Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.12 n.58, p. 931-940. March/April, 2026.
DOI: https://doi.org/10.5935/jetia.v12i58.2081

RESEARCH ARTICLE OPEN ACCESS

A NOVEL APPROACH OF TRANSFER LEARNING FOR ACCURATE BRAIN TUMOR MRI CLASSIFICATION IN BIG DATA HEALTHCARE ENVIRONMENT

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ARTICLE INFO

Article History
Received: December 31, 2025
Reviewed: January 1, 2026
Accepted: March 10, 2026
Published: April 30, 2026

Keywords:
Brain tumor Classification,
CNN,
pre-trained model,
big data healthcare environment,
MR images.

ABSTRACT

The complex structure of brain tumors and the need for prompt and accurate detection present a major challenge to the medical community. This paper suggests an improved CNN framework for classifying brain cancers in the big data healthcare arena, addressing the shortcomings of current diagnostic techniques. The CNN model was enhanced by integrating transfer learning methods and data augmentation using Magnetic Resonance (MR) images. The model's predictive performance was further improved by adding more training parameters in pre-trained deep learning models like ResNet-50, VGG-16, Inception V3, DenseNet201, Xception, and MobileNet. According to experimental results, the suggested model performs better than baseline models and achieves a 99.40% classification accuracy rate. According to this study, a more precise and effective way to diagnose brain tumors could be achieved in clinical settings by using the suggested model. The future direction suggested enhancing the dataset and further refining the model to improve its generalization capabilities in diverse clinical scenarios.

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I. INTRODUCTION

An abnormal growth of tissues in the human brain is called a brain tumor, which is a dangerous medical condition that affects the majority of people worldwide. It disrupts regular brain activity [1]. According to risk factors, the category of benign brain tumors grows gradually and does not pose a threat. On the other hand, malignant brain tumors are made up of cancer cells that start small, proliferate, and spread to other areas of the brain [2]. Early detection and diagnosis are essential for successful treatment and recovery. In this sense, scientists and medical professionals in the big data healthcare industries have invented a variety of advanced non-invasive techniques to identify and classify these tumors [3]. Recently, deep learning models have been frequently used in the process of creating automated systems for screening of tumor regions [4].

In recent times, the diagnosis of tumors using image data with the help of neural networks is becoming popular and is frequently employed for the categorization and examination of medical images. CNN models can extract more associated characteristics from the image dataset [5]. In addition, in the big data healthcare domain, recently developed sophisticated approaches, such as transfer learning, also enhance the prediction accuracy of advanced machine learning frameworks to accurately diagnose and classify brain cancers [6]. In this proposed work, we have analyzed an enhanced CNN model to diagnose brain cancer in the big data healthcare domain by classifying MR images of brain tumors.

The CNN model picks out additional detailed features from the picture data for the overall classification, making it more appropriate for the various types of tumor categorizing utilizing the tumor picture collection. Apart from boosting the model's capacity for prediction due to an insufficient image data set, we have included a transfer learning technique to ensure that the CNN model is properly aligned [7]. To smooth the implementation of the transfer learning technique, we incorporated the six popular pre-trained frameworks in this research, such as ResNet-50 [8], VGG-16 [9], Inception V3 [10], DenseNet201 [11], Xception [12], and MobileNet [13]. The training parameters generated by these frameworks are separately transferred to the CNN model to train it effectively.

The model was trained using a series of MR images of brain tumors to fine-tune it [14]. The fine-tuning process is very useful because it decreases the time complexity and does not require training deep learning frameworks from scratch. To overcome the limitations of the data size, the popular technique of data augmentation is also included in the training process [15]. At the end of the study, we compared our recommended model's performance with some baseline models, which are also equally important. The findings of the experiment verified that the recommended model accomplished more precise predictions and could be effectively implemented in the big data healthcare domain. The achievements of this proposed work are in the following order:

- In the big data healthcare domain, an enhanced CNN framework that uses advanced techniques like transfer learning for categorising and diagnosing tumors using an MRI data set is recommended.
- Some trendy frameworks, which are already trained on a huge amount of ImageNet data collection, are employed for creating training parameters or weights. The training parameters of these frameworks are separately transferred to CNN models for efficient training.
- To train models more effectively and optimise model accuracy, the advanced machine learning technique is employed to enhance the volume of the data collection.
- The estimation of the effectiveness of our suggested model is excellent when compared to baseline models.

