MRI Image Based Relatable Pixel Extraction with Image Segmentation for Brain Tumor Cell Detection Using Deep Learning Model

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***Abstract*— Biomedical technology now plays a critical role in the detection and treatment of a wide range of diseases, from minor to life-threatening. One of the most life-threatening disorders is brain tumour, which is defined as a mass development of abnormal cells in the brain. By avoiding the spread of aberrant cells, early discovery and treatment can save a person's life. In the medical field, it is vital to find a certain image categorization strategy based on tumor cell regions. The tumor region is then selected to perform the segmentation process and then classification is performed. The identification-based method helps to limit the image area and to identify the border area in a reduced time period. Automatic brain tumor classification is a difficult undertaking due to the enormous geographical and structural heterogeneity of the brain tumor's surrounding environment. The use of Deep Neural Networks classification for automatic brain tumor detection is proposed. The proposed a Relatable Pixel Extraction with Magnetic Resonance Imaging (MRI) Image Segmentation for Brain Tumor Cell Detection (RPEIS-BTCD) using Deep Learning Model. The proposed model is compared with the existing models and the results indicate that the proposed model performance the accuracy is 97%.**

Keywords*—Classification, Deep Learning, Edge Detection, Image Segmentation, Relatable Pixel Extraction, Tumor Cells, Tumor Detection.

I. INTRODUCTION

A brain tumor is an abnormal growth of brain cells that can be malignant or benign. Early, complete diagnosis and effective therapy are critical for a patient's survival while dealing with brain tumors. Approximately the last few decades, medical specialists have found over 129 different types of brain tumors [1]. These brain tumors can be broadly classified into two types: primary brain tumors that originate in the brain and secondary brain tumors that originate elsewhere in the body [2]. In general, non-invasive medical imaging techniques such as Computed Tomography (CT) and MRI are preferred over invasive procedures such as tissue biopsy during the earliest stages of brain tumor diagnosis [3]. According to the Central Brain Tumors Registry, a brain tumor is one of the leading cancer-related causes of death in India. In India, an estimated 1,00,000 persons are diagnosed with a brain tumor each year, comprising malignant (49,000) and non-malignant (51,000) tumors [4].

Deep Learning shows considerable potentiality for the identification and segmentation of medical images. This technique simplifies the process of automating non-invasive imaging-based diagnostics [5]. Its computer-aided brain tumor diagnosis has successfully leveraged advances in medical image processing [6].

MRI is increasingly being used in clinical research of brain anatomy detection. Along with the high resolution, the contrast and exact separation of soft tissue enable doctors to make precise diagnoses of certain tumors [7]. A precise segmentation of tumor cells and healthy cells in the MRI is necessary for comprehending disease [8], monitoring evolutionary trends, planning for surgery, and identifying the optimal surgical technique [9] or alternative. Automated segmentation approaches, with variable degrees of automation, are a good alternative for assisting management in tracking the edges of distinct tissue sections and automating pathologic MRI image processing model [10].

A tumor is a non-cancerous proliferation of cancer cells, but a brain tumor is an uncontrolled growth of brain cells [11]. A benign brain tumor can develop into a malignant tumor. In contrast to malignant brain tumors, benign brain tumors are morphologically identical to malignant brain tumors but lack cancer cells. Meningioma and glioma are benign tumors, whereas astrocytoma is a malignant tumor [12]. Astrocytic glioblastoma is the most aggressive subtype of glioblastoma. Along with excessively rapid blood vessel growth, glioblastoma causes necrosis within and around the tumor.

Segmentation of diseased and healthy brain tissues, as well as their sub regions, is crucial for developing cancer treatment strategies and conducting cancer research. All techniques for medical image processing rely on segmenting images to identify regions of interest. With the massive amount of data contained in each MRI image, the existing models are far too time consuming, tedious, and, in some cases, difficult [13]. When segmenting brain tumor images, the radiologist typically employs all of these MRI approaches concurrently. In typical brain tumor clinical acquisition techniques, there is a high-resolution intra-slice space and a small inter-slice space [14]. It makes use of modern imaging equipment are large-scale clinical treatment regimens [15]. The brain tumor regions located in MRI image are indicated in Figure 1.

