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Study of Identification of Multiple Sclerosis using different CNN Architectures

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Abstract

Multiple Sclerosis (MS), an autoimmune condition in which the immune cells of the body destroys the covering (myelin sheath) surrounding the nerves, hinders the brain from effectively communicating with the body. If progressed to the later stages, the condition can lead to irreparable deterioration of the nerves. Neurologists use Magnetic Resonance Images (MRI) to classify them. Due to the complexity of the brain and MRI scan images, manual examination might be time consuming. To aid doctors across the world and reduce the time taken to diagnose this disease, Convolutional Neural Networks (CNNs) have been suggested. Moreover, this paper is a comparative study using two CNN Architectures done on MRI scan images for MS diagnosis. The dataset constitutes MRI scan images of MS patients in 2 different orientations and healthy brain MRI images. Expeditious diagnosis leads to an earlier medicament which can help contain the spread of the disease. Metrics like accuracy and other evaluation criteria are considered for the comparison of the CNN models.

Keywords: Machine learning, CNN, DenseNet169, Deep learning, Multiple Sclerosis

1. Introduction

Multiple Sclerosis (MS), a central nervous system disorder, affects the communication within the cells of the brain as well as between the body and the brain. The sign and symptoms may vary from person to person depending upon the degree of damage to the nerves and the type of nerve affected. Some patients may lose their vision, while for others the control and coordination might be affected. However, the disease usually affects physical movement that might include numbness or paralysis in one or more limbs, loss of coordination, tremors, or an unsteady walk.

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Diagnosing MS can be difficult due to the heterogeneity of the disease, and a definitive diagnosis often requires a combination of clinical, radiological, and laboratory evaluations. At present, the most specific as well as sensitive diagnostic method for identifying MS is Magnetic Resonance Imaging (MRI) but other tests such as cerebrospinal fluid analysis and evoked potentials can also be helpful in certain cases. However, these procedures have limits in terms of accuracy and reliability, and more sensitive and specific diagnostic tools are required. Deep learning approaches have showed tremendous promise in medical image analysis in recent years, particularly the identification and diagnosis of MS. Convolutional Neural Networks (CNNs) are a class of deep learning algorithms that have demonstrated remarkable success in various medical image processing tasks. In the present study, an approach to detect MS by leveraging two pre-trained CNN architectures, namely DenseNet169 and CNN has been proposed.

Each of the CNN models in the proposed technique is trained on a huge dataset of MRI images of MS patients and healthy persons. Transfer learning is used to fine-tune the pre-trained models on the dataset and optimize the model hyperparameters to reach the maximum feasible accuracy. To assess the usefulness of the two CNN models in MS detection, their performance is compared. Model's performance is assessed using common measures like as recall, precision, accuracy, and F1 score. The outcomes of the investigation may pave the way for a more effective and precise diagnostic approach to MS, potentially mitigating the possibility of erroneous diagnosis and enhancing patient prognosis. Additionally, the proposed approach could be extended to other medical image analysis tasks, demonstrating the potential of deep learning in revolutionizing medical diagnosis and treatment.

2. LITERATURE REVIEW

Zhang et al., segmented the dataset into training, validation, and test sets. Using transferred learning, AlexNet was modified to better classify multiple sclerosis brain images for the challenge using AlexNet as the base model. Experiments were conducted with various transfer learning parameters, including the number of layers that were transferred and replaced. Ten times as much learning occurs in replaced layers as it does in transferred layers. Five metrics such as sensitivity, specificity, precision, accuracy, and F1 score were used to compare the findings.

Hashemi et al., discovered that U-Net and Attention U-Net are the two most effective ANNs for MS lesion segmentation. A framework for segmenting MS lesions in FLAIR and T2 MRI images using modified U-Net and modified Attention U-Net was suggested. To achieve this objective, additional pre-processing techniques were introduced to MRI images, the loss function of both U-Net and Attention U-Net models were altered, and the combined FLAIR and T2 predictions were employed for superior outcomes. The findings of this study indicate that utilizing the augmented Attention U-Net model to generate masks based on the combined FLAIR and T2 predictions yields a Dice Similarity Coefficient of 82.30% on the test dataset, signifying notable progress compared to previous research endeavors.

