International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING

ISSN:2147-6799 www.ijisae.org Original Research Paper

Brain MRI Image Analysis for Alzheimer's Disease Diagnosis Using Mask R-CNN

Madhuri Unde[#1], Abhishek Singh Rathore[#2]

Submitted: 28/11/2023 **Revised:** 08/01/2024 **Accepted:** 18/01/2024

Abstract: The most prevalent kind of dementia and the fifth-leading cause of mortality for those over 65 is Alzheimer's disease. Furthermore, in accordance with governmental statistics, there has been a significant increase in the number of fatalities attributed to Alzheimer's disease. Therefore, the early detection of Alzheimer's disease holds the potential to enhance the likelihood of survival for affected patients. Magnetic Resonance Imaging (MRI) combined with machine learning methods has facilitated and expedited the diagnosis of Alzheimer's disease. However, utilizing handmade feature extraction methods on MRI images with traditional machine learning approaches is challenging and needs the assistance of a knowledgeable user. Therefore, a technique might automate the process and reduce the necessity for feature extraction by utilizing deep learning as an automatic recognition and feature extraction. In this research, we use Mask-RCNN, a convolutional neural network approach, to demonstrate, can be used to the segmentation and object recognition of 40 moderately demented and non-demented MRI images from the train and test datasets. MRI image object recognition and object instance segmentation were the initial applications for Mask-RCNN. With this experiment, we demonstrate that Mask R-CNN is applicable and best to the treatment of Alzheimer's disease of brain from MRI images, with an accuracy of up to 97.46%.

Keywords: *Mask R-CNN, MRI, Alzheimer's disease, Deep Learning, Convolutional Neural Network (CNN), Brain Imaging,*

1. Introduction

The brain is a very complex organ and one of the most vital ones. It's responsible for a wide range of fundamental processes, such as ideation, problem-solving, reasoning, decision-making, creative thought, and amount of memory. Information or experiences can be saved in and retrieved from memory. Our physical memory serves as a permanent record of our lives and is crucial in forming the qualities that make up our personalities. Loss of memory and the inability to recognize one's environment as a result of dementia are terrible outcomes. The most well-known sort of dementia is Alzheimer's sickness (Promotion). As people live longer, their anxieties toward fostering Alzheimer's increment. Alzheimer's disease progressively destroys synapses, leading to a disconnection from the surrounding environment. This results in a loss of the ability to recognize loved ones, recall childhood memories, recognize familiar faces, and even comprehend basic instructions. They can no longer swallow, cough, or breathe in the latter stages. The expense of providing health and social care for the 50 million persons afflicted by dementia globally is equal to the 18th largest economy in the world [1]. Additionally, by 2050, it is anticipated that there would be 152 million new cases of AD and other dementias annually, or one instance every three seconds. The symptoms of AD and those of vascular dementia or normal aging overlap, making the diagnosis of AD challenging (VD) [2] [3]. Care, treatment, and prevention of Alzheimer's disease all depend on accurate and timely identification of the disease at an early stage so that patients may be monitored as they move through treatment. Several ongoing studies hope to one day utilize Magnetic Resonance Imaging (MRI) of the brain to diagnose Alzheimer's. It has the ability to measure the volume of the brain and identify individual cells. It may also be used to show that AD patients have had parietal atrophy [4]. Utilizing parallel techniques will significantly enhance the computational performance

#1Department of Computer Science and Engineering , Shri Vaishnav Vidyapeeth Vishwavidyalaya Indore, Ujjain Road, Indore, M.P.
madhuriunde123@gmail.com
#2Department of Computer Science and Engineering, Shri Vaishnav Vidyapeeth Vishwavidyalaya Indore, Ujjain Road,

of the model, enabling swift analysis of extensive datasets. Furthermore, the primary objective of this study is to gain a deeper insight into the root causes and indicators associated with Alzheimer's disease, alongside the development of a precise predictive model [5]. The identification of crucial characteristics and elements contributing to the onset of the disease may offer opportunities to uncover novel insights into its pathology and generate innovative ideas for potential treatments.

There are several organs in a human body, but the brain is the most important and significant one. Tums of the brain are a common source of cognitive impairment. Unchecked cell growth is the only component of Alzheimer's disease [5][6]. The failure of the brain happens when cancerous cells in the brain expand and devour all of the available nutrients, starving the healthy cells and tissues. As it stands, Alzheimer's disease location and patient positioning are determined by a physical examination of MRI brain pictures. This is a time-consuming process that often yields inaccurate illness diagnoses [7].

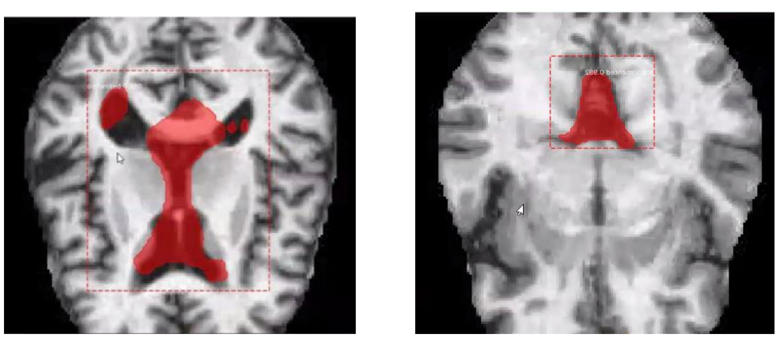
In this research, we focuses on a system that analyses MRI Images of various patients to identify disease blocks and categories the kind of disease using the Mask-RCNN algorithm.

