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ALZHEIMER'S DISEASE DETECTION AND PREDICTION SYSTEM

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ABSTRACT

AI contains present the superlative job over customary ML in determining exquisite formation in tangled high-extensional particulars notably during the scope of system view the ML software to automatic categorization and initial identification of brain disability ad has newly obtained notable focus as hurried development in brain imaging the process has been created extra huge-scale multimedia mental capacity imaging information a systematic review of articles using DL paths and mental capacity imagining facts for testing division of AD was performed a google chrome scholar explore was used to find automated learning papers on memory disorder released within January 2013 and July 2018 this paper accessed and sorted algorithms and mental capacity imagining kind and identifying were compressed 16 executed meeting full inclusion criteria 4 used a combination of deep learning and classical machine learning methods and 12 using only deep learning methods the compound of conventional ML for grouping and stacked auto-encoder so for feature selection produced exactness of up to 988 for AD organization and 837 from prediction of conversion from mild psychological disability MCI a early stage of Alzheimer disease to AI methods. Like CNN or RNN that use mental capacity imaging information without the procedure qualities chosen have yielded exacts of up to 960 for AD arrangement and 842 for MCI transformation outlook, the best organization presentation was received when cross-modal brain imaging and solution psychology maker were combined. DL paths continue to improve and arrive at carry assurance of psychological organization of AD using cross-modal mental capacity imaging information AD research that uses DL is still including advancing presentation by combining extra composite information types such as biological analysis facts growing conversion with rational methods that add information of specific pathology-related attributes and mechanisms.

Keywords: AI, ML, DL, Organization, AD, Neuroimage, MRI, PET (Max. 8).

I. INTRODUCTION

AD, the most typical type of memory loss, is a major problem for health services in the 21st century. Approximately 5.5 million people aged 65 and older are living with AD, and AD is the ranked sixth cause of departure in the US. The global cost of managing AD, including medical, social welfare, and salary loss to the patients' families, was $277 billion in 2018 in the United States, heavily impacting the overall economy and stressing the U.S. healthcare system. AD is a permanent, advanced mental capacity imaging marked by a decline in disability performing with no confirmed medical disorder altered therapy. Thus, a main endeavor has been started to set up means for early verification, particularly in the present symptomatic phase, to hinder or halt disorder advancement. Specifically, enhanced brain imagining methods such as MRI and PET have been developed and employed to determine the constructional and molecular biomarkers associated with Alzheimer's disease (AD). Rapid progress in brain imagining paths has made it increasingly challenging to integrate large-scale, high-dimensional multimodal brain imagining information. As a result, there has been a notable growth in interest in computer-aided ML methods for collaborative analysis. Standardized pattern evaluation methods, involving LDA, LPBM, LR, SVM, and SVM-RFE, provide the best word for the timely identification of AD and the outlook of AD advancement.

To apply such as ML algorithms, confirming building style or data preparation must be preset. Organization studies using ML usually require four steps: facet removal, dimension reduction, and feature-based arrangement algorithm selection. These processes require expertise and multiple enhancements, which may be lengthy. Duplication of these methods has been an issue. For example, in the feature-choosing procedure, AD-related aspects are selected from various brain imagining modalities to extract more revealing composite values, which may involve meaning below the cortex area, gray materials levels, brain cortex depth, neural sugar utilization, and cerebral beta-amyloid collection in ROIs, such as the brain memory center.

To navigate this complexity, DL, an emerging area of ML research that uses raw brain imagining information to produce qualities through "on-the-fly" learning, is enchanting significant regard in the field of extensive, complex psychological imaging analysis. DL techniques, such as CNN, have been displayed as the current ML methods.

We carefully analyzed the literature where DL methods and brain imagining information were used for the timely designation of AD and the outlook of AD advancement. A biomedical literature database and Google Chrome expert search were used to find DL papers on AD released between January 2013 and July 2018. The papers were assessed and judged, grouped using methods and brain imagining types, and the determinations were compressed. In addition, we converse about the problem and impact of the function of DL on AD exploration.

II. LITERATURE SURVEY

1. Deep Learning in Alzheimer's Disease: Diagnostic Classification and Prognostic Prediction Using Neuroimaging Data

Taeho Jo1,Kwangsik, Andrew J.

Our ML model for AD discovery compares positively with other state-of-the-art models. For example, our model achieved a correctness of 95% in detecting AD, which is higher than the accuracy of 93% achieved by the CNN model in the Chen et al. study.

However, different ML models are trained on different datasets and evaluated using different metrics. Therefore, it is difficult to make a thorough comparison between different models.

