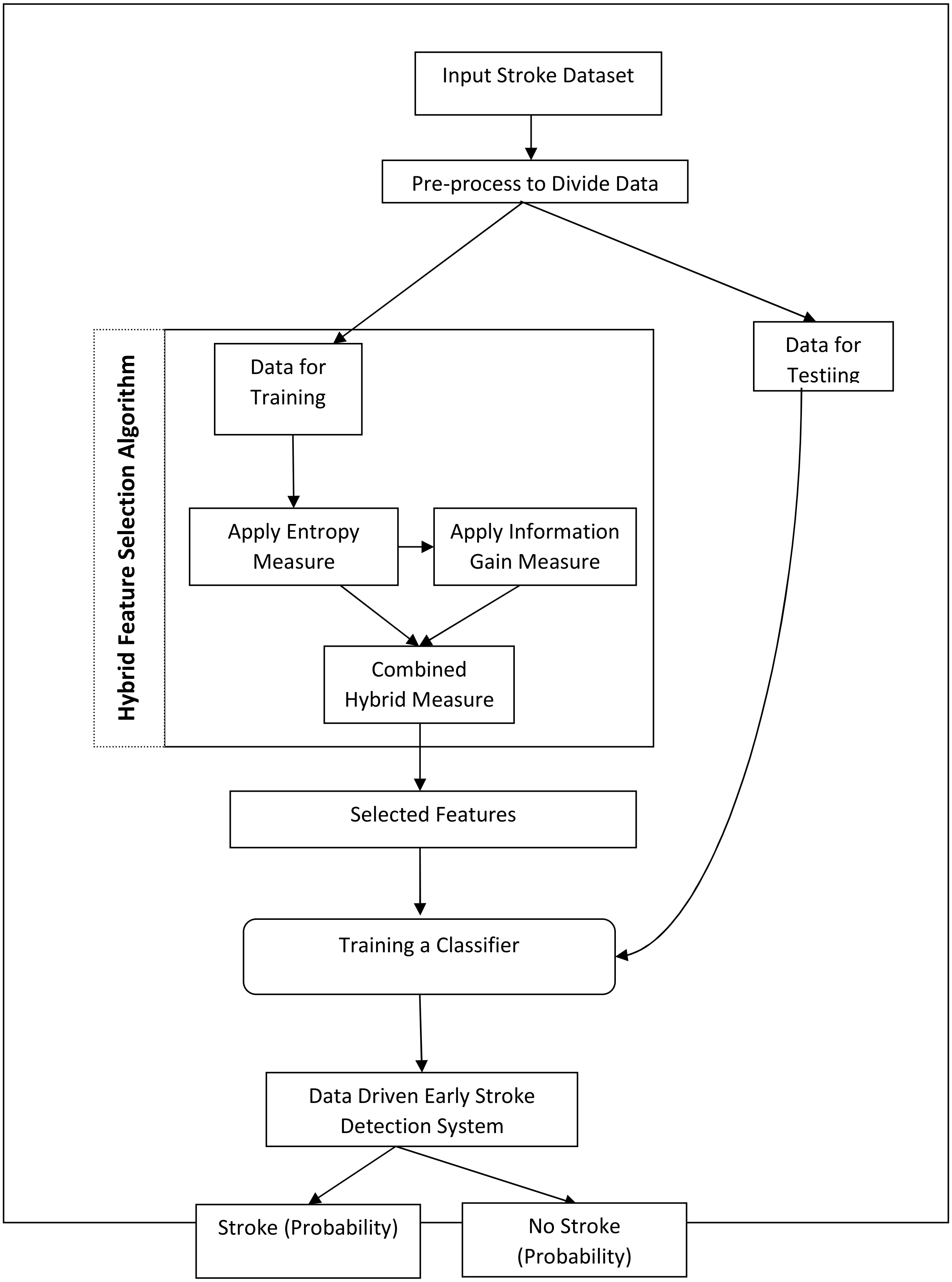


*Figure 1: Proposed AI Enabled Framework For Stroke Detection*

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Once features are selected from available features, the selected features that can contribute to class label prediction can lead to enhanced performance. In other words, the stroke prediction models such as Naïve Bayes, Logistic Regression, Random Forest, KNearest Neighbour and Decision Tree perform better with feature selection models. The proposed hybrid feature selection method uses different metrics such as symmetric uncertainty, entropy and gain are used as in Eq. 1, Eq. 2, Eq. 3 and Eq. 4.

