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RESEARCH ARTICLE

Brain Tumor Detection and Multi-Grade Segmentation Through Hybrid Caps-VGGNet Model

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ABSTRACT Around the world, brain tumors are becoming the leading cause of mortality. The inability to undertake a timely tumor diagnosis is the primary cause of this pandemic. Brain cancer diagnosis is a crucial procedure that relies on the expertise and experience of the doctor. Radiologists must use an automated tumor classification model to find brain cancers. The current model's accuracy has to be improved to get suitable therapies. Radiologists can consult various computer-aided diagnostic (CAD) models in the literature on medical imaging to assist them with their patients. Previous research has widely used CNN models for tumor detection and classification, which typically require large datasets. This research proposed the Caps-VGGNet hybrid model, which integrates the CapsNet model with the VGGNet model by adding the layers of VGGNet. The presented model addresses the challenge of requiring large datasets by automatically extracting and classifying features. The suggested algorithm's effectiveness was assessed using the Brats-2020 and Brats-2019 dataset, which contains high-quality images of brain tumors. Compared to other conventional and hybrid models, the empirical outcomes of the suggested model indicate that it exhibited the highest level of effectiveness and superior efficacy in terms of accuracy, specificity, and sensitivity. Specifically, the presented hybrid model attained an accuracy of 0.99, a specificity of 0.99, and a sensitivity of 0.98 on the Brats20 dataset.

INDEX TERMS Capsule neural network, brain tumor, multi-grade segmentation, CNN, magnetic resonance.

I. INTRODUCTION

The brain is the most advanced part of the human nervous system that dominates a series of vital activities of the human body. Brain-related diseases are characterized by high relapse rates, high disability rates, high morbidity rates, and high fatality rates, which challenge clinical diagnosis and treatment [1], [2]. Brain tumors are malignant neoplasms that arise and disseminate in the brain. According to their degree of aggressiveness, they may be categorized as benign tumors (normal) or malignant tumor(cancerous), and they can be ranked according to their malignancy employing the WHO guideline for Central Nervous System (CNS) tumors, ranging to grades 1 to 4 [3]. Meningiomas and pituitary tumors, which are often of low grade, are two examples of benign tumors that seldom spread to healthy adjacent cells [4], [5] Malignant brain tumor aggressively penetrates the parenchyma around them. The most prevalent and severe kind of malignant brain

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tumor is glioblastoma (GBM), which is frequently categorized as a grade 4 CNS tumor with a poor prognosis [5], [6]. Additionally, secondary and primary brain cancers can be distinguished based on where in the brain they originate. Additionally, primary and secondary brain tumors may be distinguished between brain tumors, with the former often developing in a different location than the secondary brain tumors [7].

Clinical and radiological data are the foundation for diagnosis and treatment, with MRI being the primary tool for evaluating patients with brain malignancies [8]. MRI is a crucial tool for clinical imaging due to its multi-sequence, multi-parameter, and multi-planar imaging capabilities that provide clear details of brain lesions [9]. MRI data can reflect different views of the patient's brain, and computer processing has become a key research area. However, traditional imaging has constraints in determining tumor size, indicating grade, and evaluating treatment response [10]. New acquisition methods are being developed to enhance lesion definition and therapy assessment. New image analysis methods are gaining popularity due to the vast data that radiological images contain [11]. The different stages of brain tumor abnormalities are exhibited in Figure 1. Due to the tendency of shape-based characteristics determined from cortical or hippocampal lobes to neglect connection across the whole brain, these characteristics may result in low precision. As aberrant changes may not suit the area suggested by earlier beliefs-based data, region-based features may not be adequate [11]. Because of their immense size, voxel-wise features may lead to a reduction in classification performance. Deep Learning (DL) technology has emerged as a prominent branch of Artificial Intelligence (AI) due to its exceptional learning capabilities in medical image processing [12], [13]. However, various complexities arising from disease types, medical ethics, and data annotation pose significant challenges. The study tackles these challenges in diagnosing brain tumors using deep learning models. Challenges include developing efficient multitask models, addressing classification issues for diseases with limited data, and improving diagnostic explanations through weakly supervised localization. Convolutional neural network technology was used to address these issues. According to the spatial interactions of neurons, these networks are unstable [14] within their last layer's kernel. Not long ago, capsule networks were suggested (CapsNets). The automated categorization of brain tumors involves feature detection and extraction, where accurate categorization often requires hand-crafted features based on expert knowledge, highlighting issues with feature extraction in cancer classification systems. In CapsNet, outputs and information stored at neurons are vectors instead of scalars. CapsNet-based techniques are fresh suggestions for removing the shortcomings of CNN-based techniques based on the best. We are unaware of any evaluations of CapsNets-based approaches. In addition, researchers have emphasized that a new approach is needed for the exhaustively computerized grading of images of brain tumors [15]. In the suggested method, rotational invariance and spatial hierarchy among brain characteristics have been considered using a CapsNet architecture. Because CNNs cause the spatial linkages between higher-level components to be lost. CNNs lack rotational invariance, making them less resistant to novel views. The suggested method's optimization was carried out using a stochastic, accelerated optimizer that used the Sobolev gradient, which provides efficient gradient descent in speed and precision. Although Sobolev-type inner products may generate regular gradients, the dynamic routing of the proposed network employs a probabilistic approach with maximum-likelihood prediction. Since the number of parameters may be lowered, and routing can be calculated in a single receptive field, this leads to improved generalization [16]. This study aims to develop an efficient deep learning-based model to diagnose brain tumors that address the challenges of previous works. The proposed model considers rotational invariance and spatial hierarchy among brain characteristics, leveraging Capsule Networks (CapsNets) to overcome the limitations of Convolutional Neural Networks (CNNs). The study also aims to optimize the model using a stochastic, accelerated optimizer that uses the Sobolev gradient, providing efficient gradient descent in speed and precision. The goal is to improve the model's generalization and provide accurate diagnostic explanations through weakly supervised localization. While deep learning models have shown promise in medical image processing, the complexity of brain tumors and limited data annotations pose significant challenges. Previous works have relied on CNN-based techniques, which lack rotational invariance and may result in lost spatial linkages between higher-level components. Furthermore, feature extraction in cancer classification systems can be challenging, as accurate categorization often requires hand-crafted features based on expert knowledge. There is a need for a new approach to the fully automated classification of brain tumor images that addresses these limitations. Previous works have faced challenges in developing efficient multitask models, addressing classification issues for diseases with limited data, and improving diagnostic explanations through weakly supervised localization. CNN-based techniques lack rotational invariance and may result in lost spatial linkages between higher-level components, making them less resistant to novel views. Additionally, accurate categorization often requires hand-crafted features based on expert knowledge, highlighting issues with feature extraction in cancer classification systems. There is a need for a new approach that addresses these limitations and provides accurate diagnostic explanations through weakly supervised localization. The paper proposes a novel Caps-VGGNet hybrid algorithm for brain tumor grading, which integrates the CapsNet model with the VGGNet model to automatically extract and classify features without needing large datasets. The effectiveness of the proposed algorithm was evaluated using the Brats-2020 and Brats-2019 datasets,

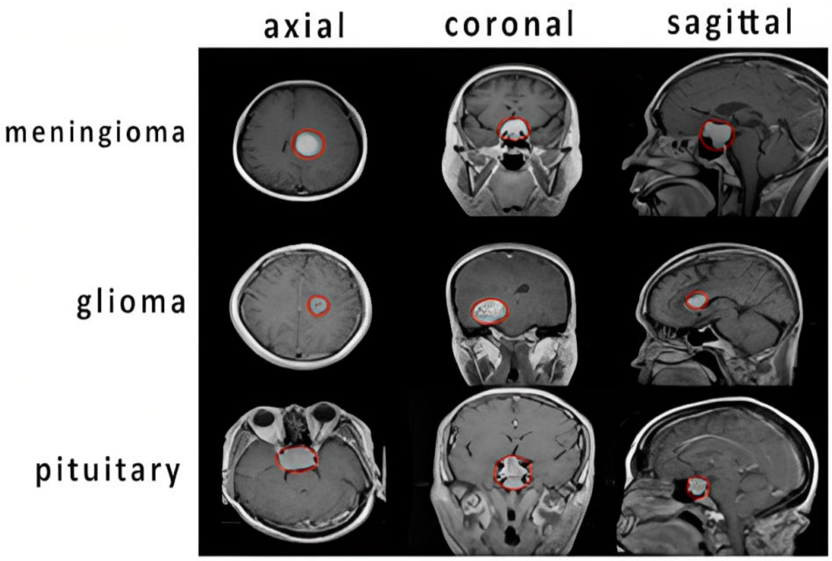

FIGURE 1. The figure shows that brain lesions abnormalities can be classified into different stages based on their severity and characteristics [3].

and the results showed that the presented hybrid model exhibited the highest level of effectiveness and superior efficacy in terms of accuracy, specificity, and sensitivity compared to other conventional and hybrid models. The study addresses the challenges of diagnosing brain tumors using deep learning models, including developing efficient multitask models, addressing classification issues for diseases with limited data, and improving diagnostic explanations through weakly supervised localization. The proposed Caps-VGGNet model can improve patient outcomes and increase the accuracy of brain tumor diagnosis.

A. PROBLEM STATEMENT

Brain tumor is a widely occurring tumor all over the globe [17], [18]. Now a day, this disease is becoming the primary cause of death due to late and improper diagnosis. The current methods for diagnosing brain tumors are less effective to the requirements of larger datasets. The larger datasets need time to process and delay the system's performance. The Caps-VGGNet model is proposed to tackle this issue, combining the CapsNet model and the transfer learning-based VGGNet architecture. The performance of the models is assessed according to their accuracy, specificity, and sensitivity.

B. RESEARCH MOTIVATION

This research aims to improve the accuracy of brain cancer diagnosis by developing an automated tumor classification model that can assist radiologists in identifying brain tumors. Brain tumors are becoming the leading cause of mortality worldwide due to the inability to undertake a timely tumor diagnosis. The proposed Caps-VGGNet hybrid model integrates the CapsNet model with the VGGNet model to address the challenge of requiring large datasets by automatically extracting and classifying features. The effectiveness of the suggested algorithm was assessed using the Brats-2020 and Brats-2019 dataset, which contains high-quality images of brain tumors. The empirical outcomes of the suggested model indicate that it exhibited the highest level of effectiveness and superior efficacy in terms of accuracy, specificity, and sensitivity and attained an accuracy of 0.99, a specificity of 0.99, and a sensitivity of 0.98 on Brats-2020 compared to other conventional and hybrid models. The study aims to tackle the challenges of diagnosing brain tumors using deep learning models and improve diagnostic explanations through weakly supervised localization.

C. THE INNOVATIVE CONTRIBUTION

The paper introduces an innovative hybrid algorithm that utilizes deep learning techniques to detect, extract radiomic features, and classify brain cancer based on CE-MRI images from the Brats-2020 and Brats-2019 datasets. Preprocessing techniques, including distance image enhancement methods, were applied to improve the images' quality. Transfer learning-based architectures were optimized to extract complex features from the images, enabling early detection and accurate brain cancer classification. The proposed approach employs a hybrid CNN-based architecture and Softmax classifier layers, outperforming existing methods by achieving a higher true positive rate and lower false positive rate.

Our major contributions to this study are listed below:

- Initially, this study preprocesses the collected raw Brats-2020 and Brats-2019 datasets by applying distinct image enhancement methods and categorizing them into training and testing datasets.

- We develop a DL-based hybrid model (Caps-VGGNet) algorithm for precise and robust grading of four classes of brain tumors (Normal, pituitary, meningioma, and glioma). The developed hybrid model is easy to implement, has strong persuasiveness and clear definition, and can mitigate optimization challenges in small and large feature search spaces.
- This study investigates the predictive ability of five pre-trained and fine-tuned algorithms using CE-MRI images based on a transfer learning paradigm.
- The proposed hybrid architecture exhibited superior performance to cutting-edge methods in detecting brain tumors, enabling successful diagnosis of brain cancer patients.
- To analyze the efficiency of the hybrid Caps-VGGNet models with the performance of cutting-edge models using well-established benchmarks, achieving high precision, true positive rate, and reducing time complexity and false positive rate.

