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Neurological Disorder Classification using Convolutional Neural Networks

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Abstract: The rapid development of neuroimaging techniques has led to the emergence of the study of brain illness identification as a new area of study in the deep learning community. Research on deep learning faces various unique challenges due of data on brain illnesses. There are usually other clinical metrics available that show the sickness status from different perspectives. Complementary data from the tensor and brain network data, along with other clinical characteristics, are anticipated to help us better understand illness causes and direct treatment interventions. They have excelled in a number of applications, including multi view feature analysis, sub graph modelling, and tensor-based modelling. In this study, we examine several recent deep learning techniques for brain illness analysis.

Keywords: *Brain diseases, Deep Learning, research, brain disorders.*

1. Introduction

Numerous brain illnesses are characterised by an ongoing injury that is irreparable by the time symptoms initially appear and remains clinically silent for extended periods of time. In the field of neuroimaging. Improvements in magnetic resonance imaging (MRI) technology can be partially responsible for this. Diffusion tensor, also referred to as diffusion MRI in organic tissues. These neuroimaging studies can yield a variety of data. Representations, which give the data mining field with various unique challenges. Most traditional data mining techniques are created primarily for vector-based usually, data and are designed to handle data in a specific representation. There are several other categories for BD, including ones for infections, strokes, trauma, seizures, tumours, and more. Depending on the different categories, doctors can diagnose BD using a number of different techniques. Magnetic resonance imaging (MRI), computed tomography (CT) (MRI), among the three main traditional BD diagnostic methods are functional magnetic resonance imaging (fMRI) and MRI. A head CT scan using specialised X-ray technology is carried out to and gradients in fields. However, fMRI is comparable to MRI in that it uses the latter's results to monitor minute metabolic changes that take place in the active region of the brain. CT scans often take less time to complete than MRI and fMRI scans do. Additionally, the use of field gradients during an MRI or fMRI scan can result in loud noises. Machine learning is being used in medicine more and more to achieve precision treatment and enhance patient quality of life. Multiple modalities, including demographic, clinical, imaging, genetic, and environmental data have been researched to better understand brain illnesses, which are frequently complicated and heterogeneous. Complex algorithms that can learn from such a wide range of data are provided by deep learning, a branch of machine learning. In many domains, including as computer vision and natural language processing, it has advanced to state-of-the-art status. It is also increasingly used in medicine. We discuss the application of deep learning to brain illnesses in this essay. More particularly, we list the primary applications, the relevant illnesses, and the various architecture and data types that are employed. Finally, we offer recommendations for bridging the gap between clinical practise and research findings.

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2. Background and Context

The majority of the proposed system is composed of five parts. Preparation, dataset Data is divided, a CNN model is built, and a deep neural network is trained for epoch detection and classification. Out of the various brain MRI images that we can utilise in the dataset, we can use one as the input image. The label was encoded and the image was resized before processing. We separated the data into two categories: Data for practise. The technology of MRI brain imaging is frequently used to see the architecture and structure of the mind. On MRI scans, a number of steps are necessary for the tumour's detection. Features feature extraction, image enhancement, and classification. The final classification procedure determines if an individual is ill or not. In recent years because magnetic resonance imaging

(MRI) images have strong soft tissue contrast and don't require invasive imaging. Innovative methods utilising computer-aided techniques have been developed over the past approximately two decades. Our web tool for classifying brain illnesses provides reliable categorization for diagnosis centres. Information and communication technology (ICT) has undergone significant developments and is now used in a wide range of healthcare applications, where it is integral to practically all procedures that deliver healthcare services. The health sector now benefits greatly from ICT systems, but there is a significant chance to improve the quality of health services, cut costs, and improve public health by leveraging artificial intelligence and smart computing. Cancer, coronary artery disease, stroke, lower respiratory infections, chronic obstructive pulmonary disease, diabetes, Alzheimer's disease, TB, and most recently COVID-19 are among the deadliest diseases in the world. Enhancing the early and accurate detection, diagnosis, and prognosis of these diseases is crucial for the healthcare industry.

