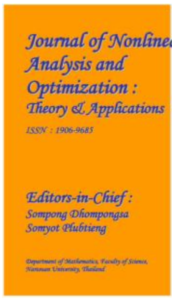
Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 15, Issue. 1 : 2024
ISSN : **1906-9685**



DETECTION OF BRAIN TUMORS THROUGH MRI EMPLOYING MACHINE LEARNING TECHNIQUES

Mrs. G. Jyothi, Associate Professor in Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.
Ch. Ravi Kumar Achari, Student, Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.
D. Prabhu, Student, Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.
K. Benny Harsha, Student, Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.
R. Satvika, Student, Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.
T. Lakshmi Sahithi, Student, Department of Information Technology, Vignan's Institute of Information Technology, Visakhapatnam.

ABSTRACT:
Automated defect perception in medical images has emerged as a critical field within various diagnostic applications. Identifying tumors in MRI scans holds significant importance, offering crucial insights into abnormal tissue for treatment planning. Traditionally, human inspection has been the standard practice for defect perception in neuroimaging with MRI, but its impracticality because of copious information necessitates the improvement of reliable and automated classification schemes. This shift is imperative to reduce human mortality rates. Consequently, self-regulating tumor perception methods have been devised to save time for radiologists while ensuring tested accuracy. The complexity and variability of brain tumors make MRI brain tumor perception a challenging task. This project introduces the practicality of machine learning strategies to mitigate the constraints observed in classic classifiers. The primary objective is to facilitate the sensing of brain tumors in MRI scans through the enhanced capabilities provided by machine learning techniques. This groundbreaking approach utilizes machine learning and image categorization techniques to capably notice cancer tissues in the brain using MRI imaging.

Keywords:
Automated defect perception, MRI, Convolutional neural network, Transfer learning, pre-initialized keras framework, Image pre-processing, data augumentation, feature elicitation, activation function, Training and testing, ResNet-50, F1 score.

1. INTRODUCTION

Brain tumors represent the foremost challenging syndromes in the field of health science, necessitating impactful and resourceful analysis, particularly in the premature stages of tumor development. The premium standard for figuring out the grade of a brain tumor is histological grading, typically performed through a stereotactic biopsy test. This procedure involves a neurosurgeon drilling an aperture inside the skull to compile tissue for analysis. However, the cellular test comes with various risk factors, including blood discharge from the tumor and the brain, leading to potential complications such as infection, convulsions, severe migraines, stroke, stupor, and even death. A significant drawback of the stereotactic biopsy is its lack of 100% accuracy, posing a risk of serious diagnostic errors that can subsequently result in incorrect clinical management of the disease.

Machine learning methodologies, particularly those employing Deep Convolutional Neural Networks (Deep ConvNets), have emerged as crucial tools in the fields of radiology and medical science. They significantly contribute to simplifying disease diagnosis, offering a plausible solution to traditional operative biopsy methods, especially for cranial tumors. This project concentrates on the perception and categorization of cranial tumors, exploring the fallouts of both binary and multi-class classification approaches. Additionally, the study evaluates the impact of Transfer Learning, utilizing pre-initialized Keras frameworks such as ResNet-50, Inception v3, and VGG16 within the CNN structure. The target is to enhance the efficiency and accuracy of cranial tumor perception through advanced machine learning techniques.

2. REVIEW OF LITERATURE

In 2012, Krizhevsky et al. achieved groundbreaking outcomes in image categorization by implementing transfer-learning methods. A substantial and deep convolutional neural network was initialized by them to classify twelve hundred thousand top-notch pictures in the ImageNet Large Scale Visual Recognition Challenge of 2010, categorizing them into 1000 variety blocks. On the test data, the framework demonstrated premium-1 and premium-5 error rates of 37.6% and 17%, specifically, surpassing the performance of previous state-of-the-art methods. The framework was further entered into the ILSVRC-2012 competition, attaining an impressive premium-5 test misclassification rate of 15.4%, surpassing the second-ranked entry, which had a rate of 26.2%.

In 2014, Simonyan and Zisserman conducted a study to delve into the consequences of varying network range on accuracy in the environment of huge-scale image localization. The outcomes of this investigation formed the basis for their participation in the ImageNet Challenge 2014, where their team obtained initial and subsequent positions in the identification and categorization tracks, specifically. The primary focus of their work involved an inclusive assessment of deeper networks, utilizing a layout featuring very small convolution filters of size (3 × 3). Their significant contribution demonstrated that substantial improvements over pre-existing designs could be attained by raising the immersion to sixteen–nineteen bulk layers.

