Brain Tumor Detection and Classification Using Convolution Neural Network

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Abstract- *In this modern day's presence of cancer is the major problem in medical field. Especially brain tumour because growth of brain tumour can't be identified until it reaches its severe stages. It causes major damages and tends to death. So here we find a solution to this problem by Machine Learning techniques using CNN. We developed an automated diagnostic system by python. This system performed and gives output by Processing the MRI images. System already knows about the brain tumour MRI images in testing and training process. Here we classify Four type of tumour which is malignant tumour, glioma tumour, pituitary tumour and no tumour.*

Keywords- Magnetic Resonance Imaging (MRI), Machine learning, CNN, Python, Google collab, Image processing, U-net.

I. INTRODUCTION

In general, brain tumours are defined as a group of brain cells that grow in an abnormal way. Such type of tumours makes the brain tissue exposed to a size declination which leads to mass damage to the neural network of the brain which consequently disrupts the work of the brain. There are two types of brain tumours (like any type of cancer), namely cancerous or non-cancerous (benign and malignant tumours) and it generally occur based on the affected area. those are meningioma, glioma, and pituitary.

Hence nowadays Brain tumours are becoming very dangerous and also doctors facing difficulties to diagnose early stages. So here we introducing the trained module using Machine Learning and AI to resolve this and also enhance the diagnosing level in early stages.

Typically, the initial evaluation of brain tumors by oncologists usually performed using medical imaging techniques such as MRI and CT scans. These two modalities are widely used to produce highly detailed images of the brain structure.

where AI can be integrated with these imaging modalities to build a CAD Systems. Such systems can help physicians to increase the accuracy of cancer early detection. Recently, many artificial intelligence techniques such as an ANN, SVM, and CNN have been applied to classify and recognize brain tumors. CNN represents the most recent advancement and the state of the art in the machine learning field, which is employed in the field of diseases diagnosis based on medical images, particularly the CT and MRI images.

II. REVIEW OF LITERATURE

Brain tumor classification using Deep learning was proposed by Nishank Dave and Divya Ghorui, has done the early detection of the tumor plays an important role in the recovery of the patient. In our proposed model, we have collected MRI scans as it helps with the information about the blood supply inside the brain. Thus, for the recognition of anomaly, for examining the increasing of the ailment, and for the diagnosis, we prepared a data set consisting of various MRI images. We then focused on removing unwanted noise and image enhancement. The image characteristics can be enhanced by using image pre-processing techniques. The image enhancement depends upon different factors like computational time, computational cost, quality of the uncorrupted image, and the techniques used for noise elimination. We have made use of various filters for the image pre-processing.

Image analysis for MRI based brain tumor detection are feature extraction using biologically inspired BWT & SVM has proposed by Arun kumar Ray al., has done to improve the performance and reduce the complexity involves in the medical image segmentation process, we have investigated Berkeley wavelet transformation (BWT) based brain tumor segmentation. Furthermore, to improve the accuracy and quality rate of the support vector machine (SVM) based classifier, relevant features are extracted from each segmented tissue. The experimental results of proposed technique have been evaluated and validated for performance and quality analysis on magnetic resonance brain images, based on accuracy, sensitivity, specificity, and dice similarity index coefficient. The experimental results achieved 96.51% accuracy, 94.2% specificity, and 97.72% sensitivity, demonstrating the effectiveness of the proposed technique for identifying normal and abnormal tissues from brain MR images. The experimental results also obtained an average of 0.82 dice similarity index coefficient, which indicates better overlap between the automated (machines) extracted tumor region with manually extracted tumor region by radiologists.

Identification and classification of brain tumor MRI images with features extraction using DWT and probabilistic neural network was proposed by N. V. Shree and T. N. R. Kumar, has done they have concentrated on noise removal technique, extraction of gray-level co-occurrence matrix (GLCM) features, DWT-based brain tumor region growing segmentation to reduce the complexity and improve the performance. This was followed by morphological filtering which removes the noise that can be formed after segmentation. The probabilistic neural network classifier was used to train and test the performance accuracy in the detection of tumor location in brain MRI images. The experimental results achieved nearly 100% accuracy in identifying normal and abnormal tissues from brain MR images demonstrating the effectiveness of the proposed technique.

