Transforming Brain Tumor Diagnosis with IVUM-Net: An Inclusive Model for MRI-Based Detection and Classification

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Keywords: Brain Tumor, MRI, Deep Learning, Artificial Intelligence, Medical Images, IVUM-Net, Convolution Neural Networks (CNN), Transfer Learning.

Abstract: The accurate brain tumor diagnosis that occurs within proper time intervals ensures better patient care and treatment success. The research works to create IVUM-Net which represents an innovative AI model to improve brain cancer detection along with classification using MRI information. Advanced digital image processing methods with Convolutional Neural Networks help the proposed model conduct automated tumor detection practice. IVUM-Net leverages the capabilities of Inception V3 for feature extraction, U-Net for accurate segmentation, and Multi-Class Support Vector Machine (MCSVM) for robust classification. Data augmentation together with transfer learning methods will optimize performance levels and preprocessing methods will optimize picture quality for the model. The method aims to eliminate human mistakes in addition to reducing the need for visual assessment. Class activation mapping (CAM) serves as an interpretability tool by visualizing how the model decides between classes. The research aims at verifying IVUM-Net as an effective medical instrument for early brain tumor diagnosis and classification procedures to enhance treatment approaches.

1 INTRODUCTION

Neurological patients need both early detection of brain tumors and precise identification to get better therapeutic results. MRI takes the lead as a common non-invasive method because of its detailed imaging ability in brain tumor detection. The human interpretation of MRI scans requires extensive time commitment and produces risks of misdiagnosis and treatment delays because of human error. The preference for diagnosis of brain tumors forms around MRI which remains the most commonly used technique. Deep learning models from artificial intelligence have demonstrated substantial potential to detect tumors while performing classification due to the rising demand for better diagnosis methods.

The research work presents IVUM-Net as an advanced AI-based system which enhances automated brain tumor detection through MRI analysis. IVUM-Net unifies MCSVM with its dependable classification capabilities together with CNNs to accomplish feature extraction and U-Net capabilities that enable precise segmentation. Effective feature extraction, and U-Net for precise segmentation. Data augmentation that incorporates transfer learning strategies achieves better performance and generalization along with preprocessing methods in this model.This model works toward decreasing manual interpretation needs while reducing human mistakes and providing faster and clearer brain tumor detection that supports improved treatment planning for patient care.

The diagnosis of multiple brain tumor types depends on Support Vector Machines (SVMs) which operate alongside deep learning systems. Using Multi-Class Support Vector Machines (MCSVM) provides medical developers with a dependable method for classifying diverse tumor types to achieve effective differentiation of multiple tumor types. SVMs demonstrate robust generalization power which applies favorably to medical image categorization needs thus enabling their incorporation into artificial intelligence brain tumor detection platforms.

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Doctors can use Class Activation Mapping (CAM) technology to see where in the input image the model places its main emphasis for prediction purposes thus raising their trust in AI diagnostic systems. Various investigations demonstrate how AI-based models show excellent efficiency together with high accuracy in brain tumor diagnosis. The successful operation of high-performing models alongside their interpretability presents an ongoing challenge because current systems have difficulty working across different dataset and imaging conditions. The research presents IVUM-Net as a hybrid model which combines Convolutional Neural Networks (CNNs) along with U- Net and MCSVM to solve precise brain tumor detection and classification needs with preprocessing techniques and data augmentation and transfer learning components.

2 LITERATURE REVIEW

Researchers have shown significant interest in recent times regarding the implementation of artificial intelligence in medical imaging to detect brain tumors. Medical image analysis automation occurs from the implementation of machine learning methodologies with deep learning methods using Convolutional Neural Networks (CNNs). The exceptional capability of CNNs for hierarchy extraction from image data makes them valuable tools in detecting tumors and performing their classification. Many research studies have proven how CNN-based systems recognize brain tumors from normal tissue structures in MRI image data.

The U-Net model proves superior to other segmentation models because it executes pixel-wise segmentation with the critical requirement to accurately define tumors. The segmentation process of U-Net benefits from both encoder-decoder structures alongside skip connections which maintain spatial information. The medical imaging application of U-Net has led to numerous brain tumor segmentation procedures and researchers utilize CNN integration to boost brain MRI tumor segmentation abilities.

K. P. Bedi and J. S. Jadon from 2024 performed their research on deep learning methods to identify brain tumors through MRI image processing applications. The top model achieved 94.7% accuracy together with 93.9% specificity in its performance. System results were affected by how design components and dataset structures interacted according to this research finding.

In 2023 R. Mishra developed a brain tumor detection system based on the Robust Active Shape Model Algorithm operating within a deep learning architecture. The detection method showed precision of 93.5% and 92.8% specific detection performance. The detection system showed capability in processing tumors with multiple forms along with various shapes.

