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Medical Image Analysis Using GAN-Based Augmentation and EfficientNet-B7 for Accurate Lesion Classification

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Abstract

Brain tumors are caused by the uncontrolled and rapid growth of brain cells, posing a serious health threat if not detected early. Despite promising advancements, accurate identification and classification of brain tumors remain difficult. The number of cases is increasing globally, leading to thousands of deaths each year. Therefore, precise diagnosis is critical for effective treatment. Traditional machine learning (ML) techniques rely on manually designed features, which require significant effort. In contrast, deep learning (DL) has gained popularity for its ability to automatically extract features, making it highly effective for brain tumor detection and classification. This study proposes a novel framework that leverages a Generative Adversarial Network (GAN) to augment medical image datasets, thereby mitigating overfitting and enhancing model robustness. To further improve image quality, Contrast Limited Adaptive Histogram Equalization (CLAHE) is employed to enhance contrast and highlight important features. The enhanced images are then classified using the EfficientNet-B7 architecture, known for its high accuracy in medical imaging tasks.A total of 3,804 images were used in this study. The proposed model achieved an impressive classification accuracy of 98.27%. Compared to existing models, this approach demonstrated superior performance and reliability, making it a promising solution for the early detection and classification of various types of lesions.

Keywords: CLAHE, Deep Learning, Generative model, GAN, Healthcare, Medical, MRI, Tumor.

1. Introduction

The brain is the most complex and heaviest organ in the human body, serving as the control center of the central nervous system. It regulates nearly all vital functions, including movement, sensation, vision, hearing, taste, and smell.. It accomplishes this by using an extensive network of connections and neurons to regulate every vital bodily function [1]. The proliferation of aberrant cells within the brain is the source of brain malfunction, which also affects the central spine and the nervous system. Its boundaries are well defined, it grows slowly, and it hardly ever goes outside of them [2]. The brain contains billions of active cells, making analysis difficult at times. One of the main causes of death in humans is brain tumors. The “World Health Organization (WHO)” prediction that brain tumors will increase by 5% annually worldwide. Compared to other diseases of the body, brain tumors are more dangerous and challenging to identify. Despite the lack of early therapy each year, 250,000 people worldwide are impacted by brain tumors. The central nervous system of the body with a brain can be affected by 130 distinct types of tumors, which can all vary from very rare to common [3].

Brain tumors result from the abnormal and uncontrolled growth of brain cells, which can impair brain tissue function and elevate intracranial pressure [4]. These tumors can appear in any region of the brain, varying in size and type, and may lead to symptoms such as severe headaches, unexpected seizures, and sensory disturbances including vision, hearing, and smell anomalies. Other symptoms include personality changes, memory issues, fatigue, nausea, and vomiting. Depending on the tumor's location, additional effects may include facial weakness, balance issues, motor dysfunction, and swallowing difficulties [5-6]. Accurate diagnosis often requires consultation with medical professionals.

Brain tumors are broadly categorized into benign (non-cancerous) and malignant (cancerous) types. Benign tumors, such as meningiomas and gliomas, are usually slow-growing and uniform in structure, posing less risk but with the potential to become malignant over time [7]. Malignant tumors like glioblastoma and astrocytoma are high-grade, aggressive, and fast-spreading, making them far more dangerous [8]. While several treatment methods exist, surgery remains the most common and preferred option due to its effectiveness and minimal side effects [9].

Magnetic Resonance Imaging (MRI) is the most widely used and effective method for diagnosing brain tumors. It provides detailed images of the brain's soft tissues in multiple directions and is often enhanced with contrast dye to better differentiate healthy and malignant tissues [10]. MRI images help detect tumor presence based on tissue characteristics, but interpretation depends heavily on the radiologist's expertise and experience, making the process time-consuming and prone to errors [11].

Early diagnosis is crucial for reducing brain tumor-related mortality, making this a key concern in neuroscience [12]. Although several techniques exist for detecting abnormalities in MRI scans, challenges remain in achieving timely and accurate classification. Manual analysis by radiologists is still the norm, but it can be slow, expensive, and susceptible to misdiagnosis, significantly impacting patient outcomes [13].

