CVG-Net: Novel transfer learning based deep features for diagnosis of brain tumors using MRI scans

Shaha Alotaibi [1] , **Amjad Rehman** [Corresp., 2] , **Ali Raza** [3] , **Jaber AlYami** [4] , **Tanzila Saba** [2]

[1] Department of Information Systems, Princess Nourah bint Abdulrahman University, Riyadh, Saudi Arabia

[2] Artificial Intelligence \& Data Analytics Lab CCIS, Prince Sultan University, Riyadh, Saudi Arabia

[3] Institute of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan, Pakistan

[4] Department of Diagnostic Radiology, Faculty of Applied Medical Sciences, King Abdulaziz University, Jeddah, Saudi Arabia

Corresponding Author: Amjad Rehman
Email address: arkhan@psu.edu.sa

Brain tumors present a significant medical challenge, demanding accurate and timely diagnosis for effective treatment planning. These tumors disrupt normal brain functions in various ways, giving rise to a broad spectrum of physical, cognitive, and emotional challenges. The daily increase in mortality rates attributed to brain tumors underscores the urgency of this issue. In recent years, advanced medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), have emerged as indispensable tools for diagnosing brain tumors. Brain MRI scans provide high-resolution, non-invasive visualization of brain structures, facilitating the precise detection of abnormalities such as tumors. This study aims to propose an effective neural network approach for the timely diagnosis of brain tumors. Our experiments utilized a multi-class MRI image dataset comprising 21,672 images related to glioma tumors, meningioma tumors, and pituitary tumors. We introduced a novel neural network-based feature engineering approach, combining 2D Convolutional Neural Network (2DCNN) and VGG16. The resulting 2DCNN-VGG16 network (CVG-Net) extracted spatial features from MRI images using 2DCNN and VGG16 without human intervention. The newly created hybrid feature set is then input into machine learning models to diagnose brain tumors. We have balanced the multi-class MRI image features data using the Synthetic Minority Over-sampling Technique (SMOTE) approach. Extensive research experiments demonstrate that utilizing the proposed CVG-Net, the k-neighbors classifier outperformed state-of-the-art studies with a k-fold accuracy performance score of 0.96. We also applied hyperparameter tuning to enhance performance for multi-class brain tumor diagnosis. Our novel proposed approach has the potential to revolutionize early brain tumor diagnosis, providing medical professionals with a cost-effective and timely diagnostic mechanism.

CVG-Net: Novel Transfer Learning Based Deep Features for Diagnosis of Brain Tumors Using MRI Scans

Shaha Alotaibi[1], Amjad Rehman[2], Ali Raza[3], Jaber AlYami[4], and Tanzila Saba[2]

[1]Department of Information Systems, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P. O. Box 84428, Riyadh 11671, Saudi Arabia; stalotaibi@pnu.edu.sa

[2]Artificial Intelligence & Data Analytics Lab CCIS Prince Sultan University Riyadh Saudi Arabia; tsaba@psu.edu.sa

[3]Institute of Computer Science, Khwaja Fareed University of Engineering and Information Technology, Rahim Yar Khan 64200, Pakistan; ali.raza.scholarly@gmail.com;

[4]Department of Diagnostic Radiology, Faculty of Applied Medical Sciences, King Abdulaziz University, Jeddah, 21589, Saudi Arabia; Imaging Unit, King Fahd Medical Research Center, King Abdulaziz University, Jeddah, 21589, Saudi Arabia; jhalyami@kau.edu.sa;

Corresponding author:

Amjad Rehman[1]

Email address: arkhan@psu.edu.sa;

ABSTRACT

Brain tumors present a significant medical challenge, demanding accurate and timely diagnosis for effective treatment planning. These tumors disrupt normal brain functions in various ways, giving rise to a broad spectrum of physical, cognitive, and emotional challenges. The daily increase in mortality rates attributed to brain tumors underscores the urgency of this issue. In recent years, advanced medical imaging techniques, particularly Magnetic Resonance Imaging (MRI), have emerged as indispensable tools for diagnosing brain tumors. Brain MRI scans provide high-resolution, non-invasive visualization of brain structures, facilitating the precise detection of abnormalities such as tumors. This study aims to propose an effective neural network approach for the timely diagnosis of brain tumors. Our experiments utilized a multi-class MRI image dataset comprising 21,672 images related to glioma tumors, meningioma tumors, and pituitary tumors. We introduced a novel neural network-based feature engineering approach, combining 2D Convolutional Neural Network (2DCNN) and VGG16. The resulting 2DCNN-VGG16 network (CVG-Net) extracted spatial features from MRI images using 2DCNN and VGG16 without human intervention. The newly created hybrid feature set is then input into machine learning models to diagnose brain tumors. We have balanced the multi-class MRI image features data using the Synthetic Minority Over-sampling Technique (SMOTE) approach. Extensive research experiments demonstrate that utilizing the proposed CVG-Net, the k-neighbors classifier outperformed state-of-the-art studies with a k-fold accuracy performance score of 0.96. We also applied hyperparameter tuning to enhance performance for multi-class brain tumor diagnosis. Our novel proposed approach has the potential to revolutionize early brain tumor diagnosis, providing medical professionals with a cost-effective and timely diagnostic mechanism.

1 INTRODUCTION

Brain tumors are abnormal growths of cells within the brain that can disrupt normal brain function and pose serious health risks Miao et al. (2023). Detecting and diagnosing brain tumors is paramount for timely intervention and treatment. MRI brain scans have become a crucial tool Zhu et al. (2023). MRI scans utilize powerful magnets and radio waves to generate detailed images of the brain structure, allowing

healthcare professionals to visualize abnormalities Liu et al. (2023b). The MRI scans are especially effective in identifying brain tumors because they provide high-resolution images that can differentiate between healthy brain tissue and tumor masses.

Brain tumors can be classified into various types, each with its distinct characteristics and potential challenges in diagnosis and treatment Mehnatkesh et al. (2023); Liu et al. (2023a). Glioma tumors originate in the glial cells, which provide support and protection to neurons Oztek et al. (2023). They are often classified according to their aggressiveness, with high-grade gliomas being particularly concerning due to their rapid growth and infiltrative nature. On the other hand, Meningioma tumors develop from the meninges, the protective membranes surrounding the brain and spinal cord. While often benign, they can cause symptoms by compressing nearby brain structures Bhatele and Bhadauria (2023). Pituitary tumors, which arise in the pituitary gland located at the base of the brain, can affect hormone production and regulation, leading to a wide range of health issues.

The mortality rates caused by brain tumors are increasing daily. Between 2014 and 2018, the average annual age-adjusted incidence rate for primary malignant brain tumors was 7.06 per 100,000 individuals. Projections indicated that in 2022, an estimated 25,050 new diagnoses and 18,280 fatalities would be attributed to primary malignant brain tumors Thierheimer et al. (2023). Brain tumors were 24.25 per 100,000 individuals, comprising 7.06 per 100,000 for malignant cases and 17.18 per 100,000 for non-malignant cases Li et al. (2023a). Similarly, based on the 2018 data from the Global Cancer Registry, a total of 18,078,957 cancer cases were reported across all genders, with 29,681 cases attributed to brain cancer Khazaei et al. (2020).

Traditional diagnostic methods for brain tumors have primarily relied on radiological imaging techniques such as computed tomography (CT) Zhang et al. (2023) and MRI. Classical treatment modalities for brain tumors encompass surgical resection, radiation therapy, and chemotherapy, with the specific approach chosen depending on tumor type, location, and patient characteristics. Deep learning based methods use MRI images analyzed using convolutional neural networks (CNN) for brain tumor recognition Rajinikanth et al. (2021, 2022); Maqsood et al. (2021, 2022); Badjie and Deniz Ülker (2022); Kurdi et al. (2023); Khan et al. (2023).

In this study, we propose an advanced image-processing mechanism that effectively diagnoses brain tumors without human intervention. We introduce a novel neural network, CVG-Net, for transfer learning-based spatial feature extraction from MRI images. These newly created transfer features are then employed to diagnose brain tumors using machine learning models.

Our contributions regarding brain tumor diagnosis are as follows:

- We have introduced a novel neural network method, CVG-Net, for feature engineering. This method combines 2DCNN and VGG16 to extract spatial features from MRI images. The resulting hybrid spatial feature set is input into machine learning models to diagnose brain tumors.

- We employed the SMOTE technique to balance the multi-class MRI image feature data, resulting in more accurate and reliable diagnoses of brain tumors. This approach addresses class imbalance issues within medical image analysis.

