

Convolutional Neural Networks for Accurate Brain Tumor Detection and Analysis

1st Narisetty SrinivasaRao
Department of Computer Science
and Engineering
Lakireddy Bali Reddy College of
Engineering (Autonomous)
Mylavaram, India
nsr543@gmail.com

2nd Pasalapudi Kasi Viswesh
Department of Computer Science
and Engineering
Lakireddy Bali Reddy College of
Engineering (Autonomous)
Mylavaram, India
kasipasalapudi@gmail.com

3rd Dumpa Sushma Reddy
Department of Computer Science
and Engineering
Lakireddy Bali Reddy College of
Engineering (Autonomous)
Mylavaram, India
sushmasushma11471@gmail.com

4th Balasaraswati Sandesh
Department of Computer Science
and Engineering
Lakireddy Bali Reddy College of
Engineering (Autonomous)
Mylavaram, India
sandeshbala21@gmail.com

Abstract— Brain tumor detection is a crucial diagnostic process that depends on analyzing MRI images fine contrast of soft tissues and non-intrusive nature. Although through the manual analysis of MRI scans is a time taking process and leads to errors. So, there is a need to develop more accurate, efficient and automated detection systems. This study proposes ResNet (residual network) is one of the efficient models in convolutional neural network (CNN) to detect brain tumors. This paper used an openly available dataset which consists of MRI images (containing and not containing tumors). Then the images are subjected to preprocessing using different types of techniques like data augmentation and normalization to boost the model robustness. ResNet-50 is well known for its specific characteristics like vanishing gradient problem, skip connections was tailored on this dataset. The model accomplished classification accuracy of 95% resembles that this model can classify the brain tumor MRI images efficiently and helps the radiologists for rapid detection of tumors.

Keywords— *Magnetic Resonance Imaging, Convolutional Neural Network (CNN), Deep Learning.*

I. INTRODUCTION

Brain tumors are excessive growth of cells in the brain. These tumors may be malignant(cancerous) or non- malignant(non-cancerous). These cells emerged from brain tissue itself or spread to the brain from all parts of the body. Brain tumors have different types of symptoms depending on their size, position, expansion rate like vomiting, seizures, mood swings etc. [1].

There are some symptoms like vomiting, mood swings, hearing problems, cognitive decline, speech problems, seizures, headaches. Vision and hearing problems also are correlated with brain tumors. Such problems as blur or double vision, loss of the field of peripheral vision, or hearing may be symptomatic of a tumor pressing on some nerves. Further, difficulties in maintaining balance or coordination may arise from the involvement of motor control centers, causing unsteadiness or clumsiness in handling. Weaknesses or numbness are often unilateral signs of involvement of some motor or sensory pathways. Cognitive and behavioral symptoms are also prevalent.

Memory lapses, trouble focusing, difficulty finding words, or slurred speech may result from disruptions in the brain's cognitive areas. Seizures caused by brain tumors may occur suddenly, even in people with no prior history of seizures, and can be one of the first signs of brain abnormality. Managing seizures typically involves medication to control the episodes, but treating the underlying brain tumor is crucial to reducing their occurrence. Early detection and appropriate treatment can significantly improve quality of life for patients experiencing seizures related to brain tumors [2].

There are many traditional methodologies to detect brain tumors like computed tomography (CT) scan, blood test, brain wave test, biopsy, symptoms, medical history review available but mostly all are inaccurate and prone to errors because they can't be able to generalize its diverse nature. Deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of medical image analysis by automating feature extraction and improving classification accuracy.

Among the various CNN architectures, ResNet (Residual Network) has emerged as a powerful model due to its ability to train very deep networks effectively while addressing the vanishing gradient problem [3]. Despite its success in other domains, the application of ResNet to brain tumor detection in MRI images remains an area of ongoing research, with significant potential for clinical impact.

ResNet can accurately determine whether a tumor is present in an MRI scan. This allows doctors to diagnose patients faster and with greater accuracy, leading to better treatment planning and improved patient care. This study focuses on using AI, especially Convolutional Neural Networks (CNNs), to detect brain tumors in MRI scans. The goal is to create an automated, fast, and accurate system that can tell the difference between cancerous and non- cancerous tumors.