The remaining components of this research are structured in the following sequence: In the literature review section, previous related work is explored. The suggested model approach and data collection have been explained in the "Materials and Methods" section. The proposed Experimental procedures are explained in the “experiments” section. We discussed the proposed work's relevance in the "Discussion" part. The "Conclusion" section suggests the concluding opinions and future areas for investigation.

II. LITERATURE REVIEW

Innovative techniques are applied in the scientific field of medical imaging, and various cutting-edge technologies work to make segmenting, classifying, and other diagnostic tools more user-friendly and functional. The following part provides a summary of the various successful research studies that have been performed in the field of modern AI technology, with the conclusions of their achievements. The latest findings are encouraging and have a considerable effect on brain tumor diagnosis and treatment. By [16] classified brain cancers by applying a model of neural networks with a sophisticated architecture and high accuracy values, applying a dataset of 5,812 MRI pictures. According to [17] proposed a customized neural network framework for classifying brain tumors based on images collected from different sources.

They used advanced 10-fold cross-validation to record the results and achieved more than 96% accuracy. The model's fundamental structure makes it incapable of studying complicated patterns. In turn [18] employed a paired GAN (generative adversarial network) framework to categorise different kinds of glioma brain tumors and obtained a mean accuracy of 88.82%. To address the lack of images for classification, enhanced MRI images are provided. By [19] presented a sophisticated CNN model using the dataset. The network is constructed using graph techniques with an accuracy of 95.49%. Scatterplots and some other graphical tools are employed to display results effectively. In contrast to several CNN models, which obtained lower accuracy with the proposed model.

To classify gliomas into subtypes [20] investigated the use of the discrete wavelet transform in combination with an advanced deep neural network model. MRI scans of brain tumors were acquired via the online repository. The framework divides the medical images into four distinct stages according to the WHO guidelines, and with the right feature extraction and selection strategies, the architecture performed excellently with 96.15% accuracy. Using the feature extractors D-SURF and [21] suggested a novel categorization approach. A dataset of 3,064 photos is used in their study to provide training SVM for the classification procedure.

Even with the meticulous Extracting characteristics procedure, it performed well and achieved an accuracy of more than 90%, which indicates requirements for extra SVM fine-tuning. A comparative deep study of the various existing frameworks, like CNN, VGG 16, Inception-V3, and Resnet-50, was carried out by [22] using a collection including 3,264 MR pictures. The accuracy ranges of the models were 80% to 93.30%, respectively. The literature study indicates that current methods for diagnosing brain tumors still lack a strong predictive capacity, making it difficult to accurately diagnose brain tumors to get the right care and make a full recovery. To properly treat and recover from brain tumors in the Big Data healthcare arena, a novel, robust way of precisely detecting them is needed.

III. MATERIALS AND METHODS

III.1 DATA SET

We employed a data set of brain tumor MRI from the Kaggle web repository, which included 3064 different forms of images. [23].

III.2 INTRODUCTIONS TO CNN FRAMEWORK

The base architecture of deep learning contains a feed-forward neural network, which contains multiple hidden layers to optimize the model's performance. Deep learning consists of various types of frameworks, among them, CNN is one of the most famous and widely used frameworks for implementing deep learning techniques (Figure 1). It is widely employed in various image processing-related research areas. It is particularly used to handle grid-like structures, such as image collections. The backpropagation algorithm can be used to train CNNs. Some important layers, such as the input layer [24], convolutional layer [25], pooling layer [26], fully connected layer [27], and output layer [28], make up a convolutional neural network's main structure (Figure 1). These layers execute several tasks, including feature extraction, classification, and dimensionality reduction [29]. The filter or Kernel [30] is slid across the input shape during the convolution process, computing the feature map and the value of each output.

Designed a Sliding Kernel using a dot product expression for quick deployment, utilizing convolution as a linear operator. Let's consider y and z as input and kernel functions. We can mathematically represent the convolution process (x * y) (a) on time index t using Eq. (1).

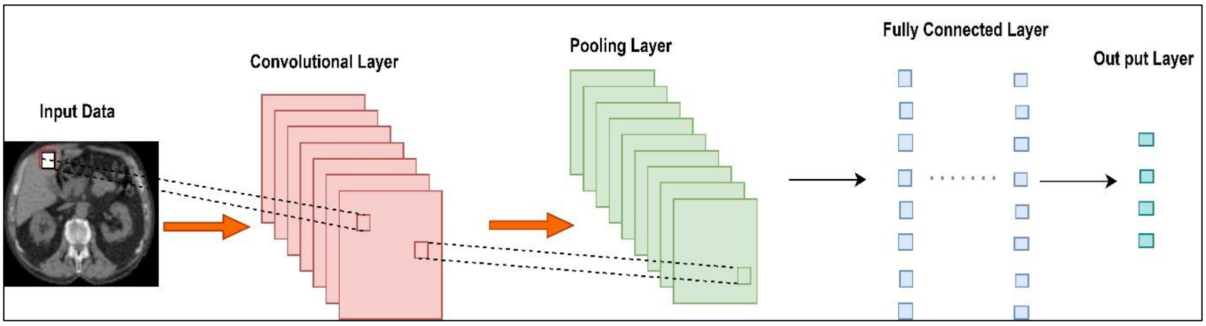

Figure 1: CNN framework for tumor classification.
Source: Authors, (2026).

