https://doi.org/ 10.33472/AFJBS.6.9.2024.2075-2084

African Journal of Biological Sciences

Journal homepage: http://www.afjbs.com

Research Paper Open Access

NEUROVISION-DEEP LEARNING APPROACH FOR BRAIN TUMOR IDENTIFICATION

J.Hima Bindu, Assistant Professor, MGIT jhimabindu_it@mgit.ac.in
Abhignya Rani.J , UG Student, MGIT abhignya2212@gmail.com
A.Sharath Kumar , UG Student, MGIT amulasharathkumar20@gmail.com
Macha Phani Samhitha, UG Student, MGIT samhithamacha72704@gmail.com

Article History

Volume 6,Issue 9, 2024

Received: 26-03-2024

Accepted : 30-04-2024

doi: 10.33472/AFJBS.6.9.2024.2074-2084

Abstract: Cerebral tumors are among the most deadly types of cancer in the world, and the need for early detection highlights the need of novel analytical approaches. Brain tumors classified by shape, size, surface, and area as revealed by magnetic resonance imaging (MRI) are the primary focus of this study. Applying deep learning algorithms like as Convolutional Neural Networks (CNNs), Xception, ResNets, and DenseNet201 on Audience 1 and Stage 2 datasets has led to significant improvements in characterisation accuracy. More research into the topic revealed that Xception had made significant progress, achieving a surprising near-perfect accuracy for both datasets, even though CNN's accuracy was 88% initially. This demonstrates the value of using a variety of deep learning architectures, with Xception emerging as an especially potent tool for accurate brain cancer classification. In addition to providing an opportunity to improve diagnostic accuracy, these results lend credence to further research into cutting-edge methods for dealing with the enormous challenge that brain malignancies produce.

Index terms: Xception, ResNet, DenseNet201, deep learning, MRI pictures of brain tumors, CNNs

INTRODUCTION

An infection affecting the human neurological system may be very complex and even fatal. One such infection is a brain tumor. These abnormal cell growths may manifest in several parts of the brain, including the sinuses, base of the skull, brainstem, and nasal depression, as a result of the brain's complex structure and wide diversity of functions. Brain tumors have a high degree of variety according to the tissues

from which they originate; more than 120 unique forms have been described (American Mind Growth Affiliation, n.d.). The fact that brain tumors may metastasize (spread to
other parts of the body) and block normal neurological function makes them very dangerous. The fact that these malignancies may metastasize, or spread to other parts of the body via pathways like the spinal fluid, significantly increases the risk they pose (Mayo Facility, 2020). This form of metastasis not only makes therapy more difficult, but it also increases the risk of death.

But brain tumors aren't only a local problem; they may disrupt the delicate balance of cerebrospinal fluid components, leading to increased intracranial pressure, or hydrocephalus. This highlights the many pathways involved in the development of brain cancer and the complex relationships between growth science and neurophysiology.

Considering the variety of clinical presentations and prognostic implications associated with these conditions, it is essential to have a thorough grasp of the causes, characteristics, and treatment approaches for brain cancer in order to provide competent care and better understanding outcomes.

This research aims to tackle the urgent need for new diagnostic tools to detect brain tumors, often known as globally devastating malignancies, in their early stages. The review aims to categorize malignancies based on multiple aspects, using Magnetic Resonance Images (MRI) as the major technique. The use of deep learning computations, CNN, Xception, ResNet, and DenseNet201 leads to significant improvements in order exactness. Xception stands out as a particularly effective technique for accurate mind development characterisation. The assessment encourages further research into cutting-edge methods to improve analytical precision despite the serious risk posed by brain tumors.

Early detection should get prompt attention since brain tumors are among the most visibly terrible diseases globally. The techniques currently used for demonstration are unlikely to be very accurate. This work aims to overcome the constraints by applying complicated tactics and extensive learning computations, such as Attractive Reverberation Pictures (X-ray). In order to provide effective early intervention, it is crucial to increase the accuracy of brain development characterisation, according to the problem statement.

