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Development and Evaluation of a Multi scale Deep Learning Model for Automated Brain Tumor Classification from MRI Scans

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ABSTRACT

Accurate and timely classification of brain tumors is critical for effective diagnosis and treatment planning. In this study, we propose a multiscale deep learning model that leverages hierarchical spatial features from magnetic resonance imaging (MRI) scans to automatically classify brain tumors. The model integrates multiple convolutional neural network (CNN) branches operating at different image resolutions to capture both global contextual information and fine-grained local details. We trained and validated our model on a publicly available brain tumor dataset, including glioma, meningioma, and pituitary tumor classes. Performance evaluation using metrics such as accuracy, precision, recall, F1-score, and AUC-ROC demonstrated that the multiscale approach significantly outperforms single-scale models. Our results suggest that multiscale deep learning offers a robust and scalable solution for clinical decision support systems in neuro-oncology.

Introduction

According to data from the Central Brain Tumor Registry (2018), cancer of the brain and other nerve systems ranks as the tenth most common cause of death for both men and women. A brain tumor is an aberrant cell growth in the brain, the body's most important organ that is characterized by mutations that alter the DNA of normal cells. Some brain tumors are benign, while others are infectious (malignant). Primary brain tumors are those that start in the brain or surrounding tissues. Gliomas meningiomas, acoustic neuromas, medulloblastomas, and pituitary tumors are examples of common primary brain tumors.

The majority of brain tumor types have similar signs and symptoms, albeit they differ depending on the size and location of the tumor. A neurological examination, imaging tests, and a sample of suspicious tissue are all part of the clinical process for identifying brain tumors. Brain tumors may be treated with chemotherapy, radiation therapy, and surgery. The kind, size, and location of a brain tumor all influence the therapy strategy that is selected [1]. Another negative aspect is taking the patient's general health into account. Infections and bleeding are common after surgery, but high intensity radiation causes adverse effects during radiotherapy. Drugs are used as part of chemotherapy in order to destroy the aberrant tissues. Understanding the kind of brain tumor helps in selecting the best course of treatment, because different brain tumor forms have different levels of susceptibility to therapy [2].

One of the following sub problems might be the focus of the tumor categorization issue. It could be the differentiation of brain tumors into low-grade and high-grade tumors, benign and malignant (cancerous) tumors, and categorization among certain tumor kinds [3]. These CAD systems use brain magnetic resonance imaging (MRI) pictures to diagnose brain tumors. The reason for this reliance on MRI is because, in contrast to computed tomography (CT) pictures, MRI may give a greater contrast for the brain's soft tissues. Additionally, MRI doesn't expose the patient to dangerous radiation. Research in this area has been aided by the availability of many open datasets for brain MRI imaging.

Research has suggested many techniques for the semi-automated and completely automated identification of brain tumors using MRI pictures [4]. In order to classify MRI pictures as either normal or tumorous, the completely automated tumor detection systems first extract information from the images. To create the area of interest (ROI), the probable tumor location must be manually selected using semi-automated tumor identification techniques. The study of the ROI for feature extraction is necessary for tumor identification.

Then, using suitable machine learning models as a support vector machine (SVM), k-nearest neighbor (KNN), artificial neural network (ANN), or fuzzy classifier, the characteristics are divided into malignant and non-cancerous categories. The preprocessing of photos prior to feature extraction significantly enhances the outcomes. A segmentation approach for skull removal and an image enhancement utilizing histogram matching were part of the preprocessing in the majority of the investigations. However, the classifier outputs are not reproducible, and the feature extraction and preprocessing procedures need time-consuming human inputs. A completely automated tumor identification process is made possible by the use of a deep convolutional neural network (CNN).The tumor detection problem's feature extraction and classification processes might be combined using deep networks. A different class of completely automated tumor identification techniques divides the brain MRI into distinct areas using various clustering algorithms [5].

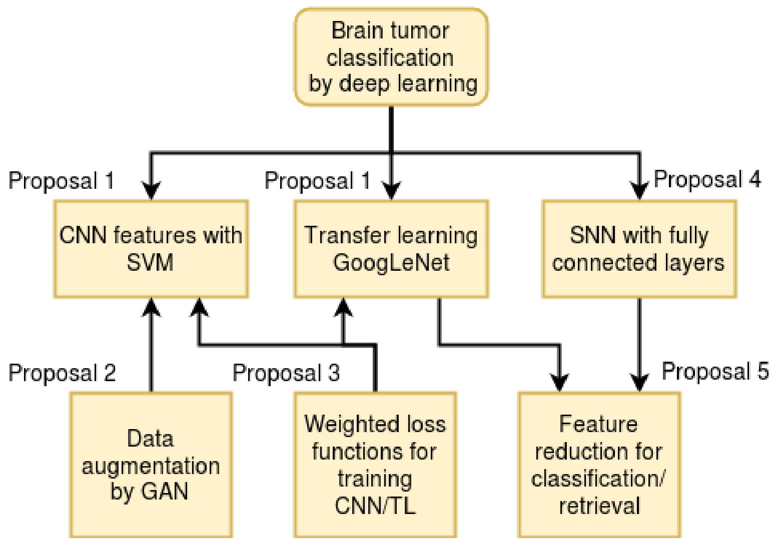

Figure 1: Overview of the works presented in this thesis (The two sections of Proposal1areshownseparatelyinthisfigure.)

