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Leveraging image fusion and transfer learning for enhanced tumor diagnosis

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ABSTRACT

In India, the number of brain tumor cases are increasing rapidly. Compared to the current treatment approaches there is a need for efficient and advanced diagnostic approaches. Doctor primarily use magnetic resonance imaging (MRI) and computed tomography (CT) scans for diagnosis, each with its own set of advantages and limitations. Accurate diagnosis of brain tumors requires detailed information about the tumor's type, size, location, and proliferation rate. But all this information must be estimated accurately and precisely. Even though MRI and CT provide anatomical information regarding tumors, they may not always correctly classify the tumor hence, often requiring the additional biopsy for more detailed analysis. This paper aims to demonstrate the fusion of MRI and CT scans by generating a fused image using transfer learning with convolution neural networks (CNN) that possesses all the important information from both modalities yields better results than using MRI and CT scans alone. This fused scan has the potential to highlight subtle details that may be overlooked on individual scans. This proposed system retains all the best possible functionalities for medical approaches to brain tumor detection. It paves the way to offer a much more impactful healthcare approach to patients by delivering accurate and reliable statistics, enhancing the diagnostic accuracy (96.43%) precedent to any single modality.

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1. INTRODUCTION

Brain tumors are caused by the proliferation of cells abnormally within the brain which disturbs the brain's working functionalities and causes severe medical illness by pressurizing inside the skull [1]. This phenomenon if happening should be detected at early stages to control further complications and neurological symptoms. For this purpose, there are two medical modalities namely magnetic resonance imaging (MRI) and computed tomography (CT) scans. The mentioned scans are very reliable and well-established powerful diagnostic tools. As the reliability is relative, this paper proposes a more promising solution which is a fusion of MRI and CT images. The mentioned scans are very reliable and well- established powerful diagnostic tools.

The primary advantages of a CT-scanner are to acquire physical information, such as size, condition and homogeneities [2], [3]. Despite continuous advancements in healthcare technology, machine learning has demonstrated cutting-edge potential in reshaping patient care procedures and favorable outcomes. Machine learning offers promising approaches, as a result, healthcare professionals may use this knowledge to aid and enhance their work. The proposed system is implemented using machine learning models and hence trusted with the most accurate results. MRI surpasses CT in visualizing soft tissues and hence boosting accuracy [4]. The brain scan must be examined very carefully since it is composed of extremely soft and smooth tissues [5]. Sometimes it is difficult to dragonize the tumor with MRI when the size of the tumor is very small. That is during the initial stages' detection of the location of the tumor becomes a risky task because differentiating from surrounding tissues is difficult. Whereas CT scans highlight clear cut bone details which pulls their ability to distinguish soft tissues down.

Although MRI and CT have their special importance, masking some subtle abnormalities in cases encountered may lead to limitations in detecting tumors which in turn makes it necessary to develop a much more promising solution. For the foregoing explanation, evaluating them using a single imaging method may be inadequate. Diagnosing brain tumors can be complex for radiologists even after reviewing images. This is because different imaging techniques, like CT scans and MRIs shown in Figures 1 and 2, provide complementary information. Each modality excels at revealing specific details about the tumor and surrounding cells [6]. To overcome the above research gaps, this study investigates the MRI and CT fusion merging for the strengths of both modalities and generating a more comprehensive image of brain scan surpassing both the individual scans.