$$(x * y)a = \int x(t)y(a-t)da \tag{1}$$

The CNN model typically uses 2 or 3-dimensional convolutions. Eq. (2) provides a mathematical expression for the convolution when a two-dimensional image I is used as the input and K as a 2D kernel.

$$(I * K)(i,j) = \sum_m \sum_n I(m,n)K(i-m,j-n) \tag{2}$$

Two activation functions, such as Sigmoid and ReLU, can be incorporated in addition to acquiring non-linearities. The sigmoid activation function [31] is expressed mathematically by Eq. (3):

$$\theta(x) = \frac{1}{1+\exp(-x)}, x \in R \tag{3}$$

When the output must fall within the range of binary [0,1], the sigmoid non-linear activation function is appropriate. Eq. (4) mathematically defines the second activation function ReLU [32]:

$$Relu(x) = \max(0,x), x \in R \tag{4}$$

Pooling layers are used to determine the dimensionality and provide a statistical summary of their inputs without affecting any important information. The final layer, referred to as a fully connected layer in a neural network, has input and output sizes of n and m, respectively. Weight matrices and other factors are used to express the output layer. The final layers are used for problem classification. After this layer, the output is flattened and appears as a single-dimensional vector [33].

III. 3 IMPORTANCE OF CNN FOR TUMOR CLASSIFICATION

CNN frameworks have produced noteworthy results recently in several fields, including image classification and diagnosis systems. CNNs are less complex and adapt more quickly than NLPs since they have fewer neurons and parameters. Medical image classification is a particular field in which the CNN model is quite beneficial. This study presents the design of the CNN network, which consists of four convolutional layers that contain alternate pooling layers, followed by an important dropout layer [34] presented after a regular pair of convolutional and pooling layers. To classify brain MR images into different categories (Meningioma, Glioma, and Pituitary), various components of convolutional neural networks, like a fully connected layer, pooling layer, sigmoid and ReLU activation function, and dropout layer, are used efficiently. Furthermore, we have employed the powerful optimistic algorithm, SGD [35], to train models efficiently.

III. 4 ENHANCED CNN FOR BRAIN TUMOR CLASSIFICATION

We have used advanced machine learning techniques like Data Augmentation (DA) and recently developed Transfer Learning technique to increase the projected accuracy of the proposed CNN framework. The issue of not having enough data for model training can be fixed via data augmentation. The modern transfer learning (TL) methods are frequently applied to image classification jobs. In the proposed research work, we included various frameworks that used transfer learning methods to increase the accuracy of the recommended CNN architecture.

III. 5 IMPORTANCE OF TRANSFER LEARNING TECHNIQUE(TL) IN IMAGE CLASSIFICATION

The concept of transfer learning [36] is breaking out from the isolated learning paradigm and applying knowledge gained from one task to another that is related (Figure 2).

The concept of transfer learning [36] is breaking out from the isolated learning paradigm and applying knowledge gained from one task to another that is related (Figure 2). Conventional learning is isolated, happening only based on certain tasks, datasets, and the training of distinct, isolated models on them. Nothing that is transferable from one model to another is retained. Through the use of features, weights, and other knowledge from previously trained models, transfer learning allows us to train fresh models. The ability to adapt knowledge from previously learned activities to more recent, related tasks is the goal of transfer learning.