A two-stage analysis is used by several tumor detection systems. Images of brain tumors are initially categorized as either normal or tumorous. The second step involves using the tumorous pictures to segment the tumor areas. Tumor areas might be efficiently characterized by texture characteristics like Gabor features or grey level co-occurrence matrix (GLCM) features. The characteristics are classified using tried-and-true models, such as SVM and random forest (RF) classifiers. Every every pixel in the pictures was classified. Semantic segmentation, which is formed by pixel-level categorization, is important for brain tumor segmentation [6]. When deep learning architectures are used, semantic segmentation performance significantly increases. U Net topologies have recently been developed for accurate brain tumor segmentation and identification. After a great deal of study on the subject, updated cost functions like the Soft Dice Metric were used to provide better outcomes.

Brain Tumour Classification

The characterization of the tumor is important for the treatment planning of the tumor after it has been identified in MRI imaging. Another group of classification sub problems is the characterization of brain tumors. A lot of study has been done on the categorization of brain tumors based on CAD into benign and malignant tumors [7]. Tumors that spread to other areas are referred to as malignant tumors. Even after removal, they are likely to return. Benign tumors, on the other hand, react well to medical treatment and do not spread to other areas of the body. Furthermore, there has been much study done on the categorization of malignant tumors into low-grade and high-grade tumors. The aggressiveness or potential growth and spread rate of a tumor is indicated by its grade. The most aggressive treatment is given to grade IV tumors. A well-known study used Hilbert transform-based analysis of textural data from tumor areas to distinguish between high-grade and low-grade gliomas. 3D CNN models and data augmentation techniques are responsible for the recent improvement in glioma sample grading.

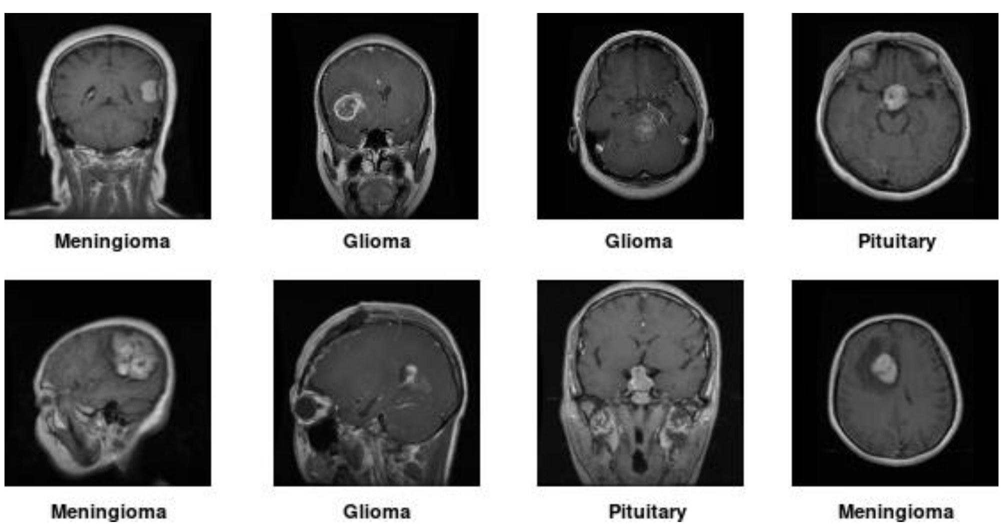

Figure 2: Sample images from Fig share dataset for brain MRI with three types of tumours

An further important related issue is the classification of brain tumors according to their subtype. The three-class categorization of brain tumors into gliomas, meningiomas, and pituitary tumors presents a challenge in this regard. To classify multi-view MRI images, a comprehensive analysis is necessary. Prior research on this issue characterized the tumor pictures using textural characteristics like GLCM, bag of visual words (BoW), or histogram of intensities. Selecting the best features and classifier was often difficult, which had an impact on the final CAD system's performance. Deep learning models were used in recent studies to address this issue and provide a more accurate and dependable completely automated brain tumor categorization system [8].

More specialized tumor instances might be added to the challenges with tumor categorization. In order to include MRI scans of the normal brain and three types of malignant tumors, a four-class classification problem was developed. The classification method used a deep neural network (DNN) classifier using discrete wavelet transform (DWT) features. An ensemble of Dense Net and a recurrent neural network (RNN) produced greater accuracy in a closely comparable four-class brain tumor classification issue.

Focus of research and significance

Meningioma, glioma, and pituitary tumors are the three kinds of brain tumors that are the subject of this research project. Gliomas, meningiomas, and pituitary tumors have the highest incidence rates of any brain tumor. Meningioma and pituitary tumors are often benign, whereas gliomas are malignant. A potentially fatal brain tumor called glioma develops from the glial cells that envelop the brain's nerve cells. Meningiomas grow extremely slowly and originate from the membranes surrounding the brain. However, meningioma may be aggressive in some circumstances. Benign tumors that impact the pituitary gland are known as pituitary tumors. Because the afflicted pituitary gland produces hormones in an uncontrolled manner, they alter body functioning [9].

