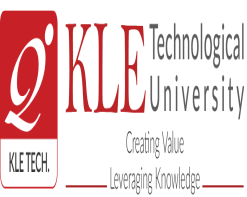
KLE Society's

KLE Technological University



**A Capstone Project Report**

**On**

**GAN Based Brain Metastases Detection Using Limited Labeled Dataset**

*Submitted in partial fulfillment of the requirement for the degree of*

**Bachelor of Engineering in**

**Computer Science and Engineering**

**Submitted By**

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**Abstract**

Computer-Assisted Diagnosis (CAD) with high sensitivity helps in early diagnosis of Brain tumors. Due to the confidentiality of the medical data, it is not easily accessible. To overcome this problem, Data Augmentation (DA) is one such technique, which helps to generate synthetic data. This data when used along with the training data, helps to handle the small medical image dataset collected from various scanners. Generative Adversarial Networks (GANs) is one of the DA techniques. GAN trained on images can generate new images that contain many authentic characteristics and look realistic to human observers. Therefore, this paper focuses on overcoming the problem of limited labeled dataset, using Deep Convolutional GANs (DCGANs). After combining the synthetic images to the training data, there was an increase in the accuracy by a factor of 13.16. To analyse the closeness between the original and synthetic images, a visualization tool called ImageJ was used. In order to validate the CAD model, a visual Turing test was conducted with the help of expert physicians.

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# **1. Introduction**

This chapter gives us the overview about the brain tumor and presents various facts and figures regarding the brain tumor cases in India. Furthermore, it describes what motivated us to do this project and shows various literary works that we went through that were based on the topic of brain tumor detection and we found out what the usual problems the authors faced. This led us to define our problem statement to work on and set the objectives to complete, by the end of our project.

## 1.1. Overview

A mass or growth of abnormal cells in the brain leads to brain Tumor. The brain is one of the largest and most complex organs in the human body. Any unexpected growth may affect human function and may spread into other body organs and affect human functions. Brain Tumors are classified based on their origin. Tumors first originating in the brain are called primary tumors and tumors which arise in any other part of the body and then transferred into the brain are called secondary tumors (malignant). The different brain tumors are glioma (Grade 1-Grade 4), Meningioma and Pituitary tumor. Detection of brain tumor is very complicated and difficult due to the size, shape, location and type of tumor in the brain, and hence early detection and classification of brain tumor helps in treatment methods.

Diagnosis is usually done by medical examination, with Computer Tomography (CT) or Magnetic Resonance Imaging (MRI). MRI is one of the commonly used techniques due to its superior image quality and using no ionizing radiation during the scan.

The dataset available can be either labeled or unlabelled. Labeled dataset with respect to an image dataset contains tags to each image. Tags are the text or binary files that provide important information regarding the images. There will be a tag associated with each image in the dataset. The algorithms applied on labeled dataset are termed as supervised learning algorithms. On the other side unlabelled dataset with respect to an image dataset do not contain any tags associated with the images, i.e., no additional information is available regarding the dataset. The algorithms applied on unlabelled dataset are termed as unsupervised learning algorithms.

***Facts & Figures of Brain Tumor Cases in India:***

According to the article by The Hindu on June 12 2016, Brain Tumor Foundation of India says that brain tumor is the second most common cancer among children after leukaemia. In India, every year 40,000-50,000 persons are diagnosed with brain tumors, out of which 20 percent are children. Until 2015, the figure was only somewhere around 5 percent. According to the official data, currently only six per cent of the children suffering from brain tumors are able to get the proper treatment.

The doctors said that if the cases are detected early, then 90 per cent of the cases are curable, provided the treatment protocol is followed correctly. The health experts have also said that if the treatment is done in time, the children can live up to 70-80 years without any problem.

## 1.2. Motivation

Accurate Computer-Assisted Diagnosis, associated with proper data wrangling, can alleviate the risk of overlooking the diagnosis in a clinical environment. However in many situations either data is limited or labelling is limited. Towards this, as a Data Augmentation (DA) technique, Generative Adversarial Networks (GANs) can synthesize additional training data to handle the small/fragmented medical imaging datasets collected from various scanners; those images are realistic but completely different from the original ones, filling the data lack in the real image distribution.