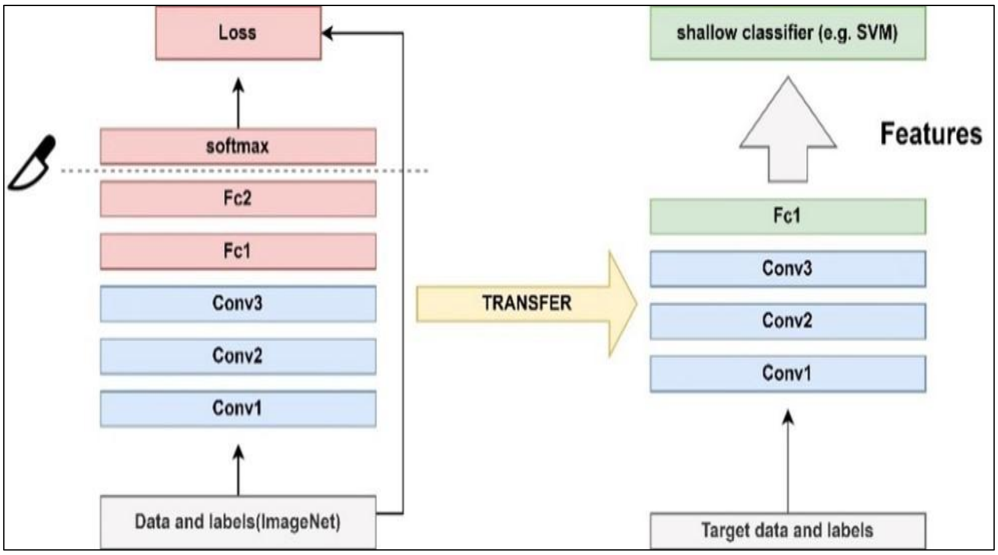

Figure 2: Transfer Learning Technique.
Source: Authors, (2026).

To increase the accuracy of the suggested CNN framework, we employed different pre-trained architectures, which have used transfer learning techniques as their core functionality. We used ResNet-50, Inception V3, VGG-16, Xception, DenseNet201, and MobileNet architectures in this research. The CNN framework was effectively trained using the training parameters provided by the above-mentioned frameworks. The CNN model was then finalized for the classification task, which is increased in volume using modern augmented technology. The distribution quantity of the data set plays an important role in the tumor classification task. The data set of tumour images used in this proposed work was split into a ratio of 70:30 for the training and testing data sets. The experimental performance is evaluated using the various performance metrics, like Matthews Correlation Coefficient (MCC), Sensitivity, Specificity, Accuracy, Precision, and F1-Score [37].

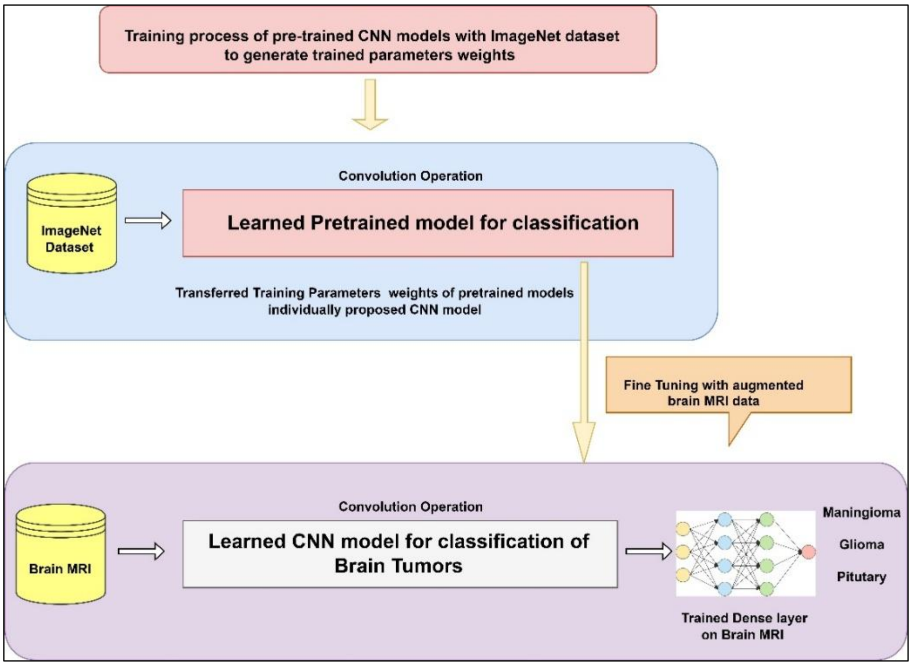

Figure 3: Functional flow chart of the proposed brain tumour classification model in a big data health care system.
Source: Authors, (2026).

CNN models are being widely used for medical image categorization issues. The CNN model can be trained more effectively with an extensive image data set because it can extract more relevant features for accurate picture categorization during the training phase. The CNN model performs worse when large picture data sets are not available, especially in the medical domain.

