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APPLIED RESEARCH

A CNN-Model to Classify Low-Grade and High-Grade Glioma From MRI Images

HAFIZ AAMIR HAFEEZ[1], MOHAMED A. ELMAGZOUB[2], NURUL AZMA BINTI ABDULLAH[1], MANA SALEH AL RESHAN[3], GHULAM GILANIE[4], SULTAN ALYAMI[5], MAHMOOD UL HASSAN[6], AND ASADULLAH SHAIKH[3], (Senior Member, IEEE)

[1]Department of Computer Science, University Tun Hussein Onn Malaysia (UTHM), Parit Raja, Johor 86400, Malaysia
[2]Department of Network and Communication Engineering, College of Computer Science and Information Systems, Najran University, Najran 61441, Saudi Arabia
[3]Department of Information Systems, College of Computer Science and Information Systems, Najran University, Najran 61441, Saudi Arabia
[4]Department of Artificial Intelligence, Faculty of Computing, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
[5]Department of Computer Science, College of Computer Science and Information Systems, Najran University, Najran 61441, Saudi Arabia
[6]Department of Computer Skills, Deanship of Preparatory Year, Najran University, Najran 61441, Saudi Arabia

Corresponding author: Ghulam Gilanie (ghulam.gilanie@iub.edu.pk)

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ABSTRACT Glioma is the most occurring brain tumor in the world. Its grade (level of severity) identification, crucial in its treatment planning, is most demanding in a clinical environment. Computer-aided methods have been experimented with to identify the grade of glioma, out of which deep learning-based methods, due to their auto features engineering, have a good impact in terms of their achieved outcomes. In this study, convolutional neural networks (CNNs) have been explored and utilized for the classification of glioma grading, for example, low grade (grade I-II) and high grade (grade III-IV). A CNN-based model, which is light-weighted in terms of layers, size, and learnable parameters, has been proposed. Experimental tests were carried out on benchmarked publicly available datasets, for example, Brats-2017, Brats-2018, & Brats-2019. A locally developed dataset from Bahawal Victoria Hospital, Bahawalpur, Pakistan, has also been employed for experimentation and research to cross-validate the outcomes. Additionally, experiments have been carried out to compare the effectiveness of the proposed model, and results have been compared with the results of state-of-the-art pertained CNN models, i.e., resnet18, squeezenet, and alexnet. The proposed model achieved maximum standard evaluation measures on the benchmarked dataset, i.e., accuracy, specificity, and sensitivity at 97.85%, 98.88%, and 99.88%, respectively. Similarly, these measures were 98.89%, 99.28%, and 99.77% on a locally developed dataset, which is the best compared to the recent state-of-the-art related studies.

INDEX TERMS Low and high-grade glioma grading, convolutional neural networks, MRI images.

I. INTRODUCTION

Most diagnostic protocols in a clinical environment rely on imaging-based tests for authentic health disorders. However, clinicians interpret this imagery data manually, and where required, other pathologies or microbiology-based tests are recommended [1]. These tests are not only time-consuming but require surgical processes also. For other anatomical structures, they are somewhat affordable; however, in the case of the brain, any surgery before treatment planning is proved dangerous. In recent decades, the use of computer vision in medicine has significantly increased. Nowadays, computer vision and machine learning are widely accepted around the globe [2], hence, changing the way medical practitioners use computers. These two combined disciplines played an essential role in medical diagnostics and the most prominent role in automated, reliable, cost-effective, and risk-free diagnosis, prognosis, automated maintaining medical history, innovative prescription, etc. Ultimately, these are increasing life expectancy and

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survival rates. Consequently, they become essential tools for diagnostics.

For example, if you have a brain tumor, the proliferation of normal brain cells is affected. Brain tumors are diagnosed, graded, and classified using biopsies and imaging-based testing. Glioma is a tumor that grows in the central nervous system and may spread to other body parts. Modern research suggests various strategies for automatically diagnosing and rating gliomas based on photographs. Convolutional neural networks (CNN) and other machine learning models are experimented with to obtain the desired results, but every situation has pros and cons. For better results, we'll train a CNN model in this study. Two modes are used for classification: feature extraction through the own designed CNN model and classification through a support vector machine (SVM). The second is feature extraction and classification through CNN. It classifies glioma into two grades, HGG and LGG. This will help the concerned officials find the actual stage of the disease and recommend a lifesaving treatment.

Classification of a brain tumor depends on its severity and where it originates or is currently present. According to the severity of the tumor, it has two types, i.e., malignant and benign [3]. Classification based on location is either primary or secondary, i.e., if it originates and remains inside the brain is primary. Otherwise, it originates in other part of the body and travels toward the brain, secondary or metastatic [4]. Based on its severity, it is classified according to world health organization grades, i.e., grades I-IV. Grade-I and grade II tumors are low grades, while Grade-IIII and Grade-IV tumors are high grades [5]. Higher-grade tumors provide a more significant threat since they are more aggressive. Among the deadliest illnesses in the world is a brain tumor. So, it's critical to get the proper diagnosis and treatment for your condition.

Besides primary or secondary and benign or malignant, brain tumor is also classified based on cells affected by the tumor. Gliomas, the brain tumor present in glial cells of the central nervous system, is one of the most occurring brain tumor types. Like brain tumors, glioma is also graded as low and high grades [6]. These grades depend on the potential and aggressiveness of the tumor. Low-graded glioma is slow-growing, while high-graded is fast-growing, hence, most dangerous. Glioma patients' average age after the diagnosis is almost 15 months only, with few patients living more than two years. Upon diagnosis, the first thing is determining its stage, as treatment planning is severely dependent upon its stage [7].

Two methods are executed in clinical environments for diagnosing, classifying, and grading brain tumors. These methods are biopsy and imaging-based tests. During a biopsy, a suspicious person's sample tissues are examined. After a surgical biopsy, the physician sends it to a neuropathologist. Then a macroscopic and microscopic examination of these samples is completed by a neuropathologist. Biopsy determines information about the disease state, tissue appearance, and structure of the cells. The accuracy of the report genuinely depends on the expertise of the neuropathologist. Treatment options, i.e., surgery, radiation therapy, observation, chemotherapy, and prognosis, depend upon biopsy findings. The biopsy process may cause a minor injury. Sometimes. The number of tissues obtained from the needle is insufficient for biopsy; in this case, the biopsy may have to be repeated. After a technically successful procedure, surgical biopsy becomes necessary if biopsy remains uncertain. A biopsy is also undesired when, for instance, subjects' follow-up is required.

Since biopsy requires a surgical process, hence, may be dangerous in case of brain tumor diagnosis [8]. Hence, computer-aided diagnoses (CAD) have become very important. CAD systems use machine learning (ML) in diagnosis. Several ML techniques, i.e., support vector machine, deep learning, extreme learning, etc., played a vital role in assisting the radiology department in diagnosing health disorders. Advanced image technology combined with AI can potentially diagnose health disorders in automated, reliable, accurate, non-invasive, and autonomous manners. The use of imaging and AI is an emerging technology in the clinical world, which assists experts in executing speedily diagnostic procedures.

Researchers are focusing their efforts on the Grading of gliomas, which is the primary focus of their work. The World Health Organization (WHO) does Grading of gliomas, which assigns a number between 1 and 2. (III, IV). Research on high and low-grade brain tumors and four other gliomas is limited. It could be found by using machine learning and feature extraction techniques. It is critical information for the prediction of glioma grade. But improvements are needed all the time. A method that grades the glioma types with good accuracy and specificity.

