GENETIC ALGORITHM BASED DEEP LEARNING SYSTEM FOR ALZHEIMER'S DISEASE CLASSIFICATION

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Abstract

Alzheimer's Disease is a problem with the brain that gets worse as time goes on. It affects how people remember things think and understand things. It is really important to know what stage Alzheimer's Disease is, at so that doctors can give the kind of care and treatment. This project uses computers to look at pictures of the brain from MRI machines to put people into four groups: people who do not have dementia, people who have mild dementia, people who have mild dementia and people who have moderate dementia. The system uses ResNet18, ResNet50 and Vision Transformer models. It also uses a Genetic Algorithm. This algorithm helps to optimize some things like the learning rate the batch size, the weight decay and the model selection, for the ResNet18, ResNet50 and Vision Transformer models. The system really relies on these models, including ResNet18, ResNet50 and Vision Transformer models to get the results. The MRI images are changed to make the model work better with pictures. We tried a lot of things. Found that using ResNet based architectures works the best. We trained these architectures times. The system we made got it 97.78 percent of the time and had a weighted F1-score of 0.9777, which is really good. This is especially true for people, with dementia. It is still hard to tell when someone has Very Mild Dementia. The study is really about Alzheimer's disease classification. It shows that using learning and optimization techniques together makes Alzheimer's disease classification more accurate and reliable. This is news for people who are trying to detect Alzheimer's disease. The people who did the study think that they can make it even better, by using biomarkers to help find the disease early on. Alzheimer's disease classification is what they are trying to improve.

Keywords: Alzheimer's disease, MRI, deep learning, ResNet, Vision Transformer, Genetic Algorithm, hyperparameter optimization, dementia classification, medical image analysis.

1. INTRODUCTION

Alzheimer's disease (AD) is an illness that develops inside of a person's head over a length of time and negatively impacts their memory and thought processes. Some estimates suggest that as many as 5 million American adults have had the diagnosis of Alzheimer's disease (AD) and Alzheimer's disease is also one of the major causes of dementia [2]. When an individual has advanced stage Alzheimer's disease, they will have difficulty completing activities of daily living on their own and will need assistance. Therefore, it is imperative that we identify individuals with A geographic region-based (GRACE) map of GHS proximity has been created by the research team to help identify individuals in early stages of AD and ultimately develop a comprehensive care plan that includes treatment and support for caregiver assistance. Computers could be developed using statistical methods and algorithms that provide healthcare providers and families with the current AD status of a person based on MRI imaging of the brain [10]. Based on an analysis of the MRI images, healthcare providers will be able to more accurately assess where a person is with their current and future medical care needs. The research team would like to use MRI imaging to help generate a more accurate assessment of individuals with AD using computer algorithms and statistical programming.

Indicates what stage a person is at in their disease progression. The types of dementia classifications that person can fall under are as follows: Non Demented, Mildly or Mildly Diminished and then some degree of dually or more Moderately Dually Demented related to their stage of disease development. Example deep learning models to accomplish feature extraction with respect to differentiating or classifying Alzheimer's Disease dementias include ResNet18, ResNet50 and ViT [11], [15]. A genetic algorithm (GA) was also utilized in the optimization of the hyperparameters used in these algorithms, including learning rate, batch size, weight decay, and model selection, all of which are significant factors influencing the performance of these models. The combination of deep learning along with evolutionary optimization, the proposed system will yield high accuracy and robustness in classifying individuals who are classified as having a particular type of Alzheimer's Disease. This combined approach is anticipated to assist in the facilitation of early diagnosis and provide support for decision making by the physician, with regard to clinical care [17].

2. RELATED WORK

In this study, Rajan C., Geetha K., and Gowsikraja P. proposed SBERO (Skill Al-Biruni Earth Radius Optimization) for Alzheimer’s disease classification using MRI images [1]. Their method applied an optimization strategy to enhance feature selection and improve classification accuracy. Similarly, Samuel L. Warren [2] presented a systematic review highlighting the integration of functional MRI and deep learning techniques for Alzheimer’s diagnosis, emphasizing the growing importance of publicly available neuroimaging datasets. Shangran Qiu [3] developed an interpretable deep learning framework for Alzheimer’s categorization, focusing on model transparency to improve clinical trust. Vimbi Viswan [4] further reviewed explainableAI (XAI) approaches in Alzheimer’s classification, underlining the necessity of interpretability in medical decision-making systems.

