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BRAIN TUMOUR DETECTION USING MOBILENET

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ABSTRACT: The research suggests a MobileNet-based CNN-based method for the automatic detection of brain cancers. The suggested approach pre-processes the data using an ImageDataGenerator and trains the model on a bespoke dataset of brain MRI pictures. The trained model is tested against a different testing dataset and exhibits good tumour detection accuracy. The project also offers charts of accuracy and loss over epochs for visualising the model's performance. The suggested method serves as a valuable illustration of how to apply a CNN-based strategy for medical picture analysis as well as a demonstration of the efficacy of deep learning models for the diagnosis of brain cancers.

Keywords: CNN, MobileNet, Brain Tumour, Accuracy.

1 .INTRODUCTION

One of the most difficult disorders to diagnose and cure is brain tumours. The success of treatment depends on the early diagnosis of brain tumours. The most used technique for identifying brain tumours is magnetic resonance imaging (MRI). Unfortunately, radiologists must manually analyse MRI pictures, which takes time and is prone to mistakes. Thus, it is essential for enhancing the standard of patient care that automated, precise techniques for brain tumour identification be developed.

Medical image analysis tasks, such as the detection of brain tumours, have been accomplished with impressive success using deep learning-based methods. Deep learning architectures such as convolutional neural networks (CNNs) have been widely applied to the interpretation of medical picture data. CNNs can automatically extract hierarchical characteristics from unprocessed photos.

In this project, we suggest a MobileNet-based CNN-based method for the automatic detection of brain cancers. The suggested approach pre-processes the data using an ImageDataGenerator and trains the model on a bespoke dataset of brain MRI pictures. The MobileNet model has been improved to perform better on the particular task of tumour detection. The trained model is tested against a different testing dataset and exhibits good tumour detection accuracy.

To increase the precision of tumour detection, the proposed approach includes a number of pre-processing procedures, including intensity normalisation and skull stripping. Also, the research compares various CNN models to show how effective the MobileNet model is at this specific task. The suggested system is workable. The initiative stresses the significance of developing precise and effective tools for medical diagnosis and demonstrates the promise of deep learning-based systems for medical image analysis. Other forms of medical image analysis jobs, including lung cancer detection or breast cancer diagnosis, can be added to the proposed system's capabilities. The initiative stresses the significance of developing precise and effective tools for medical diagnosis and demonstrates the promise of deep learning-based systems for medical image analysis.

2 .LITERATURE SURVEY

N.K. Ahmedzai, S. Bergman,*et al*.(1993) [1] , The development of a quality-of-life (QoL) tool known as the European Organization for Research and Treatment of Cancer QLQ-C30, which may be used in global clinical trials in cancer, is the main topic of the study by N.K. Ahmedzai et al. (1993). The QLQ-C30 is made up of 30 items that evaluate many aspects of quality of life, including physical, emotional, and social functioning as well as signs and symptoms like pain, exhaustion, and nausea.

Chithambaram, T, *et al*. 2017 [2], Using a combination of genetic algorithm (GA) and artificial neural network (ANN) techniques, the research provides a unique method for segmenting brain tumours from MRI data. The MRI images are first pre-processed in the suggested technique, and then GA is used to choose the best features for classification. The chosen features are then used to segment tumours via the ANN. The authors find that their suggested strategy has an average accuracy of 97.15% for classifying tumours.

Kavitha AR, Chitra L ,*et al*. 2016 [3], In the paper, a Genetic Algorithm (GA) with a Support Vector Machine (SVM) classifier segmentation technique for brain tumours was developed. The SVM classifier's parameters are optimised using the GA to increase classification accuracy. The suggested procedure first enhances the contrast of the input Magnetic Resonance Imaging (MRI) pictures before extracting features using the Gray Level Co-occurrence Matrix (GLCM) technique. The best subset of features is chosen, and the SVM parameters are optimised, using the GA. The pixels of the MRI images are then divided into classes for tumours and non-tumours using the optimised SVM classifier.

A.P. Zafar, S.Y. Uronis, *et al*. (2010) [4], intends to validate the Patient Care Monitor (PCM) version 2.0, a tool created to evaluate cancer patients' symptoms. To evaluate the construct validity and reliability of the PCM version 2.0, the authors used statistical techniques such internal consistency reliability, test-retest reliability, construct validity, and responsiveness. The study's findings demonstrated that the PCM version 2.0 had strong construct validity, test-retest reliability, and internal consistency reliability. Additionally, it was discovered that the PCM version 2.0 could adapt to shifting patient symptoms over time.

N.K, *et al*. (2003) [5], the importance of doctors' communication behaviours when interacting with cancer patients is covered in N.K.'s 2003 paper. The author emphasises the importance of good communication between doctors and cancer patients in providing high-quality medical care. The study's foundation is an analysis of audio recordings of doctor-patient consultations. To evaluate the exchanges and find communication patterns, the author employs a coding system.

