A Progress Report

on

Brain Tumor Detection Using Machine Learning and Deep Learning

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INSPIRED BY LIFE

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CERTIFICATE

This is to certify that the project entitled "***Brain Tumor Detection using Machine Learning & Deep Learning***" is a bonafide work carried out as ***Minor Project Endterm Assessment (Course Code: CS3270)*** in partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering, under my guidance by ***Ayush Kumar*** bearing registration number(209301457), during the academic semester *VI of year 2022-23.*

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Signature of the project guide: ______________________

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1. Introduction

Brain tumors are one of the serious and life-threatening conditions that affects the central nervous system of human body. They can cause a range of symptoms and disrupt normal brain function, making early detection and diagnosis crucial for successful treatment. The examination of the brain tumour and its progression is of great interest due to advances in medical image processing. According to the National Brain Tumor Foundation's (NBTF) global assessment, both the patient diagnosis and the death rate from brain tumours is decreasing compared to previous years' findings. The most recent developments in machine learning helping us to recognize, categorize, and quantify patterns in photographs of the body.

Instead of manually designing features based on unique domain expertise, the basis of these advancements is the use of hierarchical feature representations learned exclusively from data. Several recent works, such as the previous example, have presented frameworks or models to highlight the brain tumour zone, which may be followed by steps such as result forecasting, classification, and treatment planning. Medical image processing necessitates brain tumour segmentation, which is typically controlled by elements such as missing borders, noise, and low contrast. MRI segmentation of brain images using learning techniques and pattern recognition software is extremely effective. Technically, the technique is a parametric model that takes into account the functions chosen based on the density function. Early detection of these brain tumor concerns is essential to promote practical treatment and healthy life with current clinical imaging methods. The most commonly used techniques for examining brain tumours are positron emission tomography (PET), magnetic resonance imaging (MRI), and computed tomography (CT).

A popular medical tool for diagnosing and examining a wide range of illnesses, including brain tumors, neurological disorders, epilepsy, etc. Typically, a system entirely runs on hardware or computer aid in automating this procedure to get precise and quick results. On the other hand, the primary function of various computer vision and image processing solutions is image segmentation. According to some metrics, the hash procedure separates the image into various regions for later processing [4,5].

Medical professionals typically use MRI imaging to detect brain abnormalities. The large-scale manual assessment method frequently leads to misinterpretations due to fatigue and an excess of MRI slices, among other factors. Additionally, it is unpredictable and causes significant variations both within and between individuals. To alleviate these concerns, a detection system method for various brain disorders must be developed. It also aids the clinicians' ultimate decision-making process and encourages quick, dependable, and correct analysis.

Systems that have achieved incredible success in recent decades are mostly designed and automated using machine-learning approaches. To categorize the various MRI images of the brain, numerous techniques (also known as automatic detection of diseased brain systems) have been developed. Based on MRI data, these diagrams are primarily concerned with resolving binary and multiclass brain categorization disorders. Brain MRI scans are categorized as either pathogenic (abnormal) or normal in the binary category.

1.1 Motivation

We chose brain tumor identification and classification, which is a subfield of medical image analysis, after considering the fatality rate brought on by brain tumors. Medical picture tumor detection takes time since it relies on human judgment. Radiologists and other specialist medical professionals who are experts in this field evaluate CT, MRI, and PET scan images and make recommendations that affect the course of treatment. It takes time to complete this entire process. As it will be carried out by machines, automated medical picture analysis can help to reduce the time, effort, and workload of a human in this situation.

Use of machine learning (ML) and deep learning (DL) in the detection of brain tumors stems from their potential to address the challenges and limitations of existing methods. Brain tumors are heterogeneous in nature and can present with a range of symptoms, making early detection and diagnosis a complex task. Conventional imaging techniques, such as magnetic resonance imaging (MRI) and computed tomography (CT), have limitations in terms of sensitivity, specificity, and accuracy.

ML and DL have the potential to overcome these limitations by leveraging the vast amounts of data generated from medical imaging and other sources. These technologies can analyze patterns and relationships in the data that may be difficult for humans to detect, thus enabling more accurate and efficient detection of brain tumors. For example, DL algorithms can learn complex relationships between medical images and tumor characteristics, enabling the automatic identification of brain tumors in medical images.

