

Convolution Neural Network Based Brain Tumor Detection using MRI Scans

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Abstract:

A brain tumor is an uncontrollable, uncontrollable expansion of neoplasms in the brain. Brain tumors can be benign or malignant in nature. Magnetic resonance imaging (MRI) is the primary diagnostic tool, where a neurologist examines the brain using traditional diagnostic techniques. In most computer-aided design (CAD) applications, the detector helps radiologists classify MRIs more efficiently, but achieving high classification accuracy is a major concern. This paper presents a new approach to detect MRI using wavelet convolution neural network (wCNN) is proposed. The new invention is based on the incorporation of the wavelet transform into the CNN algorithm, allowing the model to better capture multi-scale features in brain MRI images. Furthermore, the study utilizes the BraTS dataset from 2023 provided by Kagal, which encompasses a diverse range of brain tumor cases, facilitating robust evaluation of the proposed method. Comparative analysis against state-of-the-art diagnostic techniques demonstrates superior performance, with an overall accuracy of 96.69 percent, showcasing the efficacy and potential of the proposed approach in enhancing brain tumor diagnosis."

Keywords: Brain tumor; cancer detection; wavelet transform; convolution neural networks; magnetic resonance imaging.

1. Introduction

Tumor is a group of tissue, which is abnormal in structure and function, proliferating in an uncontrolled unregulated manner and can be benign or malignant. Unlike malignant tumors, benign ones are usually not associated with significant morbidity and disease burden and have less mortality despite being more common. Magnitude of the problem can be assessed by the fact that cancer is the second leading cause of death after heart diseases (Ostrom, 2022).

Apart from distant metastases in case of malignant tumors, brain tumors clinically manifest as space occupying lesion causing mass effects and invasion and destruction of adjacent structures. Various physiological functions are affected leading to clinical signs and symptoms. Loss of vision or hearing, imbalance, difficulty in walking, abnormal movements, bladder and bowel disturbances, impairment of memory and higher mental functions are some of the common manifestations of brain tumors. Along with patient related characteristics, the location, size and the nature of tumor determines the clinical sign and symptoms. Brain tumors (BTs) contributes to only 1% of all latterly diagnosed cancers in the US, and nearly 2% of the deaths caused by cancers overall (Siegel, 2018). Apart from genetic risk factors and demographic factors, environmental factors such as smoking, ionizing radiations and congenital central nervous system malformations are among the

main risk factors that contribute to the development of brain tumors. Several studies have also witnessed connection between the use of cell phones and brain tumors. However, the epidemiological evidences printed earlier in 2011 in the Interphone consortium scraps any kind of relationship between the mobile phone and cause of Brain Tumor. But, even if the relationship exists, the latency period for which the mobile radiations are exposed to the body is still not known (Ostrom, 2020).

Commonly, brain cancers are classified according to the characteristics extracted from an MRI scan of the tumor-bearing regions. Related literature on the brain cancer has provided useful information for detecting brain tumors. Some features include the pixel strength of the tumor area and the structure of the tumor tissue. A categorization technique that uses first-order statistics was used to create data for pixels in tumor regions. The textural features acquired from tumor regions with wavelet transforms are used to generate categorization using neural network (Sarhan, 2018) & (Kumar, 2021). Gabor filters are used to produce textural features that can be utilized to identify brain tumors from other regions. Numerous BT treatment are available for brain cancer patients, including radiation, surgery, chemotherapy, or a combination of these therapies as used in most of the cases. Decision to choose specific treatment option depends upon various factors, which include tumor characteristics, patient related factors, cost and availability of the specific treatment modality. Furthermore, for patients with brain tumors, radiation therapy is the initial step to decrease the tumor size and makes it more amenable for surgical excision. Residual tumors can be treated with either chemotherapy or radiotherapy (Kumar, 2020) & (Kumar, 2018). MRI is the best diagnostic tool to detect a brain tumor as it produces more detailed images in comparison to CT scans. MRI is a simple and all-encompassing procedure and is carried out using magnetic imaging. MRIs for spinal cord, the brain, or both, according to the type of tumor are done before initiation of treatment to get detailed delineation of the tumor (Altman, 1992) & (Zhang, 2017).

Multiple authors have deployed Support Vector Machine (SVM) and Deep-learning based methods for the classification of the MRI images as the Cancerous and Benign (Abiwinanda, 2019) & (Kumari, 2013). But, high accuracy and receptive field size have been the major issues in the CAD using MRIs. So, in the current article we have used revolutionary categorization algorithm based on wavelet decomposition and groundbreaking neural networks, a technique known as wavelet Convolution Neural Network (wCNN), to detect cancer from MRIs and the accuracy of the proposed work is compared with the existing state-of-art technique which is SVM. Our study population consists of patients with Astrocytoma's of various grades.

