DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004 *Int. J. Exp. Res. Rev.*, Vol. 41: 43-54 (2024)

Original Article | Peer Reviewed | Open Access

International Journal of Experimental Research and Review (IJERR)

ISSN: 2455-4855 (Online)
www.iaph.in

Deep CNN-based Classification of Brain MRI Images for Alzheimer's Disease Diagnosis

D. Dakshayani Himabindu[1], B. Pranalini[2], Mirtipati Satish Kumar[3]*, Alluri Neethika[4], Bhavya Sree N[1], Manasa C[1], Harshitha B[1] and Keerthana S[1]

[1]Department of Information Technology, VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad, India; [2]Department of Computer Science and Engineering, Gayatri Vidya Parishad College of Engineering, Visakhapatnam, Andhra Pradesh, India; [3]Department of Computer Science and Engineering, Centurion University of Technology and Management, Vizianagaram, Andhra Pradesh, India; [4]Department of Information Technology, S.R.K.R. Engineering College, Bhimavaram, Andhra Pradesh, India

E-mail/Orcid Id:

DDH, dakshayanihimabindu_d@vnrvjiet.in, https://orcid.org/0000-0002-7755-5122;
BP, pranalinib@gvpce.ac.in, https://orcid.org/0009-0009-7912-4447;
MSK, satishkumarsrk@icloud.com, https://orcid.org/0009-0000-2920-7812; *AN*, neethikav@gmail.com, https://orcid.org/ 0009-0002-9624-2612;
BN, nbs0911@gmail.com; *MC*, chunbunnu21@gmail.com; *HB*, harshithaboinepally@gmail.com; *KS*, keerthanasanthai2002@gmail.com

Article History:

Received: 18th May., 2024
Accepted: 14th July, 2024
Published: 30th July, 2024

Keywords:
Alzheimer, deep learning, dementia, diagnosis, magnetic resonance imaging

How to cite this Article:
D. Dakshayani Himabindu, B. Pranalini, Mirtipati Satish Kumar, Alluri Neethika, Bhavya Sree N, Manasa C, Harshitha B, Keerthana S (2024). Deep CNN-based Classification of Brain MRI Images for Alzheimer's Disease Diagnosis. *International Journal of Experimental Research and Review*, *41*(spl.), 43-54.
DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

Abstract: As the leading cause of dementia worldwide, Alzheimer's disease afflicts millions, with progressively impaired abilities to carry out daily activities or communicate and even recognize faces. Although the cause behind lupus is not fully understood, it probably reflects lifestyle choices and environmental factors as well as genetic propensity. The largest obstacles in the diagnosis of these diseases are their often subtle early manifestations and absence of sensitive detection paradigms. Deep-learning algorithms first came to the forefront of medical imaging just a few years ago and were celebrated as sophisticated diagnostic aids, able to spot subtle signs in scans usually hidden from human eyes. We are benefitting from the use of these state-of-the-art algorithms to improve Alzheimer's detection, with one of the largest MRI datasets available today (more than 86,000 images) being used to train our model. In view of this vast data set, it was appreciably combined one to be accurate-centric diagnostic tool. The performance of our novel deep learning model is strong and provided state-of-the-art validation accuracy (99.63%), surpassing existing models These figures highlight the great promise of our model as a verifiable method for detecting early-stage Alzheimer's disease - a significant concern in controlling and managing disease progression. Our research truly is a major step forward in the field of Alzheimer's disease diagnosis by employing cutting-edge deep learning techniques. Early diagnosis allows for better treatment and lower disease burden that can prevent morbidity, mortality and even change many patient outcomes. This is a considerable improvement toward diagnosing Alzheimer's disease with the help of artificial intelligence and presents an expectation for more exact and timely finding.

Introduction

Alzheimer's disease is a condition that has an impact on the brain, leading to memory issues and changes in behaviour. It mainly impacts individuals making it challenging for them to perform tasks and causes a loss of independence. The presence of protein deposits like tangles and amyloid plaques in the brain disturbs communication between neurons and leads to the death of brain cells, which are key indicators of Alzheimer's condition. The precise reason behind Alzheimer's disease is still a mystery. Finding a cure remains challenging, hence, early detection and precise diagnosis play a role in managing and treating the condition despite research efforts in this field (Madhu et al., 2024; Biswas et al., 2024; Saha et al., 2024). Studies suggest that Alzheimer's disease is a contributor to the mortality rate among Americans, though the exact percentage remains uncertain. Moreover, there is a lack of confirmation

*Corresponding Author: satishkumarsrk@icloud.com

through autopsies citing Alzheimer’s as the main cause, making it harder to accurately assess the disease's impact (Alzheimer’s Association, 2024).

Advances in technology have greatly impacted diagnosis in the realm of neurology. Convolutional neural networks (CNNs), a form of deep learning technology, show potential in aiding the diagnosis of Alzheimer’s disease. Through the analysis of medical imaging data, like PET scans and MRIs, deep learning algorithms can identify patterns and irregularities associated with Alzheimer’s disease with accuracy.

Deep learning algorithms offer an effective way to diagnose compared to traditional methods that may overlook minute variations (Rao et al., 2022). Our study includes the use of standard CNN models such as ResNet50 (He et al., 2023; Hossain et al., 2022), VGG16 (Pora et al., 2023), Xception (Chollet, 2017; Gülmez, 2022), and a custom Deep CNN model. Custom model demonstrated better performance in terms of accuracy and precision when detecting Alzheimer’s disease compared to standard models.

Related work

According to Beheshti et al. (2017) early prediction of AD and the manner of changing MCI to AD with structural MRI scans is achieved through a CAD system. The system employs a feature-rating and genetic set of rules-based technique. It accomplished 93.01% accuracy for AD class and 75% accuracy for MCI conversion prediction. This CAD method has the capability to have an influence over conventional diagnostic strategies. Nawaz et al. (2020) used 2D-DCNN to classify Alzheimer's disease based on MRI images, with a focus on imbalanced classes. The proposed model achieves a remarkable 99.89% accuracy in classifying MRI scans into three categories: AD, MCI, and normal control. This approach simplifies the network by converting 3D MRI scans into 2D slices and handles class imbalances without requiring data augmentation. Traditionally, imbalanced datasets can pose a significant challenge for machine learning models.

Bringas et al. (2020) collected data from 35 patients having Alzheimer’s disease by using smartphones for a week. The proposed approach used a CNN model to recognize patterns in the time series data. The model achieved an accuracy of 90.01%, improving traditional feature-based classification. Hasan et al. (2021) method leverages a generative network with deep convolution for data augmentation, fine-tuned VGG16 architecture, and support vector machine (SVM). The proposed method outperforms existing approaches, achieving high accuracy and precision in diagnosing Alzheimer's disease at its initial stages. The combined utilization of DCGAN, VGG16, and SVM displays the potential for new approaches to enhance the field of medical analysis and contributes to the ongoing efforts to combat Alzheimer's disease.

Raju et al. (2021) used transfer learning with VGG16 to perform multi-class classification of Alzheimer’s disease using MRI scans. This approach achieved an accuracy of 99% by using pre-trained models, reducing the need for vast training data. "Conditional Triplet Network" is used by Orouskhani et al. (2022) in their research to improve the accuracy of AD diagnosis using brain MRI scans. The model uses a conditional triplet that addresses the limited data problem, and it is based on a modified VGG16. The model achieved remarkable results, outperforming existing models, with 99.41% accuracy for classification.