In recent years, there has been growing interest in using ML and DL for brain tumor detection, with several studies demonstrating the potential of these technologies. However, there is still a need for further research to fully realize the potential of these methods, particularly in terms of generalizability, reliability, and accuracy. This study aims to fill these gaps by assessing the performance of various ML and DL models for brain tumour detection and investigating their potential for improving patient outcomes.

Overall, the motivation for using ML and DL in brain tumor detection lies in their ability to address the limitations of conventional methods and to provide more accurate and efficient diagnostic solutions. This has the potential to improve patient outcomes as well as the accuracy and efficiency of brain tumour detection, making it an important area for future research.

2. Literature Review

2.1 Review

In recent years, brain tumour detection using ML and DL techniques has become a popular area of study. In this literature review, we will look at some of the relevant studies that have been done in this field.

Machine Learning-Based Brain Tumor Detection: Bhattacharya et al. (2020) conducted a survey paper that provides an overview of various machine learning techniques used in the detection of brain tumours, such as decision trees, support vector machines, and random forests. The authors also discuss the advantages and disadvantages of these techniques, and thus propose future research directions in this area.

Deep Learning-Based Brain Tumor Segmentation Using MRI: In this review paper, Asif et al. (2020) provide an in-depth analysis of various DL based techniques for brain tumor segmentation using magnetic resonance imaging (MRI) data. The researchers discuss the challenges associated with brain tumor segmentation and highlight the effectiveness of convolutional neural networks (CNNs) in this context.

Brain Tumor Classification Using Convolutional Neural Networks: This systematic review conducted by Roy et al. (2019) investigates the use of CNNs for brain tumor classification. The authors evaluate the performance of various CNN architectures, including AlexNet, VGG, and ResNet, and analyze the impact of different pre-processing techniques on classification accuracy.

Brain Tumor Detection and Segmentation Using Deep Learning: In this systematic review, Sharma et al. (2021) examine the use of deep learning techniques for brain tumor detection and segmentation. The authors evaluate the performance of various deep learning models, including U-Net, SegNet, and Mask R-CNN, and discuss the challenges associated with using these techniques in clinical practice.

Machine Learning Techniques for Brain Tumor Detection Using Magnetic Resonance Imaging: This review paper conducted by Prasad et al. (2020) provides an overview of various machine learning techniques used for brain tumor detection using MRI data. The authors discuss the benefits and drawbacks of these techniques, as well as future research directions to improve brain tumour detection accuracy.

Overall, the literature suggests that machine learning and deep learning techniques have the potential to improve the accuracy of brain tumor detection and segmentation. However, there are still several challenges that need to be addressed before these techniques can be used in clinical practice, including the need for larger datasets and more rigorous evaluation metrics.

2.2 Problem Statement

To develop an accurate and efficient model that can distinguish between MRI images of brains with and without tumors. The goal is to provide radiologists and medical practitioners with a reliable tool to aid in the diagnosis and treatment of brain tumours. Brain tumours are a serious and potentially fatal disease, and early detection is critical for successful treatment. Manual interpretation of MRI images, on the other hand, is time-consuming and prone to human error. Therefore, developing an automated system using deep learning techniques such as CNNs can significantly improve the speed and accuracy of brain tumor detection.

2.3 Research Objective

Our primary goal is to develop a model that can determine whether medical images contain tumours and identify their characteristics. Because brain tumor datasets are rare and challenging to obtain, gathering them is the first step in any medical picture project. Here, we thought to create a model and evaluate the performance of various machine learning (ML) and deep learning (DL) techniques for brain tumor detection. We proposed an effective and efficient method for detecting a brain tumour using both conventional classifiers and convolutional neural networks, without the need for humanitarian aid.

Existing Methods:

Method	Pros	Cons
Machine Learning	○ Machine learning can detect brain tumors by analyzing medical images and identifying patterns characteristic of tumors.	○ Limited generalizability and reliability ○ Dependent on large, high-quality data sets
Deep Learning	○ Deep learning is an advanced type of machine learning that can analyze complex medical images and identify subtle patterns or features that are characteristic of tumors. ○ It has a high accuracy and efficiency in detecting brain tumors, as it can learn from large datasets of medical images and tumor characteristics, improving its performance over time. ○	○ Dependent on large, high-quality data sets ○ Limited reliability

The project will aim to address the limitations of existing methods by evaluating the performance of various ML and DL techniques for brain tumor detection. The findings of this study will shed light on the potential of these technologies for improving patient outcomes and advancing the field of brain tumour detection.

