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Brain Tumor classification from MRI images using generative adversarial network and Hybrid deep CNN-LSTM

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Abstract
Accurate classification of brain tumors plays a vital role in clinical diagnosis and therapy. To aid in this process, we present a deep learning approach for brain tumor classification. By leveraging deep learning, radiologists can efficiently analyze the vast amount of brain MRI images, leading to faster and more accurate diagnoses. However, training deep learning models requires large centralized datasets, which can pose challenges due to privacy regulations surrounding medical data. In this study, we address this issue by developing a model that utilizes a Generative Adversarial Network (GAN) to generate synthetic brain tumor MRI images. Additionally, we propose a hybrid CNN-LSTM network to accurately identify brain tumors in MRI scans. The performance of the hybrid network achieves an impressive classification accuracy of 99.1%.

Keywords: Automated Brain Tumor detection, GAN Network, deep neural network

Small datasets pose significant obstacles in the domain of medical imaging due to their limited samples and diversity [4-6]. The collection of medical images is an expensive and time-consuming task that requires the involvement of radiologists and researchers [5]. To overcome these challenges, artificial data augmentation techniques can be employed.

Significant progress has been achieved in computer-aided medical diagnosis through recent studies, which have embraced deep learning principles. The application of deep learning techniques has been extensively utilized in the examination of breast cancer research [7] and the diagnosis of lung cancer [8]. In the field of dermatology diagnostics, a deep learning algorithm has been developed specifically for the detection of human skin [9]. The monitoring of brain metastases has been successfully accomplished using deep

1-Introduction

Here are the rephrased sentences:

Abnormal cell growth in the human brain or spinal canal is the primary cause of brain tumors [1]. Detecting these tumors early on is essential to prevent them from reaching an uncontrollable stage. Magnetic Resonance Imaging (MRI) is frequently used to detect brain tumors. Among teenagers and young individuals, brain tumors are the third most prevalent form of cancer [2]. The automated classification of brain tumors is crucial in the field of medical image processing.

Deep neural networks (DNN) have demonstrated encouraging outcomes in medical applications, but the availability of diverse training data is crucial [3]. Due to the low incidence rates of various diseases and privacy regulations surrounding medical data, obtaining a large and centralized dataset can be challenging.

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Unsupervised classification methods, which do not require uniform acquisition protocols or additional training datasets, have been adapted for tumor classification based on image data similarity [1]. Techniques of computational intelligence and machine learning have played significant roles in enabling earlier detection of brain tumors. However, the varying modalities of MRI images pose challenges in tumor classification. Various techniques, including Artificial Neural Networks (ANN), Expectation-Maximization (EM) algorithm, knowledge-based techniques, Support Vector Machine (SVM) and Fuzzy C Means (FCM), have been developed for the classification of brain tumors from MR images. These techniques leverage segmentation based on domains and extraction of useful data using medical image modalities [20]. Other methods, such as hidden Markov random fields, Gaussian mixture modeling, and non-negative matrix factorization (NMF), have been employed for brain tumor classification and segmentation [21-23]. Due to limited training data, prior knowledge is often required to generate competitive outputs [24]. Automatic methods based on machine learning classification techniques are regarded as highly effective approaches in designing systems that integrate multiple MRI modalities and essential features [1].

