RESEARCH PAPER

TLEABLCNN: Brain and Alzheimer's Disease Detection Using Attention-Based Explainable Deep Learning and SMOTE Using Imbalanced Brain MRI

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Abstract: Two of the most severe forms of neurological issues, which can be treated only when diagnosed with a high degree of accuracy with the help of MRI, are brain tumors and Alzheimer disease (AD). The project under analysis considers the datasets of MRI that are not balanced and refers to the Synthetic Minority Oversampling Technique (SMOTE) to improve the classification process. They included several ML and DL models including the RF, SVM, Voting Classifier, CNN, VGG16, ResNet50, and Inception V3, as well as the AlexNet with LSTM, Xception, and the new Transformer and LSTM Enhanced Attention-Based Explainable CNN (TLEABLCNN). TLEABLCNN model consistently performed better than its baseline models with a classification accuracy of 96.1% in Scenario A, 97.4% in Scenario B and 98.2% in Scenario C. It also possessed superior macro-precision, recall and F1-scores. To detect abnormalities in the brain; the object recognition models of YOLOv5, YOLOv8, YOLOv9 and YOLOv11 were employed. YOLOv9 got the highest best mean average precision (mAP) of 91.5%. YOLOv8 achieved the best accuracy of 91.8%. Moreover, XAI techniques, such as heatmaps, were employed to generate the heatmaps that revealed the most significant portions of MRI scans that influenced model predictions. This simplified the results and enhanced professional trust. These findings indicate the strength of the framework in the discovery of brain disorders which can be explained.

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

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INTRODUCTION

Regrettably, AD is among the most frightening brain disorders of the aged individuals in the world. It primarily impacts the areas of the brain that are responsible of recalling and cognition. In 2010, almost 600,000 individuals over the age of 65 years succumbed to AD. This resulted in the determination of projections of annual mortality of older adults in the US during the period, 2010 to 2050 [1]. AD is believed to have impacted over 50 million individuals worldwide by 2022 and it is therefore a significant issue to the social and health services [2]. The process of dying of neurons gradually with time makes it more difficult to remember the events that happened recently, identify familiar faces, and comprehend what is happening around you, which is now caused by the AD. This renders individuals with AD to sense lost. Currently, 6.9 million elderly Americans (65 years and older) are affected with AD. That figure will increase to 13.8 million by 2060 unless other methods of preventing or treating the disease are discovered [3]. In the United States alone, AD murdered 119,399 individuals in 2021 alone [4].

The causes of neurological diseases such as Alzheimer is of great essence in this case since the world is growing old. It is not yet clear how AD actually works but some of the things that expose people to risks have been discovered to be high blood pressure, smoking and lack of adequate education [5]. Brain tumors or an abnormal increase in brain tissue or structures that attach to the brain are another large issue with the nervous system, where it grows in an abnormal manner. This may occur due to growing old, metabolic and hormone alterations [6]. The lumps may be benign or cancerous. The accumulation of the beta-amyloid plaques and tau protein in the brain characterizes the disease of Alzheimer. The disease advances based on the genetic, behavioral and environmental factors [7]. The two diseases render everyday life quite challenging, and cause a great deal of emotional, mental, and financial burden to caregivers [8].

Magnetic resonance imaging also known as MRI is a highly significant method of identification and follow-up of AD as well as brain cancer. In the case of cancers, MRI provides physicians with the correct detail regarding its size, severity, and type of the cancer, which allows the physician to make a decision on how to treat it. However, with AD, emerging imaging techniques such as diffusion tensor imaging can detect the structural changes at an early stage and monitor them through time [9]. DL is a form of AI that enhances detection by extracting intricate patterns of medical images. XAI simplifies such models and makes them more trustworthy. This opens them up and establishes trust in the professional fraternity [10].

