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MRI-Based Prediction for Brain Malignancies VGG19-Net

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Abstract- Biomedical technology is crucial in the identification and treatment for life-threatening illnesses. Brain tumours (BT) has recently risen to the top of the list of the most common and severe diseases. The ability of doctors to treat brain tumours is based on their knowledge and expertise. As a result, an automated mri brain system is essential for radiologists and doctors to assist in the detection of brain tumours. Honest assessment of magnetic resonance (MRI) data is necessary to detect brain tumours, and this study gives an effective method for predicting brain malignancies. VGG19-Net, Methods include data augmentation and image pre-processing algorithms that detect extreme shapes and trim black borders from photos. The photographs are then resized to the appropriate size. A ReLU Optimizer has indeed been implemented into our network to speed up the training. To attain maximum accuracy, the MRI image dataset is used to train & test the model. With 0.91 accuracy, the efficiency of the optimized system is evaluated.

Keywords- *MRI, CNN, K-PCA, Brain Tumour detection, VGG19-Net.*

I. INTRODUCTION

Automating the task of segmenting and classifying brain tumours has a significant impact on patient diagnosis, care plans, and follow-up. Unquestionable progress has been made in automating brain tumour classification tasks using a variety of methodologies, including standard image processing, superficial machine learning, or deep learning techniques. Building an fully autonomous system which can be deployed on clinical floors, on the other hand, remains a difficult issue[1].

The brain is the most crucial and vital organ in the human body, and it is made up of several organs. A brain tumour is one of the most common causes of brain dysfunction. A tumour is nothing more than an uncontrolled growth of cells. Brain tumour cells expand to the point where they consume all of the nutrition intended for healthy cells and tissues, resulting in brain failure. Currently, clinicians manually locate the position and area of a brain tumour by looking at the patient's MR images of the brain. This leads to inaccuracy in tumour detection and is extremely time intensive. Brain cancer is a deadly disease that claims the lives of many people. A technique for detecting and classifying brain tumours is available, allowing it to be diagnosed at an early stage[2].

One of the most difficult and time-consuming jobs in medical image analysis is detecting and segmenting brain tumours. MRI (Magnetic Resonance Imaging) is a medical method used mostly by radiologists to visualise inside body structures without the need for surgery. MRI provides a wealth of information about human soft tissue, which aids in brain tumour diagnosis. When using a computer-aided clinical tool to diagnose a brain tumour, accurate segmentation of the MRI picture is critical. Tumors are diagnosed as malignant or benign after proper segmentation of brain MR images, which is a tough task due to the complexity and variety in tumour tissue characteristics such as shape, size, grey level intensities, and location. Taking into mind the aforementioned issues, the goal of this study is to highlight the strengths and limitations of previously proposed categorization algorithms that have been discussed in the recent literature[3].

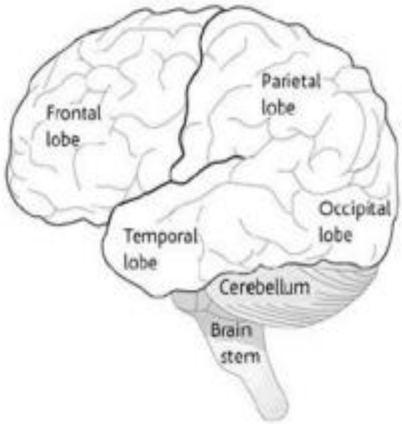

Figure 1- The major part of the human brain

Primary brain tumours are cancerous tumours that originate directly from the brain. The benign type can be non-cancerous, while the malignant variety can be cancerous. Gliomas are benign tumours that grow slowly. Astrocytes, which are non-neuronal brain cells, are the progenitors of this chemical. Several less dangerous primary tumours can cause the brain to become dysfunctional by putting a lot of burden on it[4]. Cancer grows & spreads more quickly when it is more aggressive. A tumour in another section of the human body causes a supplemental brain tumour. These tumours are made up of cancer cells which have spread to the brain from other parts of the body. Almost every brain tumour that develops later in life is malignant. Lung cancer, kidney cancer, bladder cancer, and other malignancies are the most common causes of these tumours[5].

