Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 27 No. 3 (2024)

Advanced Algorithmic Approaches for Accurate Classification and Statistical Analysis of Brain Tumors: Enhancing Diagnostic Precision

Dinesh B. Bhoyar[1],Vyankateshwar G. Girhepunje[2],Arvind R. Bhagat Patil[3],Rajesh Khobragade[4],Ajay Paithane[5],Ujwala Patil[6]

[1]Department of Electronics and Telecommunication Engineering, Yeshwantrao Chavan College of Engineering, Wanadongri, Nagpur,India. Email: dinesh.bhoyar23@gmail.com

[2]Dept. of Electronics and Telecommunication, Priyadarshini College of Engineering, Nagpur.
Email: vyenktesh1973@gmail.com

[3]Department of Computer Technology, Yeshwantrao Chavan College of Engineering, Wanadongri, Nagpur, India. Email: arbhagatpatil@gmail.com

[4]Department of E&CS, Shri Ramdeobaba College of Engineering, Nagpur, Maharashtra, India.
Email: khobragaderh@rknec.edu

[5]Dr.D.Y.Patil Institute of Engineering Management and Research, Akurdi Pune, India.
Email: ajay.paithane@dypiemr.ac.in

[6]JSPMS Rajarshi Shahu College of Engineering, Tathawade Pune, India.
Email: sakshi.paithane@gmail.com

Article History:

Received: *16-02-2024*

Revised: *26-04-2024*

Accepted: *18-05-2024*

Abstract

Brain tumor classification and examination are exceptionally vital in therapeutic examinations since they have a huge impact on how medicines are arranged and how well patients do. Utilizing cutting-edge machine learning and profound learning strategies, this consider looks into progressed factual ways to move forward the exactness of classifying brain tumors. We need to create brain tumor discovery more exact and dependable by utilizing these complex equations. This will offer assistance us get around the issues with current strategies. Our consider employments a huge collection of diverse sorts of brain tumors to prepare and test a number of progressed models, such as convolutional neural systems (CNNs), bolster vector machines (SVMs), and outfit learning strategies. To discover out how well each strategy works, we see at measures like precision, affectability, specificity, and the zone beneath the collector working characteristic bend (AUC-ROC). In expansion, we do a full measurable examination of the collection to discover vital patterns and connections that deliver us more data around the tumors and how they develop. The recommended strategies work superior at classifying tumors, which incredibly brings down the number of off-base analyze. Our comes about show that these progressed calculations can be valuable apparatuses in clinical settings, making a difference specialists make more precise analyze and come up with more personalized treatment plans. In expansion, utilizing factual examination makes a difference us get it how tumors carry on, which includes to our in general understanding of neuro-oncology. This consider appears how imperative it is to keep coming up with unused computer methods for therapeutic determination. We are making strides the way brain tumors are classified and analyzed, which leads to superior quiet care and comes about. This appears how AI has the capacity to totally alter healthcare. Within the future, analysts will center on combining distinctive sorts of information and making real-time determination apparatuses to assist specialists make superior choices.

Keywords: Brain Tumor Classification, Advanced Algorithms, Machine Learning in Diagnostics, Deep Learning for Medical Imaging, Diagnostic Precision.

1. Introduction

The brain, the most critical and intricate organ of the human body, is responsible for controlling the entire nervous system and comprises approximately 100 billion nerve cells. It emerges as an essential organ from the center of the nervous system and, thus, any abnormality present in the brain may pose a significant threat to human health. Such anomalies are commonly attributed to morbidity and cancer-related conditions. It is imperative to note that the brain, being the central processing unit of the human body, necessitates utmost care and attention to maintain its proper functioning. The brain disease is having impact on the overall health of human being. The abnormal growth of brain tissues causes brain tumor [1]. In some cases the tumor starts at other part of the body and then spread in brain .According to World Health Organization (WHO) the brain tumors are classified into four categories out of which first two, Grades 1 and 2 are less severe, whereas Grades 3 and 4 are more serious. The medical treatment of brain tumor is depends on the various parameters like size of the tumor and the location of the tumor. Magnetic resonance imaging (MRI) is used normally for detection and treatment of brain tumor. MRI gives more clear and accurate image of soft tissues compared to other imaging technique [2].

Brain tumor labeling and research are very important for medical diagnosis because they affect how patients are treated and what their outlook is. Brain tumors, which can be either normal or cancerous, are hard to treat because they are so complicated and show up in a lot of different ways. Radiological imaging and tissue analysis are the main traditional diagnostic methods [3]. However, they are not always accurate and quick at classifying, which can cause treatment delays or the wrong diagnosis. New advanced statistical methods, especially those based on machine learning (ML) and deep learning (DL), offer hopeful ways to get around these problems [4], which will improve the accuracy of diagnoses and the health of patients. Using very large amounts of computing power and complex models to look at medical data with a level of accuracy that has never been seen before is a big step forward in medical monitoring. Support vector machines (SVMs), random forests, and ensemble learning methods are some examples of machine learning algorithms that have shown a lot of promise in identifying brain tumors by finding minor trends in imaging data that humans might not be able to see [11]. Deep learning, especially convolutional neural networks (CNNs), has changed this area even more by automating the process of feature extraction and classification. This has made diagnostic methods easier and increased dependability.