2. LITERATURE REVIEW

Much research has been conducted on the AD due to the fact that this disorder is increasingly prevalent and it has a significant impact on the ability of older individuals to think and recollect. A significant part of information was provided regarding AD in Better [11]. The urgency of early detection and intervention strategies, the need to pay attention to significant facts and epidemiological trends were all highlighted. The paper emphasized the fact that AD is emerging as a larger issue throughout the globe and the significance of employing sophisticated diagnostic methods in order to reduce its impact. Moreover, Jiménez-Balado and Eich [12] investigated the role that GABAergic dysfunction contributes to human aging and AD, and it was demonstrated that the nervous system hyperactivity results in memory impairments. They provide the results in the way, in which the process of cognitive loss is complex and is caused by a number of neurological processes. The findings will assist the doctors and patients to diagnose and treat these conditions in the most appropriate way.

Recent advancement in AI has presented tremendous potentials in ensuring that AD recognition can be more precise and speedy. To classify AD, Mahim et al. proposed a Vision Transformer-Gated Recurrent Unit (ViT-GRU) model which is trained with XAI [13]. Their study revealed the relevance of interpretability to AI-based healthcare to allow physicians to understand how DL models arrive at their decision, yet maintain diagnostic accuracy high. Hassan et al. [14] presented in their paper a multimodal DL system that operates on clinical data, PET, and MRI to locate and categorize AD. This process was proved to be more successful than the one-modal systems, as it demonstrates the significance of integrating various kinds of data to obtain valuable disease analysis.

Hazarika, Kandar, and Maji [15] presented a new method of applying brain pictures and ML to categorize individuals with early-stage AD in their paper. Their approach was focused on deriving distinguishing characteristics of MRI information, yet it provided an opportunity to arrive at an early diagnosis and potentially commence treatment. Sorour et al. [16] also applied DL to classify AD and MRI data provided them with very accurate and reliable results. They found that with the help of CNN, it is possible to detect insignificant alterations in the structure of the brain which are associated with the development of a disease.

The hybrid techniques and group study have also proven to gain popularity according to new studies. In order to locate AD, Belay, Walle, and Haile [17] proposed a deep ensemble learning system in combination with quantum ML. This was because with the use of more than one classifier in their model, it was better suited to make predictions and indicated that hybrid methods of computation might be valuable in the diagnosis of neurodegenerative diseases. Sangeetha et al. [18] utilized DL in the diagnosis and classification of AD in their study. They concentrated on the issue of extracting the complicated patterns of data in images by the means of neural networks. They have demonstrated that DL techniques can be applied on large datasets and hence they can fully analyze a broad spectrum of patients.

Transfer learning is now a highly valuable technique in the study of AD. To locate and categorize AD, Goyal, Rani, and Singh [19] developed a multilayered network that incorporated a transfer-learned AlexNet network with a LSTM network. This approach was effective since it relied on the pre-trained convolutional networks that said useful features in MRI scans. The LSTM component learnt the temporal relationships, hence, improved classification. These approaches demonstrate the possibility of overcoming the issue of the lack of sufficient training data in medical imaging applications with the help of models that have already been trained.

Suchitra, Krishnasamy, and Poovaraghan [20] proposed applying the magnetic resonance images and DL to generate an early detection approach to AD. They primarily worked on automated feature extraction and classification making it possible to detect early cognitive impairments as early and as accurately as possible. They have reduced the time spent on diagnostic delays, and facilitated the ability to access assistance at the appropriate time due to an amalgamation of post processing and DL. Collectively, these research articles demonstrate how AI and DL have the ability to transform the methods of AD discovery by ensuring that it is more precise, quicker, and comprehendible. This has a definite shift toward multimodal, ensemble, and explainable in which the issues with the old diagnostic techniques are bypassed such as the necessity of manual feature extraction, biased evaluation, and variations between the competence of the clinicians involved.

3. MATERIALS AND METHODS

Based on MRI data, the proposed system develops an intelligent and interpretable model of organizing neurological diseases, including AD, brain tumors, etc. To correct the issue of unequal representation of the classes, SMOTE is applied to even the training. The framework is optimized with traditional ML models, such as the RF and the SVM. And so are state-of-the-art DL models, such as CNN, VGG16, ResNet50, InceptionV3, AlexNet-LSTM, and the suggested TLEABLCNN. To deploy it, Flask is applied to make the interface of the system simple to use, which enables real-time MRI classification and recognition to take place. Other algorithms in addition to Grad-CAM are applied such as: Xception, Voting Classifier and YOLO models so as to simplify the results to be read by point outlining important parts of the brain that influence the predictions. This increases the validity of the results, increases their readability, and makes them more effective in clinical practice.