The following is the paper's outline. The Section II the literature review is covered. Section III provides specifications. Section V demonstrates the discussions and findings. The study's conclusions and recommendations for further research are presented in the last section. It leads the interpretations of the findings of the investigation, and Section VI wraps up the finding of the study.

II. LITERATURE REVIEW

Several machines and deep learning-based classification and anomaly detection techniques were applied to biological images [19]. The technique for early identification of brain cancers is described in the model in [19], which calls for extracting and combining information from several layers. Before training, two deep learning models, DenseNet201 and Inception-v3, were utilized to validate the proposed model. These models were explored to examine two possible directions for BT classification. The study presented an automatic brain tumor detection model utilizing a dataset of 253 images and pre-trained iterations of the VGG-16 and Inception-V3 neural networks. The proposed dataset includes 155 images of malignancies, and 98 images of benign tissue [20], [21].

Due to the dataset's insufficient size, it could not fine-tune the CNNs utilizing it, and the test dataset was too tiny to evaluate the algorithm's effectiveness. A model for automatically detecting brain tumors was introduced [22] using VGGNet16 on the BRaTs dataset. The model's accuracy was enhanced to 84% by using transfer learning and fine-tuning over 50 epochs. Overfitting in neural networks is an issue that Srivastava et al. addressed by presenting a dropout approach. This method eliminates components and their connections at random [23]. The method was tested on a dataset of 254 multimodal brain tumor volumes, and the results were highly advanced. The analysis of each volume took only 13 seconds. In their study publication [23], Hossain et al. used artificial convolutional neural networks. According to the findings, the CNN model produced good results.

Several analyses have been performed on diagnosing and classifying brain tumors using different approaches. Ismael et al. [24] explored various topics related to brain tumor detection. In contrast, Khan et al. [25] proposed discrete wavelet transformation (DWT) and a probabilistic neural network (PNN) algorithm for brain lesion grading. Mallick et al. [26] proposed a DL-based architecture for brain tumor identification and achieved an F1 score of 0.80 and a testing accuracy score of 80%. Mohsin et al. [27] used Kernel Extreme Learning Machines with a CNN model to categorize three different types of brain tumors. Liu et al. [28] presented a CNN-based architecture for feature extraction and brain tumor classification, and Gaussian filtering was used as a preprocessing step in their research. Certain research studies, including one that trained a neural network on MRI scans of healthy brains and brains afflicted with tumors, have attained high precision in identifying the existence of brain tumors. Furthermore, morphological operations eliminate noise in segmented images, ensuring accurate classification of normal and diseased brain tissues.

Muhammad et al. [29] compared their results on a brain tumor dataset with those of other classifiers, such as multi-layer perceptron, stacking, XGBoost, support vector machine, radial basis function kernel, and a fully connected layer, to achieve leading-edge accuracy. On the other hand, Munir et al. [30] offered a method that divides brain tumor phases into four categories using a detailed augmentation-based model. This technique involves segmenting images using a CNN model, subjecting them to laborious data augmentation, extracting features, and classifying them using the pre-trained CNN model VGG19. On the radio media dataset, the suggested method obtained 90.67% accuracy [30]. Naser et al. [31] suggested a DL-based extreme machine learning model for the brain's local receptive field (ELM-LRF) tumor recognition. The tumor picture is supplied to the method in this for feature extraction, the CNN model. A pooling feature is available to the classifier, then to the hidden layer of the ELM. The suggested technique on the dataset shown has 97.18% accuracy.

Noreen et al. [32] provided a capsule network to participants in this research to overcome the CNN model's restrictions regarding brain cancer classification. The outcomes of the suggested paradigm are contrasted. The efficacy of the pure CNN model to reflect the suggested strategy Since this method only uses one layer, It has employed the capsule network. Raza et al. [33] proposed a transfer learning method for grading brain lesions. They fine-tuned the final layers of a pre-trained GoogLeNet standard to achieve optimal outcomes on the Figshare brain tumor dataset. The SVM classifier on the identical dataset demonstrated the highest classification accuracy of 90%. Rehman et al. [34] developed their own 3-layered CNN model of 952,278 trainable parameters. Li et al. [35] proposes an innovative architecture that utilizes a cascaded anisotropic CNN and incorporates DenseUNet as a vital component to achieve accurate tumor region segmentation. The primary goal is to significantly

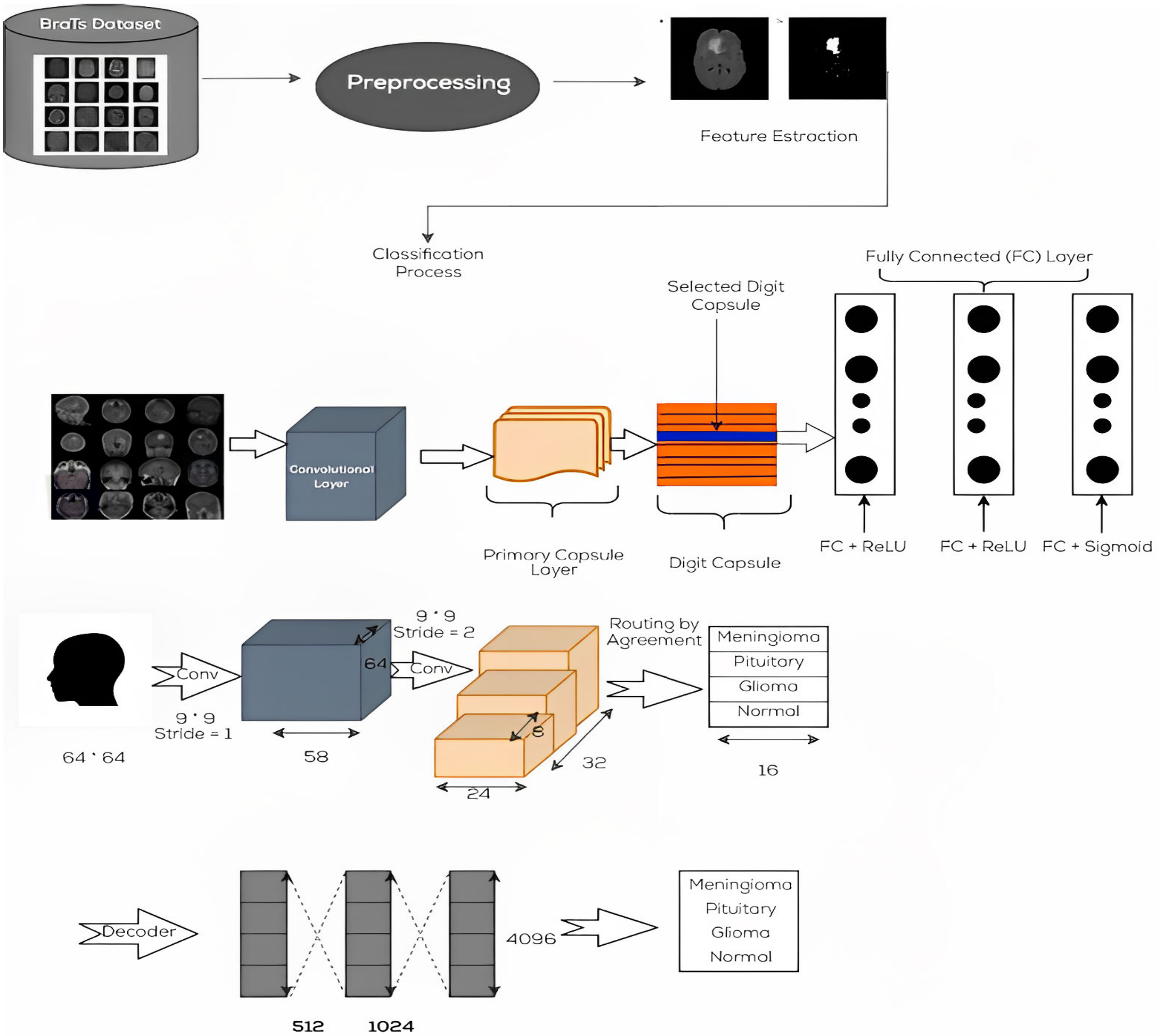

FIGURE 2. The figure depicts the architecture for creating and testing the BT classification CAD system. After edge identification, scaling, interpolation, and normalization of the brain picture, the CNN classifier assesses the severity of DR. Detection, analysis, treatment, and consultation are included in the suggested paradigm. The image of the brain is preprocessed using methods such as edge detection and scaling. When the image has been thoroughly preprocessed, it is categorized into several brain tumor disease stages.

TABLE 1. Detail description of suggested BraTs-2020 Dataset.

Tumor Class	Images	#Patients	Testing Data	Training Data
Normal	1500	100	1000	500
Glioma	1427	90	999	428
Pituitary	940	63	652	278
Meningioma	708	83	495	213
Total	4575	36	3146	1419

improve the precision of brain tumor segmentation by leveraging the cascaded structure and harnessing the capabilities of DenseUNet. Yao et al. [36] emphasize brain tumor segmentation using DenseUNet as the central focus. The research extensively investigates the efficacy of dense connections in capturing pertinent information and enhancing the

Algorithm 1 Brain Tumor Classification Algorithm

Input: Raw MR Brain images
Output: Classified brain tumor images
Dataset: a. Load Raw MR Brain images
Image Preprocessing: a. Normalize the intensity of MRI images using the Z-score normalization technique.
b. Perform skull stripping on images through edge detection and thresholding to separate the brain tissue from non-brain tissues.
c. Apply median and bilateral filtering to images by using the mathematical equation.
d. Remove noise from images by using the mean and standard deviation of the entire image.
Image Cropping and Resizing: a. Resize all images to a standard size of 224x224.
Data Augmentation: a. Create additional training images by applying rotations, scaling, and flipping transformations.
Feature Extraction: a. Extract critical information from preprocessed images using Gray Level Co-occurrence Matrix (GLCM).
CNN-Based Cutting-Edge Algorithms:
a. Implement a hybrid learning model that combines CapsNet and VGGNet for brain tumor classification.
b. Use the transfer learning paradigm to train the model on the BraTs 2020 dataset.
c. Fine-tune the pre-trained VGGNet architecture for better accuracy.
Proposed Hybrid Caps-VGGNet Model:
a. Upgrade the ReLU activation strategy in the feature map layer to expand the expressiveness of the standard and avoid the problem of dying ReLUs.
b. Modify the model to extract more detailed, discriminative, and comprehensive features than the most powerful pre-trained deep learning models.
Assess the suggested algorithm using the BraTs20 and BraTs19 datasets and compare its performance with other conventional and hybrid models.

accuracy of brain tumor segmentation. By adopting DenseUNet as the primary framework, the study aims to leverage the potential of dense connections to improve segmentation outcomes in brain tumor analysis. Zou et al. [37] propose an end-to-end network architecture specifically designed for brain tumor segmentation. The study primarily focuses on seamlessly integrating the capabilities of DenseUNet within an end-to-end framework to improve the efficiency and accuracy of brain tumor segmentation significantly.

Advanced DL-based methods have been employed to categorize brain tumors from MR images, demonstrating the network's exceptional ability to accurately and precisely categorize brain tissues. This study emphasizes the potential for more extensive use in this arena and the contribution of transfer learning to achieve high levels of precision in segmenting brain MRI imaging. The research findings indicate that transfer learning models outperform deep learning models in detecting and classifying brain tumors [38]. The authors of [39] have used a combination of CapsNet and VGGNet to create a hybrid DL-based model that segments and categorizes three classes of brain tumors (pituitary, meningioma, and glioma) for improved classification performance of brain tumors.