Motivation

Brain tumors pose important health complications because of their heterogeneity and potential morbidity. Despite advances in diagnostic imaging, accurate classification remains a challenge. Traditional methods rely on manual interpretation, which introduces variability and potential analytical errors. In this context, the motivation behind this paper is towards. First, the paper discusses the need for greater accuracy in the classification of brain tumors. Computer Assisted Diagnostic (CAD) tools, while helpful to radiologists, are rarely highly accurate. The proposed method introduces a new method that uses wavelet convolution neural networks (wCNN). By integrating wavelet transform with CNN architecture, the model captures multistate features in MRI

images efficiently, which promises excellent classification accuracy. Second, the study aims to overcome the limitations of existing datasets. The use of the BraTS dataset of 2023 provided by Kagal that includes a variety of brain tumor cases ensures a rigorous evaluation of the proposed method this dataset provides a comprehensive evaluation and have been validated, which is important for the development of brain tumor screening methods. By conducting a comparative study comparing state-of-the-art techniques, the study highlights the effectiveness and potential of the proposed technique, thereby fulfilling the important need for brain tumors addressing improved identification and patient care.

The contributions of this paper are as follows

1. Identify common brain tumors and classify them hierarchically using the proposed method, aiming for more accurate and comprehensive classification.
2. Propose wavelet-based neural networks for efficient classification of MRI images, integrating HAAR wavelet with CNNs to capture multiscale features.
3. Evaluate and compare proposed method with SVM-based classification using sensitivity, specificity, and accuracy to assess effectiveness in brain tumor detection.

2. Related Work

Numerous authors have worked on the detection of cancer through the MRI scans. Authors in (Siegel, 2017), had implemented Gene selection. It is one of the most successful approaches for cancer categorization. It selects a class of genes that improves classification accuracy. However, this is an NP-Hard task. In previous investigations, a variety of strategies for gene selection in cancer classification was presented. For this objective, a hybrid meta-heuristic algorithm has been incorporated in this paper, which is a fusion of Genetic Algorithm and Learning Automata (GALA). The findings obtained through GALA after its implementation on six cancer gene expression datasets were outstanding when compared to other recently introduced algorithms, according to the conclusions of this article. GALA had a mean classification accuracy of 94.46% on a colon dataset containing 8 genes. On the Tumors 9 and Tumors 11 datasets with 10 genes, the mean classification accuracies were 86.52% and 84.38%, respectively. The authors in (Sarhan, 2009), provide a comprehensive literature assessment of contemporary strategies for segmenting brain tumors from brain MRI data. It covers the performance of cutting-edge methods as well as their quantitative analyses. With the latest contribution of many scholars, numerous methods of picture segmentation have been discussed. Based on this work, this paper provides in-depth exploration of different existing brain tumor segmentation methods. Quantitative analysis using different evaluation factors among state-of-the-art approaches benefits readers and clinicians by not only setting new routes for study but also assisting in correct tumor identification. The efficacy of histological characteristics to predict the recurrence risk of a typical meningioma was studied in (Kumar, 2021). Meningioma that were merely identified as atypical based on minimal atypical criteria had a low chance of recurrence. Disease-free survival (DFS) was basically linked to brain invasion, high mitotic index, and sheeting ($P = 0.001$, $P = 0.01$, $P = 0.01$). The findings show that meningioma should be reclassified as atypical if just minor unusual criteria are met. The presence of brain invasion, sheeting, and a high mitotic count may help to identify high-risk subjects that could benefit from adjuvant therapy. But in

the proposed work in this paper, Pilocytic astrocytoma Grade-1 tumors, Grade 2 astrocytoma, Grade 3 astrocytoma is known as anaplastic astrocytoma and Glioblastoma- grade 4 tumors are being under detection. In (Abiwinanda, 2019), authors proposed SVM for classifying the brain tumor using the MRIs. The features extracted by them were: entropy, mean, contrast, energy and inverse difference moment. Authors used 110 MRIs and carried out the comparative analysis among Non-Linear SVM such as Radial Based Function (RBL), Linear function and Quadratic Function. The size of the data set used by the author was very small and result analysis demonstrated 98% accuracy using the SVM-RBL method. Authors in (Kumari, 2013) proposed the use of SVM for classification and Fourier Transformation for feature extraction. The data set of 100 MRIs was used. The authors have detected and classified only one category of cancer using MRI scans, but in the proposed work, the classification is being carried for four types of the brain tumor. In (Hua, 2021), authors used Improved Multi-View Fuzzy c-Means IMV FCM Clustering for the segmentation of the of the MRI Images. Using IMV FCM, authors have achieved higher segmentation accuracy, dice coefficient, similarity and segmentation coefficient in comparison to other existing clustering methods. The main objective of the paper was to increase the clustering efficiency but the classification of the MRI images was not considered.

