International Conference on Recent Trends in Data Science and its Applications
DOI: rp-9788770040723.181

Brain Tumour Classification Using Deep Learning and a comparative study of Efficientnet

Abishek.R
Dept of Data Science and Business systems
SRM Institude of Science and Technology of organization
Chennai, India
ar5640@srmist.edu.in

Dr.Vadivu.G
Professor,Dept of Data Science and Business systems, SRM Institude of Science and Technology of organization
Chennai, India
vadivug@srmist.edu.in

Dr.Evangelos.E. Milios
Faculty of Computer Science, Dalhousie University
Halifax, Nova Scotia, Canada
eem@cs.dal.ca

***Abstract* — Brain tumors have garnered significant attention in recent times as one of the most lethal diseases affecting both children and adults. Most of the primary central nervous system cancers or CNS are found in the brain. With roughly 12,000 individuals receiving a diagnosis of a brain tumor each year. There are various categories of brain tumors including Benign, Malignant, Pituitary, Glioma and others. To enhance the life expectancy of patients, it is crucial to employ appropriate care, preparation, and accurate diagnostics. Magnetic resonance imaging (MRI) is widely considered to be the most effective method for detecting brain tumors. However, due to the intricate nature of brain tumors and their characteristics, manual examination can sometimes lead to inaccurate results. The utilization of an automated system for detecting and classifying brain tumors can help doctors and patients identify and categorize these tumors at an early stage, initiate treatment sooner, and reduce mortality rates. Deep learning research is rapidly advancing, with new algorithms being developed every day to enhance accuracy. We use a combination of deep learning techniques such as Convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) to accurately detect tumors. Our approach leverages the transfer learning technique to train a new CNN model on top of the efficientnetB0 base model, allowing us to alter the final layers to match the classes we want to identify and categorize, such as benign, malignant, pituitary, and normal. This approach allows us to improve the accuracy of tumor detection and classification. Also we have done a comparative study between the pre trained heavy weight model called as Efficientnet b0 and Efficientnet B1 and we found there is a significant increase in the model performance and accuracy.**

Keywords — Central Nervous System (CNS), Magnetic Resonance Imaging, Machine Learning, Convolution Neural Network, Artificial Neural Network, and Transfer Learning.

I. INTRODUCTION

The human brain is the most crucial and noteworthy organ in the body, with brain tumours being a frequent cause of brain dysfunction. Essentially, a brain tumour is an accumulation of cells that are growing uncontrollably, resulting in a lump or unhealthy cell growth in the brain. There are numerous types of brain tumours, including both noncancerous (benign) and cancerous (malignant) varieties. Primary brain tumours originate in the brain, whereas secondary (metastatic) tumours originate in other parts of the body and spread to the brain. The rate of growth for brain tumours can vary significantly. While benign tumours do not spread to other tissues and grow slowly, they can still cause major problems despite not being carcinogenic. Additionally, they typically have more distinct borders, which facilitates surgical excision, and they do not frequently reappear following removal. On the other side, malignant brain tumours can spread to other regions of your brain or central nervous system, are carcinogenic, develop quickly, and pose a serious risk to your life. The proper functioning of your nervous system is reliant on the growth rate and location of any brain tumours you may have. The type of tumour, along with its size and placement, are all factors that determine the available treatment options. Brain tumour cells consume the nutrients intended for healthy cells and tissues, leading to brain dysfunction. Currently, manual examination of a patient's MR images of the brain is required to identify the tumour's location and size, which is time-consuming and can result in inaccurate detection. Brain cancer is a severe disease that claims many lives each year, making early detection and classification methods essential. Deep learning algorithms have been shown to be effective in detecting brain tumours from medical images such as MRI and CT scans.[1] The use of MRI scans, a non-invasive procedure that utilizes a powerful magnet, radio waves, and a computer, allows for the structures and components inside the body to be viewed with stunning clarity. Open MRI devices, however, do not produce as sharp of images as closed-bore MRI equipment. The brain is a crucial and critical organ in the human body and brain tumours have emerged as one of the leading causes of brain malfunctions. A tumour is a cluster of cells that have grown in an uncontrolled manner and form a mass in the brain. There are various types of brain tumours, ranging from benign (non-cancerous) to malignant (cancerous). Primary brain tumours originate in the brain while secondary (metastatic) tumours are those that originate elsewhere in the body and spread to the brain. In contrast, malignant tumours can grow rapidly and spread to other parts of the brain or central nervous system, posing a major threat to one's life. The treatment options for brain tumours are influenced by their type, size, and location, as well as the patient's nervous system's ability to function. The growth of brain tumour cells eventually depletes the nutrients intended for healthy cells and tissues, leading to brain failure. Convolutional neural networks (CNNs) are commonly used in brain tumor detection due to their ability to automatically learn features from images.[2] Currently, clinicians manually examine patients' MRI images of the brain to determine the location and size of the tumour, which is a time-consuming process prone to inaccuracies. Early detection and classification of brain tumours are crucial for survival, and MRI scans are the preferred choice for imaging because they produce clear and detailed images without the use of radiation. Open MRI machines, which have larger spaces on two sides and reduce the claustrophobia commonly associated with closed-bore MRI scanners, are available for patients with a fear of enclosed spaces. However, open MRI machines may not produce as sharp images as closed-bore MRI machines.

