Section A-Research paper
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A ROBUST APPROACH FOR BRAIN TUMOR DETECTION IN MAGNETIC RESONANCE IMAGES USING FINETUNED EFFICIENT NET

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Abstract : A brain tumor is a disorder caused by the growth of abnormal brain cells. The survival rate of a patient affected with a tumor is difficult to determine because they are infrequent and appear in various forms. These tumors can be identified through Magnetic Resonance (MRI) Images, which plays an essential role in determining the tumor site; however, manual detection is a time-consuming and challenging procedure that can cause some errors in results. The adoption of computer-assisted approaches is essential to help in overcoming these constraints. With the advancement of artificial intelligence, deep learning (DL) models are being used in medical imaging to diagnose brain tumors using MR images. In this study, a deep convolutional neural network (CNN) EfficientNet-B0 base model is fine-tuned with our proposed layers to efficiently classify and detect brain tumor images. The image enhancement techniques are used by applying various filters to enhance the quality of the images. Data augmentation methods are applied to increase the data samples for better training of our proposed model. The results show that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by achieving the highest classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection. Other DL algorithms such as VGG16, InceptionV3, Xception, ResNet50, and InceptionResNetV2 are used for comparative analysis.

Index Terms : Brain tumor , deep learning , convolution neural networks (CNN) , transfer learning , MRI , detection.

1. INTRODUCTION

A brain tumor is a disorder caused by the development of abnormal cells or tissues in the brain [1]. Cells generally reproduce and die in a regular sequence, with each new cell replacing the previous one. However, some cells become abnormal and continue to grow, causing severe damage to the brain functions, and often leading to death. A minimum of 120 multiple types of brain tumors and the central

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nervous system (CNS) exist. According to the American Cancer Society, 18,600 adults and 3,460 children under 15 will die due to brain and CNS tumors in 2021. The 5-year survival rate for the patients having brain tumors is only 36%, and the 10-year survival rate is 31% [2]. Furthermore, National Cancer Institute reported 86,010 multiple cases of brain cancer and CNS cancers diagnosed in the United States in 2019. It was predicted that roughly 0.7 million people in the United States suffer from brain tumors. A total of 0.86 million cases were identified, of which 60,800 patients had benign tumors, and 26,170 patients had malignant tumors [3]. World Health Organization reported that 9.6 million people worldwide are estimated to have been diagnosed with cancer in 2018 [4]. One of the most significant aspects of saving a patient's life is early brain tumor diagnosis. The proper examination of brain tumor images is vital in evaluating a patient's condition. The conventional method of detecting brain tumors includes a doctor or radiologist examining magnetic resonance (MR) images for anomalies and making decisions. However, it is strongly dependent on a doctor's medical expertise; disparities in experience levels and nature of images create extra complexity for diagnosing with naked human eyes [5]. It is challenging for a doctor to interpret these images in a limited period since they contain several abnormalities or noisy data. As the volume of information increases, assessing a massive amount of information gets even more challenging. The manual detection of a brain tumor becomes more time-consuming and costly. Therefore, an automatic computer-aided diagnostic (CAD) system is required to assist doctors and radiologists in the timely detection of these deadly tumors to save precious human lives.

