A Brain Tumor Detection System for MR Images using Modified Convolutional Neural Network

Venkatesan.B[1], Indhu.N[2], U.S. Ragupathy[3]

[1]*Ph.D, Assistant Professor (Sr.G), Department of Electronics and Instrumentation Engineering, Kongu Engineering College, Erode, (Tamilnadu - 638060), India.*

[2]*M.E, Assistant Professor, Department of Electronics and Instrumentation Engineering, Kongu Engineering College, Erode, (Tamilnadu - 638060), India. Email id:*

[3]*Ph.D, Professor, Department of Electronics and Communication Engineering, Nandha Engineering College, Vaikkaalmedu, Erode, Tamilnadu – 638052, India. (Tamilnadu), India.*

Abstract- **Brain and spine are the most important organs in human body as they control all the physical systems. It is well known that the brain is most complex organ in human body than the other organs. It is observed that brain tumour is one of the major causes for the increase in mortality among children and adults in the world. Brain tumour is an abnormal growth of cells within the brain or in central nervous system, which can be cancerous or non-cancerous (benign). It is required to develop Computer Aided Diagnosis (CAD) system for providing optimal solution for brain tumour detection. Brain tumour is generally predicted by neurologists with the help of symptoms, especially by a doctor who is specialised in treating the cancer. A non-invasive method using CAD are rapidly growing, not only to replace invasive method but also to achieve higher accuracy with less cost. It is also observed that the algorithm related to medical images are evolved in numbers. Deep learning techniques in detecting and classifying the medical image help the physicians to get a secondary opinion. An improved deep learning approaches is developed to detect the brain tumor and achieves 95.23% of classification accuracy.**

Keywords: **Brain Image, Convolutional Neural Network and Deep Learning, Magnetic Resonance Imaging, Tumor Detection**

I. INTRODUCTION

The use of diagnostic technologies in medicine is expanding quickly, and as they continue to advance, patient confidence in the sector is expected to grow. Furthermore, the manufacturing companies' services have expanded in terms of quality, speed, and geographic reach. Over the past 20 years, a number of medical imaging modalities based on traditional characteristics, including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), Electroconvulsive Therapy (ECT), and Single Photon Emission Computed Tomography (SPECT), have been developed [1]. Each imaging modality is an essential component of medical analysis and diagnosis, and it contains specific data related to frequency and the state of imaging technology advancement. Specifically, a single imaging modality cannot possibly capture all the information about the human body, organs, and cells [2]. A CT offers a detailed anatomical structure of human organs, whereas an MRI provides a multidimensional depiction of the spectral distribution of space. Additionally, it has been noticed that various-experienced physicians provide varied results for the medical image. For a diagnosis to be accurate and reliable, an algorithm to combine many modality images into a single image must be developed [3]. Medical images are problematic due to the characteristics such as lighting, bandwidth, and deflection. However, image fusion techniques can help address these issues. Image fusion preserves important information while removing unnecessary details from source images [4, 5]. Since fused image provides better performance [6], it indicates a significant increase in medical image fusion research from 2015 to the present [7].

Image registration is an essential application of image fusion [8]. The first stage in any fusion technique is image registration that align the structures of all source images with respect to the reference image. A geometrically modified source images are called reference image, allow for direct fusion. According to Wang Z, et al, image fusion can be categorised into three types: pixel level fusion, feature level fusion, and decision-level fusion [9]. Pixel level fusion approaches are further divided into two: spatial and transformed domains. Spatial domain fusion involves merging information directly using linear pixel combinations [10] [11]. Images are divided into blocks before being fused, rather than combining multiple entire images. Combining the images with different focal point in spatial domain that selects picture blocks from the source image and fuses them to create a new image is presented during 2001 [12]. Block-based fusion techniques divide images into tiny groups based on Region of Interest (RoI) using a Pulse Coupled Neural Network (PCNN) for multi-focus images [13]. The size of the block has a significant impact on the resulting image. Medical image fusion relies heavily on transform domain methods. The transform-based fusion is defined as the process of transforming a picture into a less complex feature domain and fusing the resulting information [14]. In 2017, contourlet transform was created incorporating image regional features to reduce computation complexity and surpass Wavelet Transform-based (WT) fusion [15]. Deep learning is now widely employed in computer vision, acoustic recognition, and medical images [16] [17]. Deep neural networks are widely used in biological systems because to its deeper design and ability to deliver more useful characteristics [18]. Brain tumors was exactly detected using combination of Convolutional Neural Network (CNN) with ANN [19]. A deep neural network uses several units between the input and output layers to analyse data with similar structures[20]. The successful application of multiscale CNN includes face recognition, medical image applications, speech signal processing and image fusion [21].

