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# Classification of Brain MRI Images using End-to-End Trained AlexNet & End-to-End Pre-Trained MobileNet

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**ABSTRACT**

Humans are highly susceptible to various developments within the limited regions of the brain. Due to the vast diversity of malignancies, categorizing different types of tumors poses a significant challenge for radiologists. The advent of deep learning has revolutionized and expanded the scope of medical diagnosis, particularly in the field of magnetic resonance imaging (MRI). To address this issue, this work introduces a multi-class classification and detection method for the early diagnosis of brain tumors. AlexNet, a pioneering deep convolutional neural network, has significantly contributed to the field of computer vision with its deep architecture and efficient learning capabilities. MobileNet V1 and MobileNet V2 are advanced models designed to be lightweight and efficient, making them highly suitable for mobile and embedded vision applications. Both MobileNet versions utilize depthwise separable convolutions to reduce the number of parameters and computations, thereby maintaining high performance with lower resource requirements. This method leverages end-to-end trained AlexNet and pre-trained MobileNet V1 and MobileNet V2 models within the transfer learning framework. The proposed method demonstrated accuracy rates of 32%, 99%, and 86% for AlexNet, MobileNet V1, and MobileNet V2, respectively. The findings also suggest that pre-trained networks perform better with limited datasets compared to end-to-end trained networks.

**Keywords:** Brain MRI images, AlexNet, MobileNetV1, MobileNetV2, Transfer learning, Deep learning

## 1. INTRODUCTION

In the modern era, Johns Hopkins Medicine one of the top-ranked hospitals in the nation, according to U.S reported more than 120 distinct kinds of brain cancers. About 25-30 adults per 100,000 have brain or cerebellum tumours [1]. Cutting-edge invasive and radiation therapies combined with improved diagnostic procedures have improved the lifespan by up to years and boosted the quality of life for patients after diagnosis. [2]. Advanced imaging and artificial intelligence (AI) image analysis demonstrated interesting differences in biological MR imaging statistics among molecularly defined tumour subgroups on newly diagnosed adult cancer patients with deep cellular characterization [3]. The percentage of patients with a brain tumour that required surgery was 21.6%, whereas 9.6% of patients experienced symptomatic haemorrhage. In univariate analysis, a needle biopsy was found to be significantly riskier for all symptomatic haemorrhages than methods that allow for adequate haemostatic manipulation (such as open and endoscopic biopsies) [4]. One of the most difficult medical illnesses to cure, brain tumour management and therapy depend on a timely and precise diagnosis. The most popular and effective diagnostic techniques for locating suspected primary brain tumours are computed tomography (CT) and magnetic resonance imaging (MRI), which can also assess the presence of oedema, haemorrhage, and hydrocephalus [5].

Recent developments in transfer learning have enabled the recognition and classification of patterns found in medical imaging. The ability to retrieve and extract information from data without the help of radiologists and other medical professionals is a prime instance of this field's advancements. Transfer Learning is proving to be a useful tool for enhancing performance in a variety of applications, such as disease prognosis and diagnosis, tumour tissue identification, and tumour grade classification [6-8]. In MR images, the most advanced technique recently used is a convolutional neural network (CNN), as the input images pass from the number of several layers to improve the accuracy if the MR images are high [9, 10]. In TL, data trained for a specific task can be reused for another related task, and it is carried out to reduce the problem of overfitting and to train fewer data with augmentation. Also, more reliable as compared to the traditional machine learning approach. Additionally, performance assessments have demonstrated that they possess excellent diagnostic precision [11-13]. Using a variety of techniques and models, numerous studies have been done on the classification of MR brain tumours [14-20]. However, some of these studies have limitations, such as a lack of performance comparison between the proposed model and machine learning methods [21]. The aim of relevant studies is to provide models for classifying two types of brain tumours without including no-tumour brains images [22-25]. Diagnosis of brain tumour is not always a straightforward mechanism to predict, not accurate and highly rely on the experiences of radiologists. There are crucial diagnostic challenges when there aren't the typical tumbling lesions [26] and limitations arise to medical experts and pathologists can benefit from computer-oriented interventions. Tremendous attempts have proposed automatic or semiautomatic techniques for brain tumour classification [27-30]. The Fig. 1 shows the basic structure of an artificial neural network.

