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Alzheimer's and Brain Disorder Detection Using TLEABLCNN with SMOTE-Augmented Imbalanced MRI for Enhanced Diagnostic Accuracy

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Abstract: Alzheimer's disease (AD) and brain tumors are two of the most serious neural diseases that need to be accurately diagnosed with magnetic resonance imaging (MRI) in order to be treated effectively. This study looks at MRI datasets that aren't balanced and uses the Synthetic Minority Oversampling Technique (SMOTE) to make classification work better. A number of machine learning and deep learning models were used, such as Random Forest (RF), Support Vector Machine (SVM), Voting Classifier, Convolutional Neural Network (CNN), VGG16, ResNet50, InceptionV3, AlexNet with LSTM, Xception, and the new Transformer and LSTM Enhanced Attention-Based Explainable CNN (TLEABLCNN). A comparison test with three different situations showed that TLEABLCNN regularly did better than baseline models. It achieved classification accuracy of 96.1% in Scenario A, 97.4% in Scenario B, and 98.2% in Scenario C, with better macro-precision, recall, and F1-scores. Object recognition models YOLOv5, YOLOv8, YOLOv9, and YOLOv11 were used to find brain abnormalities. With a mean average precision (mAP) of 91.5%, YOLOv9 had the best performance, while YOLOv8 had the best accuracy of 91.8%. Also, explainable AI (XAI) methods like Grad-CAM were used to make heatmaps that showed the most important parts of the MRI scans that affected the model's predictions. This made the forecasts easier to understand and increased clinical trust. It's clear from these results that the strategy for correctly identifying neurological disorders is very strong.

"Index Terms: *Brain tumor, Alzheimer's disease, deep learning, machine learning, SMOTE, XAI."*

1. INTRODUCTION

Alzheimer's disease (AD) is one of the scariest neurological diseases affecting older people around the world. It mostly affects the parts of the brain that are in charge of remembering and thinking. More than 600,000 people aged 65 and up died of AD in 2010. This led to predictions about the yearly death rate among older adults in the US between 2010 and 2050 [1]. It was thought that 50 million people around the world would have AD by 2022, making it a major problem for social and health services [2]. Progressive neuronal loss in AD makes it hard to remember recent events, recognize familiar faces, and understand what's going on around you, which can make people who have it often feel lost. AD affects 6.9 million Americans aged 65 and up right now, and that number is expected to rise to 13.8 million by 2060 if no new ways to avoid or treat it are found [3]. 119,399 people died in the United States in 2021 because of AD [4].

As the world's population ages, it is important to look into the reasons of neurological diseases like Alzheimer's. Even though no one knows for sure how AD works, a number of risk factors have been found [5], such as high blood pressure, smoking, and not having enough education. Brain tumors are another big problem for the nervous system. They happen when brain tissue or structures connected to it grows in a way that isn't normal. This can happen because of getting older, changes in metabolism, and hormones [6]. These lumps can be benign or cancerous. Alzheimer's disease is marked by the buildup of beta-amyloid plaques and tau protein deposits in the brain. Genetic, behavioral, and environmental factors affect how the disease progresses [7]. Both situations make it hard to do normal things and put a lot of emotional, mental, and financial stress on caregivers [8].

MRIs, or magnetic resonance imaging, are very important for identifying and keeping an eye on both Alzheimer's disease and brain tumors. For tumors, MRI gives exact details about size, severity, and type that help with treatment. For AD, advanced imaging methods like diffusion tensor imaging

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allow early discovery of structural changes and long-term follow-up [9]. Deep learning and other types of artificial intelligence (AI) make detection better by picking up on complex patterns in medical pictures. Explainable AI (XAI) makes these models easier to understand and more reliable, which promotes openness and trust in the professional community [10].

2. LITERATURE REVIEW

Alzheimer's disease (AD) has been the subject of a lot of study because it is becoming more common and has a big effect on how well older people can think and remember things. Better [11] gave a thorough summary of AD, focusing on important numbers, public health trends, and the pressing need for early detection and treatment plans. The study focused on how AD is becoming a bigger problem around the world and how important it is to use advanced diagnostic tools to lessen its affects. Similarly, Jiménez-Balado and Eich [12] looked into the part that GABAergic dysfunction plays in human aging and AD, showing how neural network excitement leads to memory loss. Their results show that cognitive decline is caused by complex neurological processes. These findings can be used to create more focused diagnostic and treatment methods.

