Current Journal of Engineering and Science Research
Volume 2, Issue 3, pp 6-12, March 2025
ISSN (online): 3049-1738
DOI: https://doi.org/10.47001/CJESR/2025.203002
Available Online at https://www.cjesr.com

Employing CNN Deep Learning for the Detection and Classification of Multiple Types of Brain Tumors

[1]Sugan M, [2]Helen Sunomitha Nancy

[1,2]Department of Electronics and Communication Engineering, K.L.N. College of Engineering, Tamilnadu, India

Abstract: Brain tumors, a leading cause of mortality, necessitate accurate and timely detection for effective treatment. Recent advancements in deep learning and medical imaging have significantly enhanced the capability to identify and classify cancers. This extensive study focuses on three specific tumor types: glioma, meningioma, and pituitary tumors and explores the application of deep transfer learning methods for brain tumor classification utilizing convolutional neural networks (CNN). By analyzing MRI scans, the research assesses the performance of pretrained CNN models, including ResNet-50, Inception-v3, and VGG-16 in automating tumor prediction. The study employs performance metrics such as accuracy, precision, recall, and F1 scores to evaluate how effectively each model aids in early diagnosis and improves clinical decision-making.

Keywords: MRI, Convolutional Neural Network (CNN), Deep Transfer Learning, Brain Tumor, Custom CNN, Inception-v3, Tumor Classification.

I. INTRODUCTION

Since brain tumors are a different collection of neoplasms of different sizes, places and malignancy levels, early discoveries and precise categorization are of essential importance for effective treatment and better patient results. The gliomas, meningiomes, pituitary adenomes and glioblastomas are among the various forms of brain tumors that are traditionally classified. Since every type of tumor has unique development patterns, therapeutic and prognostic reactions, the precise multiclase categorization is of crucial importance for the clinical decision. Due to its high resolution and its non -invasive nature, magnetic resonance (MRI) has become the modality of choice to see and diagnose the intelligent brain when the image methods have progressed. However, the quality and consistency of diagnostics can be influenced by the tedious manual treatment that depends on the observer of magnetic resonance images.

Deep Transfer Learning that uses information about models that have already been trained in considerable general data records such as Imagenet has become popular as a solution for these problems. If you concentrate on the exclusive subtleties of the classification of brain tumors and the maintenance of the learned characteristics that could be useful for the diagnosis of tumors, the learning transmission enables these previously formed models in smaller and more special data sets. In the medical field, this method has shown encouraging results, shortened the training period and also enables great precision with low data. Learning the transmission gives the network a solid basis for identifying basic models (such as edges, textures and forms) when the lower layers of a CNN model that was trained in millions of pictures reuse.

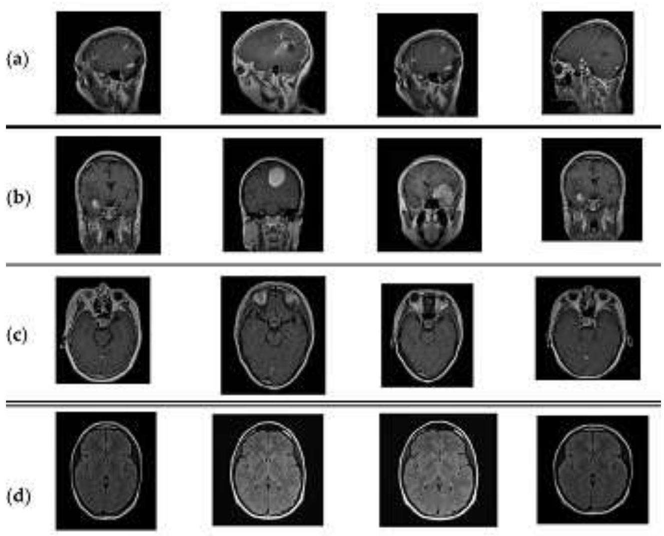

Figure 1: Different types of brain tumor images from a kaggle dataset

In addition, it enables the change in multiclase classification models when learning Devith, whereby a high sensitivity and specificity in the extraction of properties are required due to minor distinctions in the types of tumors. Sounded data models can find it difficult to demonstrate subtle

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differences in the tissue intensity and the border anomalies that may be necessary for the diagnosis of gliomas and meningiomes. With these challenges, the transfer of learning techniques, in particular those who use deep CNN architectures such as reset, which use and start, have shown an excellent performance and overcome conventional techniques in relation to precision.

II. METHODOLOGY

This work offers a comprehensive analysis of the current developments in the classification of multiclastic tumors with several classes based on deep transfer learning. The architecture and uses of the CNNs are examined, including several pre-pro-pro-courses that improve the resistance of the model, the data increased the techniques to process the rarity of data and fine adaptation techniques for magnetic resonance data records of brain tumors.