To overcome these challenges, MRI is increasingly combined with advancements in Artificial Intelligence (AI) and Machine Learning (ML) to support early and accurate diagnosis. Automated image analysis systems, particularly those using Deep Learning (DL), have attracted significant interest in recent years. DL models like Convolutional Neural Networks (CNNs), first introduced in 1980, have proven highly effective in complex data analysis, including medical image classification [14-15]. These models excel in automatically extracting significant features from large datasets, outperforming traditional ML methods that rely on handcrafted features.

This study proposes a DL-based model for fast and accurate classification of brain tumors. Publicly available MRI and skin lesion datasets are used for validation. Performance is evaluated using standard metrics such as accuracy, precision, recall, and F1-score, demonstrating the model's ability to support early diagnosis and assist clinicians in effective treatment planning.

The main contribution of this work are given below:

- A unique deep learning-based Generative Adversarial Network (GAN) is used to generate synthetic medical images.
- Image quality is enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) technique.
- The EfficientNet-B7 architecture extracts deep features for classification, and the model's performance is evaluated using various metrics and compared with previous studies. The result indicates that the proposed method achieves an impressive classification accuracy of 98.27%.

The rest of the paper is organized as follows: In the first section, the introduction related to brain disease using MRI image identification is discussed. In the second section, the previous research on brain tumors using various deep learning and machine learning models is discussed. Section 3 presents the proposed model architecture. Section 4 describes the proposed model result. Section 5 provides a final summary of this research as well as potential future opportunities in this field of study.

2. Literature Review

This section reviews previous studies related to the classification and detection of brain tumors (BT) using machine learning (ML) and deep learning (DL) techniques. Early and accurate diagnosis is vital for effective treatment, and AI-based computer-aided diagnostic (CAD) systems have shown potential to support this need. Although these systems can outperform human experts in analyzing MRI images, there is still room to improve their predictive accuracy.Saeedi S. et al. [16] proposed a convolutional auto-encoder and a 2D CNN model with eight convolutional layers, four pooling layers, and batch normalization. Budati A.K. et al. [17] developed an ML-based model using a Chan–Vese (C-V) segmentation technique and GLCM for feature extraction, followed by classification with SVM and KNN. SVM achieved over 98% accuracy.Mahmud M.I. et al. [18] evaluated ResNet-50, VGG16, and Inception V3, comparing their performances using metrics such as accuracy, recall, loss, and AUC. Nassar S.E. et al. [19] designed an automated diagnostic system based on 3,064 T1-weighted contrast-enhanced MRI scans to assist radiologists.Talukder M.A. et al. [20] used transfer learning with models such as Xception, ResNet50V2, InceptionResNetV2, and DenseNet201. ResNet50V2 achieved the highest precision at 99.68%. Zulfiqar F. et al. [21] enhanced the EfficientNetB2 model by adding top and fully connected layers, achieving 98.86% accuracy.Yousaf F. et al. [22] modified the U-Net architecture with skip connections and fine-tuned blocks, achieving 99.56% accuracy in classifying glioblastoma, meningioma, and pituitary tumors. Raza A. et al. [23] introduced “DeepTumorNet,” modifying GoogLeNet by replacing the last five layers with fifteen new ones and incorporating a leaky ReLU activation function.Bhanothu Y. et al. [24] proposed combining the Region Proposal Network (RPN) with Faster R-CNN using VGG-16 as the base architecture. Saba T. et al. [25] used VGG-19 with transfer learning, integrating it with handcrafted shape and texture features, and applied the GrabCut method for segmentation.Sadad T. et al. [26] applied a U-Net model with ResNet50 as the encoder on the Figshare dataset, achieving an IoU score of 0.9504. Li et al. [27] compared their approach with hybrid-CNN and hybrid-GAN models, reporting improved accuracy.Asiri A.A. et al. [28] explored GANs for generating realistic MRI data, achieving 96% accuracy. Deepak S. and Ameer P.M. [29] used fused deep features from various ML models, showing improved brain tumor prediction compared to standard CNNs.