In this study, we propose an efficient CNN-LSTM model for the detection of brain tumors from MRI images. The neural network architecture combines deep CNNs for feature extraction with LSTM layers for final classification. To address the limited availability of training data, we convolutional neural networks (CNN) [10]. Deep transfer learning, which is a specialized form of deep learning, has gained considerable recognition in various areas such as visual categorization, object recognition, and image classification [11]. This approach allows the utilization of pre-trained CNN models that have been developed for related applications, showing promising potential in computer-aided diagnosis of medical conditions. For instance, pre-trained models like InceptionV3 have been employed to differentiate between benign and malignant renal tumors based on CT images [12]. VGG-16 and fine-tuned AlexNet models have been applied for breast cancer classification using histopathologic images, followed by support vector machine (SVM) classification [13]. Learning models based on transfer learning and 3D CNN architecture have been introduced for the characterization of lung tumors and pancreatic tumors, surpassing traditional handcrafted engineering methods [14]. Transfer learning has also been employed in neuro-oncology applications, where deep features are extracted from brain MRI images using pre-trained networks [15,16]. The grading of glioma from MRI images has been explored using AlexNet and GoogLeNet, with GoogLeNet demonstrating superior performance [17]. Additionally, the diagnosis of Alzheimer's disease from MRI has been tackled using a pre-trained VGG-16 network [18]. Transfer learning has also shown promise in content-based image retrieval (CBIR) for brain tumors [19].

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Out of this dataset, we carefully selected 200 photos, with 100 images featuring tumors and the remaining 100 images representing normal brain scans. These two distinct classes, normal and tumor, are well-represented in the dataset. To ensure comprehensive evaluation, we divided the dataset into a training set, accounting for 70 percent of the total dataset, and a test set, encompassing the remaining 30 percent. Figure 3 showcases a selection of brain MRI images from this remarkable dataset.

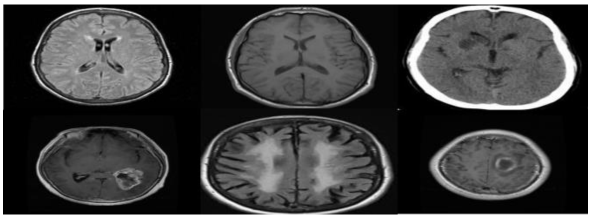

Fig. 2. The example of brain MR images in dataset

2-2- generating synthetic images with GAN Network

Generative Adversarial Networks (GANs) leverage the interplay between two competing neural networks, namely the generator and discriminator models, to generate synthetic data that closely resembles real data. These models are accompanied by visual diagrams that illustrate their respective architectures and processes.

2-2-1- Generative Model

The generative model in a GAN generates samples in the target domain using a fixed-length input random vector, typically drawn from a Gaussian distribution. During training, this vector is used in the generation process to create a compact representation of the data distribution. This multidimensional vector space is often referred to as the "hidden space" or "latent

employ a Conditional Generative Adversarial Network (CGAN) for artificial image generation and data augmentation. The contributions of this study include the CGAN-based augmentation technique and the hybrid CNN-LSTM model for brain tumor detection.

The structure of this article is as follows: Section 2 describes the dataset and CNN-LSTM architecture used for brain tumor detection. Section 3 presents the results, and Section 4 concludes the study.

2-Material and method

This section provides an overview of the dataset used in the study, the process of generating synthetic images using a GAN network, and the architecture of the CNN and LSTM neural networks. The flowchart of the proposed method is illustrated in Figure 1, which will be described in detail in the following subsections.

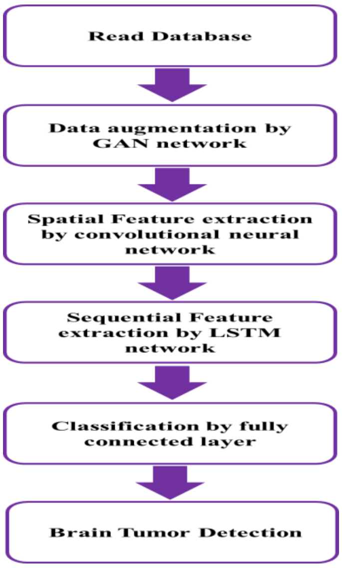

Figure 1- flowchart of proposed technique

2-1-Dataset Characteristics

In our quest to classify brain tumors, we embarked on a series of experiments using a publicly available brain MRI dataset. This dataset was sourced from the Kaggle website [25], and it provided us with a wealth of brain MRI images to work with.