Recent progress in artificial intelligence has shown a lot of promise in making AD recognition more accurate and faster. Mahim et al. [13] suggested a Vision Transformer-Gated Recurrent Unit (ViT-GRU) model combined with explainable artificial intelligence (XAI) to sort AD into different groups. Their work showed how important interpretability is in AI-driven healthcare, letting doctors know how deep learning models make decisions while still keeping diagnostic accuracy high. Hassan et al. [14] created a multimodal deep learning system that uses MRI, PET, and clinical data to find and classify AD. This method worked better than one-modal systems, showing how important it is to combine different types of data for accurate disease analysis.

Hazarika, Kandar, and Maji [15] showed a new way to use brain pictures and machine learning to classify people with early-stage AD. Their method was based on getting distinguishing traits from MRI data, which made it possible to make an early diagnosis and possibly start treatment. As Sorour et al. [16] did, they used deep learning to classify AD and MRI data to get very accurate and reliable results. Their research showed that convolutional neural networks can find small changes in the brain's structure that are linked to disease development.

In recent studies, people have also become more interested in ensemble learning and hybrid methods. Belay, Walle, and Haile [17] suggested using a deep ensemble learning system along with quantum machine learning to find AD. Their model used more than one classifier to make predictions more accurate, showing that hybrid computational methods could be useful for diagnosing neurodegenerative diseases. Sangeetha et al. [18] used deep learning to diagnose and classify AD, focusing on how neural networks can be used to find complex trends in imaging data. Their work showed that deep learning methods can be used with large datasets, which lets them do full analyses of a wide range of patient groups.

Transfer learning has proven to be a very useful method in studying AD. A group of researchers led by Goyal, Rani, and Singh [19] created a multilayered system for finding and classifying AD that used both a transfer-learned AlexNet network and an LSTM network. Their method used pre-trained convolutional networks to effectively pull out useful features from MRI scans. The LSTM part caught temporal dependencies, which led to better classification performance. These methods show that using models that have already been trained can help medical imaging applications get around the problem of not having enough training data.

In their paper [20], Suchitra, Krishnasamy, and Poovaraghan suggested using magnetic resonance images and deep learning to create an early detection method for AD. The main focus of their work was on automated feature extraction and classification, which makes it possible to find early cognitive impairments quickly and accurately. Their work helped cut down on diagnostic delays and made it easier for people to get help when they needed it by combining advanced preprocessing and deep learning processes. All of these studies show how AI and deep learning can change the way AD is found by making it more accurate, faster, and easier to understand. They consistently show a move toward multimodal, ensemble, and explainable methods that get around the problems with old diagnostic methods, like the need for manual feature extraction, biased assessment, and differences in how skilled clinicians are.

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3. MATERIALS AND METHODS

Using MRI datasets, the suggested system creates a smart and understandable framework for categorizing neurological disorders, such as Alzheimer's disease and brain tumors. For even training, the Synthetic Minority Oversampling Technique (SMOTE) is used to fix the problem of unequal class representation. Traditional machine learning models, like Random Forest (RF) and Support Vector Machine (SVM), are built into the framework. So are advanced deep learning architectures, like CNN, VGG16, ResNet50, InceptionV3, AlexNet-LSTM, and the proposed Transformer and LSTM Enhanced Attention-Based Explainable CNN (TLEABLCNN). For deployment, Flask is used to make the system's interface easy to use, which lets real-time MRI classification and recognition happen. Besides Grad-CAM, other algorithms like Xception, Voting Classifier, and YOLO models are used to make the results easier to understand visually by pointing out key brain areas that affect predictions. This makes the results more reliable, understandable, and useful in clinical settings.

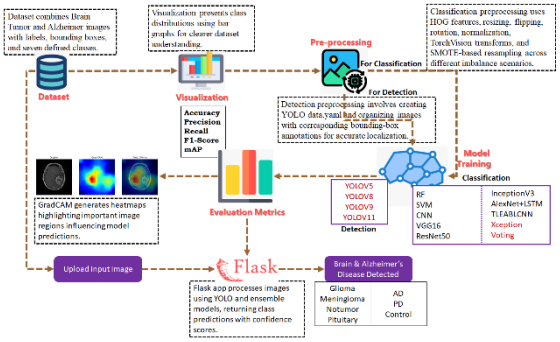


Fig.1 Proposed Architecture

The suggested system design combines MRI datasets from brain tumors and Alzheimer's into a single pipeline for detection and classification. The first visualization of the dataset helps with class distribution analysis. Next, task-specific preprocessing is done for recognition and classification. Standard performance measures are used to train and test multiple learning models. Visual interpretation of important image parts ensures that things can be explained. The trained models are put to use through a web-based framework that lets users upload MRI images and get correct disease predictions with confidence scores. This helps doctors make good decisions.