Study by Saleem et al. (2022) explores the DL techniques for Alzheimer's diagnosis. It talks about different datasets for AD diagnosis, with an emphasis on deep learning techniques such as CNNs and FCNNs. In the pursuit of a more precise and effective diagnosis of AD, the review notes that CNNs are the most widely used DL technique and highlights persistent issues like overfitting and data quality. Al Shehri (2022) used Densenet-169 and Resnet-50 to classify Alzheimer’s disease into four sub classes. The Denset-169 attained test accuracy of 83.82 while Resnet-50 attained test accuracy of 81.92, outperforming in the training and testing phases.

Using 2D T1-weighted MRI brain images, EL-Geneedy et al. (2023) presented a DL technique for Alzheimer's disease. The pipeline produced testing accuracy of 99.68% in differentiating between various stages of AD and normal cognition. It per-forms better than other deep learning models, demonstrating its promise for accurate and timely diagnosis of AD. Alsubaie et al. (2024) review paper emphasizes on deep learning algorithms potential and limitations in Alzheimer’s disease diagnosis. This study explores various convolutional neural networks, recurrent neural networks, and generative models to evaluate AD classification.

Rao et al. (2023) speak about the effective methods for identifying medical leaves by hybridizing Gaussian Mixture Model (GMM) and Convolutional Neural Networks (CNN), which boosts accuracy in leave classification and validates significant raises over traditional methods. Yavanamandha et al. (2023) discovers Machine learning methods that are used for

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

gesture recognition to enable communication for deaf and dumb people. It includes CNN for extracting features, RNN to handle temporal dependencies and SVM for classification tasks. Rao et al. (2023) presents an automated system for classifying Ayurvedic plants using machine learning and also pulls Convolutional Neural Networks (CNNs) to enrich the accuracy of plant species classification and recognition, addressing challenges in former methods that fell short in accurate classification and categorization. Mishra et al. (2023) discuss the Machine learning methods for classifying skin diseases using Convolutional Neural Networks (CNNs) and Support Vector Machines (SVMs) that show efficiency accuracy and call into question of these machine learning techniques in dermatological diseases.

based solver and tenfold cross-validation are used to enrich heart disease prediction. This improved machine learning model is appraised using the UCI Repository dataset with 90.16% superior results (Narisetty et al., 2023). Afzal et al. (2019) recommended a brand-new model for addressing class imbalances. The author introduced a method that associates class balancing techniques with feature developments by signifying improved presentation in machine learning tasks with imbalanced datasets, which shows far-reaching results using Convolution Neural networks (Keerthana et al., 2023).

Yildirim and Cinar (2020) developed a hybrid CNN model via Resnet50 as a core model to diagnose Alzheimer's disease stage classification that classify the various stages of the disease. Khvostikov et al. (2018) emphases on Alzheimer disease medical image analysis and proposes a Convolution neural network (CNN) algorithm that rages sMRI and DTI modalities on the hippocampal ROI, using data from the ADNI database. The suggested results stand out when compared with

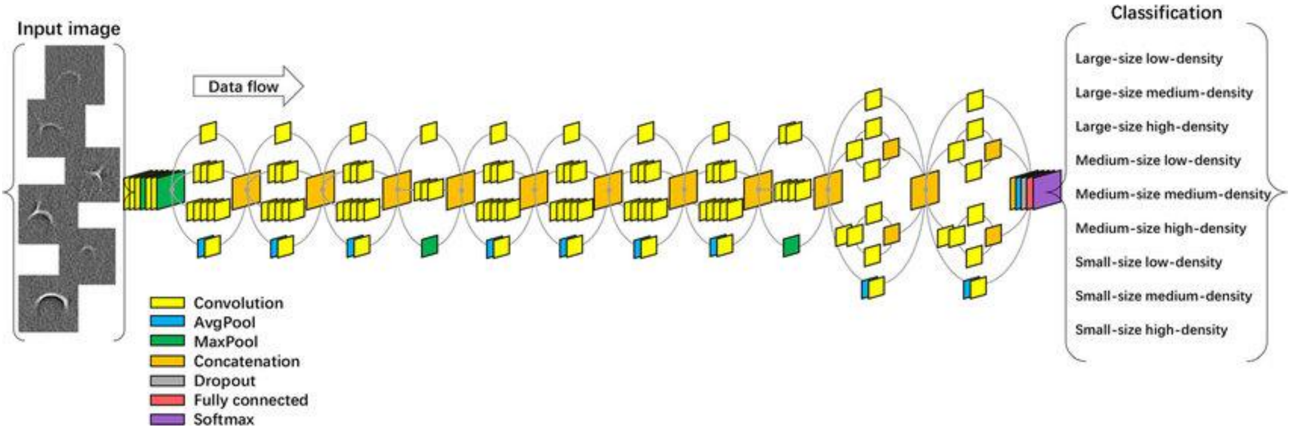


Figure 1. InceptionV3 Architecture.

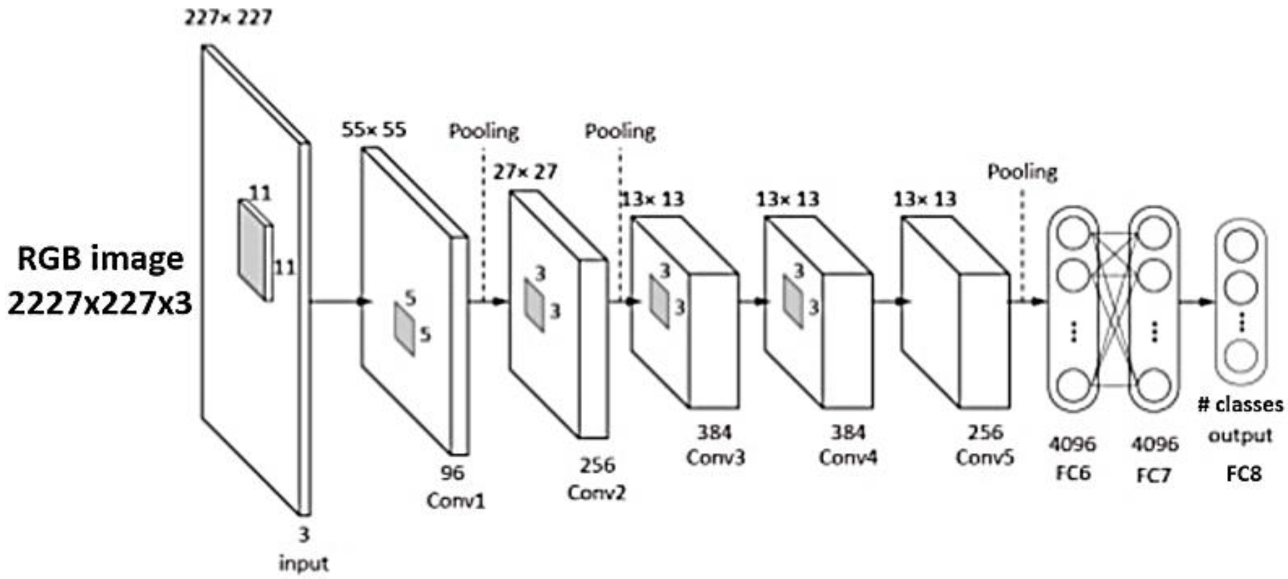


Figure 2. Alexnet Architecture.