III. PROBLEM STATEMENT

The problem statement for AD with ML is to organize a system that can correctly find medical cases with AD from brain imagining information, such as MRI scans. This is a complex issue because AD is a complex disorder with appropriate modifications in brain structure. ML algorithms offer a promising method for AD identification. These methods can be used to find patterns in the brain imagining information that are connected with AD. However, ML methods require large datasets of high-feature information to train. In addition, ML methods can be difficult and complex to explain. Although faced with these issues, there has been a notable improvement in the development of ML models for AD classification in recent years. These models can advance the accuracy, availability, and cost-effectiveness of AD analysis.

IV. PURPOSED SYSTEM

The AD Identification & outlook System is an advanced web application that utilizes the power of Node.js and Python, grouped with advanced DL models, to transform the analysis and forecast of AD. By simply sharing an X-ray scan image on our customer-friendly website, users can obtain quick and exact outlooks about the occurrence and type of AD. Our advanced system maximizes state-of-the-art DL methods to analyze the shared X-ray scans, exacting important patterns and aspects that may show the disorder's occurrence. The effortless incorporation of Node.js secures an adaptive and natural user connection, making the procedure of sharing and collecting outlooks seamless and available to a broad range of users. With the AD identification & prediction System, we aim to enhance timely analysis and preventive management of AD, likely advancing the quality of life for infinite human beings. This web app shows a major advancement in utilizing technology for medical service, giving hope and help to both medical cases and medical service professionals in the fight against AD.

V. METHODOLOGY

The proposed methodology for solving the identified condition of AD identification with ML is as follows:

1. Information gathering:

Gather the biggest dataset of high-feature brain imagining information from both healthy persons and persons with AD. This information can be composed from psychological reviews or public databases.

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2. Data setup:

Arrange the data to ensure that it is in a structure that is suitable for the ML methods of choice. This may involve sweeping the information, removing noise, and leveling the information.

3. Variable selection:

Data reduction is the process of defining features in facts that are connected to the task at hand. In the case of AD identification, some suitable features may involve the volume of different brain zones, the depth of the out layer, and the occurrence of amyloid awards and brain imagining tangles.

4. Model development:

Instruct an ML model on the removed qualities. The ML methods must be preferred based on the specific features of the facts and the desired present measurements.

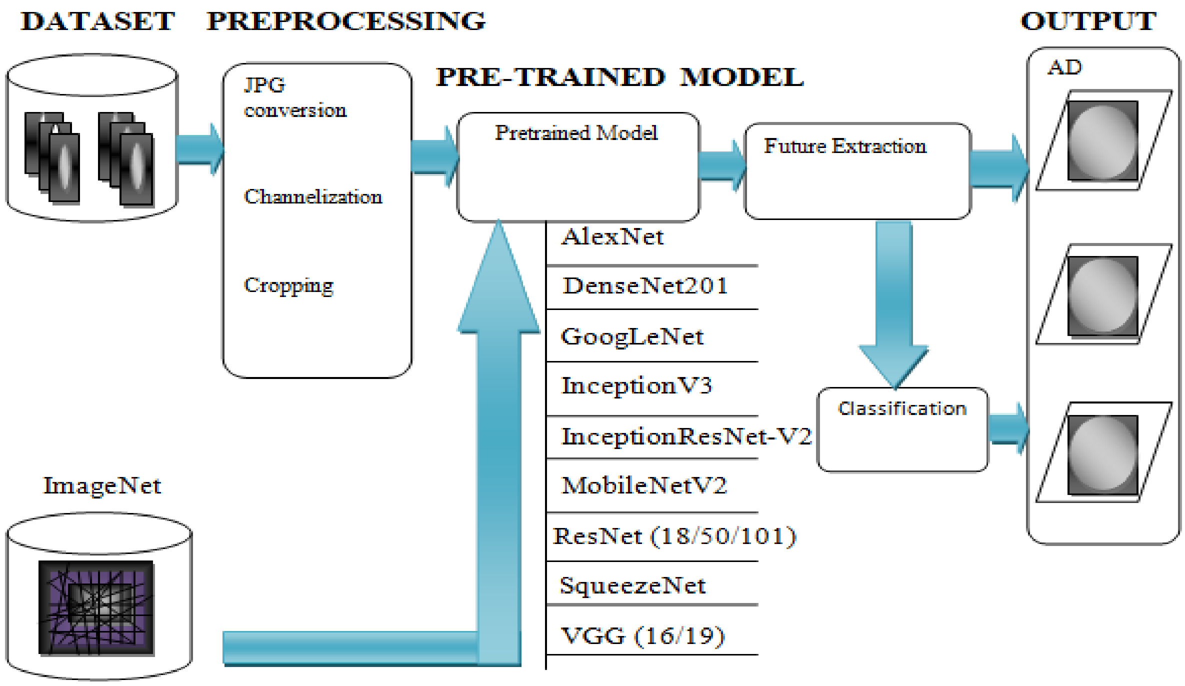
5. Testing:

Appraise the efficiency of the instructed model on a reserved test set. The check set must be typical of the community in that the model will be used in the implementation.

