Deep Learning based Brain Stroke Detection using Improved VGGNet

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Abstract: - Brain stroke is one of the critical health issues as the after effects provides physical inability and sometimes death. The inability of focus in the brain due to bleeding or clogged blood vessels leads to stroke. Early treatment and diagnosis are crucial in and following manual procedures takes more time which further increases the criticalness. Artificial intelligence and machine learning techniques hands together in medical domain and numerous applications are developed to reduce the diagnosis time and to improve the accuracy. Incorporating machine learning techniques in brain stroke detection is a familiar research arena and numerous research works are evolved with better solutions. However, the drive towards developing better system for brain stroke detection is still in progress. Thus, in this research work, deep learning-based brain stroke detection system is presented using improved VGGNet. Simulation analysis using a set of brain stroke data and the performance of learning algorithms are measured in terms of accuracy, sensitivity, specificity, precision, f-measure, and Jaccard index. The better performance of proposed model is comparatively analyzed with traditional machine learning algorithms like support vector machine, Naïve Bayes, Decision tree, K-Nearest neighbor, and recent deep learning models like ResNet, Squeeze Net, Alex Net, and Google Net algorithms. Experimental results validates that the Improved VGG model attained better performance for all the parameters. Specifically with 96.86% of detection accuracy improved VGG model detects the brain strokes effectively compared to other learning algorithms.

Key-Words: - Brain stroke detection, Machine Learning, Deep Learning, Convolution Neural Network, Detection Accuracy

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1 Introduction

Stroke is one of the serious medical issues which require immediate medical attention to avoid further complications. The major reason for stroke is improper life style and its impacts in body mass index, reduced function of heart and kidney, inappropriate level of glucose, drinking, smoking, etc., When the blood flow to brain is reduced or disrupted the cells in the brain reduces its functions which leads to stroke. Every year fifteen million people suffer due to stroke as per the report from world health organization (WHO). Center for disease control and prevention reports that stroke is the sixth leading cause of mortality specifically in India stroke occupies fourth position. Stroke is a noncommunicable disease and it is mainly classified into hemorrhagic and ischemic. Hemorrhagic stroke occurs due to bleeds in blood vessels. In critical cases, burst blood vessel leads to hemorrhagic stroke. Ischemic stroke occurs due to blocks in blood vessels which go to brain. Figure 1 depicts an illustration for different types of strokes. The ischemic stroke is further classified into thrombotic and embolic. Thrombotic occurs when there is block or clot in artery which provides blood supply to brain whereas embolic occurs when blocks in any part of the body and move towards the brain. As of now there is no medicine or treatment available to cure the stroke completely however medications are available to extend the stroke patients lifespan. Thus, it is essential to predict or detect the symptoms of strokes from health records.

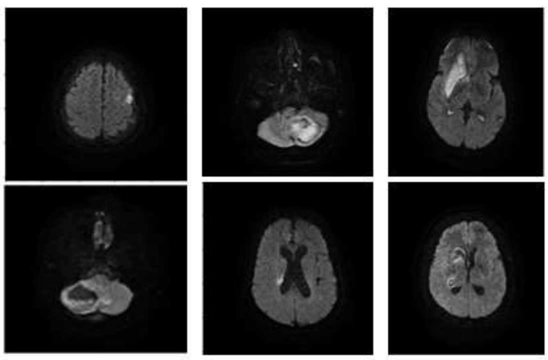

Fig. 1: Sample stroke MR Images

Currently magnetic resonance imaging (MRI) and Computed tomography (CT) scans are widely used to identify brain diseases. Through MRI the brain structure and functions can be diagnosed and the anatomical structure of brain can be observed. Anomalies in cranial cavity, vertebral column and inspection of cranial nerves are possible in MRI. Compared to CT scans the results of MRI are better and less prone to noise factors. Lesion identification and segmentation, brain parcellation and tissue segmentation can be performed using magnetic resonance images. In numerous medical applications, artificial intelligence algorithm is used to classify and detect abnormalities. Specifically, segmentation and classification of MR images using machine learning algorithms are increased to detect health issues.