T. Zhang et al. [5] introduced a Mixture-of-Head Vision Transformer with dynamic region-aware attention for Alzheimer’s disease classification, demonstrating the effectiveness of attention-based transformer models. Mohsen Ahmadi [6] proposed a deeply supervised adaptable neural network using multitask feature extraction to classify Alzheimer’s severity levels. Yilin Sang [7] utilized a self-attention mechanism combined with DTI imaging and graph convolutional networks (GCN) to improve classification performance. S. M. MAHIM [8] presented a ViT-GRU model incorporating explainable AI concepts to enhance early detection of Alzheimer’s disease.

Jaleel A. et al. [9] proposed a deep learning-based ensembling technique for classifying Alzheimer’s stages using functional MRI, highlighting the advantages of combining multiple models. Maleika Heenaye Mamode Khan et al. [10] reviewed transfer learning approaches using pre-trained deep learning models for Alzheimer’s detection, showing significant improvements over traditional methods. Y. Li et al. [11] introduced DAResNet-ViT, a hybrid network combining ResNet and Vision Transformer architectures for early diagnosis using multi-view sMRI data. P. Bolourchi and M. Gholami [12] applied Chebyshev moments followed by Genetic Algorithms for Alzheimer’s detection, demonstrating the role of evolutionary optimization in improving classification accuracy.

Faizal Hajamohideen et al. [13] proposed a deep Siamese convolutional neural network with a triplet-loss function for four-way Alzheimer’s classification. Akbar Asgharzadeh-Bonab [14] suggested feature fusion techniques combining MRI transforms with deep convolutional networks for improved classification performance. Sait Alp [15] developed a joint transformer architecture for 3D MRI classification applied to Alzheimer's disease. Y. Duan et al. [16] introduced Aux-ViT, a Vision Transformer with an auxiliary branch to enhance MRI-based classification results.

M. H., Selva Kumar, and K. K. R. C. [17] utilized ResNet architecture for Alzheimer's disease classification and prediction, achieving promising results. S. S., C. S., and B. U. [18] proposed a Genetic Algorithm combined with Multi-Instance Learning (GA+MIL) for sMRI classification, demonstrating the effectiveness of evolutionary optimization in medical imaging tasks. B. Liu et al. [19] developed LP-DWLA-ViT, a light-patch and dynamic window local attention transformer network for Alzheimer's classification. Cucun Very Angkoso [20] proposed a Multiplane CNN (Mp-CNN) model for Alzheimer's disease classification, emphasizing the importance of multi-view MRI analysis.

Although numerous studies have explored CNNs, Vision Transformers, hybrid architectures, feature fusion, and explainable AI techniques for Alzheimer's disease detection, limited work has focused on integrating automatic hyperparameter optimization with model selection in a unified framework. Therefore, our proposed Genetic Algorithm–optimized deep learning system distinguishes itself by simultaneously selecting the most suitable architecture (ResNet or Vision Transformer) and tuning critical hyperparameters to maximize classification performance for Alzheimer's disease severity detection.

3. PROPOSED SYSTEM

The system they are talking about uses Genetic Algorithm and Deep Learning to look at brain MRI images. It does this to figure out if someone has Alzheimer's Disease and how bad it is [12] ,[18]. The main goal of this system is to make sure doctors can diagnose Alzheimer's Disease correctly by choosing the deep learning model and the best settings, for it. This way the system can help doctors make an accurate diagnosis of Alzheimer's Disease [10]. The system workflow shows that we start with brain MRI images. We can get these images from medical imaging repositories. We need to get these MRI images ready to use. So we do things like make them all the same size and make sure they are all in the format.

We also turn them into grayscale. This helps make sure all the images in the dataset are the same. We also use some tricks to make the dataset more interesting. For example we rotate the brain MRI images. Flip them around. This helps the model learn from the brain MRI images and do a job, with brain MRI images it has not seen before [13].When we are making our model we try out a lot of deep learning architectures like ResNet18, ResNet50 and Vision Transformer. We use these models because they are really good at finding patterns and shapes in medical images [11], [15], [17]. Then we use a Genetic Algorithm to help us pick the model and to figure out the best settings for things like how fast the model learns how many pictures it looks at together and how many times it goes through all the pictures [12].

