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ORIGINAL RESEARCH ARTICLE

Deep learning-based approach for prediction of brain stroke from MR images for IoT in healthcare

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ABSTRACT

This study develops a technique to predict brain strokes using magnetic resonance imaging (MRI). Worldwide, brain stroke is a leading factor in death and long-term impairment. The impact of stroke on the life of survivors is substantial, often resulting in disability. Stroke analysis performed manually takes a lot of time and is subject to intra- and inter-operator variability. Consequently, this work aims to create a computer-based system for the prediction of stroke utilizing deep learning techniques, which help in timely diagnosis. The MRI images are preferred as it provides images of good contrast and no ionizing radiations are used in this imaging method. The deep learning methods included in this proposed work are DenseNet-121, Xception, LeNet, ResNet-50 and VGG-16. The DenseNet-121 classifier outperformed other classifiers and achieved acccuracy of 96%. The outcomes of the proposed approach for stroke prediction in IOT healthcare systems show that improved performance is attained using deep learning methods.

Keywords: stroke prediction; magnetic resonance images; deep learning; performance analysis; healthcare

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1. Introduction

An obstruction or constriction of a blood vessel causes the neurological disease known as a stroke[1]. Stroke may result in blood clotting in the brain and deprive the oxygen to brain cells. The brain cells may gradually die which affects the functioning of the brain and various body parts. It may impair one’s ability to move about or communicate or even cause death. As per records from World Stroke Organization 13 million individuals are affected by strokes annually, with 5.5 million of them dying due to this[2]. Since it is the biggest cause of death and disability in the world, brain stroke has a significant impact on many facets of life. Patients who suffer from strokes must deal with serious social and financial effects. Age affects the frequency of stroke, which doubles after age 55. However, a survey showed that strokes in adults 20 to 54 years of age rose from 12.9% to 18.6% from 1990 to 2016[3–5]. The second biggest cause of death worldwide, after heart disease, is brain stroke. Therefore, anticipating stroke instances can aid in ensuring that patients receive the proper care in time to prevent lifelong disability and death.

Magnetic resonance imaging (MRI) has emerged as a critical tool in clinical studies on brain anatomy[6]. MRI is the most frequently used medical imaging technique as it provides high resolution and contrast[7]. It is quite capable and progressively responsive to changes in tissue solidity required for pathological consultation with high precision. The MRI image dataset is utilized in the proposed approach to predict brain strokes. Various Researchers have presented many non-invasive methods to predict brain stroke in the Internet of Things (IoT) healthcare industries. The development of computer supported systems for the detection of brain stroke commonly makes use of Machine Learning (ML) models. However, ML-based methods are based on predefined attributes and are feature dependent. In the proposed work, an effective model for brain stroke prediction from MRI images using deep learning methods is developed for the IoT healthcare industry. This makes the model feature independent and provides improved accuracy for prediction of brain stroke.

The rest of the paper has following outline: The related works are discussed in Section 2. Section 3 describes proposed method. The outcomes of work are reported in Section 4. Section 5 contains the conclusion of work and its future aspects.

2. Related work

In literature, different approaches for predicting brain strokes utilizing machine learning methods are presented. In this section, some of those works are discussed.

A model using data science and machine learning was created by Rodríguez[8] for stroke prediction. The individual characteristics of patients including clinical data and demographic data were used as input dataset. For data comprehension and preparation, Data Mining techniques were applied, and a variety of supervised machine learning classifiers were then implemented to predict strokes. Random forest classifier provides the best accuracy of 92%, followed by XGBoost (91%) and decision tree (90%). In a similar approach, a convolution neural network (CNN) based strategy for stroke prediction was developed by Ashrafuzzaman et al.[9]. An input feature set of 11 parameters was utilized in this study, followed by feature selection using correlation. The classification was performed using selected features with high correlation and attained 95.5% accuracy using CNN classifier.

