Gaussian filter and CNN based framework for accurate detection of brain tumor by analyzing MRI images

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ABSTRACT

The diagnosis of cancer can be challenging and time-consuming due to the complex characteristics of tumors and inherent noise in medical imaging. The significance of early detection and localization of tumors must be considered. Radiological imaging techniques can detect and potentially forecast the presence of neoplastic growths at various phases. The expeditiousness of the diagnosis process can be notably enhanced by amalgamating these images with algorithms designed for segmentation and relegation. Early detection of tumors and accurate localization of their position are critical factors. Medical scans, when used with segmentation and relegation procedures, enable the prompt and precise detection of cancerous tumor regions. The identification of malignant tumors enables this achievement. The present article introduces a framework for detecting brain tumors based on a convolutional neural network (CNN). The initial step in processing brain magnetic resonance imaging (MRI) images involves the application of a Gaussian filter to eliminate any noise present. Subsequently, CNN and long short-term memory (LSTM) deep learning methodologies are employed to classify images. CNN has demonstrated improved accuracy in the classification and detection of brain tumors. CNN has achieved an accuracy of 99.25% in cancer image classification. The sensitivity and specificity of CNN are also 98.75% and 99.25%, respectively.

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1. INTRODUCTION

Encephaloma tumor fatalities are rising across all ages. Tumor malignancy is assumed to depend on its encephalon growth halt. Unlike popular belief. "Non-uniform" growth patterns imply cancerous cells have spread. The American Society for Clinical Pathology says benign tumors contain noncancerous cells. Tumor intricacy and imaging noise slow cancer diagnosis. A doctor needs spend a lot of time diagnosing a tumor. Successful treatment involves early tumor detection and localization. Medical scans with segmentation and relegation can discover early cancers [1], [2]. Brain tumor tissue segmentation from magnetic resonance imaging (MRI) images is complex and time-consuming. Background noise in medical pictures can be objectively diagnosed via segmentation. Clinical diagnosis improves. The supplemental photographs show the radiologist physically inspecting the tumor, which potentially misdiagnose it [3]. Human mistake is eliminated by automated medical picture analysis and categorization.

Digital image processing is used in medicine, microscopy, astronomy, computer vision, and geology. Medical and scientific research require steps. Computer-aided design and image segmentation require medical imaging. Human-machine interaction enhances surgical planning and precision. This method uses imaging and treatment. These components should improve doctors' diagnostic tools. Segmented body images were taken with medical instruments. MRI and computed tomography (CT) are noninvasive body imaging methods [4]. A brain tumor requires the development of abnormal tissues [5]. These abnormal tissue types cause uncontrolled tissue proliferation, growth, and death. CT is utilized more than MRI to diagnose brain cancers. CT and MRI detect brain cancers. MRI and CT scans enable doctors find brain cancers in 3D. Computerized brain tumor detection and three-dimensional characterisation saves specialists time and improves accuracy. Automated or semi-automated tumor segmentation frees doctors to plan patient care [6]. MRI image scanning is detailed in Figure 1.

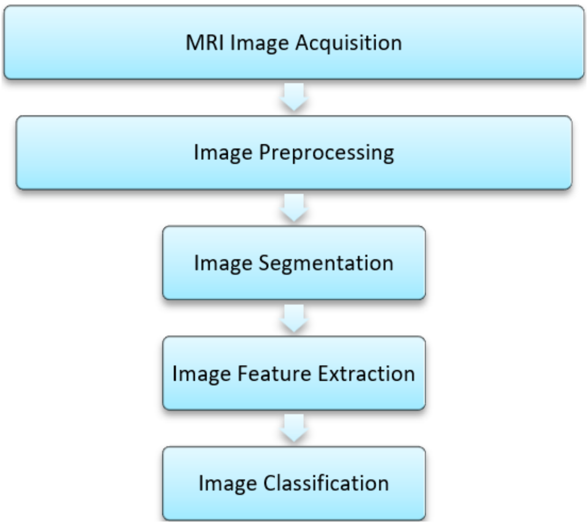

Figure 1. Steps involved in MRI image processing

Many sounds exist in MRI pictures. We can choose from many pre-processing approaches to handle this issue. After photos are properly processed, the rigorous pre-processing removes unnecessary details. "Image pre-processing" is the first step [4], and its name describes it. Pre-processing processes include picture reconstruction, black-and-white-to-grayscale conversion, and noise reduction. Grayscale pre-processing is most common [1]. Existing approaches have many limitations, especially for noise reduction. Segmentation: the scanning process produced large images, which should, within a reasonable amount of time, be easily identifiable by human clinical professionals. These images were produced as a result of the scanning process.