Picture division, picture increase, and component extraction are only few of the image processing techniques used for identifying Alzheimer's in cancer patients' MRI images [8].

There are four steps in identifying Alzheimer's using image processing techniques: pre-processing, segmentation, feature extraction, and classification. In order to better detect and categorize brain Alzheimer disease in MRI image, image processing and neural network approaches are applied [9].

1.2 Magnetic Resonance Imaging (MRI)

Raymond v. Damadian pioneered the creation of the inaugural magnetic image in 1969. Subsequently, the most cutting-edge technology, marking the inception of the first MRI scan of the human body, was developed in 1977.. We can see the inside features of the brain thanks to MRI, and by doing so, we can see the many kinds of tissues in the human body. Images obtained using MRI are of superior quality to those obtained via X-ray or CT scan [10]. Humans with Alzheimer's disease may benefit from MRI as a diagnostic tool. Figure 1 displays 40 alternative MRI images for mapping disease -induced alteration that range from mildly demented to severely demented.



a) b)

Fig. 1 – a) moderately demented, b) non-demented MRI images for Mask-RCNN Algorithms

T1 and T2 weighted images are the most used MRI sequences, as seen in figure 2. Bright FAT makes up the only kind of tissue in T1 weighted, While Bright FAT and Water constitute the two categories of tissue in T2, in the case of T1 weighting, and the repetition time (TR) is low. Conversely, for T2 weighting, both the echo time (TE) and repetition time (TR) are prolonged.. The pulse sequence parameters are called TE and TR, It means to say anything over and over again until it sounds like an echo. Sometimes their duration is quantified in milliseconds (ms)[11].

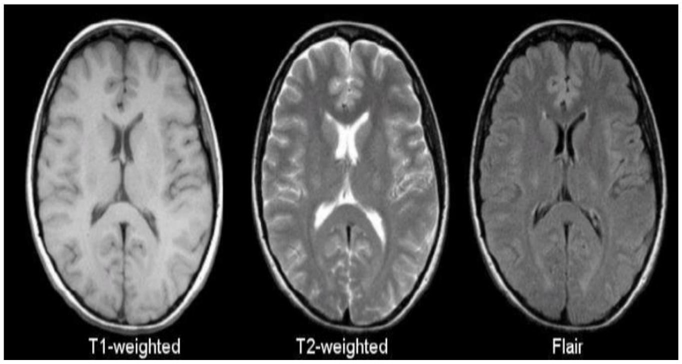


Fig. 2 - T1, T2 and Flair image [12]

Echo time is the elapsed time between the origins of the RF pulse and the echoes, while repetition time is the time gap between each repetition of the pulse and echo sequence.

1.3 Mask R-CNN

Mask R-CNN is based on a simple concept: For each candidate item, Faster R-CNN produces two outputs: a class label and a bounding-box offset. The object mask is the result of the third branch that has been added. For this reason, mask R-CNN is a practical and logical solution. In contrast to the class and box yields, the extra veil yield requires the extraction of a significantly more nuanced spatial arrangement of the object. Next, we lay the foundation for Mask R-CNN, discussing subjects like pixel-to-pixel alignment, the single most important component of R-CNN that Fast/Faster R-CNN is still lacking.

Faster R-CNN: To start, let's take a quick look at the Faster R-CNN detector [13]. Two stages make up faster R-CNN. The initial phase, known as a Region Proposal Network (RPN), suggests potential item bounding boxes. Following this, we do classification and bounding-box regression using a method called Fast R-CNN [14], which involves feature extraction using RoIPool from each candidate box. Faster inference can be achieved by combining the characteristics utilized by the two steps. For the most exceptional and complete correlations of Quicker R-CNN and other frameworks, we recommend reading [15]. The Utilization of a Cover in an R-CNN: Veil R-CNN follows a similar two-stage process, beginning with a similar first stage as customary CNN (which is RPN).

Cover R-CNN produces a twofold veil for every locale of interest (return for capital invested) notwithstanding class and box offset expectations in the subsequent stage. To the contrary, the vast majority of existing systems depend on mask predictions when determining how to classify data. Our method is in accord with Fast R-CNN [14], which employs a similar parallelization of skipping box gathering and backslide (which went out generally work on the multi-stage pipeline of exceptional R-CNN [16]).

The present research work investigation of Alzheimer's disease in brain by using MRI images of brain by Mask R-CNN algorithms. There are many methods available for detection of Alzheimer's disease such as Fast R-CNN, Cover R-CNN, R-CNN, Mask R-CNN etc., but in present research work we are going to use Mask R-CNN algorithm method for detection of Alzheimer's disease of brain in patients. Mask R-CNN is a convolutional neural network method can be used to the segmentation and object recognition of 40 moderately demented and non-demented MRI images from the train and test datasets in present research work.

The structure of this research paper are as follows: Section 1 presents the introduction of topic which included details about Alzheimer disease, Magnetic Resonance Imaging (MRI), about Mask R-CNN. Section 2 presents contributions of various researchers regarding present research work include literature about Alzheimer Imaging and Mask R-CNN review survey. Section 3 presents datasets used in current research work. Section 4 include research methodology of present research work. Section 5 presents performance analysis which includes the process of performance analysis and algorithms of Mask R-CNN model. Section 6 include result and discussion. Section 7 include conclusion of research work.