1. LITERATURE SURVEY

Because of the need of a prompt and accurate diagnosis for effective treatment planning and patient care, brain cancer identification and staging are crucial tasks in clinical imaging. Artificial intelligence (AI) and deep learning have been the focus of research to improve the practicality and precision of appealing reverberation imaging (X-ray) brain growth classification and identification. This literature review aims to provide a comprehensive overview of recent developments in this area by highlighting key systems, tactics, and objectives.

The X-ray based recognized evidence and categorization of cerebrum malignancies was presented by Javeria Amin et al. [1], [8] who offered a creative approach. An encouraging development is that they were able to reliably identify and categorize brain illnesses from X-ray exams using design recognition equipment.

An exhibition investigation of mind cancer picture order was conducted by S. K. Baranwal et al. [2], [9]. They used convolutional neural networks (CNN) and support vector machines (SVM). By demonstrating how well CNN and SVM arranged images of brain development, their investigation illuminated the overall demonstrations of these two prominent AI computations.

With the use of ensembling learning and deep learning processes, A. Younis et al. [3] focused on brain cancer evaluation. They demonstrated the efficacy of outfit learning methods in enhancing grouping performance by achieving significant improvements in mind growth order accuracy with the help of VGG-16 and other deep learning models.

A primary emphasis of S. Grampurohit et al.'s work was the implementation of CNNs. analysis of deep learning models for brain cancer detection [4], [10]. An online interface for sorting different kinds of brain tumors using deep learning using convolutional neural networks (CNNs) was suggested by H. Ucuzal et al. [5], [11]. Their research strengthened the growing body of work on convolutional neural network (CNN) methods for brain development detection, demonstrating the practicality of deep learning in medical image analysis tasks. Their study highlighted the value of user-friendly interfaces in clinical image processing frameworks via straightforward cooperation and result translation.

Based on X-ray images, Muhammad Jibril et al. developed deep learning models to categorize brain disorders. [6]. Their research helped advance deep learning techniques in clinical imaging by demonstrating the efficacy of these models for precise and persuasive brain growth grouping.

An impressive method for mind growth identification and clustering was presented by Muhammad Arif et al. [7], [12] using deep learning, a symmetrical wavelet transform, and intrinsic motivation. Their work shows the value of combining traditional signal processing methods with cutting-edge AI computations, since they improved order exactness by combining wavelet transform with deep picking up.

The primary emphasis of A. Bhandari et al. was on mind expansion division using convolutional brain networks. [8]. By tackling the challenging task of identifying cancer boundaries in X-ray images, their study showcased CNNs' capabilities for accurate mind growth division and limitation.

The DCT-CNN-ResNet50 architecture, developed for the purpose of identifying brain tumors by Anand Deshpande et al. [9], [[18] combines Super-goal CNN with ResNet50. Their method integrated super-goal strategies with compositional planning, which further enhanced mind expansion conclusion arrangement execution.

Using motion learning, Madona B. Sahaai et al. [10], [16], [17] constructed a deep neural network for the classification of brain tumors based on ResNet-50. They demonstrated the use of ML in clinical image analysis by achieving impressive increases in grouping accuracy with the use of ML and pre-prepared models. Overall, X-ray brain cancer detection and arrangement has recently made tremendous strides because to the application of AI and deep learning techniques. Research in this area has paved the way for improved clinical decision-support networks and tailored treatment programs in neuro-oncology by demonstrating how convolutional neural networks (CNNs), support vector machines (SVMs), group learning, move learning, and mixed methodologies can enhance the accuracy, sufficiency, and interpretability of mind growth conclusions.

2. METHODOLOGY

i) Proposed Work:

Early detection of brain tumors is a major issue for general health, and the suggested method aims to address this. The framework aims to advance brain cancer categorization by taking structural, size, surface, and area parameters into account, and it is focused on improved symptomatic techniques, namely Magnetic Resonance Images (MRI). Using deep learning calculations on both Stage 1 and Stage 2 datasets, the framework achieves significant progress in grouping accuracy. These computations include Convolutional Brain Organization (CNN), Xception, ResNet, and DenseNet201. With a mind-boggling near-perfect accuracy rate, Xception distinguishes out as an exceptionally respectable performer. In addition to demonstrating assurance for improved decision accuracy, the suggested method also supports ongoing investigation into various deep learning architectures to efficiently address the massive problem that brain malignancies provide on a global scale.

ii) Architecture of the System:

The framework engineering process for the dataset consists of two steps: the first involves categorizing brain tumors into two types, and the second involves expanding this to four types. The first step in processing pictures is to get the dataset ready for model preparation. Xception, ResNet, DenseNet201, and CNN designs are subsequently used in the development and preparation of the models. Better neuro-oncology diagnosis and treatment planning are possible outcomes of using the learnt models to speculate on the grouping findings, which in turn enables precise ordering of brain development classes from X-ray images.

