International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

HYBRID DEEP LEARNING AND MACHINE LEARNING APPROACH FOR BRAIN TUMOR DETECTION

Pooja N. Bhandari[1], Dr. Atul Nandwal[2]
[1]Research Scholar, Department of Computer science and Engineering, SAGE University, Indore, MP 452020, India.
[2]Associate Professor, Department of Computer science and Engineering, SAGE University, Indore, MP 452020, India.
Email: [1] bhandaripooja453@gmail.com, [2] atulnandwal@gmail.com

Abstract

The accurate and early diagnosis of brain tumors is critical due to their high mortality rates. Although Magnetic Resonance Imaging (MRI) is the primary diagnostic modality its manual interpretation is often subjective. This paper introduces an automated hybrid framework for brain tumor classification that merges deep transfer learning with classical machine learning. The approach employs DenseNet121 for initial feature extraction, augmented by a Convolutional Block Attention Module (CBAM) to enhance discriminative features and suppress noise. The resulting feature vectors are classified using multiple algorithms, including Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN) and XGBoost. Empirical results demonstrate the framework's high performance, with Logistic Regression achieving a peak accuracy of 94%. However, XGBoost proved to be the most balanced and effective model, attaining a precision of 95.35% and a recall of 95.03%, establishing it as the optimal classifier for this task while LR presents a robust alternative for efficient deployment.

Keywords: Brain Tumor (BT), Convolutional Block Attention Module (CBAM), Logistic Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN)

1. Introduction

Brain tumors represent a serious medical condition defined by the anomalous and unregulated proliferation of cells within the brain. These tumors which pose a significant mortality risk across all age groups are broadly categorized by their clinical behaviour. Benign tumors are typically slow growing and non-cancerous growth that remain localized whereas malignant tumors are cancerous that exhibit aggressive growth and have the potential to metastasize other tissues.

Primary brain tumors arise intrinsically from the brain or its surrounding structures forming abnormal masses within the central nervous system (CNS). These intracranial lesions are distinct from extracranial tumors that originate elsewhere in the body and subsequently spread to the CNS. The location and growth of a brain tumor can critically disrupt neurological function leading to symptoms such as persistent headaches, seizures, and various cognitive or behavioural impairments. The specific nature of these symptoms is largely determined by the tumor's size, histological type, and anatomical placement.

The standard diagnostic protocol involves the analysis of medical imaging, most commonly Magnetic Resonance Imaging (MRI) by specialized radiologists and neurologists. This reliance on human interpretation can introduce subjectivity and variability as diagnostic accuracy is often contingent upon the clinician's expertise. To address this limitation, recent innovations in artificial intelligence, particularly in ML and DL are being leveraged to develop automated systems. These technologies facilitate rapid and highly accurate brain tumor detection thereby providing valuable decision support to healthcare professionals and enhancing diagnostic and treatment planning processes.

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

This study proposes a hybrid framework for brain tumor detection from medical images that integrating transfer learning with classical machine learning. The pre-trained DenseNet121 architecture is leveraged for automated feature extraction from MRI scans. The resulting feature set is then used to train and evaluate a suite of machine learning classifiers such as LR, SVM, RF, KNN and XGBoost to determine the most effective model for the classification task.

The objective of this research paper is

- To design a hybrid predictive system for brain tumor identification that integrates classical machine learning classifiers with advanced deep feature extraction from MRI scans.
- To implement a feature enhancement pipeline that leverages a pre-trained DenseNet121 model for initial feature extraction followed by the CBAM to refine these features by emphasizing salient regions and suppressing non informative background data.
- To conduct a comparative evaluation of multiple ML classifiers such as LR, SVM, RF, KNN, and XGBoost using the refined, attention-weighted feature set.
- To perform a comprehensive performance analysis for each hybrid model using a suite of evaluation metrics such as accuracy, precision, recall, and F1-score.

This key contribution is to build hybrid model that extract features using DenseNet121, enhance the features using CBAM and perform classification using ML models for brain tumor diagnosis. The integration of CBAM is pivotal as it boosts model discriminative power by applying dynamic spatial and channel-wise attention to refine feature extraction. Empirical results confirm that the proposed system surpasses existing models in both overall accuracy and in providing a robust comprehensive multi-class classification.

In this section we discussed the introduction of the paper. In the second section we will discuss literature survey. In the third section we will discuss methods and material and in the last section we will discuss about result and discussion of the paper.

2. Literature Survey

Lamba et al. addressed brain tumor classification by leveraging a publicly available MRI dataset. To mitigate data limitations, they employed augmentation techniques to standardize and expand the dataset. Their methodology utilized a VGG-16 architecture which pre-trained on ImageNet for deep spatial feature extraction through transfer learning. These features were then classified using a linear SVM. The model demonstrated high efficacy of achieving an accuracy of 98.87%, a precision of 99.09%, a recall of 98.73%, a specificity of 99.02%, and an F1-score of 98.91% [1].Jakhar et al. proposed a deep learning-based segmentation model for brain tumor detection, termed the Multi-scale Fractal Feature Network (MFFN). Their architecture leverages pixel-level segmentation integrated with fractal residual learning and multi-scale feature extraction to improve sensitivity and accuracy. A key advantage of this multi-level approach is its ability to preserve crucial tumor details while suppressing false positive regions. When evaluated on The Cancer Imaging Archive (TCIA) dataset with 5-fold cross-validation, the model achieved a segmentation accuracy of 94.66%, a sensitivity of 94.42%, and a specificity of 92.81% [2]. Mohammed H and others develop a CNN model using a dataset of 4,000 MRI images. The researchers preprocessed the images by resizing them to a uniform 224x224 pixel resolution. The model trained over 60 epochs achieved a notable classification accuracy of 97.28%. This high level of performance not only demonstrates the efficacy of deep learning for brain tumor detection but also suggests a positive correlation between dataset size and model generalization. The study concludes that the deep learning approach offers significant superiority over traditional methods in both computational speed and diagnostic precision. [3]Rita Appiah et al. proposed a hybrid model that combines a low-order Proper Orthogonal Decomposition (POD) technique with a CNN. This POD-CNN framework was designed to reduce computational complexity without sacrificing predictive performance. In their comparative analysis the proposed model achieved a high accuracy of 95.88% while requiring only one-third of the computational time

