International Journal of Computer Science Trends and Technology (IJCST) – Volume 10 Issue 5, Sep-Oct 2022

RESEARCH ARTICLE OPEN ACCESS

Detection Of Alzheimers Disease Using Modified CNN Compared with Deep Learning Models

Mrs R Jhansi Rani MCA [1], Gurram Hareesh [2]

[1] Asst. Professor, Department Computer Application

[2] Student, Department of Computer Application

[1],[2] Chadalawada Ramanamma Engineering College (Autonomous)

ABSTRACT

Alzheimer's, an irreparable brain disease, impairs thinking and memory while the aggregate mind size shrinks which at last prompts demise. Early diagnosis of AD is essential for the progress of more prevailing treatments. Machine learning (ML), a branch of artificial intelligence, employs a variety of probabilistic and optimization techniques that permits PCs to gain from vast and complex datasets. As a result, researchers focus on using machine learning frequently for diagnosis of early stages of AD. This paper presents a review, analysis and critical evaluation of the recent work done for the early detection of AD using ML techniques. Several methods achieved promising prediction accuracies, however they were evaluated on different pathologically unproven data sets from different imaging modalities making it difficult to make a fair comparison among them. Moreover, many other factors such as pre-processing, the number of important attributes for feature selection, class imbalance distinctively affect the assessment of the prediction accuracy. To overcome these limitations, a model is proposed which comprise of initial pre-processing step followed by imperative attributes selection and classification is achieved using association rule mining. Furthermore, this proposed model based approach gives the right direction for research in early diagnosis of AD and has the potential to distinguish AD from healthy controls. In this project we are using Modified CNN, VGG16, AlexNet,MobileNet.

Keywords: - Alzheimers disease, VGG16, modified CNN, Deep Learning, Early Diagnosis.

I. INTRODUCTION

Alzheimer's disease (AD), a type of dementia, is characterized by progressive problems with thinking and behavior that starts in the middle or old age. The pathologic characteristics are the presence of neuritic plaques in the brain and degeneration of explicit brain cells. The symptoms usually develop slowly and get serious enough to interfere in daily life. Although the paramount risk factor is oldness but AD is not just an old age disease. In its early stages, the memory loss is mild while in the later stages, the patient's conversation and their ability to respond degrades dramatically. The current treatments cannot stop Alzheimer's disease (AD) from developing but early diagnosis can aid in precluding the severity of the disease and help the patients to improve the quality life. It has been reported that the number of individuals effected with AD will double in next 20 years (Zhang, 2011), while in 2050, 1 out of 85 individuals will be effected (Ron Brookmeyer, 2007). Thus the accurate diagnosis especially for the early stages of AD is very important.People with infectious pneumonia often have a productive cough, fever accompanied by shaking chills, shortness of breath, sharp or stabbing chest pain during deep breaths, and an increased rate of breathing. In elderly people, confusion may be the most prominent sign.Machine learning is used to interpret and analyze data. Furthermore it can classify patterns and model data. It permits decisions to be made that couldn't be made generally utilizing routine systems while sparing time (Mitchell T, 1997) and endeavors (Duda RO, 2001). Machine learning methodologies have been extensively used for computer aided diagnosis in medical image formation mining (Supekar, 2008) and retrieval (Bookheimer, 2000) with wide variety of other applications (Cruz, 2006) especially in detection and classifications of brain disease using CRT images (Cruz, 2006) and x-rays (Patrician, 2004) It has just been generally late that AD specialists have endeavored to apply machine learning towards AD prediction.

As a consequence, the literature in the field of Alzheimer's disease prediction and machine learning is relatively small. However, today's imaging technologies and high throughput diagnostics have lead us overwhelmed with large number (even hundreds) of cellular, clinical and molecular parameters. In current circumstances, the standard measurements and human instinct don't frequently work. That is the reason we must depend on intensively computational and non-traditional approaches such as machine learning. The custom of using machine learning as a part of disease prediction and visualization is a fragment of an expanding shift towards prescient (Weston, 2004) and customized prescription (Cruz, 2006). This drift is important, not only for the patients in increasing their quality of life and life style, but for physicians in making treatment decisions and also for health economists. In evaluating and analyzing the existing studies, a number of common trends and gaps has been identified. The most evident trends include a rapid growth in the AD detection and prognosis using machine learning methods.