The point of our study is to find out how well these advanced computer methods work at classifying brain tumors and analyzing their statistics. We train and evaluate various models using a large dataset that includes a wide range of tumor types and imaging methods to find the best methods. To carefully check how well each method works, we use key performance measures like accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) [5]. In addition, we do a full statistical analysis of the information to find important trends and relationships that will help us learn more about how tumors develop and change over time. This study is important because it could improve the accuracy of diagnoses and also because it has wider effects for personalized care. By making brain tumor labeling more accurate, we can make treatment plans that are more specific to each patient, which will improve the effectiveness of treatment. The results of statistical studies can also be used to guide future study and treatment practices, which adds to the body of knowledge in neuro-oncology as a whole [6]. This study shows how artificial intelligence (AI) could completely change healthcare by looking into advanced statistical methods. Artificial intelligence-based diagnoses could make doctors' jobs easier by giving them tools that can help find brain tumors early, correctly classify them, and keep an eye on them. We are getting closer to a future where diagnosis accuracy and patient care are greatly improved as we keep improving these tools and putting them to use in clinical settings. In using advanced algorithms to accurately classify and analyze brain tumors statistically is a very important next step in medical diagnosis [7]. This study [8] aims to connect old-fashioned ways of diagnosing illnesses with cutting-edge AI technologies. This will lead to better results for patients and progress in the area of neuro-oncology. In the future, researchers will focus on combining different types of data and making real-time diagnosis systems to help doctors make even better decisions. This shows that AI is still evolving in healthcare.

2. Literature Survey

In recent years, machine learning (ML) has become an important tool for making human work more efficient, especially in the area of medical imaging. A lot of research studies have shown how ML can completely change the way diagnoses are made and treatments are planned. As an example, [9], a well-known study that tried to separate brain tumors from other types of MRI data by using two networks together, shows this. This method uses the best features of convolutional neural networks (CNNs) to improve techniques for separating tumors. It shows how machine learning can be used to do difficult medical imaging jobs more accurately. The research in [9] shows that mixing several neural networks can make tumor segmentation work better. By using an ensemble method, the researchers were able to use the different powers of different networks to make the classification results stronger and more accurate. Typically exceptionally vital in restorative imaging, where precision is exceptionally vital. The utilize of CNNs to make strides strategies for upgrading tumors appears how adaptable and valuable machine learning is in therapeutic location. It [10] makes another imperative expansion to the field by proposing a theoretical demonstrate for classifying brain tumors employing a gather of profound characteristics and machine learning. Three brain MRI datasets are utilized in this study's tests, and a CNN that has as of now been taught is utilized to pull out profound highlights from the pictures. The most objective is to create the demonstrate littler so that it can be utilized for real-time therapeutic examination. This strategy is curiously since it understands one of the greatest issues with utilizing machine learning models in healthcare circumstances, which is making sure that the models work well and do not use too much computing control. After you utilize outfit profound highlights, the leading parts of a few highlight sets work together to create the sorting prepare way better. Agreeing to [12], the most objective of the think about is to make a cascaded CNN demonstrate that can consequently partitioned brain stem tumors. Two highlight combination modules are utilized in this strategy: Pyramid multiscale feature fusion and Brain stem zone moves forward include combination. These parts are implied to make strides the model's capacity to choose up critical points of interest at different sizes, which is able lead to more precise classification. This think about proposes that more investigate ought to be done to train the CNN show on a greater set of brain stem tumor cases. This may move forward the model's performance and capacity to be utilized completely different circumstances. The center on feature fusion strategies appears how ML approaches to restorative pictures are continuously changing in arrange to make conclusion devices that are more precise and solid.

In [13], an outfit demonstrate for finding and classifying brain tumors is displayed. This show is made up of three exchange learning-based models that are found the middle value of. The investigate employments three vision-based transformer models—SWIN, CCI, and EANet—and checks how well they work against standard exchange learning (TL) models. This method is vital since it looks into how to utilize progressed transformer models in conjunction with standard machine learning strategies to make tumor recognizable proof and classification more exact. Future investigate in this think about will center on testing the models' capacities utilizing reasonable AI (XAI), which can appear how the models make choices and be more open approximately them. Understanding the thinking behind a model's explanations is exceptionally vital for building believe among healthcare specialists and patients. This can be particularly genuine in the therapeutic field. More verification that machine learning can offer assistance make brain tumor division and classification more accurate and speedy is appeared by these considers. Including progressed machine learning strategies like outfit strategies, feature fusion, and transformer models to restorative pictures is a huge step forward. These strategies not as it were make strides the precision of diagnoses but too make it conceivable for AI to be utilized in clinic situations in genuine time, in a way that's proficient and simple to get it.

