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Research Article

A Novel Approach Using Deep Convolutional Neural Networks for Automated Dementia Detection and Classification

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ABSTRACT

Dementia, defined by gradual cognitive impairment affecting memory, thinking, and everyday functioning, offers considerable problems in early diagnosis and treatment. This paper offers a unique strategy leveraging deep convolutional neural networks (CNNs) for automated dementia identification and classification. CNNs specialize at learning detailed patterns from medical pictures, seeking to boost diagnostic accuracy and efficiency. The research relies on training a CNN architecture especially tuned for dementia classification utilizing a selected dataset of brain pictures. Transfer learning using a pre-trained CNN model fine-tunes it to distinguish minor neurological signals indicative of distinct dementia stages. The model undergoes training and validation on a varied dataset comprising classes such as Misdemeaned, Moderate Demented, Non-Demented, and Very Mild Demented, assuring strong performance across different degrees of dementia severity. In practical application, users may submit brain scan pictures via a web interface.

1. INTRODUCTION

Dementia is a frequent and devastating disorder characterized by gradual cognitive decline that impairs memory, thinking, and everyday functioning. As the global population ages, the prevalence of dementia continues to climb, posing considerable problems to healthcare systems globally [1]-[3]. Early and correct identification of dementia is critical for appropriate intervention and care, although existing diagnostic procedures generally depend significantly on subjective assessments and clinical evaluations, which may be prone to unpredictability and subjectivity [4]-[7]. Recent breakthroughs in artificial intelligence (AI) and machine learning (ML) have offered new options for strengthening medical diagnostics, notably in the area of neurology [8]-[9]. Deep learning, a type of ML, has shown amazing promise in processing complicated medical data, including neuroimaging scans [9]-[11].

Convolutional neural networks (CNNs), a strong family of deep learning models, excel at learning hierarchical representations directly from picture data, making them well-suited for tasks such as image classification and pattern recognition. This work suggests a unique strategy leveraging CNNs for automated dementia identification and categorization. By utilizing CNNs' capacity to extract complex information from brain scan pictures, our approach intends to enhance the accuracy, efficiency, and objectivity of dementia diagnosis [12].

Traditional approaches frequently depend on qualitative interpretations of brain imaging by radiologists or neurologists, which may be time-consuming and prone to human error. In contrast, CNNs may autonomously learn and recognize tiny patterns suggestive of various stages of dementia, hence possibly minimizing diagnostic delays and increasing patient outcomes. The foundation of our research is training a CNN architecture using a well selected collection of brain pictures gathered from multiple clinical sources.

2. LITERATURE REVIEW

This research presented in [1] the applicability of CNNs for automated dementia detection using neuroimaging data. The authors train and analyze different CNN architectures on a dataset of MRI images, demonstrating good accuracy in diagnosing dementia stages. They explore the potential clinical implications of automated diagnostic tools in enhancing early detection and treatment results.

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The review article [2] analyzes current improvements in deep learning methods, notably CNNs, for dementia classification. It highlights several CNN architectures employed, dataset features, and performance measures published in recent research. The report also examines problems and future approaches in harnessing AI for improved dementia diagnosis and treatment.
The paper [3] presents a transfer learning paradigm employing CNNs pretrained on large-scale picture datasets for dementia identification. The authors exhibit considerable increases in classification accuracy and resilience by fine-tuning pre-trained models on a particular dementia dataset. They show the efficiency of transfer learning in overcoming restricted labeled data availability in medical imaging tasks.
Thorough research [4] investigates the role of deep learning algorithms, particularly CNNs, in boosting dementia diagnosis using neuroimaging analysis. The authors address multiple CNN architectures applied, picture preparation approaches, and comparative examination of performance across different dementia stages. The report also offers future research objectives to solve present constraints and increase diagnosis accuracy.
The research studies [5] the use of CNNs for automated diagnosis of moderate cognitive impairment (MCI) and Alzheimer's disease (AD). The authors offer a CNN model trained on a huge dataset of MRI images, providing accurate categorization of illness stages. They underline the promise of CNN-based systems in early identification and monitoring of neurodegenerative disorders.
The performance of multiple CNN designs, including ResNet, VGG, and DenseNet, for dementia detection using MRI data is presented in [6]. The authors analyze model accuracy, sensitivity, and specificity across several dementia stages, emphasizing the merits and shortcomings of each design in clinical applications. The research [7] examines the performance of multiple CNN designs, including ResNet, VGG, and DenseNet, for dementia detection using MRI data. The authors analyze model accuracy, sensitivity, and specificity across several dementia stages, emphasizing the merits and shortcomings of each design in clinical applications.