Therefore, a protocol performing Grading of gliomas in non-invasive manners is highly desired in almost every medical unit where brain imaging facilities are available [9].

This research looks at the feasibility of employing a CNN-based convolutional neural network (CNN) to directly identify glioma grades from MRI scans without any harmful procedures. CNN models have been used to extract features, and CNN and SVM models have been used to classify glioma grades (SVM). The key contribution of this conducted study is as follows.

- The design and development of a CNN-based light-weighted model with 12 layers and 0.287 million parameters.
- The model with a lesser executable size could decide about LGG or HGG brain tumors from MRI slices in a reasonable time.

The entire article is arranged in this way. Section II has a literature review in which state-of-the-art studies have been discussed. After this, section III contains the proposed methodology of glioma grading, in which detail of datasets is also provided. Section IV presents the results and their discussions. Results have been organized in two ways, i.e., features extracted through deep learning and classification through SVM, and features extraction and classification using deep understanding. A comparison of the results with state-of-the-art methods is also part of this section. In the last, conclusions and future work are part of section V.

II. LITERATURE REVIEW

In a study [10], a CNN and genetic algorithm based method is proposed for gliomas grading (Grade II-IV). Datasets used in this study are taken from four databases, i.e., 600 MRI images from IXI dataset, 130 patients'' data from the REMBRANDT dataset, 199 patients' data from TCGA-GBM, and 60 patients' data from the neurosurgery section of Hazrat-e Rasool hospital Tehran, Iran. In one case study to classify three glioma grades, the accuracy achieved is 90.9%, while in another study, three tumor grades are organized with an accuracy of 94.2%.In another study [11], a non-invasive approach is used to classify gliomas grades, i.e., high-grade gliomas (HGG) and low-grade gliomas (LGG). Brain tumor segmentation (BraTS)-2018 dataset containing 285 subjects scanned through MRI is used for experiments. Out of these, 210 topics belong to HGG, while 75 belong to LGG. Random forest classifier issued for gliomas grade classification, on five-fold cross-validation. This study's accuracy, specificity, and sensitivity are 97.54%, 97.33%, and 97.62%, respectively.

In another study [12] the authors proposed a method consisting of two steps, i.e., 3D brain tumor segmentation from modified U-Net model and tumour classification in these segmented images. LGG consisting of grade II-III, and HGG consisting of grade IV, have been classified in this study. The braTS-2018 dataset has been used for research and experiments. The experimental outcomes are sensitivity=0.935, specificity=0.972, and accuracy=0.963 using two-dimensional Mask R-CNN. In comparison, the three-dimensional ConvNet method achieved sensitivity=0.947, specificity=0.968, and accuracy=0.971. In another study [13], authors proposed a method for automatic glioma tumor grade identification using the Wndchrm tool and VGG-19 MRI dataset collected from Government Medical College Calicut, India, containing 20 proven case subjects. Features are extracted after preprocessing, augmented, and then classified using these tools, where the most important features are carefully chosen based on the Fisher score. The outcomes in terms of accuracy are 92.86% for Wndchrm and 98.25% for the VGG-19 classifier.

In this study [14], authors used CNN for tumor stages estimation. 237 patients with gliomas were involved in this research. Features learned from the proposed model were considered to predict grades of gliomas. The results of the proposed study showed that learned features obtained an average correctness of 87% using radiomic features. In another research proposed by [15], authors used support vector machine (SVM) to train their proposed model 735 images of glioma patients (427 males and 308 females) are used for research. Ten-fold cross validation reported an accuracy of 75.12%.

In another study [16], glioma grade classification is done. Residual networks are used to represent features, while the Dempster-Shafer principle can be used for categorization. To prevent over-fitting, data augmentation is also used. The accuracy achieved by this method was 95.87%. In another research [17]. The Gaussian convolutional neural network classified glioma grades using images. The authors conducted experiments to differentiate three grades of glioma, namely Grades II-IV. The method was 97.14% accurate. In this study [18], three tumor types, viz; glioma, meningioma, and brainstem cancer, are detected using two publicly available datasets. Adam and Sgdam optimizers were employed in this study to assess performance. A public MRI imaging collection includes 233 and 73 individuals with 516 and 3064 T1-weighted images, respectively. The dataset produced the best results when it was partitioned using the Adam optimizer as 70% for training, 15% for validating, and 15% for testing. They developed the 25-layer CNN model. When utilizing the Adam optimizer, classification accuracy was 86.23 %, while Sgdam one accuracy was 81.6%. In this study [19], using 3D MRI data, a CNN-based architecture is proposed for brain tumor detection. The BRATS-19 dataset containing 335 glioma patients has been used to train the network. One CNN architecture is used to segregate cancers from multimodal MRI volumes, while the second one classifies it into three glioma types with the accuracy of 95.86%. This study [20] constructed a CNN model to process MRI for brain tumor diagnostics from the Kaggle small brain tumors dataset of 253 brain images. 155 MRI images of brain cancers and 98 MRI images of normal brain tissue are used for experiments. Their model achieved an F1-score of 96.50%, a precision of 96.50%, a recall of 96.49%, and an accuracy of 96.50%. This study [21] aims to categorize glioma tumors using a CNN, SVM, and k-nearest neighbours (KNN). The Cancer Imaging Archive database is used for research and experiments. CNN achieved classification accuracy (94.65%), SVM (86.1%), and KNN (66.7%).

In this study [22], using the Region-Based Convolutional Neural Network (RCNN) technique, a classification framework for a brain tumor and its types is developed. The authors used two datasets, i.e., Figshare and Kaggle. The Figshare dataset consists of 233 patients with 3064 slices of contrast-enhanced T1 images, while the Kaggle dataset consists of 255 T1 images. The outcomes using RCNN as per average confidence score is 98.83%. This study [23] offers an effective Bayesian Optimization-based technique for CNN hyperparameter optimization. Figshare brain tumor dataset with 3064 T1C MRI images of brain tumors, including Glioma, Meningioma, and Pituitary has been used for research and experiments. This dataset has been used to fine-tune and train five pre-trained CNN models, i.e., VGG16, VGG19, ResNet50, InceptionV3, and DenseNet201. VGG16, VGG19, ResNet50, InceptionV3, and DenseNet201 achieved validation accuracy of 97.08%, 96.43%, 89.29%, 92.86%, and 94.81%, respectively. This study [24] uses the VGG19 model for brain tumor categorization. The deep neural network is applied for the extraction of features. Experiments have been conducted using 3064 MRI slices belonging to 233 subjects from the Figshare dataset. The average accuracy achieved is 99.83%. The precision, recall, and specificity achieved against glioma, meningioma, and pituitary tumors detection is 96.32%, 98.26%, & 98.56%; 97.82%, 98.62%, & 98.87%; and 98.72%, 99.51%, & 99.43%, respectively. This study [25] proposes a fully automatic approach using CNN and SVM for brain tumor detection from MRI scans. Three brain tumor types, i.e., glioma, meningioma, and pituitary tumors have been diagnosed. Figshare's dataset consisting of 3064 T1C MRI slices from 233 people is sued for experiments with an overall classification accuracy of 95.82%.