Paper S.No.	Author	Technique Used	Observation	Dataset used	Advantage	Disadvantage	Limitation
1	GovindarajanAnusooya, SelvarajBharathiraja,MiroslavMahdal, KamsundherSathyarajasekaran(2023)	Self-Supervised Wavelet-Based Attention Network (SSW-AN)	Automatic tumor segmentation aids in analyzing pathological conditions by evaluating tumor size, location, structure, and grade.	BraTS challenge dataset	Provides more accurate segmentation of brain tumors compared to existing methods.	Susceptible to noise and distortions.	Susceptibility to noise and distortions limit the effectiveness of segmentation approaches.
2	Ali Farzamia, SeyedHamidrezaHazaveh; et al. (2023)	Contourlet Transform Based on Time Adaptive Self-Organizing Map (TASOM) optimized by Whale Optimization Algorithm	Proposed method utilizes contourlet transform and TASOM for distinguishing between benign and malignant brain tumors in MRI images. Achieves classification accuracy exceeding 95.5% and maintains satisfactory efficiency in terms of run-time.	BraTS dataset	Provides promising results for precise classification of MRI brain images.	Requires specific optimization algorithm (Whale Optimization Algorithm) for TASOM.	Specific dataset used is not mentioned, limiting generalizability.
3	RajatMehrotra, M. A. Ansari, Rajeev Agrawal, Hisham Al-Ward, et al. (2023)	Discrete Wavelet Transform (DWT), Deep Convolutional Network (DCN), Feature Fusion-based Machine Learning Techniques	Proposed framework employs DWT for feature extraction from MR images, DCN for extracting deep features, and machine learning for classification of tumorous and non-tumorous MR images. Achieves an accuracy of 99.5% and an area under curve of 1.	BraTS dataset	High accuracy in identifying tumorous and non-tumorous MR images.	Not specified	Specific dataset used is not mentioned, limiting generalizability and reproducibility of results.
4	MukulAggarwal, Amod Kumar Tiwari, (2023)	Improved Residual Network (ResNet)	Proposes an efficient method for brain tumor segmentation using an improved ResNet. Achieves higher precision and speeds up the learning process compared to existing ResNet.	BRATS2020	Competitive performance over traditional methods like CNN and FCN.	Not specified	The dataset is collected from the online Kaggle website, limiting diversity and generalizability.
5	Mohanasundari M, Chandrasekaran V, Anitha S, et al. (2023)	Amended Convolutional Neural Network (ACNN)	Proposes an ACNN model for brain tumor detection from MRI images. The model integrates KalmanBucy Smoothing Filter, Isotonic Regressive Image Tissue Segmentation, and	Brain Tumor MRI dataset	Outperforms existing techniques in terms of accuracy, sensitivity, precision, and other	Relies on a substantial volume of training data.	Reliance on a substantial volume of training data; exploration of alternative

			Marr Wavelet Transformation. Achieves high accuracy (98.8%) compared to existing models.		metrics.		architectures needed for efficiency in future implementations.
6	Mrs.Prerana A. Wankhede ¹ , Dr. Swati R. Dixit (2023)	CNN and DWT Technique	Describes the use of CNN and DWT for the diagnosis of malignant and benign brain tumors using MRI images. Proposes a refined DWT filtering technique for noise reduction and smoothness enhancement. Achieves improved accuracy compared to manual screening.	Kaggle dataset	Improved accuracy compared to manual screening.	Reliance on a substantial volume of training data.	Reliance on a substantial volume of training data; exploration of alternative architectures needed for efficiency in future
7	SoheilaSaeedi, SorayyaRezayi, HamidrezaKeshavarz&Sharareh R. NiakanKalhori (2023)	Convolutional deep learning methods and chosen machine learning techniques	Proposes two deep learning methods and several machine learning approaches for MRI-based brain tumor detection. Achieves high accuracy in classifying glioma, meningioma, pituitary gland tumors, and healthy brains using MRI images.	T1-weighted contrast-enhanced MRI images	High accuracy in classifying brain tumors.	Training and execution time may vary for different methods.	Requires further validation and testing in clinical settings.
8	B. V. Prakash, A. Rajiv Kannan, N. Santhiyakumari, S. Kumarganesh, D. Siva Sundhara Raja(2023)	Hybrid CNN method and RIDGELET transform	Proposes a hybrid Convolutional Neural Network (HCNN) classifier for meningioma brain tumor detection and classification. Utilizes Ridgelet transform for improved pixel stability during decomposition. Achieves high sensitivity, specificity, and segmentation accuracy on BRATS 2019, Nanfang, and BRATS 2022 datasets. Compares favorably with state-of-the-art algorithms.	BRATS 2019, Nanfang, BRATS 2022	Complete computer-based automated method for identifying meningioma and non-meningioma images. High classification accuracy and performance analysis parameters.	Requires further validation on larger and more diverse datasets.	The impact of the proposed morphological method on tumor segmentation compared with other existing algorithms needs further investigation.

