A Comprehensive Study on Computer Aided Approaches for Multiclass Neurological Disorder Classification

Binu Rajan M R
Research Scholar
Department of Computer Science and Engineering
Annamalai University
Chidambaram, India
binusunil77@gmail.com

Dr.K. Kavitha
Associate Professor
Department of Computer Science and Engineering
Annamalai University
Chidambaram, India
kavithacseau@gmail.com

Dr.Jayasudha J S
Professor and Head
Department of Computer Science and Engineering
Central University of Kerala,
Kasargod, India
jayasudhajs@cukerala.ac.in

***Abstract*—Visualizing anatomical structure benefits from medical imaging and analysis. However, employing basic imaging methods is challenging and ineffective. Brain abnormalities diagnosis and classification manually is especially a tedious task. Additionally, the approach currently in use experiences inter-observer variability while interpreting images. Diagnosis must be done with extreme care because even a small human error can have serious effects. An MRI can be used as a non-invasive method to find tumors. Early disease diagnosis can be accomplished by Computer Aided Diagnosis (CAD) systems, potentially improving survival odds and reducing the requirement for MRI analysis by a specialist. CNN have demonstrated to be quite efficient at finding tumors in brain MRIs. The automated diagnosis of brain MRI images using a unique computer-aided diagnosis method is described here. In recent decades, neuroimaging, especially MRI, has played a pivotal role in advancing our understanding of brain function and the various illnesses that can impact. Accurately identifying such illnesses from acquired neuroimaging data poses significant challenges due to the similarities in disease characteristics. This study analyses and evaluates the effectiveness of deep learning methods to identify neurological diseases. This study focuses on Alzheimer's, Picks, Huntington's, Cerebral Carcinoma and Tumors.**

***Keywords*—neurological disorder classification, brain mri, deep learning, multiclass classifier, brain abnormalities.**

I. INTRODUCTION

Brain regulates activities of numerous organs, controls thoughts, memories, speech, and movement. Any disorders or disabilities that affect the brain that are brought on by disease, trauma, or heredity are referred to as brain diseases. People all over the world have been found to have a wide range of brain illnesses. Degenerative, cerebro-vascular, neoplastic, and viral illnesses of the brain are among the conditions that affect it. These illnesses can lead to serious issues like memory loss and dysfunctions of the neurological system. Therefore, in order to receive prompt treatment, early detection using medical imaging technology is required. Medical professionals typically use manual procedures, such as visual inspection of MRI scans, to identify brain abnormalities. However, large scale detection is tedious, erroneous, and exhausting. Automated method development can solve these problems and advance the rapid, trustworthy, and accurate processing of brain MRIs. Due to these advantages, computerized diagnosis is a crucial study issue in recent years. It supports doctors in verifying their final screening procedure. An enormous amount of work has gone into automating the classification of brain MRIs. Description of the workflow used for MRI scan capture and processing depicted in Fig. 1.

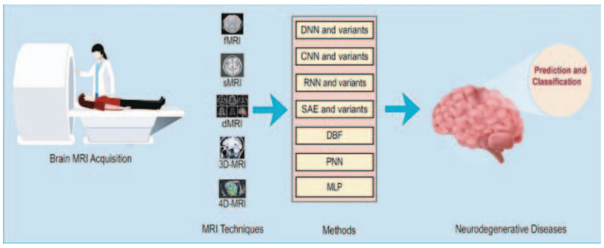

Fig. 1. Framework for the Prediction and Classification of Neurological Disorders.

Medical data (signals and images) includes a range of technologies that aid physicians in rapidly and effectively identifying, diagnosing, and treating disorders. Medical imaging, which includes Computed Tomography (CT), Mammography, PET, X-ray, and Ultrasound, has quickly emerged as dominant and efficient technologies. Neurophysiological medical signals, including Electroencephalograph (EEG), are frequently utilised to identify epilepsy. The information acquired by these technologies regarding the many human organs is useful for both diagnosis and research. In order to make choices, human specialists such as radiologists and doctors must carefully assess medical data. Since, there is so much medical information, explication takes a long time and is only influenced by the prejudices and fatigue of human specialists.