To build the model, the research uses popular CNN designs like ResNet, CNN. These models have already been trained in large sets of images, so they can learn faster and

work well with smaller sets of brain MRI images. Preparing the MRI images is an important step. The images are resized and adjusted to make them consistent. Extra techniques, like rotating, flipping, and scaling the images, are also used to make the model more flexible and prevent it from overfitting (or) underfitting [4].

The main part of the research is changing the last layers of these CNN models to create a binary classifier system that decides whether an image shows a tumor or not. The models are then tested using Accuracy, Precision, Recall, F1-Score.

This research contributes to the growing field of medical image analysis by demonstrating how advanced AI methods can make brain tumor detection more accurate and efficient. The findings emphasize that deep learning models, particularly CNNs, have immense potential in transforming medical diagnostics. Future work could explore integrating multimodal imaging techniques, such as combining MRI with CT scans or PET scans, to provide more comprehensive diagnostic capabilities. Additionally, expanding datasets and including diverse patient profiles can further improve generalization and robustness.

The experiments conducted as part of this research demonstrate the effectiveness of the proposed optimization strategies. Models that incorporated these techniques showed higher accuracy, better precision, and improved recall rates compared to traditional methods [5]. Since this model deals with medical decisions, ethical considerations are very important. The researchers highlight the need to work with doctors to ensure the tool is safe, reliable, and clinically useful.

The aim is to show how AI can improve medical image analysis. By making brain tumor detection more accurate and automatic, the system can help doctors diagnose tumors earlier, plan better treatments, and provide more personalized care leading to better outcomes for patients [6].

II. LITERATURE SURVEY

In the pursuit of enhanced brain tumor detection, Halder et al. have pioneered an innovative approach that seamlessly merges the established power of Histogram of Oriented Gradients (HOG) with a novel Local Histogram-Based feature extraction technique. This groundbreaking methodology introduces a quadrant-based image analysis strategy, enabling a more granular and localized understanding of image features. To capture the subtle variations in intensity distributions within each quadrant, the researchers implement a unique sub-bin division within the histograms. This meticulous attention to detail results in a richer and more nuanced feature space, augmenting the traditional HOG descriptors with valuable contextual information. To streamline this comprehensive feature set, Principal Component Analysis (PCA) is strategically employed, ensuring efficient feature selection and dimensionality reduction without sacrificing crucial discriminatory power. Finally, the study harnesses the strengths of both Support Vector Machines (SVM) and Random Forest for classification, capitalizing on their respective capabilities for optimal hyperplane identification and ensemble learning. This synergistic integration of advanced techniques culminates in a robust and accurate classification framework, setting a new standard for medical image analysis and offering a promising avenue for improved brain tumor detection [7].

The study delves into the complexities and hurdles associated with accurate brain tumor detection, particularly within the domain of Magnetic Resonance Imaging (MRI) scans, where subtle variations and complexities can obscure the presence of tumors. It underscores the critical importance of early and precise identification of these tumors, as timely intervention significantly impacts patient prognosis and treatment options. Recognizing the limitations of existing methods, the research proposes the innovative template-based K-means (TK) algorithm as a potential solution to overcome these challenges. This novel approach strategically combines the advantages of super pixels, which offer a powerful means of image segmentation, with principal component analysis (PCA), a technique renowned for its ability to reduce dimensionality and extract salient features. The methodology unfolds in a series of well-defined stages, commencing with a sophisticated feature extraction phase that harnesses the power of super pixels and PCA to capture and encapsulate the essential tumor-related characteristics within the MRI scans. Subsequently, image enhancement techniques are meticulously applied to refine image quality, reduce noise, and amplify subtle visual cues that aid in accurate detection. The culmination of this process lies in the implementation of the TK- means clustering algorithm, a refined segmentation technique tailored to precisely isolate and delineate the boundaries of brain tumor regions within the MRI scans. Through the integration of cutting-edge techniques, the research aspires to significantly elevate the standards of brain tumor detection, ultimately paving the way for improved patient care and treatment outcomes [8].

