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Robust deep learning approach for accurate detection of brain tumor and analysis

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ABSTRACT

Usually, one of the foremost predominant and intricate therapeutic conditions. As broadly perceived, brain tumors are among the foremost significantly harmful circumstances that can radically abbreviate a person's life expectancy. Various methods are lacking for observing the assortment of tumor sizes, shapes, and areas. When merged with strategies of profound learning, generative adversarial networks (GANs) are competent of catching the measurements, areas, and structures of tumors. Profound learning frameworks will move forward upon the shortage of datasets. It can moreover progress photographs with determination. Classifying and partitioning brain tumors productively is significant. GANs are used in conjunction with an overarching learning handle. A profound learning design called NeuroNet19, could be an intercross of visual geometry group (VGG19) and inverted pyramid pooling module (IPPM) which is utilized to recognize brain tumors. It is clear that, NeuroNet19 employments the foremost exact technique in comparison to all models (DenseNet121, MobileNet, ResNet50, VGG16). The exactness examination gave a Cohen Kappa coefficient of 99% and a F1-score of 99.2%

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1. INTRODUCTION

Brain tumors may be defined as a growing abnormality of brain cells. Such a biological complex architecture requires quite a challenging medicine and also the possibility of impairing brain functions [1]. They may exert pressure on surrounding tissues, hence eventually leading to intracranial pressure and fluid accumulation [2]. Since they could come in any part of the brain and may vary in size and severity, diagnosis and treatment turn out quite challenging.

Brain tumors are basically classified into two categories according to their origin: benign and malignant [3]. These benign types are generally non-aggressive, characterized by slow growth and pose relatively less threat to health [4]. On the other hand, malignant tumors are aggressive; they can invade surrounding areas as well as spread to almost all parts of the body and pose a serious threat to human health, if not treated with excellent effectiveness [5]. Thus, early brain tumor detection is important for patients improvement through the provision of early medical therapy.

Many techniques have been designed for the detection of brain tumors, all of which have an application and a drawback [6], [7]. However, in most conventional image diagnostics, the models rely on machine learning-based models that are easily confused with the inherent complexity of brain tumors since of variations in growth patterns and characteristics [8], [9]. Recent research has focused on deep learning techniques [10] that

may prove quite promising in augmenting detection capabilities. Karamehić *et al.* [11] presented the ensemble deep learning model as an approach to overcome these issues but may be a very computationally expensive model challenging to implement in the clinical setting. Pandiyan *et al.* [12] have used more advanced architectures of convolutional systems for the acknowledgment and classification work. However, the above techniques are challenging because of the sparsity of the available labeled medical datasets, which may cause overfitting and poor generalization.

Najeeb and Dahl [13] reviewed transfer learning techniques to use pre-trained models like VGG and ResNet for improvement. Mahmud *et al.* [14] have employed profound learning to move forward the classification of brain tumors. While these advancements are feasible, the techniques would still inherit the issue of high inter-class variability of tumor morphology and varied scenarios in imaging.

Generative adversarial networks (GANs) are the emerging technologies in medical imaging [15], as it can generate very realistic synthetic data for augmentation purposes. The work of Shoaib *et al.* [16] and Ambeshwar *et al.* [17] show the strength of GANs to overcome limitations faced with small-sized labeled datasets. However, most GAN-based models fail to ensure anatomical fidelity in generated images and fail to compose with easy classification tasks. This landscape underlines the need for innovative approaches designed to be able to effectively address the limitations of the existing methodologies for brain tumor detection. The incorporation of GAN-based enhanced techniques into quite robust architectures of neural networks significantly improves diagnostic capabilities and enhances the outcome for patients [18].

To overcome these challenges, we propose the innovative architecture called NeuroNet19 shown in Figure 1, which integrates the pros of VGG19 with inverted pyramid pooling module (IPPM). Leveraging the proven feature extraction ability of VGG19, the integration of IPPM facilitates iteratively refining an image patch. The hybrid approach therefore functions to improve the accuracy of classification for tumors by simultaneously focusing on local and global tumor characteristics. We further incorporate a GAN-based data augmentation pipeline that generates near realistic synthetic magnetic resonance imaging (MRI) images and can mitigate issues like limited datasets and enhance model robustness and Mask-region-based convolutional neural network (Mask R-CNN) to point the exact tumor location.

Our approach fills still missing gaps in existing methodologies by using a GAN-augmented framework to boost model training on sparse datasets. Using the new IPPM module, enriched feature extraction and classification. It is a computationally efficient solution that adapts to clinical workflows. It signifies a revolutionary approach that diagnoses brain tumors using advanced deep learning and GAN techniques. NeuroNet19 has a good chance of tackling early tumor detection that would result in the appropriate interventions at the right time, thus upgrading the survival rates of patients.

