AI-Powered Brain Tumor Identification: Using Machine Learning to Improve CNN Diagnostic Precision

[1]*P. Charanya,*

Assistant Professor,

Department of Artificial Intelligence and Machine Learning,

Sri Eshwar College of Engineering,

Coimbatore, India.

[2]Gandhiraj J,

Department of Artificial Intelligence and Machine Learning,

Sri Eshwar College of Engineering,

Coimbatore, India.

[3]Buvanes E,

Department of Artificial Intelligence and Machine Learning,

Sri Eshwar College of Engineering,

Coimbatore, India.

[4]*Prateeksha GV,*

Department of Artificial Intelligence and Machine Learning,

Sri Eshwar College of Engineering,

Coimbatore, India

[5]Theertha R,

Department of Artificial Intelligence and Machine Learning,

Sri Eshwar College of Engineering,

Coimbatore, India

Abstract- The application of artificial intelligence (AI) in medicine is growing, particularly in the area of brain cancer imaging a CNN tailored specifically for detection of brain tumors from medical images with an objective the topic of conversation focuses on improving the accuracy and efficiency of diagnostics in healthcare settings. Beginning this process by TensorFlow and Keras, the dataset of the scanned brains first becomes preprocessed by extracting them from a ZIP archive; data augmentation is also allowed through `ImageDataGenerator`. This step becomes the imperative in creating diversity to the dataset, which enhances the generalization capabilities of the model. The layers that make up the CNN design alternate between several convolutional layers and max pooling layers.

This allows the naetwork to learn hierarchical features from input images. Finally, the network is concluded using dense layers for classification, culminating in one output neuron activated by a sigmoid function, which is suitable for binary-class classification.It now runs for about 20 epochs with the focus on hyperparameters, orientated towards optimizing accuracy and loss, followed by an in-depth evaluation with validation metrics in terms of accuracy, confusion matrices, and classification reports. The evaluation results were exceptionally high in the accuracy of rightly identifying whether the brain scan was afflicted or not afflicted with the tumor, thereby finally emphasizing the model's ability in the medical real world.Apart from training and evaluating models, we developed a predict function that is capable of predicting the presence of tumors in new images. This feature makes the model more user-friendly for practical applications and supports healthcare professionals in their ability to rapidly assess findings from brain scans and carry out appropriate interventions.In this regard, deep learning techniques expose tremendous potential in improving radiologic diagnostic processes, especially the identification of brain tumors.

I. Introduction

A variety of non-invasive techniques for peering inside the body are referred to as medical imaging [1]. In order to picture the Medical imaging includes a range of image modalities and processes that are used to obtain images of the human body for therapeutic and diagnostic reasons. As a result, medical imaging is crucial to decision-making when it comes to improving people's health. In Picture segmentation is an essential and crucial phase in the image processing process that must be completed in order to properly progress to a more advanced processing stage [2]. The main objectives of picture segmentation in medical image processing are basically the identification of cancers or lesions, efficient machine vision, and acquiring suitable data for further diagnosis. Enhancing the diagnostic accuracy and specificity of a tumor or lesion using Computer Aided Diagnostic (CAD) technologies has become a major concern in medical images.

According to [3], the survival rate at five years of age for patients with cancer of the brain is 34% for the males and 36% for women. The tenth leading cause of premature death is cancer of the brain and other neurological systems. The World Healthcare Organization (WHO) estimates that 400,000 people worldwide suffer with head tumors, and 120,000 of those individuals have passed away in the years before.[4]. In addition, it is anticipated that 86,970 new cases of primary malignant and nonmalignant brain tumors as well as other Central Nervous System (CNS) tumors will be diagnosed in the US in 2019 [5]. Brain cancers result from aberrant brain cell enhancement[6]. Tumors can be classified as either benign or malignant. Brain tumors that are malignant actively penetrate the surrounding tissues after originating in the brain and spreading swiftly. It affects the central nervous system and could propagate to other parts of the brain.