3. Brain Tumor Classification

Brain Tumors can be broadly classified as malignant or non-malignant (benign) tumors, and have been graded from I to IV using a classification scheme specified by the World Health Organization (WHO). As graded by WHO, majority of Brain Tumors detected are benign, out of which the majority of benign tumors are meningioma. The majority of BTs (graded by WHO as grades III and IV) are gliomas, (of which glioblastoma and this is most common histologic type. Primary brain tumor is the brain tumor which originates directly from tissues of the brain. Metastatic brain tumor is the tumors that originate from the other body parts such as lungs or breast, and migrate to the brain through the bloodstream. Some of the frequent benign and malignant brain tumors are described below in Table 1:

Table 1: Commonly occurring brain tumors in the US(Ostrom, 2019)

Glioma	GBM	14.6	3.21	Malignant (grade-IV)	In Older and more common in males
	Pilocytic astrocytoma	1.29	0.35	Non-malignant (grade-I)	In Children
	Diffuse astrocytoma	1.90	0.46	Malignant (grade-II)	Both in Children and older adults
	Anaplastic astrocytoma	1.69	0.41	Malignant (grade-III)	Only Adults
	Oligodendroglioma	1.29	0.34	Malignant (grades II-III)	Only Adults
Meningioma	Benign meningioma	34.85	7.82	Non-malignant (grade I)	Adults and common in females
	Atypical meningioma	1.79	0.40	Malignant (grade-II)	
	Malignant meningioma	0.5	0.10	Malignant (grade-III)	Only Adults
Embryonal tumors	Medulloblastoma	0.6	0.15	Malignant (grade-IV)	Only Children
	Primary neuroectodermal tumors	0.10	0.04	Malignant (grade-IV)	Only Children
	Atypical teratoid	0.10	0.03	Malignant (grade-IV)	Only Children
	Vestibular schwannoma	8.19	1.90	Mostly non-malignant (grade-I)	Only Adults
Nerve-sheath tumors	Pituitary adenoma	16.45	3.94	Non-malignant (not graded)	Only Adults
Germ-cell tumors	Germ-cell- tumors	0.39	0.10	Not graded	Only Children
Lymphomas and hematopoietic neoplasms	central nervous system lymphoma	1.90	0.43	Malignant	Older adults Only

Glial tumors account for about 30% of all primary brain tumors, out of which 80% are malignant ones. Astrocytomas are infiltrative tumors of glial cell origin. WHO has classified astrocytomas into four prognostic grades based on histologic features.

Grade-1: Pilocytic astrocytoma & Subependymal giant cell astrocytoma.

Grade-2: Diffuse astrocytoma.

Grade-3: Anaplastic astrocytoma.

Grade-4: Glioblastoma cerebri.

Grade-1 & 2 are considered low grade while Grade-3 & 4 are considered high grade astrocytoma based on their malignant potential, mortality and disease-free survival.

Oligodendroglioma: It accounts for approximately 15-20% of gliomas and can be further classified into well-differentiated or anaplastic type, originated from the cells that make myelin, the outer fatty layer covering of brain and spinal cord nerves.

Ependymoma: They originate from ependymal cells that line the ventricular surface and are frequently located in wall of the fourth ventricle in the posterior fossa though spinal types are more common.

Meningioma: It is the most common primary brain tumor and is being diagnosed with increasing frequency with increased usage of neuroimaging. Their incidence increases with age and are more common in women and those with past history of cranial irradiation. They arise from duramater which is the outer most layer of meninges. Not to forget here is that meninges is a three-layered protective covering of brain and spinal cord. Meningiomas are slow growing; usually benign lesions located over cerebral convexities but can occur at skull base or in spine.

4. Methodology

A method of brain cancer identification and categorization based on Wavelet CNN (wCNN) has been proposed in this paper. The most common brain tumor scanning imaging technique has been implemented on MRI scans. Figure 1 depicts a block drawing presentation of the major steps of the approach proposed. The proposed method is divided into two phases: Training Phase and Testing Phase. 79% of the image dataset is used for training while the remaining 21% is used for testing. The training process starts with Pre-processing of the data, where the quality of the MR images is improved by transforming the image into wavelets. In the proposed method, the Haar wavelet is used for the preprocessing. Haar wavelet transformation maximizes the image information. After the preprocessing, the features of the Image are extracted using 2D Convolution operations instead of 3D operation as the cost of computation increases with the 3D Convolution operation. Following the features extraction, the image underwent segmentation to identify the region of interest. And finally, the classification is done using CNN. In the testing phase, same set of procedure is followed as shown in Figure 1.