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

of a standard CNN effectively demonstrating a favorable trade-off between efficiency and accuracy [4]

Kavita A. et al. proposed an integrated framework for brain tumor detection that leverages Digital Twin technology IoT-based cloud storage and machine learning. In their proposed system a Digital Twin-enabled device captures MRI images which are then stored centrally via an IoT system. For the analysis features are selected using Particle Swarm Optimization (PSO) and subsequently classified using a comparative analysis of CNN, SVM, and Extreme Learning Machines (ELM). Their findings highlight the superior efficiency of CNN among the tested models for accurately identifying abnormal tissues in MRI scans [5]. The authors developed and evaluated three distinct neural network architectures: a 13-layer 2D CNN, a 9-layer 2D CNN and a hybrid CNN-LSTM model. These models were trained on a dataset of MRI scans. A comparative analysis revealed that an ensemble of these models achieved superior performance compared to any of the individual architecture alone [6].To enable the early detection of brain tumors Monika Agarwal et al. implemented a hybrid methodology that combines advanced image enhancement with transfer learning. Their process begins with applying an Optimized Discrete-Time Wavelet-based Contrast Histogram Equalization (ODTWCHE) technique to improve the quality of low-contrast MRI scans. The enhanced images are then classified using a transfer learning approach based on the Inception v3 architecture. In a comparative analysis against several established models including AlexNet, VGG-16, VGG-19, DenseNet-201, GoogleNet and ResNet-50 their proposed framework demonstrated superior performance achieving a high accuracy of 98.89%. [7].

The authors developed a deep learning-based sequential model for the detection and classification of brain tumors from MRI images. The framework operates in two distinct stages: first distinguishing between neoplastic and non-neoplastic brains and second classifying the tumor types. To optimize performance the model was evaluated using four different optimizers: Adam, Nesterov Momentum, RMSProp, and Adagrad. The results indicated that the optimal optimizer was task dependent. For the initial tumor detection task, the Adam optimizer achieved perfect training accuracy of 100% and a high validation test accuracy of 98%. For the subsequent tumor type classification Nesterov Momentum was most effective, yielding 100% training accuracy with 92% validation and testing accuracy [8]. In a comparative analysis of advanced deep learning models for MRI-based brain tumor classification T. Lakshmi Prasanthi et al. evaluated architectures DenseNet121, EfficientNetB7, InceptionResNetV2, InceptionV3, ResNet50V2, VGG16, and VGG19. Their findings indicated that VGG19 and InceptionResNetV2 were particularly effective for detecting glioma tumors. The authors also proposed a hybrid CNN model which achieved a precision of 96.63%. This hybrid approach demonstrated higher performance and reliability than the individual models underscoring the potential of integrating multiple deep learning frameworks to enhance the accuracy and timeliness of brain tumor detection [9].

The authors proposed a novel deep learning architecture termed as IRNetv for brain tumor detection which integrates inception modules and residual connections within a CNN framework. This design enables the extraction of diversified features from medical images using varying convolutional filters and kernel sizes. The model was trained and evaluated on two publicly available MRI datasets comprising 4600 images and 253 images respectively. An empirical analysis of optimizers such as Adam, RMSProp, SGD and batch sizes of 16, 32 and 64 determined that the Adam optimizer with a batch size of 64 yielded optimal performance. The proposed IRNetv model achieved a high classification accuracy of 99% demonstrating its effectiveness. [10]. P. K. Ramtekkar et al. proposed an optimized methodology for accurate brain tumor detection which involves a multi-stage image processing and classification pipeline. Their approach begins with a compound filter integrating Gaussian Mean and Median filters to enhance MRI image quality. Features are extracted using the Grey Level Co-occurrence Matrix (GLCM) technique. A CNN is employed for classification achieving a high accuracy of 98.9% thereby validating the effectiveness of their pre-processing and feature extraction strategy [11].

