



AI-POWERED BRAIN TUMOR DETECTION: A CLOUD-BASED APPROACH FOR EARLY DIAGNOSIS

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Abstract: Cancer remains one of the most critical health challenges worldwide, with brain tumors being particularly life-threatening due to their late-stage detection. The uncontrolled growth of tissues in the brain reduces life expectancy, making early diagnosis crucial for effective treatment. Traditional diagnosis primarily relies on biopsy procedures, which can delay treatment initiation. To address this, the authors propose an intelligent, cloud-based e-health application for early brain tumor detection using deep learning. The system leverages the Internet of Medical Things (IoMT), allowing users to securely upload MRI scans for automated pre-diagnosis. The tumor detection and segmentation process is powered by a Generative Adversarial Network (GAN)-based anomaly detection framework Dual AutoEncoder GAN (DAEGAN). Unlike conventional GAN models, DAEGAN consists of two autoencoders acting as generator and discriminator, improving training stability while utilizing discriminator reconstruction error as an anomaly score for enhanced detection performance. Additionally, the system offers periodic model updates to ensure accuracy and reliability, with data being used for training only with user consent. However, this platform is intended for preliminary screening purposes only. It does not replace professional medical diagnosis, and users are strongly advised to consult a qualified medical practitioner to verify the results before making any healthcare decisions. Through this approach, the platform aims to enhance early detection, facilitate timely medical intervention, and

contribute to the advancement of AI-driven e-healthcare services.

1. INTRODUCTION

A brain tumor is an abnormal mass of brain cells and can be categorized as either benign (noncancerous) or malignant (cancerous) [1]. Benign tumors grow slowly and do not invade surrounding tissues, whereas malignant tumors can be further classified into primary tumors, which originate in the brain, and secondary tumors (brain metastases), which spread from other parts of the body [2]. The classification of brain tumors is critical for assessing tumor progression and guiding treatment decisions. Given the variations in tumor size, shape, contrast, and location, distinguishing between benign and malignant tumors is a challenging task. Tumor grading (I-IV) plays a key role in determining disease severity and selecting appropriate treatment options. Medical imaging techniques such as X-rays, computed tomography (CT), MRI, and ultrasound are fundamental to disease diagnosis, with MRI being the preferred modality for brain imaging due to its superior resolution and detail [3]. Anomaly detection is the task of identifying whether incoming input deviates from a set of normal behaviours. Recently, semi-supervised and unsupervised [4] approaches have gained dominance over supervised methods due to the extensive effort required for data labelling in supervised learning. In contrast, semi-supervised and unsupervised techniques require minimal labelled data, making them ideal for detecting rare or unseen anomalies. Among the most popular unsupervised methods are Variational Autoencoders (VAE), Autoencoders (AE), and Generative Adversarial Networks

(GAN). However, training GANs is often challenging due to issues such as mode collapse and non-convergence, often caused by the imbalance between the generator and discriminator. To address this, models such as Energy-Based GAN (EBGAN) [5] and Boundary Equilibrium GAN (BEGAN) [6] have been proposed, where both the generator and discriminator are autoencoders for improved stability in generating realistic images.

Inspired by these advancements, we adopt a semi-supervised GAN-based approach for anomaly detection, named DAEGAN, where both the generator and discriminator are autoencoders. In our cloud-based approach, anomalies during the testing phase are detected using the discriminator's pixel-wise reconstruction error, ensuring robust detection. This method has been evaluated on multiple datasets demonstrating its effectiveness in identifying anomalies, making it well-suited for cloud-based brain tumor detection.

With the rapid expansion of the Internet of Things (IoT), its application in healthcare has significantly improved medical services, making diagnostics more efficient and accessible [7]. As one of the most complex

medical conditions, brain tumors require precise and timely diagnosis to determine the appropriate treatment. The conventional approach relies on human observation and radiologists' expertise in interpreting MRI images, often leading to subjective assessments and potential misdiagnosis [8]. Computer-aided diagnostic (CAD) systems provide an effective solution to enhance accuracy and reliability in tumor detection. We propose an intelligent system for brain tumor pre-diagnosis. This platform allows users to securely upload MRI scans for automated analysis, providing early tumor detection while emphasizing the importance of consulting medical professionals for validation. Our approach aims to enhance early screening capabilities, reduce diagnostic errors, and contribute to the advancement of AI-driven e-healthcare solutions.

