Grenze International Journal of Engineering and Technology, June Issue

HD-CNN: Early-Stage Alzheimer Detection System using Hybrid Deep Convolutional Neural Network

Snehal Rohit Shinde[1] and Dr. Swati V. Sankpal[2]
[1]Department of Electronics and Telecommunication Engineering, Shivaji University, Kolhapur, Maharashtra, India
Email:sneha.patil2051992@gmail.com
[2]Department of Electronics Engineering, D.Y.Patil College of Engineering and Technology, Kolhapur, Maharashtra, India
Email:sankpal1987@gmail.com

***Abstract*— Recent estimates indicate that Alzheimer's disease (AD), currently the sixth leading cause of mortality in the United States, could rank third overall among senior causes of death, behind heart disease and cancer. It goes without saying that early detection and containment of this condition are critical. Alzheimer dementia (AD) diagnosis requires a battery of medical tests that provide massive volumes of multivariate heterogeneous data. It is challenging and time-consuming to manually compare, assess, and analyze this data due to the variety of medical testing. In this study, we presented a hybrid deep learning algorithm-based early-stage detection AD. Potential features are extracted using a variety of feature extraction and selection techniques. Our deep learning frameworks of choice for categorization are VGGNET and RESNET-101. Object detection and data preparation are two uses for the YOLOv8. With a 100 epoch size and 15 hidden layers, the RESNET-101 achieves a higher accuracy of 99.35% than all other experiments. Our system performs better than both VGGNET and ShallowNet in the comparison analysis that was conducted for our model evaluation.**

***Index Terms*— Alzheimer's disease, deep learning, biomarkers, positron emission tomography, Magnetic Resonance Imaging, mild cognitive impairment**

I. INTRODUCTION

The term "dementia" describes a group of illnesses that can harm brain tissue and result in progressive, irreversible memory loss in people. Based on severity, Alzheimer's disease, the most prevalent type of dementia, is divided into three categories: mild, moderate, and severe [1]. According to reports, patients with Alzheimer's disease gradually lose their ability to think over the course of the illness, which eventually results in a total loss of memory and the inability to perform even the most fundamental tasks [13, 14, 16, 17, 25, 26]. Alzheimer's disease, the most prevalent kind of dementia, is the sixth largest cause of death globally. Up to 80% of instances of dementia could be related to it. The Centres for Disease Control and Prevention (CDC) project that by 2060, there will be 14 million people with Alzheimer's disease, nearly tripling the number of those who had it in 2014. This degenerative sickness is currently incurable despite its widespread occurrence [18, 19, 20].
It has been demonstrated that diffusion tensor imaging [18] and other magnetic resonance imaging (MRI) techniques are useful for examining the white matter anatomy of the brain. Several imaging modalities have been employed to detect and investigate Alzheimer's disease, including DTI [21, 22]. The basis of DTI, a non-invasive imaging

Grenze ID: 01.GIJET.10.2.126

method, is the Brownian motion of water molecules. It could be applied to get additional insight into the size, anisotropy, and spatial orientation of water molecules as well as their distribution throughout tissues.

The presence of cerebral atrophy, or the shrinkage of brain tissue brought on by the loss of grey and white matter in the proximal temporal and temporoparietal cortical lobes, is the main factor used in MRI brain scans to identify Alzheimer's disease. Furthermore, the categorization of brain MRIs acquired at various phases may be used to quantify anatomical anomalies in the brain associated with Alzheimer's disease. Clinicians can, however, find it difficult to manually gather and process data from big, intricate DTI datasets. Furthermore, mechanical brain DTI testing may be highly incorrect and time-consuming due to inter- or intra-operator variation problems. Using currently available automated MRI categorization, representation, and registration algorithms is one way to fully automate the DTI assessment process. As a result, reliable data generation may be possible [13].

