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DETECTION OF BRAIN TUMOR USING VGG16 AS AUTOENCODER WITH BI-LONG SHORT TERM MEMORY METHOD

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Abstract. The fast proliferation of aberrant brain cells that distinguishes a Brain Tumor (BT) poses a significant health concern to adults because they can cause serious organ dysfunction and possibility of causing death. These tumors have a wide range in location, size and texture. When attempting to find malignant tumors, Magnetic Resonance Imaging (MRI) is an essential technique. However, BT detection is manually complex and task with more time consumption that may result in mistakes. The aesthetically pleasing appearance of MRI scans is improved by enhancing image technologies that employ various filters to the raw images. The paper focus on overcoming the existing gaps by introducing the integration of synergism among Bi-Long Short Term Memory (BiLSTM) as well as Convolutional Autoencoder (CAE) using VGG16 layer to optimize its united impact over predictive performance. The research's objectives include enhancing the conceptual integration of BiLSTM and CAE with VGG16 as the hyperparameter tuning to improve the model's efficiency for capturing temporal and spatial interdependence among heterogeneous datasets. Furthermore, this research concentrated on improving the prediction method output interpretability for assuring their practical application in clinical environments. The CAE has trained from the source dataset and perform in optimizing during testing using a test subject for effective computation. Moreover, the BiLSTM is utilized as RNN model with CAE VGG16 for providing improved detection of BT in healthcare industries. Hence, the proposed CAE with BiLSTM is compared to traditional AE and CAE with LSTM for evaluating BT detection using MRI dataset with various BT classes.

AMS Mathematics Subject Classification : 65D30, 65D32.
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1. Introduction

An organ that is soft, spongy, and composed of various tissues is referred to as the brain, which is protected by the skull. It is surrounded by three types of thin layered tissues collectively called the meninges (or pia mater), and a clear, watery fluid known as cerebrospinal fluid (CSF) circulates within the spaces between the meninges and the brain ventricles [1]. According to the American Cancer Society, one of the most severe diseases affecting the brain is a brain tumor (BT), characterized by the abnormal growth of tissue that impairs brain functions. The National Brain Tumor Foundation (NBTF) has reported that the incidence of BT-related deaths has increased by over 300% in the past 30 years. If not properly treated, brain tumors can lead to fatal outcomes [2].

BT complications pose significant challenges for healthcare professionals in terms of diagnosis and treatment. Early detection and intervention are vital to improving survival rates. Biopsy, the standard method for diagnosing most tumors, is especially complex for BT due to the need for invasive surgery. Therefore, non-invasive and precise diagnostic alternatives are critical. Magnetic Resonance Imaging (MRI) is a commonly used and effective technique for diagnosing BT. A brain tumor is generally identified as an abnormal mass in the brain, and it can be classified as benign or malignant (cancerous) [3]. The severity and risk associated with a tumor depend on factors such as its location, size, growth pattern, type, and progression over time [4].

Physicians classify brain tumors into different types based on their histological characteristics [5]. The first type is typically benign and composed of non-cancerous tissue, with cells that closely resemble normal brain cells, often linked to longer survival rates [6]. The second type appears slightly abnormal under the microscope and grows at a moderate pace. The third type is malignant, containing anaplastic cells that proliferate and differ significantly from normal brain cells [7]. The fourth type comprises highly aggressive and abnormal cells that rapidly invade surrounding healthy tissue [8].

Accurate and timely diagnosis of BT is crucial for effective treatment and improved patient outcomes. Radiologists often spend considerable time analyzing MRI scans [9]. Traditionally, such assessments depend on the individual expertise of radiologists and subjective interpretation of images [10]. However, due to the complexity of BT images and variability in human expertise, visual inspection alone may not always yield accurate diagnoses. MRI is widely used in neurology for detailed imaging of the brain and skull [11], offering axial, sagittal, and coronal views for comprehensive analysis [12]. Being a radiation-free and high-resolution imaging modality, MRI is considered the preferred non-invasive diagnostic tool for detecting various types of brain cancer.

Autoencoders (AEs) are a class of Artificial Neural Networks designed for unsupervised learning through data reconstruction. Unlike traditional models trained to predict a target output Y from an input X, AEs are trained to reconstruct the input itself. This involves optimizing the model to minimize

reconstruction error, thereby generating a compressed representation of the data. An AE typically comprises three layers:

(1) **Input Layer**: Receives brain MRI scans as input.
(2) **Hidden Layer**: Encodes the input into a lower-dimensional representation.
(3) **Output Layer**: Decodes the representation to reconstruct the original input.

