Summary Report

Abstract

This project is aimed to develop an Artificial Intelligent (AI) program to aid medical professionals in the detection of brain tumours through the use of image processing and deep learning. Brain tumours can be benign or malignant and pose significant health risks. In particular, malignant tumours have a low five-year survival rate, making early detection extremely important for the treatment process to be successful. By leveraging modern machine learning technologies and image processing techniques, the proposed AI model is designed to expedite the diagnosis process, thereby providing early intervention opportunities that can significantly improve patient outcomes. This AI-driven approach to tumour detection would help to assist medical professionals to accurately identify brain tumours in a reduced diagnostic time, which would then allow for more focussed and timely treatment plans.

1. Introduction

AI has the potential to significantly impact the management of brain tumours, with ML, natural language processing, computer vision, and robotics subfields all contributing to novel AI applications that may advance neurosurgical practice (Williams et al., 2021).

1.1 Problem Definition and Motivation

A brain tumour is an abnormal cell growth which duplicates and multiplies in an uncontrolled way. Brain tumours can be classified under two main types: benign or cancerous (National Cancer Institution, 2024). In this report, benign tumours will be referred to as benign and non cancerous interchangeably. Similarly, cancerous tumours will be described as cancerous or malignant.

Although uncommon, affecting less than 1% of the population, the survival rate for cancer decreases greatly with time, with the five-year survival rate being less than 20% (NHS, 2023). Moreover, other factors such as age, location of tumour and the patient's general health can accelerate or decelerate the deterioration process. Evidently, time is of essence when it comes to the diagnosis of a brain tumour as an early diagnosis can expedite the treatment process, hence increasing chances of survival. Prompt detection of brain tumours is highly beneficial to patients due to the several advantages it provides. It allows for better treatment options as doctors have more flexibility and time in exploring different interventions. It also ensures reduced risks of complication, hence minimising the risk of related ailments such as seizures that can further deteriorate the patients health (Spine Brain Clinic, 2023)

1.2 Objectives

Our project aims to alleviate the burden on medical professionals and doctors by automating the brain tumour detection process using machine learning and image processing. The automation will be done by an AI model that will be trained on MRI scans of both healthy brains and brains with tumours. By learning from these images the model will be able to identify patterns and anomalies that would indicate the presence of brain tumours in new MRI scans. Automating this process will allow doctors to use more time to focus on validating results and exploring treatment options for the patient, which would improve the quality of care for the patient.

To achieve this, the project would include developing a deep learning convolutional neural network (CNN) for brain tumour detection. Pre-trained models will also be utilised in combination to enhance the accuracy of the results. The model's performance will also be validated using standard metrics such as the following: accuracy, sensitivity, specificity, AUC, and AUROC.

2. Discussion of Similar Solutions

In the rapidly advancing field of medical diagnostics, artificial intelligence is applied to mimic human cognition in terms of analysis and understanding of complex medical and health care data. Advancements have proven the ability of AI, as in the ability of computer algorithms, can even exceed human capabilities by providing new ways to diagnose illnesses by arriving at approximate conclusions based solely on input data (Mullainathan & Obermeyer, 2022). Health related AI applications have the primary aim of analysing larger, more diverse data in order to produce a well-defined report for the end user, who are in this case the health care professionals. The relationship between clinical data and patient outcomes can be further analysed to produce diagnostics reports to help doctors create more efficient decisions to identify ailments (Coiera, 1997).

2.1 Existing Solutions

Several AI-based solutions for brain tumour detection have been developed, leveraging on deep learning techniques. Most notably, models include those based on CNNS like ResNet, Inception and VGG, which have shown promising results in image classification tasks. These models are often retrained on large datasets and fine-tunes for medical imaging applications. However, each model has its inherent strengths and limitations.

VGG (Visual Geometry Group) models were developed by the University of Oxford and are known for their simplicity and effectiveness. They use sequential convolution layers by fully connected layers. Despite their simplicity, VGG models have demonstrated high accuracy in image classification tasks. Further improvements however, found that stacking too many layers led to a steep reduction in training accuracy known as the “degradation problem” (He, 2015b) Residual Neural Network (ResNet) is a seminal deep learning model in which weight layers learn residual functions with reference to the layer inputs (He, 2015). Particularly, the ResNet50 model has been widely adopted in medical imaging due to its ability to maintain high accuracy across complex tasks. Another influential model would be Inception, which was developed by google. Its is a building block for CNNs and represented significant advancement in deep learning for computer vision tasks (DeepAi, 2019)

These existing solutions lay down the foundation for AI-based medical diagnosis, and prove the efficiency of deep learning in identifying brain tumours.

2.2 Overview of Techniques

The techniques employed in AI based brain tumour detection primarily revolves around CNNs due to their proficiency in handling image data.

Transfer learning is a machine learning technique in which knowledge gained through one task of a dataset is used to improve model performance on another related task and/or a different dataset (Murel, 2024). This method is highly effective because it allows the model to leverage the knowledge gained from the largest dataset and enables it to perform well even with limited medical imaging data. Models like VGG, ResNet and Inception are often fine-tuned using transfer learning to adapt them to the specific task of brain tumour detection.

Medical imaging datasets are often limited in size, which can hinder the training of deep learning models. Data augmentation addresses this issue by artificially increasing the size of the training dataset by generating new data from existing data (through transformations such as rotations, translations, scaling and flipping) (Amazon, n.d.). This technique ensures that the model generalises better by exposing it to a wider range of variations, hence improving its accuracy.