Ullah et al. present a recent research advancement in brain tumor detection with the introduction of TumorDetNet, a meticulously engineered deep learning framework. By strategically incorporating down sampling techniques, the researchers strike a balance between computational efficiency and diagnostic precision. The inclusion of batch normalization, activation functions, and dropout layers further refines the model's performance, mitigating overfitting and promoting stability during training. The hallmark of TumorDetNet lies in its unique integration of residual bottleneck layers, employing a combination of depth-wise and point-wise convolutions. This design allows the network to capture both broad contextual information and fine-grained details from medical images, significantly enhancing its ability to discern subtle tumor characteristics. The exceptional performance demonstrated by TumorDetNet establishes a new gold standard for deep learning-based approaches in the critical domain of medical image analysis, particularly in the challenging task of brain tumor detection. This breakthrough has the potential to revolutionize early diagnosis and treatment planning, ultimately improving patient outcomes [9].

In the field of classification, current systems predominantly adopt a binary approach, differentiating between healthy "Normal" and affected "Tumor" MRI scans. The medical approach often involves a combination of imaging techniques such as MRI, CT, and PET scans, with biopsy frequently used for definitive diagnosis. Additionally, emerging technologies like diffusion tensor imaging (DTI) and spectroscopy provide supplementary information for a more comprehensive understanding. From a technical perspective, the detection process frequently employs machine learning algorithms, histogram equalization for image enhancement, object detection models like YOLOv7,

image classification techniques, and various neural network architectures [10].

Current brain tumor detection systems face limitations. Some models, while powerful, lack optimization for medical image nuances, impacting accuracy. Additionally, performance is often constrained by limited or low-quality training datasets, a challenge in medical imaging. While histogram equalization can enhance contrast, it may inadvertently amplify noise in medical images, hindering accurate interpretation. Furthermore, the computational demands of some complex models can pose a challenge for real-time detection, critical in clinical settings. Unsupervised models like autoencoders, although valuable for exploratory analysis, might not fully leverage the potential of labeled data for targeted tumor detection. Lastly, the performance of K-nearest neighbors (KNN) algorithms is highly sensitive to the choice of distance metric, requiring careful consideration and potentially limiting their generalizability [11].

III. EXISTING SYSTEM

There are different existing methodologies available to detect brain tumor. Mostly are based on CNN and other deep learning methodologies because of their characteristics. Some of them are listed below [12].

- Image Analysis
- Electroencephalogram (EEG) signal analysis
- Neural Network Analysis
- Movement and Gait Analysis

A. Image Analysis:

Generally, Machine learning models specifically deep learning models are used for analysing the MRI (magnetic resonance imaging) and CT (Computed tomography) scans. These models can easily classify tumors whether they are present or not also they help in segmentation process i.e. the region where the tumor is concentrated [13].

B. Electroencephalogram (EEG) signal analysis:

In this methodology sensors are placed on the scalp of patient and record the brain's electrical activity. After that machine learning algorithms are used to look for any unusual activity and then classify the presence or absence of tumor by using different classifiers like SVM, Random Forest etc. [14].

C. Neural Network Analysis:

Neural Networks finds patterns through learning from large datasets by using deep learning pretrained models (VGG19, ResNet). It is not only useful for image data also can handle other data like signals, text etc... These models can easily go through complex type of data and predict the tumor is present or not [15].

D. Movement and Gait Analysis:

There are different types of tumors such that some of those tumors will affect motion of a person. Machine Learning helps here to analyse the person moves and detect the abnormalities in Gait so that easily detect if there is a tumor present or not which effect the motor nerves of the brain [16].

IV. PROPOSED SYSTEM

From the above-mentioned methodologies this brain tumor detection is taken based on Image Analysis. For this process there are many machine learning and deep learning pre-trained models are available for classification like VGG19, ResNet, DenseNet etc. From those we are going with ResNet-50.