Among the major gaps was an imbalance of events with attributes (few instances and too many attributes), the use of pathologically unproven data set (which cause uncertainty in results), class imbalance (too few instances in one class and too many instances in other class), overtraining and lack of external testing or validation. Nevertheless, the better designed and validates studies made it clear that machine learning methods, in comparison to standard statistical methods, could improve the accuracy of AD prediction.

Besides, machine learning play an important role in AD prediction and prognosis. To overcome these limitation, a model is proposed for effective diagnosis of onset of AD. While considering the pathologically proven data set, the proposed model involve a pre-processing step for eliminating the class imbalance issue. Important attributes selection using machine learning method help avoiding the problem of too few instances and too many attributes, known as curse of dimensionality (Cruz, 2006). The model divides the dataset into training and testing data. Training data on a limited testing data leads to a phenomenon of over-training (Chaves, 2010). Thus, training data should be selected to span a representative fragment of the actual data. The model presents classification using association rule mining with minimum support and minimum confidence.

II. RELATEDWORKS

Bäckström, K., Nazari, M., Gu, I.Y., Jakola, A.S. proposed An efficient 3D deep convolutional network for Alzheimer’s disease diagnosis using MR images. Automatic extraction of features from MRI brain scans and diagnosis of Alzheimer's Disease (AD) remain a challenging task. In this paper, we propose an efficient and simple three-dimensional convolutional network (3D ConvNet) architecture that is able to achieve high performance for detection of AD on a relatively large dataset. The proposed 3D ConvNet consists of five convolutional layers for feature extraction, followed by three fully-connected layers for AD/NC classification. The main contributions of the paper include: (a) propose a novel and effective 3D ConvNet architecture; (b) study the impact of hyper-parameter selection on the performance of AD classification; (c) study the impact of pre-processing; (d) study the impact of data partitioning; (e) study the impact of dataset size. Experiments conducted on an ADNI dataset containing 340 subjects and 1198 MRI brain scans have resulted good performance (with the test accuracy of 98.74%, 100% AD detection rate and 2,4% false alarm). Comparisons with 7 existing state-of-the-art methods have provided strong support to the robustness of the proposed method.

Carneiro, T., Medeiros Da NóBrega, R.V., Nepomuceno, T., Bian, G., De Albuquerque, V.H.C., Filho, proposed Performance analysis of Google colaboratory as a tool for accelerating deep learning applications. Google Colaboratory (also known as Colab) is a cloud service based on Jupyter Notebooks for disseminating machine learning education and research. It provides a runtime fully configured for deep learning and free-of-charge access to a robust GPU. This paper presents a detailed analysis of Colaboratory regarding hardware resources, performance, and limitations. This analysis is performed through the use of Colaboratory for accelerating deep learning for computer vision and other GPU-centric applications. The chosen test-cases are a parallel tree-based combinatorial search and two computer vision applications: object detection/classification and object localization/segmentation. The hardware under the accelerated runtime is compared with a mainstream workstation and a robust Linux server equipped with 20 physical cores. Results show that the performance reached using this cloud service is equivalent to the performance of the dedicated testbeds, given similar resources. Thus, this service can be effectively exploited to accelerate not only deep learning but also other classes of GPU-centric applications.

Cheng, D., Liu, and M. proposed CNNs based multi-modality classification for AD diagnosis. Accurate and early diagnosis of Alzheimer's disease (AD) plays a significant part for the patient care and development of future treatment. Magnetic Resonance Image (MRI) and Positron Emission Tomography (PET) neuroimages are effective modalities that can help physicians to diagnose AD. In past few years, machine-learning algorithm have been widely studied on the analyses for multi-modality neuroimages in quantitation evaluation and computer-aided-diagnosis (CAD) of AD. Most existing methods extract the hand-craft features after image preprocessing such as registration, segmentation and feature extraction, and then train a classifier to distinguish AD from other groups. This paper proposes to construct multi-level convolutional neural networks (CNNs) to gradually learn and combine the multi-modality features for AD classification using MRI and PET images. First, the deep 3D-CNNs are constructed to transform the whole brain information into compact high-level features for each modality. Then, a 2D CNNs is cascaded to ensemble the high-level features for image classification. The proposed method can automatically learn the generic features from MRI and PET imaging data for AD classification.