In order to be more effective, clinicians have begun adopting computerized systems to comprehend neural signals and brain images. An essential role in the analysis of medical data is played by handcrafted feature extraction, which is followed by traditional Machine Learning (ML) techniques. It is capable of extracting meaningful features to explain the underlying structures from images in Computer Aided Diagnosis (CAD) systems. On the other hand, medical data structures are exceedingly complicated, and feature selection is performed by people utilising their subject expertise. Although it has been demonstrated that sparse learning and dictionary learning are effective for quickly finding irrelevant features and these algorithms restrict representative ability.

Deep Learning (DL) algorithms enable non-experts to use them successfully because, unlike conventional handmade feature extraction techniques, they automatically extract meaningful information without the understanding of domain specialists. DL has consequently swiftly taken over as the method of choice for analysing medical data in recent years. Because of improved computing capabilities and the accessibility of vast amounts of data, DL has achieved feats in applications like speech processing, autonomous driving, and computer vision. The parallel development and triumphs of computer vision served as a motivation for using DL in the interpretation of medical data. The main four types of medical image analysis tasks are segmentation, registration, detection/localization, and classification. Categorization is the first task where DL significantly contributes to medical image processing. This position's objective is to classify medical images into two or more groups. Finding features or lesions in an entire medical image and identifying them are the tasks involved in the detection/localization problem.

Sample brain MRIs are shown in Fig. 2. Images under-consideration is obtained from a dataset of 256 x 256 images collected by HMS University. These MRIs were taken along the axial view plane and are T2-weighted.

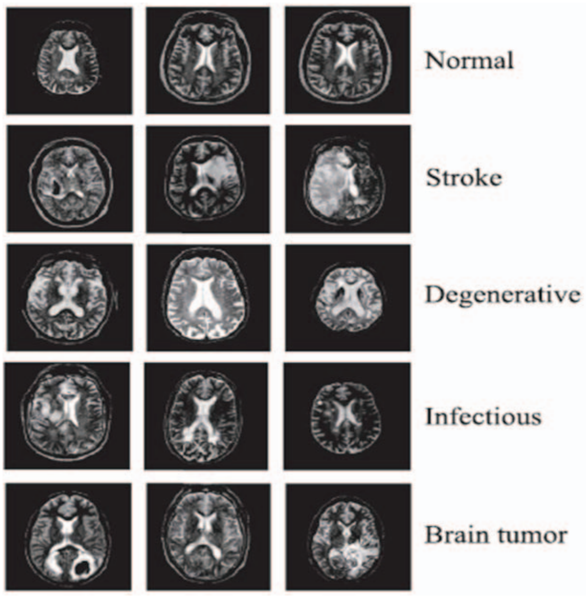

Fig. 2. Typical brain MRI scans from five distinct classes.

II. MACHINE LEARNING MODELS

Signals and/or images are typically used as input data for CAD systems. Many CAD systems employ EEG, speech and MRI to diagnose neurological disorders. MRI and Computed Tomography (CT) scans are typically utilized in image-based techniques. T1 and T2 weighted MRI scans, which measure the interval between magnetic pulses and the acquisition of the image, are frequently used to diagnose Multiple Sclerosis.

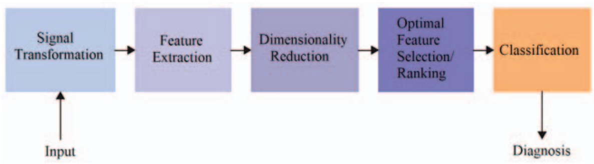

Fig. 3. Typical ML-based diagnosis system.

A typical ML-based CAD system has 5 steps, as shown in Fig. 3, including signal processing, feature extraction, feature dimensionality reduction, best feature ranking, and classification.