There are a lot of interesting areas to study in this field in the future. First, we need to look into how to combine multimodal data, which includes various types of medical images and clinical data, in order to make diagnostic models that are more complete. This could lead to more complete and accurate tests for brain cancer. Second, making models that are faster and lighter is important for real-time apps, especially in places with limited resources. In order to reach this goal, methods like model trimming, quantization, and information distillation could be looked into. Moreover, utilize of logical AI (XAI) is exceptionally vital for ML to ended up broadly utilized in healthcare. Making beyond any doubt that machine learning models are clear and simple to get it can offer assistance construct believe between specialists and patients, which makes it simpler to utilize them in ordinary therapeutic hone. The most objective of inquire about ought to be to discover ways to create ML models less demanding for healthcare labourers to utilize by giving them clear, common sense experiences. In conclusion, including more preparing datasets with a wide run of agent tests is exceptionally vital for making ML models more valuable in genuine life. When healing centers, think about teach, and healthcare bunches work together, they can make enormous records with parts of notes that appear a lot of distinctive quiet characteristics and tumor highlights. This could make machine learning models more steady and solid, making beyond any doubt they work well with a wide extend of patients and clinical circumstances. In utilizing machine learning to isolated and classify brain tumors has appeared a parcel of guarantee for making determination more exact and quicker. The works talked around appear the unused strategies that are being looked into, such as transformer models, XAI, gathering strategies, and highlight combination. As consider moves forward, these strategies are likely to ended up more vital in clinical hone. This will make strides understanding comes about and make healthcare arrangements work superior. ML contains a shinning future in therapeutic imaging, and unused consider is almost to alter this exceptionally important field indeed more.

3. Methodology

As shown in Fig.1 (a), the first block in the block diagram involves the preprocessing of the image. The image is preprocessed in the following manner.

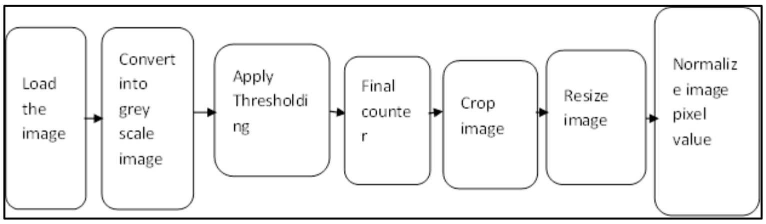


Fig 1 (a) Preprocessing of an input image

Figure-1(a) shows the block diagram of preprocessing of input image [5]. It involves several steps as shown in figure. In first step convert the image into gray scale. By using this we can reduce the pixel size. For highlighting the image function and improving its quality by reducing noise and enhancing clarity image thresholding is used [15].

After that, the contour finding is used to analyze shapes, detect objects, and recognize patterns, due to which accuracy of image boosted. After this the image cropping is done to remove any unwanted parts and resize it to fit the dimensions required by the transfer learning model. Once resized, we normalize the image to ensure the pixel values are within a consistent range. This step is essential for the network to learn patterns effectively and to prevent issues like exploding gradients. Normalization also speeds up the convergence process. The image undergoes preprocessing before it is passed to the pre-trained network. Pre-trained networks facilitate faster and easier training by simplifying the process, as they have already been trained on large datasets, typically for large-scale image classification tasks. We use transfer learning to customize pre-trained models[16][17], as depicted in Figure1 (b). After modifying the network, we fine-tune the pre-trained model. This process entails updating the model to produce more accurate and relevant outputs based on the current data, without altering its parameters or variables. Once the model is fine-tuned, we prepare new data and create separate training and validation datasets. Data is divided according to the 80:20 rule, where 80% of data is used for training and 20% for validation. We use the validation dataset to predict new data, and the final predicted data is the output.

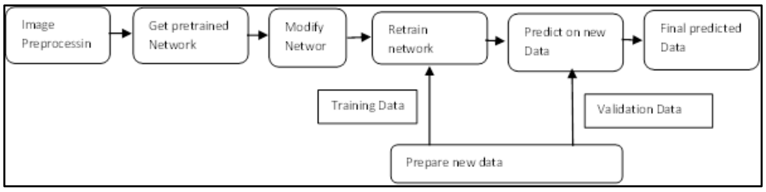


Fig 1(b) Block diagram

4. Data Set

The multiclass brain tumors dataset is composed of four categories, namely, Pituitary tumors, Gliomatumors, Meningioma tumors, and the absence of tumors. The dataset is comprised of a total of 232275 images [8]. To train and test our model, we partitioned the dataset into three distinct sets, which are training, testing, and validation, with each set containing 70%, 20%, and 10% of the data, respectively. The training set, consisting of 187092 images, was used for training purposes, while the testing and validation sets, containing 45183 images, were employed to test and validate the model.