The existing method of brain tumor segmentation and its type is time consuming and tedious and requires expert intervention or annotation tools to analyse and annotate the images. The tools available to annotate the images, lack in providing accurate results and are insufficient in many ways. Hence relying on the tools would result in high risk. Another option is for a medical expert to annotate the images manually. But due to unavailability of medical experts the data cannot be properly annotated.

Hence, the need of the hour is to develop a DCGAN based model to generate synthetic images to address the issue of limited labeled data problems in tumor detection problems.

## 1.3. Literature Survey

In [1], a Synthetic data augmentation method using GAN for improved liver lesion classification. This method has applied CNN for the Sheba Medical center dataset and has an accuracy of 85.7% and is demonstrated on a limited dataset of computed tomography (CT) images of 182 liver lesions.

In [2], a Tumor-Aware, Adversarial Domain Adaptation from CT to MRI for lung cancer segmentation, a cycle- GANS technique is applied on NSCLC datasets and has an accuracy of 80%. It has limited labeled CT scan images of 377 patients with lung cancer.

In [3], Automated Pulmonary Nodule Classification in Computed Tomography Images Using a Deep Convolutional Neural Network Trained by Generative Adversarial Networks has used DCNN classifier on Fujita Health University Hospital, Japan dataset and has an accuracy of 66.7% benign and 93.3% malignant. It has limited dataset of 60 CT scans.

In [4], Diagnostic classification of lung nodules using 3D neural networks, on LIDC-IDRI and has an accuracy of 90.47%. It has limited dataset of 147 CT scans.

In [5], V-Net-Fully Convolutional Neural Networks for Volumetric medical image segmentation, a V- Net model of CNN classifier was applied on PROMISE2012 dataset which had MRI’s of Prostate. The V-Net dice loss achieved a challenge score of 82.39.

The limitation of this dataset was that they had limited number of annotated volumes available for training.

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| --- | --- | --- | --- | --- | --- | --- | --- |
| Table 1.1 Represents different aspects of various papers | | | | | | | |
| **S. No** | **Author Name and Year** | **Proposed Method** | **Dataset** | **Classifier** | **Result** | **Application** | **Limitations** |
| 1 | Maayan Frid-Adar, 2018 | Synthetic data augmentation using GAN for improved liver lesion classification | The Sheba Medical Center | CNN | 85.7% | Liver lesion | Demonstrated on a limited dataset of computed tomography (CT) images of 182 liver lesions |
| 2 | Jue Jiang, Yu-Chi Hu | Tumor-Aware ,Adversarial Domain Adaption from CT to MRI for lung cancer segmentation | NSCLC datasets | Cycle-GANs | 80% | Lung Cancer | Labelled CT scan images of 377 patients with lung cancer |
| 3. | Yuya Onishi,1 Atsushi Teramoto,2019 | Automated pulmonary Nodule Classification in Computed Tomography Images Using a Deep Convolutional Neural Network Trained by Generative Adversaria66l Networks | Fujita Health University Hospital, Japan | DCNN | 66.7 %benign,93.3%malignant | Pulmonary nodules | 60 CT scans |
| 4 | Raunak Dey,  2018 | Diagnostic classification of lung nodules using 3D neural networks. | LIDC-IDRI | 3D CNN | 90.47% | Lung Nodules | Limited dataset(147 CT scans). |
| 5 | Fausto Milletari, 2016 | V-Net-Fully Convolutional Neural Networks for Volumetric medical image segmentation | PROMISE2012 | CNN(V-Net model) | Challenge score 82.39 | Prostate | Limited number of annotated volumes available for training. |

**Research gaps:**

The above referred papers have a limited dataset with minimum of 60 to maximum of 400 annotated images. Most of the experiments are carried on limited annotated data for brain MR Images and manual annotation of these images may result in errors which may contribute significantly to outcome.

It is observed that the performance drastically drops when BRATS or ISLES dataset is used. The differences in Modality and technical specifications have significant effects on images.

Less accuracy and false positives have been reported when tested with Conventional DNN, AI and ML.