For the purpose of detecting epilepsy and epileptic seizures, Wang *et al.* [1] introduced Discrete Wavelet Transform (DWT) based multiclass classifier involving nonlinear Sparse Extreme Learning Machine (SELM). The decomposition is accomplished using a three-level lifting DWT utilising a wavelet of Daubechies order 4. An 8-dimensional feature vector is produced for each sub-band while taking classification accuracy and computational complexity into account. 97% accuracy was obtained after comparing five multiclass SELM techniques.

Unique CAD technique for automatic analysis of MRI images was described by Gudigar *et al.* [2]. For the automated categorization of distinct kinds of disease, bi-spectral features are extracted to represent image characteristics a new subspace. The performance accuracy of 90.68% was obtained while using SVM classifier. The combination of Probabilistic Neural Networks (PNN) and DWT was developed. A generic solution to the pattern classification issues is provided by probabilistic neural networks, and classification accuracy is determined to be 85%. For the purpose of multiclass classification of the brain MRI, deep ELM was developed. A multilayer architecture with ELM-based autoencoders is called ML-ELM which is used to examine the efficacy of contemporaries.

In order to identify brain MRI outliers, Devika *et al.* [3] introduced an innovative ML approach involving Support Vector Machine (SVM). T1MRI cross-sectional data (one scan per subject) provided 87% accuracy. In order to help radiologists for diagnosing diseases in brain MRIs, Siddique *et al.* [4] developed fast DWT and Principal Component Analysis (PCA) for further analysing distinguishing features. Five alternative decision models are given by varying subset sizes of the major feature vectors. With an average accuracy of 96%, the Random Forest (RF) based classifier surpassed all other decision models that were being tested. In order to discriminate between people with various neurological disorders and healthy people, a ML method was created. For analysing MRI using publicly available datasets, and tiny groupings of images that accurately and specifically discriminate a variety of neurodegenerative disorders. They established the value of significant features in identifying neurodegenerative disorders.

Hybrid method combining Artificial Neural Network (ANN) and the Particle Swarm Optimization (PSO) was presented by Kshirsagar *et al.* [5] for the categorization and forecasting of various neurological diseases. Based on the input of MRI data, a very effective classification tool based on PNN is utilised. With graphs for anticipated signal and prediction error, the findings are extremely trustworthy. This technology makes it possible to quickly and accurately classify MRI with an accuracy rate of more than 93.10%.

Abdulbaqi *et al.* [6] developed a hybrid method for classifying and evaluating EEG signals as a first step in the diagnosis of neurological and cerebral illnesses. The strong qualities appropriate for grading were the retrieved attributes. Both KNN and SVM classifications use the division of signals into normal and abnormal groups. One of the effective ways to determine performance measures for both classifiers has shown to be the confusion matrix. The experimental results of the SVM-based classifier have delivered the maximum accuracy of 81.23% for categorization in the normal and abdominal groups.

III. Transfer Learning Models

Transfer learning (TL) is a widely-used technique in DL that enables the reuse of a pre-trained model for different tasks or situations. The popularity of TL stems from its ability to train DNN effectively even when the available data is limited, which is particularly beneficial in real-world scenarios where obtaining extensive labelled datasets can be challenging. This capability has proven to be highly advantageous in the data science field, where complex models typically demand large amounts of data for successful training. A general TL model for brain MRI classification is depicted in Fig. 4.

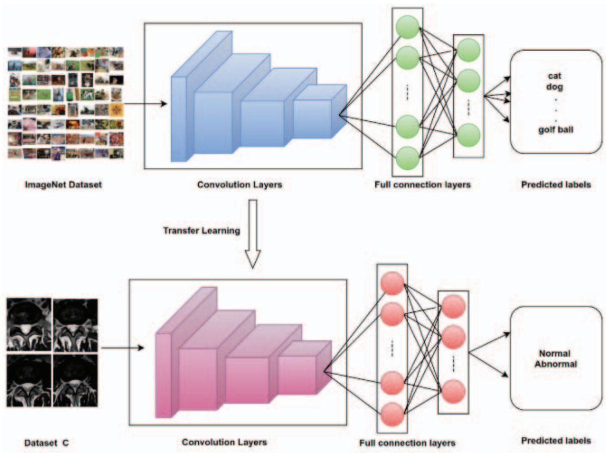

Fig. 4. Brain MRI classification using TL.

