

Survey on AI based Approach for Classification of Multi Grade Tumour in Human Brain

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Abstract-The categorization of brain tumour images is an important step in medical image processing. Doctors can use it to develop precise diagnoses and treatment strategies. One of the most common imaging techniques for studying brain tissue is magnetic resonance imaging (MR imaging). Carrying out this research, we will be further be engaging on the implementation of the three models which includes, U-net, VGG-16 and AlexNet for small, large and very large dataset, implementing the same on GPU, evaluating the performance of all the three models to compare the same and notice the contrast between the performance of the models, optimization of the parameters to assess their performance and hence, record the best performance model. The main aim of the project is to provide an environment where doctors can view and interact with patient specific anatomical form, functions and flow for improved diagnosis and more precise surgical planning. Surgeons will be able to analyse their patients' anatomy in more detail thanks to augmented reality. Without needing to operate, surgeons will be able to see bones, muscles, and interior organs. This could also aid them in determining where injections and incisions should be made, which could be useful in an emergency.

Keywords-CNN, Deep Learning, Medical Image

1. INTRODUCTION

Biomedical imaging consists of a collection of approaches which could be utilized to examine the internal organs of a body without having to surgically operate it. Medical imaging includes capturing, processing, and visualising structural pictures of the body for examination and analysis reasons, and thus contributes as a critical part in correct diagnosis decision-making. Image segmentation is a crucial step in image processing that ensures that higher-level image processing produces successful results. In

medical imaging processing, the motive of image segmentation is to detect tumours and provide useful data for further diagnosis. Tumor detection and efficient findings for subsequent diagnosis are the goals of image segmentation in medical imaging processing. A brain tumour is an abnormal growth of cells in the brain that can be malignant, non-cancerous, or both. Benign and malignant cancers are the two most common forms. A malignant brain tumour starts in the brain and quickly spreads to the surrounding tissues. Benign tumors on the other hand, grow relatively slowly. Brain tumor treatment options vary on the type of brain tumor as well as its size and location. So classification of brain tumors is very important, in order to classify which type of brain tumor really suffered by a patient. Thus, treatment planning is an important stage to improve the quality of life of patients. Hence we propose a system for classification of multigrade tumors as Benign and Malignant. For this article, we offer an effective method for the classification and identification of brain tumours.

2. LITERATURE REVIEW

One of the most complex and demanding processes is classifying the engaged area from an entity, and classifying the tumor from an Nuclear MRI is a key and significant step.

“In today's world Neural Network based segmentation gives promising outcomes, and the flow of employing this model is adding up as the days pass”[2].The goal is to use CNN to multi classify brain cancers for early diagnosis. Three different CNN models for three different categories are the focus. The first model detects brain tumours with 99.33 percent accuracy, the second model classifies brain tumours into five types (normal, glioma,

meningioma, pituitary, and metastatic) with 92.66 percent accuracy, and the third model classifies tumours into three grades (I, II, III) with 98.14 percent accuracy. Grid search optimization is used to identify the critical hyperparameters. The suggested model has been compared to other CNN models such as AlexNet and Vgg-16, and it has been discovered that using big and publicly available clinical datasets, satisfactory classification results may be obtained [3]. By taking into account exact melanoma segmentations and reducing artefacts, the suggested region-extreme CNN for Melanoma Malignancy Recognition increases recognition performance. On these lesions, decision boundaries are then defined in order to forecast Melanoma Malignancy [4]. The assessment of a specific situation Setting hyperparameters for current algorithms can take a long time and is also quite multi-dimensional. As a result, this research recommends a lower-dimensional version of the original data in order to quickly find attractive hyperparameter space areas. Various optimization techniques, including TPE, SMAC, and a GA, are used in the experiment. The experimental results suggest that by starting with lower-dimensional data representations and increasing dimensionality of the input later in the optimization process, it is possible to speed up the optimization process [5]. The goal of this paper is to look at how a combination of Gaussian Dirichlet Mixture Model (GMMD) and Unet can be used to segment the human brain from magnetic resonance imaging. On the basis of probability distribution, GMMD is used to categorise the data into categories. Unet, on the other hand, is used to correct the Gaussian Mixture Model's incorrect categorization. According to study, diagnosing a tumour in the human brain is significantly more difficult than diagnosing a tumour in any other region of the body, hence proper bisection of brain tissue is critical for detecting neural problems [6]. A brain tumour is a neurological illness in which a malignant or non-cancerous mass develops in the human brain, or unusual cells form. The primary focus of this paper is on detecting brain tumours early using CNN, a deep learning technique for picture categorization. A dataset containing brain tumour MRI is applied to train the suggested CNN model. The project is carried on six distinct datasets in order to improve its development. On brain tumour MRI, various data augmentation approaches are