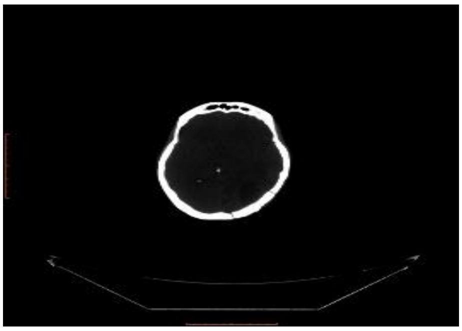

Figure 1. CT scan of brain tumor

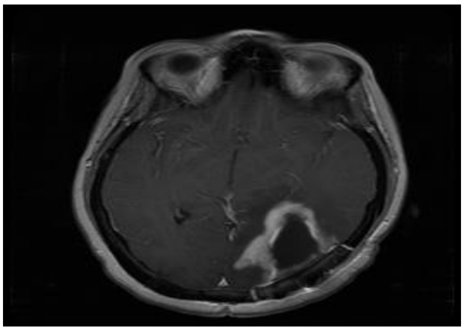

Figure 2. MRI scan brain tumor

As an alternative, fusion techniques such as discrete wavelet transforms (DWTs) and empirical mode decomposition (EMDs) are often used as they ensure the loss during the fusion process is minimal to extract salient features accurately [7]. Brain tumors are primarily classified as benign and malignant indicating healthy and unhealthy respectively [5]. Comparatively to traditional methods, convolutional neural networks (CNNs) have demonstrated superior segmentation, classification, and feature extraction capabilities. The proposed work adopted a CNN based architecture to categorize brain tumors as CNN can extract structured and important features from medical images. This classifier categorizes brain tumors into four types namely glioma, meningioma, pituitary, and no tumor. From the preceding information, fused images probably deliver more effective results when compared to MRI alone.

An improvised method for predicting the brain tumor over a robust user interface (UI) is the key objective of this research work. The UI is designed in such a way that anybody can effortlessly operate it. The complete work of the article is organized into several sections. The various studies related to the brain tumor are covered in section 2. The proposed material and method are explained in section 3. Section 4 presents the results in great depth, while section 5 delves into more detail. Finally, section 6 concludes by drawing conclusions.

2. LITERATUR REVIEW

Several studies have concentrated on developing and enhancing the performance of brain tumor detection and classification. Chandrashekar and Sreedevi [6] proposed a study using non subsampled contourlet transform (NSCT) and NSCT-SR techniques, sparse representation, and neural networks for enhanced image fusion. Rani and Lalithakumari [8] presented a hybrid fusion model that integrated MRI and CT images for detecting brain tumors includes EMD, DWT, neural networks, for effective medical image fusion free from distortion. Solanki *et al.* [3] investigated the effectiveness of different segmentation algorithms for tumor identification. Amin *et al.* [9] have developed a new approach in classifying brain tumors in MRI scans. This hybrid model, called CNN- k-nearest neighbors (KNN), combines the strengths of CNNs and the KNN algorithm. A novel method of detecting brain tumors automatically using MRI is presented by Sapra *et al.* [10]. Watershed segmentation brain tumor detection, in the domain of biomedical image processing dedicated to brain tumor detection, the research has been conducted by Dhage *et al.* [11]. The study by Nanmaran *et al.* [7], titled "Brain tumor classification and detection using hybrid deep tumor network," addresses the crucial issue of accurately classifying and identifying brain tumors. A distinguishing approach of brain tumor detection also classification using MRI Javeria Amin [12] proposed an automated method using MRI that effectively distinguishes between cancerous and non-cancerous brain scans. Nandeesh [13] introduced a promising solution: a multimodal image fusion (MMIF) algorithm that combines the strengths of different imaging modalities to create a richer tapestry of information, ultimately enhancing brain tumor detection accuracy. Zaidi *et al.* [14] explore the clinical value of combining PET, CT, and MRI scans using fusion imaging. They highlight how this approach plays a critical role in diagnosing, staging, and monitoring treatment responses for patients with malignant diseases. Abdallatif *et al.* [15] utilize wavelet transform for its ability to decompose images into different frequency bands, allowing them to selectively merge information from each modality while preserving essential features. Kumar [16] literature survey explores a comprehensive analysis of segmentation techniques for brain tumor MRI analysis, overlapping both the traditional methodologies like Otsu's thresholding, watershed transformation, and K-means clustering, as well as advanced methods such as HAAR DWT and CNNs. Logeswari and Karnan [17] presented an enhanced approach of brain tumor detection using segmentation using soft computing.

