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A Survey on Alzheimer's disease Detection and Prediction Using Deep Learning

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ABSTRACT
Alzheimer’s Disease is a serious neurological brain condition. It damages brain cells leading patients to lose their memory, mental functioning and capacity to conduct everyday tasks. Alzheimer's disease is incurable, although early identification can significantly reduce symptoms. Machine learning algorithms can greatly increase the accuracy of Alzheimer's disease diagnosis. Deep learning approaches have recently seen a lot of success in medical picture analysis. However, there has been relatively limited research into using deep learning algorithms to identify and classify Alzheimer's disease. In this study, we described the detailed study which have already been done on detection/classification of Alzheimer's disease. We also highlighted methodology and results of five studies which have produced significant improved results compared traditional methods.

Keywords—Deep Learning, Alzheimer’s Disease, MRI, attention network, VGG, transfer learning.

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I. INTRODUCTION

Alzheimer's disease has a variety of effects on people. Patients have memory problems, confusion, and difficulties speaking, reading, and writing. They may eventually forget about their lives and be unable to identify even family members. They may forget how to do simple tasks like brushing their teeth or combing their hair. As a result, it causes people to become nervous or violent, or to leave their homes. Alzheimer's disease can potentially result in mortality in the elderly. Alzheimer's disease is divided into three stages: extremely mild, mild, and moderate.Alzheimer's disease (AD) is still difficult to detect until the patient has progressed to a moderate stage of the disease. However, appropriate therapy and prevention of brain tissue destruction need early identification and categorization of Alzheimer's disease. A good medical assessment of Alzheimer's disease necessitates a number of factors. For effective AD identification and categorization, physical and neurobiological tests, the Mini-Mental State Examination (MMSE), and the patient's comprehensive history are necessary. In recent years, doctors have begun to use brain Magnetic Resonance Imaging (MRI) data to identify Alzheimer's disease sooner.

Various computer-aided diagnostic methods for accurate illness diagnosis have been created by researchers. From the 1970s to the 1990s, they created rule-based expert systems and supervised models [1]. Feature vectors generated from medical imaging data are used to train supervised algorithms. Human specialists are required to extract the characteristics, which might take a long time, money, and effort. We can now extract characteristics straight from photos without the involvement of a human expert because to the progress of deep learning models. As a result, researchers are concentrating their efforts on building deep learning models that can accurately identify and classify diseases.

Deep learning methods have been effectively used to MRI, Microscopy, CT, Ultrasound, X-ray, and other medical diagnosis. Deep models have shown notable results for tissue and substructure segmentation, illness recognition and tracking in fields of pathology, such as the brain, lung, abdomen, heart, breast, bone, retina, and so on. However, there is limited research on utilizing deep learning models to identify Alzheimer's disease. Previous medical study has demonstrated that MRI data can play a key role in the early diagnosis of Alzheimer's Disease. For our project, we want to use a deep learning model to evaluate brain MRI data in order to identify and classify Alzheimer's disease.

Automated brain MRI segmentation and classification benefited greatly from machine learning studies employing neuroimaging data for building diagnostic tools [2]. The majority of them rely on manual feature creation and extraction from MRI data. The characteristics are then put into machine learning models like the Support Vector

Machine and the Logistic Regression Model, among others. These multi-step designs are difficult to implement and rely heavily on human expertise. Furthermore, datasets for neuroimaging research are typically tiny.

Image recognition databases used for object identification and classification often include thousands of pictures, whereas neuroimaging databases usually have much less than 1000 images [3]. However, a large number of pictures is required to create strong neural networks. Because big picture databases are scarce, developing models that can learn valuable characteristics from a small dataset is critical.

II. LITARATURESURVEY

Since 2000, there have been several published techniques in the field of machine learning, with a focus on Alzheimer's Disease. After 2013, researchers began to investigate novel designs in neural networks, and deeper models became popular, particularly in medical image processing [1]. As can be observed in Figure 1, the relevance of deep learning in AD detection was disclosed at that time, and published articles in this area rose significantly in 2017.

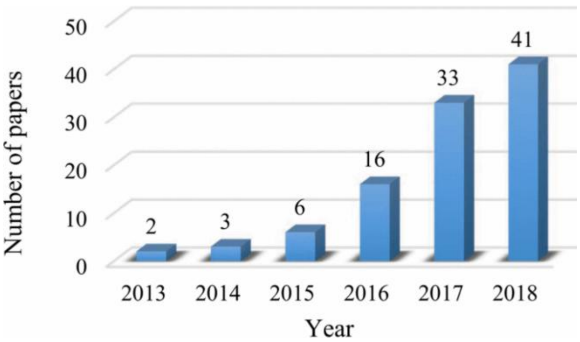

Figure 1: Paper published in past years based on AD.