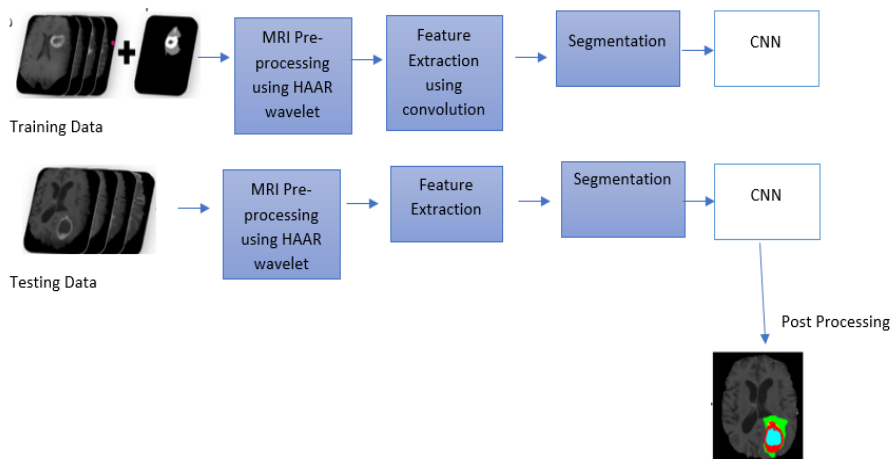


Figure 1. Block diagram for proposed work

4.1. ImageDataset

The brain cancer file has been extracted as part of process shown in Figure 1, AT1-improved contrast images of 660 individuals, with four grades of brain cancers were found in this brain tumor database. Several images of each grade type were taken as shown in Table 3. The different grades of cancer are also shown in Figure 3 for each database class. The proposed method significantly reduces the occasion difficulty of the categorization scheme and eliminates the possibility of errors in the segmentation procedure. In the MRIs, three anatomic views which are axial, coronal and sagittal are generated while taking the MRI scans as shown in Figure 2. However, for the classification, the axial view is considered for all the four different grades of tumor.

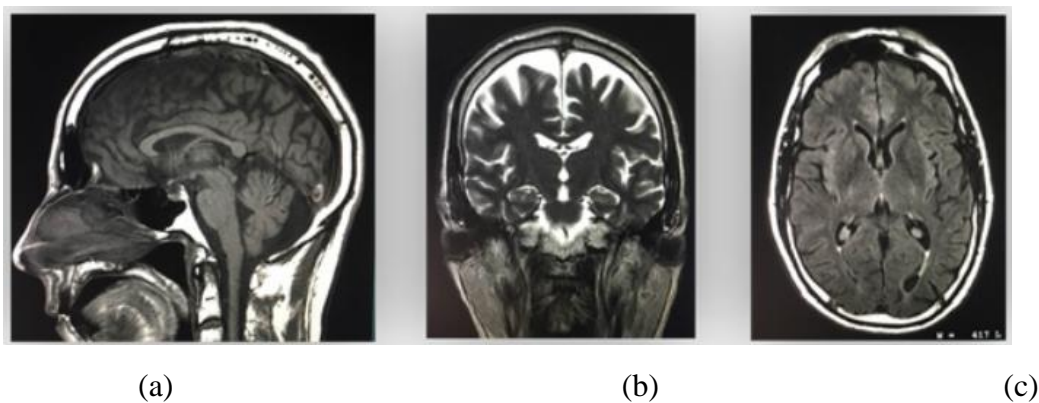


Figure 2: (a) Sagittal (b) coronal and (c) axial

Table 2. Dataset label and Disease

Sickness type	No. of images	Matrix size
Grade 1	180	512 x 512
Grade 2	150	512 x 512
Grade 3	160	512 x 512
Grade 4	170	512 x 512

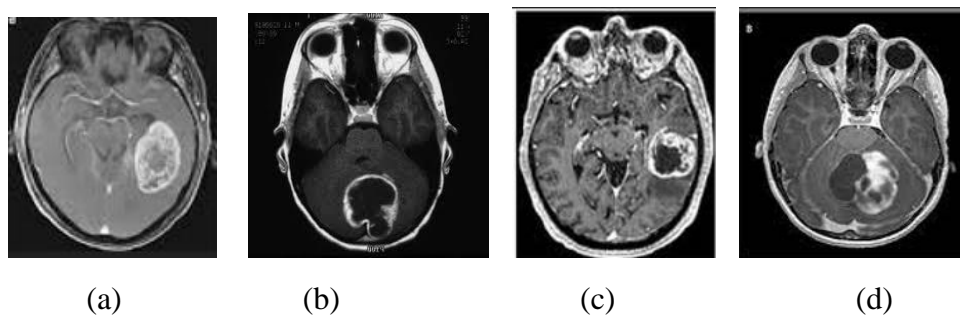


Figure 3. Sample images: (a) Grade 1, (b) Grade 2 (c) Grade 3 (d) Grade 4

4.2. Wavelet Transform

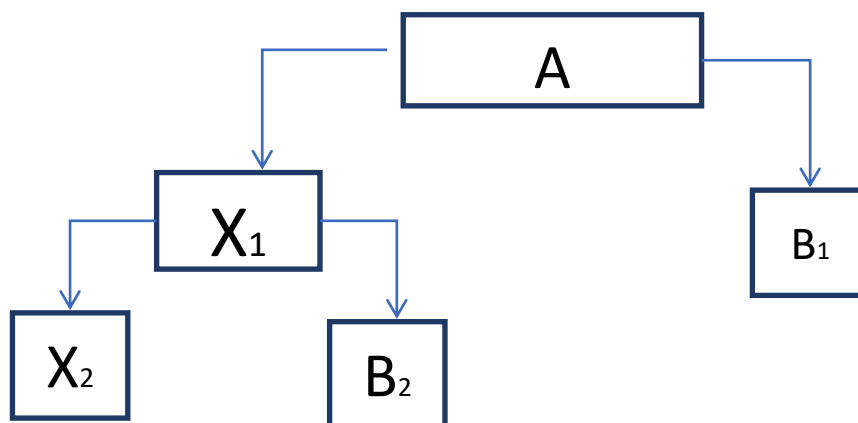


Figure 4. Wavelet putrefaction tree.