Sonavane, R., *et al*. (2007) [6], The scientists used a dataset of mammography and MRI brain tumour pictures to assess how well their suggested strategy performed. They contrasted the findings with those of other classification techniques, including Support Vector Machines (SVMs) and Backpropagation Neural Networks (BNNs). The findings demonstrated that, in terms of accuracy, sensitivity, and specificity, the suggested LVQ-based method performed better than the other methods. Overall, employing LVQ neural networks, the research described in this publication [6] offers a promising method for the precise and effective classification of medical images. The suggested approach might have a substantial impact on helping doctors diagnose diseases and might even lead to better patient outcomes.

Sudharani, *et al*. 2015 [7], They contrasted the findings with those of other classification techniques, including Support Vector Machines (SVMs) and Backpropagation Neural Networks (BNNs). The findings demonstrated that, in terms of accuracy, sensitivity, and specificity, the proposed k-NN-based method performed better than the other methods.Overall, utilising the k-NN algorithm, the research provided in this publication [7] offers a promising method for automatically classifying and identifying brain tumour lesions from MRI data. The suggested technique might have a big impact on how doctors diagnose and treat brain tumours, potentially leading to better patient outcomes.

Noreen, N. *et al*. 2020 [8], Using a deep learning model based on a concatenation approach, the work provided in this publication [8] offers a potential method for the automatic diagnosis of brain tumours. The suggested technique might have a big impact on how doctors diagnose and treat brain tumours, potentially leading to better patient outcomes.

Zulkoffli, Z. *et al*. 2019 [9], The scientists used a dataset of MRI scans including various types of brain tumours to assess the performance of their suggested technique. They contrasted their findings with those of other cutting-edge techniques, like Fuzzy C-Means (FCM) clustering and Watershed transformation. The findings demonstrated that, in terms of accuracy, sensitivity, and specificity, the proposed method performed better than the alternatives. Overall, utilising K-means clustering and morphological processes, the work provided in this publication [9] offers a promising method for the automatic detection and segmentation of brain tumours. The suggested technique might have a big impact on how doctors diagnose and treat brain tumours, potentially leading to better patient outcomes. However, it is important to note that additional study is required to assess the suggested technique on bigger.

Rashid, *et al*. 2018 [10], Overall, employing anisotropic filtering, morphological procedures, and SVM classification, the work described in this publication [10] offers a promising method for the detection of brain tumours from MR images. The suggested technique might have a big impact on how doctors diagnose and treat brain tumours, potentially leading to better patient outcomes. However, it is important to note that additional study is required to assess the suggested method on larger and more varied datasets and to contrast its performance with other cutting-edge methodologies.

3. PROPOSED SYSTEM

In order to identify a Brain tumour via image processing, this study evaluates the detection accuracy of deep learning algorithm. TensorFlow is an open-source library that we are using. Many other programmes, including Numpy, Pandas, and MatplotLib, have also been imported. One of the TensorFlow modules used for our model's implementation is Keras. Data was gathered via the picture data generator function and then loaded into the model.

A. End to End Process of CNN

The Keras module is also used to implement the CNN, Mobile Net, and Resnet-51 models. In the dataset, we used 2700 photos for training, testing, and validation. Adam Optimizer was employed to lessen the loss. All of the photos have undergone pre-processing.

It consists of Dataset, Training of data set, convolution neural network, test data set, Trained CNN model, Finally the tumour Classification.