3. PROBLEM STATEMENT

Current approaches for diagnosing dementia depend mainly on subjective evaluations and may be prone to unpredictability and inaccuracy. There is a significant need for more objective and reliable diagnostic tools that can evaluate brain scan pictures effectively. Manual interpretation by healthcare providers is time-consuming and may postpone important measures. This study intends to overcome these problems by constructing a deep learning-based system employing CNN to automate dementia diagnosis and classification from brain scans.

4. METHODOLOGY

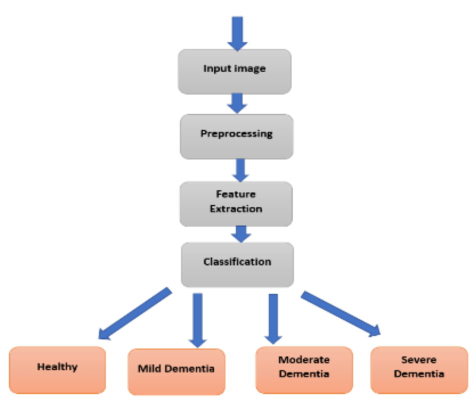

Fig: 1 Proposed Architecture of Dementia Detection

From the picture 1, the dementia detection system starts with input neuroimaging datasets, collected from sources like Kaggle, consisting of MRI recording different brain situations (healthy, mild dementia, moderate dementia, and severe dementia). Preprocessing phases comprise picture enhancement and normalization procedures to normalize images for consistent analysis. Convolutional Neural Networks (CNNs) are applied for automated feature extraction, recognizing complicated patterns and structures within the brain scans without human involvement. The heart of the system resides in the classification phase, when the CNN examines the collected data to categorize patients into one of the four dementia stages: Healthy, Mild Dementia, Moderate Dementia, or Severe Dementia.

Obtain the dementia dataset from Kaggle, ensuring it contains a range of brain scan pictures labelled with various dementia stages (MildDemented, ModerateDemented, NonDemented, VeryMildDemented). Preprocess the dataset by standardizing picture sizes, converting to RGB format if required, and using normalization methods to assist model training. Choose an appropriate deep learning architecture for image classification, such as ResNet18, pretrained on ImageNet for transfer learning advantages. Fine-tune the chosen model on the dementia dataset to fit it to the unique features of brain scan pictures linked with dementia stages. Implement training processes using PyTorch, optimizing hyperparameters and applying strategies like data augmentation to increase model generalization [11].
Set up a Flask framework to construct a web-based application for dementia diagnosis. Design and develop user interfaces including upload capabilities for brain scan photos and outcome display sites. Integrate backend features to preprocess input photos, feed them into the trained CNN model, and return predictions on dementia stages.