A model for the diagnosis of stroke disease was presented by Tazin et al.[10] combining a variety of physiological markers and ML algorithms. For the purpose of predicting strokes, they used decision trees, voting classifiers, logistic regression and random forests. With 96% accuracy rate, the random forest classifier yields the best results from this model. The authors[11] designed a model to predict patients at risk of stroke on basis of clinical and numerical attributes comprising of age, gender, medication, diabetes etc. The Multilayer Perceptron (MLP), C4.5 and Jrip classifiers were then applied to accomplish the classification, and MLP achieves the maximum accuracy of 94.42%. The effectiveness of decision tree, KNN, support vector machine (SVM) and Naive Bayes classifier for stroke prediction using psychological variables as input was examined by Sailasya and Kumari[12]. Using the Naive Bayes classifier, the highest accuracy of 82% was attained. The authors[13] developed a stroke prediction method using clinical features and different machine learning techniques. The improvised random forest algorithm presented in this method provides maximum accuracy of 96.9%. Islam et al.[14] developed a system using Random forest algorithm for stroke detection. For feature analysis, the synthetic minority over-sampling approach was used. The precision and f1-score produced by this system were 96%.

A machine learning-based algorithm for brain stroke diagnosis was proposed by Aishwarya et al.[15]. Feature extraction was carried out with Gray level co-occurence matrix (GLCM) and stroke detection accuracy of 90% was attained using SVM classifier. The diffusion-weighted Imaging (DWI) were used by Faust et al.[16] for brain stroke classification. The GLCM, Gray-Level Run Length Matrix, and Higher Order Spectra methods were used for the feature extraction. Utilizing SVM and various kernel functions, classification is performed. The maximum accuracy of 93.62% for stroke classification was provided by the SVM with Radial basis function (RBF).

Stroke prediction was carried out by Nwosu et al.[17] using multi-layer perceptron (MLP), Random Forest and decision trees. MLP produces an accuracy of 75.02%; random forest and decision tree produce accuracy of 74.53% and 74.31%, respectively.The authors[18] presented a model for prediction of stroke using ML methodss such as Decision Tree, KNN, Random Forest and DNN. The work carried out implemented K-NN, multiple linear regression and regression tree model for detection of brain stroke[19]. In this model, KNN provided the highest accuracy of 74.3% which is comparatively low.The machine learning system using Logistic Regression, Decision Tree, SVM , Random Forest and KNN was proposed by Harshitha et al.[20]. The outcomes indicate that for predicting strokes, the Random Forest classifier had the best accuracy (95%).

In the study done by Sundaram et al.[21], 14 characteristics made up of categorical and numerical parameters were used as input, and random forest classification provided accuracy of 96%. The SVM, bagging, boosting, random forest and Artificial neural network were employed by Govindarajan et al.[22]. The ML classifiers used by Rishabh et al.[23] for stroke detection include Naive Bayes ,KNN, random forest, decision trees and logistic regression. With accuracy of 95%, random forest classifier outperforms all.

The authors[24] used information from social media material to do stroke detection. For the grouping of data and stroke detection, a probabilistic neural network was used. This model achieves an accuracy of 89.90%, however, it is suitable only for short text responses. In work presented by Govindarajan et al.[25] to classify strokes, firstly, duplicate data is removed from the patient data by preprocessing and transformation. The classification performed using SVM and ensemble classifiers achieve 91% accuracy, however, artificial neural network provides an accuracy of 95%. Chantamit-o-pas and Goyal[26] suggest a deep learning-based stroke prediction algorithm. Deep learning model performance was compared to machine learning (ML) algorithms. It was observed that deep learning helps to gain unexpressed knowledge from the data which helps in the prediction of disease with better accuracy.

The majority of the works for predicting strokes, according to the literature review, included clinical and psychological factors. These characteristics may alter over time and don't offer enough information for stroke prediction. Furthermore, the traditional machine learning techniques utilized in earlier studies depend on handcrafted features and required a great deal of knowledge and skill for representation, i.e., the careful engineering of feature selection. Moreover, ML-based models are less robust to variations in data and may lead to potential bias. In the proposed work the effectiveness of deep learning methods for predicting strokes is examined. Autonomous feature learning in deep learning turns the initial data into more abstract layers for decision-making while providing the advantages of modularity. This model can be useful for early diagnosis and treatment of stroke, which can significantly improve patient outcomes.