Bhatele *et al.* [7] developed neurodegenerative diseases identification system, which is based on the Capsule network. This classifier system outperforms popular DL models, with accuracy of 96.81%. A pre-trained VGG-16 model trained using TL has been examined. Only the last few levels of the VGG-16 model were changed in the current application to accept additional image classifications. With transfer learning, the VGG-16 model was able to provide a 92% accuracy. A DL system was developed for accurate diagnosis of Alzheimer's disease and its early stages from structural MRI images. In a single arrangement, the framework analyses four separate classes concurrently. The method's testing accuracy for the diagnosis it provides is 96.88%. Transfer learning is used in experiments on binary data to achieve a 94.7% accuracy rate for multiclass categorization. Ye *et al.* [8] developed a unique TL method for identifying the gait of patients with neuro disease. The suggested model combines fuzzy logic qualitative analysis with neural network adaptive capabilities and provided accuracy of 94.44%.

Based on ResNet and TL, Lu *et al.* [9] suggested a disease affected brain identification scheme for brain MRI. First, ResNet, a well-known CNN structure, was used as the feature extractor. Following that, three randomized neural networks were applied with Extreme Learning Machine (ELM). This scheme distinguished pathological brain from normal control with 95% accuracy. Using multicriteria methodology and a specialized technology, researchers provided a streamline in early identification of neurological diseases. As a result, the suggested model serves as a cutting-edge and reliable instrument that aids in the determination of psychiatric condition diagnosis. Deep TL is a method proposed for categorizing healthy and unhealthy brain MRI. As a DL model, CNN-based ResNet34 is employed. For model training, contemporary DL approaches are utilized with optimized learning rate finder and fine-tuning. This model provided 96.32% accuracy. AlexNet classifier was introduced by Chen *et al.* [10] for the diagnosis of neurological disorders. In order to extract 256 characteristics from each image, this approach chooses TL. Finally, the classifier employed AlexNet classification and obtained accuracy of 96.61%.

In order to diagnose AD and PD using PET, Noella *et al.* [11] offered many effective DL techniques that were chosen and assessed their behaviours. TL was used for feature extraction and obtained an accuracy of 90.3%. An approach was developed by merging functional and structural data utilising a 3D fMRI scan. This algorithm can distinguish between healthy and neurological disorder patients into two groups. Hey looked at several ways to portray the functional connectivity of the brain as it relates to this classification job.

IV. Deep Learning Models

Recent improvements in DL approaches addressed the shortcomings of ML-based methods. The CNN is a DL example that has a lot of benefits over traditional ML-based CAD solutions. First and foremost, thanks to its layered architecture, it can manage enormous data collections. Additionally, it can work with unbalanced data without favouring the dominant class. Convolution, pooling, and fully connected layers often make up the CNN architecture. Numerous CNN oriented methods have demonstrated promising results in the detection of neurological diseases. However, early diagnosis of such problems may necessitate a deeper architecture. The structure of a DL model for neuro-disease classification is illustrated in Fig. 5.

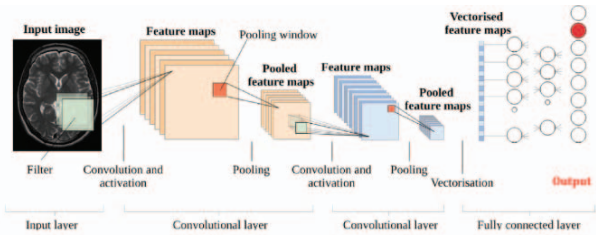

Fig. 5. Deep learning based neurological disorder classification.