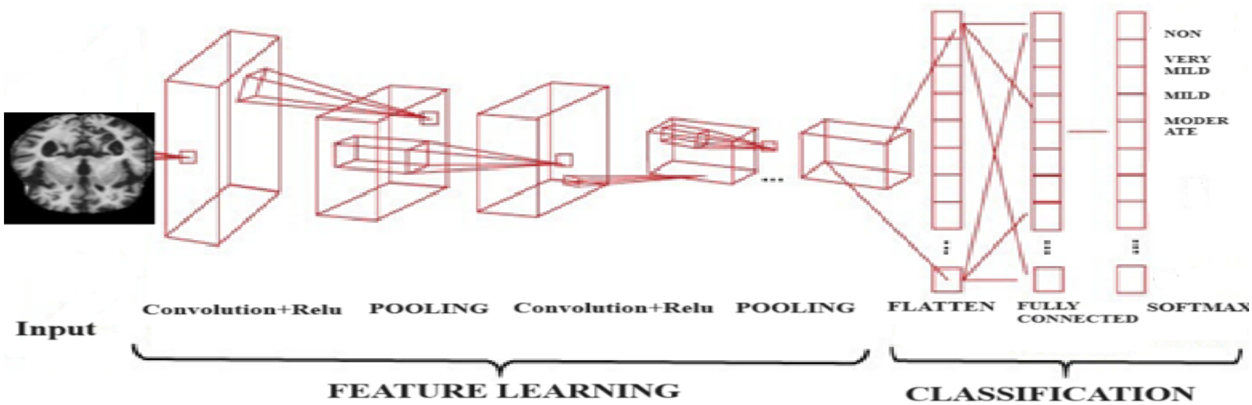

Fig 2: CNN Architecture.

Convolutional Neural Network is one of the main categories to do image classification and image recognition in neural networks. Scene labelling, object detection, and face recognition, etc., are some of the areas where convolutional neural networks are widely used. CNN takes an image as input, which is classified and processed under a certain category, such as dog, cat, lion, tiger, etc. The computer sees an image as an array of pixels and depends on the resolution of the image. Based on image resolution, it will appear as h w d, where h = height, w = width, and d = dimension. For example, an RGB image is 6 6 3 array of the matrix, and the grayscale image is 4 4 1 array of the matrix. In CNN, each input image will pass through a sequence of convolution layers along with pooling, fully connected layers, and filters (also known as kernels). After that, we will apply the softmax function to classify an object with probabilistic values 0 and 1.

Convolution Layer :

The convolution layer is the first layer to extract features from an input image. By learning image features using a small square of input data, the convolutional layer preserves the relationship between pixels. It is a mathematical operation that takes two inputs, such as an image matrix and a kernel or filter.

- The dimension of the image matrix is h..
- The dimension of the filter is FHD.
- The dimension of the output is (h-fh+1)(w-fw+1).

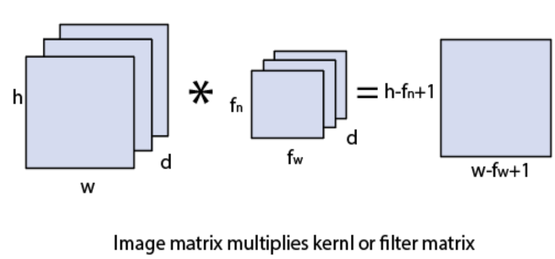

Fig 3: Working of Operation of Convolution

A sample-based discretization method is called max pooling. Its primary goal is to downscale an input representation in order to lower its dimensionality and enable assumptions to be made about the features present in the bound sub region. Applying a max filter to non-overlapping subregions of the original representation is how max pooling is carried out.

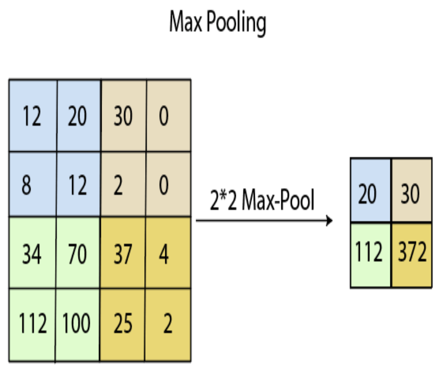

Fig 3: Pooling Layer

5. RESULTS AND DISCUSSIONS

The proposed model aims to assist in the early detection of dementia. The development process utilizes Python, with Visual Studio Code Notebook chosen for its ability to facilitate code execution and review within each cell. Additionally, Visual Studio Code supports the visual display of graphs and results, enhancing the presentation. MRI scans from individuals with and without dementia were used in the analysis. Below is an example diagnosis result for a dementia patient. Our model is also capable of assessing both the presence and absence of dementia. The initial step involved selecting the series of MRI scans to be analyzed.