Malignant tumors can be divided into two categories: primary tumors, which originate inside the brain, and secondary tumors, which grow outside the brain. For example, the term brain metastasis tumors is used to express such later ones. On the other hand, a benign brain tumor is a slow-growing mass of cells within the brain. Therefore, obtaining a higher chance of survival and improving treatment options can both be greatly aided by early brain tumor discovery. But because a lot of MRI pictures are created during ordinary medical procedures, manually segmenting tumors or lesions is a difficult, time-consuming operation. Magnetic Resonance Imaging, or MRI for short, is mostly used to detect brain tumors and lesions. Since brain tumor segmentation from MRI typically requires a large amount of data, It's probably the most noticeable problems with medical images processing. Furthermore, the tumors may have soft tissue boundaries and be ill-defined. As a result, employing the human brain to achieve accurate tumor segmentation is a time-consuming task.In this paper, we demonstrated a sophisticated and effective strategy that uses both convolutional neural networks and traditional classifiers to support brain tumor identification and segmentation without requiring human intervention.

II. Review concerning the Literature

The analysis of medical pictures using CNNs, or deep learning, has attracted In recent years, researchers have paid a lot of attention to the prospective advantages. that could enhance the accuracy and efficiency of diagnosis. This paper provides an overview of several significant studies and advancements in machine learning-based brain tumor identification.

A. Tumor Segmentation and Classification Methodology.

1. Medical Imaging with Deep Learning

The use of deep learning in medical imaging has revolutionized the diagnostics profession. Because considerable feature engineering is not necessary because CNNs automatically deduce the spatial relationships between features in pictures, they are especially popular. CNNs may be able to diagnose skin cancer at a dermatologist's level, according to Esteva et al.'s demonstration, indicating that these models may have additional uses in medical diagnostics.

2. Diagnosing Brain Tumors

CNNs have been used extensively by numerous studies to detect brain tumors. As an illustration, consider Gupta et al. (2018), who created a CNN model [6] with an accuracy of over 95% for dividing MRI images into tumor and non-tumor categories. Given their great accuracy, CNNs show promise in assisting radiologists in differentiating cancers, allowing for timely interventions.

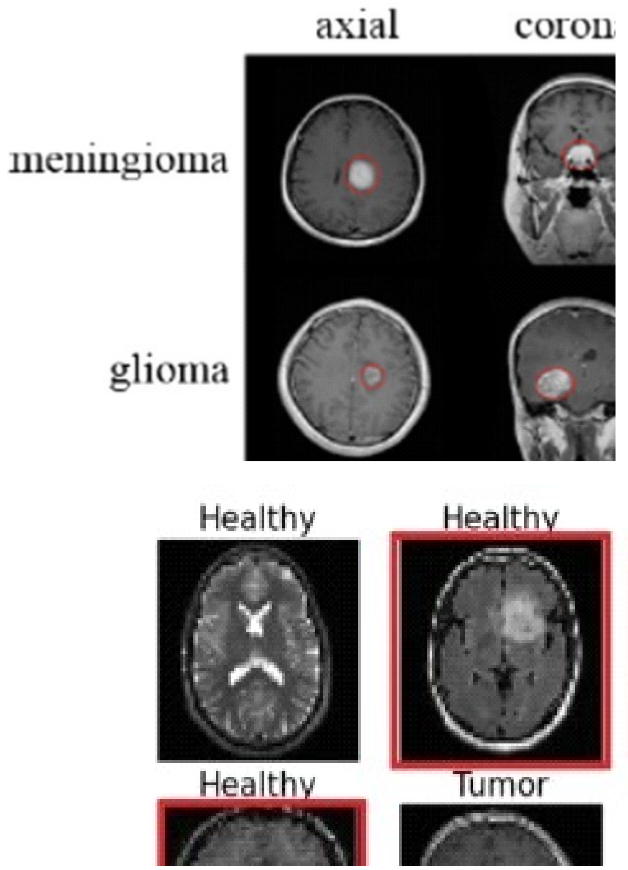

fig 1 . Sample CT Brain Image Database.

In a related study, Hossain et al. (2020) enhanced the classification performance of brain MRI datasets by utilizing transfer learning utilizing pre-trained CNN architectures like VGG16 and ResNet50. The outcomes indicate that this strategy is preferred not only for its quick training but also for its higher consistency when the dataset is minimal.