a) Dataset Collection:

For classification and detection tasks, the suggested system's dataset is made up of pictures of brain tumors and Alzheimer's disease that have been put together into a single seven-class dataset. There are 14,779 pictures in the classification branch, split into seven groups: Control (3,650), AD (3,200), No Tumor (2,000), Pituitary (1,757), Meningioma (1,645), Glioma (1,621), and PD (906). For the detection branch, 1,093 pictures are used for training and 274 images are used for testing. Bounding boxes in YOLO format (.txt) are used to find areas of interest. The dataset is organized into training, validation, and testing sets. This makes sure that all jobs related to classification and detection are covered.

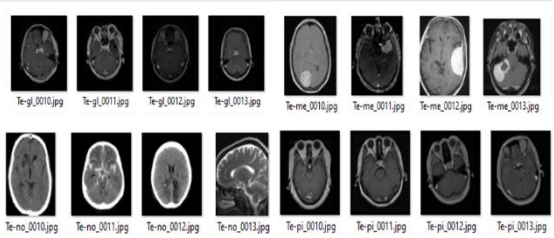


Fig.2 Dataset Collection

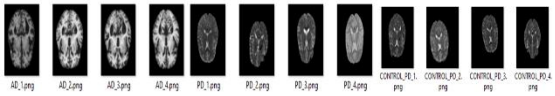
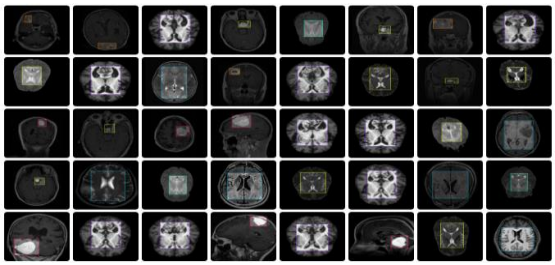


Fig.3



Fug.4

b) Visualization: In the process of visualizing a dataset, class distributions are looked at using bar graphs to show how the data is balanced across groups. Sample MRI pictures are shown with the notes that go with them so that you can get a good idea of the quality and range of the images. For the detection branch, there are also examples of bounding boxes that show specific areas of interest. This step makes sure that there is a full picture of how the data is spread out and how each class is represented before the model is trained. This helps with making smart choices about preparation and model design.

c) Pre-processing: As part of pre-processing, MRI images are resized to standard sizes, pixel intensities

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are normalized, and data enhancement methods using TorchVision transforms are used to improve model generalization. There are two sets of data that are kept in parallel: the classification branch has labeled images for categorical learning, and the YOLO detection branch has bounding box comments for finding areas of interest. This organized preparation makes sure that both classification and detection models get uniform, high-quality inputs. This makes training more efficient and improves the accuracy of predictions.

d) Algorithms:

Random Forest (RF): When used for MRI classification, RF creates many decision trees and sends out the vote of the majority, which creates a strong starting model [21]. It does a good job of handling features with a lot of dimensions, keeps things stable across datasets, and lets you compare different deep learning models by interpreting the results.

$$Gini = 1 - \sum_{i=1}^{C} (Pi)^2 \quad (1)$$

Support Vector Machine (SVM): SVM finds the best hyperplanes that separate groups and works best with smaller datasets. It is used to classify brain MRI images. It tells the difference between disease types by increasing the margins. It provides a clear, solid starting point that works well with ensemble and deep learning techniques [22] for looking at neural images.

$$minimize \ \frac{1}{2} ||W||^2 + C \sum_{i=1}^{n} \xi_i \quad (2)$$

Voting Classifier: combines predictions from several models, such as traditional and deep learning methods, to make a final result. By combining the best features of different algorithms, it makes the system more reliable and accurate, getting rid of the bias that comes from using just one model and making a fair system for classifying brain abnormalities.

$$\hat{y} = argmax_c \left(\sum_{i=1}^{n} II \ (\hat{y}_i = c) \right) \quad (3)$$