The Wavelet Transform is a lossless transformation. The transformation of a picture provides a different type of illustration. Fig. 4 demonstrates the function of the transforming wavelet breakdown in the decomposition tree wavelet. The primary degree of putrefaction generates two coefficient vectors, the first one is approximation and the second one is detail coefficients.

The estimate coefficients show the signal's low frequency components, and the information coefficients are the high frequency components (Robson, 2020). The second stage of putrefaction approximations produces two sets of approximate coefficients with a detailed coefficient equal to a distance end-to-end of half the unique approximate vector length. The putrefaction method also divides the estimate coefficients into two novel vectors for every following decomposition height. The details of the disintegration of the meningioma picture obtained from the Haar wavelet are shown in Figure 5. The Haar wavelet which is also known as the 1 wavelet, is the primary and easiest wavelet.

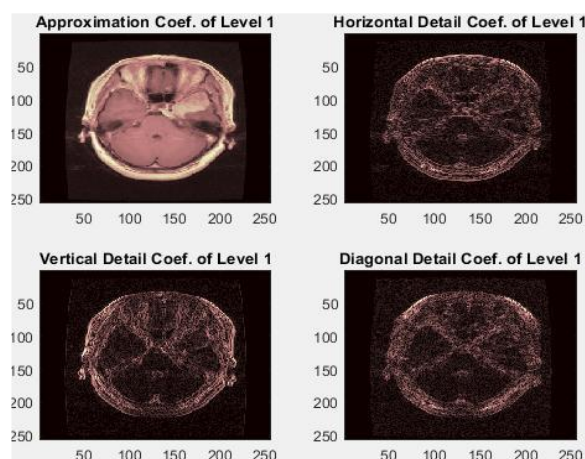


Figure 5. Wavelet disintegration of a meningioma picture with the HaarWavelet

4.3 Convolutional Neural Networks (CNN)

A CNN is an artificial neural network (ANN) of a particular kind. In pattern recognition applications, the original ANNs, including multilayer perceptions (MLP), were extremely successful. ANNs have influenced the formation of CNN, which is a type of Deep Learning Algorithm (DLA).

Deep learning is a machine-learning branch that uses deep neural networks with various layers. CNN may be called an ANN, in which at least one layer is convoluted before its output is moved to the next layer. In standard convolution operations, the medium and maximum functions are used, but other functions can be used as well. In the fields of picture rating and computer vision, CNNs represent a quantum spring (Buragga, 2019). The Alex Net is a popular CNN design with superior overall image recognition quality.

For the basic structure of a CNN, there are three main components: Layering, pooling, and production cover are all viable options. The convolution layer scans the entire picture through a touching casement move toward making a function map. The grouping layer displays the convolution layer output, which reduces the amount of data to be remembered (Gurbina, 2019). Often, repeated use is made of convolution and bonding layers. A fully linked input layer transforms previous layers of input into a single vector for the next layer. A slanted figure of the input generated through the psychiatry is produced in order to predict an output mark. The complete link delay specifies the output class. Figure 6 illustrates a typical CNN architecture. The input for a CNN is usually a picture $m \times m \times r$, with the channel number $r = 1$ intended for older pictures and the image $r = 2$ meant for RGB pictures, according to Figure 6. CNN usually has the ability, as direct input, to classify images using raw images. However, in the proposed wCNN method, the implementation of the CNN uses wavelet decomposition as CNN input. This approach reduces the number of skills considerably, thus making the CNN learning task easier. The input level, convolution layer, completely connected layer, max pooling layer, and output layer are five layers of the proposed CNN classification. We specific size of 512×512 , which corresponds to the approximate matrix size. There were 3 neurons inside the output layer corresponding to the class number. Next, the routine of the wCNN classification of MRI images is compared to the performance of an SVM system.