II. Literature Survey

A.Kahn et.al. [1] describes an challenging to detect and predict the progression of Alzheimer's disease from the early stage of Mild Cognitive Impairment (MCI). Citing: Khan et al. Regression analysis is a statistical method for determining which characteristics and indicators are most strongly correlated with a desired result. The major goal of this study is to use a total of 20 different biomarkers in combination with medical information to conduct a tailored regression analysis of cognitively typical persons and MCI converters. From a total of 1713 male and female participants, 768 female respondents were chosen to examine the prevalence of AD and MCI, the characteristics of individuals diagnosed with AD and MCI, and the variables that contribute to their development. The data utilized in this study came from the Alzheimer's Disease Neuroimaging Initiative (ADNI).

J.'s study aimed to determine. K. Medina et al. [2] aims to create a system that can consistently diagnose fish infections far earlier than the conventional method. The device uses a camera component to capture still images or stream video of goldfish, which are then pre-processed to bring out their most salient features. The YOLO method extracts characteristics after they have been segmented. Following that, the technique categorizes each identified disorder. The collected data successfully identified and classified the goldfish specimens with a 91% overall detection rate. Using CNN and YOLO, this inquiry helped solve the problem by identifying the most common sickness among goldfish.

W. The YOLO v5 technique is used by Fan et al. [3] to diagnose 14 lung illnesses through abnormal target detection in chest X-rays. The primary goal of developing this method was to aid in the diagnosis of lung ailments. The Vindr-CXR dataset made public by the Kaggle Competition was used to verify the accuracy of the YOLO version5 anomaly detection system. Experiment results show that the YOLO v5 strategy, used in this study, is more accurate than competing approaches when it comes to spotting outliers.

M. Hashim et al. [4] present a state-of-the-art, extremely effective method for diagnosing agricultural diseases. The proposed method will employ the YOLO approach to identify plant diseases. Compared to other object recognition methods, the YOLO algorithm can analyze 45 frames per second in rapid succession, making it ideal for analyzing photographs of leaves. Segmenting the picture into a grid of cells is the initial step in image analysis. One neural network can predict both the box sizes and the class probabilities in a single assessment. The offered technology will assist farmers in early disease detection, leaf disease identification, and crop management to guarantee the safety and health of plants.

A. According to Morbekar et al. [5], India is home to billions of smallholder farmers who rely on farming as their main source of income. The possibilities accessible to farmers for selecting profitable crops are vast. Farmers, however, remain in the dark about numerous diseases that might affect their crops because of a dearth of relevant information. When harvesting sick crops, many farmers have trouble and waste a lot of time. Timely analysis of the situation is crucial for avoiding costly consequences and maximizing output. The proposed system employs the YOLO technique as a novel application of the object detection approach for disease diagnosis in plants. In comparison to other technologies, YOLO's real-time processing of 45 frames per second is much faster when applied to images of leaves.

"Y" claims. Chest pain is one of the most common medical complaints, according to research by Yuan et al. [6]. Chest X-rays play a crucial role in the evaluation and diagnosis of chest illnesses. Artificial intelligence applied to X-ray images may provide a workable answer to the shortage of healthcare resources and the heavy burden imposed on clinicians. This research looks at the feasibility of using the real-time detection technique YOLOv4 to diagnose respiratory problems. Chest X-rays are generally 256-level grayscale pictures, which does not provide enough information for precise diagnosis. Therefore, a method is created to transform black-and-white X-ray images into those that seem to have colour. Grayscale X-ray pictures, which only provide a minimal amount of information, are converted to colour X-ray images, which reveal much more detail. The YOLOv4 is then put through its paces by being taught to identify the chest X-ray's colourful pictures. Publicly accessible datasets are used to evaluate the method, and the results of the trials show that the method can accurately detect and locate chest X-ray problems.