Few of the literatures have claimed better accuracy, but have not validated their results from medical experts.

## 1.4. Problem Statement

Deep Convolutional Generative Adversarial Networks (DCGAN) based Data Augmentation (DA) for brain tumor detection using limited labeled Magnetic Resonance Images (MRI).

## 1.5. Objectives

* To develop a model using Deep Convolutional Generative Adversarial Network (DCGAN) for the synthesis of brain image dataset.
* Evaluate and validate the model

# **2. Methods and Materials**

This chapter explains about all the methods and tools (software/hardware) that being used in project.

**GAN (Generative adversarial network)**

Generative adversarial networks (GANs) are algorithmic architectures that use two neural networks, pitting one against the opposite (thus the “adversarial”) so as to get new, synthetic instances of data that can pass for real data.

GAN comprises of two type of neural networks. The generator model and the discriminator model.

One neural network, called the generator, generates new data instances, while the opposite the discriminator, evaluates them for authenticity; i.e. the discriminator decides whether each instance of knowledge that it reviews belongs to the particular training dataset or not.

The generator is creating new, synthetic images that it provides as input to the discriminator. It does so within the hopes that they, too, are going to be deemed authentic, albeit they're fake. The goal of the generator is to get passable hand-written digits: to lie without being caught. The goal of the discriminator is to spot images coming from the generator as fake.

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|  |
| *Figure 2.1 Generative Adversarial Network Flow Diagram* |

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**CNN**

Computers see images using pixels. Pixels in images are related to some specific properties. For example, a particular group of pixels may signify a foothold in a picture or another pattern. Convolutions use this to help identify images.

A convolution layer multiplies a matrix of pixels with a filter matrix and sums up the multiplication values. Then the convolution slides over to subsequent pixel and repeats an equivalent process until all the image pixels are covered.

**DATASET**

Dataset is retrieved from Kaggle data repository.

Dataset contains 253 brain MRI images in which 98 tumor images 155 non-tumor images

For GAN training the entire dataset is used which has 253 images each of size 200\*200.

For Tumor detection the whole dataset is divided into training, testing and validation set.

Training Set: 261 Images

Testing Set: 39 Images

Validation Set: 38 Images

For Training the mages are labelled as X\_Train and Y\_Train

Model type**:** Sequential Model

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| CNN Archi |
| *Figure 2.2 CNN Sequential Model Architecture.* |

Sequential model in supervised learning can be used for many application that deals with detection.

The model uses “ReLu” activation function and pooling layer “MaxPooling2D” in each convolutional layer.

MaxPooling2D: It down samples the input representation by taking the maximum value over the window defined by pool size for each dimension along the features axis. The window is shifted by strides in each dimension.

Equation 1 represents the Loss Function used in the final layer that is Binary Cross Entropy loss function.

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This type of loss function involves sigmoid activation and Cross-Entropy loss. It does not depend on each vector component, it elaborates that the loss computed for every CNN output vector component is not affected by other component values. This was the reason for it to be used for multi-label classification, were the insight of an element belonging to a certain class should not influence the decision for another class.

Where ti (target vector) and si (softmax function) are the ground truth and the CNN score for each class i in Class C.

Next comes the optimizer. The optimizer used in this sequential model is Rmsprop optimizer. These Optimizers are used to change the attributes of your neural network such as weights and learning rate in order to reduce the losses.

Thisoptimizer that utilizes the magnitude of recent gradients to normalize the gradients.

Now the next step is computation of metrics such as specificity, sensitivity, recall, precision which are essential in calculating the accuracy and making predictions.

Specificity is defined as the proportion of actual negatives, which got predicted as the negative.

***Specificity*** = (True Negative)/ (True Negative + False Positive)

True Negative = Persons predicted as not having brain tumor are actually found to be not having a brain tumor (healthy) (True Negative + False Positive)

False Positive = Persons predicted of having brain tumor are actually found to be not having brain tumor (healthy).

Sensitivity is a measure of the proportion of actual positives that got predicted as positive.

***Sensitivity*** = (True Positive)/ (True Positive + False Negative)

True Positive (TP) = Persons predicted as are actually have brain tumor.