It is established from the reviewed literature that most of the recently conducted studies are trained on a limited volume of the dataset, which could not ensure robustness. Moreover, most of these studies used a pretrained CNN model, which consists of a large number of layers, hence, increasing significant training time and their executables.

III. THE PROPOSED METHODOLOGY

A. DATASETS

The datasets used for research and experiments are shown in Table 1. Samples of the dataset used for research and development are shown in Fig. 1. Any images that needed manual segmentation were done by one to four reviewers who followed the same annotation methodology and validated by professional neuro-radiologists. Notes are made on three different areas of interest: a brightly colored tumor, edema around it, and the necrotic, non-enhancing tumor core itself. Founder to the same musculoskeletal template interpolated to almost the exact resolution (1 mm x 3 mm) and skull-stripped data are given after pre-processing. Experts in neuroradiology have radiologically evaluated the glioma collections for BraTS'17. Annotated by glioma sub-region specialists, all images (135 GBM and 108 LGG) were then included in the BraTS data set for 2019.

Bahawal Victoria Hospital, Bahawalpur, Pakistan, has compiled a local dataset of 159 HGG and 176 LGG MRI scans to do research. It was possible to employ three different MRI sequences for everyone in the dataset: T1-, T2-, and Fluid Liquid Attenuation Inversion Recovery (FLAIR). T1W and FLAIR sequences have been employed in investigations, whereas T2W was employed in both axial as well as sagittal positions. Using different sequences as well as orientations, the suggested technique can handle situations when just a single sequence or orientation is available. Scanners from Philips Medical Systems were used, and identical scanning settings were used throughout the process. To get 3D scans of the anatomical structures, a 3D sequence with a time resolution of 2s, a telephoto lens of 20cm, 512×512 matrix, and 30 slices of 5mm thickness were used. There are 120 slices for each topic (30 slices of T1W Axial, T2W Axial, FLAIR Axial, and T2W Sagittal each). Where necessary, to have a large dataset volume, the rotation technique has been utilized as data augmentation.

B. PREPROCESSING

MRI images can be affected by bias field distortion, which causes the intensity of identical tissues to vary across an image. The presence of bias field disruption in MR image data is corrected with the help of the N4ITK method [18]. It is radiologically proved that the intensity distribution of a tissue type can change even if an image belongs to the same patient and the same scanner is used in the same frame of time for image acquisition. Each sequence has undergone intensity normalization [19] to ensure that the intensity ranges and contrast are consistent across all acquisitions for all subjects. For all training samples, regions containing the tumor area are segmented using k-means clustering, for a value of 'k' equal to three. Because tumuli proliferate in different directions, the middle four slices (containing the largest tumor segment) of each sequence and orientation were rotated at three distinct angles, i.e., 45^o, 90^o, and 135^o, to allow the reported method to deal with all these. Similarly, four slices having the most significant tumor section from each sequence and orientation were rotated in these three distinct angles for each of the subjects.

C. EXPERIMENTAL SETUP

Experiments were conducted in two different ways in this study: 1) features extraction through CNN models, i.e., resnet18, squeezenet, & alexnet and the proposed CNN model and classification through SVM, 2) features extraction and classification through CNN models, i.e., resnet18, squeezenet, alexnet, and the proposed CNN model.

D. THE PROPOSED CNN ARCHITECTURE

Using convolution and pooling techniques, this study developed a CNN architecture for automatically extracting deep characteristics from pictures of tumors in the brain. Grading of glioma types may be approximated with the help of the model under consideration. Glioma-grade categorization files have been used in experiments. The suggested method's results were compared to current, state-of-the-art research and CNN. As shown by their success in the ImageNet Large Scale Visual Recognition Challenge, these cutting-edge CNN models are the best in the business (ILSVRC). The proposed CNN-based architecture is shown in Fig. 2. While Table 2 shows that the suggested model is built of only 12 layers and holds only 0.287 million parameters, which is a significant difference from the other CNN-based models for glioma grading (low and high grade). The layers of the suggested model are outlined below.

1) CONVOLUTIONAL LAYER

The convolutional layer generates feature maps, reflecting learned features from the input pictures. Feature maps may

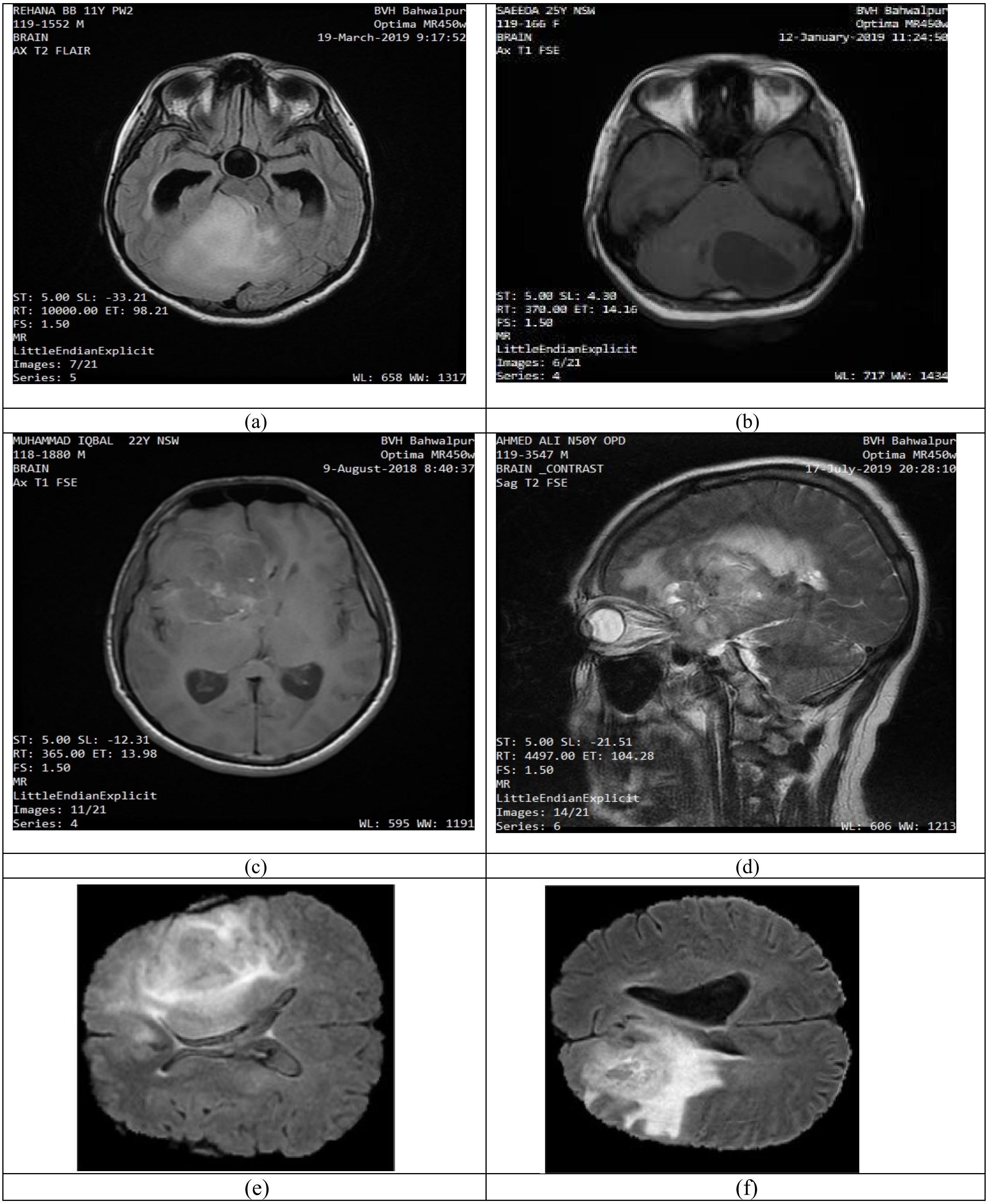

FIGURE 1. Dataset samples used for research and experiments, (a) LGG of Grade-I (FLAIR & AXIAL) of BVHB dataset, (b) LGG of Grade-II (T1W & AXIAL) of BVHB dataset, (c) HGG of Grade-III (T1W & AXIAL) of BVHB dataset, (d) HGG of Grade-IV (T2W & SAGITTAL) of BVHB dataset, (e) LGG of Grade-II (FLAIR & AXIAL) of BraTS dataset, (f) HGG of Grade-IV (FLAIR & AXIAL) of BraTS dataset.