$$SU = \frac{2*Gain}{H(x)+H(y)} \quad (1)$$

SU is a hybrid metric that combines both gain and entropy measures. Both H(x) and H(y) denote computations required by entropy as in Eq. 2 and Eq. 3.

**Algorithm:**Brain Stroke Detection (BSD)
**Input:** Dataset ***D***, prediction models **M**
**Output:** Predictions **P**

1. Start
2. Initialize training data vector T1
3. Initialize testing data vector T2
4. Initialize feature vector F
5. T1←GetTrainingData(D)
6. T2←GetTestingData(D)
7. F←Run HFS algorithm (T1)
8. For each model in M
9.    model←FitTheModel(F)
10.    For each instance s in T2
11.       Update P with the model
12.    End For
13. End For
14. Display P
15. End

**Algorithm 1:**Algorithm for Brain Stroke Detection

As presented in Algorithm 1, it takes prediction models and dataset as input and produces prediction of brain stroke. In Step 7, the algorithm invokes another algorithm known as Hybrid Feature Selection (HFS) in order to select features. From Step 8 through Step 13, it trains different prediction models and they are used for disease predictions. In Step 14, it provides the prediction results.

### 3.3 Hybrid Feature Selection

A hybrid feature selection method is defined based on measures such as entropy and gain.

$$H(X) = -\sum_{x \in X} p(x) \log p(x) \quad (2)$$

$$H(Y) = -\sum_{y \in Y} p(y) \log p(y) \quad (3)$$

$$\text{Information gain} = H(y) - H(y/x) \quad (4)$$

The information gain is computed as in Eq. 4 and the measures are used in the Algorithm 2.

### 3.1 BrainStrokeDetection Algorithm

An algorithm known as Breast Cancer Prediction and Drug Recommendation (BCD-DR) is defined and implemented. It takes dataset [21] as input and generates predictions and recommendations.

**Algorithm:** Hybrid Feature Selection
**Inputs:** Dataset ***D*,** threshold **th**
**Outputs:** Features **F**

1. Initialize symmetric uncertainty vector S
2. F←ExtractFeatures(D)
3. For each feature f in F
4.    entropy←CompEntropy(F, f)
5.    gain←CompGain(F, f)
6.    su ←CompSU(F, f)
7.   Update S
8. End For
9. F1=F
10. F←null
11. For each s in S
12.    IF s >= th Then
13.       f←GetFeature(F1)
14.       Update F with f
15.    End If
16. End For
17. Return F

**Algorithm 2:** Hybrid Feature Selection

As presented in Algorithm 2, it dataset [51] as input and produces selected features. In the process for all features, it computes gain, entropy and symmetric uncertainty. Then based the hybrid metric known as symmetric uncertainty, it filters out selected features. When these features are used in the BSD algorithm, it results in quality enhancement and finally leading to efficient disease prediction.

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## 4. PERFORMANCE EVALUATION

Most of the ML and deep learning papers used confusion matrix based metrics to know performance of their methods. In this paper also we used different metrics such as precision, recall, F1-score and accuracy derived from confusion matrix shown in Figure 2.