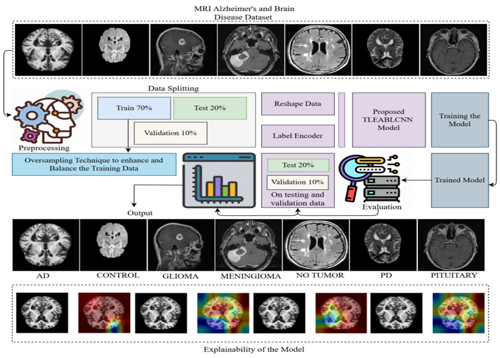


Fig.1 Proposed Architecture

The system architecture should be enabled using MRI data to enable intelligent and rational classification of neurological disorders. It begins by training the data using SMOTE to balance the datasets and separate the classes, followed by running ML algorithms with RF and SVM and DL architecture with CNN, VGG16, ResNet50, InceptionV3, AlexNet-LSTM, TLEABLCNN to extract features and classify them. Real-time interaction between the user and advanced algorithms such as Xception, Voting Classifier, and YOLO occur in the deployment layer, whereas Grad-CAM gives visual explanations of the significant parts of the brain to assist in interpretation and clinical decision-making.

a) Dataset Collection:

To support tasks such as classifying and finding things, the dataset proposed in the suggested system merges pictures of tumors of the brain and AD into one seven-class dataset. 14 779 pictures are grouped into seven categories in the classification branch, Control (3,650), AD (3,200), No Tumor (2,000), Pituitary (1,757), Meningioma (1,645), Glioma (1,621), and PD (906). In the detection branch, 1, 093 pictures are trained and 274 images are tested. Bounding boxes are appended on YOLO format (.txt) to locate points of interest. The information is properly separated into testing, validation and training sets. This ensures that there is complete coverage on all jobs pertaining classification and detection.

b) Visualization: Visualization of data sets is the examination of classes using bar graphs to depict the equilibrium of the data in groups. The presentation of sample MRI images and annotations that accompany them makes it easy to determine the goodness and variability of the images. Besides, the samples of bounding boxes are depicted to the detection branch which presents definite areas of interest. Before training the model this step ensures that one has a complete picture of how the data is distributed and the representation of each of the classes. This is useful in making intelligent decisions regarding preprocessing and model building.

c) Pre-processing: In order to enhance the generalization of models, pre-processing procedures are conducted on MRI pictures, resizing them to standard sizes, equalizing pixel intensities, and applying data enhancement procedures involving TorchVision transforms. A categorical learning classification branch that has labeled pictures and a YOLO detection branch that has comments on the bounding boxes are maintained simultaneously. Such an arranged arrangement ensures that not only classification but also detection models receive regular and high-quality inputs, which enhances the effectiveness of the training and the quality of predictions.

d) Algorithms:

Random Forest (RF): RF constructs many DT and provides the majority vote used as the strong base model when it is used to classify MRI. It is capable of doing well on features that have many dimensions, ensures a stable state when comparing across datasets, and allows one to compare different DL models through results interpretation.

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

Support Vector Machine (SVM): SVM identifies the most effective hyperplanes that divide groups and are effective with smaller datasets. It is applied in classification of brain MRI images. It assigns the distinction of the type of disease by expanding the margins. It gives a precise, reliable initial point of departure that can be effectively analyzed with ensemble and DL methods of analyzing neurological pictures.

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

Voting Classifier: is a model that uses multiple models, including the traditional and DL models, to produce a final result. It is a combination of the strongest sides of various algorithms that renders the system more stable and precise, eliminating the bias arising due to applying a single model and creating a just system to classify abnormalities in the brain.

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

Convolutional Neural Network (CNN): applies convolutional filters to extract automatically features of space such as edges and textures of MRI images. Both identifies hierarchical trends, and it is easier to categorize neurological diseases after which the magnitude of feature extraction is significant in detecting brain abnormalities.

