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Comparative Analysis of CNN and Different R-CNN based Model for Prediction of Alzheimer's Disease

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Abstract

INTRODUCTION: Medical images still need to be examined by medical personnel, which is a prolonged and vulnerable progression. The dataset used included 4 classes of 6400 training and test MRI images each and was collected from Kaggle such as cognitively normal (CN), Mild Cognitive Impairment stage (MCI), moderate cognitive impairment (Moderate MCI), and Severe stage of cognitive impairment (AD).
OBJECTIVES: There was a glaring underrepresentation of the Alzheimer Disease (AD) class. The accuracy and effectiveness of diagnoses can be improved with the use of neural network models.
METHODS: In order to establish which CNN-based algorithm performed the multi-class categorization of the AD patient's brain MRI images most accurately. Thus, examine the effectiveness of the popular CNN-based algorithms like Convolutional Neural Network (CNN), Region-based CNN (R-CNN), Fast R-CNN, and Faster R-CNN.
RESULTS: On the confusion matrix, R-CNN performed the best.
CONCLUSION: R-CNN is quick and offers a high precision of 98.67% with a low erroneous measure of 0.0133, as shown in the research.

Keywords: Alzheimer's Disease (AD), Classification, Convolutional Neural Network (CNN), Deep Learning, R-CNN, Fast R-CNN, Faster R-CNN, Magnetic Resonance Imaging (MRI)

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1. Introduction

The subject of medicine known as medical imaging is crucial. It has recently changed as a result of how helpful it is for diagnosis and therapy [1]. Radiology, ultrasound, X-ray machines, magnetic resonance imaging (MRI) are among the most frequently employed imaging methods. Each of these approaches is distinct and complements the others. Users can utilize them to share additional facts about the brain and the human body [2]. As an example, MRI is thought of as a highly helpful test in which a high contrast picture of the brain should be obtained. It is required to utilize it to identify abnormalities in brain tumors, blood clots, and a specific organ. Additionally, it may be utilized to identify issues with various brain regions, including AD.

The number of dementia sufferers has been rising as the world's population ages. According to recent studies [3], 50 million people globally suffer from Alzheimer's disease (AD), causing 50–70% of instances of dementia. Among the most prevalent neurodegenerative diseases is that AD can induce serious cognitive deterioration and behavioral issues. The composition and brain's metabolic rate alter as AD progresses. Cerebral cortices along with the hippocampus are reduced in size, the ventricles are enlarged, and the pattern of local glucose uptake is altered. Medical electromagnetic resonance imaging (MRI), computerized tomography (CT), and positron-emission tomography (PET) is examples of imaging techniques that are capable of being employed in order to quantify these alterations. Because it affects the result of the overall investigation, brain MRI segmentation is regarded as a crucial job in many clinical applications. The most typical applications of MRI segmentation include measuring and visualizing brain regions, identifying lesions, as well as for image-guided procedures [4]. Brain MRI segmentation's primary goal is to separate an image into several parts. Zones that are clearly separated from one another and comprised of pixels with similar brightness and textures. Numerous deep learning strategies have been created to enhance the procedure of detection and segmentation in MRI analysis.

Support Vector Machines (SVM), linear discriminant analysis (LDA), and Decision Trees (DT) and further well-known techniques provided by machine learning will be utilized to provide early AD diagnosis and prognosis development. Nevertheless, before utilizing such strategies, the proper pre-processing processes must be taken. Additionally, for classification and prediction, these methodologies call for dimensionality reduction, feature extraction, selection, and feature-based categorization [5]. Many processes need specialized expertise a number of time-consuming optimization steps, as well. In order to get over these obstacles, deep learning is gaining a lot of interest in the analysis of high-dimensional, large-scale neuroimaging [6]. Deep learning is a burgeoning component of artificial intelligence that employs unprocessed data from neuroimaging to train characteristics. Deep learning has been proven to be helpful for classifying images that are independent of various circumstances.

2. Related Work

Numerous cutting-edge methods are used for evaluating Alzheimer's disease. As an illustration, cite: Pan et al [7] made the comparison of three hybrid methods, PCA, or principal component analysis, as well as a support vector machines (SVM) 3D-SENet model and using an Ensemble Learning for Convolutional Neural Networks (CNN) early finding of Alzheimer's. Among them, CNN with ensemble proves to provide higher accuracy and Area under Curve of 84% and 92%. Also, Marwa et al proposes [8] the extraction of region from the image and then applies two deep-based classification techniques specifically- such as CNN and Transfer Learning models by accessing Oasis dataset for detecting disease. Then, Ria et al suggests a comparative of AlexNet, Faster R-CNN, and YoloV4, which are CNN-based algorithms, showing the most accurate diagnosis of medical images than other detectors of two stages [9].

Neela et al [10] based on structural and functional MR imaging, AD diagnosis using LeNet and GoogleNet designs. In the study's experiments, it was shown that these structures outperformed cutting-edge AD detection methods. A strategy based on CNN was developed by Gunawardena et al [11] to diagnose using structural MRI to study AD in the beginning. When the effectiveness of the recommended approach was compared to that of the SVM in the research, the CNN model triumphed. The investigators want to use two more MRI angles (traverse viewpoint and longitudinal viewpoint) in the possible future, as well as the coronal perspective employed in this study.

A CNN-based model was created by Basaia et al. to diagnose structural MR scans used in AD [12]. The work used enhancement of data and transfernet methodologies the need to prevent overfitting difficulties, as well as to improve model's effectiveness at computing. The researchers claim that the investigation addressed the restrictions of past research, which had little practical use because it frequently focused on single-center datasets.

A CNN framework with eight layers for diagnosing AD was created by Wang et al [13]. To determine the ideal model configuration, the sigmoid, leaky activation function, and rectified linear unit (ReLU) activation coefficient were all investigated by the authors, along with the three distinct stochastic, maximum, and average pooling functions [14]. The leakiest Rectified Linear Unit (ReLU) activation function and maximum pooling are both features of the Convolutional Neural Network (CNN) model. Spasov et al multi-modal CNN framework [15] for diagnosing and utilising structural MRI, genetic testing, and clinical evaluation. Compared to existing CNN models, the developed framework has much fewer parameters, like AlexNet, VGGNet, etc. The structure became quicker and less vulnerable as a result. In cases with little available data, issues like over-fitting might arise.

3. Methodologies

The following is an outline of the research techniques used in the present study.