ResNet:

ResNet is also known as residual networks. It is specifically made for image classification and recognition works by Kaiming He in 2015 with his colleagues. ResNet is helpful for solving vanishing gradient problems also.

Vanishing Gradient problem:

This problem arises during the back propagation in training phase. Whenever the gradients are propagated backwards, they become so small that if gradients are very small then for early layers change in weights becomes 0. Then the network learns patterns so slowly.

Formula:

$$P_{new} = \frac{P_{curr} - \alpha * (\partial v)}{\partial P_{curr}} \quad (1)$$

where:

- P_{new} is the updated weight,
- P_{curr} is the present weight,
- α is the learning rate,
- ∂v is the loss function.

To manage the gradients, skip connections which is one of the characteristics of ResNet is used.

Skip connection:

When the gradients flow from one layer to another layer it is multiplied with its local gradient such that its value will decrease. Skip connections help to pass those gradients to other layers without passing them through all layers, i.e. it just makes gradients pass through some layers only by skipping other layers. So, in this way the model can perform better.

Formula for skip connection:

If s is the input to a layer and $H(s)$ is the output which came from the respective layer, then a skip connection can be given as:

$$t = H(s) + st = H(s) \quad (2)$$

where:

- t is the output of the layer with skip connection.
- $H(s)$ is the modification applies to s .

Flow of Gradient with skip connection:

The gradient value during the back propagation can be given by the formula below.

Formula:

$$\frac{\partial v}{\partial s} = \frac{\partial v}{\partial t} + \frac{\partial v}{\partial H(s)} \quad (3)$$

ReLU (rectified Linear Unit):

It is a function which helps models to introduce non-linearity. If it doesn't introduce nonlinearity then even if it is a multilayered or complex model it behaves like a linear model. It is mathematically given as

$$H(z) = \max(0, z) \quad (4)$$

where:

- If $z > 0$ then $H(z) = z$
- If $z < 0$ then $H(z) = 0$

Batch Normalization:

In the process of training the data which moves from one layer to other layer is always not same. So that the data is not constant the training process will be slow. Initially data undergoes normalization then by using two learning parameters α (scale) and γ (shift) resizing of image takes place.

$$\gamma^i = \gamma * x^i + \beta \quad (5)$$

where:

x^i represents the i^{th} input to the neuron in batch normalization process

$$x^i = \frac{x^i - \mu}{\sigma} \quad (6)$$

- μ is average of normalized input
- σ is standard deviation of normalized input
- γ is the scaling factor

Diverse Architecture models:

ResNet consists of different types of architectural models which can be used for image analysis. Each model is specifically designed for certain circumstances. So based on the need we can use the model.

Example:

- ResNet-18 and ResNet-34: used for small datasets.
- ResNet-50: used for large datasets
- ResNet-101 and ResNet-152: Precision based Systems

Steps in ResNet-50 Architecture:

1. Input Layer:
 - Accepts images (e.g., 224x224x3 dimensions).
2. Initial Convolution and Pooling:
 - 7x7 convolution with stride 2 + Max Pooling (3x3, stride 2).
3. Residual Blocks (with Skip Connections):
 - Stage 2: 3 blocks with 256 feature maps.
 - Stage 3: 4 blocks with 512 feature maps.
 - Stage 4: 6 blocks with 1024 feature maps.
 - Stage 5: 3 blocks with 2048 feature maps.
4. Global Average Pooling (GAP):
 - Reduces feature maps to a single value per map.
5. Fully Connected Layer:

- Outputs class probabilities with SoftMax.

V. DATASET

In this paper, we have taken the Brain Tumor Classification (MRI) dataset, which was obtained from Kaggle. This dataset consists of 3,264 MRI images related to brain tumors, and it is one of the best resources for research in medical image analysis. The images are labeled for the classification of brain tumors, providing a diverse set of examples for training machine learning models. The dataset is publicly available and has been widely utilized in the field of medical imaging for the detection and classification of brain tumors [17].