Talo *et al.* [12] categorized MRI into neoplastic, cerebrovascular, degenerative and normal inflammatory categories using ResNet-50 models. According to the findings, the ResNet-50 model had the best accuracy 95.23% To categorize the stages of dementia, researchers created a Siamese Convolutional Neural Network (SCNN) model that was influenced by VGG-16. In this strategy, author used augmentation methodologies to supplement the sparse and unbalanced data. Using the suggested method, experiments are conducted using a publicly accessible OASIS dataset and test accuracy of 99.05% is obtained. DCNN-based automated technique was developed by Nayak *et al.* [13] for the diagnosis of multi-class brain disorders. Single fully-connected layer and 4 convolutional layers make up the learnable layers. The goal of creating a bespoke deep network of this type is to improve classification performance with fewer parameters and this model attained 97.50% accuracy.

To distinguish between various disease classes, 3D CNN was used for multiclass classification. Using a fivefold CV technique, it was discovered that blurring without augmentation performed worst in the frequency domain. Researchers used a straightforward functional mobility test on individuals with various conditions to assess CNN. As a consequence, the validation procedure showed that 90% of the individuals were accurately classified by CNN into each group. The two parametric classifiers' best pathology classification accuracy ranged from 55% to 88%. Multi-scale CNN model for MRI categorization was presented by Yazdan *et al.* [14]. This approach divides MRI scans into four categories. In order to enhance the results of the classification, MRIs are additionally denoised with fuzzy filter. According to the experimental findings, the suggested model requires less processing power and obtained91.2% accuracy. Using a novel DL technique, researchers provided an intelligent detection approach for fMRI modality. In order to extract features, autoencoder is utilized. A new fuzzy method is introduced in the classification step and subsequently optimized using genetic algorithm. Accuracy of this categorization method was 72.71%.

Mussalam *et al*. [15] suggested the improvement of MRI quality and developed a DCNN architecture for diagnosing gliomas, meningiomas, and pituitary tumors successfully. This design has a few max-pooling and convolutional layers making it a computationally light model. This design is demonstratively compared to the other models covered in this study. An exceptional competitive accuracy of 98.22% is obtained. Mehmood *et al.* [16] identified, segmented and classified medical images for the accurate diagnosis of brain cancers. The segmentation of brain tumors is then developed using a unique 17-layered DNN architecture. For feature extraction, a modified MobileNetv2 architecture that has undergone transfer learning training is used. On the datasets from BraTS 2018 and Figshare, this technique was tested. The suggested method for classifying and detecting brain tumors obtained 97.47% accuracy rate. A functional network-based classifier that has been refined from a granular standpoint is put forth by Tomesseillo *et al.* [17]. High precision is possible with granular designs without sacrificing interpretability. In order to conduct numerical experiments on publicly available data, AD and PD were considered. This architecture provided typical characteristics of such as intelligibility, transparency and comprehensibility with an accuracy of 98%, through the use of granules.

DL is used to analyze large amounts of neuroimaging data to produce computer-aided neurological disease diagnosis. DL pattern recognition techniques can be used to extract characteristics of neuroimaging signals that are specific to different neurological diseases, for the improvement of diagnosis. In order to categories various neurological illnesses utilizing MRI, MNet was created. The trained MNet achieved an accuracy of 70.7 % in categorizing the healthy patients and those with two neurological disorders. For the detection of AD, researchers presented a framework built on DL techniques. Feature fusion is essential to the framework. Findings demonstrated that the suggested framework could recognize AD MRI from different gestational ages. The outcomes were contrasted with similar work that made use of MRI in order to confirm the effectiveness of the suggested framework.

V. Discussion

MRI is the subject of automated diagnosis system research more frequently to identify PD, AD, and finally epilepsy. Most classifiers used several kernels for the detection of PD with SVM. Numerous dimensionality minimization techniques, including DWT, have been extensively used in research on Alzheimer's disease. The SVM classifier and classifiers dependent on GLCM are the most frequently utilized classifier approaches.