These brain tumors have many symptoms, and the appearance of several tumor types might be identical. To diagnose the three kinds of tumors, a detailed examination of the MRI is necessary. To help medical professionals characterize the tumor, an automated categorization system might be useful. When planning a treatment for a brain tumor, determining the kind of tumor is essential.

The following are the clinical implications of the suggested CAD-based classification of brain tumor types. Depending on the symptoms after the physical examination, medical imaging is part of the clinical process. To diagnose cancer and identify its kind and grade, a sample of tissue is often taken and examined. The patient experiences pain throughout this biopsy technique and human competence is needed for the diagnosis. Neuro oncologists would be able to determine the kind of tumor with the use of the suggested CAD system for brain tumor categorization. The right course of therapy will be recommended based on the kind of tumor.

Another set of research issues in the field is determining the aggressiveness of gliomas using a different stage of classification algorithms and measuring the tumor's volume using tumor area segmentation. Predicting the patient's survival time is the goal of the later issue [10]. Nevertheless, the importance of the suggested CAD method is restricted to the first phase of tumor type detection.

Literature review

Verma, A., & Yadav, A. K.(2025) [1] *Improved multi-class brain tumor MRI classification with DS-Net: A patch-based deep supervision approach* This study introduces DS-Net, a deep learning framework that enhances multi-class brain tumor classification by employing patch-based deep supervision. The approach aims to improve model accuracy and generalization in classifying various brain tumor types from MRI scans.

Mao, Y., Kim, J., Podina, L., & Kohandel, M.(2025) [2] *Dilated SE-Dense Net for brain tumor MRI classification* This study introduces an advanced convolutional neural network that enhances the DenseNet-121 architecture by integrating dilated convolutional layers and Squeeze-and-Excitation (SE) networks' attention mechanisms. The model was trained and evaluated on a comprehensive Kaggle brain tumor dataset, demonstrating superior performance over established convolution-based and transformer-based models across key metrics: F1-score, accuracy, precision, and recall. The results underscore the effectiveness of these architectural enhancements in medical image analysis.

Anwar, R. W., Abrar, M., & Ullah, F.(2023) [3] *Transfer learning in brain tumor classification: Challenges, opportunities, and future prospects* This paper provides a comprehensive overview of the challenges and opportunities associated with applying transfer learning in brain tumor classification. The authors discuss various pre-trained models, data augmentation techniques, and evaluation metrics, highlighting the potential of transfer learning to improve classification accuracy and generalization in medical imaging tasks.

Ullah, F., Nadeem, M., Abrar, M., Amin, F., Salam, A., Alabrah, A., & Alsalman, H. (2023) [4] This study introduces an evolutionary lightweight ensemble model for brain cancer grading and classification using Magnetic Resonance Imaging (MRI) data. The model, named "lightweight ensemble," combines multiple XG Boost decision trees through weighted averaging, enhancing prediction accuracy and interpretability. The approach integrates preprocessing steps and feature extraction techniques focusing on intensity, texture, and shape to improve classification performance. Evaluated on the Bra TS 2020 dataset comprising 285 glioma MRI scans, the model achieved 93.0% accuracy, 0.94 precision, 0.93 recall, 0.94 F1 score, and an AUC-ROC of 0.984.These results demonstrate the model's effectiveness in early brain tumor diagnosis and treatment planning.

Mzoughi, H., Njeh, I., Slima, M. B., & Hamida, A. B. (2022) [5] This comprehensive review examines the integration of machine learning and deep learning techniques in CAD systems for glioma detection using MRI. The authors discuss various preprocessing methods, feature extraction techniques, and classification algorithms, highlighting their impact on diagnostic accuracy and efficiency. The paper also addresses challenges such as data imbalance and the need for large annotated datasets.

Bhagyalaxmi, K., Dwarakanath, B., & Reddy, P. (2024) [6] This survey provides an extensive review of deep learning methodologies applied to the detection and classification of multi-grade brain tumors using MRI scans. The authors categorize various approaches based on their architecture, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models. They discuss the strengths and limitations of each approach, emphasizing the importance of dataset diversity and preprocessing techniques in enhancing model performance. The paper also highlights the challenges in achieving high accuracy across different tumor grades and suggests directions for future research.

Chen, Y., Wang, J., & TSEUnet: A 3D Neural Network with Fused Transformer and SE-Attention for Brain Tumor Segmentation. (2022) [7] The authors propose TSEU net, a novel 3D neural network architecture that integrates Transformer mechanisms and Squeeze-and-Excitation (SE) attention modules for brain tumor segmentation. The Transformer component captures long-range dependencies within the MRI volumes, while the SE-attention mechanism enhances channel-wise feature recalibration, allowing the model to focus on informative features. Evaluations on standard datasets demonstrate that TSEU net outperforms traditional CNN-based models in terms of segmentation accuracy and robustness, particularly in handling complex tumor structures.

