Multi-Type Brain Stroke Detection using Resnet architecture using cnn

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***Abstract*— It is possible for brain abnormalities to result in the loss of some essential abilities, such speech, movement, and thought. Thus, receiving the best treatment as soon as possible may be aided by early brain disease detection. Magnetic resonance imaging (MRI) is a standard technique used to diagnose various illnesses. It takes a lot of time and effort to manually diagnose brain abnormalities since it can be challenging to see even the smallest alterations in the MRI pictures, particularly in the early stages of the condition. It is difficult to choose the features and classifiers correctly in order to get the best results. For this reason, over the past few years, deep learning models have been extensively used for medical picture analysis. The pre-trained models AlexNet, Vgg-16, ResNet-18, ResNet-34, and ResNet-50 have been used in this study to automatically categorize MR images into classes for inflammatory, degenerative, neoplastic, and normal disorders. Additionally, we have contrasted their classification performance with state-of-the-art architectures, or pre-trained models. Using the ResNet-50 model, we have achieved the highest classification accuracy of 95.23% ± 0.6 out of the five pre-trained models. We are prepared to test our model using large MRI pictures of brain anomalies. The model's output will assist the physicians in verifying their conclusions following manual interpretation of the MRI pictures.**

Keywords*— *Convolutional Neural Network, Residual network, Computer vision, Graphics processing unit

I. Introduction

Examining abnormalities in human organs, such the brain, has become more easier with the use of medical imaging technologies, especially magnetic resonance imaging (MRI). Magnetic resonance imaging has been more popular than other imaging modalities because of its safety and ability to create images with high contrast (Legaz-Aparicio et al., 2017; Olson and Perry, 2013; Akkus et al., 2017). Strong magnets and radiofrequency pulses are used in MRI machines, as opposed to ionising radiation-based techniques. Technological developments have also made it possible to record functional imaging of the organs using functional magnetic resonance imaging (fMRI) (Cheng et al., 2018; Logothetis et al., 2001; Saignavongs et al., 2017; Zhou et al., 2016a, b; Michalopoulos and Bourbakis, 2015).In the healthcare field, the rapid and precise identification of diseases has been facilitated by medical imaging technologies, which generate vast amounts of data. With the advent of artificial intelligence (AI), deep learning has emerged as a key research area, offering precise solutions to challenging big data-related problems. Numerous studies have focused on the categorization and partitioning of brain MRI data, employing convolutional neural networks (CNNs) as effective deep learning techniques for tasks such as lesion segmentation and brain tumor segmentation (Carass et al., 2017; Maier et al., 2017; Lyksborg et al., 2015; Pereira et al., 2016; Zikic et al., 2014).

A. Overview

This work explores the integration of deep learning, specifically transfer learning, in classifying brain abnormalities based on MRI data. The significance of MRI lies in its ability to provide high-quality images without ionizing radiation. The study employs a substantial dataset of 1074 images, encompassing all five categories of brain diseases: inflammatory, neoplastic, cerebrovascular, degenerative, and normal.

B. Convolutional Neural Network

Convolutional Neural Networks (CNNs) are a crucial component of this research, frequently employed for tasks such as lesion segmentation, brain tumor segmentation, and brain MRI classification. The use of CNNs facilitates automatic feature extraction, eliminating the need for manual feature extraction, which was a common challenge in earlier studies.

C. Matlab

Matlab, a powerful computational tool, is utilized in this study for implementing and analyzing the deep transfer learning-based model. Its versatility in handling complex mathematical operations and data processing makes it an ideal choice for developing and testing sophisticated algorithms.

D. *Introduction To Digital Image Processing*

Digital image processing forms the foundation of this research, providing the means to analyze and interpret the vast amount of MRI data generated. The utilization of advanced algorithms and techniques enhances the accuracy and efficiency of disease classification.

E. *Fundamental Steps In Image Processing*

The research involves a systematic approach to image processing, encompassing fundamental steps such as image acquisition, pre-processing, and post-processing. Each step plays a crucial role in ensuring the accuracy and reliability of the results.

F. *Applications Of Image Processing*

The applications of image processing in medical diagnostics, particularly in the analysis of brain MRI data, are extensive. This research contributes to the field by leveraging image processing techniques to enhance the classification of various brain abnormalities.

G. *Basics Of Color*

While MRI images are typically grayscale, understanding the basics of color is essential for researchers dealing with medical images. This knowledge aids in the interpretation and enhancement of visual features in the images.