3.1. Convolutional Neural Network

The machine learning field using deep neural networks includes convolutional neural networks [16]. Deep Learning systems analyse information that is considerably more minute than what the brain of an individual can process due to the complexity of the human brain. In order to identify certain patterns in the dataset, image classification requires the extraction of features from a picture. It may end up costing a lot of money to compute to use an ANN for photo classification because of the relatively large adaptable components [17]. **Figure 1** depicts the functional and common building block of Convent.

3.1.1 Filters

While utilizing CNNs, there are many distinct sorts of filters, each with a specific function. Utilize the spatial localization of a given neuron by using filters that demand a specific local connection pattern between neurons. In its most basic form, convolution is the process of multiplying two functions to create a third function [18]. Two of the methods in this case are the filter and picture's pixel matrix. By moving the filter across the two matrices' dot product.

An "Activation Map" or a "Feature Map" is the name of the resultant matrix.

3.1.2 Rectified Linear Unit (ReLU)

After the convolution process, an activation function is added to the output to account for non-linearity. The standard activation function for a convnet is ReLU. A value of zero will be added to each negative pixel.

3.1.3 Pooling

Its objective is to progressively scale back the representation's spatial dimension to minimize the number of calculations and network parameters. The associated pooling layer will handle each feature map individually. Here are several techniques for pooling:

- Max-pooling: It chooses the most significant portion of the feature map. The primary features of a feature map are stored in the resulting max-pooled layer. Since it produces the best outcomes, it is the tactic that is most commonly used.
- Average pooling: Determining out for each region on the feature map, the average.

Reducing the number of calculations and parameters, Pooling gradually reduces the representation's spatial dimension in the network to prevent overfitting. If there is no pooling, the output has the same resolution as the input.

3.1.4 Full Layer Connectivity

Building a conventional artificial neural network, this is the final stage. A neuron in the next layer is related to the one before it. To categorize the number on the input picture, employ a softmax activation function. Three crucial components must be used to build a CNN:

- conv2d() - constructs a two-dimensional convolutional layer using the parameters padding, activation function, filter kernel size, and the number of filters.
- max pooling2d() - max-pooling technique is used to build a two-dimensional pooling layer.
- dense() - combines the hidden layers and units to create a thick layer.

Although CNNs have typically been used for image analysis, they may also be used for classification and other types of data processing. As a result, this can be applied in many different industries to produce accurate results, covering important topics like face identification, video classification, and street or traffic sign recognition, as well as interpretation and diagnosis or analysis of medical images.

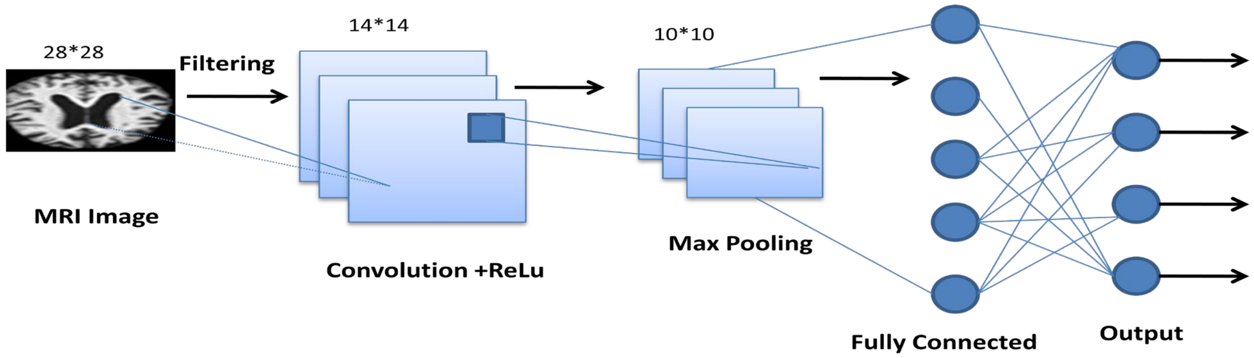


Figure 1. Functional Building Block of CNN

3.2. Region-based Convolutional Neural Network

Computer vision uses R-CNNs (Region-based Convolutional Neural Networks), a form of ANN models, and image processing [19]. The intent of R-primary CNN is to identify any image input objects. It was designed for object detection; thus, it can identify objects and define boundaries around them. R-CNN modeling employs a technique known as selective search, which is like selectively looking to glean information concerning the topic of interest from an input image. A region of interest can be shown by one of the rectangles. CNN takes advantage of this area of interest to provide output features. The given items are then grouped using the output characteristics of the SVM (support vector machine) classifier within an interest category. The R-CNN algorithm's steps are manipulated in **Figure 2**. Using the R-CNN's space extraction method, which may be used to identify areas of interest in a picture. The size that should be suited for each area of interest on CNN is controlled by the model. SVM classifiers and CNN calculate the attributes of the area which categorize the items that are shown in the region. The steps of the R-CNN algorithm are:

3.2.1 Selective Search

The selective search makes use of exhaustive search, but in addition to doing so, it also segments the colours that are displayed in the image. Selective search is a technique that isolates things by changing the coloration of the items in an image. This approach starts by creating several little windows or filters and then grows the region using the greedy algorithm. Then it finds the colours that are similar throughout the areas and combines them [20]. An essential element of object localization entails the application of selective search techniques. The three remaining stages of object detection where an extracted item can move upon localization are as follows.