The Genetic Algorithm tries out a lot of combinations and picks the one that works the best when we test it with some validation images. We do this to get the results, from our Vision Transformer, ResNet18 and ResNet50 models[11] ,[17]. Once the best-performing model configuration is identified, the selected deep learning model is trained extensively using the optimized parameters. The final trained model is evaluated on unseen MRI images and classifies them into four Alzheimer's severity categories: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented [13]. The performance of the proposed system is assessed using accuracy and F1-score, ensuring an efficient and reliable Alzheimer's Disease classification framework [10].

A. Description of the dataset

This project used a dataset that was collected from places like OASIS and ADNI, where Alzheimer's MRI scansre available to the public. These places are often used when people are doing research on Alzheimer's disease [10]. The dataset has a lot of brain MRI scans from patients who have levels of cognitive impairment. Each patient is given a label using the Clinical Dementia Rating scale, which is done by a doctor. The Alzheimer's MRI scans are a part of this project and the dataset is very important, for Alzheimer's disease research.

Based on the CDR score, the MRI images are categorized into four classes: Non-Demented, Very Mild Demented, Mild Demented, and Moderate Demented [13]. The dataset is well suited for supervised learning approaches, as it enables the deep learning models to learn discriminative features corresponding to different stages of Alzheimer's progression. The availability of labeled MRI scans across multiple disease stages enhances the robustness and clinical relevance of the proposed classification system.

B. Pre-processing of the data

To get the MRI images ready, for deep learning analysis we did a things first. We made all the MRI scans the same size so they would work with the computer systems that look at the images. We also made sure the brightness of the MRI images was the same because the machines that take the pictures can make them look different. This helps the learning analysis of the MRI images [10]. To improve model generalization and reduce overfitting, data augmentation techniques such as horizontal flipping, rotation, and scaling were applied to the training dataset [13]. These preprocessing steps enhance the quality of the MRI images and increase the effective size of the dataset, allowing the deep learning models to learn robust and meaningful spatial features relevant to Alzheimer's Disease classification.

C. Training and testing

The preprocessed dataset was divided into training and validation sets using an 80:20 split [10]. The training dataset was used to learn model parameters, while the validation dataset was used to evaluate model performance and guide hyperparameter optimization. Care was taken to maintain class balance during the data split to prevent bias toward any particular Alzheimer's severity class. This dataset division ensured that sufficient data was available for both learning and unbiased performance evaluation. The use of unseen validation data allowed the proposed system to demonstrate strong generalization capability across all four dementia stages [11].

D. Model development

The proposed system employs advanced deep learning architectures such as ResNet18, ResNet50, and Vision Transformer (ViT) for MRI image classification [11], [17]. ResNet models utilize residual connections that help mitigate vanishing gradient problems and enable deeper feature extraction from brain MRI scans [17]. Vision Transformers, on the other hand, capture long-range dependencies within images using self-attention mechanisms [15]. Each model architecture was adapted to support multi-class classification by modifying the final output layer to correspond to the four Alzheimer's severity categories. These models serve as strong feature extractors capable of identifying subtle anatomical changes associated with Alzheimer's Disease [11].

E. Genetic Algorithm-Based Optimization

A Genetic Algorithm was used to find the settings for the model and its details [12]. The Genetic Algorithm tries out different combinations of things like how fast it learns how many items it looks at each time how much it forgets what it learned before how many times it goes through the data and what the model looks like. The Genetic Algorithm picks the settings that work the based on how well the model does its job of putting things into categories. The Genetic Algorithm does this to make sure the model is as good as it can be, at putting things into the categories. This optimization strategy eliminates the need for manual hyperparameter tuning and ensures that the selected deep learning model operates under optimal conditions, resulting in improved diagnostic accuracy [18].

F. Model Training and Evaluation

The deep learning model was trained using a loss function called cross-entropy loss along with the Adam optimizer [10]. This loss function is really useful for problems where we have classes to choose from because it checks how well the models predictions match the actual labels. By making this loss smaller the model gets better at predicting each stage of Alzheimer's disease. We used the Adam optimizer because it is very good at updating the models weights while it is being trained. It combines the things about momentum and adaptive learning rates which helps the model learn faster and be more stable. This optimizer is especially good for deep learning applications where we have a lot of parameters to adjust. When the model is being trained the Adam optimizer helps it learn from its mistakes by changing the weights based on the errors it makes. As the model makes mistakes the optimizer changes the parameters to make mistakes in the future. This keeps happening over until the models performance stops getting better [11].