employed to improve the proposed model's performance, resulting in a high average sensitivity of about 0.99 for all datasets and up to 100% accuracy. [7]. The primary goal of this research to pinpoint the source of brain hemorrhage. They used a deep learning strategy to overcome this challenge. They divided the brain CT images into two categories: hemorrhage and non-hemorrhage. They used the equal quantity of computer tomography images to train the model using three primary networks : CNN, Alexnet neural network, and Alexnet support vector machine. As a result of training all of these network models, alexnet svm was able to identify the brain hemorrhage with more accuracy than CNN and Alexnet [8]. This research is to use a deep learning approach to analyse the performance of various networks for image characteristics. they created various datasets to see how well image categorization networks perform, taking into account various factors. many tests were carried out to investigate the factors that influence the picture categorization network. they obtained twenty-seven image datasets from three image factors after examining all of the experimental findings, with the classification performance of alexnet, vggnet, googlenet, and dense net being the most accurate [9]. The goal of this study is to check the efficiency of deep learning methods that they have chosen for locating and differentiating tumour lesions using magnetic resonance imaging contrasts. The TCGA datasets, which contain lower grade gliomas and glioblastoma, were used in the trials. They employed the Grad Cam approach to visualise the network's performance. Finally, they looked into using AI to show the features of trained models. As a consequence, using the testing dataset, densenet121, googlenet, and mobilenet attained a validated prediction accuracy [10]. The goal of this article is to experiment with and test health-care professionals' technology acceptability for various forms of 3D interaction with smart glasses in wound documentation. Initially, they provided all of the volunteers a brief summary of the experiment in order to document wounds. They then reproduced several wounds for Hololens-related treatment. They used an ANOVA test to look at the data that was combined with technology. When compared to the standard process, the trial proved that smart glass documentation systems are far more advantageous in

terms of exhibiting performance[11].Brain tumor is a deadly cancers among adults and children .It is very important to identify and classify the tumor into their specific grade so that it can be treated effectively.According to the World Health Organization (WHO), central nervous system brain tumours are classified as malignancy grades I through IV. Histopathology is the most used approach for distinguishing grade IV tumours. Because of its wide range of biologically authoritative tissue identification, MRI is widely employed [12].Muscle diseases are public health issues known to have high mortality and morbidity risk factors. Deep learning is a method for locating the muscle site and interpreting ultrasound pictures that may assist inexperienced clinicians. The identification, evaluation, and interpretation of muscle ultrasound pictures have been improved thanks to deep learning. The classification uses CNN models such as AlexNet, Deep-CNN and VGG. Deep learning is useful for diagnosing skeletal and smooth muscle disorders, as well as landmark recognition, muscle site identification, and reliability testing utilising ultrasonic image segmentation or classification[13].Humans are affected by brain tumours, which are critical disorders. Understanding the phases of a brain tumour is critical for both prevention and treatment. Brain cancers are frequently detected with magnetic resonance imaging (MRI). The outcome reveals whether the brain is healthy or not. In the event of an abnormality, it determines the type of tumour. A combined architecture consisting of neural autoregressive distribution estimation and a convolutional neural network was used to create MR pictures[14].Deep learning has gotten a lot of attention in the scientific community. Multiple layers of deep learning models

are trained using supervised or unsupervised training methodologies. Deep learning is efficient and capable of processing big MRIs from databases. For tumour identification and localization, the technology has two steps. The first step is to classify tumours using an MRI classification system, which then divides MRIs into normal and abnormal pictures. The second phase is locating the tumour within the aberrant photos [15]. Deep neural networks feature a variety of hyperparameters that may be modified based on the input data, resulting in a large search space. The effective dimensionality of hyperparameter optimization problems is typically minimal. The difficulty with optimising hyperparameters in CNNs is that the training process takes a long time, making evaluating many potential hyperparameter combinations more expensive. Convolutional neural networks are a frequently used learning technique that has its hyperparameters optimised [16]. The paper aims towards understanding what AR technology is. It comprises the information about AR technology, its types and its benefits in comparison to the traditional methods. It analyzes the challenges faced by Health care professionals and addresses the methods which can be used to overcome them by the use of AR. In order to show the applications of AR in health care they use the example of the technique that enables real-time visualization of 3D lung dynamics during the surgery. They show that high resolution computed tomography can be superimposed to visualize the internal dynamics of the lungs. Augmented Reality is fairly applied to medical treatments and surgeries. The experiment shows the advantages of AR in healthcare. We apply the concept of Augmented Reality in our project which would help in better diagnosis[17]