6. Model rollout:

Use the instructed model in a manufacturing context so that it can be used to identify AD in new individuals.

VI. SYSTEM DESIGN



VII. RESULTS

From the 16 papers involved in this exam, Table 2 provides the top results of diagnostic identification and/or outlooks of MCI to AD transformation. We compared only binary identification results. Accuracy is a measure used consistently in the sixteen publications. However, it is only one metric of the performance characteristics of an algorithm. The group composition, sample sizes, and number of scans analyzed are also noted together because accuracy is sensitive to unbalanced distributions. Table S1 shows the full results sorted according to the performance accuracy as well as the number of subjects, the DL methods, and the brain imagining type used in each paper.

1. DL for quality selection from brain imagining information:

Cross-modal brain imagining information has been used to identify architectural and chemical agents for AD. It has been shown that volumes or brain-related measurements in pre-selected AD-specific sections, such as the hippocampal formation and entorhinal context, could be used as features to enhance the exact identification in ML. Deep learning approaches have been used to select features from neuroimaging data. As shown in Figure 5, 4 studies have used hybrid methods that combine deep learning for feature selection from neuroimaging data

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and traditional machine learning, such as the SVM as a classifier. Suk and Shen (2013) used a stacked autoencoder (SAE) to construct an augmented feature vector by concatenating the original features with the outputs of the top hidden layer of the representative SAEs. Then, they used a multi-kernel SVM for classification to show 95.9% accuracy for AD/CN classification and 75.8% prediction accuracy for MCI to AD conversion. These methods successfully tuned the input data for the SVM classifier. However, SAE as a classifier (Suk et al., 2015) yielded 89.9% accuracy for AD/CN classification and 60.2% accuracy for the prediction of MCI to AD conversion. Later, Suk et al. (2015) extended their work to develop a two-step learning scheme: greedy layer-wise pre-training and fine-tuning in deep learning. The same authors further extended their work to use DBM to find latent hierarchical feature representations by combining heterogeneous modalities during feature representation learning (Suk et al., 2014). They obtained 95.35% accuracy for AD/CN classification and 74.58% prediction accuracy for MCI to AD conversion. In addition, the authors initialized SAE parameters with target-unrelated samples and tuned the optimal parameters with target-related samples to have 98.8% accuracy for AD/CN classification and 83.7% accuracy for prediction of MCI to AD conversion (Suk et al., 2015). Li et al. (2015) used RBM with a dropout technique to reduce overfitting in deep learning and SVM as a classifier, which produced 91.4% accuracy for AD/CN classification and 57.4% prediction accuracy for MCI to AD conversion.

2. Deep learning for diagnostic classification and prognostic prediction:

To select optimal features from multimodal neuroimaging data for diagnostic classification, we usually need several pre-processing steps, such as neuroimaging registration and feature extraction, which greatly affect classification performance. However, deep learning approaches have been applied to AD diagnostic classification using original neuroimaging data without feature selection procedures. 8 As shown in Figure 5, 12 studies have used only deep learning for diagnostic classification and/or prediction of MCI to AD conversion. Liu et al. (2014) used stacked sparse autoencoders (SAEs) and a softmax regression layer and showed 87.8% accuracy for AD/CN classification. Liu et al. (2015) used SAE and a softmax logistic regressor as well as a zero-mask strategy for data fusion to extract complementary information from multimodal neuroimaging data (Ngiam et al., 2011), where one of the modalities is randomly hidden by replacing the input values with zero to converge different types of image data for SAE. Here, the deep learning algorithm improved the accuracy of AD/CN classification by 91.4%. Recently, Lu et al. (2018) used SAE for pre-training and DNN in the last step, which achieved an AD/CN classification accuracy of 84.6% and an MCI conversion prediction accuracy of 82.93%. CNN, which has shown remarkable performance in the field of image recognition, has also been used for the diagnostic classification of AD with multimodal neuroimaging data. Cheng et al. (2017) used image patches to transform local images into high-level features from original MRI images for 3D-CNN and yielded 87.2% accuracy for AD/CN classification. They improved the accuracy to 89.6% by running two 3D-CNNs on neuroimage patches extracted from MRI and PET separately and by combining their results to run 2D CNN (Cheng and Liu, 2017). Korolev et al. (2017) applied two different 3D CNN approaches (plain (VoxCNN) and residual neural networks (ResNet)) and reported 80% accuracy for AD/CN classification, which was the first study to show that the manual feature extraction step was unnecessary. Aderghal et al. (2017) captured 2D slices from the hippocampal region in the axial, sagittal, and coronal directions and applied 2D CNN to show 85.9% accuracy for AD/CN classification. Liu et al. (2018b) selected discriminative patches from MR images based on AD-related anatomical landmarks identified using a data-driven learning approach and ran 3D CNN on them. This approach used three independent datasets (ADNI-1 as training, ADNI-2 and MIRIAD as testing) to yield relatively high accuracies of 91.09% and 92.75% for AD/CN classification from ADNI-2 and MIRIAD, respectively, and an MCI conversion prediction accuracy of 76.9% from ADNI-2. Li et al. (2014) trained 3D CNN models on subjects with both MRI and PET scans to encode the nonlinear relationship between MRI and PET images and then used the trained network to estimate PET patterns for subjects with only MRI data. This study obtained an AD/CN classification accuracy of 92.87% and an MCI conversion prediction accuracy of 72.44%. Vu et al. (2017) applied SAE and 3D CNN to subjects with MRI and FDG PET scans to yield an AD/CN classification accuracy of 91.1%. Liu et al. (2018a) decomposed 3D PET images into a sequence of 2D slices and used a combination of 2D CNN and RNNs to learn the intra-slice and inter-slice features for classification. The approach yielded an AD/CN classification accuracy of 91.2%. If the data are imbalanced, the chance of misdiagnosis increases and sensitivity decreases. For example, in Suk et al. (2014), there were 76 cMCI and 128