Machine learning algorithms are like support vector machine, naïve bayes, decision tree, random forest algorithms are used to detect stroke type from brain images. The traditional machine learning based stroke detection models classifies the abnormalities based on the features. A separate feature detection and extraction models are required for the machine learning algorithms then only the features can be classified to detect the abnormalities. However deep learning models comes with automatic feature extraction and it does not require any separate model for initial feature selection and extraction. Various deep learning models are used in numerous image processing applications. Thus, in this research work the performance of deep learning models is analyzed in addition to the proposed model. The major objective of this research work is to obtain maximum detection accuracy in brain stroke detection with minimum false positive rates. To attain this, an improved VGGNet model is proposed which effectively detects different types of strokes. The major contributions of this research work are presented as follows.

1. An improved deep learning model I-VGGNet is presented for classifying the brain images to detect brain stroke types.
2. An intense experimental analysis is presented to demonstrate the proposed model performance using different type of stroke and normal brain images.
3. A detailed comparative analysis is presented with traditional machine learning models and recent deep learning models to validate the proposed model better performance in terms of accuracy, specificity, sensitivity, precision, f-measure and Jaccard index.

The remaining discussion in the article is presented as follows. a brief literature review is presented in section 2. Proposed improved VGGNet model is presented in section 3. Detailed experimental analysis and results are presented in section 4 and the summary is presented in the last section.

2 Problem Formulation

2.1 Related Works

The magnetic induction tomography (MIT) brain pictures are analyzed by the hemorrhagic stroke detection model that is provided in. Images generated via induction tomography are analyzed using the weighted frequency difference adaptive thresholding split Bregman method, which detects stroke with the least amount of reconstruction. The given approach, according to experimental findings, has a lower reconstruction error than more traditional multifrequency-based induction tomography image processing techniques [1]. In all 2D and 3D situations, the proposed fully automatic MI-UNet stroke lesion segmentation outperformed UNet. Results generated by 3D MI-UNet have superior segmentation performance as assessed by the Dice score, Hausdorff distance, average symmetric surface distance, and precision [2]. With the best location accuracy of 0.9859 for detection, 0.8033 Dice score, and 0.6919 IoU for segmentation, the suggested model achieves competitive performance with human experts on two separate datasets. The findings show how the suggested deep learning model is efficient, reliable, and advantageous in automatically diagnosing haemorrhage lesions, making it possible to use it as a clinical decision support tool for stroke diagnosis [3]. The bio-signals were collected at a sampling rate of 1,000Hz per second from the three electrodes of the ECG and the index finger for PPG while walking in the suggested system, which takes into account the convenience of wearing the bio-signal sensors for the elderly [4]. The goal of this research is to use the convolutional neural network (CNN) model to categorize brain CT pictures as normal, surviving ischemia, or cerebral hemorrhage. We suggest employing computed tomography images to classify cerebral strokes using a computer-aided diagnostic system (CAD). Techniques for horizontal flip data magnification were applied to gain more precise categorization. The accuracy and recall of numerous estimation parameters were both enhanced by the suggested strategy [5]. This research employs a deep generative adversarial network-based method for detecting brain lesions from brain scans. The proposed method first creates fake magnetic resonance images using computed tomography data. Using the proposed adversarial network, the lesions are searched from the MR images and validated against conventional methods [6]. The brain computer interface model used electroencephalography and augmented reality to detect brain strokes. The suggested technique firstly identifies spatial and spectral features from EEG signals. The identified features are extracted and categorized using regularized discriminant analysis. A kernel density estimation function is also included to enhance classification performance, providing more reliable detection results than traditional approaches [7]. This study proposes novel automated classification and segmentation algorithms to simultaneously identify hemorrhage and ischemic lesions (infarcts) from noncontrast brain CT images for the treatment of patients with brain strokes. The goal of the U-Net segmentation model is to accurately and automatically detect stroke lesions [8]. The author has suggested a mechanism for detecting brain tumors using MR images that is based on fusion. Making use of machine learning algorithms [9]. To identify the ischemic stroke lesions, a brand-new, optimized fuzzy level segmentation approach is put forth in this study. The multi-textural features are extracted following segmentation to create a feature set. The proposed weighted Gaussian Naive Bayes classifier uses these features as input to distinguish between classes of normal and pathological stroke lesions [10]. This study uses Support Vector Machine (SVM) classifier algorithms and explicit highlight extraction techniques to identify benign and malignant brain tumors [11]. By blocking and adaptively sequencing the convolution layers, optimizing the number of activation functions and hyperparameters, and dimensional U-Net (D-UNet) optimization, a convolutional deep network architecture is suggested. In order to ascertain whether there has been a brain stroke, the suggested method looks at the computed tomography (CT) pictures from the dataset. Once a stroke has happened, it is possible to establish whether it was caused by ischemia or hemorrhage [12]. The author briefly discussed about five major phenotypes of stroke occurs via thrombogenic paths [13]. This article discussed about various segmentation and classification of tumour images [14].