A. Wavelet based fusion

Applications in signal processing such as compression, image restoration, and image analysis are well suited for the wavelet transform. By dividing the image into subbands [22] [23], the Discrete Wavelet Transform (DWT) may provide both spatial and spectral information simultaneously. Conventional orthogonal wavelet transforms cause phase distortion and produces images with warped edges because they lack linear phase properties. The most significant parts of an image are its edges. To address the shortcomings of orthogonal wavelet, a different approach is used that employs a lifting strategy based biorthogonal wavelet transform [24]. One effective image fusion method that demonstrates enhanced directionality through complex wavelet transform is Dual Tree Complex Wavelet Transform with Modified Central Force Optimisation [25]. In novel image decomposition, a hybrid approach combining Principal Component Analysis (PCA) with the Stationary Wavelet Transform (SWT) is presented [26]. The highest eigenvector values in the fused image are obtained by individually fusing each SWT subband. The outcomes include improved visual perception, distinct edge information, and a less distorted image.

B. Deep Learning Based Fusion

An optimal Deep Neural Network model is proposed during 2020 to classify the fused image [27, 28]. Initially, the medical images are fused in shearlet domain to combine valuable information from multiple sources for medical investigation. The experimental results prove to be effective with the quality metrics of fusion factor and spatial frequency. The shearlet transform has the advantage of detecting directionality to overcome the conventional wavelet transform in fusion application. The low and high frequency coefficients from source images are fused with respect to energy. The main drawback of this exploration function is that it requires extremely long processing times.

A Deep Learning (DL) based system is proposed to classify the brain tumour in MR image. An image resizing and normalization are utilized to preprocess the input image to make it significant for classification. Convolution layer in the proposed CNN extract features from the preprocessed input image. ReLU is used to increase the linearity as the input images are nonlinear. The proposed method of classification using CNN achieves better accuracy.
Decision making algorithms are upgraded in recent times, and deep learning techniques in detecting and classifying the brain tumour may help the physicians to get a secondary opinion. In DL, the feature extraction and classification are not spatially depended and higher levels of feature are extracted as the input process through a greater number of convolution layers. It is noted that the deep learning algorithms accurately classify brain tumors in medical images.

On going through various literature, it is clearly observed that the decision-making algorithms are performing better in medical image classifications. Especially, DL models are found to be effective in object detection and classification applications. It is also observed that the modifications at different layers may help to improve the system performance. Hence, it is proposed to develop tumor detection system in MRI using modified CNN.

The paper is divided into four sections, the first of which contains the introduction. Section 2 outlines the suggested CNN model, whereas Section 3 presents the results. Finally, Section 4 concludes the proposed system.

II. PROPOSED CNN BASED FUSION METHOD

CNN process and recognize image data like that of standard Artificial Neural Network (ANN). ANN are made up of neurons with learnable weights and biases. In ANN, each neuron takes inputs, performs dot product with weight values, and optionally applies a non-linear activation function. CNN uses kernels instead of weights and performs convolution on the input image. Image augmentation is one of the useful techniques for building convolutional neural networks by increasing the size of the training set without requiring new images to preserve the key features for better predictions.

A. Data Base

The images are collected from radiopeadia and atlas database and classified using CNN. Typically, the dataset is divided into testing and training subsets. The deep network model learns from the training set, which includes a known output, in order to predict the other data in the future. The brain images are collected from Atlas, radiopaedia database. Totally, 80 images are collected from the online sources and considered for constructing deep neural network. The parameters of for training the deep network are as follows:

- Training data: This represents the set of images used to train the network. Out of the entire data, 75% of data are considered for training.
- Testing data: CNN generally takes an amount of training dataset to test it by itself. This parameter decides the data size that can be used to split the training data. This is given as a fraction, in the proposed network where testing data size is 0.2, 20% of the data is split into the testing dataset.

