

# A Deep Learning Approach for Brain Tumor Detection from MRI Scans Using Attention-Guided CNNs

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**Abstract**—Brain tumors are life threatening conditions of the nervous system, in which prompt diagnosis is important to treat successfully. MRI is one of the methods of diagnosing brain abnormalities but manual interpretation of MRI scan is often time-intensive and subject to human variability. This paper presents a deep learning-based learning method on the basis of a Convolutional Neural Network (CNN) with added attention mechanism. CNN automatically learns spatial patterns and their relevant features based on image data, while the attention mechanism enables the model to focus on the most relevant regions, improving detection performance. The model is trained and evaluated on a publicly available Brain Tumor MRI dataset consisting of 3,264 images categorized into four classes: glioma, meningioma, pituitary tumor, and no tumor. The proposed model provides better classification than conventional methods as it effectively learns discriminative features from MRI images and can help clinicians make more diagnostic and fast decisions.

**Keywords**—Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Convolutional Neural Network (CNN), Deep Learning, Attention Mechanism, Medical Image Classification.

## I. INTRODUCTION

Brain tumors are malformations of brain tissues that consist of cells that may seriously impair normal brain functions [1]. These tumors can be benign or malignant, although both can cause severe neurological effects, depending on their size, location, and rate of growth [2]. Brain tumors need to be detected early to be treated properly and significantly improve patient survival rates. Magnetic Resonance Imaging (MRI) is a common diagnostic imaging that has been adopted as a reliable method because it can generate high-resolution images with distinct contrast between various soft tissues [3].

There are benefits of MRI but interpreting of MRI scans is not an easy task and need to be done manually, taking long and expert knowledge. Radiologists are asked to review several cuts of MRI scans and that may result in fatigue and inconsistency in diagnosis [2]. Even minute variations in the appearance of tumors, uneven edges as well as noise in images compounds the challenge of proper detection.

The Conventional methods of brain tumor detection are mainly based on the image processing methods like threshold, segmentation and edge detection [4]. Although these techniques have a low level of noise, they are strongly sensitive in changes image intensity and noise, which reduce their reliability. By utilizing handcrafted elements, machine learning algorithms, such as Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) have enhanced the performance [5]. Such techniques however demand domain knowledge in the feature extraction and usually do not capture complex spatial patterns occurring in medical images.

In recent years, the new influencing trend in deep learning was the development of Convolutional Neural Networks (CNNs), which have turned out to be a valuable means of medical imaging analysis [6]. The CNNs are capable of extraction of hierarchical features through self learning of raw image information and eliminates manual feature engineering. This is because they are very appropriate in the analysis of complex MRI images and the patterns of tumors. Moreover, there are introduced attention mechanisms, which improve deep learning models in the sense that they allow them to pay attention to the most important parts of an image, thus increasing the classification accuracy [7].

Although deep learning-based tumor detection has made significant progress, the models currently used are high-computationally complex and lack interpretability, particularly when there are resource constraints. Besides, the performance of many methods cannot be used to effectively target tumor-relevant regions and achieve the best classification.

In this work, a CNN-based model is proposed that is combined with an attention mechanism to effectively detect brain tumours using MRI images. The proposed method aims to enhance feature representation by highlighting tumour-relevant regions, resulting in more reliable and consistent classification. The system is designed as a supportive tool to assist medical professionals in reducing workload and improving diagnostic accuracy.

## II. LITERATURE REVIEW

### A. Image Processing Procedures, Which are traditional

The initial techniques to identify brain tumor were primarily based on the conventional techniques of image processing; threshold based segmentation, edge extraction, and analysis through region-wise [4]. These techniques were to find the differences in pixel intensity in a bid to localize abnormalities in MRI images. Despite the fact that they provided a basic arrangement of tumor association, the performance was poor and limited in practical application since they are very sensitive to noises, shifts in picture contrast and inaccurate tumor forms. As a result, these methods are likely to deliver inconsistent and unreliable results utilized in medical data on the real world.