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

VGG16: Having 16 convolutional layers and with small convolutional kernels, it provides deeper learning of representations and simplifies the extraction of features out of MRI images. It provides a higher accuracy and generalization of classification than shallow CNNs such that complex patterns beneficial in identifying brain disorders can be detected.

ResNet50: It is a skip-connected 50-layer deep residual design that employs a 50-layer deep residual design to obtain fine-grained MRI features. Solves vanishing gradient issues and enables hierarchical representation learning that can help discover brain abnormalities more accurately and improve findings of medical pictures.

InceptionV3: Conveniently depends on inception modules to perform parallel convolutions to generally capture features in a variety of scales. It removes local and global patterns in MRI images, which enhances accuracy in classification besides optimum utilization of computing power in hard medical imaging tasks.

$$O = concat\left(F_1(X), F_2(X), F_3(X), F_4(X)\right) \quad (5)$$

AlexNet + LSTM: unites the convolutional layers of AlexNet and LSTM to process information sequentially based on features of MRI and aid in enhancing the classification of neurological disease cases.

TLEABLCNN: uses CNN, LSTM and attention techniques in one to locate features, model temporal relations and attract attention to key areas. Among the support of high accuracy and interpretable outputs of brain abnormalities MRI based classification Supports strong and understandable classification of brain abnormalities based on the MRI image.

Xception: It employs depth-wise separable convolutions to acquire fine picture features in a short amount of time. It is quick and precise, which enhances the functionality of MRI classification and allows you to compare it with other highly developed DL systems.

YOLOv5: Solves problems through the brain by disaggregating the MRI scans (into grids) and making a guess of the edges of those grids using class odds. Enables real time object recognition during neurological imaging experiments through rapid and precise localization of the affected regions.

YOLOv8: It is based on YOLOv5 and improves it by optimizing the architecture of the system to achieve better accuracy and speed. Locates diseased regions faster in MRI images and thus small issues can be located without compromising the speed of the computer.

$$\mathscr{L} = \lambda_{box}\mathscr{L}_{box} + \lambda_{obj}\mathscr{L}_{obj} + \lambda_{cls}\mathscr{L}_{cls} \quad (6)$$

YOLOv9: Enhances feature aquisition and bounding box estimating to achieve the best identification. Records minute details in MRI images, and thus, it becomes easier to locate minor issues that are required to make a proper neurological diagnosis.

$$\mathscr{L}_{YOLOv9} = \lambda_{box}\mathscr{L}_{box} + \lambda_{obj}\mathscr{L}_{obj} + \lambda_{cls}\mathscr{L}_{cls} + \lambda_{dfl} + \mathscr{L}_{dfl} \quad (7)$$

YOLOv11: Enhances speed, accuracy and generalization in a manner that offers fairness. Locates issues in MRI images correctly, which complements previous versions of YOLO and provides good detection results suitable for clinical-grade analysis.

e) Integration of XAI and Flask Framework

The system of neurological diseases identification is made more transparent and user-friendly when Explainable XAI is added to the Flask framework. This update together with YOLO models is based on Xception and an ensemble Voting Classifier to locate issues in MRI images. The heatmaps are created with Grad-CAM and demonstrate the areas of the most significant importance that influence model decisions. Such heatmaps simplify the process of making forecasts and provide some insight on the methods of prediction. This ensures that clinicians will be able to believe and interpret the results of the model, bridging the gap between the model predictions and the actual physician practices.

The interface of the Flask framework will provide healthcare workers with easy access to upload their MRI images and get real-time predictions using trained models. With XAI and Flask being deployed simultaneously, the system will be interesting, scalable, and useful in clinical practice. It offers simplified, reliable assistance on the detection and diagnosis of the AD and brain tumors in their early stages.