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

S. Anantharajan et al. developed a hybrid deep learning and machine learning model for brain tumor classification. Their methodology employs a multi-stage pipeline beginning with image preprocessing where an Adaptive Contrast Enhancement Algorithm (ACEA) and a median filter are applied to improve MRI quality. Fuzzy C-Means clustering is used for segmentation followed by feature extraction (energy, mean, entropy, contrast) via Grey Level Co-occurrence Matrix (GLCM). The final classification of abnormal versus normal brain tissues is performed using an Ensemble Deep Neural Support Vector Machine (EDN-SVM) classifier. Evaluated on a publicly available MRI dataset the proposed model achieved a high accuracy of 97.93%, along with a sensitivity of 92% and a specificity of 98% demonstrating robust diagnostic capability [12]. Novsheena Rasool et al. conducted a comparative analysis of ML and DL techniques for brain tumor detection. Their study evaluated various DL architectures, including CNN, VGG16, ResNet50 and several hybrid models which were trained on publicly available datasets like BraTS and Figshare. The methodology involved an initial phase of image pre-processing and augmentation. Among the models tested a hybrid deep learning approach achieved the highest accuracy of 95%. The authors highlight that the strength of this DL model lies in its capacity to effectively capture intricate spatial and textural features from MRI scans a capability that can potentially reduce diagnostic delays and support enhanced clinical decision-making [13]. A. Priya et al. proposed a hybrid deep learning model that integrates an AlexNet convolutional network with a Gated Recurrent Unit (GRU) for the multi-class classification of brain tumors from MRI data. Their methodology begins with image pre-processing using a non-local means filter to enhance quality. The AlexNet component is responsible for extracting spatial features while the GRU network analyzes sequential dependencies and mitigates the vanishing gradient problem. To optimize performance hyperparameter tuning was employed to improve generalization and prevent overfitting. The model successfully classifies images into four categories: glioma, meningioma, pituitary tumor, and normal tissue. The proposed AlexNet-GRU hybrid achieved impressive results including an accuracy of 97%, a precision of 97.63%, a recall of 96.78%, and an F1-score of 97.25%, demonstrating its high efficacy **[14].**

D. S. Wankhede et al. developed a methodology for predicting glioblastoma (GBM) grades using MRI images. The data sourced from a hospital underwent a pre-processing pipeline that involved subtracting the mean intensity value and standard deviation of the brain region followed by noise reduction using bilateral filters. Tumor regions were then automatically segmented via Modified Fuzzy C-Means Clustering (MFCM). From these segments significant features were identified to differentiate between high-grade and low-grade GBM. For the final classification the authors proposed a novel Multilevel Layer modelling approach within a Faster R-CNN framework (MLL-CNN). [15]. To address the challenges of irregular tumor morphology and the shortage of specialized radiologists particularly in developing regions Tripty Singh et al. introduced a novel convolutional neural network named BrainNet for the accurate classification of brain tumors from MRI images. The proposed BrainNet architecture was benchmarked against several pre-trained models such as VGG13, VGG16, VGG19, InceptionResNetV2 and SqueezeNet. Their results demonstrated the model's superior performance with BrainNet achieving a precision of 94.75% with a training accuracy of 99.96% and a testing accuracy of 97.71% [17]. K. Bhagyalaxmi et al. conducted a comparative analysis to evaluate the impact of optimization techniques on feature extraction for medical image classification. Their methodology involved a hybrid approach that combined CNN-derived features with both Support SVM and ensemble learning classifiers. The study implemented advanced architectures such as Mask R-CNN integrated with DenseNet-41 and GoogleNet for segmentation and analysis tasks [18]. Praveen Kumar Ramtekkar et al. developed an optimized system for the accurate detection of brain tumors in MRI images. Their methodology begins with image pre-processing where noise is reduced using a combination of Gaussian, mean, and median filters. Features are extracted using GLCM. To enhance the model's efficiency feature selection is optimized through a suite of nature-inspired algorithms including Ant Colony, Bee Colony, Particle Swarm, Genetic, Gray Wolf and Whale Optimization. An optimized CNN performs the classification achieving a high accuracy of 98.9% [19].

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Sandeep Kumar Mathivanan et al. evaluated several transfer learning models including ResNet152, VGG19, DenseNet169, and MobileNetv3 for brain tumor classification using MRI images. Their methodology incorporated five-fold cross-validation and image enhancement techniques. Among the models tested MobileNetv3 achieved the highest accuracy of 99.75%. The authors caution that this result may not fully demonstrate the model's generalization capability across more diverse and heterogeneous datasets [20]. Baiju Babu Vimala et al. focused on the classification of brain tumors using MRI images. Their study utilized the Figshare dataset for both training and evaluation. To improve model robustness data augmentation techniques were implemented. The researchers employed a transfer learning approach with the EfficientNet architecture finding that the EfficientNetB2 variant delivered the best performance achieving an accuracy of 99.06%, a precision of 98.73%, a recall of 99.13%, and an F1-score of 98.79% [21]. The authors developed and evaluated two deep learning models using a dataset of 3,264 MRI brain images which included cases of glioma, meningioma, pituitary tumors and healthy scans. To enhance the dataset's diversity and improve model generalization image augmentation techniques were applied. The first model was a 2D CNN architecture comprising eight convolutional and four pooling layers. The second was a convolutional auto-encoder network designed for combined encoding and classification. In their results the 2D CNN achieved a superior accuracy of 96.47% and a recall of 95%, while the auto-encoder model attained an accuracy of 95.63% [22].

3. Methods & Materials

This research employs a DL framework for the multi-class classification of brain tumors from MRI scans. The dataset comprising 6,000 MRI images was sourced from a public repository like Kaggle. The image set is categorized into four distinct classes: glioma, meningioma, pituitary tumor, and a no-tumor control group.

Glioma tumors originate in the brain's glial cells whereas meningiomas develop from the meninges the protective membranes enveloping the brain and spinal cord. Pituitary tumors are located in the pituitary gland and can disrupt hormonal regulation. The no-tumor class consists of images without pathological findings providing a baseline for comparison.

To facilitate robust model development and evaluation, the dataset was partitioned into training and testing subsets. A standard 80:20 split was adopted allocating 4,800 images for training the model and 1,200 for testing. This division is critical for mitigating overfitting and ensuring an unbiased assessment of the model's generalization capability. The dataset's structure makes it suitable for applying transfer learning techniques.