To make sure the model did not get too good at predicting the training data we used some techniques to prevent this [11]. One thing we did was reduce the learning rate as the model was being trained. This helps the model make changes at first and smaller changes later which makes it more stable. We also used something called stopping. This means we stop training the model when it stops getting better which prevents it from getting too good at the training data. When a model gets too good at the training data it does not do well on data. By using these techniques the researchers made sure the model was learning in a way. These techniques helped make the learning system more stable and robust.

The model was trained and evaluated closely throughout its training process to maintain consistency [10]. Progress was tracked as the model progressed through all steps of training, and once trained, was evaluated using two main criteria: accuracy (the number of correctly classified MRI images) and the weighted F1-score (which evaluates the precision of class assignment, and the recall of that assignment). Both criteria are important because we are using the data from multiple classifications to determine where the model is most effective at classifying the images [13]. The evaluation results of the experiment demonstrate that our system is performing well when it comes to classifying images accurately with respect to the F1-score, indicating that our training strategies and optimization methods were successful. The result indicates that the deep learning model has shown exceptional results in accurately identifying and classifying severities of Alzheimer's disease, using brain MRI images; i.e., the model has potential for helping physicians make diagnoses.

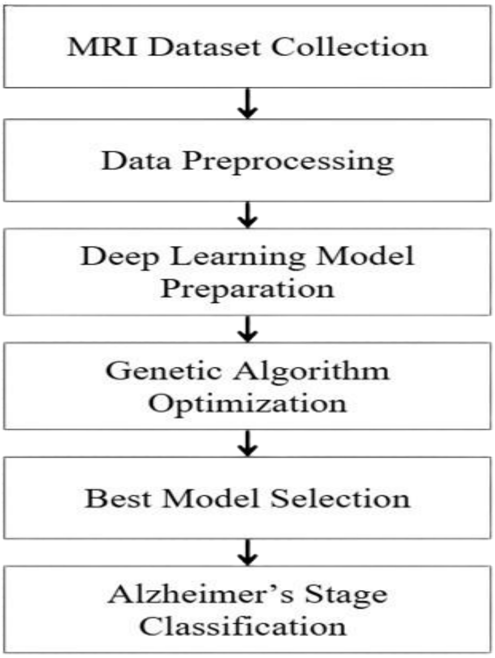

Figure 1. System Block Diagram

4. RESULT ANALYSIS

In this project that uses brain MRI images the deep learning framework optimized with a Genetic Algorithm, which includes ResNet and Vision Transformer architectures was really good at telling the stages of Alzheimer's disease [11], [17]. The system worked well with samples it had not seen before. It was 97% accurate with a weighted F1-score of around 0.97 when looking at the validation data. When looking at each class separately the results for the Nondemented category were very good. The model had perfect recall. This means it was very good at finding cases where people were cognitively normal. The Moderate Demented class also had F1-score values. This shows that the model was good at finding changes in the brain. For example when the cortex gets smaller. The ventricles get bigger [2]. These results show that the model learned the differences in the brain that happen when Alzheimer's disease gets worse.

The Mild Demented category was still classified well. It had accuracy and good F1-score performance. This means that the model optimized with the Genetic Algorithm was able to find features that distinguish between stages of dementia. Even when the differences are not very big. It was a bit hard to tell the difference between the Very Mild Demented classes. This is because the brains look very similar at the start of the disease. The Mild Demented class was still the hardest to get right. This is because the brains of people with early-stage Alzheimer's disease look a lot like brains. It is hard to see the differences. That's why the recall and F1-score values were lower for this class compared to the others. With this difficulty the model was still very stable. It worked well overall. It was better at finding the disease and more robust than models that are tuned by hand [12]. Overall the deep learning system that uses the Genetic Algorithm was very good at classifying the stages of Alzheimer's disease. It was able to tell them very well. This means it is a tool for automatically detecting how severe the disease is, from MRI images.