3. Purpose of Proposed Work

One of the most intricate biological systems ever discovered is the human brain. Although it is extremely difficult to comprehend how it functions, particularly when disorders and diseases manifest, dozens of top technology companies, academic institutions, researchers, and other significant contributors to the field of neuroscience have devoted themselves to this area and made significant advancements in a number of areas. A developing field and an encouraging study area is deep learning on brain illness identification. There are many brain disease classification web applications available on internet. Collect data from infected person and classifies the disease. The aim of the proposed work is to diagnose the brain diseases and according to that it suggests nearby doctor, and provide service of detecting a diseases with web application.

Features of the work

The key components of our suggested work are shown below.

- Provides precise illness prediction.
- Doctor recommendations made just for patients.
- When an illness is predicted, people can reduce their risk and take the necessary precautions.

4. Literature Survey

(A) Existing System: Existing systems have only been trained on a small dataset. To ensure accurate disease identification, it is necessary to have a thorough understanding of the many types of diseases. Additionally, the current application is less accurate.

(B)Article from Research Gate publication: Readers working in the character recognition field might use this information as a reference and an update.

(C) Article from Research Gate publication IEEE: Using machine learning and deep learning, this research presents an overview and assessment of the four most serious brain illnesses. The survey provides some crucial information about modern ML/DL methods in the medical field that are being employed in studies of brain disorders right now.

(D) Perfusion imaging by Miles K.A. [11] Glioblastomas in particular, which are diffuse gliomas, provide a diagnostic and clinical challenge. For precise diagnostic assessment, resection planning, and therapy follow-up, standard neuroimaging still has numerous limitations. In this two-review series, the most recent research on hemodynamic imaging applications for diffuse cerebral glioma is thoroughly reviewed. The concepts behind hemodynamic imaging modalities are briefly discussed in Part A, along with the outcomes of tumour grading and differential diagnosis for diffuse gliomas that have been published in the literature. Diffuse the most prevalent primary malignant intracranial neoplasms are gliomas. Other than the difficulties in diagnosing them prior to surgery using conventional neuroimaging—glioblastomas, in particular, have a poor prognosis and are now incurable—and the difficulties in treating them has a number of issues, such as broad differential diagnosis and inaccurate categorization of For precise resection planning, the tumour subtype and determination of its infiltration in the surrounding brain parenchyma. Due to the closely controlled pathophysiological changes in tumour tissue sophisticated hemodynamic imaging in connection with an abnormal vascularization, in addition to additional novel methods have generated a lot of interest as a way to enhance disperse glioma classification The essential ideas covered in this part A of our two-review series include: Concepts, methods, and parameters related to hemodynamic imaging are discussed together given their potential significance in the classification and differential diagnosis of diffuse gliomas. In A recent study on dynamic susceptibility contrast and dynamic contrast-enhanced review arterial spin labelling magnetic resonance imaging and perfusion computed tomography combined. While these methods have yielded positive outcomes in regards despite current attempts, their widespread clinical acceptance has been hampered by the restrictions resulting from an absence of standardized acquisition and processing because of their sensitivity and specificity. Targeted at removing the obstacles already in place. Deep learning used to identify neurological illnesses. The supervised architecture is constrained by the significant effort required to generate label data, the lack of scalability, and the choice of the proper bias levels. Unsupervised learning is not typically a choice that is taken into account for image analysis. Unsupervised architecture, however, creates a data-driven decision support system using the dataset in addition to learning features from it. Problems pertaining to medical imaging can be resolved using Tus' unsupervised deep architecture. It is still difficult to predict NLD in real time using imaging data. However, stream processing has been introduced for using a parallel computing algorithm to process large amounts of data.