3.1. Flow of algorithm

Step 1: Data Pre-processing
Input: MRI medical images having four categories: glioma, meningioma, pituitary tumor and a no-tumor control group.
For each image I in dataset do
    Resize I to (224 × 224)
    Normalize I ← $\frac{I}{255}$
    Apply augmentation on I
  End For
Step 2: Feature Extraction using transfer learning DenseNet121
Load DenseNet121 pretrained on ImageNet (exclude final classification layer)
  For each preprocessed image x do
    F_{res} ← DenseNet121(x)
  End For

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Step 3: Attention Refinement using CBAM

For each feature map F_{res} do

3.1 Channel Attention Module

$M_c(F) \leftarrow \sigma(MLP(AvgPool(F)) + MLP(MaxPool(F)))$

$F_{cam} \leftarrow M_c(F_{res}) \times F_{res}$

3.2 Spatial Attention Module

$M_s(F) \leftarrow \sigma\,(f^{7x7}\,(\,AvgPool\,(F_{cam}\,);\,MaxPool\,(F_{cam}\,)))$

$F_{cbam} \leftarrow M_s\,(F)\ X\ F_{cam}$

End For

Step 4: Global Average Pooling

Converts the feature map $F_{cbam} \in R^{c\ X\ H\ X\ W}$ to a 1D vector by averaging across spatial dimensions

For each refined feature map Fcbam do

$F_{gap} = \frac{1}{H.W} \sum_{i=1}^{H} \sum_{j=1}^{W} \text{Fcbam}\ (i, j).$

End For

Step 5: Model Training

For each classifier $M_j = \in$ {LR, SVM, RF, KNN, XGBoost} do

Train M_j using training feature vectors F_{gap}

End for

Step 6: Model Evaluation

For each trained model M_j do

Evaluate test set and compute:

Accuracy, Precision, Recall, F1-score

End For

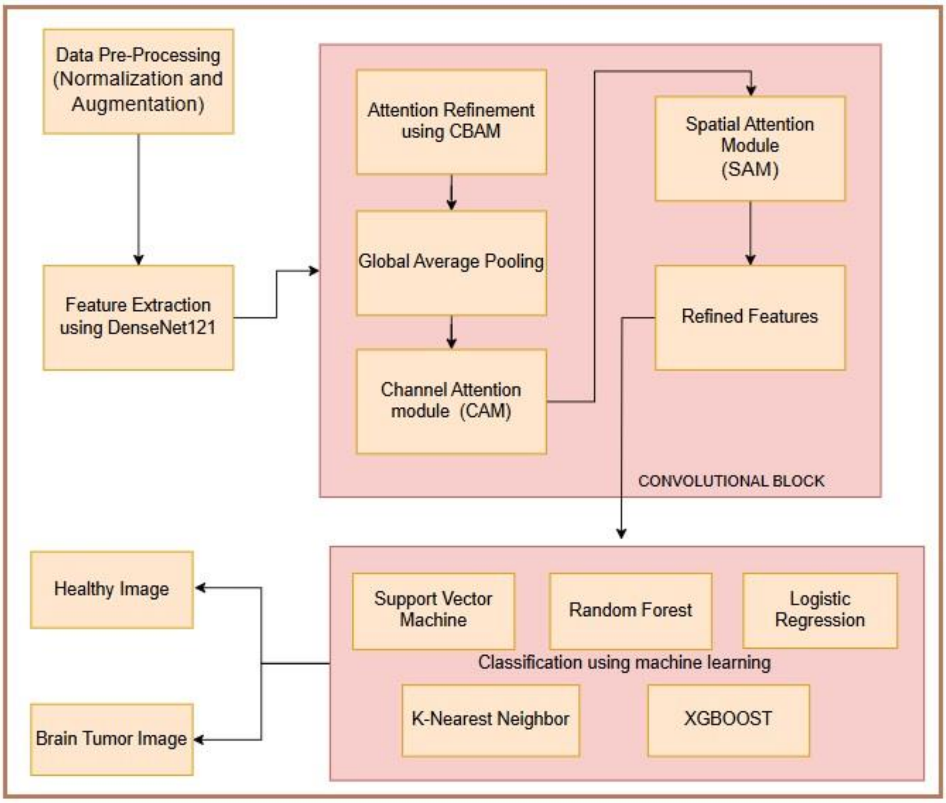

Figure 1: Proposed Methodology

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The above figure 1 demonstrates the proposed methodology for brain tumor classification that integrates DL based feature extraction with attention refining and machine learning model to enhance accuracy of the systems. In the Data pre-processing step brain MRI images undergo normalization that ensure pixel intensity falls within consistency range. The features are extracted from the pre-processed images using DenseNet121 transfer learning model. This model ensures that both high level and low-level spatial information is preserved. In the next phase **CBAM** is used to further refine extracted features. In the channel attention module (CAM) it learns from most informative features and supress the features which are irrelevant. In the next phase spatial attention module (SAM) it minimizes the background noise and focuses on spatially significant regions of the image that enhancing tumor related features. The combination of CAM and SAM allows the network to selectively prioritize **important tumor regions** that result in refined features. In the next phase refined features are used as input for classification of the images using LR, SVM, RF, KNN and XGBOOST. This machine learning model results input image into healthy bran image and image having brain tumor. This proposed model combines transfer learning DenseNet121 model with CBAM for strong feature extraction and performs classification using machine learning model.