2.1 Methodology

The proposed deep learning based brain stroke detection model is presented in this section. The presented approach incorporates an improved version of VGGNet to obtain better detection accuracy. The traditional VGGNet has more layers and the time required to train the network is high. Moreover, traditional network performs more calculations thus it reduces the convergence speed. Additionally due to large parameters requirement the memory requirement of traditional network is high. Thus, an improved VGGNet is presented in this research work for brain stroke detection. A complete overview of proposed model is presented in Figure 2. The input image is initially preprocessed to remove the noise artifacts using gaussian filtering. Then the data is fed into network model to extract the features and classified in the last layer. The convolution layers in the network extracts the features and max pooling reduces the feature dimensions. The final SoftMax function in the classifier layer classifies the features as normal, hemorrhage, ischemic strokes.

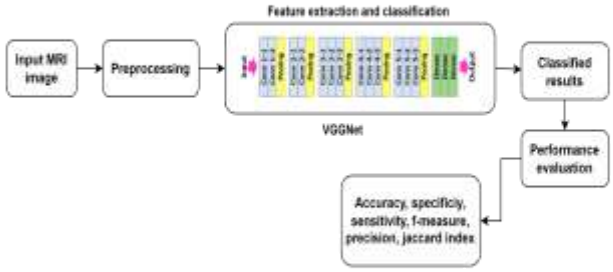

Fig. 2: Proposed stroke detection model overview

VGGNet is a type of convolutional neural network which is developed by visual geometry group of oxford university. Compared to other CNN models, the feature extraction capabilities of VGGNet are high and it can able to perform multiple tasks. compared to Google Net, the performance of VGGNet will be better in image processing applications. The architecture of traditional VGGNet is depicted in Figure 3. The architecture included series of convolution layers and max pooling layers. Total five blocks of layers are present in the VGGNet in which the first two blocks has two convolution layers and one max pooling layer. The next three blocks have three convolution layers in addition to a max pooling layer. Total 13 convolution layers and 5 pooling layers are present in the architecture. A flatten layer is used after last pooling layer to convert the two-dimensional features into one-dimensional features. Followed by three fully connected network is used and finally classification layer classifies the features using SoftMax function. The kernel size of the convolution layers is increased for each block. ReLU activation function is used after convolution layers and fully connected layers and to avoid data overfitting a dropout is used after fully connected layers.