False Negative (FN) = Persons who are actually suffering from the brain tumor disease are actually predicted to be not suffering from the brain tumor disease (healthy).

***Accuracy*** = ((TP+TN)/ (TP+TN+FP+FN))

***Efficiency*** = (sensitivity + specificity + Accuracy) / 3

***Precision***=TP / (TP+FP)

***Recall***=TP / (TP+FN)

***F1 score***

**F1 score** is defined as the harmonic **mean** between precision and recall. It is used as a statistical measure to rate performance.

**Platform and Tools**

1. ***Google collab***

Collaboratory may be a product from Google Research. Collab allows anybody to write down and execute python code through the browser, and is particularly compatible for machine learning and data analysis implementations. Collab hosts Jupyter notebook service that needs no setup to use, while providing free access to computing resources including GPUs which is liberal to use.

1. ***ImageJ***

ImageJ is image processing tool used to compare profiles of original and synthetic images. It can create histograms and line profile plots. It supports image processing functions like contrast manipulation, convolution, Fourier analysis, sharpening, smoothing and edge detection.

Histogram. Calculates and displays a histogram of the distribution of grey values within the active image or selection. The x-axis represents the possible grey values and the y-axis shows the number of pixels found for each grey value

Plot Profile

This type of plot displays a two-dimensional graph of the intensities of pixels along a line within the image. The x-axis represents distance along the line and the y-axis is the pixel intensity.

1. ***Creately***

Creately is a dynamic diagramming tool that can be deployed from the cloud or on the desktop and application, you do not need highfalutin technical skills to build your diagrams, be they flowcharts, infographics, or others. Thus, you can focus on your creations rather than be bothered by tools with steep learning curves.

# **3. System Diagram**

System Diagrams are models that are a visible tool accustomed express the dynamic forces which are acting upon the components of a process and also the interactions between those forces. System diagrams are so powerful tools that facilitate your to grasp how complex systems work.

## 3.1. System Architecture.

A system architecture is one of the conceptual models that is used to describe the structure, behaviour and many more views of the system used.it is a formal description of the system.

### 3.1.1. Generator and Discriminator Architectural Flow and Functionalities.

**Hyper parameters**

**Noise**: The generator takes random noise as an input .the Generator then transforms that noise into a meaningful and required output. The noise introduction to the GAN makes it possible to produce a wide range of data instances, sampling from different places in the target distribution. The noise provides an initial point for the GAN generator, the noise provided is 100.

**Learning rate**: In machine learning and statistics, the learning rate is a tuning parameter in an optimization algorithm that determines the step size at each iteration while moving toward a minimum of a loss function. The generator learns to produce images realistic as possible and the discriminator learns to identify the image real or synthetic. The learning rate for generator is 0.00003 and the learning rate for the discriminator is 0.0003

**Batch size**: Batch size is the number of training examples utilized in one iteration. The batch size is set to 64 and 4.

**Epochs**: Epoch refers to one cycle through the full training dataset. Usually, training a neural network takes more than few epochs. The epochs is set to 1000 because of the limited amount dataset available

**Beta 1**: Beta is the hyper parameter provided to make the GAN system stable and run smoothly. The beta 1 value is set to 0.5

**Epsilon**: Epsilon is added to 0 if the expected output is x < 0 or it is subtracted from 1 if the expected output is 1 < x (the boundaries for the output are [0,1])

**Sample size**: sample size is the number of input images required for generated per epochs. The sample size is set to 85

**Rmsprop**: stands for Root Mean Square Propagation.it is the very widely-known gradient descent optimization algorithm for mini-batch learning of neural networks.

**Filters:** In convolutional (filtering and encoding by transformation) neural networks (CNN) every network layer acts as a detection filter for the presence of specific features or patterns present in the original data.

Figure 3.1 shows the system model of generator model.

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| *Figure 3.1 Generator Model* |

The generator model starts with the image size of 8\*8 with the 1024 number of filters, then the batch normalization is done using the LeakyReLU activation function. The image is up scaled to16\*16 with 512 filters, and then a batch normalization is applied using LeakyReLU activation function. This cycle continues for 2 more times the images is up scaled to32\*32 and then to 128\*128 and the batch normalization is applied using LeakyReLU activation function at last the hyperbolic tangent activation function is applied.