4. EXPERIMENTAL RESULTS

Accuracy: A test is true to the extent that it can precisely distinguish between sick and healthy individuals. To achieve an idea of the accuracy of a test, we must determine the percentage of cases which are true positives and true negatives. Mathematically this can be represented as:

$$Accuracy = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \, (8)$$

Precision: Precision examines the percentage of correct classified cases or samples with respect to the correct classified cases that were classified correctly as hits. To calculate the accuracy is, then, the following:

$$Precision = \frac{\text{True Positive}}{\text{True Positive } + \text{False Positive}} \, (9)$$

Recall: Recall is a ML evaluation criterion, which indicates the ability of a model to locate all the significant examples of a particular category. It is the right number of correctly foreseen positive ones divided by the actual number of positives. The number indicates the level of instances of a particular class that a model can recreate.

$$Recall = \frac{\text{TP}}{\text{TP } + \text{ FN}} \, (10)$$

F1-Score: One method of measuring the accuracy of a ML model is F1 score. It sums up the accuracy and the recall scores of a model. The accuracy measure will display the number of times that a model succeeded in the estimation over the entire dataset.

$$F1\ Score = 2 * \frac{Recall \text{ X } Precision}{Recall + Precision} * 100 (11)$$

mAP: Mean Average Precision (MAP) is applied as a method of ranking quality. It also checks the list of the useful number of suggestions and their positions on the list. The MAP of K represents an average of the Average Precision (AP) of K given each user or search.

$$mAP = \frac{1}{n}\sum_{k=1}^{k=n} AP_k \quad (12)$$

AUC-ROC Curve: It is used to measure the performance of a classification problem on the AUC-ROC Curve at various levels of the benchmark. False Positive Rate and True Positive Rate are plotted on ROC. AUC is a value of the model ability to distinguish between classes; the higher the AUC, the better the model functions.

$$AUC = \sum_{i=1}^{n-1} (FPR_{i+1} - FPR_i) \cdot \frac{TPR_{i+1} + TPR_i}{2} \quad (13)$$

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
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

According to the Table 1, TLEABLCNN is the best of all the models of classification tested, indicating that it is more precise and trustworthy.

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

As indicated in Table 2, TLEABLCNN performs the most with all the other models being beaten and making sure that MRI pictures are classified properly.

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

Table 3 indicates that TLEABLCNN performs the best where it is revealed that it is very good in identifying neurological diseases based on MRI scans.

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

Table 4 indicates that the total detection performance of YOLOv9 is the best, which implies that it is highly effective in finding a problem with the brain and highly accurate in doing so.

Fig.2 Comparison Graph – Classification (Scenario A)

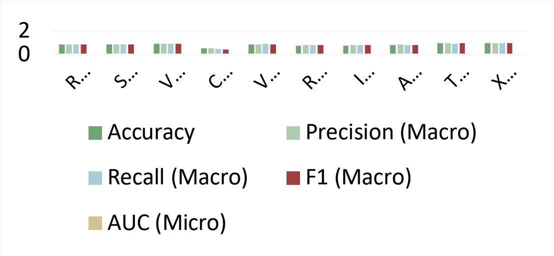
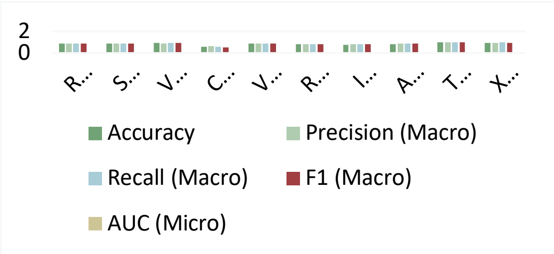


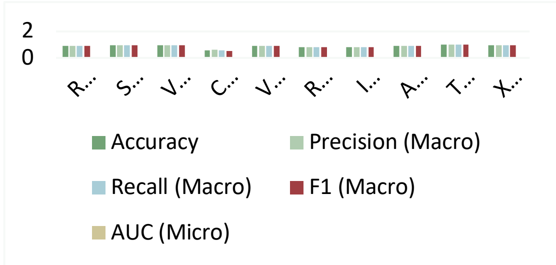
Figure 2 indicates that TLEABLCNN performs better as compared to other models. They are accuracy in green, precision in light green, recall in blue, F1 in dark red, and AUC in gold.

Fig.3 Comparison Graph – Classification (Scenario B)



The accuracy is indicated by green color in Fig.3, precision is indicated by light green color, recall is indicated by blue color, F1 score is indicated by dark red color and AUC is indicated by gold color. This indicates that TLEABLCNN takes the lead in the classes.