DOI: rp-9788770040723.181

II. Overview of Data

A. DataSet Description

The primary source of data is from Kaggle. Brain tumours can be complex and unpredictable in terms of their size and location. This makes it challenging to fully understand the nature of the tumor. An experienced neurosurgeon is required for MRI analysis. In underdeveloped countries, the lack of skilled medical professionals and limited knowledge of malignancies can make it challenging to effectively analyse MRI results. This problem can be solved with a cloud-based automated solution. The dataset includes around 4,000 MRI images of the brain. There are 400 images designated for testing and 4,000 for training. A large dataset is necessary for proper training of a Convolutional Neural Network (CNN).

B. Contents of the Dataset.

• Glioma Tumour: A type of tumour called a glioma develops in the brain and spinal cord and arises from glial cells, which support nerve cells. Gliomas are classified based on their genetic characteristics, which can help predict their behaviour and effective treatment options.

• Meningioma Tumour: A tumour called a meningioma develops from the meninges, the membranes covering the brain and spinal cord. Although not strictly a brain tumour, it can affect nearby structures like nerves, blood vessels, or brain tissue. Meningiomas are most common in women and often found in older individuals. They grow slowly and may not show symptoms, thus, they may be monitored rather than treated immediately.

• Pituitary Tumour: Tumours of the pituitary gland are abnormal growths that affect the production of hormones. Most pituitary tumours are benign (noncancerous) adenomas and don't spread to other parts of the body. Treatment options include removal, hormone management, and growth control, and observation may be recommended.

• No Tumour: A tumour doesn't always indicate malignancy. The term "tumour" refers to a swelling of any kind, including benign or malignant cell growth. Technically, even a pustule can be considered a tumour.

This dataset contains 6 different features i.e. date, open, high, low, close, volume.

III. Motivation

The detection and classification of brain tumours are critical in providing effective medical intervention. In addition to detecting the presence of a tumor, the ability to accurately classify its type is crucial in determining the best course of treatment. For instance, it is important to determine if the tumor is malignant or benign. By analysing MRI images, our project seeks to revolutionize the current approach to brain tumor detection and classification. Transfer learning, where a pre-trained CNN is fine-tuned for brain tumor detection, has been shown to improve performance and reduce training time.[3]

The primary objective of our project is to develop a cutting-edge system that can accurately identify various types of brain tumours using MRI images of patients. Our goal is to create a system that is more efficient, accurate, and reliable than current methods. By leveraging advanced imaging techniques, our system will provide medical professionals with valuable insights into the characteristics of brain tumours. This will allow them to make informed decisions regarding patient care and treatment options.

Ultimately, our project aims to contribute to the advancement of medical science by improving the way brain tumours are detected and classified. Through the development of a sophisticated system that can accurately analyse MRI images, we hope to facilitate early detection and effective treatment of brain tumours. The system uses convolution neural network algorithms to detect tumor blocks and classify the type of tumor present in the image. The system is designed to be user-friendly, where doctors can simply upload an MRI image, and the model will predict the presence of a brain tumor and the type of tumor present, with high accuracy. This project has the potential to save lives by detecting brain tumours at an earlier stage, leading to early treatment and better outcomes. Brain tumours are a significant concern worldwide and are responsible for taking many lives every day. Our aim is to tackle this problem head-on by developing a reliable and innovative solution that can accurately detect and classify brain tumours. By doing so, we hope to help improve the lives of patients, and ultimately, save lives.

C. Application

Brain tumours are a pressing concern worldwide, causing many fatalities on a daily basis. Early detection of these tumours by patients, doctors, and healthcare specialists can significantly improve the chances of survival and lead to happier outcomes. Our aim is to develop a solution that is both innovative and reliable in detecting brain tumours. Our project involves the creation of a system where doctors can upload MRI images and the model will predict whether there is a presence of cancer and the type of tumor present. The current state of brain tumours is one of the most dangerous issues in the world and it has become a matter of great concern. However, early detection can be life-saving for many individuals. That is why we aim to create a solution that is both precise and dependable in detecting brain tumours.

D. Scope of the Project

With the help of the AI and DL we can use the methods and algorithms effectively for predicting and detecting diseases like these. Brain Tumor detection is one of the most important and efficient way to detect brain tumor. The main scope of the project is to deliver this product to health care services and health care workers and doctors for detecting brain cancer with high accuracy. If this project is made as a full-fledged product surely it will be a great success for the college and also we can make a good profit from it. Ensemble learning, where multiple CNNs are combined, has also been shown to improve performance in brain tumor detection [4]. Brain tumor detection is a crucial and effective method for detecting brain cancer, and with the use of AI and DL, we can utilize these techniques and algorithms for accurate predictions and diagnoses. Our

DOI: rp-9788770040723.181

project's main objective is to deliver this product to healthcare services, staff, and doctors for efficient brain tumor detection. If this project is developed into a full-fledged product, it will bring great success to the college and provide financial benefits. As a benefit to users, we can also offer a free trial period for those who want to test the product before committing to it.

E. Problem Statement

To counter this, we aim to bridge the gap and ensure that predictions and diagnoses are accurate and precise. By utilizing AI and DL technologies, we can assist or guide doctors in determining the type of cancer present in an MRI image and detect the tumour at an early stage. This will greatly increase confidence in the results, as these models are trained on vast amounts of data to achieve high accuracy and reliability. The outcome of this solution will be a higher level of trust in the doctors' diagnostics and the ability to provide appropriate treatment accordingly.