### B. ML Methods

Machine learning has introduced more advanced classification techniques. Common algorithms that have been used to classify the brain tumors include the Support Vector Machines (SVM), K-Nearest Neighbors (KNN), support tree, and forest algorithms [5]. These models were based on handcrafted characteristics including texture, form and intensity as obtained in MRI images. Even though machine learning methods yielded better results than the conventional methods, their performance highly relied on the feature extraction quality. Designing robust features required domain knowledge and extensive preprocessing, which limited scalability and adaptability.

### C. Deep Learning and CNN-based Methods

The advent of deep learning has entirely revolutionized the medical image analysis. Convolutional Neural Network (CNNs) based approaches have proved a strong effectiveness in the automatic extraction of hierarchical features applied directly to image data. In contrast to the classical machine learning techniques, CNNs do not require manual engineering of features and they are able to learn the complex spatial patterns inherent in MRI images. Some have recorded classification accuracies of over 90 percent with CNN-based models; therefore, they are a favourite in detecting tumors in the brain. The analysis of medical images has made great progress [8] [6] using CNN-based models.

### D. Attention based and advanced Models

The recent studies have been devoted to the enhancement of CNN performance by means of the usage of attention mechanisms. The attention-based models allow the network to concentrate on the most important parts of an image, which improves the representation of features and correct classification. These methods all come in handy especially with medical imaging, where the areas of tumors might only take a small part of the image. Besides, developed architecture and hybrid frameworks with CNNs and other deep learning methods have been delved to enhance even better robustness and generalization. Attention-based models also improve the performance of CNN by concentrating on the significant areas [7].

### E. Research Gap

Although there has been tremendous improvement, there have been some challenges seen in the current solutions.

Numerous deep learning models are highly complicated and need massive computational power, thus are challenging to execute on academic or resource-limited settings. Alongside, there are studies in which much of the attention is paid to obtaining high accuracy without clear and structured workflow structure of implementation and assessment. Thus, an easy-to-follow yet efficient model that provides the overall process of brain tumor detection and ensures high readability is necessary. The given work bridges this gap by coming up with a CNN-based model combined with an attention mechanism that offers the trade-off between accuracy, efficiency, and straightforwardness of implementation.

### F. Comparative Analysis

Over the years, several approaches have been proposed for brain tumor detection. Initial approaches used were predominantly based on conventional ways of processing images e.g., thresholding, edge-detection and image-segmentation [4]. Whereas these approaches offered a fundamental framework, they were very receptive to noise and image differences in the MRI images that led to reduced reliability. The later introduced machine learning algorithms are Support Vector Machines (SVM) and K-Nearest Neighbors (KNN) are used to improve classification performance [5]. Such methods were also moderately accurate (ranging between 80 and 88 per cent) but they were labor-intensive in terms of manually crafted feature extraction, necessitating domain knowledge. The progress of deep learning has resulted in the CNN-based models, which have significantly improved with automatic hierarchical features being learnt through MRI images [6] [8]. The accuracy of these models tends to be on the 90-92 range. The standard CNN models however consider all image pieces as equal and so may not be effective when the tumors only make up a small segment of the image. In the recent past, Vision Transformer (ViT) and other Transformer-based models have been utilized in analyzing medical images as well. The models are able to form global dependencies in images and have an accuracy of approximately 91-94, however the models needs large datasets and extensive computing capabilities. To address this limitation, attention-based mechanisms have been introduced, allowing the model to focus on the most relevant regions of the image [7]. The proposed CNN with attention mechanism achieves an accuracy of 93.3%, outperforming traditional and basic deep learning approaches.

**Table I:** Comparative Analysis of Brain Tumor Detection

Method	Approach	Accuracy (%)	Limitations
SVM / KNN [5]	Traditional ML	80–88	Handcrafted features, limited scalability
Basic CNN (Seetha & Raja, 2018) [8]	Deep Learning	90–92	Treats all regions equally
Vision Transformer (ViT) [3]	Transformer-based	91–94	Needs large data, high compute cost
CNN + Attention (Proposed)	Hybrid Deep Learning	93.3	Binary classification only

Methods

### III. DATASET AND PREPROCESSING

#### A. Dataset Description

The paper is devoted to the discussion of the brain Magnetic Resonance Imaging (MRI) data analysis in tumors. In contrast to geographical studies, the geographical area in this work is the sphere of medical imaging, MRI scans of a human brain. The use of MRI in the clinical practice is very effective as it helps to get a very detailed view of the soft tissue structure, and hence it is most appropriate to identify the presence of abnormality like brain tumors. The dataset of this work represents the heterogeneous collection of MRI-based images of the various tumor conditions along with the normal brain cases that creates the possibility of successful model training and testing.