The rest of the paper is structured as follows: **Section II** provides an overview of the IoMT-based cloud application. **Section III** presents a brief description of the GAN-based tumor detection method. **Section IV** integrates both approaches to formulate a tumor pre-diagnostic framework. **Section V** outlines the advantages and conclusion of the system.

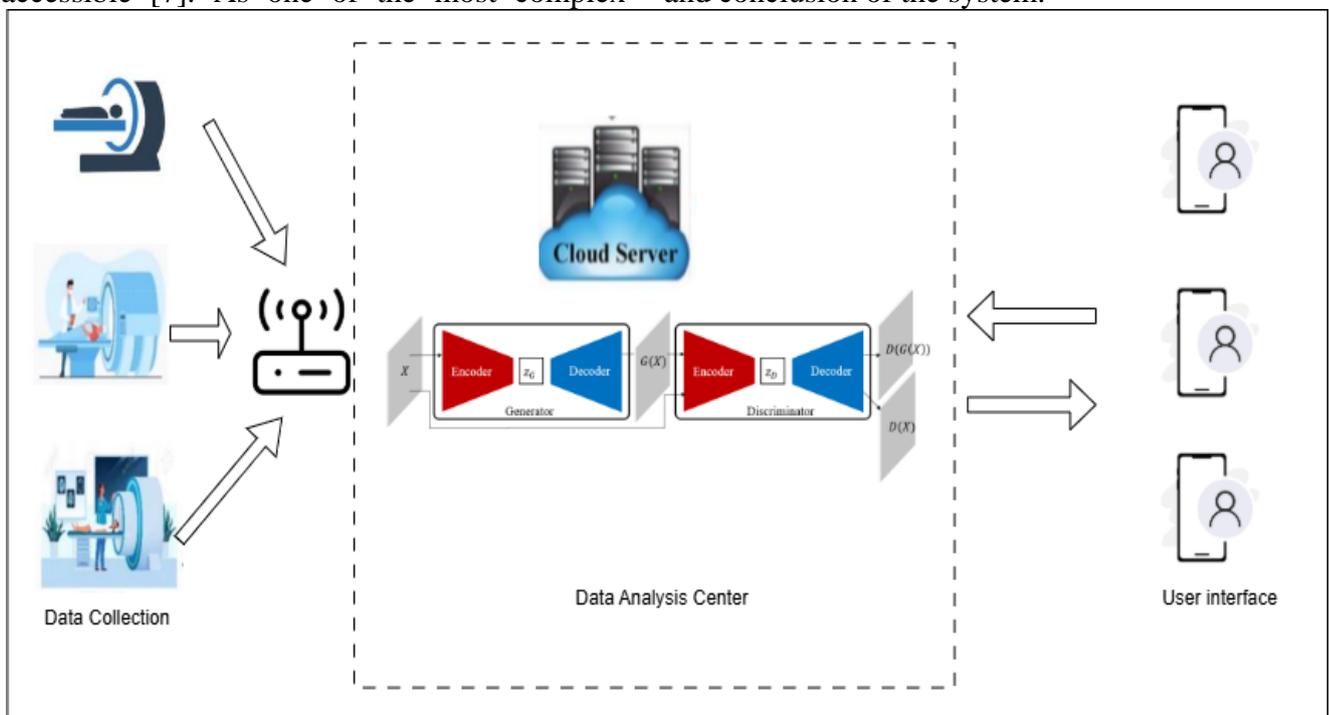


Fig.1. Proposed model architecture

2. IoMT BASED CLOUD APPLICATION

The IoT system supporting our model facilitates the transmission of brain images to the cloud for classification, as illustrated in Fig. 1. This architecture operates as a multi-user access

system, enabling multiple users to connect to the cloud simultaneously.