Each neuron in the AE corresponds to a feature in the input layer [13]. Functionally, the AE consists of two main components: the encoder, which extracts features and maps the input to a lower-dimensional vector, and the decoder, which reconstructs the data using a probabilistic model to ensure similarity with the original input [14]. AEs are widely used for dimensionality reduction and feature extraction, and they are typically trained using backpropagation techniques such as the conjugate gradient method [15].

The urgent need to improve BT identification, which demands fast and accurate diagnosis, forms the basis for this research. Traditional methods relying on manual image interpretation are time-consuming and prone to errors. This study proposes the use of deep learning techniques such as Convolutional Autoencoders (CAE) and Recurrent Neural Networks (RNN), specifically a Bidirectional Long Short-Term Memory (BiLSTM) network combined with CAE-based transfer learning (TL), to automate and enhance BT detection accuracy. This approach aims to facilitate earlier interventions, improve patient outcomes, and reduce reliance on manual image interpretation. The developed model demonstrates the ability to distinguish between normal and abnormal brain images and has the potential to classify different BT types, a task that remains challenging. The proposed BiLSTM-CAE model offers a promising solution with improved precision over existing methods and could significantly contribute to developing reliable diagnostic tools for healthcare practitioners.

2. Related works

U. M. Butt et al. [16] introduced an advanced method for brain tumor (BT) diagnosis using a feature-enhanced Stacked Autoencoder (SAE), improving upon the limited results obtained from a default Autoencoder (AE). The proposed approach consists of four major stages:

- **Data Pre-processing:** Noise removal and grayscale image conversion.
- **Feature Extraction:** Essential features are extracted using Discrete Wavelet Transform (DWT) and channelization.
- **Model Classification:** MRI brain images are classified into four categories: normal, stroke, Alzheimer's, and stroke (duplicated likely in error).
- **Model Validation:** The model was validated using 40% to 60% of the test dataset and achieved an accuracy of 96.55%.

A Deep Wavelet Autoencoder (DWAE) method was also developed to segment input data into normal and pathological tumor regions [17]. In the preprocessing stage, high-pass filters were employed to handle non-homogeneous MRI brain images, while a high median filter was used to merge segmented portions. Image quality was enhanced by edge refinement and image smoothing. Ultimately, segmentation classes were generated using a seed-growing thresholding method, yielding a segmentation accuracy of 96.5%.

Chen et al. [18] proposed a two-stage Convolutional Autoencoder (CAE)-based method for constructing unsupervised models to detect lung nodules:

- **Stage 1:** CAE is used for unsupervised feature learning on unlabeled image data.
- **Stage 2:** The CAE output is integrated with a dense neural network and trained in a supervised manner using labeled data.

This hybrid strategy demonstrates high efficiency with minimal labeled data and can be generalized for related image analysis tasks.

Seyfioğlu et al. [19] developed a three-layer CAE architecture for radar-based classification of assisted and unassisted human activities. Upon completing unsupervised training, the decoder was removed and replaced with dense layers and a softmax classifier, forming a hierarchical supervised model. Experimental results confirmed that the proposed method outperformed various deep learning classifiers, including Support Vector Machines (SVM), Extreme Gradient Boosting (XGB), and Random Forests (RF).

Alanazi et al. [20] proposed a transfer learning (TL)-based approach for early BT detection, classifying MRI images into subclasses such as meningioma, glioma, and pituitary tumors. A 22-layer CNN model was constructed from scratch, using transfer learning to optimize the neuron weights. The binary classification of "tumor" vs "no tumor" was achieved with an accuracy of 96.9%.

Alsaif et al. [21] conducted a comparative study on CNN architectures including VGG, AlexNet, and ResNet. Their CNN-based approach, coupled with data augmentation, was applied to MRI datasets for BT detection. Among the models, VGG yielded the best results, with an accuracy of 93%, an F1-score of 0.93, precision of 0.94, and recall of 0.93.

R. Anwar et al. [22] presented a comprehensive review of transfer learning applications in BT classification. The study covered various approaches such as interpretable TL, domain adaptation, and multimodal data fusion. The authors discussed both the opportunities and challenges of employing TL in healthcare, along with ethical considerations. The findings aim to guide the development of reliable and efficient diagnostic tools for clinical applications.