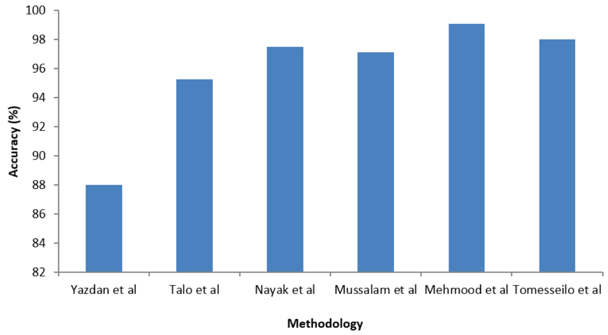

Fig. 6. Accuracy of deep learning-based models.

Fig. 6 compares the total accuracy of each classifier model in CNN based methods. Each classifier model's average accuracy was greater than 88% when the maximum number of main components was applied. But as the number of features increased, Mehmood et al. increased the average accuracy and attained the highest accuracy rate of 99.1%. The outcomes once more demonstrate that the overall average accuracy of the classifier remained steady and not impacted by growing feature subset sizes. When the smallest number of principal characteristics were utilised for classification, Mussalam et al. produced the best results.

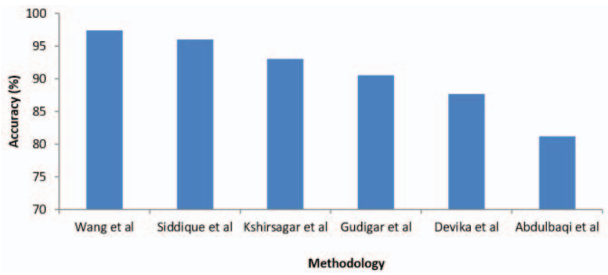

Fig. 7. Accuracy of ML based models.

Fig. 7 compares the accuracy of ML methods in automated diagnosis of neurological disorders. Wang et al. method provided better accuracy of 97% when compared with other approaches. The experimental results of the SVM-based classifier by Abdulbaqi et al. have delivered the maximum accuracy of 81.23% for categorization in the normal and abnormal groups as least in these methods.

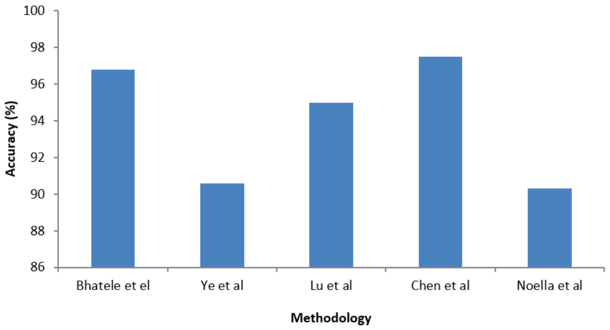

Fig. 8. Accuracy of TL based models.

Fig. 8 compares the accuracy of TL based approaches. In this Chen et al. proposed a classifier that employed linear regression classification achieves a 97.51% accuracy, a 96.71% sensitivity, and a 97.73% specificity. The classification accuracy of Ye et al. using the ANFIS model for differentiating the neurological disorders, groups was 90.63%when tested with this method.

VI. CONCLSION

In this study MRI is classified as cerebral calcinosis, Alzheimer's, metastatic, glioma or normal using a multi-class classifier. It is made up of 3 separate artificial intelligence models like ML, DL and TL. This study offers a thorough evaluation of the effectiveness of various decision models and comes to the conclusion that DL model categorize precisely compared to other models. The outcomes clearly show that DL classifier has the potential for correctly classifying MRI. Additionally, according to these encouraging outcomes, automatic ML based multi-classifier to make a decision more rapidly. The suggested method can be expanded in the future to automatically classify various pathological states through the analysis of MRI. Additionally, these techniques are expected to provide better results in datasets from PET and CT.

REFERENCES

[1] Y. Wang, Z. Li, and L. Feng, "Automatic detection of epilepsy and seizure using multiclass sparse extreme learning machine classification," Computational and Mathematical Methods in Medicine, vol. 17, no. 1, pp. 435-678, 2017.