A. Mohandas et al. [7] provide an algorithm that can identify and recognize the plant illnesses that damage the leaves by using techniques often connected with the identification of objects in Image Processing. The YOLO v4 architecture, which is based on convolutional neural networks (CNNs), is used to do real-time object identification. Tomatoes, mangoes, strawberries, beans, and potatoes are just few of the plants whose leaves are the subject of this study. Bacterial and fungal diseases, as well as blight, are major causes of leaf damage in plants. One probable cause of these conditions is exposure to biological agents, sometimes called pathogens. The focus of this study is on recognizing and identifying illnesses of plant leaves using a specific model called YOLOv4-tiny in order to provide a preventative approach against the related ailment. The approach culminated in the system's incorporation into an android-based application. Users of this app would have a direct line to a diagnostic service for leaf diseases in real time.

III. RESEARCH GAP

The research gap in HD-CNN, an Early-stage Alzheimer Detection system using a Hybrid Deep Convolutional Neural Network, lies in the quest for improved accuracy and efficiency in diagnosing Alzheimer's disease at its earliest stages. While existing diagnostic methods show promise, they often rely on subjective interpretation or invasive procedures, leading to limitations in sensitivity and specificity. The emergence of deep learning, particularly convolutional neural networks (CNNs), offers a potential solution by enabling automated analysis of medical imaging data, such as MRI or PET scans. However, current CNN architectures may not fully leverage the diverse information available in multi-modal imaging data, nor effectively integrate clinical data and biomarkers crucial for early diagnosis. Thus, there is a need for research focusing on the development of hybrid CNN architectures, like HD-CNN, that can effectively fuse multi-modal imaging data with clinical information to enhance diagnostic accuracy and enable early detection of Alzheimer's disease. Addressing this research gap holds the potential to revolutionize early-stage Alzheimer detection, paving the way for timely intervention and improved patient outcomes.

IV. PROPOSED SYSTEM DESIGN

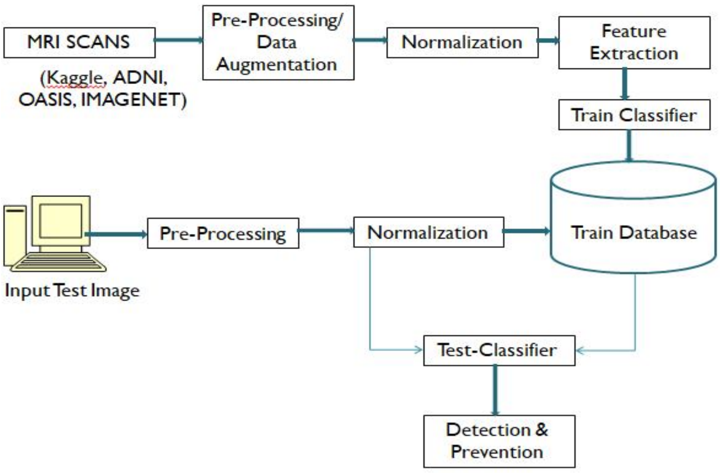

Figure 1: Proposed system architecture for Alzheimer disease detection and classification

V. RESULT

The accuracy of the Alzheimer detection algorithms can be measured through train and testing model. The i7 Intel processor has used with 16 GB RAM. The model has run with different methods such as RESNET-50, RESNET-100 and RESNET-101 with deep CNN. In below Table 1 and Figure 2 to 6 demonstrates proposed model evaluation and Figure 7 describes comparative analysis of proposed system.

TABLE I: PERFORMANCE ANALYSIS OF PROPOSED MODEL

Epoch size	Method	No. of hidden layers	Detection Accuracy
20	RESNET-50	5	96.15
	RESNET-100	10	96.95
	RESNET-101	15	97.00
40	RESNET-50	5	96.45
	RESNET-100	10	97.60
	RESNET-101	15	98.50
60	RESNET-50	5	97.10
	RESNET-100	10	97.80
	RESNET-101	15	98.55
80	RESNET-50	5	97.4
	RESNET-100	10	98.30
	RESNET-101	15	98.95
100	RESNET-50	5	97.95
	RESNET-100	10	98.40
	RESNET-101	15	99.35

Table I provides a description of three distinct deep learning modules of RESNET, each with frameworks consisting of 50, 100, and 100 layers respectively. The study demonstrates that increasing the number of hidden layers results in an increase in time required and also improves the accuracy of the module.