The study [18] introduces a working methodology combining CNNs with the "Adaptive dynamic sine-cosine fitness grey wolf optimization (ADSCFGWO)" algorithm for accurately detecting brain tumor and classification. In 'CT scan based brain tumor recognition and extraction using prewitt and morphological dilation' proposed by Soni and Rai [19], developed a system mainly consists of 6 steps namely, data wrangling using adaptive histogram equalization, thresholding, prewitt edge discovery filter, morphological dilation process, flood filling, ROI extraction. Another study on Brain Tumor proposed by Kamil in [20], introduces a machine-learning approach for calculating tumor size with high accuracy, outperforming existing methods used in CT scans. Rahman *et al.* [21] proposed a novel IoT-based system in brain tumor detection using physical activities on MRI scans. This method is cost-effective and avoids the challenges associated with image segmentation in MRI-based techniques. Abbood *et al.* [22] proposed an automated brain tumor classification system using shallow deep learning models. Four models, AlexNet, VGG16, GoogleNet, and ResNet50, are evaluated. El Hamdaoui *et al.* proposes a new intelligent system for brain tumor detection and classification using RMI images in [23]. It tackles the challenge of limited training data by employing deep transfer learning from pre-trained CNNs on a large image dataset. An improved method than artificial neural network (ANN) and support vector machines (SVM) techniques is anticipated in [24] which includes four distinctive models, k-means clustering segmentation, high concentration slurry disposal (HCSD) method, extraction of features, and KNN classifier. A hybrid feature extraction method was used based on DWT and principal component analysis to identify the brain tumor [25].

Brain tumors pose a significant challenge in healthcare. Accurate and timely detection is critical for effective treatment, yet both MRI as well as CT scans, the current diagnostic have limitations. The existing research on brain tumor detection with image fusion and neural networks, there are still some gaps and opportunities for further exploration of structural similarity index (SSIM), peak signal-to-noise ratio (PSNR), and mean square error (MSE) values along with accuracy. Many studies mention concerns about high CPU time consumption, especially in real-world clinical settings where quick diagnosis is crucial. There's a need for research focused on optimizing algorithms to reduce execution time and resource requirements without compromising accuracy. In spite of the promising results of existing research, there is still a lack of clinical validation of these models. MRI-CT fusion offers a promising leap forward in brain tumor detection. The fusion of MRI and CT enhances healthcare professionals' capacity to make better decisions and solve problems by leveraging both of their strengths and overcoming their drawbacks.

3. METHOD

The prevalence of brain tumors is on the rise. It is necessary to develop a comprehensive risk assessment system in order to deal with this issue. To achieve optimal prediction accuracy, stringent machine learning methodologies must be implemented. This section discusses the several steps involved in the methodology of the proposed system. The proposed methodology contains of the following stages. i) collection of brain tumor MRI and CT scan, ii) generating the fused images, and iii) classification.

3.1. Collection of brain tumor MRI and CT scan

For any machine learning algorithm, the dataset plays a key role. The datasets are downloaded from Kaggle each for MRI and fused images generated from MRI and CT images exclusively. The datasets are internally further divided into types of tumors namely glioma, meningioma, pituitary, and no tumor. Each dataset consists of 2,961 training images which include 826 glioma, 247 meningioma, 827 pituitary, and 327 no tumor images. Apart from training the dataset consists of 393 testing images which include 100 glioma, 115 meningioma, 104 no tumor, and 74 pituitary images. The dataset is split into training and testing respectively. The validation data is split into a ratio of 90:10. A ten-fold cross validation is applied to avoid the overfitting, where one set every time is used to validate, except that all other sets are used for training. This process is performed iteratively for all the 10 folds giving 10 different results for each iteration. The average of all these results is considered as the result (based on which the training and testing accuracies are compared).

3.2. Generating the fused images

The second part of the methodology is a multimodal fusion of MRI and CT scans to generate the fused image to prepare the dataset. Multimodal fusion of MRI and CT images is a technique to fuse two brain scans of the same patient as shown in Figure 3. The fusion methodology is carried out in two main phases. The initial step is registration, to bring MRI and CT images into a common coordinate system, Landmark-based image registration is performed by selecting a minimum of 5 and a maximum of 10 coordinate points (CT points and MRI points) to map the images generating registered images for both MRI and CT scans by preprocessing the images using techniques like reflection, scaling, translation to generate an optimum transformation matrix for the given CT image keeping it fixed and modifying MRI according to CT. Now, the resulting registered images can be directly fused to generate a fused image that contains all the information from both MRI and CT scans.