#### B. Dataset Properties

The data-set used in this for study of the Brain Tumor MRI has been taken from Kaggle [9]. There are a total of 3,264 images of MRI has been classified into four different category that include: a glioma tumor, meningioma tumor, pituitary tumor and no tumor. The classes depict the variations of the brain tumors as well as normal brain images thus, the dataset is applicable for classification work. The data is separated into training, validation and testing sets in the proportions of 70%, 15% and 15% respectively. All MRI images are resized to 224 × 224 pixels to maintain a uniform input dimensions. The model parameters are learned using the training set, hyperparameter tuning is done using the validation set and evaluation of the overall performance of the model on unseen data is done using the testing set.

#### C. Dataset Preprocessing

To improve the accuracy and robustness of the model, a number of preprocessing steps are performed to refine the data

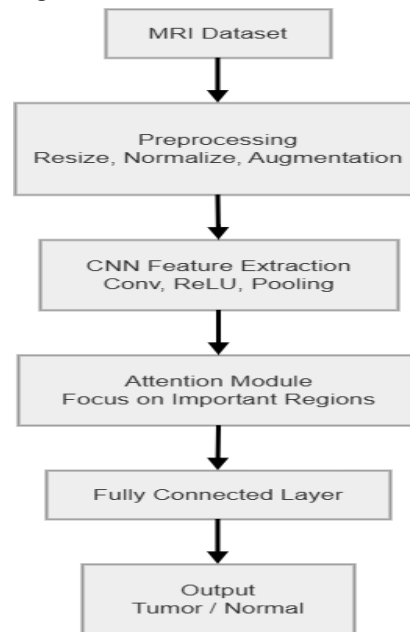
provided before putting them into the model. All MRI images are down sampled to a constant resolution to maintain a consistent input dimensions through all given samples. The values of pixel intensity are scaled to a standard range which assists with quicker and more consistent pattern convergence. Also data augmentation methods are used that are rotation and horizontal flipping along with brightness modification which will enhance diversity in the datasets and reduce the risk of over-fitting. These preprocessing stages will make sure that the data set becomes standardized and well-structured, consistent and can be used to train a deep learning model. The ample and proper data preparation plays an essential role in the improvement of its accuracy and resistance especially in the medical image analysis where such differences in quality and acquisition are usually present.

### IV. METHODOLOGY

#### A. Overview of the Proposed System

The created system will be based on a deep learning system that is applicable in the automated brain tumor detection of MRI images. The entire process comes into play by image preprocessing, CNN-based feature removal, attention-based feature refinement, and the ultimate classification. The MRI images are fed into the system and are predicted to be a tumor or not. In this paper, the multi-class dataset is reduced to two classes, with glioma, meningioma, pituitary tumor as one group, that is, tumor, and the other group, that is, no tumor. This simplification is useful in enhancing the efficiency of classification and minimizing the complexity of the models.

The whole process of the recommended system is reflected in Fig. 1.



**Fig. 1:** General architecture on brain tumor detection through CNN and attention mechanism.

Fig. 1. shows the preprocessing of MRI images followed by a forwarding of the processed images to CNN model to extract features. The attention mechanism is used to draw

significant areas of interest and ultimately, classification is done to ascertain the existence of a tumor.

### B. Image Preprocessing

Manipulation up to MRI images also provide uniformity and improvement of model performance. Images are also resized to a fixed size as well as normalized so that the pixel values do not exceed a standard range. The use of data augmentation like rotation, flipping and brightness adjustment is done to diversify the datasets and minimize over-fitting.