3. Material and Methods

This section describes the overall study of the dataset, and methodology for the detection, and classification of disease. The steps are discussed below.

3.1 Dataset Collection

Data was gathered for the purpose of detecting skin cancer [30] and brain tumors [31] from a publicly available database. The dataset for this purpose was constructed using pictures from "Magnetic Resonance Imaging (MRI)" scans. Since MRI is thought to be the most reliable technique for detecting brain tumors and also contains some pictures of skin lesions, we chose to include both in our investigation.

Table 1 Dataset Details

Type of Images	Total Count
“Glioma Tumor”	926
“Meningioma Tumor”	937
“No Tumor”	500
“Pituitary Tumor”	901
“Skin cancer”	540

In our dataset, a total of 3264 MRI scans altogether with 540 images of skin cancer. The descriptions of dataset distribution are given in Table 1, and the MRI images are organized by type of brain tumor in Figure 1 and also skin images.

Fig. 1: Summary of the dataset used for the proposed model.

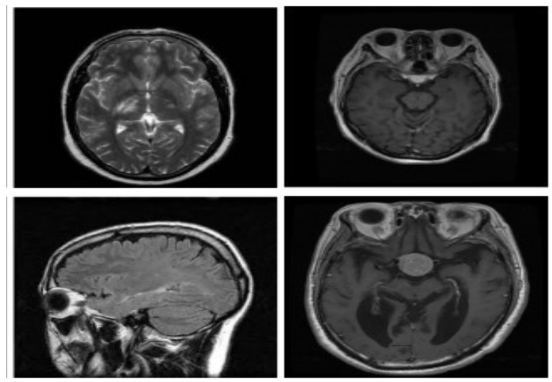
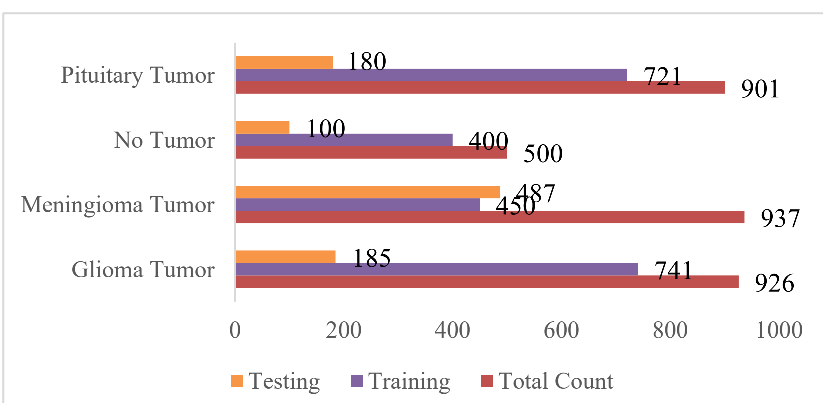


Fig.2: Sample images of brain tumor

Figure 2 represents some of the same images of the dataset used in this work. Brain tumor disease is further of three types “Glioma Tumor”, “Meningioma Tumor”, and “Pituitary Tumor”. The dataset contains no tumor images with some tumor images shown in row

3.2 Image Generator

In this work, the **Generative Adversarial Network (GAN)** is utilized as a data augmentation technique to expand the dataset and minimize overfitting. GAN [32] employs conventional convolutional layers to generate image-like matrices from random noise. It consists of two primary components: a **generator**, which produces synthetic (pseudo) images, and a **discriminator**, which distinguishes between real and generated images. Both components are trained simultaneously in a competitive manner, where the generator aims to create increasingly realistic images, and the discriminator strives to improve its ability to detect fake ones. The overall workflow of this approach is illustrated in Figure 2.