4. Result and Discussion

This chapter shows the experimental results and provides a comparative analysis against established benchmarks. The proposed methodology leverages transfer learning utilizing a deep convolutional neural network to extract discriminative features which subsequently feed into a classifier. All experiments were implemented in Python and executed on the Google Colab platform leveraging T4 GPU acceleration. The primary objective is to empirically validate the efficacy and performance of the proposed framework.

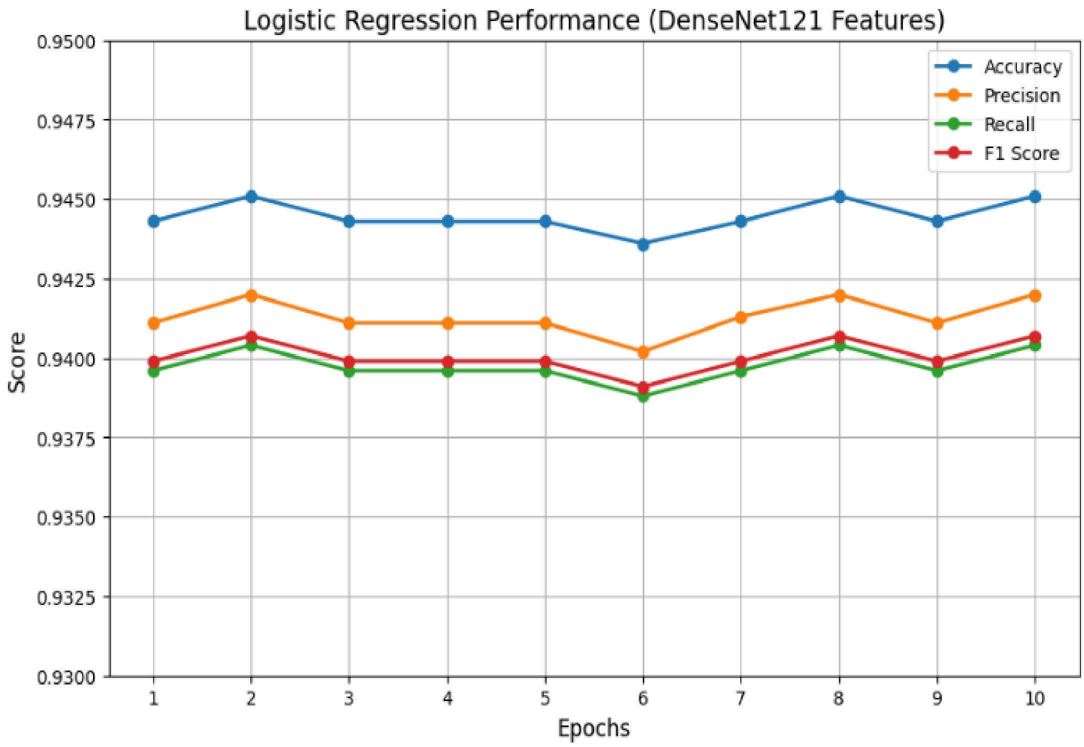

Figure 2: Logistic regression metric over epoch for DenseNet121

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The figure 2 above demonstrates the performance over 10 epochs of training of the LR working using DenseNet121 features. Figure 2 demonstrates high performance in evaluation metrics such as accuracy, precision, recall and F1 score in training the model. Experimental findings corroborate the validity of a hybrid approach using DenseNet121 for feature extraction and Logistic Regression for classification. This framework reached the highest accuracy of 94.51% with F1-score of 94.07%, thus demonstrating its very good performance. An essential feature in the training was stability after the second epoch with limited metric variations. Such stability offered a very fast convergence and no overt signs of overfitting. The features extracted by DenseNet121 were immensely discriminative and logistic regression with very few parameters was deemed unable to overfit them. Identical precision and recall further imply the balanced nature of the predictive power of such a model ensuring insignificant false-positive and false-negative error. As a result this pipeline combines the strong representational learning power of deep convolutional networks with the efficiency and transparency of traditional machine learning algorithms making it a practical and powerful solution for a real-world classification scenario.