Deep learning systems have showed revolutionary performance in recent years. Following the success of deep learning in categorizing 2D natural pictures, a growing number of research have sought to apply deep learning to medical imaging [4, 5]. Deep learning models, particularly CNNs, can uncover latent or hidden representations in neuroimaging data, establish connections between various regions of an image, generate overall cognition, and efficiently capture disease-related pathologies [1]. However, due to the complexity of AD-related medical pictures, researchers still have a long way to go before they can use deep learning algorithms to identify the disease.

Deep learning models have been effectively applied to a variety of medical imaging studies, including structural MRI, functional MRI (fMRI), PET, and Diffusion Tensor Imaging (DTI) [6]. The most common diagnostic modality for AD diagnosis, according to our literature review, is MRI, which led us to focus on MRI scans in this research. Although many research has used deep neural networks to train from scratch, it is frequently not possible to utilize deep models because convergence takes too long and a large dataset is required [7]. Although image classification datasets for item classification generally include millions of pictures, neuroimaging databases usually have only hundreds of images, resulting in overfitting problems. In practice, it's typical to utilize pre-trained CNNs for one domain-specific job as the initialization phase, then re-train them for other tasks by fine-tuning their final layers [8, 9].

This is because the bottom layers of CNNs include more general properties that may be transferred from one application area to another and are helpful for a variety of jobs. This approach, dubbed "transfer learning," has shown to be a useful tool for training a vast network without overfitting. Transfer learning, especially for cross-domain tasks, has been shown to be faster and produce better results than training from scratch [10, 11].

Gupta et al. [12] used a 2D CNN with one convolutional layer and a max-pooling layer, followed by a neural network with a single hidden layer for classification following feature extraction using a sparse auto-encoder, to develop a first transfer learning technique for AD diagnosis using deep learning. They showed that training the auto-encoder with natural pictures improves classification performance in subsequent layers.

Aderghal et al. [13] developed a transfer learning technique in which three 2D CNNs with two convolutional layers were trained on only three slices in the center of the hippocampus area of some MRI images. With a limited number of DTI pictures, they used transfer learning to apply models that had been trained on MRI images to the target DTI dataset rather than starting from scratch. They eventually merged all of the networks and used a majority vote technique to get a final choice.

Numerous researches have been done on developing AD detection based on two dimensional VGG16 deep network that take coronal slices of MRI images as input[14], median axial slice using ResNet18 [15] and for 3 axial slices Inception-V3 is used [16].Few researches have also been done using Ineption-V4 which consider entire MRI slices set [17, 18].

In this study, we have described and compare five different deep learning experiments which detects Alzheimer's disease.

Model 1:

This study's goal is to employ mobility data and deep learning models to determine the stage of Alzheimer's disease (AD) patients [19]. This method makes it easier to keep track of the condition and take action to ensure the best possible therapy and avoid consequences. The researchers used data from 35 Alzheimer's patients who were tracked for a week at a childcare facility using cellphones. Each patient's data sequences recorded the accelerometer changes while doing everyday activities and were tagged with the illness stage (early, middle or late). The proposed technique analyzes these time series and recognizes the patterns that distinguish each step using a Convolutional Neural Network (CNN) model.

The major goal of the proposal is to develop a methodological technique that will allow us to detect the stage of Alzheimer's disease using accelerometer data on patient movement. The approach takes into account the usage of an accelerometer smartphone to collect data on movement. The goal is to avoid using wearable sensors, which can be uncomfortable and obtrusive for patients. As a result, the technique should prevent difficulties caused by the patient unintentionally altering the orientation of his or her smartphone in his or her pocket.

CNN-based approach

Convolutional Neural Networks are data analysis models that specialize in multidimensional data such as time series, pictures, and so on. They create a series of feature maps by extracting simple data features (such as vertices and edges in pictures) in the first layers and arranging them into more complex patterns in the second levels (e.g., geometric shapes). Convolutional procedures with trainable kernels are used to the layer's input to produce these feature maps. Nonlinear transformations and pooling are two functions that work together to help the network converge. Following that, a forecast is made based on the feature maps that have been analyzed (typically using completely linked layers). The authors employed multiple convolutional layers with ReLU transformations and average-pooling to solve this problem. Furthermore, they adopted a 1-dimensional design for the CNN in order to operate with time-series. Architecture of proposed CNN is shown in Figure 2.