H. *Morphological Operations*

Morphological operations are applied to shape the structure of image components, aiding in the extraction of relevant features. In the context of brain MRI classification, morphological operations contribute to refining the analysis of abnormalities.

I. *Feature Extraction*

Feature extraction is a critical step in medical image analysis. The use of deep learning techniques, particularly CNNs, automates this process, enabling the model to discern essential features without manual intervention.

J. *Edge Detection*

Edge detection techniques play a role in outlining and emphasizing key structures in MRI images. The incorporation of edge detection enhances the model's ability to identify and classify abnormalities accurately

II. Literature Survey

In the ever-evolving landscape of medical diagnostics, the fusion of advanced technology and medical expertise holds the promise of transforming patient outcomes. This review delves into the domain of brain stroke detection, where the integration of Convolutional Neural Networks (CNNs) and deep learning methodologies has sparked significant advancements. As students navigating this intricate realm, we explore key studies that showcase the potency of these technologies in enhancing stroke diagnosis accuracy.

1. Brain Stroke Detection Using Convolutional Neural Network and Deep Learning Models:

Machine learning's historical role in medical data analysis has been complemented by the advent of deep learning, particularly in computer vision and natural language processing. This research is a poignant example of this merger, emphasizing the utilization of CNNs and deep learning in diagnosing brain strokes using MRI images. By deploying LeNet and SegNet architectures, the study achieved impressive classification and segmentation accuracies. This underscores the potential of deep learning models, even in the context of medical imagery, to expedite accurate stroke detection.

2. An Automated Early Ischemic Stroke Detection System using CNN Deep Learning Algorithm:

The urgency of early ischemic stroke detection, evident by its prominence as a leading cause of death, prompted the development of automated diagnostic systems. Leveraging CNNs and deep learning, this study presents an innovative approach that significantly enhances the diagnostic process. By preprocessing CT brain images, selecting patch images, and utilizing CNN modules, the proposed algorithm achieved accuracies exceeding 90%. The study's outcomes not only reflect the potency of CNNs but also underscore their potential in aiding medical practitioners' diagnoses.

Performance Analysis of Machine Learning Approaches in Stroke Prediction:

Shifting our focus to stroke prediction, this study employs machine learning methods to anticipate stroke occurrences. The amalgamation of attributes such as hypertension, BMI, and smoking culminated in a predictive model that achieved a commendable 97% accuracy. The weighted voting classifier's prowess highlights the potential of ensemble learning approaches in enhancing prediction accuracy, ultimately aiding physicians and patients in proactive stroke prevention.

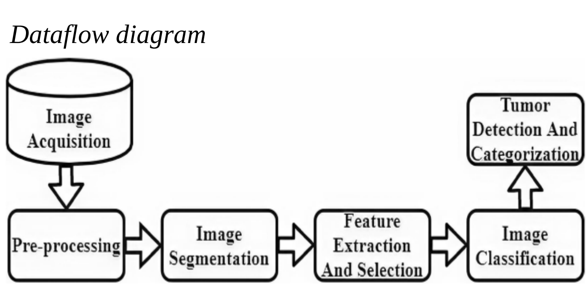
Machine Learning and Deep Learning Approaches for Brain Disease Diagnosis: Principles and Recent Advances:

The transformative potential of artificial intelligence (AI) in neurology and medicine is captured through this comprehensive survey. Encompassing a range of brain diseases, the review accentuates AI's role in revolutionizing diagnosis accuracy. It underscores the significance of feature extraction techniques, the diversity of datasets, and the evolving landscape of AI-based diagnostics.

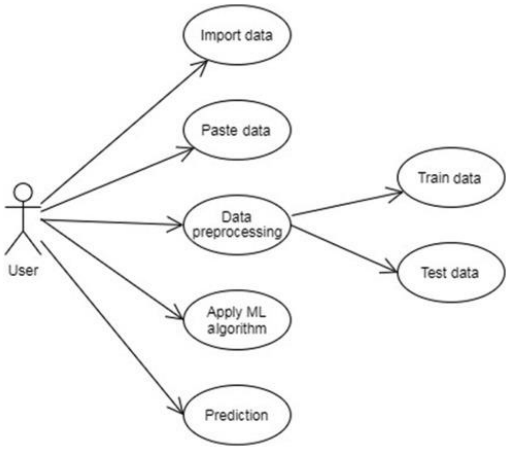
In the journey to revolutionize medical diagnostics, these studies illuminate the dynamic interplay between cutting-edge technology and healthcare. As students navigating this terrain, these explorations fuel our aspiration to contribute to the transformative synergy of deep learning, CNNs, and medical expertise, paving the way for more accurate and timely brain stroke detection.