Convolutional Neural Network (CNN): uses convolutional filters to automatically pull out aspects of space like edges and textures from MRI images. Captures hierarchical patterns, which makes it easier to classify neurological diseases [23] and shows how important feature extraction is for finding brain abnormalities.

$$S(i,j) = \sum_{m} \sum_{n} I(i+m, j+n) \cdot K(m,n) \quad (4)$$

VGG16: With 16 convolutional layers and small kernels, it offers deeper representation learning and makes it easier to pull out features from MRI pictures [24]. It improves the accuracy and generalization of classification compared to shallow CNNs, finding complex patterns that are useful for finding brain disorders.

$$O_{i,j,k} = \sum_{m} \sum_{n} \sum_{c} X_{i+m,j+n,c} \ W_{m,n,c,k+} \ b_k \quad (5)$$

ResNet50: To get fine-grained MRI features [25], it uses a 50-layer deep residual design with skip connections. Fixes problems with vanishing gradients, allowing hierarchical representation learning for more accurate finding of brain abnormalities and better medical picture analysis.

InceptionV3: Using inception modules that do parallel convolutions to easily capture features at multiple scales. Gets both local and global patterns from MRI pictures [26], which improves the accuracy of classification and makes the best use of computing power for difficult medical imaging tasks.

$$O = concat \left(F_1(X), F_2(X), F_3(X), F_4(X) \right) \quad (6)$$

AlexNet + LSTM: brings together AlexNet's convolutional layers and LSTM for sequential feature analysis. combines information about space and time, detecting trends of disease progression across MRI features and helping to improve the classification of neurological disorders.

TLEABLCNN: combines CNN, LSTM, and attention methods to find features, model temporal relationships, and draw attention to important areas. Supports strong and understandable MRI-based classification of brain abnormalities by ensuring high accuracy and outputs that can be interpreted.

Xception: It uses depth-wise separable convolutions to get fine picture features quickly. It is fast and accurate, which improves the performance of MRI classification and lets you compare it to other advanced deep learning systems.

YOLOv5: Finds problems in the brain by breaking up MRI scans into grids and guessing the edges of those grids using class odds. Fast and accurate localization of affected areas, which allows object recognition in real time in neurological imaging tasks [27].

$$x = \sigma(t_x) + C_x, \qquad y = \sigma(t_y) + C_y \quad (7)$$

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YOLOv8: It builds on YOLOv5 and makes it better by optimizing the architecture for better accuracy and speed. Easily finds diseased areas in MRI pictures [28], making it easier to find small problems while keeping the computer's speed up.

$$\mathcal{L} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} \quad (8)$$

YOLOv9: Improves feature extraction and bounding box prediction to get the most accurate identification. Captures small details in MRI scans, making it easier to find subtle problems that are needed for a correct neurological evaluation [29].

$$\mathcal{L}_{YOLOv9} = \lambda_{box}\mathcal{L}_{box} + \lambda_{obj}\mathcal{L}_{obj} + \lambda_{cls}\mathcal{L}_{cls} + \lambda_{dfl} + \mathcal{L}_{dfl} \quad (9)$$

YOLOv11: Improves speed, accuracy, and generalization in a way that is fair. Finds problems in MRI scans accurately, adding to earlier versions of YOLO and offering strong detection capabilities fit for clinical analysis [30].

e) Integration of XAI and Flask Framework

Adding Explainable Artificial Intelligence (XAI) to the Flask framework makes the neurological disease classification system more clear and easy to use. Along with YOLO models, this update uses Xception and an ensemble Voting Classifier to find problems in MRI images. Grad-CAM is used to make heatmaps that show the most important areas that affect model decisions. These heatmaps make forecasts easier to understand and give us more information about how predictions are made. This makes sure that clinicians can understand and believe the model's results, which closes the gap between what AI can predict and what doctors actually do.

Healthcare workers can upload MRI images and get real-time predictions from trained models through the Flask framework's easy-to-use interface. When XAI and Flask deployment are used together, the system becomes engaging, scalable, and clinically useful. It provides easy-to-understand, dependable help for finding and diagnosing Alzheimer's disease and brain tumors early on.