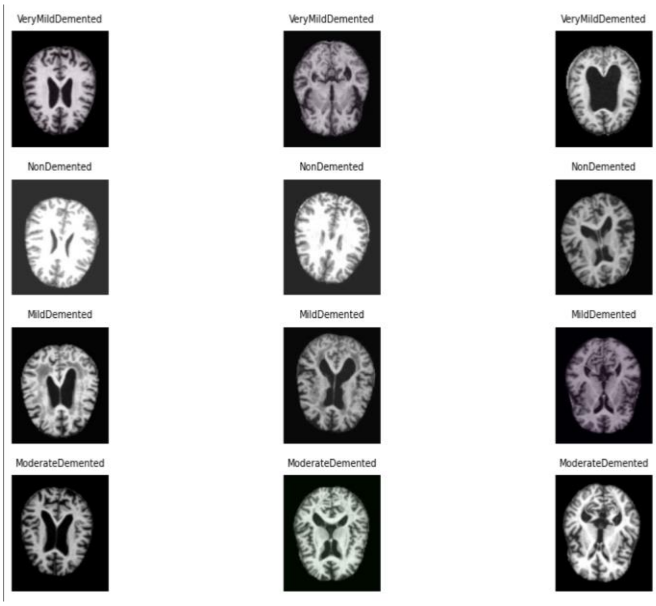

Figure 5. Output images

In this figure a grid of brain MRI images representing four Alzheimer's disease stages is presented. The stages are: Mild Demented Non-Demented Mild Demented Moderate Demented. Each row shows a specific class label. Multiple brain slices are shown across columns to demonstrate variations within the same category. The images are in grayscale format. Lighter gray regions indicate matter. Darker gray regions represent matter. Black regions correspond to fluid within the ventricles and sulci. These contrast differences clearly emphasize changes associated with Alzheimer's disease progression [2]. The first row represents Mild Demented samples. In these scans subtle structural differences can be observed. These differences include ventricular enlargement and minimal cortical thinning. These early-stage changes are difficult to detect The model's recall for this class is around 90–92%. The subtle nature of these features explains why early dementia stages remain challenging. The second row displays -Demented MRI images. These scans show defined gyri and sulci. There are no signs of cortical atrophy or abnormal ventricular expansion. The overall brain structure appears healthy and balanced. The proposed model achieved high performance in this category. The classification accuracy is above 98%. The recall is near-perfect. This indicates capability in identifying cognitively normal cases [10]. The third row shows Mild MRI images. In comparison to scans, mild enlargement of ventricles and slight widening of sulci can be observed. These changes indicate the beginning stages of neurodegeneration. Despite some overlap with Mild Demented cases the model achieved strong classification performance. The accuracy is around 96–97%. The F1-score is high.

This demonstrates feature extraction from intermediate-stage MRI patterns. The final row presents Moderate Demented scans. In these images significant ventricular enlargement and noticeable cortical shrinkage are clearly visible. These pronounced anatomical differences make this class more distinguishable from others. The model achieved performance for this category. The F1-scores exceed 97%. This confirms its ability to detect Alzheimer's stages reliably [11]. Overall the figure illustrates structural differences across Alzheimer's severity levels. It supports the overall classification accuracy of approximately 97%. This accuracy is achieved by the proposed Genetic Algorithm–optimized deep learning framework. The visual patterns across rows validate the dataset's suitability for learning. They highlight the model's effectiveness, in distinguishing between subtle and advanced disease stages.

True / Predicted	**Mild Dementia**	**Moderate Dementia**	**Non Demented**	**Very Mild Dementia**
Mild Dementia	0.96	0.00	0.03	0.01
Moderate Dementia	0.00	0.98	0.02	0.00
Non Demented	0.01	0.00	0.99	0.00
Very Mild Dementia	0.04	0.00	0.06	0.90