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Due to the generative model's ability to effectively extract features from examples in the target domain, there are opportunities to apply it to new tasks. Transfer learning techniques can be employed to leverage the feature extraction layers of the generative model when working with similar input data. This allows for the transfer of learned features and knowledge from the original training task to new applications, potentially improving performance and efficiency.

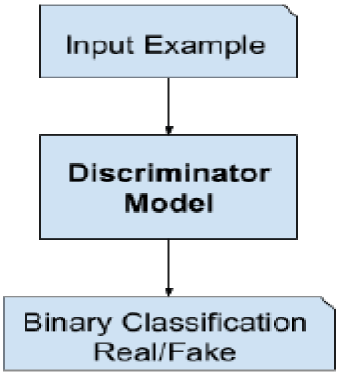

Figure 4: An example of a GAN network discriminator model

This study utilizes a GAN network consisting of two generator and discriminator models, designed based on the architecture of CNN networks. The primary objective of this work is to generate artificial MR images of the brain using the GAN network.

2-3- Feature extraction using CNN and LSTM neural network

To enhance the performance of brain tumor classification and diagnosis using artificial images, effective features are extracted. Convolutional neural networks (CNNs) are employed for feature extraction due to their superior performance in analyzing image data. Subsequently, an LSTM deep network is utilized for classification, leveraging its space" as it contains hidden variables that capture important elements of the target domain.

The latent variables and latent space act as predictors or compressions of the data distribution. They provide a condensed representation or high-level understanding of the original observed data, such as its distribution. In GANs, the generative model operates on points in the chosen hidden space, allowing for the presentation of new points from this space as inputs to generate fresh and novel output samples.

Once trained, the generative model is retained and can be utilized to produce new and diverse examples in the target domain, expanding the range of generated outputs beyond the original training dataset.

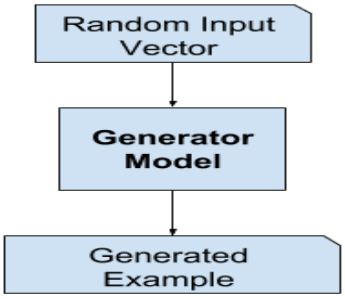

Figure 3: An example of a generative model in a GAN network

2-2-2- Discriminator Model

The discriminator model in a GAN is responsible for predicting a binary class label (true or false) for input samples from the domain. During training, the discriminator learns to distinguish between real-world examples from the training dataset and the generated samples created by the generative model. The discriminator essentially acts as a popular and widely-used classification model.

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satisfies the ω(.) function. In summary, we can express it concisely as follows:

The pooling layer minimizes file size by applying ω(.) to analyze pixels and their surroundings, selecting the pixel that fulfills the criteria. This can be represented as:

$$\omega(I_{x,y}) = \max_{i,j\in\{-1,0,1\}} I_{x-i,y-j} \quad (2)$$

The image resizing can be computed as $\frac{w-k}{s+1} \times \frac{h-k}{s+1}$, where s represents the shift of the kernel or the size of the neighborhood. These resizing and convolutional layers can be applied multiple times before reaching the final fully connected (FC) layer. Similar to artificial neural networks (ANNs), CNNs consist of multiple hidden layers and one output layer. In our CNN model, as depicted in Figure 5, there are two convolutional layers followed by two pooling layers. The output of the second pooling layer is then fed into the fully connected layer for classification. Our CNN is designed to process MRI images with a resolution of 224 by 224 pixels and produces two probability values for each of the two classes of interest.

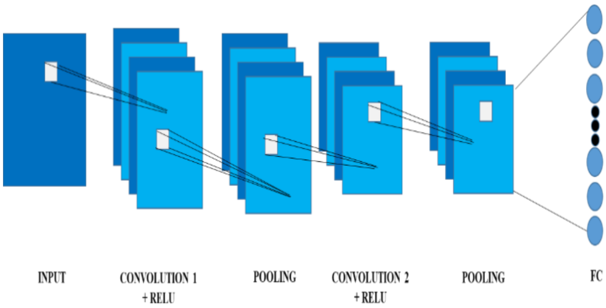

Fig. 5. Structure of CNN model in this work.

