

CNN and GAN Based Stroke Detection Using CT Scan Images

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Abstract: The objective of the research work is to detect stroke using CT scan images. In the research work an analysis of 3D CNN method for stroke detection is presented. The work also presents a new method of stroke detection using semi-supervised Adversarial Networks (SGAN). 3D CNN is the traditional approach to any type of image classification problem. But being data-hungry, it becomes difficult to use them when data is scarce. High-quality medical data is difficult to find and hence alternative approaches seem worth approaching. The relatively new GANs can generate images like the training images, and its SGAN variant can use these generated images for training the classifier. We investigate the usefulness of SGANs comparatively with CNNs in this paper. The proposed SGAN method is compared with state of art methods in literature using accuracy, sensitivity and specificity. The SGAN method demonstrates an accuracy of 93%, Sensitivity of 100% and Specificity of 90%. For small data sets in medical imaging the proposed SGAN method exhibit an encouraging performance as compared to other methods using large datasets. In the research paper, we propose methodologies for detecting strokes by using 2 approaches: 3D CNNs and SGANs. The relatively new GANs can generate images like the training images, and its SGAN variant can use these generated images for training the classifier. We investigate the usefulness of SGANs comparatively with CNNs in this paper.

Index Terms: Stroke, CT Scan, Artificial Intelligence, bio-signals, 3D-CNN, GAN, SGAN

1. Introduction

Stroke is a major type of cardiovascular disease, and it causes functional disorders like paralysis. A stroke happens when the blood vessels in the brain either become clogged or burst, thus blocking the supply of a sufficient amount of oxygen to the brain, which results in necrosis of, brain tissue [1]. As cells in the brain die, certain parts of the body lose functionality. This leads to multiple symptoms such as loss of speech, sensory impairment, and body coordination.

Earlier, various devices were used to measure stroke which included computed tomography (CT) and magnetic resonance imaging (MRI). After comparing the results of the two devices, images taken from CT scans proved to be more accurate and had better performance than MRIs as MRI scan are good for differentiation of soft tissues [1]. Also, MRIs are mostly used in situations where there is no time pressure to provide treatment, which is usually as follow-up

imaging. Detecting images with CT scans helped identify the stroke areas and increased radiology percentages. CT is the first line treatment for diagnosing Stroke. A radiologist typically looks in conjunction at the above factors and the neurological deficits of the patients to diagnose a Stroke.

Many feature extraction and classification methods are used in many conventional stroke detection methods. In the research work, the analysis and implementation of the conventional method of 3D-CNN used for Stroke prediction is carried out along with a new method. The work also presents a comparison with conventional methods for performance evaluation.

1.1 Related work

Numerous studies have employed artificial neural networks (ANNs) for stroke diagnosis and prediction based on patient data. One such study by Kasabov et al. [2] utilized ANN to forecast the risk rate of stroke with 95.33% accuracy based on 300 experimental data. Similarly, Shanthi et al. [3] applied ANN to stroke patient data and improved diagnostic accuracy through the learning algorithm. However, this system's mechanism is difficult to analyze as it primarily focuses on prediction accuracy. In contrast, Bentley et al. [4] developed a predictive method for symptomatic intracranial hemorrhage during melting treatment for ischemic stroke using SVMs, which successfully reported 9 out of 16 patients from CT scans of 116 ischemic stroke patients. Khosla et al. [5] proposed a prediction model for stroke risk factors by tuning the hyper-parameters of the SVM kernel function, but it is not suitable for detecting or predicting pre-symptoms of stroke diseases using real-time bio-signals.

To address these limitations, Yu et al. [6] conducted an analytical study using the decision tree algorithm to automatically classify the gravity of NIHSS results. However, the decision tree algorithm's essence only provides a partial explanation of the prediction model algorithm. Amini et al. [7] predicted stroke based on more than 50 risk factors using algorithms such as KNN, resulting in relatively accurate predictions. Still, it is not convenient for use as a prediction model for detection before onset.

Moreover, several studies have explored the detection and segmentation of stroke through CT and MRI images using Neural Networks. Karthik et al. [8] summarized deep learning stroke detection approaches, including Kamnitsas et al. [9], who achieved 77% precision using a multimodal approach to stroke lesion detection. Lisowska et al. [10] and Chin et al. [11] used the traditional CNN approach to lesion detection and achieved 96.4% and 92.9% accuracy, respectively. Nielsen et al. [12] attempted stroke detection on multimodal MRI images with 85% accuracy. Shimohara et al. [13] performed CNN-based stroke detection on 18,396 samples to achieve 86% accuracy, while Barman et al. [14] used CTA images and obtained a higher accuracy of 97%. Finally, Cho et al. [15] performed CNN based on the Caffe framework and obtained an accuracy of 98.2% on a dataset for hemorrhagic stroke.