However, modern techniques are integrated to enhance the capacity of the recommended image classifier framework. In this work, some modern advanced techniques have been used to optimize the performance of the proposed model [38]. The previously mentioned pre-trained architecture was trained on a huge multidisciplinary ImageNet data repository, which has 10,000 object classes and 1.4 billion images. The trained parameters, which have been obtained from the above architectures, were passed to the CNN framework for efficient training on its own. The CNN architecture was improved, and its final classification in the big data healthcare system was determined with the support of MRI data collection.

Additionally, several MR images were used for training and testing work on the suggested deep-learning framework. After performing both activities, the results were compared among the transfer learning models. The suggested approach for training and testing models uses a holdout cross-validation mechanism. To enhance the proposed framework's capacity, the common method of zooming was employed in the data augmentation process to boost the original dataset. The incorporation of modern techniques significantly improved the CNN model's predicted accuracy [39]. Several assessment metrics have been utilized to determine the model's evaluation criteria. The functional flow chart of our proposed framework is presented in Figure 3, and the algorithm in Figure 4.

Algorithm : Proposed brain tumor classification model in Big data healthcare system

Input: E Number of epochs; w: Transfer learning model parameters; η: Learning rate; b : Batch size; X_{train} : Brain tumor training data set; X_{test}: Brain tumor test data set; X' : ImageNet data set.

Output: P_{test} : The assessment metrics are computed on the test data Initialize transfer learning models parameters w

Transfer Learning :

for local epochs $e \leftarrow 1 \; to \; E$ **do**

  for $b = (x, y) \in$ random batch from X'_t **do**

    Optimize model parameters

    $w_i \leftarrow w_i - \eta\,(\Delta(\varphi(w_i\,;\,b)))$

  end

end

Initialize upper layers of classification model parameters θ with trained transfer model parameters w and freeze

Tumor classification Training :

Pre-process brain tumor data set

$X_{train} \leftarrow preData(\; X_{train})$

$X_{test} \leftarrow preData(\; X_{test})$

while θ has not converged **do**

  for local epoch $e \leftarrow I$ to E **do**

    for s = (x,y) ∈ random batch from X_{train} **do**

      Update model parameters

      $\theta_i \leftarrow \boldsymbol{\theta_i} - \eta\,(\boldsymbol{\Delta}(\boldsymbol{\varphi}(\theta_i\,;\,\mathbf{s})))$

    end

  end

end

Evaluate trained model with brain tumor test dataset $X_{test} \leftarrow$ computeMetrics(θ_i; X_{test})

return P_{test}

Figure 4: Algorithm for the proposed brain tumour classification model in a big data health care system.
Source: Authors, (2026).

Table 1: CNN Framework Performance Based on Original and Augmented Image Collection.

Image data set	**Training Parameters**		**Framework Assessment matrix**					
	Framework Optimizer	**Learning Rate**	**Accuracy (%)**	**Specificity (%)**	**Sensitivity %)**	**precision (%)**	**MCC(%)**	**F1-Score(%)**
Original data set	SGD	0.0001	97.30	98.04	96.15	99.03	98.82	97.35
Augmented data set			98.52	99.00	98.10	97.16	98.40	98.04

Source: Authors, (2026).

IV. EXPERIMENTS

❖ **Experimental setup.**

We tested the feasibility of our suggested structure in the big data healthcare system through several evaluations. In the proposed research work, the brain tumour MRI collection was utilized to test the proposed model. To produce trained parameters (weights), we used six CNN frameworks that are already trained on large image data sets. For effective model training, we transferred the trained parameters to the CNN architecture separately. The CNN framework's prediction accuracy was enhanced as an output. The CNN model's final classification and fine-tuning were performed using MRI data collection. The various forms of MRI images (glioma, meningioma, and pituitary) represent 233 patients and 3064 slices in the data.

This data collection is far too small to train the CNN model efficiently. A modern data enhancement method augmentation has been utilized to address the issue of tiny brain tumours. The three types of photos are added to existing photographs using the data augmentation approach (zooming), which involves zooming both horizontally and vertically [40]. The SGD Optimization technique is used to optimize the model efficiently. Furthermore, in every experiment, some important parameters like learning rate (LR), batch size = 120, epochs = 50, SGD = 0.0001, and outer and inner activation function ReLu are employed. It is important to note that the softmax activation function was applied to our CNN model's final prediction layer. Evaluation indicators are integrated to assess the accuracy of the framework. The experimental results were graphed and tabulated.