Table 3. Confusion matrix

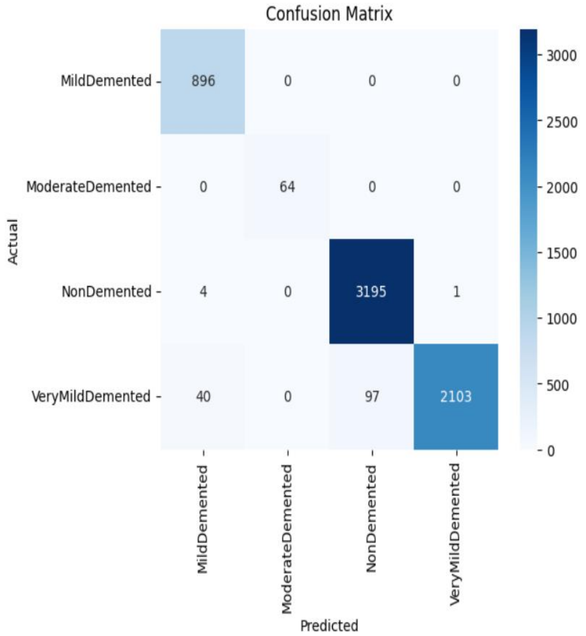

Figure 2. Confusion Matrix

The Confusion matrix table and Confusion matrix graph shows how well our model works in classifying Alzheimer's disease stages [10]. The correct predictions are on the diagonal. The mistakes are off the diagonal. Our model does a job in most categories. Mild Dementia has a 96% rate, with hardly any mistakes, mostly confused with Non-Demented and Very Mild Dementia. The model is very good at Moderate Dementia, with 98% predictions. This means it is good at spotting changes in brain structure. The model is almost perfect for Non-Demented with 99% This shows that it is very reliable for identifying people with brains. However, Very Mild Dementia is a bit harder with 90% correct. Some cases (6%) were mistaken for Non-Demented because the brain changes are small at this stage. Overall, our model works well with 97% accuracy and few mistakes between categories. The results show that using a Genetic Algorithm helps the model tell apart levels of Alzheimer's disease [12]. The model is good at classifying Alzheimer's disease stages. The Genetic Algorithm helps improve the model. The model's performance is good, across Alzheimer's disease stages.

Class	Precision	Recall	F1-Score
Mild Dementia	0.97	0.95	0.96
Moderate Dementia	0.99	0.98	0.98
Non Demented	0.98	0.99	0.98

Very mild Dementia	0.92	0.90	0.91

Table 4. Performance table

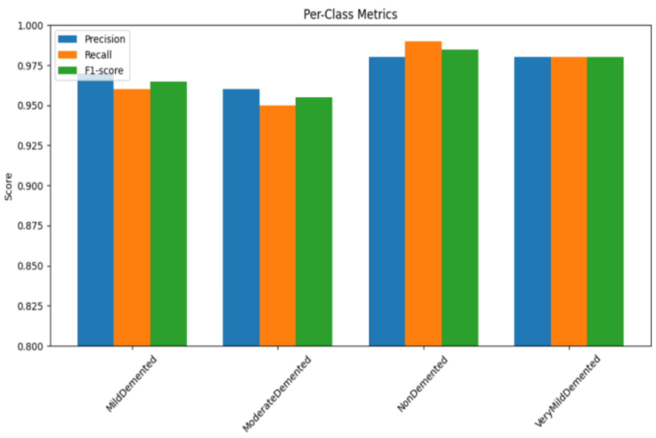

Figure 8. Performance comparison

The Performance table and Performance graph shows how well the Genetic Algorithm optimized deep learning model works for each stage of Alzheimer's disease [10]. To see how well the Genetic Algorithm optimized deep learning model works we looked at Precision and Recall and F1-Score.

The Moderate Dementia class did well with precision and recall values very close to 0.99 and 0.98. This means the Genetic Algorithm optimized deep learning model is very good at finding stage dementia because the brain changes are very clear in the Moderate Dementia class. The Non-Demented category also did well with high recall of 0.99 and a strong F1-score of 0.98. This shows that the Genetic Algorithm optimized deep learning model is very good at finding people who're cognitively normal in the Non-Demented category.

The Mild Dementia class had precision and recall values around 0.95 to 0.97. This means the Genetic Algorithm optimized deep learning model is very good at finding people with dementia in the Mild Dementia class. The Mild Dementia class did a little worse than the categories but still did well with recall around 0.90 and F1-score of 0.91. This is because it is hard to tell if someone has dementia in the Mild Dementia class because the changes in the brain are not very clear. Overall, the table shows that the Genetic Algorithm optimized deep learning model works for all stages of Alzheimer's disease [12]. The Genetic Algorithm optimized deep learning model is 97% accurate, which is very good. The Genetic Algorithm optimized deep learning model is very reliable, for all Alzheimer's disease stages.