- Warping
- Feature extraction using CNN
- Classification

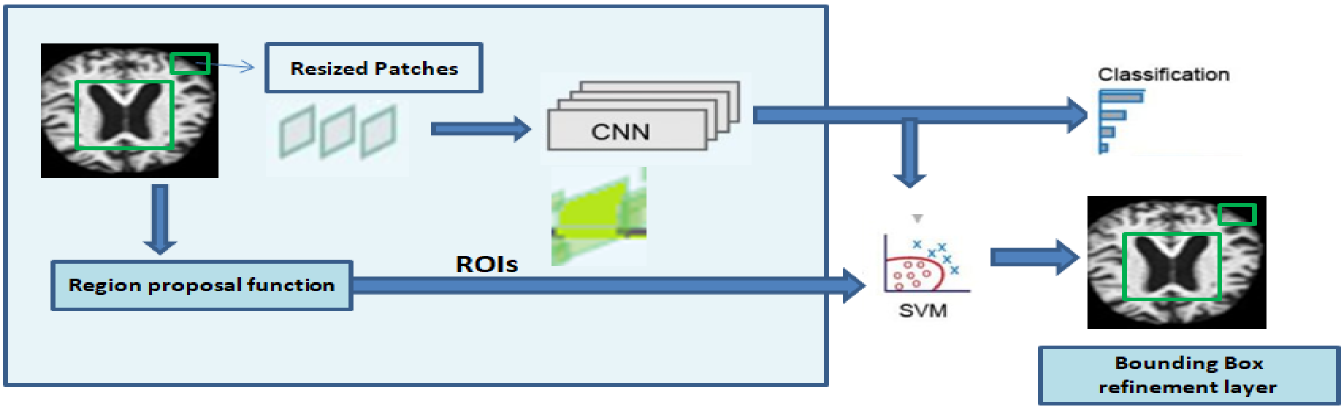


Figure 2. Architectural Framework of R-CNN

3.3 Fast R-CNN

The Fast R-CNN consists of a Convolutional Neural Network block with a new pooling layer over its previous one. An R-CNN typically pre-trained on the ImageNet classification objective with a "ROI pooling". The last convolution layer's features are acquired after the full image is passed into the core CNN. Depending on the picture size, the generated feature maps are much smaller than the backbone CNN employed.

The region of the backbone map of the features that correlates with this window is subsequently sent to the layer of ROI Pooling [21]. Using just one pyramid level, the spatial pyramid pooling (SPP) layer is a particular instance of the layer that pools ROI. The region proposal algorithm generates the selected proposal windows, which are simply divided into smaller windows by the ROI Pooling layer. The next FC layers, as well as the softmax and BB-regression branches, receive the output features. The softmax classification branch calculates the likelihood that each ROI will fall into a particular broad baseline category and K-specific categories. The region proposal algorithm's bounding boxes are improved using the BB regression branch result. Because calculations for overlapping the effectiveness of the Fast R-CNN detector surpass that of the traditional R-CNN since regions are shared in the detector [22]. **Figure 3** depicts the architecture of the Fast R-CNN algorithm.

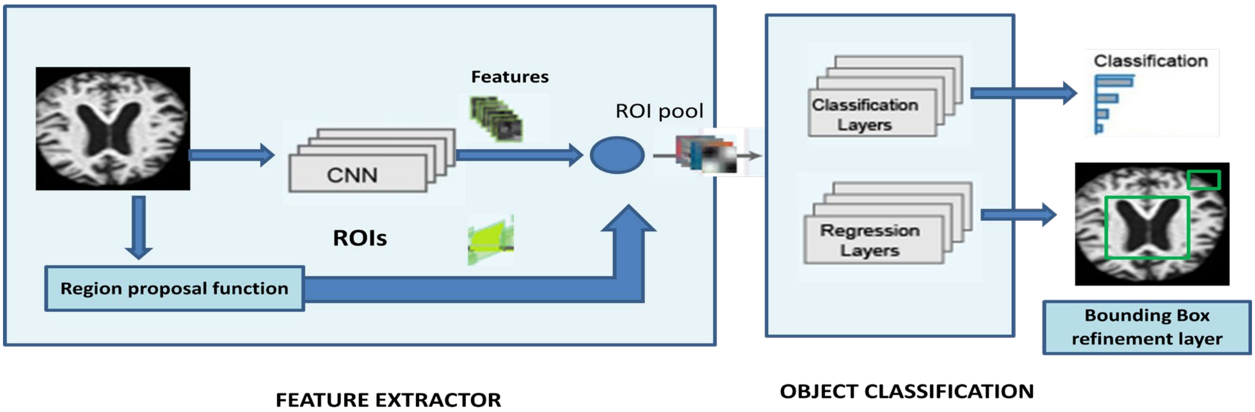


Figure 3. Architectural Framework of Fast R-CNN

3.4 Faster R-CNN

As implied by its name, Faster R-CNN is faster than Fast R-CNN. It leverages a fully convolutional network known as the region proposal network (RPN) and produces suggestions varying in size and aspect ratio [23]. In order to instruct the object detection where to look, RPN utilizes nomenclature for neural networks. This research proposed anchor boxes as an alternative to picture pyramids (i.e. numerous instances) narrowing filters arranged in the form of pyramids (it means several narrowing of different sizes), or different scales of the picture. The term "anchor box" refers to a referencing box with certain dimensions and proportions of aspect [24]. If there are several anchor boxes of reference, then the same depending on the locale. Sizes and aspect ratios may vary. Like a pyramid composed of anchor box references. Following that, some regions are mapped for the identification of objects with varying sizes and aspect ratios to a distinct reference anchor box. **Figure 4** illustrates the operational process of faster R-CNN.

The Fast model and RPN both employ the same convolutional computations. The length of the computation is reduced as a consequence. Producing region suggestions is the responsibility of the module proposal. The idea for focus is implemented using neural networks, which directs to seek for items in a picture is determined by the Fast R-CNN detection segment. In this approach, the model operates:

- RPN produces regional proposal ideas.
- Using a ROI Pooling layer, extract a feature with a set length vector from each region suggested in the illustration.
- The resulting feature coordinates are classed using the Fast R-CNN.
- Along with their score within class for the bounding-boxes, discovered objects are as well provided.

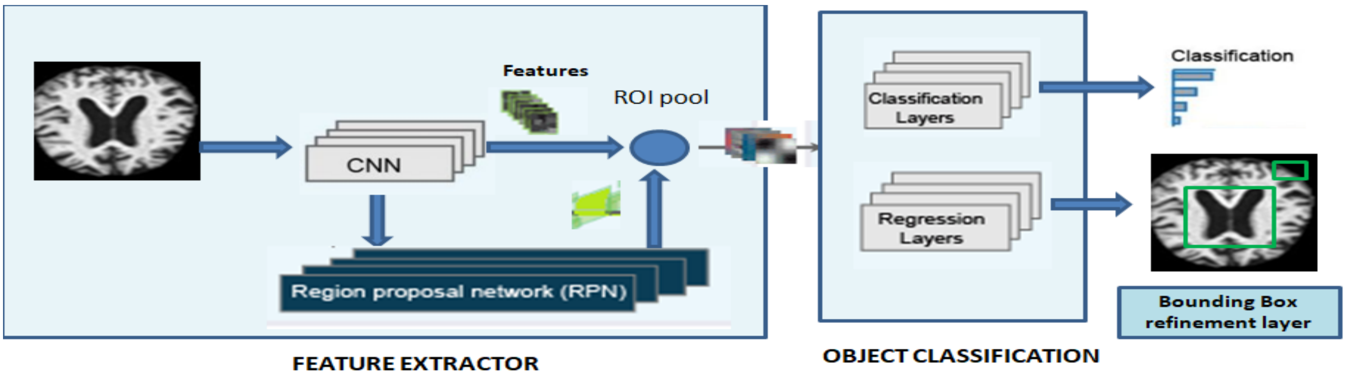


Figure 4. Architectural Framework of Faster R-CNN

3.4.1 Region Proposal Network

The region proposals can be created using a network referred to as the RPN (region proposal network) [25]. Here are a few advantages:

- To deliver region alternatives, an arrangement that can be learned and tailored to the detection task is utilized.
- The ideas can be created from a framework which may be learned from the beginning till final point, specifically in the detecting job. Consequently, it produces better region suggestions than more all-encompassing methods like Selective Search and EdgeBoxes.
- The convolutional layers of the Fast R-CNN detection network are utilized in the processing of the RPN. The RPN generates ideas in a comparable amount of time to algorithms like Selective Search.
- Creating a single Fast R-CNN and RPN network may be combined, since both can employ convolutional layers. Thus, training is only carried out once.

RPN's work is constructed above the shared Fast R-CNN and the final convolutional layer.

3.4.2 Anchor

Each recommendation has a parameter in accordance with a reference box, an anchor box [26]. The two anchor box parameters are as follows:

- Ratios of scale
- aspect

The shortcoming of quicker R-CNN means faster is that all of the mini-batch's anchors are created from just one source picture when the RPN is proficient. Since there may be correlation between all samples from one picture, it may take the network a while to reach convergence.

4. Comparative Analysis of Neural Network Models

4.1 Dataset Collection

The Alzheimer‘s MRI dataset is utilized, which is available on the kaggle. The dataset has 6400 images of axial view segmented MRI scans of the brain which is composed of four categories based on the severity of Alzheimer‘s.

- MCI – Mild Cognitive Impairment (2240 images): At this point, the patient begins to forget recent events, other people's identities, where the things were left, etc. Through a test of cognitive capacity, it is challenging to find.
- Moderate MCI (896 images): At this stage, patients lose their ability to focus, remember words, or find their way to a destination. Patients even begin to forget that their memory is lost at a certain point. It can be discovered from this point by using cognitive testing.
- AD – Alzheimer’s Disease (64 images): Begins to forget current events and significant past events, struggles with budgeting, finds it difficult to leave the house alone, and loses empathy.
- CN – Cognitively Normal (3200 images)

The MRI dataset is classified as a learning set and testing set at a split of 4:1 on a ration. Table 1 represents the number of images distributed in each category and separated into training and testing sets based on their division. The sample brain MRI image dataset from Kaggle is divided into four categories in **Figure 5.** It shows the distribution of the training dataset.

Table 1. Distribution of Image in each Category

Labels	MCI		Moderate MCI		AD		CN	
	Learn Set	Test set	Learn Set	Test set	Learn Set	Test set	Learn Set	Test set
Count	1792	448	717	179	52	12	2560	640

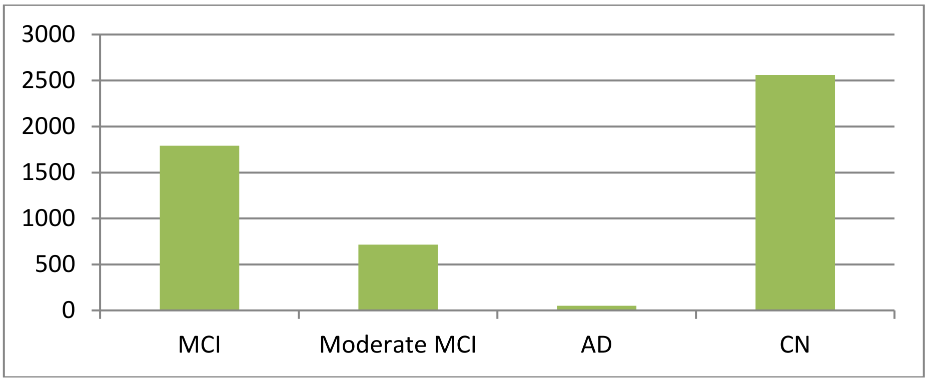


Figure 5. Data Distribution of training set in Classification of Brain MRI dataset

4.2 Dataset Preparation

For simpler categorization by the model, the whole collection of MRI pictures was manually annotated in the format requested by the Darknet for various CNN algorithms. The photographs were then stored on the Roboflow image management platform, which also created a link for simple access. RoboFlow was used to transform picture and COCO JSON files with annotations converted from.txt files since the Faster R-CNN requires COCO JSON structured images.

4.3 Pre-processing

The image is pre-processed by normalization technique. Image normalization modifies the assortment of individual pixel brightness and is a common step in image processing. The name "normalization" refers to the process typical function, which is to transform an input image into a range of pixel values that are more used to normal for the senses. A procedure that creates a standardized input picture in either grayscale or RGB. Next, a depiction of the image's scale's range of values between 0 and 255 is displayed. A digital picture is linearly normalized using the equation (1). The Greyscale picture is normalized using just one channel.

$$Outputchannel = 255 * (Inputchannel - minimum)/(maximum - minimum \quad (1)$$

4.4 System Structure

The Alzheimer's MRI dataset is collected from a kaggle database and is prepared and preprocessed, which is divided as a learning set and a testing set. 80% of the learning set has been used to train the neural network and 20% of data is used for testing and then it is classified using different CNN based neural network. The prediction model is carried out using Matlab software. The model has two splits between feature extraction and classification. The structure of the comparative model is shown in **Figure 6**. The MRI brain training data is extracted and classified by CNN, R-CNN, Fast R-CNN and Faster R-CNN. The sample learning set is loaded into the Matlab software and is shown in **Figure 7**. The model has inbuilt feature extraction which extracts the features, and it is fed into the classification module to predict the output. The trained prediction model classifies Alzheimer's disease based on its severity as cognitively normal, mild cognitive impairment, moderate MCI or Alzheimer. The testing dataset is given as input to the trained classifier which predicts the output of Alzheimer's. In the final stages of solution, deep learning and brain connectors aid in the working model's automation. A common method of K- fold cross-validation (k= 10-CV) was employed for the learning and testing to evaluate the suggested AD detection model fairly and effectively. Subsequently, a functioning of the prototype or model was created, allowing for a more precise way to identify the stages of Alzheimer's illness.