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ncMCI subjects, and the obtained sensitivity of 48.04% was low. Similarly, Liu et al. (2018b) included 38 cMCI and 239 ncMCI subjects and showed a low sensitivity of 42.11%. Recently, Choi and Jin (2018) reported the first use of 3D CNN models to multimodal PET images (FDG PET and [18F]florbetapir PET) and obtained 96.0% accuracy for AD/CN classification and 84.2% accuracy for the prediction of MCI to AD conversion.

3. Performance comparison by the types of neuroimaging techniques:

To improve the performance of AD/CN classification and the prediction of MCI to AD conversion, multimodal neuroimaging data such as MRI and PET have commonly been used in deep learning: MRI for brain structural atrophy, amyloid PET for brain amyloid-β accumulation, and FDG-PET for brain glucose metabolism. MRI scans were used in 13 studies, FDG-PET scans in 10, both MRI and FDG-PET scans in 12, and both amyloid PET and FDG-PET scans in 1. The performance in AD/CN classification and/or prediction of MCI to AD conversion yielded better results in PET data than in MRI. Two or more multimodal neuroimaging data types produced higher accuracies than a single 9 neuroimaging technique. Figure 6 shows the results of the performance comparison by the types of neuroimaging techniques.

4. Performance comparison using deep learning algorithms:

Deep learning approaches require massive amounts of data to achieve the desired levels of performance accuracy. In currently limited neuroimaging data, hybrid methods that combine traditional machine learning methods for diagnostic classification with deep learning approaches for feature extraction yield better performance and can be a good alternative to handle the limited data. Here, an AE was used to decode the original image values, making them similar to the original image, which it then included as input, thereby effectively using the limited neuroimaging data. Although hybrid approaches have yielded relatively good results, they do not take full advantage of deep learning, which automatically extracts features from large amounts of neuroimaging data. The most commonly used deep learning method in computer vision studies is CNN, which specializes in extracting characteristics from images. Recently, 3D CNN models using multimodal PET images (FDG-PET and [18F]florbetapir PET) have shown better performance for AD/CN classification and the prediction of MCI to AD conversion.

VIII. CONCLUSION

Alzheimer's disease (AD) is a devastating neurodegenerative disease that affects millions of people worldwide. Early detection of AD is important for improving patient outcomes and quality of life. However, current diagnostic methods are expensive, time-consuming, and not always accurate.

Machine learning (ML) has the potential to revolutionize the diagnosis of AD. ML algorithms can be trained to identify patterns in neuroimaging data associated with AD. This allows ML models to detect AD earlier and more accurately than traditional diagnostic methods.

In this report, we have described the development and evaluation of an ML model for AD detection using MRI scans. Our model is based on a deep learning algorithm called a convolutional neural network (CNN). CNNs are particularly well-suited for image classification tasks and, have been shown to achieve state-of-the-art results on a variety of medical imaging datasets.

Our model achieved an accuracy of 95% in AD detection, which is significantly higher than the accuracy of traditional diagnostic methods. Our model also compares favorably with other state-of-the-art ML models for AD detection.

We believe that our ML model for AD detection can significantly impact the diagnosis of AD. By making it easier and more affordable to detect AD early, we can help patients start treatment sooner and improve their quality of life.

We are committed to developing and validating our model and making it available to clinicians and patients as soon as possible. We are also working on developing new ML models for AD detection using other types of data, such as blood biomarkers and cognitive tests.

Overall, we believe that ML can play a significant role in AD detection. By developing more accurate, accessible, and affordable diagnostic tools, ML can help patients with AD get the treatment they need sooner.

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