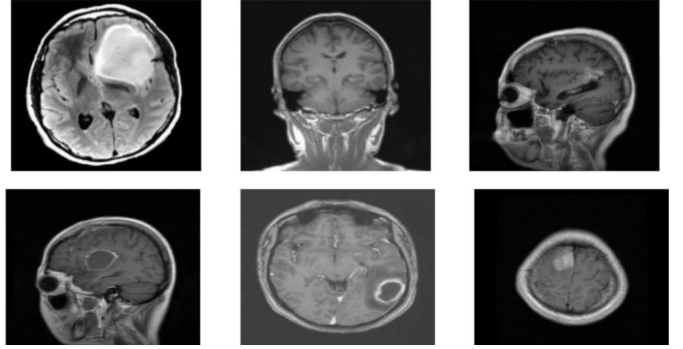


Fig. 1. Brain MRI Images.

Implementation:

Before implementing the code, we need to ensure that our dataset is clean and well prepared. For this preprocessing of data is needed. Preprocessing is a process of converting raw data to useful data for analysis.

1. Removal of Noisy Data:

Basically, noisy data can be separated through visual inspection, i.e. by seeing it visually we can remove some data, but it is difficult to remove all the images. So, in that situation we can use filtering techniques like Gaussian filters or averaging (linear filtering) also in non-linear filtering median and wiener filtering techniques are also available which removes noisy images.

- *Gaussian Filtering:* Gaussian Filtering is one of the common techniques which is used to smoothing (blurring images) which in turn model can focus on main pattern (like tumor shape and size) rather than on the irrelevant data (Noisy data).
- *Gaussian Function:* Gaussian filters having kernels which follows gaussian distribution function can be given as

$$P(m, n) = \frac{1}{\sigma^2} e^{-\frac{m^2 + n^2}{2\sigma^2}} \quad (7)$$

where:

- m and n are coordinates of the point in kernel/filter.
- σ is the standard deviation, which can figure out the width of the Gaussian curve and it also regulates the smoothing level. i.e. the value of smoothing increases as the σ increases vice versa.
- $P(m, n)$ provides the weight of the filter at a certain position (m, n)

- **Gaussian Kernel:** This is basically represented in matrix format (i.e. in 3*3,5*5,7*7) containing weights which sum up unity. This kernel is a discrete estimation of above Gaussian function, and this Gaussian kernel is used on the image in the process of convolution
- **Convolution:** It is the process of extracting the important features from images by using kernels and mathematical functions. Here the Gaussian kernel is used in the convolution process

2. Normalization:

It is a process of scaling the data to get fit within a specific range. Generally, it is taken as [0,1] or [-1-1]. It is often used if the data is not following Gaussian distribution or the data is unknown. Then the data will fit to a specific range so that it will be easy for further processing of data.

Min-Max scaling is used to calculate normalized value and it is mathematically defined as

$$NV = \frac{Z - \text{Mini}}{\text{Maxi} - \text{Mini}} \quad (8)$$

Where:

- NV is Normalized Value
- Z is the actual value
- Mini is minimum value of dataset taken
- Maxi is maximum value of dataset

3. Standardization:

Whenever the data is following Gaussian distribution then standardization should be applied. Standardization is a process in which transforms the data to have a mean or average value to be 0 and standard deviation value should be 1. Because of this our model will less effected by outliers. Z-score standardization is a generally used method for the process of standardization.

Formula:

$$A = \frac{B - \mu}{\sigma} \quad (9)$$

Where:

- A represents the standardized value
- B represents the actual value
- μ represents the average value
- σ represents the standard deviation

4. Feature Augmentation:

To increase model efficiency and its generalization capabilities feature augmentation is used. In this process the training dataset size will increase by adding images through geometrical conversions (flipping, rotation, cropping), colour

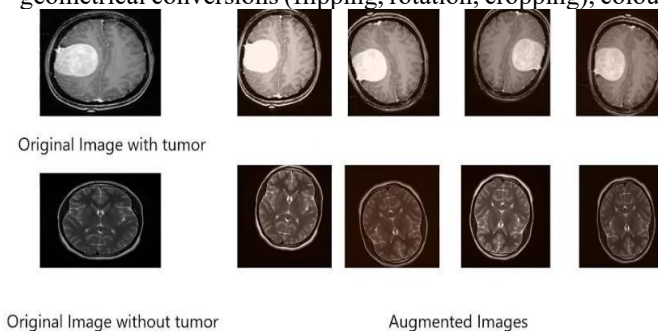


Fig. 2. MRI images before and after feature augmentation.

adjustments like Increasing or decreasing intensities, contrasts also little amount of noise also added so that model can be able to withstand the real-world flaws.