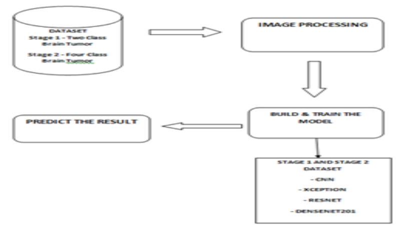

Fig 1 Proposed Architecture

iii) Dataset:

The dataset was first organized into two categories in Stage 1, or double grouping, and it is composed of X-ray photos of brain tumors. Differentiating features, such as the presence or absence of growths or benign vs harmful illnesses, are common among these categories. Stage 2 involves the incorporation of four distinct categories into the dataset, allowing for a more precise categorization of brain tumors. These descriptions take into account a more detailed evaluation of the pathology as they may represent distinct cancer types, grades, or other features. Careful selection of the dataset's test coverage guarantees robust model creation and assessment across a range of neuro-oncology growth types and complexity levels.

iv) Processing of Images:

Picture handling is essential when utilizing X-ray images for pre-processing to group brain growths. To begin, the raw X-ray images undergo a series of preprocessing steps designed to improve their quality and isolate useful information. This includes techniques like noise exclusion, contrast enhancement, and standardization to guarantee uniformity throughout the dataset. Image enrollment may also be used to enhance comparison and analysis by adjusting images captured at different periods or from different patients. Additionally, regions of interest may be isolated from surrounding brain tissue using division methods, such as the borders of tumors. Because of this, it is possible to single out important characteristics for further evaluation. In order to provide strengths for the subsequent model development and order phases, image handling solutions generally aim to improve the consistency, quality, and interpretability of the X-ray photos. v) Algorithms: because they find out how to differentiate designs and can efficiently extract highlights from photographs, they are suitable for tasks such article recognized proof, picture division, and characterization.

Xception is the name of a 71-layer convolutional neural network [19]. You may get your hands on a pretrained version of the algorithm that was trained on over a million images from the ImageNet collection. The pretrained network is able to sort images of a thousand distinct object categories, such as a computer, a pencil, a mouse, and a few animals. One deep learning framework that was developed to address the vanishing slope problem in deep learning networks is ResNet, which stands for Leftover Brain Organization [13], [14], [15]. It simplifies the preparation of very deep neural networks and improves data stream by revealing residual connections that bypass explicit layers. the DenseNet1201: One member of the DenseNet family of deep learning algorithms is DenseNet201. It is characterized and made possible for highlight reuse by thick layer relationships, in which each layer immediately receives input from the one below it. Reducing evaporation slope concerns in deep brain organizations, improving angle stream, and working on model productivity are all goals of this engineering.

2. 1. EXPERIMENTAL RESULTS

Accuracy: The accuracy with which a test can distinguish between valid and invalid events is not conclusive. If we want to know how accurate a test is, we should keep track of how many true positives and negatives there were in each sample. If we break it down mathematically, we get: Accuracy = TP + TN. Add TP, TN, FP, and FN.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

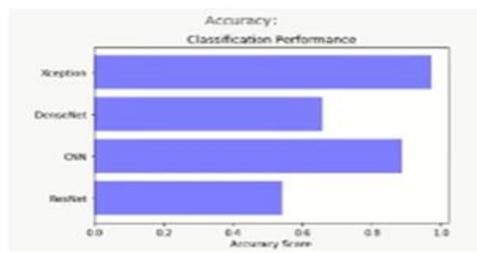

Fig 2 Accuracy Comparison Graph

Precision: The accuracy of the positive instances is evaluated by how many of them are correctly sorted. Therefore, the formula for estimating accuracy is as follows:

Preciseness is TP divided by (TP plus FP), which is the sum of true positives and false positives.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

Fig 2 Precision Comparison Graph

Fig 3 Home Page

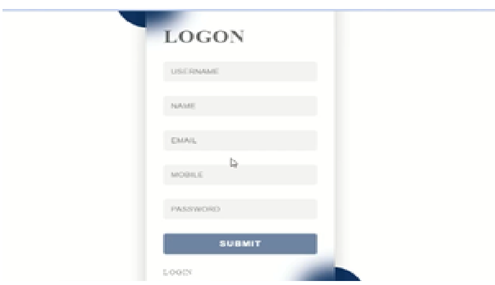

Fig 4 Registration Page

Fig 5 Login Page

Fig 6 Main Page

Fig 7 Click on Stage 1 Detection

Fig 8 Upload Input Image

Fig 9 Predict Result

Fig 10 Upload Another Input Image

Fig 11 Final Outcome

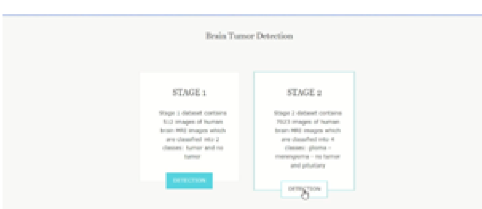

Fig 12 Now Click On Stage 2 Detection

Fig 13 Upload Input Image

Fig 14 Predict Result for Given Input

Fig 15 Upload Input Image to Predict Output

Fig 16 Final Outcome for Given Input Image

Fig 17 Upload Another Input Image for Output

Fig 18 Output for Given Input

3. CONCLUSION

Briefly put, a paradigm shift toward cutting-edge demonstration methods is necessary to address the critical global medical issue of brain tumors. The review's focus on using appealing reverberation imaging (X-ray) and deep learning computations, such as Convolutional Neural Network (CNN), Xception, ResNet, and DenseNet201, has significantly improved the accuracy of brain cancer characterisation. An important characteristic of the potential to increase analytical accuracy with Xception is the essential improvement of almost 100% precision. The findings highlight the critical need of varying deep learning designs to enhance mind development arrangement. The study highlights the rapid prospects for improved determination accuracy and improves ongoing research into state-of-the-art solutions. With a clear goal of working on early detection and treatment for worked on persistent outcomes, this research presents a strong dedication to the ongoing efforts to overcome the problematic issue that cerebrospinal tumors present.

VI. OUTLINE FOR THE FUTURE

The next step of our investigation is to study and improve cutting-edge deep learning structures for brain cancer classification. Improving accuracy rates may be aided by using state-of-the-art technology such as suitable artificial intelligence and continuously improving computations. In the end, the suggested approach—which would focus on subtle outcomes and early differentiating evidence—could be easier to incorporate into clinical practice if institutions and clinical experts worked together. Research with backing in this area has the potential to revolutionize brain development studies globally.

REFERENCES

[1] Javeria Amin, Muhammad Sharif, Mussarat Yasmin and Steven Lawrence Fernandes, "A distinctive approach in brain tumor detection and classification using MRI", *Pattern Recognition Letters*, vol. 139, pp. 118-127, 2020, [online] Available: https://doi.org/10.1016/j.patrec.2017.10.036, ISSN 0167-8655.

[2] S. K. Baranwal, K. Jaiswal, K. Vaibhav, A. Kumar and R. Srikantaswamy, "Performance analysis of Brain Tumour Image Classification using CNN and SVM", *2020 Second International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2020.

[3] A Younis, L Qiang, CO Nyatega, MJ Adamu and HB Kawuwa, "Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches", *Applied Sciences*, vol. 12, no. 14, pp. 7282, 2022, [online] Available: https://doi.org/10.3390/app12147282.

[4] S. Grampurohit, V. Shalavadi, V. R. Dhotargavi, M. Kudari and S. Jolad, "Brain Tumor Detection

Using Deep Learning Models", *2020 IEEE India Council International Subsections Conference (INDISCON)*, 2020.

