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Brain Tumour detection

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Abstract:

Imaging techniques are used to detect problems in the human body. Multiple medical images needed to understand the problems or diseases in human body and provide better treatment for them. The medical image makes us understand is carried out by experienced medical experts. Nevertheless, the less accessibilty of human experts and to reduce the exhaustion experienced by the experts in estimating the disease and treating it . CNN is a tool used for extracting raw data from sample images and helps in analysing them. The CNN excels in comparison to the great human experts in numerous image understanding tasks.

This piece of writing intends to give a thorough understanding of the applications of CNNs in medical image analysis. The primary goal is to encourage researchers in medical field to understand and utilize CNNs in their research works and detecting and treating the disease . A concise breif of the CNN is presented. A brief description of CNN and its various types are discussed , award-winning frameworks are shown. The major aim of brain tumour image analysis is detecting a anomaly in the brain .

Convolutional neural network in brain tumour image analysis using deep learning and other algo like SVM can be put to use to detect various diseases like glaucoma , skin cancer , brain tumour detection.

Introduction:

Medical Imaging :

In the of medical imaging lies an essential field known Computer-Aided diagnosis (CAD), where ML algorithms are used for analysing the imaging data from past patient , building a model to evaluate the patient. This neural network model helps the Doctors for fast decision making.

The most of the technologies that used for analysing the medical images are X-Ray, CT Scan , MRI Scan. The main objective of medical image processing is to enhance software functionality so that it offers detailed information.

A convolutional neural network (CNN), which is a type of neural networks that mainly focus on the pixel of the images , plays a significant role in image classification. CNN uses mathematical concepts to recognize patterns within images. While earlier CNN architectures used to contains convolutional layers that are placed one over other, contemporary designs like Inception, ResNet, and DenseNet introduce fresh and innovative techniques to construct convolutional layers, enhancing learning efficiency.CNN serves as not only a classifier but also a feature extractor, it extracts raw pixel data and transform them into numerical data that can are processed while preserving original data . The initial feature extractors can be recouped by CNNs to extract complicated features that depict images more brilliantly. These features can be incorporated into a network or applied by the complicated machine learning algorithms for classification purposes.

Instead of the numerous benefits of deep learning in radiology, concerns persist regarding its application in the field. A primary challenge is the necessity for extensive and well-defined Radiology images, as the effectiveness of CNN heavily relies on input data. Creating such database demands substantial labour and is financially demanding.

Literature Survey:

ML Architectures for medical image analysis of Brain to detect Tumour

- CNN, FCN, Deep Belief Network, Autoencoders
- Hu et al. presented four deep learning architectures used for brain tumour x-ray.
- Recent works on brain tumour identification and diagnosis were compiled.
- Transfer Learning for Medical Diagnostic Problems
- Shin et al. explored interstitial brain tumor detection classification using three CNN models.
- They discussed how cnn learning improved the result of each model.
- ONNX: Open Neural Network Exchange
- ONNX is an interchange format to facilitate passing deep learning models between different frameworks.
- The initiative aims to make various frameworks more accessible to developers.
- Popular Deep Learning Libraries and Tools
- Torch: Open-Source Machine Learning Library
- Torch is a scientific computing platform based on Lua programming language.
- PyTorch, an extension module of Torch, is used by companies like IBM and Facebook AI Research Group.
- Keras: High-Level Programming Interface
- Keras runs on top of Theano and TensorFlow, serving as an interface for deep learning.
- It is known for its rapid growth and ease of use for new users.
- MatConvNet: MATLAB's Deep Learning Library
- MatConvNet is a commonly used deep learning library in MATLAB.
- Distributed Deep Learning
- IBM DDL interfaces with frameworks like TensorFlow and Caffe to accelerate deep learning algorithms.
- It optimizes neuron computa

Methodology:

Dataset:

In this project, we utilized a dataset consisting of MRI images of brain tumors. The dataset contains 500 different images from CT Scans, MRI, and X-Rays of the brain to detect the presence of tumors. This valuable dataset was sourced from the popular website "Kaggle.com".

- The importance of clean data cannot be overstated in machine learning models.
- The necessity of data cleaning plays a vital role in preparing the data for accurate and reliable results.
- The data quality directly impacts the performance of the model.

Data Cleaning:

The dataset we obtained from the website contained numerous uncleared and blurred images that required processing. To ensure the accuracy of the data, we meticulously removed these unwanted values. It is essential for a machine learning model to learn from clean, well-prepared data.

Clean data is crucial for the model to learn from accurate and reliable information.

Labelling:

Labelling the images helps in annotating whether they contain a tumor or are normal. This step is essential for training the model to accurately classify the images based on the presence of tumors.

Splitting Data:

Dividing the dataset in training, validation, and test sets is crucial for training & evaluating the CNN. This process allows us to assess the performance of the model on unseen data.