3. Methodology

The proposed work aims to build a framework for brain stroke prediction using MRI images based on deep learning (DL) methods as demonstrated in **Figure 1**. The MRI image dataset is collected and preprocessed so as to perform brain stroke analysis with improved accuracy. Initially, images are loaded from the dataset, followed by data preprocessing. Next, the images are processed through deep learning architecture to perform the brain stroke prediction. The effectiveness of the proposed model based on deep learning is also evaluated in comparison to that of conventional machine learning methods.

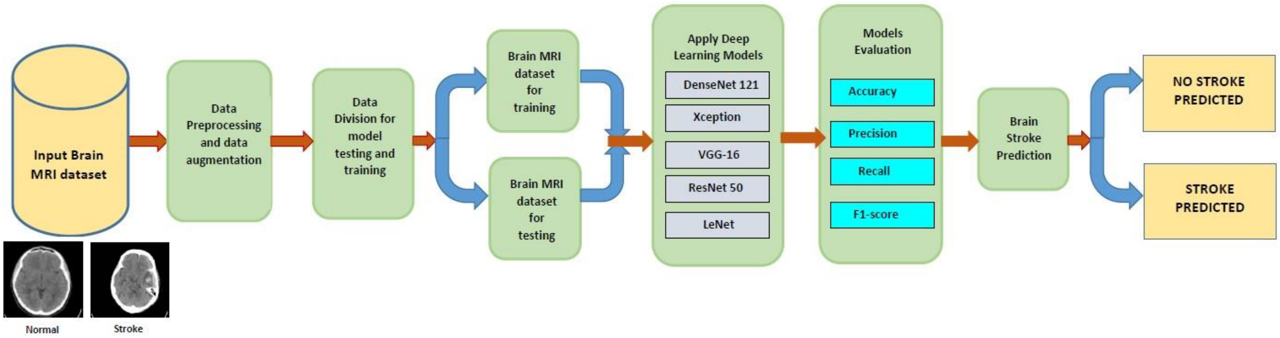

Figure 1. Proposed method framework.

3.1. Input dataset and preprocessing

The MRI image dataset from Kaggle[27] was used in the proposed work to perform brain stroke prediction. There are 2551 MRI images altogether in the dataset. The suggested system is trained and evaluated using these MR images. 2251 images are used to train the model, and 250 images are used to test it.

The preprocessing is performed on the input dataset so as to improve the generalization, reduce overfitting and make the model to perform in a better way. Image scaling, reorientation, and noise removal are all part of the preprocessing. The dataset includes MRI images of different sizes, these were resized to 224 × 224 pixels before being fed into the deep learning architecture. **Figures 2** and **3** illustrate sample brain MRI slices of normal and stroke patients respectively from dataset.

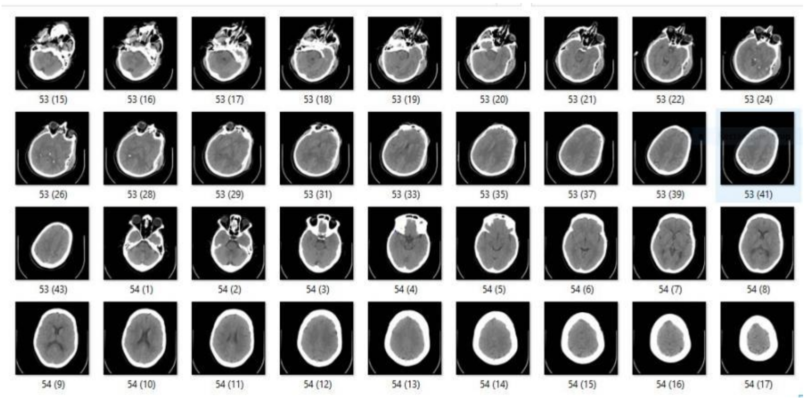

Figure 2. Normal brain MRI slices from dataset.[27]