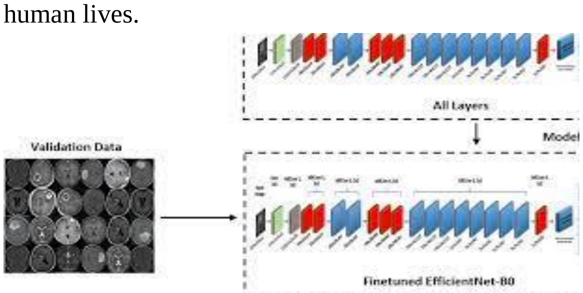

Fig 1 Example Figure

Artificial intelligence (AI) is a field of computer science that aims to give computers human-like intelligence, allowing them to learn, think, and resolve issues when confronted with various information. AI plays an essential role in identifying and diagnosing brain tumors. The discipline of brain tumor surgery is an excellent choice for additional AI integration due to its complicated and elaborate processes. Multiple attempts have been made to establish a highly accurate and reliable approach for brain tumor classification. However, the wide range of shape, texture, and contrast changes across and among individuals remains a difficult challenge to solve. Machine learning (ML) and deep learning (DL), subsets of AI, have recently revolutionized neurosurgical procedures. They consist of data preprocessing, feature extraction, feature selection, feature reduction, and classification. According to the study [6] because of AI, neurosurgeons can leave the operating room more confident than ever in terms of their patient's brain tumor diagnosis. Deep learning, particularly neural networks, gains substantial importance when it obtains promising results. Convolutional neural networks (CNNs) are remarkable for learning features and providing unlimited precision. Many deep learning applications have been developed, including pattern categorization, object detection, voice recognition, and other decision-making tasks, [7], [8]. In previous studies, traditional ML algorithms such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, and Naive Bayes and DL algorithms, such as custom CNNs, VGGNets [9], GoogleNet [10], and ResNets [11], approaches are used to help the healthcare community diagnose such malicious diseases. Although researchers have made various attempts to detect tumors from MRI scans, many deficiencies exist (i.e., low accuracy, big and slow models, and high computational costs). Additionally, the more extensive data always remains a challenge in the healthcare domain because researchers cannot openly share medical information due to the privacy concerns of their patients. Furthermore, existing approaches have lower precision and recall levels, resulting in low efficiency and requiring more time for image classification, which could delay the patient's treatment [12].

2. LITERATURE SURVEY

Deep learning approach for brain tumor detection and segmentation:

Brain tumor is a serious health condition which can be fatal if not treated on time. Hence it becomes necessary to detect the tumor in initial stages for planning treatment at the earliest. In this paper we have proposed a CNN model for detection of brain tumor. Firstly brain MRI images are augmented to generate sufficient data for deep learning. The images are then pre-processed to remove noise and make images suitable for further steps. The proposed system is trained with pre-processed MRI brain images that classifies newly input image as tumorous or normal based on features extracted during training. Back propagation is used while training to minimize the error and generate more accurate results. Autoencoders are used to generated image which removes irrelevant features and further tumor region is segmented using K-Means algorithm which is a unsupervised learning method.

Near real-time intraoperative brain tumor diagnosis using stimulated Raman histology and deep neural networks:

Intraoperative diagnosis is essential for providing safe and effective care during cancer surgery1. The existing workflow for intraoperative diagnosis based on hematoxylin and eosin staining of processed tissue is time, resource and labor intensive2,3. Moreover, interpretation of intraoperative histologic images is dependent on a contracting, unevenly distributed, pathology workforce4. In the present study, we report a parallel workflow that combines stimulated Raman histology (SRH)5,6,7, a label-free optical imaging method and deep convolutional neural networks (CNNs) to predict diagnosis at the bedside in near real-time in an automated fashion. Specifically, our CNNs, trained on over 2.5 million SRH images, predict brain tumor diagnosis in the operating room in under 150 s, an order of magnitude faster than conventional techniques (for example, 20–30 min)2. In a multicenter, prospective clinical trial (n = 278), we demonstrated that CNN-based diagnosis of SRH images was noninferior to pathologist-based interpretation of conventional histologic images (overall accuracy, 94.6% versus 93.9%). Our CNNs learned a hierarchy of recognizable histologic feature representations to classify the major histopathologic classes of brain tumors. In addition, we implemented a semantic segmentation method to identify tumor-infiltrated diagnostic regions within SRH images. These results demonstrate how intraoperative cancer diagnosis can be streamlined, creating a complementary pathway for tissue diagnosis that is independent of a traditional pathology laboratory.