The convolution layers in the VGGNet extracts the features from the input. The convolution kernel in this layer is obtained by convoluting feature map with series of filters. Mathematically the convolution process is formulated as

$$f_g = L \otimes k_g + b_g \tag{1}$$

where, k indicates the convolution kernel, f_g indicates the feature map, L represents the input image and b_g represents the bias term. A non linear function is generally introduced after convolution process which introduces non-linearity in the output feature map and it is mathematically expressed as

$$N_{i,j} = n\left(\sum_{d=0}^{D-1} \sum_{x=0}^{s-1} \sum_{y=0}^{s-1} w_{x,y,d} L_{v+x,g+y,d} + b\right) \tag{2}$$

where, $N_{i,j}$ indicates the output feature map, the location of feature is indicated as i,j. The term $L_{v+x,z+y,d}$ indicates the input pixel value, weight and convolution kernel. Followed by convolution layers, pooling layer is employed for each block which reduces the feature map dimensions without removing the essential information. The pooling function is mathematically expressed as

$$M_{i,j,g} = PL_{(x,y)\in R_{i,j}}\left(I_{x,y,g}\right) \tag{3}$$

where $M_{i,j,g}$ indicates the feature map after pooling operation, $R_{i,j}$ indicates the pooling region. In the proposed VGGNet model, max pooling is employed so that largest value in the convoluted feature is selected to obtain new feature output.

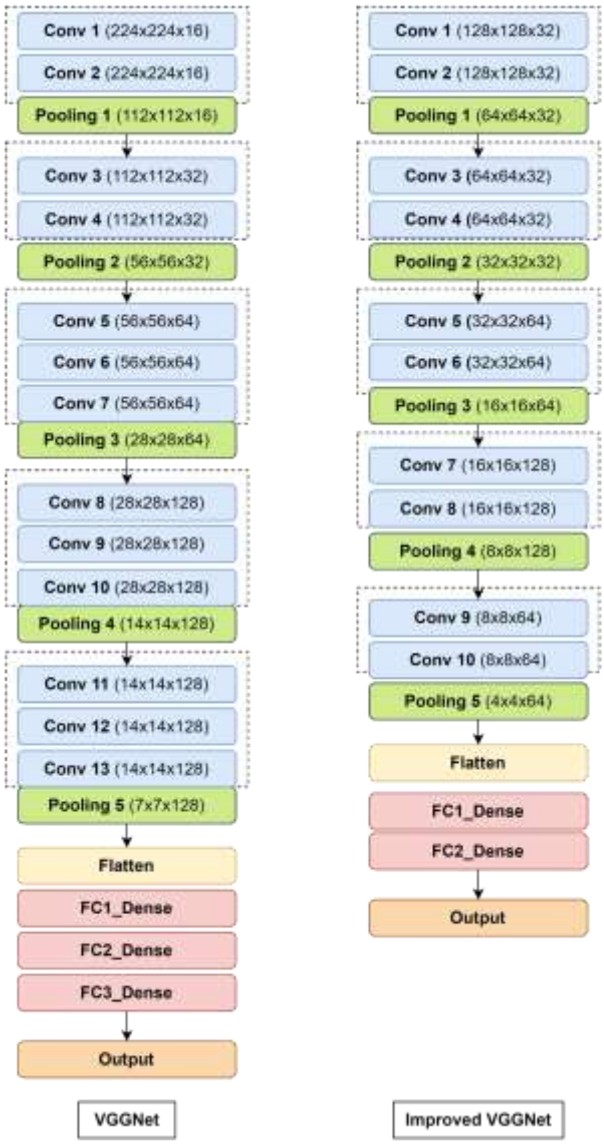

Fig. 3: Architecture of VGGNet and Improved VGGNet

After final pooling operation, the features are flattened which provides a one-dimensional feature vector and it's processed through three fully connected layers. after fully connected layers SoftMax function in the final classifier layer classifies the features and provides the class probabilities. Mathematically the SoftMax function is expressed as

$$P = \max(H_c \odot w^T + b_n) \tag{4}$$

where P indicates the detected class, number of hidden neurons in fully connected layer is indicates as H_c and weight matrix is indicated as w^T. b_n indicates the bias term.