1.1 Brain tumour and stroke lesions

Brain tumours are characterised as slow-growing or aggressive. A benign (slow-growing) tumour doesn't really infiltrate surrounding tissues; a malignant (aggressive) tumour, on the other hand, spreads from one area to another[6]. The World Health Organization[7] A BT is given a letter grade ranging from I to IV. The following is a list of brain tumour grades.

Grade I Tumors are slow-growing and do not spread widely. These are linked to a higher chance of long-term survival and can be surgically removed almost entirely. This form of tumour includes pilocytic astrocytoma of grade 1.

Although **Grade II** Tumors grow slowly, can spread to neighbouring tissues, and can reach high grades. Even after the operation, these BTs may reappear. Oligodendroglia is one example of this type of tumour.

Grade III Malignancies progress more quickly than grade II tumours and can infect nearby organs. For such tumours, surgery alone is insufficient, and postoperative radiation or chemotherapeutics are required. Anaplastic astrocytoma is an example of this tumour.

Grade IV Tumors are the most hazardous and are the most likely to spread. They may even use blood vessels to accelerate their growth. Glioblastoma multiforme is an example of this type of tumour[8].

Ischemic Stroke is a potentially lethal brain disease that is the leading cause of disability and death worldwide. When the blood supply to the brain is cut off, an ischemic stroke occurs. Within hours, tissue hypoxia and gradual tissue death occur. Stroke lesions are classed as acute (0–24 h), subacute (24 h–2 weeks), or chronic (> 2 weeks) depending on their severity[9].

II. RELATED WORK

Brain tumours can be classified in a variety of ways. Among the most prominent are neural network-based algorithms, CNN, and DL methods. The researchers investigated the use of deep features extracted from CNNs that had previously been trained to predict survival time[10]. It adds to the evidence that fine-tuning domain-specific parameters can improve performance. On the internet, you may find the standard dataset. It has an accuracy of roughly 81 percent when using leave-one-out cross-validation. For recognising brain tumour tissues in pictures, the researchers designed a hybrid approach.

Ramesh Babu and Rajesh introduced a noise-corrupted image detection approach for brain tumours. The Edge Adaptive Part Of the factors Denoising Technique is used to denoise the image (EATVD). In the act of denoising an image, this approach is employed to maintain the edges. After the image has been cleaned of noise, it is classified using mean shift clustering, which is a fully automated image segmentation technique. For feature extraction, the segmented sections are submitted to a grey level co-occurrence matrix. Contrast, Correlation, Energy, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogeneity, Homogen Multi class SVM uses the features to detect the tumour in the photos. The next step extracts the tumour from noisy photos with greater precision. In comparison to previous approaches, the PSNR values achieved are high[11].

Sahar Gull et al. suggested a new framework for exploiting magnetic resonance (MR) pictures to detect brain tumours. The system is based on transfer learning and fully convolutional neural networks (FCNN). Preprocessing, skull stripping, CNN-based tumour segmentation, postprocessing, then transfer learning-based brain tumour binary classification are the five stages of the proposed framework. The MR images are done to remove noise and improve contrast during pre-processing. The proposed CNN architecture is employed for segmentation of brain tumour pictures, and the thresholding technique is used for postprocessing to remove small nontumor regions that improved segmentation results. On three publicly available datasets, the GoogleNet model is used for categorization. On the BRATS2018, BRATS2019, and BRATS2020 datasets, the suggested technique achieved average accuracies of 96.50 percent, 97.50 percent, and 98 percent for segmentation and 96.49 percent, 97.31 percent, and 98.79 percent for brain tumour classification, respectively. The results show that the suggested framework is successful and efficient, as it outperformed the other two datasets on the BRATS2020 dataset[12].

Nilesh Bhaskarrao et al. Berkeley discrete wavelet transform (BWT) based brain tumour segmentation was researched in order to improve performance and simplify the medical image analysis procedure. Relevant features are retrieved from each segmented tissue to increase the accuracy & quality rate of a support vector machine (SVM) driven classifier. On the basis of accuracy, sensitivity, specific, the dice similarity index coefficient, the experimental findings of the suggested technique have been reviewed and validated for performance and overall analysis on magnetic resonance brain pictures. The experimental results showed that the suggested technique is effective at distinguishing normal and pathological tissues from brain MR images, with 96.51 percent accuracy, 94.2 percent specificity, and 97.72 percent sensitivity. The trial findings also showed an average dice similarity index coefficient of 0.82, indicating that the automated (machine) extracted tumour region and the manually extracted tumour region by radiologists have a better overlap. In compared to state-of-the-art methodologies, the simulation results demonstrate the significance in terms of the quality parameters and accuracy[10].