- We utilized four advanced machine learning models and two deep learning models based on neural networks for comparative performance evaluations. Each method's performance is optimized through hyperparameter tuning and validated using k-fold cross-validation. Additionally, we calculated the computational complexity of each method for diagnosing brain tumors.

The rest of the study is organized as follows: Section 2 analyzes the limitations in previous literature. Section 3 demonstrates our proposed research methodology for diagnosing brain tumors. Section 4 comparatively evaluates the results of the applied neural network approaches. Our findings are concluded in Section 5.

2 LITERATURE ANALYSIS

This literature analysis section comprehensively examines existing studies and methodologies related to both neural network applications in medical imaging and transfer learning techniques. It delves into the foundational work in medical image analysis, emphasizing the pivotal role of neural networks in automating the detection and diagnosis of various pathologies, including brain tumors. Additionally, it

97   synthesizes the key findings and methodologies from relevant studies, providing a robust foundation for
98   the subsequent implementation of transfer learning techniques in the proposed diagnosis framework for
99   brain tumors using MRI scans.

100   This study Archana et al. (2023) introduces a comparative analysis of several optimizers employed
101   in Convolutional Neural Networks (CNNs) for the purpose of brain tumor detection. Within Deep
102   Learning (DL), Artificial Neural Networks (ANNs) play a crucial role in discerning brain tumors. The
103   medical image dataset is employed for applied methods training and evaluation. Among the various
104   approaches investigated, the application of the AlexNet architecture in conjunction with the Stochastic
105   Gradient Descent (SGD) optimizer demonstrated superior performance. This proposed approach achieved
106   a diagnostic accuracy of 0.80.

107   The author of this Sudharson et al. (2022) study proposed a hybrid deep learning-based neural system
108   for the detection of brain tumors. The study introduced fundamental concepts of image separation to
109   address the challenges associated with partitioning brain MRI images. Various MRI pre-processing
110   techniques were then elaborated, encompassing tasks such as image registration, bias field correction, and
111   non-brain tissue removal. Additionally, the author presented a Hybrid CNN-based partitioning approach,
112   which proved advantageous for delineating brainstem tumors in MRI scans when augmented with prior
113   knowledge. The proposed approach demonstrated an accuracy score of 0.93.

114   This article Sharif et al. (2020) introduces a novel approach to actively employ deep learning for
115   the segmentation and recognition of brain tumors in MRI images. The authors utilize the pre-trained
116   Inception V3 Convolutional Neural Network (CNN) model for robust deep feature extraction during
117   the classification phase. These features are integrated with the dominant rotated Local Binary Pattern
118   (DRLBP) to enhance texture analysis. Subsequently, a particle swarm optimization (PSO) technique is
119   employed to fine-tune the concatenated feature vector for classification using a softmax classifier. The
120   study is conducted in two phases. In the initial phase, the segmentation approach (SbDL) is validated
121   on BRATS2017 and BRATS2018 datasets, demonstrating promising Dice scores. For instance, the
122   BRATS2017 dataset achieves Dice scores of 83.73% for the core tumor, 93.7% for the whole tumor, and
123   79.94% for the enhanced tumor. Moreover, the BRATS2018 dataset attains a Dice score of 88.34%. In
124   the subsequent phase, the classification strategy is applied to BRATS2013, 2014, 2017, and 2018 datasets,
125   yielding an average accuracy of over 92%.

126   The study Kibriya et al. (2022) is focused on developing an automated method for precise brain cancer
127   identification through tumor diagnosis. Previous systems have struggled with issues related to subpar
128   accuracy and high false-positive rates. To address this, the study introduces a pioneering 13-layer CNN
129   architecture specifically designed for classifying brain tumors from MRI scans. The effectiveness of the
130   proposed model was assessed using a standardized dataset comprising 3064 MRI images encompassing
131   three distinct categories of brain cancer: glioma, pituitary, and meningioma. The results demonstrated an
132   average accuracy of 97%.

133   The study Yazdan et al. (2022) introduces an innovative approach to diagnosing brain tumors. It
134   employs a dual-pronged strategy, utilizing a Multi-Scale CNN (MSCNN) architecture to develop a robust
135   classification model, while also addressing the impact of Rician noise on MSCNN performance. This
136   model enables the multi-classification of MRIs, distinguishing between glioma, meningioma, pituitary,
137   and non-tumor cases. Additionally, a denoising process is implemented using a Fuzzy Similarity-based
138   Non-Local Means (FSNLM) filter to enhance classification results. The study utilizes an openly accessible
139   MRI dataset comprising 3264 MRIs. Experimental results demonstrate that the proposed MSCNN model
140   outperforms both AlexNet and ResNet, exhibiting superior accuracy and efficiency while incurring lower
141   computational expenses. Specifically, the MCNN2 iteration achieves an impressive accuracy and F1-score
142   of 91.2% and 91%, respectively.

143   The study Stadlbauer et al. (2022) investigates the potential of employing multiclass machine learning
144   (ML) algorithms on an extensive array of radiomic features derived from advanced MRI (advMRI) and
145   physiological MRI (phyMRI) data. This innovative methodology, referred to as radiophysiomics, aims
146   to achieve precise classification of contrast-enhancing brain tumors. The study leveraged a substantial
147   MRI database, encompassing more than 1700 MR examinations of brain tumor patients, for the purpose
148   of model development. The findings revealed that the application of Adaptive Boosting and Random
149   Forest algorithms in conjunction with both advMRI and phyMRI data surpassed human reading in various
150   performance metrics, including accuracy (0.875 vs. 0.850), precision (0.862 vs. 0.798), and F-score
151   (0.774 vs. 0.740). Nevertheless, it was observed that radiologists demonstrated higher sensitivity (0.767

152 vs. 0.750) and specificity (0.925 vs. 0.902) compared to the machine learning models.

153 The study Fabelo et al. (2019) introduces a novel framework centered on deep learning techniques,
154 tailored for the analysis of hyperspectral images depicting live human brain tissue. Through rigorous
155 evaluation using a diverse database of 26 in vivo hyperspectral cubes from 16 individual patients,
156 encompassing a total of 258,810 annotated pixels, the framework proves adept at generating a thematic
157 representation that delineates the brain's parenchymal area and accurately identifies the tumor's position.
158 This information serves as a crucial aid to surgeons, significantly enhancing the precision of tumor
159 resection procedures. Notably, the deep learning pipeline 2D convolutional neural network exhibits an
160 impressive overall accuracy of 80% for multiclass classification, which is low compared to baseline.

161 The study Latif et al. (2022) introduces an innovative method for categorizing Glioma tumors, utilizing
162 features based on deep learning in conjunction with a Support Vector Machine (SVM) classifier. Through
163 the application of a deep convolutional neural network for feature extraction from MR images sourced
164 from the BraTS dataset, the study achieved noteworthy levels of accuracy in classification. Specifically,
165 an accuracy of 96.19% was observed for the HGG Glioma type using the FLAIR modality, and a
166 commendable accuracy of 95.46% was obtained for the LGG Glioma tumor type when employing the T2
167 modality. Notably, this method encompassed the classification of four distinct Glioma classes, including
168 Edema, Necrosis, Enhancing, and Non-enhancing. This pioneering approach shows promising potential
169 in the domain of Glioma tumor classification.

170 The analyzed works with their research limitations are summarized in Table 3.

Table 1. The literature summary and limitations analysis.

Ref	Dataset	Proposed Technique	Performance Accuracy	Research Limitations
Archana et al. (2023)	Brain tumours medical images	AlexNet with SGD	0.80	Low diagnose performance scores
Sudharson et al. (2022)	Brain MRI image scans	Hybrid CNN	0.93	Low performance with a state of art approach
Sharif et al. (2020)	BRATS2017 and BRATS2018 datasets	Inception V3 pre-trained CNN model	0.92	Old datasets with low performance accuracy for diagnosis
Kibriya et al. (2022)	3064 MRI images	13-layer CNN architecture	0.97	Classical neural networks were used for classification
Yazdan et al. (2022)	3264 MRIs Scans	Multi-Scale CNN (MSCNN) architecture	0.91	Poor accuracy performance for multi class data
Stadlbauer et al. (2022)	1700 MRI examinations from advanced MRI (advMRI) and physiological MRI (phyMRI) data	Adaptive Boosting and Random Forest	0.87	Low diagnose performance scores
Fabelo et al. (2019)	26 in vivo hyperspectral cubes from 16 different patients, among which 258,810 pixels	2D convolutional neural network	0.80	Poor accuracy performance for multiclass classification
Latif et al. (2022)	BraTS dataset	Support Vector Machine (SVM)	0.96	Classical machine learning approaches were used

3 PROPOSED METHODOLOGY

172 This section comprehensively describes the materials and methods used to evaluate our research experi-
173 ments. We examine the MRI scans dataset and the advanced neural network approaches applied. Figure 1

illustrates our novel proposed research methodology for diagnosing brain tumors. The following steps outline the process carried out in our proposed methodology for conducting experiments.