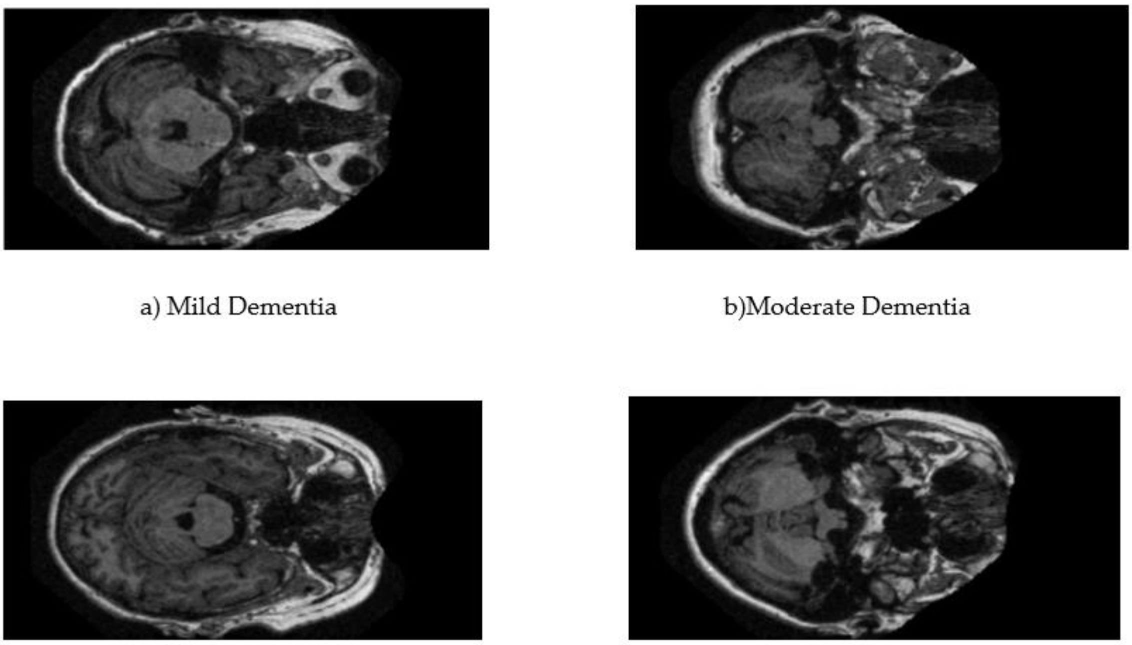
Kompalli et al. (2023), with the help of a tool that is designed to support colour-blind people by using the image processing technique openCV, indicates the name RGB(Red, Green, Blue)values and helps people to discriminate and identify several shades. Logical regression in line with hyperparameter tuning via gridmany other approaches and this study also introduced data argumentative for class balancing. Basheera and Satya Sai Ram (2020) objective of the study is to depict a model that differentiates. Mild Cognitive Impairment (MCI) and Cognitive Normal (CN) that is used to predict early diagnosis of the disease. The model has been tested with 10 fold cross validation that outperforms with 98% accuracy.

Risk of Overfitting: AlexNet is prone to overfitting, particularly when working with small datasets.

Materials and Methods

Dataset

Deep Convolutional Neural Networks are a type of network specifically created for tasks that involve analyzing images and spatial data (Zhang et al., 2018).



a) Mild Dementia

b)Moderate Dementia

c)Non-demented

d)Very mild

Figure 3. Alzheimer's disease dataset.

Existing System

InceptionV3

A DCNN architecture called InceptionV3 (Guan et al., 2019) is well-known for its exceptional image classification accuracy (figure 1).

***Challenges*:**

Complexity: Each Inception module contains multiple parallel convolutional operations, making the architecture somewhat complex.

Resource-intensive: InceptionV3 is less appropriate for real-time applications since it necessitates a large amount of computational power.

Alexnet

AlexNet (Alom et al., 2018) can automatically extract hierarchical features from raw image data because it has several convolutional and pooling layers (figure 2).

Challenges:

Computational Intensity: The depth and abundance of parameters in AlexNet make it computationally demanding. Real-time application training and deployment of AlexNet can be difficult.

These networks have the ability to identify patterns, in data by detecting features in input images. By going through layers, these networks can abstract information more and more while also capturing spatial relationships through convolution processes.

The significance of Deep CNNs in the field of intelligence is evident through the accomplishments of architectures like VGG16, ResNet50 and Xception across tasks. In particular, Deep CNNs play a role in examining MRI data to detect AD at a stage. These networks automatically extract patterns and characteristics from brain images.

The "Oasis Alzheimer's Dataset" (Aithal, 2023) on Kaggle comprises of over 86,000 images divided into four categories, shown in Figure 3: 'Very Mild Dementia', 'Mild Dementia', 'Moderate Dementia' and 'Non Demented'. This dataset is useful for training models due to its coverage of age groups and spatial arrangements in the images. The inclusion of subcategories also offers an understanding of Alzheimer's disease, aiding in diagnosis and influencing treatment plans.

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

Data preprocessing

During preprocessing of the images from the "Oasis Alzheimer's Dataset" are being readied for training a learning model. The file paths of each image sourced from the subclasses are combined with their classes. Following that, a one-hot encoding method is utilized to represent the labels of these subclasses. Each subclass receives a value, and the encoder is adjusted accordingly to reflect this mapping. Subsequently, the images are resized to 128x128 pixels and transformed into a NumPy array. If an image meets the size criteria of 128x128, it is included in the data set along with its corresponding one label, in label set.