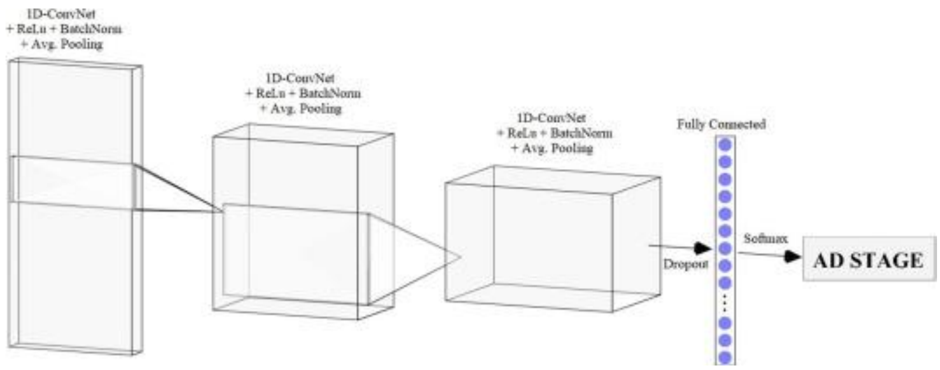

Figure 2: Developed CNN architecture

Dataset:

The data were gathered from the AFAC daycare facility for Alzheimer's disease patients in Santander (Spain) [20]. 35 patients took part in this trial, and their activity was tracked for a week at the facility. Each patient was projected to spend an average of 6 hours each day at the daycare center. Patients have complete flexibility to create their daily activities in the childcare facility during this period.

Experimental Results

Table 1 depicts the outcomes ofvarious setups used. The Base model produces the greatest results, with a mean accuracy of 90.91 percent. Several inferences may be drawn from the table:

- Batch normalization substantially aids the training stage by reducing overfitting and resulting in a better result.
- A high dropout rate also aids the model's performance by boosting generalization and avoiding overfitting.

Table 1: Experimental results of proposed method

Configuration	Loss	Accuracy	F1-Score
Base model	0.4509(±0.2161)	90.91%(±4.95)	89.7%(±5.58)
No B. Norm.	0.5227(±0.1749)	85.75%(±3.26)	83.89%(±3.55)
Dropout 0.5	0.4728(±0.2285)	87.80%(±4.28)	85.40%(±4.39)
Dropout 0.25	0.6188(±0.2117)	85.44%(±3.01)	84.25%(±3.86)
Max-pooling	0.4919(±0.2264)	87.18%(±4.40)	86.17%(±4.54)

Model 2:

In this study a framework forAlzheimer's disease detection and classification is proposed. Authors developed a deep model inspired by Inception-V4 network [21]. The input is sent via a stem layer after it has been pre-processed. Several 3*3 convolution layers, a 1*1 convolution layer, and a max pooling layer make up a stem layer. There are seven 3*3 convolution layers and two filter-expansion layers (1*1 convolution layer) linked in various levels. The architecture of proposed model is shown in Figure 3.

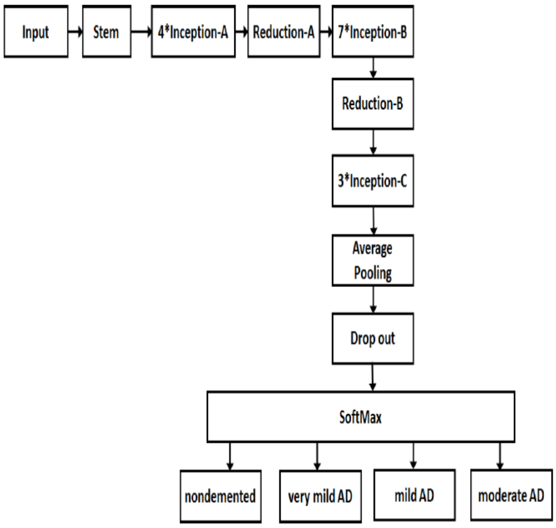

Figure 3: Block diagram of proposed method.

Dr. Randy Buckner of Harvard University's Howard Hughes Medical Institute (HHMI), theNRG (also known as Neuro informatics Research Group) at Washington University, and the Biomedical Informatics Research Network (BIRN) created the OASIS dataset [22]. The database consists of 416 individuals whose age belongs to the range from 18 to 96 years, with 3 or 4 T1-weighted MRI images available for each. It also includes data from around 100 individuals having very mild to severe Alzheimer's disease who are above the age of 60.