- **Step 1:** At the outset of our research experiments, we acquired a brain tumor-related dataset of MRI scan images for evaluating results. This dataset encompasses multiple target classes, allowing for a comprehensive assessment of our findings.

- **Step 2:** Next, for the extraction of rich-level features from MRI images, we have proposed a novel neural network approach that leverages transfer learning for spatial feature extraction, ultimately creating a new feature set.

- **Step 3:** We then analyzed the dataset and identified an imbalance. To address this issue, we applied the SMOTE approach to balance the features of the dataset for multi-class classification.

- **Step 4:** The image feature data is then divided into two portions: training and testing. The split ratio employed is 80% for training and 20% for testing.

- **Step 5:** We have employed advanced machine learning and deep learning approaches in this step. Using 80% of the training data, we have implemented the applied methods.

- **Step 6:** Then, the 20% portion of the data is utilized for the evaluations and predictions of applied methods through various performance metrics in comparison.

- **Step 7:** Ultimately, the superior neural network method during experiments is employed for brain tumor diagnosis.
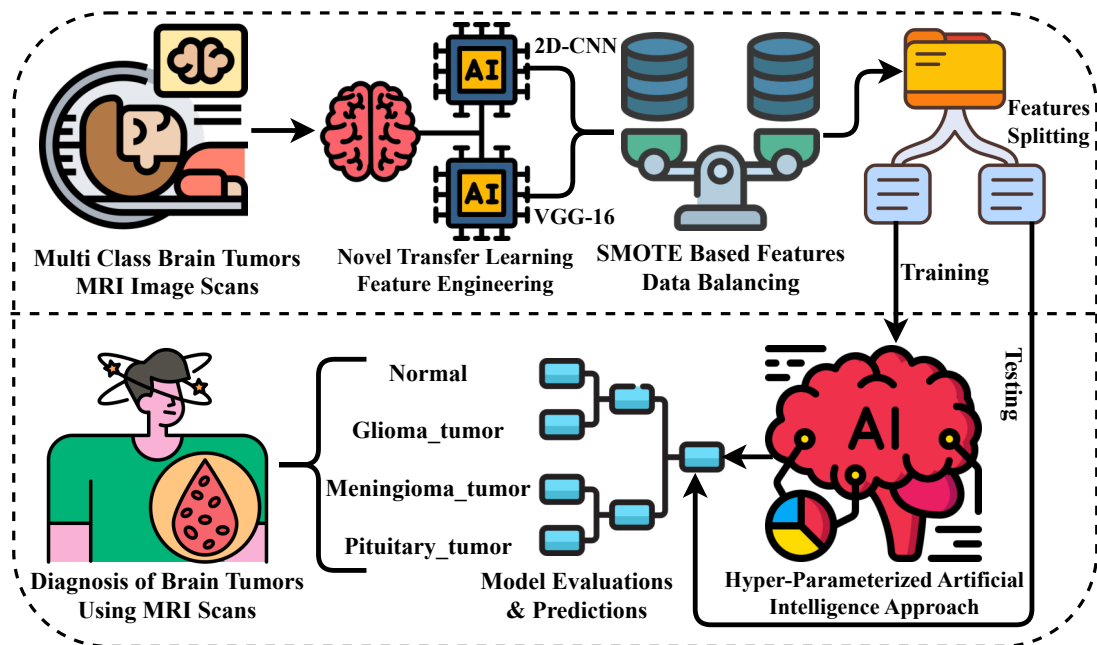
Figure 1. Workflow diagram of our proposed methodology for brain tumor diagnosis.

3.1 Multi class Brain Tumors MRI Image Data

This research used multiclass MRI scan images Hashemi (2023) related to brain tumors to conduct experiments. The dataset comprises 21,672 MRI scan images. Figure 2 illustrates the distribution of multi-class target labels. This analysis reveals that the 'Normal' target class (0) contains 3,066 samples, the 'Glioma_tumor' target class (1) contains 6,307 samples, the 'Meningioma_tumor' target class (2) contains 6,391 samples, and the 'Pituitary_tumor' target class (3) contains 5,908 samples. Additionally, we conducted a sample image analysis, as shown in Figure 3.
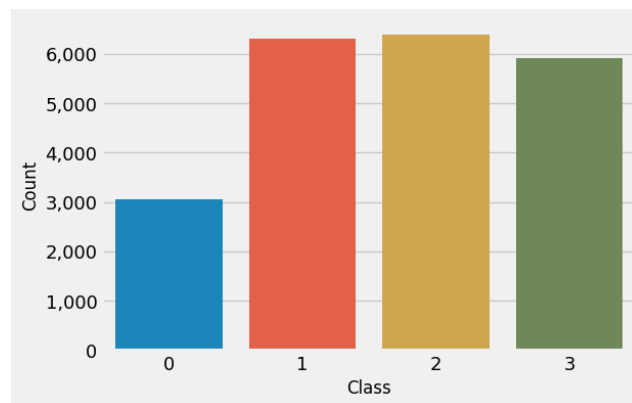
Figure 2. The target class labels distributions analysis.
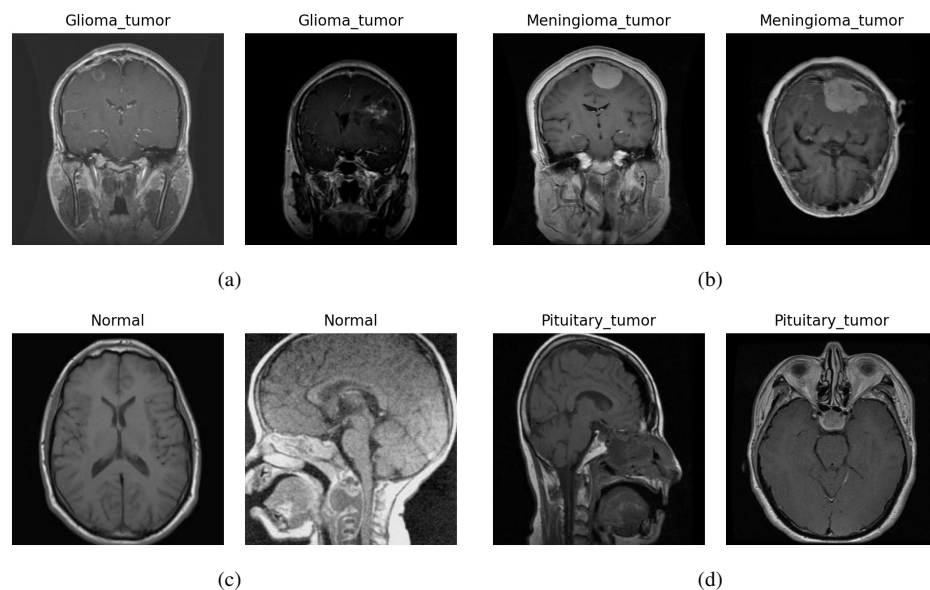
Figure 3. The sample dataset image analysis with the target class.

3.2 Novel Transfer Learning Approach

This section comprehensively describes our novel proposed CVG-Net approach for transfer feature engineering. The step-by-step architectural workflow of the proposed approach is illustrated in Figure 4. The brain tumor MRI image data is initially fed into the VGG16 approach, which extracts rich-level spatial features based on transfer learning. Similarly, the brain tumor MRI image data is input into the 2DCNN approach, which also extracts rich-level spatial features using transfer learning. The spatial features obtained from both approaches are then combined to create a new feature set. This newly generated feature set is subsequently employed in building the machine learning models applied in this study and for further results evaluations.

The algorithm 1 shows the step-by-step workflow of the proposed transfer learning feature engineering.