be caused by using weights that can be trained. An image with dimensions (M, N) and a filter of (p, q) is represented in Eq. (1) by convolution. A convolutional technique was used to build feature maps from the left to the right of the input

TABLE 1. Details of the datasets used for research and experiments.

Sr.	Dataset	Patients	Sequences used for experiments	Orientations
1	Brats-2017	HGG=210 and LGG=75	Native (T1), post-contrast T1-weighted (T1Gd), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (FLAIR)	Axial
2	Brats-2018	HGG=210 and LGG=75		
3	Brats-2019	HGG=259 and LGG=76		
4	Locally developed	HGG=159 LGG=176	Native (T1), T1-weighted with contrast enhanced (T1C), T2-weighted (T2), and T2 Fluid Attenuated Inversion Recovery (FLAIR)	Axial orientation of T1W, and Axial FLAIR samples and sagittal orientations of T2W

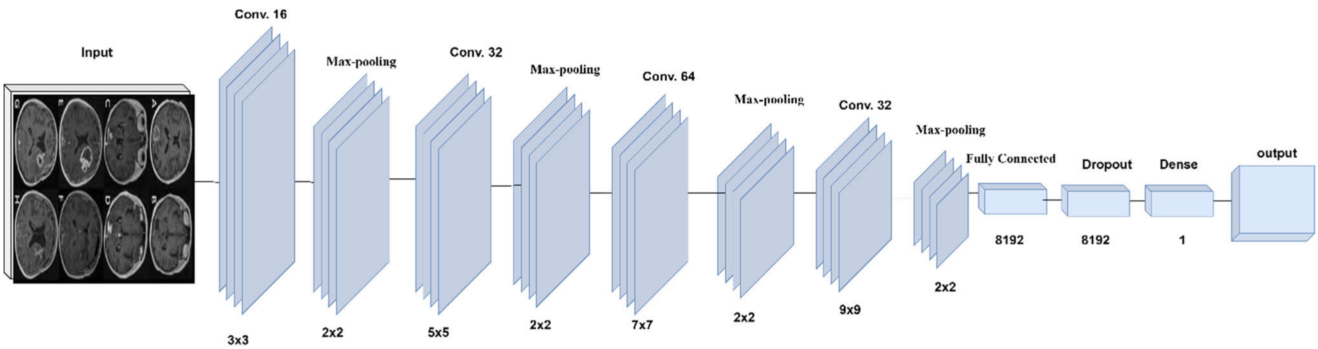

FIGURE 2. The architecture of the proposed CNN model.

image.

$$conv = (Img * F)(\mathrm{x}, \mathrm{y}) = \sum_M \sum_N I(x-p, y-q) F(p,q) \tag{1}$$

2) POOLING LAYER

After convolution, the pooling procedure is usually conducted, which is both easy and effective. The pooling technique generates extracted features with local perceptual fields. According to our model for rice age estimate from the dataset, a pooling layer is employed to identify and minimize dimensions of key variables that aided in the model's age estimation.

3) RECTIFIED LINEAR UNIT (RELU) LAYER

Neuronal networks cannot function properly without this layer present. If the operational amplifier is not applied, the computation of a network under training may result in a linear network. It is common to use Eq. (2) to describe the sigmoid function as an activation function. Eq. (3) is used to determine the gradient, although the gradient descent technique heavily relies on the sigmoid function.

$$\mathrm{s}(\mathrm{x}) = \frac{1}{1 - \mathrm{e}^{-\mathrm{x}}} \tag{2}$$

$$\mathrm{S}'(\mathrm{x}) = \mathrm{S}(\mathrm{x})(1 - \mathrm{S}(\mathrm{x})) \tag{3}$$

In deep architectures, sigmoidal functions produce gradient vanishing, which results in a delayed learning process. As a result, for deep architectures, such as CNN, the Rectified Linear Unit (ReLU) is a popular option. Eq. (4) is used to derive ReLU's formula.

$$ReLU(x) = max(x, 0) \tag{4}$$

4) FULLY CONNECTED LAYER

This layer is often found at the very end of CNN models, where it aids with object identification.

TABLE 2. Summary of the proposed CNN architecture for glioma grade estimation.

Sr.	Layer	Type	Shapes	Parameter
1.	Input	rescaling_2	256, 256, 3	0
2.	conv_1	Conv2D	256, 256, 16	448
3.	max_pooling2d	Max-Pooling	128, 128, 16	0
4.	conv_2	Conv2D	128, 128, 32	12832
5.	max_pooling2d	Max-Pooling	64, 64, 32	0
6.	conv_3	Conv2D	64, 64, 64	100416
7.	max_pooling2d	Max-Pooling	32, 32, 64	0
8.	conv_4	Conv2D	32, 32, 32	165920
9.	max_pooling2d	Max-Pooling	16, 16, 32	0
10.	flatten_5	Flatten	8192	0
11.	dropout_1	Dropout	8192	0
12.	output	Dense	1	8193
Total Parameters				**287,809**

An important factor to note is that the suggested model can accept input images of dimension 256 $\times$ 256 pixels in size and has 12 layers overall. The hyper-parameters, their values, and the tweaking carried out while fine-tuning the proposed model are described in Table 3.

The proposed model's efficacy is validated in two ways, whether it extracts out more appropriately and what is its classification rate for glioma grades classification. The suggested CNN model was used to extract features in the first stage.

For comparison, other state-of-the-art CNN-based features have also been retrieved, such as resnet18, squeezenet, and alexnet. When parts were successfully extracted, classification was performed using the standard model, i.e., SVM, one of the best classifiers for binary classification. Secondly, features have been removed, but the classification is also performed using the proposed CNN model. To compare again, state-of-the-art CNN models, i.e., resnet18, squeezenet, and alexnet, were also used to extract and classify glioma grades. The overall methodology to differentiate between low- and high-grade gliomas using the proposed CNN model is represented in Fig. 3.

IV. RESULTS AND DISCUSSION

Experiments have been conducted to test the proposed CNN model's applicability, which included extracting features from state-of-the-art CNN models, including the proposed one, and classifying them using SVM. Both feature extraction and classification were carried out using the suggested CNN model in the second experiment mode. Table. 4 represents the results obtained while features extraction through resnet18, squeezenet, alexnet, and the proposed CNN model while the classification of these features was performed using SVM.

TABLE 3. Hyperparameters of the proposed CNN architecture for glioma grading.