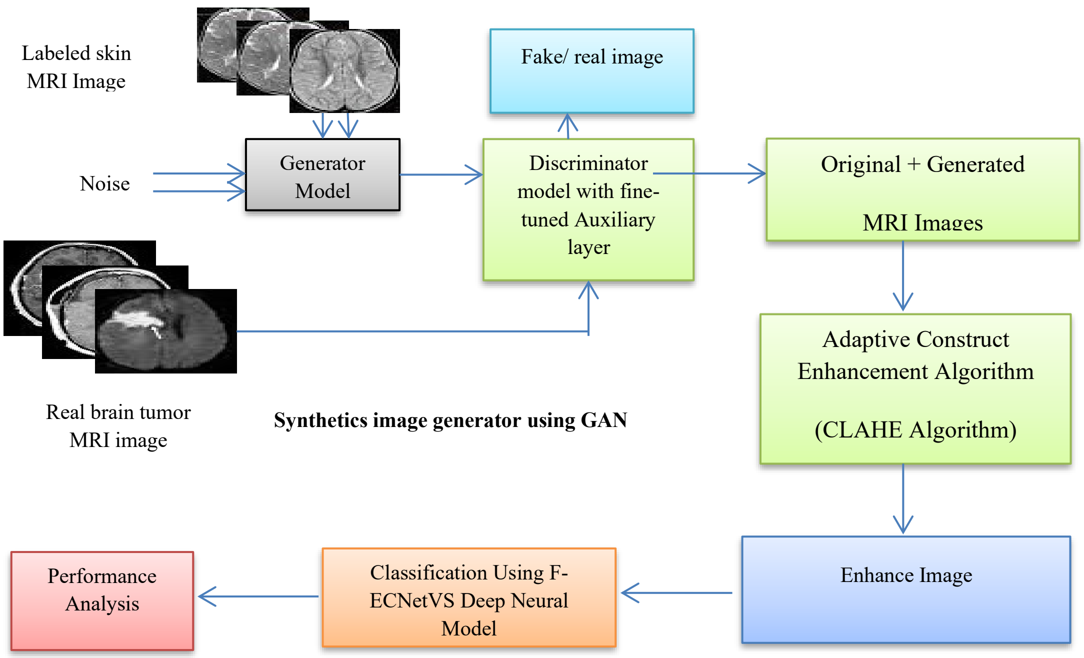


Fig.3: Flow Chart representing the work flow

The GAN discriminator model comprises several key components, including an input layer, embedding layer, dense layer, reshape layer, and concatenate layer. These are followed by four convolutional layers [33]. Each convolutional layer is succeeded by a **Leaky ReLU** activation function, which is used in place of the standard ReLU. After the final Leaky ReLU layer, a dropout layer, a flatten layer, and a dense layer are applied. The complete model consists of **771,454 trainable parameters**. Details of the network layers and the discriminator model parameters are presented in **Table2**.

Table 2: GAN Discriminator Model Description

Layer Name	No. of Parameters
Input	[224x228x3]
Dense	sigmoid activation
Leaky ReLU	max(0,x)
Conv2D	[32x32], [16x16], [8x8], [4x4], stride=[2x2], padding same
Flatten	[0,2048]
Dropout	[0,2048]

The input layers, embedding layer, Leaky ReLU layer, dense layer, reshape layer, and concatenate layer make up the GAN generator model. An ultimate convolutional layer is added after the penultimate Leaky ReLU layer. There are 1,735,904 total parameters in the model that may be learned. Table 3 presents the network layers and parameters structure and features of the generator model.

Table 3: GAN Generator Model Description

Layer Name	No. of Parameters
Input	[4,4,3]
Dense	sigmoid activation
Leaky ReLU	max(0,x)
Conv2D	[32 32], [16 16], [8,8], [4 4], stride=[2 2], padding same

As defined in **Equation 1**, the generator model creates both synthetic and realistic-looking images, while the discriminator model DiD_iDi is designed to optimize its ability to accurately classify these as real or fake.The generator model GeG_eGe receives latent vectors and random noise as input to generate synthetic images. The discriminator DiD_iDi is responsible for distinguishing between real images and those produced by the generator. In this setup, NdN_dNd represents the noise distribution in GeG_eGe, DDD refers to the dataset, and **AD** corresponds to the additional class label information.

$$\min \_max\ O(D_i, G_e) = A_{data}[\log D_i(I|L)] + [\log(1 - D_i G_e(Z|L)] \quad (1)$$

In the proposed approach, Generative Adversarial Networks (GANs) are employed to generate synthetic images of various brain tumor types. The process begins by training the GAN model on real brain tumor images. During training, the discriminator receives labeled real brain tumor images, while the generator is provided with random noise and corresponding labels. The generator then produces a synthetic brain tumor image, which is subsequently passed to the discriminator for evaluation.