3.3 SMOTE based data balancing

SMOTE has emerged as a pivotal tool in addressing class imbalance issues within medical image analysis, particularly in diagnosing brain tumors using multi-class MRI image datasets Li et al. (2023b). Class imbalance, where certain classes are underrepresented relative to others, can significantly hinder the performance of machine learning models, as they tend to be biased towards the majority class. In medical imaging, this can have critical implications for patient care. SMOTE operates by generating synthetic samples in the feature space of the minority class, thereby alleviating the imbalance. When applied
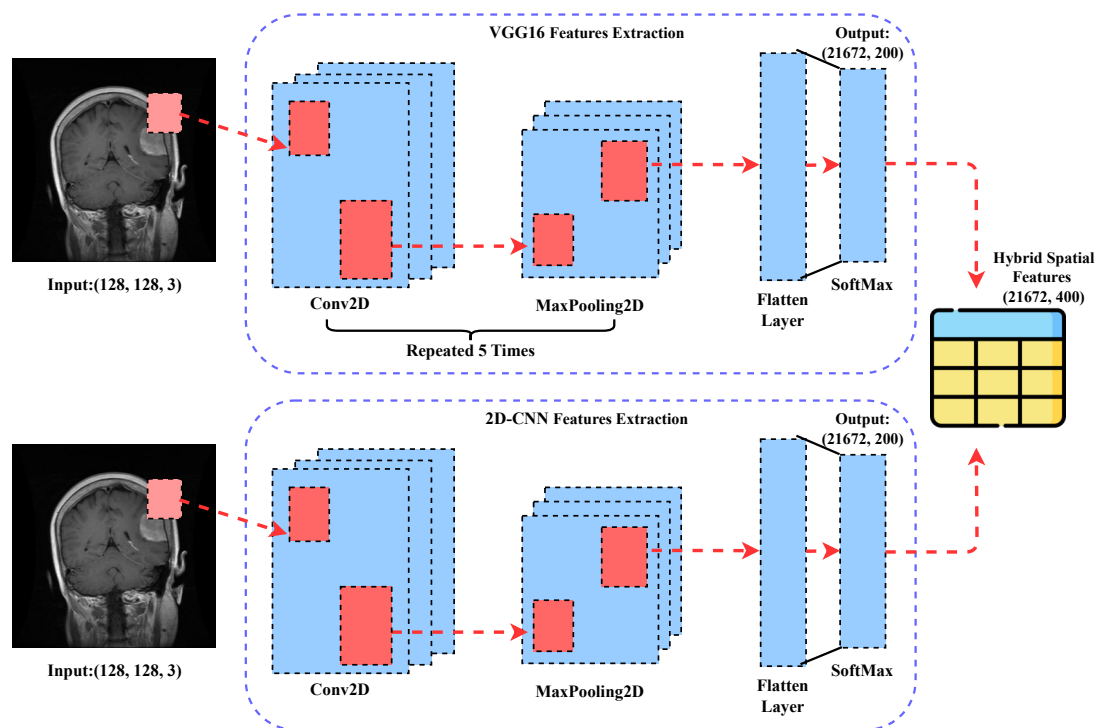
Figure 4. The architectural workflow analysis of our proposed CVG-Net feature engineering.

Algorithm 1 CVG-Net Algorithm

Input: Multi-class MRI scans related to brain tumors.
Output: New Transfer learning-based deep features.

initiate;
1- $F_{cnn} \longleftarrow CNN_{prediction}(MiS)$ // $MiS \, \varepsilon \, MRI \, images \, set$,   here MiS is original image data and F_{cnn} is the deep spatial feature set extracted.
1- $F_{vgg16} \longleftarrow VGG16_{prediction}(MiS)$ // $MiS \, \varepsilon \, MRI \, images \, set$,   here MiS is original image data and F_{vgg16} is the deep spatial feature set extracted.
3- $F_{Spat} \longleftarrow F_{cnn} + F_{vgg16}$ // here F_{Spat} is final hybrid deep spatial features set used for osteoarthritis detection.
end;

---

to multi-class MRI datasets for brain tumor diagnosis, SMOTE ensures that the model is exposed to a more representative data distribution, effectively discriminating between various tumor types. This methodology has demonstrated promising results, contributing to more accurate and reliable diagnoses, paramount in clinical decision-making processes.

3.4 Applied Neural network methods

The application of artificial intelligence (AI) based machine learning, deep learning, and transfer learning methods has emerged as a transformative approach in medical imaging Rehman et al. (2023); Qadri et al. (2023); Raza et al. (2022b), particularly in diagnosing brain tumors using brain MRI scans. These advanced techniques have revolutionized the way medical professionals analyze and interpret complex neuroimaging data. Machine learning algorithms can efficiently extract intricate patterns and features from large datasets of MRI scans, enabling them to differentiate between normal brain tissue and pathological regions associated with brain tumors.

Deep learning, in particular, has been instrumental in automating the tumor detection, segmentation, and classification process, as it can automatically learn hierarchical representations from raw MRI data, making it highly effective in identifying subtle abnormalities. Transfer learning techniques leverage pre-

Table 2. The working mechanism description analysis of applied neural network approaches.

Method	Working Description
2D-CNN	A 2D-CNN Archana et al. (2023); Zhou et al. (2023) works by systematically scanning and analyzing small regions (kernels) of a 2D input image, such as a Brain MRI scan. These kernels extract features like edges, textures, and patterns through convolution operations. Multiple layers of convolutions and pooling are used to hierarchically learn and combine these features, enabling the CNN to detect complex patterns indicative of brain tumors, making it an effective method for automated diagnosis using MRI scans.
VGG-16	The VGG-16 neural network method Rohith et al. (2023); Shourie et al. (2023) for diagnosing brain tumors using brain MRI scans operates by utilizing a deep CNN architecture. It employs a series of convolutional layers to extract intricate features from the MRI images, gradually learning hierarchical representations of the input data. These features are then passed through fully connected layers for classification, distinguishing between tumor and non-tumor regions based on learned patterns, ultimately aiding in accurate brain tumor diagnosis.
KNC	K-Neighbors Classifier (KNC) method for diagnosing brain tumors using brain MRI scans operates by analyzing the proximity of each MRI scan to its neighboring data points in a high-dimensional feature space. KNC assigns a class label to a given MRI scan based on the majority class among its k nearest neighbors, where k is a user-defined parameter. This proximity-based approach allows KNC to effectively identify brain tumors by leveraging the collective characteristics of nearby MRI scans in the dataset, making it a valuable tool in medical image analysis Raza et al. (2023, 2022a).
LR	Logistic Regression (LR) van Ravesteijn et al. (2010) for diagnosing brain tumors using MRI scans begins by collecting a dataset of brain MRI images along with corresponding binary labels indicating the presence or absence of tumors. The LR model calculates the probability of a brain tumor being present in each MRI scan by applying a logistic function to a linear combination of image features extracted from the scans. It learns the optimal weights for these features during training. Once trained, the LR model can classify new MRI scans as tumor-positive or tumor-negative based on the probability threshold (typically 0.5), providing a valuable tool for non-invasive brain tumor diagnosis.
RF	Random Forest (RF) Dutta et al. (2023) for diagnosing brain tumors using MRI scans work by first collecting a diverse dataset of brain MRI images with corresponding tumor labels. The RF algorithm then creates multiple decision trees using random subsets of the data and features, allowing each tree to classify tumor presence or absence independently. RF combines the results from these trees through voting or averaging, resulting in a robust and accurate diagnosis of brain tumors from MRI scans.

trained models on large datasets and have shown promise in enhancing diagnostic accuracy by transferring knowledge learned from other domains or medical imaging tasks to improve the performance of brain tumor diagnosis. Integrating AI-driven methods in brain tumor diagnosis accelerates the detection process and aids healthcare providers in making more accurate and timely decisions.

In this research, we employed several advanced machine learning and deep learning-based approaches for performance evaluations. We utilized two neural network approaches, 2D-CNN and VGG16, for both classification and transferring feature mechanisms from MRI images. The machine learning models we employed include the k-neighbors classifier, logistic regression, and random forest. We have provided a detailed description of the working mechanisms of each applied neural network in Table 3.

3.5 Hyper-parameter setting

Hyperparameter tuning is a crucial aspect of optimizing neural network models in machine learning. These hyperparameters are configurations external to the model and can significantly impact its performance. In our research, we focus on systematically exploring and optimizing these hyperparameters to enhance the overall efficiency and effectiveness of neural networks. We employ a recursive process of training and evaluations to determine the best-fit hyperparameters. The selected hyperparameters for the neural

Table 3. The layered architecture analysis of applied neural network approaches.

Layer (type)	Output Shape	Param #
2D-CNN		
conv2d (Conv2D)	(None, 126, 126, 64)	1792
max_pooling2d (MaxPooling2D)	(None, 63, 63, 64)	0
dropout (Dropout)	(None, 63, 63, 64)	0
flatten (Flatten)	(None, 254016)	0
dense (Dense)	(None, 4)	1016068
VGG-16		
vgg16 (Functional)	(None, 4, 4, 512)	14714688
dropout_2 (Dropout)	(None, 4, 4, 512)	0
flatten_2 (Flatten)	(None, 8192)	0
dense_2 (Dense)	(None, 4)	32772

246 network applied to diagnose brain tumors are presented in Table 4.