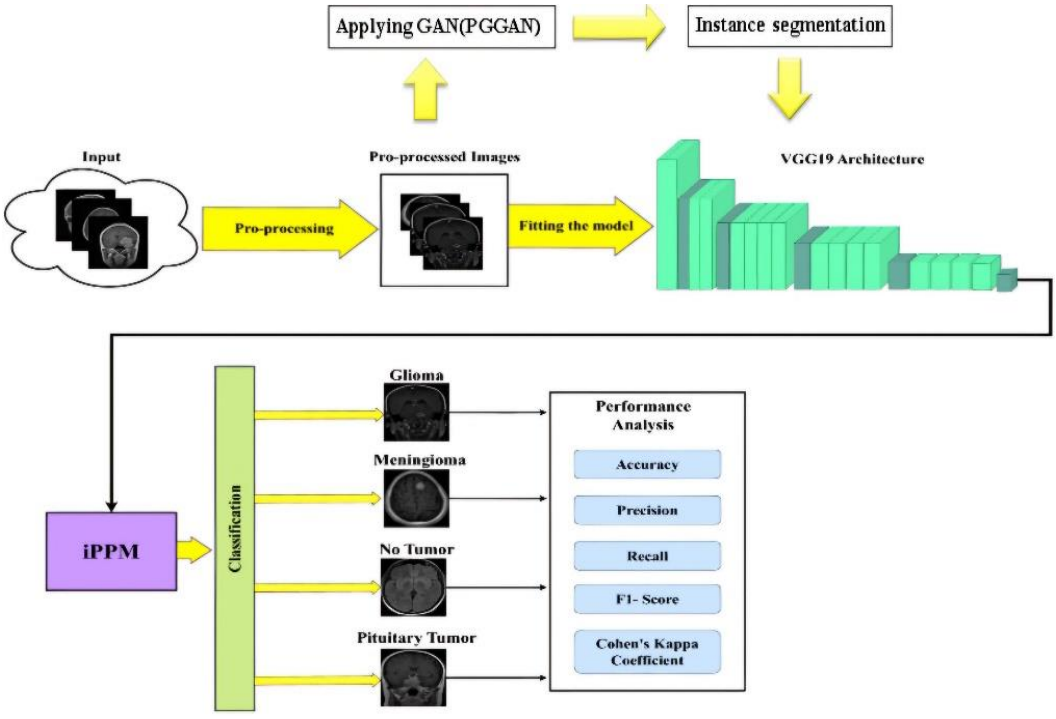

Figure 1. Proposed architecture

2. METHOD

In this study, the detection of brain tumors would combine advanced preprocessing techniques with the novel architecture called NeuroNet19 and progressive growing GANs. Our framework significantly enhances the speed and accuracy of the detection of brain tumor because of the robust features extracted by VGG19, enhanced even better by the IPPM. Moreover, precise segmentation is accomplished through Mask R-CNN while ensuring proper localization of the tumors. These models were selected due to their illustrated effectiveness in taking care of complex datasets and giving precise expectations.

2.1. Details of dataset

The dataset consists of 7,023 restorative MRI images belonging to training, validation and test sets to ensure the thorough testing of a well-trained model. Further separated into four different classes: glioma, meningioma, pituitary tumor, and no tumor. The training set is meant for the training of the NeuroNet19 model, so that it gains robust feature representations. The validation set is mainly useful in the process of training to fine-tune the model further in arrange to avoid overfitting. A proper check of the model on such unseen data is finally intended to be done by the testing set.

2.2. Data preprocessing

Preprocessing may be a pivotal multi-step strategy that improves the quality of MRI pictures by decreasing clamor, adjusting artifacts, and standardizing the information for dependable investigation. This prepare includes an arrangement of changes, such as concentrated normalization, cranium stripping, and picture enrollment, to guarantee consistency over filters. These refined pictures serve as the establishment for precise symptomatic appraisals and AI-based forecasts in therapeutic imaging [19].

2.2.1. Normalization

Numerous strategies are accessible for normalizing information, counting z-score, min-max, and scaling of decimal [20]. By utilizing this min-max strategy, the concentrated values in the input MRI images are scaled to the extend (1, 1) or (0, 1). "z-score standardization" is a method that normalizes each escalated esteem seen in an attractive reverberation picturing such that the standard deviation and mean are '0' [21].

2.2.2. Skull stripping

MRI of brain checks habitually uncover zones of non-brain tissues such as the cranium, dura mater, scalp and meninges. When these things are incorporated in the show, the operation of classification ordinarily proceeds. So, the brain tumor categorization assignments regularly utilize this method as a to begin with step to improve execution where the non-brain zones are expelled.

2.2.3. Resizing

We got to scale all the photographs some time recently nourishing into the models of neural network classification, since deep neural systems need reliable estimate input [22]. In case a picture is bigger than fundamental, it may be scaled down by altering the pixels interior the outline or by adjusting the picture. Thus, all MRI pictures are resized to a steady measurement, of 224×224 pixels to meet input prerequisites of the VGG19 engineering.

2.2.4. Transformed picture

Taking after the process of trimming, pixel values of this trimmed picture are normalized such that the value drops between '0' and '1'. It guarantees dependable and continuous exchange of complex progressive data. This image at that point experiences a beta (or power-law) redress to focus on it is special features. It is shown in (1).

$$P = k \times Q\beta \quad (1)$$

In the specific scenario, an esteem of 1.5 is allotted to alter value. The proportionality steady is represented by k, initial esteem of pixel by Q, and changed over esteem of pixel by P.