The cloud-based approach is particularly well-suited for medical applications, providing doctors with seamless access to patient data in a

distributed environment. Our proposed IoT framework consists of three key phases: data collection, image processing, classification and diagnosis, and user interface. The primary objective is to reduce mortality rates through the early detection of malignant tumors.

The system begins with data collection, where MRI equipment captures brain images. These images are then resized to match the input requirements of the proposed DAEGAN model. The model extracts relevant features from the processed images and applies a SoftMax classifier to detect brain tumors. The images are then transmitted via a Wi-Fi module to the cloud for preprocessing and classification. During the analytics phase, patients can access their classification results through a cloud-based database. Radiologists can upload an MRI scan and receive classification results within seconds, allowing them to identify potential tumors almost instantly. In the final phase, the patient's doctor receives a detailed report and determines the most appropriate course of action.

Each user in the system operates with a transmitter and receiver. The transmitter prepares the scanned image for transmission, while the receiver decodes the image upon arrival and extracts essential features for early tumor detection. At the transmitter stage, high-quality brain images are first generated using magnetic fields and computer-binary data and transmitted wirelessly. A patient identifier generated radio waves. The images are then converted into (ID) is added as a header to the binary data vector before it is structured into frames. The data frame is subsequently encrypted using convolutional codes with a coding rate of 2/3 before being transmitted.

The coding rate (r) can be defined as:

$$r = \frac{k}{n}$$

Where k represents the number of parallel input bits, and n represents the number of parallel output encoded bits generated in a single time period. The receiver operates in two modes, as shown in Fig. 2:

1. Registration Mode: A new user only needs to complete the registration process once. During this phase, the patient is assigned a unique ID number,

which allows them to securely access their account in the system.

2. Operation Mode: This mode begins with an authentication process to verify the registered user. After authentication, the image preparation step is performed to process the received image for further analysis. Noise reduction is applied using a Weiner filter to enhance image quality. The processed image is then resized to fit the input specifications of the DAEGAN model.

The process begins at the Start node, indicating the initiation of the system. The system receives incoming data, which could be user credentials, biometric information, or other relevant input needed for authentication and classification. The system checks whether the user is already registered by evaluating the "User Registered?" decision node. Two possible paths emerge based on the answer. If the user is registered, the process proceeds to User Authentication. If the user is not registered, they must go through the Registration Process.

If the user is new, the system enters the Registration Mode and performs the necessary steps to collect and store the user's information. Once registration is complete, the process terminates at the End node. If the user is already registered, they go through an Authentication phase where the system verifies their identity. After successful authentication, the system pre-processes the received data to ensure it is in the correct format and quality for further processing. This step may involve normalization, noise reduction, or other necessary transformations.

