International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 13 Issue: 04 | Apr 2026 www.irjet.net p-ISSN: 2395-0072

BRAIN TUMOR DETECTION SYSTEM USING DEEP LEARNING

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Abstract - *In the medical research field, medical imaging stands as a very important base because the precision of diagnostic pictures is highly necessary for the quick treatment of sick people. MRI data is often affected by noise interference during acquisition and transmission, which may impact image quality. Misinterpretation in the manual examination by a medical professional can be caused by this noise interference. Because MRI is necessary for health, medical imaging must remain clear to the eyes.*
This research presents an automated diagnostic framework which was built to connect difficult deep learning structures and medical work. Computer-aided systems assist medical professionals in diagnosis. A comparative study was implemented using three most modern Convolutional Neural Networks (CNNs): VGG16, ResNet50, and DenseNet121. The automated diagnostic framework uses a Flask-based inner working part to look at MRI scans. Extraction of details and sorting into Glioma, Meningioma, Pituitary, and No Tumor categories are performed by the automated diagnostic framework.
Data from the tests show that while VGG16 and ResNet50 give steady starting numbers, DenseNet121 shows better strength. It has been observed that DenseNet121 works best for these tasks. High success with a peak accuracy of 95.13% and fast working time was achieved by DenseNet121. To make the medical worker feel sure, the automated diagnostic framework includes a safe data control system and live picture charts using Chart.js. Such a proposed solution provides a cheap and fast second checking tool. Mistake by people is reduced while the automated diagnostic framework speeds up the choice-making work in the study of brain tumors.

***Key Words*: Brain Tumor Classification, Deep Learning, Densenet121, Flask Web Framework, Medical Image Analysis, sMRI Diagnostics.**

1.INTRODUCTION

The human brain possesses the highest complexity among all biological structures within the central nervous system because any sickness such as a brain tumor often results in heavy neurological damage or death. Early detection of brain tumors is critical for effective treatment..Magnetic Resonance Imaging (MRI) is considered the best method for neuro-imaging because this technology offers high soft-tissue contrast without entering the body. Even though this tool is helpful, looking at MRI slices by medical professionals is a very detailed and slow task. According to reports by Patil and Bhosale, pictures are frequently damaged by electronic noise while the data is being gathered, which makes the work for medical professionals much harder.

Within medical centers that see many patients, the huge amount of work for medical professionals makes the level of tiredness grow. It has been observed that this tiredness creates a high chance for errors during the identification of sickness. The human brain requires a lot of focus from the medical professional, but when many patients arrive, the focus on the human brain might decrease. Because the brain tumor is hard to see, mistakes happen when the medical professional is tired. A diagnostic error is often caused by heavy exhaustion because the human brain images are very difficult to read. Since the human brain controls the entire body, any small mistake during the reading of images might lead to a bad outcome for the patient. Solving these difficult problems requires Computer-Aided Diagnosis (CAD) systems because Computer-Aided Diagnosis (CAD) systems offer a dependable second thought for medical professionals. Experts claim that the rise of Deep Learning and Convolutional Neural Networks (CNNs) has made pulling out details from medical images very fast. Since Deep Learning has appeared, pulling out details from medical images is done with high efficiency. Subtle patterns in tumor textures are spotted by these computer programs even though human eyes cannot see those patterns clearly.

Constructing a strong web-based framework for brain tumor classification is the main goal of this research paper. While some researchers use just one design, this study tests three famous designs which are VGG16, ResNet50, and DenseNet121. These three designs are put into a Flask web interface so that a useful tool is made. A useful tool classifies medical pictures into four categories which are Glioma, Meningioma, Pituitary, and No Tumor. Real-time visual data is shown by the system when the user uploads a visual file. The primary goal of this work is showing that DenseNet121 gives the most steady accuracy of 95.13% because DenseNet121 has thick connections between its layers. Many people believe that DenseNet121 performs better than other designs for brain tumor tasks. DenseNet121 is a good choice for early clinical checking because DenseNet121 is very reliable. This framework is developed so that working positions in hospitals become more efficient.