2.2.5. Denoising

Noise of high frequency, frequently called "speck clamor," prevents accuracy about afterward examination and elucidations amid preparing of restorative images. Therefore, Gaussian obscure is utilized upon photos for diminishing the dot clamor and progress it is clarity and smoothness. This Gaussian blur serves as establishment for the extend.

$$GB(a,b) = \frac{1}{2\pi\sigma^2} e^{-\frac{a^2+b^2}{2\sigma^2}} \quad (2)$$

We speak to the Gaussian part esteem at point (a,b) utilizing image GB (a,b) as appeared in (2). 11×11 part measure is utilized according to our examination. Standard deviation is calculated by preparing program inside, with the equation.

$$\sigma = \frac{n-1}{6} \quad (3)$$

'n' speaks to bit measurement in (3).

2.2.6. Data enlargement

We utilize the "information increase" method [23] to extend the dataset by applying different changes to existing information tests, counting turn, flipping, zooming, trimming, and thresholding, as outlined in Figure 2. These adjustments present differences inside the preparing set, improving the model's capacity to generalize over diverse varieties of input information. By consolidating a wide run of modifications, this approach progresses visual quality, fortifies show execution, and contributes to a more profound hypothetical understanding of the information.

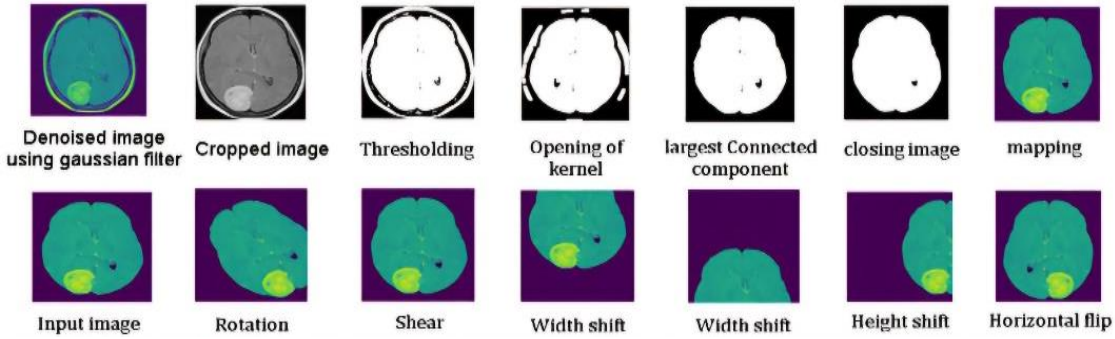

Figure 2. Data augmentation for brain tumor segmentation

2.3. NeuroNet19 architecture

The NeuroNet19 model is one of the deeply specialized profound learning structures that have been outlined to classify pictures of brain tumors from a dataset of MRI images. It is an advancement over the VGG19 architecture and comprises a novel feature extraction module known as the inverted pyramid pooling module or IPPM. Its hybrid innovative design aims at achieving excellent capabilities for both feature extraction and classification accuracy, mainly in the application space of brain tumor location.

2.3.1. VGG19 Backbone

The NeuroNet19 model fundamentally builds on the architecture of VGG19. VGG19 is the one among prominent neural networks used for image classification. The VGG19 model comprises mainly 19 weighted layers counting convolutional layers (16 layers), fully connected layers (3 layers), and the pooling layers. Structure is shown in Figure 3.

Convolutional layers (16 layers): VGG19 backbones start with 16 convolutional layers. It is these layers that can be used for feature extraction [24]. Convolutional filters are applied to the input MRI images, which permits to detect fundamental visual patterns-edges, surfaces, and straightforward shapes within the initial layers. However, as this data goes deeper through the network, these layers start to capture more complex and abstracted patterns [25]. This process lets the model steadily construct a high-level understanding of the image that is inevitable to recognize tumor-related features in brain MRIs.

Max-pooling layers (5 layers): After each convolutional layer, max-pooling layers are used. The max-pooling layers decrease spatial measurements about include maps originated from the convolutional layers. Max-pooling keeps the most prominent features and downsamples the data. This reduces the amount of computation required to predict the values of the data points while also ensuring there is less overfitting. Max-pooling also improves invariance of the model to small shifts or distortions of the input images [26].

Fully connected layers (3 layers): Now, after feature extraction, the yield from the convolutional and pooling layers is straightened and passed through three completely associated layers. These layers perform high-level thinking and decision-making based on the highlights extricated from the MRI pictures [27]. After these processes, proper full extraction takes place to map the final features toward tumor classification.

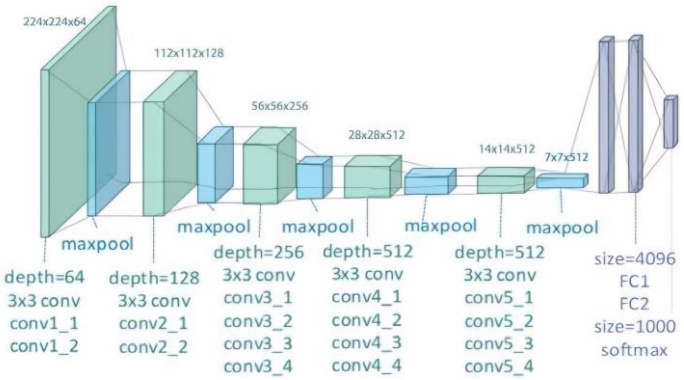

Figure 3. Architecture of VGG19

Convolution handle is connecting to the input picture 'M' using channel 'F'. Regarding every coordinate (u, v):

$$Cu, v = \Sigma(F \odot Msub) \tag{4}$$

Cu, v alludes to esteem detected at arranges (u, v) in (4), within consequent network 'C', whereas $Msub$ speaks to the segment of input grid 'M' which is presently defended through the route. Every convolution layer interfaces different routes for extricating unmistakable features among input information.