The work proposes a new method for stroke detection using CT images by semi-supervised Adversarial Networks (SGAN). The work also presents an analysis of CNN model for stroke detection. Comparison of the proposed work with related works demonstrates enhanced performance in terms of accuracy, sensitivity and specificity.

In the research work Section 1 presents the introduction to the topic. Section 2 summarizes the related literature on stroke detection using CT images based on deep learning. Section 3 discusses the proposed method for stroke detection using SGAN. Section 4 exhibits the experimental results along with discussion. Section 5 presents the conclusions of the research work.

2. Method for Stroke Detection Using CT Images

The proposed system suggests a novel approach for detecting stroke diseases based on CT scan images utilizing AI techniques. Current CT-based stroke detection methods rely on CNNs. However, the proposed system aims to enhance detection accuracy by incorporating GANs.

In machine learning, generative modeling is an unsupervised learning approach that involves the automatic learning and recognition of input data patterns so that the model can generate new models from the original dataset. GANs are an effective means of training a generative model by framing the problem as a supervised learning task. This approach comprises two sub-models: the generator model, which is trained to produce new examples, and the discriminator model, which distinguishes between real (from the domain) and fake (generated) examples. The system utilizes attribute subset selection from preprocessed CT scans to generate learning models using machine learning algorithms for early stroke detection and prediction. The primary goal of this research work is to improve the accuracy of stroke disease analysis and prediction while enhancing current experimental techniques for analyzing head CT scans for stroke.

The section proposes the proposed method using GAN and SGAN. The section also discusses in brief the 3D Convolutional neural network model for stroke detection using CT scans.

2.1 3D Convolutional Neural Network (3D-CNN)

A deep learning method known as Convolutional Neural Network (CNN) can analyze an image input by assigning significance to different elements based on learnable weights and biases. The CNN requires less preprocessing than other classification algorithms. While in traditional methods, filters are manually designed, CNNs can learn these filters with sufficient training.

A convolution neural network applies three general ideas

- 1) Local receptive fields
- 2) Convolution
- 3) Pooling

The local receptive field allows hidden neurons to process input data within a specific area without considering changes outside that boundary. Each connection in the convolution process learns the weight of the hidden neuron with reference to its movement from one layer to another. Pooling layers are applied immediately after the CNN is defined, taking the feature map output from the convolutional network and producing a condensed feature map.

Fig. 1 represents a general block diagram of a 3D CNN model. Fig. 2 represents the 3D CNN structure implemented in the work for analysis of stroke detection using CT scan.

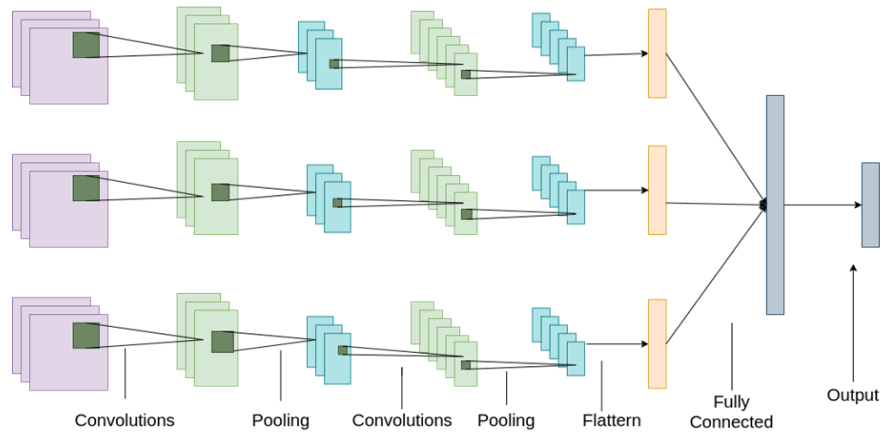


Fig. 1. Block Diagram of 3D-CNN. Adapted from [16]

2.2 Generator Adversarial Networks (GAN)

The GAN model is comprised of a generator and a discriminator. The primary objective of the discriminator is to differentiate between the data samples that are real and those that are generated by the generator. On the other hand, the generator aims to create data samples that can deceive the discriminator. The generator operates by taking in a random noise vector as input and generating a data sample that is similar to the target distribution. At the same time, the discriminator evaluates the data samples and determines whether they are real or fake. It takes in the input data, which could be either real or generated by the generator, and produces a probability value indicating how confident it is that the input is real. If the discriminator outputs a high probability, it implies that the input is genuine, while a low probability indicates that the input came from the generator network. Fig. 3 presents the block diagram of GAN.