3.3 Adaptive Contrast Enhancement Algorithm for MRI image

The **Contrast Limited Adaptive Histogram Equalization (CLAHE)** algorithm is an advanced image enhancement technique commonly used to improve the quality of **MRI images**. Unlike global histogram equalization, which adjusts contrast across the entire image, CLAHE operates on small regions or tiles within the image, enhancing contrast locally. This makes it particularly effective for medical images, where fine details and subtle differences in tissue intensity are critical. In MRI scans, CLAHE enhances visibility of features such as tumors, lesions, and tissue boundaries, especially in areas with low contrast. One of CLAHE's key features is the **contrast limiting step**, which prevents over-amplification of noise by capping the histogram values within each tile. This is particularly useful for MRI images, which often contain low-intensity noise that can be exaggerated by other enhancement techniques. After local enhancement, CLAHE applies **bilinear interpolation** to merge neighboring tiles smoothly and avoid artificial boundaries. The algorithm relies on two main parameters: the **tile grid size**, which defines the number of tiles the image is divided into, and the **clip limit**, which controls the degree of contrast enhancement. By adjusting these parameters, CLAHE can significantly improve the clarity of MRI scans, making it a popular choice for preprocessing in computer-aided diagnosis systems and deep learning pipelines.

Algorithm 1: Normalization of the Image using Adaptive Contrast Enhancement (CLAHE)

Inputs: Dataset $\boldsymbol{S_k(D\ )_{dig}}$, $\boldsymbol{s \times s}$ as tile size, $\boldsymbol{CL}$ as contrast limit
Outputs: Set of enhanced images $\boldsymbol{S_k(D\ )_{ct}}$

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1. Take $S_k(D\ )_{dig}$ dataset and set $s \times s$ pixel tile
2. Divide $S_k(D\ )_{dig}$ into non-overlapping tiles set $S = \{s_{1,}s_{2,}s_{3,} \dots \dots \dots .. s_{n,}\}$.
3. For each tile S in $S_k(D\ )_{dig}$
4. Compute the histogram as $H_i = card\{u, v | i(\ u, v)| = i\}$ H of pixel intensities in $S_k(D\ )$. Where $card$ set of the size of the pixel such that $i(\ u, v) \epsilon [0, k-1]$ and $K = 2^8 = 256$ and u, v pixel value.
5. Clip the histogram H at the contrast limit CL to obtain the clipped histogram H_i.
6. Compute the Cumulative Distribution Function (CDF) for H' as $CDF(x) = \sum_{i=0}^{n} p(u')\ \forall\ u' \leq u$ where $(u') = \frac{p(u')}{s \times s}$ and $s \times s$ pixel intensities for $s \times s$ as $u' = CDF(u)$
7. Append $S_k(D\ )_{dig}$ to the set $S_k(D\ )_{ct}$.
8. Return→ $S_k(D)_{ct}$

In CLAHE, the image is divided into tiles of size s×s pixels. The tile size controls how locally the contrast is enhanced. Smaller tiles allow for finer, localized contrast improvements, which helps reveal subtle details like small tumors. However, very small tiles can increase computation and cause visible seams between tiles. Larger tiles provide smoother, more uniform enhancement but may miss local variations. Choosing the right tile size balances detailed enhancement with smooth image appearance and processing efficiency.