V. RESULTS AND ANALYSIS

There are 233 participants and 3064 slices in the Brain Tumor data set. Of these, 82 subjects have meningioma (with sections 708), 91 have gliomas (with slices 1426), and 60 have pituitary tumours (with segments 930). As a result, there are 233 subjects in the data overall, and there are 3064 slices total. To effectively train the model, the dimension of 512 × 512 × 1 must be reduced to 224 × 224 × 1. The popular data augmentation approach was employed on the source dataset of brain tumour images by applying random zooming to address the imbalance issue in the dataset. Every slice is being magnified, and a new data collection has appeared, which contains 6128 image slices.

V.1 EXPERIMENTAL RESULT ANALYSIS OF THE CNN MODEL, WITH AUGMENTED AND ORIGINAL DATA COLLECTION

The source and enhanced tumour MRI data collection are employed to analyse the efficiency of the suggested CNN framework. The recommended CNN architecture is set up with the necessary hyperparameters. 70% of the image collection is utilized for model training, while 30% is used for testing the model. Various assessment matrices were employed to examine the accuracy of the architecture. Table 1 summarizes all these hyper-parameter values as well as the output of the experiments. Table 2 shows the results, based on the suggested CNN frameworks with original and augmented MRI data collection. The various forms of tumors (glioma, meningioma, and pituitary) are efficiently classified by our CNN design, as evidenced by the 97.30% accuracy rate.

The Proposed CNN model's 98.04% specificity demonstrates that it is an excellent detection model for identifying healthy patients, and its 96.15% sensitivity indicates that it detected the affected subjects with significant accuracy. Conversely, after being trained and assessed on an expanded image collection, the recommended architecture demonstrated exceptionally high efficiency. The suggested framework yielded 98.52% of training accuracy, 99.00% of specificity, 98.10% of sensitivity, and 98.40% of MCC. The framework's training accuracy increased from 97.30 to 98.52%, highlighting the significance of the data augmentation procedure. Additionally, it showed that additional data is needed for the recommended framework to be trained and work efficiently. Figure 5 represents the above analysis in chart format.

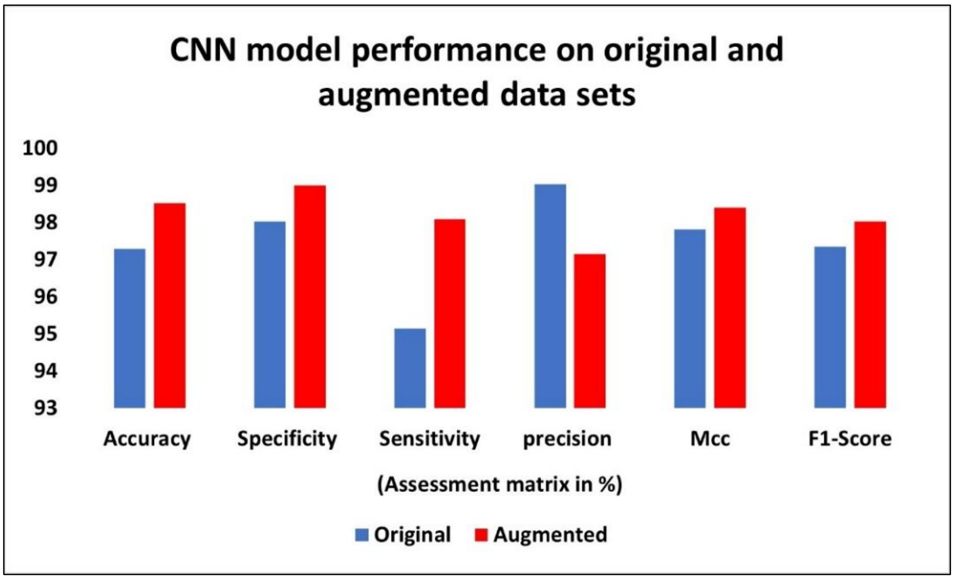

Figure 5: CNN framework efficiency chart based on original & augmented data collection.
Source: Authors, (2026).

Table 2: Comparative Analysis of Different Transfer Learning Frameworks' Efficiency Based on Original and Augmented Data Collection

Pre-trained frameworks	Proposed data set types	LR	Assessment metrics					
			Accuracy (%)	Specificity (%)	Sensitivity (%)	precision (%)	MCC(%)	F1-Score(%)
ResNet50	Original	0.0001	99.05	100.00	89.50	98.74	98.65	99.52
	Augmented	-	99.40	99.06	96.12	99.21	99.15	99.42
VGG-16	Original	-	96.76	99.21	95.00	96.98	98.92	97.97
	Augmented	-	97.87	98.01	100.00	96.97	98.78	99.01
Inception V3	Original	-	97.01	99.01	99.86	98.81	95.75	98.08
	Augmented	-	98.01	100.00	98.65	97.54	99.01	97.20
DenseNet201	Original	-	97.01	99.97	98.12	99.13	97.97	99.08
	Augmented	-	97.80	100.00	97.44	95.67	99.02	99.31
Xception	Original	-	98.10	98.86	97.30	99.01	99.12	98.64
	Augmented	-	98.87	99.01	98.50	97.23	97.98	99.20
MobileNet	Original	-	98.07	99.42	93.10	99.11	97.64	93.23
	Augmented	-	98.57	100.00	99.66	93.97	99.31	99.04

Source: Authors, (2026).