III. MATERIALS AND METHODOLOGY

The study addresses the challenges of diagnosing brain tumors using deep learning models, including developing efficient multitask models, addressing classification issues for diseases with limited data, and improving diagnostic explanations through weakly supervised localization. The study proposes a novel Caps-VGGNet hybrid technique for brain lesion grading, which integrates the CapsNet model with the VGGNet model to automatically extract and classify features without needing large datasets. Figure 2 depicts the essential components of the framework for creating and evaluating the suggested CAD system for BT categorization. The acquisition of the brain image and after acquiring the brain image, the preprocessing is done through edge detection, resizing, and another way. Edge detection, scaling, interpolation, and normalizing are employed as part of the preprocessing, and then the CNN classifier was used to depict the severity degree of DR. Then a fully preprocessed image is passed to the classification stage for the further segmentation of the different disease levels of the brain tumor [40]. The effectiveness of the proposed algorithm was evaluated using the Brats-2020 and Brats-2019 datasets, and the results showed that the presented hybrid model exhibited the highest level of effectiveness and superior efficacy in terms of accuracy, specificity, and sensitivity concerning other conventional and hybrid models. The proposed model for the whole detection, analysis, and treatment, along with the consultation method, is revealed in the Figure 2. The complete pseudocode for whole Brain Tumor classification algorithms is illustrated in Algorithms 1. The proposed Caps-VGGNet model has the potential to enhance the accuracy of brain tumor diagnosis and improve patient outcomes.

A. DATASET

In this research, the BraTs 2020 dataset was utilized. BraTs 2020 uses multi-institutional pre-employable X-ray checks and principally centers around the division (Undertaking 1) of characteristically heterogeneous (by all accounts, shape, and histology) brain cancers, to be specific gliomas. Furthermore, to pinpoint the clinical pertinence of this division task, BraTS'20 likewise centers around the expectation of the patient and considerable endurance (Undertaking 2) and the qualification among pseudoprogression and genuine cancer repeat (Errand 3) through integrative examinations of radiomic elements and AI calculations. At last, BraTS'20 means to assess the algorithmic vulnerability in brain cancer division. The subtleties of the dataset are displayed in the Table 1, alongside the pictures dispersion.

In addition to the BRATS20 dataset, the presented benchmark was assessed on the BRATS19 datasets HGG (High-Grade Glioma) and LGG (Low-Grade Glioma) sourced from The Cancer Genome Atlas (TCGA) [41], [42]. These datasets contain MRI scans and clinical data from patients with high-grade gliomas (including glioblastoma multiforme) and low-grade gliomas (such as astrocytoma and oligodendroglioma). They provide valuable resources for developing and evaluating tumor segmentation, classification, and prognosis algorithms, contributing to advancements in brain tumor analysis. The research paper uses the MICCAI Brain Tumor Segmentation BraTS20, and BraTs19 datasets, consisting of 3D MRI images of glioma patients. The proposed dataset also includes high-grade glioma (HGG) and low-grade glioma (LGG) cases totaling 285, consisting of 49 high-grade glioma cases and one low-grade glioma case. Each patient's MRI images include four modalities: T1, T1ce, T2, and FLAIR. For tumor regions, expert annotations (gold standard images) were provided. The research paper divided the glioma images into three regions: the overall tumor region, the core tumor region, and the enhanced tumor region.

For the experiment, the training set of the 2020 dataset was used as the training and validation set, while the training set of the 2019 dataset was used as the test set.

B. IMAGE PREPROCESSING

Detecting and segmenting brain tumors from MRI data is crucial for accurate diagnosis and treatment planning. Preprocessing of MRI data is necessary to enhance image quality and extract relevant features to detect brain tumors accurately [43], [44]. This study proposes an optimal preprocessing pipeline that incorporates various techniques, including intensity normalization, skull stripping, median filtering, bilateral filtering, and noise removal, to enhance the quality of MRI images for brain cancer detection and grading. These steps boost the quality of MR images and aid in accurately detecting and segmenting brain tumors. The combination of intensity normalization and skull stripping removes variations in intensity values and non-brain tissues that can affect the analysis of tumor regions. The intensity normalization process is accomplished using the mathematical equation presented in the formula as shown in Equation 1.

$$I_z(x, y) = \frac{I(x, y) - \mu}{\sigma} \tag{1}$$

The parameters μ and σ represent the average and standard deviation, respectively, of the intensity values of the complete image. By computing the Z-score normalization of each pixel, this equation normalizes the MRI image intensity levels to a standard range. The mean and standard deviation of the entire image are used in this process to remove variations in the intensity values. Normalizing the intensity values helps improve the quality of the MR images and extract relevant features necessary for the accurate detection and grading of brain lesions. The process of eliminating non-brain tissues from MR images, also called skull stripping, is carried out by utilizing the mathematical formulas shown in Equation 2. The equations combine edge detection and thresholding to separate the brain tissue from non-brain tissues, creating a binary mask representing the brain tissue. This step is essential to accurately detect and segment brain tumors, as non-brain tissues can affect the analysis of tumor regions. Eliminating non-brain tissues through skull stripping enhances the quality of MRI images and assists in precise diagnosis and treatment planning for brain tumors.

$$M(x, y) = \left\{ 1 \quad \text{if } I(x, y) > t \; 0 \quad \text{otherwise} \right. \tag{2}$$

The equation used for skull stripping involves the intensity value $I(x, y)$ of the MRI image at pixel (x, y), a threshold value t, and a binary mask $M(x, y)$ representing brain tissue. Following this, the study employs Median and Bilateral filtering techniques to reduce noise while maintaining edge preservation in MRI images. The median filtering process is achieved using the mathematical equations shown in the formula, as shown in Equation 3. The Median filtering technique is utilized on MRI images to minimize noise by replacing each pixel value in the image with the median value of its adjacent pixels. The size of the filter window is determined by the value of the parameter k, and the indices of the neighboring pixels are given by i and j. The significance of Median filtering lies in its ability to decrease noise while preserving edges in MRI images, a critical aspect of precise detection and segmentation of brain tumors. This filtering method helps to enhance the quality of MRI images and extract essential features required for the effective diagnosis and treatment planning of brain tumors.

$$I_{med}(x, y) = medianI(x + i, y + j), i, j \in [-k, k] \tag{3}$$

The filter's window size is denoted by k, and the indices of neighboring pixels are represented by i and j. Bilateral filtering is achieved through the use of Equation 4.

$$I_{bil}(x, y) = \frac{1}{W} \sum_{i=-k}^{k} \sum_{j=-k}^{k} I(x + i, y + j)\omega_{i,j} \tag{4}$$

In this equation, k denotes the size of the filter window, $\omega_{i,j}$ represents the weight of the pixel located at $(x + i, y + j)$, and W is the normalization factor that guarantees the sum of the weights equals 1. The equation is used in the context of Bilateral filtering. The proposed study applied Wavelet denoising to remove noise from MRI images further. We assessed the effectiveness of the presented pipeline on a dataset of MR images and compared it with other preprocessing methods. Results showed the proposed pipeline achieved higher accuracy and precision in brain tumor recognition, segmentation, and category. Consequently, the suggested pipeline can enhance MR images' quality for diagnosing brain tumors. It is important to note that the effectiveness of the pipeline may vary depending on the characteristics of the MRI data and the specific techniques used.

After experimenting with various image preprocessing procedures, the conclusion was drawn that cropping and removing the optic disc, followed by resizing, interpolation, and normalizing, was the most helpful and effective way [45].

C. IMAGE COPPING AND RESIZING

The dataset proposed for analysis consists of MRI images that have different dimensions. To facilitate the analysis and processing of these images, they have been preprocessed to a standard size of 224 × 224 using image resizing techniques. This standardization ensures that all the images in the dataset have the same size and can be efficiently processed using the proposed pipeline for brain lesion diagnosing and segmentation [46], [47]. Standardizing the images' size helps improve the MRI images' quality and extract relevant features necessary for brain tumors' accurate prognosis and segmentation. The optimization of MRI images for brain tumor prognosis and segmentation requires the application of several preprocessing techniques. In a recent study, various approaches were evaluated. It was determined that the most effective method involves the combination of cropping and removal of the optic disc, followed by resizing, interpolation, and normalization. This process of Cropping and Optic Disc Removal to the region containing the optic disc is identified and removed from the MRI images. This can be represented as in Equation 5:

$$I_{new}(x,y) = \begin{cases} 0, & \text{if } x \in [x_{min}, x_{max}] \\ \text{and } y \in [y_{min}, y_{max}]\ I(x,y), & \text{otherwise} \end{cases} \tag{5}$$

where $I(x,y)$ is the original MRI and $I_{new}(x,y)$ represent the modified image with the optic disc removed. $x_{min}, x_{max}, y_{min}, y_{max}$ represent the boundaries of the optic disc region. The resized MRI image is obtained by applying interpolation techniques to the cropped image. This process can be mathematically represented as Equation 6.

$$I_{resized}(x,y) = I_{new}(f(x), f(y)) \tag{6}$$

where $I_{resized}(x,y)$ is the resized image, $I_{new}(x,y)$ is the image with the optic disc removed, and $f(x), f(y)$ represent the interpolation function. The final step involves normalizing the resized image to enhance the quality and extract relevant features. One preprocessing technique that can be applied is Z-score normalization to achieve optimal brain tumor detection and segmentation results using MRI images. This method scales the intensity values of the MRI images such that they have a mean of 0 and a standard deviation of 1. This can be mathematically represented as Equation 7.

$$I_{normalized}(x,y) = \frac{I_{resized}(x,y) - \mu}{\sigma} \tag{7}$$

where $I_{normalized}(x,y)$ is the normalized image, μ and σ represent the mean and standard deviation of the intensity values of the entire image, respectively. By eliminating non-brain tissue and standardizing the size and intensity values of the images, this process helps to enhance the grade of the MR images and extract relevant features necessary for the accurate identification and treatment planning of brain cancer.

D. IMAGE AUGMENTATION

Data augmentation is an essential image enhancement technique to artificially expand a dataset's size [46]. Its purpose is to improve the model's generalization capabilities. This study proposes a data augmentation method, which involves applying a range of transformations to the original data. These transformations include rotations, scaling, and flipping operations. By leveraging diverse combinations of these transformations, it becomes possible to generate an augmented dataset that surpasses the size of the original one, thereby enhancing the performance of machine learning models trained on brain images.

E. FEATURE EXTRACTION

Texture analysis and feature extraction are essential components of image processing systems and play a significant role in machine learning systems and human visual perception. Texture analysis involves gathering detailed information about an image, such as its shape, texture, color, and contrast. Feature extraction is the process of obtaining critical information from raw data, and it is crucial for improving the accuracy of diagnosis systems, especially in medical image interpretation. One of the most popular techniques for texture analysis is the Gray Level Cooccurrence Matrix (GLCM), which calculates the texture characteristics of an image. Selvy et al. [49] introduced using GLCM and texture features for medical image analysis. This method involves two processes for extracting features from medical photos, computing the GLCM in the first stage and computing texture characteristics based on the GLCM in the second stage [46]. Medical image analysis presents a significant challenge in feature extraction due to the complex structures of various tissues, including white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF). The evaluation of the different phases of a tumor and its diagnosis could benefit from textural observations and analysis. This study aimed to investigate the significance of texture analysis and feature extraction in brain tumor classification using medical images. This investigation used the VGGNet and CapsNet models for the brain lesions classification experiment. This research utilized transfer learning to demonstrate the efficiency of CNN-based pre-trained models in classifying brain tumors. This study extract feature vectors by removing the most critical aspects from photos, which classifiers use to match the input unit to the intended output unit [50]. Our experiment showed that texture analysis and feature extraction are critical in