2. Literature Survey

Researchers have developed a number of different categorization methods for use in AD detection and diagnostic systems. This section summarizes current research on AD segmentation and detection systems that used Mask R-CNN and R-CNN techniques. Traditional machine learning methods, such R-CNN or Mask R-CNN, have been utilized in a portion of the prior examinations on Alzheimer's disease diagnosis. They are dedicated to creating models that can examine MRIs of the brain and other structural pictures of the brain, as well as test for abnormalities in brain activity, in order to diagnose neurological diseases.

Additionally, it relied largely on physically developed highlights and element portrayals with respect to the voxel, district, or fix based approaches, and treated segmentation problems as classification challenges.

2.1 Alzheimer MRI imaging related work

For the categorization of AD/MCI, **Liu et al. (2016)** [17] presented the Intrinsic Structure-based Multiview Learning (ISML) technique. The three stages of the suggested method are as follows First, tissue-segmented brain images containing grey matter (GM) are used to extricate Multiview highlights utilizing various layouts; second, subclass bunching based include choice utilizes voxel determination to support the force of elements; and third, SVM-based gathering grouping is utilized to arrange the separated elements. They assessed the viability of the proposed procedure [18] utilizing the X-ray standard dataset of 549 members (70 Promotion and 30 Ordinary Control — NC) given by the ADNI information base (http://adni.loni.usc.edu , got to on 5 February 2022). In light of the consequences of the trial, the proposed ISML technique has an exactness of 93.83 percent, an explicitness of 95.69 percent, and a responsiveness of 92.78 percent while looking at Promotion and NC.

The creators of [19, 20] gave an outline of potential clinical use instances of these strategies by characterizing the means important to begin a profound learning project in radiology. Future applications of deep learning in radiology practice have been the primary focus of these two research projects. Given the success of existing radiology applications, claims that the DL can replace a radiologist in his diagnostic role are premature. Radiologists and DL, however, may work together to improve patient results. Consequently, several studies have been conducted utilizing MRI scans to classify and segment the brain.

El Abbadi et al [19]'s innovative approach to classifying Alzheimer's disease uses SVD as a classifier. The system has been trained using typical brain MRI pictures at the first level. At the next level, it was able to distinguish between healthy and unhealthy pictures of the brain. This technique's accuracy was up to 97%.

2.2 Mask-RCNN related work

With the use of a classifier based on Mask R-Convolutional Neural Networks, **Sheikh Basheera et al.** [21] concentrated on the categorization of brain Alzheimer's disease in MRI images (M-RCNN). The proposed approach's fundamental concept is built upon two phases. The first one uses an ICA mixed mode model to segment the Alzheimer disease area (Independent Component Analysis). The extraction of deep characteristics is the second phase.

A unique multi-grade brain disease classification system based on Convolutional Neural Networks (CNN) was suggested by **Muhammad Sajjad et al.** [22]. Using a deep learning approach, the disease areas are initially segmented from an MR picture. To effectively train the system, they then used extensive data augmentation. A pre-trained VGG-19 CNN model is then enhanced with new data in order to classify the grade of brain tumors.

Using an image processing method, Sunanda Das et al. [23] trained a Mask R-CNN model to detect several types of brain tumors, achieving an accuracy of 94.39% and an average precision of 93.33%.

Deep transfer learning was used by **Muhammed Talo et al.** [24] to automatically categorize normal and abnormal brain MRI images. On 613 MR images, the suggested model, which utilized ResNet34, produced a 5-fold classification accuracy of 100%.

The ResNet50 pre-trained model was utilized by **Ahmet Inner et al.** [25], who added 8 extra layers after removing the network's last 5 levels. Afterward, comparing its accuracy to other previously trained models such as ResNet50, AlexNet, and GoogleNet. By obtaining 97.2% accuracy, the improved ResNet50 model demonstrated successful results. In his suggested machine learning approach, he identified the photos with a 90% accuracy as normal and abnormal.

Using a modified version of AlexNet, the authors of [26] were able to achieve an average classification accuracy of 91.6% when detecting and classifying brain pictures of Alzheimer's disease.

Brain Alzheimer disease identification using a different method in view of a changed ResNet50 model was laid out in [27]. Five convolutional layers and three completely associated layers make up the modified layer model of the proposed design, which depends on the ResNet50 model.

Graph theory methods were employed [28] to find brain anomalies. The primary model used to categorize brain pictures was a VGG16 architecture. The authors of this study discussed their method for more precisely detecting and identifying brain Alzheimer's disease using the Mask R-CNN model.

2.3 Potential Gaps Found

After reviewing almost 50 papers e found following research gaps:

1. The complexity of the training model is high [18]
2. Fine tuning of convolutional layer may Improve the performance [27
3. Unable to verify the regression across multiple datasets [25]
4. The 3D CNN holds the capability to capture the three-dimensional context of MRI scans, whereas the 2D CNN can only filter scans for 2D local patterns [26].
5. Fine tuning of convolutional layer may Improve the performance [27]
6. The CNN has a less performance when trained with MCI patches rather than AD/NC patches [28]

3. Datasets

The man made brain MRI image dataset comprises 40 MRI pictures from various patients. Each of these dataset contains one of the two categories of Alzheimer illness MRI images of dataset train and value: moderate demented and non-demented. The images have an in-plane resolution of 512x512 with pixel sizes of 0.49x0.49 mm^2. Figure 2 shows sample images from each class, and Table 1 shows the distribution of images with various Alzheimer's disease categories. Along with manmade dataset, we also use dataset from ADNI. The dataset utilized for the Alzheimer's disease Prediction challenge incorporates information from three different stages: ADNI Discovery, ADNI Exploration, and ADNI Advancement. According to the source, Approximately 1,600 biomarkers were collected from 1,832 individuals (950 men and 882 women) during the course of 1,200 visits at 22 different time periods between 2002 and 2018 [16].