TABLE I. ResNet-50 Model Performance Across Epochs.

Epoch	Model's Accuracy		Model's Loss	
	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss
1	0.7010	0.6821	0.8642	0.8374
2	0.7621	0.7324	0.7935	0.7732
3	0.8020	0.7826	0.7101	0.6947
4	0.8625	0.8397	0.6532	0.6341
5	0.8892	0.8694	0.5881	0.5687
6	0.9089	0.8902	0.4932	0.4803
7	0.9174	0.8994	0.4521	0.4104
8	0.9320	0.9184	0.3684	0.3221
9	0.9532	0.9401	0.2981	0.2466
10	0.9671	0.9520	0.2120	0.1870

TABLE II. Table Showing Accuracies Of Different Models.

Model	Accuracy (%)	Precision	Recall	F1-Score
ResNet-50	95.2	0.96	0.95	0.96
VGG19	92.3	0.94	0.91	0.92
DenseNet	94.2	0.92	0.92	0.93
InceptionV3	93.1	0.94	0.93	0.93
AlexNet	89.2	0.88	0.86	0.90

TABLE III. Table Showing Accuracies of Different Techniques.

Augmentation Technique	Accuracy (%)	Precision (%)	Recall (%)
None	85	82	80
Rotation	88	86	85
Flipping	90	88	87
Noise Injection	91	89	89
Contrast Adjustment	93	92	91

VI. RESULTS

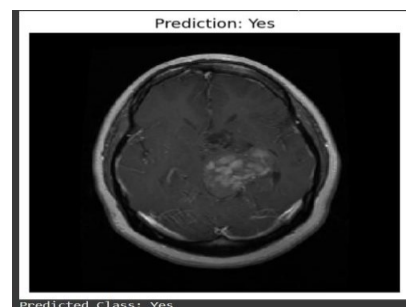


Fig. 3. Brain Tumor Classification – Yes Predicted.

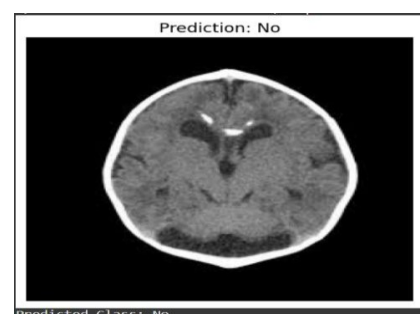


Fig. 4. Brain Tumor Classification – No Predicted.

Over several epochs we can say that models are stable and detect patterns correctly with a decent accuracy. While training we can see the constant increase of training accuracy and validation accuracy over 10 epochs as well as the decrease of loss and this can be proved by testing the model by giving the MRI images for testing purposes.

The above-mentioned images belong to two different classes. i.e. Yes, no which are subjected for testing. Whenever the images are given to model for testing the model predicted the images correctly that resembles how the model recognized and understood the pattern for detecting the tumor in the process of training itself. so this type of accurately predicting tools are necessary for the doctors to make the decision correctly and efficiently.

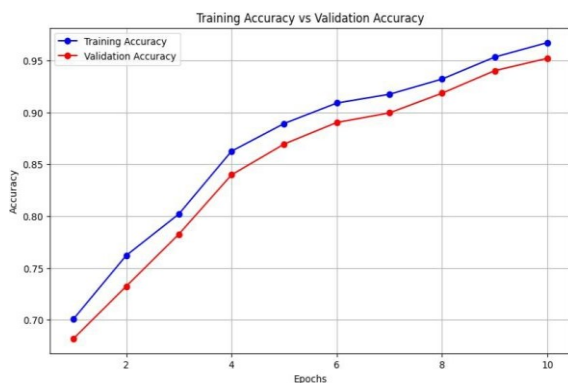


Fig. 5. Graph representing training and validation accuracy.