Fig.4 Comparison Graph – Classification (Scenario C)



As shown in Figure 4, TLEABLCNN is better than other models. The accuracy, precision, recall, F1 score, and AUC are displayed in green, light green, blue, dark red, and gold respectively.

Fig.5 Comparison Graph - Detection

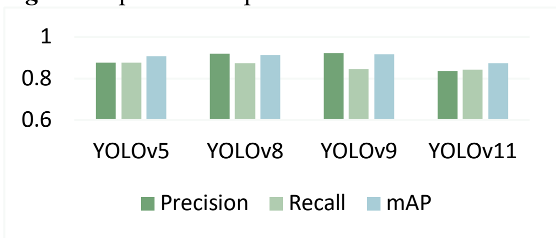


Figure 5 demonstrates that YOLOv9 is the most effective in detecting things, and accuracy, recall, and mAP are presented in green, light green, and blue color, respectively.

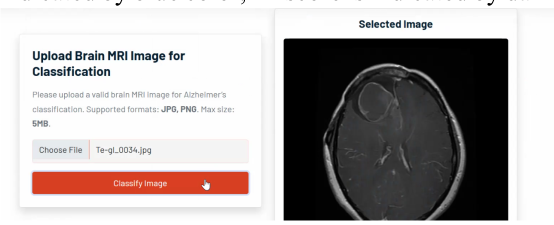


Fig.6 Upload Input Image

Figure 6 represents the interface allowing people to share brain MRI pictures so that they can be automatically classified and diagnosed with tumor disease.

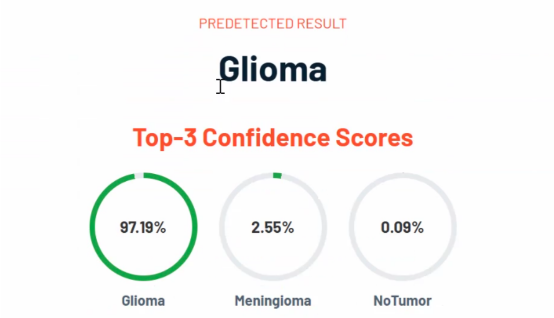


Fig.7 Predicted Results

Figure 7 of uploaded MRI image has a rating of glioma with 97.19% confidence, meningioma with 2.55% confidence and no tumor with 0.09% confidence.

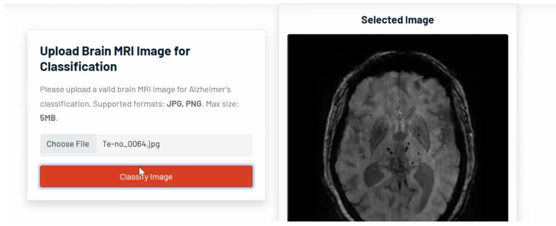


Fig.8 Upload Input Image

Figure 8 indicates that the interface is capable of supporting brain MRI scans, which enables the user to initiate automatic analysis to classify the tumor type quickly and correctly.

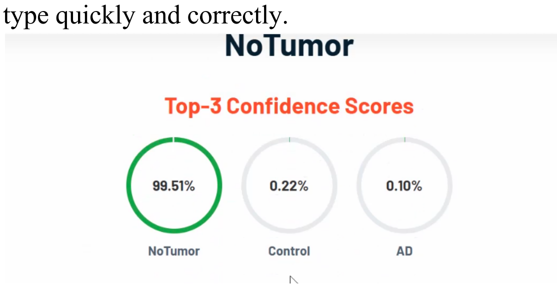


Fig.9 Predicted Results

In Fig.9, the interface displays the result of analysis of the posted MRI where 99.51 is the surety on the absence of tumor.

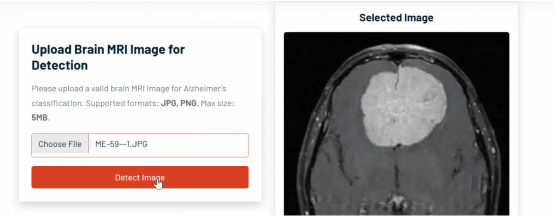


Fig.10 Upload Input Image

Fig.10 the interface displays an area to upload media of brain MRI in order to start an automatic analysis and find a tumor precisely.