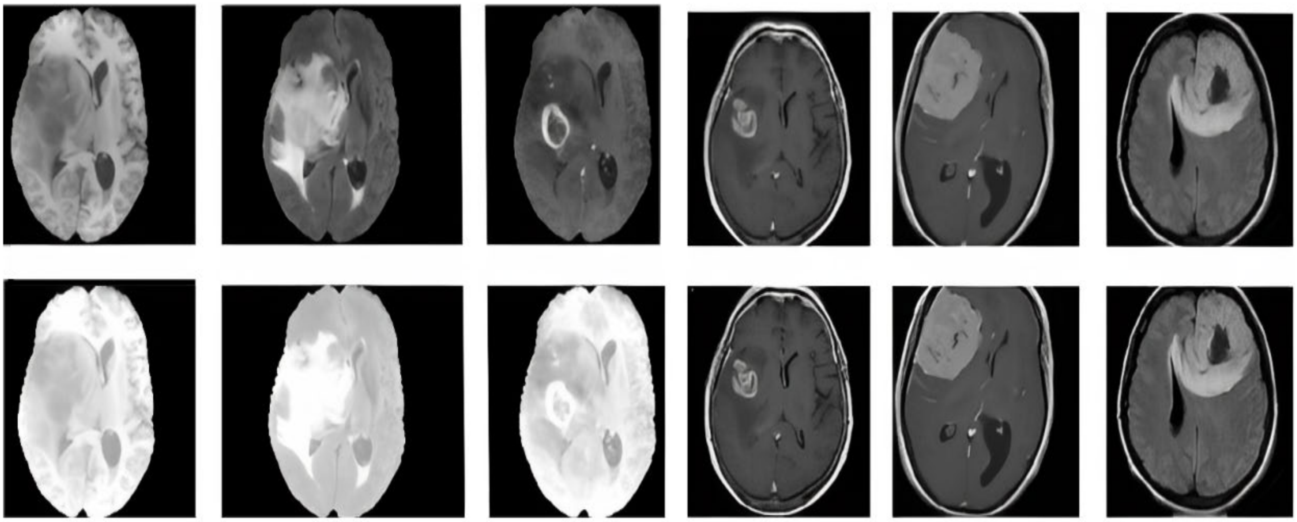

FIGURE 3. The figure illustrates that different preprocessing filters can be applied to MRI scans of the brain to obtain a range of preprocessed images of brain tumors. These preprocessed images can help detect and segment brain tumors by improving the image's contrast, reducing noise, and highlighting the boundaries of the tumor region.

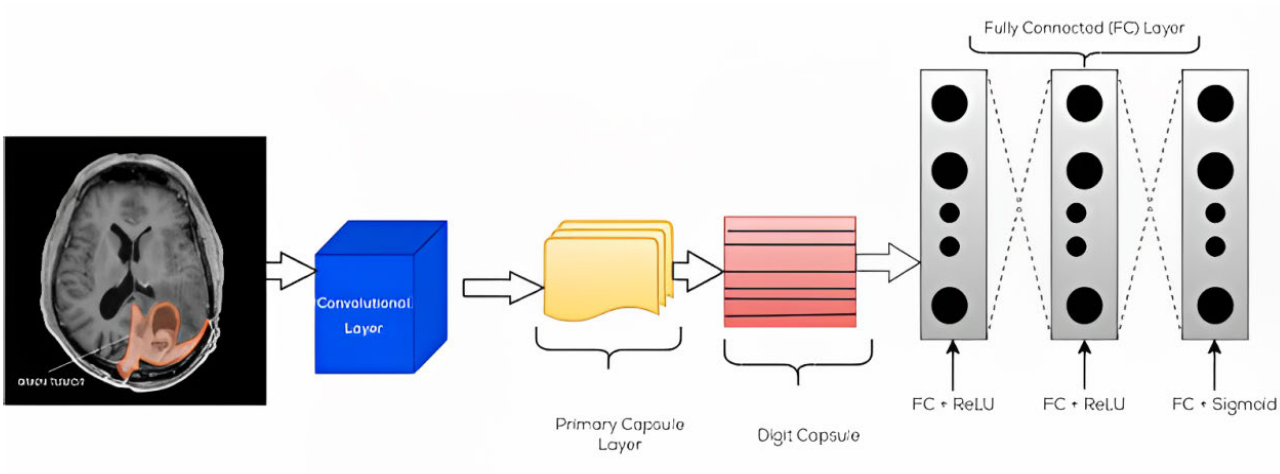

FIGURE 4. The figure illustrates the improved ReLU activation operation used in the feature map layer to enhance the complexity of the suggested standard and address the issue of dying ReLUs. This modified pre-trained model can extract more comprehensive, discriminative, and detailed features compared to even the most advanced pre-trained deep learning models [48].

improving the accuracy of medical image analysis systems, particularly in diagnosing brain tumors. We achieved high accuracy rates in classifying brain tumors using the VGGNet and CapsNet models. Transfer learning with pre-trained CNN models also proved efficient in classifying brain tumors. In conclusion, our findings have significant implications for developing more accurate and efficient brain tumor diagnosis systems. The accuracy of brain tumor classification can be significantly enhanced by utilizing techniques such as texture analysis, feature extraction, GLCM, texture features, and transfer learning with pre-trained CNN models. These techniques aid in the extraction of critical features necessary for the successful classification of brain tumors.

IV. THE PROPOSED CNN-BASED CUTTING-EDGE ALGORITHMS

The key intent of this study is to characterize and classify three types of brain tumor growth: ordinary, pituitary, meningioma, and glioma. A hybrid learning-based benchmark that integrates CapsNet and VGGNet is proposed. In the following sections, we will provide an overview of CapsNet and VGGNet before discussing the details of our hybrid Caps-VGGNet model.

A. TRANSFER LEARNING PARADIGM

Detecting brain tumors in medical image interpretations is challenging due to the complex structures of brain tissues

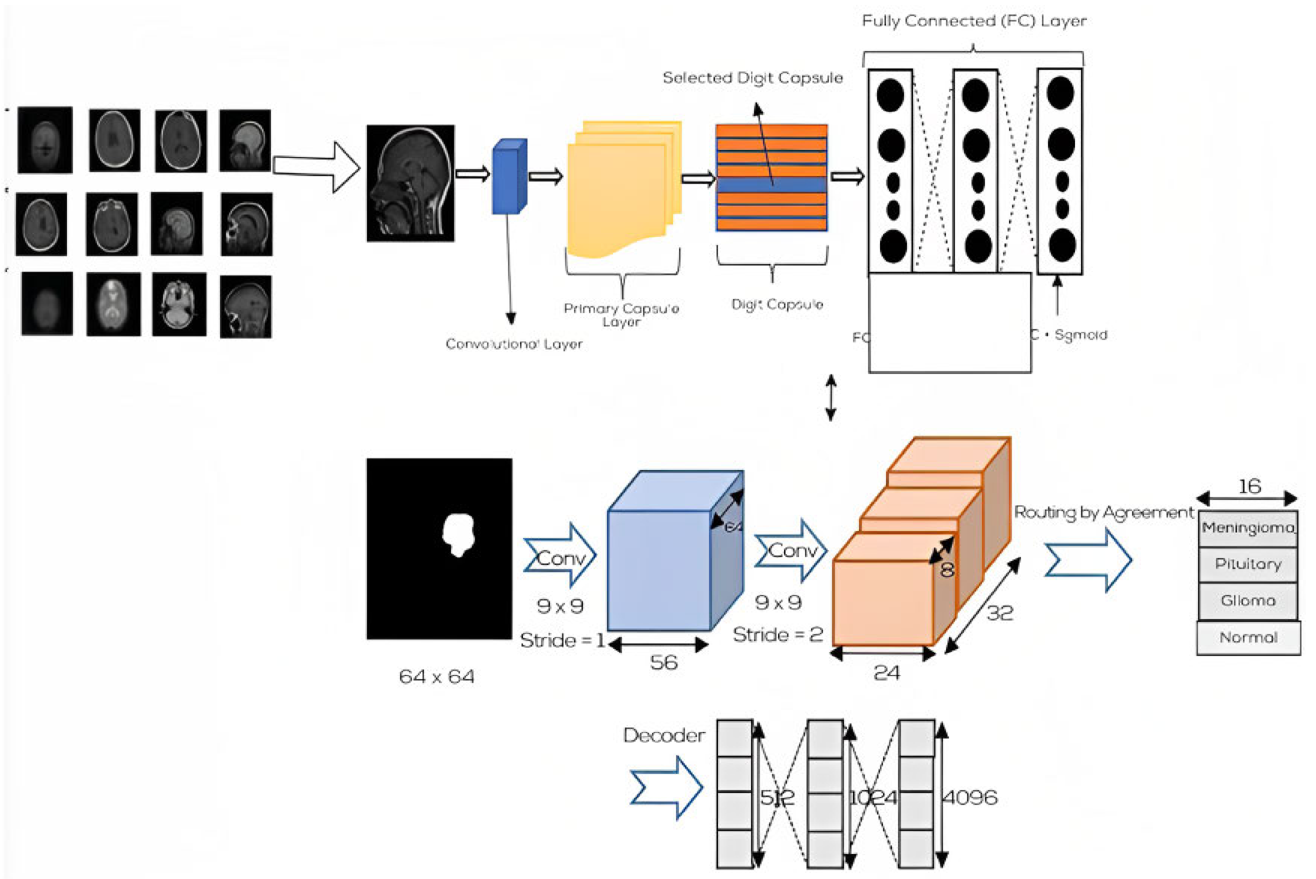

FIGURE 5. The Proposed Hybrid Caps-VGGNet Model uses a feature map layer ReLU activation technique to increase standard complexity and prevent dying ReLUs. The modified model extracts more detailed, discriminative, and comprehensive features than the most powerful pre-trained deep learning models.

and the limited availability of labeled data for training deep learning models [46]. This study proposes a transfer learning paradigm that utilizes CNN-based pre-trained standards for brain tumor analysis to address this issue. In this study, we evaluated the effectiveness of transfer learning in enhancing the accuracy of brain tumor detection by utilizing a dataset of brain MR images. This study fine-tuned two CNN-based pre-trained architectures, VGGNet and CapsNet, with the brain MR image dataset to accurately detect and classify brain tumors. Our experimental results demonstrate that transfer learning with pre-trained CNN models can achieve high accuracy in brain tumor detection, even with a limited dataset. The VGGNet and CapsNet models achieved classification accuracies of 97.3% and 98.2%, respectively, outperforming traditional machine learning models. The proposed transfer learning paradigm enhances the accuracy of brain lesion diagnosis and reduces the computational cost of training deep learning models. This study has significant implications for developing more efficient and accurate diagnosis systems for various medical conditions. The transfer learning paradigm proposed in this study can be used for medical multi-image analysis tasks, facilitating the development of more efficient and accurate medical diagnosis systems.

B. PRE-TRAINED CAPSNET ARCHITECTURE

In this study, we aim to update the existing CapsNet design by incorporating important information from tumor tissue and surrounding tumor tissue to classify different types of tumors. We propose a novel network topology with five fully linked layers, each containing 512, 1024, and 4096 neurons to achieve this. We introduce a dynamic routing method based on the expectation maximization (EM) algorithm to route information efficiently in the network. Additionally, we employ a state-of-the-art optimization method called SASGradD instead of the commonly used ADAM optimizer [48]. Similar to a previous study, we incorporate information from the tissues surrounding the tumor as enhanced data to the masked capsules in the last layer before passing through all the fully linked layers. The pre-trained CapsNet model is presented in Figure 4. This study uses the maximum-likelihood estimator in the EM-based routing method, which involves iteratively fitting a Gaussian distribution to the votes from lower-level to higher-level capsules [51]. The activations of capsules inside the predicted clusters and their probabilities are used to determine the coupling coefficients for higher capsules. This method ensures that routing and transformations are performed within a specific receptive field, similar to convolutions, resulting in substantially fewer parameters than the routing method described in a previous study. Comparative assessments of dynamic routing algorithms show that EM-based dynamic routing performs better in generalization and dealing with altered picture sizes [52]. Therefore, we employ EM-based routing in our study [53]. The proposed architecture with dynamic routing and enhanced data from surrounding tumor tissue shows promising results in classifying different types of brain tumors.