Liang, J., Yang, C., Zhong, J., & Ye, X. (2022)[8]This study introduces BTS win U net, a 3D U-shaped symmetrical network that combines the S win Transformer with U-Net architecture for brain tumor segmentation. The model leverages self-supervised pre-training to enhance feature extraction capabilities, addressing the challenges of capturing long-range dependencies in medical images. Experimental results demonstrate its effectiveness in accurately segmenting brain tumors from MRI scans.

Karthik, A., Sahoo, S. K., Kumar, A., Patel, N., Chinnaraj, P., Maguluri, L. P., Shuaib, M., & Rajaram, A. (2025) [9] This research presents a unified framework that integrates Attention-Augmented Convolutional Neural Networks (CNN), Random Forest (RF), and U-Net for multi-classification and segmentation of brain tumors. The attention mechanism enhances feature extraction, RF provides robust classification, and U-Net ensures precise segmentation. The model achieves high accuracy in classifying and segmenting brain tumors from MRI images, demonstrating its potential for clinical applications.

Saxena, P., Maheshwari, A., & Maheshwari, S. (2020) [10] This study explores the application of deep learning models, specifically Convolutional Neural Networks (CNNs), for classifying brain tumors from MRI scans. The authors employ transfer learning using pre-trained models such as ResNet-50, VGG-16, and Inception-V3. Among these, ResNet-50 achieved the highest accuracy of 95% with zero false negatives, demonstrating its effectiveness in brain tumor classification.

Mehnatkesh, H., Jalali, S. M., Khosravi, A., & Nahavandi, S. (2023) [11] This paper presents an enhanced deep residual learning framework for brain tumor classification. The authors introduce an Improved Ant Colony Optimization (IACO) algorithm, incorporating differential evolution strategies and multi-population operators, to optimize deep learning architectures. The proposed framework achieved an average accuracy of 98.694%, indicating its high efficacy in classifying brain tumors from MRI images.

Khan, M. A., & Park, H. (2024) [12] This study introduces a convolutional-block-based architecture tailored for the multiclass detection of brain tumors using MRI scans. The proposed model leverages the strengths of Convolutional Neural Networks (CNNs) to effectively distinguish between different tumor types. Evaluations on three diverse datasets demonstrate the model's robustness, achieving an average accuracy of 97.52%, precision of 97.63%, recall of 97.18%, specificity of 98.32%, and an F1-score of 97.36%. These results surpass those of state-of-the-art models such as VGG16, VGG19, Mobile Net, Efficient Net, ResNet50, Xception, and DenseNet121. The model's adaptability across various MRI modalities underscores its potential for broad clinical application.

Asiri, A. A., et al. (2024) [13] This paper presents a dual-module framework aimed at enhancing brain tumor detection in MRI images. The first module focuses on image enhancement to improve the quality of MRI scans, while the second module employs a deep learning-based classification approach to accurately identify tumor regions. The integrated system demonstrates improved performance in terms of detection accuracy and processing efficiency, offering a promising solution for automated brain tumor diagnosis.

Rastogi, D., Johri, P., Tiwari, V., & Elngar, A. A. (2024) [14] This study introduces a multi-branch convolutional neural network (CNN) architecture enhanced with inception blocks for the classification of brain tumors in MRI images. The model employs five-fold cross-validation to ensure robust evaluation. Experimental results demonstrate the model's effectiveness in accurately classifying various brain tumor types, highlighting its potential for clinical applications.

Zhu, Z., He, X., Qi, G., Li, Y., Cong, B., & Liu, Y. (2023) [15] This paper presents a novel approach for brain tumor segmentation by integrating deep semantic features with edge information from multimodal MRI images. The proposed method enhances the segmentation accuracy by effectively capturing both global context and detailed boundaries of tumor regions. Experimental results validate the superiority of this fusion strategy over traditional methods.

Haq, E. U., Jianjun, H., Huarong, X., Li, K., & Weng, L. (2022) [16] This study presents a hybrid framework combining deep convolutional neural networks (CNNs) with machine learning classifiers for the segmentation and classification of brain tumors in MRI images. The model achieved an accuracy of 98.3% and a Dice Similarity Coefficient (DSC) of 97.8% in classifying gliomas, meningiomas, and pituitary tumors.

Díaz-Pernas, F. J., Martínez-Zarzuela, M., Antón-Rodríguez, M., & González-Ortega, D. (2021) [17] The authors propose a deep learning model utilizing a multi scale convolutional neural network for the classification and segmentation of brain tumors in MRI images. The model processes images at three spatial scales and achieved a classification accuracy of 97.3% across meningioma, glioma, and pituitary tumor categories.

Mathur, P., Raghuvanshi, A. S., Kumari, A., & Chandra, A. (2023) [18] This paper introduces a computer-aided diagnosis system that integrates various image processing and machine learning techniques for the classification and segmentation of brain tumors. The system demonstrated improved accuracy and efficiency in processing MRI images, aiding in the early detection of brain tumors.

Lakshmi, K., Amaran, S., Subbulakshmi, G., Padmini, S., Joshi, G. P., & Cho, W. (2025) [19] The authors present an explainable artificial intelligence framework combining U Net-based segmentation with Bayesian machine learning for the classification of brain tumors in MRI images. The approach achieved an accuracy of 97.75%, offering interpretable results that can assist clinicians in decision-making processes.