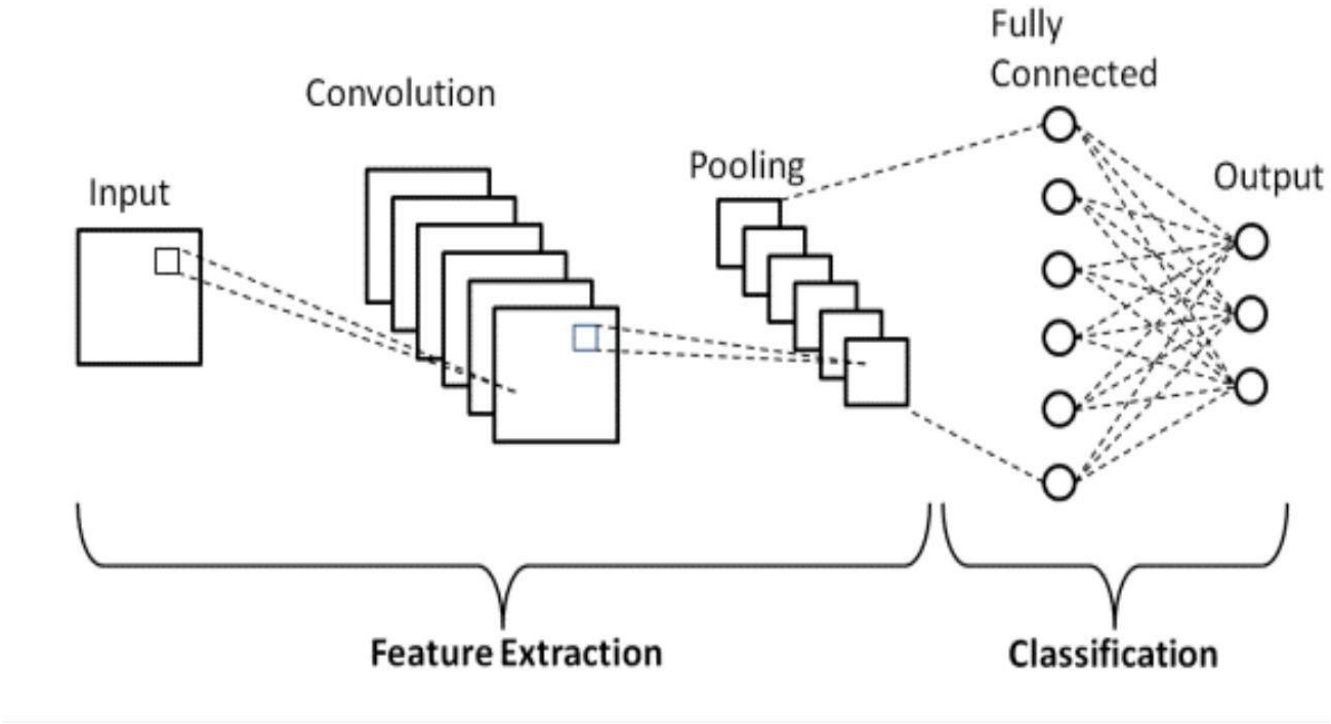
In conclusion, the methodology implemented in this project underscores the significance of clean data, meticulous data cleaning, accurate labelling, and strategic data splitting. By following these essential steps, we can develop a robust machine learning model for detecting brain tumors effectively.

Algorithm Used:

Convolutional Neural Networks:

CNNs are the backbone of many machine learning approaches in medical imaging. They're adept at automatically learning features from images and are used for tasks like classification, segmentation, and detection. CNN is a supervised deep learning framework

that can accept images as input,and extract pixel from images and convert image pixels into features, and apply those features to differentiate one type of data from another.



Generative Adversarial Networks:

Algorithm is used to optimize the performance of CNN. GANs consist of a generator and a discriminator and have been applied in medical imaging for tasks like image synthesis, data augmentation, and anomaly detection.

Building The model:

Building the Show

Classification

When it comes to brain tumor discovery utilizing Convolutional Neural Systems (CNN), different learning models like VGG, ResNet, or custom plans are commonly utilized. These models play a vital part in precisely recognizing and classifying brain tumors in therapeutic imaging.

Accuracy could be a key metric utilized to decide the exactness of positive forecasts. The algo calculates the ratio of genuine positive expectations to the full number of positive forecasts. Basically, accuracy measures how numerous of the anticipated positive cases were really positive. ## Review On the other hand, review measures the model's capacity to distinguish positive tests precisely. It is calculated as the proportion of true positive tests accurately classified as positive to the whole number of positive samples. A better review shows that more positive tests were identified by the show. ## Exactness Exactness may be a crucial degree that gives the extent of rectify forecasts over all forecasts made by the demonstrate. It takes into the esteem of genuine positives and genuine negatives in connection to all positive and negative cases. In substance, exactness reflects the by and large rightness of the forecasts made by the demonstrate. F1-Score The F1-Score could be a weighted metric that combines both accuracy and review to supply a comprehensive assessment of the model's execution. It strikes a adjust between these two measurements, guaranteeing that the demonstrate can successfully classify occurrences as positive or negative. In double classification scenarios, the F1-Score is calculated employing a equation that considers both accuracy and review. Within the domain of brain tumor discovery utilizing CNN models, precision and proficiency are foremost. By understanding and assessing measurements such as exactness, review, exactness, and F1-Score, researchers and specialists can gage the effectiveness of these models in recognizing and classifying brain tumors precisely. The experiences determined from these measurements not as it were progress the performance of the models but moreover contribute to the headway of therapeutic imaging innovations for way better conclusion and treatment results.

Result:

Result Analysis

The research findings have shed light the impressive performance of the 2D cnn and auto-encoder network in terms of training accuracy. The 2-D cnn boasted an exceptional training accuracy of 96.47%, edging out the auto-encoder network which achieved a respectable 95.63% accuracy. These high accuracy rates signify the effectiveness and robustness of both networks in handling the data and making accurate predictions.

Training Accuracy: The 2D CNN and auto-encoder networks have demonstrated their prowess with remarkably high training accuracy rates of 96.47% and 95.63%, respectively. This showcases the capability of these networks to learn from the data provided and make accurate predictions.

Average Recall Values: Moving on to the mean recall values, we see that the 2D cnn and auto-encoder network achieved impressive recall rates of 95% & 94%, respectively. This indicates the network ability to correctly identify the relevant information within the dataset.

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