Based on the experimental findings, we deduced that the suggested convolutional neural network framework successfully categorized the different kinds of tumor MR images. Additionally, the augmentation procedure enhanced the CNN model's performance by providing additional data to extract more relevant attributes. The performance of various previously mentioned pre-trained frameworks has been measured on both the source and augmented MRI data collection. The experimental findings based on various pre-trained deep learning models and their hyperparameter values have been represented in Table 2, Figure 7 represents the above comparison in a pictorial format using the graphical chart method. After analysing the findings, we deduced that the method of augmenting data improved ResNet-50's training accuracy and that the model successfully identified the different kinds of brain tumours based on MRI.

V.2 ACCURACY COMPARISON OF THE PROPOSED (RESNET 50) FRAMEWORK WITH LEADING-EDGE ARCHITECTURES

In Table 3, we have contrasted the accuracy of our ResNet-50 model with cutting-edge techniques. The graphical representation of the accuracy comparison is depicted in Figure 6. The suggested model achieved 99.40% accuracy, which is the highest when compared to other cutting-edge methods. The suggested method's great performance showed that tumour images (gliomas, meningioma, and pituitary) are accurately classified by it and that it is a simple process to use in the big data health care domain.

Table 3: Performance Comparison with Previous Models.

Model	Accuracy (%)	Reference
ANN and KNN	97.98	[38]
GA-CNN	94.2	[39]
SVM and KNN	85.88	[40]
CNN-TF	94.82	[41]
Proposed method ResNet	99.40	2025

Source: Authors, (2026).

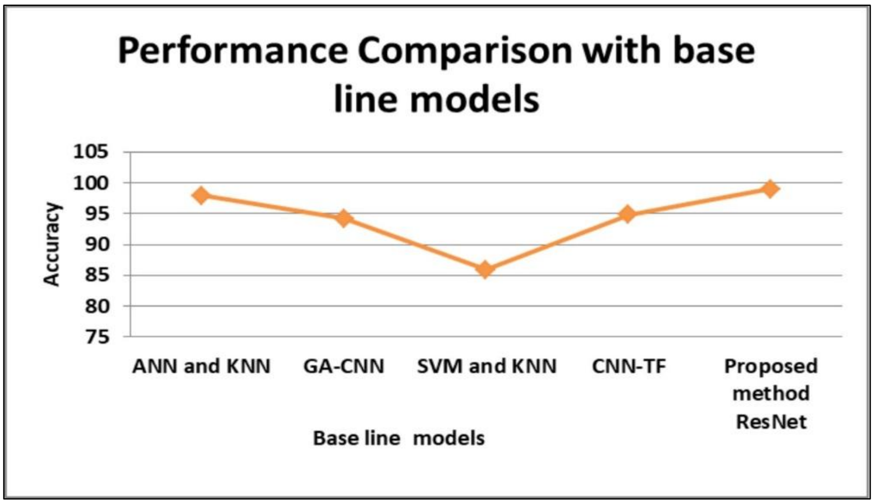

Figure 6: Proposed framework comparison with some baseline methods
Source: Authors, (2026).