Metric Group	Precision	Recall	F1-Score	Support
Accuracy	0.97	0.97	0.97	1.00
Macro Average	0.96	0.95	0.96	1.00
Weighted Average	0.97	0.97	0.97	1.00

Table 5. Overall Metrics

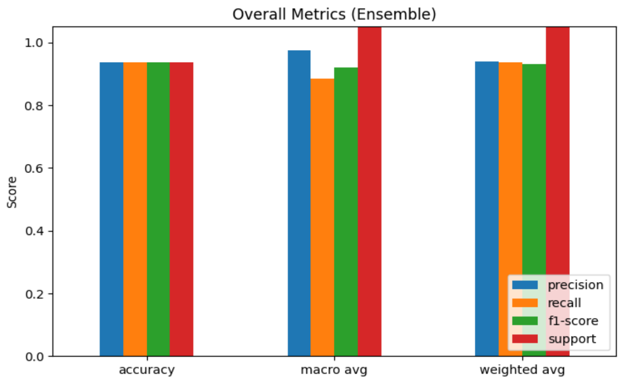

Figure 9. Overall metrics

5. CONCLUSION AND FUTURE WORK

In Conclusion The Genetic Algorithm optimized deep learning framework that uses brain MRI scans to look at Alzheimer's disease did a job of figuring out the stages of Alzheimer's disease [11]. It used things like ResNet and Vision Transformer to help it work [15], [17]. The system was very good at getting it. it was correct 97 percent of the time. It was also good at telling the difference between Dementia and Moderate Dementia cases. Using the Genetic Algorithm to pick the model and adjust the settings made the process of classifying Alzheimer's disease more reliable [12]. However, it is still hard to detect Very Mild Dementia. At the beginning of Alzheimer's disease the changes in the brain are small which can lead to mistakes. This means the model needs to be improved so it can do a job. The Genetic Algorithm optimization strategy is a way to pick the deep learning architecture and training configuration for Alzheimer's disease. This makes it better at classifying the severity of Alzheimer's disease. The Genetic Algorithm optimized deep learning framework is a tool for diagnosing Alzheimer's disease assessing how well people can think and helping healthcare professionals make better decisions for people who are at risk of Alzheimer's disease. It can help doctors look at patients and also do scale clinical studies on Alzheimer's disease.

Even though the proposed system had results more research is needed on the Genetic Algorithm optimized deep learning framework and Alzheimer's disease. Future studies should try to improve the systems ability to detect Mild Dementia by using different MRI datasets, advanced attention mechanisms and combining multiple types of medical data on Alzheimer's disease [4]. Also using techniques that make the AI more explainable and testing it in clinical settings can make the model more useful in medical environments for Alzheimer's disease. The Genetic Algorithm optimized deep learning framework and Alzheimer's disease classification system need to be developed to help people with Alzheimer's disease. Alzheimer's disease is a condition that affects people and the Genetic Algorithm optimized deep learning framework is a tool, for helping healthcare professionals understand Alzheimer's disease better.