Table 1- Distribution of the dataset in two classes

Dataset	**Number of images**	
	Moderate demented	**Non-demented**
Train	16	6
Val	4	4
Total	40	

4. Proposed Work

Mask R-CNN is a leading object recognition and segmentation framework, which follows from Faster R-CNN, an object detection framework.

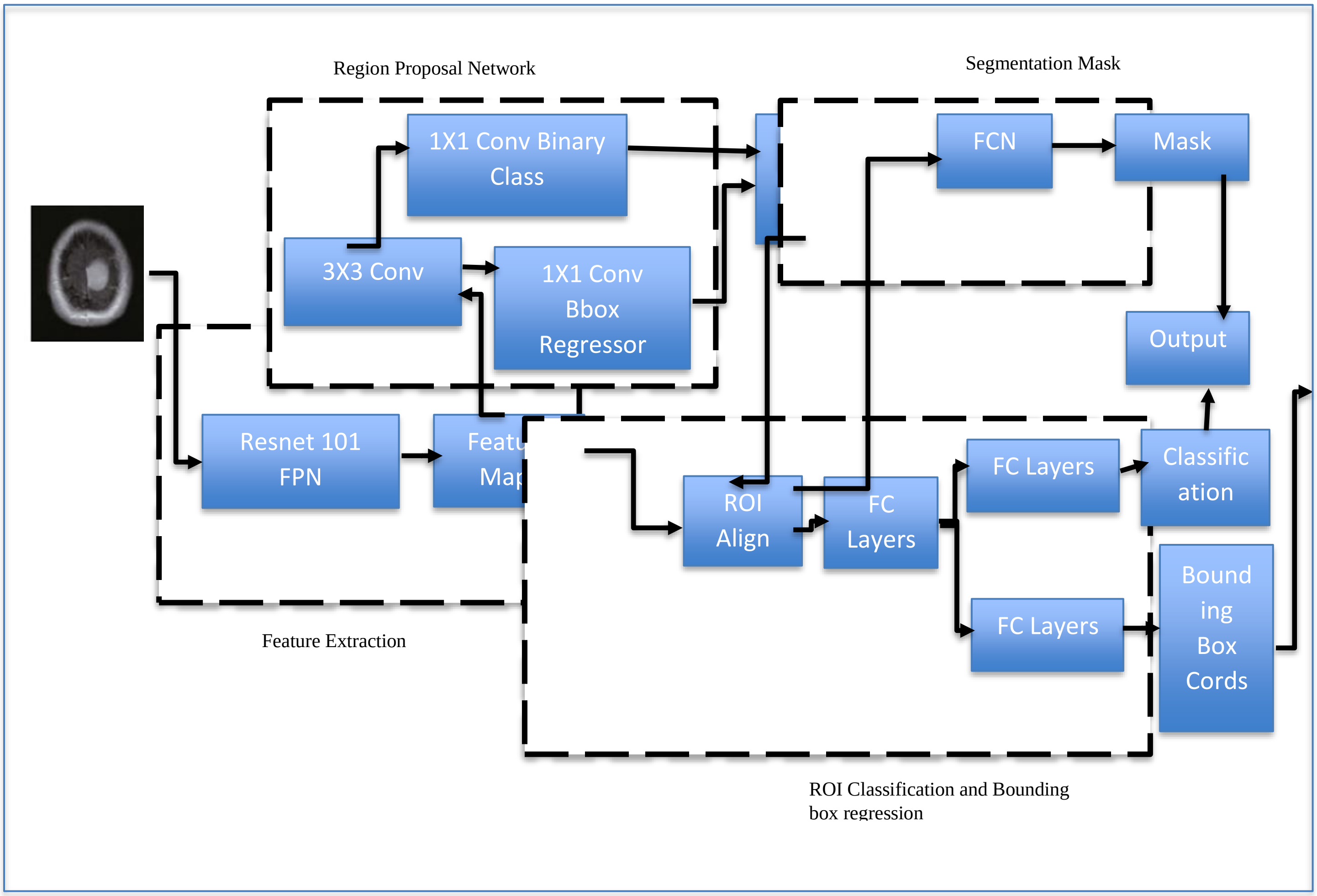


Fig. 3 - Architecture of the proposed framework

Stage 1: In the initial phase of Mask R-CNN, the process entails scanning images and producing proposals for regions that are deemed probable to contain an object.

Stage 2: The ideas are categorized in the second step, and bounding boxes and masks are constructed. The framework's backbone is a CNN with ResNet101, with early layers detecting low-level features and subsequent layers detecting higher-level characteristics. To improve upon the conventional feature extraction pyramid, Mask R-CNN makes use of a Feature Pyramid Network (FPN) to extract high-level features and feed them to the lower layers. This gives each layer access to both the high- and low-level information.