In 2015, Szegedy et al. promoted a deep variable filtering neural network structure named Inception, that played a pivotal role in establishing a new state-of-the-art for categorization and perception in the Challenge of visual recognition 2014. The standout feature of this overwhelming structure lies in its enhanced usage of many sophisticated computing resources within the range. This improvement was attained through a meticulously designed structure that allows for extending the immersion and breadth of the network while maintaining a constant processing allowance. The results obtained yielded compelling evidence that estimating the expected normal sparse structure using conveniently accessible huge elements is a practical approach. for enhancing neural networks in the domain of machine vision.

In 2022, the literature on brain tumor detection using convolutional neural networks (CNNs) and selected machine learning techniques revealed several notable findings. Notably, there was a significant improvement in accuracy attributed to the adoption of deep learning methods, particularly CNNs, which outperformed traditional machine learning algorithms. Various CNN architectures, including AlexNet, VGG, ResNet, and DenseNet, were explored, with researchers fine-tuning pre-trained models through transfer learning to adapt features learned from datasets like ImageNet to the task of brain tumor detection. Ensemble learning techniques such as bagging and boosting were also utilized to enhance model robustness. Despite these challenges, the field showed rapid progress and a commitment to improving patient outcomes through innovative computational approaches.

In2023, a comprehensive survey of brain tumor detection revealed a landscape dominated by deep learning methodologies, particularly convolutional neural networks (CNNs), which offered notable advancements over traditional machine learning approaches by autonomously extracting relevant features from medical images. Researchers focused on innovating CNN architectures tailored specifically for medical imaging analysis, aiming to enhance model efficiency, interpretability, and generalization performance. Transfer learning strategies remained prominent, enabling the adaptation of pre-trained CNN models to the task of brain tumor detection, thereby improving performance even with limited labeled data. Despite significant progress, challenges such as dataset heterogeneity, model interpretability, and clinical validation remained, signaling opportunities for future research to improve model robustness and facilitate seamless integration into clinical settings, ultimately enhancing patient care and outcomes.

3. METHODOLOGY

IMAGE ACQUISITION

The dataset from Kaggle is diverse, containing information in myriad formats like txt, csv and data files available in monochrome, RGB, or HSV. It is organized with 98 MRI images showcasing healthy conditions and 155 MRI images displaying tumors. These files are stored in the .zip format.

BRAIN TUMOR

The human brain, being a highly receptive organ, controls bodily actions and deciphers sensory input like vision, auditory cues, tactile sensations, flavor perception, and discomfort.Tumor presence is identified based on factors such as tissue quantification, the location of anomalies, dysfunctions, diseases, and imaging studies. Neoplasms within the cerebral region have the potential to influence sensory data and motor functions, potentially culminating in grave outcomes, including mortality. The classification of tumors hinges on their origin, distinguishing between primary and secondary variants. Primary cerebral tumors have their genesis within the cranial cavity, whereas subsequent tumors spring elsewhere in the physique and relocate to the cerebral region.

Tumors can be classified on the axial plane into types such as glioblastoma, sarcoma, and metastatic bronchogenic carcinoma. While some tumors, like meningiomas, are relatively easy to segment, others, such as gliomas and glioblastomas, pose challenges in localization. Nevertheless, the bulk part of LGG tumors showcase a more gradual expansion measure and demonstrate responsiveness to therapeutic interventions, a subset of untreated LGG tumors has the potential to progress to glioblastoma (GBM). Punctual and precise determination of the tumor grade is paramount for meticulous treatment strategizing, encompassing potential interventions like surgery, radiotherapy, and chemotherapy, either individually or in tandem. Survival expectations for GBM or HGG patients are generally restricted, falling within the range of 12 to 15 months.

DATA AUGMENTATION

Data augmentation encompasses various techniques to enhance a dataset's diversity and size. These methods include converting images to grey scale, implementing reflection through vertical or horizontal flips, applying Gaussian blur to reduce image outliers, performing histogram equalization to boost global contrast, and incorporating rotations, though these may not necessarily maintain the original image size. Additionally, translation involves moving images along the cartesian coordinates and rectilinear mappings, such as stochastic rotations within a specified degree range, as well as horizontal and vertical shifts, along with flips in both directions.