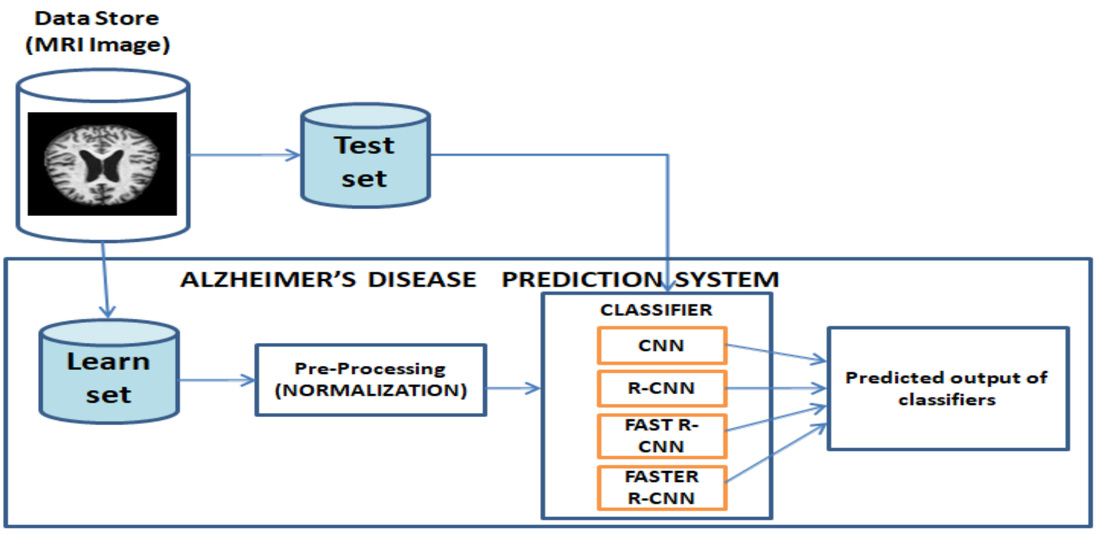


Figure 6. System Structure of Comparative Model

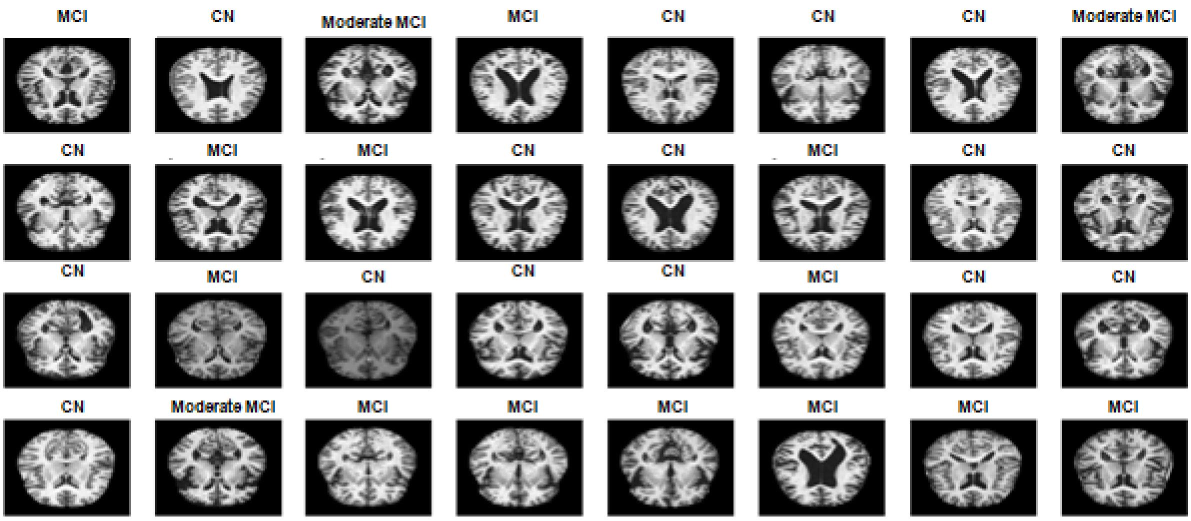


Figure 7. Sample Loaded Learning set

For any neural network, the hyper parameters are required to maximize the performance of the network. Important hyper parameters for the Convolutional Neural Network are the quantity of layers, neurons per layer, activation function, dropout rate, and learning rate are all characteristics of a network. The other parameters can be analyzed as batch_size, nb_classes, epochs, dimensions of image, channels, filters, convolution layers and pooling layers. R-CNN requires some of the hyper parameters like Optimizer, step size, decay epoch, total epoch and batch size. Fast R-CNN needs hyper parameters num_classes, image_resizer, fixed_shape_resize, keep_aspect_ratio_resizer, feature_extractor, type, scales, aspect_ratios, height_stride, width_stride, score_threshold, iou_threshold, max_proposals, maxpool_kernel_size, maxpool_stride, dropout_keep_probability and num_steps. Faster R-CNN require some of the hyper parameters like train_ROIs_Per_Image, Max_GT_Instances, Image_Minimum_Dimension, Image_Maximum_Dimension, rpn_class_loss, rpn_boundingbox_loss and Minimum_Confidence.

4.5 Results and Discussions

The discussion was carried out on different types of CNN and R-CNN models with the help of their experimental analysis and evaluation metrics.