3. Methodology and Framework

Literature Review: To gain an understanding of the current state of the art, a comprehensive review of the existing literature on brain tumour detection, including conventional imaging techniques, ML, and DL methods, will be performed.

Data Collection: A dataset of medical images of brain tumors will be collected and preprocessed for use in the analysis. The data will include a diverse range of imaging modalities, including MRI and CT scans, and will be annotated with information about the type and location of tumors.

Feature Extraction: Features will be extracted from the medical images using a combination of traditional image processing techniques and ML/DL algorithms. These features will be used as inputs for the subsequent analysis.

Model Development: ML and DL models will be developed and trained using the extracted features and annotated data. The models will be evaluated using a range of metrics, including accuracy, sensitivity, specificity, and AUC.

Model Comparison: The performance of the ML and DL models will be compared with each other and with existing methods for brain tumor detection.

Results and Discussion: The results of the study will be analyzed and interpreted, and the strengths and weaknesses of the various techniques will be discussed. The results will be used to identify promising avenues for future research.

Frontend: A web application has been developed using Flask framework, which can determine whether a given medical image contains a brain tumor or not.At the backend, a Convolutional Neural Network (CNN) model has been used, which has been trained on a large dataset of medical images to accurately classify them as tumor or non-tumor. When a user uploads a medical image through the web application, the image is passed through the CNN model, which analyzes the image and predicts whether it contains a brain tumor or not.The result is then displayed to the user on the web page. This can help doctors and patients to quickly identify the presence of brain tumors and take appropriate action.

Conclusion: The findings of the study will be summarized, and the implications for brain tumor detection and future research will be discussed.

3.1 System Architecture

CNN

- The architecture is a Convolutional Neural Network (CNN) for binary classification.
- The first layer is a Zero Padding layer with a pool size of (2,2) to prevent image size reduction during convolution.
- The second layer is a Convolutional layer that has 32 filters of size (7,7) and stride of 1, resulting in a 32-channel feature map.
- The third layer is a Batch Normalization layer to normalize the feature map.
- The fourth layer is a ReLU Activation layer, which is responsible for introducing non-linearity into the network.
- The fifth and sixth layers are Max Pooling layers with pool size of (4,4) and stride of 4 to reduce feature map size.
- The seventh layer is to convert the 3D feature map into a 1D vector, flatten layer.
- The eighth and final layer is a Dense output layer with one neuron and a sigmoid activation function, producing the binary classification prediction.
- The network uses a combination of convolutional, activation, pooling, and fully connected layers to extract features and make a prediction.

VGG-16

- Input size: The VGG-16 network takes as input images of size 224x224
- pixels.
- Layers: The network consists of 16 layers, including 13 convolutional layers and 3 fully connected layers.
- Convolutional layers: The convolutional layers use 3x3 filters with a stride of 1 and padding of 1. The first convolutional layer has 64 filters, and the subsequent layers have either 128 or 256 filters.

- Max pooling: After every two convolutional layers, the network applies max pooling with a 2x2 filter and a stride of 2.
- Activation function: The network uses the Rectified Linear Unit (ReLU) activation function after each convolutional and fully connected layer.
- Fully connected layers: The three fully connected layers have 4096 units each, followed by a final output layer with two units for binary classification (tumor present or not).
- Training: The network is trained using backpropagation with stochastic gradient descent (SGD) and dropout regularization.
- Pretrained model: A pretrained VGG-16 model is often used as a starting point for transfer learning on new datasets. This can help to improve performance and reduce training time.

3.2 Algorithms, Techniques

- Convolutional neural networks (CNNs): CNNs are a type of deep learning model that have been shown to be highly effective at image recognition tasks. They are particularly well-suited for detecting complex patterns and structures in images.

- Transfer learning: Transfer learning is a method of training a new model by using a previously trained CNN model as a starting point. Because the pre-trained model has already learned many useful features that can be reused in the new model, this can save a significant amount of time and computational resources.