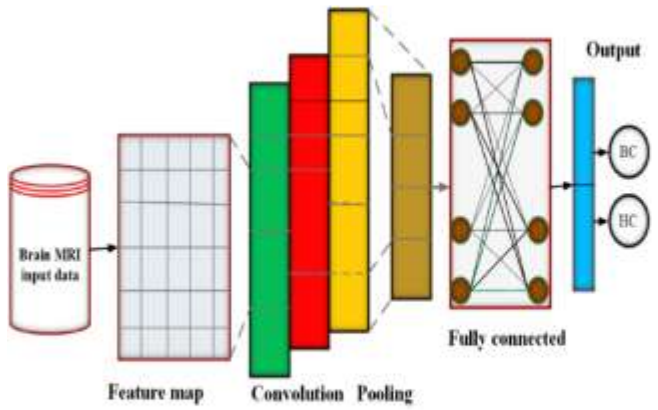

Figure 2: Study Architecture Flow Diagram

This survey also analyzes important problems such as data availability, class disorders and interpretability needs in clinical contexts. This study examines the condition of the approaches of transfer learning in the classification of brain tumors in order to identify effective approaches and to offer fascinating ways for a larger study, which will ultimately lead to more precise and reliable tumor recognition models in the field of medicine.

Detection process in CNN model

Data acquisition, pretreatment, selection of the model of the model and the evaluation are some of the decisive stages of the learning approach in depth transmission for the diagnosis of multiclasting brain tumors. Each step is described in detail in this section, with appointments to remarkable works that have influenced these approaches.

III. EVALUATION

As explained in the previous section, the evaluation of learning in the profound transfer of a multi -luclase -Brain tumor -recognition system is of essential importance in order to determine the efficiency, reliability and clinical ability of the model. In order to evaluate the accuracy of classification, sensitivity, specificity and robustness in different types of tumors, a variety of quantitative criteria are used in the evaluation process. In addition, the therapeutic relevance of the system is validated using interpretation tools and a user input. Here you will find a detailed examination of the evaluation procedure:

1. Quantitative metrics

Precision: The accuracy quantifies the proportion of precise predictions between all predictions of all models. Although Precision offers a general assessment, it is possible that it does not represent exactly how the model works in multiclastic environments if there can be a class light weight. In this case, the accuracy helps to evaluate the general efficiency of the model in all types of tumors, but must be understood in connection with other measures.

Precision (positive prediction value): This metric evaluates the way the algorithm can identify a form of the tumor while the others are faulty. In clinical environments, an incorrect diagnosis is inappropriate treatment options that are essential. A high precision indicates that the model is necessary to identify any specific tumor class, which reduces false alarms, which is of crucial importance for reducing unnecessary treatments or additional tests.

Do not forget (sensitivity): The recording evaluates to what extent the model recognizes the cases of each tumor type by identifying the actual positive aspects of all real positive cases. In clinical contexts, in which a positive example (e.g. without identification of a malignant tumor) was missing, a high retirement could have catastrophic effects, a high retirement implies that the model manages to recognize any kind of tumor.

F1 point number: The F1 score compensates for the compensation between precision and memory if the harmonious average of the two measures is taken. Since it offers unique statistics that takes into account both false positive and false negative consideration, it is particularly useful in unbalanced data records. The reliability of the diagnosis depends on the ability of the model to recognize every tumor type with a high F1

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score in all classes and at the same time minimize false positive and negative.

Specification: This metric effectively evaluates the effectiveness of the obvious model by identifying the negative with accuracy. This statistics are of crucial importance to assess how the model rejects benign or non -tumor instances and reduces the likelihood of unnecessary processes and overdiagnosis.

2. Cross-Validation Techniques

K-compartment cross validation: K-fold cross validation is a process that takes into account the consistency of the model in various data subgroups. In this process, the training data is divided into the equal sizes subgroup. The model is formed and tested in K-1 parts of the data and then tested in the remaining part. The entire procedure is repeated in times, then the average yield is calculated in all wrinkles.

Layer K-Fach: crossed validation stratified k-fold is particularly useful for multiclastic and unbalanced data records, so that all wrinkles share the same class distribution as the general data set.

LOOCV: This is a strict cross -validation technology in which each case the data record is only used as a test instance, while the remaining instances are used for training. This makes it possible to find the strength of the model in small data records, but it takes a long time for large data records.