Fig. 1. Brain Tumor MRI Image

To discuss the automatic segmentation of meningioma in multispectral brain data sets obtained via MR imaging. Meningioma is one of the rare benign brain tumors. In older patients with intracranial meningioma, accurate tumor detection results in surgical indications [16]. Support vector machine (SVM) techniques to MRI segmentation have demonstrated exceptional performance in detecting a variety of neurological disorders in recent years. Segmentation is used in medical imaging modes to detect adulterated tumor tissues [17]. Segmentation is critical and necessary for image analysis; the procedure splits an image into numerous blocks or portions that share similar and common characteristics, such as grayscale, texture, color, contrast, boundaries, and brightness [18].

Image scalability is not possible in a traditional neural network. Deep convolution neural network, the image can be scaled, 3D input volume to a 3D output volume [19]. The input layer, convolution layer, Rectified Linear Unit (ReLU) layer, pooling layer, and fully connected layer make up the Deep Convolution Neural Network (DCNN). The given input image is divided into small sections in the convolution layer. The ReLU layer performs element-by-element activation [20]. The use of a pooling layer is required. The pooling layer, on the other hand, is mostly utilized for down sampling. The class score or labelling score value is generated in the final layer based on the range of 0 to 1 [21]. The proposed model selects the relatable features from the MRI image and then applies the classifier for tumor detection.

The paper is organized as follows; the existing work is discussed in section 2 and then proposed model Relatable pixel extraction with image segmentation discussed in section 3. Then the experiment results in Section 4 and the conclusion in section 5.

II. RELATED WORK

Author et al. [1] used Histogram equalisation, image segmentation, picture improvement, and feature extraction to perform image processing. In comparison to previous classifiers, the suggested technique for classifying brain pictures using ANN as a classifier has a high classification efficiency. Sensitivity, specificity, and accuracy have all improved.

For the diagnosis of meningioma, glioma, and pituitary tumours, Fausto et al. [2] proposed a model using Convolution Neural Network, which has an overall accuracy of 91.3 percent and a record of 88 percent respectively. For categorizing brain tumour types from MRI image segments, a deep learning architecture based on 2D convolutional neural networks was used. The data collection, data pre-processing, pre-modelling, model optimization, and hyper parameter tuning. In addition, the model's generalization was tested using 10-fold cross validation on the entire dataset.

In [3], author based on Hough transform, which is a mechanism for automatically locating and segmenting anatomical structures of interest analyzed the images for brain tumour detection. It also employs a robust, multi-region, flexible segmentation strategy based on learning approaches that may be used to a variety of modalities. Different training data and data dimensions are used to forecast the final outcomes. The picture analysis employs cutting-edge neural networks. Hough CNN uses CNN, Voxel-based categorization, and fast patch-based evaluation. The author tested on dataset 80 images in that 73 images are malignant and 7 images are benign. The classification method is SVM and accuracy is 95.62 percent.

Javeria et al. [5] studied that the brain is a vital organ in the human body that regulates and directs the functions of the rest of the body. It is the control center of the central nervous system, and it is in charge of the human body's daily voluntary and involuntary functions. The tumour is a fibrous network of unwanted tissue growth within our brain that proliferates uncontrollably. Radiologists frequently use MRI to examine brain tumour stages in attempt to prevent and cure the tumour. The findings of this examination reveal the presence of a brain tumour.

Shakeel et al.[8] recommended the Mechanical Learning-Based Neural Propagation Network (MLBPNN) method for brain tumour classification systems. Furthermore, the technique could aid doctors in scanning the image cell by colouring phone properties utilizing order and package calculations. Acquisition, upgrade and division, extraction, picture representation, characterization, and necessary management are only a few of the many phases required to prepare images from biopsy photos in order to detect a disease. MLBPNN is investigated in this work employing infrared image sensor technology.