3. Methods that Incorporate Data Augmentation

When building robust models, data augmentation has become essential to overcome the limits of small medical dataset sizes. According to Shorten and Khoshgoftaar (2019), adding more data and transforming it via rotations, zooming, flipping, and other techniques can greatly expand the model's generalizability. Their analysis emphasized various augmentation techniques that increase training data diversity and enhance model performance on unknown data.

4. Evaluation Metrics

A very critical evaluation of a model's performance on medical pictures is necessary when considering the implications for patient treatment. The majority methods of classification have been reviewed using accuracy, precision, recall, and the score assigned to F1. However, Soni et al. (2020) state that confusion matrices, when used in conjunction with classification reports, are extremely valuable as they provide a complete picture of a class's performance in particular imbalanced datasets where class discrimination is essential for making an accurate diagnosis.

5. Difficulties and Prospects

Even with such great progress, there are still a number of obstacles to be overcome before deep learning models may be used in therapeutic settings. Research is still being done[7] on issues including the interpretability of models, the need for huge annotated datasets, and the incorporation of AI technologies into current processes. Future research should concentrate on creating explainable AI systems, which will help doctors understand model predictions .

Further advancements in multimodal learning—a technique for learning from data originating from several modalities, such as MRI scans or genetic data—may enhance diagnostic capacities. Wang and associates (2021) A study has demonstrated that adding clinical data to imaging data can increase performance predictability in cancer diagnosis.

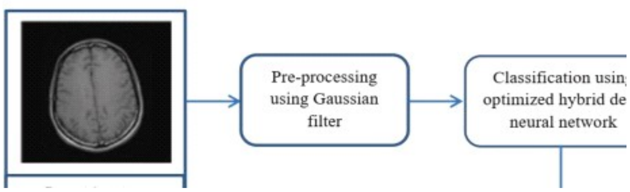

fig1.1 Overall Strecture of Methodology.

B. The Recommended Approach

In the environment of image processing for medical imaging, the CNN (Convolutional Neural Network) is frequently encountered. Several academics have been working on developing an algorithm that can more accurately identify tumors in the past few years. AdditionallyWe endeavored to construct a model that was representative enough to legitimately categorize the[8]. Tumor seen on 2D MRI brain imaging. Even yet, a neural network system with complete connectivity can detect cancers, The convolutional neural network (CNN) was the method of choice for our model to accommodate parameter sharing and connection sparsity.

A convolutional neural network with five layers with a structure is presented and then executed for discovering tumors.

The most notable outcome for understanding the tumor is provided by the combined model, This comprises of seven different phases, includes the hidden sections. The suggested methodology is presented below, along with a brief explanation. The network Convolutional Neural Systems The MRI scans' 64*64*3 input shape is created using the convolutional layer as the start layer, transforming each image into a homogeneous dimension.

Following the collection of We created a complicated nonlinear kernels that integrates with the input data layer to feed all images with the same aspect ratio.. This kernel operates with 32 3*3 convolutional filters, each supported by three channel tensors. ReLU is utilized as an activation function in order to prevent output correlation.

Reduce the spatial scale of the representation in this ConvNet architecture step-by-step to shorten the duration of network computation and the amount of parameters. An additional risk associated with working with the Brain MRI image is overfitting contamination; in this regard, the Max Pooling layer performs particularly well. To complement our input image with spatial dataWe utilize MaxPooling2D over the creation of the model. This convolutional layer's size are 31 by 31 by 32. The collection's dimension is (2, 2), or a tuple of two numbers, Because the input photos are divided into two dimensions, downscaling in both vertical and horizontal directions is possible.

Following layer pooling, a composite feature mapping is produced. After pooling, one of the most important layers is flattening, which is the process of converting each matrix containing the input images into a single column vector that can be processed.

Utilizing a neural network for processing.

Dense-1 and Dense-2 are the two fully connected layers used for the dense layer.