SoftMax activation: After applying the last fully connected layer, there is a SoftMax activation operation. This SoftMax operation is a mathematical operation which turns the output of this neural network into a probability distribution. Here, too, it creates a probability for each of the three classes and the negative class, which is no tumor. The model concludes its prediction by taking the class with maximum probability.

$$SoftMax\ (zij) = \sum \frac{e^{zi}}{k_{j=i}\, e^{zj}} \tag{5}$$

We utilize the $SoftMax$ calculation to change over sorted out yields into K-class likelihood conveyances. In (5) the numerical steady Eulers number (e) speaks to input to every path, indicated as z_i. Exponential esteem about abdicates appraise z_i for each lesson is decided utilizing the equation e^z. Adding institutionalizes the SoftMax yield to every class 'i' (too called $SoftMax(z_i)$) in connection with yields to every other class.

2.3.2. IPPM

The inverted pyramid pooling module is proposed for further improvement upon the ability of the feature extractor VGG19. Further extension of this model's expertise to capture features throughout scales is also important for tumor identification mainly based on size and shape differences. The IPPM employs the pooling with the window sizes of 2×2, 3×3, 4×4, and 6×6, which enables multi-scale pooling. This allows the model to capture several layers of spatial information. The small sizes of the pooling are likely to capture the finer details, in this case, the edges of the tumor, whereas the larger pool sizes capture information at a global level, thus outlining the general shape of the tumor [28]. This is particularly important in brain tumor detection since sizes could be greatly varied and so can structures.

$$U\ (i, j) = I^{\frac{'i'}{s}, \frac{'j'}{s}} \tag{6}$$

'I' stands for the tensor input in (6), in this case it is equally matching with the value of pixel at the position (i, j) of upsampled result. 's' is upsampling operation. For the purposes of the operation, the sizes of pool furnished by NeuroNet19 are used.

Feature refinement: features extracted by the VGG19 backbone contain fundamental visual information. However, they may not be enough to incorporate all the possible patterns for the proper classification of tumors. That is where the IPPM operated multi-scale pooling toward the expression and combination of features learned across different scales with a view to improvising the concept capability of this model over various classes of tumors and MRI scan variations.

In (7), the communication of mix of incorporate maps among unmistakable layers from IPPM is showed up:

$$C = Concat(F1, F2, F3, \ldots, Fi) \quad (7)$$

Here, the integrated abdicate is demonstrated as 'C', and mixing of spotlight maps consolidates $F1, F2, F3, \ldots, Fn$. These maps are from some levels of worldwide open arrangement organization. The utilize of a couple of upsampling stages and reasonable strategies of pooling in the IPPM of NeuroNet19 grants them to reasonably catch a contrasting amplify about highlights.

2.3.3. PGGAN for data augmentation

The major challenge in training the deep learning models in medical image analysis is that no annotated data is available [29]. For this problem, PGGAN is utilized to create synthetic MRI images to act as an augmentation for the existing training dataset. There are two major components to PGGAN architecture as shown in Figure 4: the generator and the discriminator. These complement each other perfectly when creating and evaluating artificially produced MRI-scanned images.