The suggested model is significantly quicker, taking less than an hour to train and test for Alzheimer's disease detection and classification using the OASIS dataset. All prior conventional approaches pale in comparison to this performance. Human specialists would need weeks to examine and classify all of the MRI data. In our model, no human hand-crafting is required for feature creation.

Table 2: Performance results of 5-fold cross validation using OASIS dataset.

Epochs	Traditional Network	Developed Model
Five	60%	71.25%
Ten	64%	73.75%

Model 3

By integrating 2D CNNs with LSTM, the scientists hope to incorporate spatial relations among 2D MRI slices. The ADNI research provided the dataset. After an initial phase of feature extraction using a CNN model pre-trained on ImageNet and re-trained on the ADNI dataset, the authors used an LSTM architecture to collect valuable information for AD detection on a sequence of images.

The LSTM is a recurrent neural network with a more sophisticated structure than a recurrent neural network. It has three gate units: a forgetting gate, an input gate, and an output gate, as well as a memory cell unit. To evaluate the performance of each CNN, authors performed tests on multiple models using different combinations of CNN and LSTM to see which model is more accurate on our dataset. The authors also experimented with single-view and Multiview techniques to determine which is more discriminative in AD detection and whether the Multiview strategy is more accurate. Figure 3 depicts these configurations.

On axial, coronal, and sagittal perspectives, Results describes the classification performance of various CNNs + LSTM. Each CNN was in charge of extracting features from each picture slice, whereas the LSTM network was in charge of determining the relationship between image sequences for each subject and making a judgment based on all input slices rather than each slice.An improvement in the accuracy is observed when model is trained with LSTM which is 87.5%, 90.62%, 90.62%, and 90.62% for Axial, Coronal, Sagittal and Multi-view, respectively.

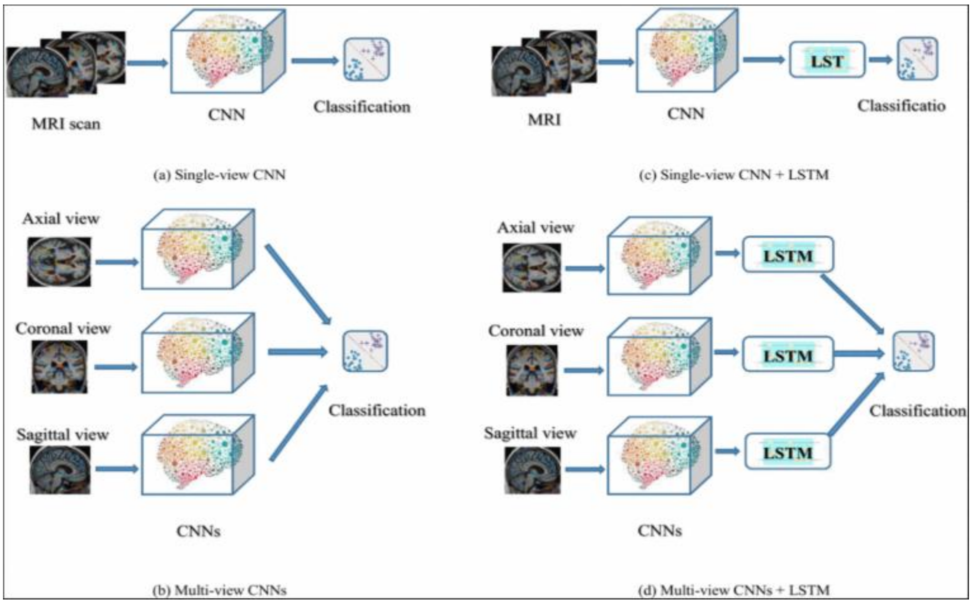

Figure 3: The architecture of Multi-view CNN and Multi-view CNN+LSTM model.

Based on the axial, coronal, or sagittal perspective, the LSTM network would then make a single decision. The findings of the experiments also reveal that there are no significant differences between any of the views, albeit the coronal view is somewhat better on average.

Model 4

CNN, a type of deep learning approach, was utilized to extract characteristics from MRI imaging in this work [23]. CNN uses the human visual system to memorize and learn the edges and characteristics of visuals in order to produce the most effective recognition impact possible.

CNN has four primary structures: a convolutional layer, a pooling layer, a fully connected layer, and a classifier. The picture features were extracted using the convolutional layer, which could then be utilized to produce feature maps. The convolutional layer's number of features was reduced using the pooling layer.