IMAGE PRE-PROCESSING

Our early-stage processing methodology involves several key steps. Initially, we rescaled the image to reduce memory space usage, adjusting the monochrome pixels within the 0-255 range. Subsequently, we employ a Gaussian smoothing to effectively de-noise, opting for this over a Median filter due to its superior results in preserving the brain's outline while segmenting tumors. Additionally, we apply Binary Thresholding to enhance image quality and implement morphological operations, such as erosion and dilation, for further refinement. The final step incorporates contour formation through an edge-based methodology. This comprehensive pre-processing sequence aims to optimize the image for subsequent analysis and classification. The partition of cranial tumors is a crucial process that entails separating tumor tissues, identified as the designated area, from normal cerebral tissues and solid cranial tumors. This segmentation is achieved through the scrutiny of MRI visuals or other pertinent diagnostic methods.

MACHINE LEARNING TRAINING AND TESTING

In the context of image categorization, frameworks with pre-initialized weights on ImageNet include Xception, ResNet, ResNet-2, Inception v3, MobileNet v2, ResNet-50, MobileNet, v2 Inception, Dense Net, Alex Net, VGG16, VGG19 and others. These frameworks are employed for training and testing within the machine learning framework.

EVALUATION METRICS

Accuracy is the most instinctive performance metric, denoting the proportion of accurate outlooks relative to the total number of outlooks made. The accuracy formula is expressed as Accuracy = TP +

TN / (TP + FP + TN + FN). Exactness is delineated as the quotient of true positives divided by the sum of true positives and false positives. The exactness formula is articulated as Exactness = TP / (TP + FP). Recall, also recognized as sensitivity, represents the fraction of the entire count of pertinent instances that were successfully retrieved. The recall formula is expressed as Recall = TP / (TP + FN). The F1 Score serves as the harmonic mean of Exactness and Recall, considering both metrics in the equation: F1 Score = 2 × exactness × recall / (recall + exactness). Additional metrics for evaluation include sensibility, distinctiveness, and misclassification rate. Sensibility signifies the likelihood of correctly predicting the true High-Grade Glioma (HGG) class, while distinctiveness defines the accuracy in predicting the Low-Grade Glioma (LGG) class. These metrics assist in assessing the potential for excessive or insufficient segmentation of the tumor sub-regions. The misclassification measure (ERR) quantifies instances of inaccurately classified predicted classes by a knowledge framework. The overall categorization is assessed through the Area under the Curve (AUC), where a larger area under the curve implies superior classification.

4. SYSTEM ANALYSIS

Designing a system for brain tumor perception using convolutional neural networks (CNNs) and machine learning (ML) algorithms involves several key components.The project encompasses a comprehensive approach to address the challenge of detecting brain tumors from medical images, specifically focusing on MRI and CT scans. The problem is explicitly defined, specifying the types of tumors to be detected, such as gliomas and meningiomas.

The data collection involves assembling a diverse and well-labeled dataset, subsequently partitioned into training, validation, and testing sets. Preprocessing steps include resizing, normalization, and augmentation techniques to enhance dataset variability and address class imbalance. For framework selection, a suitable CNN architecture, such as VGG16 or ResNet, is chosen, with an emphasis on transfer learning and consideration of framework size and complexity. Feature elicitation is achieved through convolutional layers, extracting meaningful representations for tumor perception. Machine learning algorithms like PCA and t-SNE are explored for feature elicitation and dimensionality reduction.

The training process involves fine-tuning the CNN on the training dataset, optimizing hyperparameters, and monitoring for overfitting using the validation set.Continuous improvement mechanisms are implemented for ongoing framework monitoring and updates, with regular retraining based on new data. Regulatory compliance with healthcare and data protection regulations, such as HIPAA, is prioritized.Collaboration with medical professionals is emphasized throughout the development and testing phases, ensuring insights, validation, and feedback are incorporated into the project's evolution.

In our project, the partitioning of brain tumor process is executed through manual assortment of the designated area, half-mechanized, or fully self-regulating methods. Various ML methods are employed for the categorization of cranial tumors, embracing Artificial Neural Networks (ANN), K-Nearest Neighbour (KNN), Filtering Networks, Random Field algorithm, Support Vector Machine through regression mining, Bayesian categorization, and Decision Trees. In our study, utilization of (CNN) is done to detect and classify cranial tumors, with a focus on sagittal MRI images. This approach contributes to the automation of the segmentation process and augments the veracity of tumor perception and classification.