The Extreme Learning Machines with Local Receptive Fields (ELM-LRF) were developed by Ari et al. [9] for the classification and diagnosis of brain tumour. To begin, noise is ignored using non-local smoothing methods and procedures. ELM-LRF classified cranial MRI images as malignant or benign in the second step. The tumour segmented in the third phase. The main purpose of this study was to use bulk cerebral MR images. The classification accuracy of cranial MR images was 94 percent in experimental tests.

Bahadure et al. [10] used the Berkeley Wavelet Transformation and Support Vector Machine, for image analysis and diagnosis of brain tumour. The characteristics are histogram-based and texture-based method. Compare to existing models are ANFIS, Back propagation and K-NN classifier. The many performance variables increase other metrics such as PSNR, mean, MSE, accuracy, specificity, sensitivity, and a coefficient with the provided algorithm. The 96.51 percent accuracy is more in proposed model.

III. PROPOSED RELATABLE PIXEL EXTRACTION MODEL

The deep learning algorithm to break down and diagnose brain tumours. The suggested brain segmentation system comprises various phases; skull striping, screening and upgrading, segmentation; tumour contouring. The handling of MRI scans of big size and complexity makes it a discouraging and challenging process for professionals to get information manually. Because the operator does multiple types of variability analysis on the device, this manual examination is time-consuming and prone to errors [22].

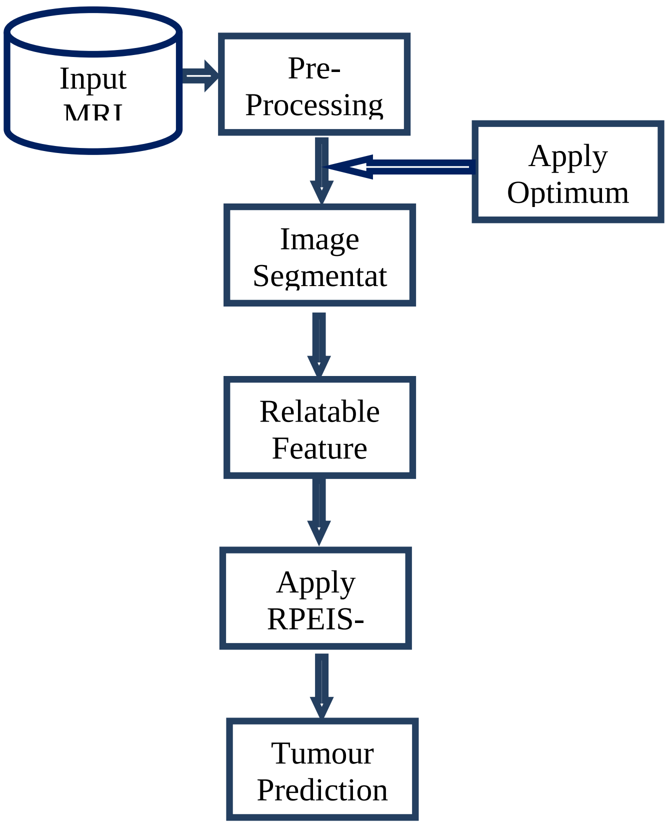

Fig. 2. Proposed Model Architecture

In order to accurately portray the extent of the lesion, careful selection of certain features and traits is critical, as the image must convey the lesion in its whole. The functional derivative approaches sift through the items to identify the most distinctive attributes that can be used to separate various types of objects. A feature is utilized to assign the instances to their class, which is the classifier's ingredient. Unique attributes or features are used to set apart one input layout from another, with the end goal of minimizing the original data. The figure. 2 proposed architecture model.