2.3 Semi-supervised Generator Adversarial Networks (SGAN)

SGAN stands for Semi-supervised GAN. This model of GAN can work on supervised Data and can be used for classification. In the proposed work the main advantage of SGANs in cases where there is less availability of training data for neural networks. GANs are used to generate images that are similar to test images. SGANs take it a step further by using these similar generated images as test data. This results in an improvement in the performance of the model as it has more GAN-generated data to train on. The process of SGANs is similar to traditional GANs with a few changes. In SGANs, the generator takes in the class label along with random noise, so it can generate images of specific classes. The discriminator also has 2 outputs, the real/fake image classification, and image label classification. Fig. 4 presents the block diagram of semi supervised generative adversarial networks.

The SGAN consists of 2 neural networks- the generator model and the discriminator model. The generator model in SGAN works by taking 2 inputs- a randomized initialization vector and a class label. In the proposed method implementation of SGAN early on in the model creates a feature map of the class label and merges it suitably with a feature map created by up sampling the random vector. The model then up samples by deconvoluting till the appropriate image dimensions are reached. Fig. 5 demonstrates the structure of the GAN model and Fig. 6 presents the Discriminator neural network in the proposed method. The Discriminator model contains a single input, which can be both- the training image and the image created by the generator. The output of the discriminator in SGAN is two-fold- the real/fake classification and the image classification. The SGAN with the GAN and the Discriminator model proves useful for stroke detection for small datasets.