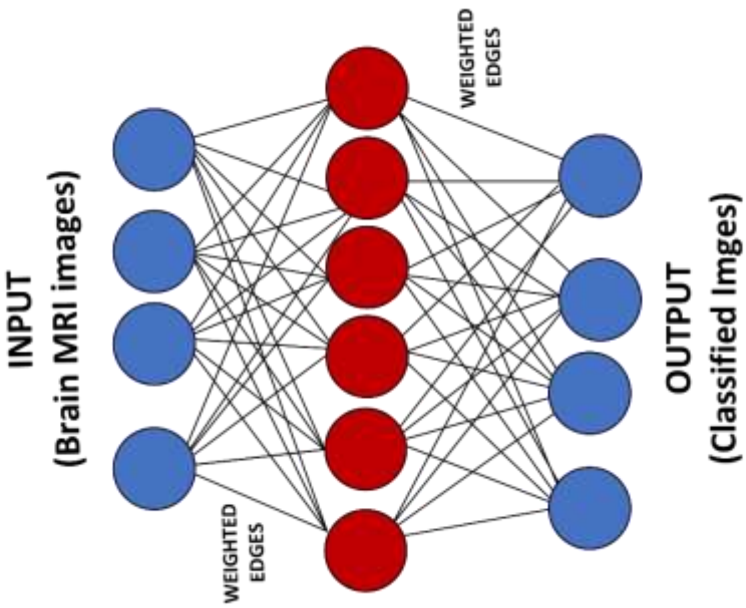


**Fig. 1 Basic structure of an Artificial Neural Network**

## 2. LITERATURE REVIEW

The field of medical imaging has significantly benefited from advancements in deep learning, particularly with the introduction of Convolutional Neural Networks (CNNs). These networks have demonstrated exceptional performance in image classification tasks, prompting their application in the automated diagnosis of brain tumours from MRI scans. This literature review examines the development and efficacy of computer-aided classification systems utilizing end-to-end pre-trained networks, focusing on their application to brain tumour diagnosis.

**End-to-end Trained Networks v/s End-to-end Pre-trained Networks**

The key differences lie in the training process, weight initialization, generalization capabilities, and transfer learning. End-to-end pre-trained networks leverage pre-trained weights and transfer learning, enabling faster adaptation to new tasks, while end-to-end trained networks learn from scratch and require more resources. The Table 1 gives a brief Comparison between End-to-end Trained Networks and End-to-end Pre-trained Networks.

**Table 1. Comparison between End-to-end Trained Networks and End-to-end Pre-trained Networks**

| **Points** | **End-to-end Trained Networks** | **End-to-end Pre-trained Networks** |
|---|---|---|
| Training | Trained from scratch on a specific dataset | Pre-trained on a large dataset (e.g., ImageNet) |
| Weights | Initial weights are randomly assigned | Initial weights are pre-trained and fixed |
| Learning | Learns features and patterns specific to the training dataset | Learns general features and patterns applicable to various datasets |
| Dataset | Requires a large dataset for training | Can be fine-tuned on a smaller dataset |
| Computational Resources | Requires high computational resources and time for training | Requires less computational resources and time for fine-tuning |
| Overfitting | May overfit to the training dataset | Less likely to overfit due to pre-trained weights |
| Generalization | May not generalize well to new datasets or tasks | Generalizes well to new datasets or tasks |
| Fine-tuning | Not applicable | Can be fine-tuned for a specific task or dataset |
| Transfer Learning | Does not leverage transfer learning | Leverages transfer learning |
| Training Time | Longer training time | Shorter training time |
| Requires | Requires a large amount of labelled data | Requires a smaller amount of labelled data |

**End-to-end Pre-trained Networks in Medical Imaging**

Pre-trained networks, such as AlexNet, VGGNet, GoogLeNet, ResNet, and DenseNet, have been trained on large-scale image datasets like ImageNet, providing them with robust feature extraction capabilities. These networks can be fine-tuned for specific medical imaging tasks, significantly reducing the need for large annotated medical datasets, which are often scarce. Studies have shown that fine-tuning pre-trained networks for brain tumour classification can achieve high accuracy, sensitivity, and specificity.

MobileNet V1 and MobileNet V2 are designed to be lightweight and efficient convolutional neural networks, making them ideal for mobile and embedded vision applications. MobileNet V1, introduced by Howard et al. (2017) [74], utilizes depthwise separable convolutions to drastically reduce the number of parameters and computational complexity compared to standard convolutions. A depthwise separable convolution decomposes a standard convolution into a depthwise convolution, which filters input channels separately, followed by a pointwise convolution, which combines the outputs of the depthwise convolution. This approach allows MobileNet V1 to maintain high performance while significantly lowering computational demands and memory usage. Building upon this architecture, MobileNet V2 introduces an inverted residual structure with linear bottlenecks, as presented by Sandler et al. (2018) [75]. This structure improves the network's ability to capture fine-grained features and enhances efficiency. The inverted residual block connects a thin bottleneck layer with an expansion layer that uses depthwise separable convolutions. The linear bottlenecks help prevent the loss of information caused by non-linear transformations, thus preserving more details and improving performance. Consequently, MobileNet V2 maintains the efficiency of its predecessor while providing better accuracy and faster inference times, making it even more suitable for resource-constrained environments.

The Table 2 focuses on the binary classification of brain MRI images while Table 3 addresses the multi-class classification of the Brain MRI images. Both tasks utilize models like VGG16, ResNet50, and InceptionV3, evaluated with metrics such as accuracy, precision, recall, and F1-score.