- Data augmentationData augmentation is the process of creating new training data from existing data by applying various transformations such as rotation, flipping, and zooming. This can help to reduce overfitting and improve the model's generalisation ability.

- Dropout: Dropout is a regularisation technique that prevents overfitting by randomly removing some neurons during training. This can improve the robustness and generalization ability of the model.

3.3 Detailed Design Methodologies:

The following design methodologies may be used in brain tumor detection using CNN:

- Data collection: The first step in developing a brain tumor detection system is to collect a large dataset of brain scans with and without tumors. This dataset should be diverse and representative of the population being studied.
- Data preprocessing: The input images should be preprocessed to remove noise and artifacts that could interfere with the detection process. This may involve techniques such as filtering, segmentation, and normalization.
- Model selection: A suitable CNN architecture should be selected based on the requirements of the problem and the available computational resources. This may involve comparing the performance of different pre-trained models on the dataset.
- Training and validation: The selected model should be trained on the dataset using techniques such as transfer learning, data augmentation, and dropout. To ensure that the model generalises well to new data, its performance should be evaluated using a separate validation dataset.
- Testing: The final step is to test the trained model on a separate test dataset to evaluate its performance on new, unseen data. The outcomes should be compared to existing methods and evaluated using metrics such as accuracy, sensitivity, specificity, and area under the ROC curve.

4. Work Done

4.1. Details

- Convolutional Neural Networks (CNNs) have been widely used for detecting brain tumours in magnetic resonance images (MRI). The steps involved in training a CNN for brain tumour detection are summarised below:
- Data Preparation: Collect and preprocess the MRI data to be used for training the CNN. This may involve resizing, cropping, and normalization.

- Model Architecture: Choose a CNN architecture suitable for the task at hand. Some commonly used architectures for brain tumor detection include VGGNet, ResNet, and Inception.
- Training: Train the CNN using the preprocessed MRI data. This involves optimizing the CNN parameters through backpropagation and minimizing a loss function.
- Testing: Evaluate the trained CNN on a separate set of MRI data to assess its performance.
- VGG16 is a convolutional neural network architecture that is commonly used for image classification tasks.
- The VGG16 model was trained on a large dataset of brain MRI images to detect the presence of tumors.
- The model was evaluated on a separate test set of MRI images, and achieved the following metrics:
- Accuracy: 0.800000 (80% of the predictions were correct)
- Precision: 0.714286 (71.4% of the predicted tumor cases were actually true positives)
- Recall: 1.000000 (100% of the actual tumor cases were correctly identified)
- F1 score: 0.833333 (a balanced measure of precision and recall)
- These metrics indicate that the VGG16 model is relatively accurate at detecting brain tumors, but may still have some room for improvement in terms of precision (reducing false positives) and overall F1 score. Further improvements to the model could potentially be made by fine-tuning the hyperparameters, increasing the size of the training dataset, or exploring other neural network architectures.

4.2. Results and Discussion

Several factors influence the performance of a CNN for brain tumour detection, including the architecture chosen, the size and quality of the training data, and the optimisation algorithm used during training. In recent years, several studies have reported high accuracies for CNN-based brain tumor detection systems.

For example, a study published in the Journal of Medical Systems in 2021 reported an accuracy of 98.6% for a CNN-based brain tumor detection system. The study used a VGGNet architecture and a dataset of 306 brain MRI scans. The authors reported that their system outperformed several other cutting-edge methods for detecting brain tumours.

Another study published in the Journal of Healthcare Engineering in 2020 reported an accuracy of 93.8% for a CNN-based brain tumor detection system. The study used a ResNet architecture and a dataset of 306 brain MRI scans. The authors reported that their system achieved comparable performance to several other state-of-the-art methods for brain tumor detection.

Overall, these results suggest that CNN-based brain tumor detection systems have the potential to achieve high accuracies and may be useful in clinical settings for assisting radiologists in the diagnosis of brain tumors. More research, however, is required to validate these systems' performance on larger and more diverse datasets.

The VGG16 model achieved an accuracy of 80%, precision of 71.4%, recall of 100%, and an F1 score of 0.8333 in detecting brain tumors from MRI images. The accuracy indicates that the model predicted 80% of the cases correctly. The high recall score indicates that the model was able to detect all the actual tumor cases in the test set, but the precision score of 71.4% indicates that 28.6% of the predicted tumor cases were false positives. This means that while the model was good at identifying true positive cases, it also misclassified some healthy cases as tumor cases.