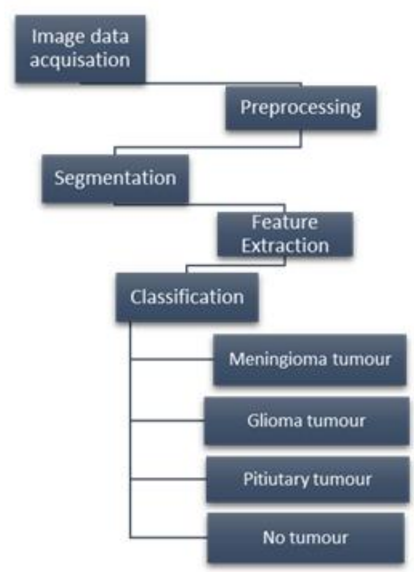
III. PROPOSED SYSTEM

The proposed system for brain tumor classification using Convolutional Neural Networks (CNNs) in Python encompasses several key stages. Initially, data acquisition involves gathering a diverse dataset of brain tumor images from medical institutions or public repositories such as BRATS. Preprocessing steps include standardizing image sizes to 224x224 pixels, normalizing pixel intensities to a range of 0 to 1, augmenting the dataset for increased diversity, and splitting it into training, validation, and testing subsets.
For model design and architecture, the system allows for selecting either pre-existing CNN architectures like VGG, ResNet, or Inception, or designing a custom CNN tailored specifically for brain tumor classification tasks. Transfer learning techniques can be employed by leveraging pre-trained models with weights from ImageNet and fine-tuning them to extract relevant features for brain tumor analysis. The model architecture typically includes convolutional layers for feature extraction, pooling layers for spatial down-sampling, dense layers with dropout regularization for classification, and an output layer with softmax activation for multi-class classification or sigmoid activation for binary classification (tumor vs. non-tumor).

The training phase involves compiling the model with suitable loss functions (e.g., binary cross-entropy, categorical cross-entropy), optimizers (e.g., Adam, RMSprop), and evaluation metrics (e.g., accuracy, precision, recall). During training, the system monitors progress using validation data, adjusts hyperparameters such as learning rate and batch size, and employs techniques like early stopping to prevent overfitting and improve generalization.

Once trained, the model undergoes evaluation using the testing dataset, where metrics such as accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC) are calculated to assess its performance. The system also generates a confusion matrix for visualizing classification results and identifying any class-specific performance issues.
For deployment and integration, the system facilitates deploying the trained model for inference in real-world or clinical settings using frameworks like TensorFlow Serving, Flask, or FastAPI. It includes developing a user-friendly interface such as a web application or API for clinicians or end-users to interact with the model and obtain predictions. Integration with existing medical systems like Picture Archiving and Communication Systems (PACS) ensures seamless workflow integration and patient data management.
To ensure model maintenance and continuous improvement, the system advocates for regular updates by retraining the model with new data to adapt to evolving trends and variations in brain tumor images. Feedback from medical professionals is incorporated to refine the model's performance, address clinical needs, and enhance interpretability through techniques like generating heatmaps to highlight tumor regions. Staying informed about the latest res earch and advancements in CNNs, medical imaging, and brain tumor classification is emphasized to incorporate cutting-edge techniques and continually enhance model efficacy.

FLOW CHART:



Flow chart:1

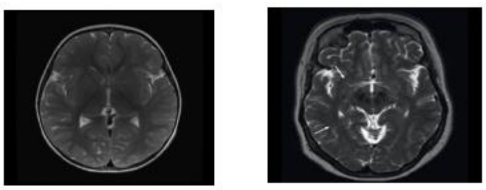
I/O MRI IMAGE:

Input to the system is MRI images of the brain, preprocessed for uniformity and suitability. The images Processing via CNN it extracts features and classifies based on tumor presence or absence. The final Output Predictions or probabilities indicating likelihood and type of brain tumor. Enables accurate diagnosis and automated analysis of structural MRI data.