IV. LITERATURE STUDY

The use of deep learning for diagnosing and classifying brain tumours remains a prominent area of research. Early detection and treatment of brain tumours has the potential to save millions of lives each year. Researchers have explored using machine learning and deep learning algorithms to address medical image diagnosis problems. Convolutional Neural Networks (CNN), one of the most well-known deep learning algorithms, have yielded significant results in the field of brain tumour classification.

A. Works Related To Brain Tumour Classification Using Deep Learning Approach And Idea for transfer learning

If a tumour is detected early, doctors can treat the patient and improve their chances of survival. According to statistics, in 2016, over 200 studies were conducted using deep learning on medical images, with 190 of them utilizing CNNs. Some of the most widely used CNNs for classifying medical images include AlexNet, VGG, and GoogLeNet. This section delves into the recent studies used for categorizing brain tumours. The use of Generative Adversarial Networks (GANs) in computer vision is becoming increasingly popular. Data augmentation, where synthetic data is generated from existing images, has been shown to improve CNN performance in brain tumor detection.[5] These networks can be trained to generate a variety of images, including style transfer, image synthesis from noise, image-to-image translation, and image segmentation. In the field of medical imaging, where datasets tend to be smaller, GANs have gained traction as a solution. When it's not possible to gather multiple imaging modalities for each patient, CycleGAN, a novel algorithm, can be used to compensate for the missing data. In this research, we explored the different entropy functions used in MRI image analysis to segment and detect tumours. The choice of entropy function has a significant impact on the threshold values and, subsequently, the segmentation results. Attention mechanisms, where important regions in the image are highlighted, have been shown to improve CNN performance in brain tumor detection.[6] Gliomas, the most common brain tumours, are classified based on the presence or absence of mitotic activity, necrosis, and vascular growth, resulting in a WHO grade of II, III, or IV. Both types of brain tumours can be detected easily, but they grow in a diffuse, infiltrative manner and are accompanied by an increase in water in the area around the tumor. Early detection and classification of these tumours are crucial for effective treatment. With the help of advanced technological advancements in automated healthcare systems, medical professionals can now provide more effective treatment for patients. GANs, where synthetic data is generated by a generator network and evaluated by a discriminator network, have been shown to improve CNN performance in brain tumor detection.[7] This article presents a new MRI-based method for classifying and identifying brain tumours by combining the properties of deep convolutional neural networks (CNNs).

The MRI images undergo normalization and enhancement before being input into three different CNN models for feature extraction. The Fuzzy C-Means (FCM) segmentation method is used to divide the brain into tumor and non-tumor regions, and wavelet features are extracted using the multilevel DWT method. 3D CNNs, where image volumes are used instead of individual slices, have been shown to improve performance in brain tumor detection.[8] Finally, a Deep Neural Network (DNN) is employed for highly accurate brain tumor classification. This method of brain tumour classification and identification using deep CNNs is compared to other approaches such as KNN, LDA, and SMO. AlexNet filters were utilized in the convolution layers of the CDLLC with a size of 3 x 3. The training process employed SGD as an estimator and the activation function used was ReLU. Transfer learning combined with data augmentation has been shown to achieve state-of-the-art performance in brain tumor detection using deep learning algorithms.[9]

This study aimed to diagnose normal and malignant brains using Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs). ANNs, with their ability to learn and store information through multiple interconnected layers of neurons, were able to train on the training data using basic processing units. The idea of this project was to use transfer learning, which has been previously explored in the field of brain tumour diagnosis

V. PROPOSED METHODOLOGY

The main aim of the project is to deliver a useful and effective solution for doctors who need to detect and diagnose what type of cancer a patient has using the MRI scanned image photographs of the scan from the patient. This project mainly focus to improve the accuracy to the maximum extent and provide a reliable deep learning model which will effectively identify the cancer present in the tumour image. Deep learning-based brain tumor detection methods have the potential to significantly improve diagnosis accuracy and treatment planning for patients with brain tumours.[10] We have used a latest technique called as the transfer learning which will help us identify the model input more accurately.

DOI: rp-9788770040723.181

A. Transfer Learning

Transfer learning is a branch of machine learning that focuses on the reuse of knowledge acquired from one problem and its application to another, similar but unrelated problem. Deep learning algorithms have been shown to be effective in differentiating between low-grade and high-grade gliomas, which can help in determining the appropriate treatment for patients.[11] For example, the skills learned from identifying vehicles can be transferred to identifying trucks. This concept has similarities to the psychological literature on learning transfer, where knowledge obtained from one task can be used to improve efficiency in learning new tasks. In transfer learning, the learned features from a base network trained on a base dataset and task are transferred to a target network trained on a target dataset and task. The success of this process depends on the generalizability of the learned features, as opposed to being task-specific. Transfer learning is the process of training a base model with another model and then training our target model on top of the base model. Using a pre-trained model as the base model improves accuracy and efficiency in detecting new information.

B. Efficientnetb0

The efficientnetb0 model is the foundation of our transfer learning approach. Typically, convolutional neural networks (CNNs) are constructed with a fixed resource budget and then expanded as additional resources become available to enhance accuracy. The use of multi-modal imaging, such as combining MRI and CT scans, can improve the accuracy of brain tumor detection using deep learning.[12] For example, ResNet can be scaled from ResNet-18 to ResNet-200 by adding more layers, and GPipe recently improved a baseline CNN by a factor of four, resulting in 84.3% ImageNet top-1 accuracy. Traditionally, scaling a model involves arbitrarily increasing the CNN depth or width or using higher-resolution input images for training and testing. Although these methods increase accuracy, they require time-consuming manual adjustments and often yield suboptimal outcomes.