Stage 3: Mask R-CNN detects objects using the Region Proposal Network (RPN), which divides the picture into anchors from which sliding windows traverse the image and discover regions containing the item of interest. This framework employs a high number of anchors, which causes training to be slower but more comprehensive. The RPN output is the bounding boxes.

Stage 4: The planned ROI and feature map are then sent into this network (Fig. 4). Regions of Interest (ROIs) are categorised, and the bounding boxes are specified further.

Stage 5: Finally, Mask R-CNN creates masks for the areas from the identified ROIs. The binary masks can be detailed by the low resolution and floating-point representation of the mask.

Stage 6: Multi-task loss function used by Mask R-CNN is provided by (1)

$$L = L_{cls} + L_{box} + L_{mask} \quad \ldots (1)$$

Where L_{cls} and L_{box} are the same as in Faster R-CNN and L_{mask} is given by equation (2)

$$L_{mask} = -\frac{1}{m^2}\sum_{1\le i,j\le m}\left[y_{ij}\log y_{ij}^{k} + (1-y_{ij})\log(1-y_{ij}^{k})\right] \quad \ldots (2)$$

In this equation, yij represents the label of a cell (i, j) in the actual mask for the region of size m x m, and is the predicted value of the corresponding cell in the mask learned for the ground truth class k.

5. Performance Analysis

5.1 Process of Performance Analysis

Dataset

Pre-Processing

Split the Data

Build Mask R-CNN Models

Train and test image by Mask Regional Conventional Neural Network

Prediction

There are six key modules in the proposed system. Pre-processing, dataset Divvy up the data, Create Mask R-CNN models and train Deep Neural Networks for classification and epochs. As the input image, we may utilize a single MRI scan, while the multiple MRI pictures in the dataset serve as the output. The picture was downscaled and the label encoded before it was processed. When we divided the data for the MRI Following steps are used for the creation of an algorithm for detection of Alzheimer's disease by using Mask R-CNN algorithm.

Step 1 – Class CustomConfig

Step 2 - Inspect the model in training or inference modes values

scan, we used a split of 80% Training Data and 20% Test Data. Make a model using a Mask R-CNN, and then train a deep neural network for subsequent iterations. Then, using the Mask RCNN, we identify either Alzheimer disease or non-Alzheimer disease areas in the provided MRI images.

5.2 Algorithms of Model

In the initial step we have to customize the class of the dataset of sample (40 samples). Steps per epoch used in this research work is 10

Next step is to inspect the model in training model values. The uploaded previously customized dataset 'value'.

```
# Inspect the model in training or inference modes values: 'inference' or 'training'
TEST_MODE = "inference"
```

```python
ROOT_DIR = "E:\\Users\\ABC\\Downloads\\mrccn\\Dataset"


def get_ax(rows=1, cols=1, size=16):
   _, ax = plt.subplots(rows, cols, figsize=(size*cols, size*rows))
  return ax
# Load validation dataset
# Must call before using the dataset
CUSTOM_DIR = "E:\\Users\\ABC\\Downloads\\mrccn\\Dataset"
dataset = CustomDataset()
dataset.load_custom(CUSTOM_DIR, "val")
dataset.prepare()
print("Images: {}\nClasses: {}".format(len(dataset.image_ids), dataset.class_names))
```

Step 3 – Creation of model in inference mode

Then we have to create an algorithm model in inference mode. In this step we have to assign weights values to datasets and then load the weighted dataset values.

Step 4 – Code for predicting images which are not present in dataset

It is important to note that we have to create code for prediction images which are not in the present dataset i.e. in 80 % training and 20 % test dataset.

Step 5 – Recognition and segmentation results for code by selecting MRI images

After the code is created, the final step is to recognize and segment selected MRI images for Alzheimer's detection.

Step 6 – Information of selected images for prediction

Following image shows that processing parameters of one selected image. Processing parameters included shape of MRI image, shape of molded MRI image, shape of MRI image metas and anchors shape of MRI image.

Images:10

Classes:[‘BG’,’demented’,’non demented’]

Processing 1 images

Image	**shape(208,176,3)**	**Min:0.00000**	**Max:255.00000**	**Unit8**
Molded images	**shape(1,1024,1024,3)**	**Min:-123.700000**	**Max:150.10000**	**Float64**
Image_metas	**shape(1,15)**	**Min:0.00000**	**Max:1024.00000**	**Float64**
anchors	**shape(1,261888,4)**	**-0.35390**	**Max:1.29134**	**Float32**