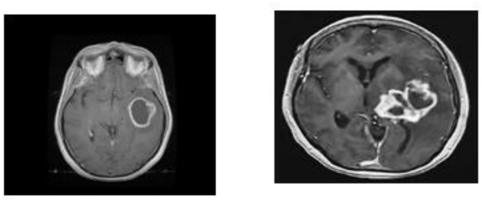
Data Collection and Preparation:

Collect a dataset of labeled MRI brain images, with annotations indicating the presence or absence of tumors. Preprocess the images as described in the previous response (skull stripping, normalization, segmentation, etc.).

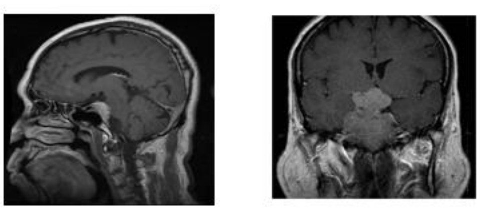
SAMPLE IMAGES



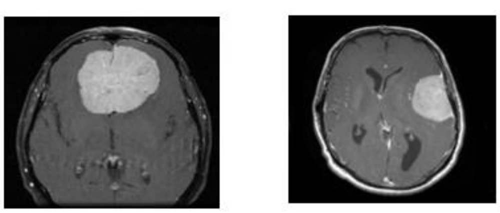
SAMPLE NORMAL MR IMAGES



SAMPLE GLIOMA TUMOR MR IMAGES



SAMPLE PITUITARY TUMOR MR IMAGES



SAMPLE MENINGIOMA TUMOR MR IMAGES

Data Augmentation:

Augment the dataset by applying transformations like rotation, scaling, flipping, and shifting to create additional training samples. This helps improve the model's robustness and generalization.

Training:

Split the dataset into training, validation, and test sets. Train the CNN using the training set and validate its performance using the validation set. Use binary cross-entropy loss and optimizer like Adam or RMSprop for training. Monitor metrics such as accuracy, precision, recall, and F1 score during training to assess model performance.

U-Net:

The U-Net architecture is a convolutional neural network (CNN) model designed for semantic segmentation tasks, particularly in medical image analysis. It consists of an encoder-decoder structure with skip connections that preserve spatial information during image segmentation. The encoder captures hierarchical features, while the decoder reconstructs the segmented image at a pixel-wise level.

SVM:

Support Vector Machines (SVMs) are classifiers that find the best hyperplane to separate data points of different classes while maximizing the margin. They can handle non-linear data using kernel functions and are effective for high-dimensional datasets. SVMs are widely used in various applications for their robustness and ability to handle both linearly and non-linearly separable data.

Max pooling:

Max pooling is a down sampling operation in convolutional neural networks (CNNs) that reduces the spatial dimensions of feature maps by retaining the maximum pixel value in each region. It helps in capturing the most important features while reducing computational complexity and overfitting.

Python with Tenser flow:

In Python with TensorFlow, designing a neural network typically involves importing TensorFlow and relevant libraries, preparing data through loading and preprocessing, defining the model architecture using TensorFlow's API (like Sequential or Functional), compiling the model with optimizer and loss function, training the model with fit method using training data and validation, evaluating its performance on test data, and considering deployment options such as TensorFlow Serving or TensorFlow Lite for production or mobile applications, respectively.