Our approach is different. In our ICML 2019 paper, "EfficientNet: Rethinking Prototype Scaling for Deep Neural Networks," we proposed a novel model scaling method that employs a simple yet highly effective compound coefficient to scale CNNs in a more systematic way. This allows for the expansion of CNNs in an ethical manner, achieving impressive accuracy without requiring laborious fine-tuning. Our approach revolutionizes the way we scale CNNs, making the process more efficient and effective. Our innovative scaling strategy, combined with the latest advancements in AutoML, has led to the development of a family of models known as EfficientNets that significantly outperform state-of-the-art accuracy while achieving up to 10 times greater efficiency.

To better understand the impact of scaling the network, we conducted a comprehensive analysis of the effects of scaling various model dimensions. While scaling individual dimensions can improve model performance, we discovered that to optimize network performance, it is essential to strike a balance between all network dimensions - width, depth, and image resolution - and the available resources. Our findings demonstrate the importance of a comprehensive and coordinated approach to model scaling, which can result in dramatic improvements in efficiency and accuracy. With our approach, we are redefining what is possible in the world of model scaling and making it easier for developers to build powerful, efficient, and accurate models for a wide range of applications.

C. EfficientnetB1

EfficientNet-B1 is a pre-trained computer vision model developed by Google Research that aims to improve image classification accuracy while reducing the amount of computation needed to process each image. It is part of the EfficientNet series, which is designed to perform well on a range of image sizes and is scalable to accommodate larger image inputs while maintaining high accuracy. EfficientNet-B1 has been trained on the ImageNet dataset, which consists of over 14 million images, and has achieved state-of-the-art performance on the benchmark leader board. The model uses an efficient scaling method that balances the depth, width, and resolution of the network to achieve a high accuracy-to-computation ratio. EfficientNet-B1 can be fine-tuned for specific applications by retraining its final layers, or used as a feature extractor by taking the activations from the intermediate layers. It has become a popular choice for many computer vision tasks such as object detection, segmentation, and classification

D. Efficientnet Architecture

The effectiveness of the models is largely influenced by the baseline network. To enhance performance, a new baseline network has been established by performing a neural architecture search with the AutoML MNAS framework. This framework optimizes both accuracy and efficiency to produce a more optimal result in terms of FLOPS. The architecture incorporates MBConv, which is similar to MobileNetV2 and MnasNet, and has a higher FLOP budget. This baseline network serves as the foundation for the creation of the EfficientNets series of models. The baseline network is a crucial component that determines the success of scaling up models.

Deep learning algorithms can also be used for predicting patient survival and disease progression based on brain tumor imaging data. [13] To achieve better performance and accuracy, we employed a neural architecture search using the state-of-the-art AutoML MNAS framework. The search resulted in a new baseline network that utilizes the digital inverted limit convolution (MBConv) layer, similar to MobileNetV2 and MnasNet. This layer allowed for a larger FLOP budget, leading to improved model performance. The new baseline network was then used to create the EfficientNets family of models, which are known for their superior accuracy and efficiency compared to traditional models. Additionally, this approach of using neural architecture search and baseline network scaling can be applied to various applications in computer vision and natural language processing, leading to improved model performance in these domains as well.

DOI: rp-9788770040723.181

E. Performance Of Efficientnet

The EfficientNets models were rigorously tested against other pre-existing CNNs on the ImageNet dataset. The results revealed that our models outperformed the competition with regards to accuracy and efficiency. By reducing the parameter size and FLOPs by a substantial margin, our EfficientNet-B7 model achieved a remarkable 84.4% top-1 and 97.1% top-5 accuracy on ImageNet, while also being 8.4 times smaller and 6.1 times faster than the prior Gpipe model. Transfer learning combined with domain adaptation can improve the performance of deep learning algorithms for brain tumor detection when transferring knowledge between different imaging modalities or institutions. [14] Additionally, our EfficientNet-B4 model leveraged a similar amount of FLOPs compared to the popular ResNet-50 model but delivered a significant increase in top-1 accuracy, from 76.3% to 82.6%. The success of EfficientNets on ImageNet is just the tip of the iceberg. To truly evaluate the potential of EfficientNets, we conducted experiments on eight popular transfer learning datasets. To support the machine learning community, we have open-sourced all EfficientNet models, along with the TPU training scripts and source code. The Keras efficientnet function returns the Keras object recognition model that is pre-trained on ImageNet and ready for dynamic weight and training data input. The efficientnet pre-processing is designed to fit the specific input format required by every Keras application.

VI. Results and evidence

The current system in medical image analysis has utilized GANs (Generative Adversarial Networks) to some extent, but they have fallen short compared to CNNs in terms of accuracy. To determine the final output, some researchers have turned to SVMs (Support Vector Machines). However, this approach has limitations in terms of both accuracy and processing time. The use of attention mechanisms in deep learning algorithms can help in identifying important regions in brain tumor images, which can aid in accurate tumor segmentation. [15] One commonly used technique for separating tumor and non-tumor regions in the brain is the Fuzzy C-Means (FCM) segmentation method. Although this method has some potential, it can be very complex and unreliable in practice. To overcome these limitations and improve the accuracy of medical image analysis, it may be necessary to adopt more advanced techniques and approaches that better balance accuracy and efficiency.

