Enhancing MCI Detection with a Hybrid Machine Learning Approach

B A Sujathakumari[1], Sudharshan Patil Kulkarni[2], Chinmaya A[3*], H J Suhas[4], Jayanth K G[5] and Gowtham R[6]

[1,2,3,4,5,6]Sri Jayachamarajendra college of Engineering, JSSSTU, Mysuru

chinnuanchan176@gmail.com

Abstract. Mild Cognitive Impairment (MCI) is a prodromal stage of dementia, is often native with very high risk of evolving into Alzheimer's disease. Early detection and accurate classification of MCI can significantly aid in timely intervention and personalized treatment planning. In the study conducted, we put forward a hybrid machine learning approach to enhancing MCI detection using a combination of feature engineering, feature selection, and ensemble learning algorithm. by using standalone Recurrent Neural Networks (RNN) as well as Convolutional Neural Networks (CNN). The proposed method leverages the temporal dependencies captured by RNN and the spatial information extracted by CNN to increase the robustness and accuracy of MCI classification. We used a comprehensive dataset ADNI consisting of neuroimaging and clinical data from a large cohort of subjects, including MCI sufferers and healthy controls. The neuroimaging data encompassed structural MRI scans, while the clinical data encompassed various cognitive assessments. Neuroimaging data is preprocessed to extract relevant features and combine them with the clinical data to create a unified input representation for the hybrid model.

Keywords: Hybrid ML, Alzheimer's Disease, MCI, RNN.CNN.RF.SVM

1. Introduction

The majority of older individuals experience a degeneration of central nervous system resulting in a gradual decline in cognitive function known as dementia. This is a significant issue, with approximately 4.6 million cases of dementia reported annually, with 60-70% attributed to Alzheimer's disease [1]. The symptoms of disease include memory loss, mood and personality changes, difficulties in social interactions, and impaired abstract thinking. Early detection is crucial in order to receive appropriate treatment from specialist's Magnetic resonance imaging (MRI) is a non-intrusive approach used to diagnose and observe brain tissue in individuals with Alzheimer's. MRI results of Alzheimer's patients often reveal abnormalities in the cortical and periventricular regions, hippocampal atrophy and amygdala changes in the subcortical region which are early indicators of dementia [6-10].AD has a prolonged preclinical phase, which

C. Kiran Mai et al. (eds.), *Proceedings of the Fourth International Conference on Advances in Computer Engineering and Communication Systems (ICACECS 2023)*, Atlantis Highlights in Computer Sciences 18,
https://doi.org/10.2991/978-94-6463-314-6_14

begins around 10 to 16 years at the least before appearance of noticeable symptoms. The brains of older individuals are examined for clinical diagnosis with no cognitive impairment (CN) or mild cognitive impairment (MCI), similar pathological symptoms to those with confirmed AD are often kept under observation suggesting presence of an asymptomatic phase of AD that varies among the elderly population. These findings have spurred research in the development of biomarkers that can identify individuals in the earlier preclinical stages of AD. The aim is to enable early intervention and potentially delay as well as prevent the onset of clinical symptoms. Additionally, biomarkers for AD progression could be valuable in monitoring the effectiveness of potential disease-modifying treatments [5]. The training dataset exploited for the study is sourced from “Alzheimer Disease Neuroimaging Initiative” (ADNI), which serves as a collaborative platform for researchers studying about Alzheimer’s Disease (AD).

2. Literature Survey

Deep learning techniques have demonstrated potential in the early detection employing information from magnetic resonance imaging (MRI), of Alzheimer's disease (AD). alone. Researchers have conducted various studies to investigate the effectiveness models of deep learning in accurately dividing AD patients and healthy controls into categories, in addition to foreseeing the transition from MCI to AD. In one study, researchers utilized structural MRI data and employed a deep learning approach. This involved training a model to analyze patterns and features in MRI images associated with AD. The results demonstrated that the deep learning model achieved high sensitivity and specificity, accurately segregating between AD sufferers and healthy individuals. Another study took a more comprehensive approach by incorporating both structural and functional MRI data. By leveraging the information from both types of MRI scans, researchers aimed to enhance the accuracy of early AD detection. They developed a deep learning model that effectively learned the complex relationships between different brain regions and their functional activity patterns. This model successfully predicted the likelihood of conversion from MCI to AD with a high level of precision. In summary, the existing literature suggests that deep learning techniques applied to MRI data alone can be effective in the early detection of AD. By leveraging the structural and functional information obtained from MRI scans, these models can accurately classify both healthy controls and AD patients, as well as predict the conversion from MCI to AD. The potential of deep learning in AD detection using MRI data offers promising avenues for further research and clinical application [11-16].