Qin, J., et al. (2025) [20] This study introduces BTS eg Diff, a brain tumor segmentation method that leverages a diffusion probability model guided by multimodal MRI data. The model incorporates dynamic conditional guidance and Fourier domain feature fusion to enhance segmentation accuracy, achieving superior performance on BraTS2020 and BraTS2021 benchmarks.

Research methodology

The learnable parameters in a CNN model are the weights of the convolution filters and the weights corresponding to the complete connections. Two FC layers (fc_1 and fc_2) and five convolution layers (conv_1 to conv_5) make up the suggested CNN model for classifying brain tumors. The suggested CNN model's 256x256 input layer can handle input pictures of these dimensions. A convolution layer uses many filters to record different activations for the same input picture. The output activation y(m, n) coming from the linear convolution operation with a filter k(m, n) of size F x F and an input image x(m, n) is x(i, j)k(m − i, n − j)(3.1) i=−F/2 j=−F/2. gives each convolution layer's kernel size. To capture feature representations at different resolutions, different kernel sizes are used at different layers. To maintain the picture boundaries, a padding of "1" pixel thickness is added. The volume of each layer is determined by the number of filters. The following rule governs a layer's dimensions. The size of the output is (X2, Y2, K) for an input volume of dimensions (X1,Y1, Z1) convolved with K filters. The formula for calculating X2 and Y2 is $X2 = X1 - F + 2P + 1$ (3.2).

$Y2 = Y1 - F + 2P + 1$ (3.3),

where P and S stand for stride values and paddings, respectively. In this design, they represent unity and two, respectively. A batch normalization layer comes after each convolution layer. For the training data in the specified batch, the layer normalizes the outputs from the preceding layers. Each batch normalization layer is followed by the Re LU activation function. Each Re LU function is followed by a max-pooling. The output's dimensions are intended to be decreased between phases. This design's standard pooling operation makes use of a max pool filter with size (2,2), stride (2,2), and no padding. Ten neurons make up the fc_1 layer, whereas three neurons make up the fc_2 layer. Lastly, the FC levels are followed by a classification layer based on soft max [11].

Computational complexity of CNN

The computational complexity and memory requirements are among the elements taken into account in the construction of the suggested CNN. Due to this design concern, the CNN was only able to contain two FC layers and smaller convolution filters. The majority of calculations in a deep CNN model are made by the convolution stages and the dense connections of the FC layer or layers. Multiplications and additions are the convolution operation. As a result, the calculations match multiplication and accumulation (MAC) processes. According to the relation,

Opsconv = F1 ∗ F2 ∗ K ∗ X ∗ Y ∗ Z,

the number of MAC operations in a convolution layer (Opsconv) is dependent on the filter dimension (F1, F2, K) and the output feature map dimension

(X, Y, Z) (3.4).

An FC layer's number of MAC operations (OpsFC) is equal to its number of parameters (weights). As a result, the sum of the MAC operations for each network layer represents the total number of MAC operations for the whole network.

Memory requirements of CNN

The amount of parameters determines how much RAM is needed to construct deep CNN models [12]. The convolution layers and the FC layers contribute to the learnable parameters. The formula for determining a convolution layer's (Paramconv) number of parameters is F1 ∗ F2 ∗ K Zin + K (3.5).

Where Zin is the number of the layer's input channels. The FC layer's parameter count (Param FC) is determined as follows: X pre v Y pre v Z pre v NFC + NFC = Param F C (3.6) Where X pre v, Y pre v, and Z pre v stand for the layer's dimensions before the FC layer. The FC layer's output node count is denoted by NFC. The amount of time needed for training and testing a CNN depends on its computational overhead and memory needs.

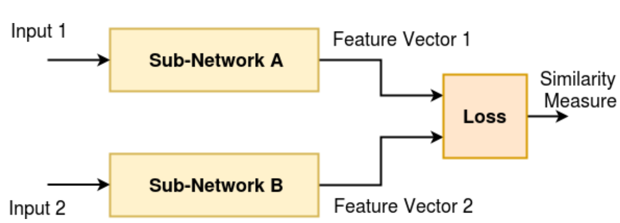

Figure 3: Conceptual block diagram of as iamese network

Transfer learning

The process of using a previously trained model's expertise to learn a new set of data is called transfer learning. The goal of transfer learning is to enhance learning in Dt by applying the knowledge in Ds and Ts. This is given a target domain (Dt) and the associated learning task (Tt), as well as a source domain (Ds) and a learning task (Ts) in the source domain. Different parameters are established for transfer learning depending on the kind of task and the type of data available at the source and destination domains. When labeled data is available in both the source and destination domains for a classification job, the transfer learning method is referred to as inductive transfer learning.