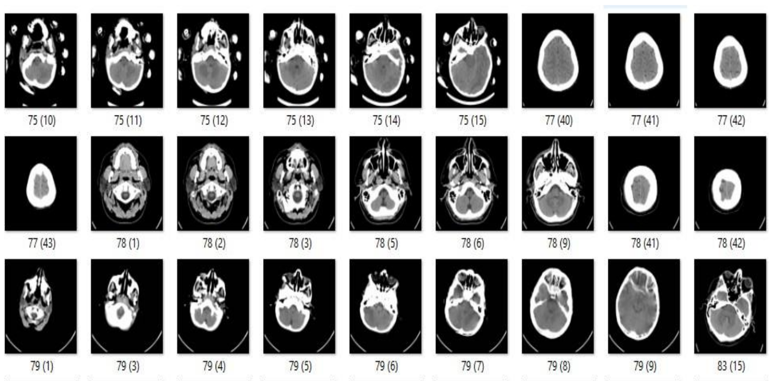

Figure 3. Stroke affected brain MRI slices from dataset.[27]

3.2. Deep learning methods

The ability of deep learning to learn from data has made it the most widely utilized and basic technique in the domain of artificial intelligence and computer-based learning at the moment. Recently a considerable advancement is observed in the use of deep learning algorithms to solve research problems in different fields, such as sentiment analysis, object detection, finance, and many others. The field of medicine has particularly benefited from the advancements in artificial intelligence and IoT-based models, which have the potential to save time and yield accurate results. In order to represent the data abstractions needed to build computational models, the architecture of deep learning algorithms employs a number of hidden layers. This also supports finding solutions for complex and non-linear problems[28].

In the proposed model various deep learning algorithms are implemented to perform brain stroke prediction and their performance is analyzed. The deep learning models receive the preprocessed images as input and use them to determine whether the input image is normal or stroke-related. The deep learning classifiers implemented in this proposed work are DenseNet-121, Xception, VGG16, LeNet-5 and ResNet-50. In the ensuing subsections, the models are described.

3.2.1. DenseNet-121

A DenseNet is a type of CNN model in which Dense Blocks are used to create dense connections between its layers. This architecture is referred regarded as "dense" because it employs a special concatenation technique that connects every layer to every other layer in a feed-forward fashion as opposed to standard neural networks, in which each layer is only connected to the previous one. This connectivity pattern leads to high parameter efficiency, allowing the network to achieve good performance with fewer parameters than other architectures[29].

DenseNet-121 is a specific implementation of the DenseNet architecture with 121 layers. It is made up of several convolutional layers that are followed by dense blocks with several convolutional layers that concatenate their feature maps. The spatial dimensions of the feature maps are then decreased by separating these dense blocks using pooling and convolutional layers[30].The architecture of the DenseNet-121 network used in the proposed work is shown in **Figure 4**.

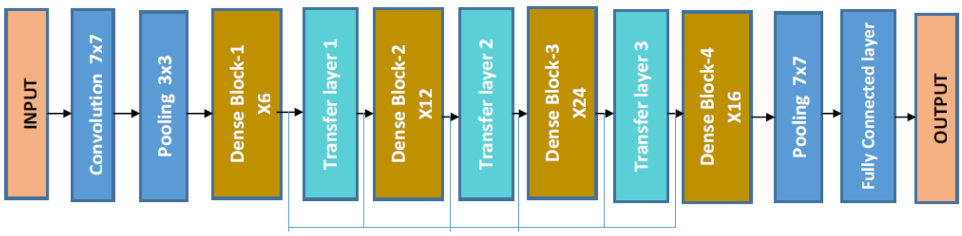

Figure 4. Architecture of DenseNet-121 model.