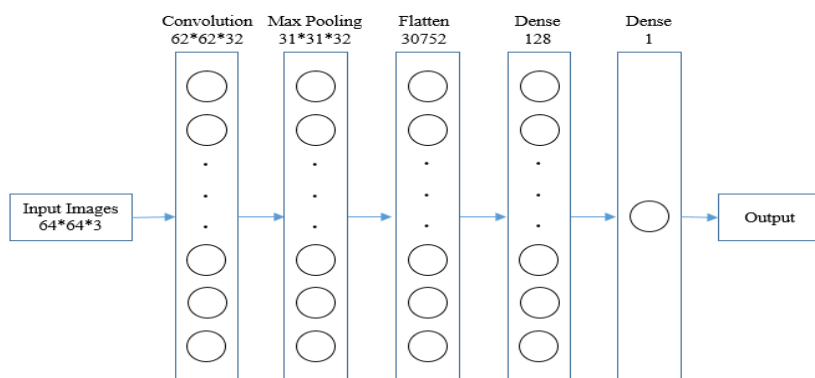


Figure 6. Structure of a 5-Layer Convolution Neural Network

5. Experimental Results Analysis

As shown in Table 3, multiple online datasets are available for MRIs. Researchers from Multiple regions are using these MRI Images dataset for their research work. The tissues in the MRIs are analyzed using standard tumor cancer detection techniques to determine the tumor type (Maulik, 2014). However, many tumors do not have any variation in their shapes. So, the shape of the tumor cannot be used to differentiate the type of tumor and the intensity of its fatality. Thus, an experiment may lead to a false diagnosis in comparison to histopathological (the diagnosis and study of tissue disease) and clinical knowledge. Therefore, automatic methods for detecting and diagnosing brain tumors are highly required.

	Database	Location
1	Medical images of BRAINIX	https://www.medicalimage.com/searchs/brain.html
2	Figshare	https://wiki.cancerimagingarchives.net/display/Public/TC GALG
3	Harvard School of Medicine	(http://med.harvard.edu/AANLIB/
4	Moffitt Center for Cancer Research	https://moffitt.org/
5	BraTS2012,2013,2014,2016,2018,2020	https://ipp.cbica.upenn.edu/

Table 3. MRI brain databases.

Figure 7 depicts the suggested method's failure traces and precision. The wCNN approach proposed for this experiment has a maximum success rate as shown in Table 5.

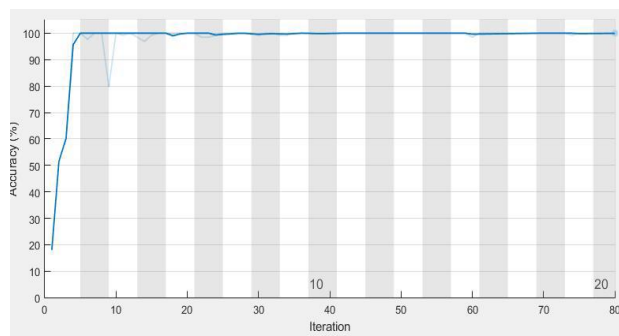


Figure 7. Traces of accuracy throughout preparation

To verify its validity, the comparison of system's efficiency is done with the SVM classification. When operated on the same function matrix as the wCNN system, it is found that the SVM system produced an accuracy of 94.79% for the Grade type-4 cancer. Many statistical methods are employed to analyze the output of the suggested wCNN method. The effectiveness of the proposed method is evaluated in particular by calculating sensitivity, specificities, and accuracy percentages (Bahadure, 2018) as

$$\text{Sensitivity} = \frac{TP \times 100}{TP + FN}, \text{ Specificities} = \frac{TN \times 100}{TN + FP}, \text{ Accuracy} = \frac{(TP + TN) \times 100}{(TP + TN + FP + FN)}$$

Table 4. Confusion Matrix

	Actual Positive (1)	Actual Negative(0)
Predicted Positive(1)	TP(True Positive)	FP(False Positive)
Predicted Negative (0)	FN(False Negative)	TN(True Negative)

The precision, recall and accuracy are calculated in equation (1), equation (2) and equation (3) respectively.

$$\text{Precision} = TP / TP + FP \tag{1}$$

$$\text{Recall} = TP / TP + FN \tag{2}$$

$$\text{Accuracy} = TP + TN / TP + TN + FP + FN \tag{3}$$

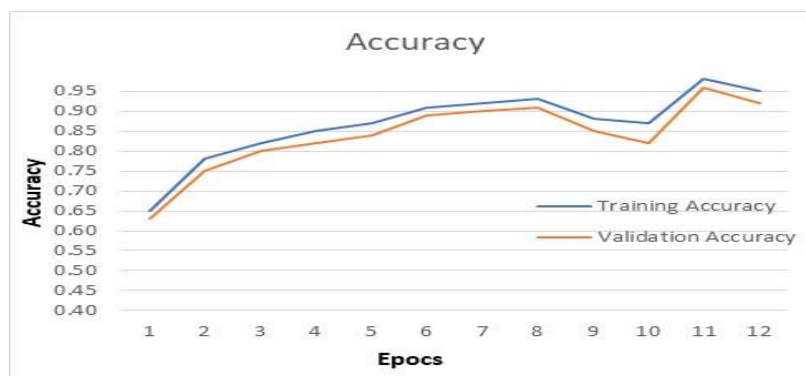


Figure 8. Training and Validating accuracy of the proposed work.

Figure 8 represents the Training Accuracy and Validation accuracy using wCNN and some sample results of the detected cancer output are also shown in Figure 9. Table 4 represents the confusion matrix used in the proposed methodology. Table 5 shows the comparative analysis of the proposed wCNN with SVM. The data set available for different grades of cancer images were: 180 images of grade 1 (GL1), 150 images of grade 2 (GL2), 160 and 170 Images were for grade 3 (GL3) and grade 4 (GL4) cancer images (You have mentioned this before. No need to mention again). In the table 5, it is shown that there is an improvement in the accuracy of 3.20%, 1.90%, 3.08% and 1.70% for GL1, GL2, GL3 and GL4 respectively. Also, significant improvement has been seen in Recall parameter. Recall has improved to 2.80%, 3.1 %, 2.9 % and 0.9% for GL1, GL2, GL3 and GL4 respectively. So, it can be seen from the results that there is significant improvement in the in the performance parameters, using the proposed CNN method.