4. EXPERIMENTAL RESULTS

Accuracy: How well a test can tell the difference between sick and healthy people is called its accuracy. To get an idea of how accurate a test is, we should figure out what percentage of cases are true positives and true negatives. In terms of math, this can be written as

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} (10)$$

Precision: Precision is the percentage of correctly classified cases or samples compared to those that were correctly classified as positives. So, here is the method to figure out the precision:

$$Precision = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}} (11)$$

Recall: In machine learning, recall is a metric that shows how well a model can find all the important instances of a certain class. It shows how well a model captures instances of a certain class. It is calculated by dividing the number of correctly predicted positive observations by the total number of real positives.

$$Recall = \frac{\text{TP}}{\text{TP} + \text{FN}} (12)$$

F1-Score: The F1 score is a way to rate the correctness of a machine learning model. It takes a model's accuracy and recall scores and adds them together. The accuracy metric counts how many times, across the whole dataset, a model made a correct guess.

$$F1\ Score = 2 * \frac{Recall\ \text{X}\ Precision}{Recall + Precision} * 100 (13)$$

mAP: Mean Average Precision (MAP) is a way to measure quality and rank things. It looks at how many related suggestions there are and where they are on the list. To find MAP at K, take the average precision (AP) at K for all users or searches and multiply it by 100.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (14)$$

AUC-ROC Curve: The AUC-ROC Curve shows how well a classification problem is solved at different benchmark levels. The True Positive Rate is plotted against the False Positive Rate by ROC. AUC measures how well the model can tell the difference between classes; a higher AUC means the model works better.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \quad (15)$$

Table.1 Performance Evaluation – Classification (Scenario A)

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1 (Macro)	AUC (Micro)
RF	0.854533	0.857028	0.878086	0.864170	None
SVM	0.872124	0.881033	0.880378	0.880570	None

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Voting	0.910690	0.900691	0.911469	0.905263	None
CNN	0.534168	0.556790	0.477916	0.449082	None
VGG16	0.853180	0.872061	0.895679	0.877940	None
ResNet50	0.781123	0.802354	0.819472	0.803851	None
InceptionV3	0.778417	0.794831	0.810109	0.799841	None
AlexNet +LSTM	0.811231	0.856292	0.826126	0.830766	None
TLEABLCNN	**0.961096**	**0.972170**	**0.943932**	**0.954967**	**None**
Xception	0.949594	0.964043	0.960437	0.960347	None

Table 1 shows that TLEABLCNN does the best out of all the classification models tested, showing that it is more accurate and reliable.

Table.2 Performance Evaluation – Classification (Scenario B)

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1 (Macro)	AUC (Micro)
RF	0.866373	0.869524	0.895475	0.877327	None
SVM	0.868742	0.876438	0.875302	0.875619	None
Voting	0.913735	0.904102	0.924884	0.911942	None
CNN	0.569350	0.635263	0.562340	0.527999	None
VGG16	0.853180	0.872061	0.895679	0.877940	None
ResNet50	0.794993	0.810204	0.829993	0.817594	None
InceptionV3	0.784506	0.807122	0.812042	0.806981	None
AlexNet +LSTM	0.841001	0.859652	0.882357	0.866290	None
TLEABLCNN	**0.974290**	**0.978324**	**0.971410**	**0.974648**	**None**
Xception	0.960758	0.966109	0.967780	0.966359	None

Table 2 shows that TLEABLCNN has the best performance, beating out all the other models and ensuring that MRI pictures are correctly classified.

Table.3 Performance Evaluation – Classification (Scenario C)

Model	Accuracy	Precision (Macro)	Recall (Macro)	F1 (Macro)	AUC (Micro)
RF	0.919178	0.920332	0.919178	0.916648	None
SVM	0.944618	0.944128	0.944618	0.943789	None
Voting	0.955577	0.956287	0.955577	0.954788	None
CNN	0.562427	0.626670	0.562427	0.524097	None
VGG16	0.891781	0.892590	0.891781	0.889586	None
ResNet50	0.811155	0.817301	0.811155	0.813122	None
InceptionV3	0.789824	0.802207	0.789824	0.792650	None
AlexNet +LSTM	0.887671	0.886658	0.887671	0.884938	None
TLEABLCNN	**0.981996**	**0.982152**	**0.981996**	**0.981946**	**None**
Xception	0.971037	0.972913	0.971037	0.971074	None

In Table 3, TLEABLCNN has the best results, showing that it is very good at correctly identifying neurological diseases based on MRIs..