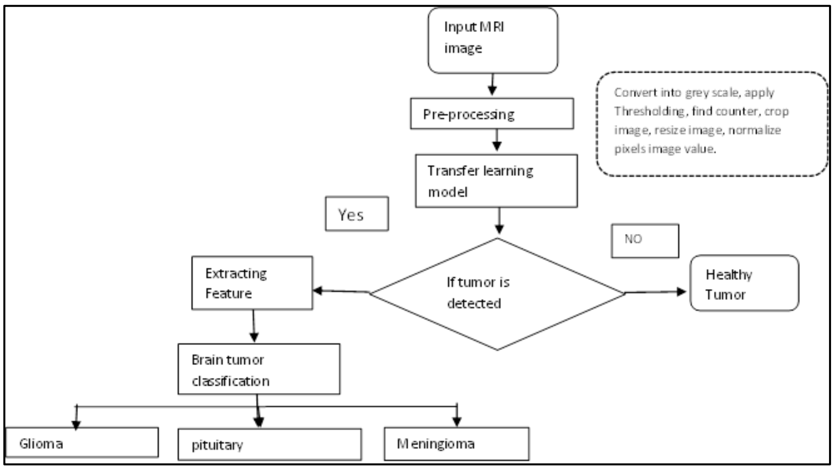


Fig 2 Flow chart

6. Technique Used

Transfer learning Model

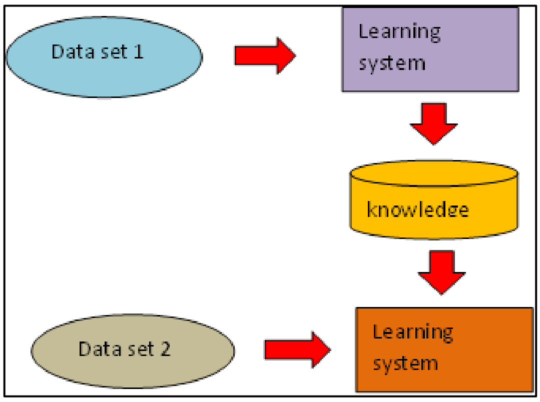


Fig 3 Block diagram of a transfer learning model

Transfer learning is used to improves the performance of related tasks by using knowledge from a specific task. The technique of transfer learning is a valuable method to leverage previously acquired knowledge from learned tasks and apply it to novel, related ones. This approach is particularly useful when one has significantly more data for a particular task, T1, and aims to generalize this knowledge, including features and weights, to a different task, T2 [9], that has far fewer data points. In computer vision, this method may involve knowledge transfer of low-level features such as edges, shapes, corners, and intensity, between different tasks. A domain, D, can be represented mathematically as a two-element tuple D = {ϕ, P(X)}, where it consists of a feature space, ϕ, and a marginal probability, P(X). This representation allows for a clear distinction between the space of possible features and the probability of a specific feature, enabling more precise modelling and analysis.

A domain consists of two components: D={$\chi, p(X)$}

- Feature space: χ
- Marginal distribution: P(X), X = {x_1….., x_n} $x_i \epsilon \chi$

For a given domain D, a task has two parts:

- T = {γ, P(Y|X)} = γ, η
- Y = {y1, ..., yn}, with each yi belonging to γ
- A label space: γ
- A predictive function η, which learns from pairs of feature vectors and labels (xi, yi), where xi belongs to χ and yi belongs to γ.
- For each vector in a domain, η predicts its corresponding label: η(xi) = yi

Transfer learning is a technique that uses knowledge from one task or domain to help with another.

A DenseNet [10] is a type of neural network called a densely connected convolutional network, which performs well in image recognition tasks. In this network, each layer is connected to every other layer in a feed-forward manner. This means that the output of each layer is used as an input for all following layers. This design allows for feature reuse, which reduces the number of parameters and improves the model's accuracy. The diagram below shows how the layers are connected. DenseNet was created to solve the problem of accuracy in complex neural networks caused by the vanishing gradient issue.

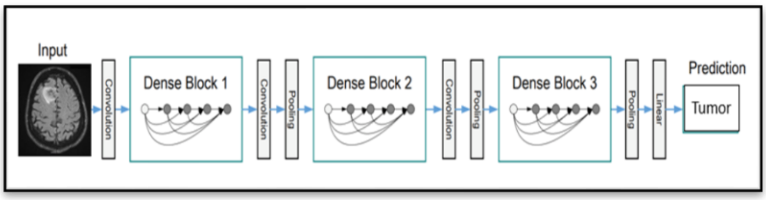


Fig 4 Block diagram of a dense Net model

In such networks, the distance between the input and output layers is often too long, resulting in information vanishing before reaching its destination.

Step 1: Input and Initial Convolution

The input image X is passed through an initial convolution layer:

$$Y_0 = f(W_0 * X + b_0)$$

where W_0 are the weights, b_0 are the biases, * denotes the convolution operation, and f is the activation function (e.g., ReLU).

Step 2: Dense Block - Layer 1

Each dense block consists of multiple layers, each taking input from all previous layers. For the first layer within a dense block:

$$Y_1 = f(W_1 * [Y_0] + b_1)$$

where [Y_0] represents the concatenation of all previous feature maps.

Step 3: Dense Block - Layer l

For the l-th layer in the dense block, the input is the concatenation of the output of all preceding layers:

$$Y_l = f\left(W_l * \left[Y_0, Y_1, \dots, Y_{\{l-1\}}\right] + b_l\right)$$

where [Y_0, Y_1, ..., Y_{l-1}] denotes the concatenation of feature maps from layers 0 to l-1.

Step 4: Transition Layer

Between dense blocks, transition layers reduce the number of feature maps and perform downsampling:

$$Z_l = f(W_t * Y_l + b_t)$$

$$Y_{\{l+1\}} = Pool(Z_l)$$

where W_t and b_t are the weights and biases of the transition layer, and Pool is a pooling operation (e.g., average pooling).

Step 5: Bottleneck Layer

DenseNet can include bottleneck layers to reduce the number of parameters and improve computational efficiency:

$$B_l = f(W_b * Y_l + b_b)$$

where W_b and b_b are the weights and biases of the bottleneck layer.