The brain was examined with MRI and a deep neural network to break down twenty various parameters such as the mean radius, mean texture, mean perimeter, mean area, mean fractal dimension, and mean smoothness into their respective elements. Identifying the boundaries of the MRI image by way of calculating the areas where the darkest and brightest pixels P and Q respectively in the image differ greatly is crucial for doing the tumour identification,

$$\text{contrast} = \sum_{i,j=0}^{N} Img_{i,j}\,(P-Q)^2$$

$$\text{Dissimilarity} = \sum_{i,j=0}^{N} \text{Img}|i-j| + P(i,j)$$

$$\text{Entropy} = \sum_{i,j=0}^{N} -\ln(P_{ij})Q_{ij}$$

The image segmentation is performed on the considered MRI image. The segmentation divides the images into partitions so that the pixels are accurately extracted. The segmentation process is performed as

$$Segment(IMGS(P,Q)) = \sum_{i,j=0}^{M} \frac{P(i,j)+\sum_{i,j=0}^{M-1} Q_{i,j}(i-j)^2}{(i-j)^2+T} + \sum_{i,j} \frac{|IMGSj^i|}{|IMGS|} + \max(contrast) + \text{Th}$$

For calculating homogeneity of the segments, OT is an optimum threshold vector with the property of homogeneity evaluation performed as

$$\delta(\text{O}\delta\text{T}(\text{IMGS}(\text{P},\text{Q})) = \max_{1\le k\le L} P_B^2(OT) + \sum_{i=1}^{N} HG\,(i) + HG(j)_N$$

Pixels are initially taken from an MRI picture found in a two-dimensional image set (IMGS). To store the pixel representation of a two-dimensional image, a two-dimensional data set is used that is represented as

$$PixSet(IMGS[N]) = \left(\frac{\delta_{P,Q}}{Sement(IMGS(i)_{i,j}}\right) + \left(\frac{2\delta(OT(\min(P,Q)))}{(P_i)^2 + (Q_j)^2 + Th}\right)$$

For a picture with a given angle, ϑ, the classification procedure is executed in each node using a defined criterion by several groups on a tree-like model representing the decision tree algorithm. The data is categorised hierarchically into smaller subsets. The following representation is often used to divide training and test data.

$$SplitsSet(IMGS[N]) = Pixelset(M) - \sum_{i,j \in IMGS} \frac{|\delta^i|}{|Segment(N)|} + \sum_{i,j} \frac{|\max(OT)^N|}{|\min(OT)|}$$

The relatable features are extracted from the pixel matrix. The edges are identified and the pixels inside the edges are extracted and then the relatable features are considered and maintained as a set. The feature extraction is performed as

$$FeatureSet(\mathrm{IMGS(i)}) = \left(\sum_{i \in M_j^l} \sum_{i,j} \frac{|\min(SplitSet(IMGS(i))^i|}{|\delta|} + \sqrt{\sum_{x=0}^{P-1} \sum_{y=0}^{Q-1} \omega^2(i,j)} \right)$$

Because tumour pixels are a very small portion of the image as a whole, tumour segmentation is a difficult, imbalanced task. To better address the problem of imbalanced classes, the model adopts a class-balanced cross-entropy loss function. The target function is computed for tumour prediction with all network layer factors considered, and the entropy parameter set.

$$TargetF(FeatureSet) = \max(OT) + \sum_{Ig \in IS} \sum_{i \in Ig} FeK_j^l + \log PixelSet(Q_j = 1|X;W) + \sum_{j \in Y} \log PixelSet(P_i = 0|X;W)$$

The auto correlation among the features are generated and the set is maintained as

$$\mathrm{autocorrelation} = \sum_{i=1}^{m} \sum_{j=1}^{n} \frac{(i*j)(i,j) - (\delta_x * \delta_y)}{(\vartheta)} + \min(TargetF(IMGS(i)))$$

The brain tumour region is identified and the type of the tumour is predicted and maintained as a tumour predicted set as

$$Tumor\,Predict(DS(IMGS(i))) \leftarrow \arg \max_{OT,autocorrelation} \frac{P(Y=yk) + \max(\delta(Q(i))) + P_1 * Q}{\sum_{i=1} P(Q=yk) + Target F(P(i))} + \max(PixelSet(i))$$