Stage	Hyper-parameter	Value	Tweaking of a value
Initialization	bias	0.1	This value was empirically settled to 0.1 after several experiments performed on datasets.
	weights	random	Using random function these values were selected initially, then tweaked using training process.
	learning rate	α	The value for learning rate was empirically decided to set as 0.00001.
Dropout	p	0.3	This value was selected using different experiments. Initially, it was selected as 0.9, 0.8, 0.7 and so on. On 0.3, the model performed well as per validation accuracy.
Training	epochs	05	it was selected keeping in the mind, that if lower values are selected the system may not be robust, and if a higher value is selected, training time may increase significantly. So, based on previous experience, it was selected as 05.
	v	0.9	Empirically this value was selected as 0.9.
	initial ϵ	0.0002	Empirically this value was selected as 0.0002.
	final ϵ	0.0002	Empirically this value was selected as 0.0002.
	batch	128	The dataset holds a medium volume, therefore, 128 batch sizes are more suits. For large volume datasets, large size as a batch, while for small volume datasets, the small batch size is recommended by the researchers working in the domain of classification.

Similarly, Table 5 represents the results obtained while both feature extraction and classification have been performed using resnet18, squeezenet, alexnet, and the proposed CNN model. For the sake of discussion, results have been discussed in these modes of experiments wise.

A. FEATURE EXTRACTED THROUGH DEEP LEARNING AND CLASSIFICATION

When discussing the results, as per features extraction through CNN-based models, i.e., resnet18, squeezenet, & alex_net, and the proposed CNN-based model.

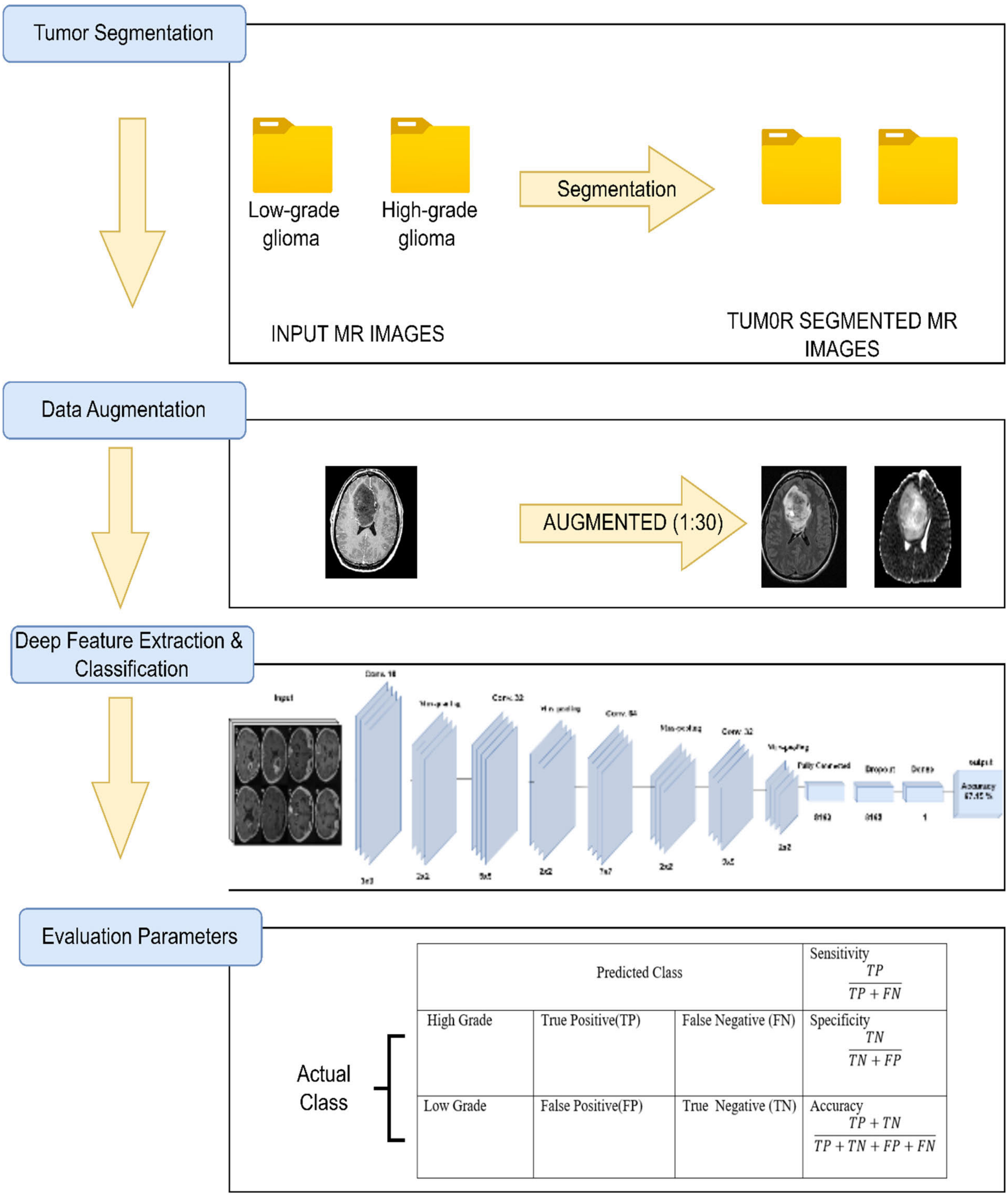

FIGURE 3. **Overall methodology to classify low- and high-grade gliomas using the proposed CNN model.**

Then these features have been used for classification through SVM. On Brats-2017, Brats-2018, Brats-2019, and locally developed datasets, the proposed CNN model00 achieved the best results. These are as per accuracy, specificity, and sensitivity against Brats-2017 97.87%, 98.68%, 99.37%, Brats-2018 97.67%, 98.28%, 98.98%, Brats-2019 96.88%, 97.56%, 98.37%, and locally developed dataset 98.89%, 99.28%, 99.77% respectively.

B. FEATURE EXTRACTED AND CLASSIFICATION THROUGH CNN MODELS

While discussing the results in terms of feature extraction and classification through CNN-based models. Again, the

TABLE 4. Results of glioma grading after features extraction through deep learning and classification using SVM.

Sr No.	Dataset	Features extracted through	Accuracy (%)	Specificity (%)	Sensitivity (%)	AUC-value
1	Brats-2017	resnet18	88.49	89.15	90.85	0.93
2		squeezenet	86.98	88.16	91.85	0.92
3		alexnet	90.89	93.61	95.15	0.90
4		The proposed model	97.87	98.68	99.37	0.98
5	Brats-2018	resnet18	85.49	87.65	92.85	0.91
6		squeezenet	91.89	93.36	95.57	0.93
7		alexnet	93.45	94.56	95.45	0.94
8		The proposed model	97.67	98.28	98.98	0.98
9	Brats-2019	resnet18	90.49	93.55	94.85	0.92
10		squeezenet	88.98	90.96	93.99	0.90
11		alexnet	89.77	91.56	94.85	0.91
12		The proposed model	96.88	97.56	98.37	0.97
13	BVHB	resnet18	90.22	93.35	94.65	0.92
14		squeezenet	89.98	90.86	92.78	0.91
15		alexnet	87.57	89.56	91.87	0.90
16		The proposed model	98.89	99.28	99.77	0.98

TABLE 5. Results of glioma grading after features extraction and classification through CNN models.