Figure 3 depicts architectures of traditional VGGNet and improved VGGNet with essential layer details. It can be seen from the improved VGGNet layer details the number of parameters is reduced by reducing the layer depths. This reduces the possibilities of data overfitting or underfitting problem in the training process. The first two blocks in the improved VGGNet and traditional VGGNet are same and it is used to extract the features. The consecutive convolutional kernels extract the features however the input size is changed in the improved VGGNet. The input size used in the Improved VGGNet is 128×128 whereas in traditional model, the input size is 224×224. The next three blocks in the traditional VGGNet have four layers in which three are convolution layers and 1 pooling layer. However in the improved VGGNet it is reduced and the kernel size is changed for each block as 64, 128 and 64 respectively. This reduced kernel reduces the parameter requirements, finally the pooling layer reduces the feature dimensions and the feature maps are converted into one-dimensional vectors in flatten layer. Three fully connected layers in the traditional VGGNet is reduced into two in the Improved VGGNet model to reduce the parameters further and finally classified to detect the stroke type.

3 Results and Discussion

The proposed brain stroke detection model using learning algorithms is verified through simulation analysis performed in MATLAB. The dataset used for the experimentation is prepared manually by collecting sample images. Total 606 images are collected in which 186 images are Hemorrhagic, 33 samples belong to Ischemic and the remaining 387 samples are normal samples. The dataset is divided in the ratio of 80:20 for training and testing purpose and the details of samples are presented in Table. 1.

Table 1. Data samples used for training and testing

S.No.	Type	Training Images	Testing Images	Total
1	Haemorrhagic	149	37	186
2	Ischemic	26	7	33
3	Normal	310	77	387
			Total	606

The performance of proposed models evaluated using the performance metrics like accuracy, sensitivity, specificity, precision, F-measure and Jaccard index. Based on the results of confusion matrix elements like true positive values, false positive values, true negative values and false negative values the metrics are calculated. mathematical expression to calculate the performance metrics are presented as follows.

$$Accuracy = \frac{TP + TN}{FN + FP + TP + TN} \quad (5)$$

$$Sensitivity\ (or\ Recall) = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

$$F1\ Score = 2 * \frac{TP}{2 * TP + FP + FN} \quad (9)$$

$$Jaccard\ Index = \frac{Dice}{2 - Dice} \quad (10)$$

Table 2. Proposed model performance metrics

S.No	Performance metrics	Range (%)
1	Accuracy	96.86
2	Sensitivity	96.71
3	Specificity	97.02
4	Precision	97.03
5	F1 Score	96.87
6	Jaccard Index	93.93

Table 2 depicts the performance metrics of proposed model. The results obtained by the proposed model are presented for all the metrics. To validate that the proposed model is better, a detailed comparative analysis with traditional machine learning algorithms like support vector machine, Naïve Bayes, Decision tree, K-Nearest neighbor and recent deep learning models like ResNet, Squeeze Net, Alex Net, and Google Net algorithms are presented. The performance metrics of all the models are obtained through individual experimentation and the results are summarized to present the comparative performance analysis. since the analysis included 8 models thus instead of executing all the models combined in simulation platform those models are trained and tested individually. For each model the essential parameter settings are made to obtain the results and summarized as graphs in Microsoft excel. Figure 4 depicts the comparative analysis of all the models for sensitivity and specificity parameter.