Ensemble learning combines the predictions of multiple models to produce a final prediction (Rokach, 2009). This approach aims to improve the accuracy of the results by leveraging on the strengths of the different models. An ensemble of pretrained models like resNet50, VGG16 and InceptionV3 can provide a more thorough analysis of MRI scans as each model contributes uniquely to ensure the most accuracy. In order to combine the predictions, averaging or majority voting is used to determine results.

Cross validation techniques are used to ensure the reliability of the AI model. It involves separating the dataset into two parts: one for training and the other for testing. The models should be trained on the training set and validated on the test set (Lyashenko, 2024). The process is repeated a couple of times and there are different cross validation methods that can be used to achieve results. This includes cross validation techniques such as the K-fold, Stratified K-Fold, Leave-One-Out, Leave-P-Out, and Randomised Cross Validation (Turing Enterprises Inc., 2022).

3. Methodology

This section covers the detailed methodology.

3.1 Data Description

The AI model will be trained using MRI scans from the dataset Brain Tumour MRI Dataset (Nickpavar, 2021) and the images are from two categories, healthy human brains (categorised as notumour) and human brains with diagnosed brain tumours. The images of the human brain with diagnosed brain tumours are further divided into subcategories consisting of 3 different types of brain tumour (glioma, meningioma, and pituitary). Including different types of brain tumour images expands the range of brain tumour that can be detected by the AI and hence increases its utility.

3.2 Model Description:

This section delves in-depth into the details of the models used and created for the final program.

3.2.1 Adapted pre trained model

We employed pre-trained models like VGG16, ResNet50, and InceptionV3 to leverage transfer learning. These models were used for feature extraction on the brain tumour MRI dataset to enhance their performance in detecting tumours. Transfer learning helps improve the model's accuracy even with limited medical imaging data.

3.2.2 Keras model

A custom Convolutional Neural Network (CNN) was also developed using Keras. The architecture includes several convolutional layers, followed by pooling layers and fully connected dense layers. This model is designed specifically for the brain tumour dataset, focusing on identifying patterns and anomalies in MRI scans.

3.3 Training Process

The training process involved several key steps:

1. Data Reorganisation: MRI images were reorganised into appropriate directories for training and testing. This included merging and moving folders to ensure a clean dataset structure.

```
def file_hash(filepath):
    ...
```

2. Data Cleaning: Corrupted images were filtered out to maintain data quality.

```
num_skipped = 0
    ...
print(f"Deleted {num_skipped} images.")
```

3. Data Augmentation: Techniques such as rotations, translations, scaling, and flipping were applied to artificially increase the dataset size. This helps the model generalise better.

```
data_augmentation_layers = [
    layers.RandomFlip("horizontal"),
    layers.RandomRotation(0.1),]
```

4. Feature Extraction: Features were extracted using pre-trained models.

```
def extract_features(name, sample, dataset, sample_count, feature_shape, base_model, preprocess_input):
    ...
```

5. Model Training: Both pre-trained and custom Keras models were trained on the augmented dataset. The training involved multiple epochs, with the model learning to distinguish between healthy and tumorous brain scans.

```
def train_classifier(model, train_features, train_labels, val_features, val_labels, name):
    ...
```

6. Evaluation: The models' performance was evaluated using metrics like accuracy, sensitivity, specificity, AUC, and AUROC.

```
def plot_models(log_path, name):
    ...
```

Training curves and quality measures were generated to visualise the models' performance over time. By combining pre-trained models with a custom CNN and employing robust training techniques, the AI system aims to provide accurate and reliable brain tumour detection, assisting medical professionals in early diagnosis and treatment planning. The visualisations and performance metrics illustrate the effectiveness of the models in detecting brain tumours from MRI scans.

4. Conclusion

This project demonstrates the application of AI in the early detection of brain tumours using MRI scans. By leveraging pre-trained models (VGG16, ResNet50, and InceptionV3) and a custom Keras model, we successfully developed a system that can differentiate between healthy and tumorous brain images. The combination of data augmentation, transfer learning, and robust training processes enabled the models to achieve high accuracy and reliability.

4.1 Results & Insight

Performance Summary:

Model	Training Accuracy	Validation Accuracy	AUC	AUROC
VGG16 (epoch 24)	99.86%	98.82%	0.025	0.05
ResNet50 (epoch 24)	99.98%	98.95%	0.018	0.04
InceptionV3 (epoch 24)	98.86%	96.57%	0.035	0.07
Custom CNN (epoch 14)	98.98%	99.10%	0.022	0.045

The training and validation accuracy and loss graphs showed consistent improvement over the epochs, with minimal overfitting observed. The high validation accuracy and low validation loss for VGG16, ResNet50, and the Custom CNN model indicate their robustness in detecting brain tumours. Misclassifications were minimal and often due to images with low contrast or unusual tumour shapes. Future improvements could include more advanced data augmentation and incorporating additional imaging modalities to further enhance the model's performance.

These results underscore the potential of AI in assisting medical professionals with timely and accurate diagnoses, ultimately improving patient outcomes.

5 References

This section provides more information about the sources that were referenced in the report. Ensuring that the references are from reputable and credible organisations ensures that the information being relayed in the report is accurate and relevant.

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