The deep CNN Google Net won the 2014 Image Net Large-Scale Visual Recognition Challenge (ILSVRC14), achieving the state-of-the-art classification performance. Inception modules in a CNN architecture were first proposed by the model [13]. 1x1 convolutions, 3x3 convolutions, 5x5 convolutions, and 3x3 max poolings are among the operations that make up an inception module. the amount of convolution filters in each inception module and the architectural specifics of the Google Net layers. It is anticipated that convolution filters with varying kernel sizes would identify distinct patterns in the data. At each module's output, the feature maps that correspond to various filters are concatenated. The output volume's number of channels is decreased by a 1x1 convolution. Consequently, the design outperformed the other deep CNN models in terms of computing with fewer layers and parameters. It has an FC layer, two convolutional layers, two pooling layers, and nine inception modules. 1.2 million natural photos from the Image net dataset were used to pre-train Google Net. Every picture in Image net was a member of one of the 1000 classes that were established. As a result, the source job is a 1000-class classification issue, and the source domain is defined by Image net training samples [14].

Table1: Details of layers in Google Net architecture

Layer	**Type**	**Patch size/ stride**	**Size**	**1x1**	**#3x3**	**#5x5**	**#7x7**
'data'	input		224x224x3				
' conv1-7x7_s2'	convolution	7x7/2	112x112x64				64
'pool1-3x3_s2'	Max pool	3x3/2	56x56x64				
' conv2-3x3'	convolution	3x3/1	56x56x192		192		
'pool2-3x3_s2'	Max pool	3x3/2	28x28192				
' inception_3a'	inception		28x28x256	64	128	32	
'inception_3b'	inception		28x28x480	128	192	96	
'pool3-3x3_s2'	Max pool	3x3/2	14x14x480				
' inception_4a'	inception		14x14x512	192	208	48	

To adapt Google Net to the target domain, its last three layers are changed. Initially, the original Google Net's FC layer was eliminated. Rather, a brand-new FC layer with a three-output size is added. Next, additional layers are added to replace the cross-entropy-based classification layer at the output and the soft max layer, which comes after the FC layer. Next, MRI pictures from Fig share are used to train the modified Google Net. At the FC layer, the learning parameters for bias and weights were assigned to a high value of 10. The goal is to teach the network abstract high-level domain-specific properties. It is anticipated that the pre-trained layers from the original Google Net would learn the low-level characteristics. Experiments using MRI data from the Figs hare dataset may then be conducted using the transfer learnt model.

Classifier

The output of the last FC layer of a CNN-based deep learning model for classification has a soft max layer. CNN is a stand-alone classifier that incorporates a soft max layer [15]. This study examines how well-established classifier models perform on CNN features and how well CNN performs as a stand-alone classifier (with its soft max layer). The research is motivated by the following reason. An extensive tuning procedure is required for a deep CNN (or transfer learnt) model on the target domain. The intricate model may over fit data in the target domain even after adjustments.

Soft max

Following the last FC layer, CNN employs a soft max activation function. Sk=1 xk is the definition of the function.

where Yi represents the predicted probability measures for each class, per sample, and Ti indicates the class label for the training sample in the batch, represented as a one-hot vector. When the real and predicted values are closer together, the cross-entropy, which gauges how close the true measure and predictions are, yields a lower number. The loss function is appropriate for gradient computations during error back propagation and training.

SVM

As an optimization problem, SVM is a maximum margin classifier. In order to classify test samples, SVM maximizes the margin between classes. Considering the class label yi, weight vector w, and feature vector xi the issue is then described as

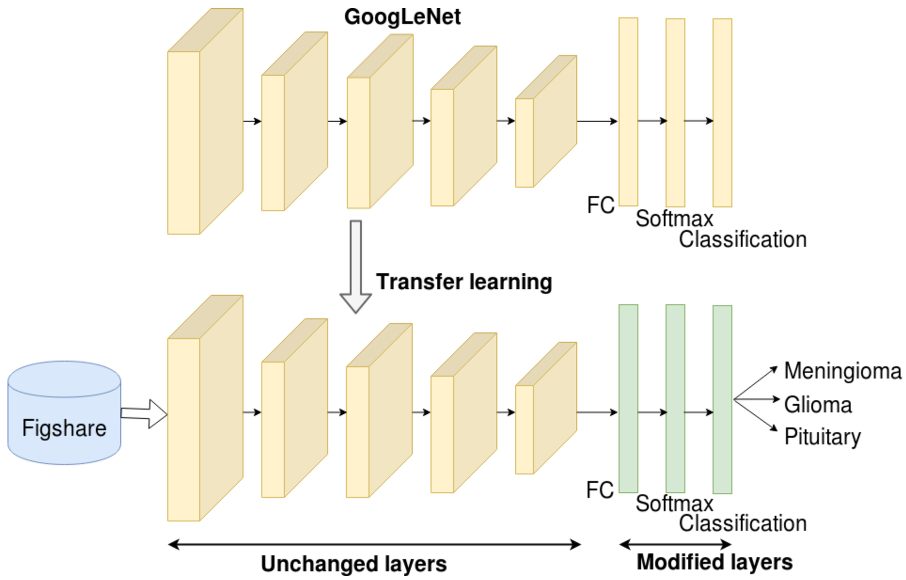

Figure 4: Modifying Google Net for the application

Yiw T xi + w0 > 1(3.10), where i is the number of samples, C is the cost parameter that governs margin maximization and classification error reduction, and ξ is the training error [16]. It is simple to extend SVM to multi-class issues. The one-versus-all and one-versus-one methods are often used in practice. The former method calls for c binary SVM classifiers for a c-class classification problem. When using the latter method, c(c−1) binary classifiers are required. The suggested study employs a three-class classifier model using three SVM binary classifiers, taking a one-versus-all stance. The SVM classification method uses Hinge Loss (Lh) as its loss function.