B. Data Augmentation

Image augmentation uses various modifications to generate additional data from existing data. This technique reduces overfitting, allows successful learning and generalise with limited data. Image modification techniques include flipping, colour space, contrast adjustment, translation, brightness, noise injection, etc.

The CNN classifiers always perform better with a greater number of images in the training dataset. Likely, the same image with different orientations during training helps to improve the classification accuracy. As the proposed approaches deal with medical images, the dataset is of major concern to meet out the fusion requirement. Image augmentation would help in generating many images from the existing images using geometrical transformation. The database generated would also be more realistic in nature as it does not alter any information, but changes only the image orientation. In image classification, image flipping and image shearing are considered for generating more images from the image database.

Original images are considered for horizontal flip, vertical flip and shearing to a minimal amount of angle to maintain the realistic nature of the source image. The image of a patient of 31 years old man is obtained from Atlas database and the manipulated image using image augmentation is shown in Figure 1.

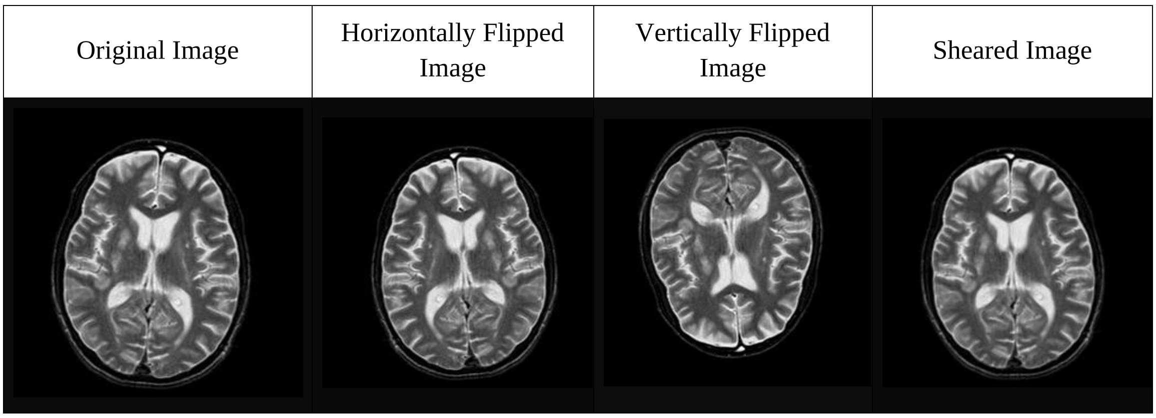

Figure 1. Original Image and Augmented Images using Image Flipping

C. *Construction of CNN Modal*

The proposed system contains a sequence of layers like convolution, ReLU, max pooling, dropout, and dense layers. The CNN layers are shown in Figure 2.