Table.4 Performance Evaluation - Detection

Model	Precision	Recall	mAP
YOLOv5	0.875	0.876	0.906
YOLOv8	0.918	0.873	0.912
YOLOv9	**0.922**	**0.844**	**0.915**
YOLOv11	0.836	0.841	0.873

In Table 4, YOLOv9 has the best general detection performance, showing that it is the most accurate and reliable way to find brain problems.

Fig.5 Comparison Graph – Classification (Scenario A)

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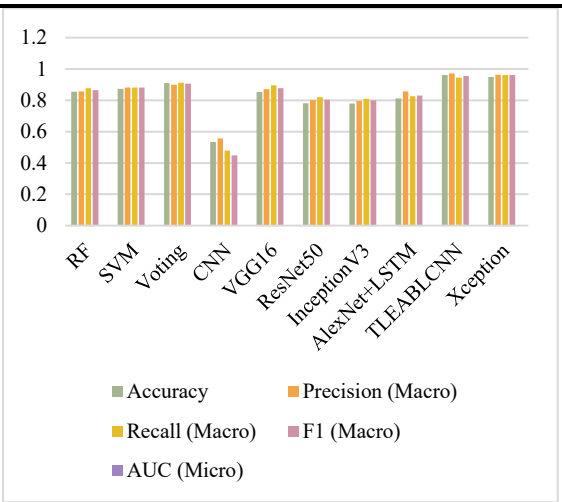

Figure 5 shows that TLEABLCNN does better than other models. Accuracy is shown in green, precision in orange, recall in yellow, F1 in pink, and AUC in purple.

Fig.6 Comparison Graph – Classification (Scenario B)

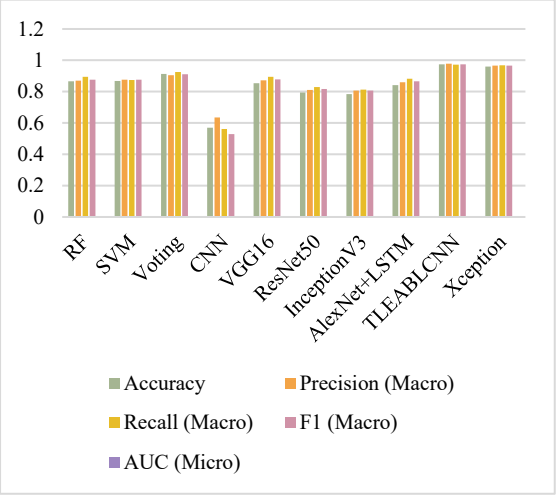

Figure 6 shows that TLEABLCNN is ahead, with accuracy in green, precision in orange, recall in yellow, F1 in pink, and AUC in purple

.***Fig.7*** Comparison Graph – Classification (Scenario C)

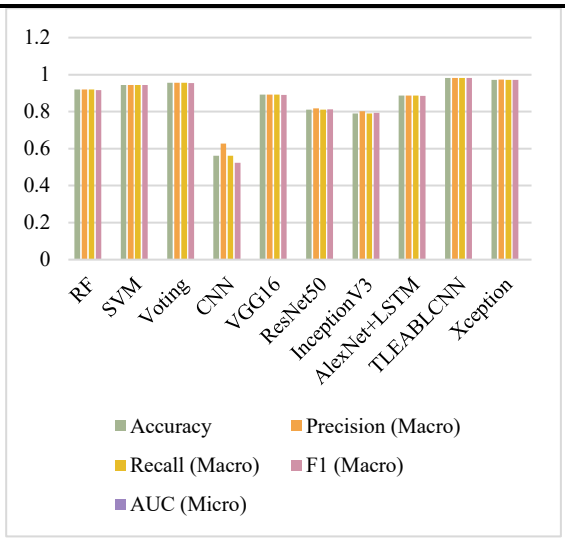

Figure 7 shows that TLEABLCNN does better than other models. Accuracy is shown in green, precision in orange, recall in yellow, F1 in pink, and AUC in purple.

Fig.8 Comparison Graph - Detection

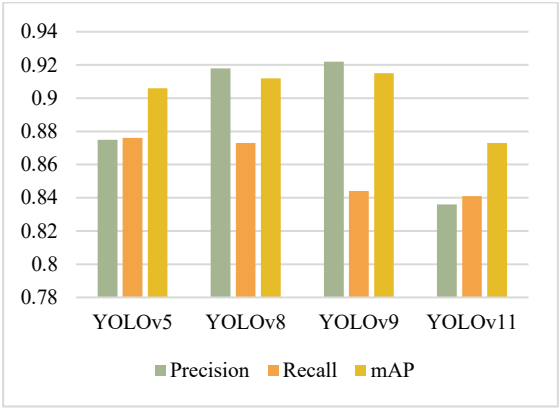

Figure 8 shows that YOLOv9 is the best at detecting things, with accuracy shown in light green, recall in orange, and mAP shown in yellow.