Table 4. The hyper-parameters tuning analysis of applied neural network approaches.

Method	Hyper-parameters Description
2D-CNN	activation= 'softmax', Dropout=0.02, optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy','Precision','Recall']
VGG-16	weights = 'imagenet', include_top = False, activation= 'softmax', Dropout=0.02, optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy','Precision','Recall']
KNC	n_neighbors=3, weights='uniform', leaf_size=30, p=2
LR	penalty='l2', tol=1e-4, C=1.0, solver='lbfgs'
RF	max_depth=50, criterion="gini", random_state=0, n_estimators=50, max_features="sqrt"

4 RESULTS AND DISCUSSIONS

248 The results and discussions of our study methods proposed for the diagnosis of brain tumors using brain
249 MRI scans are analyzed in this section. We have provided a comprehensive analysis of the results obtained
250 through the application of neural network methods. In this section, we dive into the key findings and their
251 implications for the field of medical imaging and brain tumor diagnosis.

4.1 Experimental setup

253 Our proposed experimental study setup includes the use of the Google Colab platform to evaluate research
254 results. The platform offers GPU backend support, providing 90 GB of disk space and 13 GB of RAM.
255 We have employed the Python 3.0 programming language to build the neural network used in our research.
256 We utilized the Sklearn, Tensorflow, and Keras modules for evaluating the results. During performance
257 evaluations, True Positives (TP), True Negatives (TN), False Positives (FP), and False Negatives (FN)
258 are used as basic parameters. The performance metrics used for performance evaluation are examined as
259 follows:

260 • **Accuracy:** in diagnosing brain tumors using brain MRI scans refers to measuring how effectively

the diagnostic system or method correctly identifies and classifies the presence or absence of brain tumors in the MRI images.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

- **Precision:** in diagnosing brain tumors using brain MRI scans refers to measuring how accurately the diagnostic test identifies TP cases among all the positive cases it detects.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

- **Recall:** in diagnosing brain tumors using brain MRI scans, is a fundamental performance metric that measures the ability of a diagnostic model or process to correctly identify and classify TP cases of brain tumors among all the actual cases of brain tumors present in the MRI scans.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

- **F1:** in diagnosing brain tumors using brain MRI scans, is a measure that combines precision and recall to assess the accuracy of the classification model.

$$F1\ Score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} \tag{4}$$

- **Runtime Computations:** is a neural network method's brain tumor diagnosis time by inputting MRI images.

- **Standard Deviations (SD):**a refers to a statistical measure of the variability of the evaluation metrics obtained from multiple folds of the dataset during the cross-validation process.

$$\sigma = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \mu)^2} \tag{5}$$

4.2 Performance analysis with classical approaches

The performance analysis of the applied classical deep learning-based approaches, 2DCNN and VGG16, is conducted in this section. MRI brain scan images are fed into the 2DCNN and VGG16 methods, and the results are then evaluated.

4.2.1 Results of CNN Model

The performance results of the applied CNN model during training are illustrated in Figure 5. We conducted a time series analysis over 20 epochs of the CNN model. The evaluation is based on loss scores, accuracy, precision, and recall. The analysis reveals that the training loss is very high in the first two epochs. Subsequently, there is a notable reduction in loss, while the validation loss gradually increases. Similarly, the training accuracy starts off low in the initial two epochs, but then exhibits a steady increase. The validation accuracy scores fluctuate around 0.80. The precision and recall metrics exhibit a similar pattern to the accuracy performance scores throughout training. In conclusion, this analysis indicates that the CNN model achieved acceptable scores for brain tumor diagnosis during training. Nevertheless, there is still a need for performance enhancement.

The performance analysis of the applied CNN model for unseen testing data is described in Table 5. The analysis shows that the CNN model achieved an acceptable score of 0.76 during brain tumor diagnosis. However, the loss scores are high for the testing data. The class-wise performance scores also demonstrate moderate results. This analysis concludes that classical approaches have not proven fruitful in this case; there is a need for advanced mechanisms for performance enhancement.
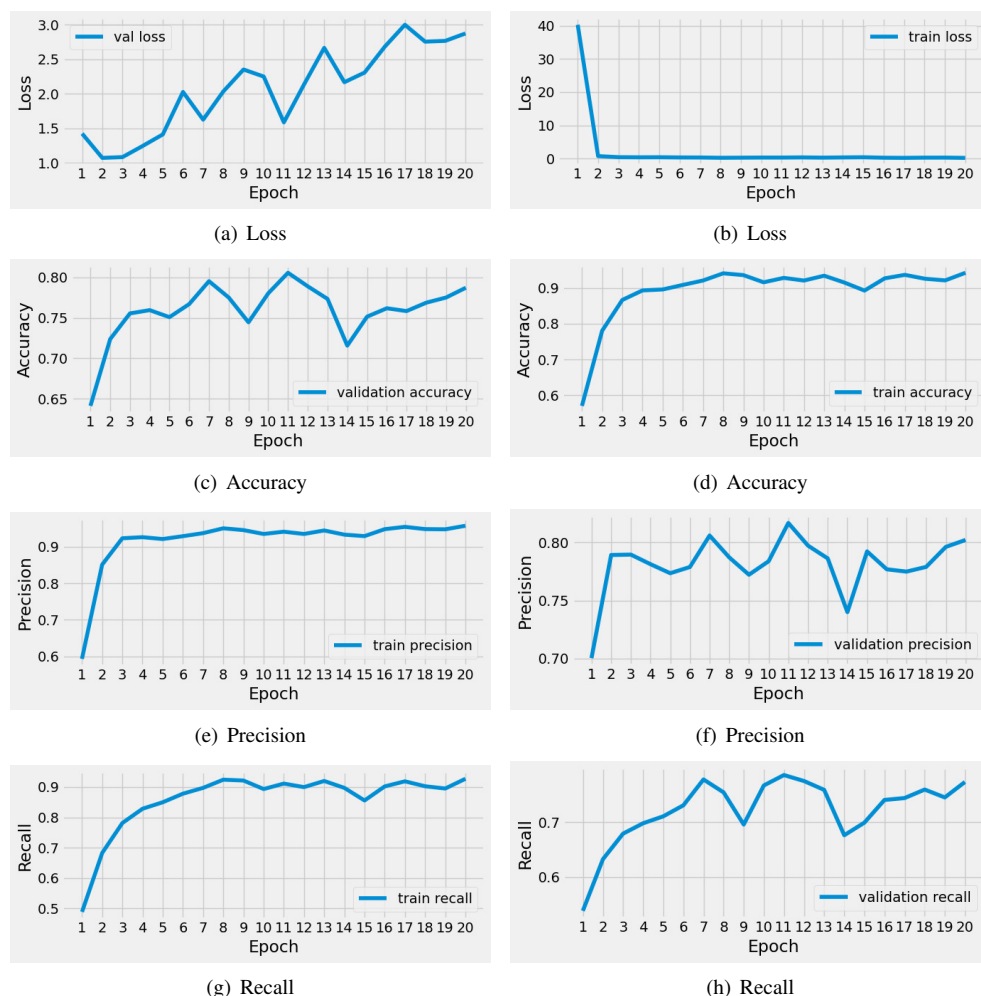
Figure 5. The time series-based results comparison of CNN model during training.

Table 5. The results analysis of applied 2D-CNN neural network.

Accuracy	Loss	Target Class	Precision	Recall	F1
0.76	3.64	Normal	0.72	0.76	0.74
		Glioma_tumor	0.70	0.68	0.69
		Meningioma_tumor	0.78	0.75	0.77
		Pituitary_tumor	0.87	0.87	0.87
		Average	0.77	0.76	0.77

4.2.2 Results of VGG16 Model

The performance results of the applied pre-trained VGG16 model during training are illustrated in Figure 6. We conducted a time series analysis over 20 epochs of the VGG16 model. The analysis reveals that the training loss is very high in the first five epochs. Subsequently, there is a notable reduction in loss, while the validation loss gradually increases. Similarly, the training accuracy starts off low in the initial two epochs, but then exhibits a steady increase. The validation accuracy scores fluctuate around 0.92. The precision and recall metrics exhibit a similar pattern to the accuracy performance scores throughout training. In conclusion, this analysis indicates that the VGG16 model achieved good scores for brain tumor diagnosis during training. Nevertheless, there is still a need for performance enhancement.