Sr No.	Dataset	Features extracted through	Accuracy (%)	Specificity (%)	Sensitivity (%)	AUC-value
1	Brats-2017	resnet18	93.11	95.18	96.47	0.94
2		squeezenet	89.66	92.47	93.88	0.90
3		alexnet	85.99	86.67	91.70	0.89
4		The proposed model	97.85	98.88	99.88	0.99
5	Brats-2018	resnet18	91.47	94.37	95.33	0.92
6		squeezenet	87.66	91.45	92.67	0.90
7		alexnet	89.48	92.22	95.89	0.91
8		The proposed model	97.15	98.18	98.55	0.98
9	Brats-2019	resnet18	91.77	93.54	95.77	0.92
10		squeezenet	87.46	93.27	93.28	0.90
11		alexnet	89.44	90.67	91.27	0.92
12		The proposed model	97.15	98.18	97.67	0.99
13	BVHB	resnet18	92.55	94.37	94.99	0.92
14		squeezenet	86.75	88.22	92.34	0.90
15		alexnet	85.88	87.67	91.32	0.90
16		The proposed model	97.99	98.18	99.66	0.98

proposed model achieved the best results. On Brats-2017, Brats-2018, Brats-2019, and locally developed datasets, the proposed CNN model00 achieved the best results. These are against Brats-2017 (accuracy of 97.85%), specificity (98.88%), sensitivity (99.88%), Brats-2018 (accuracy of 97.15%, specificity of 98.18%, sensitivity of 98.55%), Brats-2019 (97.15% for accuracy, 98.18% for specificity, 97.67% for sensitivity), and locally developed dataset (accuracy as 97.99%, specificity as 98.18%, sensitivity as 97.67%).

C. COMPARISON WITH STATE-OF-THE-ART METHODS

As represented in Table 6, results obtained through the proposed CNN model have been compared with recently conducted studies for low- and high-grade glioma. In the

TABLE 6. Comparison of the results obtained through the proposed model for glioma grading with the results of recently conducted state-of-the-art studies.

Study	Reported method	Dataset details	Evaluation measures	Classification of
[10]	CNN+ Genetic Algorithm	600 MRI images from IXI dataset, 130 patients' data from REMBRANDT dataset, 199 patients' data from TCGA-GBM, and 60 patients' data from the neurosurgery section of Hazrat-e Rasool hospital Tehran, Iran	Accuracy first study=90.9% Accuracy second study=94.2%	Glioma's Grade (II-IV)
[11]	Wavelet Based Radiomics Approach	BraTS-2018	Accuracy=97.62% Specificity=97.33% Sensitivity=97.62%	HGG and LGG
[12]	U-Net Model	BraTS-2018	2D Mask R-CNN Sensitivity=93.5% Specificity=97.2% Accuracy=96.3% 3DConvNet Sensitivity=94.7% Specificity=96.8% Accuracy=97.1%	Glioma Grade II Glioma Grade III Glioma Grade IV
[13]	Wndchrm tool-based classifier And VGG-19 DNN	Locally developed dataset from Government Medical College Calicut India	Wndchrm Classifier accuracy=92.86% VGG-19 DNN accuracy=98.25%	Glioma Grade I Glioma Grade II Glioma Grade III Glioma Grade IV
[14]	CNN	Locally developed dataset of 237 glioma patients	Accuracy=87%	Glioma Grade I Glioma Grade II Glioma Grade III Glioma Grade IV
[15]	SVM	735 images of glioma patients (427 males and 308 females)	Accuracy=75.12% AUC=65.2	HGG and LGG
[16]	Residual neural networks+ Dempster-shafer Theory	5088 low-grade and 2304 high-grade T2-weighted MRI scans	Accuracy=95.87%	Gliomas grades
[17]	Gaussian CNN	516 T1-weighted images of 73 patients	Accuracy=97.14%	Glioma Grade-II-IV
[18]	CNN (Adam and Sgdam optimizers)	Dataset of 233 patients' data (3064 MRI images, 708 images of meningioma, 1426 images of glioma, and 930 images of pituitary) and locally developed dataset obtain from Nanfang Hospital and General Hospital, Tianjing Medical University, China	Accuracy=81.6%	Glioma, meningioma, and pituitary
[19]	CNN	BRATS 19 dataset (355 patients' data, 158 cases of HGG, 255 cases of LGG)	Accuracy=95.86%	Glioma
[20]	CNN	Kaggle dataset (253 brain MRI images, 155 tumorous brain MRI images, and 98 nontumorous brain MRI images)	Accuracy=96.50 %	Low-grade gliomas
[21]	CNN, SVM and KNN	MRI Images	SVM and KNN have an accuracy of 86.1% and 66.7%	Glioma

TABLE 6. *(Continued.)* **Comparison of the results obtained through the proposed model for glioma grading with the results of recently conducted state-of-the-art studies.**

[22]	RCNN	Figshare dataset of 233 patients' (3064 images, 426 MRI samples of 92 Glioma patients, 708 MRI samples of 82 Meningioma patients and 930 MRI samples of 62 Pituitary tumor patients) Kaggle dataset (255 MRI images, 98 MRI slices of healthy and 155 MRI slices of tumor)	Accuracy=98.83%	Glioma, meningioma, and pituitary
[23]	Bayesian Optimization-based and CNN	Figshare dataset (3064 T1C MRI images of 233 patients)	Accuracy=98.70%	Glioma, meningioma, and pituitary
[24]	CNN-Based Deep Learning	Figshare dataset (3064 MRI images of 233 patients	Accuracy=99.83%	Glioma, meningioma, and pituitary
[25]	CNN and SVM	Figshare dataset of 233 patients (3064 MRI images, 1426 images of glioma, 708 images of meningioma and 930 images of pituitary)	Accuracy=95.82%	Glioma, meningioma, and pituitary
The propo sed	CNN	Dataset of 233 patients' data (3064 MRI images, 708 images of meningioma, 1426 images of glioma, and 930 images of pituitary) and locally developed dataset obtain from Nanfang Hospital and General Hospital, Tianjing Medical University, China	Accuracy=81.6%	Glioma, meningioma, and pituitary

study [10], a CNN-based method is proposed for glioma grading (Grade II-IV). Using the CNN model, they achieved an accuracy of 90.9% and 94.2% for two case studies. In another study reported by [11], a non-invasive approach is used to classify glioma grades, i.e., HGG and LGG using a random forest classifier with 97.62% accuracy. Another study investigated by [12], segmented brain tumors using a modified U-Net model and then classify segmented brain tumor images using mask R-CNN. They used the BraTS-2018 dataset, with achieved accuracy between 96.3% and 97.1%. In another study [13], authors proposed a method of glioma grade identification using the Wndchrm tool and VGG-19 classifiers. The method obtained accuracies of 92.86% and 98.25% for the Wndchrm tool and VGG-19 respectively. In this study [14] authors used a CNN model for glioma grade estimation. Two hundred thirty-seven (237) patients with gliomas were involved in this research and achieved an accuracy is 87%. In another research [15], the SVM model has been used for the classification of glioma grades. A total of 735 images of glioma patients (427 males and 308 females) are used and the achieved accuracy is 75.12%.