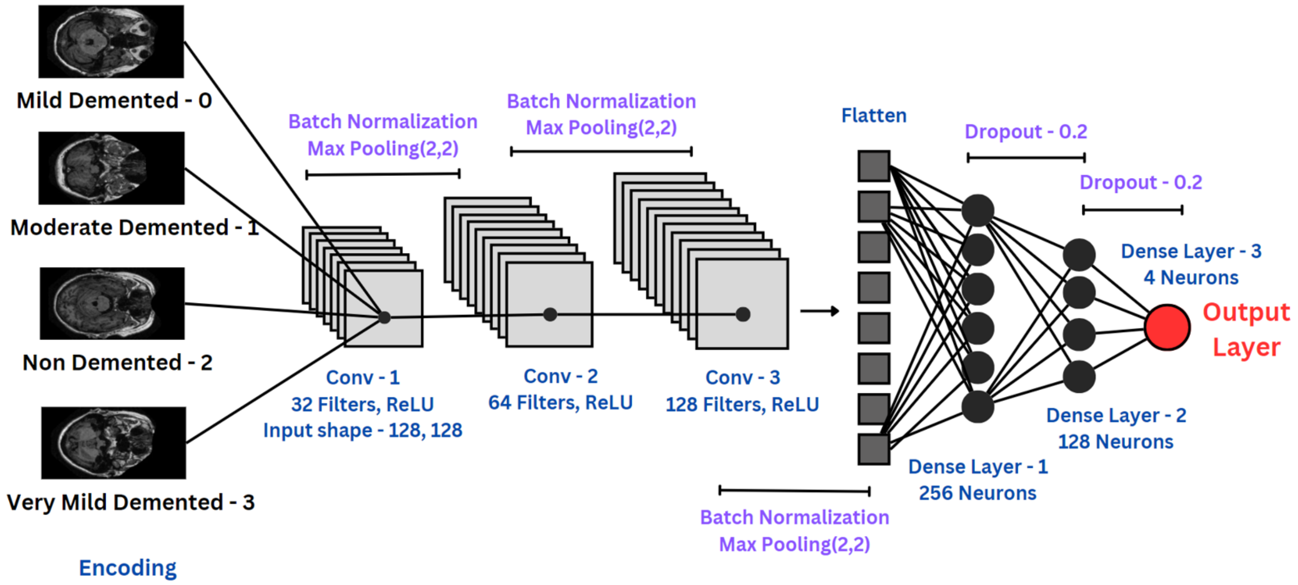


Figure 4. Proposed system architecture.

DCNN model

The model follows a step-by-step approach, stacking layers one on top of the other, consisting of a total of 15 layers, as shown in Figure 4. The primary layer consists of ReLU activation (refer with: Equation 1) and 32 filters sized at (3, 3). This layer processes input data in the form of (128, 128 3) representing images with dimensions of 128 by 128 pixels and three RGB color channels.

$$f(x) = \max(0, x) \tag{1}$$

ReLU and its derivative are both the same. If the function gets an input of negative values, it returns 0. Otherwise, it returns the same value when it is positive. Due to this, the range of ReLU function is from zero to infinite.

Batch normalization is applied after each convolutional layer to standardize the input data and enhance the efficiency of network training. Max pooling with a size of (2, 2) is utilized to reduce the dimensions of the feature maps identifying details within the images. The output from the layers is flattened into one array to prepare it for input into fully connected layers. Two connected layers with 256 and 128 units, respectively are added, both employing ReLU activation functions. L2 regularization (refer with: Equation 2) is employed with a penalty value of 0.001 on these layers weights to prevent overfitting.

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} Cost\left(h_\theta\left(x^{(i)}\right), y^{(i)}\right) + \frac{\lambda}{m}\sum_{j=1}^{n} |\theta_j| \tag{2}$$

L2 regularization does not mandate the model's coefficients to be zero, rather it prefers them to be small. It prevents overfitting by utilizing multiple features.

Dropout regularization, with a rate of 0.2 is implemented after each layer to mitigate overfitting risks by deactivating 20% of neurons during training sessions. The final layer consists of four neurons, each representing a class and providing probabilities, for each class through SoftMax activation.

Evaluation metrics

We evaluated the performance of each method using metrics like accuracy, loss, f1 score, and precision to conclude which implemented model is better.

Result and Discussion

The dataset was utilized with models like ResNet50, VGG16 and Xception, as shown in Figure 5. Table 1 depicts the experiment results for Accuracy, Loss, Precision, and F-score. VGG16 stands out for its accuracy of 92.03% and depth and image categorization capabilities. Similarly, Xception excelled with an accuracy of 93.93% due to its inception modules adeptness at capturing features across scales. ResNet50, a learning architecture achieved an impressive accuracy

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

score of 97.50%. On the other hand, our customized Deep CNN surpassed all models with an exceptional accuracy rate of 99.63%.

The accuracy graph in Figure 6 illustrates how the model's accuracy changes during training and validation. The validation accuracy curve aligns closely with the

Table 1. Experiment Results for Accuracy, Loss, Precision and F-score.

Model	Validation Accuracy	Validation Loss	Precision	F1 score
Resnet50	97.50	10.31	97.53	97.50
VGG16	92.03	20.93	92.39	92.03
Xception	93.93	25.56	94.46	93.93
DCNN	99.63	8.59	99.75	99.63

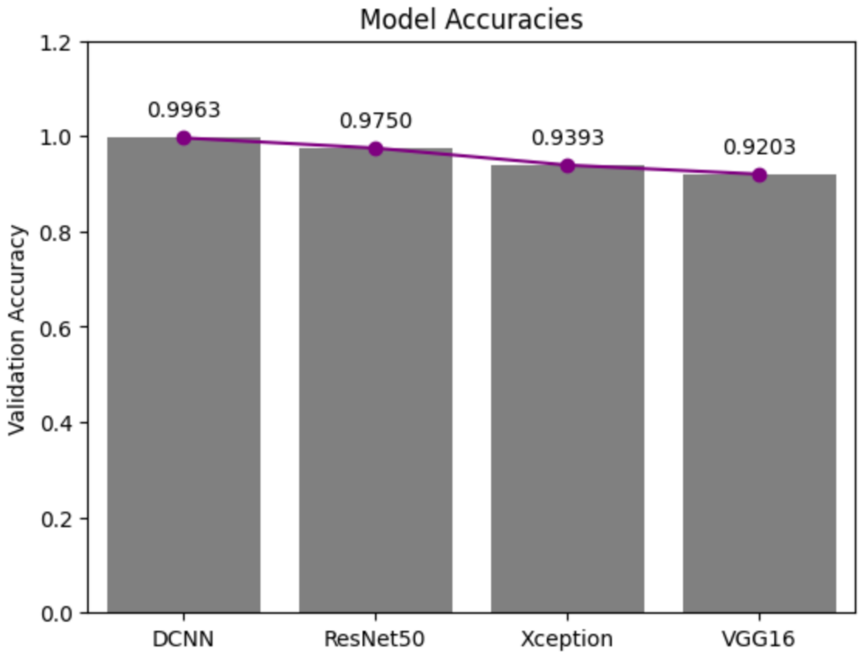


Figure 5. Accuracy comparison among all models.

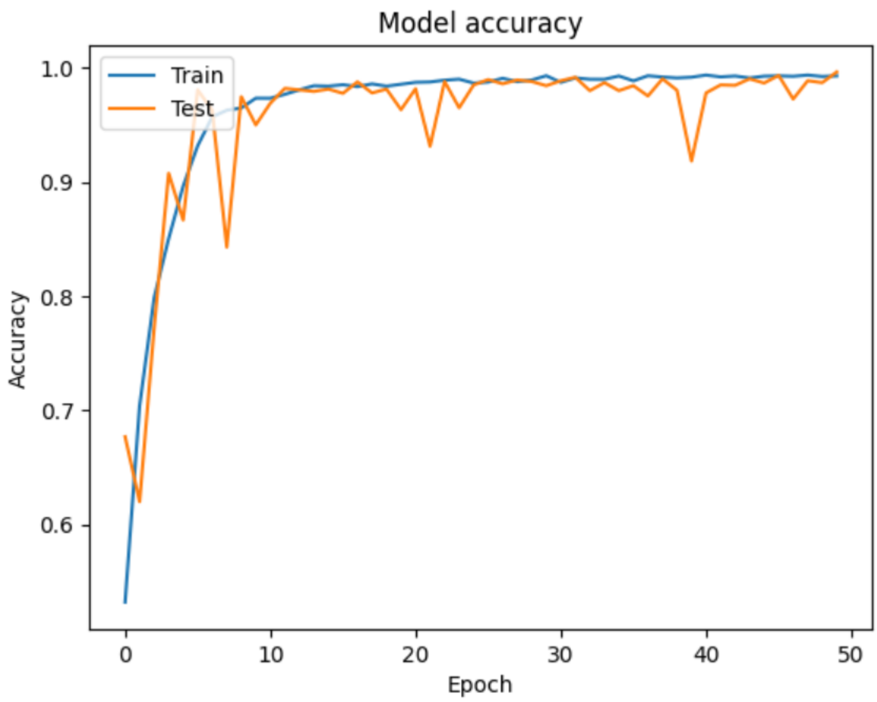


Figure 6. Training and validation accuracy graph for DCNN model.