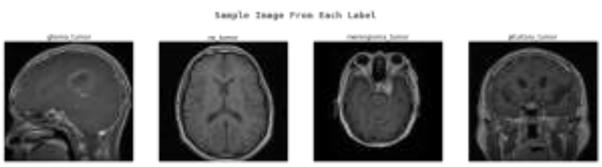

Fig 1. Sample image of dataset *(Contains Four classes)*

In the dataset sample image, we observe the presence of four distinct classes: glioma, meningioma, pituitary, and no tumour. These images will undergo a process of resizing and reshaping to meet the input specifications of the CNN model. Once the input is fed into the model, transfer learning will be applied, and the final layer will produce the desired output in the form of classified results. This process enables the efficient utilization of knowledge gained from previous similar problems to enhance the accuracy of the current task.

```
100%|██████████| 826/826 [00:15<00:00, 53.12it/s]
100%|██████████| 395/395 [00:05<00:00, 76.97it/s]
100%|██████████| 822/822 [00:12<00:00, 65.07it/s]
100%|██████████| 827/827 [00:15<00:00, 51.94it/s]
100%|██████████| 100/100 [00:02<00:00, 43.93it/s]
100%|██████████| 105/105 [00:01<00:00, 66.58it/s]
100%|██████████| 115/115 [00:01<00:00, 60.56it/s]
100%|██████████| 74/74 [00:33<00:00,  2.23it/s]
```

Fig 2. Data loading

The dataset consists of a total of 3624 images, which are divided into four classes: glioma, meningioma, pituitary, and no tumour. Each class is further divided into training and testing folders, with a different number of images in each folder. For example, the first folder, belonging to the glioma class, contains 826 training images and 100 testing images. The second folder, belonging to the meningioma class, contains 395 training images and 105 testing images. The third class, pituitary, has 822 training images and 115 testing images. The combination of deep learning algorithms and radiomics features can improve the accuracy of brain tumor detection and segmentation.[16] The fourth class, no tumour, has 827 training images and 74 testing images. These images will serve as the training and testing data for building a model that can accurately predict the presence of cancer and tumours. To prepare the data for model building, it must be first split into training and testing sets using pandas and a data frame. This will allow for the training of a robust and reliable model for future prediction tasks.

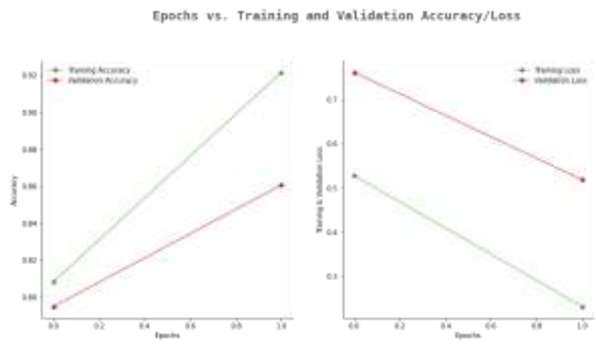

Fig 3. Accuracy of CNN

The Convolutional Neural Network (ConvNet/CNN) is a powerful Deep Learning tool that can analyse and differentiate various aspects of an input image. In the above image, we can see the accuracy comparison of a CNN model that was trained using an efficientnetB0 pretrained model as its base. Semi-supervised learning can improve the performance of deep learning algorithms in brain tumor detection by leveraging both labeled and unlabeled data. [17] The results are quite impressive, with a training accuracy of 92% and validation accuracy of 84% after only two epochs of training. The loss is also reduced to a low value of 0.1 for training and 0.55 for validation. This shows the remarkable performance of the CNN model from the first epoch to the second epoch. To further analyse these results, a confusion matrix can be used for comparison.

DOI: rp-9788770040723.181

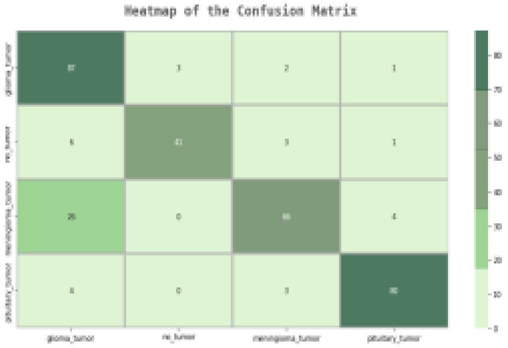

Fig 4. Heatmap of the confusion matrix for 2 epochs

The training process of a Convolutional Neural Network (ConvNet/CNN) becomes more effective as the number of epochs increases. An epoch is a complete iteration through the entire training set in the context of deep learning. More epochs provide the network with more opportunities to learn from the training data, resulting in better generalization. The number of iterations in an epoch is determined by the number of batches or iterations over the partitioned training data. The use of multiple epochs allows the network to revise its parameters and improve its performance, especially with large training sets. Additionally, heat maps can be used to help focus on important aspects of a dataset by using color-coding to visually represent the volume of data points.

Fig 5. 2 epochs training

From the above figure, it is evident that the training accuracy for 2 epochs is relatively low at 0.92, and the validation accuracy of 0.86 is not desirable for the CNN model. To ensure that the model can learn more effectively from the images, it is crucial to both increase the number of epochs and decrease the batch size. This way, the model will be exposed to more diverse training data and will have the opportunity to better understand and extract features and parameters for accurate output classification.