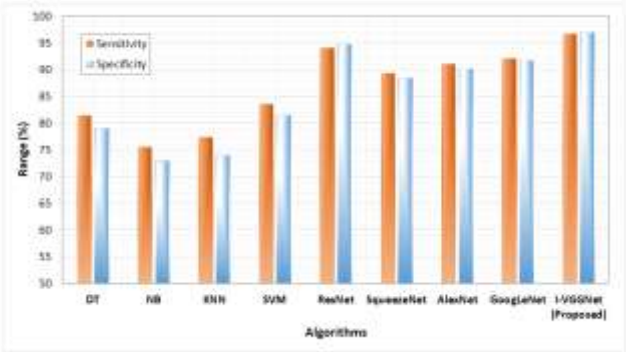

Fig. 4: Sensitivity and Specificity analysis

From the results given for sensitivity and specificity for all the models, it can be observed that the performance of proposed VGGNet is better than other models. The sensitivity obtained by the proposed model is 96.71% which is 21% greater than the Naïve Bayes algorithm, 19% greater than the kNN algorithm, 15% greater than the decision tree algorithm, 13% greater than the SVM algorithm. When the performance is compared to deep learning models, the sensitivity obtained by the proposed model is 7% greater than the Squeeze Net model, 6% greater than the Alex Net model, 5 % greater than the Google Net model and 3% greater than the ResNet model. Similarly for specificity the proposed model obtained maximum specificity as 97.02% which is 24% greater than the Naïve Bayes, 23% greater than the kNN, 18% greater than the decision tree, 16% greater than the SVM model. When specificity is compared with deep learning algorithms, the proposed model performance is 9% greater than the Squeeze Net model, 7% greater than the Alex Net model, 5 % greater than the Google Net model and 2% greater than the ResNet model.

Figure 5 depicts the comparative analysis of all the models for precision and F-measure metrics. The performance of proposed model is maximum for precision and f-measure and it is clearly visible in Figure 2 The precision obtained by the proposed model is 97.03% which is 23% greater than the Naïve Bayes algorithm, 22% greater than the kNN algorithm, 18% greater than the decision tree algorithm, 15% greater than the SVM algorithm. When the performance is compared to deep learning models, the precision obtained by the proposed model is 9% greater than the Squeeze Net model, 7% greater than the Alex Net model, 5% greater than the Google Net model and 2% greater than the ResNet model. Similarly for F-measure the proposed model obtained maximum F-measure as 96.87% which is 22% greater than the Naïve Bayes, 21% greater than the kNN, 16% greater than the decision tree, 14% greater than the SVM model. When f-measure is compared with deep learning algorithms, the proposed model performance is 8% greater than the Squeeze Net model, 6 % greater than the Alex Net model, 5% greater than the Google Net model and 2% greater than the ResNet model.