**Activation Function**

LeakyReLU-Activation functions such as ReLU are used to address the vanishing gradient problem in deep convolutional neural networks and promote sparse activations (e.g. lots of zero values).The generator uses the hyperbolic tangent (tanh) activation function in the output layer and inputs to the generator and discriminator are scaled to the range [-1, 1].For the discriminator, the last convolution layer is flattened and then fed into a single sigmoid output.

Figure 3.2 shows the system model of discriminator model.

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| Figure 3.2 Discriminator Model |

The discriminator model breaks down the images in reverse order as the generator model constructed it from 128\*128 to 8\*8 with batch normalization using LeakyReLU function with the same number of filters at each step.

## 3.2. Data Flow diagram.

A data-flow diagram represents how the data flows in the system or process. The data flow diagram provides all the information related to each entity's inputs and outputs, it does not contain any control flow, no rules, and no loops.

### 3.2.1. Data Flow Diagram (Level 0)

Data flow diagram level 0 is a context diagram, shows the system as a whole and how the system interacts with the external entities. The data flow diagram level 0 made to be an abstract view, representing the whole system as a single point and how it interacts with the external entities. The interaction is represented by incoming/outgoing arrow lines. The main single process is brain tumor detection system which has relationship with external entities that are input image dataset which consists of MRI scans of brain and the end result of this process is images with detected tumors or no tumors.

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| Figure 3.3 Data Flow Diagram Level 0 |

### 3.2.2. Data Flow diagram (level 1)

In 1-level DFD, context diagram is decomposed into multiple bubbles/processes.in this level we highlight the main functions of the system and breakdown the high level process of 0-level DFD into sub-processes. The main process of brain tumor detection is sub divided to many process which constitutes of processes such as GAN which is data augmentation technique used to generate synthetic images from the original images which is given as input. The next process is the tumor detection which is also a neural network used to determine whether the images are tumors or non-tumors.

Figure 3.4 shows the dataflow diagram of level 1.

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|  |
| Figure 3.4 Data Flow Diagram Level 1 |

## 3.3 Use case diagram

It is the simplest representation of a user's interaction with the system that shows the relationship between the user and the different [use cases](https://en.wikipedia.org/wiki/Use_case) in which the user is involved. A use case diagram can identify the different types of users of a system and the different use cases and will often be accompanied by other types of diagrams as well.

The use case might drill into a lot of details about every part of the system possible. A use case diagram will provide a higher-level view of the system being used .a use case diagrams are like the blueprints of the system.

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| Figure 3.5 Use Case Diagram**.** |

In our system the user can interact with the system by giving the image input ,check the image format if it matches the required for the processing and the user gets the result whether the MR Image contains tumor or not.

# **4. Results & Discussions**

In order to evaluate the effectiveness of GAN generated image for limited labeled data in medical applications following four experiments are carried out. First experiment is basic one where we perform comparative study of brain tumor classification using CNN model without GAN generated synthetic images and later with GAN generated synthetic images. It is expected that data augmentation with GAN generated synthetic image should have positive effect on accuracy for brain tumor MRI image classification. Second test we have performed to visualize the extent of closeness that synthetic brain images do have with original images. This is performed by comparing histogram and associated statistics as well as profile comparison using ImageJ software tool. Third experiment is visual Turing test, where all 187 images which are ensemble of original MRI images and GAN generated synthetic images are subjected to blind review to expert physicians. Experts are supposed classify the given image as original or synthetic. In the fourth experiment the comparison was done with other papers to check the increment factor once DA was applied to their respective model. Following section presents all these experiment details.

**Experiment No 1: Performance evaluation of CNN with and without GAN generated images.**

The main problem in training the network described above is the lack of a large labelled training dataset. To enlarge the training data and improve the classification results in the brain tumor classification task, we augmented the data in two ways: 1) Classic augmentation that includes varieties of known image manipulations on given data examples; 2) Synthesis of new examples which are learned from the data examples using generative models.