6. Results And Discussion

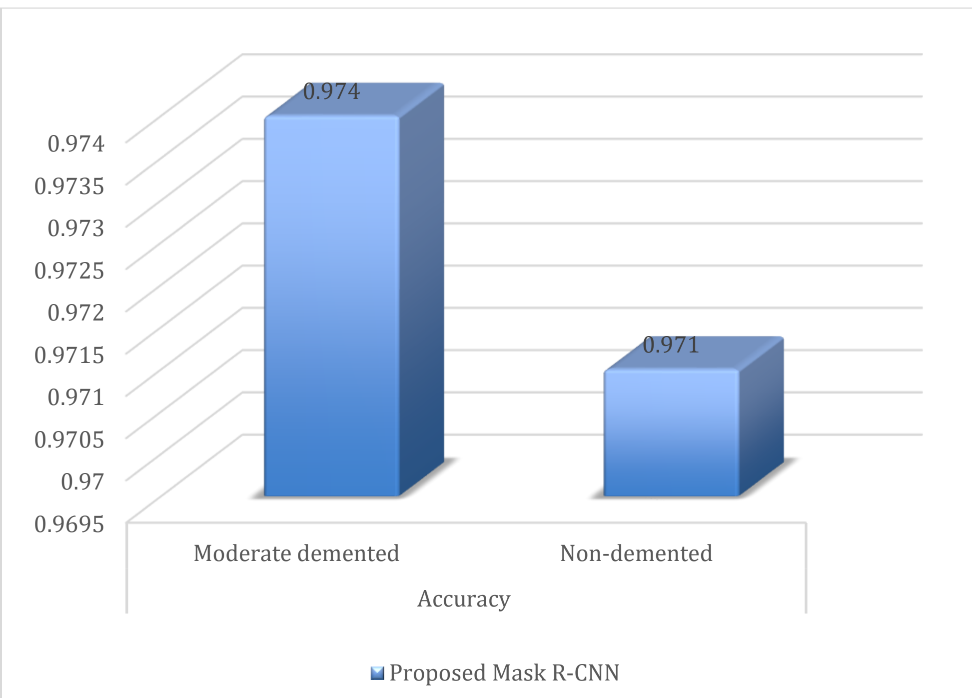
ResNet-101, FPN for feature extraction, and Jupyter Notepad were used to construct the model. Subsequent to initializing the model utilizing pre-prepared loads acquired from the dataset, we utilized a move figuring out how to calibrate the model for use in recognizing instances of Alzheimer's illness utilizing X-ray information. We executed an experiment in which we arbitrarily divided our data into training (80) and test inference (20) sets.

6.1 Mask R-CNN results

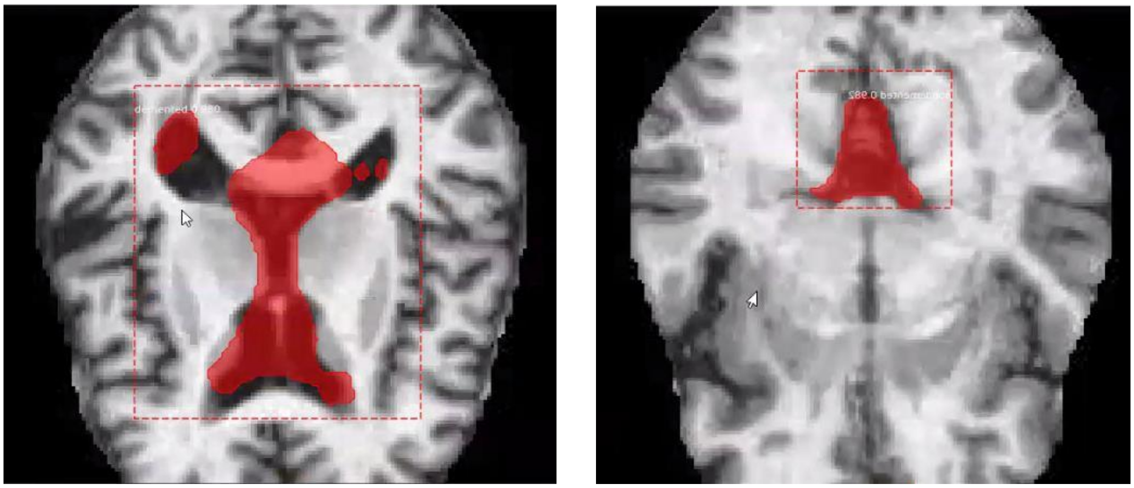
A description of the findings from three distinct experiments is provided in this section. We examined the performance of our technique on the demented and non-demented datasets in our first research. As may be seen in Fig. 6, Mask R-CNN produces some very outstanding segmented brain illness score findings. The proposed method can precisely localize the presence of Alzheimer's disease (AD) in contrast with solid tissues in spite of irregular or fluffy limits and X-ray picture antiquities like commotion, predisposition field impact, and securing point (normal accuracy 0.974 on the moderately demented dataset and 0.971 on the non-demented dataset; Graph 1). . Additionally, by overcoming the difficulties presented by variations in location, shape, and size, our method can precisely segment the Alzheimer's disease (AD).

Table 2- Proposed accuracy of the Mask R-CNN technique

Methods	Accuracy	
	Moderate demented	Non-demented
Proposed Mask R-CNN	0.974	0.971



Graph 1: Accuracy of Proposed Mask R-CNN Method



a) b)

Fig. 4 - Visualization of Alzheimer disease detection results in MRI images – a) Moderate demented, b) non-demented

To further comprehend how well our technique performs, we have developed a boxplot of the assessment measurements for both datasets (Fig. 4). In a boxplot, the results are broken down into their four quartiles, the median, and an outlier. When applied to the dataset of people with mild cognitive impairment, our method achieved an average accuracy of 97.4%, whereas when applied to the dataset of people without cognitive impairment, it achieved an accuracy of 97.1%. (Graph 2). Due to visual similarities with healthy tissues in a few images, our approach is unable to locate the Alzheimer disease (AD) location effectively, as demonstrated in Fig. 5.