The performance analysis of the applied VGG-16 model on unseen testing data is outlined in Table 6. The analysis reveals that the VGG-16 model achieved a commendable score of 0.90 in brain tumor
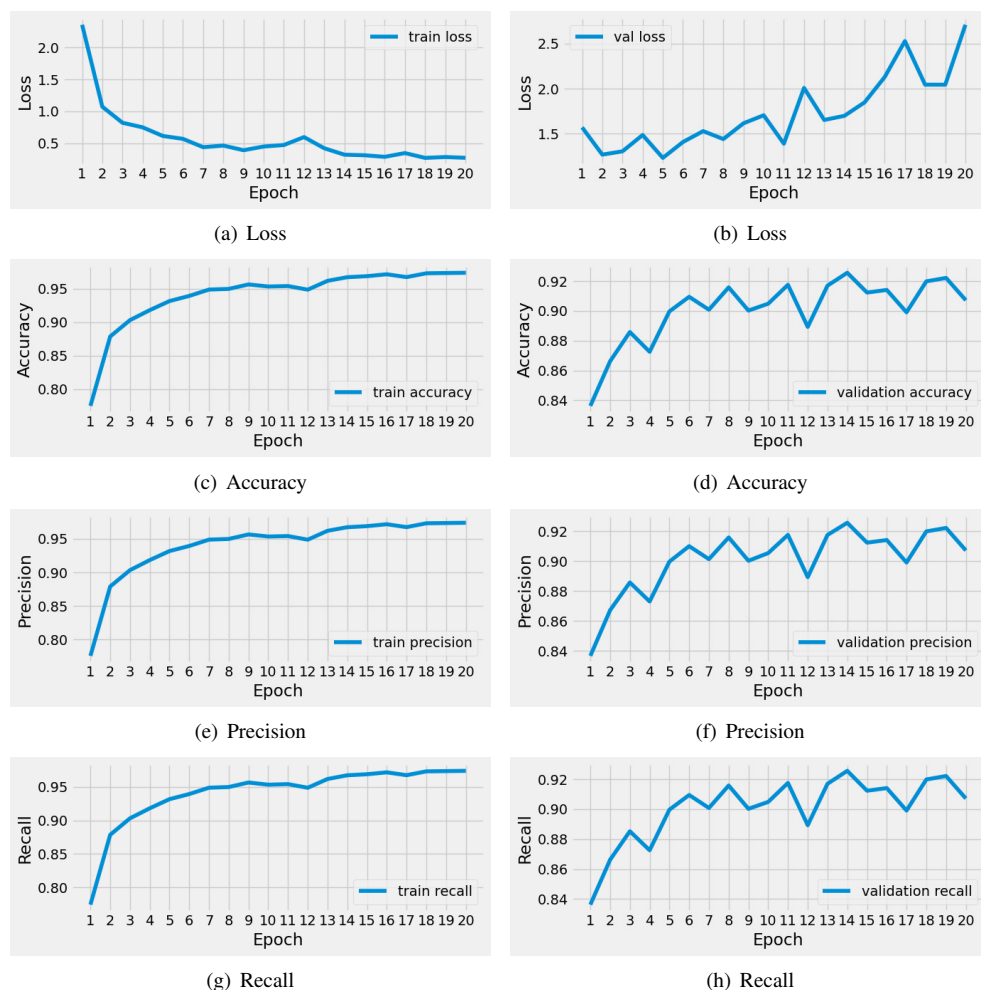
Figure 6. The time series-based results comparison of VGG16 model during training.

diagnosis. Nevertheless, the loss scores were notably high for the testing data. The class-wise performance scores also demonstrate positive results, with 0.91 precision and f1 scores. This analysis leads to the conclusion that classical approaches yielded a moderately satisfactory performance. However, there is a pressing need for advanced mechanisms to enhance performance.

Table 6. The results analysis of applied VGG-16 neural network.

Accuracy	Loss	Target Class	Precision	Recall	F1
0.90	2.66	Normal	0.99	0.89	0.94
		Glioma_tumor	0.91	0.85	0.88
		Meningioma_tumor	0.83	0.93	0.87
		Pituitary_tumor	0.96	0.95	0.95
		Average	0.91	0.90	0.91

4.3 Performance analysis with Novel approach

The performance analysis of the applied advanced machine learning methods with the novel proposed CVG-Net feature engineering is presented in this section. The proposed approach extracts novel transfer features by inputting MRI brain scan images into the 2DCNN and VGG16 methods, creating a hybrid feature set. The newly created features are then input into machine learning models, and the results are subsequently evaluated.

4.4 Results with unbalanced features

In this section, the novel extracted features that are unbalanced are inputted into applied machine learning methods for performance evaluations. The performance results of machine learning methods with unbalanced features are described in Table 7. The analysis demonstrates that applied machine learning models achieved high-performance scores using the novel extracted transfer features. The LR and RF achieved accuracy performance scores of 0.81 and 0.85, respectively. The applied KCN approach achieved a good score of 0.94. This analysis concludes that with unbalanced novel features, good performance is achieved. However, the performance can be further improved by applying advanced data-balancing approaches.

Table 7. The results analysis of applied neural networks with novel unbalanced features.

Method	Accuracy	Target Class	Precision	Recall	F1
LR	0.81	Normal	0.87	0.81	0.84
		Glioma_tumor	0.79	0.82	0.81
		Meningioma_tumor	0.76	0.73	0.75
		Pituitary_tumor	0.87	0.91	0.89
		Average	0.82	0.82	0.82
RF	0.85	Normal	0.95	0.85	0.90
		Glioma_tumor	0.82	0.83	0.83
		Meningioma_tumor	0.81	0.78	0.80
		Pituitary_tumor	0.87	0.95	0.91
		Average	0.87	0.85	0.86
KNC	0.94	Normal	0.94	0.93	0.94
		Glioma_tumor	0.91	0.96	0.93
		Meningioma_tumor	0.96	0.87	0.91
		Pituitary_tumor	0.95	0.98	0.96
		Average	0.94	0.94	0.94

4.5 Results with balanced features

After evaluating the performance scores with unbalanced feature data, we applied the famous data balancing Synthetic Minority Oversampling Technique (SMOTE) to the extracted feature data. The evaluation results of the applied machine learning approach with a balanced dataset are demonstrated in Table 8. The analysis reveals that balanced features help improve performance scores for the diagnosis of brain tumors. The proposed KNC method outperformed other applied methods with a high accuracy of 0.95 in comparison. This analysis concludes that SMOTE-based dataset balancing helps us improve performance scores.

The confusion matrix allows visualization of the performance of applied machine learning methods for the diagnosis of brain tumors. The overall performance validation, based on the confusion matrix, is illustrated in Figure 7. The analysis shows that the applied LR and RF have high wrong predictions for target classes 2 and 3. The minimum error rate, indicating the fewest wrong predictions, is achieved by the proposed K-Nearest Neighbors Classification (KNC) approach. This analysis validates the high-performance scores of the proposed KNC method for the diagnosis of brain tumors using MRI scans.

4.6 validating performance with k-fold mechanism

We have validated the performance of applied machine-learning approaches in this section using both unbalanced and balanced feature data. The results of k-fold cross-validations are demonstrated in Table 9. To validate accuracy performance results, we used a fold split of 10 and determined the outcomes. The analysis shows that with unbalanced features, LR and RF achieved acceptable validation accuracy scores in the range of 0.81 to 0.84. The proposed approach achieved a commendable score of 0.94. When we evaluated results with the balanced dataset, performance scores increased for each applied approach. The analysis concludes that the proposed KNC approach achieved the highest k-fold accuracy scores of 0.96 for the diagnosis of brain MRI scans.

Table 8. The results analysis of applied neural networks with novel balanced features.