In each case we have recorded Accuracy, Sensitivity, Specificity, Efficiency, F1-score-Testing data, F1-score-validate data and ROC and are presented in Table 4.1. The following table presents the record of observation when batch size is 64 and 4 respectively.

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| *Table 4.1 Record of Observation* | | | | | |
|  |  | **Batch size=64** | | **Batch size=4** | |
| **Parameters** | **Without GAN** | **With-GAN**  **(60 Images)** | **With-GAN**  **(85 Images)** | **With-GAN (60 Images)** | **With-GAN (85 Images)** |
| Accuracy | 81.57 | 94.73 | 84.21 | 81.57 | 84.21 |
| Sensitivity | 100 | 100 | 100 | 100 | 100 |
| Specificity | 53.33 | 86.67 | 60 | 53.33 | 60 |
| Efficiency | 78.30 | 93.80 | 81.40 | 78.30 | 81.40 |
| F1-score-Testing data | 86.79 | 95.83 | 88.46 | 86.79 | 88.46 |
| ROC | 0.767 | 0.933 | 0.791 | 0.80 | 0.80 |

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Figure 4.1. Accuracy of brain tumor classification with and without GAN synthetic images

From the figure it is observed that adding only 60 synthetic images has given the best accuracy over conventional CNN and 85 synthesized images.

**Experiment No 2: Similarity study using Histogram and Image profile**

This experiment is carried out to assess the similarity between original images and GAN generated synthetic images. Parameter SSIM (structural similarity index matrix) is not employed as we don’t have one-to-one image mapping. We have used ImageJ software tool for this experiment. Following figure presents the original and GAN generated synthetic images as well as Histogram and its Profile respectively.

|  |  |
| --- | --- |
| **Original Brain MRI Image** | **GAN generated synthetic (Batch size=64)** |
| **C:\Users\Sony\Desktop\img94.png** | **C:\Users\Sony\Desktop\samples_1155_45.png** |
|  |  |
| **Histogram (Original Image)** | **Histogram (Synthetic Image)** |
|  |  |
|  |  |
| **Image Profile (Original Image)** | **Image Profile (Synthetic Image)** |
|  |  |
|  |  |

This experiment was performed on 5 look-alike original and synthetic images were performed. In each case mean, standard deviation are recorded for histogram. The following table presents the records.

|  |  |  |  |
| --- | --- | --- | --- |
| Table 4.2. Represents the results of experiments made to study the similarity between the real images and the synthesized images. | | | |
| **Original Brain MRI Image** | | **GAN generated synthetic** | |
| Mean | Standard Deviation | Mean | Standard Deviation |
| 80.727 | 51.178 | 85.442 | 49.068 |
| 44.633 | 42.996 | 39.611 | 44.209 |
| 54.605 | 47.269 | 42.461 | 38.954 |
| 39.614 | 45.698 | 36.868 | 52.632 |
| 105.882 | 77.673 | 123.437 | 69.893 |

From Table it is observed that, when we compare the histogram of the original images and the synthetic images there is a similar pattern observed the mean of the both images are similar with little difference and standard deviation implies the same results when compared. When we plot the profile of the both original and synthetic images both the graphs show similar plot when we observe the graphs the gray values of both the images are similar.

|  |  |  |  |
| --- | --- | --- | --- |
| Table 4.3. Represents the results of experiments made to study the similarity between the real images and the synthesized images. | | | |
| **Original Brain MRI Image** | | **GAN generated synthetic (Batch size=4)** | |
| **Mean** | **Standard Deviation** | **Mean** | **Standard Deviation** |
| 68.054 | 49.841 | 66.888 | 53.243 |
| 100.837 | 56.007 | 72.481 | 65.935 |
| 54.378 | 30.299 | 89.326 | 66.916 |
| 106.046 | 77.610 | 36.092 | 39.807 |
| 54.485 | 47.142 | 60.154 | 48.207 |

**Experiment No 3: Visual Turing Test Results**

Table 4.4 shows the confusion matrix for the Visual Turing Test. The expert physicians easily recognize 256×256 synthetic images due to the lack of sharp edges and brain details. However, when GANs is trained and synthetic images are of size 200x200, the experts classify a considerable number of synthetic tumor images as real; it implies that the GAN generated synthetic images remarkably facilitate the realism of both healthy and pathological brain parts while they do not include abnormality; thus, GANs might perform as a tool to train medical students and radiology trainees when enough medical images are unavailable, such as abnormalities at rare positions/sizes. Such GAN applications are clinically prospective, considering the expert physicians’ positive comments about the tumor realism.