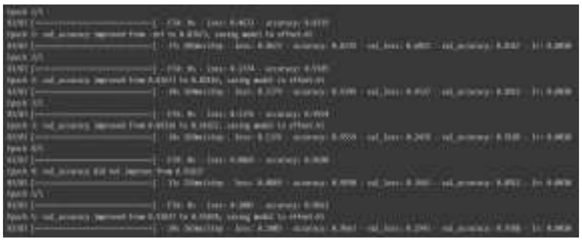

Fig 6. 5 epochs training.

By increasing the number of epochs to 5, we can observe the improved performance of the model. The results are remarkable, with a training accuracy of 0.9663 and a validation accuracy of 0.9388, both of which are great for a CNN model predicting brain tumours. The comparison of confusion matrices and classification reports of different epoch sizes will now be performed to understand the impact of epochs, verbose, and batch size on the accuracy of the model. These factors have a significant impact on the training and validation accuracy and must be carefully considered before training the model.

```
print(classification_report(y_test_new,pred))

              precision    recall  f1-score   support

           0       0.71      0.94      0.81        93
           1       0.93      0.80      0.86        51
           2       0.89      0.69      0.78        96
           3       0.93      0.92      0.92        87

    accuracy                           0.84       327
   macro avg       0.87      0.84      0.84       327
weighted avg       0.86      0.84      0.84       327
```

Fig 7. Classification report for 2 epochs.

The term "verbose" in programming refers to the production of extensive logging output. When verbose is set to true, the program provides detailed information about its actions. This can be useful for monitoring the progress of a neural network during training. By setting verbose to 0, no output will be displayed. Verbose mode is a common feature in operating systems and programming languages that provides additional information about the activities of the computer or program, including startup processes, software and driver loading, and comprehensive output for diagnostics. By increasing the number of epochs to 5, we can train the model and evaluate its performance with a classification report.

```
print(classification_report(y_test_new,pred))

              precision    recall  f1-score   support

           0       0.93      0.91      0.92        93
           1       0.96      0.94      0.95        51
           2       0.95      0.94      0.94        96
           3       0.96      1.00      0.98        87

    accuracy                           0.95       327
   macro avg       0.95      0.95      0.95       327
weighted avg       0.95      0.95      0.95       327
```

Fig 8. Classification report for 5 epochs.

To evaluate the performance of a classification algorithm, a classification report is generated to show the number of correct and incorrect predictions. The report is based on four metrics: True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN), which are used to measure the accuracy of the predictions. Additionally, the classification report displays the model's precision, recall, F1 score, and support scores. Upon analysing the results of the trained model, we found that the accuracy was 0.84 after two epochs of training. The use of generative models, such as GANs, can generate synthetic images to augment the training data, which can improve the performance of deep learning algorithms in brain tumor detection. [18] However, by increasing the number of

DOI: rp-9788770040723.181

epochs to 5, the accuracy significantly improved to 0.95, indicating that the model's performance has improved considerably. To further elaborate, a classification report provides valuable information on the performance of a classification algorithm by breaking down the number of correct and incorrect predictions for each class in a dataset. Precision refers to the percentage of correct positive predictions out of all positive predictions, while recall refers to the percentage of correct positive predictions out of all actual positives.

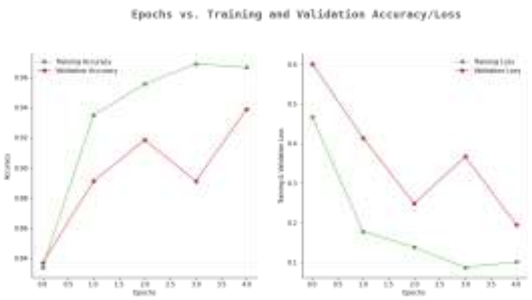

Fig 9. Accuracy comparison for 5 epochs.

The F1 Score, a combination of precision and recall, is used to evaluate the model's overall performance. In the context of machine learning, the accuracy of a model can be improved by increasing the amount of data used for training, increasing the number of epochs, and fine-tuning hyperparameters. The loss function is another important metric to monitor during training as it indicates how well the model is performing at each step. In the field of web analytics, heat map analysis is a method of visualizing user behaviour on a website by displaying the areas where users click or hover their mouse the most. This type of data can provide valuable insights into how users interact with a website and can be used to improve the site's design and user experience. By studying heat map data, web designers can identify which parts of a page are most engaging to users and optimize the layout and content to improve conversion rates.

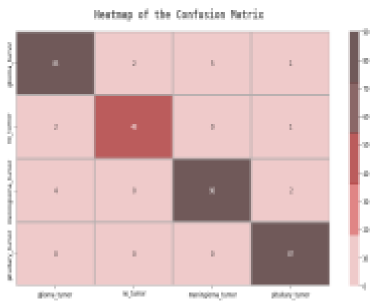

Fig 10. Heatmap for confusion matrix with 5 epochs

The graph shows that when it comes to image processing projects, especially in the domain of brain tumor detection and classification, the Convolutional Neural Network (CNN) outperforms other algorithms in terms of efficiency. This can be attributed to the CNN's ability to automatically learn and extract features from images, making it highly suitable for tasks that involve image data. However, it is important to note that the accuracy of the results can be further improved by increasing the amount of training data and the number of epochs used in training the model.