3.2.2. Xception

A deep convolution network called the Xception makes use of Depthwise Separable Convolutions. The "Xception" model advances the core concepts of the Inception algorithm and is an acronym for "extreme inception". Inception first applied 1 × 1 convolutions to the initial input to compress it, after which different types of filters were applied to each depth space from each of the input spaces. The Xception model on other hand uses 1 × 1 convolution to compress the input space all at once before applying the filters to each depth map independently. Moreover, the depthwise convolution comes after a pointwise convolution in Xception[31]. The data is processed in three steps: entery flow, middle flow, which is iterated eight times, and exit flow. The architecture of Xception is shown in **Figure 5**.

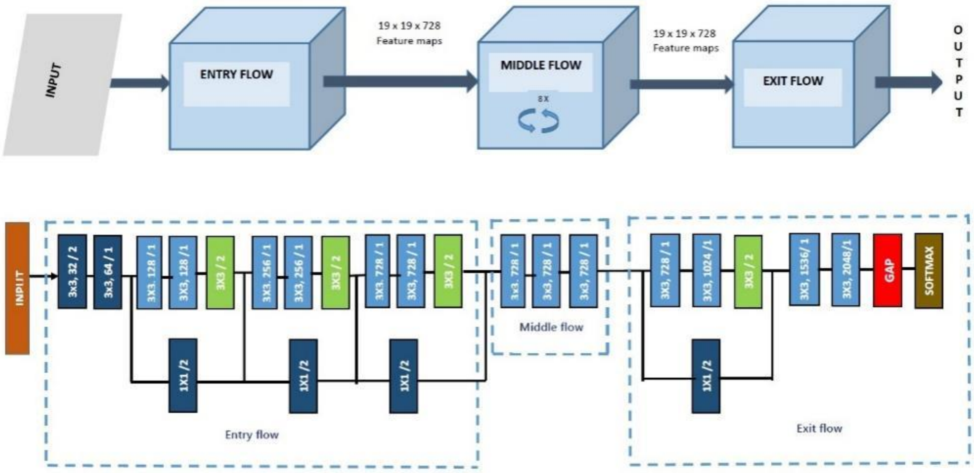

Figure 5. Architecture of Xception model.

3.2.3. VGG-16

The VGG is a series of the CNN model developed by Visual Geometric Group. Here, 16 refers to number of weighted layers. VGG16 has a total of 21 layers, including 13 convolutional layers, 5 Max Pooling layers, and 3 Dense layers. However, only sixteen of these are weight layers or learnable parameters layers[32,33]. The activation function of all hidden layers is ReLU. ReLU is more computationally effective since it expedites learning and lessens the possibility of vanishing gradient issues. The architecture of VGG-16 is demonstrated in **Figure 6**.

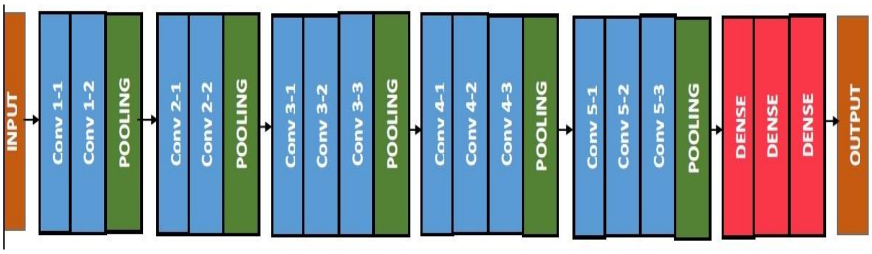

Figure 6. Architecture of VGG-16 model.

3.2.4. LeNet-5

LeNet is a commonly used neural network design that was primarily created for character recognition applications[34]. There are 5 learnable layers in it. Three sets of convolutional layers, two average pooling layers, and two fully linked layers make up the LeNet-5 architecture. **Figure 7** shows the LeNet-5 architecture utilized in the proposed work.