3. Methodology

In below Figure 1, the methodology implemented for early detection of progressive MCI is represented.

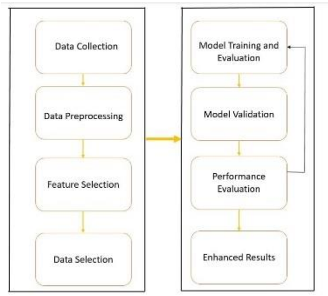

Fig. 1. Methodology Block Diagram

Collection of dataset consisting of clinical and neuroimaging data from individuals, including those diagnosed MCI and cognitively healthy controls. To verify the quality and usefulness of the collected data for analysis, preprocess it. This process might entail feature extraction, data cleaning, normalization, and addressing missing values. Apply feature selection techniques to identify the preprocessed data's most relevant and informative features. This step aims to reduce the dimensionality of the dataset while retaining critical information. Design and implement a hybrid machine learning model that combines multiple algorithms or techniques to improve MCI detection accuracy. This can involve the integration of different machine learning algorithms, such as support vector machines (SVM), random forests, or deep learning models. Split the preprocessed training and validation sets with the data. Prepare the hybrid machine learning model on the training set and validate its performance on the validation set. This step may involve hyper parameter tuning and model optimization. Determine the best evaluation metrics for assess the performance of the hybrid machine learning model. Metrics including accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) are frequently used.

Analyze the performance of the hybrid model and compare it with existing methods or baseline approaches. Evaluate its effectiveness in enhancing MCI detection accuracy and discuss the obtained results. Interpretability and Explain-ability: Explore methods to analyze and justify the choices made by the hybrid model. This step aims to share information on important features and factors contributing to MCI detection. Cross-Validation and Reproducibility: Perform cross-validation to assess the generalization capability of the hybrid model. Ensure the reproducibility of the results by documenting the methodology, code, and configurations used.

4. Algorithms Implemented

4.1. RNN

A particular type of artificial neural network called a recurrent neural network (RNN) can be used to are solely developed to handle sequential data. The basic neuron architecture of an RNN is called a recurrent neuron, which is capable of capturing temporal dependencies in the input data and is depicted in Figure 2.

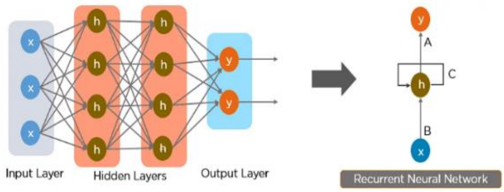

Fig. 2. RNN Architecture

Input layer of an RNN receives sequential information, including time series data or text. Each and every input in the sequence is represented as a feature vectors. The hidden state of an RNN is a vector that represents the memory of the network. or internal state. The hidden state is updated at every time step and captures information from previous time steps. Recurrent connections in an RNN allows information to pass from one-time step to the next time-step. An activation function is applied to the input and recurrent connections in RNN to introduce non-linearity. Commonly used activation functions in RNNs contain Rectified Linear Unit (ReLU) and hyperbolic tangent (tanh) functions. An RNN's output layer generates forecasts or outputs based on the processed sequential information. During training, the RNN is typically unrolled through time, meaning that the network is unfolded into multiple time steps. LSTM and GRU are popular variations of RNNs that address this issue by incorporating memory cells and gating mechanisms.

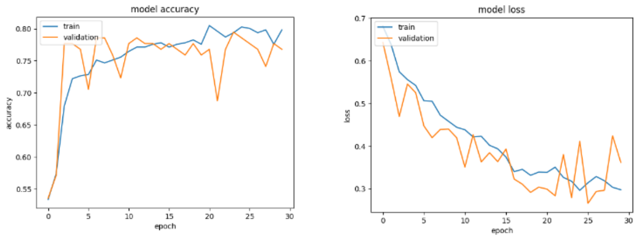

Fig. 3. RNN model accuracy and loss

In the above Figure 3 of model accuracy of RNN learning module we can observe the gradual smooth improvement in training of the data on recognizing MCI. Whereas the validation of the model is rather abrupt and crude.