3.4 Classification using Improved Efficient Net B7 model

The Improved EfficientNet-B7 model incorporates several enhancements to boost classification performance, particularly for medical image analysis. Firstly, additional fully connected layers are added to the original EfficientNet-B7 base architecture to better capture domain-specific features. These layers are typically accompanied by dropout and batch normalization to prevent overfitting and improve generalization. Secondly, the model is initialized with pretrained weights from large datasets such as ImageNet and then fine-tuned on the target medical imaging dataset. This transfer learning approach accelerates convergence and improves accuracy, especially when training data is limited. Moreover, data augmentation techniques—including random rotations, flips, and color adjustments—are used to increase the model's robustness. Regularization methods like dropout and weight decay further reduce the risk of overfitting. The training process employs advanced optimizers such as Adam or RMSprop and learning rate scheduling to ensure stable convergence, while early stopping based on validation performance helps prevent overtraining. Finally, the model's output layer uses a softmax activation function to classify input images into predefined categories, providing class probabilities for accurate and interpretable predictions. Together, these improvements enable the EfficientNet-B7 model to achieve high accuracy, precision, and recall in brain tumor classification tasks, making it an effective tool in computer-aided diagnosis systems [3].

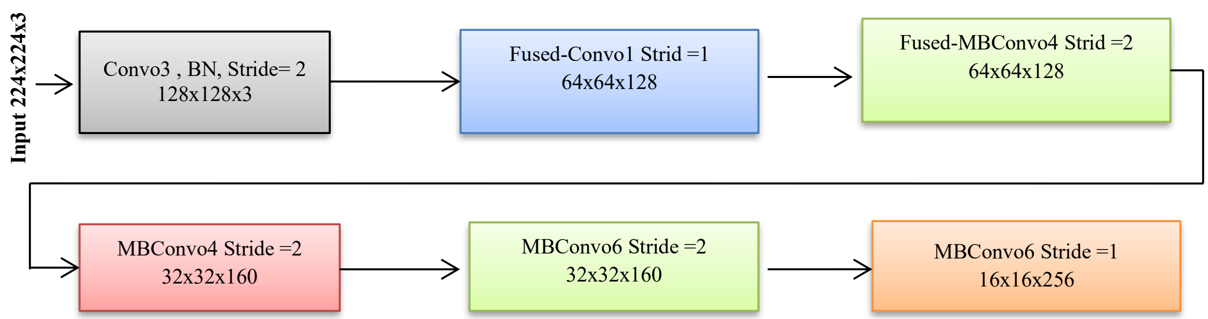

Fig. 4: Architecture of EfficientNet B7

- **Input Layer:** Takes in images, typically resized to 224x224 pixels for B7.
- **Stem:** Initial convolution and batch normalization layers.
- **MBConv Blocks:** Multiple Mobile Inverted Bottleneck Convolution blocks with squeeze-and-excitation layers, stacked in stages with different filter sizes, depths, and resolutions.
- **Top Layers:** Final convolution, global average pooling.
- **Fully Connected Layers:** Dense layers followed by a softmax output for classification.

4.Result and Discussion

4.1 Metrics

Various metrics were employed in the tests to assess the suggested models' performance and compare it with two baseline models: "EfficientNet B7", These minimal memory models were compared with models that were put forth. The "F1-score", "recall", "accuracy", and "precision' were the initial metrics. Our metrics were also extended to multiclass categorization by computing the "macro-average".

Table 4: Evaluation parameters.

Metrics Name	Equation	Define
"Precision (P)"	$\frac{TP}{TP+FP}$	The proportion of all expected positive observations to correctly anticipated positive observations.
"Recall (R)"	$\frac{TP}{TP+FN}$	The percentage of real positives that are accurately detected is known as recall.
"F1-score (FS)"	$\frac{2 \times P \times R}{P+R}$	Precision and recall are both taken into consideration by the f1-score.
"Accuracy (A)"	$\frac{TP+TN}{TP+FP+TN+FN}$	The ratio of properly predicted observations to total observations.
"Macro-Average (M-A)"	$\frac{P_1 + P_2 + P_3 + \cdots..+P_N}{N}$	Is the average precision of every class.

Accuracy is the most logical metric to gauge performance since it represents the percentage of correctly identified cases relative to all instances. "TP (true positives)," or cases that were accurately detected as positive, is used to compute this accuracy. To put it simply, accuracy is yes if both the expected and actual classes are yes. True negatives, or TNs for short, are examples of situations when the actual and anticipated class values are both 0 and were accurately classified as negative. When the expected class is yes but the actual class is no, this is known as a false positive, or FP. On the other hand, when the expected class is no but the actual class is yes, this is known as a false negative, or FN. Table 4 represents the evaluation parameters for calculating the model performance.