III. System Design

A. *Dataflow diagram*



B. 5.2 Use case diagram



IV. PROPOSED APPROACH

It can be difficult and important to detect multiple brain strokes using deep learning techniques such as ResNet (Residual Neural Network). Popular deep learning architecture ResNet is renowned for its capacity to manage challenging image recognition tasks. The following are some suggested methods for utilizing ResNet to detect multiple brain strokes:

Image Preparation:

First, obtain high-quality CT or MRI scans of the brain.

To enhance the quality of the images, use preprocessing techniques like resizing, normalization, and contrast enhancement.

Data Enrichment:

Expand the dataset to boost its quantity and variety. Rotating, flipping, and adding noise are examples of useful techniques.

Data division:

To guarantee appropriate training and assessment, separate the dataset into testing, validation, and training sets.

Choice of Architecture:

Select a suitable ResNet architecture (such as ResNet-50 or ResNet-101) to serve as the foundation of your model. ResNet models are renowned for their ability to capture complex features through deep and skip connections.

Transference of Learning

Make use of pre-trained ResNet models on big image databases such as ImageNet. Utilize your brain stroke dataset to fine-tune the model and take advantage of the knowledge gained from the large dataset.

Differential Classification:

Multiple classes of brain strokes, such as ischemic strokes, hemorrhagic strokes, or other conditions, are frequently involved in their detection. Create a ResNet model with an output layer that predicts these classes.

Loss Mechanism:

For multi-class classification, choose a suitable loss function, like cross-entropy loss.

Instruction:

Using the proper hyperparameters, train the model on the training set. To prevent overfitting, keep an eye on the validation set's accuracy and loss.

Standardization:

Use strategies such as L2 regularization and dropout to avoid overfitting.

Data Distribution:

If there is a class imbalance in the dataset, address it because the frequency of brain strokes can vary.

Measures of evaluation:

To evaluate the performance of the model, use suitable evaluation metrics like recall, accuracy, precision, F1-score, and ROC curves.

Group Education:

An ensemble is made up of several ResNet models combined. This can enhance the stroke detection system's overall functionality and resilience.

After processing:

Use post-processing methods, such as non-maximum suppression or false positive filtering, to improve the detection results.

Comprehending Models:

Provide techniques for interpreting the model's conclusions; this is a critical task in the medical field.

Clinical Approval:

Work together with medical experts to confirm that the model satisfies clinical standards by validating its performance on actual patient data.

Constant Enhancement:

As more data becomes available and as the model's performance is assessed in real-world scenarios, update and improve it on a regular basis.

Considering Ethics:

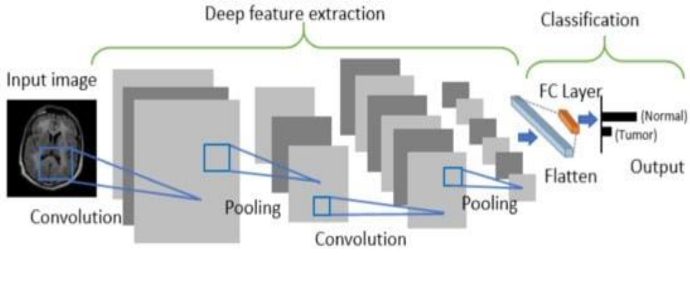
When using AI in healthcare settings and working with medical data, make sure privacy and ethical issues are taken into account.

V. MODULE DESCRIPTION

A. Convolutional neural network

CNN is a class of deep neural networks that uses convolutional layers for filtering inputs for useful information. The convolutional layers of CNN apply the convolutional filters to the input for computing the output of neurons that are connected to local regions in the input. It helps in extracting the spatial and temporal features in an image. A weight-sharing method is used in the convolutional layers of CNN to reduce the total number of parameters [

CNN is generally comprised of three building blocks: (1) a convolutional layer to learn the spatial and temporal features, (2) a subsampling (max-pooling) layer to reduce or downsample the dimensionality of an input image, and (3) a fully connected (FC) layer for classifying the input image into various classes. The architecture of CNN is shown in Figure 3.