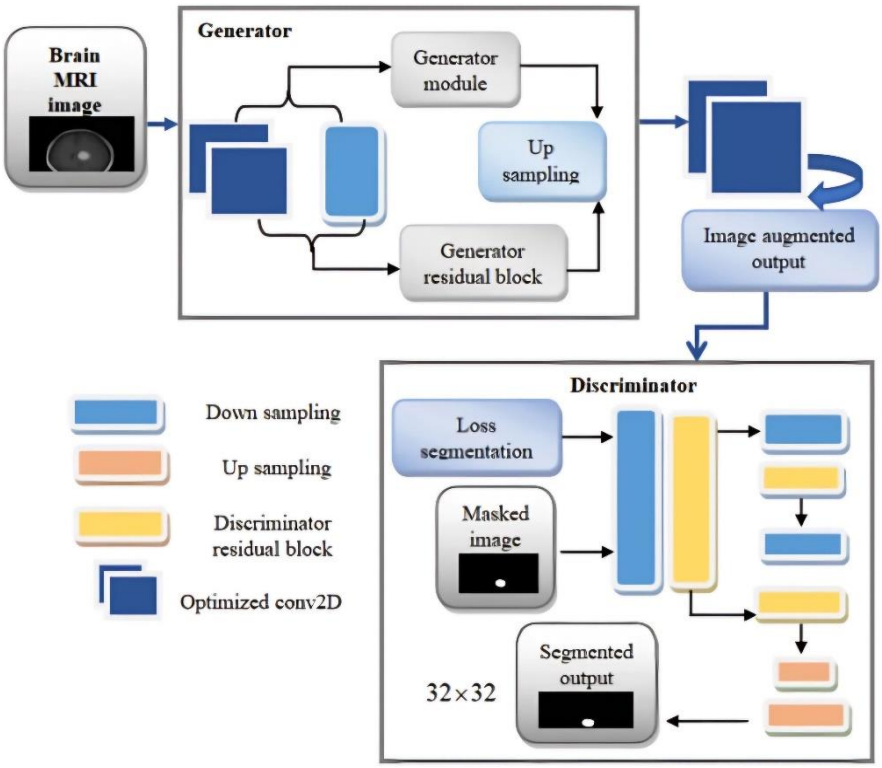

Figure 4. Architecture of PGGAN

The generator has an influential role in generating novel, synthetic MRI images which closely resemble legitimate MRI data; it begins with a low-resolution image and develops from this over time. During the course of the training process, the generator learns how to develop very realistic images, where it gains fine-grained points of interest and complex patterns in MRI pictures. The discriminator assesses the images created by the generator. It differentiates between authentic and synthetic images, offering crucial feedback to the generator. The primary aim of the discriminator is to correctly identify images as either real or fake, thereby assisting the generator in honing its output and enhancing the realism of the images it produces [30].

PGGAN uses progressive training. It begins solving generated images at low resolution and gradually increases the resolution. This way, it avoids training instability but lets the model capture complex features on higher resolutions. Yet another guarantee which is progressive for PGGAN is that the generator improves the ability to generate quality images over time. The images that result from PGGAN appear to blend very well with the training set, thereby supplementing it and making it richer while also making a greater variety of examples available for NeuroNet19 to absorb. This augmentation seems to aid in better generalization especially when faced by deficiency of actual data available.

2.4. Segmentation with Mask R-CNN

Mask R-CNN is a strong model for cancerous tumor detection and spatial segmentation by using MRI images. It produces high-accuracy segmenting masks delineating tumor boundaries, therefore being very valuable for very sensitive medical applications requiring excellent detail. This means the model starts with region proposal network (RPN), which identifies where possible tumors might be located, and it produces bounding boxes based on features from the image, like irregularities or abnormal patterns. The proposals are refined in two stages: Bounding boxes are adjusted precisely for accuracy, then a binary mask to establish exactly where the tumor might be. The pixel-level segmentation masks provided in the output enable precise identification of tumors, differentiation of multiple tumors, and advanced analyses like volume estimation or treatment planning. Mask R-CNN's ability to achieve high-accuracy instance segmentation makes it an excellent choice for various medical imaging applications.

Finally, the tumor detection system follows a structured workflow, beginning with preprocessing steps such as normalization, skull stripping, and resizing of MRI images. The NeuroNet19 model is then trained on these preprocessed images, incorporating synthetic data generated by PGGAN to enhance dataset diversity. Mask R-CNN is utilized for precise segmentation of tumor regions within the images, after which the system classifies the detected tumors into any one of four classes: glioma, meningioma, pituitary, and no tumor.

2.5. Performance analysis

We evaluate prediction of each category based on the assessment criteria counting F1-score, Cohen's kappa, re-call. We also calculate every execution pointer utilizing the perplexity of four-cell cross section:

a. Genuine positive (TP): Occasions in which, the appear precisely decides the tumor's correct location.
b. Genuine negative (TN): Circumstances where, the computer program precisely forecasts that the tumor is not present.
c. Untrue positive (FP): Circumstances where, the appear erroneously categorize the check of sound as tumor.
d. Untrue negative (FN): Circumstances where, the appear erroneously ignores the tumor, driving it is categorization as sound channel.

2.5.1. Accuracy

Accuracy measures the performance of a model by suggesting number of precisely forecasted instances and the whole instances. It is at various points in the dataset an important measure of model efficiency, and a higher value of accuracy means better performance and decreased prediction errors. We execute the calculation using the formula (8).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (8)$$

2.5.2. Precision

Precision measures how accurately the model identifies the positive cases in all of the identified positives, which is an important aspect in reducing false positives (FP). High precision implies that, demonstrate has precisely recognized the positive cases, and therefore prediction will be reliable. It is characterized as represented in (9).

$$Precision = \frac{TP}{TP+FP} \quad (9)$$

2.5.3. Recall

Recall or sensitivity measures how well a model classifies what are known to be true positives-it minimizes the false negative (FN) of all actual positives-out of all. Recall is critical for applications where failure to classify positive instances means the end as shown in (10).

$$Recall = \frac{TP}{TP+FN} \quad (10)$$

2.5.4. F1-score

Equation (11) calculates the F1-score, in which recall and precision balances out each other, which makes it a very useful measure to check models on imbalanced datasets. The larger the F1-score, the better the trade-off between recall and precision.

$$F1 - score = \frac{2\times(Precision \times Recall)}{Precision \times Recall} \quad (11)$$

2.5.5. Cohen's Kappa coefficient

It evaluates the degree of concordance among model's forecasts and genuine names. Scientific operation is represented as (12).

$$K = \frac{(po-pe)}{(1-pe)} \quad (12)$$

The Kappa coefficient calculates the degree in which genuine comprehension outflanks irregular possibility. Genuine values demonstrate tall stage about information, solid certification, and total need about misconception; less values show profitable abnormality. Expected consent is spoken to by the variable p_e, though watched understanding is spoken to by the variable p_o. The performance analysis is shown in Figure 5.