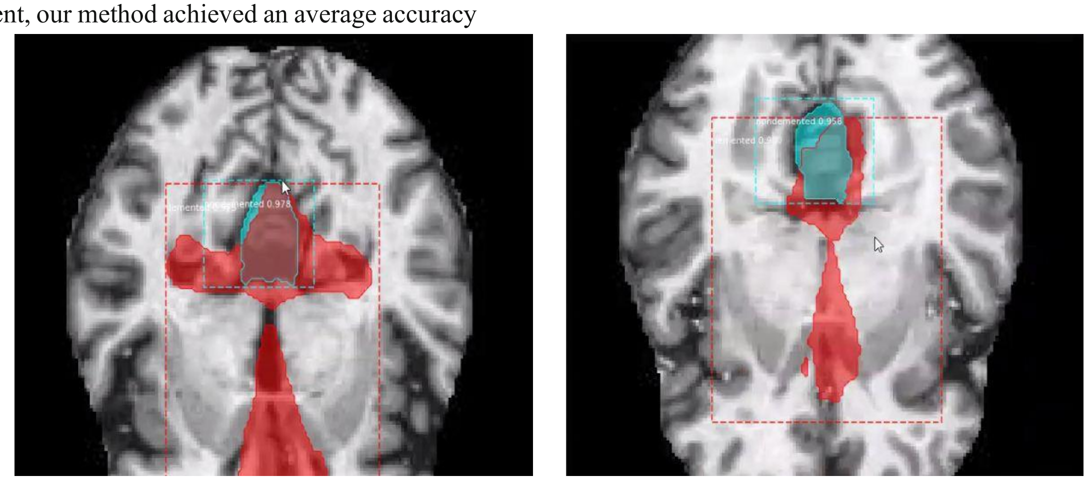
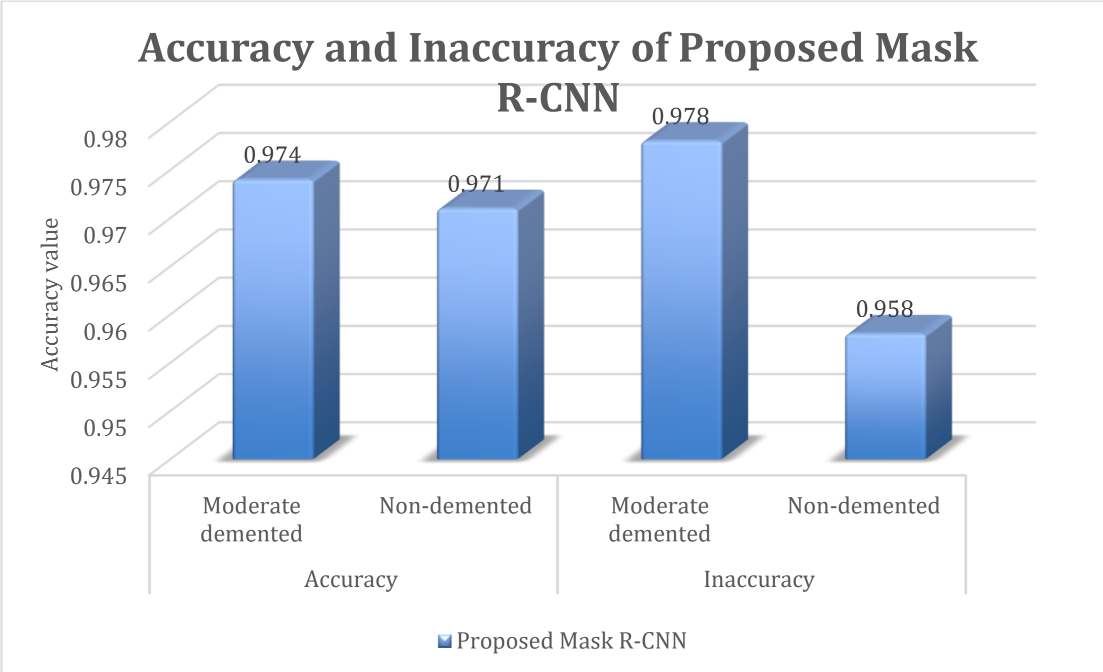


Fig. 5 - Example images of inaccurately localized Alzheimer disease

Table 3- Accuracy and inaccuracy of proposed method

Methods	**Accuracy**		**Inaccuracy**	
	Moderate demented	**Non-demented**	**Moderate demented**	**Non-demented**
Proposed Mask R-CNN	0.974	0.971	0.978	0.958



Graph 2: Accuracy and inaccuracy of proposed method

Table 4. Comparison of the Proposed Method to Other RCNN Techniques [1][12][15]

Methods	Accuracy
RCNN	0.92
Faster RCNN	0.94
Proposed Mask RCNN	0.97

Table 4 above details the results of some of the tests we ran to assess the model's efficacy using state-of-the-art methods; these tests were done using the Moderate demented and non-demented dataset. The proposed method makes use of profound highlights, which are more prejudicial, solid, and give a more powerful portrayal of Alzheimer infection districts than hand-crafted features used by methods like [1], which are limited in their ability to do so due to the structural complexity of the disease. Since segmentation is done directly to the complete image in some earlier algorithms [2-4], misclassification occurs due to the intricate background, thereby reducing the accuracy of the segmentation (such as brain tissues overlapping with disease boundaries, MRI artifacts, etc.). Our model, in contrast to existing methods, conducts division on the confined returns for capital invested, which restricts the division space, and utilizes the return for capital invested Adjust layer to expand the precision of the last division result.

7. Conclusion

In this study, we used Mask R-CNN, a deep learning approach, on Alzheimer's disease MRI data to identify the disease. 40 MRI image samples of two different Alzheimer disease types— moderate demented and non-demented—were used to train a model. Given that the acquired detection confidence accuracy is 97.46%, which is greater than the results of comparable work using the same dataset, it can be inferred that the Mask R-CNN technique is a good fit for this task. Additionally, some cases of the condition have been seen to be appropriately identified with low scores.