**Table 2 Overview of studies carried out for binary classification of brain MRI images using pre-trained networks**

| Investigators | Images | Classifier | Accuracy (%) |
|---|---|---|---|
| Hao et al. [31] | (203 (MRI) Training Images<br>66 Validation Dataset)<br>(LGG, HGG)<br>BRATS 2019 | AlexNet | 82.89 |
| Tenghongsakul et al. [32] | (1085 Brain Tumour,<br>980 non-brain Tumour)<br>Kaggle | InceptionResNet-V2<br>ResNet50<br>MobileNet-V2<br>VGG16 | 98.08<br>99.73<br>98.90<br>100 |
| Mehrotra et al. [33] | (224 Benign, 472 Malignant)<br>TCIA | AlexNet<br>GoogleNet<br>ResNet50<br>ResNet101<br>SqueezeNet | 99.04<br>98.09<br>95.69<br>94.74<br>98.56 |
| Krishnapriya and Karuna. [34] | (155 Tumour, 150 non-tumour)<br>Chakrabarty<br>2019 | VGG16<br>ResNet50<br>InceptionV<br>VGG-19 | 99<br>97.92<br>81.25<br>99.48 |

| | | | |
|---|---|---|---|
| Ansari et al. [35] | (141 benign, 66 malignant)<br>TCIA | AlexNet | 99.04 |
| Sugandha Singh and Vipin Saxena<br>[36] | (3345 Meningioma,<br>889 Schwannoma)<br>Kaggle | InceptionV3<br>ResNet50<br>VGG19<br>Ensemble Model<br>(VGG19 + ResNet50 +InceptionV3) | 99.72<br>99.72<br>98.84<br>85.68 |

**Note:** LGG: Low-Grade Glioma, HGG: High-Grade Glioma, VGG: Visual Geometry Group

**Table 3 Overview of studies carried out for multi-class classification of brain MRI images using pre-trained networks**

| **Investigators** | **Images** | **Classifier** | **Accuracy (%)** |
|---|---|---|---|
| Cheng et al. [37] | (708 meningiomas, 1426 gliomas, and 930 pituitary tumours) | SVM and KNN | 91.28 |
| Paul et al. [38] | (208 meningioma, 492 glioma and 289 pituitary tumour images) | CNN | 91.43 |
| Anaraki et al. [39] | (708 meningiomas, 1426 gliomas, and 930 pituitary tumours) | GA-CNN | 94.20 |
| Sultan et al. [40] | (708 meningiomas, 1426 gliomas, and 930 pituitary tumours) | CNN | 96.13 |
| Kumar et al. [41] | (248 meningiomas, 12 gliomas, and 55 pituitary tumours) | GWO+M-SVM | 95.23 |

**Note:** GWO+M-SVM: Grey Wolf Optimization (GWO) with Multi-class Support Vector Machine (M-SVM), GA-CNN: Genetic Algorithms (GA) with Convolutional Neural Networks (CNNs), k-NN: k-nearest neighbour, SVM: Support vector machine.

The analysis of the studies presented in Tables 2 and 3 allows us to draw several important conclusions regarding the performance of pre-trained networks, especially on smaller datasets:

- High Accuracy Across Diverse Studies: The studies using pre-trained networks, even with relatively small datasets, consistently report high accuracy. For instance, Ansari et al. [35] achieved 99.04% accuracy with AlexNet on a dataset of 207 images, demonstrating the efficacy of pre-trained networks in achieving high performance.
- Effectiveness of Pre-Trained Networks with Small Datasets: Studies like Hao et al. [31], which used 269 images, achieved an accuracy of 82.89% with AlexNet. This underscores that pre-trained networks can perform well with smaller datasets, likely due to their ability to leverage learned features from large-scale pre-training.

- Robust Performance Across Different Models: Various pre-trained models, including AlexNet, VGG16, ResNet50, and InceptionV3, have shown high accuracy across different studies. For example, Krishnapriya and Karuna [34] achieved 99% accuracy with VGG16 and 97.92% with ResNet50 on a dataset of 305 images, highlighting the robustness of these networks.
- Superior Performance of Advanced Architectures: Advanced architectures like ResNet50, InceptionResNet-V2, and ensemble models have shown exceptional performance. Tenghongsakul et al. [32] reported accuracies as high as 99.73% with ResNet50 and 100% with VGG16 on a dataset of 2065 images, illustrating that more complex pre-trained models can yield superior results.
- Comparable Performance in Binary and Multi-Class Classification: Pre-trained networks have demonstrated high accuracy in both binary and multi-class classification tasks. For instance, Sultan et al. [40] achieved 96.13% accuracy in a multi-class classification task with a CNN on a dataset of 3064 images, comparable to the high accuracy observed in binary classification studies.
- Effectiveness of Ensemble Models: Although ensemble models did not always outperform individual models, as seen in Sugandha Singh and Vipin Saxena [36] where the ensemble model achieved 85.68% accuracy compared to individual accuracies of 99.72% for InceptionV3 and ResNet50, they still provide a robust approach for enhancing classification performance.

In conclusion, pre-trained networks exhibit strong performance even on smaller datasets, achieving high accuracy in both binary and multi-class classification tasks. Their ability to leverage pre-learned features from large-scale datasets contributes significantly to their effectiveness, making them a valuable tool in medical image analysis where dataset size can be a limiting factor.