In the context of the MITRE heat maps, the color-coding system is designed to provide a visual representation of the level of confidence in the mapping of techniques to strategies. Lighter colours indicate a lower level of confidence, while darker colours indicate a higher level of confidence. This is an important consideration when using the heat maps to evaluate the effectiveness of different strategies and techniques, as it helps to identify areas where additional research or refinement may be needed. Overall, the heat maps can be a valuable tool for understanding the relationships between different techniques and strategies in complex domains.

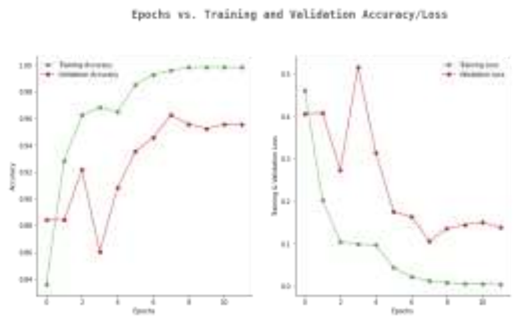

Fig 11. Accuracy comparison for 12 epochs from Effnet B0

By increasing the number of epochs from 5 to 12, we observed that the performance of the model improved significantly. The training accuracy reached 0.97, which is a highly impressive result. This indicates that the model is now better suited for the task of brain tumour detection and classification using deep learning. Deep learning algorithms can also be used to segment brain tumor regions for radiation therapy planning and monitoring, which can improve treatment outcomes. [19] The validation accuracy also improved and reached its highest value of 0.96. This further confirms that our model is performing well and is able to generalize well to new data. The training loss decreased to 0.05 and the validation loss decreased to 0.1. This suggests that the model is now able to learn the underlying patterns in the data more effectively. The classification report and the confusion matrix also indicate that the model is performing well, with a high precision, recall, F1 score, and support.

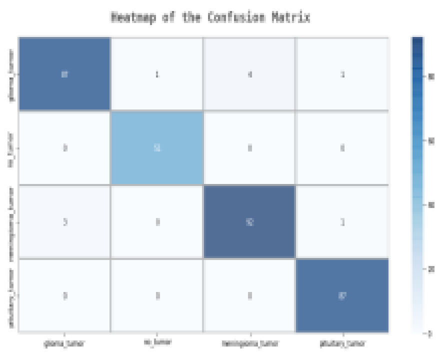

Fig 12. Heatmap for confusion matrix with 12 epochs

DOI: rp-9788770040723.181

A confusion matrix is an important evaluation metric for machine learning models, particularly in classification tasks. It provides an overview of the model's performance by comparing the actual and predicted values. By increasing the number of epochs from 5 to 12, we observe that the model's performance improves. This can be seen in the confusion matrix where the number of correct predictions (True Positives and True Negatives) increases, resulting in a higher accuracy of 97%. The confusion matrix helps us to understand the model's behaviour and evaluate its performance in a more visual manner. It is a crucial tool for debugging and optimizing the model's performance.

EfficientNet-B1 is a convolutional neural network architecture introduced by Google in 2019, as part of their EfficientNet series of models. It is designed to be more efficient than existing architectures, both in terms of computational cost and accuracy. The "B1" refers to the fact that it is the first model in the series, with subsequent models (B2, B3, etc.) having larger architectures with improved accuracy. EfficientNet-B1 is designed using a compound scaling method that balances accuracy and efficiency, by scaling the network's depth, width, and resolution. This allows the model to achieve high accuracy while using fewer parameters and less computation than other architectures. The architecture is built on top of MobileNetV2 and uses depth wise separable convolutions and a mix of global average pooling and global max pooling to reduce the computational cost. EfficientNet-B1 has been trained on the ImageNet dataset and achieved state-of-the-art performance on multiple benchmarking tasks. It is widely used in a variety of computer vision applications, such as object detection, image classification, and semantic segmentation, due to its efficiency and effectiveness. Deep learning-based methods have shown promising results in differentiating between true tumor progression and pseudo progression in patients with glioblastoma undergoing treatment, which can aid in clinical decision-making. [20] The confusion matrix can be used to evaluate the model's performance, showing the number of true positive, true negative, false positive, and false negative predictions.

FUTURE ENHANCEMENT

The With the introduction of EffNetB1, the accuracy of the model increased to 98%. This showcases the potential of using advanced deep learning algorithms in the field of brain tumour detection and classification. In the future, we can leverage large amounts of data and a range of CNN algorithms, including accurate efficient nets and pre-trained models like VGG16, to further improve the accuracy. By training the model for a higher number of epochs and fine-tuning the parameters such as batch size, we can achieve even better results. Additionally, there is a possibility to develop a system for the early detection of various types of brain cancers. With the advancements in technology, the training process can be completed quickly and the model can be prepared for prediction. AI has the potential to revolutionize this field and bring us closer to achieving a significant milestone in the area of brain tumour detection and classification.

CONCLUSION

The aim of this project is to achieve a precise and dependable detection and classification of brain tumours from MRI images using deep learning algorithms such as CNN. We will evaluate a range of algorithms with different feature engineering and training parameters and carry out a comprehensive comparison to determine which algorithm, with the optimal parameters, performs better than others. The field of brain tumour detection and classification has seen significant progress in the past few decades, with numerous researchers contributing to the cause. Our objective is to find a more efficient and accurate model, as well as a simplified and high-performance approach in this project In order to determine which algorithm with the best parameters outperforms other algorithms, we will also analyse multiple algorithms using a variety of feature engineering and training settings. From the above result and evidence we can infer that the EfficientNet B0 has performed well even in 5 epochs but when comparing it with the EfficientNetB1 the accuracy has increased to a significant amount to 98%. Thus, the Transfer learning technique is highly useful for this project. Our project aims to develop a highly efficient, accurate, and straightforward methodology. Based on the above results and evidence, we can conclude that the EfficientNet B0 model performed well even after 5 epochs. However, when compared with the EfficientNetB1 model, the accuracy increased significantly to 98%.