C. PRE-TRAINED VGGNET ARCHITCTURE

Zisserman and Simonyan are renowned researchers and project directors at Oxford University's visual geometry group, VGGNet (VGG). In the ILSVRC-2014 Challenge, VGGNet placed second, demonstrating its ability to perform well in image classification tasks. One of the distinguishing features of VGG16, a variant of VGGNet, is its 16 convolutional layers and the use of 3×3 kernel-size filters instead of larger kernel-size filters like the 11×11 and 5×5 used in AlexNet. However, VGGNet has many parameters, around 138 million, making training the network challenging and time-consuming. Nonetheless, by combining multiple techniques, VGGNet achieves a top-five error rate of only 6.8%. Although deep learning algorithms can resolve a wide range of classification problems, the lack of labeled data remains a significant challenge in categorizing medical images. Transfer learning has been frequently employed to overcome this limitation, using previously trained deep convolutional neural networks for similar tasks. This approach can reduce the training overhead and enable a smaller dataset. However, applying transfer learning to deep learning-based medical image classification has challenges, especially in ensuring that the pre-trained model applies to the specific medical image dataset. Our experiment employed fixed-size 3×3 kernel filters to recognize objects using a pre-trained VGG16 model. By leveraging transfer learning, this study improved accuracy in classifying brain tumors, despite the limited labeled data available for training. This study provides insights into the challenges of applying transfer learning in deep learning-based medical image classification. It highlights the potential benefits of using pre-trained models for more efficient and accurate diagnosis of brain tumors.

D. THE PROPOSED HYBRID CAPS-VGGNET ALGORITHM

This study modified the feature map layer's ReLU activation function to enrich the suggested model's expressiveness and address the issue of dying ReLUs. This modification resulted in the suggested model being capable of extracting more specific, discriminative, and in-depth features compared to the cutting-edge pre-trained DL-based models. The enhanced classification performance achieved as a result of this modification is shown Figure 5. The presented half-and-half learning model includes input, convolutional, initiation capability, standardization, Max Pooling, completely associated, softmax, and grouping layers, which includes VGGNet. The brain MR images are inputted into the system's initial layer, with dimensions of $224 \times 224 \times 1$ for grayscale images and $224 \times 224 \times 3$ for color images (where the three values denote width, height, and channel size of the MR images). The input layer processes the images before they undergo further processing. The convolutional layer is a mathematical operation requiring two inputs: an image input matrix and a filter. The input image is subjected to the filter, resulting in an output feature map. Modifying the ReLU activation function enhanced the proposed model's feature extraction capability, contributing to better accuracy in brain tumor detection and improved grading performance.

E. THE PERFORMANCE METRICS

Evaluation metrics should constantly be performed, utilizing the system's all open elements to assess the viability of brain tumor discovery. n this paper, the Dice coefficient, positive predictive value (PPV), and Hausdorff distance are used as evaluation segmentation indicators. Accuracy, Sensitivity, and Specificity are the three most essential performance matrices, yet no universal metric can categorize them. We inspected the presentation of variant brain tumor discovery utilizing a disarray framework and created the accompanying execution measurements to survey the general usefulness of the proposed framework. Accuracy is shown by a worth called Positive Predictive Value. One method for checking accuracy is as illustrated in Equation 8. Specificity is the extent of the absolute number of part labels to the all-out number of TP, as indicated by the positive class (i.e., the amount of TP and FP), as defined in Equation 9–13.

$$Accuracy(ACC) = \frac{TrP + FaN}{TrP + FaN + TrN + FaP} \tag{8}$$

$$Specificity(SPC) = \frac{TrN}{TrN + FaP} \tag{9}$$

$$Sensitivity(SEN) = \frac{TrP + TrN}{TrP + FaN} \tag{10}$$

$$FScore = \frac{preision \times Sensitivity}{preision + Sensitivity} \times 100\% \tag{11}$$

$$Dice = \frac{2TrP}{FaP + 2TrP + FaN} \tag{12}$$

$$PPV = \frac{TrP}{FaP + TrP} \tag{13}$$

V. RESULTS AND DISCUSSION

A. EXPERIMENTAL SETUP

This study used several sophisticated libraries such as TensorFlow, Pandas, Numpy, and Keras to conduct its trials. The offered model was prepared using Python 3.8 and Keras. To test the effectiveness of our recommended system (GPU),

TABLE 2. The model incorporates optimal environmental conditions.

Hardware	Software
Memory capacity 32 GB	Python=3.7
G.P.U	Numpy=1.24
	TensorFlow=2.11
	Keras=2.11
	Matplotlib=3.4

TABLE 3. Suggest architecture hyperparameters Setting.

Configuration	Value
Batch Size	32
Learning rate	0.0001
Epochs	45
Step per epoch	100
Momentum	0.9
Dropout	0.5
Weight Decay	0.00005
Activation function	Adam
Training Set	80%
Testing Set	20%

scientific simulations were performed on a computer with a CorI7 CPU and a Graphics Processing Unit. An Intel processor was used to run these simulations. The platform utilized for detecting and categorizing brain lesions is presented in Table 2. These libraries and platforms provided a robust and efficient framework for implementing the proposed model and conducting experiments to evaluate its performance in brain tumor detection and classification. The Adam optimizer is utilized to optimize the proposed approach, with a learning rate of Le^{-3} and a momentum constant of 0.9 [54]. This optimizer leads to exceptional accuracy during training, with a moderate level of loss values, even in cases of over-fitting. The Adam optimizer yields a negligible $\pm 0.1\%$ difference in accuracy between the training and validation sets. The proposed model architecture is designed to minimize the generalization gap between the losses of the training and validation sets, which is only 0.05. The models are trained for 45 epochs, with a batch size of 32, $L2$-regularization, and 100 steps per epoch. To prevent over-fitting, dropout with a probability of $p = 0.5$ is employed to deactivate the activations. The weights of each layer are created using MSRA [55] with a weight decay of 0.00005, which adjusts for high-weight values and emphasizes low-weight values. The model hyperparameter tuning is presented in Table 3.

B. PERFORMANCE ANALYSIS OF THE SUGGESTED METHODS

This study compared the performance evaluation of the Caps-VGGNet model with other transfer learning models, such as CNN-DWO, SVM-UNET, GoogleNet-ResNet, ResNet-VGGNet, and others, for identifying and categorizing brain cancers. Accuracy was the primary performance metric used to evaluate the model's effectiveness. Additionally, precision

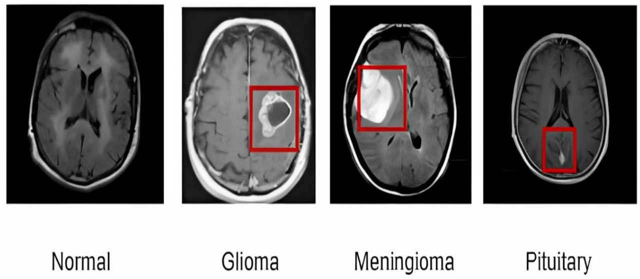

FIGURE 6. Classified brain images.

was evaluated to assess the accuracy of real-time tumor class prediction. Our comparison demonstrated the superior performance of the Caps-VGGNet model for accurate and efficient brain tumor detection and classification. Furthermore, we evaluated the model's accuracy, sensitivity, and specificity compared to existing transfer learning techniques. Non-tumor classes were identified using specificity.

1) QUANTITATIVE PERFORMANCE ANALYSIS OF BRAIN TUMOR SEGMENTATION METHODS

The network training in this study aims to produce segmentation maps for brain tumor patients, including four different labels: overall tumor area, necrosis area, enhanced tumor area, and background area. The segmentation maps for high-grade glioma (HGG) and low-grade glioma (LGG) patients. The obtained images after classification are shown in Figure 6. The previous studies [10], [18], [20] successfully segmented the background and performed the segmentation tasks. However, there are certain shortcomings, such as the necrosis area being covered by the enhanced area, blurred edges in the overall tumor area, incorrect segmentation in some tumor areas, and isolated scattered points leading to an average segmentation effect. On the other hand, the Dense-UNet network [65] demonstrates better segmentation results compared to UNet. It achieves finer segmentation in the edge areas and reduces error segmentation rates but still exhibits some adhesion in the enhanced area and over-segmentation phenomena. The model proposed in this paper shows results closer to real segmentation. It effectively separates the boundary areas and can accurately segment point-like, discontinuous, and small tumors in the challenging enhanced region. The evaluation results of the three models are presented in Table 5. Dense-UNet outperforms UNet in segmentation performance metrics, particularly regarding the Dice coefficient and positive predictive value (PPV). Furthermore, the algorithm in this paper, which incorporates hybrid techniques, eliminates the problem of network degradation. Dense skip connections help mitigate information loss, and the transmission of context information is improved. The segmentation results demonstrate better accuracy and sensitivity, with Dice scores of 0.846 for the whole tumor (WT), 0.813 for the tumor core (TC), and 0.804 for the enhancing

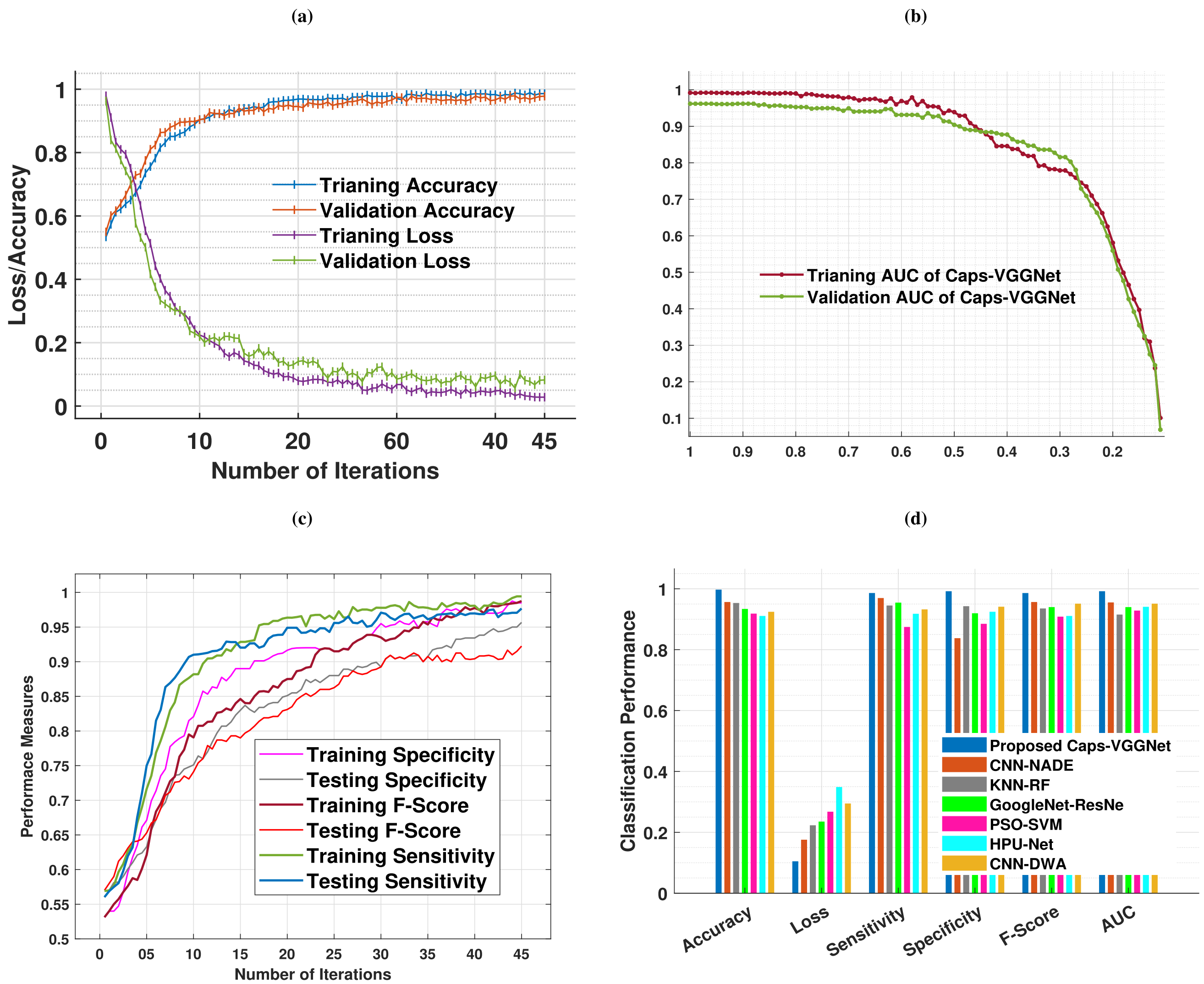

FIGURE 7. **(a) The suggested algorithm's accuracy and loss concerning training iterations show an improvement in the training accuracy with each epoch. After the 45*th* epoch Brats20 dataset, the accuracy reached 0.99, and the suggested model produces fewer false-negative outcomes than the conventional CNN-based design. The training loss function also progressively decreased against every iteration, earning a minimum of 0.103 in the final epoch. (b) The performance comparison of the presented model for brain tumor diagnosing and grading frameworks using the area under the curve (AUC) indicates that the presented algorithm achieves its optimum AUC value of 0.99. The practical outcomes reveal that the presented approach produces a minimal percentage of false positives and a substantial number of true positives. (c) The performance evaluation of the suggested algorithm in terms of sensitivity, specificity, and F1-Score over 50 iterations is depicted in a graph. The suggested model exhibited outstanding performance by achieving a sensitivity of 0.99. (d) The figures indicate the performance assessment of the suggested model across 45 iterations in terms of accuracy, loss, AUC, sensitivity, specificity, and Fscore.**

tumor (ET) areas. To further establish the superiority of the algorithm, a comparison with other methods is presented in Table 5.