The ResNet, is Residual Networks, is a specific form of deep neural network structure that was developed to tackle the issue of the vanishing gradient problem in networks with a large number of layers. The primary advancement of ResNet lies in the incorporation of residual blocks, which consist of skip connections or shortcuts that allow for bypassing certain levels. This facilitates the training of more complex networks by enabling a smoother flow of gradients across the network.

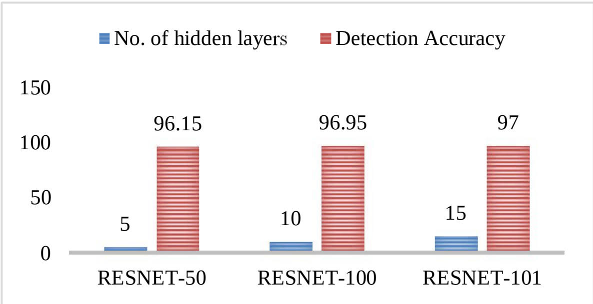

Figure 2 : Detection accuracy of proposed model using different RESNET architecture and hidden layers with 20 epoch size

The above Figure 2 demonstrates an 5,10 and 15 hidden layers performance analysis with 20 epoch size using RESNET-50, 100 and 101 layers.

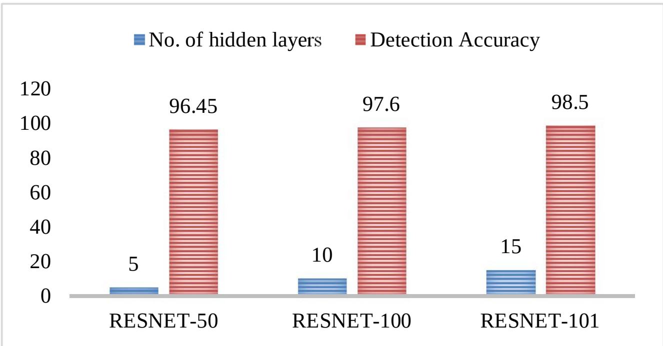

Figure 3: Detection accuracy of proposed model using different RESNET architecture and hidden layers with 40 epoch size

The performance study of 5, 10, and 15 hidden layers with 40 epoch size using RESNET-50, 100, and 101 layers is shown in Figure 3 above.

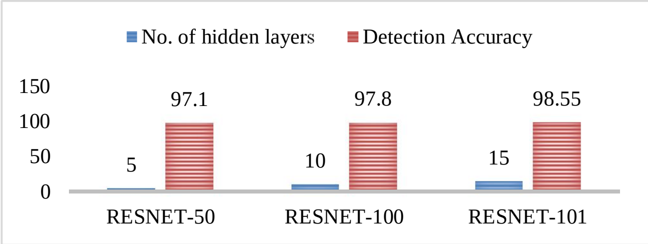

Figure 4 : Detection accuracy of proposed model using different RESNET architecture and hidden layers with 60 epoch size

The above figure 4 describes classification accuracy with different hidden layers such as 5, 10 and 15. The epoch size has given as a 60 for entire execution. As a result we conclude RESNET-101 with 60 epochs provides higher accuracy than RESNET-50 and RESNET-100 framework.

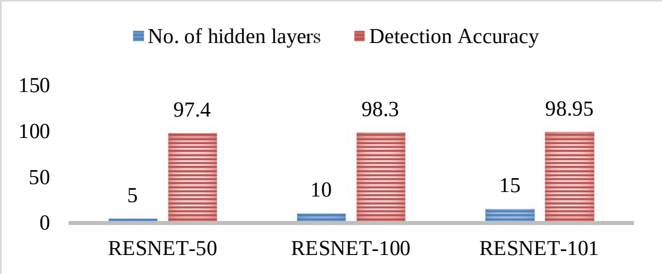

Figure 5 : Detection accuracy of proposed model using different RESNET architecture and hidden layers with 80 epoch size

Figure 5, provides a description of the accuracy of classification using several hidden layers, including 5, 10, and 15. A value of 80 has been assigned to the epoch size throughout the whole operation. We have come to the conclusion that the RESNET-101 framework, which has sixty epochs, offers a better level of accuracy than the RESNET-50 and RESNET-100 frameworks.