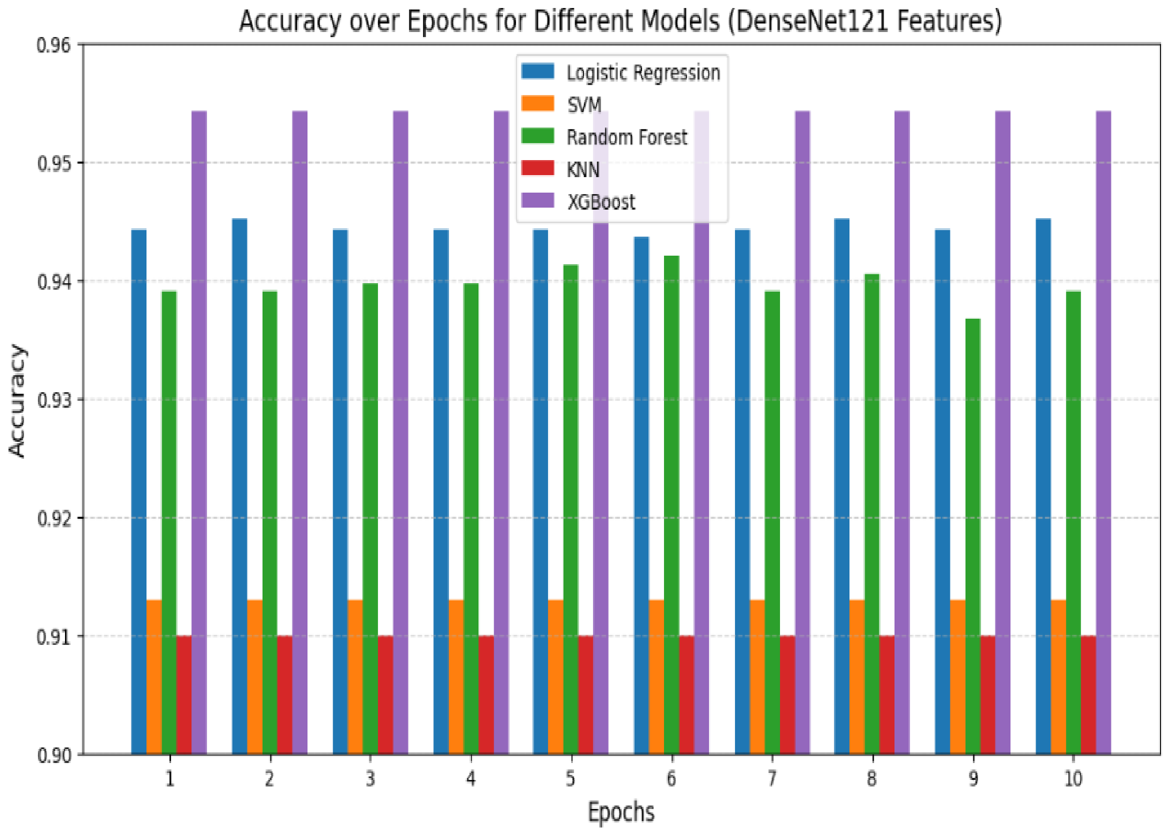

Figure 3: Accuracy over epoch for ML Models

We looked at five different classifiers using features from DenseNet121. Turns out there were some big differences in how they performed. The linear ones, like LR and SVM did really well. They had better accuracy and stayed stable always beating out the others. Right behind them came the ensemble types like XGBoost and Random Forest. KNN ended up at the bottom. This kind of ranking tells us a lot about the feature space itself. Linear models taking the lead pretty much means those DenseNet121 embeddings separate nicely in a straight line. So classifiers like that can draw a good boundary pretty easily. The tree-based ones handle complicated patterns in the data But they are not as quick. KNN struggles which happens a lot with high-dimensional stuff. Proximity does not mean as much in spaces like that. Pairing DenseNet121 with LR gives best result.

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

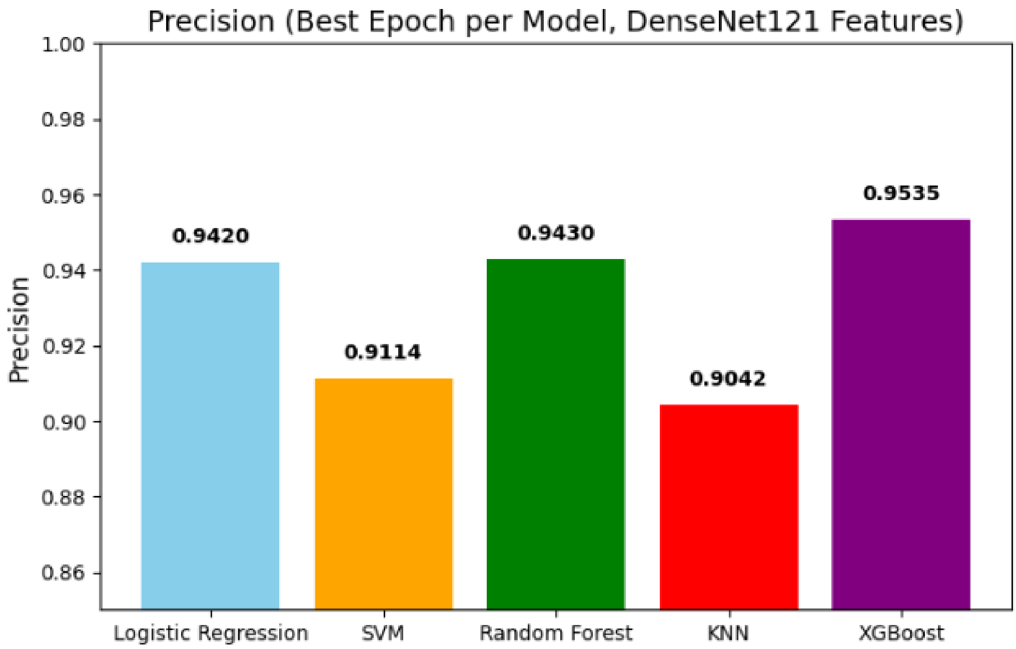

Figure 4: Precision result for best epoch

The above figure 4 demonstrates the result for precision of best epoch. We checked out five classifiers using features from DenseNet121. Precision demonstrates a clear picture of how they stacked up. XGBoost led the pack with a score of 0.9535. Random Forest was right behind at 0.9430 and Logistic Regression hung close with 0.9420. SVM and KNN they kind of lagged a bit lower. For the top precision XGBoost shows highest result.