Method	Accuracy	Target Class	Precision	Recall	F1
LR	0.84	Normal	0.91	0.93	0.92
		Glioma_tumor	0.82	0.79	0.80
		Meningioma_tumor	0.74	0.72	0.73
		Pituitary_tumor	0.87	0.90	0.89
		Average	0.84	0.84	0.84
RF	0.88	Normal	0.96	0.97	0.96
		Glioma_tumor	0.83	0.83	0.83
		Meningioma_tumor	0.82	0.76	0.79
		Pituitary_tumor	0.90	0.95	0.92
		Average	0.88	0.88	0.88
KNC	**0.95**	Normal	0.96	0.99	0.97
		Glioma_tumor	0.93	0.95	0.94
		Meningioma_tumor	0.95	0.88	0.91
		Pituitary_tumor	0.96	0.99	0.98
		Average	**0.95**	**0.95**	**0.95**
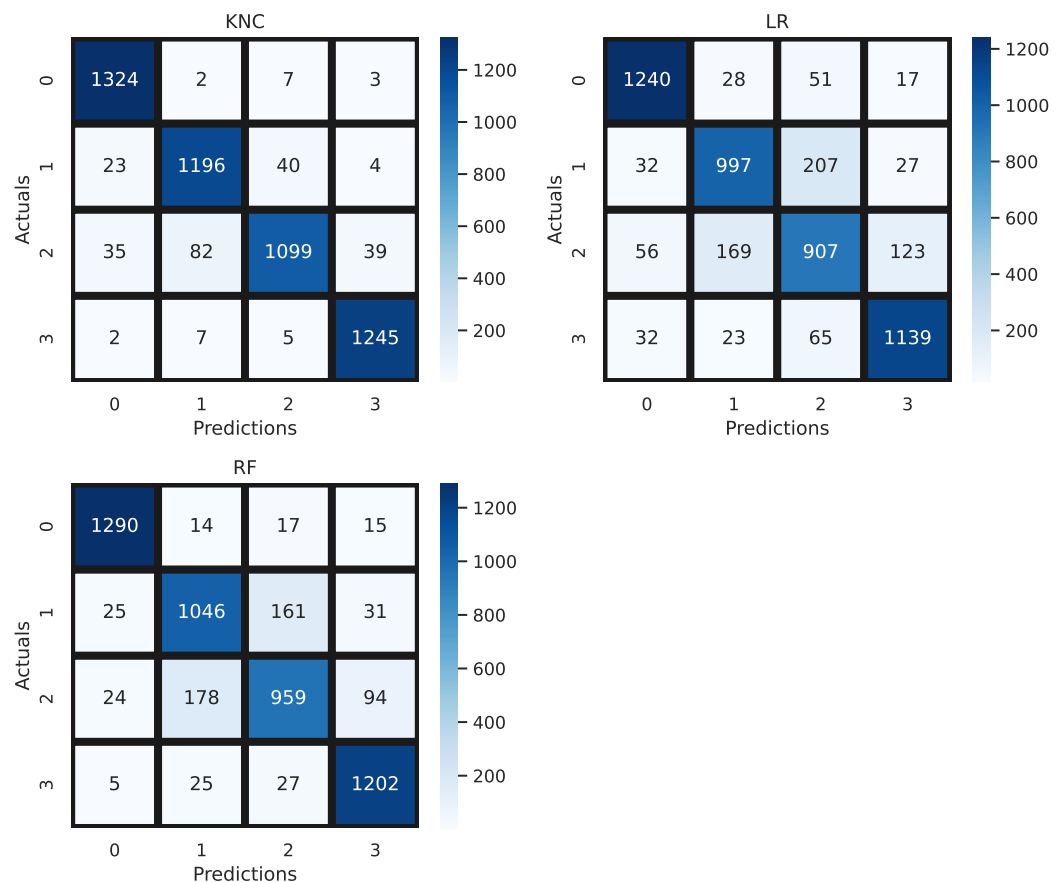
Figure 7. Confusion matrix analysis of applied neural network approaches.

4.7 Computational Complexity analysis

In this section, we present a computational complexity analysis of applied machine learning methods. The runtime computations, measured in seconds, of these applied machine learning methods, are determined during each model-building process using a newly created features dataset. The computation results are

Table 9. K-fold cross-validations results analysis of applied neural networks.

Method	Unbalanced Features		Balanced Features	
	10-fold Accuracy	SD (+/-)	10-fold Accuracy	SD (+/-)
LR	0.81	0.005	0.83	0.009
RF	0.84	0.007	0.88	0.005
KNC	**0.94**	**0.004**	**0.96**	**0.005**

350 reported in Table 10. Our analysis demonstrates that the proposed KNC method achieved the minimum
351 runtime computations compared to other applied methods. The proposed KNC method takes only 0.0281
352 seconds to diagnose brain tumors.

Table 10. Computational complexity analysis of applied neural networks with novel balanced features.

Method	Runtime (seconds)
LR	3.7201
RF	24.215
KNC	**0.0281**

4.8 Comparison with state-of-the-art studies

354 For a fair performance comparison, we have included state-of-the-art studies in brain tumor diagnosis
355 in this analysis. The performance comparison of our proposed approach is illustrated in Table 11. The
356 studies considered for performance comparison are from the years 2020, 2022, and 2023. The analysis
357 reveals that our proposed approach outperformed state-of-the-art studies with high-performance scores of
358 0.96 for the diagnosis of brain tumors using MRI brain scans.

Table 11. The performance comparison with state-of-the-art studies for brain tumor diagnosis.

Ref.	Year	Proposed Technique	Accuracy
Archana et al. (2023)	2023	AlexNet with SGD	0.80
Sudharson et al. (2022)	2022	Hybrid CNN	0.93
Sharif et al. (2020)	2020	Inception V3 with CNN	0.92
Yazdan et al. (2022)	2022	Multi-Scale CNN	0.91
Our	**2024**	**CVG-Net-KNC**	**0.96**

5 CONCLUSIONS AND FUTURE WORK

360 This research proposes an effective neural network approach for the timely diagnosis of brain tumors.
361 Our experiments utilized a multi-class MRI image dataset comprising 21,672 images related to glioma
362 tumors, meningioma tumors, and pituitary tumors. We introduced a novel neural network-based feature
363 engineering approach called CVG-Net, which combines 2DCNN and VGG16. The proposed CVG-Net
364 method extracts spatial features from MRI images using 2DCNN and VGG16 without human intervention.
365 The newly created hybrid feature set is then input into machine learning models to diagnose brain tumors.
366 We utilized four advanced machine learning models and two deep learning models based on neural
367 networks for comparative performance evaluations. We also balanced the multi-class MRI image features
368 data using the SMOTE approach. Extensive research experiments demonstrate that utilizing the proposed
369 CVG-Net, the k-nearest neighbors classifier outperformed state-of-the-art studies with a k-fold accuracy
370 performance score of 0.96. We also applied hyperparameter tuning to enhance performance for multi-class
371 brain tumor diagnosis.

5.1 future work

373 In future, we intend to design a graphical user interface app for medical specialists to facilitate the effective
374 diagnosis of brain tumors using MRI scans. Also we plan to enhance the performance by implementing

375 transfer learning-based advanced neural networks. The designed app will utilize the proposed approach in
376 the backend for diagnosis.

ACKNOWLEDGMENTS

378 This research is supported by Princess Nourah bint Abdulrahman University Researchers Supporting
379 Project number (PNURSP2023R136), Princess Nourah bint Abdulrahman University, Riyadh, Saudi
380 Arabia. The authors are also thankful to Prince Sultan University, Riyadh Saudi Arabia for support of
381 APC for this publication.

REFERENCES

383 Archana, B., Karthigha, M., and Suresh Lavanya, D. (2023). Comparative analysis of optimisers used
384   in cnn for brain tumor detection. In *2023 5th International Conference on Inventive Research in
385   Computing Applications (ICIRCA)*, pages 687–692.

386 Badjie, B. and Deniz Ülker, E. (2022). A deep transfer learning based architecture for brain tumor
387   classification using mr images. *Information Technology and Control*, 51(2):332 – 344.

388 Bhatele, K. R. and Bhadauria, S. S. (2023). Multiclass classification of central nervous system brain tumor
389   types based on proposed hybrid texture feature extraction methods and ensemble learning. *Multimedia
390   Tools and Applications*, 82(3):3831–3858.

391 Dutta, P., Paul, S., Jana, G. G., and Sadhu, A. (2023). Hybrid genetic algorithm random forest algorithm
392   (hgarf) for improving the missing value imputation in hepatitis medical dataset. In *2023 International
393   Symposium on Devices, Circuits and Systems (ISDCS)*, volume 1, pages 01–05.

394 Fabelo, H., Halicek, M., Ortega, S., Shahedi, M., Szolna, A., Piñeiro, J. F., Sosa, C., O'Shanahan, A. J.,
395   Bisshopp, S., Espino, C., et al. (2019). Deep learning-based framework for in vivo identification of
396   glioblastoma tumor using hyperspectral images of human brain. *Sensors*, 19(4):920.

397 Hashemi, S. M. H. (2023). Crystal clean: Brain tumors mri dataset. https://www.kaggle.com/ds/3505991.
398   (Accessed on 09/05/2023).