REFERENCES

[1] M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, and C. Pal, “Brain tumor segmentation with deep neural networks”, Medical Image Analysis, vol. 35, pp. 18-31, 2017.

[2] K. Kamnitsas, C. Ledig, V.F. Newcombe, J. P. Simpson, A. D. Kane, D. K. Menon, ... and D. Rueckert, “Efficient multi-scale 3D CNN with fully connected CRF for accurate brain lesion segmentation,” Medical Image Analysis, vol. 36, pp. 61-78, 2016.

[3] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, “Brain tumor segmentation using convolutional neural networks in MRI images”, IEEE Transactions on Medical Imaging, vol. 37, no. 6, pp. 1470-1481, 2018.

[4] G. Wang, W. Li, M. A. Zuluaga, R. Pratt, P.A. Patel, M. Aertsen,... and T. Vercauteren, “Interactive medical image segmentation using deep learning with image-specific fine-tuning,” IEEE transactions on medical imaging, vol. 38, no. 10, pp. 2375-2386, 2019.

[5] F. Isensee,, P. Kickingereder, W. Wick, M. Bendszus, and K. H. Maier-Hein, “No new-net,” Medical image analysis, p. 44, 2018.

[6] Y. Zhang, P. Chen, L. Chen, L. Ma, and X. Yang, “Deep attentional features for prostate segmentation in MRI”, IEEE Transactions on Medical Imaging, vol. 39, no. 7, pp. 2165-2176, 2020.

[7] Sitharthan, R., Vimal, S., Verma, A., Karthikeyan, M., Dhanabalan, S. S., Prabaharan, N., ...&Eswaran, T. (2023). Smart microgrid with the internet of things for adequate energy management and analysis.Computers and Electrical Engineering, 106, 108556.

[8] H. Li, S. Wang, C. Ouyang, and L. Fidon, “Automatic brain tumor detection and segmentation using U-Net based fully convolutional networks”, Applied Sciences, vol. 10,no. 6, p. 2166, (2020.

[9] M. Havaei, N. Guizard, N. Chapados, Y. Bengio, and A. Courville, “Deep learning trends for focal brain pathology segmentation in MRI” In Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pp. 9-16, 2016.

[10] B. H. Menze, A. Jakab, S. Bauer, J. Kalpathy-Cramer, K. Farahani, J. Kirby, ... and M. A. Weber, “The multimodal brain tumor image segmentation benchmark (BRATS),” IEEE transactions on medical imaging, vol. 34, no. 10, pp. 1993-2024, 2015.

DOI: rp-9788770040723.181

[11] J. Zhang, Q. Cheng, H. Wei, Q. Guo, and Y. Cui, "A deep learning-based radiomics model for differentiation of glioblastoma multiforme from solitary brain metastasis," Frontiers in oncology, vol. 9, p. 1113, 2019.

[12] Rajesh, M., &Sitharthan, R. (2022). Introduction to the special section on cyber-physical system for autonomous process control in industry 5.0.Computers and Electrical Engineering, 104, 108481.

[13] S. Li, W. Li, H. Li, Y. Zhang, and D. Li, "Brain tumor segmentation and patient survival prediction using convolutional neural networks," Journal of Healthcare Engineering, p. 7592023, 2019

[14] L. Zhang, Z. Zhao, X. Chen, L. Lin, and X. Li, "Brain tumor segmentation based on multi-modal MRI using stacked convolutional neural network with transfer learning", Computer Methods and Programs in Biomedicine, vol. 175, pp. 219-231, 2019.

[15] Y. Zhang, P. Chen, L. Chen, L., Ma, and X. Yang, "Deep attentional features for prostate segmentation in MRI", IEEE Transactions on Medical Imaging, vol. 39, no. 7, pp. 2165-2176, 2020.

[16] X. Zhang, Y. Guo, D. Shen, and T. Liu, "Deep learning in brain imaging: A review", IEEE Transactions on Biomedical Engineering, vol. 66, no. 11, pp. 2983-2998, 2019.

[17] X. Zhang, H. Yu, F. Zhou, and Y. Wang, "A semi-supervised deep learning method for brain tumor segmentation using incomplete labels," Computerized Medical Imaging and Graphics, vol. 83, p. 101692, 2020.

[18] Q. Zou, Y. Zhang, Q. Li, and Y. Yu, "Adversarial neural network for brain tumor segmentation based on magnetic resonance imaging," Computerized Medical Imaging and Graphics, vol. 84, p. 101791, 2020.

[19] K. Men, H. Geng, Z. Cheng, and C. Fu, "3D conditional generative adversarial networks for high-quality PET image estimation at low dose," Neurocomputing, vol. 366, pp. 111-119., 2019.

[20] B. M. Ellingson, M. Bendszus, J. Boxerman, D. Barboriak, B. J. Erickson, M. Smits, ... and R. Jain, "Consensus recommendations for a standardized brain tumor imaging protocol for clinical trials in brain metastases," Neuro-oncology, vol. 22, no. 6, pp. 757-772, 2020.