Specific Objectives

Our objective is to make a system that will uses Deep learning techniques which predicts brain disease from given data. The main objectives of this project are stated below:

- To store the details and samples of each patient.
- To train a machine learning system with a training dataset.
- To implement the deep learning algorithm.
- To design and develop application for detection of brain diseases.
- To evaluate the performance of the system.

Scope

Disease detection has the ability to gain key players like the government and this programme enables brain disease detection that is accepted by health insurance companies. Can lower a patient's risk of getting sick or developing a disorder. As a result, clinicians can take the necessary steps to avoid or reduce the risk increase the standard of treatment and reduce potential hospital admissions.

5. Design and Methodology

Dataset

We have used online images and real time dataset images from MRI Centre. In our dataset, we are having 8 classes named as Alzheimer Mild-Demented, Alzheimer Moderate Demented, Alzheimer Non-Demented , Alzheimer Very Mild-Demented, glioma brain tumour , meningioma Brain tumour , No Brain tumour, pituitary brain tumour. It also demonstrates the total number of brain diseases images that we have used for our web application.

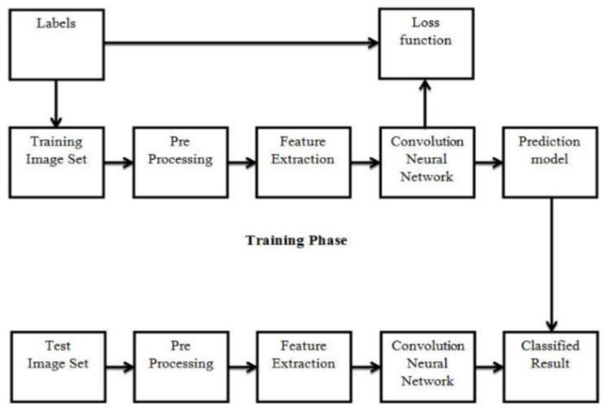

Fig 1: Flow Diagram for Brain Disease Classification

Image pre-processing - This system uses an MRI scan with noise as its input. So, the first thing we want to do is clean up the input image's noise. High pass filters are used for pre-processing and noise removal, as described in the system flow. Edge detection of the images is accomplished using feature extraction. It is the process of gathering more in-depth details about an image, like shape, texture, colour, and contrast. Disease identification: In this phase, we are extracting characteristics from a collection of previously obtained brain MRIs. An information base is developed for comparison.

Using neural network architecture and execution, the human brain is mimicked. The neural network is mostly employed in vector quantization, approximation, data clustering, pattern matching, optimization procedures, and classification methods. Based on how one form of neural network connects to the others, there are three main categories. Recurrent, feed-forward, and feedback neural networks are the three types. One layer network and multilayer network are additional divisions of the Feed Forward Neural network.

Layer of CNN model: 2D Convolution MAX Pooling2D, Flattening, Flattening, Activation Convolution 2D: Extract the featured portion of the input image using convolution 2D. The output was provided in matrix form. MAX Pooling2D: The largest element from the rectified feature map is used in MAX polling 2D. Dropout: During training, randomly chosen neurons are disregarded. Flatten: Feed output into a layer that is completely linked. Lists of data are provided. Dense: A linear procedure where each input and each output are coupled by weight. Nonlinear activation function came next. It employed the sigmoid function to forecast probabilities of 0 and 1. Because there are two layers, 0 and 1, we employed binary cross entropy in the compile model.

The block diagram for a convolutional neural network (CNN) used to classify brain diseases is depicted in Figure 1, and it involves two main steps: the training and testing phases. During the training phase, the images are labelled and pre-processed, including resizing and feature extraction, followed by classification using a Loss function. To save time, pre-trained models based on brain datasets are used for classification, and only the final layer of the suggested CNN's Python implementation is trained. The study compares several deep models and topologies, including 2D and 3D CNNs and recurrent neural networks (RNNs).