Jannat and colleagues proposed a novel approach to expedite the diagnostic process while ensuring readability and precision by incorporating a fluid-attenuated inversion recovery (FLAIR) series. The technique relied on CNNs and transfer learning to train the model, while SoftMax served as the activation function for disease progression classification. The study's findings revealed the efficacy of MRI in detecting MS lesions, as the approach accurately predicted disease progression in 30 patients and 100 healthy brain MRIs. The manual detection of lesions by clinical experts is a challenging and time-consuming task, given the extensive MRI data analysis required. The method demonstrated a high accuracy rate (up to 98.24%).

Gao et al., introduced channel attention mechanism into the YOLOv4 algorithm to enhance the feature representation ability of images and proposed an object detection algorithm with channel attention mechanism. The global average pooling operation was first carried out on the features extracted by YOLOv4. Subsequently, an interactive local cross-channel operation was conducted on the feature channels employing one-dimensional convolution to enhance correlation between the features of channels, so as to improve the positioning accuracy of YOLOv4. The method has achieved good results in the PASCAL VOC dataset. Compared with the original YOLOv4 algorithm, the mAP of this algorithm in the PASCAL VOC test set was improved.

To enhance the performance of supervised machine learning algorithms, Salem et al., devised a strategy to improve the effectiveness of supervised machine learning algorithms by fabricating synthetic multiple sclerosis lesions on MRI images. To achieve this objective, a fully connected CNN model with two inputs and two outputs to simulate MS lesions in MRI images was employed. Through discrete binary intensity level overlays that were superimposed with the input pictures and transmitted to the model, information was encoded. Next, artificial lesions were created on healthy people. These findings clearly demonstrate the value of registering patient photos with artificial MS lesion images.

3. ARCHITECTURE

Fig.1 illustrates the steps involved in the architecture of the proposed machine-learning method. First, the dataset is procured from diverse sources such as files, databases, sensors, and a plethora of other data collection tools. However, data collected from these sources cannot be used directly for carrying out the analysis process because they may contain significant amounts of missing data, extremely large values, or messy text data. In order to address this problem, data preparation is done. Additionally, resources like Kaggle and the UCL Machine Learning Repository can be used, where the collection of labelled instances is divided into training, validation, and testing sets.

The validation set is used to fine-tune the model's hyperparameters and avoid overfitting, while the training set is utilized to improve the model's parameters. The testing set is intended to gauge how well the finished model performs on hypothetical data. The feature extraction algorithm designed next is used to extract pertinent characteristics from the input data. The methodology for extracting features may be based on manually created features or features that have been learnt using deep learning methods like CNN.

Following feature extraction, a classification method is applied to the resultant features. The labelled dataset is used to train the classification algorithm by teaching it how to translate input characteristics to output labels. Cross-validation is used during training to optimize the classification algorithm's hyperparameters. The efficiency of the model is evaluated using established industry metrics, which encompass recall, precision, accuracy, and F1 score. Lastly, predictions may be generated based on fresh, unexplored data using the trained model. To get the anticipated output labels, this can entail pre-processing the input data, extracting the features, and running them through the trained classifier.

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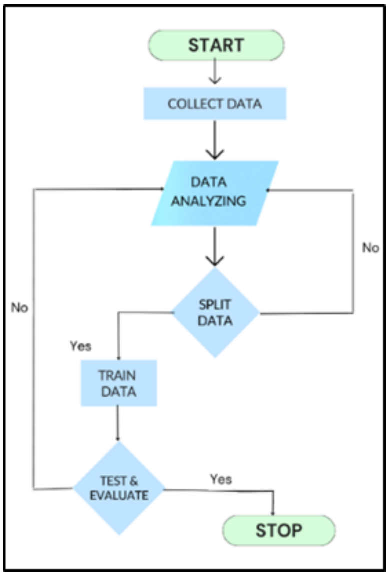

Figure 1. Steps involved in the proposed architecture

Fig.2 illustrates the architecture applied in the CNN model.

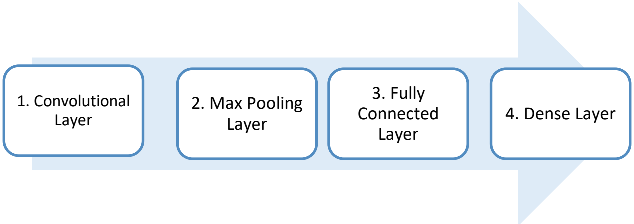

Figure 2. CNN Architecture

Fig.3 illustrates the architecture applied in DenseNet169 model.