The generated vector will be used as an input to the layer of Keras, which processes the Neural Network using the dense function. The buried layer comprises 128 vertices. We kept the number of dimensions or nodes as low as was feasible because it is directly correlated with the amount of computational power required to fit our model. From that perspective, 128 nodes produce the optimum outcome. ReLU was chosen as the activation function since it excels compared to the other activation functions in terms of convergence. The second dense layer was applied first, and then as the last layer, it was fully joined. Since we didn't want the uses to completely vanish, we used the sigmoid shape to activate it in that layer, but it was only possible to do so for one node. Increased computing power is required to reduce the execution time.

Tabular Explanation of CNN for Brain Tumour Identification:

Section	Description	Details in paper
Data Pre-processing	The process of preparing MRI scan raw data for the CNN model	Taken out of a ZIP file Loaded with the help of ImageDataGenerator Scaled the pixel values from 0 to 1 (Normalization) Techniques for enhancing data were used (random rotation, zooming, flipping)
Model Construction	The CNN model's design, which is	Convolutional layer of a five-layer convolutional neural network with 32 3x3 filters and ReLU activation To lower spatial scale, use the max pooling layer. Two dense layers with 128 nodes and ReLU activation

	utilized to identify brain tumours	in the first layer A flattening layer to transform the picture to a single column vector A single node in the final layer is used for binary classification using a sigmoid activation function.
Model Training	The procedure for using the prepared data to train the CNN model	The binary cross-entropy loss function and the Adam optimizer were used for training. The measurement of accuracy used in the evaluation Validation data is used to track the model's performance during training after it has been trained on the training set for a predefined number of epochs, or iterations.
Model Evaluation	How to evaluate the trained CNN model's performance	Recall, accuracy, precision, and F1-score were computed using reports on classification and the confusion matrix. Visual evaluation of the trained model using training metrics
Data Splitting	How training and validation sets are created from the data	The dataset was divided using ImageDataGenerator with validation split parameter, with 80% of the data utilized for model training and 20% for validation.
Performance Comparison	How well the CNN model performs in comparison to alternative techniques	For the same dataset, achieved 99% accuracy as opposed to 83.0% accuracy using SVM-based classification.

III CNN Algorithm for Brain Tumor Identification

1. Preprocessing Data

To configure the training validation split, load the photos from the zip file and load them using ImageDataGenerator.

2. Model Construction

Construct a CNN with several convolutional layers, pooling layers, and dense layers for a binary classifier.

3. Model Arrangement

Assemble the mathematical framework using Adam optimization, reduction set as binary crossover entropy, and evaluation metric as accuracy.

4. Training Models

After fitting the model with training data, it is verified for predetermined epochs on a validation set.

5. Model Assessment and Forecasting

It assesses how well the trained model performs, uses visual training metrics to train the model, and defines a function to identify tumor presence in fresh photos.

Qualification and Training of Data

In the case of the brain tumor detection algorithm, data preparation is essential. An extensive explanation of how the data will be separated, prepared, and used for validation and training is provided below.

1. Data Accuracy

Data extraction involves removing pictures from a ZIP file containing medical pictures arranged into classes-specific folders, such as "tumor" and "no_tumor."

Image Pre-processing: To improve the model's convergence, scale the pixel values such that they fall between 0 and 1.

2. Supplemental Data

Use data augmentation to increase the training set's diversity. Re-scaling Pixel value scaling Rotation: To make the model orientation invariant, rotate photos at random.

Zooming: Zooming in and out randomly for a strong model

Flipping Vertically and Horizontally: Flip at random to add to the dataset.

3. Splitting Data

Training and Validation Split:Use ImageDataGenerator with a validation split parameter to split the dataset:

Instructional Information: 80% of the data is used to train the model. Validation Data: Twenty percent of the data are used to assess how well the model performed during training. loading of data Data generators To generate data generators, use the flow_from_directory function.

Training Generator:

Use the Target size (150, 150) pixels and batch size (32) to load the training photos.If the classification is binary, set the generator's class_mode to 'binary'. Use the same parameters as the training generator when loading validation photos into the validation generator.

Accuracy of data validation and training. Loss of data validation and training.