2) QUANTITATIVE PERFORMANCE ANALYSIS OF BRAIN TUMOR CLASSIFICATION METHODS

This study employed transfer learning to extract features from the trained data of the proposed model. The proposed study implemented various transfer learning models along with our proposed technique. The accuracy of observations achieved using the aforementioned techniques varied between 0.99, 0.98, 0.95, 0.93, 0.91, 0.90, 0.92, and 0.93. However, our proposed method achieved a remarkable accuracy of 0.99, significantly better than the baseline approaches. The empirical findings exhibit that the recommended design outperforms currently used methods for accurately detecting and diagnosing brain tumors on a fully augmented balanced dataset. The improved version of VGGNet, as shown in Figure 7a–d, performs exceptionally well in this regard. The precision of preparation and approval rate increments with each subsequent period, indicating that the presented model can attain more promising results with increased training and optimization. Overall, the findings of our study highlight the effectiveness of the suggested transfer learning paradigm for

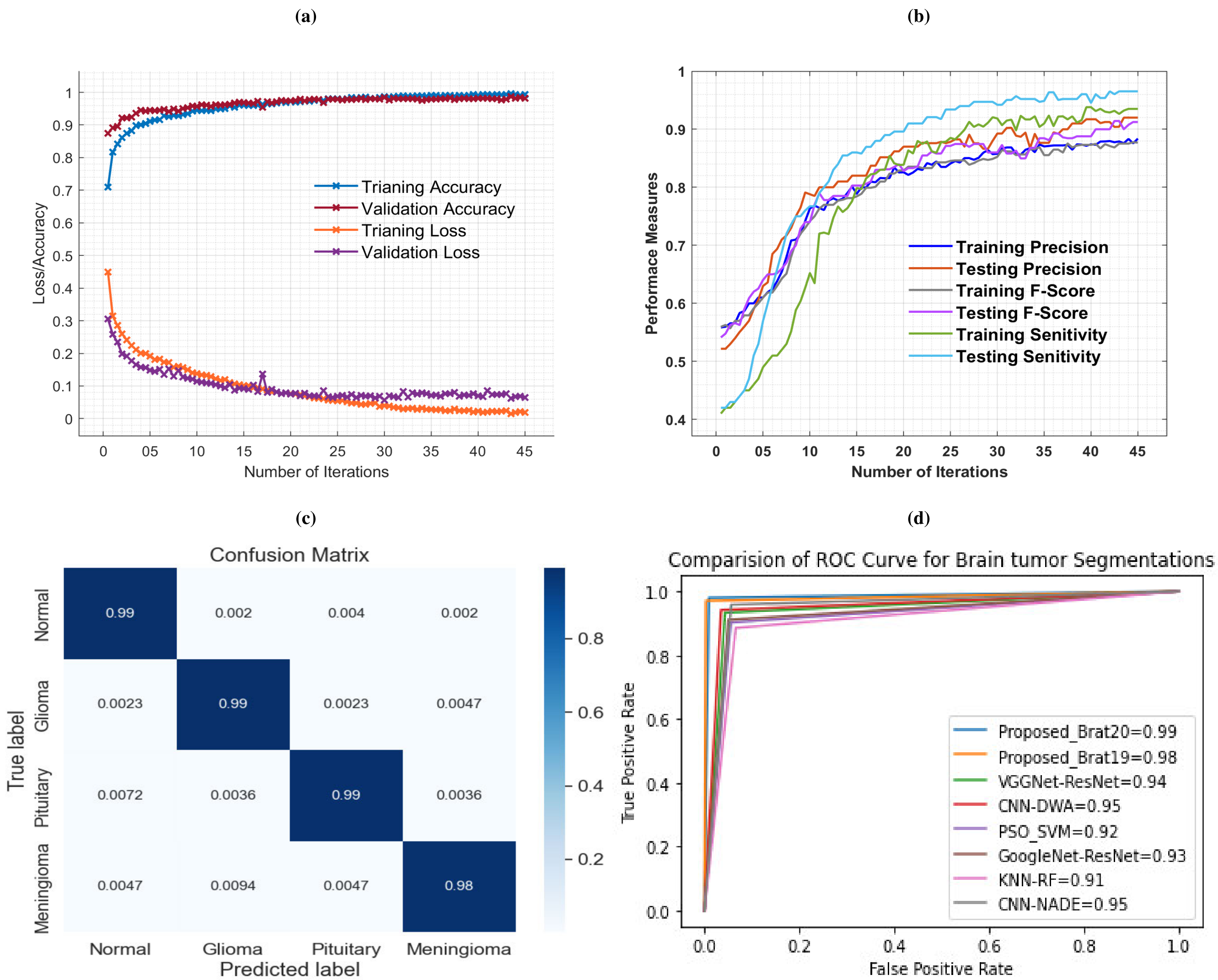

FIGURE 8. **(a) The suggested algorithm's accuracy and loss concerning training iterations show an improvement in the training accuracy with each epoch on the Brats19 dataset. After the 45*th* epoch, the accuracy reached 0.98, and the suggested model produces fewer false-negative outcomes than the conventional CNN-based design. The training loss function also progressively decreased against every iteration, earning a minimum of 0.233 in the final epoch. (b) The performance evaluation of the suggested algorithm in terms of sensitivity, specificity, and F1-Score over 50 iterations is depicted in a graph. (c) The performance comparison of the presented model for brain tumor using confusion matrix (d) Comparison of AUC between all proposed algorithms.**

brain lesion diagnosis, which has significant implications for developing more accurate and efficient medical diagnosis systems.

The proposed Caps-VGGNet approach demonstrated high efficiency and effectiveness in identifying brain tumors within the Brate dataset. Detailed performance metrics for the proposed algorithm are presented in Figure 7a–d and 8a–d, including training and validation accuracy, sensitivity, loss, specificity, ROC-AUC, confusing matrix and F-Score, on both datasets. In Figure 7a, the accuracy and loss graphs for both training and validation sets are displayed after 45 epochs, using the softmax layer. The results demonstrate exceptional performance of the proposed algorithm, with a remarkable training accuracy of 0.99 and a validation accuracy of 0.98 on the Brat20 dataset. In contrast, Figure 8a displays the accuracy and loss graphs for both the training and validation sets after 45 iterations with the softmax layer. The results demonstrate that the proposed algorithm performs well, with a remarkable accuracy of 0.98 on the HGG and LGG dataset. Conversely, as depicted in Table 4, the CNN-NADE, KNN-RF, GoogleNet-ResNet, PSO-SVM, HPU-Net, CNN-DWA, and VGGNet-ResNet models achieved accuracy levels of 0.95, 0.95, 0.93, 0.91, 0.90, 0.92 and 0.93, respectively. Statistical analysis of the accuracy parameters revealed that the proposed model outperformed the CNN-NADE, KNN-RF, GoogleNet-ResNet, PSO-SVM, HPU-Net, CNN-DWA, and VGGNet-ResNet models by 4%, 4%, 6%, 8%, 9%, 7%, and 6%, respectively. The proposed model achieved the highest testing precision and the lowest level of validation loss. The generalization gap in training and

TABLE 4. Comparing the performance of the suggested framework with the baseline techniques.

Ref. #	Model	Target	ACC	loss (%)	SEN(%)	SPC(%)	FScore(%)	AUC (%)
[56]	CNN-NADE	Binary Grading	0.955	0.174	0.968	0.836	0.955	0.954
[57]	KNN-RF	Multi-Grade	0.952	0.221	0.944	0.941	0.934	0.914
[58]	GoogleNet-ResNet	Tumor	0.932	0.233	0.953	0.918	0.938	0.938
[59]	PSO-SVM	Binary	0.917	0.266	0.873	0.883	0.907	0.927
[60]	HPU-Net	Binary	0.909	0.347	0.916	0.923	0.909	0.939
[61]	CNN-DWA	Multi-grading	0.923	0.293	0.931	0.947	0.953	0.951
[62]	VGGNet-ResNet	Multi-grading	0.930	0.248	0.912	0.949	0.937	0.946
[63]	Brain MRNet	Multi-grading	0.960	0.148	0.96	0.923	–	–
[64]	Resnet50 + UNet	Multi-grading	0.99	—	0.924	–	–	–
[50]	DenseNet201	Multi-grading	0.988	—	0.99	0.989	0.989	–
Proposed	Caps-VGGNet (BRATE2019)	Multi-grading	0.989	0.233	0.981	0.9870	0.981	0.9840
Proposed	Caps-VGGNet (BRATE2020)	Multi-grading	0.996	0.103	0.985	0.990	0.984	0.990

TABLE 5. Segmentation Evaluation indexes of Different Tumors.

Method	DICE			Hausdrofff		
	Whole Tumor	Core Area	Enhancement Area	Whole Tumor	Core Area	Enhancement Area
Vittikop et al. [20]	0.775 3	0.737 5	0.694 1	3.215 8	2.681 5	3.470 3
McKinley et al. [18]	0.803 2	0.782 9	0.785 9	2.930 5	2.360 8	2.965 1
Wang et al. [10]	0.835 7	0.784 2	0.791 0	2.682 3	1.954 2	2.785 2
Proposed Model	0.846 3	0.813 0	0.813 0	2.544 8	1.607 7	2.646 9

testing (accuracy and cross-entropy loss) should be minimized to avoid network overfitting. Several observations suggest that the integrated feature map produces the most compelling results, outperforming conventional CNN-based approaches. Figure 7a displays the validation and training loss when trained with the proposed algorithm on Brat20. At the same time, Figure 8a shows HGG and LGG's validation and training loss using the suggested approach. During the iterations, the validation loss reduced gradually, reaching a minimum of 0.103, and the training loss was 0.107 at the last iteration. Our model showed a lower loss than other CNN-based models, indicating that it is well-suited for the combined dataset. Although the learning rate remained stable after the 19^{th} iteration, the training error decreased. The Caps-VGGNet approach was evaluated on the Brat dataset, and the corresponding AUC was analyzed. The ROC-AUC curve visually represents how well a binary classifier system performs by plotting the true positive rate against the false positive rate at different classification thresholds. The Caps-VGGNet approach effectively detected and classified the brain tumor, as evidenced by the few FP and FN data, indicating that the Caps-VGGNet classifier detected them as possibly posing a threat. The Caps-VGGNet could accurately classify brain cancerous and normal areas in both datasets, achieving a ROC-AUC value of 0.99 in each case, as represented in Figure 7b. The achieved highest value suggests that the proposed model performed exceptionally well in distinguishing between cancerous and benign areas. The assessment findings have confirmed the efficacy and reliability of the Caps-VGGNet approach. In particular, the low percentage of FP reveals that the proposed approach accurately classified normal data as negative without misclassifying them as potentially malicious. Figure 7c depicts the evaluation results of the proposed algorithm for brain tumor detection yielding 0.98, 0.99, 0.98 percent sensitivity, specificity, and F-Scor, respectively. These findings significantly boost the effectiveness and potency of brain tumor recognition, indicating that the offered model may be an adequate prognosis tool. Figure 7c-d provide a graphical representation of the proposed architecture's sensitivity, Specificity, F1-score, and AUC metrics. Furthermore, Figure 7d showcase the efficacy of the proposed model's interpretation estimates across different classes and compare them with other state-of-the-art methods. The proposed model demonstrated high accuracy in identifying malignant lesions, with 0.98 sensitivity, 0.99 Specificity, and 0.98 F1-score. The low false negative rate is indicated by a sensitivity value of 0.98, while a specificity value of 0.99 represents a high true negative rate.