KNN

The closest neighborhood density estimate is the foundation of the KNN classifier model. Using distance measurements, the KNN model predicts the class label of every test sample (feature vector) by mapping it to the feature space (spanned by training feature vectors). The distance measure, k, and the number of closest neighbors are the primary KNN parameters. The stages involved in putting the model into practice are listed below.

1. Determine how far the test sample is from the training samples. (At the same time, take note of the training sample labels.)

2. Put the distances in increasing order

of distance.

3. Determine the mode of the class labels for the first k recordings [17].

4. Give the test sample the mode as its label.

Table2: Details of layers in the CNN model

Layer	Type	size	Filter size	#Filters	Stride	Padding
'image_ input'	Input	256x256x1				
'conv_1'	Convolution	256x256x8	3x3	8	1	1
'maxpool_1'	Max pool	128x128x8			2	
'conv_2'	Convolution	128x128x16	3x3	16	1	1
'maxpool_2'	Max pool	64x64x16			2	
'conv_3'	Convolution	62x62x32	5x5	32	1	1
'maxpool_3'	Max pool	31x31x32			2	
'conv_4'	Convolution	27x27x64	7x7	64	1	1
'maxpool_4'	Max pool	13x13x64			2	
'conv_5'	Convolution	7x7x64	9x9	64	1	1
'fc_1'	Dense	1x1x10				
'fc_2'	Dense	1x1x3				

Proposed classification framework

It is possible to employ the deep CNN (or transfer learnt) model as a stand-alone system or to feed the deep CNN features into existing pattern classifiers. As a result, in the proposed study, the deep CNN features are evaluated on two sets of classifier models apart from the soft max classifier. These classifiers are KNN and SVM [18]. SVM was used for the trials because it has shown high performance in CNN feature classification in several previous publications. A classifier based on density estimates may be more useful when data points are difficult for SVM planes to separate. In keeping with this idea, KNN is also included into the experimental investigation. the general structure of the suggested categorization scheme. Inputs to the classifier model include class labels for the training data and deep CNN features of the test and training data.

Result analysis

The cross-entropy loss function (Lce) typically drives CNN training, and the CNN's soft max function comes after the last FC layer. The loss quantifies the probability similarity between the actual and anticipated classes.

The logarithmic function is used to scale the fc measurements, and w(c) is obtained by normalizing them. The idea of focus loss was recently presented for the issue of object detection. A binary classification issue between foreground and background pixels is object detection. The formula for focused loss in a multi-class classification context is f = −∑(1 − Yi). Tilog (Yi) (5.5) I=1.

where γ, also known as the focusing parameter, raises the weight of samples that are misclassified (during training) and decreases the weight of samples that are readily classified. Lwf in (5.5) decreases to Lce in (5.1) when γ = 0.

where W has the definition given in (5.3). By assigning weights to classes, the class weighted focus loss gives minority classes more weight while training the CNN model. For the weighted focused loss, the backward loss function (during backward propagation) is dY = W⊤. {γYilog(Yi) + (Yi − 1)} [T(1 − Yi)γ] (5.7)

The number of calculations is not much enhanced when W is a column vector (size equal to number of classes) [19].

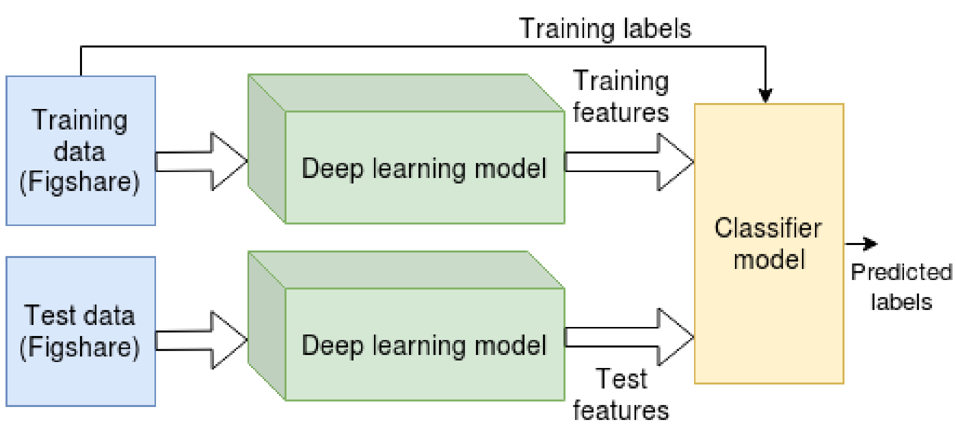

Figure 5: Overall framework for brain tumour classification

Deep Feature fusion

Deep feature fusion in image processing

might mean combining deep features with hand-crafted or traditional image attributes, or combining deep features that were retrieved using several deep learning models. In recent research, CNN properties are combined with texture and form data to identify breast cancer in mammograms. The hybrid feature vector enhanced an ELM classifier's performance. For sentiment analysis, a hybrid deep learning model was put forward, in which long short term memory (LSTM) networks caught characteristics with long-term dependencies while CNNs captured local picture data. Once again, scholars had a somewhat different viewpoint on deep feature fusion. Three distinct levels of a transfer-learned feature the state-of-the-art performance in scene recognition is attained by concatenating and classifying Google Net using SVM.