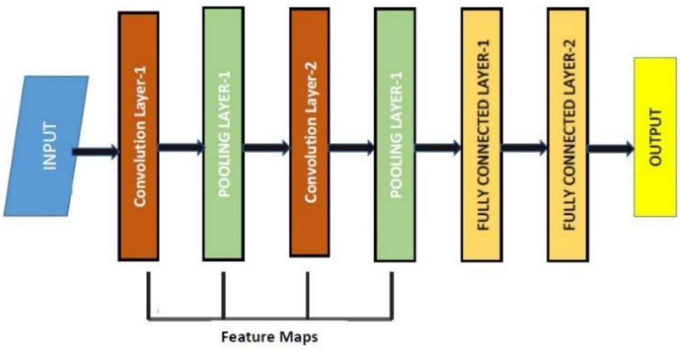

Figure 7. Architecture of LeNet-5 model.

3.2.5. ResNet-50

The term "residual network" (abbreviated "ResNet") refers to the utilization of leftover connections in the network. The 50 layers that make up the ResNet-50 architecture include a convolutional layer, a max pooling layer, and several residual blocks[35]. Although the ResNet50 architecture was created for computer vision activities such as identification of objects and image classification, it can also be used to enhance depth, improve accuracy, and cut costs in non-computer vision operations. Archiecture of ResNet-50 used in this study is illustrated in **Figure 8**.

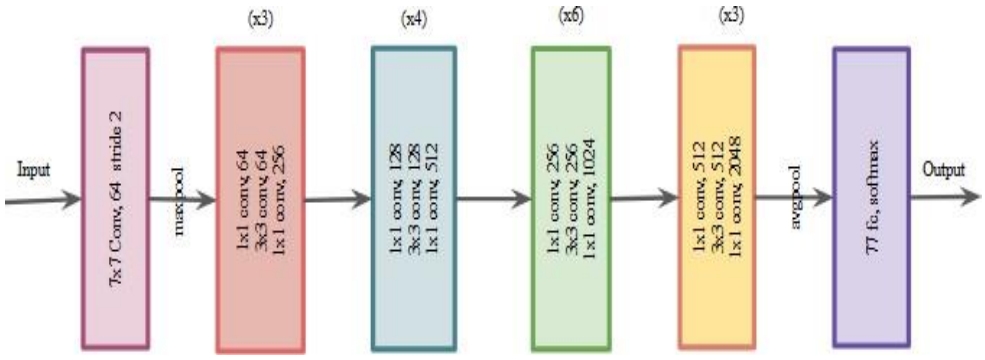

Figure 8. Architecture of ResNet-50 model.

4. Parameters for performance analysis

The performance of the proposed brain stroke prediction framework is determined by computing five significant assesment metrics namely—Accuracy, Sensitivity, Specificity, Precision and F1 Score. These parameters are calculated by computing the confusion matrix values[10] as descibed in **Figure 9**.

		Actual Values	
		Positive	Negative
Predicted values	Positive	True Positive (TP)	False Positive (FP)
	Negative	False Negative (FN)	True Negative (TN)

Figure 9. Confusion matrix.

1) *Accuracy*: It reflects the proportion of correctly predicted cases of brain stroke among all predictions.

$$Accuracy = \frac{(TN + TP)}{(TN + FP + FN + TP)} \tag{1}$$

2) *Precision:* It reflects the number of true positives (actual stroke cases) from total positive predicted by model.

$$Precision = \frac{TP}{(FP + TP)} \tag{2}$$

3) *Sensitivity:* It is proportion of all data samples for a class that a model properly recognizes as belonging to the positive class (actual stroke cases).

$$Recall = \frac{TP}{(TP + FN)} \tag{3}$$

4) *Specificity:* It is proportion of data samples from that class out of all samples that a model correctly recognizes as being in the negative class (no stroke).

$$Specificity = TN/\frac{TN}{(TN+FP)} \times 100 \quad (4)$$

5) *F1-score:* It combines both precision and recall scores of a model to provide a balanced evaluation of its overall performance.

$$F1-score = \frac{TP}{TP + \frac{1}{2}(FP+FN)} \quad (5)$$

5. Result analysis

The outcomes of the proposed framework for predicting brain strokes using deep learning (DL) techniques are described in this section. The performance metrics are compued from different DL classifiers-DenseNet-121, Exception, LeNet-5, ResNet-50, and VGG-16. Additionally, the effectiveness of decision trees and support vector machines for brain strokes prediction is computed.The features computed for feature extraction are GLCM parametrs extacting texture information from input images[15,36]. Furthermore, the efficacy of deep learning and machine learning methods for predicting brain strokes is described. The proposed approach is then compared with earlier works on stroke prediction from the literature.