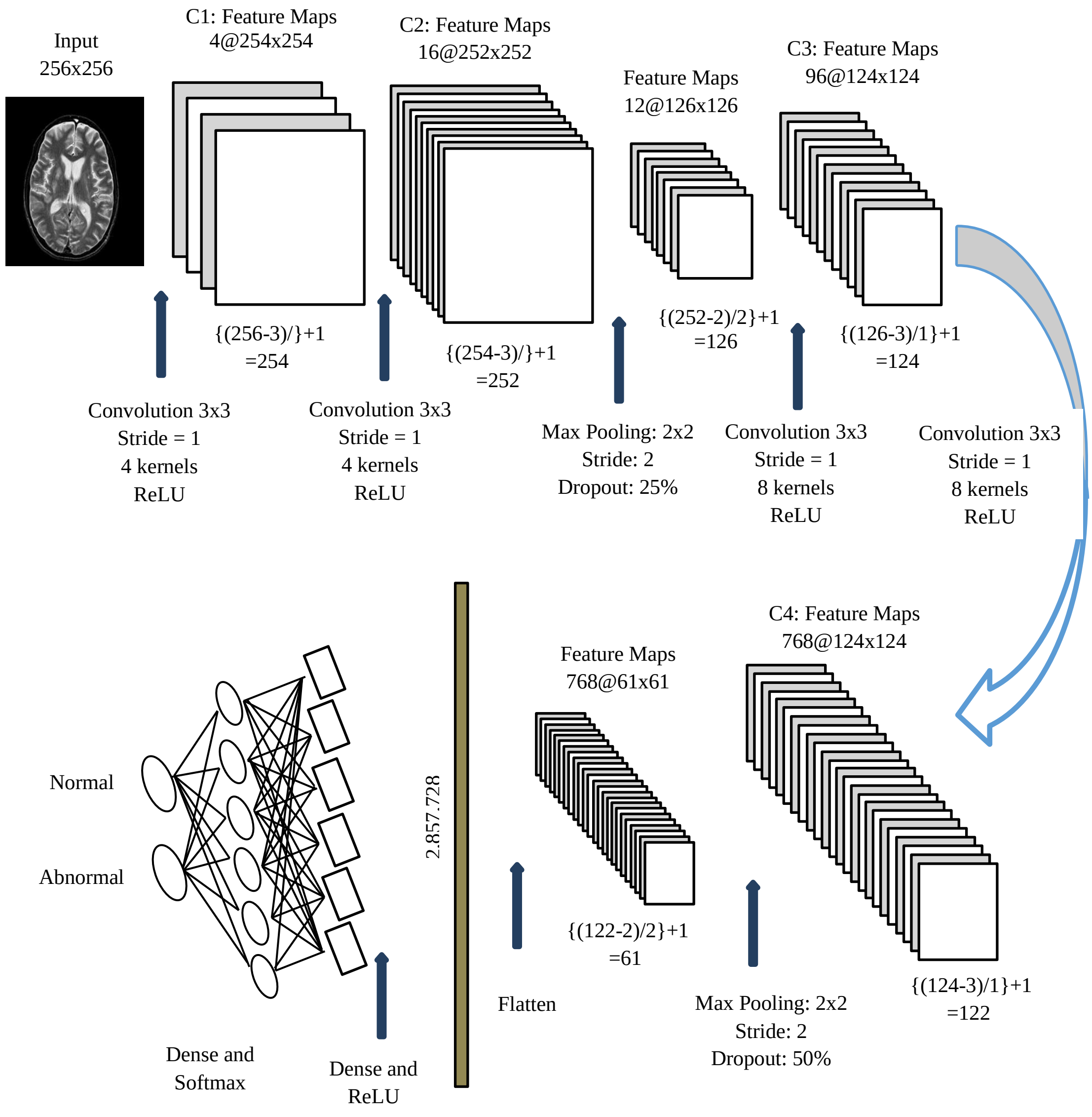

Figure 2. Architecture of CNN used for Classification

D. Convolutional Neural Network for Classification

This work implements modified CNN using convolutional, non-linear, pooling, and sigmoid layers.

Convolutional layer

The first convolutional layer uses four filters to identify edges using the ReLU activation function. The kernel size is 3x3, and the input shape is 256x256. The second convolutional layers are identical to the first, with eight sets of three-by-three filters. CNN-based image classification takes images as an array to extract features based on image resolution. Convolution learns visual features from small squares of an image, preserving pixel relationships. It is a 2D convolution that takes the image as a matrix and a kernel. Convolution of an image with different kernels can predict edges, blurriness and sharpens. Let the input image of the size that represents the dimensions to be taken. In this, HF and WF represent the dimension of the height and the width of the filter respectively. Height and weight of the convolution results are given in equation 1 & 2.

$$L_0 = \frac{L_i - L_F + 2P}{S} + 1 \qquad (1)$$

$$W_0 = \frac{W_i - W_F + 2P}{S} + 1 \qquad (2)$$

Rectified Linear Unit

The convolutional layer's output is biased and then sent via the sigmoid function, like in a standard neural network, as shown in Equation 3.

$$S_f = \frac{1}{1+e^{(-x)}} \qquad (3)$$

It is an element-wise operator that replaces all negative values with zeros in the feature map. Equation 4 provides a mathematical formulation of the ReLU activation function.