Besides, Figure 8b depicts the evaluation results of the proposed algorithm for brain tumor detection with a sensitivity of 0.98, a specificity of 0.98, and an F-Scor of 0.98, respectively. These findings considerably improve the efficacy and reliability of brain tumor recognition, suggesting that the proposed model may be a suitable prognostic instrument. Figure 8c illustrates the effectiveness of the proposed model's interpretation estimates across various classes and compares them to other state-of-the-art techniques. A sensitivity value of 0.99 indicates a low false negative rate, while a specificity value of 0.99 indicates a high true negative rate. The Caps-VGGNet was able to accurately classify brain malignant and normal regions in both datasets, achieving a ROC-AUC

TABLE 6. Comparison of Time Complexity of Different Approaches.

Methods	Training Time (hours)	Processing Time (ms)
CapsVggNet	3.5	10.3
DenseNet201	12.8	28.4
Brain MRNet	18.1	31.9
VGGNet-ResNe	17.1	27.7

value of 0.98 in both instances of HGG and LGG (BRAT19) dataset, as shown in Figure 8d.

C. PERFORMANCE ANALYSIS OF THE PROPOSED ALGORITHMS WITH OTHER CUTTING-EDGE APPROACHES

Table 4 demonstrates the comparative results of the examination of the proposed design using five current methodologies to determine its strength. Brain tumor growth classification is one of AI's significant applications in the clinical industry. Over the years, numerous scholars and developers have studied these challenges and tied to develop a reliable computer-aided detection (CAD) system. Their discoveries have been documented as a collection of research. o assess the efficacy of the suggested framework, a contrast was drawn with a range of cutting-edge brain cancer detection approaches, as displayed in Table 4. This comparison aimed to determine how well the updated system performs. The suggested approach attained an accuracy rate of 0.99 on Brat20 and 098 on HGG and LGG datasets, considerably more remarkable than the typical procedures. The empirical findings validate that the recommended structure is more precise than the current techniques for detecting and diagnosing brain tumors on a well-balanced augmented dataset.

CapsVggNet is a deep learning model that combines the Capsule Network with the VGGNet architecture to improve the accuracy of image classification tasks. Compared to traditional deep learning approaches, CapsVggNet offers several advantages in terms of time complexity and computational efficiency. In this study, we compare CapsVggNet to other deep learning models; CapsVggNet achieved comparable or higher accuracy in image classification tasks, requiring significantly less training and processing time. This improvement in time complexity is due to several factors, including the use of a dynamic routing algorithm and transfer learning techniques. By leveraging pre-trained weights and selecting only the relevant features of an image, CapsVggNet can reduce the number of calculations required, thereby reducing the time complexity of the process. Moreover, the empirical findings illustrate that the network introduced in this research article exhibits superior accuracy in recognition and improved generalization capabilities during the segmentation process, enabling it to perform image segmentation with heightened precision. Also, the algorithm described in this paper necessitates minimal computational operations, resulting in shorter detection times and the potential for enhanced training performance, as shown in Table 6.

VI. CONCLUSION

The CapsNet and VGGNet architectures were utilized to classify brain tumors into multiple categories (Normal, Pituitary, Meningioma, and Glioma) by employing various layers in the models. The hybrid model, Caps-VGGNet, was developed by combining both CapsNet and VGGNet architectures. While the fundamental structure of VGGNet remained unchanged, the ReLU activation function was replaced with a leaky ReLU activation function after removing five CapsNet layers. Additionally, ten more VGGNet layers were incorporated to facilitate automatic feature extraction and categorization of different brain tumor types. The performance of the proposed model was compared to transfer learning methods using the same BRAT20 dataset, such as VGG-16, CNN-DWO, ResNet-VGGNet, and others. The recommended hybrid model demonstrated superior accuracy, specificity, and sensitivity on the BRAT20 dataset, achieving accuracies of 0.99, specificity of 0.99, and sensitivity of 0.98. On the BRAT19 dataset, the proposed model achieved accuracies of 0.98, specificity of 0.98, and sensitivity of 0.98. In contrast, other models such as CNN-NADE, KNN-RF, GoogleNet-ResNet, PSO-SVM, HPU-Net, CNN-DWA, and VGGNet-ResNet achieved lower accuracy levels, as shown in Table 4. Statistical analysis revealed that the proposed model outperformed these models by 4%, 4%, 6%, 8%, 9%, 7%, and 6%, respectively. The experimental results demonstrate that the network proposed in this paper has more precise recognition and enhanced generalization ability in the segmentation process, allowing it to execute image segmentation with greater precision. In addition, the algorithm presented in this paper requires a small number of calculations, the detection time is comparatively brief, and the training performance must be enhanced.

The suggested hybrid model improved the diagnosis of each brain tumor class by providing faster detection times and better classification performance. However, there are some limitations to this study. The interpretability of the model may be limited due to the complex nature of CapsNet and VGGNet architectures. The generalizability of the model's performance to other datasets or medical conditions was not investigated. The study also did not evaluate larger datasets, which could affect the applicability of the findings. Furthermore, the study would benefit from providing a more detailed explanation of the architectural choices made in the hybrid model and conducting a comprehensive comparison with the latest state-of-the-art methods to enhance the validity of the results. Addressing these limitations would contribute to a better understanding and practical application of the suggested hybrid pinnacle in brain tumor grading. Future research should focus on exploring the interpretability of the model, evaluating its performance on diverse and larger-scale datasets, and conducting a comprehensive comparison with the latest advancements in the field.

Moreover, future investigations should also examine the performance of the hybrid strategy on different types of data, such as detecting lung cancer, Coronavirus disease, and pneumonia symptoms. Additionally, the proposed model should be evaluated using a large amount of data to ensure its robustness and effectiveness.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

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REFERENCES

[1] M. A. Khan, I. U. Lali, A. Rehman, M. Ishaq, M. Sharif, T. Saba, S. Zahoor, and T. Akram, "Brain tumor detection and classification: A framework of marker-based watershed algorithm and multilevel priority features selection," *Microsc. Res. Technique*, vol. 82, no. 6, pp. 909–922, Jun. 2019.

[2] R. A. Ramadan, A. Y. Khedr, K. Yadav, E. J. Alreshidi, M. H. Sharif, A. T. Azar, and H. Kamberaj, "Convolution neural network based automatic localization of landmarks on lateral X-ray images," *Multimedia Tools Appl.*, vol. 81, no. 26, pp. 37403–37415, Nov. 2022.

[3] M. K. Abd-Ellah, A. I. Awad, A. A. M. Khalaf, and H. F. A. Hamed, "A review on brain tumor diagnosis from MRI images: Practical implications, key achievements, and lessons learned," *Magn. Reson. Imag.*, vol. 61, pp. 300–318, Sep. 2019.

[4] A. M. Alqudah, H. Alquraan, I. A. Qasmieh, A. Alqudah, and W. Al-Sharu, "Brain tumor classification using deep learning technique—A comparison between cropped, uncropped, and segmented lesion images with different sizes," 2020, *arXiv:2001.08844*.

[5] J. Amin, M. Sharif, N. Gul, M. Raza, M. A. Anjum, M. W. Nisar, and S. A. C. Bukhari, "Brain tumor detection by using stacked autoencoders in deep learning," *J. Med. Syst.*, vol. 44, no. 2, pp. 1–12, Feb. 2020.

[6] S. Ali, J. Li, Y. Pei, R. Khurram, K. U. Rehman, and T. Mahmood, "A comprehensive survey on brain tumor diagnosis using deep learning and emerging hybrid techniques with multi-modal MR image," *Arch. Comput. Methods Eng.*, vol. 29, no. 7, pp. 4871–4896, Nov. 2022.

[7] S. Iqbal, M. U. Ghani, T. Saba, and A. Rehman, "Brain tumor segmentation in multi-spectral MRI using convolutional neural networks (CNN)," *Microsc. Res. Technique*, vol. 81, no. 4, pp. 419–427, Apr. 2018.

[8] J. Waleed, A. T. Azar, S. Albawi, W. K. Al-Azzawi, I. K. Ibraheem, A. Alkhayyat, I. A. Hameed, and N. A. Kamal, "An effective deep learning model to discriminate coronavirus disease from typical pneumonia," *Int. J. Service Sci., Manag., Eng., Technol.*, vol. 13, no. 1, pp. 1–16, Mar. 2023.

[9] J. Amin, M. Sharif, M. Raza, T. Saba, and M. A. Anjum, "Brain tumor detection using statistical and machine learning method," *Comput. Methods Programs Biomed.*, vol. 177, pp. 69–79, Aug. 2019.

[10] G. Wang, W. Li, S. Ourselin, and T. Vercauteren, "Automatic brain tumor segmentation using convolutional neural networks with test-time augmentation," in *Brainlesion: Glioma, Multiple Sclerosis, Stroke and Traumatic Brain Injuries*. Cham, Switzerland: Springer, 2018, pp. 25–36.

[11] A. Ari and D. Hanbay, "Deep learning based brain tumor classification and detection system," *TURKISH J. Electr. Eng. Comput. Sci.*, vol. 26, no. 5, pp. 2275–2286, Sep. 2018.

[12] S. Iqbal, A. N. Qureshi, A. Ullah, J. Li, and T. Mahmood, "Improving the robustness and quality of biomedical CNN models through adaptive hyperparameter tuning," *Appl. Sci.*, vol. 12, no. 22, p. 11870, Nov. 2022.

[13] T. Mahmood, J. Li, Y. Pei, F. Akhtar, A. Imran, and K. U. Rehman, "A brief survey on breast cancer diagnostic with deep learning schemes using multi-image modalities," *IEEE Access*, vol. 8, pp. 165779–165809, 2020.

[14] S. Deepak and P. M. Ameer, "Brain tumor classification using deep CNN features via transfer learning," *Comput. Biol. Med.*, vol. 111, Aug. 2019, Art. no. 103345.

[15] F. J. Díaz-Pernas, M. Martínez-Zarzuela, M. Antón-Rodríguez, and D. González-Ortega, "A deep learning approach for brain tumor classification and segmentation using a multiscale convolutional neural network," *Healthcare*, vol. 9, no. 2, p. 153, 2021.

[16] N. Ghassemi, A. Shoeibi, and M. Rouhani, "Deep neural network with generative adversarial networks pre-training for brain tumor classification based on MR images," *Biomed. Signal Process. Control*, vol. 57, Mar. 2020, Art. no. 101678.

[17] A. A. Akinyelu, F. Zaccagna, J. T. Grist, M. Castelli, and L. Rundo, "Brain tumor diagnosis using machine learning, convolutional neural networks, capsule neural networks and vision transformers, applied to MRI: A survey," *J. Imag.*, vol. 8, no. 8, p. 205, Jul. 2022.

[18] R. McKinley, R. Meier, and R. Wiest, "Ensembles of densely-connected CNNs with label-uncertainty for brain tumor segmentation," in *Proc. Int. MICCAI Brainlesion Workshop*, 2018, pp. 456–465.