5.1. Performance of DL algorithms for stroke prediction

The analysis of various deep learning (DL) algorithms for stroke prection is carried out. The accuracy, sensitivity and specificity results for various classifiers for proposed model are illustrated in **Figure 10**. The comparative analysis of precision and F1-score rates for different classifiers is illustrated in **Figures 11** and **12**. As observed from the results, DenseNet-121 provides better results for brain stroke prediction with accuracy of 96% and outperforms other deep learning classifiers implemented in this study. DenseNet-121 technique yields F1-score of 0.95 and best precision value of 0.96. Additionally, the DenseNet-121 classifier achieves the best value for the sensitivity parameter measuring the model's ability to detect true positives, i.e., stroke patients. DenseNets utilize fewer parameters leading to more compact models. They have outperformed other deep learning models used in this study and generates better results.

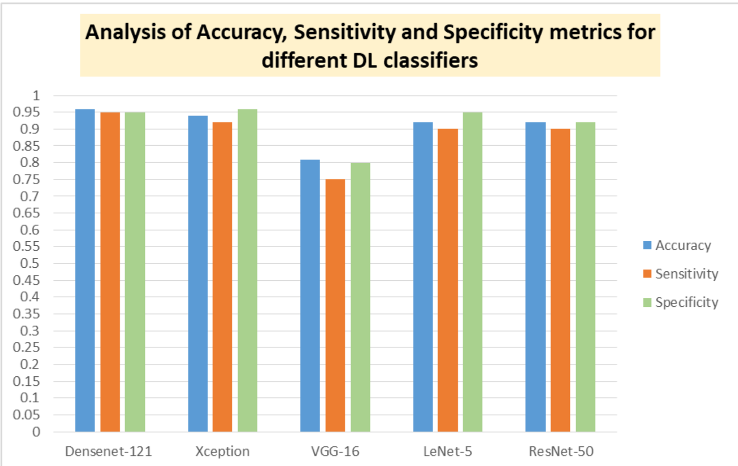

Figure 10. Performance analysis of accuracy, sensitivity and specificity for proposed model.

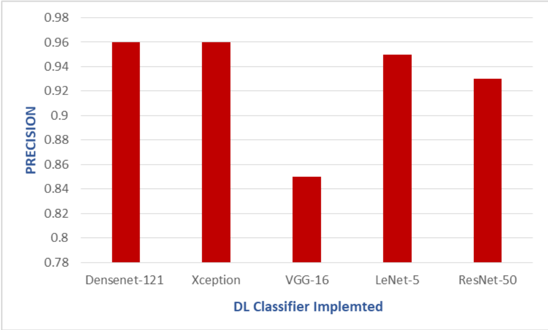

Figure 11. Precision comparison for different DL classifiers implemented in proposed model.

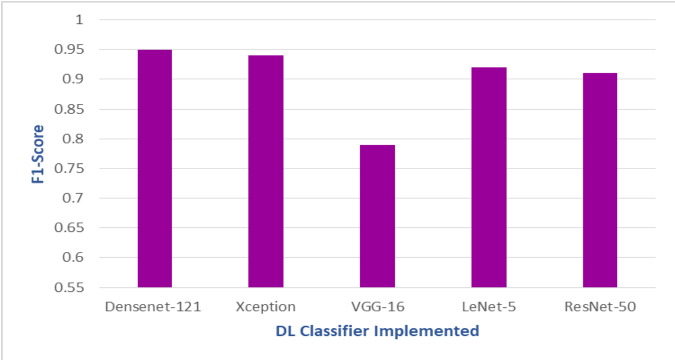

Figure 12. F-Measure comparison for different DL classifiers implemented in proposed model.

