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Deep Learning Based Method for Brain Tumor Detection

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ABSTRACT

A brain tumour is considered to be a group of anomalous cells in the brain. The skull is very hard where the brain is enclosed. The growth of any type of tumour in this restricted area causes many problems. The brain tumour is detected in various steps such as to pre-process the image, segment it, extract the features and classify the tumor. In the previous research work, numerous techniques are proposed which include snake segmentation for the segmentation, image filtering using PNLM filtering techniques. In the last transfer learning will be used for the classification. The transfer learning model is the combination of VGG16 and CNN models. Python is executed to simulate the introduced model. Accuracy, precision and recall are employed for computing the results. The proposed model shows high accuracy in comparison with existing ML models for the brain tumour detection

Keywords: Brain Tumour, Snake Segmentation, PNLM Filter, VGG16, CNN

1. INTRODUCTION

The brain and spinal cord collectively known as the CNS (Central Nervous System), play an important role in controlling many biological functions, such as organizing, analyzing, decision-making, issuing commands, and integrating information. The human brain is extremely complex due to its intricate physical structure. Disorders affecting the CNS, such as stroke, infections, brain tumors, and migraines, pose significant problems in terms of diagnosis, evaluation and treatment development [1][2]. Brain tumors, which result from the abnormal growth of brain cells, present particular challenges for early diagnosis. Detecting brain tumors through MRI (magnetic resonance imaging) remains a difficult and error-prone manual process. Brain tumors can range from benign to malignant and from rare to common, with approximately 130 different types identified in the brain and CNS (Central Nervous System). Malignant brain tumors can either originate in the brain (primary brain tumors) or spread to the brain from other parts of the body (secondary or metastatic brain tumors). Primary brain tumors develop directly within the brain, arising from brain cells or the nerve cells surrounding it [3][4]. These tumors can be either benign or malignant and vary in characteristics. On the other hand, secondary brain tumors also known as metastatic tumors, are the most common type of malignant brain tumor. While benign tumors do not spread to other areas of the body, secondary brain tumors are always cancerous and present a serious health risk.

A rapid and precise diagnosis of brain tumors is essential for effective treatment planning and improved patient outcomes. Nonetheless, radiologists sometimes encounter considerable obstacles while analyzing images in such situations. The traditional method of diagnostic assessment is mainly based on their skills and their subjective evaluation of images, performed manually. Discrepancies in the skills of practitioners and the intricacy of brain tumors may give rise to variability in diagnostic accuracy [5][6]. Diagnosis and treatment planning depend mainly on clinical and radiological data, while MRI is the dominant imaging method for brain malignancies. The multi-sequential, multi-parametric, and multi-planar imaging abilities of MRI make it a must-have instrument that allows thorough examinations of brain lesions. MRI data, thanks to their ability to provide different views of the brain, are now a highlight for computational research. However, conventional imaging methodologies have their drawbacks, such as difficulties with tumor size determination, tumor grading, and evaluation of treatment effects. Innovations in imaging acquisition are being developed to improve lesion definition and facilitate therapy evaluation. In addition, it is noticeable that sophisticated image analysis methods, which are based on substantial data in radiological images, are on the rise [7][8]. Shape-based features can be derived from cortical or hippocampal lobes, but they often fail to take into account the interconnections across the whole brain, and this can possibly be the source of the inaccurate results. Features that are divided by regions may not be adequate either because the pathological developments may deviate from the independent existing data-driven assumptions. Moreover, although voxel-wise features provide thorough information, their enormous size may have a negative impact on the classification process. AI (Artificial Intelligence) is a branch of computer science focused on enabling computers to mimic human-like intelligence, allowing them to learn, reason, and solve problems based on different information. Artificial intelligence has become an important tool in the detection and diagnosis of brain tumors. Given the complexity and intricacy of brain tumor surgery, it presents a promising area for further integration of AI [9][10]. While there have been numerous efforts to develop accurate and reliable methods for brain tumor classification, the significant variability in tumor shape, texture, and contrast between different individuals continues to pose a major problem. ML (Machine learning) and DL (deep learning), both subsets of AI, are transforming neurosurgical procedures. These technologies include key steps such as data preprocessing, feature extraction, feature selection, feature reduction, and classification. Thanks to AI, neurosurgeons now have more confidence in diagnosing brain tumors, knowing that advanced algorithms assist in their decision-making [11][12]. Deep learning, especially neural networks play an important role by delivering highly promising results. CNNs (Convolutional neural networks) are particularly effective at learning features offering remarkable precision. A variety of deep learning applications are now in use including pattern recognition, object detection, voice recognition, and other tasks requiring decision-making. A typical CNN architecture consists of an input layer, multiple hidden layers, and an output layer with a fully connected layer. Hidden layers in neural networks comprise convolution layers, rectified linear unit (ReLU) layers, and pooling layers. Convolution layers perform essential convolution computations, extracting features from input data. As the layers of a neural network become deeper, they progressively extract more specialized characteristics, moving from more tangible representations to increasingly abstract ones. ReLU layers utilize activation functions to present nonlinearity into the computation, enabling for the modeling of more complex relationships between inputs and outputs [13][14]. Pooling layers, typically using either average or max pooling, play an important role in deep learning. While they select only one result from a set, they still preserve important invariance attributes, reduce the number of parameters, decrease computational costs, and help prevent overfitting. In a sequence-based model, the operation is repeated based on the outcomes of previous computations. However, due to their dependence on prior data, RNNs (Recurrent Neural Networks) face problems in capturing long-term dependencies effectively. To solve these limitations, some researchers present LSTM (Long Short-Term Memory) networks as a more advanced solution. LSTMs are an enhanced form of RNNs that are especially effective in managing and predicting significant occurrences within time series data, particularly those with long-term dependencies and intervals. These networks have been successfully applied to a variety of tasks, including document summarization, image recognition, speech processing, handwriting recognition and music composition. Unlike traditional RNNs, LSTMs incorporate a unique "cell" structure that governs the significance of input data [15][16]. This cell contains three distinct gates: the input gate, output gate and forget gate. When data is received, the LSTM assesses it according to specific criteria. The forget gate decides which information is irrelevant and can be discarded, while keeping only the data that is considered valuable for the task at hand. This mechanism lies at the core of LSTM's ability to effectively manage long-term dependencies and deliver high performance in complex tasks.