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

training accuracy even though there are few drops. This suggests that the model is effectively adapting to unseen data meaning the model is understanding complex patterns.

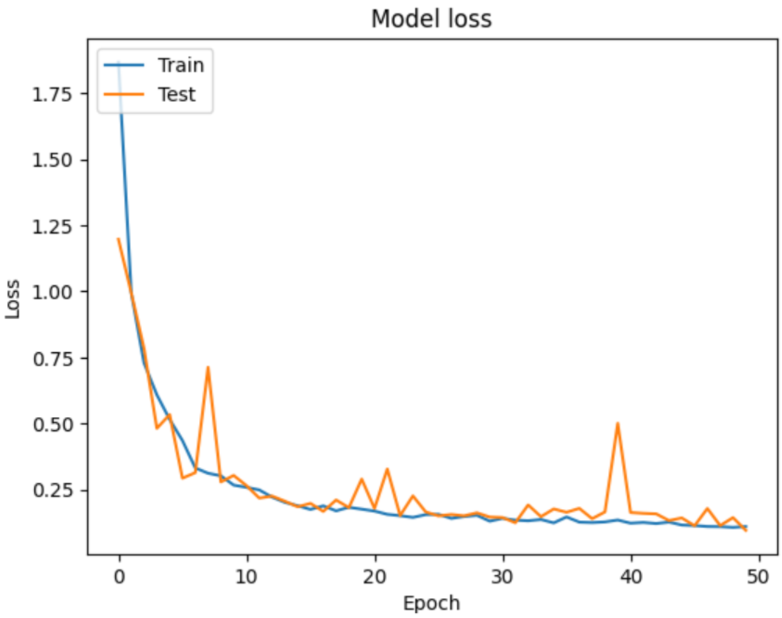


Figure 7. Training and validation loss graph for DCNN model.

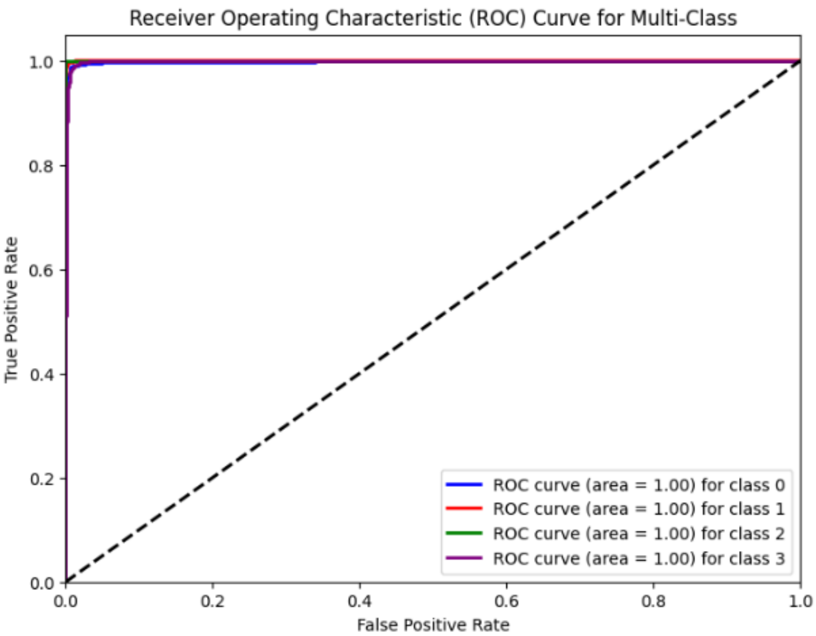


Figure 8. ROC curve for DCNN model.

The loss curve in Figure 7 illustrates the changes in the model's loss during training and validation epochs. The training loss shows the difference between the expected values and the model's predictions. There are times when the validation loss curve shows some spikes, but it stays in line with the training loss curve. This suggests that the model isn't memorizing noise in the data and overfitting; instead, it's focusing on learning meaningful patterns and representations.

The ROC curves area gives us a measure of the model's performance in Figure 8. An ideal classifier achieves an AUC ROC of 1, whereas a random classifier is associated with an AUC ROC of 0.5.

he confusion matrix in Figure 9 represents how a classification model works by comparing the predicted values with actual values in the training dataset.

Similarly, the training and validation accuracy graph for Resnet50, Figure 10, shows that the model is not generalized to unseen data. The model memorized noise in the data rather than the patterns hence, overfitting occurred.

In the training and validation loss graph for Resnet50, Figure 11, there is a sudden peak indicating that the model's performance on the training data has declined abruptly. It could be due to various reasons like an unstable learning rate or other issues during training.

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

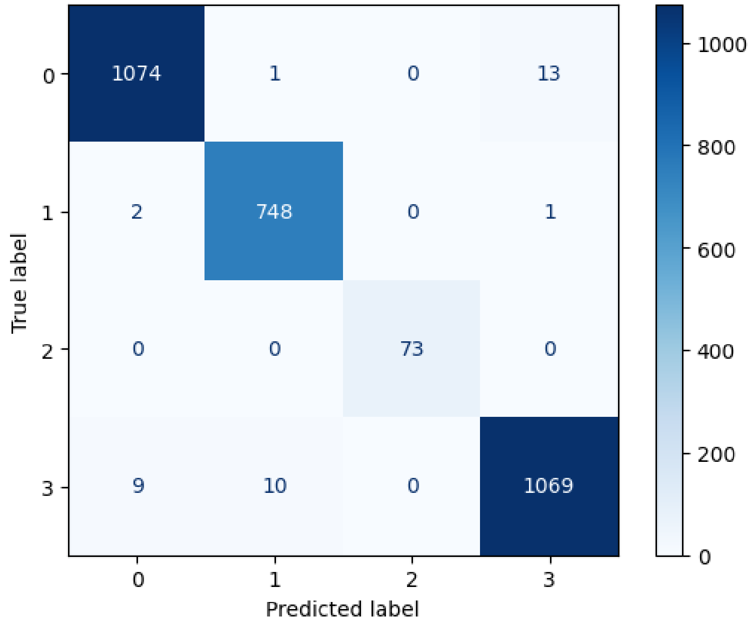


Figure 9. Confusion matrix for DCNN model.