4.5.1 CNN Analysis

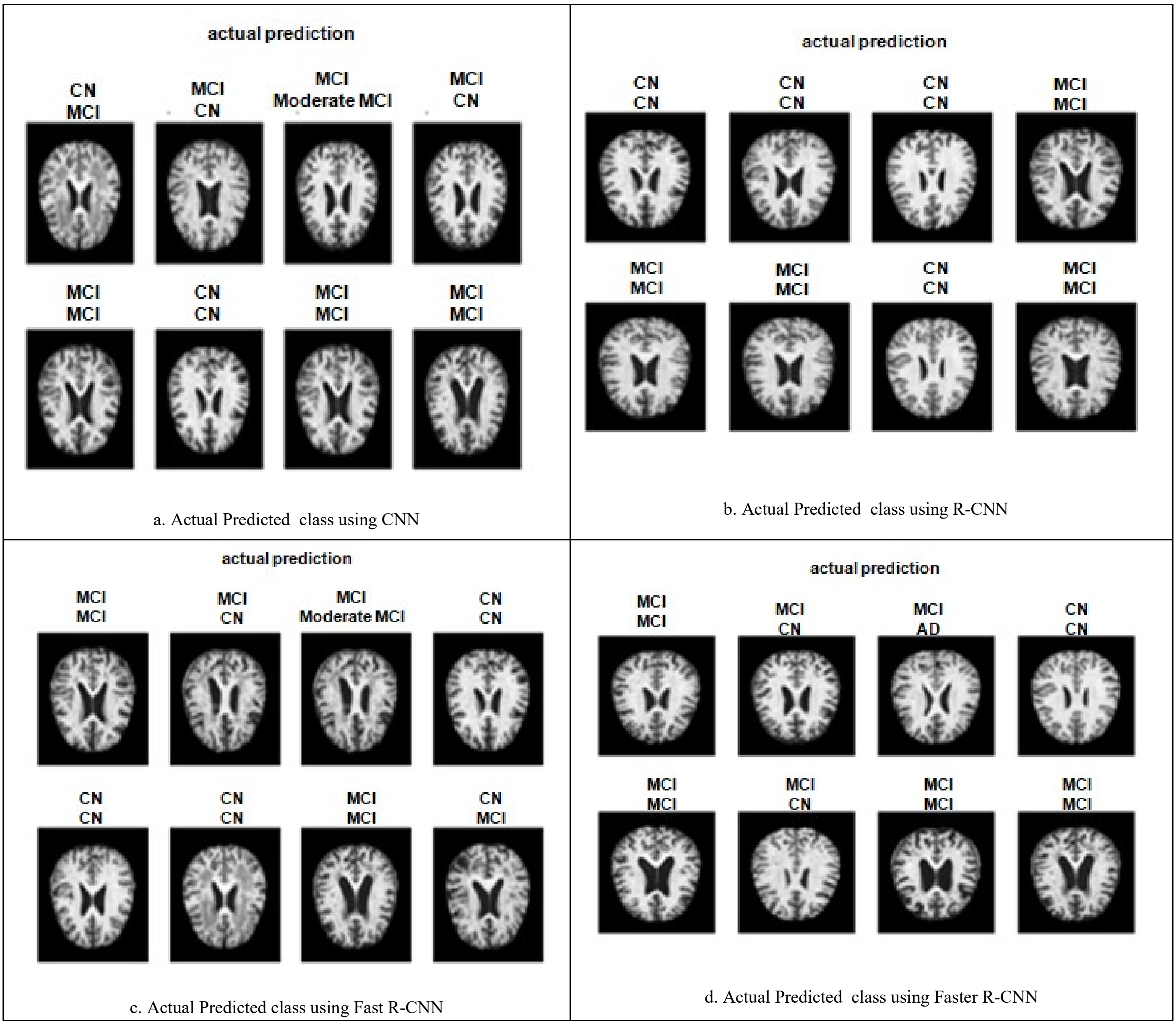
The CNN model had trained for 800 epochs. It is demonstrated that the best performance in classifying the test data in relation to alternative algorithms evaluated. **Figure 8** depicts the actual predicted data using a CNN classifier. Specifically, when examining the recall scores for each class, the results were as follows: moderate mild cognitive impairment, had a recall of 44.1%, correctly identifying 79 out of 179 images; severe stage of impairment (AD) had a recall of 16.7%, correctly identifying 2 out of 12 images; cognitively normal had a recall of 69.9%, correctly identifying 448 out of 640 images and mild cognitive impairment had a recall of 87.9%, correctly identifying 373 out of 445 images. It's worth noting that 29.7% of the cognitively normal images were misclassified as mild cognitive impairment. The confusion matrix, shown in **Figure 9**, provides a visual representation of the classification results. Finally, after training, the CNN model had an ultimate precision of 86% and a dropped value of 0.14 was attained as indicated in Table 2**.** These metrics demonstrate the performance and effectiveness of the CNN model in the task of classifying dementia-related image data.

4.5.2 R- CNN Analysis

The R-CNN model was trained for 800 epochs. However, during the evaluation on the test dataset, the R-CNN algorithm initially struggled with classifying the moderate MCI and AD images. **Figure 8** shows the current predicted data using the R-CNN classifier. It obtained a true positive of 0% for both classes, correctly identifying none of the 179 moderate MCI images and none of the 12 AD images. On the other hand, it performed slightly better in the mild cognitive impairment images, with a recall score of 3.3%, correctly identifying 15 out of 448 images. It showed significant improvement in classifying cognitively normal images, achieving a recall score of 96.9% by correctly identifying 620 out of 640 images. It's noteworthy that the R-CNN model misclassified 96.1% of the moderate MCI images and 96.7% of the MCI images as cognitively normal. The confusion matrix, shown in **Figure 9**, provides a visual representation of these classification results. This indicates a potential issue of excessively constraining due to the imbalanced data collection's nature, with a larger proportion of cognitively normal images. Finally, after training the R-CNN model, 98.6% eventual accuracy was attained with a decline value of 0.0133, as indicated in Table 2**.** These metrics demonstrate the high performance and effectiveness of the R-CNN model in the task of classifying dementia-related image data, despite the challenges posed by the dataset's imbalance.