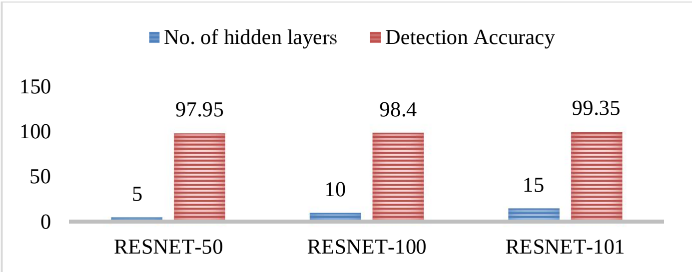

Figure 6 : Detection accuracy of proposed model using different RESNET architecture and hidden layers with 100 epoch size

Figure 6 above shows the classification accuracy with 5, 10, and 15 hidden layers. The whole execution has an epoch size of 100. We find that RESNET-101, with its 60 epochs, outperforms the RESNET-50 and RESNET-100 frameworks in terms of accuracy.

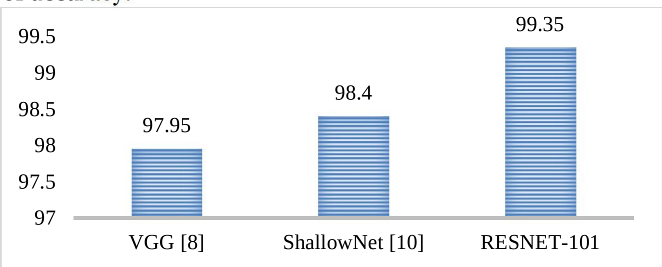

Figure 7: Comparative analysis of proposed model with existing systems

The above Figure 7 describes an comparative analysis for proposed model, the evaluation has done with VGGNET [8] and ShallowNet [10]. The proposed model shows around 1% higher accuracy with both existing models.

VI. CONCLUSION

This work aimed to apply the well-known YOLOv4 and YOLOv8 algorithms to the multiclass classification task, particularly with regard to brain DTI scans obtained from individuals diagnosed with Alzheimer's disease. These models could be used successfully, and the research that produced that finding gave medical imaging a significant boost in fresh knowledge. The study has broadened the potential field of future research by offering insightful information about the application of machine learning in medical imaging diagnosis. Radiologists can use method predictions, like as those generated by YOLOv8, to augment their comprehensive understanding of the medical problems of patients with Alzheimer's disease. By modifying the parameters of the YOLOv4 and YOLOv8 algorithms and performing performance optimization, the models that have been discussed can be enhanced. This calls for longer training times for the models, improved picture enhancement to improve recognition, and increased image production to help balance out disparities in the training dataset. The classification of ensembles using a "voting ensemble," in which the most widely supported prediction is put into practice, will be the subject of the study's subsequent phase. The primary benefit of adopting an ensemble classification model is that it allows a classifier to integrate the output of multiple classification models to achieve the highest possible accuracy and repair errors caused by individual classification models.

REFERENCES

[1] Khan, S. Zubair and S. Khan, "An Epidemiological-based Regression Analysis of Alzheimer's disease and Mild Cognitive Impairment Converts in the Female Population," IEEE EUROCON 2021 - 19th International Conference on Smart Technologies, Lviv, Ukraine, 2021, pp. 77-81, doi: 10.1109/EUROCON52738.2021.9535564.

[2] J. K. Medina, P. Jasper P. Tribiana and J. F. Villaverde, "Disease Classification of Oranda Goldfish Using YOLO Object Detection Algorithm," 2023 15th International Conference on Computer and Automation Engineering (ICCAE), Sydney, Australia, 2023, pp. 249-254, doi: 10.1109/ICCAE56788.2023.10111494.