F. Ullah et al. [23] proposed a hybrid CNN-based approach for enhanced BT segmentation from MRI scans. The method incorporated intensity-, shape-, and texture-based handcrafted features, combined with features automatically extracted by a customized CNN architecture. The model was evaluated using

the BRATS dataset and showed superior performance compared to traditional and standard CNN-based methods for BT segmentation.

2.1. Research Gap. Long Short-Term Memory (LSTM) models are often described as "black-box" architectures due to their lack of interpretability, which can be a limitation in domains where explainability is crucial. Despite their notable success, several drawbacks have been highlighted in the literature, including challenges in understanding internal mechanisms and the risk of overfitting.

To address these limitations, Bidirectional LSTM (BiLSTM) networks have gained prominence for their ability to capture both forward and backward temporal dependencies, making them effective in handling long-range dependencies in time series data. Yao [24] demonstrated the utility of BiLSTM in time-series reinforcement learning frameworks, particularly for capturing complex financial patterns. Similarly, Huang and Yang [25] emphasized the issue of feature redundancy in time series modeling and suggested techniques that support this research's aim of improving generalization and reducing overfitting.

Thus, this study proposes a hybrid deep learning framework that integrates BiLSTM with Convolutional Autoencoder (CAE) based on the VGG16 architecture to enhance brain tumor classification accuracy.

3. Research Methodology

The proposed method leverages unsupervised learning to minimize human intervention while maintaining robust classification performance. The framework includes multiple preprocessing stages to enhance image quality and normalize brain MRI inputs. These procedures yield high-resolution outputs and improve segmentation sensitivity and tumor detection accuracy.

Following preprocessing, the data is passed to a self-encoding neural network (CAE) for feature extraction, which compresses the image space and reduces dimensionality. This allows the network to isolate true tumor regions while suppressing false positives.

Next, a hybrid deep learning model combines CAE with BiLSTM to learn spatial features (via CNN/VGG16) and temporal dependencies (via BiLSTM), resulting in a comprehensive understanding of tumor characteristics. The pretrained VGG16 network, initialized on ImageNet weights, is used for feature extraction, and its output is fine-tuned using BiLSTM. Figure 1 illustrates the proposed model's overall architecture.

4. Data Collection

According to recent statistics, approximately 11,700 individuals are diagnosed with primary central nervous system (CNS) tumors annually. The five-year survival rates for CNS tumors are 34% for men and 36% for women. In this study, a brain MRI dataset was collected, comprising 3,264 image samples categorized into four classes: *no tumor*, *glioma tumor*, *pituitary tumor*, and *meningioma*

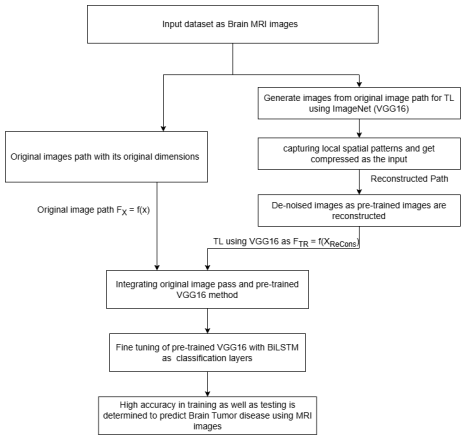

FIGURE 1. Architecture of Brain Tumor Diagnosis using VGG16 with BiLSTM

tumor. The MRI scans, with a resolution of 495×619 pixels, were obtained through medical imaging centers with expert validation by radiologists.

To reduce human error and improve classification accuracy, the dataset was partitioned into 88% training and 12% testing sets. This segmentation supports the robust development and evaluation of the proposed deep learning model [26].

5. Working of CAE (VGG16) for Feature Extraction

The Convolutional Autoencoder (CAE) compresses the input MRI images while preserving critical spatial features. The CAE is configured using the VGG16 architecture, which includes four symmetric blocks of 2D convolutional and deconvolutional layers with Rectified Linear Unit (ReLU) activations. Deconvolution (or transposed convolution) reconstructs high-dimensional representations from compressed inputs.

VGG16 employs small 3×3 convolution filters, capable of capturing fine spatial details in multiple directions. Five max-pooling layers follow the convolutional layers, performing spatial pooling using a 2×2 window with stride 2. After convolution, the data passes through three fully connected (FC) layers, with the final FC layer consisting of $1 \times 1 \times 1000$ outputs for classification via a softmax layer (Figure 2).