In this study [18], three tumor types, viz; glioma, meningioma, and brainstem cancer are classified as brain tumors using Adam and Sgdam optimizers with an accuracy of 81.6%. however, a very small number of images are used for experiments. In this study [19], using 3D MRI data, a CNN-based architecture is proposed for non-invasive tumor evaluation with an accuracy of 95.86%. This technique does not grade glioma according to low and high-grade. In this study [20], a CNN-based technique for MRI images validated on the Kaggle dataset was proposed with an accuracy of 96.50%. The volume of the dataset is small. This study [21], classifies brain tumors using CNN, SVM, and KNN. The precision of the improved CNN is 94.60% and the accuracy of SVM and KNN is 86.1% and 66.7%, respectively. In this study [22], using the RCNN technique, a classification framework for brain tumors and their types is developed using two public datasets, i.e., Figshare and Kaggle with an accuracy of 98.83%. these two studies are unable to determine the grades of brain tumors. In this study [23], Bayesian Optimization-based technique is used for CNN hyperparameter optimization using the Figshare brain tumor dataset with an accuracy of 98.70%. In this study [24], a VGG19 model is used for brain tumor detection using Figshare dataset with an accuracy of 99.83%. In this study [25], a brain tumor detection approach, trained on the Figshare dataset is proposed, with an accuracy of 95.82%. These models are trained on a small number of images.

The accuracy of 97.15 for low- and elevated gliomas obtained by the proposed classification algorithm is obvious from the data. Not only that but compared to other previously published models, the suggested model is trained and verified on a vast volume of the dataset.

V. CONCLUSION AND FUTURE WORK

In this research work, a CNN-based light-weighted model with 12 layers and 0.287 million parameters has been proposed to classify images of low- and high-grade gliomas scanned through MRI scanners. The proposed model can classify the images with dimensions 256×256 image. Experiments and results proved that the proposed CNN model is the best model to classify low- and high-grade glioma compared to other state-of-the-art CNN models and some recently published studies. It is established by the experiments that the split ratio of the dataset used for training, testing, and validation has a significant impact on the results. A large volume of the dataset was split to train the model, which improved the accuracy of the model as it provides more data for the model to learn from. Moreover, the large ratio of the dataset also ensured the generalizability of the model, which served the reason that the proposed model deals with both BraTS and locally developed datasets. Further enhancement in this work will be a classification of four types of glioma grade, i.e., grade-I to Grade IV, and further classification of glioma types, i.e., astrocytomas, oligodendrogliomas, brainstem glioma etc.

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CONFLICTS OF INTEREST

The authors declare no conflict of interest.

REFERENCES

[1] H. Sotoudeh, O. Shafaat, J. D. Bernstock, M. D. Brooks, G. A. Elsayed, J. A. Chen, P. Szerip, G. Chagoya, F. Gessler, E. Sotoudeh, A. Shafaat, and G. K. Friedman, "Artificial intelligence in the management of glioma: Era of personalized medicine," *Frontiers Oncol.*, vol. 9, p. 768, Aug. 2019.

[2] G. Gilanie, U. I. Bajwa, M. M. Waraich, and M. W. Anwar, "Risk-free WHO grading of astrocytoma using convolutional neural networks from MRI images," *Multimedia Tools Appl.*, vol. 80, no. 3, pp. 4295–4306, Jan. 2021.

[3] Y. Liu, Y. Li, S. Dong, L. Han, R. Guo, Y. Fu, S. Zhang, and J. Chen, "The risk and impact of organophosphate esters on the development of female-specific cancers: Comparative analysis of patients with benign and malignant tumors," *J. Hazardous Mater.*, vol. 404, Feb. 2021, Art. no. 124020.

[4] P. Roth, A. Pace, E. Le Rhun, M. Weller, C. Ay, E. C.-J. Moyal, M. Coomans, R. Giusti, K. Jordan, R. Nishikawa, F. Winkler, J. T. Hong, R. Ruda, S. Villà, M. J. B. Taphoorn, W. Wick, and M. Preusser, "Neurological and vascular complications of primary and secondary brain tumours: EANO-ESMO clinical practice guidelines for prophylaxis, diagnosis, treatment and follow-up," *Ann. Oncol.*, vol. 32, no. 2, pp. 171–182, Feb. 2021.

[5] M. A. Naser and M. J. Deen, "Brain tumor segmentation and grading of lower-grade glioma using deep learning in MRI images," *Comput. Biol. Med.*, vol. 121, Jun. 2020, Art. no. 103758.

[6] Y. Yang, L.-F. Yan, X. Zhang, Y. Han, H.-Y. Nan, Y.-C. Hu, B. Hu, S.-L. Yan, J. Zhang, D.-L. Cheng, X.-W. Ge, G.-B. Cui, D. Zhao, and W. Wang, "Glioma grading on conventional MR images: A deep learning study with transfer learning," *Frontiers Neurosci.*, vol. 12, p. 804, Nov. 2018.

[7] G. Gilanie, U. I. Bajwa, M. M. Waraich, and Z. Habib, "Automated and reliable brain radiology with texture analysis of magnetic resonance imaging and cross datasets validation," *Int. J. Imag. Syst. Technol.*, vol. 29, no. 4, pp. 531–538, Dec. 2019.

[8] G. M. Shankar, L. Balaj, S. L. Stott, B. Nahed, and B. S. Carter, "Liquid biopsy for brain tumors," *Expert Rev. Mol. Diag.*, vol. 17, no. 10, pp. 943–947, Oct. 2017.

[9] H.-H. Cho, S.-H. Lee, J. Kim, and H. Park, "Classification of the glioma grading using radiomics analysis," *PeerJ*, vol. 6, p. e5982, Nov. 2018.

[10] A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," *Biocybernetics Biomed. Eng.*, vol. 39, no. 1, pp. 63–74, Jan. 2019.

[11] R. Kumar, A. Gupta, H. S. Arora, G. N. Pandian, and B. Raman, "CGHF: A computational decision support system for glioma classification using hybrid radiomics- and stationary wavelet-based features," *IEEE Access*, vol. 8, pp. 79440–79458, 2020.

[12] Y. Zhuge, H. Ning, P. Mathen, J. Y. Cheng, A. V. Krauze, K. Camphausen, and R. W. Miller, "Automated glioma grading on conventional MRI images using deep convolutional neural networks," *Med. Phys.*, vol. 47, no. 7, pp. 3044–3053, Jul. 2020.

[13] K. V. A. Muneer, V. R. Rajendran, and K. P. Joseph, "Glioma tumor grade identification using artificial intelligent techniques," *J. Med. Syst.*, vol. 43, no. 5, pp. 1–12, May 2019.

[14] S. Gutta, J. Acharya, M. S. Shiroishi, D. Hwang, and K. S. Nayak, "Improved glioma grading using deep convolutional neural networks," *Amer. J. Neuroradiol.*, vol. 42, no. 2, pp. 233–239, Feb. 2021.

[15] S. Rathore, T. Niazi, M. A. Iftikhar, and A. Chaddad, "Glioma grading via analysis of digital pathology images using machine learning," *Cancers*, vol. 12, no. 3, p. 578, Mar. 2020.

[16] P. C. Tripathi and S. Bag, "A computer-aided grading of glioma tumor using deep residual networks fusion," *Comput. Methods Programs Biomed.*, vol. 215, Mar. 2022, Art. no. 106597.

[17] M. Rizwan, A. Shabbir, A. R. Javed, M. Shabbir, T. Baker, and D. A.-J. Obe, "Brain tumor and glioma grade classification using Gaussian convolutional neural network," *IEEE Access*, vol. 10, pp. 29731–29740, 2022.