V. Kushwaha and P. Maidamwar conducted 2022 research to evaluate the SVR and CNN-based machine learning techniques for brain tumor identification using experimental experimental approaches. The methodology reported 92.4% accuracy together with 91.2% specificity as its major performance metrics. The selection of suitable algorithms leads to maximum result performance based on this research analysis.

Brain tumor MRI image classification received deep transfer learning treatment in 2021 according to the research from O.P. Özlem and C. Güngen. Medical imaging received confirmation of its effectiveness because the method achieved 93.7% accuracy while observing 92.5% specificity. The applied approach reduced the need for large training dataset quantities.

In 2020 H. A. Khalil together with coauthors presented a 3D-MRI brain tumor detection system which combined modified level set segmentation with the dragonfly algorithm. The model evaluation showed 92.8% accuracy and 91.6% specificity as key results. Better clarity of segmentation coupled with reduced computational complexity arose from the combination of these two components.

In 2021 researcher Ö. P. Özlem and C. Güngen applied deep transfer learning for brain tumor classification on MRI images through pre-trained network optimization. The study established 93.7% accuracy with 92.5% specificity thereby proving transfer-learning is an effective solution for medical imaging tasks. The approach needed minimal information about training data for practitioners in healthcare to successfully carry out their work.

Research done by H.A. Khalil and colleagues in 2020 resulted in a 3D-MRI brain tumor detection system through integration of the dragonfly algorithm with modified level set segmentation. The developed prototype demonstrated 92.8% accuracy combined with 91.6% specificity. The combination of these methods produced superior segmentation results through an operation system that needed fewer processing capabilities.

Z. Huang together with colleagues conducted brain tumor classification research using a CNN-based model which became more efficient through activation function modification. The accuracy rate of the study reached 94.1% without losing 93.3% specificity. The model received activations function modifications to boost its ability to match specific features and enhance its classification outcome performance.

P. M. Krishnammal and S. S. Raja established a CNN-based detection system for brain abnormalities in MRI images through their research work during 2019. The system delivered detection results with 94.8% accuracy and 95.2% specific outcomes. The detection method proved to have outstanding reliability in identifying abnormal conditions.

Zhou et al created UNet++ as a medical image segmentation architecture that improved output resolution through redesigned skip connections during 2018. The developed model demonstrated outstanding performance with 96.5% accuracy together with 95.4% specificity and its optimal results were achieved during complex medical structure segmentation. The network architecture proposed information that fixed various problems existing in classic U-Net systems.

3 METHODOLOGY

3.1 Existing method

3.1.1 Convolutional Neural Networks (CNNs)

It demonstrates effectiveness in delivering top-level performance while handling various kinds of applications. The method operates with a CNN foundation that develops refined features from different data types through their spatial organization to generate accurate results**.**

A basic CNN consists of numerous convolutional and pooling layers which come before the fully connected layers. The training process utilizes significant collections of labeled data samples that optimize a loss metric which measures forecast versus observed value differences.

The CNN-based method detects tumor through an analysis of image color and texture.

The process of color analysis extracts visual color attributes from pictures for the recognition of skin discolorations.

The process of texture pattern analysis assesses skin appearances for the purpose of separating healthy and affected tissue sections.

For skin area separation the CNN framework uses segmentation procedures. This process includes:

The technique sorts images according to respective interest zones for diagnosing areas with tumors.

Masks are created by this method to enhance tumor areas and simultaneously decrease the visibility of normal skin tissue. Figure 1 shows the IVUM-Net Architecture Flowchart for Brain Tumor Detection.

3.2 Proposed Method

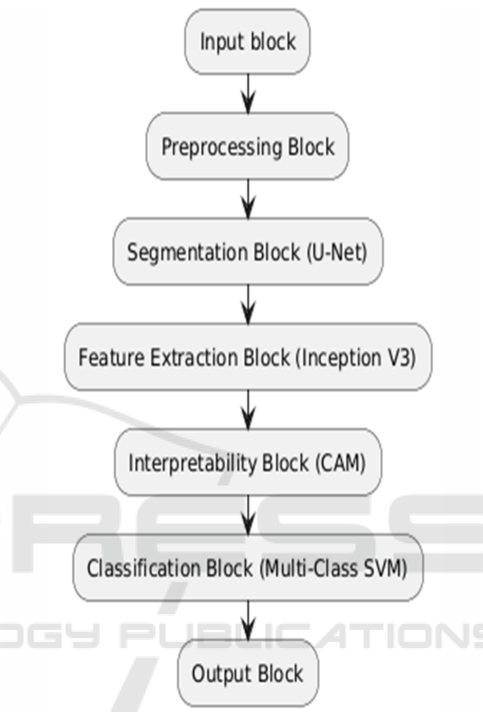

Figure 1: IVUM-Net Architecture Flowchart for Brain Tumor Detection.