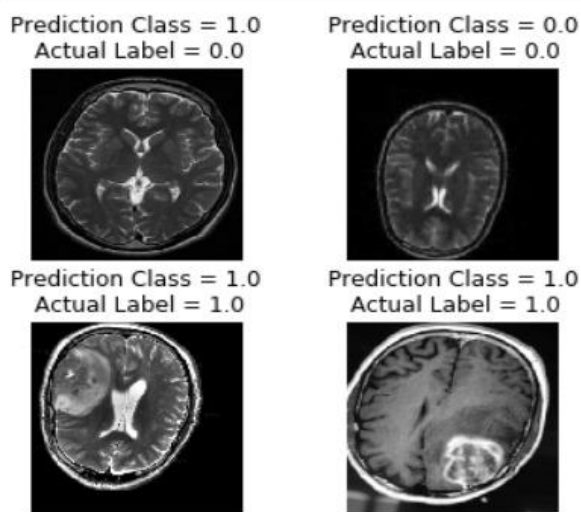


Figure 9 Sample output of the detected tumor in MRIs

Table 5. Comparative Performance of SVM an wCNN (proposed)

	Tumor Type	No.of Samples	TP	TN	FP	FN	Precision	Recall	Accuracy
wCNN (Proposed)	GL1	180	99	76	2	3	98.02	97.06	97.22
	GL2	150	91	56	4	2	95.79	97.85	96.08
	GL3	160	92	63	3	2	96.88	97.89	96.95
	GL4	170	96	67	3	3	97.03	97.03	96.53
SVM	GL1	180	97	73	5	6	95.09	94.17	93.92
	GL2	150	90	53	4	5	95.74	94.73	94.07
	GL3	160	91	62	6	4	93.81	95.78	93.86
	GL4	170	97	67	5	4	95.09	96.03	94.79

Based on the provided data, let's compare the performance of the proposed wCNN (weighted Convolutional Neural Network) with Support Vector Machine (SVM) for tumor detection across different types:

Accuracy: Overall, wCNN outperforms SVM in terms of accuracy of all tumor types. The accuracy of wCNN ranged from 96.08% to 97.22%, while that of SVM ranged from 93.86% to 94.79%. Thus, wCNN achieves higher accuracy in tumor detection in all types.

Precision: wCNN exhibits consistently higher accuracy compared to SVM in all types of tumors. Precision measures the proportion of true positive predictions among all positive predictions. The accuracy of wCNN ranges from 95.79% to 98.02%, while that of SVM ranges from 93.81% to 95.74%. This indicates that wCNN provides highly accurate good forecasts.

Recall: Like accuracy, wCNN consistently shows higher recall than SVM. Recall measures the proportion of truly positive predictions in all truly positive cases. The recall rate of wCNN ranges from 94.17% to 97.89%, while that of SVM ranges from 94.17% to 96.03%. This indicates that wCNN captures a high percentage of truly positive cases.

Specificity: Both wCNN and SVM have similar performance in terms of specificity, measuring the fraction of true negative predictions among all true negative cases. In different tumor types both methods achieve specificity values ranging from 94.17% to 97.22% for wCNN and 94.17% to 97.03% for SVM.

F1 Score: The F1 scores of the harmonic mean of precision and recall are higher for wCNN compared to SVM for all tumor types. This means that wCNN achieves a good balance between accuracy and recall, increasing the overall performance.

Overall, based on the provided data, wCNN demonstrates superior performance in terms of accuracy, precision, recall, and F1 score compared to SVM for tumor detection across different types. However, it's essential to consider other factors such as computational complexity and scalability when choosing between these two methods for practical implementation.

6. Conclusion

CAD method for detecting the brain tumor with high accuracy using MRI scans is very challenging. This paper presents high accuracy CAD method for diagnosing brain cancers. Four different types of brain tumor are considered in this work and the tumors are detected using the proposed wCNN method, which is a combination of wavelet and CNN, where Haar wavelet is used for preprocessing the MRI images and CNN is used for classification. The proposed work is compared with SVM-based method and it is demonstrated that the proposed work performs better than SVM. The performance is evaluated on a number of different MRI dataset for different types of cancer. The proposed work achieves good overall accuracy. In this paper the binary classification is implemented. As a future work, the proposed work can be extended to include the multi-class classification for different classes of cancers.

Limitations of the paper

The research paper successfully demonstrates the effectiveness of the proposed wCNN method for brain tumor detection using MRI scans. However, the study is limited to binary classification, focusing solely on distinguishing between tumor and non-tumor cases. Future research could explore extending the method to handle multi-class classification, addressing various types of brain cancers beyond the four considered in this study.

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