IV. RESULT

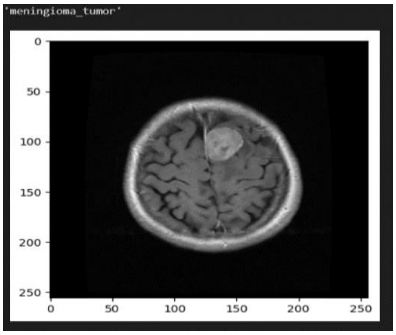


Fig:1 Sample result

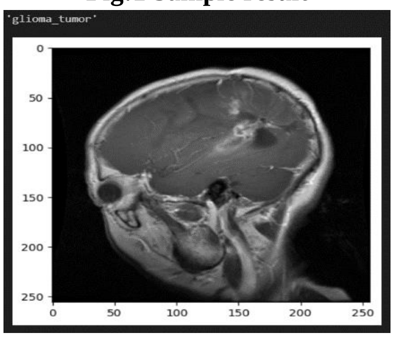


Fig:2 Original result

So many abnormalities and different diseases uneven presence of tissue in brain where identifies by Magnetic resonance imaging (MRI) technique. Among these categories tumour is the major problem it is present as a unwanted tissue growth. and it has no age limits. Different types of tumors are identified by this system. can be further classified, such as Meningioma tumor, glioma tumor, pituitary tumor, No tumor. The classified output was shown as Result.

Algorithm: Coustum CNN Algorithm

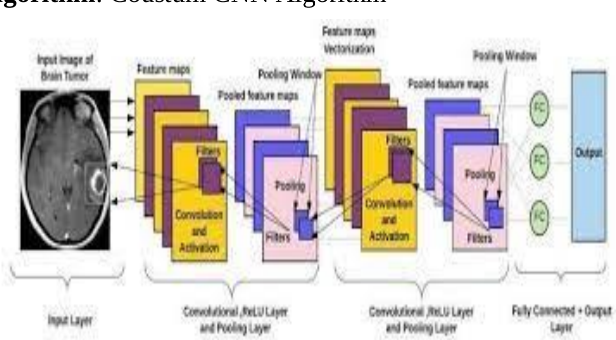


Fig3: Algorithm Model

Algorithm : Coustum CNN algorithm
Input image : 224x224pixel
Code language : Python
Architecture : Tenser flow
Epochs : 15

COMPILE:

Learning rate : 10e^-4
Train and validation split : 20%
Remains same as phase : 1
Accuracy : 98%
Loss : 0.03%
Validation accuracy : 98%
Validation loss: 0.07%

ACCURACY AND LOSS PLOT:

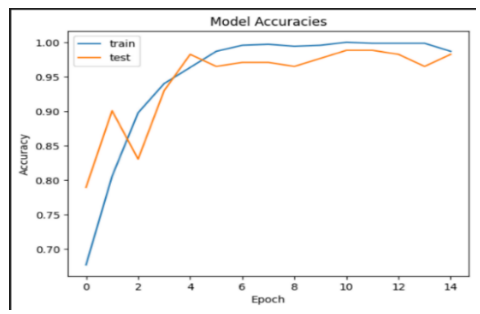


Fig3: Accuracy plot

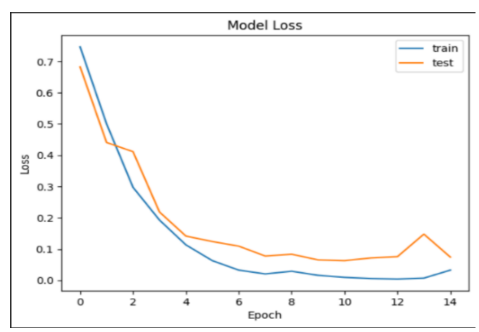


Fig 4: Loss plot

V. CONCLUSION

In conclusion we developed a model for brain tumor detection and also classifies its type include meningioma, glioma, pituitary, no tumor. It improves detection accuracy to 98%. It goes through to 15Epochs so it magnifies itself in higher accuracy rate. The whole system have9 layers convolution and pooling layers 4 convolution 2d layer, 4 Max pooling layer, 1 dropout layer. All with the kernel size 2x2. We gather all dataset as MRI images in huge number to train our module. It improves our model accuracy and also enhance the image detection and classification. Drop out, and batch normalization to train the model effectively while preventing over fitting. CNN module for brain tumor detection can be developed by improving Epochs and adjust weights for more type classification.

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