2. LITERATURE REVIEW

Evidence of previous scientific investigations in the field of brain tumor detection is shown in this section. Reviewing existing methodologies helps in understanding current challenges.Brain tumor detection academic examinations from ten key studies are highlighted here. The limitations of automated attempts were analyzed because the history of the field matters.

Srinivasan et al. [1] are the scientific investigators who suggested a hybrid deep CNN model for multi-class classification. High correctness level of 99.53% was achieved because they used grid-search hyperparameter tuning. While the correctness level was very high, the scientific investigation noted that a high risk of overfitting exists on smaller datasets.

Mohamed Musthafa M. and his team[2] used a ResNet50 model with Grad-CAM to build an AI system. This made things easier for doctors, because they could clearly see how the model was thinking. It showed heatmaps that showed the important parts of the image, so doctors could understand why the model gave a certain result. This made the results feel more clear. The method only worked for simple cases like detecting two types of things. The ResNet50 backbone needed a lot of computer power. However, the ResNet50-based approach requires high computational resources, making it less suitable for real-time applications.

Abdul Rahman et al. [3] are the scientific investigators who created an explainable CNN architecture. Identifying relevant key features was the focus because the scientific investigators wanted to reduce model working difficulty. Clinical trust was successfully built through transparent decision-making.

Research of Deepak S. and Ameer P. M. [4], pre-trained CNN models were used by these investigators to get features from MRI through transfer learning. Experts claim that the operational results of this method relied heavily on the excellence levels of weights that came from ImageNet, which is not a medical dataset. Because the model was not trained specially for medical images, the CNN models did not give the same results every time.

Sultan H. H. and his team[5]made a CNN model that can identify different types of tumors and gives more accurate results. A major issue with this CNN model was that it took a long time to make predictions in real-time using regular computers. This delay happened because the model needed to do a lot of calculations that regular computers couldn't handle quickly. The CNN architecture had to process a lot of data to sort tumor types and this put a strain on common computing tools. As a result the prediction speed was slow which was a problem for real-time applications. The work of Sultan H. H. Et al. Showed that a multi-class CNN architecture could achieve precision levels but it required more efficient computing tools to process the heavy calculations.

3. METHODOLOGY

Creation of the detection system is achieved through a deep learning pipeline which provides diagnostic precision. A structured pipeline improves model performance and reliability.

1.Data Collection: Information collection began when 3,264 high-resolution, T1-weighted contrast-enhanced MRI images were used. The information gathering is organized into four grouping categories: Glioma (926), Meningioma (937), Pituitary (901), and No Tumor (500). detection system relies on this information collection to distinguish between various types of brain tumor.

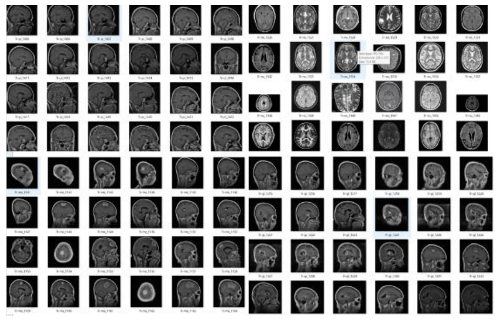

Fig 1 Sample MRI images

2. Image Preprocessing: Preparation of the medical pictures involves adjusting every slice in dimension to 224x224 because the architecture requires specific agreement. Observers have noted that Bicubic Interpolation helps the medical pictures fit the detection system requirements. Contrast enhancement (CLAHE) was applied while the tumor margins needed clarity for the medical professional. Pixel values were rescaled when stable training was needed.