5.2. Performances of ML algorithms

In the sub-section, the results obtained for stroke prediction using machine learning (ML) classifier is analyzed. The **Figure 13** shows the accuracy attained for decision tree and SVM classifier. The prediction accuracy for ML methods is compared with DenseNet-121 results obtained from proposed framework based on deep learning approach. The findings show that the proposed deep learning framework employing the DenseNet-121 classifier achieves more accuracy than decision tree and SVM classifiers.

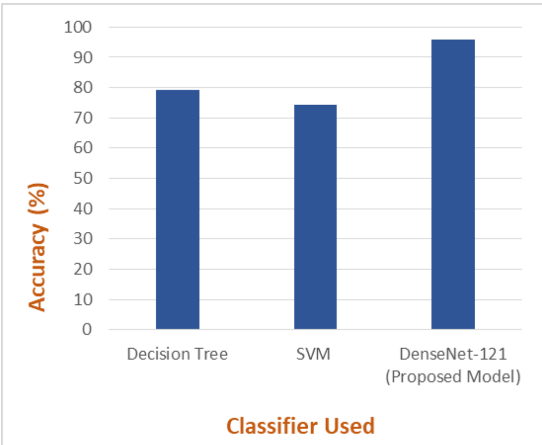

Figure 13. Comparison of machine leaning and proposed model.

5.3. Comparison with previous works

The effectiveness of the suggested model for predicting brain strokes is evaluated in comparison to previous works from the literature. **Table 1** summarizes the comparitive analysis for proposed and previous works. As observed proposed model using MRI images for prediction of brain stroke outperformed existing models. Most of existing methods used pychological parameters including clinical and demographic features for stroke prediction. These handcrafted features doesn't provide sufficient information for predicting stoke and may leads to potential bias. However, in proposed framework deep learning classifiers are implemented for analyzing MRI images for stroke prediction. These classifier provides recurrent information and extensive analysis of input images thereby generating better prediction accuracy.

Table 1. Comparative analysis of proposed and previous models.

S.No	Authors	Classifier used	Accuracy (%)
1.	Jose-A Tavares[8]	Random forest	92%
2.	Almadani and Alshammari[11]	Multilayer perceptron (MLP)	94.4%
3.	Sailasya and Kumari[12]	Naïve Bayes	82%
4.	Aishwarya et al.[15]	Support Vector Machine	90%
5.	Faust et al.[16]	Support Vector Machine	93.62%
6.	Nwosu et al.[17]	Random Forest	75.02%
7.	Shen-Feng Sunga et al.[19]	MLP,KNN, Regression Tree	74.3%
8.	Harshitha et al.[20]	Random Forest, KNN, Logistic Regression	95%
9.	Pradeepa et al.[24]	Probability Neural Network	89.90%
10.	Proposed Model	DenseNet-121	96%
11.	Proposed Model	Xception	94%

6. Conclusion and future scope

The research work proposed here aims to develop a framwork for brain stroke prediction for IoT healthcare using deep learning algorithms. The MRI images are used as input data for analysis of brain and perform stroke prediction. The deep learning models implemented in this study are DenseNet-121, Xception, LeNet-5, ResNet-50 and VGG16. The dense network connections of DenseNet-121 provided highest acuracy of 96% with sensitivity and specificity of 95% for stroke prediction in proposed framework. Additionally, comparisons are made between deep learning techniques and machine learning techniques as well as other works from literature. The findings demonstrate that the suggested model offers a reliable and effective architecture for MRI-based brain stroke prediction. Future research can be extended using larger dataset collected from hospitals and perform stroke prediction using multimodal MRI images.

Author contributions

Conceptualization, MG, PM and KHR; methodology, MG; software, MG and KHR; validation, MG, PM and KHR; formal analysis, MG; investigation, PM and KHR; resources, MG and PM; data curation, KHR; writing—original draft preparation, MG, PM and KHR; writing—review and editing, MG; visualization, MG and KHR; supervision, MG; project administration, MG. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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