Feature extraction: the process of determining a strong candidate for a character's identity is known as feature extraction, and it involves the process of assigning a feature vector to each individual character. Among the objectives are the generation of a feature set that is consistent across multiple instances of the same symbol and the extraction of features that maximise the recognition rate while using the fewest number of components possible. The currently available feature extraction systems were not capable of selecting the most important features for further diagnostic work.

Classification: each piece of information contained in a set is assigned to one of a fixed number of categories after being sorted. This technique is utilised extensively in the process of analysing brain scans in the search for indications of cancer. The primary goal of classification is to arrive at an accurate prediction of the target class. To accomplish this, images of the brain are analysed and categorised according to whether or not they show a tumor.

This article presents a convolutional neural network-based (CNN) framework for brain tumor detection. Brain MRI images are first preprocessed using Gaussian filter (GF) to remove noises. Then images are classified by CNN and long short-term memory (LSTM) deep learning techniques. CNN is achieving higher accuracy for classification and detection of brain tumor.

2. LITERATURE SURVEY

This section presents literature survey of various existing techniques for image preprocessing, image segmentation, feature extraction, feature selection, and classification.

2.1. Preprocessing techniques

Image processing can analyze brain scans. MRIs are used for medical diagnosis and treatment. Picture pre-processing has these main components: Eliminating background noise and unpleasant artifacts more effectively. This image should make tumor detection easier. Suryavamsi *et al*. [7] suggested three ways to modify astrocytoma-affected MRI brain pictures. Performance measurements and computations have proven these three techniques. Mean squared error (MSE), peak signal-to-ratio (PSNR), and root mean square error (RMSE) measure accuracy.

Before extracting signal from MRI data, background noise must be removed. Independent component analysis (ICA) and nuisance regression are common pre-processing methods. De blasi and her team use LD cleaning therapies on healthy people and temporal lobe epilepsy sufferers to remove non-BO LD signals. After each preprocessing cycle, temporal characteristics including SNR and power spectrum density in the idle frequency band (0.01-0.1 Hz) improved. The default mode network (DMN) was found in the two ICA preparation pre-processing pipeline. These pipelines and organizations characterized the posterior cingulate cortex better than others [8]. Poornachandra and Naveena [9] improved pre-processing techniques help classify glioma tumors. Brain cancer cutting-edge medical imaging now uses deep learning methods. Researchers who know more about brain tumors can better diagnose and treat patients thanks to the segmentation discoveries.

MRI of the brain to determine the tumor's anatomical features has been debated. The image's uniformity makes segmentation difficult due to low contrast. In some cases, intensity-derived models are used. Preprocessing ensures the 2D sigmoid function is normal at the tumor margin. An extra 2D-sigmoid function was used during image preprocessing to increase brain MRI scan contrast [10].

2.2. Feature extraction techniques

Key traits are crucial to segmenting tumors. Jui *et al*. [11] improved feature extraction to segment brain tumors more precisely. Author quantitative and qualitative research shows that the recommended component works. Jun Zhang's landmark-based feature for Alzheimer's disease (AD) identification uses longitudinal structural MR images without nonlinear registration or tissue segmentation. Zhang's work includes this. We employ a method to quickly identify landmarks without nonlinear registration or tissue segmentation. These points of reference are used to characterize the brain's spatial absorption. The AD neuro imaging initiative's data showed that the suggested approach classified AD and mild cognitive impairment (MCI) with 883.0% accuracy. Fully automated breast computer-aided detection (CAD) system will help diagnose breast cancer. 42 histologically proven lesion patients were selected for cross-validation. The testing showed that the BLADeS system can diagnose breast lesions without human intervention [12]-[14].

Tsai *et al*. [15] explained how to parallelize feature extraction using the gray-level co-occurrence matrix (GLCM). Instead of using a single machine for code development and editing, the proposed method uses GPUs to execute the code. Comparing the suggested approach to its sequential equivalent shows a speedup of 25 to 105 times. MRI measured the brain. Return on investment (ROI) is related to effectiveness. Segmentation methods [15] recommended using CNN to segment the tiny 3×3 kernels. Reduced weights prevent overfitting and allow designers to develop more intricate structures. Data augmentation and this pre-processing phase have successfully segmented brain tumors in MRI images, despite not being typical of CNN-based segmentation algorithms.