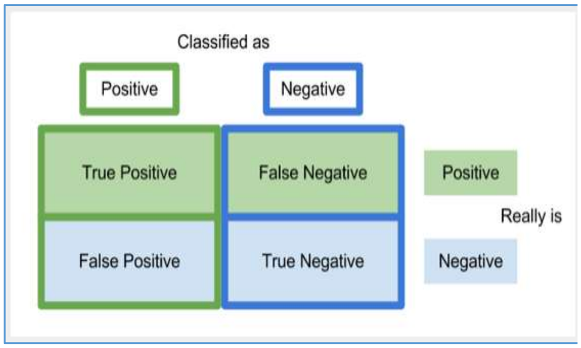


*Figure 2: Confusion Matrix*

Based on the confusion matrix presented in Figure 2, the confusion matrix shows the measures like true positive (TP), false positive (FP), false negative (FN) and true negative (TN). These are determined by comparing result of ML algorithm when compared with the ground truth. The derived metrics are shown in Table 1.

*Table 1: Performance Metrics Used For Evaluation*

| **Metric** | **Formula** | **Value range** | **Best Value** |
|---|---|---|---|
| Precision (p) | $\frac{TP}{TP+FP}$ | [0; 1] | 1 |
| Recall (r) | $\frac{TP}{TP+FN}$ | [0; 1] | 1 |
| Accuracy | $\frac{TP+TN}{TP+TN+FP+FN}$ | [0; 1] | 1 |
| F1-Score | $2*\frac{(p*r)}{(p+r)}$ | [0; 1] | 1 |

Precision refers to positive predictive value while the recall refers to true positive rate. F1-score is the harmonic mean of both precision and recall which is used to have a measure without showing imbalance while accuracy measure may show imbalance.

*Table 2: An Excerpt From Stroke Dataset*

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | id | gender | age | hypertension | heart_disease | ever_married | work_type | Residence_type | avg_glucose_level | bmi | smoking_status | stroke |
| 2 | 9046 | Male | 67 | 0 | 1 | Yes | Private | Urban | 228.69 | 36.6 | formerly smoked | 1 |
| 3 | 51676 | Female | 61 | 0 | 0 | Yes | Self-employed | Rural | 202.21 | N/A | never smoked | 1 |
| 4 | 31112 | Male | 80 | 0 | 1 | Yes | Private | Rural | 105.92 | 32.5 | never smoked | 1 |
| 5 | 60182 | Female | 49 | 0 | 0 | Yes | Private | Urban | 171.23 | 34.4 | smokes | 1 |
| 6 | 1665 | Female | 79 | 1 | 0 | Yes | Self-employed | Rural | 174.12 | 24 | never smoked | 1 |
| 7 | 56669 | Male | 81 | 0 | 0 | Yes | Private | Urban | 186.21 | 29 | formerly smoked | 1 |
| 8 | 53882 | Male | 74 | 1 | 1 | Yes | Private | Rural | 70.09 | 27.4 | never smoked | 1 |
| 9 | 10434 | Female | 69 | 0 | 0 | No | Private | Urban | 94.39 | 22.8 | never smoked | 1 |
| 10 | 27419 | Female | 59 | 0 | 0 | Yes | Private | Rural | 76.15 | N/A | Unknown | 1 |
| 11 | 60491 | Female | 78 | 0 | 0 | Yes | Private | Urban | 58.57 | 24.2 | Unknown | 1 |
| 12 | 12109 | Female | 81 | 1 | 0 | Yes | Private | Rural | 80.43 | 29.7 | never smoked | 1 |
| 13 | 12095 | Female | 61 | 0 | 1 | Yes | Govt_job | Rural | 120.46 | 36.8 | smokes | 1 |
| 14 | 12175 | Female | 54 | 0 | 0 | Yes | Private | Urban | 104.51 | 27.3 | smokes | 1 |
| 15 | 8213 | Male | 78 | 0 | 1 | Yes | Private | Urban | 219.84 | N/A | Unknown | 1 |
| 16 | 5317 | Female | 79 | 0 | 1 | Yes | Private | Urban | 214.09 | 28.2 | never smoked | 1 |
| 17 | 58202 | Female | 50 | 1 | 0 | Yes | Self-employed | Rural | 167.41 | 30.9 | never smoked | 1 |
| 18 | 56112 | Male | 64 | 0 | 1 | Yes | Private | Urban | 191.61 | 37.5 | smokes | 1 |
| 19 | 34120 | Male | 75 | 1 | 0 | Yes | Private | Urban | 221.29 | 25.8 | smokes | 1 |
| 20 | 27458 | Female | 60 | 0 | 0 | No | Private | Urban | 89.22 | 37.8 | never smoked | 1 |
| 21 | 25226 | Male | 57 | 0 | 1 | No | Govt_job | Urban | 217.08 | N/A | Unknown | 1 |
| 22 | 70630 | Female | 71 | 0 | 0 | Yes | Govt_job | Rural | 193.94 | 22.4 | smokes | 1 |