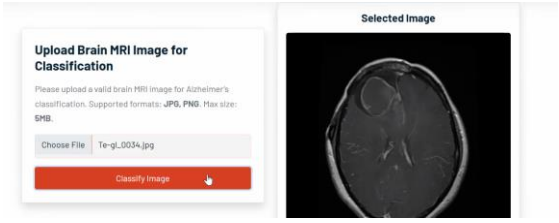

Fig.9 Upload Input Image

In Fig.9, the interface lets users share brain MRI images so that tumor diseases can be automatically categorized.

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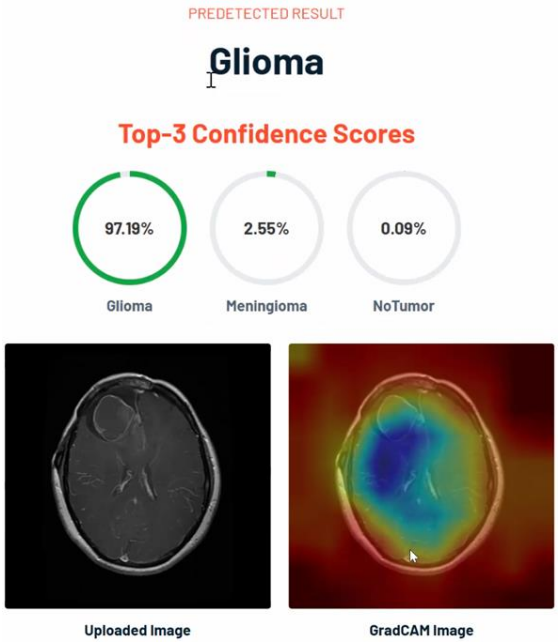

Fig.10 Predicted Result

In Fig.10, the uploaded MRI picture is labelled as a "glioma" with a 97.19% confidence level, and GradCAM visualizations back this up.

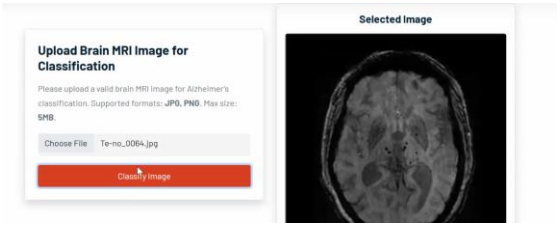

Fig.11 Upload Input Image

In Fig.11, the interface can handle brain MRI scans, which lets users start automatic analysis for quick and accurate tumor type classification.

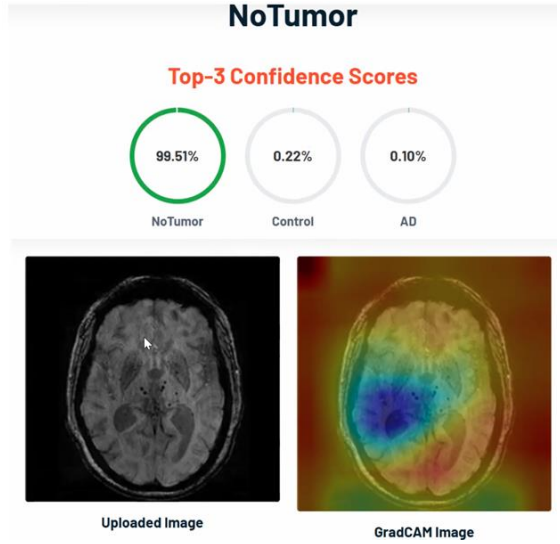

Fig.12 Predicted Results

As shown in Fig.12, the interface shows the analysis result of the uploaded MRI, which with 99.51% certainty says there is no tumor.