Convolutional neural network based early fire detection:

The detection of manmade disasters particularly fire is valuable because it causes many damages in terms of human lives. Research on fire detection using wireless sensor network and video-based methods is a very hot research topic. However, the WSN based detection model need fire happens and a lot of smoke and fire for detection. Similarly, video-based models also have some drawbacks because conventional algorithms need feature vectors and high rule-based models for detection. In this paper, we proposed a fire detection method which is based on powerful machine learning and deep learning algorithms. We used both sensors data as well as images data for fire prevention. Our proposed model has three main deep neural networks i.e. a hybrid model which consists of Adaboost and many MLP neural networks, Adaboost-LBP model and finally convolutional neural network. We used Adaboost-MLP model to predict the fire. After the prediction, we proposed two neural networks i.e. Adaboost-LBP model and convolutional neural network for detection of fire using the videos and images taken from the cameras installed for the surveillance. Adaboost-LBP model is to generate the ROIs from the image where emergencies exist Our proposed model results are quite good, and the accuracy is almost 99%. The false alarming rate is very low and can be reduced more using further training.

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Machine learning based approach for multimedia surveillance during fire emergencies:

Video based surveillance of manmade disasters such as fire has become very hot topic in research and it is playing an important role in the development of smart environment. The disasters like fire cause many economic and social damages. We can prevent these damages by early detection of the fire. The current advancement in embedded processing have permitted the detection of fire using vision-based i.e. Convolutional Neural Networks (CNNs) for the surveillance. Therefore, we proposed a method using machine learning techniques for Multimedia Surveillance during fire emergencies. Our proposed model has two main deep neural networks models. Firstly, we used a hybrid model made of Adaboost and many Mulit-layer perceptron (MLP) neural networks. The purpose of hybrid Adaboost-MLP model is to predict fire efficiently. This model used different sensors data like smoke, heat, and gas for training. After predicting the fire, we proposed a CNN model to detect the fire immediately. These results show that our trained model has near 91% fire detection accuracy. We can the false positive results are quite low. These results can be improved more by further training.

Very deep convolutional networks for large-scale image recognition:

In this work we investigate the effect of the convolutional network depth on its accuracy in the large-scale image recognition setting. Our main contribution is a thorough evaluation of networks of increasing depth using an architecture with very small (3x3) convolution filters, which shows that a significant improvement on the prior-art configurations can be achieved by pushing the depth to 16-19 weight layers. These findings were the basis of our ImageNet Challenge 2014 submission, where our team secured the first and the second places in the localisation and classification tracks respectively. We also show that our representations generalise well to other datasets, where they achieve state-of-the-art results. We have made our two best-performing ConvNet models publicly available to facilitate further research on the use of deep visual representations in computer vision.

3. METHODOLOGY

In previous study traditional ML algorithms such as support vector machines (SVMs), k-nearest neighbor (k-NN), decision trees, and Naive Bayes and DL algorithms, such as custom CNNs, VGGNets, GoogleNet, and ResNets, approaches are used to help the healthcare community diagnose such malicious diseases. Although researchers have made various attempts to detect tumors from MRI scans, many deficiencies exist (i.e., low accuracy, big and slow models, and high computational costs). Additionally, the more extensive data always remains a challenge in the healthcare domain because researchers cannot openly share medical information due to the privacy concerns of their patients. Furthermore, existing approaches have lower precision and recall levels, resulting in low efficiency and requiring more time for image classification, which could delay the patient's treatment.

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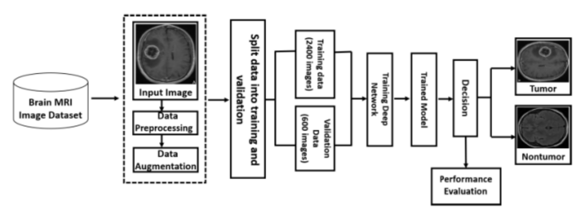

Fig 2 Proposed Architecture

Deep learning has recently been used in studies to boost the effectiveness of computer-aided medical diagnostics in brain cancer investigation. They play an essential role in the healthcare profession and act as valuable tools in various vital disorders, including brain disease diagnosis and skin cancer image analysis. DL methods based on transfer learning and fine-tuning are preferred and widely used for the

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classification of Brain tumors. The motivation of this research is to conduct extensive experimentation using deep convolutional neural networks, transfer learning, and fine-tuning to automate the process of brain tumor classification and detection.