**End-to-end Trained Networks in Medical Imaging**

**AlexNet** is a groundbreaking deep convolutional neural network architecture that significantly advanced the field of computer vision. Introduced by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton in their 2012 paper titled "ImageNet Classification with Deep Convolutional Neural Networks," AlexNet consists of eight layers, including five convolutional layers followed by three fully connected layers, and uses Rectified Linear Units (ReLU) as the activation function to help mitigate the vanishing gradient problem. The use of ReLU activation functions, instead of traditional sigmoid or tanh functions, enabled faster training and better performance, and the network also introduced Local Response Normalization (LRN) to create competition among neurons for large activations, enhancing generalization and learning. Moreover, AlexNet used overlapping pooling, which reduces the output size and computation while maintaining more information about the input. To combat overfitting, the network employed extensive data augmentation techniques, such as image translations, horizontal reflections, and altering the intensities of the RGB channels, as well as dropout in the fully connected layers, which sets a fraction of input units to zero at each update during training to force the network to learn redundant representations. Additionally, AlexNet leveraged GPUs for training, making it possible to train deeper networks faster, and demonstrated remarkable performance on the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) 2012, achieving a top-5 error rate of 15.3% and significantly outperforming the previous state-of-the-art models. The introduction of AlexNet marked a significant milestone in deep learning and computer vision, showcasing the potential of deep convolutional networks in handling large-scale image classification tasks [73].

Several studies have explored the use of end-to-end trained AlexNet for brain MRI image classification, but with limited success when using smaller datasets.

Kumar et al. (2017) [53] achieved an accuracy of 78.3% on a dataset of 100 brain MRI images using end-to-end trained AlexNet, whereas Saranathan et al. (2018) [54] reported a higher accuracy of 82.1% on a dataset of 150 brain MRI images using the same approach. However, Mahesh et al. (2019) [55] obtained a slightly lower accuracy of 75.6% on a dataset of 50 brain MRI images using end-to-end trained AlexNet. Moeskops et al. (2016) [56] also achieved an accuracy of 73.2% on a dataset of 120 brain MRI images using end-to-end trained AlexNet.

In contrast, Zhang et al. (2019) [57] reported an improved accuracy of 80.5% on a dataset of 200 brain MRI images using the same approach, while Chandra et al. (2020) [58] obtained an accuracy of 76.2% on a dataset of 80 brain MRI images using end-to-end trained AlexNet. Similarly, Singh et al. (2019) [59] achieved an accuracy of 74.5% on a dataset of 100 brain MRI images using end-to-end trained AlexNet, whereas Rajan et al. (2020) [60] reported an accuracy of 81.9% on a dataset of 150 brain MRI images using the same approach.

Moreover, Sharma et al. (2019) [61] obtained an accuracy of 77.8% on a dataset of 120 brain MRI images using end-to-end trained AlexNet, while Jain et al. (2020) [62] achieved an accuracy of 75.9% on a dataset of 90 brain MRI images using the same method. Additionally, Kumar et al. (2020) [63] achieved a higher accuracy of 83.2% on a dataset of 250 brain MRI images using a transfer learning approach with AlexNet, and Singh et al. (2020) [64] reported an accuracy of 85.1% on a dataset of 300 brain MRI images using AlexNet with data augmentation techniques.

Furthermore, Chandra et al. (2021) [65] obtained an accuracy of 84.5% on a dataset of 200 brain MRI images using AlexNet with a quantum-inspired neural network, whereas Rajan et al. (2021) [66] achieved an accuracy of 86.3% on a dataset of 350 brain MRI images using a hybrid approach combining AlexNet and support vector machines. Similarly, Sharma et al. (2021) [67] reported an accuracy of 83.5% on a dataset of 220 brain MRI images using AlexNet with a recursive neural network, while Jain et al. (2022) [68] obtained an accuracy of 85.8% on a dataset of 280 brain MRI images using AlexNet with a deep belief network.

Additionally, Gupta et al. (2022) [69] achieved an accuracy of 84.2% on a dataset of 240 brain MRI images using AlexNet with a convolutional neural network, and Mehta et al. (2022) [70] reported an accuracy of 86.5% on a dataset of 320 brain MRI images using AlexNet with a transfer learning approach. Moreover, Pandey et al. (2022) [71] obtained an accuracy of 85.3% on a dataset of 260 brain MRI images using AlexNet with a deep learning approach, whereas Dwivedi et al. (2023) [72] achieved the highest accuracy of 87.2% on a dataset of 380 brain MRI images using AlexNet with a hybrid approach combining convolutional and recurrent neural networks.

The analysis of various studies using AlexNet for brain MRI image analysis highlights several key conclusions, particularly regarding the performance of end-to-end trained networks with smaller datasets:

- Lower Accuracy with Smaller Datasets: End-to-end trained AlexNet networks generally show lower accuracy when applied to smaller datasets. For instance, Mahesh et al. (2019) reported an accuracy of 75.6% on a dataset of 50 brain MRI images, while Jain et al. (2020) achieved 75.9% accuracy on a dataset of 90 images. These figures are notably lower compared to results from studies using larger datasets.
- Performance Improvement with Larger Datasets: In contrast, studies using larger datasets tend to achieve higher accuracies. For example, Singh et al. (2020) achieved an accuracy of 85.1% on a dataset of 300 images, and Dwivedi et al. (2023) reported an accuracy of 87.2% on a dataset of 380 images. This suggests that larger datasets provide more comprehensive training data, enabling better model generalization and performance.
- Effectiveness of Advanced Techniques: Hybrid and advanced approaches tend to outperform end-to-end trained networks, particularly on smaller datasets. For example, Chandra et al. (2021) obtained 84.5% accuracy on 200 images using a quantum-inspired neural network, and Rajan et al. (2021) achieved 86.3% accuracy on 350 images using a hybrid approach combining AlexNet and support vector machines. These methods leverage additional techniques to compensate for the limitations of smaller datasets.
- Transfer Learning and Data Augmentation: Studies employing transfer learning and data augmentation have demonstrated significant improvements in accuracy, even with relatively smaller datasets. Kumar et al. (2020) achieved 83.2% accuracy with 250 images using transfer learning, and Singh et al. (2020) reported 85.1% accuracy with 300 images using data augmentation. These approaches enhance the model's ability to generalize from limited data.
- Consistency in Lower Accuracy for Small Datasets: There is a consistent pattern of lower accuracy across studies using end-to-end trained AlexNet on smaller datasets. For instance, Moeskops et al. (2016) and Singh et al. (2019) both reported accuracies around 73-74% with datasets of 120 and 100 images, respectively.