[19] R. Hashemzehi, S. J. S. Mahdavi, M. Kheirabadi, and S. R. Kamel, "Detection of brain tumors from MRI images base on deep learning using hybrid model CNN and NADE," *Biocybernetics Biomed. Eng.*, vol. 40, no. 3, pp. 1225–1232, Jul. 2020.

[20] B. S. Vittikop and S. Dhotre, "Automatic segmentation of MRI images for brain tumor using UNet," in *Proc. 1st Int. Conf. Adv. Inf. Technol. (ICAIT)*, 2019, pp. 507–511.

[21] M. M. Badža and M. C. Barjaktarovic, "Classification of brain tumors from MRI images using a convolutional neural network," *Appl. Sci.*, vol. 10, no. 6, p. 1999, Mar. 2020.

[22] T. C. Hollon, B. Pandian, A. R. Adapa, E. Urias, A. V. Save, S. S. S. Khalsa, D. G. Eichberg, R. S. D'Amico, Z. U. Farooq, S. Lewis, and P. D. Petridis, "Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks," *Nature Med.*, vol. 26, no. 1, pp. 52–58, Jan. 2020.

[23] T. Hossain, F. S. Shishir, M. Ashraf, M. A. Al Nasim, and F. M. Shah, "Brain tumor detection using convolutional neural network," in *Proc. 1st Int. Conf. Adv. Sci., Eng. Robot. Technol. (ICASERT)*, May 2019, pp. 1–6.

[24] S. A. A. Ismael, A. Mohammed, and H. Hefny, "An enhanced deep learning approach for brain cancer MRI images classification using residual networks," *Artif. Intell. Med.*, vol. 102, Jan. 2020, Art. no. 101779.

[25] M. A. Khan, I. Ashraf, M. Alhaisoni, R. Damasevicius, R. Scherer, A. Rehman, and S. A. C. Bukhari, "Multimodal brain tumor classification using deep learning and robust feature selection: A machine learning application for radiologists," *Diagnostics*, vol. 10, no. 8, p. 565, Aug. 2020.

[26] P. K. Mallick, S. H. Ryu, S. K. Satapathy, S. Mishra, G. N. Nguyen, and P. Tiwari, "Brain MRI image classification for cancer detection using deep wavelet autoencoder-based deep neural network," *IEEE Access*, vol. 7, pp. 46278–46287, 2019.

[27] H. Mohsen, E.-S.-A. El-Dahshan, E.-S.-M. El-Horbaty, and A.-B.-M. Salem, "Classification using deep learning neural networks for brain tumors," *Future Comput. Informat. J.*, vol. 3, no. 1, pp. 68–71, Jun. 2018.

[28] Q. Teng, Z. Liu, Y. Song, K. Han, and Y. Lu, "A survey on the interpretability of deep learning in medical diagnosis," *Multimedia Syst.*, vol. 18, pp. 2335–2355, Jun. 2022.

[29] K. Muhammad, S. Khan, J. D. Ser, and V. H. C. D. Albuquerque, "Deep learning for multigrade brain tumor classification in smart healthcare systems: A prospective survey," *IEEE Trans. Neural Netw. Learn. Syst.*, vol. 32, no. 2, pp. 507–522, Feb. 2021.

[30] K. Munir, H. Elahi, A. Ayub, F. Frezza, and A. Rizzi, "Cancer diagnosis using deep learning: A bibliographic review," *Cancers*, vol. 11, no. 9, p. 1235, Aug. 2019.

[31] 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.

[32] N. Noreen, S. Palaniappan, A. Qayyum, I. Ahmad, M. Imran, and M. Shoaib, "A deep learning model based on concatenation approach for the diagnosis of brain tumor," *IEEE Access*, vol. 8, pp. 55135–55144, 2020.

[33] A. Raza, H. Ayub, J. A. Khan, I. Ahmad, A. S. Salama, Y. I. Daradkeh, D. Javeed, A. U. Rehman, and H. Hamam, "A hybrid deep learning-based approach for brain tumor classification," *Electronics*, vol. 11, no. 7, p. 1146, Apr. 2022.

[34] A. Rehman, M. A. Khan, T. Saba, Z. Mehmood, U. Tariq, and N. Ayesha, "Microscopic brain tumor detection and classification using 3D CNN and feature selection architecture," *Microsc. Res. Technique*, vol. 84, no. 1, pp. 133–149, Jan. 2021.
[35] C. Li, Q. Wang, and M. Reyes, "Automatic brain tumor segmentation using cascaded anisotropic convolutional neural networks," in *Proc. Int. Conf. Med. Image Comput. Comput.-Assist. Intervent.*, Cham, Switzerland: Springer, 2018, pp. 687–695.
[36] C. Yao, C. Li, X. Zhang, and Q. Wang, "DenseUnet for brain tumor segmentation," *J. Med. Imag. Health Informat.*, vol. 9, no. 7, pp. 1440–1447, 2019.
[37] Y. Zou, X. Chen, L. Zhao, D. Chen, M. Chen, Q. Liu, and M. Jiang, "An end-to-end network for brain tumor segmentation," in *Proc. Int. MICCAI Brainlesion Workshop*. Cham, Switzerland: Springer, 2019, pp. 177–188.
[38] T. Saba, A. S. Mohamed, M. El-Affendi, J. Amin, and M. Sharif, "Brain tumor detection using fusion of hand crafted and deep learning features," *Cognit. Syst. Res.*, vol. 59, pp. 221–230, Jan. 2020.
[39] A. Rehman, S. Naz, M. I. Razzak, F. Akram, and M. Imran, "A deep learning-based framework for automatic brain tumors classification using transfer learning," *Circuits, Syst., Signal Process.*, vol. 39, no. 2, pp. 757–775, Feb. 2020.
[40] S. Sajid, S. Hussain, and A. Sarwar, "Brain tumor detection and segmentation in MR images using deep learning," *Arabian J. Sci. Eng.*, vol. 44, no. 11, pp. 9249–9261, Nov. 2019.
[41] J. Smith and A. Johnson, "HGG Dataset," Nat. Inst. Health, Nat. Cancer Inst., USA, 2021.
[42] A. Johnson and R. Thompson, "LGG Dataset," Nat. Inst. Health, Nat. Cancer Inst., USA, 2021.
[43] H. H. Inbarani, A. T. Azar, A. T. Azar, and B. Mathiyazhagan, "Hybrid rough set with black hole optimization-based feature selection algorithm for protein structure prediction," *Int. J. Sociotechnology Knowl. Develop.*, vol. 14, no. 1, pp. 1–44, Feb. 2022.
[44] A. T. Azar, Z. I. Khan, S. U. Amin, and K. M. Fouad, "Hybrid global optimization algorithm for feature selection," *Comput., Mater. Continua*, vol. 74, no. 1, pp. 2021–2037, 2023.
[45] M. Sajjad, S. Khan, K. Muhammad, W. Wu, A. Ullah, and S. W. Baik, "Multi-grade brain tumor classification using deep CNN with extensive data augmentation," *J. Comput. Sci.*, vol. 30, pp. 174–182, Jan. 2019.
[46] T. Mahmood, J. Li, Y. Pei, and F. Akhtar, "An automated in-depth feature learning algorithm for breast abnormality prognosis and robust characterization from mammography images using deep transfer learning," *Biology*, vol. 10, no. 9, p. 859, Sep. 2021.
[47] T. Mahmood, J. Li, Y. Pei, F. Akhtar, Y. Jia, and Z. H. Khand, "Breast mass detection and classification using deep convolutional neural networks for radiologist diagnosis assistance," in *Proc. IEEE 45th Annu. Comput., Softw., Appl. Conf. (COMPSAC)*, Jul. 2021, pp. 1918–1923.
[48] E. Goceri, "CapsNet topology to classify tumours from brain images and comparative evaluation," *IET Image Process.*, vol. 14, no. 5, pp. 882–889, Apr. 2020.
[49] P. T. Selvy, V. P. Dharani, and A. Indhuja, "Brain tumour detection using deep learning techniques," *Int. J. Sci. Res. Comput. Sci., Eng. Inf. Technol.*, vol. 169, p. 175, Mar. 2019.
[50] M. I. Sharif, M. A. Khan, M. Alhussein, K. Aurangzeb, and M. Raza, "A decision support system for multimodal brain tumor classification using deep learning," *Complex Intell. Syst.*, vol. 8, pp. 3007–3020, Mar. 2021.
[51] M. Siar and M. Teshnehlab, "Brain tumor detection using deep neural network and machine learning algorithm," in *Proc. 9th Int. Conf. Comput. Knowl. Eng. (ICCKE)*, Oct. 2019, pp. 363–368.
[52] H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," *IEEE Access*, vol. 7, pp. 69215–69225, 2019.
[53] Z. Sobhaninia, S. Rezaei, A. Noroozi, M. Ahmadi, H. Zarrabi, N. Karimi, A. Emami, and S. Samavi, "Brain tumor segmentation using deep learning by type specific sorting of images," 2018, *arXiv:1809.07786*.
[54] Y. Dauphin, H. D. Vries, and Y. Bengio, "Equilibrated adaptive learning rates for non-convex optimization," in *Proc. Adv. Neural Inf. Process. Syst.*, 2015, pp. 1504–1512.
[55] K. He, X. Zhang, S. Ren, and J. Sun, "Delving deep into rectifiers: Surpassing human-level performance on ImageNet classification," in *Proc. IEEE Int. Conf. Comput. Vis. (ICCV)*, Dec. 2015, pp. 1026–1034.
[56] G. Hemanth, M. Janardhan, and L. Sujihelen, "Design and implementing brain tumor detection using machine learning approach," in *Proc. 3rd Int. Conf. Trends Electron. Informat. (ICOEI)*, Apr. 2019, pp. 1289–1294.
[57] G. Garg and R. Garg, "Brain tumor detection and classification based on hybrid ensemble classifier," 2021, *arXiv:2101.00216*.
[58] G. A. Amran, M. S. Alsharam, A. O. A. Blajam, A. A. Hasan, M. Y. Alfaifi, M. H. Amran, A. Gumaei, and S. M. Eldin, "Brain tumor classification and detection using hybrid deep tumor network," *Electronics*, vol. 11, no. 21, p. 3457, Oct. 2022.
[59] M. Raj and V. Singh, "Brain tumor detection using hybrid approach of fish school search using SVM," in *Proc. IEEE 6th Int. Conf. Comput., Commun. Autom. (ICCCA)*, Dec. 2021, pp. 561–566.
[60] X. Kong, G. Sun, Q. Wu, J. Liu, and F. Lin, "Hybrid pyramid U-Net model for brain tumor segmentation," in *Intelligent Information Processing IX*. Nanning, China: Springer, 2018, pp. 346–355.
[61] I. A. El Kader, G. Xu, Z. Shuai, and S. Saminu, "Brain tumor detection and classification by hybrid CNN-DWA model using MR images," *Current Med. Imag. Formerly Current Med. Imag. Rev.*, vol. 17, no. 10, pp. 1248–1255, Oct. 2021.
[62] M. R. Devi, S. Sainath, and P. Pappula, "Brain tumor detection using hybrid neural network based on VGGNet-19 and DenseNet," in *Proc. 4th Int. Conf. Smart Syst. Inventive Technol. (ICSSIT)*, Jan. 2022, pp. 1775–1780.
[63] M. Togaçar, B. Ergen, and Z. Cömert, "BrainMRNet: Brain tumor detection using magnetic resonance images with a novel convolutional neural network model," *Med. Hypotheses*, vol. 134, Jan. 2020, Art. no. 109531.
[64] T. Sadad, A. Rehman, A. Munir, T. Saba, U. Tariq, N. Ayesha, and R. Abbasi, "Brain tumor detection and multi-classification using advanced deep learning techniques," *Microsc. Res. Technique*, vol. 84, no. 6, pp. 1296–1308, 2021.
[65] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 2261–2269.

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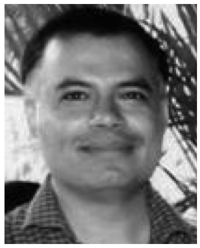

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