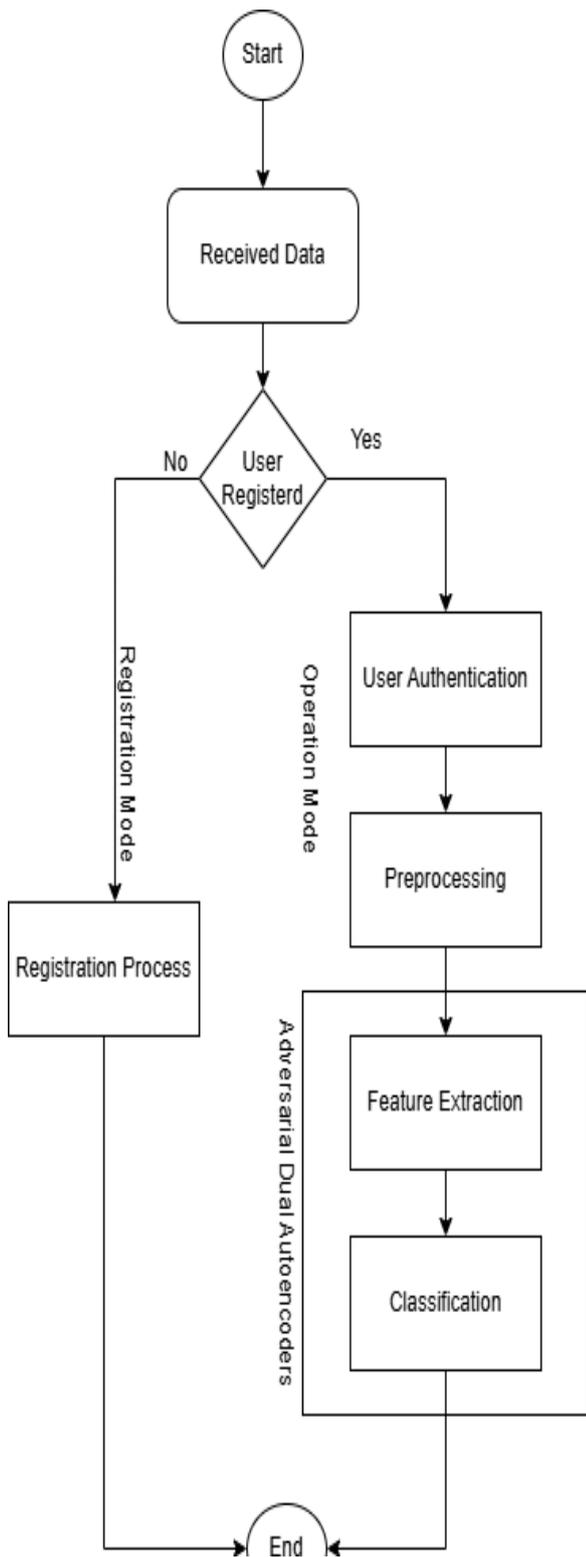


Fig.2. Process Flow diagram

Using DAEGAN, the system extracts meaningful features from the input data. Autoencoders help in dimensionality reduction and representation learning, allowing for better classification. The extracted features are fed into a classification model, which determines

the appropriate category, identity, or decision related to the input data. The process concludes after classification, leading to the End node.

The Registration Mode handles new users by storing their information for future authentication. The Operation Mode is for registered users, where the system authenticates them before proceeding with further data analysis. The DAEGAN mechanism ensures efficient feature extraction and classification, optimizing the overall performance of the system.

3. DUAL AUTOENCODER GAN

In the field of brain tumor detection and segmentation, semi-supervised and unsupervised approaches have demonstrated promising performance without requiring labeled data. The key concept behind these methods, particularly for tumor segmentation (pixel-wise detection), is that models trained only on normal brain data struggle to reconstruct tumors. Consequently, the residual image, obtained by computing the difference between the test input and its reconstructed version, highlights the tumor region.

A method combining Variational Autoencoders (VAE) and Generative Adversarial Networks (GAN) has been proposed [8] to create an end-to-end model for anomaly detection. Another approach utilizes an Adversarial Autoencoder (AAE) with a consistency constraint in the latent space, enforcing the reconstruction of normal brain structures while excluding tumors [9]. For tumor detection (slice-wise detection), a technique integrating context encoding and VAE has been developed to improve reconstruction accuracy and model-internal variations [10]. The anomaly score, derived from evaluating the Estimated Lower Bound (ELBO) of the test inputs, serves as a metric to assess how well a sample conforms to normal brain data.

For anomaly detection, it is crucial to map the image space to the latent space ($X \rightarrow Z$), a capability not inherently provided by standard GAN training. To achieve this, an encoder is typically introduced. A pipeline architecture consisting of an encoder (GE), decoder (GD), and a second encoder (E) is utilized in [11]. Here, GE learns the mapping $X \rightarrow Z$, and the

model minimizes the latent space reconstruction error between the two encoders for normal data. The anomaly score (\hat{x}) for a test input x is computed using the latent space reconstruction error:

$$(\hat{x}) = \|G(\hat{x}) - E(G(\hat{x}))\|$$

where $GE(x)$ represents the latent representation of the input in the generator encoder, and $E(G(x))$ is the latent representation of the generated image in the second encoder. If the model fails to reconstruct the latent representation in