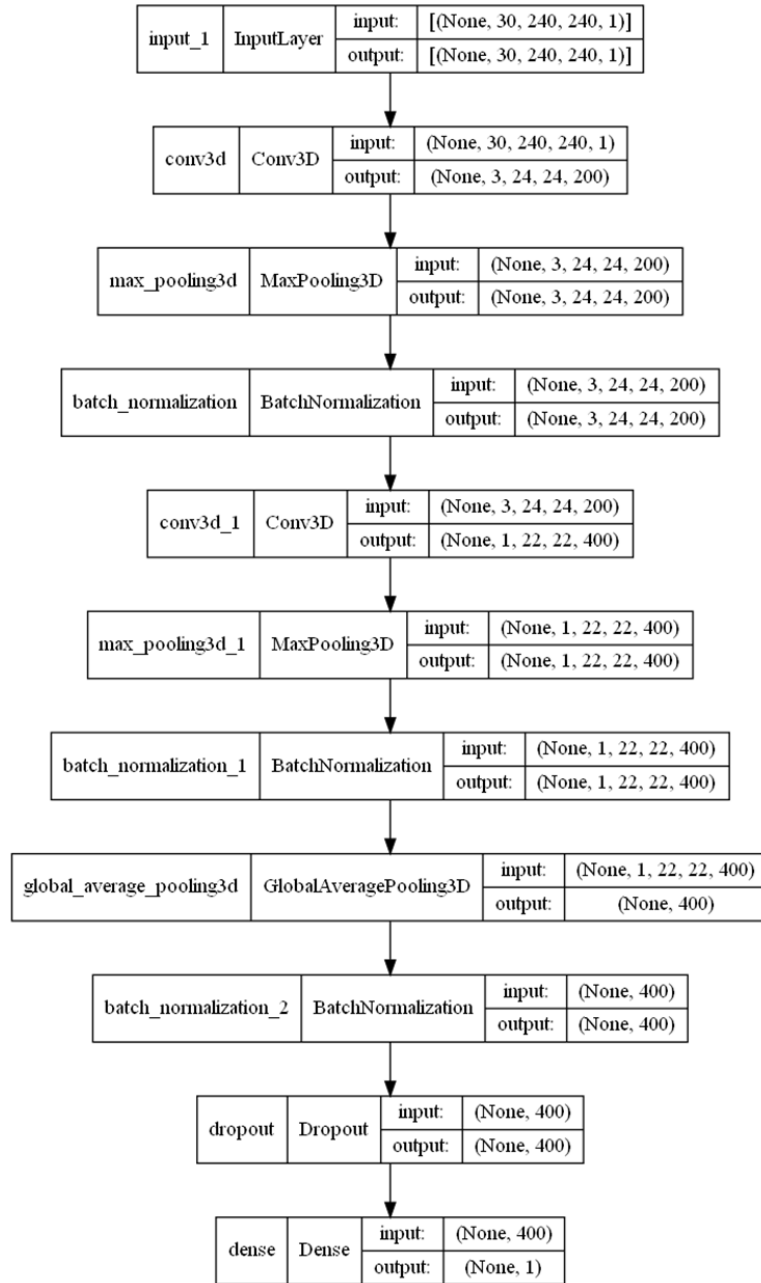


Fig. 2. 3D CNN structure

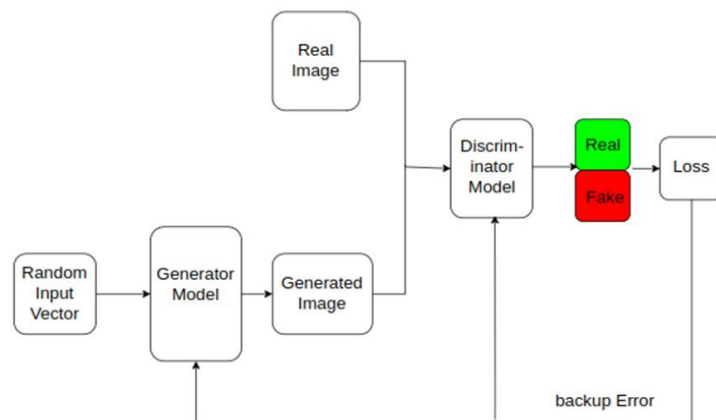


Fig. 3. Generative Adversarial Networks

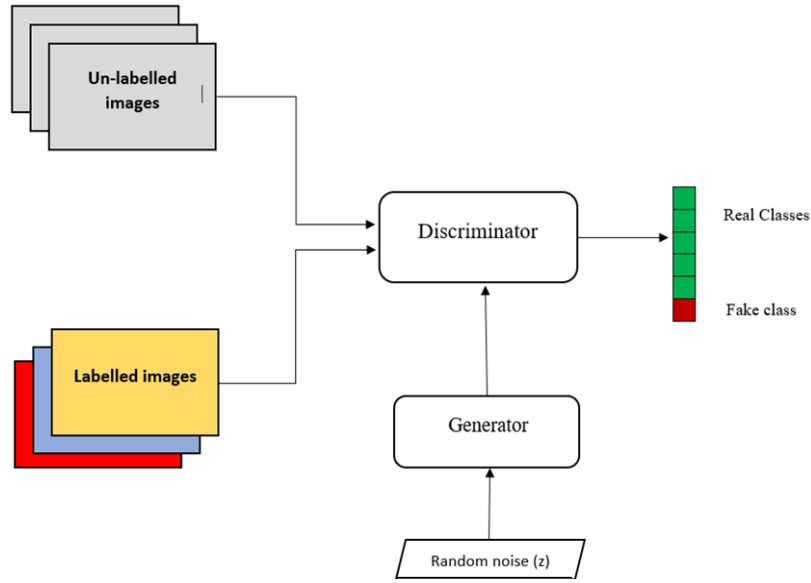


Fig. 4. Block Diagram of Semi-Supervised Generative Adversarial Networks Adapted from [17]

3. Results

The following section describes the CT dataset used for the experiments. It also summarizes the performance metrics used for evaluation of the proposed method. The section presents a comparison on the experiments and results for the proposed method with different state of the art methods in literature

3.1 Database Description

A dataset of 2500 images has been used for this project [18]. The data set is in the form of jpeg slices of a CT scan and hence needs preprocessing to form a volume necessary for this application. The dataset contains 52 volumes of CT images of which 32 are positive samples and 29 are negative. The overall bias of the database is moderate but can be mitigated by batching and shuffling the database. Fig. 7 represents a few samples for the CT scan dataset for normal brain and hyperintense regions responsible for stroke.

3.2. Performance Metrics

The proposed method is validated using the following performance metrics: Accuracy, Sensitivity and Specificity. Accuracy represents how well a binary classification test correctly identifies a specific condition. Sensitivity demonstrates the probability of a stroke given the condition is present. Specificity, gives the probability of a negative condition that is also identified as negative by ground truth. The accuracy is given as Eq. 1

$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}} \quad (1)$$

Sensitivity is computed as given in Eq. 2

$$Sensitivity = \frac{\text{True Positive}}{\text{True Postivies} + \text{False Positives}} \quad (2)$$

Specificity is evaluated using the Eq. 3 as follows

$$Specificity = \frac{\text{True Negatives}}{\text{True Negatives} + \text{False Postivies}} \quad (3)$$