Cui, R., Liu, M.: Hippocampus analysis by combination of 3-D DenseNet and shapes for Alzheimer’s disease diagnosis. Hippocampus is one of the first involved regions in Alzheimer's disease (AD) and mild cognitive impairment (MCI), a prodromal stage of AD. Hippocampal atrophy is a validated, easily accessible, and widely used biomarker for AD diagnosis. Most of existing methods compute the shape and volume features for hippocampus analysis using structural magnetic resonance images (MRI). However, the regions adjacent to hippocampus may be relevant to AD, and the visual features of the hippocampal region are important for disease diagnosis. In this paper, we have proposed a new hippocampus analysis method to combine the global and local features of hippocampus by three-dimensional densely connected convolutional networks and shape analysis for AD diagnosis. The proposed method can make use of the local visual and global shape features to enhance the classification This model emphasizes an existing method that which is designed using the some of the algorithms of deep learning. Here the process is performed using the Google Net, which is one of the transfer learning method, but this could not get the high accuracy.

III. PROPOSED SYSTEM ARCHITECTURE

In proposed system we are using Modified CNN, MobileNet, and VGG16for the Alzheimer’s disease classification. By using these algorithms we can get better accuracy with CNN and mobilenet.

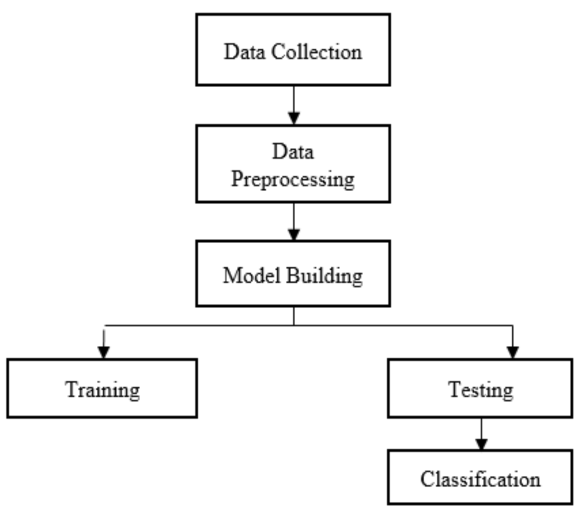

Fig. Block diagram of proposed method

Advantages of proposed system:

- Accurate classification
- Less complexity
- High performance

The first building block in our plan of attack is convolution operation. In this step, we will touch on feature detectors, which basically serve as the neural network's filters. We will also discuss feature maps, learning the parameters of such maps, how patterns are detected, the layers of detection, and how the findings are mapped out. The second part of this step will involve the Rectified Linear Unit or Relook. We will cover Relook layers and explore how linearity functions in the context of Convolutional Neural Networks. Not necessary for understanding CNN's, but there's no harm in a quick lesson to improve your skills. This will be a brief breakdown of the flattening process and how we move from pooled to flattened layers when working with Convolutional Neural Networks. In this part, everything that we covered throughout the section will be merged together. By learning this, you'll get to envision a fuller picture of how ConvolutionalNeural Networks operate and how the "neurons" that are finally produced learn the classification of images. The VGG network architecture was introduced by Simonyan and Zisserman in their 2014 paper, Very Deep Convolutional Networks for Large Scale Image Recognition. This network is characterized by its simplicity, using only 3×3 convolutional layers stacked on top of each other in increasing depth. Reducing volume size is handled by max pooling. Two fully-connected layers, each with 4,096 nodes are then followed by a Softmax classifier. The "16" and "19" stand for the number of weight layers in the network.

AlexNet is a deep learning model and it is a variant of the convolutional neural network. This model was proposed by Alex Krizhevsky as his research work. His work was supervised by Geoffery E. Hinton, a well-known name in the field of deep learning research. Alex Krizhevsky competed in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC2012) in the year 2012 where he used the AlexNet model and achieved a top-5 error of 15.3%, more than 10.8 percentage points lower than that of the runner up. The AlexNet proposed by Alex Krizhevsky in his work has eight layers including five convolutional layers followed by three fully connected layers. Some of the convolutional layers of the model are followed by max-pooling layers. As an activation function, the ReLU function is used by the network which shows improved performance over sigmoid and tanh functions. The network consists of a kernel or filters with size 11 x 11, 5 x 5, 3 x 3, 3 x 3 and 3 x 3 for its five convolutional layers respectively. The rest of the parameters of the network can be tuned depending on the training performances.