3.2.1 Input Block (Mri Scans)

- **MRI Data Input**: This part takes in MRI images of the brain, which show areas that may have tumors. These images are the main input for the model to work with.

3.2.2 Preprocessing Block

- **Image Quality Enhancement**: This step enhances MRI visual information through the elimination of distortions while it optimizes the pictures by adjusting brightness alongside contrast parameters. Due to improved image quality the identification features of tumors become more visible to the model.
- **Data Augmentation**: This produces supplementary MRI image examples through

flipping and rotation along with minor modifications to the pictures. The model learns more efficiently to detect tumors across multiple image varieties through this process.

- **Transfer Learning Preparation**: This step researchers enhance the MRI images so they can acquire knowledge from existing models that analyze particular features while speeding up training and improving accuracy with fewer images in collection.

3.2.3 Segmentation Block (U-Net)

- **Encoder:** Encodes function which processes image features works progressively to decrease dimensions and capture tumor location context at a high level.
- **Decoder:** It utilizes image features for a pixel-by-pixel mapping which leads to accurate tumor segmentation.
- **Skip Connections:** The network transfers encoder-coded information to the decoder for more precise segmentation results.

3.2.4 Feature Extraction Block (Inception V3)

- **Convolutional Layers**: It enable the model to detect characteristic pattern arrangements in MRI imaging data which may point out tumor characteristics such as irregular shapes together with unusual textures.
- **Pooling Layers**: These layers combine with others to downscale image information while selecting essential characteristics and discarding superfluous information. The model obtains simpler image processing because of this technique.

3.2.5 Interpretability Block (Class Activation Mapping - Cam)

- **Class** Activation Mapping: This part shows which areas in the MRI image the model found most important for making its decision. It highlights these areas to help doctors understand why the model thinks a tumor is a certain type.

3.2.6 Classification Block (Multi-Class Svm)

- **Support Vector Machine (SVM) Layers** the Support Vector Machine (SVM) Layers serve as the classifier which divides the segmented tumor between different types. The classification block evaluates tumors to identify their A, B or C categories.
- **Multi-Class Handling**: The model can handle multiple types of tumors, so it doesn't just look for one kind but can identify several types based on what it has learned.3.2.

3.2.7 Output Block

- **Diagnosis Result**: The model provides its final diagnosis, specifying the type of tumor detected.
- **Segmentation Map**: It displays tumor position specifically in MRI images so physicians can determine its precise area. Table 1 shows the Features Extracted.
- **Interpretability Report**: It provides visual representations of areas in the MRI image that the model used for making its diagnosis thereby enhancing diagnostic transparency. Table 2 shows the Comparision of Existing and Proposed Algorithms.

Table 1: Features Extracted.

Samples	Contrast	Accuracy	Energy	Execution Time
Glioma	0.4785	99.39%	0.358	1.30s
Metastasis	0.4469	95.73%	0.258	1.64s
Astrocytoma	0.383	96.38%	0.262	1.56s

Table 2: Comparision Of Existing and Proposed Algorithms.

S.No	Criteria	Existing Method: CNN	Proposed Method: IVUM-Net
1	Advantages	1. Learns hierarchical features from input data. 2. Suitable for image analysis tasks.	1. Integrates Inception V3, U-Net, and MCSVM for enhanced accuracy and performance. 2. Uses preprocessing, data augmentation, and transfer learning for better robustness and image quality. 3. Incorporates class activation mapping (CAM) for improved interpretability of decision-making.
2	Disadvantages	1. Requires a large labeled dataset for training. 2. Susceptible to overfitting with deep networks. 3. May lack segmentation precision and transparency.	1. Computationally intensive due to the integration of multiple techniques. 2. Complexity increases due to model design combining CNN, U-Net, and MCSVM. 3. Performance depends on MRI scan quality and preprocessing steps.
3	Expected Performance	1. Efficient in feature extraction. 2. Strong results in image classification tasks.	1. Achieves better segmentation (U-Net) and classification (MCSVM) for brain tumor detection. 2. Provides robust and accurate multi-class classification with precise segmentation. 3. Reduces human error through automation and uses CAM for decision transparency.