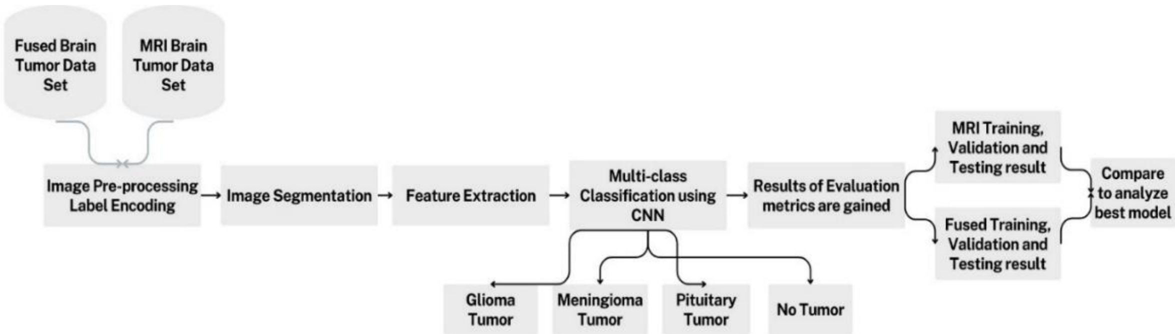

Figure 3. Methodology of MRI and CT scans fusion using VGG-19

The second step is the main fusion performed using transfer learning and DWT. Transfer learning is a technique to use the intelligence from a pre-trained framework to gain faster progress in further tasks. visual geometry group (VGG-19) CNN architecture is used in the proposed fusion process. DWT utilizes the PyWavelets library ('pywt'), and the function applies the DWT to both the MRI and CT images using the 'haar' wavelet. This decomposes the images into approximation (LL) and details (LH, HL, HH) coefficients across different scales. Each set of coefficients (LL, LH, HL, HH) from both MRI and CT images are saved as separate grayscale images. For each coefficient set, a fusion process is conducted.

This fusion process begins by converting input images to the YCbCr color space, a common color space used in image processing. If the input images are not grayscale, they are converted to YCbCr and normalized. Otherwise, grayscale images are directly normalized. Normalization involves converting the pixel values to the range [0, 1]. The normalized images are then converted into PyTorch tensors, facilitating further processing within the deep learning framework. Now, each input image is passed through the model, which extracts feature maps from the images and combines them to create "sum maps" representing the importance of different features across images.

The fusion strategy involves calculating weights for each input image based on its feature importance which in other terms is called weighted fusion. The weights are obtained by applying a 'softmax' function to the feature maps and interpolating them to match the dimensions of the input images. The input images are then multiplied by their respective weights and summed to produce the fused image. A max fusion strategy is applied to ensure the preservation of salient features across images. This involves iteratively comparing and updating the fused image to preserve the maximum valued pixels from each input image. Finally ensuring compatibility with standard image formats, the fused image is reconstructed and returned as an array of pixel values on performing inverse wavelet transform (IDWT) rooting to increase in brain tumor classification accuracy, robustness, and effectiveness detection of tumor even during initial stages.

3.3. Brain tumor detection

The third part is implementing a brain tumor classification model on exclusive MRI, exclusive CT, and fused images to compare the accuracy attained by each of the model proving fused images tend to classify brain tumor much better than MRI and CT alone. The detailed procedure is depicted in Figure 4. The multi-class classification of brain tumor is performed using CNN architecture. The input dataset, consisting of images, is pre-processed and then split into training and testing sets. The dataset consists of multiple classes, so label encoding is performed where different classes are encoded as numerical values to facilitate model training using TensorFlow/Keras utilities.