4.2 Comparative performance of GAN and CLAHE

This presents a comparison of PSNR (Peak Signal-to-Noise Ratio) values for medical images generated using a Generative Adversarial Network (GAN), both before and after applying CLAHE (Contrast Limited Adaptive Histogram Equalization). PSNR is a common metric used to evaluate image quality, where higher values indicate better image fidelity and lower noise levels.For each dataset, the PSNR value of the GAN-generated images is recorded, followed by the PSNR value after CLAHE enhancement. In all cases, the CLAHE-enhanced images show improved PSNR values, indicating that the enhancement process helped increase image clarity and reduce artifacts or noise.

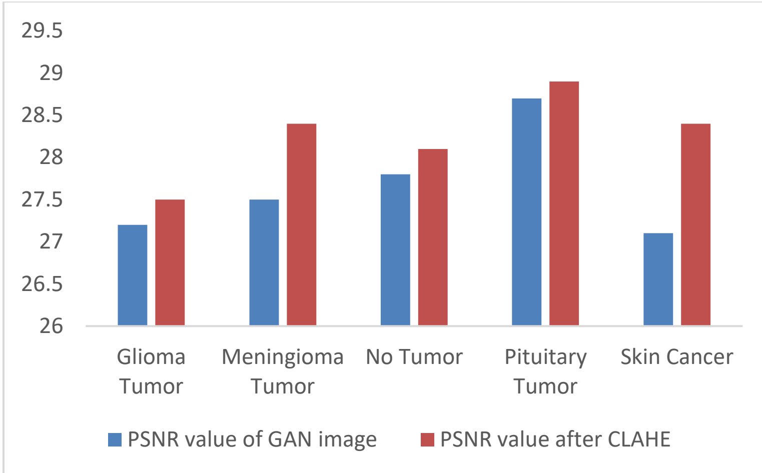

Fig. 5: PSNR values for image generated using GAN, both before and after applying CLAHE

This indicates that CLAHE is particularly effective for enhancing contrast and improving visual quality of GAN-generated medical images, making it a valuable step in image preprocessing pipelines used in medical imaging and diagnostic support systems.

Table 5: PSNR values for image generated using GAN, both before and after applying CLAHE

Type of Dataset	PSNR value of GAN images	PSNR value after CLAHE
"Glioma Tumor"	27.2	27.5
"Meningioma Tumor"	27.5	28.4
"No Tumor"	27.8	28.1
"Pituitary Tumor"	28.7	28.9
"Skin Cancer"	27.1	28.4

4.2 Performance Evolution of Improved Models

With 196 layers and 54.4 million trainable parameters, the improved version of EfficientNet B7 witnessed an increase in accuracy from the beginning of training to the 40th epoch, reaching 95.98% on both test and training sets. As seen in figure 13, the accuracy trend continued after this, eventually stabilizing at 97.91% for the training set and 98.27% for the test set. With a high accuracy of 91.68%, the accuracy trend for the EfficientNet B7 training data grew quickly.

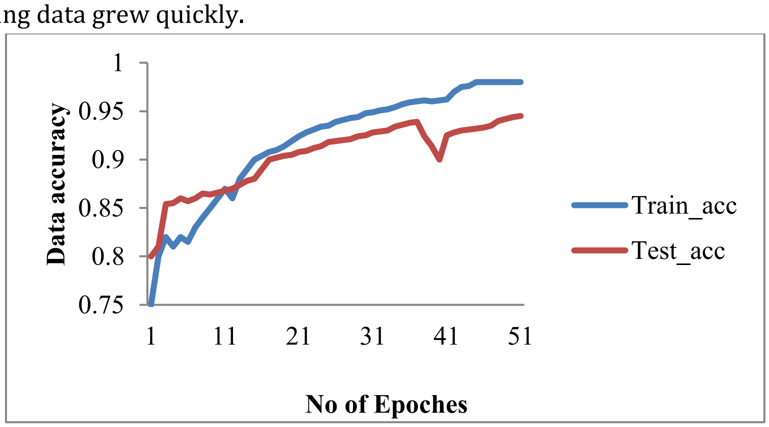

Fig.6: Accuracy curve of EfficientNet B7 model

We calculate the specificity, F1-score, accuracy, and recall rates for every pre-trained model by assessing its efficacy. With an F1-score of 96.58% and an accuracy rate of 98.27%, EfficientNet B7 outperformed other models by a substantial margin. Table 5 shows the performance in terms of different evaluation metrics.