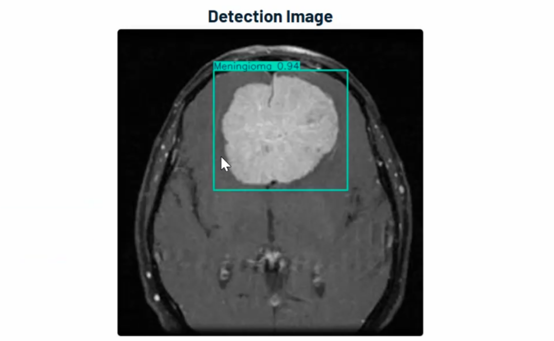


Fig.11 Predicted Results

The automated interface has done a good job of finding the MRI picture in Fig.11 as the uploaded MRI picture was correctly identified as a meningioma with a confidence level of 0.94.

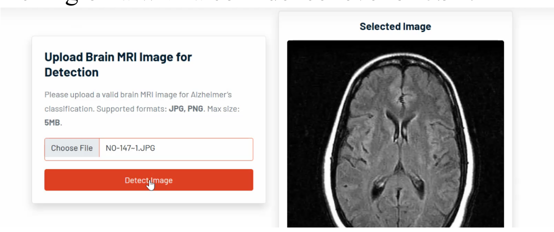


Fig. 12 Upload Input Image

Fig.12 indicates that the interface can be used to upload brain MRI images and begin automated evaluation to detect tumors correctly.

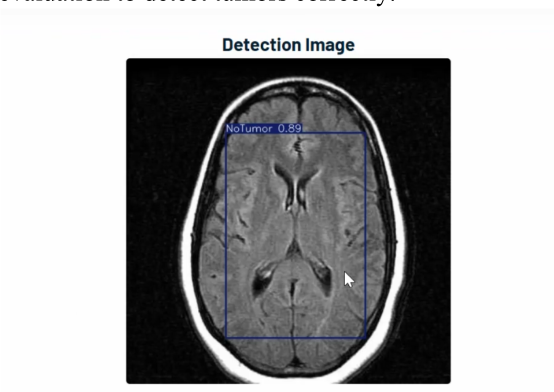


Fig.13 Predicted Results

The uploaded MRI image at Fig.13 indicates a prediction that there is no tumor with 0.89 confidence and that implies that it is highly unlikely that there is one.

5. CONCLUSION

In the study, it is demonstrated that it is significantly easier to find neurological diseases with the combination of the advanced explainable DL and the SMOTE to handle unbalanced data in MRI. Numerous experiments with conventional ML algorithms such as RF and SVM and with a DL model such as CNN, VGG16, ResNet50, InceptionV3, AlexNet+LSTM, and Xception have shown that the TLEABLCNN was much more effective. The TLEABLCNN scored 96.1% accuracy in Scenario A, 97.4% accuracy in Scenario B, and 98.2% accuracy in Scenario C, impressing its performance each of the times, being ranked higher than the traditional and hybrid systems. These data show that TLEABLCNN is the most appropriate and simple to comprehend brain MRI classification model. The frameworks to detect objects using YOLO were considered in the case of finding abnormalities. YOLOv8 had the highest accuracy score of 91.8% and the mean average precision (mAP) was 91.5% with YOLOv9. This demonstrates that they are both efficient with MRI detection. The findings indicate that TLEABLCNN is an effective method of classifying things and YOLOv9 the most effective in locating things. This aids in the late, correct, and massive diagnosis of the AD and brain cancer.

To enhance the study in the future, more MRI records of more than one hospital can be included such that it is more universal and valid. The inclusion of multidimensional data, such as PET and CT scans, in the electronic health records can assist the physician in making an even more accurate diagnosis. Through diverse ensemble approaches that integrate a variety of architectures, robustness can be enhanced in a broad group of patient populations. The domain adaptation and transfer learning techniques would allow institutions having varying imaging protocols to be more adaptable. Real-time implementation of optimized lightweight models will be considered to be used in the real world in clinical environments. Besides, privacy-protective training such as federated learning can enable training in groups without revealing personal patient information, and XAI models will enhance clinical trust and decision support.

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