Indra and Yessi proposed a model based on the GLCM feature extraction method and the T-test classification method. Before the characteristics were removed, the brain's light signal was converted into a grey matrix. The experiment was based on the findings of 40 tests. By extracting characteristics, the GLCM approach developed an image of the brain and a disordered brain. The extracted characteristics were determined to have a P value of less than 0.05 for each character, indicating that they were employed for brain tumour classification on the public dataset[13].

Akil et al. provided a model for segmentation of gbm brain tumours based just on CNN model. The retrieved features of MR images were improved using a selective attention technique. To tackle the class imbalance problem, the spatial imbalance relationship has been used as an equal sample of image patches. The dice score range for the radiologist was 74 to 85 percent. On the BRATS2018 dataset, the median dice score of the WT, TC, and ET was 0.90, 0.83, and 0.83, respectively[14].

III. PROPOSED METHODOLOGY

A. Attainment of images

Brain MRI images were collected from different medical centres. These brain MRI images were converted into two dimensional matrices using Python and NumPy array.

B. Enhancement of MRI images

Enhancement techniques are used to increase the quality of photographs. It is critical to increase visual information about human viewers in order to acquire correct results. The approaches described below are used to improve brain MRI images. The very first step is to improve the MRI. To improve perceptibility, only the luminance of the pictures was enhanced. To enhance the quality of a brain MRI images, this was completed.

- Improved contrast- MRI pictures are RGB images that are transformed to grey scale images. Intensity images are grayscale images with a high level of detail. Using the python package, intensity values were mapped into higher and lower intensity values.
- • Stretching in the mid-range is also an enhancing strategy. The midrange MRI image pixel intensities are extended in this procedure. As a result, the quality of mri Brain images improves. Gray scale image pixels are transferred between 0 and 1 value in this technique by dividing 255 intensity difference as illustrated in (1)..

$$X_{ij} = Image_i/255 \tag{1}$$

Here i for row index of brain image matrix and j for column.

C. Kernel Principal Component Analysis (K-PCA)

Kernel PCA is determined by breaking down a convolution's kernel variation into its eigenvalues. When the linear kernel k(x, y) = (x, y) is applied, kernel PCA is simplified to PCA. As a result, kernel PCA is a simple extension of PCA that just requires linear optimization.

The kernel function must satisfy Mercer's theorem in order to generate a translation into the a domain where K works as a dot product. Two of the most widely used kernels are the polynomial or Gaussian kernels. When built with kernel functions, a Gram matrices is also known as a Kernel Matrix. Finally, the KPCA is carried out in the original space as follows:

1. Compute the kernel Matrix $K_{ij} = K(x_i , x_j)$.
2. Centre $K_c = K\text{-}1_N K\text{-}K 1_N + 1_N K 1_N$.
3. Diagonalizable Kc and normalize eigan vector.

Extract the k first principal.

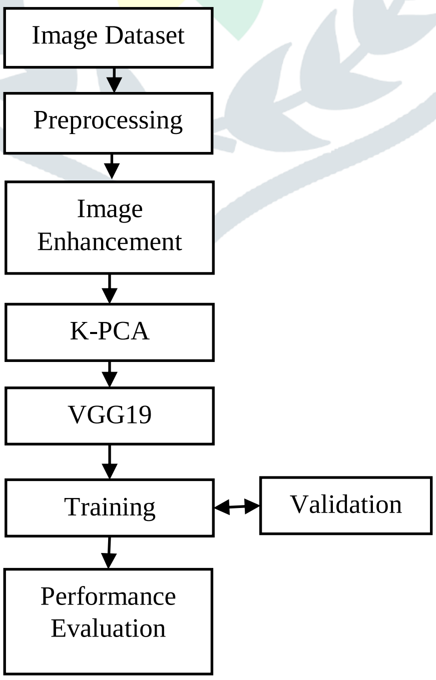

Figure 1- Proposed Methodology FlowChart.