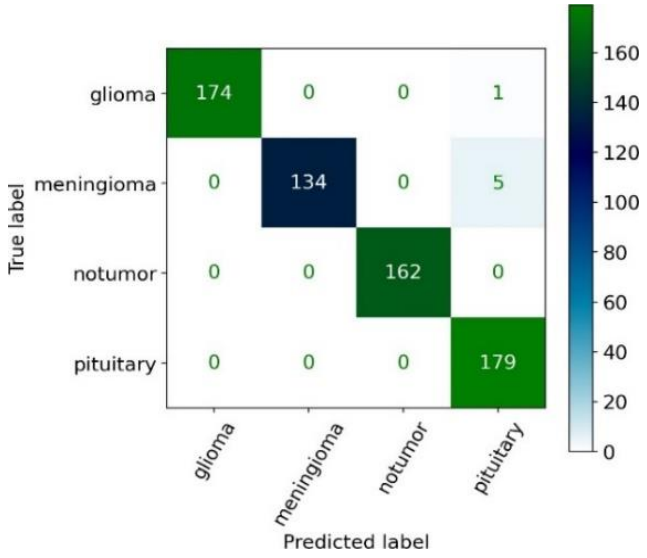

Figure 5. Confusion matrix for NeuroNet19

3. RESULTS AND DISCUSSION

NeuroNet19 can identify tumors in the brain with excellent advantages, especially when compared to other leading models. This framework gets test accuracy of 99.5% and validation accuracy of 97.9%. It is indeed the first architecture able to outperform leaders like DenseNet121, MobileNetV2, ResNet50, VGG16, and VGG19. Furthermore, each of its evaluation metrics: precision, recall, and F1-score, keeps rising above 98% on all tumor types, namely meningioma, glioma, pituitary, and no tumor

Other models, such as DenseNet121 and MobileNetV2, perform differently on tests, yielding 90.2% and 92.3%, while ResNet50 and VGG16 are moderately performing, with test accuracies 93.5% and 95.6%. Despite the prevalence of such models in tasks applied in medical imaging, NeuroNet19 seems to outperform them by performing well on account of its optimized architecture, which integrally includes the application of VGG19 features and inverted pyramid pooling module. This unique design enhances feature extraction and spatial resolution, which are critical for accurately identifying tumors, even in complex scenarios.

The sophisticated architecture, especially the IPPM of NeuroNet19, much enhances multi-scale feature aggregation for the identification of all sizes of tumors. Adding PGGAN-generated synthetic images makes the model more robust by enlarging dataset's size where, at start, the lack of annotated medical data is overcome. With this enhancement, NeuroNet19 obtains better accuracy and evaluation metrics than other models. However, the quality and diversity about input data will sway this framework's aptness and ability to

easily identify small or atypical tumors. A comparative analysis is given in the Figure 6 that shows models, such as DenseNet121, MobileNetV2, ResNet50, VGG16 have shown good performance but lack at intricate tumor details and confronts NeuroNet19's brilliant features that it has shown in delivering consistent and reliable outcomes for all tumor categories.

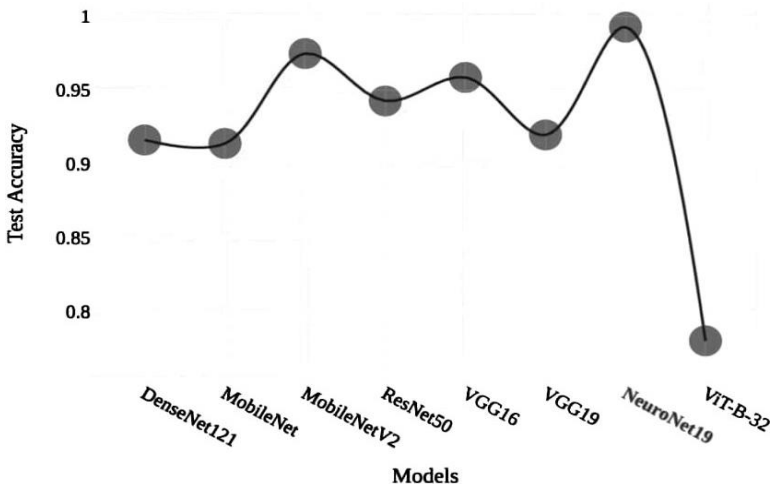

Figure 6. Comparison of NeuroNet19 with other models

4. CONCLUSION

This paper establishes NeuroNet19 as a state-of-the-art deep model for a particular task of brain tumor detection that outperforms other models, such as MobileNetV2, ResNet50, and DenseNet121, with increased effectiveness. In order to get 99.5% test accuracy, IPPM for multi-scale feature aggregation with data augmentation through PGGAN is used; this also gives an evaluation that is more than 98% in most categories of tumors observed. These results can cross the issue of limited annotated data and describe subtle tumor characteristics; therefore, it is a useful solution for medical imaging analysis.