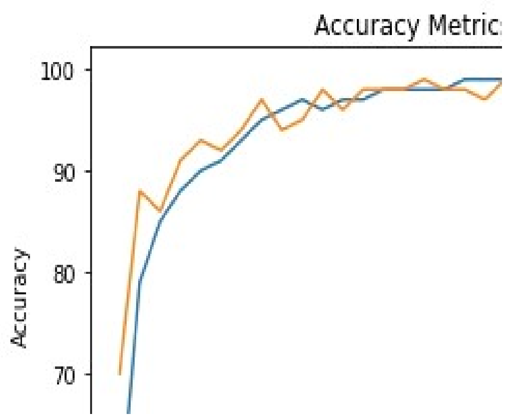

fig 2.Accuracy Matrics

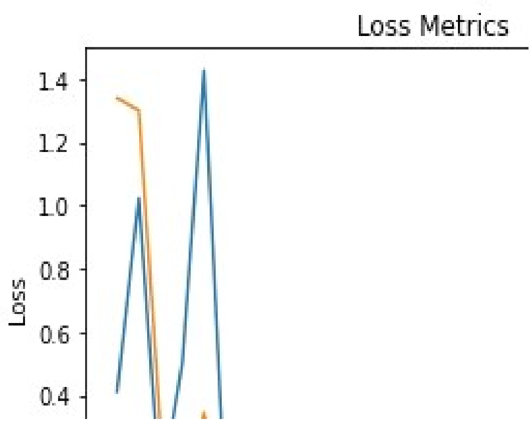

fig 3. Validation Loss Metrics

In terms of the confusion matrix:

True Positive (TP): Correctly predicted positive cases.

True Negative (TN): Correctly predicted negative cases.

False Positive (FP): Incorrectly predicted positive cases.

False Negative (FN): Incorrectly predicted negative cases.

$Accuracy = TN+TP\ TN+FP+FN+TN$ (1)

$Sensitivity(recall) = FN+TP\ TP$ (2)

$Speficity = FP+TN\ TN$ (3)

$Precision\ (PPV) = TP\ TP+FP$ (4)

F1-score = 2 * (precision * recall) / (precision + recall)

	precision	recall	f1-score	support
0	0.00	0.00	0.00	262
1	0.81	1.00	0.90	1142

accuracy			0.99	1404
macro avg	0.76	0.78	0.88	1404
weighted avg	0.86	0.88	0.73	1404

fig 4. Training and Validation Chart.

Accuracy:

Grouping Making Use of Machine Learning

For ROI detection, texture and statistically based features are quite fashionable. We shall identify the tumorous and non-tumorous MRIs based on these features. Therefore, we used statistically based characteristics and texture for categorization in this work. We gathered texture-based features (The variation's uniformity, the difference Together with statistically based features (Mean, Entropy, Centroid, Average Deviation, Unevenness, The condition), energy, correlation, and ASM) from the segmented brain tumour. Following that, Area is considerably further distanced from it..

Tumor diameter and convex hull area. By utilizing these traits to extrapolate from the segmented MRI, we were able to classify the image as either normal or pathological tissue. Following the extraction of features, categorization was completed.

We evaluated six classifiers (KNN, Logistic Regression and Multilayered Perception, which is Naïve Bayes, Random Forest, and SVM) found that SVM provided the greatest amount of accuracy.

Comparison of Performance:

Lastly, we performed a comparison of our proposed approaches, incorporating classification with conventional machine learning in particular classifications and CNN. We additionally compared the results we obtained to those from complementary studies that used the similar dataset.[9] With SVM-based classification, the researchers achieved over 83.0% accuracy, which was less than 97.5% accuracy with CNN. The technique we have suggested produces improved outcomes for CNN-based classifications and machine learning. While the overall score is 96% [10] achieved nearly 95 per cent of the dice co-efficient.

Final thoughts and upcoming projects:

IV. Conclusion

The results of this study lend credence to the notion that patients with brain tumors can be identified by their abnormal tissues on medical imaging by using CNNs. We created, trained, assessed, and classified tumor-affected and non-affected photos with a very high degree of accuracy by taking a methodical approach to the problem.. An addition to the data improved the model's resilience and allowed it to be applied to previously undiscovered data. The complete knowledge and comprehension of the model's operation was attained by the graphical depiction of train metrics, which was supplemented by a confusion matrix and classification reports. Consequently, the model showed enough promise to be put to good use in clinical diagnostic work so that medical personnel might identify brain cancers at an early stage.