[2] A. Gudigar, U. Raghavendra, and E. J. Ciaccio, "Automated categorization of multi-class brain abnormalities using decomposition techniques with MRI images: A comparative study," IEEE Access, vol. 7, no. 1, pp. 28498-28509, 2019.

[3] K. Devika, D. Mahapatra, and R. Subramanian, "Dense Attentive GAN-based One-Class Model for Detection of Autism and ADHD," Journal of King Saud University-Computer and Information Sciences, vol. 34, no. 10, pp. 10444-10458, 2022.

[4] M. F. Siddiqui, G. Mujtaba, A. W. Reza, "Multi-class disease classification in brain MRIs using a computer-aided diagnostic system," Symmetry, vol. 9, no. 3, pp. 37-44, 2017.

[5] P. R. Kshirsagar, S. G. Akojwar, and N. D. Bajaj, "A hybridised neural network and optimisation algorithms for prediction and classification of neurological disorders," International Journal of Biomedical Engineering and Technology, vol. 28, no. 4, pp. 307-321, 2018.

[6] A. S. Abdulbaqi, and M. T. Younis, "A hybrid technique for EEG signals evaluation and classification as a step towards to neurological and cerebral disorders diagnosis," International Journal of Nonlinear Analysis and Applications, vol. 13, no. 1, pp. 773-781, 2022.

[7] K. R. Bhatele, A. Jha, and K. Kapoor, "Neuro-degenerative diseases-caps: A capsule network based early screening system for the classification of neurodegenerative diseases," Cognitive Neurodynamics, vol. 16, no. 6, pp. 1-17, 2022.

[8] Q. Ye, Y. Xia, and Z. Yao, "Classification of gait patterns in patients with neurodegenerative disease using adaptive neuro-fuzzy inference system," Computational and Mathematical Methods in Medicine, vol. 18, no. 1, pp. 678-689, 2018.

[9] S. Lu, S. H. Wang, and Y. D. Zhang, "Detecting pathological brain via ResNet and randomized neural networks," Heliyon, vol. 6, no. 12, pp. 5625-5637, 2020.

[10] Y. Chen, Y. Shao, and J. Yan, "A feature-free 30-disease pathological brain detection system by linear regression classifier," CNS and Neurological Disorders-Drug Targets, vol. 16, no. 1, pp. 5-10, 2017.

[11] R. S. Noella, and J. Priyadarshini, "Diagnosis of Dementia Using a Generative Deep Convolution Neural Network," Arabian Journal for Science and Engineering, vol. 13, no, 4, pp. 1-10, 2021.

[12] M. Talo, O. Yildirim, and U. B. Baloglu, "Convolutional neural networks for multi-class brain disease detection using MRI images," Computerized Medical Imaging and Graphics, vol. 78, no. 1, pp. 10167-10173, 2019.

[13] D. R. Nayak, R. Dash, and B. Majhi, "Automated diagnosis of multi-class brain abnormalities using MRI images: A deep convolutional neural network-based method," Pattern Recognition Letters, vol. 138, no. 1, pp. 385-391, 2020.

[14] S. A. Yazdan, R. Ahmad, and N. Iqbal, "An efficient multi-scale convolutional neural network based multi-class brain MRI classification for SaMD. Tomography, vol. 8, no. 4, pp. 1905-1927, 2022.

[15] A. S. Musallam, A. S. Sherif, and M. K. Hussein, "A new convolutional neural network architecture for automatic detection of brain tumors in magnetic resonance imaging images. IEEE Access, vol. 10, no. 1, pp. 2775-2782, 2022.

[16] S. Mahmood, R. Damasevicius, and R. Maskeliunas, "Multi-modal brain tumor detection using deep neural network and multiclass SVM," Medicina, vol. 58, no. 8, pp. 1090-1099, 2022.

[17] S. Tomasiello, A granular functional network classifier for brain diseases analysis. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization, vol. 8, no. 4, pp. 382-388, 2020.