The benefits of proposed system Data augmentation methods are applied to increase the data samples for better training of our proposed model. The results show that the proposed fine-tuned state-of-the-art EfficientNet-B0 outperforms other CNN models by achieving the highest classification accuracy, precision, recall, and area under curve values surpassing other state-of-the-art models, with an overall accuracy of 98.87% in terms of classification and detection.

Modules :

To carry out the aforementioned project, we created the modules listed below.

- Data exploration: using this module we will load data into system
- Processing: Using the module we will read data for processing
- Splitting data into train & test: using this module data will be divided into train & test
- Model generation: Mobilenet, Googlenet, Resnet50, InceptionResnetV2, VGG16, Xception, InceptionV3, Fine tuned efficientnetB5, Ensemble model- Inception + Mobilenet. Algorithms accuracy calculated
- User signup & login: Using this module will get registration and login
- User input: Using this module will give input for prediction
- Prediction: final predicted displayed

4. IMPLEMENTATION

Mobilenet: Mobilenet is a model which does the same convolution as done by CNN to filter images but in a different way than those done by the previous CNN. It uses the idea of Depth convolution and point convolution which is different from the normal convolution as done by normal CNNs.

Googlenet: GoogLeNet is a convolutional neural network that is 22 layers deep. You can load a pretrained version of the network trained on either the ImageNet [1] or Places365 [2] [3] data sets. The network trained on ImageNet classifies images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

Resnet50: Residual Network (ResNet) is a deep learning model used for computer vision applications. It is a Convolutional Neural Network (CNN) architecture designed to support hundreds or thousands of convolutional layers.

InceptionResnetV2: Inception-ResNet-v2 is a convolutional neural network that is trained on more than a million images from the ImageNet database. The network is 164 layers deep and can classify images into 1000 object categories, such as the keyboard, mouse, pencil, and many animals.

VGG16: VGG16 is object detection and classification algorithm which is able to classify 1000 images of 1000 different categories with 92.7% accuracy. It is one of the popular algorithms for image classification and is easy to use with transfer learning.

Xception: Xception is a convolutional neural network that is 71 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals.

InceptionV3: The Inception V3 is a deep learning model based on Convolutional Neural Networks, which is used for image classification. The inception

V3 is a superior version of the basic model Inception V1 which was introduced as GoogLeNet in 2014. As the name suggests it was developed by a team at Google.

Fine tuned efficientnetB5: EfficientNet B5 model architecture from the EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks paper. Parameters: weights (EfficientNet_B5_Weights , optional) – The pretrained weights to use. See EfficientNet_B5_Weights below for more details, and possible values.

Ensemble model- Inception + Mobilenet: Ensemble modeling is a process where multiple diverse models are created to predict an outcome, either by using many different modeling algorithms or using different training data sets. The ensemble model then aggregates the prediction of each base model and results in once final prediction for the unseen data.