Step 6: Growth Rate

The growth rate k controls the number of feature maps added by each layer in the dense block. If the growth rate is k, the output of each layer is:

$$Y_l = f\left(W_l * \left[Y_0, Y_1, \dots, Y_{\{l-1\}}\right] + b_l\right)$$

where each Y_l has k feature maps.

Step 7: Final Classification Layer

After the last dense block and transition layer, the final feature map is passed through a fully connected layer for classification:

$$P = softmax\left(W_f * Y_L + b_f\right)$$

where W_f and b_f are the weights and biases of the fully connected layer, Y_L is the output of the last layer, and softmax is the softmax activation function.

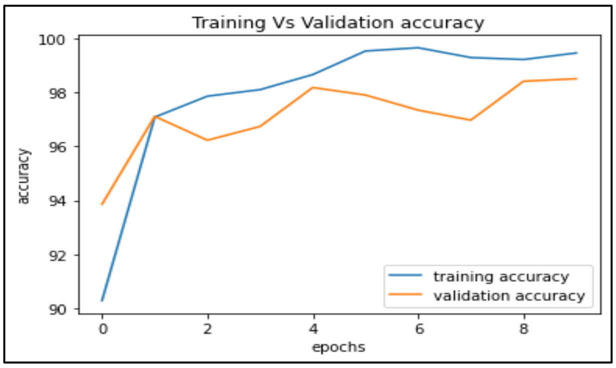
In a DenseNet, there will be approximately L and L plus one by two connections (L(L+1)/2), allowing over 100 layers to be trained in the model using this technique. Furthermore, DenseNet has several advantages, including parameter efficiency, improved flow of gradient through the network, and implicit deep supervision. Within a dense block, each layer receives input feature maps from the previous layer, providing dense connectivity. Composite functions consist of batch normalization followed by a convolution layer. Transition layers are responsible for combining the feature maps produced by a dense block and decreasing their size. Max Pooling is enabled in these layers. The primary advantage of the DenseNet architecture is that when a layer takes input, it not only takes input from the previous layer but also from the layer before that. This feature enhances the model's training effectiveness, enabling it to learn better features.

7. Result

Table.1 Final Accuracy of Fine-tuned DenseNet model on real-time Dataset

Test Accuracy score	test precision score	Recall Score	f1 score
98.74	98.76	98.74	98.746

When the fine-tuned DenseNet demonstrate is utilized on a real-time dataset, Table 1 appears the conclusion exactness measures. The show got a test precision score of 98.74%, which suggests that it accurately sorted most of the cases. The test exactness score of 98.76% appears that the show is exceptionally great at speculating the positive lesson whereas too diminishing the number of fake positives. Too, the review score of 98.74% appears that the show accurately finds nearly all genuine positive cases, with exceptionally few fake negatives. The F1 number, which equalizations exactness and review, is 98.746%, appearing that the demonstrate does a great work of taking care of both untrue positives and untrue negatives. These estimations show that the DenseNet plan is sweet at accurately sorting complicated real-time information. The refined model got great scores on all measures, which recommends it'll work well in genuine life, where precision and memory are critical for constancy.



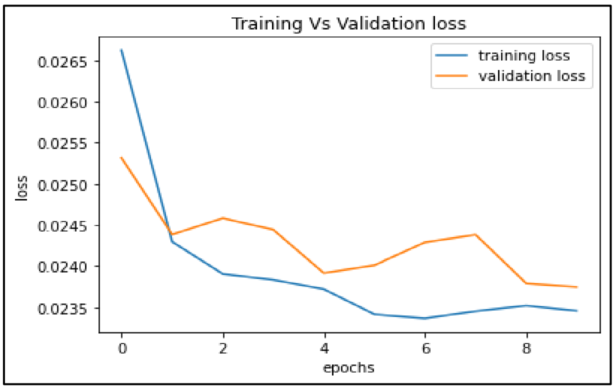


Fig.5 Resnet 50 Comparison of Training verses Accuracy and Loss

Resnet 50: The Resnet50 architecture figure 5 employs a residual approach by assembling layers as residual functions. As per the authors of [46], this unique approach makes Resnet50 one of the deepest architectures

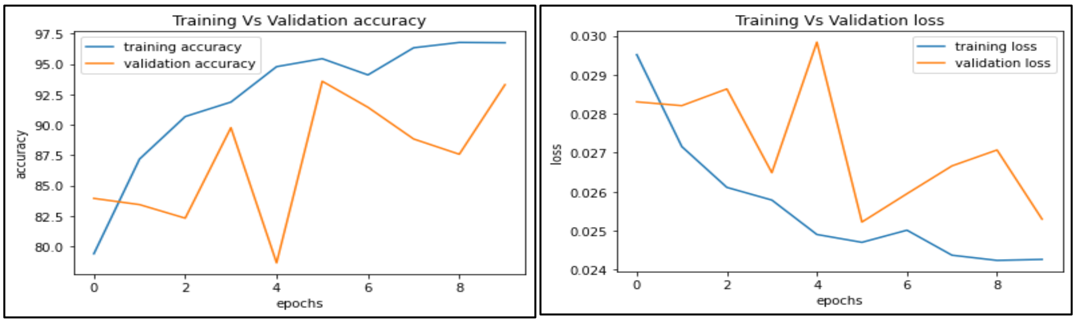


Fig.6 Alexnet Comparison of Training verses Accuracy and Loss

Alexnet: This is a type of advanced computer network as shown in figure 6 called an 8-layer deep convolutional neural network. You can use an already-trained version of it that has been designed to work with over a million different pictures from ImageNet.