Authors decreased and transferred the feature maps into a column feature map after they were ideally minimized, which simplified the parameter into an optimal quantity. The classifiers were then utilized to detect Alzheimer's disease. Figure 4 shows the architecture of deep neural network used to train the model.

The CNN models were trained for 50 epochs to assure the best execution model, and their performance was assessed on the validation group.

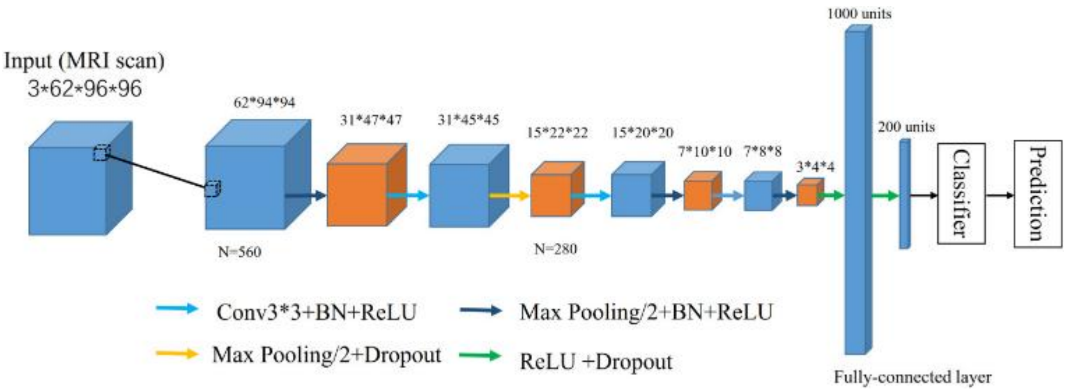

Figure 4: The architecture of deep network used to train model.

The differences between 2D-CNN and 3DCNN-SVM were shown using specificity, sensitivity, accuracy, and receiver operating characteristic curves (ROCs) and area under curves (AUCs) to determine which technique produced the most efficient and dependable result. Figure 5 shows confusion matrix generated by experiment while accuracy plot is shown in Figure 6.There were no significant variations in age or gender across the three groups, according to the authors. The performance of 3D-CNN-SVM in ternary classification was substantially superior than that of others which is found to be 96.73% accurate for AD diagnoses.

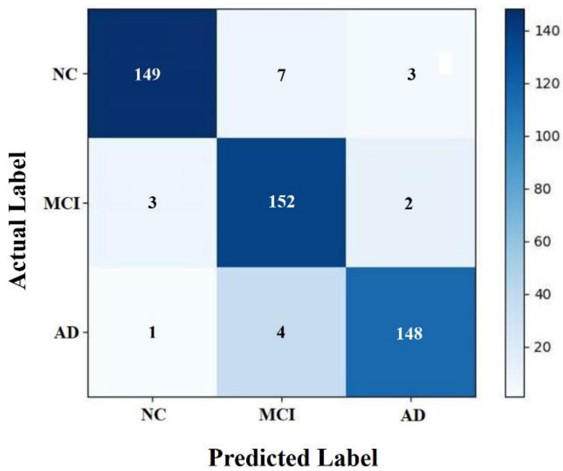

Figure 5: Confusion matrix results generated by experiment

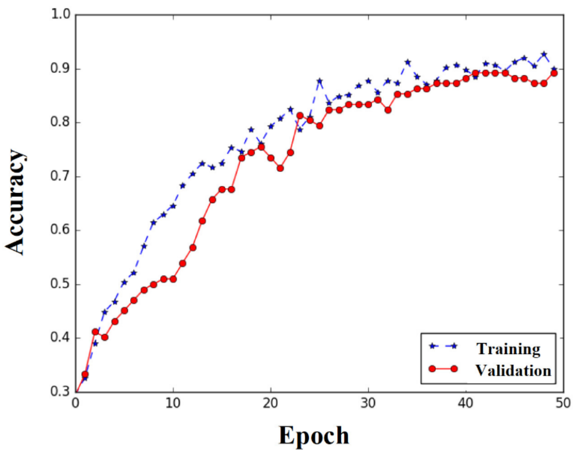

Figure 6: Accuracy curve of model.

Model 5

The authors suggest a VGG-inspired network (VIN) and look at the usage of attention processes. Authors presented the Alzheimer's Disease VGG-Inspired Attention Network (ADVIAN), in which convolutional block attention modules are combined on a VIN backbone. To minimize overfitting, 18-way data augmentation is also recommended. To report the unbiased performance, ten runs of 10-fold cross-validation are performed.Architecture of proposed network is shown in Figure 7.