The further implications from this work are its ability to improve diagnostic accuracy and aid doctors in the special localization and classification of tumors. It also has its limitation in that it demands proper high-quality training data, and it is not possible to detect small or atypical tumors. These limitations can be removed in future studies by adding diversified and high-resolution datasets, improving the more advanced augmentation methods, or researching the domain adaptation that tends to find the outliers. Additional work on optimizing NeuroNet19 for clinical workflows or use through a cloud-computing platform may also pay off in the future. Future advances in the direction of interpretability and explainability may further speed up this technology to potentially make it end up in clinical practice.

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AUTHOR CONTRIBUTIONS STATEMENT

Each author has contributed significantly to this study, ensuring its completion and accuracy. Lanke Pallavi was responsible for conceptualization, software, resources, validation, formal analysis, writing review & editing, supervision, and project administration. Thati Ramya contributed to methodology, software, data curation, writing original draft, writing review & editing, and visualization. Singupurapu Sai Charan played a key role in methodology, software, validation, formal analysis, writing original draft, and writing review &

editing. Sirigadha Amith provided resources, conducted investigation, managed data curation, and contributed to writing review & editing and visualization. Thodupunuri Akshay Kumar focused on validation, investigation, writing original draft, and writing review & editing. All authors have read and approved the final manuscript.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Thati Ramya		✓	✓					✓	✓	✓	✓			
Singupurapu Sai Charan		✓	✓	✓	✓				✓	✓				
Sirigadha Amith						✓	✓	✓		✓	✓			
Thodupunuri Akshay Kumar				✓		✓			✓	✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Not applicable, as no human participants were involved in this study.

ETHICAL APPROVAL

This study does not involve human or animal subjects; therefore, ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, TR, upon reasonable request.

REFERENCES

[1] A. B. Abdusalomov, M. Mukhiddinov, and T. K. Whangbo, "Brain tumor detection based on deep learning approaches and magnetic resonance imaging," *Cancers*, vol. 15, no. 16, 2023, doi: 10.3390/cancers15164172.

[2] A. A. Nayan *et al.*, "A deep learning approach for brain tumor detection using magnetic resonance imaging," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 13, no. 1, pp. 1039–1047, 2023, doi: 10.11591/ijece.v13i1.pp1039-1047.

[3] S. Alsubai, H. U. Khan, A. Alqahtani, M. Sha, S. Abbas, and U. G. Mohammad, "Ensemble deep learning for brain tumor detection," *Frontiers in Computational Neuroscience*, vol. 16, 2022, doi: 10.3389/fncom.2022.1005617.

[4] B. Babu Vimala, S. Srinivasan, S. K. Mathivanan, Mahalakshmi, P. Jayagopal, and G. T. Dalu, "Detection and classification of brain tumor using hybrid deep learning models," *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-50505-6.

[5] B. B. Gupta, A. Gaurav, and V. Arya, "Deep CNN based brain tumor detection in intelligent systems," *International Journal of Intelligent Networks*, vol. 5, pp. 30–37, 2024, doi: 10.1016/j.ijin.2023.12.001.

[6] H. Chen, Z. Qin, Y. Ding, and T. Lan, "Brain tumor segmentation with generative adversarial nets," in *2019 2nd International Conference on Artificial Intelligence and Big Data, ICAIBD 2019*, 2019, pp. 301–305, doi: 10.1109/ICAIBD.2019.8836968.

[7] G. B. Mohan *et al.*, "Enhancing brain tumor diagnosis with generative adversarial networks," in *Proceedings of the 14th International Conference on Cloud Computing, Data Science and Engineering, Confluence 2024*, 2024, pp. 846–851, doi: 10.1109/Confluence60223.2024.10463384.

[8] C. Ge, I. Y. H. Gu, A. S. Jakola, and J. Yang, "Deep semi-supervised learning for brain tumor classification," *BMC Medical Imaging*, vol. 20, no. 1, 2020, doi: 10.1186/s12880-020-00485-0.

[9] S. Gupta, M. Aggrawal, A. Shukla, and A. Tyagi, "Brain tumor detection using deep learning techniques based on MRI images," *Lecture Notes in Networks and Systems*, vol. 726 LNNS, pp. 569–577, 2023, doi: 10.1007/978-981-99-3716-5_46.

[10] C. Han *et al.*, "Combining noise-to-image and image-to-image GANs: Brain MR image augmentation for tumor detection," *IEEE Access*, vol. 7, pp. 156966–156977, 2019, doi: 10.1109/ACCESS.2019.2947606.

[11] S. Karamehić and S. Jukić, "Brain tumor detection and classification using VGG16 deep learning algorithm and python imaging library," *Bioengineering Studies*, vol. 4, no. 2, pp. 1–13, Nov. 2023, doi: 10.37868/bes.v4i2.id252.

[12] Pandiyan M, Jenisha E, Madhuranjani G, B. Dharshini S, "Brain tumor detection using deep transfer learning," *Interantional Journal of Scientific Research in Engineering and Management*, vol. 08, no. 03, pp. 1–5, Mar. 2024, doi: 10.55041/IJSREM29704.