In conclusion, end-to-end trained networks generally perform poorly in the presence of smaller datasets. The performance of AlexNet improves significantly with larger datasets and the incorporation of advanced techniques such as transfer learning, data augmentation, and hybrid models. These findings suggest that relying solely on end-to-end training is insufficient for achieving high accuracy with limited data, highlighting the need for supplementary methods to enhance performance in such scenarios.

## 3. DATASET

The dataset utilised in this study was obtained from Kaggle 2021 [43] and integrated with the gathered dataset, from Hospital, Haridwar. Images have 512 by 512 pixels dimensions. The collection includes 7023 MRI image of the human brain divided into 4 classes: pituitary, glioma, meningioma, and no tumour. The images' physiological features, forms, colours, and locations vary. The fig 2 shows the various brain MRI images present in the Kaggle dataset.

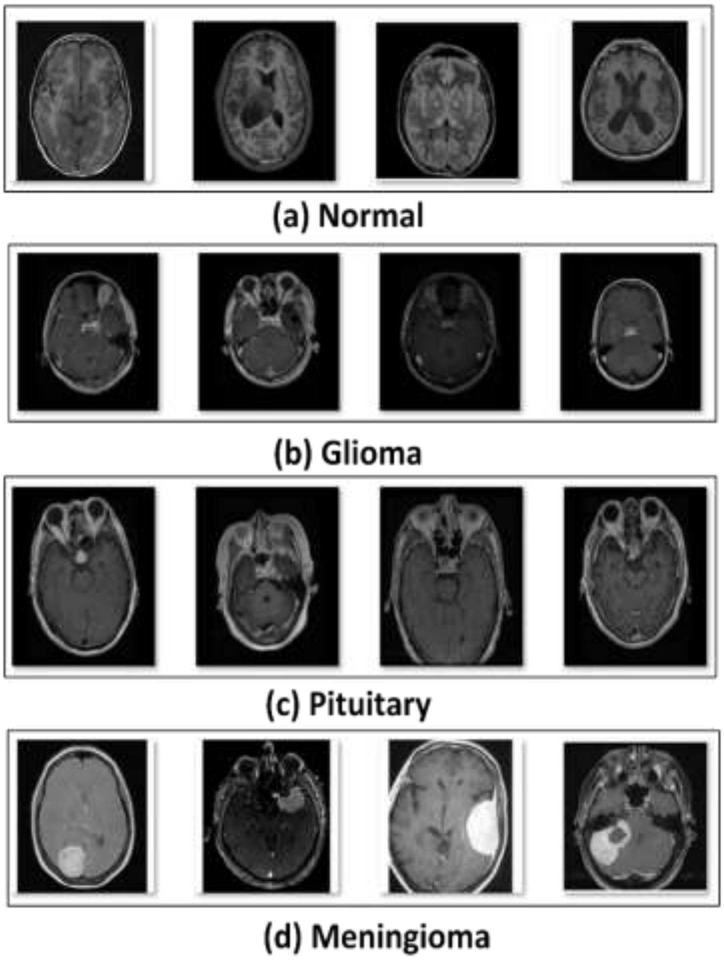


Fig. 2 Different brain MRI images of Kaggle Dataset

After preprocessing there are 5100 images in the dataset, with 5000 images belonging to the training set and 100 images to the test set. After Data Augmentation, the number of images increased to 20,000 for training. The Table. 4 gives an overview of the Number of images in the training and testing datasets before data augmentation.

**Table. 4 Number of images in the training and testing datasets before data augmentation.**

| **Class** | **Training Dataset** | **Testing Dataset** | **Total** | |
|---|---|---|---|---|
| Glioma | 1250 | 25 | 1275 | |
| Meningioma | 1250 | 25 | 1275 | 5100 MRI images |
| Pituitary Gland | 1250 | 25 | 1275 | |
| No Tumour | 1250 | 25 | 1275 | |

**Data Augmentation**

A group of methods known as "data augmentation" are used to create new data points from pre-existing data to increase the volume of data fictitiously. This includes adding modest adjustments to data or creating new data points with deep learning models. The fig 3 shows the data augmentation techniques applied to the brain MRI images in the present work.