D. VGG 19

The CNN is a cutting-edge artificial neural network (ANN) utilised in image processing & computer vision applications such as picture segmentation, classification, or recognition. A standard CNN is made up of input layers, hidden layers, then output layers. The most frequent hidden layers are convolutional layers (CL), pooling layers (PL), and totally linked layers. VGG19 is indeed a 19-layer CNN with a lot of applications. Among the 19 total layers, there are 16 CL, 5 PL, 3 FCL, & 1 SoftMax (SM) layer.

The architecture of VGG19 is built in six phases.

• The image is first supplied as an input to the structure; typically, an image with a resolution of (224, 224, 3) is used.

• After that, a kernel of size (3, 3) was used to uncover the image's hidden pattern.

• The outcome of the layers is typically linear, thus an FCL was used to convert the linear output into the non-linear output

• Ultimately, the SM layer was employed to estimate the probability distribution of various groups.

Because training VGG19 from scratch is time-consuming and challenging, pre-trained VGG19 is usually trained on larger datasets, such as ImageNet, where the complex patterns are simple and effective.

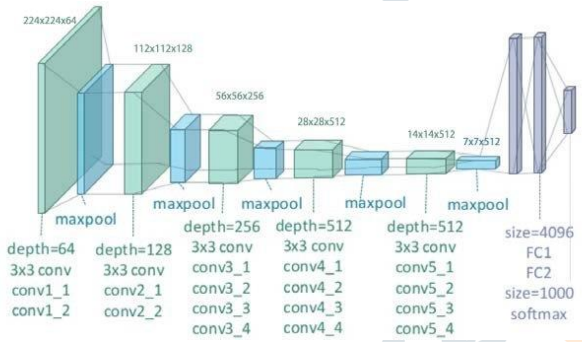

Figure 2- VGG-19 architecture.

IV. EXPERIMENTAL ANALYSIS

A. Performing EDA- The first phase is exploratory data analysis (EDA). It aids in the analysis of the complete dataset and the summary of key components such as class and size distribution. Visual tactics are widely used to present the findings of this inquiry. The distribution in brain class counts is depicted in Figure 3.

B. Data Pre-processing- Following steps were performed in pre-processing of data.

Filtering Image Data to Remove Noisy Images- Filtering image data is a common step in practically all systems. To reduce photo noise while maintaining image details To eliminate noise from photographs, both noise masks and filters are utilised.

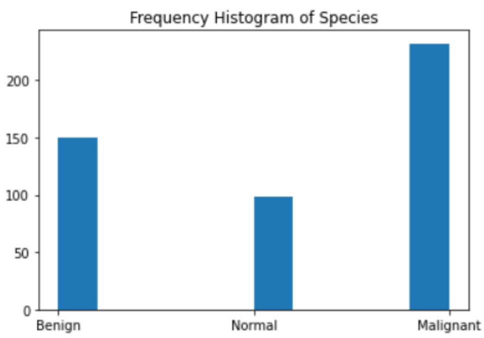

Figure 3- Distribution Tumour Classes.

Data Augmentation- In data processing, data augmentation refers to strategies for increasing the quantity of data by attaching minimally changed duplicates to existing information or synthesising new data from old data. It functions as a stabiliser and aids in the prevention of generalisation errors during training. It's a technique for experts to significantly expand the diversity of data accessible for learning algorithms while having to gather more. Cropping, padding, and horizontal flipping are examples of standardised data augmenting techniques used to train large neural networks.

Resizing images- Image scaling refers to the process of resizing a digital image. When you reduce the size of an image, it becomes smaller, and when you increase the size, it becomes larger. Although raster and vector drawings can both be scaled, the results are not identical. Picture interpolation is a technique for enlarging or modifying images based on a one-pixel grid. You'll need to resize an image if you want to change the overall number of pixels in it.

Normalization- Normalization is the process of joining two pixels and changing the intensity value of the pixel. Its main purpose is to convert an input image into the a value that reflects the sensory experience of such scanned object.

C. Training and Validation

For improved performance using transfer learning, we created a model with Sequential and immediately fused it with layers and the VGG19model. Under FCN, several designs are being explored; in this study, the VGG19 architecture was used, which is ideal for biomedical image categorization. The discovered tumours are segmented using a set of FC (completely connected) layers, following which the segmented mask is categorised using FCs. The proposed method guarantees a result that meets conventional medical imaging criteria. CNN (Convolutional Neural Network), often known as ConvNet, is a deep machine learning technique used to analyse images. It employs a variety of multilayer perspectives framed to achieve a significantly decreased pre-processing time. The steps involved in the proposed method are data collecting and pre-processing, which eliminates noisy data. Classification and identification of VGG19 CNN Significant relationships and patterns in the data can be retrieved and predicted using deep learning algorithms.