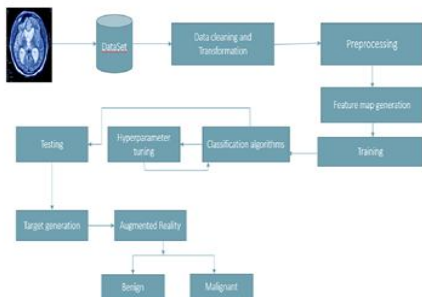
3. LITERATURE SUMMARY

Sl. No	Author	Year of Publication	Methodology	Results obtained
1	Nudrat Nida, et Al [3]	2021	CNN architecture	Deep features combined with ELM classifiers produce accurate melanoma recognition models.
2	EmrahImarak,et Al [4]	2021	Convolutional neural network	Hyperparameter optimization in CNN
3	Tobias Hinz, et Al [5]	2018	Deep CNN	The hyperparameters can be optimised on a series of smaller representations that grow in size until the original data size is reached.
4	Jiawei Lai, et Al [6]	2019	U-net, CNN	The IBSR 18 dataset's experimental brain MRI results demonstrated the efficiency of GMMD-U on segmentation tasks.

5	Asma Naseer, et Al [7]	2021	Deep Learning	The average accuracy is roughly 98.8%.
6	Awwal Muhammad Dawud, et Al [8]	2019	CNN, AlexNet, and AlexNet-SVM	“CNN, AlexNet, and AlexNet-SVM attained accuracies of 90.65%, 92.13 percent, and 93.48 percent, respectively.”[8]
7	QIANG LI, et Al [9]	2021	AlexNet,GoogleNet, VggNet,DenseNetResNet,Squee zeNet, ShuffleNet,MobileNet,	A brain tumour is a neurological condition that can manifest as a malignant or non-cancerous mass, or as the growth of a tumour. AlexNet, Vggnet, and DenseNet all have results above 0.95. ResNet.On a noise-free image, it's a 0.7663.
8	MortezaEsmacili, et Al [10]	2021	GoogLeNet, MobileNet,DenseNet-121	On the testing dataset, the considered models had the precision of 92.1%, 87.3%, and 88.9%.
9	Kai Klinker, et Al [11]	2019	Augmented Reality	Improved Diagnosis Precision
10	Muhammad Sajjad, et Al [12]	2018	InputCascadeCnn,VGG-19	For grades 1,2,3, and 4, the accuracy utilising the radiopaedia dataset is 90.03 percent, 89.91 percent, 84.11 percent, and 85.50 percent, respectively.
11	Peter Ardhianto, et Al [13]	2021	Comparison between Machine learning and Deep Learning	Deep learning performance evaluation
12	RahelehHashemzahi, et Al [14]	2020	Deep Learning	The accuracy rate is 95%.
13	Mahmoud khaled Abd-Ellah, et Al [15]	2018	AlexNet,VGG-16,VGG-19	The proposed CNN technique had a 99.55 percent accuracy rate, while the traditional method had a 66.96 percent accuracy rate.
14	Bijen Khagiand, et Al [16]	2018	CNN architecture	The dice similarity index is around 0.8. Jaccard is around 0.6.
15	Augmented Reality in Health Care [17]	2021	Super imposing high resolution computed tomography	Helps in better diagnosis

3. METHODOLOGY

In the proposed model, the aim is to improve the accuracy and precision of the results. Since the mortality rate due to tumors is evidently high we are making an effort to reduce that by developing a more precise system. The first step in our project is acquisition of the dataset which is MRI images and then perform data cleaning and transformation, this step is mainly performed to transform the obtained dataset into the required format.



The next step is to perform the data preprocessing steps to remove the noise and unwanted data parts. In

this step, we remove the unwanted text,noise, smoothen the image and enhance it. It also includes segmentation of the data to separate the gray matter, white matter, cerebrospinal fluid and the tumor. After the preprocessing step we obtain the clean data. After this we begin the classification training that is training the system to classify the multigrade tumor in the human brain. This step is performed by using the classification algorithms available with the CNN architecture. Once the training process is complete, the next step is to test our system, in order to ensure the precise and accurate results. The role of Augmented Reality in our project is simply to develop a system that is more precise than the ones that already exist.