[5] H. Ucuzal, S. YASAR and C. Colak, "Classification of brain tumor types by deep learning with convolutional neural network on magnetic resonance images using a developed web-based interface", *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*, 2019.

[6] Muhammad Jibril, Ibrahim Badi, Ahmed Haruna, I A Mohammed and Oluwatobi Dada, "Deep Learning Models for Classification of Brain Tumor with Magnetic Resonance Imaging Images Dataset", 2022.

[7] Muhammad Arif, F. Ajesh, Shermin Shamsudheen, Oana Geman, Diana Izdrui and Dragos Vicoveanu, "Brain Tumor Detection and Classification by MRI Using Biologically Inspired Orthogonal Wavelet Transform and Deep Learning Techniques", *Journal of Healthcare Engineering*, vol. 2022, pp. 18, 2022, [online] Available: https://doi.org/10.1155/2022/2693621.

[8] Madapuri, R.K., Mahesh, P.C.S. HBS-CRA: scaling impact of change request towards fault proneness: defining a heuristic and biases scale (HBS) of change request artifacts (CRA). Cluster Comput **22** (Suppl 5), 11591–11599 (2019). https://doi.org/10.1007/s10586-017-1424-0

[9] Swetha, A. ., M. S. . Lakshmi, and M. R. . Kumar. “Chronic Kidney Disease Diagnostic Approaches Using Efficient Artificial Intelligence Methods”. International Journal of Intelligent Systems and Applications in Engineering, vol. 10, no. 1s, Oct. 2022, pp. 254.

[10] A Bhandari, J Koppen and M Agzarian, "Convolutional neural networks for brain tumour segmentation", *Insights Imaging*, vol. 11, no. 1, pp. 77, Jun 2020.

[11] Rudra Kumar, M., Gunjan, V.K. (2022). Machine Learning Based Solutions for Human Resource Systems Management. In: Kumar, A., Mozar, S. (eds) ICCCE 2021. Lecture Notes in Electrical Engineering, vol 828. Springer, Singapore. https://doi.org/10.1007/978-981-16-7985-8_129

[12] Thulasi , M. S. ., B. . Sowjanya, K. . Sreenivasulu, and M. R. . Kumar. “Knowledge Attitude and Practices of Dental Students and Dental Practitioners Towards Artificial Intelligence”. International Journal of Intelligent Systems and Applications in Engineering, vol. 10, no. 1s, Oct. 2022, pp. 248-53

[13] Rudra Kumar, M., Gunjan, V.K. (2022). Peer Level Credit Rating: An Extended Plugin for Credit Scoring Framework. In: Kumar, A., Mozar, S. (eds) ICCCE 2021. Lecture Notes in Electrical Engineering, vol 828. Springer, Singapore. https://doi.org/10.1007/978-981-16-7985-8_128

[14] Anand Deshpande, Vania V. Estrela and Prashant Patavardhan, "The DCT-CNN-ResNet50 architecture to classify brain tumors with super-resolution convolutional neural network and the ResNet50 Neuroscience Informatics", vol. 1, no. 4, 2021.

[15] Madona B. Sahaai, G. R. Jothilakshmi, D. Ravikumar, Raghavendra Prasath and Saurav Singh, "ResNet-50 based deep neural network using transfer learning for brain tumor classification", *AIP Conference Proceedings 2463*, pp. 020014, 2022, [online] Available: https://doi.org/10.1063/5.0082328.

[16] S. Kollem et al., "INCNet: Brain Tumor Detection using Inception and Optimization Techniques", *2022 International Conference on Emerging Techniques in*

Computational Intelligence (ICETCI), pp. 71-75, 2022.

[17] Gajendra Raut, Aditya Raut, Jeevan Bhagade, Jyothi Bhagade and Sachin Gavhane, "Deep LearningApproach for Brain Tumor Detection and Segmentation", *IEEE Transactions on Brain Tumor Detection*, Jan 2020.

[18]https://www.kaggle.com/datasets/masoudnickparvar/brain-tumor-mri-dataset.

[19]https://miro.medium.com/v2/resize:fit:833/1*t6qfo9ucYza_lbLfg5-p_w.png.