Normalization of the values of pixel intensity is determined as following:

Antecedent to feeding of the MRI images into the model, it is necessary to normalize the pixel values in such a way that the images depicting the sample images have the same scale. This will guarantee that the model learns quicker and enhances stability when learning.

$$X_{norm}(i, j) = \frac{X(i, j) - X_{min}}{X_{max} - X_{min}} \quad (1)$$

This equation scales the pixel values of the image between 0 and 1 by subtracting the minimum value and dividing by the range. It guarantees that all inputs images follow a consistent format and are normalized uniformly.

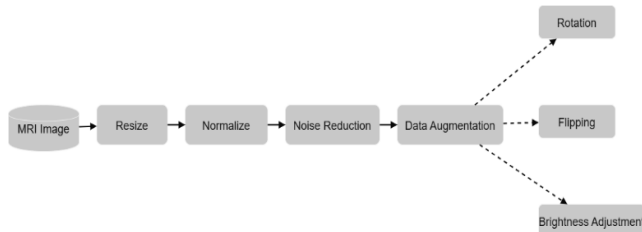
Data augmentation can be represented as:

Data augmentation is applied to normalized images to increase dataset's diversity and reduce over-fitting.

$$X_{aug}(i, j) = T(X_{norm}(i, j)) \quad (2)$$

Here, T represents transformation operations such as rotation, flipping, or brightness adjustment, which help in generating varied training samples.

The preprocessing pipeline is shown in Fig. 2.



**Fig. 2:** The steps of preprocessing and data augmentation that are used on MRI images.

Fig. 2 represents the preprocessing steps applied to MRI images before feeding them into the model. These steps include resizing, normalization, and data augmentation, which help in improving data quality and model generalization.

### C. Feature Learning by Attention

Attention mechanism is incorporated into CNN in a bid to increase the features representation. This process allows this model to target the most potential parts of the MRI image. The CNN model processes MRI images in multiple stages to learn important patterns automatically. In the first stages, the convolution layers obtain simple characteristics of the picture like edges and textures. These features are further grouped

together as the network gets more in depth, thus identifying more intricate features such as tumor deposits. The activation functions and pooling layers have a role in enhancing learning and lowering the computation complexity [6]. The attention mechanism also enhances the model as it enables the model to give more attention to the significant areas of the image as opposed to giving the same attention to all the regions of the image. This helps in better detection of tumor areas.

Convolution operation can be expressed as: The main step of CNN is the convolution operation during which the filters are developed and applied to an input image to identify the key characteristics of the image like edges and textures [6].

$$f(i, j) = \sum_m \sum_n X(i + m, j + n) \cdot W(m, n) + b \quad (3)$$

This equation represents how a filter (W) slides over the image

(X) to compute feature maps. The bias term (b) is added to adjust the output.

A non-linear activation function is applied using ReLU:

After convolution, a non-linear activation function is applied to introduce non-linearity into the model.

$$ReLU(x) = \max(0, x) \quad (4)$$

This function replaces all negative values with zero while keeping positive values unchanged, allowing the model to learn complex patterns.

To reduce spatial dimensions Pooling is used:

Pooling is used to reduce the spatial size of feature maps, which helps in reducing computation and preventing overfitting.

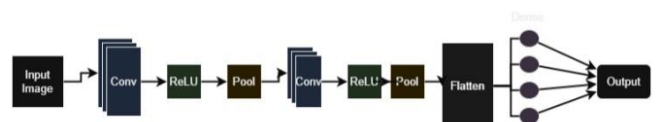
$$P = \max(f(m, n)), (m, n) \in R \quad (5)$$

This operation selects the maximum value from a region (R) of the feature map, preserving important features while reducing dimensions.

The CNN architecture follows the structure as:

Input → Conv → ReLU → Max Pool → Conv → ReLU → Max Pool → Flatten → Dense → Output

The architecture is demonstrated in Fig. 3.



**Fig. 3:** CNN architecture used for feature extraction and classification.

Fig. 3 illustrates the CNN architecture used in this study. It shows the sequence of convolution, activation, and pooling layers, followed by fully connected layers for classification. This structure enables the model to learn both low-level and high-level features from MRI images [6].

#### D. Attention-Based Features Learning

To enhance feature representation, an attention mechanism is integrated into CNN. This mechanism enables the model to focus on the most relevant regions of the MRI image.