$$ReLU(x) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \qquad (4)$$

Pooling Layer

When the size of the image exceeds the computing process, the output of the ReLU layer is fed into the pooling layer, which minimizes the size of the input parameters. It also lowers the computational burden, shortens training time and prevents overfitting. In the suggested network, max pooling is used instead of other pooling procedures such as sum pooling, average pooling, and so on. Equation 5 defines Q as the pooling zone, and A as the activation set.

$$A = \{a_i | i \in Q\} \qquad (5)$$

The max pooling M_P is defined in Equation 6.

$$M_P = max(A_Q) \qquad (6)$$

Max pooling creates the output image of size height L_1 and width W_1, as shown in Equations 7 and 8.

$$L_2 = (L_1 - F)/S + 1 \qquad (7)$$
$$W_2 = (W_1 - F)/S + 1 \qquad (8)$$

Where F = Filter, S = Stride, L_2 = output volume height and W_2 = width.

Dropout layer

The dropout layer prevents overfitting while training. It randomizes the outgoing edges of hidden neurons to zero to minimize the weight matrix. The parameter value is determined randomly, with a probability of 0.25 at the first layer and 0.5 at the second layer.

Fully Connected Layer

The fully connected layer is the last layer in the CNN, carrying input from the convolution and pooling layers to each neuron in the following layer. The final fully connected layer uses the sigmoid activation function to classify input image attributes into the appropriate classes. The proposed classification network designed with the help of two dense functions, and an activation unit. The first fully connected layer consists of 256 dense units with the ReLU activation function, and the second fully connected layer consists of two dense units with the softmax activation function to determine whether the class label is normal or abnormal.

III. EXPERIMENTAL RESULTS

The experimental model using CNN is carried out in MacBook Air, 1.8 GHz Dual-Core Intel Core i5, 8 GB 1600 MHz DDR, with Intel HD Graphics 6000 1536 MB. During the training the input data taken from Atlas and radiopaedia brain tumour database are considered. In total, 80 normal and abnormal brain images are considered. As most of the images are of size 256x256 and few of the images are RGB in nature, all the image dimensions are converted into 256x256 in gray scale. The training size of data is increased up to 400 images with the help of image augmentation technique. The normal images are named as N1, N2, N3 and so on, images with abnormalities are named as AB1, AB2, AB3 and so on.

A. Quality metrics

The major performance metrics, namely sensitivity, specificity, precision, accuracy and Mathew's Correlation Coefficient (MCC) are calculated from the confusion matrix using equation 9 to equation 13.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \qquad (9)$$
$$\text{Specificity} = \frac{TN}{TN+FP} \qquad (10)$$
$$\text{Precision} = \frac{TP}{TP+FP} \qquad (11)$$
$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \qquad (12)$$
$$\text{MCC} = \frac{[(TP*TN)-(FP*FN)]}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}} \qquad (13)$$

B. Analysis of Experimental Results

As mentioned earlier the images are considered as data and all image dimension of 256x256 are initialized to CNN at the beginning. Besides this, the data are partitioned for training cum validation and testing with 59 and 21 images respectively, and during testing the test size and random state are fixed to be 0.2 and 42 respectively. During the training, the 59 images are fed into CNN.

Table 1 Training and Testing Performance of CNN

Image category	No. of training images	No. of testing images	Error
Normal	37	13	0
Benign	22	8	1

Table 2 Confusion Matrix Obtained from Classified Output

Predicted / Actual	Normal	Abnormal
Normal	13	0
Abnormal	1	7

Table 1 gives the number of images considered for training and testing. From the classified output of brain tumour, a confusion matrix is formulated as shown in Table 2. From the confusion matrix, the performance metrics, namely sensitivity, specificity, precision, accuracy, and Mathew's Correlation Coefficient (MCC) are calculated and tabulated in Table 3.