The CNN architecture comprises multiple convolutional, max-pooling, dense, and dropout layers to extract hierarchical features and prevent overfitting. The model starts with a convolutional layer using 32 filters, followed by a rectified linear unit (ReLU) activation function for non-linearity. The network then uses several convolutional layers with increasing filter sizes (64, 128, 256) to progressively extract more complex features from the images. In between these layers, max-pooling with a 2x2 window reduces the size of the data and lowers computational cost. Dropout layers (set at 30% dropout rate) are inserted to avoid the model from overfitting on the training data. Dropout layers by a dropout rate of 0.3 are added to regularize the model and overconme overfitting. Flattened feature maps are fed into densely connected layers to perform classification. Two dense layers with 512 units and ReLU activation functions are added to capture high-level abstractions from the extracted features. The final output layer consists of four units with softmax activation, producing probabilities for each class in the classification task. To train the model effectively, it is set up to minimize errors in its predictions. This is achieved using a specific mathematical function (categorical cross-entropy) and an optimization algorithm (Adam) that helps the model learn from its mistakes and improve its accuracy over time. The model is trained designed for 17 epochs with a validation split of 10% and an early stopping criterion to prevent overfitting. All the parameter settings of the model are listed in Table 1. Model performance is monitored using accuracy as the assessment metric. The trained model's performance is evaluated on the test set to assess its generalization ability and effectiveness in classifying unseen data.

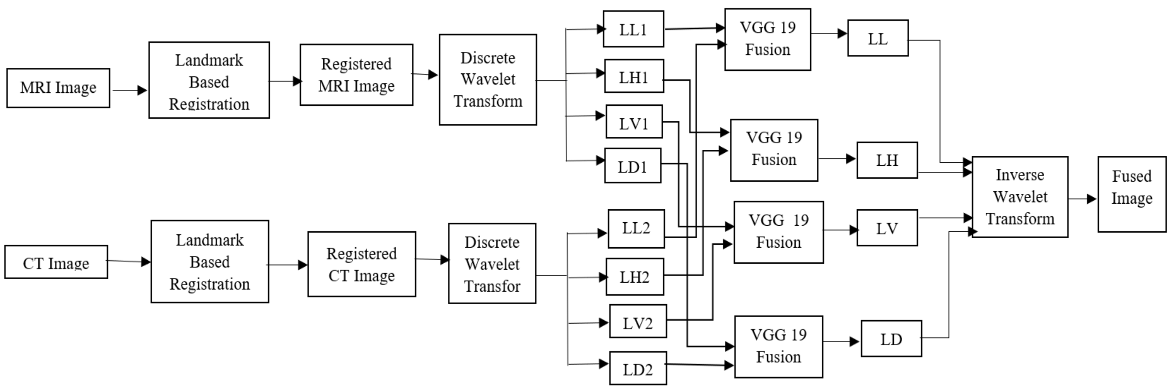

Figure 4. Methodology of brain tumor classification using CNN

Table 1. Parameters used in CNN architecture

Model	Sequential
Convo2D	9
Maxpooling	4
Dropout	6
Dense	3
Flatten	1
Activation Function	ReLU, SoftMax
Loss function	Categorical cross entropy
Optimizer	Adam
Metrics	Accuracy
Image input shape	(150, 150, 3)

This brain tumor classification model is carried out on an exclusive MRI dataset and fused images dataset. The accuracy of all three models is compared to analyze which dataset is more efficient than the other two datasets in classifying the tumor precisely. The user must upload MRI and CT pre-processed scans in the website shown in Figure 5 and enter the number of points for registration. This registration is a landmark-based registration with a minimum of 5 and maximum of 10 registration points can be selected by the user manually during registration.

In the previous step the selection of common coordinate points is performed as shown in Figure 6, and the corresponding result of the selection is displayed in webpage shown in Figure 7. It shows the registered MRI and registered CT scans displayed. The button to perform fusion of the registered images is given below the displayed images.