Attention score between the two features is:

The attention mechanism helps the model to pivot on important regions of the scans by assigning weights to different features [7].

$$euv = \text{LeakyReLU}(\alpha T[Whu \parallel Whv]) \quad (6)$$

The normalized attention coefficient is defined as following:

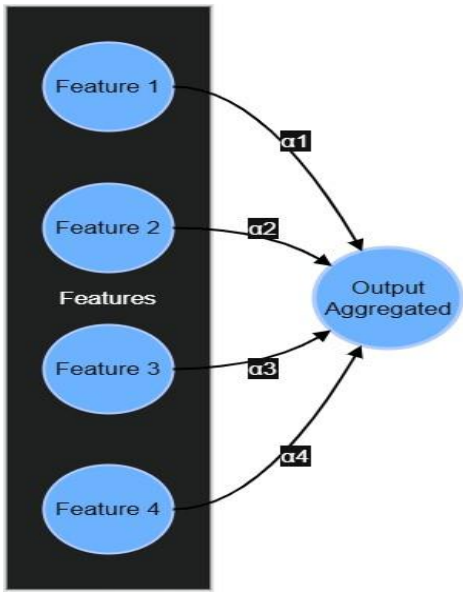
$$\alpha_{uv} = \frac{\exp(euv)}{\sum_{v' \in N(u)} \exp(euv')} \quad (7)$$

The weighted response of attention-attainable feature map can be written as:

$$h_u' = \sigma(W_0 h_u + \sum_{v \in N(u)} \alpha_{uv} W_1 h_v) \quad (8)$$

These equations calculate attention scores and normalize them to determine how much importance should be given to each feature. Higher weights are assigned to more relevant regions.

Attention mechanism enhances the capability of the model to identify fine tumor patterns. The process is shown in Fig.4



**Fig. 4:** The mechanism of attention-based learning of features.

Fig. 4 demonstrates the working of the attention mechanism. It highlights how the model assigns more importance to relevant regions in the image, improving the detection of tumor-specific features [7].

#### E. After training and maximizing the models, we will get the following

Features are then fed into the fully connected layer for classification. The output can be derived from the sigmoid activation function:

In the last step, a sigmoid activation function is applied to the output to get the probability values used for classification.

$$y^{\wedge} = \frac{1}{1+e^{-z}} \quad (9)$$

The values generated by this step lie in the range of [0-1], wherein high values close to 1 denote the presence of a tumor, whereas low values denote its absence.

For model training, the binary cross-entropy loss function is used. The following equations are applied for optimizing the model using the Adam optimizer:

For training the model, the following loss function is used to determine the differences between actual and predicted values.

$$L = -\sum_{i=1}^N [y_i \log(y^{\wedge}_i) + (1 - y_i) \log(1 - y^{\wedge}_i)] \quad (10)$$

This loss function is computed to evaluate the errors between actual and predicted values, which help the model learn better in subsequent iterations.

The following equation helps optimize the model parameters using the Adam optimizer:

For training the model, the Adam optimizer is widely applied because of its fast and efficient results. The model parameters are optimized using the Adam optimizer by updating them based on the following equation.

$$\theta_{t+1} = \theta_t - \eta \cdot \frac{m_t}{\sqrt{v_t+s}} \quad (11)$$

This equation updates the model weights iteratively using gradient information, helping the model converge faster and more efficiently.

#### F. Evaluation Strategy

The measures that have been chosen to evaluate the model's effectiveness is evaluated using accuracy, precision, recall, and F1-score. Such measures ensure comprehensive evaluation of the result of classification of unseen MRI images. Such measures are commonly used in research on medical image classification [6], [8].

## V. RESULT

#### A. Model Performance

The CNN model with attention-based feature learning mechanism was applied to the test data to test its classification performance. Although in the identification of tumor and non-tumor MRI scans the final accuracy of this model was 93.2, it demonstrates the efficiency of this model in distinguishing between two different images. Besides accuracy, other metrics of evaluation were taken into account to have a more detailed examination. The accuracy of the model was 92.5, the recall was 94.1 and F1-score was 93.3. These results indicate that the model can be used generally when detecting affected and normal brain images of tumors.