Original images = 100

GAN generated = 87

Batch size: 64

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| --- | --- | --- | --- | --- | --- |
| Table 4.4. Represents the results of the visual Turing test conducted with 2 expert physicians. | | | | | |
|  | **Accuracy** | **TP**  **(Real as real)** | **FN**  **(Real as Synthetic)** | **FP**  **(Synthetic as Real)** | **TN**  **(Synthetic as Synthetic)** |
| Physician 1 | 96.25% | 98 | 2 | 5 | 82 |
| Physician 2 | 96.25% | 97 | 3 | 4 | 83 |

From the above table it is observed that when we conducted the visual Turing test by combining the original and synthetic images the results are in the above table .the Physician 1 observed the images and marked 5 synthetic images as real MR Images. Physician 2 observed the images and marked 4 synthetic images as real MR Images.

**Experiment No 4: Model Evaluation**

Table 4.5 shows the comparison between the proposed model and existing models. The maximum and minimum increment factor as observed from the table is 8.74 and 1.02 respectively. It can be inferred that the proposed model has better performance with increment factor of 13.16.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| *Table 4.5 Comparison of proposed Model with Existing Models* | | | | |
| **Paper** | **Method used** | **Results without DA (%)** | **Results with DA (%)** | **Increment Factor** |
| Inﬁnite Brain MR Images: PGGAN-based Data Augmentation for Tumor Detection,  Changhee Han | Progressive Growing of GANs (PGGANs) | 90.06 | 91.08 | 1.02 |
| Brain Tumor Classiﬁcation Using ResNet-101 Based Squeeze and Excitation Deep Neural Network,  Palash Ghosal | The transformations were Flip, Rotate, Elastic transform and Shear with variable degrees of transformations | 89.93 | 98.67 | 8.74 |
| Multi-Grade Brain Tumor Classiﬁcation using Deep CNN with Extensive Data Augmentation,  Muhammad Sajjad | Various augmentation techniques used: rotation, flipping, skewness, and shears for geometric transformations | 93.34 | 96.12 | 2.78 |
| **Proposed Model** | **Deep Convolutional GANs (DCGANs)** | **81.57** | **94.73** | **13.16** |

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# **5. Conclusion and Future Scope**

In recent days Computer Aided Diagnosis (CAD) is one of the blooming technologies in the field of medical research. However, there are complications that lead to the research getting less efficient or less accurate. One such complication is the unavailability of medical images due to the confidentiality of patient data in the hospitals and limited public data access. After studying the literary works of authors who have worked on the topic of brain tumor detection, we observed that most of the times the data is either unlabelled or is too limited and this makes it difficult to train a model, as it needs more knowledge to learn. To overcome this limitation we are using a data augmentation technique called GAN. There are various types of GAN available like ACGAN, DCGAN, PGGAN, CPGGAN etc. Each of these are used according to the type of application it is being used, ACGAN is ideal technique for data images having labels, similarly DCGAN is ideal with data images not having labels. Since our dataset doesn’t consist of data labels for MRI images DCGAN is used for data augmentation. We used the dataset available from Kaggle wherein out of the 255 images, 98 were tumored and 157 were non-tumored. The batch size used for training the GAN should be less than or equal to 64, we have trained it for two batch sizes of 4 and 64. With respect to both the batches we had generated 60 and 85 synthetic images, and it was found that 60 synthetic images with batch size 64 had better accuracy of 94.73%. We conducted 3 different experiments in order to assess and validate the model.