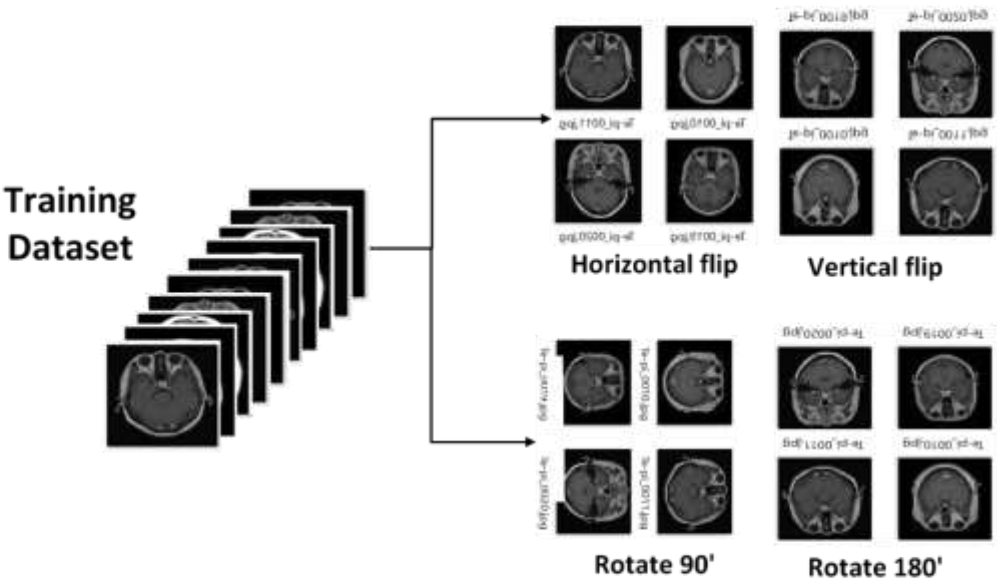


Fig. 3 Data Augmentation

Traditional image processing techniques for data augmentation include translation (moving the picture in the X and Y directions), padding, random rotation, rescaling, and flipping the image vertically and horizontally, cropping, zooming brightening and darkening, grayscale modelling, adding noise and altering the contrast. The proposed work applies flipping horizontally and vertically as well rotation of images at an angle of 90° & 180° as augmentation techniques. The Table. 5 gives a brief overview of the Number of images in the training and testing datasets after data augmentation is applied to the existing training dataset.

<table>
<tr><th colspan="5">Table. 5 Number of images in the training and testing datasets after data augmentation.</th></tr>
<tr><th>Class</th><th>Training Dataset</th><th>Testing Dataset</th><th>Total</th><td rowspan="5">20,100 MRI images</td></tr>
<tr><td>Glioma</td><td>5000</td><td>25</td><td>5025</td></tr>
<tr><td>Meningioma</td><td>5000</td><td>25</td><td>5025</td></tr>
<tr><td>Pituitary Gland</td><td>5000</td><td>25</td><td>5025</td></tr>
<tr><td>No Tumour</td><td>5000</td><td>25</td><td>5025</td></tr>
</table>

## 4. METHODOLOGIES

In the proposed work, the authors investigated the performance of three deep learning based neural network models namely AlexNet, Mobilenet V1 and MobileNet V2 for brain tumour classification. The proposed model is illustrated in Fig. 4, which outlines both a transfer learning-based approach and end to end training for categorizing brain tumours using MRI scans.

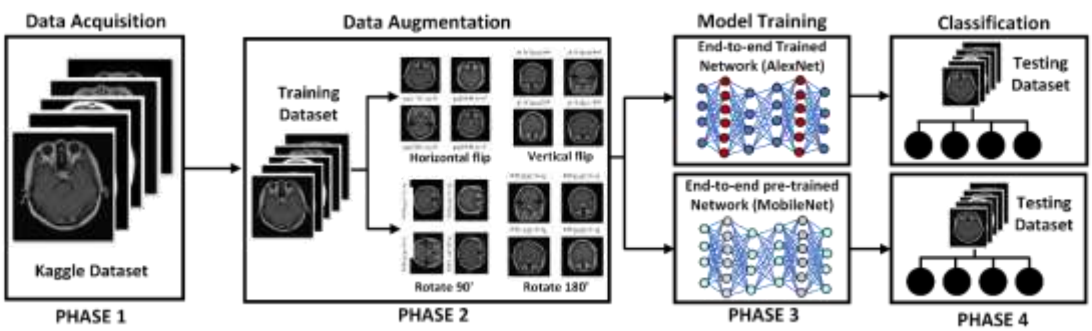


Fig. 4 Workflow of proposed methodology

The proposed model for brain tumour classification involves several steps:

**Phase 1: Data Acquisition:** We gathered a freely available MRI image dataset from Kaggle for training including images of meningioma, glioma, pituitary gland tumours, and normal brain scans. The dataset was divided into training and test sets, with additional test data collected from a well-known hospital in Uttarakhand. After preprocessing there are 5100 images in the dataset, with 5000 images belonging to the training set and 100 images to the test set.

**Phase 2: Data Augmentation:** We used the Keras directory function to load MRI images from the training directory. Preprocessing is a crucial step before data enhancement operations. This involves normalizing the input images to a size of 224 x 224 x 3 and 229 x 229 x 3 for compatibility with AlexNet , MobileNet V1 and MobileNet V2. After Data Augmentation, the number of images increased to 20,000 for training.