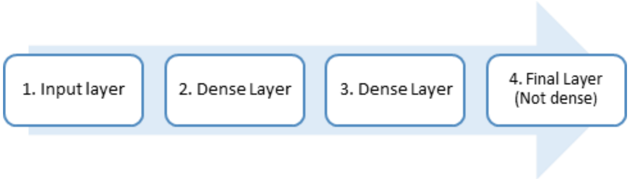

Figure 3. DenseNet169 Architecture

4. METHODOLOGY

In the study, three different datasets are used. One contains brain MRI scan images in Axial orientation, the second one contains brain MRI scan images in Sagittal orientation and the third one contains healthy brain MRI images. The total images in the dataset are around 3000 and approximately 50MB in size. To use the images in the dataset, the folder containing the images are zipped and uploaded to the google drive, and later this zip file is accessed and the images are loaded into the working environment in the Google Colab by mounting the drive. Data augmentation and image resizing are carried out during data pre-processing.

Libraries such as NumPy, Pandas, and sklearn are imported into the proposed model. The dataset is subdivided into 20% “testing data” and 80% “training data” using the “train test split()” procedure. There are 3000 images for training, 1023 images for validation in each training and testing set, and 1279 testing images in each testing set. The following algorithms are used in the proposed work.

4.1. Convolutional Neural Network

CNN refers to a specialized network architecture that is tailored for deep learning algorithms and is typically employed for applications involving image recognition and pixel data processing. Conv2D is a 2D convolution layer and applying sliding convolutional filters to 2-D input is its function. The input is convolved by relocating the filters across the input vertically and horizontally, generating the dot product of the weights and the input and then adds a bias term. Max Pooling is a convolution process where the greatest value of the area it convolves is selected by the kernel. This preserves the most important attributes of the feature map. Dropout is a training method in which a subset of neurons is ignored at random. Flattening is converting the data into a 1-dimensional array for inputting it to the next layer. The result is a long vector of input data which is passed for classification. Dense layer is a layer that is strongly linked with its antecedent layer. This layer is used quite frequently used in neural networks.

Algorithm

•Dataset is uploaded on Google drive in the form of a zip folder, and while it is mounted, permission to access is granted.

• Zip folder is unzipped.

• Libraries such as numpy, keras, tensorflow, and seaborn are imported.

• The number of images in each class i.e., 'Control-Axial', 'Control-Sagittal', 'healthy' are displayed.

• Images in the dataset are labelled.

• Training and testing datasets have been separated from the dataset.

• Functions including Conv2D, MaxPooling2D, Dropout, Flatten and Dense are applied.

• Optimizer such as RMSprop is used.

• The Confusion matrix, Accuracy and Classification report are generated.

• Finally, the model is saved.

4.2. DenseNet169

DenseNet-169 has been chosen because it adequately handles the disappear gradient problem. Convolutional layers, maxpool layers, dense layers (completely linked layers), and transition layers are all part of the architecture. The model utilizes the ReLU activation function for the entirety of the construction process, except for the final layer, which implements SoftMax activation. The stochastic gradient descent extension known as Adam optimizer can be used in a variety of deep learning applications. For multi-class classification models with two or more output labels, categorical cross entropy is used as a loss function.

Process

• Convolution Layer: The output of repeatedly applying the filter to an input is a feature map that shows the strength of the found features at various locations within the input.

• Feature map is passed through activation function such as ReLU. ReLU activation is employed in all except the last layer.

• The MaxPool layer summarizes the features in the area that the pooling filter covers by applying a filter to the feature map.

• Dense layer: Every neuron in the dense layer is linked to every last neuron in the former layer.

• Transition Layer: CNN uses a transition layer to simplify the model.

• SoftMax function: The term softmax represents a smooth version of the activation function. The unit which has maximum input has output of 1 while the additional units have output 0.

5. RESULTS

The models' performance is assessed using the following set of parameters:

- Accuracy
- Precision
- Recall
- F1-score
- Support

Accuracy can be calculated as total correctly predicted values to the actual values. Precision represents what number of positive detections are correct. Precision is 1.0 if a model produces no false positives. Recall represents if the identified actual positives are correct. If recall is 1.0, then no false negatives are produced. Harmonic mean of the Precision and Recall computes the F1-score. A good F1-score would also indicate good Precision and a good Recall value. Support is the number of genuine instances of the class in the specified dataset. In Scikit-learn, the sklearn. Metrics module calculates the Accuracy, Precision and Recall parameters.