Table 2 shows an excerpt of dataset used for stroke prediction. It is collected from [51]. It has 12 attributes and 5110 instances reflecting patients' data.

## 5. EXPERIMENTAL RESULTS

An application built using Python data science platform is used to observe results of experiments. Five stroke detection models such as Naïve Bayes, Logistic Regression, Random Forest, KNearest Neighbour and Decision Tree are used along with three existing feature selection method and the proposed hybrid feature selection method. This section provides results of exploratory data analysis first followed by stroke detection performance evaluation.

### 5.1 Exploratory Data Analysis

Exploratory data analysis is made based on the dataset [51] considered for empirical study. This sub section provides different research related aspects found in the dataset.

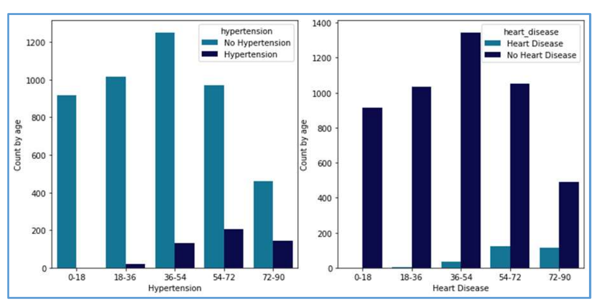


*Figure 3: Age Wise Details Of Hypertension And Occurrence Of Heart Disease*

As presented in Figure 3, it shows the count of patients suffered from hypertension and heart disease age wise. It thus provides age wise statistics on how many people are free from hypertension and heart disease.

### 5.2 Performance Evaluation

Performance of stroke prediction models in presence and absence of feature selection methods is observed in terms of precision, recall, accuracy and F1-score.

*Table 3: Performance Comparison In Terms Of Precision*

| Stroke Detection Model | Precision Performance (%) | | | | | |
|---|---|---|---|---|---|---|
| | Without Feature Selection | With Feature Selection | | | | |
| | | SFFS | SBFS | EFS | RFS | Hybrid |
| Naïve Bayes | 79.11 | 82.01 | 85.47 | 83.24 | 84.71 | 91.40 |
| Logistic Regression | 80.19 | 85.47 | 81.59 | 86.15 | 80.99 | 89.71 |
| Random Forest | 75.01 | 77.54 | 76.12 | 80.89 | 76.31 | 85.52 |
| KNearest Neighbour | 78.12 | 82.79 | 81.45 | 79.10 | 80.11 | 84.35 |
| Decision Tree | 79.19 | 79.53 | 84.26 | 82.14 | 86.42 | 92.15 |

As presented in Table 3, performance of stroke detection models is presented with and without feature selection in terms of precision.

*Table 4: Performance Comparison In Terms Of Recall*

| Stroke Detection Model | Recall Performance (%) | | | | | |
|---|---|---|---|---|---|---|
| | Without Feature Selection | With Feature Selection | | | | |
| | | SFFS | SBFS | EFS | RFS | Hybrid |
| Naïve Bayes | 74.21 | 86.15 | 76.31 | 80.32 | 75.01 | 90.58 |
| Logistic Regression | 76.35 | 79.54 | 80.14 | 84.35 | 76.56 | 88.22 |
| Random Forest | 78.14 | 79.12 | 80.17 | 84.23 | 83.33 | 91.85 |
| KNearest Neighbour | 79.21 | 79.36 | 80.36 | 80.39 | 81.22 | 87.21 |
| Decision Tree | 76.34 | 71.25 | 75.32 | 78.58 | 81.36 | 92.45 |

As presented in Table 4, performance of stroke detection models is presented with and without feature selection in terms of recall.