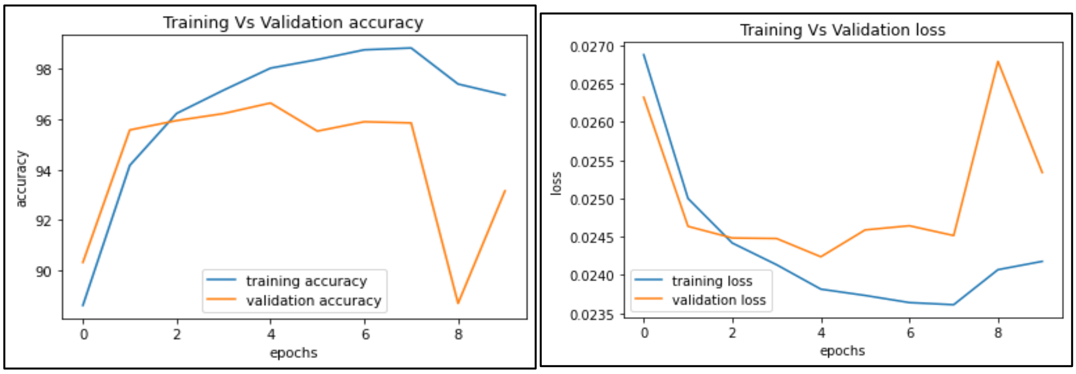


Fig.7 VGG Comparison of Training verses Accuracy and Loss

VGG: Visual Geometry Group (VGG) as shown in figure 7 is a deep Convolutional Neural Network (CNN) architecture that consists of multiple layers. VGG-16 and VGG-19 are the two variants of VGG architecture, which contain 16 and 19 convolutional layers respectively.

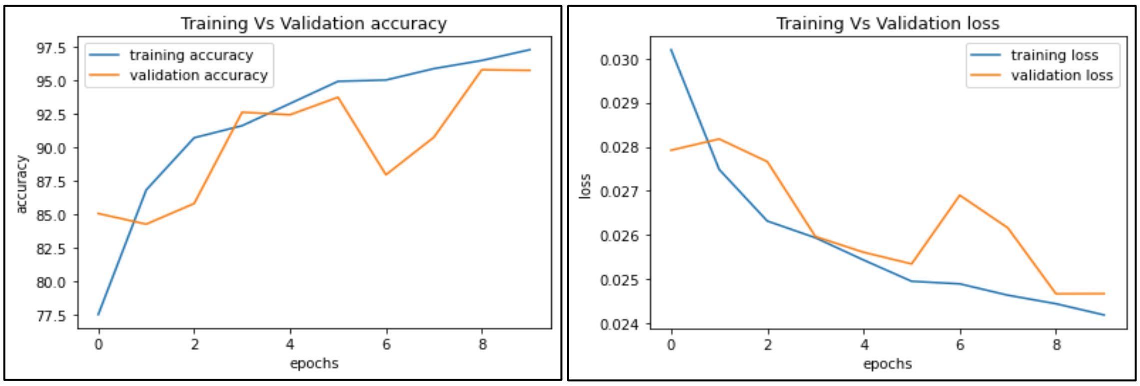


Fig8 Squeezenet Comparison of Training verses Accuracy and Loss

Squeezenet: This is a convolutional neural network as shown in figure 8 that utilizes fire modules that utilize 1x1 convolutions to "squeeze" parameters and reduce their number.