Table 3 Performance Metrics for CNN in Classifying the Brain Tumour

Classification Parameter	Result
True Positive (TP)	13
False Positive (FP)	1
True Negative (TN)	7
False Negative (FN)	0
Sensitivity (%)	100
Specificity (%)	87.5
Precision (%)	92.85
Accuracy (%)	95.23
MCC	0.901

Table 4 Comparative analysis of Proposed Custom CNN Model

S. No.	Method	Sensitivity (%)	Specificity (%)	Precision (%)	Accuracy (%)
1.	ResNet [29]	94.73	95.61	90.47	95.87
2.	Deep feature fusion Model [30]	-	-	90.1 to 98.9	94.9
3.	Deep Learning Networks [31]	-	-	-	93.30%
4.	Custom CNN Model [32]	84.35	93.65	-	90.7
5.	Custom CNN model [33]	95.24	92.00	-	94.28
6.	Pre-trained Alexnet with transfer learning [34]	91.37 to 98.17	97.25 to 98.96	92.44 to 97.65	91.84 to 97.92
7.	Deep fine-tuned CNN Model [35]	94.75	94.77	89.30	94.74
8.	Proposed Custom CNN Method	100	87.5	92.85	95.23

The proposed CNN model is compared with various existing MR brain tumour classification models in Table 4. The performances in terms of sensitivity, precision and accuracy are improved when compared with the existing CNN based models.

IV. CONCLUSION

The presented work of a modified deep learning system for brain tumor detection achieves 100% training accuracy and 75% testing accuracy. The detection system achieves lesser accuracy during testing due to the complexity in multiclass data and the similarity among the data. The system achieves sensitivity of 100%, specificity of 87.5%, precision of 92.85%, and MCC of 0.901. The trained CNN is further considered for testing with a new set of 21 images and it achieves 95.23% of classification accuracy. Due to imbalance in picking the random sample during training, the specificity decreases which need to be improved by considering a greater number of images along with some real time data.

REFERENCES

[1] Kavitha, C. and C. Chellamuthu, *Fusion of SPECT and MRI images using integer wavelet transform in combination with curvelet transform.* The Imaging Science Journal, 2015. 63(1): p. 17-23.

[2] Kaufman, L. and R.S. Hattner. *Comparison of medical imaging modalities: Clinical realization and engineering potential of nuclear imaging*. in *Recent and Future Developments in Medical Imaging II*. 1979. International Society for Optics and Photonics.

[3] Wang, Z. and Y. Ma, *Medical image fusion using m-PCNN.* Information Fusion, 2008. 9(2): p. 176-185.

[4] Tannaz, A., et al., *Fusion of multimodal medical images using nonsubsampled shearlet transform and particle swarm optimization.* Multidimensional Systems and Signal Processing, 2020. 31: p. 269-287.

[5] Tannaz, A., et al., *Fusion of multimodal medical images using nonsubsampled shearlet transform and particle swarm optimization.* Multidimensional Systems and Signal Processing, 2020. 31(1): p. 269-287.

[6] Venkatesan, B., U. Ragupathy, and I. Natarajan, *A review on multimodal medical image fusion towards future research.* Multimedia Tools and Applications, 2023. 82(5): p. 7361-7382.

[7] Hermessi, H., O. Mourali, and E. Zagrouba, *Multimodal medical image fusion review: Theoretical background and recent advances.* Signal Processing, 2021. 183: p. 108036.

[8] Oliveira, F.P. and J.M.R. Tavares, *Medical image registration: a review.* Computer methods in biomechanics and biomedical engineering, 2014. 17(2): p. 73-93.

[9] Wang, Z., et al., *Medical image fusion based on convolutional neural networks and non-subsampled contourlet transform.* Expert Systems with Applications, 2021. 171: p. 114574.

[10] Luo, X., et al., *Multi-focus image fusion using HOSVD and edge intensity.* Journal of Visual Communication and Image Representation, 2017. 45: p. 46-61.

[11] Zhang, Y., X. Bai, and T. Wang, *Boundary finding based multi-focus image fusion through multi-scale morphological focus-measure.* Information fusion, 2017. 35: p. 81-101.

[12] Li, S., J.T. Kwok, and Y. Wang, *Combination of images with diverse focuses using the spatial frequency.* Information fusion, 2001. 2(3): p. 169-176.

[13] Huang, W. and Z. Jing, *Multi-focus image fusion using pulse coupled neural network.* Pattern Recognition Letters, 2007. 28(9): p. 1123-1132.