*Table 5: Performance Comparison In Terms Of F1-Score*

| Stroke Detection Model | F1-Score Performance (%) | | | | | |
|---|---|---|---|---|---|---|
| | Without Feature Selection | With Feature Selection | | | | |
| | | SFFS | SBFS | EFS | RFS | Hybrid |
| Naïve Bayes | 79.21 | 85.47 | 76.12 | 79.10 | 71.01 | 85.24 |
| Logistic Regression | 76.35 | 77.88 | 79.54 | 81.25 | 75.57 | 84.27 |
| Random Forest | 78.14 | 80.17 | 84.23 | 78.58 | 75.32 | 87.21 |
| KNearest Neighbour | 75.01 | 71.25 | 80.17 | 79.54 | 80.36 | 89.25 |
| Decision Tree | 80.19 | 79.12 | 80.32 | 83.33 | 84.23 | 90.58 |

As presented in Table 5, performance of stroke detection models is presented with and without feature selection in terms of F1-score.

*Table 6: Performance Comparison In Terms Of Accuracy*

| Stroke Detection Model | Accuracy Performance (%) | | | | | |
|---|---|---|---|---|---|---|
| | Without Feature Selection | With Feature Selection | | | | |
| | | SFFS | SBFS | EFS | RFS | Hybrid |
| Naïve Bayes | 81.91 | 85.28 | 80.99 | 79.75 | 84.01 | 88.55 |
| Logistic Regression | 84.01 | 84.79 | 81.47 | 81.47 | 85.22 | 90.14 |
| Rando | 82.85 | 88. | 89. | 86. | 89. | 93.2 |

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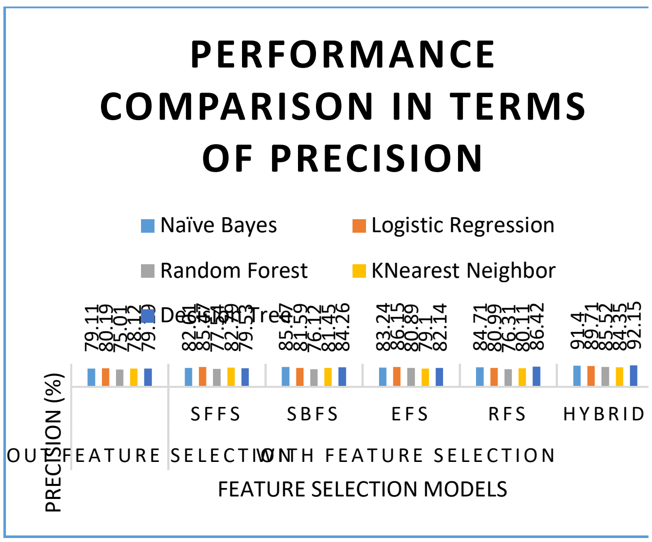
| | | | | | | |
|---|---|---|---|---|---|---|
| m Forest | | 76 | 21 | 26 | 29 | 5 |
| KNearest Neighbour | 77.80 | 94.19 | 93.72 | 65.75 | 95.26 | 100 |
| Decision Tree | 77.92 | 77.92 | 83.43 | 77.80 | 82.85 | 100 |

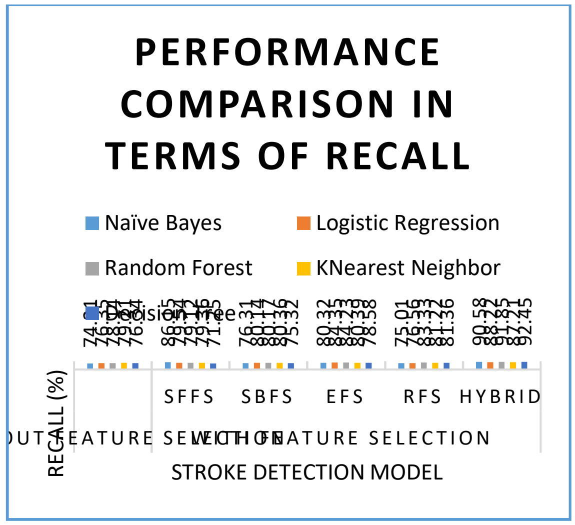
As presented in Table 6, performance of stroke detection models is presented with and without feature selection in terms of accuracy.