4.2. RNN+RF

Random Forest is an ensemble learning model which merges several decision trees for making predictions. A random selection of features is used to construct and train each decision tree. independently. The hybrid model combines the strengths of RNN and RF to leverage both temporal dependencies and ensemble learning. One approach is to use the RNN to capture sequential patterns and extract hidden representations. The outputs of the RNN at each time step can then be fed as features to an RF model.

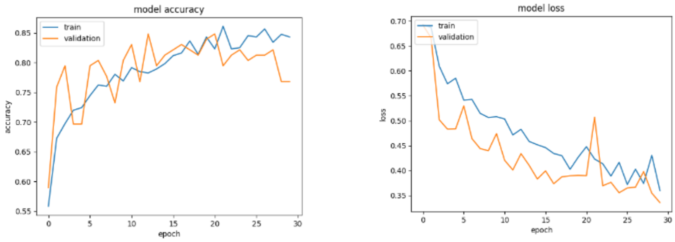

Fig. 4. RNN+RF model accuracy and loss

The model accuracy for a RNN hybridized with RF model provides better results as given in Figure 4 with consistent and stable prediction processes where the validation model just tries to keep up to the training trace of the model. In the model loss plot of RNN hybridized with RF learning model it's clear that after 25th epoch the losses in the training and validation drastically drops.

4.3. RNN+SVM

The combination of Support Vector Machines (SVMs) and Recurrent Neural Networks (RNNs) mentioned in Figure 5 isnot a commonly used hybrid approach. RNNs are primarily used for sequential data analysis, while SVMs are popular for supervised classification tasks. Support Vector Machines (SVM) is a supervised learning procedure used in classification tasks.

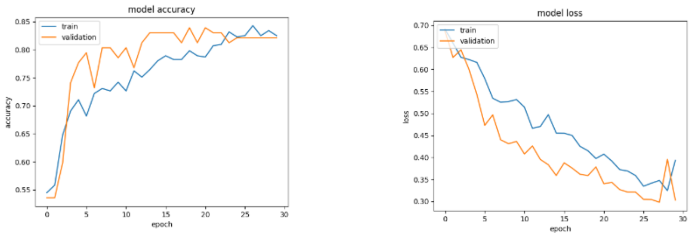

Fig. 5. RNN+SVM model accuracy and loss

It's a clear observation in the case of RNN hybridized with SVM that the model is not stable in producing consistent result, but can be used in predicting crude results of onset of MCI. Both training and validation saturates by the end of 27th epoch

4.4. CNN

One kind of deep learning architecture is convolutional neural networks (CNNs). precisely designed to analyze visual data, such as pictures. Here's an overview of the structure of an average CNN in Figure 6:

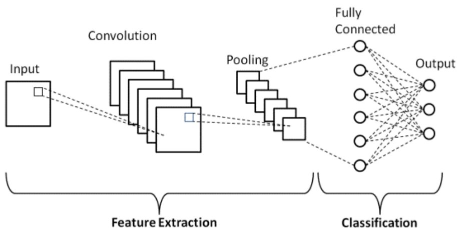

Fig. 6. CNN Architecture

The convolutional layer is the principle building block of CNN. Each filter detects specific local patterns by performing element-wise multiplications and summations on small local regions of the input. An activation function is typically applied element-wise to the outputs of the convolutional layer. The activation function introduces non-linearity into the CNN, enabling it to simulate intricate relationships between image features. CNNs often include numerous stacked convolutional and even pooling layers. Each subsequent layer captures increasingly complex and abstract features by combining and transforming the features learned in previous layers. The classification or regression task based on is the responsibility of the fully connected layer. the extracted features. It connects every neuron from every neuron in the current layer to the preceding layer, allowing for complicated combinations of features. An activation function is applied to the output of the fully connected layer. CNNs are trained using gradient-based optimization algorithms, typically through backpropagation. Regularization techniques are commonly applied to prevent overfitting and improve generalization.

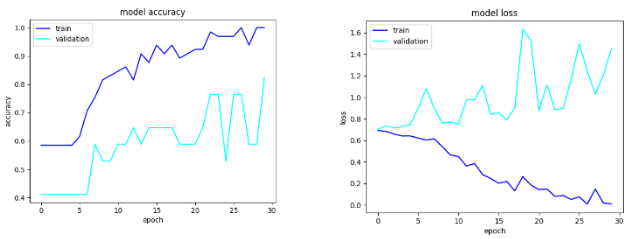

Fig. 7. CNN Model Accuracy and Loss

We can clearly observe in Figure 7 that CNN is one of the best model to be used for reprocessed MRI slices to be trained to detect early onset of MCI leading to AD the training accuracy almost reaches to 98% but the lower dataset amount setbacks the validation of the model thereby reducing its overall accuracy. The fact that CNN model requires relatively very huge dataset shows us why there is increase of loss in the CNN model with increasing epoch.