1. Performance evaluation of CNN with and without DCGAN generated images: The results showed accuracy of 81.57% when the model was trained on original images. However, when the synthetic images were combined with the original images the accuracy was increased to 94.73% with an increment factor of 13.16.
2. Similarity study using histogram and image profile: To obtain and observe the histogram and image profiles we used the ImageJ tool kit facilitated us to study image similarity by providing different methods. The ImageJ tool calculates the mean and standard deviation of individual images which makes easier by comparing the numbers than by comparing the histograms and image profile graphs.
3. Visual Turing Test: in this experiment, the synthetic images are combined with real MR Images and give 2 Physicians to identify the synthetic and original images, the results were quite impressive the physicians marked a considerable number of synthetic images as real MR Images.
4. Model evaluation: This experiment was done to compare the increment factor of the accuracy once after applying DA to the conventional model. The results showed that the proposed model showed greater increment factor of 13.16 compared to other papers that worked on DA.

The results obtained from the above experiment were impressive. By experiment 1 we can say that the system gives far better results with DCGAN generated images; we got 13.16 of the increase in the result. By experiment 2 we can say that the images look a lot more similar when we compare the histogram and image profiles. By experiment 3 we can interpret that the DCGAN generated images are a lot more similar not only in mean and standard deviation but also visually the DCGAN generated are well generated to be considered as real, these images can be used to train the medical exports in future. By experiment 4 we found out that the proposed model provided greater hike in the accuracy of the model when compared to other Data Augmentation techniques used by other authors. Through this systematic experimentation and analysis we conclude that DCGAN is found to be effective tool to address the issue of limited labelled dataset problem. As a future scope one shall experiment with other medical cases such as breast cancer classification or other cases.

# **References**

* [1] Frid-Adar, Maayan, et al. "Synthetic data augmentation using GAN for improved liver lesion classification." *2018 IEEE 15th international symposium on biomedical imaging (ISBI 2018)*. IEEE, 2018.
* [2] Jiang, Jue, et al. "Tumor-aware, adversarial domain adaptation from ct to mri for lung cancer segmentation." *International Conference on Medical Image Computing and Computer-Assisted Intervention*. Springer, Cham, 2018.
* [3] Onishi, Yuya, et al. "Automated pulmonary nodule classification in computed tomography images using a deep convolutional neural network trained by generative adversarial networks." *BioMed research international* 2019 (2019).
* [4] Dey, Raunak, Zhongjie Lu, and Yi Hong. "Diagnostic classification of lung nodules using 3D neural networks." *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 2018.
* [5] Milletari, Fausto, Nassir Navab, and Seyed-Ahmad Ahmadi. "V-net: Fully convolutional neural networks for volumetric medical image segmentation." *2016 Fourth International Conference on 3D Vision (3DV)*. IEEE, 2016.
* [6] Article by “The Hindu” regarding the statistics of Brain Tumor Cases in India: https://www.thehindu.com/sci-tech/health/Over-2500-Indian-kids-suffer-from-brain-tumour-every-year/article14418512.ece
* [7] ImageJ- The tool used to visualize the closeness between the original and synthesized images: https://imagej.net/Welcome
* [8] The dataset from Kaggle on which the project was worked on: https://www.kaggle.com/navoneel/brain-mri-images-for-brain-tumor-detection
* [9] Information about GAN and DCGAN:https://medium.com/@jonathan\_hui/gan-dcgan-deep-convolutional-generative-adversarial- networks-df855c438f
* [10] Sajjad, Muhammad, et al. "Multi-grade brain tumor classification using deep CNN with extensive data augmentation." Journal of computational science 30 (2019): 174-182.
* [11] Han, Changhee, et al. "Infinite brain MR images: PGGAN-based data augmentation for tumor detection." Neural Approaches to Dynamics of Signal Exchanges. Springer, Singapore, 2020. 291-303.
* [12] Ghosal, Palash, et al. "Brain Tumor Classification Using ResNet-101 Based Squeeze and Excitation Deep Neural Network." 2019 Second International Conference on Advanced Computational and Communication Paradigms (ICACCP). IEEE, 2019.
* [13] Han, Changhee, et al. "Learning more with less: Conditional PGGAN-based data augmentation for brain metastases detection using highly-rough annotation on MR images." Proceedings of the 28th ACM International Conference on Information and Knowledge Management. 2019.