The F1 score, which takes both precision and recall into account, was 0.8333. This suggests that the model has a relatively good balance between precision and recall, but there is still room for improvement.

Overall, the results of the VGG16 model are promising for the detection of brain tumors from MRI images, but further improvements can be made to reduce the false positives and enhance the overall performance of the model. Further research could explore ways to improve the model by fine-tuning the hyperparameters, increasing the size of the training dataset, or trying other neural network architectures.

4.3 Individual Contribution of project members

During the initial phase of our project, my project partner Sonam and I extensively researched various research papers related to brain tumor detection using DL and ML. After analyzing and discussing these papers, we decided to explore the potential of using CNN, ResNet50, VGG16, and Inception models for our project. To ensure an even distribution of work, we decided that I would focus on the data augmentation part of the project, while Sonam would handle the data preprocessing tasks like cropping and scaling the images.

As we began to work on the CNN model, we collaborated to determine the best parameters for our system, including the number of epochs, batch size, and image input size. We also figured out the number of layers of the CNN architecture layers, the number of layers needed for our specific problem, and the ideal batch size for training the model. We were able to fine-tune the CNN model to achieve the best results for brain tumour detection in MRI images by collaborating. Overall, the project's individual contributions were evenly distributed and collaborative, resulting in a successful outcome. Transfer learning is a powerful technique that allows us to leverage the pre-existing knowledge of a pre-trained model on a large dataset to solve a related problem. In our case, we used the VGG-16 model, which was pre-trained on the large-scale ImageNet dataset, to classify brain tumor images. We fine-tuned the VGG-16 model on our brain tumor dataset, which consisted of MRI images of the brain with and without tumors.

To fine-tune the VGG-16 model, we first removed the last fully connected layer and replaced it with a new fully connected layer with two output neurons, one for each class (tumor and non-tumor). We then froze the weights of all the other layers except the newly added layer and trained the model using our brain tumor dataset. By doing so, we were able to transfer the knowledge learned from ImageNet to our specific problem of brain tumor detection, which allowed us to achieve better performance with less training data.

During the training process, we used various techniques to prevent overfitting, such as data augmentation, regularization, and early stopping. We also experimented with different hyperparameters, such as the learning rate, batch size, and number of epochs, to find the optimal configuration for our specific problem.

Once the model was trained, we evaluated its performance on a separate validation set of MRI images.

Conclusion and Future Plan

5.1 Conclusion

Convolutional Neural Networks (CNNs) have demonstrated promising results in detecting brain tumours from MRI data. Several studies have reported high accuracies for CNN-based brain tumor detection systems, indicating their potential for use in clinical settings. The choice of CNN architecture, size and quality of the training data, as well as the optimisation algorithm used during training, are all important factors that can have an impact on the performance of these systems. While CNN-based brain tumor detection systems are still in their early stages, they hold promise for improving the accuracy and efficiency of brain tumor diagnosis.

5.2 Future Plan

In the future, there are several directions that research in CNN-based brain tumor detection could take:

Large-scale studies: While several studies have reported high accuracies for CNN-based brain tumor detection, the size of the datasets used in these studies has been relatively small. Future studies could use larger and more diverse datasets to validate the performance of CNN-based systems.

Data from multiple modalities: In addition to MRI, other modalities such as computed tomography (CT) and positron emission tomography (PET) could be used to detect brain tumours. CNNs could be trained on multimodal data to improve the detection of brain tumours.

Interpretability: One limitation of CNN-based systems is their lack of interpretability. Future research could focus on developing methods to explain the decision-making process of CNN-based systems, making them more transparent and accountable.

Clinical translation: While CNN-based brain tumor detection systems hold promise for improving the accuracy and efficiency of brain tumor diagnosis, their clinical translation requires validation in larger and more diverse datasets, as well as regulatory approval.

Overall, the development of CNN-based brain tumour detection systems has the potential to significantly improve the accuracy and efficiency of brain tumour diagnosis, and future research in this area will almost certainly have a significant impact on clinical practise.

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