4.5. CNN+RF

Combining Convolutional Neural Networks (CNNs) with Random Forest (RF) is an example of a hybrid model that leverages the strengths of both approaches. By combining the capability of Random Forest's ensemble learning with the feature extraction capabilities of CNNs, the hybrid model can leverage the CNN's ability to capture spatial features from images and the RF's ability to handle high-dimensional feature spaces and handle non-linear relationships.

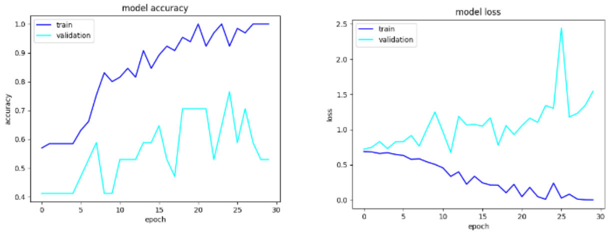

Fig. 8. CNN+RF model accuracy and loss

In the hybridized model of CNN and RF the training accuracy is of top tier but the validation struggles to keep up with the trained accuracy, given more time and over trained as given in Figure 8.

4.6. CNN+SVM

By combining the feature extraction capabilities of CNNs with the classification power of SVMs, the hybrid approach can potentially improve the accuracy and robustness of the overall model. The CNN extracts relevant and discriminative features from the input data, while the SVM utilizes these features to perform classification tasks.

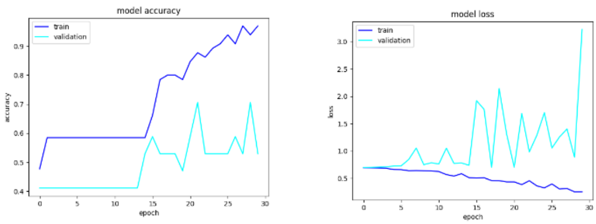

Fig. 9. CNN+SVM model accuracy and loss

The hybridized combination of CNN and SVM given in Figure 9 performs comparatively better than just the CNN model in terms of accuracy even though the accuracy stalls from 1st to14th epoch, it then gradually picks up the pace to improve its prediction on onset of MCI.

5. Results

Table 1. Model parameters of RNN and CNN hybridised algorithm

Parameter	RNN	RNN+RF	RNN+SVM	CNN	CNN+RF	CNN+SVM
EPOCH's used	30	30	30	30	30	30
No. of Lay-ers	6	5+1	5+1	10	4+1	4+1

Table 2. Comparison of results and errors

Models	Accu-racy(%)	F1 score(%)	Preci-sion(%)	MSE(%)	MAE(%)	RMSE(%)
RNN	80.62	87.63	87.78	4.53	7.56	5.23
CNN	84.23	82.71	80.46	2.13	6.84	3.95
RNN+RF	94.46	91.47	91.50	3.32	6.12	4.62
CNN+RF	92.8	90.01	89.68	2.95	5.16	3.75
RNN+SVM	83.69	83.55	88.88	6.23	10.48	8.62
CNN+SVM	87.5	86.66	85.84	8.62	10.94	12.56

The outcomes of all models may be compared, and it can be said that RF provided better results than individual models and that the hybrid version of each method performed better than its traditional equivalent as given in table 1 and table 2. Compared to the straightforward ensemble technique, hybrid RF performs better., we can clearly observe in the obtained results in CNN performs similarly to RNN in identifying oncoming MCI in the patient. The training dataset includes about 1500 MRI scan images preprocessed using HAAR wavelets, each in patients classified into AD, CN and MCI. When these machine learning techniques are hybridized the performance of the code increases. Where the accuracy of the RNN and CNN hybridized with RF increases to 91.46 and 92.8. whereas RNN and CNN hybridized with SVM accuracy reduces to 83.69 and 87.5 as well as is not that stable in providing consistent results.

6. Conclusion

We can expect the accuracy of the CNN model to increase with a more processed data set for RNN by increasing the epochs in the model the performance can be enhanced to a particular fed dataset. We even observe the FALSE negative reduce with repeated training by providing F1 scores that are satisfactory in the testing stages. Finally, the more the model is trained and continuously vigorously trained and tested we can expect better and more accurate prediction of MCI in patients that lead to AD can be called to provide early treatment and care.

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