[3] W. Fan, X. Guo, L. Teng and Y. Wu, "Research on Abnormal Target Detection Method in Chest Radiograph Based on YOLO v5 Algorithm," 2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI), Fuzhou, China, 2021, pp. 125-128, doi: 10.1109/CEI52496.2021.9574450.

[4] L. K R, P. B, S. G, N. J. J, G. T and M. Hashim, "Yolo for Detecting Plant Diseases," 2023 Third International Conference on Artificial Intelligence and Smart Energy (ICAIS), Coimbatore, India, 2023, pp. 1029-1034, doi: 10.1109/ICAIS56108.2023.10073875.

[5] A. Morbekar, A. Parihar and R. Jadhav, "Crop Disease Detection Using YOLO," 2020 International Conference for Emerging Technology (INCET), Belgaum, India, 2020, pp. 1-5, doi: 10.1109/INCET49848.2020.9153986.

[6] Y. Yuan, S. Yao, X. Ren, Y. Xiao, Z. Zhou and Y. Lu, "Chest X-ray disease diagnosis method based on YOLO model and pseudo color conversion," 2022 5th International Conference on Data Science and Information Technology (DSIT), Shanghai, China, 2022, pp. 1-5, doi: 10.1109/DSIT55514.2022.9943871.

[7] A. Mohandas, M. S. Anjali and U. Rahul Varma, "Real-Time Detectionand Identification of Plant Leaf Diseases using YOLOv4-tiny," 2021 12th International Conference on Computing Communication and Networking Technologies (ICCCNT), Kharagpur, India, 2021, pp. 1-5, doi: 10.1109/ICCCNT51525.2021.9579783.

[8] S. Degadwala, D. Vyas, U. Chakraborty, A. R. Dider and H. Biswas, "Yolo-v4 Deep Learning Model for Medical Face Mask Detection," 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), Coimbatore, India, 2021, pp. 209-213, doi: 10.1109/ICAIS50930.2021.9395857.

[9] K. Mahajan and P. Mane, "Follicle Detection of Polycystic Ovarian Syndrome (Pcos) Using Yolo," 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2023, pp. 1550-1553, doi: 10.1109/ICACCS57279.2023.10112821.

[10] Y. Li and X. He, "COVID-19 Detection in Chest Radiograph Based on YOLO v5," 2021 IEEE International Conference on Computer Science, Electronic Information Engineering and Intelligent Control Technology (CEI), Fuzhou, China, 2021, pp. 344-347, doi: 10.1109/CEI52496.2021.9574463.

[11] A. Koirala et al., "Deep Learning for Real-Time Malaria Parasite Detection and Counting Using YOLO-mp," in IEEE Access, vol. 10, pp. 102157-102172, 2022, doi: 10.1109/ACCESS.2022.3208270.

[12] L. R and A. Padyana, "Detection of Diabetic Retinopathy in Retinal Fundus Image Using YOLO-RF Model," 2021 Sixth International Conference on Image Information Processing (ICIIP), Shimla, India, 2021, pp. 105-109, doi: 10.1109/ICIIP53038.2021.9702677.

[13] M. Velazquez, R. Anantharaman, S. Velazquez, Y. Lee and for the Alzheimer's Disease Neuroimaging Initiative, "RNN-Based Alzheimer's Disease Prediction from Prodromal Stage using Diffusion Tensor Imaging," 2019 IEEE International Conference on Bioinformatics and Biomedicine (BIBM), San Diego, CA, USA, 2019, pp. 1665-1672, doi: 10.1109/BIBM47256.2019.8983391.