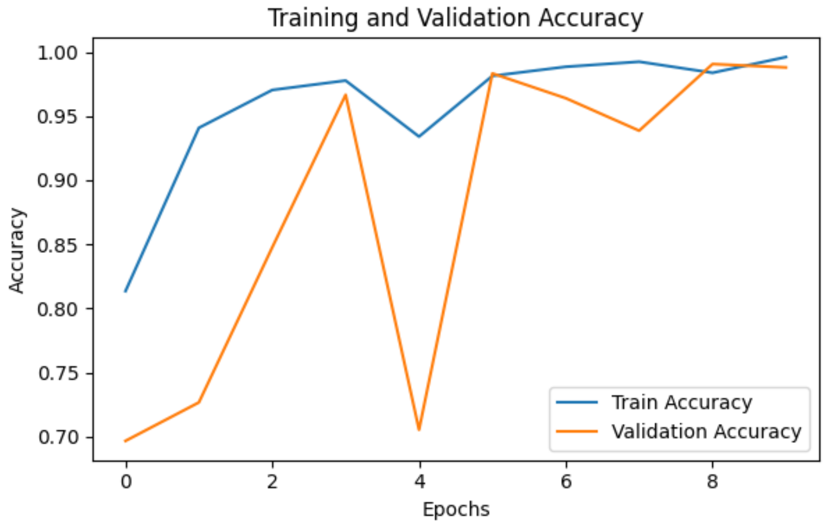


Figure 10. Training and validation accuracy graph for Resnet50.

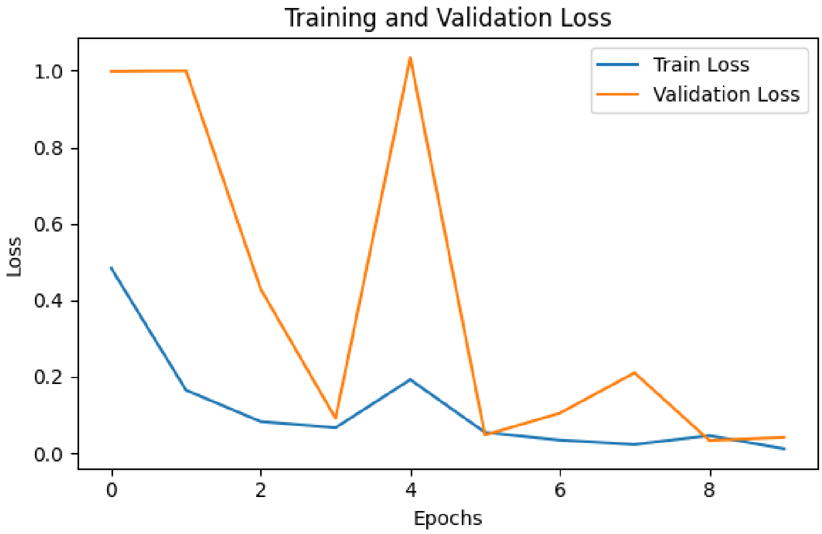
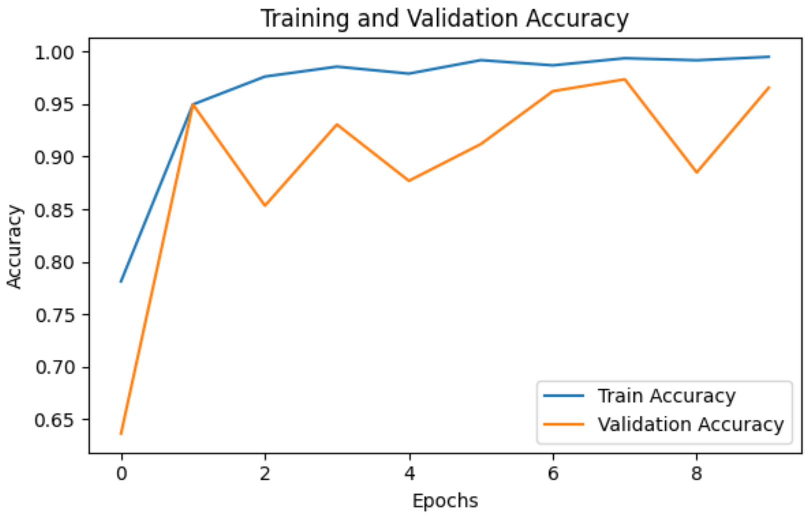
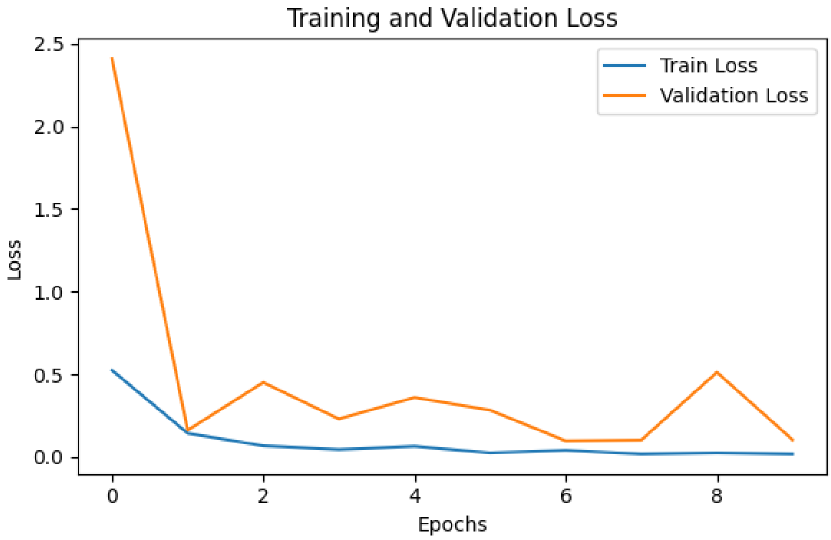


Figure 11. Training and validation loss graph for Resnet50.

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004



(a)



(b)

Figure 12(a). Training and validation accuracy graph for Xception (b) Training and validation loss graph for Xception.

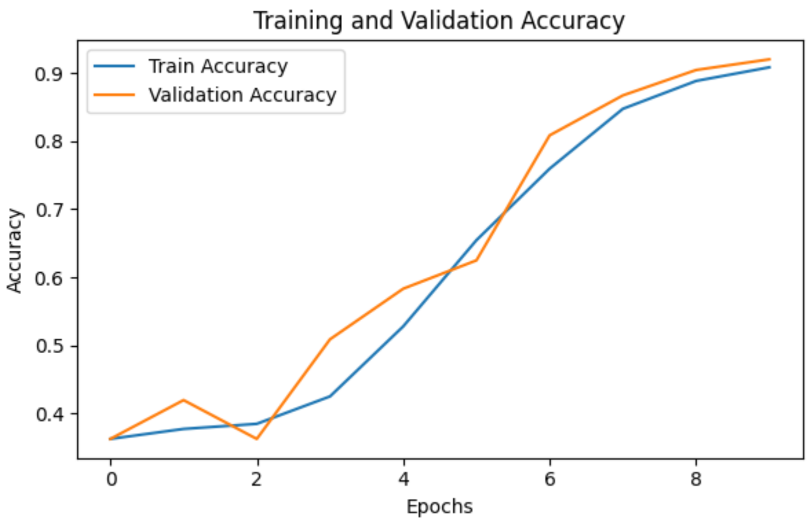


Figure 13. Training and validation accuracy graph for VGG16.