4. CONCLUSION

Health being one of most important concerns, cure and effective diagnosis of health problems becomes necessary. Hence, we propose an approach for classifying the brain tumor based on their features. Through literature survey we have noticed that the best way to detect brain tumors is by using MRI

images. We also see that a classification model may give 95% accuracy by the use of Convolution Neural Network which is based on Deep Learning Technique. Techniques of digital image processing are also important in the detection of brain tumor by using MRI images. In order to remove noise, clean the image and image transformation different preprocessing techniques are used. After that, the clean data is fed into ML algorithms. The final step is to take the input image and classify the same as Benign or Malignant.

REFERENCE

- [1] Brain Tumor: Statistics, Cancer.Net Editorial Board, 11/2017(Accessed on 17th January 2019)
- [2] Brain Tumor Detection Using Convolutional Neural Network Tonmoy Hossain , Fairuz Shadmani Shishir, Mohsena Ashraf MD Abdullah Al Nasim, Faisal Muhammad Shah,2019
- [3] Awwal Muhammad Dawud , Kamil Yurtkan, HuseyinOztoprak (2019) “Application of Deep Learning in Neuroradiology: Brain Haemorrhage Classification Using Transfer Learning”, Article ID 4629859.
- [4] Qiangli, Yingjian Yang, Yingwei Guo,Wei Li , Yang, Hanliu, AND Yan Kang (2021) "Performance Evaluation of Deep Learning Classification Network for Image Features", vol. 9, pp. 9318-9333, 2021.
- [5] MortezaEsmaeili, RiyasVettukattil, Hasan Banitalebi, Nina R. Krogh and JonnTerjeGeitung (2021) “Explainable Artificial Intelligence for Human-Machine Interaction in Brain Tumor Localization”Volume11.
- [6] Kai Klinker, ManuelWiesche, Helmut Krcmar (2019) “Digital Transformation in Health Care: Augmented Reality for Hands-Free Service Innovation”,Inf sys front 22,1419-1431.
- [7] Jiawei Lai , Hongqing Zhu, Xiaofeng Ling (2019) “Segmentation of Brain MR Images by Using Fully Convolutional Network and Gaussian Mixture Model with Spatial Constraints”, Article ID 4625371.
- [8] Asma Naseer, Tahreem Yasir,Arifah Azhar , Tanzeela Shakeel , and Kashif Zafar (2021) “Computer-Aided Brain Tumor Diagnosis: Performance Evaluation of Deep Learner CNN Using Augmented Brain MRI” , Article ID 5513500.
- [9] Muhammad Sajjad, Salman Khan, Khan Muhammad, Wanqing Wu, Amin Ullah, Sung WookBaik (2018)“Multi-Grade Brain Tumor Classification using Deep CNN with Extensive Data Augmentation”,Volume 30.
- [10]Peter Ardhianto , Jen-Yung Tsai, Chih-Yang Lin 3 , Ben-Yi Liao 4, Yih-Kuen Jan ,Veit Babak Hamun Akbari and Chi-Wen Lung (2021) “A Review of the Challenges in Deep Learning for Skeletal and Smooth Muscle Ultrasound Images”, volume 11,Issue 9.
- [11]RahelehHashemzehi ,Seyyed Javad Seyyed Mahdavi, Maryam Kheirabadi, Seyed Reza Kamel (2020) “Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE”, Volume 40, Issue 3
- [12]Mahmoud khaled Abd-Ellah, Ali Ismail Awad, Ashraf A. M. Khalaf, Hesham F. A. Hamed (2018) “Two-phase multi-model automatic brain tumour diagnosis system from magnetic resonance images using convolutional neural network”, J image video.
- [13]BijenKhagiand Goo-Rak Kwon (2018) ” Pixel-Label-Based Segmentation of Cross-Sectional Brain MRI Using Simplified Seg Net Architecture-Based CNN”, Journal of health care engineering, volume 2018, Article ID 3640705.
- [14]Nudrat Nida , AunIrtaza , and Muhammad Haroon Yousaf (2021) “A Novel Region-Extreme Convolutional Neural Network for Melanoma Malignancy Recognition”, Article ID 6671498.
- [15]Emrah Imarak (2021) “Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework”, Iran J sci Technal Trans Electr Eng 45, 1015-1036.
- [16]Tobias Hinz, Nicolas Navarro-Guerrero, Sven Maggand Stefan Wermtter (2018) “Speeding up the Hyperparameter Optimization of Deep Convolutional Neural Networks”, Volume 17.
- [17]BijenKhagiand Goo-Rak Kwon (2018) “Pixel-Label-Based Segmentation of Cross-Sectional Brain MRI Using Simplified Seg Net Architecture-Based CNN”, Journal of health care engineering, volume 2018, Article ID 3640705.