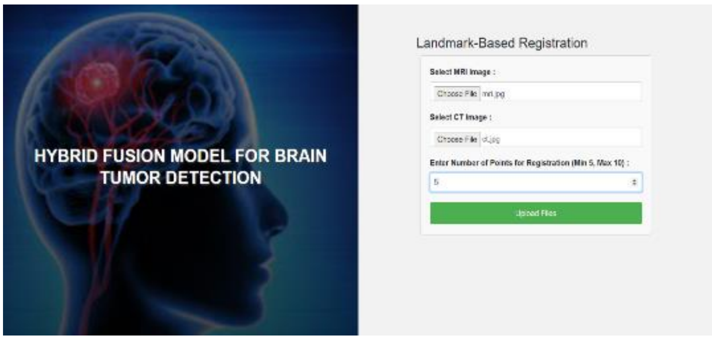

Figure 5. Web landing to give MRI and CT scans of same patient as inputs along with number of registration points

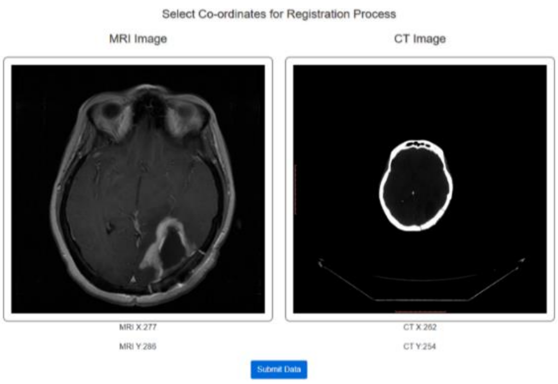

Figure 6. Display of uploaded MRI and CT scans to MRI and CT for common coordinate points on both for registration

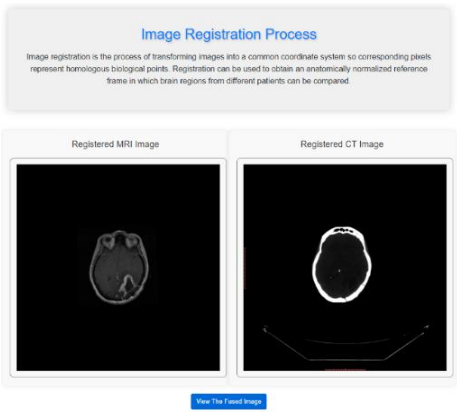

Figure 7. Display of registered select scans ready fusion

If user is sure about the common coordinate space the fusion of the registered scans can be initiated. The fusion result of MRI and CT scans is displayed in Figure 8 webpage. This fused image contains the combined information of MRI and CT scans. Hence overcoming individual disadvantages of both scans to some extent.

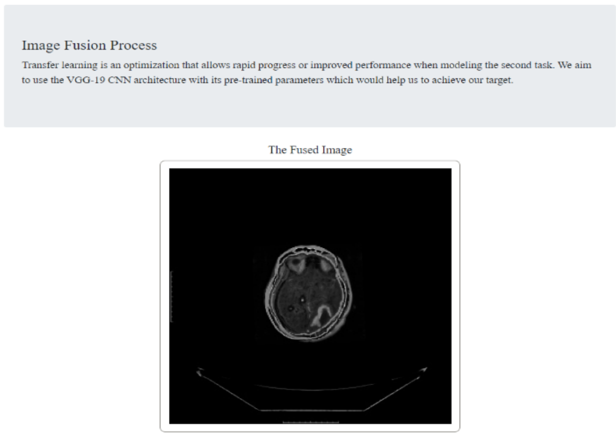

Figure 8. Display of finally fused image of registered MRI and CT scan

4. RESULTS AND DISCUSSION

A fused image's quality is assessed by three criterion measures: MSE, PSNR, and SSIM. By comparing three characteristics of two images, SSIM calculates how similar they are, including luminance, contrast, and structure. A high SSIM value indicates a good preservation of structural information. PSNR values greater than 1 indicate better reconstruction quality between fused and reference pictures. A PSNR value of 21.09 is moderate, suggesting that the fused image has a decent level of overall fidelity. It is also less compared to the value of PSNR in [11]. The MSE calculates differences at the pixel level, but ignores structural or perceptual similarity, so SSIM is more accurate. SSIM measures how well the fusion algorithm preserves structural details, which is a major goal of image fusion. SSIM should be weighed alongside PSNR and MSE even if they offer more context requiring preservation of shapes, edges, and textures, such as medical imaging, remote sensing, and photography. According to Table 2, the value of SSIM 0.91 indicates that the fused image retains the shape, edge, and texture of the reference image. Hence, the model is reliable for the fusion of MRI and CT scans.