The AlexNet employing the transfer learning which uses weights of the pre-trained network on ImageNet dataset has shown exceptional performance. But in this article, we will not use the pre-trained weights and simply define the CNN according to the proposed architecture.

Modules of the work are

1. System:

1.1 Create Dataset:

The dataset containing images of the MRI images with the Alzheimer's diseases in training of 7600 images and testing of 3800 images.

1.2 Pre-processing:

Resizing and reshaping the images into appropriate format to train our model.

1.3Training:

Use the pre-processed training dataset is used to train our model using Modified CNN algorithm along with other deep learning models.

1.4 Classification:

The results will be displayed are which type of Alzheimer's diseases.

1) Mild Demented
2) Moderate Demented
3) NonDemented
4) VeryMildDemented

2. User:

2.1 Upload Image

The user has to upload an image which needs to be classified.

2.2View Results

The classified image results are viewed by user.

IV. RESULTS AND DISCUSSION

The output screens obtained after running and executing the system are shown from Fig.2 to Fig.8

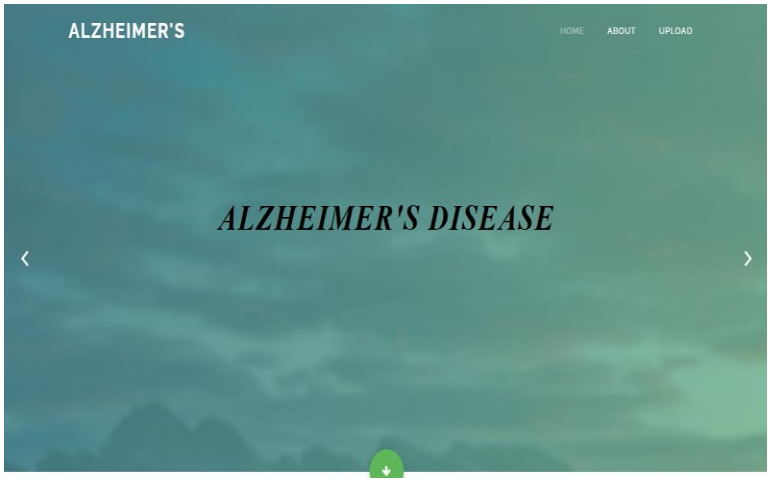

Fig.2 Home Page

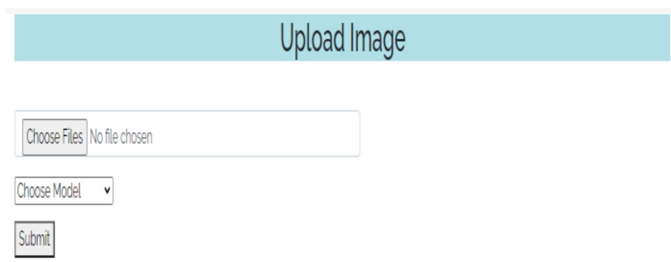

Fig.3 Upload Image

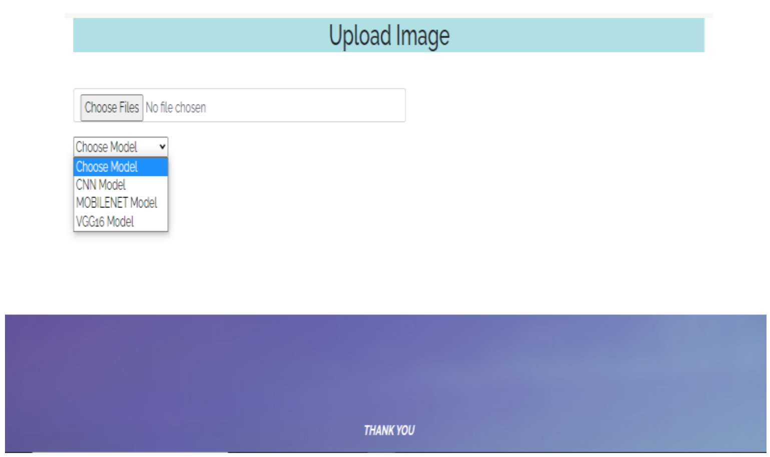

Fig.4 View Algorithms

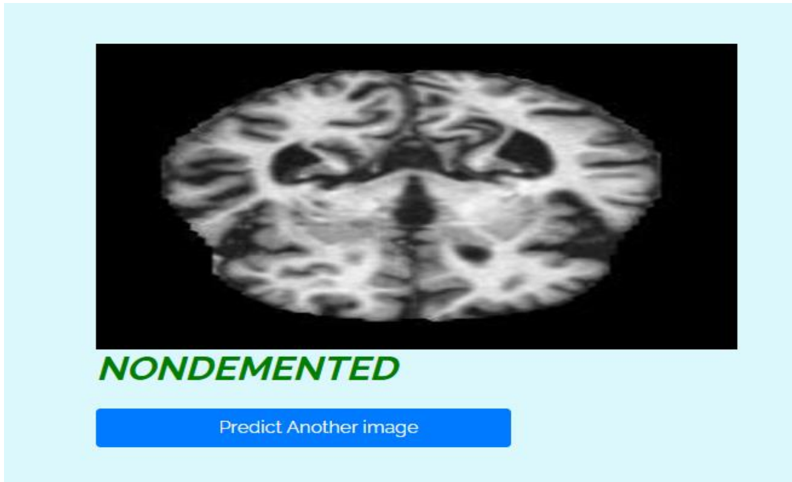

Fig.5 Nondemented