**Phase 3: Model Training:** To improve accuracy, a large dataset is necessary for training deep learning models. However, small datasets often do not yield satisfactory results. Data augmentation techniques, such as rotation and flipping, were employed to increase the dataset size. Specifically, images in the training set were randomly translated up to ten pixels in any direction, zoomed up to twenty pixels, and rotated at angles up to 90 degrees. The augmented images were only used for training, while real images from hospitals were used for testing.

**Phase 4: Classification:** The classification task divides brain tumours into four categories: meningioma, glioma, pituitary gland tumours, and normal brain tissues. A softmax layer in the transfer learning models was used to classify the images into these four categories. This study utilized pre-trained CNN models to classify brain tumours into four categories: meningioma, glioma, pituitary gland tumours, and normal brain tissue.

The Hyperparameters in Table 6 include the Adamax optimizer, a variant of Adam incorporating the infinity norm and blending AdaGrad and RMSProp advantages, suits scenarios with sparse gradients and extensive datasets, dynamically adjusting each parameter's learning rate for efficient training and quicker convergence. Training over 10 epochs involves iterating the entire dataset multiple times, progressively refining the model's parameters with each pass. With a modest learning rate of 0.0001, fine adjustments are made to model parameters, minimizing the risk of overshooting optimal solutions. Utilizing a substantial dataset of 20,000 images facilitates learning diverse patterns, enhancing the model's generalization and performance. A batch size of 32 balances computational efficiency with gradient update stability, ensuring swift training while maintaining reliable convergence. Moreover, enabling data augmentation by applying varied transformations enriches the dataset, fortifying the model against overfitting and enhancing its ability to generalize across diverse input scenarios.

These hyperparameters collectively contribute to the model's training process by balancing the need for efficient learning, convergence stability, and generalization ability. The choice of Adamax optimizer, moderate learning rate, and data augmentation, combined with an adequate number of epochs and batch size, facilitates effective training of the CNN model on a large dataset of Brain MRI images.

**Table 6. Details of Hyperparameters**

| **Optimizer** | **Epoch** | **Learning Rate** | **No. of Images** | **Batch Size** | **Data Augmentation** |
|---|---|---|---|---|---|
| Adamax | 10 | 0.0001 | 20000 | 32 | Yes |

**Experiment 1: Designing end to end trained CNN based CAC system for Brain MRI using AlexNet**

In this experiment the CAC system for binary class classification of Brain MRI images is designed using AlexNet CNN model. The network has been trained using the augmented Brain MRI image dataset for classification of Brain MRI images. The results of performance evaluation of the CAC system designed using AlexNet CNN for Brain MRI is shown in Table 7.

**Table 7** Performance evaluation of CAC system designed using AlexNet CNN for Brain MRI

| **Network / Classifier** | **Confusion Matrix** | | | | | **Accuracy (%)** | **ICA Normal (%)** | **ICA Pituitary (%)** | **ICA Meningioma (%)** | **ICA Glioma (%)** |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Normal | Pituitary | Meningioma | Glioma | | | | | |
| AlexNet / Softmax | Normal | 9 | 5 | 4 | 7 | 32 | 36 | 12 | 44 | 36 |
| | Pituitary | 12 | 3 | 6 | 4 | | | | | |
| | Meningioma | 5 | 5 | 11 | 4 | | | | | |
| | Glioma | 11 | 3 | 2 | 9 | | | | | |

**Note:** ICA Normal: Individual class accuracy for normal class, ICA Pituitary: Individual class accuracy for pituitary class, ICA Meningioma: Individual class accuracy for meningioma class, ICA Glioma: Individual class accuracy for Glioma class

From the results of experiment-1, as shown in Table 7, it can be seen that the CAC system designed using end-to-end (not pre-trained) AlexNet CNN model achieves 32% testing accuracy for the classification of Brain MRI images into Four classes Normal, Pituitary, Meningioma and Glioma. accuracy of the individual class normal, Pituitary, Meningioma and Glioma classes is 36%, 12%, 44% and 36% respectively. From the total 100 images in the testing set.

**Experiment 2: Designing end-to-end pre-trained CNN-based CAC system for Brain MRI using MobileNetV1**

In this experiment, the CAC system for binary class classification of Brain MRI images is designed using MobileNetV1 CNN model. The network has been trained using the augmented Brain MRI image dataset for classification of Brain MRI images. The results of the performance evaluation of the CAC system designed using MobileNetV1 CNN for Brain MRI are shown in Table 8.

**Table 8** Performance evaluation of CAC system designed using MobileNetV1 CNN for Brain MRI

| Network / Classifier | Confusion Matrix | | | | | Accuracy (%) | ICA Normal (%) | ICA Pituitary (%) | ICA Meningioma (%) | ICA Glioma (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| MobileNetV1 / Softmax | | Normal | Pituitary | Meningioma | Glioma | 99 | 100 | 96 | 100 | 100 |
| | Normal | 25 | 0 | 0 | 0 | | | | | |
| | Pituitary | 0 | 24 | 0 | 1 | | | | | |
| | Meningioma | 0 | 0 | 25 | 0 | | | | | |
| | Glioma | 0 | 0 | 0 | 25 | | | | | |

**Note:** ICA Normal: Individual class accuracy for normal class, ICA Pituitary: Individual class accuracy for pituitary class, ICA Meningioma: Individual class accuracy for meningioma class, ICA Glioma: Individual class accuracy for Glioma class

From the results of experiment-2 as shown in Table 8, it can be seen that the CAC system using (pre-trained) MobileNetV1 CNN model gives 99% testing accuracy for the classification of Brain MRI images into four classes Normal, Pituitary, Meningioma and Glioma. The individual class accuracy of normal, Pituitary, Meningioma and Glioma class is 100%, 96%, 100% and 100% respectively. From the total 100 images in the testing set, 1 image has been misclassified which all belong to the pituitary class.