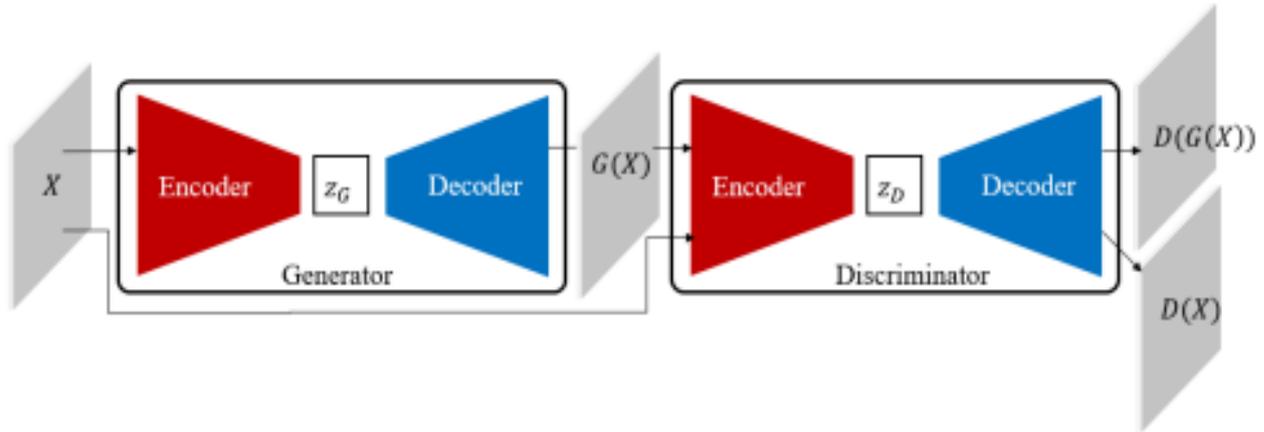


Fig.3. DAEGAN Architecture

the second encoder, the anomaly score is high, indicating an anomalous sample.

An alternative approach, [12], employs a Bidirectional GAN (BiGAN) [13] to train an encoder as the inverse of the generator for mapping image space to latent space, i.e., $E = G^{-1}$. The anomaly score is then determined using a combination of reconstruction loss (LG) and discriminator-based loss (LD). Similarly, [14] builds upon BiGAN by learning latent space representations for multimodal normal data. It further refines the representation by leveraging IGMM to cluster the latent space. Anomalous samples are identified using the Mahalanobis distance to the nearest cluster, calculated based on the means and variances of the clusters. Samples farther from the learned clusters are considered anomalies.

3.1 Architecture of DAEGAN

The architecture is shown in Fig.3. A Generative Adversarial Network (GAN) consists of two competing neural networks: a Generator (G) and a Discriminator (D) [15]. The goal of the generator is to create realistic images that belong to the data distribution, while the discriminator tries to distinguish between real images from and generated images. Instead of a conventional binary classifier as the discriminator, an autoencoder-based discriminator can be used to achieve better balance between the two networks [16]. The adversarial training objective is then

defined as the pixel-wise error between the reconstructed real image and the generated image through:

$$loss = \|G(x) - D(G(x))\|_1$$

where $\| \cdot \|$ represents the L1 norm.

The discriminator is trained to maximize the reconstruction error for generated images while minimizing it for real images. The discriminator acts as a binary classifier, distinguishing between real and generated data. It learns to improve its classification ability through training, refining its parameters to detect fake samples more accurately.

When dealing with image data, the discriminator often employs convolutional layers or other relevant architectures suited to the data type. These layers help extract features and enhance the model's ability to differentiate between real and generated samples. The discriminator reduces the negative log likelihood of correctly classifying both produced and real samples. This loss incentivizes the discriminator to accurately categorize generated samples as fake and real samples with the following equation.

$$D_{loss} = \|X - D(x)\|_1 - \|G(x) - D(G(x))\|_1$$

The generator aims to minimize the reconstruction error so that the generated images resemble real ones.

$$G_{loss} = \|X - G(x)\|_1 + \|G(x) - D(G(x))\|_1$$

These equations formalize how the generator and discriminator compete, leading to the production of more realistic generated data as training progresses. We utilize the reconstruction error in the discriminator as the anomaly score, as the discriminator is trained to differentiate between normal and generated data distributions.