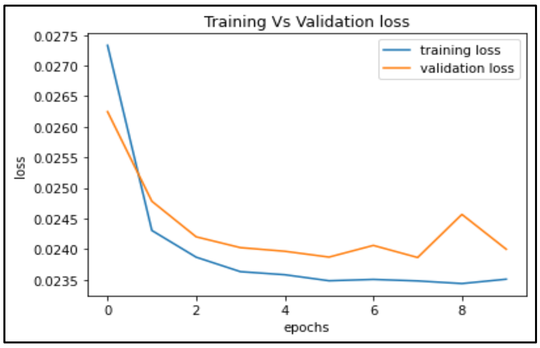


Fig9 Densenet (Final model) Comparison of Training verses Accuracy and Loss

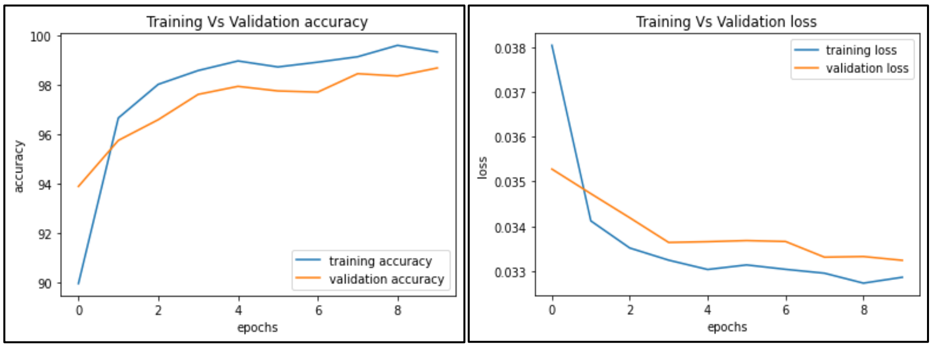


Fig 10 Inception v3 Comparison of Training verses Accuracy and Loss

Inception v3: Google has developed a model known as InceptionV3 as shown in figure 10, which represents a modified version of the Inception architecture. Notwithstanding the 42 layers it encompasses, InceptionV3's computation cost is merely 2.5 times higher than that of GoogleNet. It is noteworthy that InceptionV3 secured the first runners-up prize for image classification from the ILSVRC. Training Vs validation accuracy and loss of six Fine-tuned transfer learning models as shown in table-1 . As the **DenseNet** result is more stable, so, we are going to choose a **dense net** as our **finalmodel**. Here is the final accuracy and performance matrix. S shown in figure 11.

:

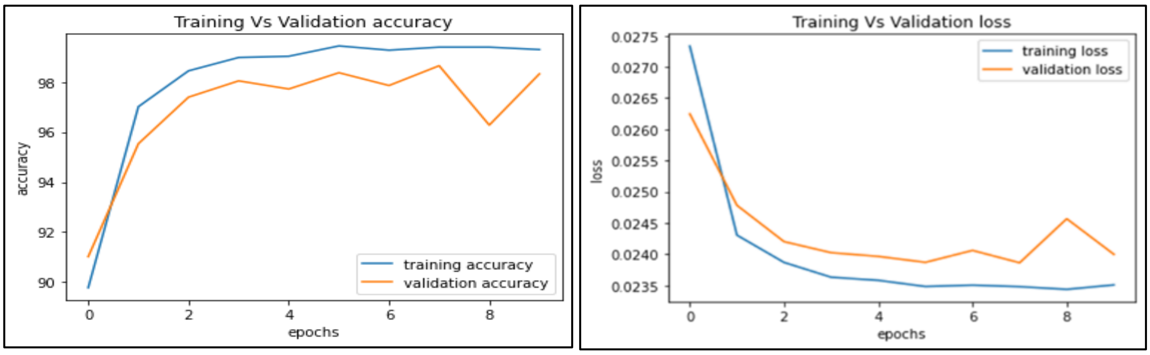


Figure 11 Training vs Validation accuracy curve of DenseNet network Training vs Validation loss on DenseNet network

Advances in Nonlinear Variational Inequalities
ISSN: 1092-910X
Vol 27 No. 3 (2024)

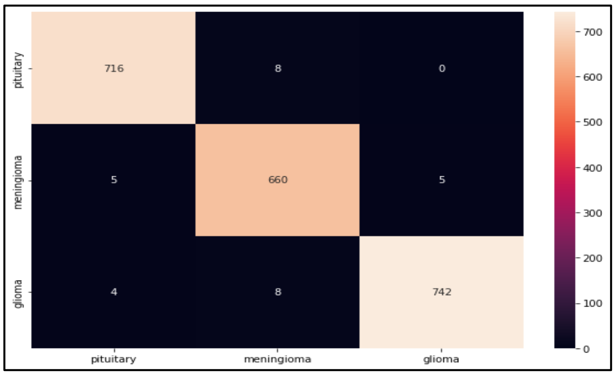


Fig. 12 Confusion matrix

A confusion matrix as shown in figure 12 is often used to check how well a machine-learning algorithm is working. It shows the number of times the model predicted true or false positives and negatives, which helps to measure how accurate it is.

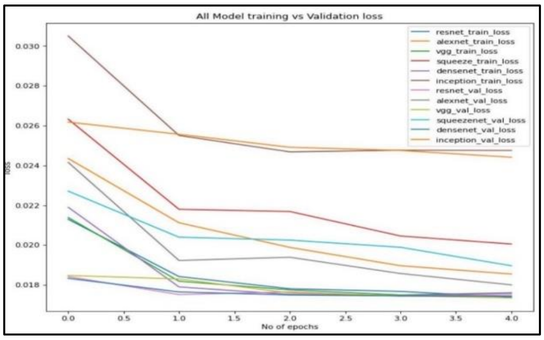


Figure 13 (a) Training and Validation Accuracy and Loss plotted for all six models