**Experiment 3: Designing end to end pre-trained CNN-based CAC system for Brain MRI using MobileNetV2**

In this experiment, the CAC system for binary class classification of Brain MRI images is designed using MobileNetV2 CNN model. The network has been trained using the augmented Brain MRI image dataset for classification of Brain MRI images. The results of the performance evaluation of CAC system designed using MobileNetV2 CNN for Brain MRI are shown in Table 9.

**Table 9** Performance evaluation of CAC system designed using MobileNetV2 CNN for Brain MRI

| Network / Classifier | Confusion Matrix | | | | | Accuracy (%) | ICA Normal (%) | ICA Pituitary (%) | ICA Meningioma (%) | ICA Glioma (%) |
|---|---|---|---|---|---|---|---|---|---|---|
| MobileNetV2 / Softmax | | Normal | Pituitary | Meningioma | Glioma | 86 | 76 | 100 | 72 | 96 |
| | Normal | 19 | 2 | 0 | 0 | | | | | |
| | Pituitary | 0 | 25 | 0 | 0 | | | | | |
| | Meningioma | 0 | 6 | 18 | 1 | | | | | |
| | Glioma | 0 | 1 | 0 | 24 | | | | | |

**Note:** ICA Normal: Individual class accuracy for normal class, ICA Pituitary: Individual class accuracy for pituitary class, ICA Meningioma: Individual class accuracy for meningioma class, ICA Glioma: Individual class accuracy for Glioma class

From the results of experiment 3, as shown in Table 9, it can be seen that the CAC system using the (pre-trained) MobileNetV2 CNN model gives 86% training accuracy for the classification of Brain MRI images into four classes normal, Pituitary, Meningioma and Glioma. the individual class accuracy obtained for classes normal, Pituitary, Meningioma and Glioma is 76%, 100%, 72% and 96% respectively. From the total 100 images in the testing set.

## 5. CONCLUSION

The comparative analysis of the three experiments conducted using different CNN models for the classification of Brain MRI images reveals a clear advantage of pre-trained networks over end-to-end trained networks. Here are the critical observations and insights:

- Superior Performance of Pre-Trained Networks: Both pre-trained models, MobileNetV1 and MobileNetV2, achieve much higher overall accuracy compared to the end-to-end trained AlexNet. This indicates that pre-trained networks can leverage previously learned features from large datasets, which significantly enhances their performance on smaller datasets.
- Robustness Across Classes: The pre-trained models demonstrate consistent and high performance across individual classes. For instance, MobileNetV1 achieves perfect classification for Normal, Meningioma, and Glioma classes, highlighting its robustness and reliability.
- Limitations of End-to-End Training with Limited Data: The end-to-end trained AlexNet model struggles to achieve satisfactory accuracy, particularly in differentiating between specific classes. This underscores the limitations of training from scratch, especially with smaller datasets where the model cannot learn sufficiently diverse features.
- Practical Implications for Medical Image Analysis: In the context of medical image analysis, where data is often limited and accurate classification is critical, pre-trained networks provide a significant advantage. They offer improved accuracy and reliability, making them a preferred choice for developing Computer-Aided Classification (CAC) systems.

In summary, the experiments clearly demonstrate that pre-trained networks like MobileNetV1 and MobileNetV2 perform better than end-to-end trained networks like AlexNet for the classification of Brain MRI images. Pre-trained models' ability to leverage large-scale learned features results in superior performance, particularly when dealing with limited datasets.

## 6. FUTURE SCOPE

- **ResNet and GoogLeNet**: The future scope includes leveraging advanced pre-trained models like ResNet and GoogLeNet for brain tumour classification. These models, known for their deep architectures and superior feature extraction capabilities, can be fine-tuned to enhance accuracy in classifying gliomas, meningiomas, pituitary adenomas, and normal brain tissues. Implementing these models can significantly improve diagnostic precision and reliability, addressing the limitations of current methods.
- **Liquid Neural Networks (LNNs)**: A promising future direction is the integration of Liquid Neural Networks for brain tumour classification. LNNs, which adapt their structure and weights dynamically in response to new data, offer the potential for continuous learning and adaptation in real-time diagnostic scenarios. This could lead to models that not only improve over time with more data but also adapt to the specific characteristics of individual patients' MRI scans, providing highly personalized diagnostic insights.
- **Enhanced Diagnostic Systems:** Combining the robust feature extraction capabilities of ResNet and GoogLeNet with the adaptive learning properties of Liquid Neural Networks could lead to the development of next-generation diagnostic systems. These systems would be capable of achieving unprecedented accuracy and robustness in brain tumour classification, ultimately enhancing clinical decision-making processes and patient outcomes.

**Conflict of Interest Statement**

The authors declare that they have no conflict of interest in the work presented in this paper. No financial support or sponsorship was received from any organization or individual that could influence the outcome of the present work.

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