[14] A. Thushara, C. UshaDevi Amma, A. John and R. Saju, "Multimodal MRI Based Classification and Prediction of Alzheimer's Disease Using Random Forest Ensemble," 2020 Advanced Computing and Communication Technologies for High Performance Applications (ACCTHPA), Cochin, India, 2020, pp. 249-256, doi: 10.1109/ACCTHPA49271.2020.9213211.
[15] K. Aderghal, A. Khvostikov, A. Krylov, J. Benois-Pineau, K. Afdel and G. Catheline, "Classification of Alzheimer Disease on Imaging Modalities with Deep CNNs Using Cross-Modal Transfer Learning," 2018 IEEE 31st International Symposium on Computer-Based Medical Systems (CBMS), Karlstad, Sweden, 2018, pp. 345-350, doi: 10.1109/CBMS.2018.00067.
[16] T. -A. Song et al., "Graph Convolutional Neural Networks For Alzheimer's Disease Classification," 2019 IEEE 16th International Symposium on Biomedical Imaging (ISBI 2019), Venice, Italy, 2019, pp. 414-417, doi: 10.1109/ISBI.2019.8759531.
[17] X. Guo, Y. Yang, Y. Wang, N. Gao and H. T. Ma, "The Correlation Analysis Between DTI Network Parameters and AVLT Scale Scores of Alzheimer's Disease," 2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Honolulu, HI, USA, 2018, pp. 1132-1135, doi: 10.1109/EMBC.2018.8512460.
[18] Y. -t. Lv, X. -f. Yao, X. -x. Bu, S. Xu and G. Huang, "Evaluation of Diffusion Tensor White Matter Network of Alzheimer's Disease," 2021 IEEE 5th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 2021, pp. 1252-1256, doi: 10.1109/IAEAC50856.2021.9390844.
[19] R. Chitra, K. Bairavi, V. Vinisha and A. Kavitha, "Analysis of structural connectivity on progression of Alzheimer's disease using diffusion tensor imaging," 2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN), Chennai, India, 2017, pp. 1-5, doi: 10.1109/ICSCN.2017.8085686.
[20] A. Massalimova and H. A. Varol, "Input Agnostic Deep Learning for Alzheimer's Disease Classification Using Multimodal MRI Images," 2021 43rd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC), Mexico, 2021, pp. 2875-2878, doi: 10.1109/EMBC46164.2021.9629807.
[21] Menagadevi, M.; Mangai, S.; Madian, N.; Thiyagarajan, D. Automated Prediction System for Alzheimer Detection Based on Deep Residual Autoencoder and Support Vector Machine. Optik 2023, 272, 170212.
[22] Murugan, S.; Venkatesan, C.; Sumithra, M.G.; Gao, X.Z.; Elakkiya, B.; Akila, M.; Manoharan, S. DEMNET: A Deep Learning Model for Early Diagnosis of Alzheimer Diseases and Dementia from MR Images. IEEE Access 2021, 9, 90319–90329.
[23] Loddo, A.; Buttau, S.; Di Ruberto, C. Deep Learning Based Pipelines for Alzheimer's Disease Diagnosis: A Comparative Study and a Novel Deep-Ensemble Method. Comput. Biol. Med. 2022, 141, 105032.
[24] Sharma, S.; Gupta, S.; Gupta, D.; Altameem, A.; Saudagar, A.K.J.; Poonia, R.C.; Nayak, S.R. HTLML: Hybrid AI Based Model for Detection of Alzheimer's Disease. Diagnostics 2022, 12, 1833. [PubMed]
[25] Mohammed, B.A.; Senan, E.M.; Rassem, T.H.; Makbol, N.M.; Alanazi, A.A.; Al-Mekhlafi, Z.G.; Ghaleb, F.A. Multi-Method Analysis of Medical Records and MRI Images for Early Diagnosis of Dementia and Alzheimer's Disease Based on Deep Learning and Hybrid Methods. Electronics 2021, 10, 2860.
[26] Balasundaram, A.; Srinivasan, S.; Prasad, A.; Malik, J.; Kumar, A. Hippocampus Segmentation-Based Alzheimer's Disease Diagnosis and Classification of MRI Images. Arab. J. Sci. Eng. 2023, 1–17, online ahead of print.