Nondemented Very Mild Demented MildD emended Moderate Demented

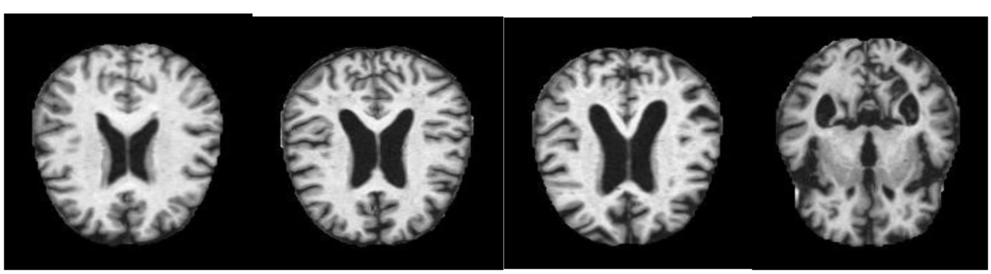

Fig 4: Classification of the Stages of dementia

In Figure 4, you can observe some of the MRI scan images utilized for training the model. This model categorizes the images into non-dementia, Very Mild dementia, Mild dementia, and Moderate dementia, and also predicts disease stages with accuracy metrics for confirmation. Accuracy calculations and predictions are displayed based on a predefined batch size in the code. The training of the model progresses step by step. Figure 5 illustrates the training and validation loss, as well as the accuracy throughout the training process.

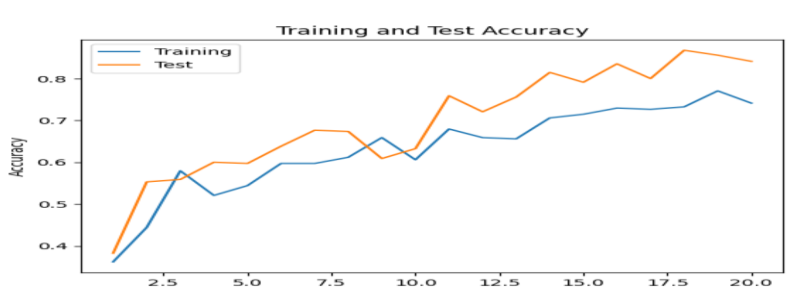

Fig 5: Model Training

Upon completing the model training, we need to test it to determine if its accuracy the accuracy of this model is 84.12 %.

6. CONCLUSION

This study has successfully built an automated dementia diagnosis method utilizing Convolutional Neural Networks (CNNs) applied to MRI data. The CNNs were taught to identify dementia stages—healthy, mild, moderate, and VeryMild based on neuroimaging data, attaining great accuracy in diagnosis. The relevance of this system resides in its capacity to expedite and optimize the diagnostic process, delivering rapid and accurate evaluations important for early intervention and patient care. The tools and apps produced include a powerful CNN model trained on a dataset acquired from sites like Kaggle, assuring complete coverage of dementia phases and trustworthy classification outputs. This system's significance is clear in its ability to aid healthcare workers by minimizing diagnostic mistakes, optimizing treatment planning, and boosting patient outcomes via early diagnosis. Compared to current approaches such as manual feature extraction and classic machine learning algorithms like SVMs, the CNN-based approach delivers improved performance in feature learning and classification accuracy. Future initiatives for the study include increasing the dataset to cover more varied populations and upgrading the CNN architecture to handle bigger datasets effectively. Integration with cloud-based systems for real-time diagnosis and cooperation among medical specialists is also envisioned to boost scalability and accessibility. Overall, this initiative represents a big step towards harnessing AI in healthcare for better dementia diagnosis and treatment.

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Conflicts of Interest:

The authors declare that there are no conflicts of interest regarding this publication.

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