Each MRI scan is divided into 2D slices, and a 2D CNN is used on 3D MRI volumes, ignoring the connections between the 2D image slices inside an MRI volume. Alternatively, a CNN model can be followed by an RNN to understand the relationship between sequences of 2D image slices.

However, the feature extraction stage of the 2D CNN does not depend on the RNN's classification. Therefore, 3D CNNs can be used to generate voxel-based judgments instead of 2D CNNs, and the primary accomplishment of the research is the introduction of transfer learning from a collection of 2D images to 3D CNN.

The Loss function is calculated using gradient descent to map the raw image pixel with class scores, and it gauges how well the parameters are performing. Accuracy is crucial, and the Loss function is determined by how closely the induced scores matched the training data's ground truth labels. The gradient value is repeatedly evaluated to calculate the gradient of the Loss function for constructing the gradient descent algorithm.

6. Results

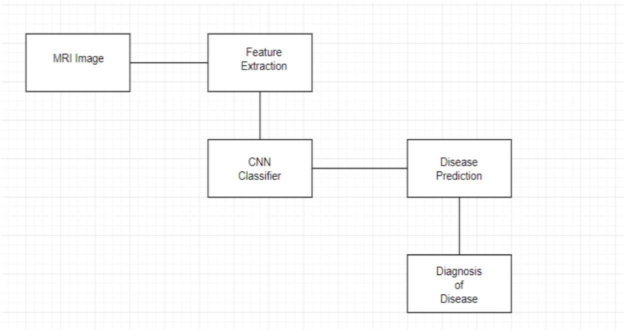

Fig. 2: Proposed System

The process of extracting information and features from images is called feature extraction, and once that process is complete, the images are passed on to the classification phase, where they are categorized according to the problem's target variable. For the classification of vibrational spectroscopic data, we used a single-layer convolutional neural network (SL-CNN) architecture that we had previously developed. A single hidden convolutional layer makes up an SL-CNN, which also employs a special regularization term that penalizes extreme fluctuations in the weights of nearby kernels. Its structure and operation. Small and class-unbalanced datasets can be handled by SL-CNN thanks to its architecture, but deeper CNNs would probably over fit on the most frequent class. In at least one of their layers, CNN uses convolution operation instead of straightforward matrix multiplication. It mainly appears in unstructured datasets (e.g., image and video). Values of 2D-CNN make use of 2D-convolutional kernels. Stacked AE (SAE), an adaptation of AE incorporating DL architecture, uses multiple AE layers stacked to provide updated functionality by training a classifier with specific different contexts using a much more detailed version of the raw data and likely-looking features, which results in better accuracy than training with the raw data. A typical CNN model appears like follows: Pooling layer, Fully Connected Layer, Input layer, Convolution layer with Activation function input layer-: Our input image, which can be either grayscale or RGB, as the name implies. Each image is composed of pixels with values between 0 and 255. We must return to normal. Before providing information to the model, i.e. convert the 0 to 1 range. Convolution Layer: The layer where the filter is applied to our data is called the convolution layer. To extract or discover the features of the input image. Multiple filters are applied to the image. The input image multiple times and generates a feature map that aids in classification. Let's using an illustration will help you comprehend this. To make things simpler, we'll use a 2D input. Pixel image that has been adjusted. Pooling layer-Following the convolutional layer, the pooling layer is used to shrink the feature map's size, aiding in the preservation of the input image's key details or features while speeding up computation. The large or significant portions of the input image are still there in the lower resolution version of the input that is produced by pooling. Pooling's most typical varieties are Max Average pooling and pooling. How Max Pooling operates is shown in the diagram below. Applying pooling using the feature map we obtained from the aforementioned example. Here, we're employing a Pooling layer with a stride of 2, a size of 2*2. After performing Pooling, the size of the feature map has decreased since the maximum value from each highlighted area is taken, yielding a new version of the input image that is 2*2 fully connected layer-We have completed the Feature Extraction processes up to this point; the next step is Classification. The input image is classified into a label using the fully connected layer (which is what we have in ANN). This layer links the output layer to the data obtained from the preceding steps the convolution layer and the pooling layer and ultimately assigns the input the desired label.