Table 6: Models performance in terms of different evaluation metrics

Accuracy (%)	98.27
Precision (%)	95.85
Sensitivity (%)	94.18
Specificity (%)	98.58
F1-Score (%)	96.58

Table 6 shows that the EfficientNet B7 model outperforms the other pre-trained models in terms of chest illness prediction. Furthermore, figure 15 shows the EfficientNet B7 model's performance in relation to several assessment measures.

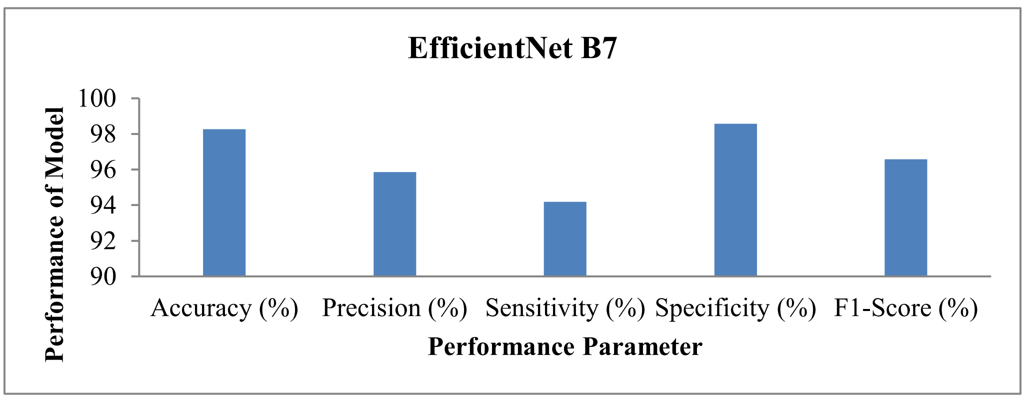

Fig.7. performance of EfficientNet B7 in terms of different evaluation terms

5. Conclusion

This study shows how well the EfficientNet B7 model performs while classifying photos of skin diseases and brain tumors from the NCBI GEO collection as a super series GSE10847 dataset. In several areas, including "Glioma Tumor," "Meningioma Tumor," "No Tumor," "Pituitary Tumor," and "Skin Cancer," the GAN model demonstrated the performance, achieving PSNR value 27.2%, 27.5%, 27.8%, 28.9%, and 27.1% respectively. After applying CLAHE on GAN generated image we got better PSNR value Compared to GAN generated image. The EfficientNet-B7 model exhibits outstanding performance across all key evaluation metrics, indicating its robustness and reliability for classification tasks. With an accuracy of 98.27%, the model correctly classifies the vast majority of instances. Its high precision (95.85%) and specificity (98.58%) suggest it is particularly effective at minimizing false positives, making it suitable for applications where incorrect positive predictions carry high risk.Moreover, the sensitivity (94.18%) shows that the model effectively identifies true positives, though there is a slight trade-off compared to its specificity. The F1-score of 96.58%, which balances precision and recall, reinforces the model's overall effectiveness.EfficientNet-B7 is a highly capable and well-balanced model, particularly suitable for tasks requiring both high accuracy and careful handling of false positives and negatives.

To increase the model's performance, several methods can be explored. Dataset expansion using larger, diverse datasets that include imaging techniques, images from various soruces, and institutions will assits the model generalize better to real-world scenarios. Addressing potential ethical concerns such as data privacy, algorithmic bias, and the appropriate use of AI in medical decision-making ensures the responsible deployment of deep learning algorithms in healthcare.

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Competing Interest

The Authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethics Declarations

The authors declare that they have no conflict of interest

Data Availability

The authors are ready to provide data on request.

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