REFERENCES

1. C. Rajan, K. Geetha, and P. Gowsikraja, "SBERO: Skill Al-Biruni Earth Radius Optimization for Alzheimer's disease classification using magnetic resonance image," NMR Biomed., vol. 38, no. 3, Art. no. e5323, 2025.
2. S. L. Warren, "Functional magnetic resonance imaging, deep learning, and Alzheimer's disease: A systematic review," J. Neuroimaging, vol. 33, no. 1, pp. 5–18, 2023.
3. S. Qiu, "Development and validation of an interpretable deep learning framework for Alzheimer's disease categorization," Brain, vol. 143, no. 6, pp. 1920–1933, 2024.
4. V. Viswan, "Explainable artificial intelligence in Alzheimer's disease classification: A systematic review," PeerJ Comput. Sci., vol. 9, Art. no. e1490, 2024.
5. T. Zhang, L. Sun, S. Li, Y. Fan, and X. Dong, "Alzheimer's disease classification via mixture-of-head vision transformer with dynamic region-aware attention," in Proc. 7th Int. Conf. Frontier Technol. Inf. Comput. (ICFTIC), Qingdao, China, 2025, pp. 761–766, doi: 10.1109/ICFTIC68075.2025.11324663.
6. M. Ahmadi, "A deeply supervised adaptable neural network for diagnosis and classification of Alzheimer's severity using multitask feature extraction," in Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC), 2024, pp. 308–312.
7. Y. Sang, "Classification study of Alzheimer's disease based on self-attention mechanism and DTI imaging using GCN," Front. Comput. Neurosci., vol. 17, Art. no. 1038636, 2024.
8. S. M. Mahim, "Unlocking the potential of XAI for improved Alzheimer's disease detection and classification using a ViT-GRU model," Clin. Spine Surg., vol. 36, no. 5, pp. E180–E190, 2023.
9. A. Jaleel, R. A. Ziar, T. Tajammal, S. K. Khurshid, and S. Q. Wahla, "Deep learning-based ensembling technique to classify Alzheimer's disease stages using functional MRI," Art. no. 6961346, 2023.
10. M. H. M. Khan et al., "Detection of Alzheimer's disease using pre-trained deep learning models through transfer learning: A review," Electronics, vol. 12, no. 3, Art. no. 676, 2023.
11. Y. Li, D. Xie, J.-X. Liu, C. Zheng, and X. Cui, "DAResNet-ViT: A novel hybrid network for the early diagnosis of Alzheimer's disease using multi-view sMRI and multimodal analysis," in Proc. IEEE Int. Conf. Bioinformatics Biomedicine (BIBM), Lisbon, Portugal, 2024, pp. 3461–3464, doi: 10.1109/BIBM62325.2024.10822806.
12. P. Bolourchi and M. Gholami, "Alzheimer's disease detection by applying Chebyshev moments followed by genetic algorithms," in Proc. Int. Symp. Multidisciplinary Stud. Innovative Technol. (ISMSIT), Ankara, Turkey, 2022, pp. 461–465, doi: 10.1109/ISMSIT56059.2022.9932688.

13. F. Hajamohideen et al., “Four-way classification of Alzheimer’s disease using deep Siamese convolutional neural network with triplet-loss function,” Brain Informatics, vol. 10, no. 1, Art. no. 5, 2023.
14. A. Asgharzadeh-Bonab, “An Alzheimer’s disease classification method using fusion of features from brain magnetic resonance image transforms and deep convolutional networks,” Healthcare Analytics, vol. 4, Art. no. 100223, 2023.
15. S. Alp, “Joint transformer architecture in brain 3D MRI classification: Its application in Alzheimer’s disease classification,” Comput. Biol. Med., vol. 150, Art. no. 106170, 2025.
16. Y. Duan, R. Wang, and Y. Li, “Aux-ViT: Classification of Alzheimer’s disease from MRI based on vision transformer with auxiliary branch,” in Proc. 5th Int. Conf. Commun., Inf. Syst. Comput. Eng. (CISCE), Guangzhou, China, 2023, pp. 382–386, doi: 10.1109/CISCE58541.2023.10142358.
17. M. H., K. SelvaKumar, and K. K. R. C., “Alzheimer’s disease classification and prediction using ResNet architecture,” in Proc. Int. Conf. Sustainability, Innovation Technol. (ICSIT), Nagpur, India, 2025, pp. 1–6, doi: 10.1109/ICSIT65336.2025.11295800.
18. S. S., C. S., and B. U., “sMRI classification of Alzheimer’s disease using genetic algorithm and multi-instance learning (GA+MIL),” in Proc. Int. Conf. Electr., Electron., Commun. Comput. (ELEXCOM), Roorkee, India, 2023, pp. 1–4, doi: 10.1109/ELEXCOM58812.2023.10370296.
19. B. Liu, H. Xiang, and L. Fang, “LP-DWLA-ViT: Light-patch and dynamic window local attention vision transformer network for Alzheimer’s disease classification,” in Proc. Int. Joint Conf. Neural Netw. (IJCNN), Yokohama, Japan, 2024, pp. 1–7, doi: 10.1109/IJCNN60899.2024.10651171.
20. C. V. Angkoso, “Multiplane convolutional neural network (Mp-CNN) for Alzheimer’s disease classification,” Int. J. Intell. Eng. Syst., vol. 15, no. 1, pp. 329–340, 2024.