However, in order to address issues with data imbalance, the deep feature fusion investigations used resampling approaches. The sample strategies comprised modified closest neighbors and random oversampling or under sampling. Due to data limitations, under sampling is not appropriate for medical applications, while oversampling only slightly improves performance [20]. This thesis study approaches deep feature fusion from a somewhat different angle. The approach makes use of the same CNN for three separate models, each of which is trained using a different loss function and the same training data. The goal is to use a shift in loss functions to take advantage of the variations in learning behaviors. The fused feature vector is created by extracting features from each model and fusing them together using linear concatenation. F(j) = [F1(j), F2(j), F3(j)] (5.8) yields the fused feature vector of the jth sample, where F1(j), F2(j), and F3(j) are the row-wise feature vectors taken from CNN trained with L c e, L w c e, and L w f, respectively. A classifier model receives the training set's fused feature vector together with its class labels. The classifier models used in this investigation are KNN and SVM.

Table3: Experimental hyper para meters for the deep learning models

Model	**Hyperpara meters**	**Values**
Designed deep CNN	Initial learning rate mini-batch size learning algorithm loss function maximum epochs L2 Regularization factor	0.001128Adam cross entropy 300.0001
Transfer learned Google Net	initial learning rate mini-batch size learning algorithm loss function maximum pochs learning factor @ F C layer L2 Regularization factor	0.000330Adam cross entropy10100.0001

Majority voting on classifier predictions

When using ensemble voting approaches, the majority vote among the choices made by several classifiers determines the test sample's final prediction. Combining the predictions of weak learners is the aim of ensemble classifier configurations. The ensemble techniques of bagging and boosting have been investigated on a variety of image classification applications. For instance, random forest ensemble-based classification methods have proven effective for hyper spectral pictures in remote sensing. For the classification of mammograms, ensemble methods outperformed single classifiers in the medical field.

Although inspired by ensemble classifiers' effectiveness, this thesis offers an alternative to majority voting. This experiment uses three distinct feature sets, each of which is fed into the same classifier. the ensemble voting method for classifying different feature sets. The same CNN trained with different loss functions is used to extract each feature set. In particular, the goal is to combine the weak characteristics that were individually learnt on various loss functions.

Table 4: Experimental hyper para meters for the classifier models

Model	Hyperpara meters	Values
SVM	Model sub-type loss function coding learner kernel regularization solver	ECO Chinge one- vs -all SVM linear L2 BFGS
KNN	Number of neighbours, *k* distance	49Euclidean

Deep feature fusion and classification

The studies examine the effects of employing fused feature vectors and the classifier's performance on various CNN feature sets (trained using distinct loss functions). An SVM classifier records an accuracy of 93.8% for the features taken from the CNN based on cross-entropy loss, and the computed F-score (average) is 93.0%. Using features produced by CNN models trained with the other loss functions, classification tests were conducted again. Thorough discussion of the experimental findings. CNN trained using class-weighted focal loss (Lw f) outperforms models trained with alternative loss functions, such as Lce and Lwce, among the independent feature extractors. A significant increase in classification in terms of overall accuracy and F-scores for meningioma is seen when CNN is trained using (Lw f).Notably, pituitary tumors have a somewhat impacted F-score. Using fused deep features from the CNN models each of which is trained using a distinct loss function the trials were conducted again. The findings of the experiment show that combining any two or more deep characteristics improves the tumor categorization overall. Deep feature fusion significantly improves performance across all tumor classifications. The best results are obtained by combining features from CNN models based on Lce and CNN models based on Lw f. The enhancement of performance measures suggests that the suggested merging of deep characteristics will result in a more precise and efficient characterization of brain tumors.

Experiments

This section, which is divided into two sections according to the tests carried out, gives the relevance of various loss functions on the CNN properties. Initially, tests limited to the suggested deep feature fusion approach demonstrated the importance of deep feature fusion in the categorization of brain tumors. Second, tests of the suggested majority vote system for better classification of brain tumors. The holdout test validation process is followed in all of the experiments that are shown here. After testing with values in the range (1.2, 2), the hyper-parameter γ (in Lw f) is heuristically adjusted to 1.3 in the set of tests. While a lower number ignores the designated focusing function, a bigger value is thought to have an impact on convergence.

Conclusion

This study presents a multi scale deep learning approach for the automated classification of brain tumors from MRI scans, demonstrating improved accuracy and robustness compared to conventional single-scale models. By capturing both coarse and fine-grained image features through multiple resolution pathways, the proposed model effectively differentiates among glioma, meningioma, and pituitary tumors. The comprehensive evaluation shows that multi scale architectures can significantly enhance diagnostic performance, providing a reliable and scalable solution for clinical decision support. Future work will focus on expanding the model to include additional tumor subtypes, integrating multimodal imaging data, and validating the system in real-world clinical settings to support its deployment in healthcare environments.

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