Figure 4 displays the final photos after the model has been trained. The images on the left show an MRI image with a benign tumour, the images on the middle show a malignant tumour that symbolises a tumour in an MRI image, and the images on the right show normal MRI images with no tumour detection.

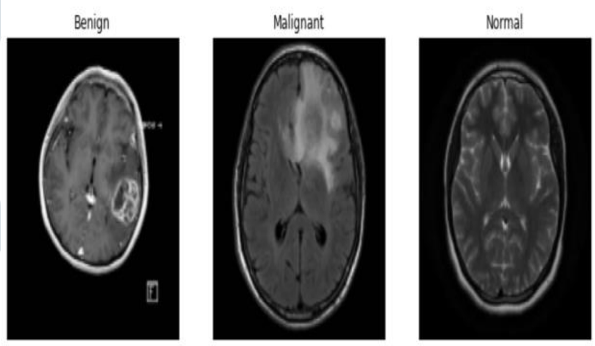

Figure 4- Predicted Tumour Classes.

The VGG19 model results from outstanding performance with an accuracy of 0.91 as compared to the base models (0.83). Figure 5 and 6 shows the accuracy and loss graph of the proposed model. Figure 7 shows the confusion matrix of predicted classes.

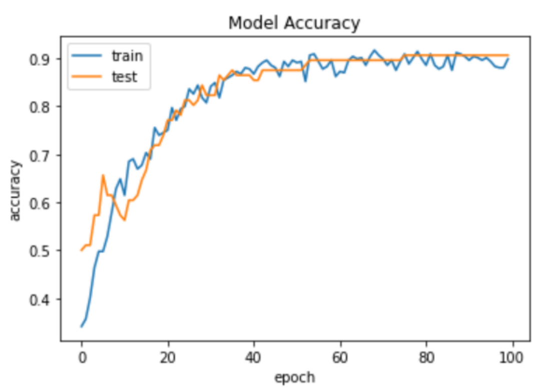

Figure 5- Figure showing the accuracy graph.

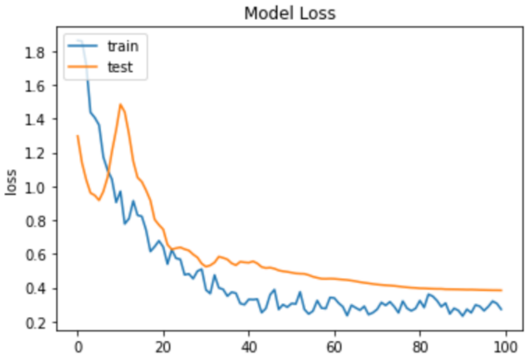

Figure 6- Figure showing the loss graph.

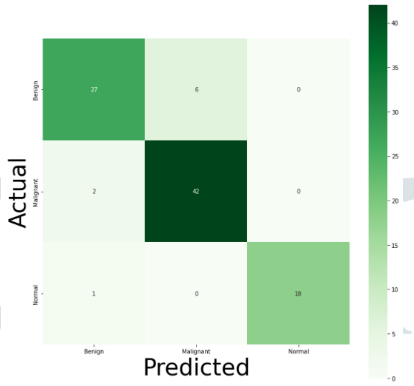

Figure 7- Figure showing the Confusion Matrix.

Table 1- Evaluated Results.

Evaluation	Accuracy	Loss	Precision	Recall	F Score
SVM[15]	83%	-	-	-	-
VGG19 with KPCA	91%	10%	90%	95%	97%

IV. CONCLUSION

There are several image classification methods offered; nonetheless, a good segmentation methodology is essential to differentiate the brain tumour from MRI images in order to properly detect a brain tumour. Precision data from multiple photos from various slices must be analysed for proper diagnosis, planning, and therapy. The emphasis is on improving the information received from the pictures via sliced alignment and refining the segmentation technique in order to offer a suitable part of the brain tumour known as that of the region of interest. The suggested model correctly detects the Brain Tumour in MRI images with a 0.91 accuracy.

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