As the model converges, the generator learns to reconstruct normal data that belong to the original distribution. When normal data passes through the generator, it can be reconstructed effectively at the discriminator. However, for anomalous inputs, the generator fails to reconstruct them accurately. This failure amplifies the reconstruction error at the discriminator, as it determines that the inputs from the generator do not belong to the normal data distribution. Formally for each input x the anomaly score $P(x)$ is calculated as follows.

$$P(x) = \|x - D(G(x))\|_2$$

4. CLOUD BASED DAEGAN: DISCUSSION

Choosing a dual autoencoder-based anomaly detection approach instead of supervised learning for brain tumor detection offers several advantages, particularly in handling real-world medical imaging challenges [17]. Supervised learning requires a large, well-annotated dataset with clearly labeled tumor and non-tumor MRI scans. However, obtaining high-quality labeled data is often expensive, time-consuming, and prone to inconsistencies due to inter-observer variability among radiologists. Additionally, medical datasets tend to be highly imbalanced, where normal MRI scans significantly outnumber tumor-affected scans, making supervised learning models susceptible to bias and poor generalization when encountering rare tumor cases.

DAEGAN on the other hand, follows an unsupervised or semi-supervised anomaly detection approach, which eliminates the need for extensive labeled datasets. Instead, the model is trained primarily on normal brain MRI images, learning to reconstruct and represent their distribution effectively.

During inference, when an anomalous (tumor-affected) image is passed through the model, the reconstruction process fails, leading to a high anomaly score. This approach works exceptionally well for medical applications, where abnormal cases often have diverse and complex characteristics that may not be well-represented in a limited labeled dataset. The discriminator further amplifies the difference between normal and anomalous reconstructions, improving the reliability of anomaly detection.

Another reason for choosing this method is its adaptability and real-world applicability. Unlike supervised learning models that require retraining when new tumor patterns emerge, the DAEGAN model can generalize to detect previously unseen anomalies without requiring new labels. This is crucial for medical imaging, where new tumor types or variations may be discovered over time. Additionally, a dual autoencoder setup allows the model to preserve fine-grained details while filtering out redundant information, improving its ability to differentiate subtle abnormalities from normal anatomical structures. By leveraging the reconstruction error at the discriminator, the model provides a more interpretable anomaly detection mechanism, making it a superior choice for robust and scalable tumor detection in a cloud-based medical system.

A cloud-based tumor detection system leverages the DAEGAN (Dual Autoencoder GAN) model, which is pre-trained on various benchmark datasets, including MNIST, CIFAR-10[18], and medical datasets such as BRATS 2017 [19] and Human Connectome Project (HCP) [20]. The model is designed to detect anomalies in MRI images and identify the presence of brain tumors. The cloud-based platform allows users to upload MRI images, analyze them using DAEGAN, and obtain an anomaly score that indicates the likelihood of a tumor.

4.1 overview

4.1.1. User Authentication and Access

- Users register for an account on the cloud-based tumor detection platform.
- Upon successful registration, they receive login credentials.
- Users log in to the system to access the tumor detection service.

4.1.2. MRI Image Upload

- Users upload MRI images directly to the cloud server.
- The system ensures that images are in the correct format and resolution (e.g., 32x32 after preprocessing for consistency).
- Uploaded images are temporarily stored for processing.

4.1.3. Preprocessing of MRI Images

- Images undergo preprocessing, including:
 - **Normalization:** Scaling intensity values to a range of $[-1, 1]$.
 - **Resizing:** Ensuring dimensions are compatible with the trained model.
 - **Z-Score Normalization:** Standardizing pixel intensity to reduce variations between subjects.