6. Working of BiLSTM

The Bidirectional LSTM processes the input sequence in both forward and backward directions as in figure 3, enhancing the model's capacity to learn contextual dependencies. A BiLSTM consists of two LSTM layers:

- **Forward Layer (FL):** Processes the sequence from $t = 1$ to T.

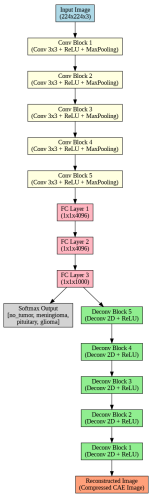

FIGURE 2. CAE Algorithm Architecture Based on VGG16

- **Backward Layer (BL):** Processes the sequence from $t = T$ to 1.

Each LSTM unit is composed of three gates—input, forget, and output—defined by the following equations:

$$i_t = \sigma(A_i x_t + B_i h_{t-1} + \epsilon_i) \tag{1}$$

$$f_t = \sigma(A_f x_t + B_f h_{t-1} + \epsilon_f) \tag{2}$$

$$\tilde{C}_t = \tanh(A_c x_t + B_c h_{t-1} + \epsilon_c) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

$$g_t = \sigma(A_g x_t + B_g h_{t-1} + \epsilon_g) \tag{5}$$

$$h_t = g_t \odot \tanh(C_t) \tag{6}$$

The combined BiLSTM output is represented as:

$$V_t = [\overrightarrow{h_t}; \overleftarrow{h_t}] \tag{7}$$

Where V_t is the concatenated output from both LSTM directions. BiLSTM processes data point embeddings—dense vector representations capturing semantic meaning—and outputs a richer sequence representation.

7. Algorithm: CAE-VGG16 with BiLSTM

(1) **Data Preprocessing:** Convert MRI images into pixel sequences and generate a structured data frame.
(2) **Feature Extraction:** Use a pretrained VGG16-based CAE to extract multistage deep features from MRI images.
(3) **Classification:** Apply BiLSTM to fine-tune and classify extracted features through sequential modeling.

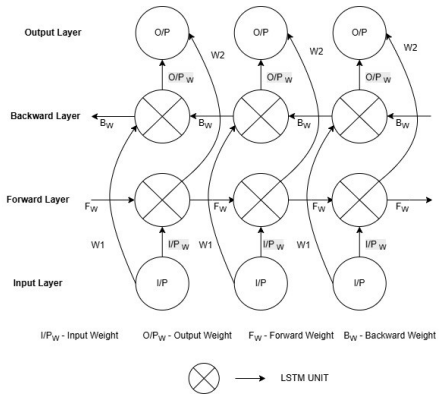

FIGURE 3. BiLSTM Architecture

(4) **Training:** Train the combined CAE-BiLSTM model using multiple epochs.
(5) **Evaluation:** Validate the model's performance using metrics derived from the confusion matrix.

8. Results and Discussion

In this study, the experiments were conducted on a high-performance server configured with 16 GB RAM, an Intel Core i7 DMI2 CPU, and 256 GB SSD. The system operated on Ubuntu 18.04.3 LTS. The model was implemented using Keras, leveraging its pre-built VGG16 module. The training process utilized the binary cross-entropy loss function and the Adam optimizer.

The CAE model was constructed using VGG16 as the backbone, where key arguments such as `include_top`, `input_shape`, and `weights` were defined. The `include_top` parameter added the classifier with dense layers at the top of the network, while `input_shape` specified the image tensor dimensions.

A total of 3,264 brain MRI images were utilized, categorized into four classes: *no tumor*, *meningioma tumor*, *pituitary tumor*, and *glioma tumor*. Table 1 shows the distribution of training and validation images for each tumor category.

TABLE 1. Training and Validation Image Distribution

BT Category	Total Images	Training	Validation
No Tumor	500	395	105
Meningioma Tumor	937	822	115
Pituitary Tumor	901	827	74
Glioma Tumor	926	826	100

The proposed model architecture employed a Convolutional Autoencoder (CAE) with VGG16 for feature extraction, followed by a Bidirectional Long

Short-Term Memory (BiLSTM) network for classification. The CAE module included convolutional layers with 3×3 filters, max-pooling with 2×2 windows, and 'same' padding. The encoder was completed with fully connected layers and softmax activation for multi-class classification.