5. EXPERIMENTAL RESULTS

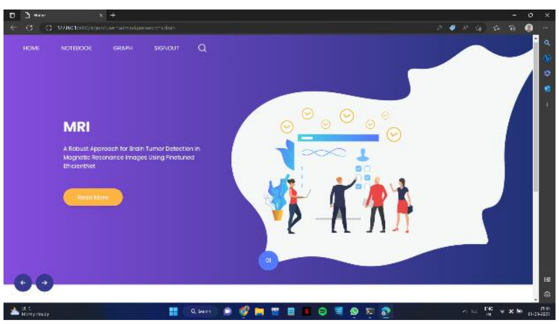

Fig 3 Home page

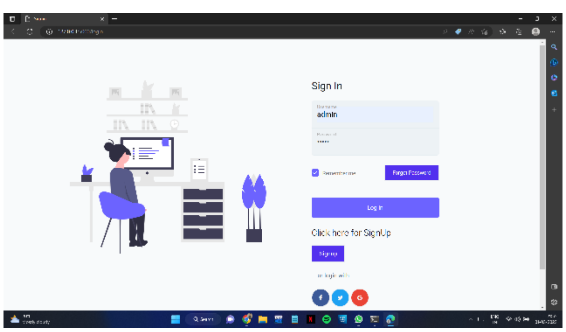

Fig 4 Registration Page

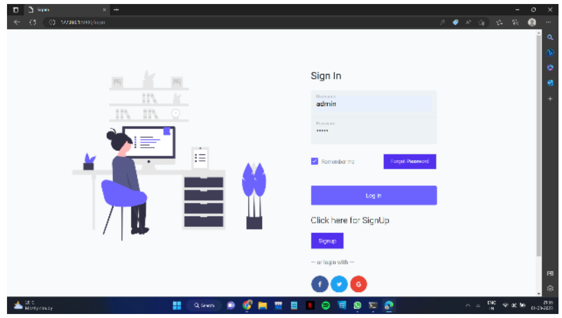

Fig 5 Login or Sign in page

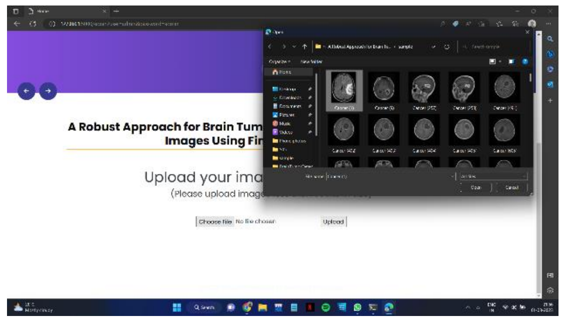

Fig 6 Upload image

Fig 7 Prediction Result

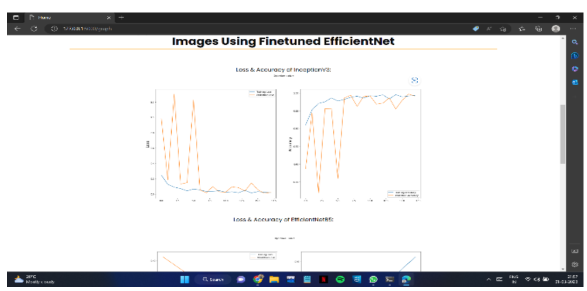

Fig 8 Loss and Accuracy Graph for Efficient Net B5

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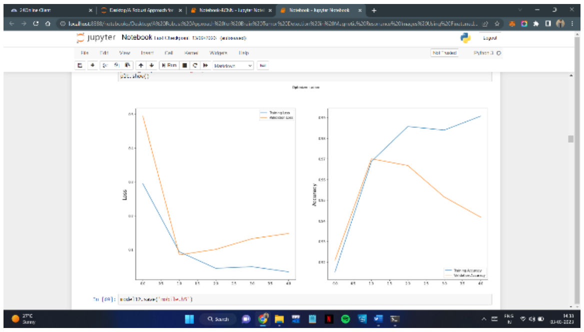

Fig 9 Loss and Accuracy for Ensembel Model

6. CONCLUSION

MR imaging for the detection of brain tumor research has gained significant popularity because of the rising requirement for a practical and accurate evaluation of vast amounts of medical data. Brain tumors are a deadly disease, and manual detection is time-consuming and dependent on the expertise of doctors. An automatic diagnostic system will be required to detect abnormalities in MRI images. Therefore, this study developed an efficient, fine-tuned EfficientNetB0 based transfer learning architecture to identify brain cancers from MRI scans. The proposed technique achieved the maximum performance in brain tumor detection, with 98.87% validation accuracy. Although this study focused on five other convolutional models and transfer learning designs for brain tumors in the medical imaging field, further research is needed. We will investigate more significant and influential deep CNN models for brain tumor classification and conduct segmentation with reduced time complexity in future approaches. Also, to improve the accuracy of the proposed model, we will increase the number of MRI scans in the dataset used for this study. Furthermore, we will also be applying the proposed approach to other medical images such as x-ray, computed tomography (CT), and ultrasound which may serve as a foundation for future research.

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