**Table II:** CNN Model Proposed Performance Metrics.

Metric	Value
Accuracy	93.2%
Precision	92.5%
Recall	94.1%
F1-Score	93.3%

Since the model was right in 93.2% of cases, it shows that there is a relatively good rate of MRI images that have been classified well. It indicates that the approach works efficiently for the separation of tumors from other non-tumor cases. The accuracy of 92.5% shows that the approach has correctly classified the MRI images at a very high rate of 92.5%. It limits the percentage of MRI images that have been predicted wrongly for a positive tumor case; hence it avoids unnecessary patient concerns in a healthcare context. With 94.1% recall, it is evident that the algorithm detects many true positive cases of tumors. The use of high recall is critical in dealing with medical conditions since the presence of an undetected tumor could be driving the disease progression.

A value of 93.3% F1-score suggests a good trade-off between precision and recall.

In summary, the excellent model performance is attributable to the use of the attention mechanism, which enables the network to concentrate more on significant regions of the MRI image, improving the accuracy of the extracted features and classification process [7].

The validation and training accuracy plots are illustrated in Fig. 5.

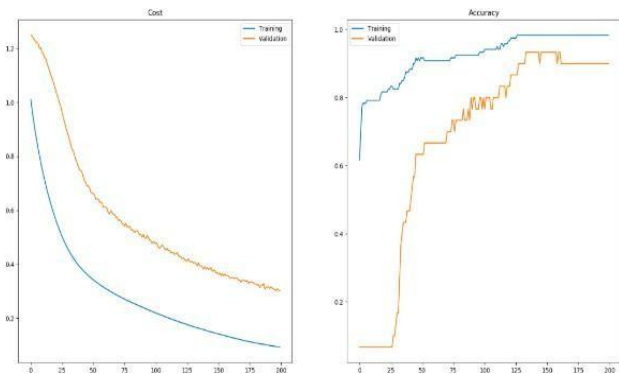


Fig. 5: Validation and training accuracy and loss curves graph.

Fig. 5 represents the training and validation accuracy curves for the proposed model. As can be seen from Fig. 5, both training and validation accuracy curves increase as time progresses. This indicates that the model does not exhibit any over-fitting behavior, and the learning of the model takes place successfully.

### B. Confusion Matrix Analysis

In order to measure the effectiveness of the proposed classifier, confusion matrix analysis was conducted. In the confusion matrix, the predicted values from a classifier are compared with the real values. The outcomes of the confusion matrix indicate that the classifier can predict almost all tumor and non-tumor images with very few wrong classifications of the images. Therefore, we can conclude that the classifier has fewer false positives and false negatives.

An analysis of the classification process can be done through table III, that is, through confusion matrix analysis.

Table III: Confusion Matrix

	<b>Predicted Normal</b>	<b>Predicted Tumor</b>
<b>Actually Normal</b>	TN	FP

<b>Actual Tumor</b>	<b>FN</b>	<b>TP</b>
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The evaluation metrics are calculated using the following formulas:

$$\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$$

$$\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$$

$$\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$$

$$\text{F1 Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

The confusion matrix provides an extensive analysis of the accuracy of the model in classifying data. The confusion matrix shows that the number of accurately predicted samples is significantly greater than the number of inaccurately predicted samples. Since the number of false positives and false negatives is extremely low, it means that the model is accurate and reliable. This further justifies the effectiveness of using the model to diagnose tumors in real-life scenarios.

### C. Comparison with the existent methods.

The proposed model was compared to the performance on the traditional machine learning and simple deep learning approaches. Traditional based methods like Support vector Machines (SVM) and K-Nearest Neighbors (KNN) are based on handcrafted features and usually are less accurate. Simple CNNs also enhance their performance in a manner that it learns features automatically, but it might not be effective when it comes to concentrating on most relevant area of the MRI images. The attention mechanism built into the proposed model improves the case of feature representation by focusing on tumor-relevant features and this leads to better classification.