4.5.3 Fast R- CNN Analysis

The Fast R-CNN model had been trained for 800 epochs. It demonstrated significantly improved performance in classifying the test data compared to the previous algorithms. **Figure 8** shows the actual predicted data using Fast R-CNN classifier. Specifically, when examining the recall scores for each class, the results were as follows: moderate MCI had a recall of 35.75%, correctly identifying 64 out of 179 images; AD stage had a recall of 66.7%, correctly identifying 8 out of 12 images; cognitively normal had a recall of 62.5%, correctly identifying 400 out of 640 images and MCI had a recall of 54.01%, correctly identifying 242 out of 448 images. The confusion matrix, shown in **Figure 9** provides a visual representation of the classification results. Furthermore, after training, the Fast R-CNN model obtained a 95% eventual accuracy with a 0.05 decline as indicated in Table 2. These metrics demonstrate the performance and effectiveness of the Fast R-CNN model in the task of classifying dementia related image data.



a. Actual Predicted class using CNN

b. Actual Predicted class using R-CNN

c. Actual Predicted class using Fast R-CNN

d. Actual Predicted class using Faster R-CNN

Figure 8. Sample Actual Predicted Image Class using CNN, R-CNN, Fast R-CNN & Faster R-CNN

4.5.3 Faster R- CNN Analysis

The Faster R-CNN model trained within 8000 epochs, doesn't function appropriately in classifying the moderate MCI and AD images. **Figure 8** shows the current predicted data using the Faster R-CNN classifier. It achieved a recall score of 0.0% for both classes, indicating that it did not correctly identify any of the moderate MCI or AD images. However, the model showed better performance in classifying CN and MCI images. It achieved a recall score of 39.8%, correctly identifying 255 out of 640 cognitively normal images. For mild cognitive impairment images, the recall score was 70.31%, correctly identifying 311 out of 445 images. The confusion matrix, shown in **Figure 9**, provides a visual representation of these classification results. Interestingly, the Faster R-CNN model incorrectly designated 46.1% of the cognitively normal images as a mild cognitive impairment. Finally, the Faster R-CNN model achieved a significant improvement in accuracy, reaching 84%, with a loss value of 0.16, as indicated in Table 2. These metrics show how the Faster R-CNN model conducts better in the task of classifying dementia-related image data, despite its limitations in correctly identifying moderate MCI and AD images.