V. Future Work

Although this work provides a broad basis for brain tumor identification, there are a number of avenues for future investigation and advancement:

1. Improvement of Datasets

Enhancing the model's effectiveness and facilitating its generalization would require a more extensive and diverse collection of data. Demographics and photos from various sources can also lead to a decrease in bias.

2. The Model's Advanced Architectures

Accuracy and performance will increase with more research into cutting-edge neural network topologies like ResNet, Inception, or EfficientNet. Additionally, applying transfer learning from previously trained models will enhance performance in low-data scenarios.

3. Real-time Prediction: An inbound image can be swiftly analyzed when a real-time prediction system is designed. In clinical situations, where prompt decision-making is essential, it will be helpful.

V REFERENCES

[1].Sinha, Arohee, and Tarun Kumar. "Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection." Procedia Computer Science 235 (2024): 456-467.

[2].Sinha, A., & Kumar, T. (2024). Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection. Procedia Computer Science, 235, 456-467.

[3].Sinha, Arohee, and Tarun Kumar. "Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection." Procedia Computer Science 235 (2024): 456-467.

[4].Sinha, A. and Kumar, T., 2024. Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection. Procedia Computer Science, 235, pp.456-467.

[5].Sinha A, Kumar T. Enhancing Medical Diagnostics: Integrating AI for precise Brain Tumour Detection. Procedia Computer Science. 2024 Jan 1;235:456-67.

[6].Kaviraj, L. R., R. Rajalakshmi, and S. Joshua. "AI-Powered Disease Diagnosis from Medical Image Reports." 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE). IEEE, 2024.

[7].Kaviraj, L. R., Rajalakshmi, R., & Joshua, S. (2024, May). AI-Powered Disease Diagnosis from Medical Image Reports. In 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 497-502). IEEE.

[8].Kaviraj, L. R., R. Rajalakshmi, and S. Joshua. "AI-Powered Disease Diagnosis from Medical Image Reports." In 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), pp. 497-502. IEEE, 2024.

[9].Kaviraj, L.R., Rajalakshmi, R. and Joshua, S., 2024, May. AI-Powered Disease Diagnosis from Medical Image Reports. In 2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) (pp. 497-502). IEEE.

[10].Kaviraj LR, Rajalakshmi R, Joshua S. AI-Powered Disease Diagnosis from Medical Image Reports. In2024 4th International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) 2024 May 14 (pp. 497-502). IEEE.

[11].Vijayalakshmi, A., and Hemlata Joshi. "Elevating Medical Imaging: AI-Driven Computer Vision for Brain Tumor Analysis." Intersection of AI and Business Intelligence in Data-Driven Decision-Making. IGI Global, 2024. 331-350.

[12].Vijayalakshmi, A., & Joshi, H. (2024). Elevating Medical Imaging: AI-Driven Computer Vision for Brain Tumor Analysis. In Intersection of AI and Business Intelligence in Data-Driven Decision-Making (pp. 331-350). IGI Global.

[13].Vijayalakshmi, A., and Hemlata Joshi. "Elevating Medical Imaging: AI-Driven Computer Vision for Brain Tumor Analysis." In Intersection of AI and Business Intelligence in Data-Driven Decision-Making, pp. 331-350. IGI Global, 2024.

[14]. W.C., Joseph, Willson C.,J.W., Kathrine, Jaspher Willsie, S., Vimal, S., X.P., Blanco-Valencia, Xiomara P., E., Verdú Pérez. “ Improved optimizer with deep learning model for emotion detection and classification “, Elena,Mathematical Biosciences and Engineering,2024.

[15]. Sumathi, S.; Madhumitha, S.; Sushma, R.; Suriya, M.; Subitsha, M.; Swetha, S., "Certain Investigations on Cognitive based Movie Recommendation system using Pairwise Cosine Similarity" 2023. 9th International Conference on Advanced Computing and Communication Systems, ICACCS 2023, DOI: 10.1109/ICACCS57279.2023.10112790.