The two models implemented using exclusive MRI and fused images respectively are compared based on accuracy. The findings of the proposed methodology shows that fused images can perform effectively in detecting tumors. The training accuracy and validation loss of model must be evaluated to know how the model underfits or overfits in provided data. As estimated, the model tested using fused images resulted in 94.63% training accuracy which is a better score compared to the model trained using MRI with a 92.98% accuracy. Additionally, testing accuracy using fused images (93.98%) is far better than MRI alone with a lower 67.97%. These results sufficiently prove that fused images can more precisely and accurately classify brain tumors than MRI or CT taken individually. The reason for the higher accuracy of the fused images is that the fused images contain all the important information from the CT as well as MRI images resulting in peaking model correctness.

Table 2. Fusion model metrics and results

Metrics	Values
SSIM	0.91
PSNR	21.09
MSE	506.32

This research examines how well brain tumors may be detected by combining CT and MRI data using the DWT. Good structural similarity and acceptable noise levels in the fused picture are shown by the assessment metrics (SSIM, PSNR, and MSE), which validate successful image fusion. The accuracy of training and assessing the fused model was significantly higher than that of models based on individual MRI or CT data. This demonstrates the benefit of image fusion: the fused image offers a more complete view of the brain, enabling the model to classify tumors better. These results suggest incorporating image fusion into the diagnostic workflow could enhance brain tumor detection accuracy.

The careful observations from the Figure 9 is that the model trained on fused images achieved a remarkable training accuracy of 94.63%, showcasing an improvement compared to the 92.98% accuracy obtained with the model trained on MRI scans alone. This advantage translated to testing accuracy as well. The fused model achieved a testing accuracy of 93.98%, whereas the model trained on MRI scans alone yielded a much lower accuracy of 67.97%. This substantial difference highlights the power of image fusion. Fused images offer a more complete view of the brain by combining the precise bone structure data from CT scans with the detailed soft tissue information from MRI scans. Using this extensive information, the model can classify tumors more accurately, which may result in earlier diagnosis and better patient outcomes.

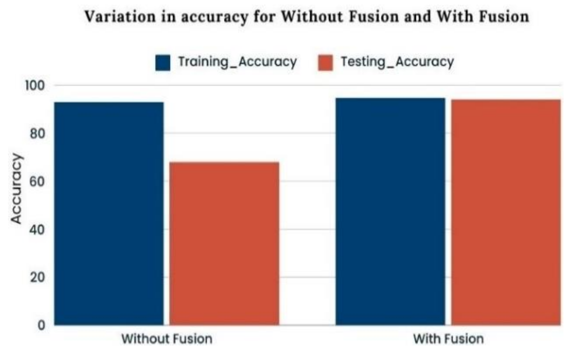

Figure 9. Accuracy variation for both models

The training accuracy and validation accuracy of model must be evaluated to know how the model fits in provided data. Figures 10 and 11 shows the training and validation of loss and accuracy variation through all 17 epochs. The training accuracy constantly peaked and validation overall results are efficient. The training accuracy constantly decreased and validation overall results are efficient as they decreased in the end.

The training accuracy and validation accuracy of model must be evaluated to know how the model fits in provided data. Figure 12 shows the training and validation accuracy variation through all 17 epochs. The training accuracy constantly peaked and validation overall results are efficient. Even though validation accuracy has many ups and downs the overall results for fused model are efficient than MRI model. The training accuracy and validation loss of model must be evaluated to know how the model underfits or overfits in provided data. Figure 13 shows the training and validation loss variation through all 17 epochs. The training accuracy constantly decreased, and validation overall results are efficient as they decreased in the end. By using fused images, the proposed methodology significantly reduced the value of PSNR from [11] and achieves an improved accuracy (96.43%) when compared to the state-of-the-art methods [12].