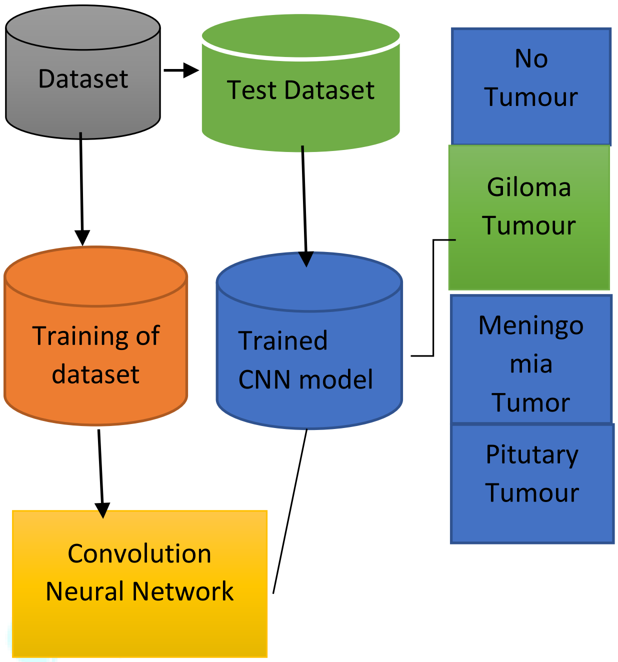

Figure 1: End to End process of CNN

B. *Dataset*

Dataset makes up this model. A dataset consists of a variety of images, all of which are brain MRI scans. All people could have tumours or not. We divide the MRI scans into four groups: meningoma tumour, pituitary tumour, Giloma tumour, and no tumour. The CNN Algorithm is used to train this batch of data. This model, which is referred to as a Trained CNN Model, can be saved after using the CNN algorithm. Now, the testing photos are used to evaluate the trained model. If the model is accurate, it will display a pituitary tumour, meningoma tumour, glioma tumour, or no tumour at all.

C. Creating the Deep CNN Model

The last 1000-neuron classification layer is first removed from the MobileNet model once it has been imported and pre-trained on the ImageNet dataset. Three Dense layers with ReLU activation functions are added to the network's end, followed by a GlobalAveragePooling2D layer

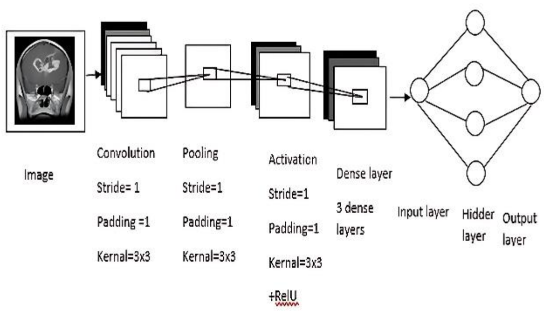

Figure 2: Deep CNN model

The last 1000-neuron classification layer is first removed from the MobileNet model once it has been imported and pre-trained on the ImageNet datase. Three Dense layers with ReLU activation functions are added to the network's end, followed by a GlobalAveragePooling2D layer. Four neurons in the fourth layer, with a softmax activation function, are used for multi-class categorization. By default, the network's layers are not trainable. The network's final 20 layers are meant to be trainable, though.

The MobileNet's pre-process input method is used to pre-process the data before feeding it to an ImageDataGenerator. Training and test data batches are produced using this generator. The model is created using the Adam optimizer, and it is trained over 35 iterations on training data using the fit generator technique. The accuracy and loss over the epochs are displayed using matplotlib to visualise the training history. the training data is kept in a directory called "dataset/Training," while the testing data is kept in "dataset/Testing," according to the code.

(i).Convolution layer:

There are 28 depthwise separable convolutional layers, With Stride 1, Padding 1, kernel 3x3.

(ii). Pooling layer:

The GlobalAveragePooling2D layer is used in pooling layer it has stride 1, padding equal to 1, with kernel 3x3.

(iii). Activation layer:

It uses ReLu Activation function with stride is 1, padding with 1, Kernal with 3x3. Further it uses 3 dense layers.

(iv). Dense Layer 1:

The three dense layers, each with 1024 neurons, use the ReLU activation function to add nonlinearity to the model. These deep layers are used to learn more intricate details that the convolutional layers are unable to capture.

(v). Dense Layer 2:

Dense Layer with 1024 neurons, use ReLu activation function.

(vi). Dense layer 3:

The Softmax activation function, a popular activation function in multi-class classification problems, is utilised in the last dense layer. The output of the dense layer is transformed into a probability distribution over the 4 classes that the model is attempting to categorise by the softmax activation function.

The batch size is set to 32, and the desired size for the input photos is (224, 224). A softmax probability distribution over 4 classes is the model's output. Dense layers with a rectified linear unit (ReLU) activation function make up the next three hidden layers. They each have 512, 1024, and 1024 neurons. The probability distribution over the four classes is produced using a dense layer with four neurons and a softmax activation function in the output layer. In conclusion, there are four hidden layers, one output layer, and one input layer that aren't explicitly described in the code for the neural network.

C. Training of Deep CNN Model

Using model.fit_generator (), the deep CNN model is trained. Except for the final few levels, all of the model's layers are set to be untrainable. In doing so, the model will be able to learn more characteristics from the training data and avoid being overfit to the data.

The next step is to use an ImageDataGenerator to preprocess the input data and to construct a generator for training and test data. Both the training and testing sets of data are loaded from the directories "dataset/Training" and "dataset/Testing," respectively. To achieve a desired size of (224,224), the generators resize the photos.

E. Testing of Deep CNN Model

The accuracy of the model's performance throughout training and testing is depicted in the first plot. The number of epochs is represented on the x-axis, while the model's accuracy is shown on the y-axis. Two lines make up the plot: one for accuracy in training, the other for accuracy in testing. Training accuracy is shown by the green line, and testing accuracy is represented by the blue line.