DOI: https://doi.org/10.52756/ijerr.2024.v41spl.004

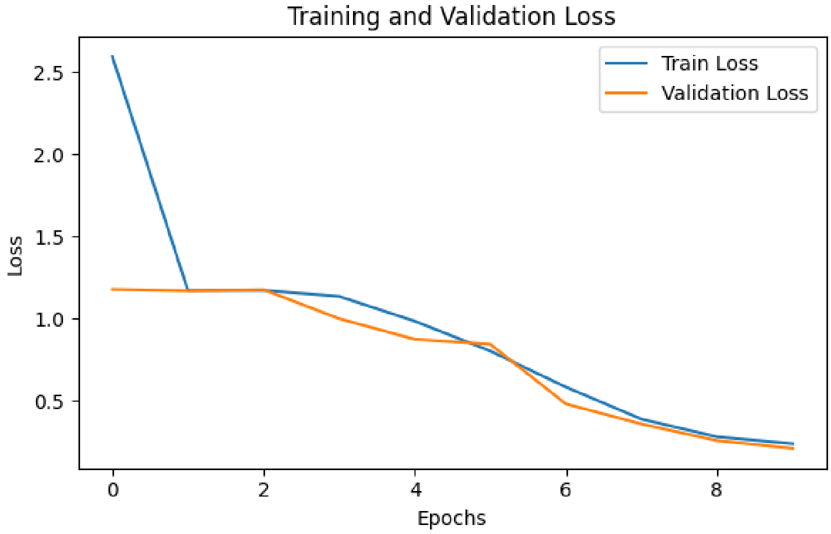


Figure 14. Training and validation loss graph for VGG16.

In case of Xception, both the accuracy graph, Figure 12(a) and the loss graph, Figure 12(b), for the training and validation phases, have fluctuating validation curves. This indicates that the model is unstable and is learning variability. The inconsistent flow in the validation curve may indicate that the model is struggling to generalize due to overfitting.

Whereas in the case of VGG16 Figure 13, the "S" shape in the validation curve indicates that the model has reached its maximum learning capacity and further training doesn't significantly improve performance. The model is underfitting as it fails to learn the complex patterns in the data.

Even though the validation loss curve is on par with the training loss curve for VGG16, as shown in Figure 14, the graph indicates that the model's capacity and complexity are not enough to learn the patterns in data.

Conclusion

The use of deep convolutional neural networks (DCNNs) to detect Alzheimer's disease from MRI scans represents an advancement in the domain of medicine. These sophisticated CNN structures have demonstrated promising outcomes in spotting patterns and irregularities in brain images, facilitating the diagnosis of AD. Moving forward, the future direction for detecting Alzheimer's disease involves segmenting identified tumours within brain scans. The development of CNN-based segmentation techniques can aid in pinpointing. Characterizing Alzheimer' s-related anomalies can contribute to a thorough diagnosis. By integrating the capabilities of CNNs for detection with segmentation approaches, we can improve our understanding of the disease progression, potentially leading to more accurate and personalized treatment strategies for individuals with Alzheimer's disease.

References

Afzal, S., Maqsood, M., Nazir, F., Khan, U., Aadil, F., Awan, K. M., Mehmood, I., & Song, O.-Y. (2019). A Data Augmentation-Based Framework to Handle Class Imbalance Problem for Alzheimer's Stage Detection. *IEEE Access*, *7*, 115528–115539. https://doi.org/10.1109/access.2019.2932786

Aithal, N. (2023). *Oasis Alzheimer's Detection Large-scale brain MRI dataset for deep neural network analysis*. https://www.kaggle.com/datasets/ninadaithal/imagesoasis

Al Shehri, W. (2022). Alzheimer's disease diagnosis and classification using deep learning techniques. *PeerJ Computer Science*, *8*, e1177. https://doi.org/10.7717/peerj-cs.1177

Alom, M. Z., Taha, T. M., Yakopcic, C., Westberg, S., Sidike, P., Nasrin, M. S., Van Esesn, B. C., Awwal, A. A. S., & Asari, V. K. (2018). *The History Began from AlexNet: A Comprehensive Survey on Deep Learning Approaches*. arXiv. https://doi.org/10.48550/ARXIV.1803.01164

Alsubaie, M. G., Luo, S., & Shaukat, K. (2024). Alzheimer's Disease Detection Using Deep Learning on Neuroimaging: A Systematic Review. *Machine Learning and Knowledge Extraction*, *6*(1), 464–505. https://doi.org/10.3390/make6010024

Alzheimer's Association. (2024). *Alzheimer's Disease Facts and Figures. Alzheimers Dement 2024*. https://www.alz.org/media/documents/alzheimers-facts-and-figures.pdf

Basheera, S., & Satya Sai Ram, M. (2020). A novel CNN based Alzheimer's disease classification using hybrid enhanced ICA segmented gray matter of MRI. *Computerized Medical Imaging and Graphics*, *81*, 101713. https://doi.org/10.1016/j.compmedimag.2020.101713

Beheshti, I., Demirel, H., & Matsuda, H. (2017). Classification of Alzheimer's disease and prediction of mild cognitive impairment-to-Alzheimer's conversion from structural magnetic resource imaging using feature ranking and a genetic algorithm. *Computers in Biology and Medicine*, *83*, 109–119. https://doi.org/10.1016/j.compbiomed.2017.02.011

Biswas, G., Madhu, N.R., Sarkar, B., Paul, S., Erfani, H., Alam, Q. (2024). Rare Genetic Disorders: Unraveling the Pathophysiology, Gene Mutations, and Therapeutic Advances in Fabry Disease and Marfan Syndrome. In: Umair, M., Rafeeq, M., Alam, Q. (eds) Rare Genetic Disorders. Springer, Singapore. pp. 199-219., ISBN: 978-981-99-9323-9, DOI: https://doi.org/10.1007/978-981-99-9323-9_7

Bringas, S., Salomón, S., Duque, R., Lage, C., & Montaña, J. L. (2020). Alzheimer's Disease stage identification using deep learning models. *Journal of Biomedical Informatics*, *109*, 103514. https://doi.org/10.1016/j.jbi.2020.103514

Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 1251-1258.

EL-Geneedy, M., Moustafa, H. E.-D., Khalifa, F., Khater, H., & AbdElhalim, E. (2023). An MRI-based deep learning approach for accurate detection of Alzheimer's disease. *Alexandria Engineering Journal*, *63*, 211–221. https://doi.org/10.1016/j.aej.2022.07.062

Guan, Q., Wan, X., Lu, H., Ping, B., Li, D., Wang, L., Zhu, Y., Wang, Y., & Xiang, J. (2019). Deep convolutional neural network Inception-v3 model for differential diagnosing of lymph node in cytological images: a pilot study. *Annals of Translational Medicine*, *7*(14), 307. https://doi.org/10.21037/atm.2019.06.29

Gülmez, B. (2022). A novel deep neural network model based Xception and genetic algorithm for detection of COVID-19 from X-ray images. *Annals of Operations Research*, *328*(1), 617–641. https://doi.org/10.1007/s10479-022-05151-y

Hasan, M. M., Asaduzzaman, M., Rahman, M. M., Hossain, M. S., & Andersson, K. (2021). D3mciAD: Data-Driven Diagnosis of Mild Cognitive Impairment Utilizing Syntactic Images Generation and Neural Nets. In *Lecture Notes in Computer Science*, pp. 366–377. Springer International Publishing. https://doi.org/10.1007/978-3-030-86993-9_33

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770-778.