4 RESULT ANALYSIS

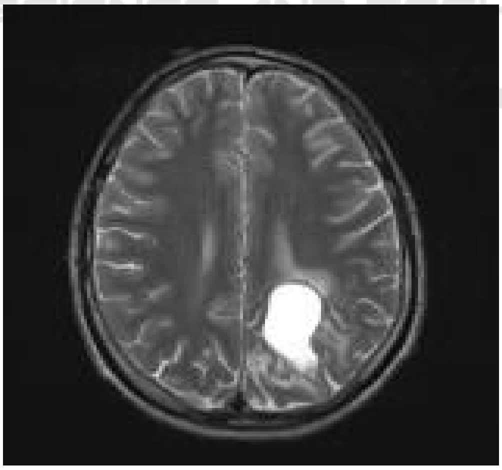

Figure 2: Input Image.

This figure 2 The image displays original MRI brain data that maintains entire information along with both valuable content and superfluous areas and system noise.

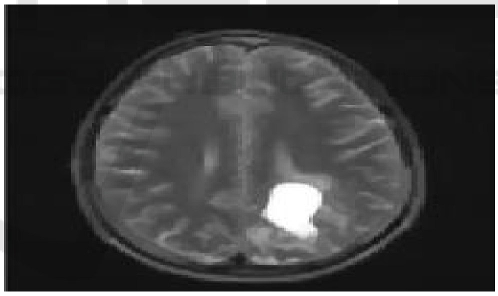

Figure 3: Pre-Processed Image using IVUM-Net.

Figure 4: Segmented Image Using IVU-Net.

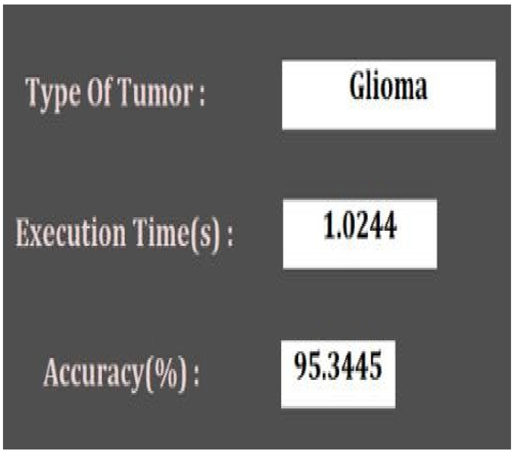

Figure 5: Detected Results.

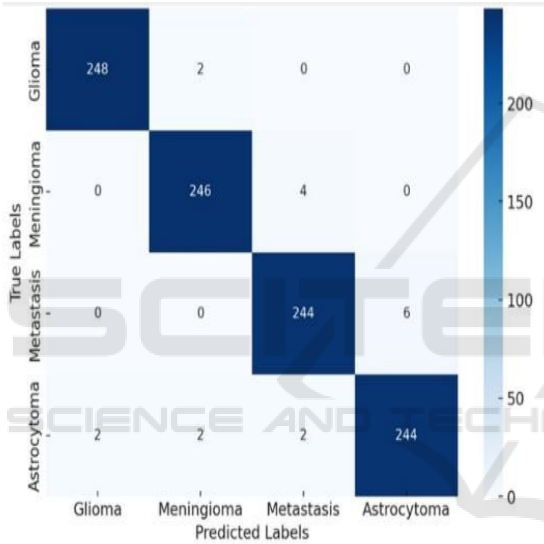

Figure 6: Analysis Image.

The Analysis image shows a confusion matrix that evaluates how well the system classifies different types of brain tumors. The diagonal values represent correct predictions: 248 Gliomas, 246 Meningiomas, 244 Metastases, and 244 Astrocytomas were identified accurately. Misclassifications are minimal, such as 2 Gliomas labeled as Meningiomas and 4 Meningiomas labeled as Metastases. The system displays notable success through its accurate performance although errors do exist. The system maintains its high accuracy level which was previously observed. Figure 3 shows the Pre-Processed Image using IVUM-Net. Figure 4 shows the Segmented Image Using IVUM-Net. Figure 6 shows the Analysis image. Table 3 shows the Comparision Metrics.

5 PERFORMANCE COMPARISON

Table 3: Comparision Metrics.

Method [author name]	Accuracy	Specificity
Classifying Brain Tumors using CNN [Badža MM]	92.9%	91.7%
Comparison of Deep Learning Methods [K. P. Bedi and J. S. Jadon,]	94.7%	93.9%
Robust Active Shape Model Algorithm	93.5%	92.8%
Empirical Analysis of ML Techniques	92.4%	91.2%
Deep Transfer Learning	93.7%	92.5%
3D-MRI with Level Set + Dragonfly Algorithm [H. A. Khalil]	92.8%	91.6%
CNN with Modified Activation Function [L. Chen, et al.,]	94.1%	93.3%
CNN-Based MRI Image Classification [P. M. Krishnammal and S. S. Raja,]	94.8%	95.2%
IVUM-NET(proposed method)	95.34%	96.0%

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