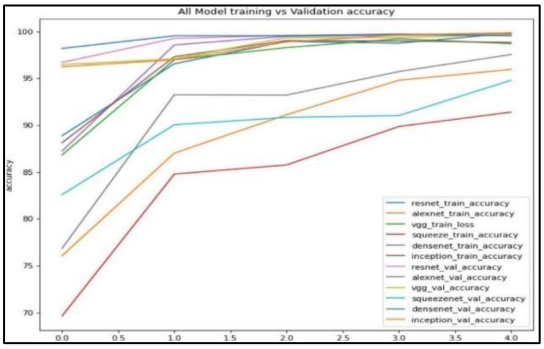


Figure 13 (b): Training and Validation Loss plotted for all six models

8. Conclusion

We needed to utilize exchange learning models on real-time data to sort brain tumors into distinctive bunches for this work. The models were exceptionally precise, with scores of 97%, 96%, 97%, 93%, 98%, and 98%, in that arrange. Strikingly, DenseNet turned out to be the most excellent show, with a 99% victory rate. The tall level of exactness come to by DenseNet appears how progressed computer strategies seem offer assistance make strides the exactness of brain tumor diagnoses. DenseNet does way better since it contains a thick association design that lets way better slope stream and highlight reuse. This makes learning more proficient and makes strides demonstrate execution. This work demonstrates that DenseNet can handle troublesome restorative imaging assignments, which makes it indeed way better for utilize in clinic settings. Our comes about appear that profound learning models have the capacity to totally alter how therapeutic diagnoses are done. The truth that diverse models consistently do well appears that exchange learning could be a solid way to classify tumors, because it can utilize what it as of now knows to induce superior comes about on modern datasets. These comes about too appear how vital it is to select the correct models based on the highlights of a dataset in arrange to urge the foremost precise diagnostics. The progressed calculations strategies talked about in this consider make it conceivable for neuro-oncology to induce way better and more exact conclusion apparatuses. To progress classification exactness indeed more, future study ought to see into combining diverse sorts of information, like DNA and clinical information. Real-time application and assessment in clinical settings are moreover required to form beyond any doubt that these models can be utilized in genuine life. When transfer learning models, especially DenseNet, are used, they make brain tumor detection much more accurate. This study shows the promise of AI-driven methods in healthcare and adds to the current work to improve assessment accuracy and patient results in medical imaging.

References

[1] Mahoor Ali, Syed Omer Gilani, AsimWaris, Kashan Zafar, and MoshinJamil.”BrainTumor Image Segmentation Using Deep Networks. 10.1109/ACCESS 2020.3018160, IEEE

[2] Jeyong Kang Zaid Ullah and Jeonghwan Gawk “MRI- Based brain tumor classification using Ensemble of deep features and machine learning Classifier. 2021,21,2222

[3] Jai Liu, Fang Chen, Changchun, Mingyu Zhu, Xinran Zhang, Liwei Zhang, And Hongen Liao “ A cascaded deep convolutional neural network for joint segmentation and genotype prediction of brainstem Gliomas10.1109/TBME.2018.2845706.

[4] S. Bakas et al,” Identifying the best machine learning algorithm for brain tumor segmentation, progression assessment and overall survival prediction in the BRATS challenge. arXivprepr. arXiv 18111.02629,2018

[5] B.H. Menze et al., “The multimodel brain tumor image segmentation benchmark (BRATS) IEEE Trans. Med. Imaging vol 34, no.10, app1993-2024,2014.

[6] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the Inception Architecture for Computer Vision,” 2015.

[7] K. He, X. Zhang, S. Ren, and J. Sun,” Deep Residual Learning for Image Recognition,” In. Proc. of IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Las Vegas, NV, USA, 2016.

[8] Shahriar Hossain, AmitabhaChakrabarty, Thippa Reddy Gadekallu, Senior Member, IEEE, MamounAlazab, Senior Member, IEEE, and Md. JalilPiran, Senior Member, IEEE “Vision Transformers, Ensemble Model, and Transfer Learning Leveraging Explainable AI for Brain Tumor Detection and Classification”,2017

[9] B. Shyamala, Dr. Brahmananda S.H.” Brain tumor Classification using Optimized and Relief-based Feature Reduction and Regression Neural Network”, September 2023, 105279.

[10] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, “A deep learning model based on concatenation approach for the diagnosis of brain tumor,” IEEE Access, vol. 8, pp. 55 135–55 144, March 2020.

[11] 7.Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., & Parati, N. . (2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[12] Iorgulescu, J.B.; Sun, C.; Neff, C.; Cioffi, G.; Gutierrez, C.; Kruchko, C.; Ruhl, J.; Waite, K.A.; Negoita, S.; Hofferkamp, J.; et al. Molecular biomarker-defined brain tumors: Epidemiology, validity, and completeness in the United States. Neuro-Oncology 2022, 24, 1989–2000.

[13] Ranjbarzadeh, R.; Bagherian Kasgari, A.; Jafarzadeh Ghoushchi, S.; Anari, S.; Naseri, M.; Bendechache, M. Brain tumor segmentation based on deep learning and an attention mechanism using MRI multi-modalities brain images. Sci. Rep. 2021, 11, 10930.

[14] Rahman, M.L.; Reza, A.W.; Shabuj, S.I. An internet of things-based automatic brain tumor detection system. Indones. J. Electr. Eng. Comput. Sci. 2022, 25, 214–222.

[15] Ayadi, W.; Elhamzi, W.; Charfi, I.; Atri, M. Deep CNN for Brain Tumor Classification. Neural Process. Lett. 2021, 53, 671–700.

[16] Al-Galal, S.A.Y.; Alshaikhli, I.F.T.; Abdulrazzaq, M.M. MRI brain tumor medical images analysis using deep learning techniques: A systematic review. Health Technol. 2021, 11, 267–282.

[17] Mahmud, M.I.; Mamun, M.; Abdelgawad, A. A Deep Analysis of Brain Tumor Detection from MRImages Using Deep Learning Networks. Algorithms 2023, 16, 176.