Epochs are the total number of iterations the dataset is put through. Batch size is the number of training examples in one forward/backward pass. The higher the batch size, the more memory space needed.

Fig.4 illustrates "the confusion matrix" obtained for the CNN model. It has been observed that 600 images are correctly classified as Control Axial, 599 images as Control Sagittal and 600 as healthy brain images.

Figure 4. Confusion matrix of CNN model

Fig.5 represents the classification report of the CNN with an accuracy of 0.9841.

Classification Report

	precision	recall	f1-score	support
0	1.00	1.00	1.00	600
1	1.00	1.00	1.00	600
2	1.00	1.00	1.00	600
accuracy			1.00	1800
macro avg	1.00	1.00	1.00	1800
weighted avg	1.00	1.00	1.00	1800

Figure 5. Classification model of CNN model

Fig.6 illustrates "the confusion matrix" obtained for DenseNet169 model. The observation is that, 301 images are correctly classified as Control Axial, 296 images as Control Sagittal and 299 as healthy brain images.

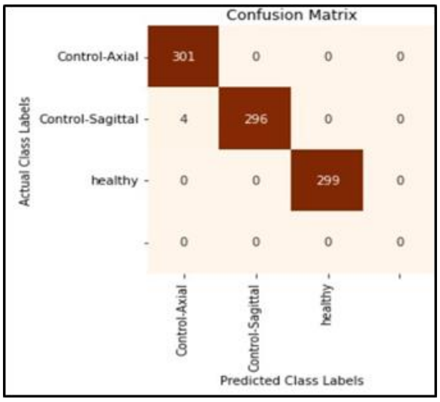

Figure 6. Confusion matrix of DenseNet169 model

Fig.7 presents the classification report of DenseNet169 with an accuracy of 0.9974.

	precision	recall	f1-score	support
Control-Axial	0.99	1.00	0.99	301
Control-Sagittal	1.00	0.99	0.99	300
healthy	1.00	1.00	1.00	299
micro avg	1.00	1.00	1.00	900
macro avg	0.75	0.75	0.75	900
weighted avg	1.00	1.00	1.00	900

Figure 7. Classification model of DenseNet169

As per the accuracy values observed from the two matrices, the conclusion is that CNN has better accuracy compared to DenseNet169.

6. CONCLUSION

In conclusion, this study has demonstrated the effectiveness of using Convolutional Neural Networks (CNNs) and specifically DenseNet 169 in identifying Multiple Sclerosis (MS) lesions in MRI scans. The results show that the proposed approach achieved high accuracy and outperformed other models previously used for this task. The use of transfer learning with pre-trained models like DenseNet169 has significantly improved the model’s performance. The model is trained as well as validated using a substantial dataset of MRI scans from MS patients, and the results indicate that this technique could be employed in clinical settings for early diagnosis and monitoring of MS lesions. Deep learning algorithms in medical imaging have huge promise for increasing diagnostic accuracy and speed, resulting in better patient outcomes. Overall, the findings of the work show that deep learning models may be used to detect MS lesions in MRI images and open a way for further research in this field.

7. BENEFITS

The accuracy of recognizing MS in MRI scan pictures can be greatly increased by using CNN and DenseNet169. These deep learning models can identify MS lesions with a high degree of accuracy since they are built to discover patterns in vast datasets. These models allow medical professionals and radiologists to diagnose MS more quickly and effectively. This may result in earlier treatment and better patient outcomes. The possibility of human errors in MS diagnosis can be decreased by using deep learning models. Large datasets used to train the models allow to precisely detect lesions that a human eye could miss. It is a helpful tool for medical professionals in a variety of sectors because the CNN and DenseNet169 approach is easily adaptable to other medical imaging applications.

8. FUTURE DEVELOPMENTS

Future study may combine additional imaging techniques such as Computed Tomography and Positron Emission Tomography to improve MS diagnostic accuracy. The current study employed solely MRI images to identify MS lesions. Deep learning models used in real-time MS diagnosis can greatly enhance patient outcomes. Future studies might concentrate on creating algorithms that can instantly detect MS and provide treatment. Using augmented reality, it is possible to see MS lesions in three dimensions, improving one's comprehension of the condition. Future studies might concentrate on combining deep learning models with augmented reality technology to better diagnose and treat MS.

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