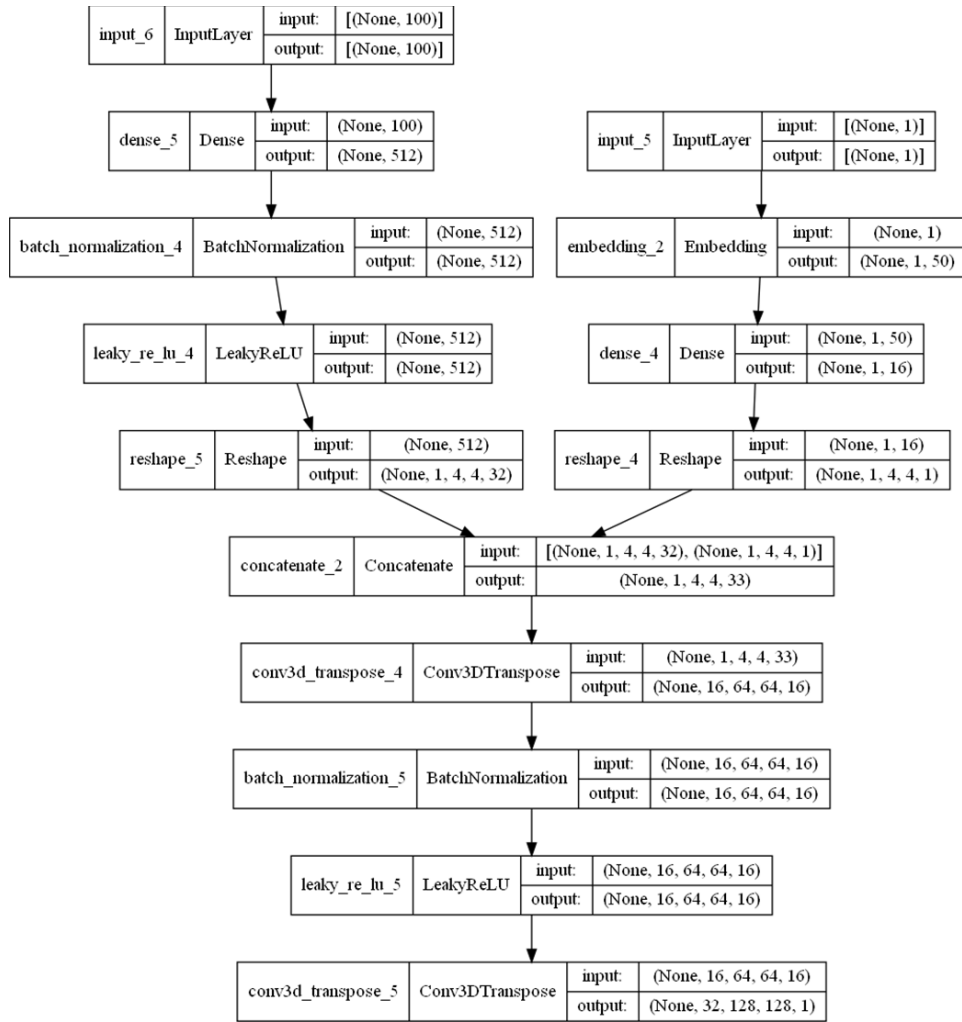


Fig. 5. GAN Generator Model

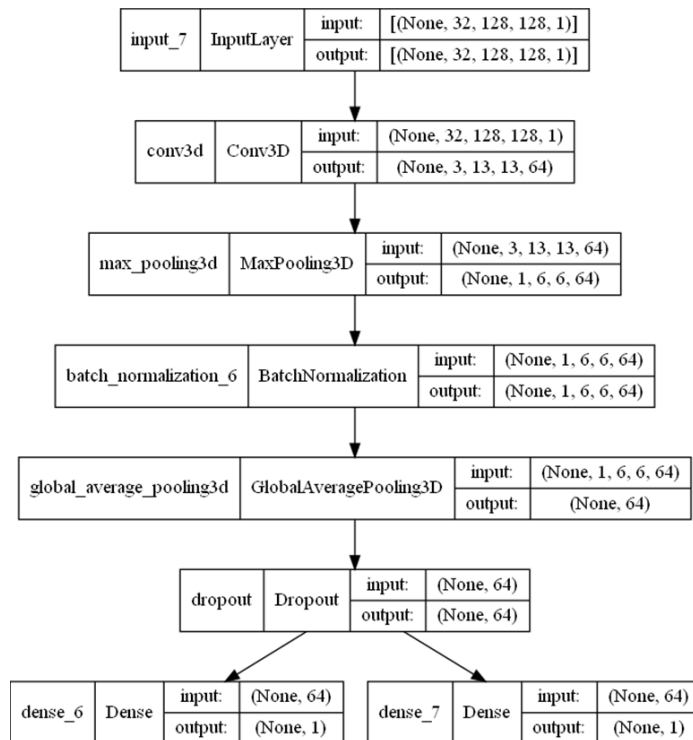


Fig. 6. GAN Discriminator Model

3.3 Experiments

3.3.1 Experiments performed for stroke detection using 3D CNN

Fig. 8 represents the 3D CNN model implementation for stroke detection using CT scans. The input to the 3D CNN is a volumetric image (as given by CT) resized to 30x240x240 in grayscale. The original image is 30x650x650, but the image was downsized for performance reasons. The input image goes through 3D CNN consisting of 2 Convolution Layers, with appropriate pooling, batch normalization, and dropout optimized for maximum accuracy.

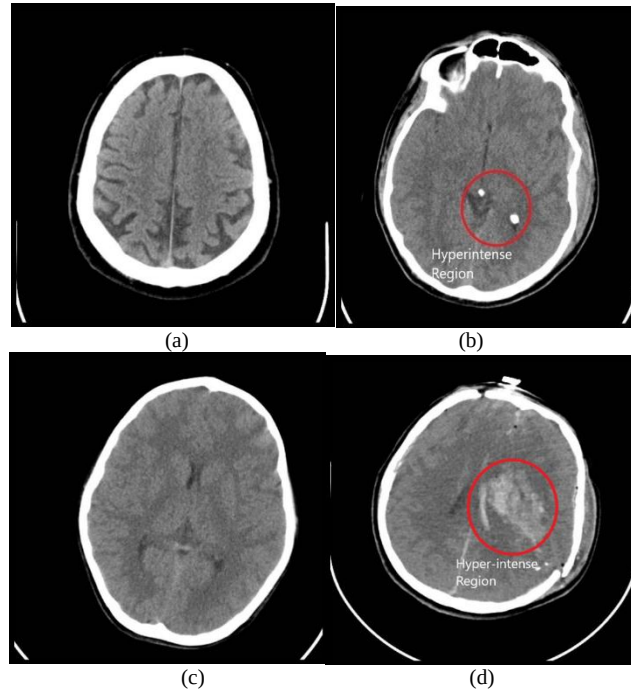


Fig. 7. Sample slices from the CT datasets representing normal brain and hyper intense regions (a) normal brain CT scan image (b) Stroke brain CT scan image represent hyper intense region responsible for stroke in red circle (c) normal brain CT scan image (d) Stroke brain CT scan image hyper intense region responsible for stroke in red circle.

Layer (type)	Output Shape	Param #
conv3d_8 (Conv3D)	(None, 3, 24, 24, 200)	25200
max_pooling3d_8 (MaxPooling 3D)	(None, 3, 24, 24, 200)	0
batch_normalization_12 (Batch Normalization)	(None, 3, 24, 24, 200)	800
conv3d_9 (Conv3D)	(None, 1, 22, 22, 400)	2160400
max_pooling3d_9 (MaxPooling 3D)	(None, 1, 22, 22, 400)	0
batch_normalization_13 (Batch Normalization)	(None, 1, 22, 22, 400)	1600
global_average_pooling3d_4 (GlobalAveragePooling3D)	(None, 400)	0
batch_normalization_14 (Batch Normalization)	(None, 400)	1600

Fig. 8. 3D CNN model implementation for stroke detection using CT scans

Fig. 9 demonstrates the accuracy against the number of epochs for 3D CNN model. The figure represents the accuracy the model achieved after each iteration. A graph flattening out at a fixed number indicates that the model has achieved the highest accuracy or that the algorithm has gotten stuck at a local minimum. Having tried multiple learning rates, we have achieved the highest possible accuracy in this case. The accuracy of the 3D CNN model is not sufficient enough for any realizable purpose. One of the reasons for such performance is the data-hungry nature of CNN. CNNs tend to perform very well when there is plenty of data. But in the case of medical imaging, having well-documented high-quality data is very difficult. Medical imaging data also tends to be volumetric, which increases its size and makes it increasingly difficult to handle. This limitation of CNN is seen to be overcome by use of GANs to greatly increase accuracy in low memory scenarios. Table 1 demonstrates the confusion matrix of 3D CNN model for prediction of accuracy, sensitivity and specificity.