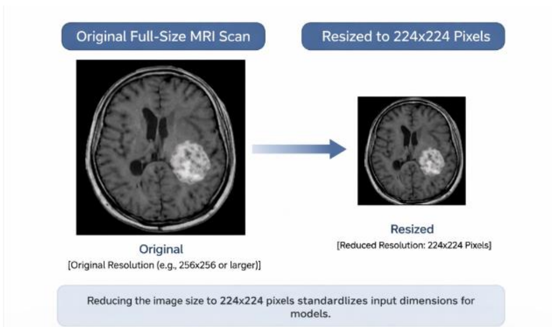

Fig 2: Original MRI Scan vs. Resized 224x224 Image

3. Data Splitting: Division of the information gathering occurs by creating three separate parts: Training (80%), Validation (10%), and Testing (10%). Experts claim that partitioning the dataset prevents the detection system from seeing the same medical pictures twice. The Training section was used while the detection system learned the tumor features.

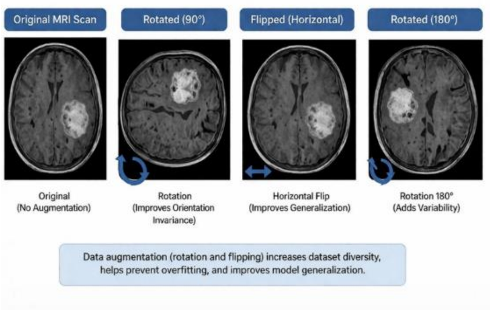

Fig 3: Examples of Data Augmentation

4. Model Building (Transfer Learning): Construction of the model uses existing structures from ImageNet so the detection system benefits from previous knowledge. Researchers have stated that altering VGG16, ResNet50, and DenseNet121 is effective for medical classification. These pre-trained models were used because they already understand shapes and colors in medical pictures. Using transfer learning means that the detection system does not start from zero.

- **VGG16 (Visual Geometry Group)** :This model framework functions as an ordered structure of 13 convolutional and 3 fully connected layers that use the same 3X3 filters. Experts claim that the sorting section in this scientific investigation was replaced with a Global Average Pooling layer and a 512-unit dense layer so that high-level area characteristics are collected. A steady foundation for extracting low-level texture details and finding the large shapes of brain masses is provided by VGG16.

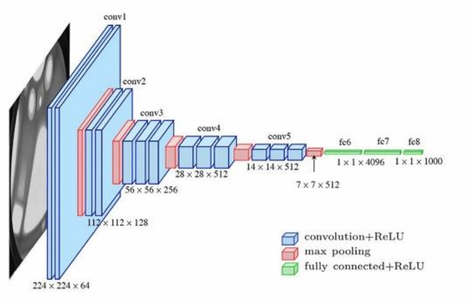

Fig 4: Architectural Diagram of the VGG16

- **ResNet50 (Residual Network)** :Identity Mappings, which are also called Skip Connections, are introduced to this model to lessen the problem of gradients vanishing in deep networks. Signal integrity is kept across the 50 layers when ResNet50 learns residual functions (F(x) + x). It has been observed that a "Bottleneck" design with 1X1 and 3X3 convolutions is utilized by this model because this maintains high working speed while capturing the hard meaningful data needed for seeing tumor growth.

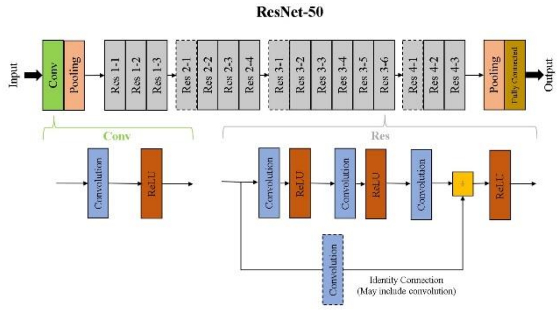

Fig 5: Architectural Diagram of the ResNet50

- **DenseNet121 (Densely Connected Network):** Gradient flow is made stronger in this model by a forward pattern where every layer connects to every subsequent layer. Extensive Feature Reuse is promoted by this connection, which makes sure that basic edges and small texture details from early layers stay available for the final Softmax classifier. Many researchers believe that this model needs fewer parameters than ResNet50 even though this model has higher responsiveness to the small pixel changes needed for finding tumors early