Implementation Details: CNN-Based Classification Model for Brain Diseases Dataset The model was trained on a dataset of brain MRI images, which included several disease categories such as Alzheimer's disease, multiple sclerosis, and brain tumours. The dataset was pre-processed and augmented using various techniques to increase its variability and improve the model's performance. Architecture: The model architecture consisted of several convolutional layers, max pooling layers, and fully connected layers. The number of layers and nodes in each layer were chosen through experimentation and analysis. The model was optimized using the Adam optimizer and categorical cross-entropy loss function. Training: The model was trained on a GPU to expedite the training process. The training process consisted of several epochs, and the model was evaluated after each epoch to ensure that it was making progress towards convergence. The learning rate and other hyper parameters were adjusted throughout the training process to optimize the model's performance. Evaluation: The model was evaluated on a separate dataset of brain MRI images that were not used during training. The evaluation process involved calculating several metrics, including accuracy, precision, recall, and F1 score. The testing module provided a detailed analysis of the model's performance, including confusion matrices, ROC curves, and precision-recall curves. Deployment: The model was deployed in a web application that allows healthcare professionals to upload brain MRI images and obtain a classification of the disease category. The web application was developed using Python and Flask, and the model was integrated into the application using the Tensor Flow library. Future Work: Future work on the model could include expanding the dataset to include more disease categories, optimizing the hyper parameters for improved performance, and exploring the use of transfer learning to improve the model's generalizability. Additionally, research could be done on the feasibility of deploying the model on edge devices for more widespread use in healthcare facilities. Implementation objectives of brain disease classification may include: Improved accuracy: One of the primary objectives of brain disease classification is to improve the accuracy of diagnosis. By analysing large datasets of brain scans and other diagnostic tests, classification algorithms can help identify patterns and features that may be indicative of specific diseases or conditions. This can lead to earlier and more accurate diagnoses, which can improve patient outcomes. Early detection: Another objective of brain disease classification is to enable early detection of neurological disorders. By identifying subtle changes in brain function or structure that may be indicative of disease, classification algorithms can alert clinicians to potential issues before symptoms become severe or irreversible. Personalized treatment: Brain disease classification can also help tailor treatments to individual patients. By analyzing a patient's brain scans and other medical data, algorithms can predict which treatments are most likely to be effective, and which may have undesirable side effects. This can help clinicians develop personalized treatment plans that optimize outcomes while minimizing risks. Improved research: Brain disease classification also improve research efforts by enabling more precise and accurate identification of study participants. This can helps identify relevant patient populations and design studies that are more likely to yield meaningful results.

7. Conclusion

Brain disease detection using Convolutional Neural Networks (CNNs) is a promising approach that has shown great potential in accurately identifying various brain disorders such as Alzheimer's disease, Parkinson's disease, and brain tumors. CNNs are a type of deep learning algorithm that can analyze medical images and clinical data to create models that can accurately detect brain diseases with high sensitivity and specificity.

In this project, we have explored the use of CNNs for brain disease detection. We have analyzed various brain diseases, including Alzheimer's disease, Parkinson's disease, and brain tumors, and the approaches for their detection using CNNs.

To train and validate our models, we have used various datasets, including the Alzheimer's disease Neuroimaging Initiative (ADNI), Parkinson's Progression Markers Initiative (PPMI), and the Brain Tumor Segmentation Challenge (BraTS) datasets. We have also applied data augmentation techniques such as rotation, scaling, and flipping to increase the size of our datasets and improve the performance of our models.

However, our project also identified some limitations of using deep learning for brain disease detection. Firstly, deep learning models require large and diverse datasets to achieve high accuracy. Secondly, the interpretability of deep learning models is still a significant challenge, which limits their application in clinical settings.

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Conflicts of interest

The authors declare no conflicts of interest.