Kim *et al*. [16] developed a semi-automatic segmentation method using ultrahigh field MRI (7 T) images with greater resolution. This method uses edge data from structural MRI techniques. Integrating susceptibility-weighted, T2-weighted, and diffusion MRI data creates a novel edge indicator function. Due to data from all three modalities, this function is customized for each modality. Geometric active surfaces develop better when they grasp subcortical structure shape and organization. To avoid overlapping segments, excessive segmentation at neighboring structures was penalised during repeated segmentation.

Makropoulos *et al*. [17] advocate dividing the brain into fifty sections from early preterm to term-equivalent. We use a new segmentation technique to replicate intensity across the brain, taking into account structural hierarchy and physical limits. This solution improves label overlaps for human-created reference segmentations compared to atlas-based approaches. The experiments showed that the technique is reliable from 24 weeks to full term.

2.3. Classification

Fully convolutional networks (FCNs) segment most brain tumors. To produce FCNs, we segmented voxels with a direct spatial link between feature map (FM) units at a given place and the similar categorized voxels. It ensured FCN correctness. Channel mixing may be important since the convolutional layer mixes FMs to create new FMs. FMs evaluate categories differently. Squeeze-and-excitation (SE) blocks re-calibrate FMs and delete less valuable ones to address classification difficulties. Improve categorization accuracy. However, FCN's best spatially relating voxels to units solution is not this.

CNNs, a scribble-based segmentation pipeline, and bounding boxes were used to construct a deep learning-based interactive segmentation system by Wang *et al*. [18]. A CNN model for supervised or unsupervised image processing was created using picture-specific fine tuning. We created an interaction-based uncertainty function and network-aware weighted loss function for fine adjustment. This framework segmented organs using fetal MR slices. 2 organ categories were specified throughout training. Meyer *et al*. [19] introduced deep learning to machine learning. The "deep learning process" conventional designs used CNN. Next, radiation-related deep learning experiments were examined and divided into seven patient workflow-related divisions, along with potential application insights. This study was inspired by breakthrough radiation-deep learning cooperation to expand patient treatment radiotherapy applications.

Akkus *et al*. [20] measured brain MRI. They analysis helps diagnose numerous neurological illnesses by segmenting the system. This allows them to self-learn and make early inferences from vast datasets. This paper's preliminary review presents a modern deep learning segmentation algorithm. Deep learning architecture segmentation gets brain anatomy and lesions inputs. Deep learning speeds and properties are explored in the end. Deep learning has promising applications. Lakshmi *et al*. [21] say categorization is key to identifying damaged land. Use SVMs and PKCs to classify anomalous picture segmentation from input images. Its sensitivity, specificity, and accuracy were compared to existing systems. Thus, a method has been developed to stabilize the PKC. Better results prove the anticipated PKC works.

Xing *et al*. [22] created a nucleus segmentation framework. A deep CNN and selection-based sparse form generated this system. To accurately segment the brain nucleus, the method alternates between top-down shape inference and bottom-up shape deformation after initiating the curves with a deep learning-based iterative strategy. This depicts nucleus structure perfectly. The research enhances multiracial brain tumor segmentation. This method was compared to gabor-like multiscale tumor feature segmentation text. Expanding AdaBoost produced a patient-independent tumor segmentation method. Improved AdaBoost gives greater weight to classifiers who confidently classify challenging instances. Isin *et al*. [23] investigated numerous MRI-based brain tumor division strategies. Deep learning automates segmentation. They solved more numerical problems and produced cutting-edge findings. Our enormous MRI scan data was analyzed and estimated using deep learning. Many validated MRI brain image technologies were tested in this study. This study enhanced deep learning brain tumor segmentation. The seminar began with a brain tumor segmentation introduction. Later, deep learning was cutting-edge. Finally, novel strategies integrated MRI-based brain tumor segmentation into clinical practice.

3. METHOD

This section presents a Gaussian filter and convolutional neural network (GFCNN) based framework for brain tumor detection. Brain MRI images are first preprocessed using GF to remove noises. Then images are classified by CNN and LSTM deep learning techniques. Proposed framework is shown in Figure 2.