VI. Methods and Algorithm

Generally, CNN has better performance in a larger dataset than a *smaller* one. Transfer learning can be used when it is not feasible to create a large training dataset. The concept of transfer learning can be depicted in Figure 4, where the model pre-trained on large benchmark datasets (e.g., ImageNet [43]) can be used as a feature extractor for the different task with a relatively smaller dataset such as an MRI dataset. In recent years, transfer learning technique has been successfully applied in various domains, such as medical image classification and segmentation, and X-ray baggage security screening [44,45,46,47]. This reduces the long training time that is normally required for training deep learning models from scratch and also removes the requirement of having a large dataset for the training model

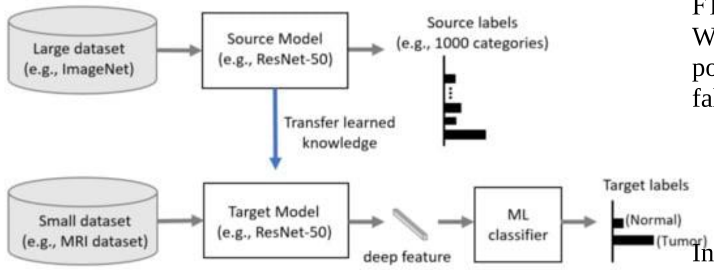
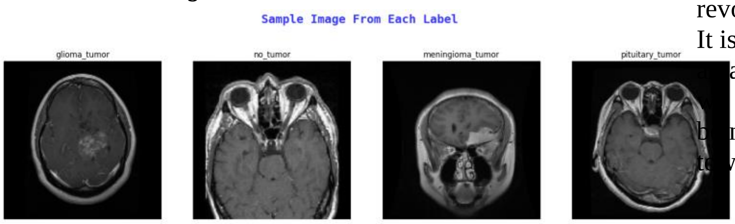


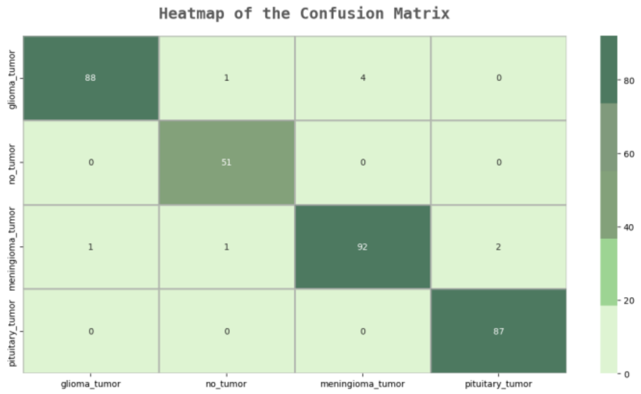
Figure 4. Concept of transfer learning.

VII. MODULE DESCRIPTION

A. *Observed Image*



B. *confusion Matrix*



C. Performance metrics

To evaluate the performance of “50-layer CNN” and “resnet50” architectures and compare our results with previous studies, we use different evaluation metrics including, accuracy, precision, recall, false-positive rate (FPR), true negative rate (TNR), and F1-score. These metrics are calculate as follows:

	precision	recall	f1-score	support
0	0.99	0.95	0.97	93
1	0.96	1.00	0.98	51
2	0.96	0.96	0.96	96
3	0.98	1.00	0.99	87
accuracy			0.97	327
macro avg	0.97	0.98	0.97	327
weighted avg	0.97	0.97	0.97	327

Accuracy=TP+TNTP+TN+FP+FN

Precision=TPTP+FP

Recall=TPTP+FN

FPR=FPTN+FP

TNR=TNTN+FP

F1−score=2×recall×precisionrecall+prcision

Where TP stands for true positive, FP stands for false positive, TN stands for true negative, and FN stands for false negative.

VIII. Conclusion

In conclusion, we have seen the severity and prevalence of stroke in the world and the limitations of current methods of stroke detection. However, we have also explored the promise of deep learning in improving stroke detection, specifically through our approach of using it for multi-type stroke detection. This technology has the potential to revolutionize neurological care and save countless lives.
It is imperative that we continue to research and develop this a. By advancing neurological care through deep learning, can make a significant impact on the health and well-b ng of individuals worldwide. Let us work together t ards this goal.

IX. Future Enhancement

i. Utilising 3D convolutional networks to enhance the study of brain anatomy.

ii. employing recurrent neural networks (RNNs) to examine how stroke patterns vary temporally over time.

iii. putting real-time processing into practise to provide quick clinical decision support.

iv. Collaborative learning is being introduced to boost model generalisation by securely aggregating data from several healthcare facilities.

v. creating a mobile application that is easy to use in order to quickly and easily assess stroke risk and provide early intervention

X. REFERENCES

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