2. LITERATURE REVIEW

K. Lamba, et al. (2024) presented new integrated method using advanced artificial intelligence methodologies, including deep learning and supervised learning algorithms [17]. This novel technology showed exceptional potential in accurately identifying significant patterns within input data, which aided healthcare professionals in detecting abnormal brain cell growth. The method leveraged publicly accessible brain MRI (magnetic resonance imaging) datasets to design an automated system capable of diagnosing brain tumors. To improve the quality of the images and ensure consistency, data augmentation techniques were used. The method incorporated a 16-layer VGG (Visual Geometry Group) model via transfer learning, thereby reducing the cognitive load on medical practitioners when making precise diagnoses. By extracting important features, the system significantly improved both the speed and accuracy of diagnostics, using a supervised learning technique with linear SVM (support vector machines). The presented model surpassed existing techniques, achieving an impressive accuracy of 98.87%, precision of 99.09%, recall of 98.73%, specificity of 99.02% and an F1-score of 98.91%.

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M. Naim, et al. (2024) aimed to create a highly accurate system for detecting and categorizing BTs (brain tumors) through the application of ml and dl techniques [18]. This system was specifically designed to distinguish between brain tumor data and healthy data by integrating three combined datasets. A variety of deep learning models were used, such as 13-layer 2D CNN (Convolutional Neural Network), a CNN integrated with LSTM (Long Short-Term Memory) and a 9-layer 2D CNN, all aimed at improving classification performance. Of these, the 2D CNN LSTM model achieved the best performance, reaching an accuracy of 98.47%. It was followed by the 9-layer 2D CNN, which recorded an accuracy of 97.71%, and the 13-layer 2D CNN with a lower accuracy of 92.36%. To further boost performance, the models were merged using ensemble learning to form a hybrid network, which resulted in a significant improvement in accuracy. When compared, the ensemble deep learning models surpassed all other classifiers, achieving an accuracy of 98.82%, precision of 99% and recall of 99%.

K. R. Pedada, et al. (2023) presented an enhanced version of the U-Net architecture, built upon residual networks and designed to include periodic shuffling in the encoder and sub-pixel convolution in the decoder. Sub-pixel convolution, in contrast to conventional resizing convolution, improved the model's ability to capture intricate patterns by proposing additional parameters, all while keeping the computational complexity consistent and avoiding the problems caused by overlap in de-convolution operations [19]. The performance of this upgraded U-Net model was tested using two benchmark datasets from the BraTS 2017 and 2018 brain tumor segmentation challenges, where it achieved segmentation accuracies of 93.40% and 92.20%, respectively. The tumors were categorized into three different regions: TC (tumor core), WT (whole tumor) and EC (enhancing core). The results of these experiments showed that the improved U-Net model significantly outperformed existing segmentation methods.