IV. EXPERIMENTAL RESULT

The segmentation method of brain tumour using deep convolutional neural networks to achieve tumour segmentation automatically and accurate brain tumour detection. Python is used to implement the proposed model, which is then simulated in ANACONDA SPYDER. Brain tumour detection is a challenging and delicate task that requires the classifier's expertise. In this paper, the usage of a Deep Convolutional Neural Network system to categorise brain tumour types is discussed. Tumour can be identified by extracting relevant features from MRI images and utilizing Relatable Pixel Extraction with Image Segmentation for Brain Tumor Cell Detection (RPEIS-BTCD) model for accurate tumour prediction. The proposed RPEIS-BTCD model is compared with CNN based Brain Tumor Detection (CNN-BTD) in terms of Image Segmentation Time Level, Relatable Pixel Extraction Accuracy Levels, Relatable Pixel Extraction Time Levels, Feature Extraction Accuracy, Classification Accuracy Levels, Tumor Detection Accuracy, False Positive Rate. The image segmentation time levels of the proposed and existing models are clearly illustrated in Figure 3.

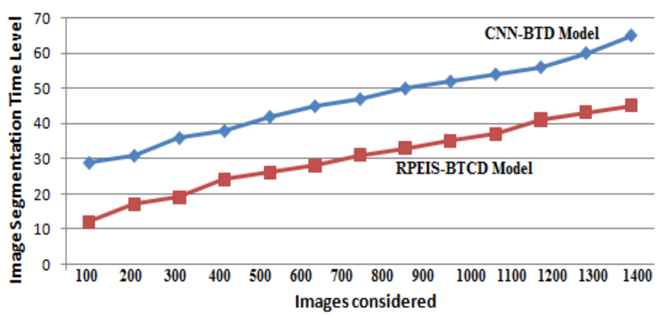

Fig. 3. Image Segmentation Time Level

The image dataset are considered using Relatable Pixel Extraction. The tumour identification procedure is applied depending on the attributes selected, allowing for reliable tumour detection. The levels of pixel extraction accuracy are depicted in Figure 4. When compared to the existing model, the suggested model requires less time to extract relatable pixels.

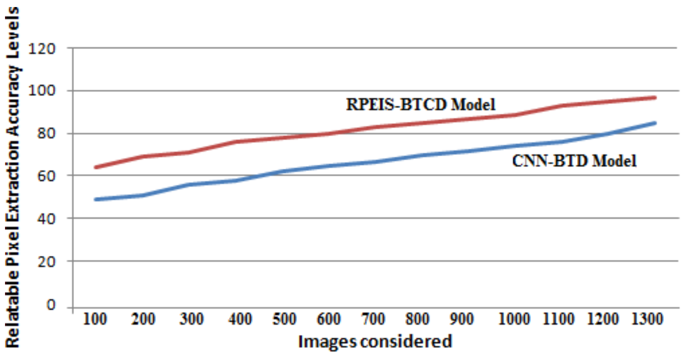

Fig. 4. Relatable Pixel Extraction Accuracy Levels

Manual classification is said to be time-consuming and subjective, which can lead to inappropriate treatment. By using a precise classification method based on various medical images, prediction accuracy is improved efficiency. The proposed model in very less time extracts the relatable pixels from the segmented image. The pixel extraction time levels of the proposed and traditional models are indicated in Figure 5.