[18] S. Kumar and D. Kumar, "Human brain tumor classification and segmentation using CNN," *Multimedia Tools Appl.*, vol. 82, no. 5, pp. 7599–7620, Feb. 2023.

[19] P. C. Tripathi and S. Bag, "An attention-guided CNN framework for segmentation and grading of glioma using 3D MRI scans," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, early access, Nov. 9, 2022, doi: 10.1109/TCBB.2022.3220902.

[20] J. Liu, F. Deng, G. Yuan, C. Yang, H. Song, and L. Luo, "An efficient CNN for radiogenomic classification of low-grade gliomas on MRI in a small dataset," *Wireless Commun. Mobile Comput.*, vol. 2022, pp. 1–9, Jun. 2022.

[21] J. A. Jeba, S. N. Devi, and M. Meena, "Modified CNN architecture for efficient classification of glioma brain tumour," *IETE J. Res.*, pp. 1–14, 2022, doi: 10.1080/03772063.2022.2101553.

[22] N. Kesav and M. G. Jibukumar, "Efficient and low complex architecture for detection and classification of brain tumor using RCNN with two channel CNN," *J. King Saud Univ.-Inf. Sci.*, vol. 34, no. 8, pp. 6229–6242, Sep. 2022.

[23] M. A. Amou, K. Xia, S. Kamhi, and M. Mouhafid, "A novel MRI diagnosis method for brain tumor classification based on CNN and Bayesian optimization," *Healthcare*, vol. 10, no. 3, p. 494, Mar. 2022.

[24] A. K. Mandle, S. P. Sahu, and G. P. Gupta, "CNN-based deep learning technique for the brain tumor identification and classification in MRI images," *Int. J. Softw. Sci. Comput. Intell.*, vol. 14, no. 1, pp. 1–20, Jul. 2022.

[25] S. Deepak and P. M. Ameer, "Automated categorization of brain tumor from MRI using CNN features and SVM," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 8, pp. 8357–8369, Aug. 2021.

HAFIZ AAMIR HAFEEZ received the B.Sc. degree in electrical (computer) engineering from the COMSATS Institute of Information Technology, Lahore Campus, Pakistan, and the M.S. degree in information technology from Charles Sturt University, Australia, in 2018. He is currently pursuing the Ph.D. degree with Universiti Tun Hussein Onn Malaysia Parit Raja, Malaysia. He was a Lecturer with the Department of Computer Science, University of Central Punjab (Bahawalpur Campus), Pakistan. His research interests include image/video processing, computer vision, machine learning, data mining, and networks.

MOHAMED A. ELMAGZOUB was born in Riyadh, Saudi Arabia, in 1985. He received the B.S. degree (Hons.) in electrical and electronic engineering from Omdurman Islamic University, Sudan, in 2007, and the master's degree in electrical communication engineering and the Ph.D. degree in electrical engineering (communications) from Universiti Teknologi Malaysia (UTM), Malaysia, in 2012 and 2016, respectively. He was a Telecommunication Engineer with the Department of Communication, Dams Implementation Unit, Sudan, from 2008 to 2009. He is currently an Assistant Professor with the Department of Network and Communication Engineering, Najran University. He has authored ten ISI articles, two of them highly cited review articles in the area of passive optical networks and hybrid optical and wireless communication systems. His research interests include passive optical networks, hybrid optical and wireless communication systems, optical OFDM communications, MIMO, and next-generation access networks.

NURUL AZMA BINTI ABDULLAH received the B.Sc. degree in information technology from Universiti Utara Malaysia and the M.S. degree in knowledge extraction from the University of East Anglia, U.K., in 2005. She is currently pursuing the Ph.D. degree with Universiti Tun Hussein Onn Malaysia (UTHM), Malaysia. She is a Senior Lecturer with the Department of Information Security, Faculty of Computer Science and Information Technology, UTHM, and works in digital forensics and physical security domain.

MANA SALEH AL RESHAN received the B.S. degree in information systems from King Khalid University, Abha, Saudi Arabia, in 2007, the M.S. degree (Hons.) in computer, information, and network security from DePaul University, Chicago, IL, USA, in 2011, and the Ph.D. degree in computer science from The Catholic University of America (CUA), Washington, DC, USA, in 2019. He was a Teaching Assistant with the College of Computer Science and Information System, Najran University, Saudi Arabia, from 2007 to 2009. He was a Lecturer with the College of Computer Science and Information System, Najran University, in 2012, where he is currently an Assistant Professor and the Head of the Department of Network Engineering. His current research interests include computer network and security, system security, wireless and mobile security, body area networks, and cloud security.

GHULAM GILANIE received the master's degree in philosophy in computer science from The Islamia University of Bahawalpur, Pakistan, and the Ph.D. degree in computer science from COMSATS University Islamabad, Lahore Campus, Pakistan. He is currently an Assistant Professor with the Department of Artificial Intelligence, Faculty of Computing, The Islamia University of Bahawalpur, and possesses 15 years of diversified experience in research and development. He has remained associated with well-reputed software houses. He has international journal publications and is the author of several books. His research interests include bio-computing, medical image processing, computer vision, and robotics.

SULTAN ALYAMI received the B.S. degree in computer science from King Faisal University, Alahsa, Saudi Arabia, in 2010, and the M.S. degree in machine learning and the Ph.D. degree in computer science from the University of Connecticut, Storrs, CT, USA, in 2015 and 2020, respectively. He was a Teaching Assistant with the College of Computer Science and Information System, Najran University, Saudi Arabia, from 2010 to 2017. He was a Lecturer with the College of Computer Science and Information System, Najran University, in 2017, where he is currently an Assistant Professor. His current research interests include data compression, health informatics, machine learning, data mining, cybersecurity, and cloud computing.

MAHMOOD UL HASSAN received the B.S. degree (Hons.) in computer science from Hazara University, Pakistan, the M.S. degree in computer science from COMSATS University, Pakistan, and the Ph.D. degree in computer science from the IIC University of Technology, Cambodia. He is currently an Assistant Professor with the Department of Computer Skills, Deanship of Preparatory Year, Najran University, Najran, Saudi Arabia. He has more than 40 publications in the area of computer networks, image processing, and cloud computing in well-reputed international journals and conferences. His research interests include ad hoc networks, connectivity and coverage restoration in wireless networks, image processing, and cloud computing.

ASADULLAH SHAIKH (Senior Member, IEEE) received the B.Sc. degree in software development from the University of Huddersfield, U.K., the M.Sc. degree in software engineering and management from Goteborg University, Sweden, and the Ph.D. degree in software engineering from the University of Southern Denmark. He was a Researcher with UOC, Barcelona, Spain. He is currently an Associate Professor, the Head of research, and a Coordinator of seminars and training with the College of Computer Science and Information Systems, Najran University, Najran, Saudi Arabia. He has more than 150 publications in the area of software engineering in international journals and conferences. He has vast experience in teaching and research. His current research interests include UML model verification, UML class diagrams verification with OCL constraints for complex models, formal verification, and feedback technique for unsatisfiable UML/OCL class diagrams. He is an Editor of the *International Journal of Advanced Computer Systems and Software Engineering* (IJACSSE) and an International Advisory Board of several conferences and journals. More information is available at www.asadshaikh.com.