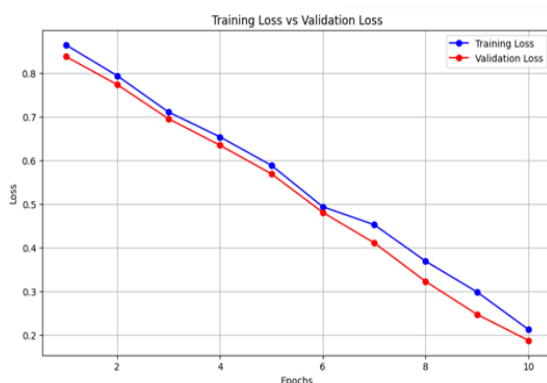


Fig. 6. Graph representing training and validation loss.

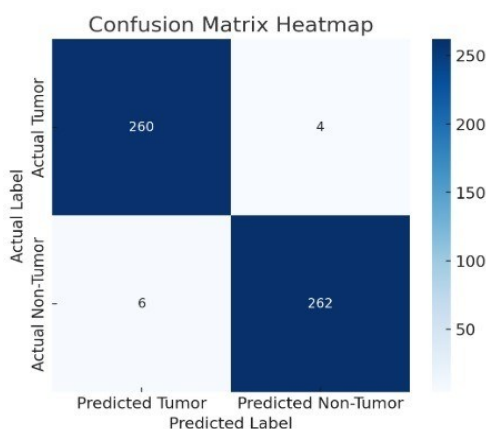


Fig. 7. Confusion Matrix.

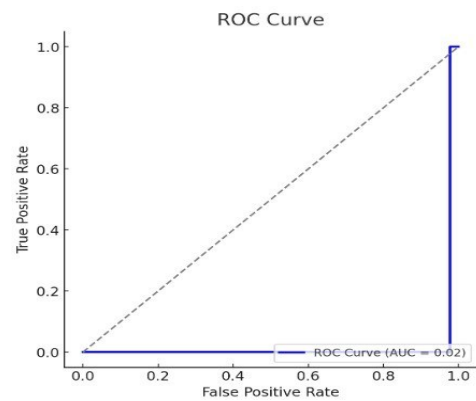


Fig. 8. Receiver Operating Characteristic (ROC) Curve.

The above results of ResNet-50 model table describe the accuracy and loss in training and validation phases in 10 epochs. Initially training accuracy started at 0.7010 and ended at 0.9671 describes that the model has significantly learnt feature extraction and pattern detection from images. validation accuracy value at initial epoch is 0.6821 and at final epoch is 0.9520 resembles the model can predict brain tumor effectively and increase from initial to final epochs reflects its prediction rate is significantly increased and depletion of loss values in training and testing resembles the model is completely stable and its performance is significantly increased over 10 epochs.

VII. CONCLUSION

This study showcases the effectiveness of ResNet-50 in detection of brain tumor from images. The model achieved high accuracy which resembles the model was successful in detecting patterns automatically for effective classification without any external effort. These results resemble ResNet-50's ability in medical imaging mainly for early and precise detection. This model will be helpful for radiologists by improving the classification and reducing the errors in clinical practice.