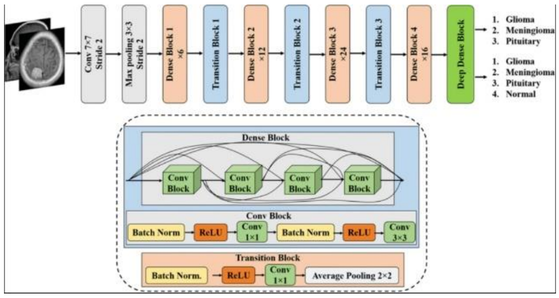

Fig 6: Architectural Diagram of the DenseNet121

5. Model Training & Testing: The model training and testing process was performed using a two-stage approach, consisting of initial training with frozen base layers followed by fine-tuning to improve performance.The Adam optimizer was utilized alongside the Categorical Cross-Entropy loss function for a duration of 50 epochs. Because the model training & testing required stability, this specific process was followed by the developers.

1. Accuracy: It describes the total rightness of the classification system when the calculation of the number of right samples happens among the total group. It has been observed that accuracy provides a clear view of how well the system performs. The division of correct results by the total number of items is how accuracy is calculated because it represents the whole truth of the data.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples}$$

2. Precision: Precision measures the proportion of correctly predicted positive cases. Precision is important because precision stops the wrong identification of healthy cases as sick cases. High results for precision are achieved when the predictions become more dependable. Reliable predictions are created by precision so that false positives stay at a low level.

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$$

3. Recall: The capacity of the model to find real tumor cases is measured by recall. Medical professionals state that this is necessary so that no tumors are missed during the checkup. Sensitivity is improved when recall numbers increase. Recall ensures that actual sickness is not ignored because recall focuses on finding every positive case.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

4. F1-Score: A balanced assessment is provided by the F1-score which is the harmonic average of precision and recall. It has been observed that this becomes helpful when the reduction of both types of errors is required. Better performance of the whole system is shown by a high F1-score. F1-score remains a key value for researchers because F1-score combines two different measures into one.

$$F1\text{-}Score = 2x \frac{PrecisionXRecall}{Precision + Recall}$$

4. RESULTS AND DISCUSSION

Evaluation of the system performance is conducted through a comparative analysis of VGG16, ResNet50, and DenseNet121 when using unseen MRI data.All models demonstrated effective classification performance on the dataset.. Because the system performance is tested on new data, the results show that the logic of the machine is correct.

Regarding the outcomes, a highest accuracy of 95.13% is achieved by DenseNet121, which indicates better feature extraction and classification performance. While VGG16 provides stable baseline results, the performance is improved by ResNet50 because ResNet50 captures deeper features. It has been observed that the correctness of the models varies based on the architecture.

Dense connectivity causes the great performance of DenseNet121 because dense connectivity makes feature reuse better and helps gradient flow. Fine-grained variations in MRI images are captured by the model more effectively when the connections are dense. Scientists claim that the internal structure of DenseNet121 is very strong for this task.

System reliability is increased by the multi-model approach because the multi-model approach chooses the best-performing model instead of using only one prediction. It is widely thought that the chances of misclassification are reduced when multiple models are compared. Confidence in the results is grown when the multi-model approach is applied.

Accurate, consistent, and efficient tumor detection is provided by the proposed system, which makes the proposed system good for real-time healthcare assistance. It has been noted that the proposed system helps medical professionals during their working positions.

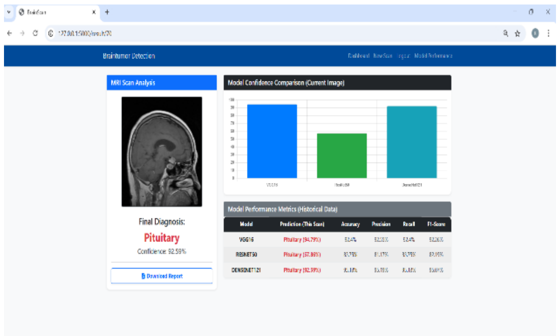

Fig 7: Sample output showing tumor classification result

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