Figure 4 illustrates the training and validation accuracy of the CAE using VGG16 with BiLSTM. Training accuracy improved steadily after 12 epochs, rising from 96.35% to 98.39%. Validation accuracy increased to 96.27%.

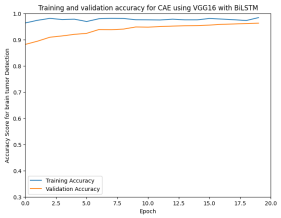

FIGURE 4. Accuracy Curve for CAE Using VGG16 with BiLSTM

Figure 5 shows the training and validation loss. The training loss decreased from 0.0926 to 0.0439, and the validation loss dropped from 0.099 to 0.0517, indicating effective convergence.

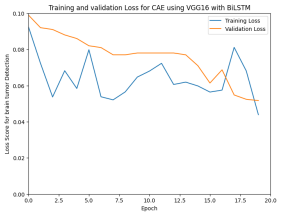

FIGURE 5. Loss Curve for CAE Using VGG16 with BiLSTM

For comparison, the performance of a CAE with standard LSTM was also evaluated. As shown in Figure 6, the training accuracy improved from 93.67% to 96.20%, while validation accuracy peaked at 86.32%.

The loss curves in Figure 7 show that training loss reduced from 0.4286 to 0.1172, while validation loss declined from 0.5874 to 0.3625.

Table 2 compares the evaluation metrics for both models.

Figures 8 and 9 illustrate the accuracy and loss comparisons between the two models. The proposed CAE (VGG16) with BiLSTM significantly outperformed the CAE with LSTM in both training and testing phases.

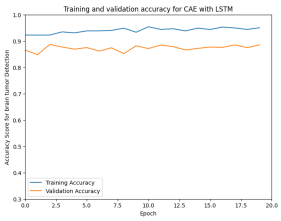

FIGURE 6. Accuracy Curve for CAE with LSTM

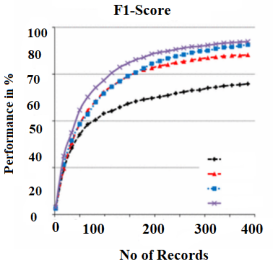

FIGURE 7. Loss Curve for CAE with LSTM

TABLE 2. Evaluation Metrics for CAE with LSTM and CAE (VGG16) with BiLSTM

Metric	Model	Training	Testing
Accuracy	CAE with LSTM	96.20%	86.32%
	CAE (VGG16) with BiLSTM	**98.39%**	**96.27%**
Loss	CAE with LSTM	0.1172	0.3625
	CAE (VGG16) with BiLSTM	**0.0517**	**0.0439**

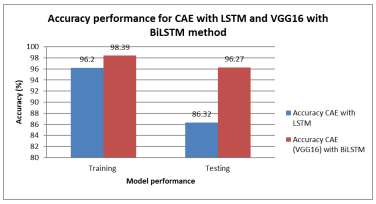

FIGURE 8. Accuracy Comparison of CAE with LSTM and CAE (VGG16) with BiLSTM

9. Conclusion

This research has enhanced the performance of LSTM by introducing CAE technique on image classification tasks. The proposed study is to concentrate in

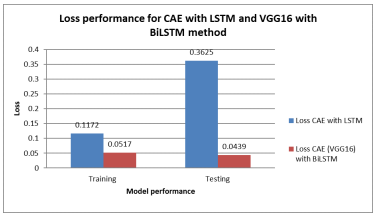

FIGURE 9. Loss Comparison of CAE with LSTM and CAE (VGG16) with BiLSTM

using CAE as data preparation technique to reconstruct robust and compressed representations of features. In image classification models, the RNN models and BiRNN model with CAE are typically taken into consideration. This research concentrated to prove that TL with BiRNN based method may leads to the highest performance than traditional and evaluated CAE using VGG16 with BiLSTM as 98.39% and 96.20% for training and testing results compared to CAE with LSTM image classification models is 96.2% and 86.32%. Moreover, the proposed model is evaluated with CAE with LSTM model through the combination as well as incorporation of the BT image dataset. Therefore, the usage of CAE using VGG16 with BiLSTM for image classification methods which is a adequate layer in DL model selection for leading the reliable and robust experimental results. Thus, the prediction of BT diagnosis is high accuracy in CAE using VGG16 with BiLSTM.

Conflicts of interest : The authors declare no conflict of interest

Data availability : Not applicable

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