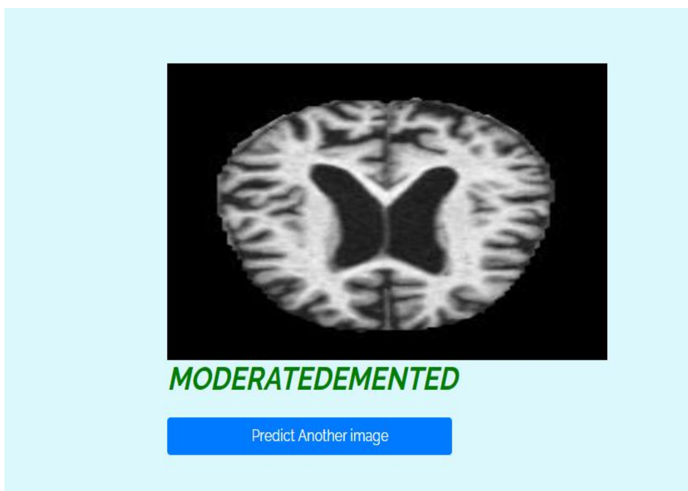

Fig.6 moderate demented

Fig.7 very mild demented

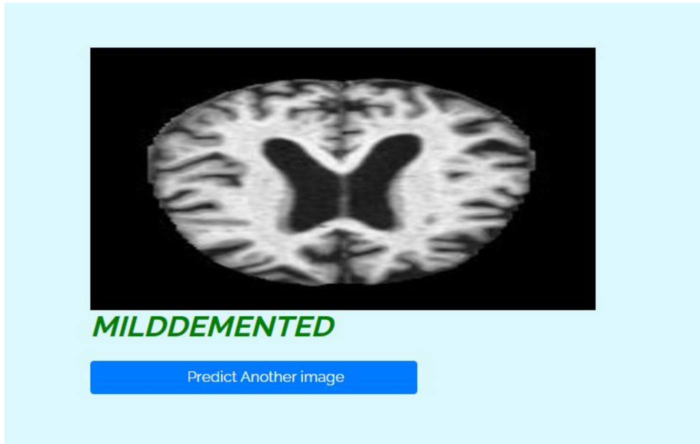

Fig.8 mild demented

V. FUTURE SCOPE AND CONCLUSION

In this project we have successfully classified the images of MRI images of a person, is either Mild Demented or Moderate Demented or Non Demented or Very Mild Demented using the deep learning algorithms. Here, we have considered the dataset of MRI images which will be of 4 different types and trained using Modified CNN with MobileNet, VGG16 algorithms. After the training we have tested by uploading the image and classified it. This can be utilized in future to classify the types of different classifications easily that which can tend to easy to find out the infections in early stages and can be cured in the initial stages only. Overall, on the basis of high-level literature review, we found that the published papers in this area tend to focus on two main areas of research, namely, biomarkers and neuro-imaging, but with increasing interest in image analysis. Although regarded thorough and extensively conducted, the work adds little knowledge to the initial detection of AD, as the majority of selected patients are already known to have AD. This study reviewed the some of the important related AD datasets and
diagnose techniques and detection. This approach is feasible for early-stage neuro-imaging research.