5. CONCLUSION

In conclusion, automated defect perception in imaging studies, facilitated by ML has emerged as a significant domain in various biological therapeutic services. Its implementation in the perception of cranial tumors in neuroimaging scans holds significant importance, furnishing essential details about peculiar tissues that are imperative for effective treatment organization. Recent scholarly works emphasize that the automated computerized perception and diagnosis of diseases, employing medical image analysis, presents a promising and viable alternative. This not only economizes the time of radiologists but also guarantees verified veracity.

In the future, the scope of brain tumor perception holds promising avenues for innovation and advancement in medical imaging and treatment planning. Some potential directions include

developing a mobile application interface tailored for hospitals to enable doctors to efficiently assess tumor impacts and prescribe suitable treatments.
This app would provide a user-friendly tool for medical professionals to access and interpret relevant information seamlessly, improving workflow efficiency and patient care. Additionally, exploring the possibility of predicting tumor location and stage using three-dimensional (3D) imaging techniques, such as Volume Net combined with Convolutional Neural Networks (ConvNets), aims to enhance the accuracy of tumor assessments and enable personalized treatment strategies tailored to individual patient needs. Another initiative involves developing 3D anatomical frameworks based on individual patient data to assist in surgical training, planning, and providing computer-guided assistance during surgeries.
This initiative aims to enhance surgical precision and efficiency by providing detailed anatomical insights to surgeons, leading to improved patient outcomes. The use of Volume Net with a Leave-One-Patient-Out (LOPO) testing scheme has shown high accuracy (>95%), despite its computational demands. This robust approach is particularly useful in scenarios where individual patient test results are crucial, allowing for thorough examination and analysis in case of misclassification. These advancements in Convolutional Neural Networks in medical imaging hold promise for enhancing diagnostic accuracy and treatment planning, potentially revolutionizing brain tumor perception and its treatment.

REFERENCES:

1. S. Balmer, L.-P. Novel, and M. Raees. (2013). "Fully automatic segmentation of brain tumor images using support vector machine categorization in random field regularization," in Medical Image Computing and Computer-Assisted Intervention-MICCAI 2011. New York: Springer, pp. 355–369.
2. Saleem Khan, M.A.; Arif, I.; Alhassani, M.; Tamasvini's, R.; Schuda, R.; Rahim, A.; Brown,S.A.C. (2021). Comprehensive Brain Tumor Classification Utilizing Deep Learning and Resilient Feature Selection: A Machine Learning Approach Tailored for Radiologists. Published in Diagnostics, volume 10, page 565. [Google Scholar] [Cross Ref] [PubMed].
3. J.C. Targa, J.K. Murial, H. Jail, F. Rot, M. Hemsworth, L. Bruggman. Dinku, and M.S. Yaung. (2012). Convolutional networks can learn to generate affinity graphs for image segmentation. Neural Computation, 23(2):514–568.
4. B. Mittal et al. (2015). "The metatemplate brain tumor image partition benchmark," IEEE Trans. Med. Imag., vol. 34, no.10, pp. 1993–2024.
5. B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, et al. (2015). "The Multimodal Brain Tumor Image Segmentation Benchmark (BRATS)," IEEE Transactions on Medical Imaging 34(10), 1993-2024 DOI: 10.1109/TMI.2014.2377694.
6. S. Bakas, M. Reyes, A. Jakab, S. Bauer, M. Rempfer, A. Crimi, et al (2018). "Identifying the Best Machine Learning Algorithms for Brain Tumor Segmentation, Progression Assessment, and Overall Survival Outlook in the BRATS Challenge".
7. A.Vidyarthi, Mittal. (2019). "CLAP: Closely link associated pixel-based elicitation of brain tumor in MR images," International Advance Computing Conference on Signal Processing and Communication (IACC), pp. 202 -206.
8. Hemanth, D.J.; Anitha, J.; Naaji, A.; Gaman, O.; Popescu, D.E.; Son, L.H.; Hoang, L. (2018). A Revised Deep Convolutional Neural Network for the Classification of Abnormal Brain Images. Published in IEEE Access, volume 7, pages 4275–4283. [Google Scholar] [Cross Ref].
9. Banerjee, Mitra, and B.U. Shankar. (2017). "Synergetic neuro-fuzzy feature selection and classification of brain tumors," in IEEE International Treaty on Fuzzy Systems 2017.
10. K. Ramya and L. K. Joshila Grace (2016). "Brain tumor perception based on watershed transformation," International Conference on Communication and Signal Processing (ICCSP).