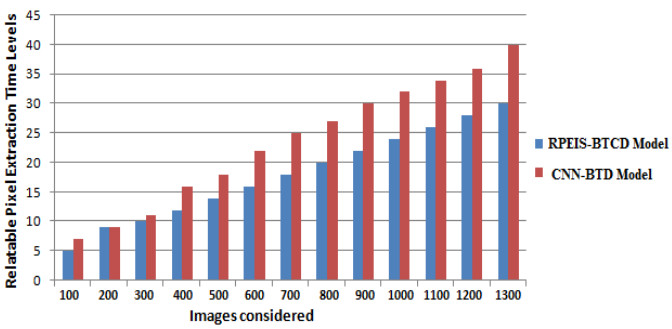

Fig. 5. Relatable Pixel Extraction Time Levels

To limit the number of extraneous features, feature extraction is used to filter data. After deciding on the features to use, the tumor-identification method is implemented to make it possible to detect tumours accurately. As shown in Figure 6, the temporal levels of feature extraction are as follows. Compared to the existing model, the proposed approach accuracy in extracting features is better.

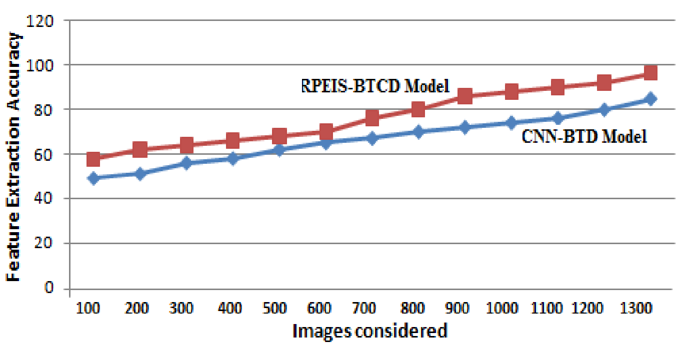

Fig. 6. Feature Extraction Accuracy

Classification is the process of categorising things based on shared characteristics. That strategy is really just grouping together comparable objects. The proposed model accurately classifies the tumour and non-tumour cells. The classification accuracy of the proposed and traditional models are represented in Figure 7.

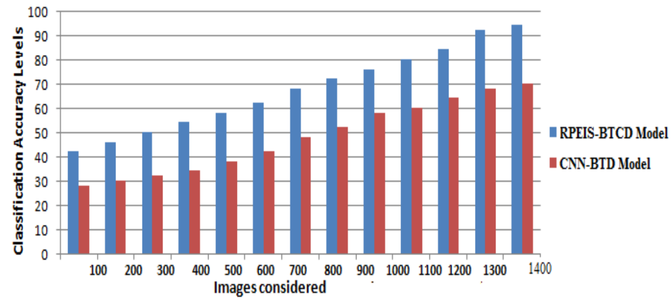

Fig. 7. Classification Accuracy Levels

Brain tumour are first detected by a MRI scan. The proposed model detects the tumour accurately in less time by considering the relatable features. The tumour detection accuracy of the proposed and traditional models are shown in Figure 8.

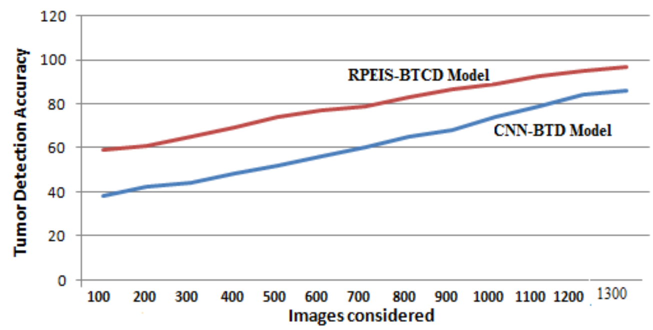

Fig. 8. Tumor Detection Accuracy

The proposed model has very less false prediction rate as the model considerably uses the most useful features in tumour detection. The false prediction rate levels of the proposed and existing models are shown in Figure 9.