2-3-2- LSTM Network

LSTM networks are a subgroup of recurrent neural networks (RNNs) that excel in learning and predicting based on sequential dependencies. They have ability to model sequential data and capture long-range dependencies. This integrated approach aims to achieve accurate classification and diagnosis of brain tumors based on the extracted features.

2-3-1- Convolutional neural network

The Convolutional Neural Network (CNN) is a popular neural architecture used in computer vision tasks. It differs from the Artificial Neural Network (ANN) mainly in terms of its architecture and input data. While ANN processes numerical values, CNN is designed for image data.

An image is represented as a collection of pixels, with dimensions given by width (w), height (h), and depth (d). The depth of an image corresponds to the number of color channels used, such as RGB (Red-Green-Blue), which has a depth of 3.

The CNN architecture consists of convolutional, pooling, and fully-connected layers. Convolutional layers apply filters to the image, highlighting and extracting specific details. This is achieved through the convolution operation, denoted by the star symbol (*), performed between the image $I_{x,y}$ and a filter k of size $p \times p$ at each pixel location (x, y).

$$k * I_{x,y} = \sum_{i=1}^{p}\sum_{j=1}^{p} k_{i,j} . I_{x+i-1,y+j-1} + b_1 \quad (1)$$

where b_1 denotes a bias. To optimize the image's file size, the pooling layer is applied, utilizing the function ω(.) to analyze the pixel and its neighboring area based on operations such as minimum, maximum, or average. The resulting reduced image retains the pixel that including precision, recall (sensitivity), F1-score, and specificity. Precision measures the classifier's ability to avoid false positives, while recall measures the classifier's ability to correctly identify all positive samples (true positive rate). The F1-score is the weighted average of recall and precision. Specificity measures the classifier's ability to correctly identify negative samples (true negative rate). In addition to overall accuracy, we also computed macro-average and weighted average metrics. The following are the formulas for these metrics:

$$Precision = \frac{TP}{TP + FP} \qquad (3)$$

$$Sensitivty = Recall = \frac{TP}{TP + FN} \qquad (4)$$

$$F1score = 2 \times \frac{Recall \times Precision}{Recall + Precision} \qquad (5)$$

$$Total\ Accuracy = \frac{\sum TP}{Total\ Covid19\ Sampels} \qquad (6)$$

In the above formulas, TP represents true positives, TN represents true negatives, FP represents false positives, and FN represents false negatives.

3-2- The Proposed Networks Architecture

To implement the proposed method, we start by utilizing the GAN network to augment the database images. In this study, we utilized a total of 200 database images, and an additional 200 synthetic images were generated using the GAN network. As a result, our dataset consists of 400 images. Next, we allocate 70% of these images for training the proposed network and reserve 30% for testing and evaluating the network. The tables below, effectively overcome the technical challenges faced by traditional RNNs. For instance, while ordinary RNNs struggle to learn the relationship between input and output events beyond a few discrete time steps, LSTM networks can learn with "constant error carousels" (CECs) that can span up to a thousand time delays. This is achieved by utilizing specialized units called cells, which maintain a constant error flow within the CEC during the learning process.

The structure of each memory cell in LSTM ensures a continuous error flow throughout the CEC's constant error cycle, enabling the network to bridge long delays. Each LSTM layer consists of two gate units that determine when to allow or block access to the error flow within each memory cell. The multiplicative input gate safeguards the CEC from irrelevant inputs, while the multiplicative output gate prevents memory contents from affecting other units that are currently irrelevant.

3- Experiment and results

This section presents the numerical results obtained from simulating the proposed method for brain tumor diagnosis. The simulations were conducted using MATLAB software version 2021. Brain MRI images were used for the simulation in this study. The following provides a description of the database used. Additionally, the measurement criteria, LSTM network parameters, and numerical results of the proposed method will be discussed in the following subsections.