Hossain, M. B., Iqbal, S. M. H. S., Islam, M. M., Akhtar, M. N., & Sarker, I. H. (2022). Transfer learning with fine-tuned deep CNN ResNet50 model for classifying COVID-19 from chest X-ray images. *Informatics in Medicine Unlocked*, *30*, 100916. https://doi.org/10.1016/j.imu.2022.100916

Keerthana, B., Vana, T. R., Rao, M. S., Sambana, B., & Mishra, P. (2023b). Using CNN technique and webcam to identify face mask violation. In *Springer proceedings in mathematics & statistics* (pp. 245–254). https://doi.org/10.1007/978-3-031-15175-0_20

Khvostikov, A., Aderghal, K., Benois-Pineau, J., Krylov, A., & Catheline, G. (2018). *3D CNN-based classification using sMRI and MD-DTI images for Alzheimer disease studies*. arXiv. https://doi.org/10.48550/ARXIV.1801.05968

Kompalli, P. L., Kalidindi, A., Chilukala, J., Nerella, K., Shaik, W., & Cherukuri, D. (2023). A Color Guide for Color Blind People Using Image Processing and OpenCV. *International Journal of Online and Biomedical Engineering (IJOE)*, *19*(09), 30–46. https://doi.org/10.3991/ijoe.v19i09.39177

Madhu, N.R., Biswas, G., Paul, S., Adhikari, S., Sarkar, B., Rafeeq, M.M., & Umair, M. (2024). Challenges and Future Opportunities in Rare Genetic Disorders: A Comprehensive Review. In: Umair, M., Rafeeq, M., Alam, Q. (eds) Rare Genetic Disorders. Springer, Singapore. pp. 251-275. ISBN: 978-981-99-9323-9, DOI: https://doi.org/10.1007/978-981-99-9323-9_9

Mishra, S., Satpathy, S., Malkani, S., Yadav, V., Gupta, V., Rawat, S. S., Malsa, N., Ghosh, A., & shaw, R. N. (2023). A Comprehensive Review on Skin Disease Classification Using Convolutional Neural Network and Support Vector Machine. In *Advanced Communication and Intelligent Systems* (pp. 726–746). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-25088-0_64

Narisetty, N., Kalidindi, A., Bujaranpally, M. V., Arigela, N., & Ch, V. V. (2023). Ameliorating Heart

Diseases Prediction using Machine Learning Technique for Optimal Solution. *International Journal of Online and Biomedical Engineering (IJOE)*, *19*(16), 156–165. https://doi.org/10.3991/ijoe.v19i16.42071

Nawaz, A., Anwar, S. M., Liaqat, R., Iqbal, J., Bagci, U., & Majid, M. (2020, November). Deep Convolutional Neural Network based Classification of Alzheimer's Disease using MRI Data. *2020 IEEE 23rd International Multitopic Conference (INMIC)*. https://doi.org/10.1109/inmic50486.2020.9318172

Orouskhani, M., Zhu, C., Rostamian, S., Shomal Zadeh, F., Shafiei, M., & Orouskhani, Y. (2022). Alzheimer's disease detection from structural MRI using conditional deep triplet network. *Neuroscience Informatics*, *2*(4), 100066. https://doi.org/10.1016/j.neuri.2022.100066

Pora, W., Kasamsumran, N., Tharawatcharasart, K., Ampol, R., Siriyasatien, P., & Jariyapan, N. (2023). Enhancement of VGG16 model with multi-view and spatial dropout for classification of mosquito vectors. *PLOS ONE*, *18*(7), e0284330. https://doi.org/10.1371/journal.pone.0284330

Raju, M., Thirupalani, M., Vidhyabharathi, S., & Thilagavathi, S. (2021). Deep Learning Based Multilevel Classification of Alzheimer's Disease using MRI Scans. *IOP Conference Series: Materials Science and Engineering*, *1084*(1), 12017. https://doi.org/10.1088/1757-899x/1084/1/012017

Rao, M., Kumar, S., & Rao, K. (2023). Effective medical leaf identification using hybridization of GMM-CNN. *International Journal of Experimental Research and Review*, *32*, 115-123. https://doi.org/10.52756/ijerr.2023.v32.009

Rao, M.S., Uma Maheswaran, S.K., Sattaru, N.C., Abdullah, K.H., Pandey, U.K., & Biban, L. (2022). A Critical Understanding of Integrated Artificial Intelligence Techniques for the Healthcare Prediction System. 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), Greater Noida, India, 2022, pp. 728-731. https://doi: 10.1109/ICACITE53722.2022.9823678.

Rao, M.S., Kumar, S.P., & Rao, K.S. (2023b). A Methodology for Identification of Ayurvedic Plant Based on Machine Learning Algorithms. *International Journal of Computing and Digital Systems*, 2023, 10233-10241. http://dx.doi.org/10.12785/ijcds/140196

Saha, A., Sanyal, T., Mukherjee, P., Sen, K., & Madhu, N.R. (2024). Response of Cellular Stress Toward the Hormetic Phytochemicals in Brain Aging. In: Pathak, S., Banerjee, A. (eds) Neuroprotective Effects of Phytochemicals in Brain Ageing. Springer, Singapore. pp. 57-95. https://doi.org/10.1007/978-981-99-7269-2_4

Saleem, T. J., Zahra, S. R., Wu, F., Alwakeel, A., Alwakeel, M., Jeribi, F., & Hijji, M. (2022). Deep Learning-Based Diagnosis of Alzheimer's Disease. *Journal of Personalized Medicine*, *12*(5), 815. https://doi.org/10.3390/jpm12050815

Yavanamandha, P., Keerthana, B., Jahnavi, P., Rao, K. V., & Kumar, C. R. (2023). Machine Learning-Based Gesture Recognition for Communication with the Deaf and Dumb. *International Journal of Experimental Research and Review*, *34*(Special Vo), 26–35. https://doi.org/10.52756/ijerr.2023.v34spl.004

Yildirim, M., & Cinar, A. (2020). Classification of Alzheimer's Disease MRI Images with CNN Based Hybrid Method. *Ingénierie Des Systèmes d Information*, *25*(4), 413–418. https://doi.org/10.18280/isi.250402

Zhang, Q., Yuan, Q., Zeng, C., Li, X., & Wei, Y. (2018). Missing Data Reconstruction in Remote Sensing Image With a Unified Spatial–Temporal–Spectral Deep Convolutional Neural Network. *IEEE Transactions on Geoscience and Remote Sensing*, *56*(8), 4274–4288. https://doi.org/10.1109/tgrs.2018.2810208

How to cite this Article:

D. Dakshayani Himabindu, B. Pranalini, Mirtipati Satish Kumar, Alluri Neethika, Bhavya Sree N, Manasa C, Harshitha B, Keerthana S (2024). Deep CNN-based Classification of Brain MRI Images for Alzheimer's Disease Diagnosis. *International Journal of Experimental Research and Review*, *41*(spl.), 43-54.

DOI : https://doi.org/10.52756/ijerr.2024.v41spl.004