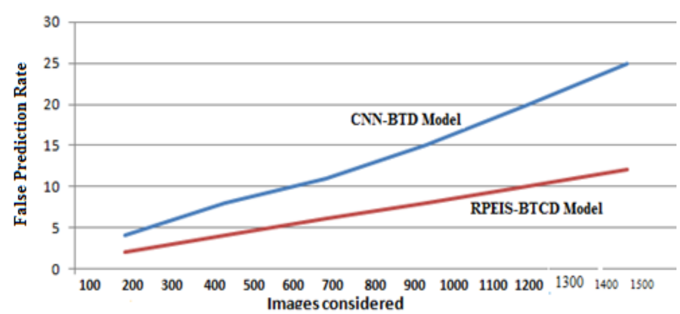

Fig. 9. False Prediction Rate

The confusion matrix is a method of analyzing classification algorithms' effectiveness. When the quantity of observations in each class is unequal or when more than two classes are considered in a dataset, classification accuracy is misleading. The confusion matrix representations of training and testing datasets are represented in Figure 10.

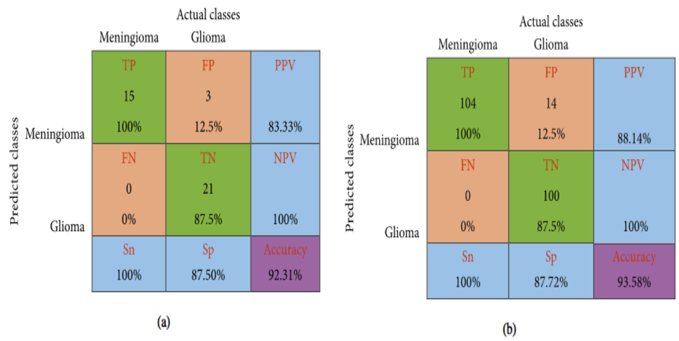

Fig. 10. Testing and Training Confusion Matrix Representations

The loss values are calculated and the loss values of the training and testing samples of the images considered in the provided dataset is clearly indicated in Figure 11.

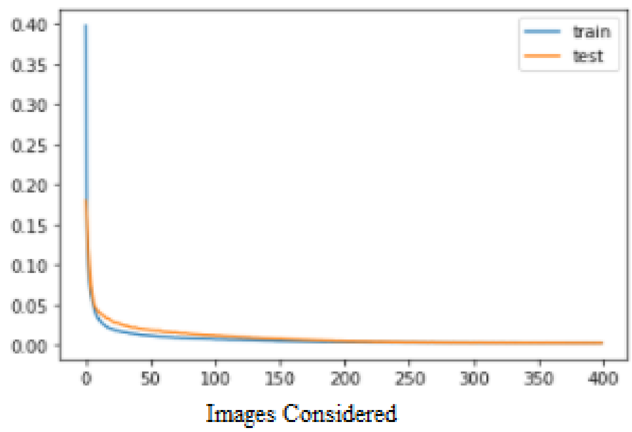

Fig. 11. Train and Test Loss Levels

V. CONCLUSION

The most lethal disease that affects most people, causing death, is brain tumour. Initially, neural networks that encompass the entirety of brain tumour data are constructed. The background of a tumour segment is an extremely dense region, making it difficult to separate malignancies from their surroundings. In order to deal with the difference in training results, the loss function has been employed. The combination of pixels in the overlapping area helps to segment a large brain area. The suggested system does segmentation by finding tumor-relevant features in an MRI image, after which it identifies tumour cells with segmentation. The major aim of this study is to create a highly accurate, efficient brain tumour classification method with low complexity. During conventional classification of brain tumours, Relatable Pixel Extraction with Image Segmentation for Brain Tumor Cell Detection is used for feature extraction and classification. The new method provided in the proposed scheme uses a deep convolution neural network classification by considering relatable pixels, which both improves accuracy and cuts computation time. To determine the training accuracy, validation accuracy, and validation loss, a training set and a validation set are created. Training accuracy is a success rate of 97 percent. The accuracy of validation is great and the loss of validation very low. In future, the segmentation process can be simplified by forming sub sections of segmented image that can improve the precision rate. The number of features can also be reduced further to reduce the time complexity levels also.

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