[14] Venkatesan, B., et al. *Inspection of faults in textile web materials using wavelets and ANFIS*. in *2012 International Conference on Machine Vision and Image Processing (MVIP)*. 2012. IEEE.

[15] Huang, H., X.a. Feng, and J. Jiang, *Medical image fusion algorithm based on nonlinear approximation of contourlet transform and regional features.* Journal of Electrical and Computer Engineering, 2017. 2017.

[16] Kaur, J. and C. Shekhar, *Multimodal medical image fusion using deep learning*, in *Advances in computational techniques for biomedical image analysis*. 2020, Elsevier. p. 35-56.

[17] Wang, H., et al., *A novel convolutional neural network based fault recognition method via image fusion of multi-vibration-signals.* Computers in Industry, 2019. 105: p. 182-190.

[18] Hammad, M., Y. Liu, and K. Wang, *Multimodal biometric authentication systems*

using convolution neural network based on different level fusion of ECG and fingerprint. IEEE Access, 2018. 7: p. 26527-26542.

[19] Woźniak, M., J. Siłka, and M. Wieczorek, *Deep neural network correlation learning mechanism for CT brain tumor detection.* Neural Computing and Applications, 2023. 35(20): p. 14611-14626.

[20] Saurav, S., et al., *An attention-guided convolutional neural network for automated classification of brain tumor from MRI.* Neural Computing and Applications, 2023. 35(3): p. 2541-2560.

[21] Du, C. and S. Gao, *Image segmentation-based multi-focus image fusion through multi-scale convolutional neural network.* IEEE access, 2017. 5: p. 15750-15761.

[22] Amolins, K., Y. Zhang, and P. Dare, *Wavelet based image fusion techniques—An introduction, review and comparison.* ISPRS Journal of photogrammetry and Remote Sensing, 2007. 62(4): p. 249-263.

[23] Mallat, S., *A wavelet tour of signal processing*. 1999: Elsevier.

[24] Sweldens, W., *The lifting scheme: A construction of second generation wavelets.* SIAM journal on mathematical analysis, 1998. 29(2): p. 511-546.

[25] El-Hoseny, H.M., et al., *An efficient DT-CWT medical image fusion system based on modified central force optimization and histogram matching.* Infrared Physics & Technology, 2018. 94: p. 223-231.

[26] Aymaz, S. and C. Köse, *A novel image decomposition-based hybrid technique with super-resolution method for multi-focus image fusion.* Information Fusion, 2019. 45: p. 113-127.

[27] Parvathy, V.S., S. Pothiraj, and J. Sampson, *Optimal Deep Neural Network model based multimodality fused medical image classification.* Physical Communication, 2020. 41: p. 101119.

[28] Balamurugan, T. and E. Gnanamanoharan, *Brain tumor segmentation and classification using hybrid deep CNN with LuNetClassifier.* Neural Computing and Applications, 2023. 35(6): p. 4739-4753.

[29] Tripathi, P.C. and S. Bag, *A computer-aided grading of glioma tumor using deep residual networks fusion.* Computer methods and programs in biomedicine, 2022. 215: p. 106597.

[30] Deepak, S. and P. Ameer, *Brain tumor categorization from imbalanced MRI dataset using weighted loss and deep feature fusion.* Neurocomputing, 2023. 520: p. 94-102.

[31] Mahmud, M.I., M. Mamun, and A. Abdelgawad, *A deep analysis of brain tumor detection from mr images using deep learning networks.* Algorithms, 2023. 16(4): p. 176.

[32] Ge, C., et al., *Deep semi-supervised learning for brain tumor classification.* BMC Medical Imaging, 2020. 20(1): p. 1-11.

[33] He, M., et al., *Hierarchical-order multimodal interaction fusion network for grading gliomas.* Physics in Medicine & Biology, 2021. 66(21): p. 215016.

[34] Kaur, T. and T.K. Gandhi, *Deep convolutional neural networks with transfer learning for automated brain image classification.* Machine vision and applications, 2020. 31(3): p. 20.

[35] Swati, Z.N.K., et al., *Brain tumor classification for MR images using transfer learning and fine-tuning.* Computerized Medical Imaging and Graphics, 2019. 75: p. 34-46.