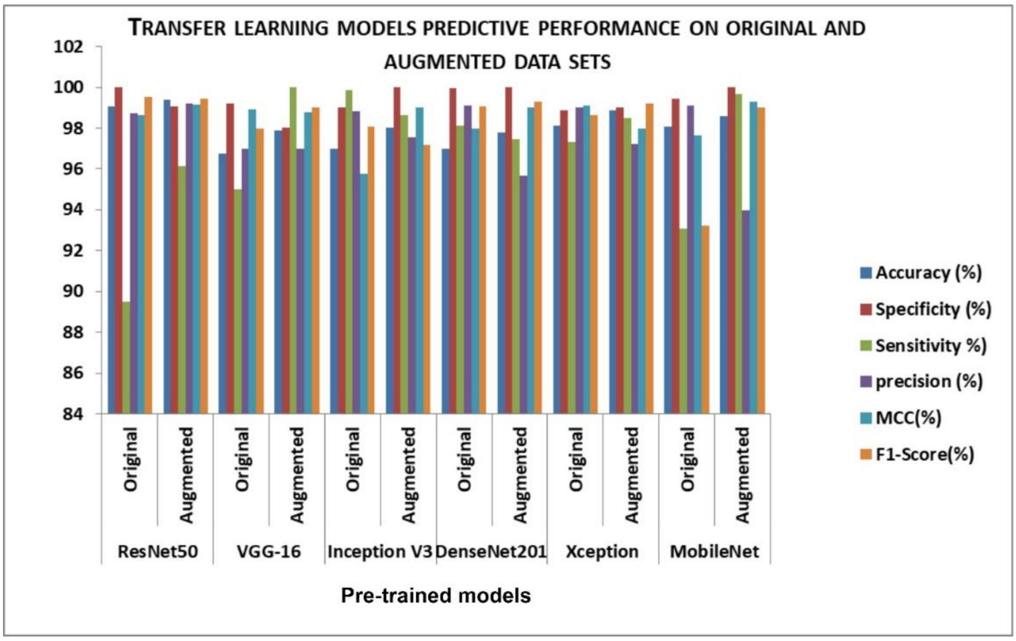

Figure 7: Comparative analysis of various transfer learning models' performance based on source and augmented data collection.
Source: Authors, (2026).

VI. DISCUSSION

The identification and classification of MR images are essential for the analysis of brain cancer in big data healthcare systems. In a big data healthcare system, computer-automated diagnostic systems (CAD) based on artificial intelligence (AI) can accurately diagnose many diseases. Deep learning methods, particularly CNNs, are extensively employed in CAD systems for the diagnosis of serious illnesses. The advanced machine learning-based deep learning framework is mostly employed for the detection and classification of medical pictures. Deep characteristics that are extracted from image data by the CNN model were crucial to the final classification of the images. Researchers have suggested several techniques for diagnosing brain cancer utilizing deep learning models and brain MR image data. Nevertheless, the accuracy of these current techniques is lacking.

To overcome this medical problem, which is related to MR images, an advanced and efficient approach is required for the precise and effective diagnosis of the illness in big data healthcare systems. In the proposed work, a CNN framework is recommended that categorizes different tumors from magnetic resonance imaging. For final classification, the recommended frameworks collect detailed attributes from the brain MRI collection. We have implemented a transfer learning approach to enhance the CNN model's predictive capacity [41]. In comparison to baseline approaches, the suggested method produced excellent results, as shown in Table 3, Figure 6, regarding meningioma, glioma, and pituitary categorization. Moreover, the suggested approach might be effortlessly used for the identification and categorization of tumor images in the big data healthcare domain.

VII. CONCLUSION

The CNN model is important for accurately classifying medical images, and it is utilized in the majority of CAD systems to analyze medical image data. We have presented an advanced diagnosis technique for classifying brain tumors in our proposed research work. In the suggested approach, we have employed brain tumor MR imaging data to perform training of various neural networks for the classification of tumor images which are related to the brain. We have included two modern and popular approaches to improve the recommended framework's prediction power.

Comparing the testing findings to baseline approaches, the recommended architecture(ResNet 50) achieved 99.40% enhanced accuracy, which is excellent in comparison to any other frameworks. The suggested method's good prediction results defined efficient data pre-processing and model parameter adjustments, including layer counts, optimizer, and activation functions. The suggested ResNet 50 model performs well, which makes it potentially useful for diagnosing brain cancer and classifying brain tumors in the context of a big data Healthcare system. To diagnose brain tumours in the future, we'll employ further deep-learning methods and datasets about brain tumors.

VIII. AUTHOR'S CONTRIBUTION

Conceptualization: Sunill Kumar Agarwal, Yogesh Kumar Gupta.
Methodology: Sunil Kumar Agarwal, Yogesh Kumar Gupta.
Investigation: Sunil Kumar Agarwal, Yogesh Kumar Gupta.
Discussion of results: Sunil Kumar Agarwal, Yogesh Kumar Gupta.
Writing – Original Draft: Sunil Kumar Agarwal, Yogesh Kumar Gupta.
Writing – Review and Editing: Sunil Kumar Agarwal.
Resources: Sunil Kumar Agarwal.
Supervision: Yogesh Kumar Gupta.
Approval of the final text: Sunil Kumar Agarwal, Yogesh Kumar Gupta.

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