3. Analysis in a confusion matrix

A confusion matrix examines real positive, real negative, false positive and false negatives for each class that can give an idea of the strengths and weaknesses that the class of the class a. For a multiclase, the matrix helps to determine which tumor classes are most likely to be classified and the adjustments of the model parameters are considered an account. Such an analysis can be very useful to identify the types of tumors that have to be diagnosed for better performance.

4. Interpretability tools

Checking the Grad Cam Chamber Chamber of the third cycle The model of the model for suitable features for classification, which can represent clinical acceptance: tumor limits and clear textures. Quality cards: Salecia cards are a visual interpretation by the contribution at the pixel level for the production of the model. This helps to identify the specific properties on which the model is based on every tumor type. This is important for trust in the construction with doctors, since it shows that what we know medically, which is what this model focuses on.

5. Performance in different types of tumors

Since the classification of several tumor classes tries to classify between different types of tumors, we in turn check the performance of each class. The calculation of memory, precision and F1 score in relation to the classes guarantees that the model does not work very well with a series of classes and one projection with another. This assessment is very important in clinical applications, in which different types of tumors have different effects on treatment.

6. Clinical acceptance and user feedback

The comments of doctors in the form of feedback from doctors and radiologists to measure the practical applicability, conviviality and usefulness of the model in real scenarios. The user's qualitative feedback is of great importance, while you understand whether the predictions of models and the interpretation take place according to the clinical expectations and workflows.

Evaluation of the response time: In clinical practice, the response time is essential because radiologists would require real and precise feedback. This is a prerequisite for the development of this tool as a applicable solution by enabling use in real or real time applications in hospitals with the minimal latency of the system and, above all, minimal response times for magnetic resonance analysis.

7. Robust model and generalization

Tests in other data records: Model reviews are carried out using data records of other institutions or image methods to check the robustness. Try the model of the model to generalize the data that only corresponded to training. This is crucial because we will be so safe that the model is not overly and can really classify the tumor, regardless of the origin.

Sensitivity to noise and artifacts: Although robustness, as mentioned above, diamond artifacts and images are detected that have been added to the magnetic resonance analyzes. This could be a realistic illness in which pictures may not be of good quality. Therefore, the reliability of the model was guaranteed under less than perfect visual conditions.

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IV. FUTURE SCOPE AND DIRECTIONS

Although there are many obstacles in the classification of brain tumors, there is always a list of problems that have to be remembered for an additional improvement in the classification of the brain tumor.

The most important concept is the development of a pretreatment framework that carries out color compensation in magnetic resonance analyzes in order to use new and advanced features. Tumor classification and although the segmentation draws maximum attention to research has been investigated much less when tumors detected.

Another that we could use if we have a relatively smaller data set that is available to us is the learning transfer. It is a very useful tool that we have not researched in its entirety.

Another form of precision improvement is the method called total learning and in which many algorithms are used together and the best precision is generated.

In order to achieve better results for our model, optimal and effective optimizations are required. Generative negative networks occur due to their ability to imitate distributions from which image samples are derived have not yet been fully exploited. In addition to the GAN applications described above, this architecture can be used to create spectacular realistic images that fill the gap to the lack of marked data when classifying brain tumors. The deepest CNN models that work better than those formed in very few photos form these pictures.

Promising progress in learning profound transmission to detect multiclastic brain tumors despite the progress of the recognition of multiclastic brain tumors, there are great opportunities for future research and development. Future work should expand the robustness, scalability and interpretability of these models so that they are effective in a variety of clinical environments. Important instructions for future work are:

1. Data quality and heterogeneity

Development of additional data records: This work is seriously lacking with large sentences and various sets of classification of brain tumors. Future work would be the creation and healing of an MRI data record with coherent labeling and various image sources. Data records more representative for a transverse section of hospitals, research institutions and data exchange platforms, the profiles of various demographic and magnetic resonance methods of the patients.

Management of data asymmetry: ClassaSyMedry In the analysis of medical images, there is a very low representation in the sense that certain types of tumors have a very low representation. Additional studies in these lines can include research into more advanced data increase techniques such as goose and the production of synthetic images. The recently introduced increased methods include adapting the domain and the transformation of the style, which generate very realistic variations of tumor images and thus enrich the underrepresented classes.

2. Increased Model Interpretability

Development of advanced interpretability techniques: Although the third cycle chamber and similar tools open a window for the model decision, much more advanced interpretation techniques are required, so that the learner is transparent for the clinician. Future work will concentrate on new methods to see the importance of functions, create basic explanations and explain what they do friendlier for the clinical condition.