5. RESULTS

The following plot shows the Epochs vs Training accuracy

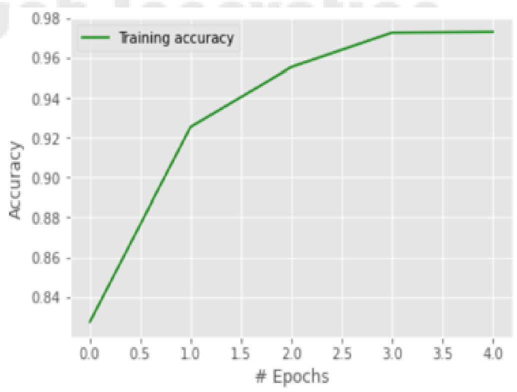

Figure 3: Epochs vs Accuracy

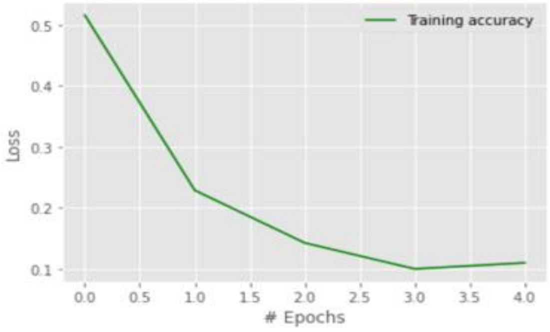

Figure 4: Epochs vs loss

Above plots conclude that Accuracy of the model high when model runs on 35 epochs where the loss minimum. Figure 4 shows Epochs vs loss where loss occurs minimum at 35 epochs.

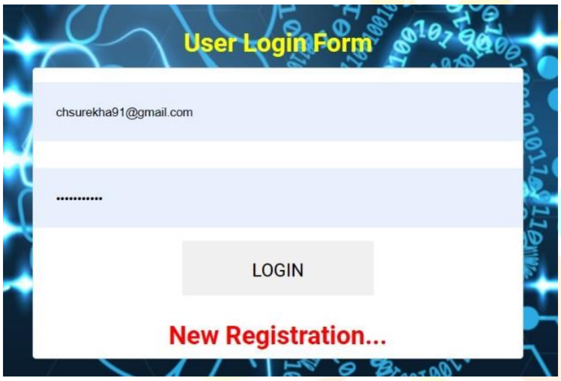

Figure 5: User registration of the model

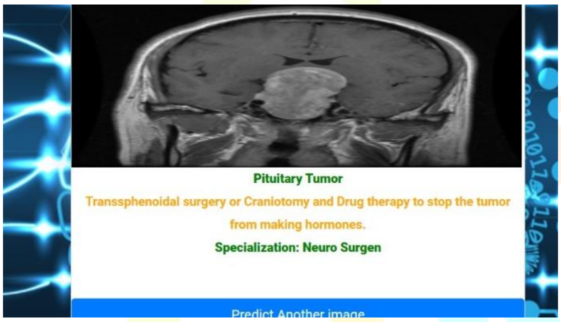

Figure 6: Output of the model

Parameter	CNN	MobileNet and ResNet
Number of image used	2870 Training-2000 Testing-500	2870 Training-2000 Testing-500
Time Consumed	0:37:10 [37mins:10sec]	0:40:25 [40mins:25sec]
Epochs carried out	35	35
Accuracy	0.891	0.986

Figure 7: Result Comparison

6. CONCLUSION AND FUTURE SCOPE

The promise of machine learning and image processing methods for the early diagnosis of brain cancers is demonstrated by our experiment, in conclusion. Our research emphasises how crucial early detection is to the successful management of brain tumours. Our brain tumour detection model's accuracy offers hope for its possible application in clinical situations. Our project has the potential to save lives and improve patient outcomes by enhancing the precision and speed of brain tumour detection. Our project demonstrates the importance of continuing to conduct research and development in the area of identifying and treating brain tumours. We think that our work can provide the groundwork for future developments in the field of brain tumour identification. The accomplishment of our effort shows the potential of interdisciplinary partnerships between the domains of computer science and medicine. our project's strong points. The creation of more sophisticated machine learning models and algorithms to increase the precision of brain tumour identification. combining brain tumour detection technology with other diagnostic techniques, such MRI and CT scans, to assess brain cancers more thoroughly. The creation of real-time brain tumour detection devices will help with earlier and more precise diagnosis. Using tailored medicines in conjunction with brain tumour detecting technology to enhance treatment results. investigation into the application of brain tumour detection technology to tumour recurrence and patient prognosis prediction. creation of technology for brain tumour detection that is available to more patients and healthcare facilities globally. Combination of telemedicine systems and brain tumour detection technology to allow for remote diagnosis and treatment. Clinical trials using brain tumour detection technology to evaluate the effectiveness of new.

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