REFERENCES

1. Alzheimer's Disease Neuroimaging Initiative: Study Design (2017). http://adni.loni.usc.edu/study-design/
2. Bäckström, K., Nazari, M., Gu, I.Y., Jakola, A.S.: An efficient 3D deep convolutional network for Alzheimer's disease diagnosis using MR images. In: 2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018), pp. 149–153, April 2018. https://doi.org/10.1109/ISBI.2018.8363543
3. Carneiro, T., Medeiros Da NóBrega, R.V., Nepomuceno, T., Bian, G., De Albuquerque, V.H.C., Filho, P.P.R.: Performance analysis of Google colaboratory as a tool for accelerating deep learning applications. IEEE Access **6**, 61677–61685 (2018). https://doi.org/10.1109/ACCESS.2018.2874767
4. Cheng, D., Liu, M.: CNNs based multi-modality classification for AD diagnosis. In: 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), pp. 1–5, October 2017. https://doi.org/10.1109/CISP-BMEI.2017.8302281
5. Cohen, J.P., Bertin, P., Frappier, V.: Chester: A Web Delivered Locally Computed Chest X-Ray Disease Prediction System. arXiv:1901.11210 (2019)
6. Cui, R., Liu, M.: Hippocampus analysis by combination of 3-D DenseNet and shapes for Alzheimer's disease diagnosis. IEEE J. Biomed. Health Inform. **23**(5), 2099–2107 (2019). https://doi.org/10.1109/JBHI.2018.2882392
7. Graber, M., Franklin, N.: Diagnostic error in internal medicine. Arch. Intern. Med. **165** (2005). https://doi.org/10.1001/archinte.165.13.1493

8. Hara, K., Kataoka, H., Satoh, Y.: Can spatiotemporal 3D CNNs retrace the history of 2D CNNs and ImageNet? In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 6546–6555 (2018)
9. He, G., Ping, A., Wang, X., Zhu, Y.: Alzheimer's disease diagnosis model based on three-dimensional full convolutional DenseNet. In: 2019 10th International Conference on Information Technology in Medicine and Education (ITME), pp. 13–17, August 2019. https://doi.org/10.1109/ITME.2019.00014
10. Huang, G., Liu, Z., Van Der Maaten, L., Weinberger, K.Q.: Densely connected convolutional networks. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Honolulu, HI, pp. 2261–2269 (2017). https://doi.org/10.1109/CVPR.2017.243
11. Jabason, E., Ahmad, M.O., Swamy, M.N.S.: Classification of Alzheimer's disease from MRI data using an ensemble of hybrid deep convolutional neural networks. In: 2019 IEEE 62nd International Midwest Symposium on Circuits and Systems (MWSCAS), pp. 481–484, August 2019. https://doi.org/10.1109/MWSCAS.2019.8884939
12. Khan, S., Rahmani, H., Shah, S., Bennamoun, M.: A Guide to Convolutional Neural Networks for Computer Vision. Synthesis Lectures on Computer Vision, No. 1. Morgan & Claypool Publishers (2018). https://doi.org/10.2200/S00822ED1V01Y201712COV015
13. Kollias, D., Tagaris, A., Stafylopatis, A., Kollias, S., Tagaris, G.: Deep neural architectures for prediction in healthcare. Complex Intell. Syst. **4**(2), 119–131 (2017). https://doi.org/10.1007/s40747-017-0064-6
14. Lee, C.S., Nagy, P.G., Weaver, S.J., Newman-Toker, D.E.: Cognitive and system factors contributing to diagnostic errors in radiology. Am. J. Roentgenol. **201**(3), 611–617 (2013). https://doi.org/10.2214/AJR.12.10375
15. National Institute of Biomedical Imaging and Bioengineering: Magnetic Resonance Imaging (MRI). https://www.nibib.nih.gov/science-education/science-topics/magnetic-resonance-imaging-mri.