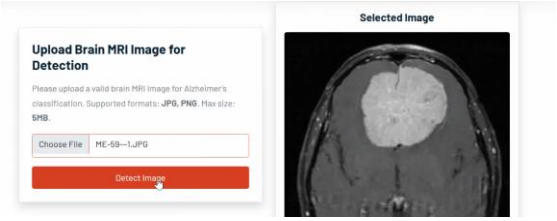

Fig.13 Upload Input Image

In Fig.13, the interface shows a way to upload brain MRI images and start automated analysis for accurate tumor discovery.

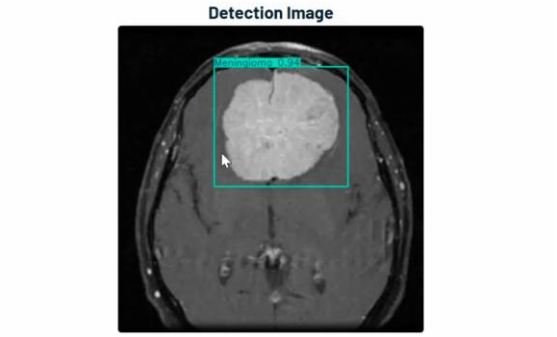

Fig.14 Predicted Results

In Fig.14, the uploaded MRI picture is correctly identified as a meningioma with a confidence level of 0.94, showing that the automated interface did a good job.

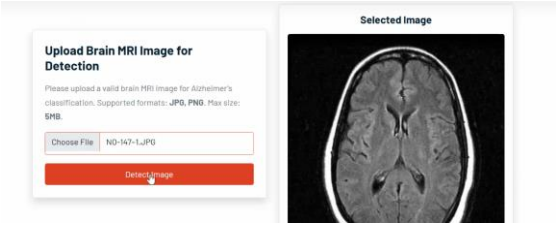

Fig. 15 Upload Input Image

In Fig.15, the interface shows a way to share brain MRI images and start automated analysis for accurate tumor detection.

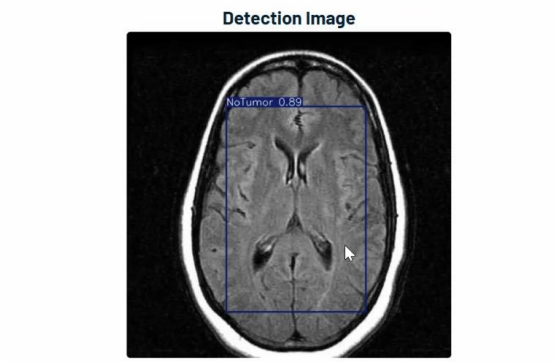

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Fig.16 Predicted Results

The uploaded MRI picture in Fig.16 shows a prediction of no tumor with 0.89 confidence, which means there is a very small chance that there is one.

5. CONCLUSION

The study shows that finding neurological diseases is much easier when you combine advanced explainable deep learning with SMOTE for dealing with unbalanced MRI data. A lot of testing with traditional machine learning methods like Random Forest and SVM, as well as deep learning models like CNN, VGG16, ResNet50, InceptionV3, AlexNet+LSTM, and Xception, showed that the Transformer and LSTM Enhanced Attention-Based Explainable CNN (TLEABLCNN) worked better. The TLEABLCNN did amazingly well, beating both traditional and hybrid designs in every test. It got 96.1% accuracy in Scenario A, 97.4% accuracy in Scenario B, and 98.2% accuracy in Scenario C. These results show that TLEABLCNN is the best model for brain MRI classification, as it is both accurate and easy to understand. We looked at YOLO-based object detection frameworks for jobs that needed to find abnormalities. Among them, YOLOv9 had the best mean average precision (mAP) score of 91.5%, and YOLOv8 had the best precision score of 91.8%, showing that they were effective for MRI-based recognition. Overall, the results show that TLEABLCNN is a strong way to classify things and YOLOv9 is the best at finding things. This helps with the accurate, early, and large-scale diagnosis of Alzheimer's disease and brain cancer.

To make the study more general and reliable, it could be improved in the future by adding more MRI files from more than one hospital that are bigger and more varied. Combining different types of data, like PET and CT scans, with electronic health records can help doctors make even better diagnoses. Combining various architectures with advanced ensemble techniques may lead to better robustness across a wide range of patient populations. Using domain adaptation and transfer learning methods could help institutions with different imaging protocols be more flexible. We will look into how to use real-time application of optimized lightweight models in clinical settings. Additionally, privacy-protecting methods such as federated learning can allow for group training without exposing private patient data, and AI models that can be explained will improve clinical trust and decision support.

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