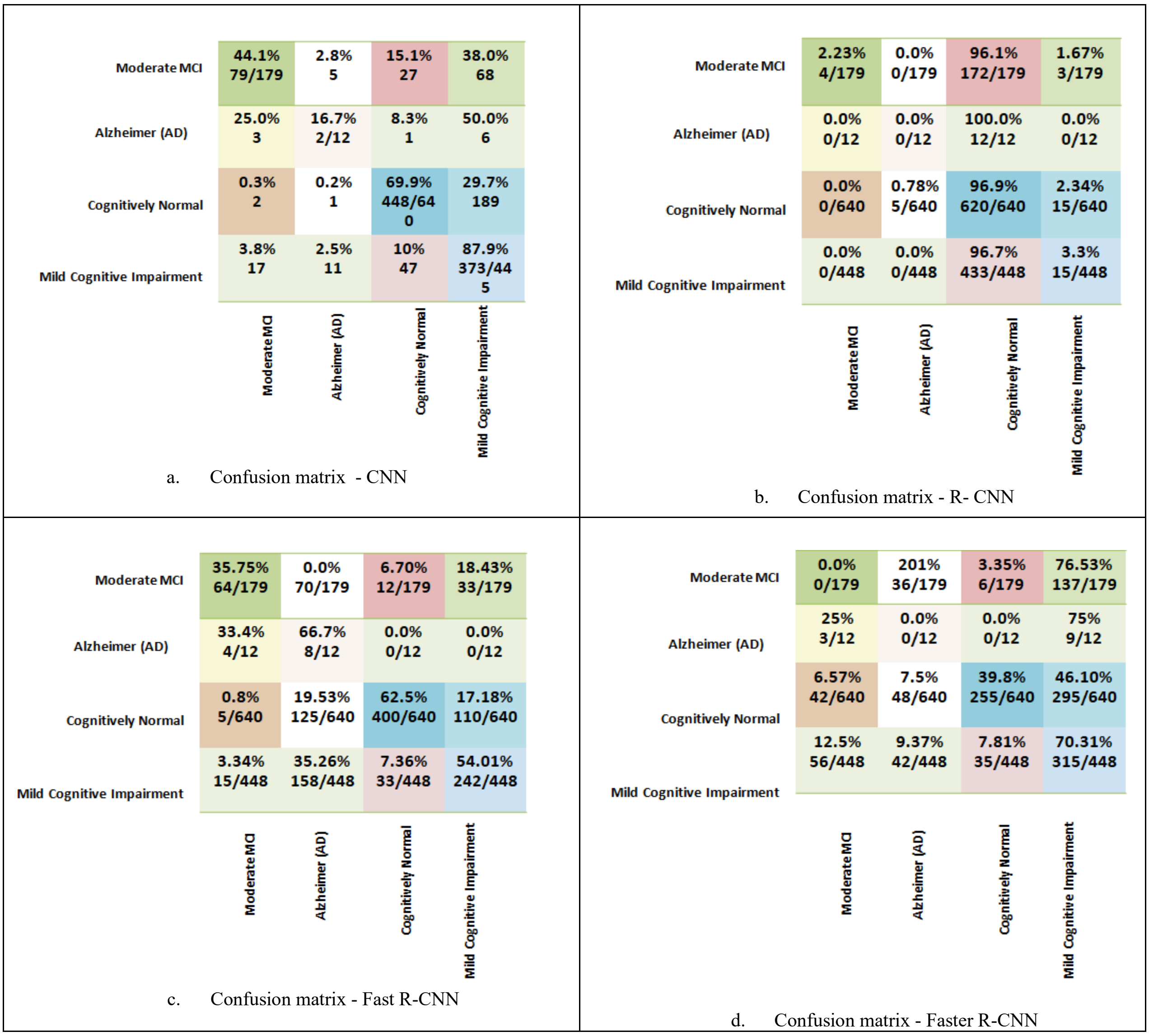


Figure 9. Confusion Matrix - CNN, R-CNN, Fast R-CNN & Faster R-CNN

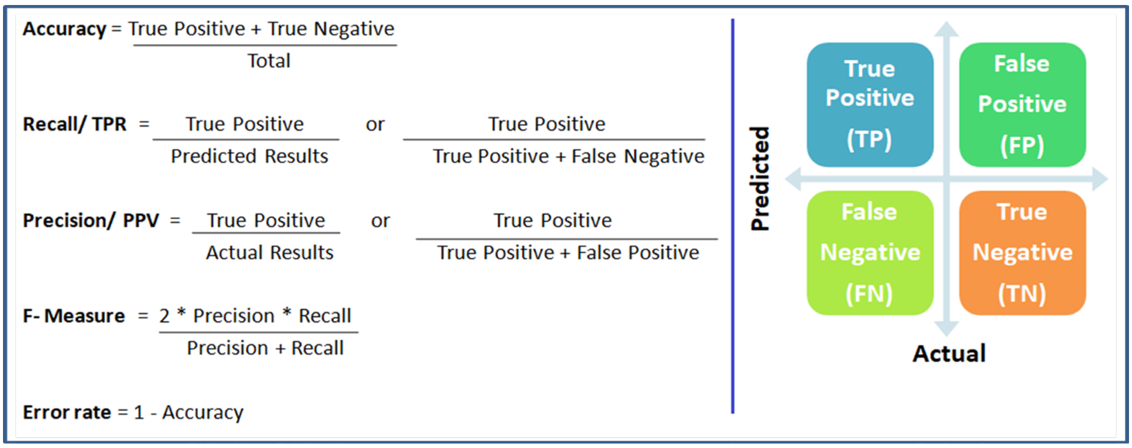


Figure 10. Performance metrics to evaluate the Network

4.6 Evaluation Metrics

The evaluation of deep learning models in medicine is difficult because the choices have a big effect, so it's important to know for sure when a model works on a patient and when it doesn't. Various metrics, including sensitivity, specificity, predictive values or precision, are key ingredients in evaluating models in medical settings. From accuracy, derive sensitivity and specificity to core concepts in medical evaluation. The critical model evaluation metric is precision and recall. Optimizing both the metrics at the same time is not feasible. Recall or TPR (true positive rate) are other terms used to describe sensitivity. When computing the accuracy on a test set, the percentage of all samples the model correctly classified is considered and prevalence is said to be the number of image samples with the satisfying features. The other two very important metrics are the F-measure and the error rate. The metrics are calculated as per equations given in **Figure 10**. The effectiveness of the classifiers is measured due to accuracy, error rate, precision, f-measure and recall is calculated for the classifiers such as CNN, R- CNN, Fast R- CNN and Faster R- CNN.

Table 2. Performance analysis of CNN Based Classifiers

Models	Metrics				
	Accuracy	Precision	Recall	F-Measure	Error rate
CNN	0.86	0.94	0.95	0.97	0.14
R-CNN	0.9867	0.99	0.96	0.98	0.0133
Fast R-CNN	0.95	0.64	1.00	0.77	0.05
FASTER R-CNN	0.84	0.71	1.00	0.71	0.16

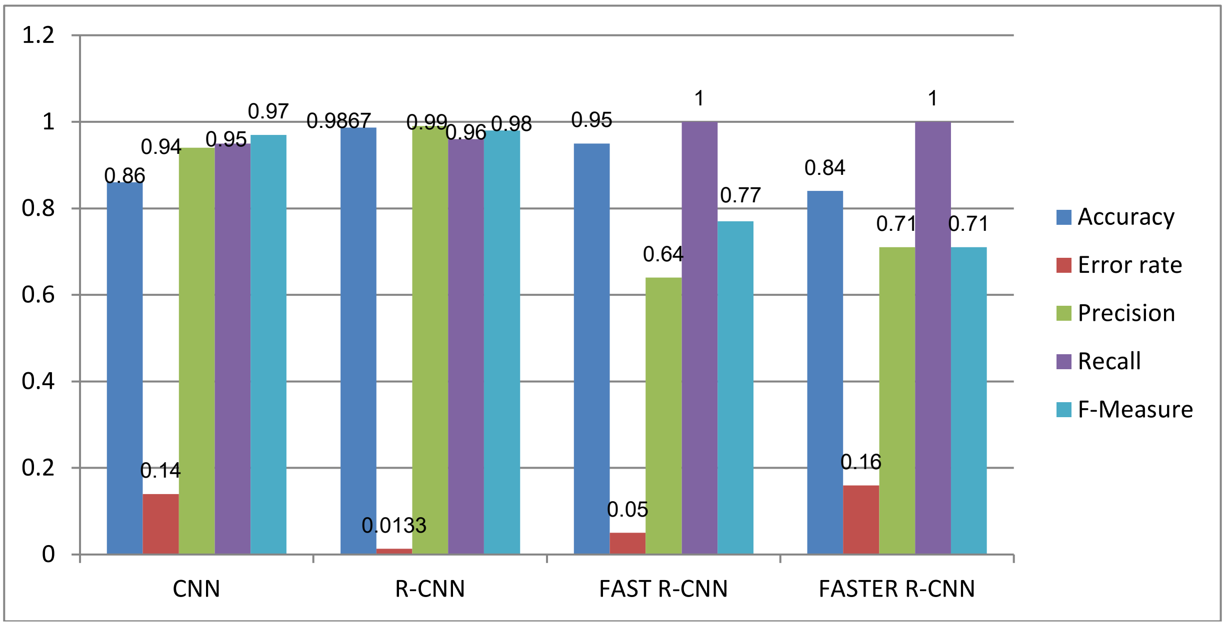


Figure 11. Comparison of Performance Measures for different Classifiers

Table 2 describes the performance of the classifiers in which, utilising an R-CNN (regional convolutional neural network), of the greatest accuracy of 98.67% with reduced error rate of 0.0133. It also provides higher value for recall, precision, and f-measure. The graphical representation of the classifier depicts that R-CNN has the highest accuracy and the lower error rate is shown in **Figure 11**.

5. Conclusion

The intent of this work is to classify the Alzheimer disease patients' MRI brain scans into many classes using well-known CNN-based algorithms such as CNN, R-CNN, Fast R-CNN, and Faster R-CNN. Not only these models were effectively implemented, but it added significant and insightful knowledge to the area of medical recording image identification. Training images were also manually labeled and this annotated dataset may be deployed for more analysis. Researchers hope that this work has advanced knowledge of machine learning-based medical picture diagnosis that may be used as a foundation for future research. Radiologists in actuality can enhance their expert judgment of a patient's Alzheimer‘s state with predictions from algorithms like R-CNN. Since the CNN in deep learning can be formed more thoroughly and exploited for geographic data, it works best for categorization. As a result, a deeper network is built and feed it with better quality medical pictures, since researchers believe that the hippocampus region itself might be a helpful reference in the diagnosis of AD.

6. Future Work

In the future, will tweak the settings and boost the CNN and Faster R-CNN performances to enhance our models. These would entail improving model parameters for more accurate recognition, enhancing the imagery for improved image identification and producing more images to compensate for the uneven representation in the learning set. Performing a voting ensemble, ensemble classification for all four approaches which forecasts the most votes that will be used. The benefit of an ensemble classifier is that it can integrate different classifiers to attain the best efficiency while also rectifying mistakes produced by individual classifiers.

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