*Figure 4:Performance Evaluation Of Stroke Detection Models In Terms Of Precision*



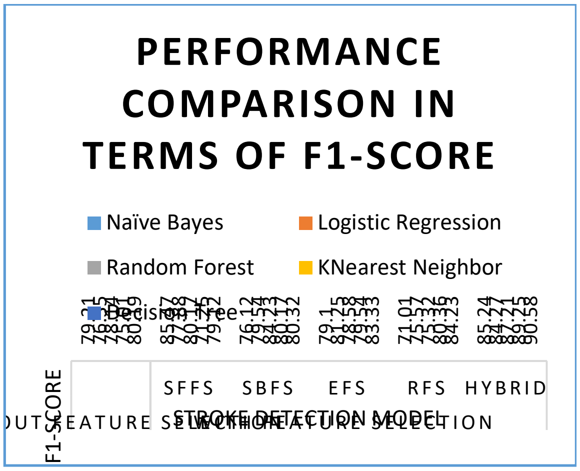

As presented in Figure 4, stroke detection models with and without feature selection methods are evaluated in terms of precision. Feature selection models are provided in horizontal axis and vertical axis shows precision performance for different stroke prediction models. Without feature selection methods employed, the least precision is shown by Random Forest with 75.01% and highest precision is exhibited by decision tree with 79.19%. When SFFS is applied, the least performance is shown by RF with 77.54% recall and highest performance is shown by LR with 85.47%. When SBFS is applied, least performance is shown by RF with 76.12% precision and highest performance is shown by NB with 85.47%. When EFS is applied, least performance is shown by KNN with 79.1% recall and highest performance is shown by LR with 86.15%. When RFS is applied, least performance is shown by RF with 76.31% precision and highest performance is shown by DT with 86.42%.When hybrid feature selection is applied, least performance is shown by KNN with 84.35% precision and highest performance is shown by DT with 92.15%. From the results it is observed that the proposed hybrid feature selection method shows better performance over existing methods in terms of precision.