To get the desired result, the picture must first be filtered and then enhanced. The results of segmentation performed on photographs obtained with a mobile phone may be affected by a broad variety of factors due to the nature of the photographs themselves. Resizing a picture, lowering the amount of noise in it, and improving it are all examples of processes that are included in pre-processing. It's possible for a digital picture to include a broad array of sounds. Because of this, there is a possibility of picture noise, which renders conventional thresholding ineffective. It is necessary to reduce the amount of noise in the photos. Image noise is the accidental change in a photograph's brightness or coloring that occurs across the image. A picture may include several kinds of noise, including gaussian noise, noise with salt and pepper patterns, noise with shot patterns, and quantization noise. There is a possibility that filters such as the median and the Wiener can eliminate these blips in the data. A number of different morphological techniques may be used in order to reduce the overall loudness of an audio source. The median and gaussian filters each have their own unique effect on how bright individual pixels are made to seem. In order to achieve the aim of reducing the amount of background noise, GF was used. In the process of gaussian filtering, the significance of the intensity of any particular pixel is replaced by a weighted average of the intensities of the pixels that are next to it [24].

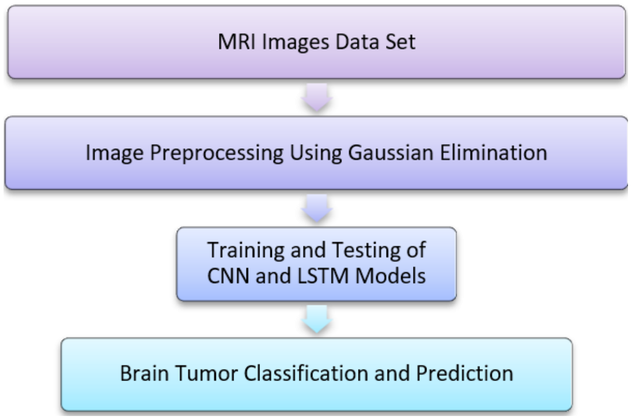

Figure 2. GFCNN framework for brain tumor detection

Because it is an recurrent neural network (RNN) network with gates such as I/P, forget, and O/P in addition to an additional memory cell, the LSTM [25] algorithm is a well-liked option. The need for gradient descent may be avoided by using LSTM networks because of their capacity to remember information for a protracted period of time. This enables the networks to better recognise patterns and sequences. The data is kept current by using input and output gates in between the time steps. When using (1), the information that will be stored in the memory cell is determined by the input gate I. The forget gate (f) erases all prior memories by reorganising the cell's present state in accordance with (2).

$$i_t = \sigma(w_i.[y_{t-1}, x_t] + b) \quad (1)$$

$$f_t = \sigma(w_f.[y_{t-1}, x_t] + b) \quad (2)$$

This renders all previous information superfluous. The output gate (y), which is the last phase, is responsible for controlling the data that is sent on to the succeeding stage. As a result of the fact that all three gates are connected to the memory cell, it is possible to monitor the timing of the output. LSTM is shown in Figure 3.

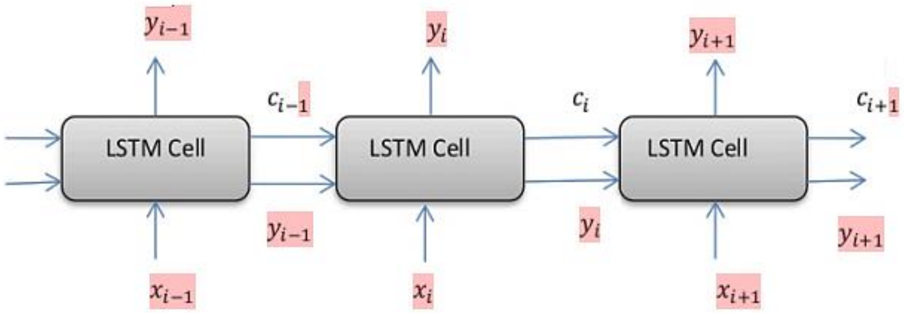

Figure 3. LSTM network

The LSTM network is outlined in Figure 4. At each time step, an input i.e., the embedding x_i is fed into the network and the output y_i is determined based on the current embedding x_i, previous output y_{i-1} and the past cell state c_{i-1}. Cell state is capable of adding or removing the information. There are several hidden layers in a CNN, and two of those levels are the convolution and pooling layers [26]. Image processing is one of its strong suits, and it has the ability to discover dependencies. The features are extracted from the information that is fed into the system using the convolution layer. Convolutional operations are carried out on the embedding matrix using this process. The embedding matrix is where the word embedding vectors that were generated by the word embedding approaches may be found stored. Following the convolution layer in a CNN is a layer called the pooling layer, which is responsible for performing operations such as dimensionality reduction and feature selection through pooling. It is conceivable to carry out a process that involves maximum pooling, a procedure that involves minimum pooling, or an operation that involves average pooling.