TABLE IV: Comparison of Methods

Method	Accuracy (%)
SVM	85-88
KNN	80-85
Basic CNN	90-92
Proposed CNN + Attention	93.2

### D. Observations

The experimental evidence shows that the suggested model is effective with varying MRI images and generalizes itself on unknown data very well. The attention mechanism assists the model in targeting tumour-relevant regions, which enhances better detection. It is noted that the model is slightly effective in the detection of tumour images as there are patterns of features that are more pronounced. In this regard, the system illustrates good performance, stability as well as the ability to classify brain tumour tasks.

## VI. DISCUSSION

The results obtained from the proposed model demonstrate its successfulness in detecting brain tumors from MRI scans. The high accuracy and balanced performance across different metrics indicate that the model is able to generalize well to unseen data.

### A. Performance Analysis

The obtained experiment shows that the CNN model with an attention mechanism has high brain tumour detection accuracy. The high accuracy, precision and recall rates can be used to suggest that the model can be used to successfully differentiate between tumour and non-tumour MRI images. The use of the attention mechanism helps a lot in enhancing the performance because the model can concentrate on the areas that are important especially those affected by the tumour.

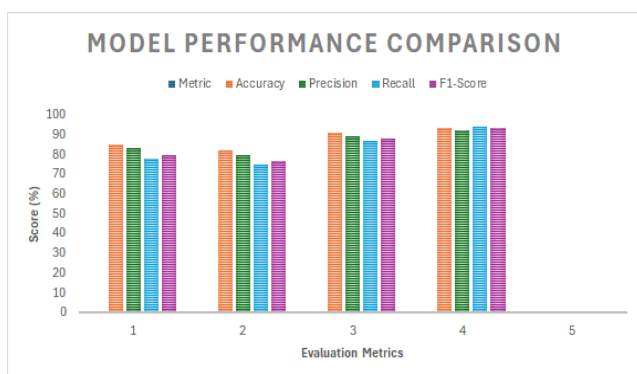
### B. Impact of Attention Mechanism

The mixture of attention-based feature learning and CNN is also among the most important contributions of this work. The attention mechanism uses variable weights on different parts of the image unlike traditional CNN models that consider all features as equal. This assists in highlighting critical aspects and withholding insignificant data. Consequently, the model will be more suited to represent minor differences in the structure of the tumour and its borders, resulting in an increase of the accuracy of classification.

### C. Comparison with Existing Approaches

The proposed approach offers high performance as compared to traditional image processing and machine learning because it has the capability of automatically learning hierarchical levels of data. Whereas classical approaches ensure that strong emphasis is given on handcrafted characteristics, deep learning algorithms like CNN possess greater flexibility and scalability [5]. The fact that attention is added is yet another boosting factor to improve performance by paying attention to key areas of the image [7].

Fig. 6 presents an evaluation of various models in terms of evaluation metrics.



**Fig. 6:** Analysis of performance indicators of the proposed model against the current methods.

### D. Limitations

Although the proposed system has performed better, there are limitations associated with the system. A model has been trained using a publicly accessible dataset, which might not be a completely appropriate representation of clinical variations in the real world. Also, the existing implementation gives emphasis to binary classification (tumour vs. non-tumour), and does not do tumour localization or tumour segmentation.

There is also the possibility that the model is sensitive to changes in the image quality and the conditions of acquisition.

### E. Future Scope

The further work may be concentrated on generalisation of the suggested system to the multi-class tumour classification and tumour segmentation with the help of such modern architectures as U-Net. It is also possible to enhance performance with the help of the transfer learning methods where pre-trained models, such as ResNet or EfficientNet, are used. Moreover, by incorporating the system into a real-time clinical application or web-based platform, it would become easier to make it more useful in the healthcare setting.

## VII. CONCLUSION

This work presents a CNN-based approach combined with an attention mechanism for brain tumor detection using MRI images. The model effectively learns important features and focuses on relevant regions, which improves overall detection performance. The results shows that the model achieves high accuracy, precision, and recall, making it a reliable approach for medical image classification. At the expense of some existing traditional techniques and the simple CNN models, the introduction of attention considerably boosts the performance [10]. The suggested system can be offered as an assistive instrument to medical practitioners in the initial diagnosis. Future directions could involve expansion of the model to multi-classification, tumor segmentation and real-time clinical use. Accuracy of the proposed model is 93.2 which illustrates its performance relative to the traditional and existing deep learning models.

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