[13] R. S. M. Najeeb and I. O. A. M. Dahl, "Brain tumor segmentation utilizing generative adversarial, resnet and UNet deep learning," in *2022 8th International Conference on Contemporary Information Technology and Mathematics, ICCITM 2022*, 2022, pp. 85–89, doi: 10.1109/ICCITM56309.2022.10031760.
[14] M. I. Mahmud, M. Mamun, and A. Abdelgawad, "A deep analysis of brain tumor detection from MR images using deep learning networks," *Algorithms*, vol. 16, no. 4, 2023, doi: 10.3390/a16040176.
[15] M. S. I. Khan *et al.*, "Accurate brain tumor detection using deep convolutional neural network," *Computational and Structural Biotechnology Journal*, vol. 20, pp. 4733–4745, 2022, doi: 10.1016/j.csbj.2022.08.039.
[16] M. R. Shoaib *et al.*, "Improving brain tumor classification: An approach integrating pre-trained CNN models and machine learning algorithms," *Heliyon*, p. e33471, 2024, doi: 10.1016/j.heliyon.2024.e33471.
[17] M. Agarwal, G. Rani, A. Kumar, P. K. K, R. Manikandan, and A. H. Gandomi, "Deep learning for enhanced brain tumor detection and classification," *Results in Engineering*, vol. 22, 2024, doi: 10.1016/j.rineng.2024.102117.
[18] P. Tiwari *et al.*, "CNN based multiclass brain tumor detection using medical imaging," *Computational Intelligence and Neuroscience*, vol. 2022, 2022, doi: 10.1155/2022/1830010.
[19] P. Gayathri, A. Dhavileswarapu, S. Ibrahim, R. Paul, and R. Gupta, "Exploring the potential of VGG-16 architecture for accurate brain tumor detection using deep learning," *Journal of Computers, Mechanical and Management*, vol. 2, no. 2, 2023, doi: 10.57159/gadl.jcmm.2.2.23056.
[20] P. K. Ramtekkar, A. Pandey, and M. K. Pawar, "A comprehensive review of brain tumour detection mechanisms," *Computer Journal*, vol. 67, no. 3, pp. 1126–1152, 2024, doi: 10.1093/comjnl/bxad047.
[21] P. Raut, G. Baldini, M. Schöneck, and L. Caldeira, "Using a generative adversarial network to generate synthetic MRI images for multi-class automatic segmentation of brain tumors," *Frontiers in Radiology*, vol. 3, 2023, doi: 10.3389/fradi.2023.1336902.
[22] S. Ahmad and P. K. Choudhury, "On the performance of deep transfer learning networks for brain tumor detection using MR images," *IEEE Access*, vol. 10, pp. 59099–59114, 2022, doi: 10.1109/ACCESS.2022.3179376.
[23] Y. Sankararao and S. Khasim, "An effective analysis of brain tumor detection using deep learning," *EAI Endorsed Transactions on Pervasive Health and Technology*, vol. 10, 2024, doi: 10.4108/eetpht.10.5627.
[24] S. Anantharajan, S. Gunasekaran, T. Subramanian, and V. R, "MRI brain tumor detection using deep learning and machine learning approaches," *Measurement: Sensors*, vol. 31, 2024, doi: 10.1016/j.measen.2024.101026.
[25] S. Solanki, U. P. Singh, S. S. Chouhan, and S. Jain, "Brain tumor detection and classification using intelligence techniques: An overview," *IEEE Access*, vol. 11, pp. 12870–12886, 2023, doi: 10.1109/ACCESS.2023.3242666.
[26] V. N. V. L. S. Swathi, K. Sinduja, V. Ravi Kumar, A. Mahendar, G. V. Prasad, and B. Samya, "Deep learning-based brain tumor detection: an MRI segmentation approach," *MATEC Web of Conferences*, vol. 392, p. 01157, 2024, doi: 10.1051/matecconf/202439201157.
[27] S. Y. Kandimalla, D. M. Vamsi, S. Bhavani, and M. V.M., "Recent methods and challenges in brain tumor detection using medical image processing," *Recent Patents on Engineering*, vol. 17, no. 5, 2022, doi: 10.2174/1872212117666220823100209.
[28] V. K. Bairagi, P. P. Gumaste, S. H. Rajput, and K. S. Chethan, "Automatic brain tumor detection using CNN transfer learning approach," *Medical and Biological Engineering and Computing*, vol. 61, no. 7, pp. 1821–1836, 2023, doi: 10.1007/s11517-023-02820-3.
[29] A. Younis, L. Qiang, C. O. Nyatega, M. J. Adamu, and H. B. Kawuwa, "Brain tumor analysis using deep learning and VGG-16 ensembling learning approaches," *Applied Sciences (Switzerland)*, vol. 12, no. 14, 2022, doi: 10.3390/app12147282.
[30] A. Younis, Q. Li, M. Khalid, B. Clemence, and M. J. Adamu, "Deep learning techniques for the classification of brain tumor: a comprehensive survey," *IEEE Access*, vol. 11, pp. 113050–113063, 2023, doi: 10.1109/ACCESS.2023.3317796.

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