Table 1. Four values of the Confusion matrix of 3D CNN: True Negative(Tn), False Positive(Fp), False Negative(Fn), and True Positive(Tp)

	Predicted: NO	Predicted: Yes
Actual: NO	Tn=0	Fp=0
Actual: YES	Fn=20	Tp=26

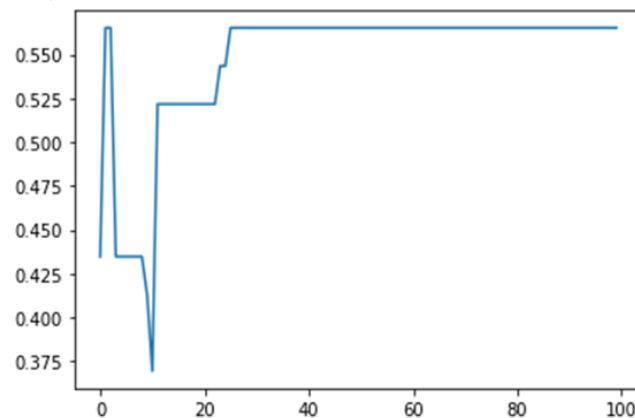


Fig. 9. Accuracy against number of epochs for 3D CNN model

3.3.2 Experiments performed for stroke detection using SGAN

Table 2 demonstrates the confusion matrix for the stroke detection using the SGAN mode. The loss of the generator is calculated from the output of the fake input of the discriminator. Due to this the model learns to minimize this loss function even on biased or low-quality data, potentially perpetuating biases present in the training data. As the image classification is binary, binary cross-entropy has been used for the loss function and sigmoid as the final activation function. Binary cross-entropy is effective for measuring the difference between the predicted and actual labels in a binary classification setting, guiding the generator to produce images that lead to a correct classification.

Fig. 10 demonstrates the implementation of the SGAN model for stroke detection. Fig. 11 demonstrates the accuracy against the number of epoch's for the proposed method using SGAN for stroke detection. Fig. 11 represents the relationship between accuracy the model achieved after each iteration and demonstrates that the model achieved a stable accuracy after much iteration.

Table 2. Four values of the Confusion matrix of SGAN: True Negative(TN), False Positive(FP), False Negative(FN), and True Positive(TP)

	Predicted: NO	Predicted: Yes
Actual: NO	TN=9	FP=1
Actual: YES	FN=0	TP=4

Layer (type)	Output Shape	Param #	Connected to
input_2 (InputLayer)	[(None, 100)]	0	[]
dense_1 (Dense)	(None, 512)	51200	['input_2[0][0]']
input_1 (InputLayer)	[(None, 1)]	0	[]
batch_normalization (Batch Normalization)	(None, 512)	2048	['dense_1[0][0]']
embedding (Embedding)	(None, 1, 50)	100	['input_1[0][0]']
leaky_re_lu (LeakyReLU)	(None, 512)	0	['batch_normalization[0][0]']
dense (Dense)	(None, 1, 16)	816	['embedding[0][0]']
reshape_1 (Reshape)	(None, 1, 4, 4, 32)	0	['leaky_re_lu[0][0]']
reshape (Reshape)	(None, 1, 4, 4, 1)	0	['dense[0][0]']
concatenate (Concatenate)	(None, 1, 4, 4, 33)	0	['reshape_1[0][0]', 'reshape[0][0]']
conv3d_transpose (Conv3DTranspose)	(None, 16, 64, 64, 16)	14256	['concatenate[0][0]']
batch_normalization_1 (Batch Normalization)	(None, 16, 64, 64, 16)	64	['conv3d_transpose[0][0]']
leaky_re_lu_1 (LeakyReLU)	(None, 16, 64, 64, 16)	0	['batch_normalization_1[0][0]']
conv3d_transpose_1 (Conv3DTranspose)	(None, 32, 128, 128, 16)	432	['leaky_re_lu_1[0][0]']

Fig. 10. Implementation of the SGAN model for stroke detection using CT images

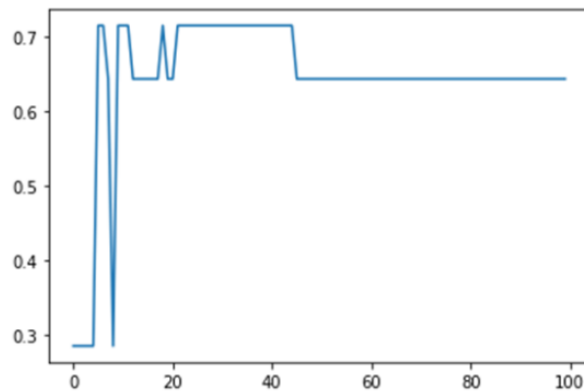


Fig. 11. Accuracy against number of epoch for SGAN model

4. Results and Discussions

Table 3 exhibits the performance comparison of the proposed SGAN over 3D CNN and state of art methods in literature for stroke detection.