References

[1] [World Alzheimer Report 2018, Alzheimer’s Disease International; London, UK: The State of the Art of Dementia Research: New Frontiers. New Frontiers, 2018.

[2] Huang J et al., Altered d-glucose in brain parenchyma and cerebrospinal fluid of early Alzheimer’s disease detected by dynamic glucose-enhanced MRI., Sci. Adv. 2020;6:eaba3884. doi: 10.1126/sciadv.aba3884.

[3] Castellazzi G et al., "A Machine Learning Approach for the Differential Diagnosis of Alzheimer and Vascular Dementia Fed by MRI Selected Features," Front. Neuroinform, no. 10.3389/fninf.2020.00025, 2020.

[4] "How MRI Is Used to Detect Alzheimer’s Disease," https://www.verywellhealth.com/can-an-mri-detect-alzheimers-disease-98632

[5] M. Andriluka et al., "2D human pose estimation: New benchmark and state of the art analysis," In CVPR, 2014. DeAngelis, "Brain tumors," N. Engl. J. Med, vol. 344, p. 114–123, 2001.

[6] L Guo et al., "Alzheimer detection in MR images using oneclass immune feature weighted SVMs," IEEE Transactions on Magnetics, vol. 47, no. 10, p. 3849–3852, 2011.

[7] R.Kumari, "SVM classification an approach on detecting abnormality in brain MRI images," Interational Journal of Engineering Research and Applications, vol. 3, p. 1686–1690, 2013. h.-v. DICOM Samples Image Sets.

[8] R. A. Novellines et al., "Squire's fundamentals of radiology," Six Edition; UPR, 2004.

[9] D. C. preston, "Magnetic Resonance Imaging (MRI) of the Brain and Spine from Basics," casemed.case.edu, 2006.

[10] R. E. Hendrik, "Glossary of MR Terms from American College of Radiology .," 2005.

[11] S. Ren et al., "Towards real-time object detection with region proposal networks.," in In NIPS, 2015.

[12] Girshick et al., "Fast R-CNN," in In ICCV,, 2015.

[13] J. Huang et al., "Speed/accuracy trade-offs for modern convolutional object detectors," in In CVPR,, 2017.

[14] R. Girshick et al., "Rich feature hierarchies for accurate object detection and semantic segmentation," in In CVPR,, 2014.

[15] Liu et al., "Inherent Structure-Based Multiview Learning With Multitemplate Feature Representation for Alzheimer’s Disease Diagnosis," IEEE Trans. Biomed. Eng. 2016;63:1473–1482. doi: http://10.1109/TBME.2015.2496233 , 2016.

[16] Jack C. R. et al., "The Alzheimer’s Disease Neuroimaging Initiative (ADNI): MRI methods," J. Magn. Reson. Imaging. 2008;27:685–691. doi: http://10.1002/jmri.21049 .

[17] M. McBee, O. Awan, A. Colucci, C. Ghobadi, N. Kadom, A. Kansagra, S. Tridandapani and W. Auffermann, "Deep learning in radiology," Acad. Radiol, vol. 25, p. 1472–1480, 2018.

[18] Mazurowski et al., "Deep learning in radiology: An overview of the concepts and a survey of the state of the art," arXiv 2018,, 2018.

[19] S Basheera et al., "Classification of brain Alzheimer's using deep features extracted using CNN.," in In Journal of Physics: Conference Series; , Secunderabad, India, 2019.

[20] M Sajjad et al., "Multi-grade brain diseases classification using deep CNN with extensive data augmentation," J. Comput. Sci., vol. 30, p. 174–182, 2019.

[21] Sunanda Das et al., "Brain Alzheimer's classification using convolutional neural network," in In Proceedings of the 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), Dhaka, Bangladesh, 2019.

[22] Muhammed Talo et al., "Application of deep transfer learning for automated brain abnormality classification using MR images," in Cogn. Syst. Res., 2019.

[23] Ahmet Inner et al., "Detection of Alzheimer's on brain MRI images using the hybrid convolutional neural network architecture.," Med. Hypotheses, Vols. 139,, p. 109684, 2020.

[24] Khawaldeh et al., "Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks.," Appl. Sci., vol. 8, 2017.
[25] H. Sharma et al., "Enhanced Watershed Segmentation Algorithm-Based Modified ResNet50 Model for Brain disease Detection," BioMed Res. Int., 2022.
[26] N. Mamatha et al., "Graph Theory Based Segmentation of Magnetic Resonance Images for Brain Alzheimer's disease Detection," Pattern Recognit. Image Anal, vol. 32, p. 153–161, 2022.
[27] N M Sultan et al., "Multi-classification of Brain Tumor Images using Deep Neural Network," IEEE Access, vol. 7, p. 69215–69225, 2019.
[28] "Brain web: Simulated Brain Database". [Online]. Available: Obtainable Online: www.cancer.ca/~/media/CCE 10/08/2015..
[29] J. C. Buckner et al., "Central nervous system tumors," in In Mayo Clinic Proceedings, October 2007..
[30] S. A. Deepa, "Review of Brain Alzheimer's Disease Detection from tomography.," in International Conference on Computing for Sustainable Global Development (INDIACom), 2016.