After the features have been acquired, they are utilised as input into a neural network that has already had all of its connections fully constructed. The activation functions are responsible for producing the output. The CNN is seen here in Figure 4. This study made use of two convolution layers together with average pooling to achieve its results.

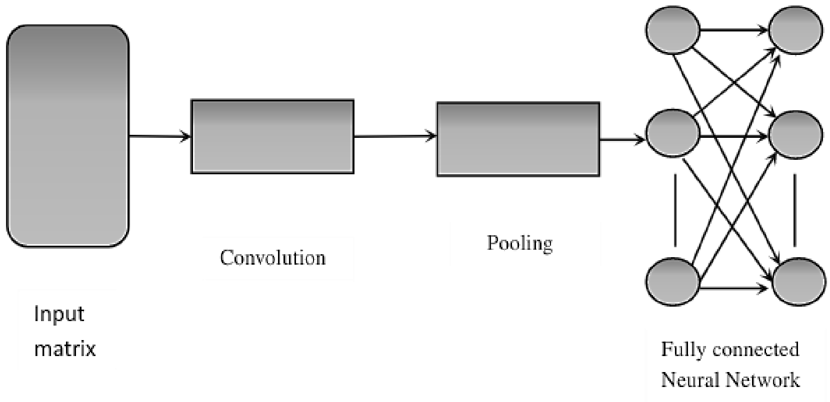

Figure 4. Convolution neural network

4. RESULT ANALYSIS

For experimental work, total 400 images are selected at random [27]. 320 images are used for training of model, 40 images are used for validation and remaining 40 images are used for the testing of the model. Images are preprocessed to remove noise using GF. Classification is performed using CNN and LSTM deep learning techniques. Results are shown in Table 1 and Figure 5.
Sensitivity:

$$\text{Sensitivity} = \frac{\text{TP}}{(\text{TP}+\text{FN})} \tag{3}$$

Where: TP is true positive and FN is false negative.
Specificity:

$$\text{Specificity} = \frac{\text{TN}}{(\text{TN}+\text{FP})} \tag{4}$$

Where: TN is true negative and FP is false positive.
Accuracy:

$$\text{Accuracy} = \frac{\text{TN}+\text{TP}}{(\text{TN}+\text{TP}+\text{FN}+\text{FP})} \tag{5}$$

Table 1. Accuracy comparison

Algorithm	Classification accuracy (%)	Sensitivity (%)	Specificity (%)
CNN	99.25	98.75	99.25
LSTM	94.50	94.50	98.25

The accuracy of CNN is 99.25%. It is 4.75% more than the accuracy of LSTM technique. Sensitivity of CNN technique is 98.75% whereas the sensitivity of LSTM algorithm is 94.50%. Specificity of CNN is 99.25% and it is 1% higher than the specificity of LSTM algorithm. In this way, CNN is outperforming LSTM technique in terms of accuracy, sensitivity, and specificity.

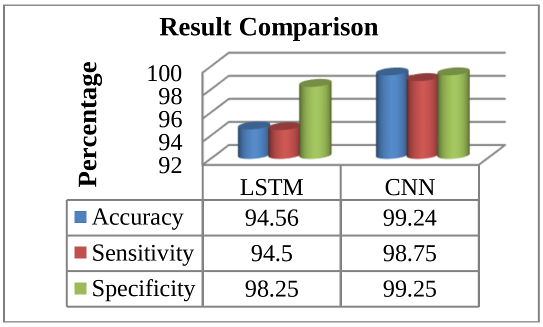

Figure 5. Result comparison of classifiers

5. CONCLUSION

The distinct attributes of tumors and the increasing levels of background noise in magnetic resonance images have rendered the duties of medical professionals in this domain more arduous and time-intensive. The interaction between these two elements exacerbates the complexity of the already challenging situation, rendering it more difficult to resolve. Rapid identification and localization of growth are of paramount significance. The integration of segmentation and relegation techniques in medical imaging has the potential to enable the detection of cancerous masses at an earlier stage than was previously feasible. The possibility of detecting potentially cancerous growths at an earlier stage in their progression is facilitated by cancer screenings. The method presented in this study utilizes CNN as a foundation for diagnosing brain tumors. The GF is utilized for optimal preprocessing of brain MRI images to eliminate unwanted noise. Subsequently, LSTM and CNN are employed to assign labels to the images. The precision of CNN's capacity to identify and classify distinct varieties of brain tumors is increasing.

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