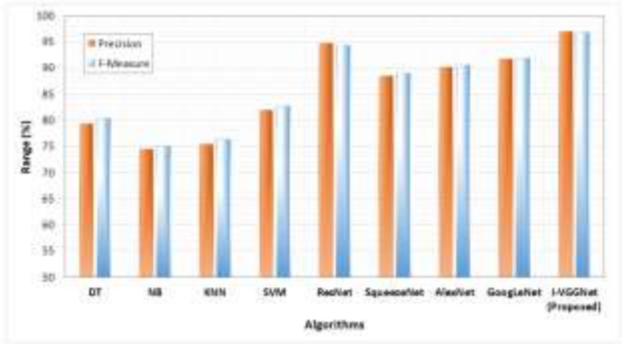

Fig. 5: Precision and F1 Score (F-measure) analysis

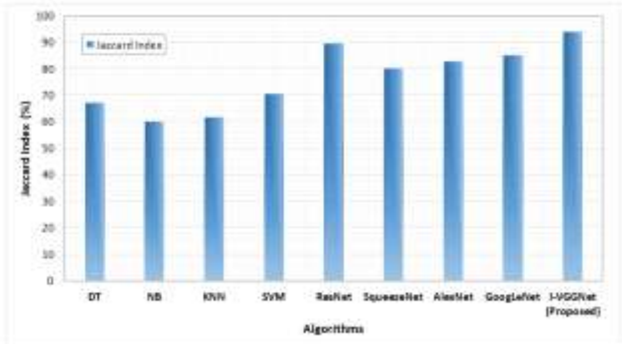

Fig. 6: Analysis of Jaccard Index

Further the Jaccard index is calculated based on the f-measure and compared with all the existing methods. Figure 6 depicts the comparative analysis of Jaccard index values obtained by the proposed model and other learning models. The maximum index value is attained by the proposed model which is 93.93%. when compared to other models the index obtained by the proposed model is 34% greater than the Naïve Bayes algorithm, 32% greater than the kNN algorithm, 27% greater than the decision tree algorithm, 23% greater than the SVM algorithm. When the performance is compared to deep learning models, the index value obtained by the proposed model is 14% greater than the Squeeze Net model, 11% greater than the Alex Net model, 9% greater than the Google Net model and 5% greater than the ResNet model.

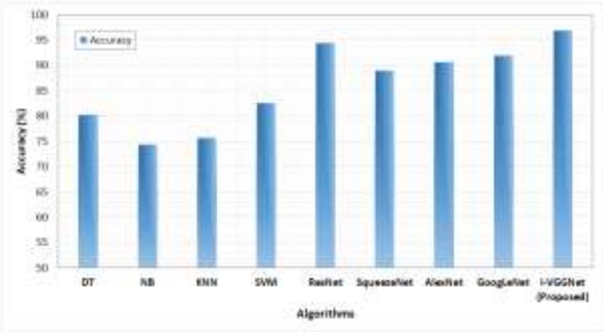

Fig. 7: Accuracy comparative analysis

Figure 7 depicts the comparative analysis of detection accuracy obtained by the proposed model and other learning models. The maximum accuracy attained by the proposed model is 96.86%. When compared to other models the accuracy obtained by the proposed model is 23% greater than the Naïve Bayes algorithm, 21% greater than the KNN algorithm, 17% greater than the decision tree algorithm, 14% greater than the SVM algorithm. When the performance is compared to deep learning models, the accuracy obtained by the proposed model is 8% greater than the Squeeze Net model, 6% greater than the Alex Net model, 5% greater than the Google Net model and 2% greater than the ResNet model.

For better understanding details of comparative analysis are presented as numerical data in Table 3. From the results given in Table. 2, it can be observed that the performance of improved VGG model is better than other models for all the metrics. Thus, brain stroke can be effectively detected through the presented improved VGG model.

4 Conclusion

A deep learning-based brain stroke detection model is presented in this research work using improved VGGNet. The proposed work extracts the essential features and detects the type of stroke as hemorrhagic and ischemic. The detection model performance is verified through experimentation using brain stroke dataset and the performances are compared with machine learning and deep learning models. The performance analysis considered traditional machine learning models and recent deep learning methods for evaluation through the performance metrics like precision, specificity, sensitivity, f-measure, precision and Jaccard index. From the comparative analysis the better performance of proposed improved VGGNet model is observed with 96.86% detection accuracy which is much better than the other deep learning and machine learning models. Further, this research work can be extended to attain better detection performances by incorporating optimization algorithms with deep learning models to finetune the parameters of network model.

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APPENDIX

Table 3. Overall performance analysis

Method	Accuracy	Sensitivity	Specificity	Precision	F-Measure	Jaccard Index
Decision Tree	80.20	81.46	78.95	79.35	80.39	67.21
Naïve Base	74.26	75.48	72.97	74.52	75.00	60.00
KNN	75.66	77.35	73.91	75.39	76.36	61.76
SVM	82.51	83.61	81.40	81.99	82.79	70.64
ResNet	94.39	94.10	94.68	94.72	94.41	89.41
Squeeze Net	88.94	89.40	88.49	88.52	88.96	80.12
Alex Net	90.59	91.09	90.10	90.20	90.64	82.88
Google Net	91.91	92.11	91.72	91.80	91.95	85.11
Proposed (I-VGGNet)	96.86	96.71	97.02	97.03	96.87	93.93

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

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Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.