This can also contribute to the standardization of the interpretability of the model with the use of explanatory frames that are dedicated to the classification models of brain tumors. Future work can be interfaces that show the interpretation of the medical model with the context, which is provided by the image of the corresponding magnetic resonance, so that trust or improvement that is generated in the decision is the result.

3. Use of the multimodal data fusion

Through the interrelation of magnetic resonance with other medical data: the integration of magnetic resonance data into other medical data sources, including patient files, genetic data and histopathology images, can improve the robustness and accuracy of the developed models. Multimodal models are useful because they work in different forms of information and at the same time offer a more comprehensive view of the patient's condition, which can lead to better tumor characterization and real treatment recommendations.

Future architectures could develop future work that can intelligently integrate multimodal data into the classification model for brain tumors. Attention -based mechanisms, transformers and other architectures that are adapted to multimodal learning can be considered for effective

CJESR JOURNAL

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combinations of these multi -purpose data.

4. IA implementation in real time and real time

Real -Time treatment of clinical working flows: Deep -Learning models offer extremely high precision, but are very expensive when calculating. The optimization of the inference model opens up a possibility that enables real conclusion. And the additional progress could be made easier by compressing the model with trimming, quantification and distillations of knowledge. The treatment of real -time makes the model for clinical working flows more practicers, in which quick decisions in diagnostic environments should be made.

Ki Edge and Mobile Implementation: EDGE AI would make it possible to implement classification models on real devices, reduce the dependence on high -performance servers and to provide and accelerate the point of the attention of diagnosis. Mobile implementation can also enable doctors to apply classification models directly to mobile devices, which expands their effects on the health environments for health shortages.

5. Advanced Deep Learning Techniques Exploration

The self-monitoring and semi-semi-learning notice of large data in clinics is very slow and depends on the task. With less labeled data, but larger quantities of non -marked data, self -rated and half -monitoring learning methods can be useful for reducing the requirements for comments. This can also be treated in additional work to develop more effective models in data that should actually be manufactured taking into account the limited amounts of the marked data.

Architectures based on transformers for medical images: So far, architectures based on transformers such as Vits have already shown promising results in certain classification tasks in images. It will be interesting if this success also classifies brain tumors with life or hybrid models of the CNN -CNN transformer.

6. Image and variability

Different management compared to the scanner of the magnetic resonance scanner: variability in relation to the type of magnetic resonance scanner, the configuration and protocols lead to inconsistency of the quality and the representation of the image as well as the model output. Future work must include techniques through which the models are generalized in various machines and image protocols, such as:

The robustness towards noise and real magnetic resonance artifacts includes artifacts or noise that can reduce models. Future studies on training the opponent can be carried out among other things, among other things, renovation algorithms to develop models with great robustness in a common form of artifacts in magnetic resonance analyzes that guarantee the reliability of the practice under different visual conditions.

7. Validation and clinical implementation

Clinical studies with great competition: These models must be verified in important studies at several centers, several institutions and multipacatán hospitals. Future work includes studies on validation in the real world, in which predictions of models would be compared with the ratings and the results of radiologists in order to evaluate their diagnostic effects. The integration into yours is something different. The perfect integration of classification models for brain tumors in hospital information systems would guarantee their introduction to clinical environments. Future work can be directed to make the model compatible with electronic health systems (DSE), since the results for medical care in your workflow are easily accessible.

V. CONCLUSION

This paper focuses on our efforts to advance multiclass brain tumor detection through deep transfer learning, emphasizing the critical roles played by CNN architectures, transfer learning strategies, data augmentation, and ensemble techniques in shaping the results. The notable success achieved in classifying various brain tumors via deep learning, particularly through the use of transfer learning with pre-trained models such as ResNet and InceptionV3, has provided solutions to challenges related to limited and imbalanced medical imaging datasets. These models can be further refined to target MRI-specific features, resulting in high classification accuracy and functioning as effective clinical diagnostic tools. We also aim to develop a custom CNN specifically designed for this classification task. Nonetheless, several challenges persist, including the necessity for large and diverse datasets, model interpretability, and the ability to generalize across different MRI scanner types and imaging protocols. Interpretability tools like Gradcam and saliency maps offer valuable insights into model decisions, helping clinicians understand the predictions made. While ensemble learning and hybrid approaches can enhance classification accuracy, improving the usability and adaptability

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of these models in real-world applications remains a key area for future research. Incorporating these models into clinical practice.

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Citation of this Article:

Sugan M, & Helen Sunomitha Nancy. (2025). Employing CNN Deep Learning for the Detection and Classification of Multiple Types of Brain Tumors. *Current Journal of Engineering and Science Research*. 2(3), 6-12. Article DOI: https://doi.org/10.47001/CJESR/2025.203002

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