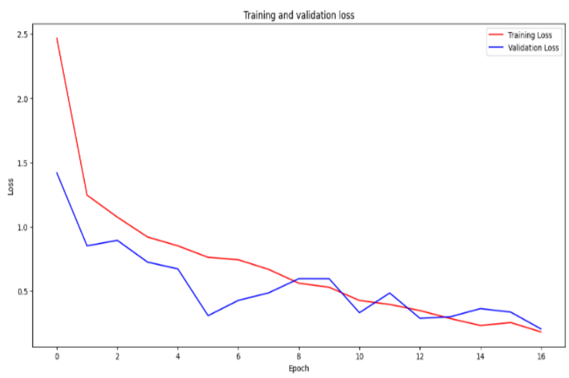

Figure 10. Training and validation loss for MRI model

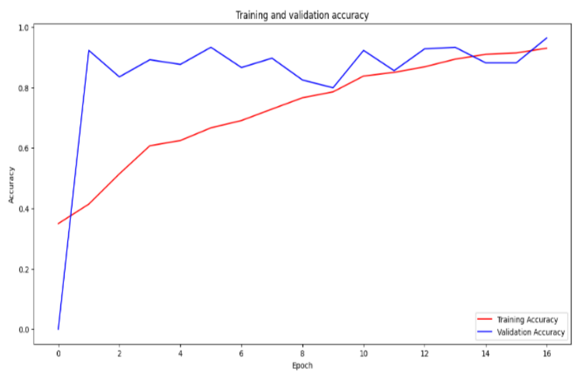

Figure 11. Training and validation accuracy for MRI model

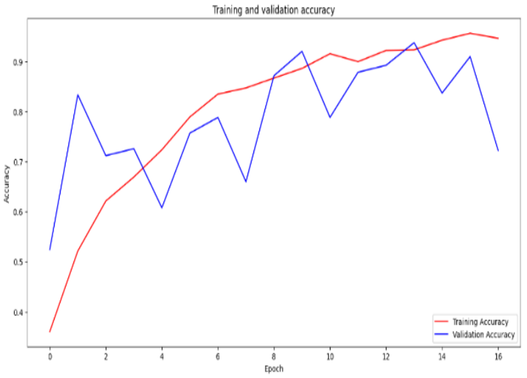

Figure 12. Training and validation accuracy of fused model

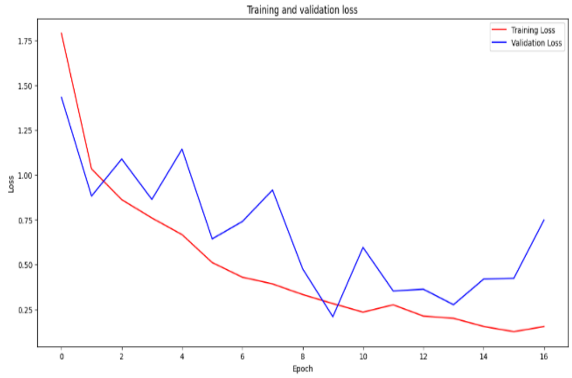

Figure 13. Training and validation loss for Fused model

5. CONCLUSION

Comparing the existing method with a new cutting-edge method, deep learning methods were found to be more effective for brain tumor segmentation based upon MRI images. The current study proposes the hybrid fusion based brain tumor classification unprecedented application using deep learning and data analysis in detecting brain tumors. The VGG-19 is used for fusing the MRI and CT images. Later these images are input to the CNN model. By using fused images, the proposed methodology significantly reduced the value of PSNR and achieves an improved accuracy (96.43%) when compared to the state-of-the-art methods. In contrast to the pre-trained models the proposed approach achieves best level accuracy. However, this study only examined one model and did not compare it with other models and time complexity. Furthermore, the dataset used in this study is form Kaggle, which may not represent the whole population. For addressing all of these limitations, future studies will investigate supervised machine learning methods, ensemble models, and time complexity. In addition, a web application can be uploaded in a cloud-based environment once it is ready in full-fledged so that it can be accessed from anywhere in the world. This study may assist in providing doctors a robust and enhanced way to treat patients effectively.

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