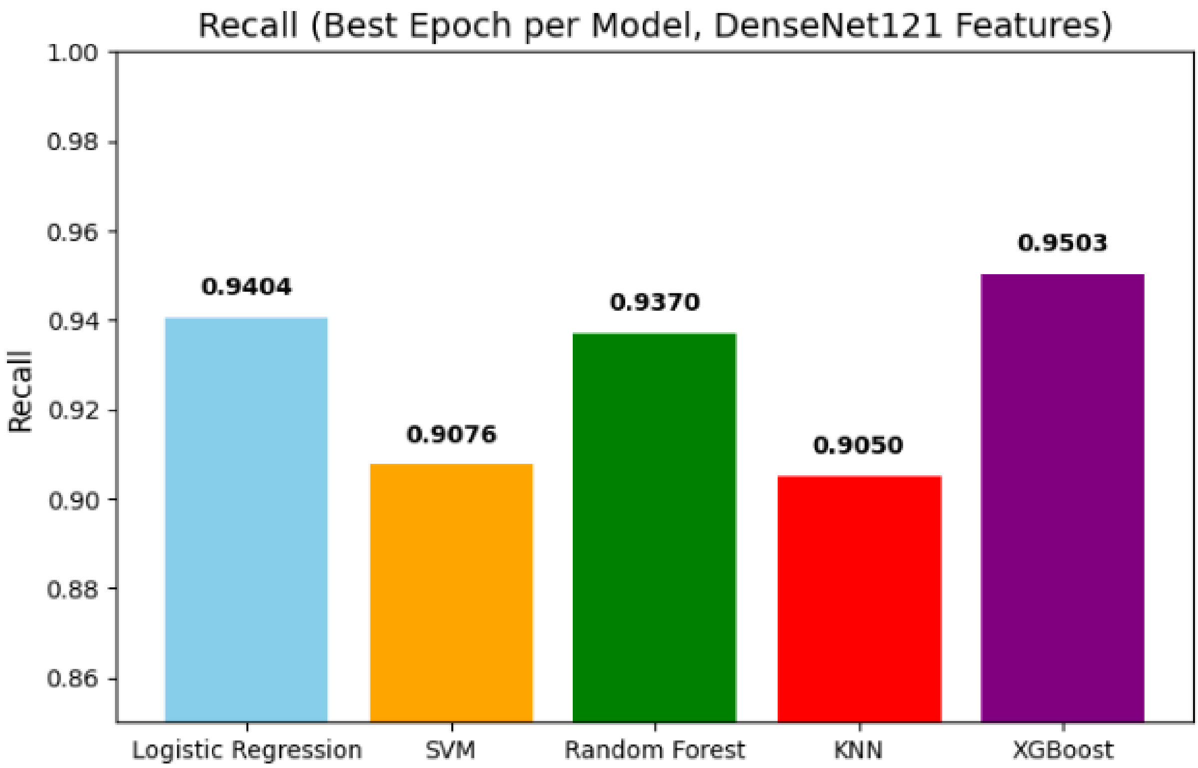

Figure 5: Recall result for best epoch

Received: November 4, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

The above figure 5 demonstrates the result for recall. We checked out five classifiers such as LR, SVM, RF, KNN and XGBoost using features from DenseNet121. XGBoost shoes the highest recall score of 0.9503. LR shows result of 0.9404. SVM and KNN model shows lower result as compares with LR and XGBoost. The evaluation of precision and recall for models using DenseNet121 features indicates a consistent performance ranking. XGBoost proved most effective and leading in both precision of 0.9535 and recall of 0.9503 which underscores its balanced accuracy. The close agreement between these two metrics for every classifier suggests the features produce well-defined class clusters avoiding the typical compromise between precision and recall. XGBoost is identified as the optimal model with Logistic Regression serving as a highly efficient and robust substitute for deployment.

The methodological framework proposed in this research offers distinct advantages when contextualized within the current landscape of brain tumor classification studies. Whereas prior efforts have often relied on legacy architectures such as VGG-16 [1] the present approach harnesses DenseNet121 a more contemporary network renowned for its parameter efficiency and superior representational learning through dense connections. A significant departure from the trend of designing highly customized, complex models [10, 14], multi-stage pipelines dependent on manual feature engineering [5, 12], this work advocates for a streamlined and reproducible paradigm. This paradigm leverages transfer learning for direct feature extraction, eliminating superfluous processing stages.This study provides a more nuanced and practical contribution than works presenting singular, monolithic deep-learning solutions [21]. It conducts a rigorous empirical benchmark of five distinct classifiers atop a unified deep feature space. This analysis not only confirms the high performance of a complex model like XGBoost of achieving 95.35% precision but identifies a simple Logistic Regression model as a highly efficient and robust alternative for resource-conscious deployment. This data-driven strategy for model selection delivers a flexible framework that empowering practitioners to make informed trade-offs between peak accuracy and operational efficiency so addressing a key gap in the existing literature. In the proposed research we used DenseNet121 for feature extraction. The proposed methodology shows the flexible results and it provides a clear performance hierarchy, identifies highly efficient alternatives and demonstrates a stable pipeline.

5. Conclusions

This research successfully proposed and validated a hybrid deep-learning framework for the automated classification of brain tumors from MRI scans. The model effectively synergized the feature extraction power of DenseNet121, refined using a Convolutional Block Attention Module (CBAM) with the discriminative ability of classical machine learning classifiers. The empirical evaluation demonstrated the high efficacy of this approach. Despite LR achieving a peak accuracy of 94% the XGBoost classifier was identified as the most optimal due to its balanced and superior performance for a precision of 95.35% and a recall of 95.03%. This result highlights its exceptional capability to limit both false positive and false negative predictions, making it the most robust model evaluated.

References

[1] Kamini Lamba , Shalli Rani, Monika Anand, Lakshmana Phaneendra Maguluri, “An integrated deep learning and supervised learning approach for early detection of brain tumor using magnetic resonance imaging” , Healthcare Analytics 5 (2024) 100336.