*Figure 5: Performance Evaluation Of Stroke Detection Models In Terms Of Recall*



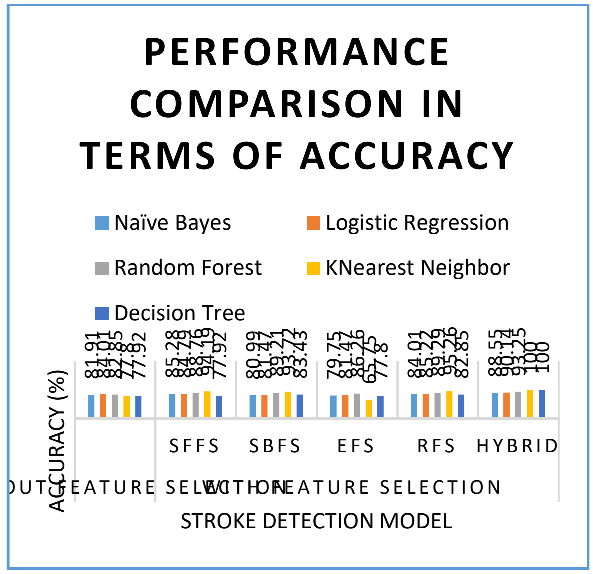

As presented in Figure 5, stroke detection models with and without feature selection methods are evaluated in terms of recall. Feature selection models are provided in horizontal axis and vertical axis shows recall performance for different stroke prediction models. Without feature selection methods employed, the least recall is shown by Random Forest with 74.21% and highest precision is exhibited by KNN with 79.21%. When SFFS is applied, the least performance is shown by DT with 71.25% recall and highest performance is shown by NB with 86.15%. When SBFS is applied, least performance is shown by DT with 75.32% recall and highest performance is shown by KNN with 80.36%. When EFS is applied, least performance is shown by DT with 78.58% recall and highest performance is shown by LR with 84.35%. When RFS is applied, least performance is shown by NB with 75.01% recall and highest performance is shown by RF with 83.33%.When hybrid feature selection is applied, least performance is shown by KNN with 87.21% recall and highest performance is shown by DT with 82.45%. From the results it is observed that the proposed hybrid feature selection method shows better performance over existing methods in terms of recall.

Figure 6: Performance Evaluation Of Stroke Detection Models In Terms Of F1-Score




As presented in Figure 6, stroke detection models with and without feature selection methods are evaluated in terms of F1-score. Feature selection models are provided in horizontal axis and vertical axis shows F1-score performance for different stroke prediction models. Without feature selection methods employed, the least F1-score is shown by KNN with 75.01% and highest precision is exhibited by DT with 80.19%. When SFFS is applied, the least performance is shown by KNN with 71.25% F1-score and highest performance is shown by NB with 85.47%. When SBFS is applied, least performance is shown by NB with 76.12% F1-score and highest performance is shown by RF with 84.23%. When EFS is applied, least performance is shown by RF with 78.58% F1-score and highest performance is shown by DT with 83.33%. When RFS is applied, least performance is shown by NB with 71.01% F1-score and highest performance is shown by DT with 84.23%.When hybrid feature selection is applied, least performance is shown by LR with 84.27% F1-score and highest performance is shown by DT with 90.58%. From the results it is observed that the proposed hybrid feature selection method shows better performance over existing methods in terms of F1-score.

Figure 7: Performance Evaluation Of Stroke Detection Models In Terms Of Accuracy




As presented in Figure 7, stroke detection models with and without feature selection methods are evaluated in terms of accuracy. Feature selection models are provided in horizontal axis and vertical axis shows accuracy performance for different stroke prediction models. Without feature selection methods employed, the least accuracy is shown by KNN with 77.08% and highest precision is exhibited by LR with 84.01%. When SFFS is applied, the least performance is shown by DT with 77.92% accuracyand highest performance is shown by KNN with 94.19%. When SBFS is applied, least performance is shown by NB with 80.99% accuracyand highest performance is shown by KNN with 93.72%. When EFS is applied, least performance is shown by KNN with 65.75% accuracyand highest performance is shown by RF with 86.26%. When RFS is applied, least performance is shown by DT with 82.85% accuracyand highest performance is shown by KNN with 95.26%.When hybrid feature selection is applied, least performance is shown by NB with 88.55% accuracy and highest performance is shown by KNN and DT with 100%. From the results it is observed that the proposed hybrid feature selection method shows better performance over existing methods in terms of F1-score.

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## 6. CONCLUSION AND FUTURE WORK

In this paper, we proposed a framework for early stroke detection. It is based on machine learning algorithms coupled with the proposed hybrid feature selection method. It is a data driven approach that is cheaper means of detecting stroke probability detection early. Different stroke prediction models such as Naïve Bayes, Logistic Regression, Random Forest, KNearest Neighbour and Decision Tree are used in the empirical study. Each model is observed with and without feature selection method. The feature selection methods that are existing such as Step Forward Feature Selection (SFFS), Step Backward Feature Selection (SBFS), Exhaustive Feature Selection (EFS) and Recursive Feature Selection (RFS) are used in the experiments. In addition to this, a hybrid feature selection method is proposed and used along with stroke prediction models. The experimental results revealed many useful insights. First, all brain stroke prediction models could perform well with feature selection methods when compared with the models without feature selection. Second, the stroke prediction models exhibited highest performance with the proposed hybrid feature selection model. In future we intend to explore ensemble of stroke prediction models for improved performance.

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