3-1- Evaluation metrics

Using the synthetic data augmentation approach, we evaluated the performance of the CNN model using several metrics

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individuals with brain tumors, and the second class represents healthy individuals. From the confusion matrix, it can be observed that all cases related to brain tumors in the first class are correctly detected by the proposed method. However, in the second class, there is one case of a healthy individual being wrongly classified as having a brain tumor. The overall accuracy of the proposed method for detecting brain tumors is 99.1%.

Table 3: Confusion matrix for Brain Tumor identification using CNN-LSTM, augmenting real data with generated data.

		Actual		
		Positive	Negative	
Predicted	Positive	TP=60	FP=1	61
	Negative	FN=0	TN=59	59
		60	60	

Table 4 and Figure 6 provide a comparison between the proposed method in this study and other methods in terms of evaluation criteria. The accuracy of the proposed method is 99.1%, which is the highest among the compared methods. The HBTC-MLP method achieves an accuracy of 98.3%. The comparison of the results demonstrates the superiority of the proposed method, attributed to the utilization of the GAN network for generating synthetic images and the hybrid CNN-LSTM neural network employed.

Table 4: Comparison of the suggested method's outcomes with those from previous works

specifically Table 1 and Table 2, provide an overview of the Hybrid CNN-LSTM layers and their corresponding parameters.

Layer Number	Layer Name
1	Feature Input Layer
2	fully Connected Layer
3	Sigmoid Layer
4	Fully Connected Layer
5	Sequence Input
6	LSTM
7	Dropout
8	LSTM
9	Dropout
10	Fully Connected
11	Fully Connected
12	Softmax
13	Classification Output

Table 1- Proposed Hybrid CNN-LSTM network layers

Table 2- LSTM network parameters

Parameter	Amount
num HiddenUnits	40
maxEpochs	20
miniBatchSize	15
Dropout probability	0.2
Learning Algorithm	stochastic gradient descent with momentum (SGDM)

3-3- Evaluation of Simulation Results

In this subsection, we present the performance of the suggested approach. Table 3 displays the confusion matrix of the proposed network on the test data. The dataset used in this study consists of two classes: the first class represents demonstrating its efficacy and potential impact in medical research.

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Method	Accuracy
ANN [26]	**94**
Linear SVM [27]	**89.6**
VGG-16 [28]	**96**
HBTC + MLP [29]	**98.3**
Proposed method (GAN-CNN-LSTM)	**99.1**

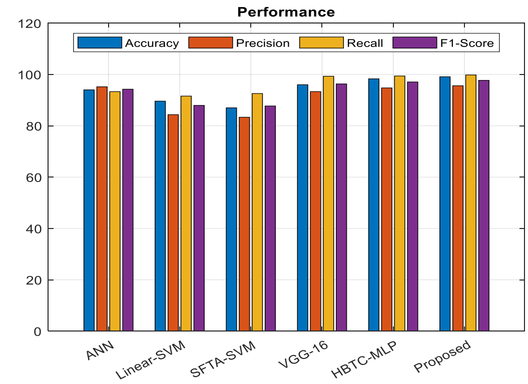

Figure 6: Comparison of the suggested method's outcomes with those from previous works

4- Conclusion

Addressing the challenge of limited medical data, this study introduces a novel approach for brain tumor diagnosis. The proposed method leverages the GAN neural network to augment the available data by generating artificial brain MRI images. A combination of pre-trained deep networks and the LSTM network is employed for accurate diagnosis. The dataset consists of 200 original images, which are augmented with 200 artificial images created using the GAN network, resulting in a total of 400 images. The CNN network is utilized to extract spatial features from the brain MRI images, while the LSTM network captures temporal relationships. This integration of CNN and LSTM networks enhances the accuracy of brain tumor identification. The proposed method achieves an impressive accuracy of 99.1% in diagnosing brain tumors,

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