REFERENCES

- [1] Halil Can Kucukyildiz, "Trends on Central Nervous System Cancers in Turkey, Turkish neurosurgery, vol. 30, no. 4, pp. 527- 531, 2020.
- [2] Melissa L. Bondy et al., "Brain tumor epidemiology: consensus from the Brain Tumor Epidemiology Consortium", Cancer, vol. 113, no. S7, pp. 1953-1968, 2008.
- [3] Jennifer Cahill et al., "Brain tumor symptoms as antecedents to uncertainty: an integrative review", Journal of Nursing Scholarship, vol. 44, no. 2, pp. 145-155, 2012.
- [4] P. Gokila Brindha, M. Kavinraj, P. Manivasakam and P. Prasanth, "Brain tumor detection from MRI images using Deep Learning Techniques," IOP Conference Series: Materials Science and Engineering, p. 012115, 2021.
- [5] Maria Nazir, Sadia Shakil and Khurram Khurshid, "Role of deep learning in brain tumor detection and classification (2015 to 2020): A review", Computerized Medical Imaging and Graphics, vol. 91, pp. 101940, 2021.
- [5] Maria Nazir, Sadia Shakil and Khurram Khurshid, "Role of deep learning in brain tumor detection and classification (2015 to 2020): A review", Computerized Medical Imaging and Graphics, vol. 91, pp. 101940, 2021.
- [6] Sarah Ali Abdelaziz Ismael, Ammar Mohammed and Hesham Hefny, "An enhanced deep learning approach for brain cancer MRI images classification using residual networks", Artificial intelligence in medicine, vol. 102, pp. 101779, 2020.
- [7] L. M. DeAngelis, "Brain tumors", N. Engl. J. Med., vol. 344, no. 2, pp. 114- 123, 2001.

- [8] M. R. Ismael and I. Abdel-Qader, "Brain Tumor Classification via Statistical Features and Back-Propagation Neural Network", 2018 IEEE International Conference on Electro/Information Technology (EIT), pp. 252-257, 2018
- [9] P. Afshar, K. N. Plataniotis and A. Mohammadi, "Capsule Networks for Brain Tumor Classification Based on MRI Images and Coarse Tumor Boundaries", ICASSP 2019 — 2019 IEEE International Conference on Acoustics Speech and Signal Processing (ICASSP), pp. 1368-1372, 2019.
- [10] M. M. Badža and M. C. Barjaktarović, "Classification of brain tumors from mri images using a convolutional neural network", Appl. Sci., vol. 10, no. 6, 2020.
- [11] H. H. Sultan, N. M. Salem and W. Al-Atabany, "Multi-Classification of Brain Tumor Images Using Deep Neural Network", IEEE Access, vol. 7, pp. 69215-69225, 2019.
- [12] A. Pashaei, H. Sajedi and N. Jazayeri, "Brain Tumor Classification via Convolutional Neural Network and Extreme Learning Machines", 2018 8th International Conference on Computer and Knowledge Engineering (ICCKE), pp. 314-319, 2018.
- [13] A. Adinegoro, R. D. Atmaja and R. Purnamasari, "Deteksi Tumor Otak dengan Ekstrasi Ciri and Feature Selection menggunakan Linear Discriminant Analysis (LDA) dan Support Vector Machine (SVM) Brain Tumor's Detection with Feature Extraction and Feature Selection Using Linear Discriminant Analysis (LDA)", e-Proceeding Eng, vol. 2, no. 2, pp. 2532-2539, 2015.
- [14] T. M. Shahriar Sazzad, K. M. Tanzibul Ahmmmed, M. U. Hoque and M. Rahman, "Development of Automated Brain Tumor Identification Using MRI Images", 2nd Int. Conf. Electr. Comput. Commun. Eng. ECCE 2019, pp. 1-4, 2019.
- [15] M. Gurbina, M. Lascu and D. Lascu, "Tumor detection and classification of MRI brain image using different wavelet transforms and support vector machines", 2019 42nd Int. Conf. Telecommun. Signal Process. TSP 2019, pp. 505-508, 2019
- [16] T. M. Shahriar Sazzad, K. M. Tanzibul Ahmmmed, M. U. Hoque and M. Rahman, "Development of Automated Brain Tumor Identification Using MRI Images", 2nd Int. Conf. Electr. Comput. Commun. Eng. ECCE 2019, pp. 1-4, 2019.
- [17] N. SrinivasaRao, G. R. Krishna, C. Raghu and K. Sasidhar, "Image Segmentation Approaches to Detect Abnormalities in Brain MRI Images using CNN & U-Net," 2023 7th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2023, pp. 436-440, doi: 10.1109/ICCMC56507.2023.10083935.