[2] Shyo Prakash Jakhar, Amita Nandal, Arvind Dhaka, Adi Alhudhaif, Kemal Polat, “Brain tumor detection with multi-scale fractal feature network and fractal residual learning” Applied Soft Computing Journal 153 (2024) 111284

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[3] Mohammed H. Al-Jammas , Emad A. Al-Sabawi , Ayshaa Mohannad Yassin , Aya Hassan Abdulrazzaq "Brain tumors recognition based on deep learning" e-Prime - Advances in Electrical Engineering, Electronics and Energy 8 (2024) 100500.
[4] Rita Appiah, Venkatesh Pulletikurthi, Helber Antonio Esquivel-Puentes, Cristiano Cabrera, Nahian I. Hasan , Suranga Dharmarathne, Luis J. Gomez , Luciano Castillo, "Brain tumor detection using proper orthogonal decomposition integrated with deep learning networks" Computer Methods and Programs in Biomedicine 250 (2024) 108167
[5] Kavita A. Sultanpure, Jayashri Bagade, Sunil L. Bangare, Manoj L. Bangare, Kalyan D. Bamane , Abhijit J. Patankar , "Internet of things and deep learning based digital twins for diagnosis of brain tumor by analyzing MRI images" Measurement: Sensors Volume 33, June 2024, 101220.
[6] Md. Naim Islam, Md. Shafiul Azam , Md. Samiul Islam, Muntasir Hasan Kanchan, A.H.M. Shahariar Parvez , Md. Monirul Islam "An improved deep learning-based hybrid model with ensemble techniques for brain tumor detection from MRI image" Informatics in Medicine Unlocked 47 (2024) 101483.
[7] Monika Agarwal , Geeta Rani, Ambeshwar Kumar, Pradeep Kumar K, R. Manikandan , Amir H. Gandomi," Deep learning for enhanced brain Tumor Detection and classification" Results in Engineering 22 (2024) 102117.
[8] Alain Marcel Dikande Simo, Aurelle Tchagna Kouanou, Valery Monthe, Michael Kameni Nana, Bertrand Moffo Lonla, "Introducing a deep learning method for brain tumor classification using MRI data towards better performance", Informatics in Medicine Unlocked 44 (2024) 101423.
[9] T. Lakshmi Prasanthi, N. Neelima, "Improvement of Brain Tumor Categorization using Deep Learning: A Comprehensive Investigation and Comparative Analysis" Procedia Computer Science Volume 233, 2024, Pages 703-712.
[10] Chandni , Monika Sachdeva, Alok Kumar Singh Kushwaha, "IRNetv: A deep learning framework for automated brain tumor diagnosis" Biomedical Signal Processing and Control 87 (2024) 105459.
[11] Praveen Kumar Ramtekkar, Anjana Pandey, Mahesh Kumar Pawar "Accurate detection of brain tumor using optimized feature selection based on deep learning techniques" Springer Multimedia Tools and Applications (2023) 82:44623–44653.
[12] Shenbagarajan Anantharajan, Shenbagalakshmi Gunasekaran, Thavasi Subramanian, Venkatesh R, "MRI brain tumor detection using deep learning and machine learning approaches" Measurement: Sensors Volume 31, February 2024, 101026.
[13] Novsheena Rasool, Javaid Iqbal Bhat ," Brain tumour detection using machine and deep learning: a systematic review", Springer Multimedia Tools and Applications, 2024
[14] A. Priya , V. Vasudevan, "Brain tumor classification and detection via hybrid alexnet-gru based on deep learning" Biomedical Signal Processing and Control 89 ,2024, 105716.
[15] D. S. Wankhede, R. Selvarani (2022) "Dynamic architecture based deep learning approach for glioblastoma brain tumor survival prediction" Neuroscience Informatics 2, 100062.
[16] Takowa Rahman, Md Saiful Islam. "MRI brain tumor detection and classification using parallel deep convolutional neural networks" Measurement: Sensors 26 (2023) 100694.
[17]Tripty Singh, Rekha R Nair, Tina Babu, Atharwa Wagh, Aniket Bhosalea, Prakash Duraisamy , "BrainNet: A Deep Learning Approach for Brain Tumor Classification" Procedia Computer Science, Volume 235, 2024, Pages 3283-3292
[18] K. Bhagyalaxmi, B. Dwarakanath, P. Vijaya Pal Reddy "Deep learning for multi-grade brain tumor detection and classifcation: a prospective survey" Springer Multimedia Tools and Applications, 2024
[19] Praveen Kumar Ramtekkar, Anjana Pandey, Mahesh Kumar Pawar "Innovative brain tumor detection using optimized deep learning techniques" Springer 2023,14(1):459–473.
[20] Sandeep Kumar Mathivanan , Sridevi Sonaimuthu , Sankar Murugesan and other "Employing DLand transfer learning for accurate brain tumor detection" Nature Scientific report, 2024:14-7232.

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

[21] Baiju BabuVimala, Saravanan Srinivasan, Sandeep Kumar Mathivanan, Mahalakshmi, Prabhu Jayagopal & GemmachisTeshite Dalu, "Detection and classifcation of brain tumor using hybrid deep learning models" Scientific reports, (2023) 13:23029.

[22] Soheila Saeedi, Sorayya Rezayi, Hamidreza Keshavarz and Sharareh R. Niakan Kalhori, "MRI-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques" BMC Medical Informatics and Decision Making, (2023) 23:16