4.1.4. Tumor Detection Using DAEGAN

- The uploaded MRI image is fed into the pre-trained DAEGAN model.
- The autoencoder reconstructs the image and computes the anomaly score based on the reconstruction error.
- Find out anomaly score from DAEGAN model

4.1.5. Tumor Classification

- A threshold ϕ is defined to determine the presence of a tumor.
- If $A(x) > \phi$ the MRI image is classified as anomalous (potential tumor).
- Otherwise, the image is classified as normal.

4.1.6. Performance Evaluation and Metrics

- Once the anomaly score is calculated, performance metrics are generated:
- **Receiver Operating Characteristic (ROC) Curve:** Plotted using True

Positive Rate (TPR) vs. False Positive Rate (FPR).

- **Area Under ROC (AUROC):** Measures model performance in distinguishing normal from tumor images.
- **Binary Classification:** Labels MRI images as 'Tumor' or 'Normal' based on thresholding.

4.1.7. Visualization and Reporting

- The system provides a detailed report including:
 - Anomaly score and classification result.
 - ROC curve visualization.
 - AUROC value to assess model confidence.
- Users can download the report or view results in the web dashboard.

4.1.8. Continuous Model Improvement

- New MRI images uploaded by users can be used to fine-tune the model.
- Anomaly detection results can be verified by medical professionals to enhance accuracy.
- The system periodically updates DAEGAN to incorporate new medical data sources and improve tumor detection accuracy.

This cloud-based tumor detection system using DAEGAN provides a scalable, efficient, and accessible platform for early brain tumor detection. By leveraging state-of-the-art deep learning and cloud computing, the system ensures accurate diagnosis while allowing continuous model updates based on real-world data.

V. CONCLUSION

The integration of DAEGAN, a dual autoencoder GAN model, into a cloud-based tumor detection system offers a transformative approach to brain tumor diagnosis. By leveraging advanced deep learning techniques, the system enables automated detection and analysis of tumors in MRI images with high accuracy. Users can securely log in to the cloud platform, upload MRI scans, and receive detailed insights into potential anomalies. The system's ability to compute anomaly scores using the reconstruction error in the discriminator ensures precise differentiation

between normal and tumor-affected brain structures. This anomaly detection mechanism, combined with evaluation metrics such as the ROC curve and AUROC score, provides a reliable assessment of the model's performance. Furthermore, the cloud-based framework ensures accessibility for medical professionals and researchers, eliminating the need for high-end local computing resources while allowing seamless integration with hospital imaging systems and MRI machines.

One of the key advantages of this cloud-based tumor detection system is its scalability and adaptability. As more MRI scans are processed, the model continuously refines its ability to detect anomalies, improving its performance over time. The integration of real-world medical imaging data, including datasets such as BRATS 2017 and HCP, ensures that the model is well-trained on a diverse set of cases. This adaptability makes it suitable for deployment in various medical institutions, allowing for widespread usage in diagnosing and monitoring brain tumors. Additionally, the system's ability to analyze trends over time enables medical professionals to assess the progression of a detected tumor by comparing multiple MRI scans for a single patient. By offering an automated and efficient approach to tumor detection, this system reduces the workload of radiologists and enhances the speed of diagnosis, ultimately leading to improved patient outcomes and early intervention strategies.

The Internet of Medical Things (IoMT)-based cloud architecture for brain tumor detection further enhances the system's functionality by enabling seamless integration with connected medical devices. In an IoMT framework, MRI machines, hospital databases, and cloud-based analytics platforms are interconnected to facilitate real-time data sharing and processing. This architecture allows MRI images to be directly uploaded from imaging devices to the cloud, where the DAEGAN model processes them and provides instant diagnostic insights. The use of secure data transmission protocols ensures patient confidentiality while allowing healthcare professionals to access diagnostic results remotely. Additionally, AI-driven predictive analytics within the cloud system can help in identifying high-risk cases, prioritizing critical scans for faster review. By combining IoMT with deep learning and cloud computing,

this approach not only enhances the accuracy and efficiency of brain tumor detection but also establishes a robust framework for future advancements in medical imaging and AI-assisted diagnosis.

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