From the Table 3, it is observed that the work proposed by Lisowska et al. based on CNN has achieved higher accuracy than the proposed method using SGAN. It is because of using a bigger dataset (170 scans versus 52 scans) as CNNs because of their data-hungry nature tend to perform much better with a large dataset. Chin et al. performed their test on a dataset specific for ischemic stroke, which narrows down the variability in the scans. Nielsen et al. conducted their tests MRI scans only for Acute Ischemic Stroke scans. Shinohara et al. performed their test on CT scans to specifically detect hyperdense middle cerebral artery- which is a sign of ischemic stroke as it signifies a block in the artery. Barman et al. performed their test by using CT angiography scans which are not as commonly performed for diagnosing a stroke. These scans are used to visualize the blood flow through the blood vessels and emboli - which are a marker for ischemic stroke - are much more clearly visible in these scans which might explain the increased accuracy of this model. The disadvantage is that CTA is not routinely performed for diagnosing stroke. Cho et al. performed their experiments on a dataset specific for hemorrhagic stroke. Hemorrhagic strokes affect a larger area of the scan compared to ischemic strokes which might explain the higher accuracy for the cascaded CNN model.

Table 3. Comparison of proposed SGAN model with state of art methods in literature

Method reference	Algorithm	Accuracy	Sensitivity	Specificity
Algorithms proposed by this research paper	3D CNN	56.4 %	56.52%	0%
	SGAN	93%	100%	90%
Lisowska et al [10]	CNN	96.4%	-	-
Chin et al [11]	CNN	92.9%	-	-
Nielsen et al [12]	Shallow CNN	85%	-	-
Shimohara et al [13]	CNN	86%	-	-
Barman et al [14]	DeepSymNet (original)	90.1%	85.9%	94.3%
	DeepSymNet (brain tissue only)	97.9%	100%	95.9%
Cho et al [15]	Cascaded CNN	98.2%	97.91%	98.76%

It is well known that CNNs need a large amount of data to be effective in making a good predictive model. The datasets available for stroke CT scans are often not larger in size because of various reasons like size of the 3D image (because it is made up of a large number of slices) and patient privacy issues. SGAN employs 2 CNNs - one that classifies the images as positive or negative, and another that generates more images from the dataset that are supposed to be indicative of stroke - making it an effective generator of additional data. This generation of additional images from the original data effectively manages to solve the problem of the data-hungry nature of CNNs which causes a problem in data limited scenarios like that of in Stroke Detection from CT images.

Overall, it is observed that SGAN to be less resource-intensive at the cost of being complicated to implement. SGAN being a recent development in computer vision, there are very few good resources to refer to for implementing SGAN. In medical imaging, SGAN might prove to be useful as its disadvantages of being complicated are easily outweighed by its performance improvements on a smaller dataset which is more common in medical imaging.

5. Conclusions

Recent years have witnessed tremendous strides in our understanding of risk factors and the prevention of stroke. Detailed research into stroke risk factors has increasingly displayed the heterogeneous subtypes of strokes, including hemorrhagic stroke, ischemic stroke, and also the several etiologic subtypes of stroke.

The work presents an analysis of 3D CNN for stroke detection. It also proposes a new method based on Semi-supervised Generator Adversarial Networks. The proposed work demonstrates an accuracy of 93% for small datasets. The performance of the proposed method is encouraging as compared to different state of art methods which implement CNN on large datasets.

The performance of the proposed SGAN method can thus benefit medical imaging analysis with small datasets. Much research needs to be done in SGAN for medical imaging as few implementations are seen in research. SGAN seems like a promising bet according to proposed research and its further development and usage are much warranted.

The challenges or the limitations of SGAN as observed for the experimental analysis for stroke detection can be summarized in a few points as follows; data bias and representation: The performance of the SGAN model heavily relies on the quality and representativeness of the training data. If the training data is biased in terms of demographics, data acquisition methods, or other factors, the generated synthetic data and the model's predictions may inherit those biases. This could result in the model being more accurate for certain groups while performing poorly for others, leading to disparities in healthcare outcomes. Hyper parameter Sensitivity: SGAN models involve various hyper parameters, such as learning rates, the architecture of the generator and discriminator networks, and the choice of optimization techniques. The model's performance can be sensitive to these hyper parameters, making it challenging to fine-tune the model for optimal results. Finding the right set of hyper parameters require significant experimentation and computational resources. Small Datasets: When working with small datasets, SGANs may struggle to generate diverse and realistic synthetic data, potentially leading to overfitting. This limitation can affect the model's generalization to unseen cases.

Future directions for research are exploring the use of GANs for medical image analysis where data set availability is limited.

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