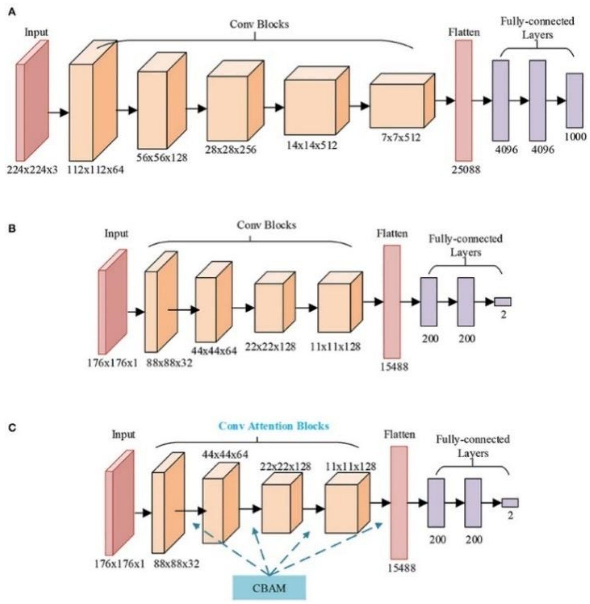

Figure 7: Architecture of Deep neural network

OASIS-1 dataset is used to train and evaluate the model's performance. The pre-processing is applied to dataset as shown in Figure 8.Statistical parameters are calculating as a result. Sensitivity and specificity are 97.65% and 97.86%, respectively. While model is found to be 97.76% accurate.

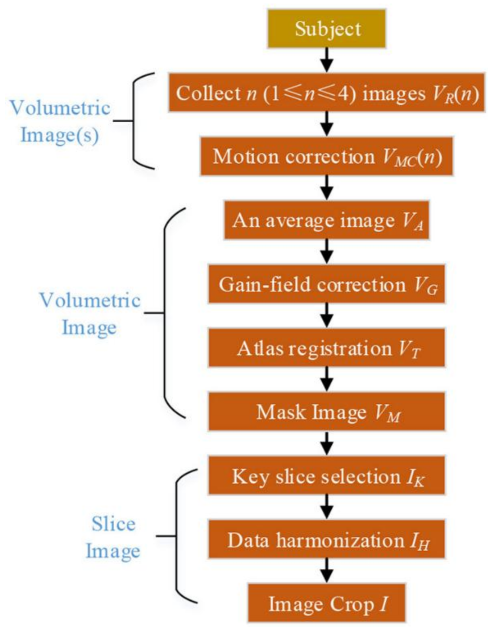

Figure 8: Pre-processing flow diagram

Comparison of Studies:

In all five studies, authors used state-of-the-art methods to detect and classify Alzheimer's disease. It has also been observed that, experimental results produced significant results when compared to traditional algorithms. Model 1 describes the effectiveness of CNN to identify stages of diseases with maximum accuracy of 90.91% using base model. While, inspired by Inception-V4, a novel deep model architecture is proposed in Model 2. Authors have reported that, proposed architecture outperform the traditional Inception model by measuring accuracy such as 64.25% and 73.75% for traditional as well as proposed model respectively. Model 3 proposed hybrid of networks such as CNNs + LSTM. Architecture is trained using MRI samples and performance is evaluated by calculating statistical parameters. In model 4, authors have proposed 3D CNN to show the difference in the performance of 2D CNN and 3D CNN. Models are trained using OASIS dataset samples and results are calculated by plotting confusion matrix. Recently, attention-based model is used to detect and classify Alzheimer's disease. Effective pre-processing techniques are used in a pipeline to reduce training time. Statistical parameters are calculated and model is analyzed by plotting ROC curves. In the results, it is reported that model can classify disease with an accuracy of 97.76% which is higher than all other models compared in this study.

III. CONCLUSION

This article includes a variety of methodologies for detecting and classifying Alzheimer's disease. It also highlights recent research in this field that has been published in the literature during the last several years. Finally, we examined five studies that focused on Alzheimer's disease detection/classifications and found that they outperformed state-of-the-art methods by a substantial margin. It included experimental findings as well as the methodology used in the studies, as well as the database used for training and evaluating the model's performance.

This will assist researchers in leveraging existing functionalities of various tools, interpreting vast amounts of data, and focusing on potential improvements by selecting features appropriate for the investigation.

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