399 Khan, M. A., Khan, A., Alhaisoni, M., Alqahtani, A., Alsubai, S., Alharbi, M., Malik, N. A., and
400   Damaševičius, R. (2023). Multimodal brain tumor detection and classification using deep saliency
401   map and improved dragonfly optimization algorithm. *International Journal of Imaging Systems and
402   Technology*, 33(2):572 – 587.

403 Khazaei, Z., Goodarzi, E., Borhaninejad, V., Iranmanesh, F., Mirshekarpour, H., Mirzaei, B., Naemi, H.,
404   Bechashk, S. M., Darvishi, I., Ershad Sarabi, R., et al. (2020). The association between incidence and
405   mortality of brain cancer and human development index (hdi): an ecological study. *BMC Public Health*,
406   20(1):1–7.

407 Kibriya, H., Masood, M., Nawaz, M., and Nazir, T. (2022). Multiclass classification of brain tumors using
408   a novel cnn architecture. *Multimedia Tools and Applications*, 81(21):29847–29863.

409 Kurdi, S. Z., Ali, M. H., Jaber, M. M., Saba, T., Rehman, A., and Damaševičius, R. (2023). Brain tumor
410   classification using meta-heuristic optimized convolutional neural networks. *Journal of Personalized
411   Medicine*, 13(2).

412 Latif, G., Ben Brahim, G., Iskandar, D. A., Bashar, A., and Alghazo, J. (2022). Glioma tumors'
413   classification using deep-neural-network-based features with svm classifier. *Diagnostics*, 12(4):1018.

414 Li, S., Wang, C., Chen, J., Lan, Y., Zhang, W., Kang, Z., Zheng, Y., Zhang, R., Yu, J., and Li, W. (2023a).
415   Signaling pathways in brain tumors and therapeutic interventions. *Signal Transduction and Targeted
416   Therapy*, 8(1):8.

417 Li, Z., Wang, Y., Jiang, Z., Luo, Z., Wu, J., and Toe, T. T. (2023b). Ensemble of cnn models for
418   identifying stages of alzheimer's disease: An approach using mri scans and smote algorithm. In
419   *2023 3rd International Symposium on Computer Technology and Information Science (ISCTIS)*, pages
420   496–500.

421 Liu, H., Huo, G., Li, Q., Guan, X., and Tseng, M.-L. (2023a). Multiscale lightweight 3d segmentation al-
422   gorithm with attention mechanism: Brain tumor image segmentation. *Expert Systems with Applications*,
423   214:119166.

424 Liu, Z., Tong, L., Chen, L., Jiang, Z., Zhou, F., Zhang, Q., Zhang, X., Jin, Y., and Zhou, H. (2023b). Deep
425   learning based brain tumor segmentation: a survey. *Complex & intelligent systems*, 9(1):1001–1026.

426 Maqsood, S., Damasevicius, R., and Shah, F. M. (2021). An efficient approach for the detection of

brain tumor using fuzzy logic and u-net cnn classification. *Lecture Notes in Computer Science*, 12953 LNCS:105 – 118.

Maqsood, S., Damaševičius, R., and Maskeliūnas, R. (2022). Multi-modal brain tumor detection using deep neural network and multiclass svm. *Medicina (Lithuania)*, 58(8).

Mehnatkesh, H., Jalali, S. M. J., Khosravi, A., and Nahavandi, S. (2023). An intelligent driven deep residual learning framework for brain tumor classification using mri images. *Expert Systems with Applications*, 213:119087.

Miao, Y.-B., Zhao, W., Renchi, G., Gong, Y., and Shi, Y. (2023). Customizing delivery nano-vehicles for precise brain tumor therapy. *Journal of Nanobiotechnology*, 21(1):32.

Oztek, M. A., Noda, S. M., Romberg, E. K., Cole, B. L., Wright, J. N., Ishak, G. E., and Perez, F. A. (2023). Changes to pediatric brain tumors in 2021 world health organization classification of tumors of the central nervous system. *Pediatric Radiology*, 53(3):523–543.

Qadri, A. M., Raza, A., Munir, K., and Almutairi, M. S. (2023). Effective feature engineering technique for heart disease prediction with machine learning. *IEEE Access*, 11:56214–56224.

Rajinikanth, V., Kadry, S., Damasevicius, R., Sujitha, R. A., Balaji, G., and Mohammed, M. A. (2022). Glioma/glioblastoma detection in brain mri using pre-trained deep-learning scheme. page 987 – 990.

Rajinikanth, V., Kadry, S., and Nam, Y. (2021). Convolutional-neural-network assisted segmentation and svm classification of brain tumor in clinical mri slices. *Information Technology and Control*, 50(2):342 – 356.

Raza, A., Rustam, F., Siddiqui, H. U. R., Diez, I. d. l. T., and Ashraf, I. (2023). Predicting microbe organisms using data of living micro forms of life and hybrid microbes classifier. *Plos one*, 18(4):e0284522.

Raza, A., Rustam, F., Siddiqui, H. U. R., Diez, I. d. l. T., Garcia-Zapirain, B., Lee, E., and Ashraf, I. (2022a). Predicting genetic disorder and types of disorder using chain classifier approach. *Genes*, 14(1):71.

Raza, A., Siddiqui, H. U. R., Munir, K., Almutairi, M., Rustam, F., and Ashraf, I. (2022b). Ensemble learning-based feature engineering to analyze maternal health during pregnancy and health risk prediction. *Plos one*, 17(11):e0276525.

Rehman, A., Raza, A., Alamri, F. S., Alghofaily, B., and Saba, T. (2023). Transfer learning-based smart features engineering for osteoarthritis diagnosis from knee x-ray images. *IEEE Access*, 11:71326–71338.

Rohith, S., Prakash, M. S., Anitha, R., Kumar, K. S., and Yogeswara Sai, K. (2023). Detection of brain tumor using vgg16. In *2023 8th International Conference on Communication and Electronics Systems (ICCES)*, pages 1400–1405.

Sharif, M. I., Li, J. P., Khan, M. A., and Saleem, M. A. (2020). Active deep neural network features selection for segmentation and recognition of brain tumors using mri images. *Pattern Recognition Letters*, 129:181–189.

Shourie, P., Anand, V., and Gupta, S. (2023). An intelligent vgg-16 framework for brain tumor detection using mri-scans. In *2023 International Conference on Smart Systems for applications in Electrical Sciences (ICSSES)*, pages 1–6.

Stadlbauer, A., Marhold, F., Oberndorfer, S., Heinz, G., Buchfelder, M., Kinfe, T. M., and Meyer-Bäse, A. (2022). Radiophysiomics: brain tumors classification by machine learning and physiological mri data. *Cancers*, 14(10):2363.

Sudharson, K., Sermakani, A., Parthipan, V., Dhinakaran, D., Eswari Petchiammal, G., and Usha, N. (2022). Hybrid deep learning neural system for brain tumor detection. In *2022 2nd International Conference on Intelligent Technologies (CONIT)*, pages 1–6.

Thierheimer, M., Cioffi, G., Waite, K. A., Kruchko, C., Ostrom, Q. T., and Barnholtz-Sloan, J. S. (2023). Mortality trends in primary malignant brain and central nervous system tumors vary by histopathology, age, race, and sex. *Journal of Neuro-oncology*, 162(1):167–177.

van Ravesteijn, V. F., van Wijk, C., Vos, F. M., Truyen, R., Peters, J. F., Stoker, J., and van Vliet, L. J. (2010). Computer-aided detection of polyps in ct colonography using logistic regression. *IEEE Transactions on Medical Imaging*, 29(1):120–131.

Yazdan, S. A., Ahmad, R., Iqbal, N., Rizwan, A., Khan, A. N., and Kim, D.-H. (2022). An efficient multiscale convolutional neural network based multi-class brain mri classification for samd. *Tomography*, 8(4):1905–1927.

Zhang, H., He, H., Gao, Y., Mady, A., Filipović, V., Dyck, M., Lv, J., and Liu, Y. (2023). Applications

482   of computed tomography (ct) in environmental soil and plant sciences. *Soil and Tillage Research*,
483   226:105574.

484 Zhou, Q., Huang, Z., Ding, M., and Zhang, X. (2023). Medical image classification using light-weight
485   cnn with spiking cortical model based attention module. *IEEE Journal of Biomedical and Health*
486   *Informatics*, 27(4):1991–2002.

487 Zhu, Z., He, X., Qi, G., Li, Y., Cong, B., and Liu, Y. (2023). Brain tumor segmentation based on the
488   fusion of deep semantics and edge information in multimodal mri. *Information Fusion*, 91:376–387.