S. Dharshini, et al. (2023) introduced new method for brain tumor detection, combining CNN (Convolutional Neural Networks) with BAT (Bat Algorithms) to improve both the accuracy and speed of brain tumor diagnosis using medical imaging methods like MRI (Magnetic Resonance Imaging) or CT (Computed Tomography) scans [20]. The method focused on extracting tumor properties including size, shape and functional attributes by mapping the tumor's contours and edges. These identified features were crucial in classifying the tumor and evaluating its severity, which could then be represented through color-coded labels to reflect varying degrees of tumor impact. The CNN was trained to recognize patterns and features typical of tumors, while the Bat Algorithm was used to fine-tune the CNN's parameters, optimizing its performance. This combined technique offered a promising solution for assisting healthcare professionals in making more accurate and efficient brain tumor diagnoses.

A. Chattopadhyay, et al. (2022) presented an algorithm for segmenting brain tumors from 2D MRI (Magnetic Resonance Imaging) scans by using a CNN (Convolutional Neural Network) in conjunction with traditional classifiers and dl techniques [21]. To train the model effectively, a comprehensive set of MRI images was used, encompassing a wide range of tumor properties including size, location, shape and intensity. The method also incorporated a SVM (Support Vector Machine) classifier and explored many activation functions, such as softmax, RMSProp, and sigmoid, to evaluate the method's performance. The implementation was carried out using TensorFlow and Keras in Python, providing a highly efficient platform for rapid development. The CNN model achieved an impressive accuracy of 99.74%, outperforming previous studies in this field.

S. Koshti, et al. (2022) aimed to create a web application for hospitals that could aid in detecting brain tumors from MRI scans. To accomplish this, a CNN (Convolutional Neural Network) model was presented, which was capable of accurately identifying whether an uploaded brain MRI scan showed the presence of a tumor. To improve the model's training effectiveness, Transfer Learning was used. The dataset was divided into three sections training, testing and validation following an 80:10:10 ratio to ensure optimal performance and generalization [22]. The model was trained for 12 epochs, and callbacks are implemented to automate the model saving process. The model achieved a test accuracy of 97%. This trained model will be integrated with the web application via an API. The web application provided users with four main routes: a welcome page containing system information, a page with medical information and awareness about brain tumors, and additional functionalities to be detailed in the application.

N. M. Dipu, et al. (2021) presented an automatic brain tumor detection and segmentation system developed using some of the most popular deep learning-based object detection algorithms [23]. Seven different neural network-based methods were implemented including YOLO V3 (Pytorch), YOLO V4 (Darknet), Scaled YOLO V4, YOLO V4 Tiny, YOLO V5, Faster-RCNN, and Detectron2. The system was trained on 641 MRI scan images from the Brain-

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Tumor-Progression dataset sourced from TCIA (The Cancer Imaging Archive). After evaluating the models, it was found that YOLO V5 outperformed the others, achieving the highest mAP@0.5 score of 95.07%, while YOLO V3 Pytorch had the lowest accuracy, with a score of 84.30%. Real-time implementations of these models could provide medical professionals with an efficient, automatic tool for brain tumor diagnosis, potentially transforming the field of neuroscience.

S. Maharjan, et al. (2020) aimed to improve classification accuracy by tackling the issue of overfitting and supporting multi-class classification [24]. The system was built around a CNN (Convolutional Neural Network) that integrated an advanced softmax loss function along with regularization strategies. To evaluate performance, both classification accuracy and processing speed were measured by assessing the probability scores of labeled data and the time required for their execution. Upon testing with many MRI image samples, the system outperformed existing solutions, showing a 2% increase in accuracy and a decrease in processing time by 40 to 50 milliseconds compared to current methods.

M. Siar, et al. (2019) examined CNN (Convolutional Neural Network) CNN to determine tumors in brain MRI (Magnetic Resonance Imaging) images [25]. The CNN was initially applied to these images and its effectiveness was assessed through many classification techniques. The Softmax Fully Connected layer yielded an accuracy of 98.67%, the RBF (Radial Basis Function) classifier achieved an accuracy of 97.34%, and the DT (Decision Tree) classifier reached an accuracy of 94.24%. Beyond accuracy, the network's performance was also measured using additional metrics, such as Sensitivity, Specificity and Precision. Among the classifiers the Softmax classifier showed the highest accuracy in the CNN based on testing image data. The proposed method combined feature extraction techniques with the CNN, achieved an accuracy of 99.12% on test data. This improvement in diagnostic accuracy significantly aided physicians in diagnosing and treating brain tumors and ultimately improving patient care.

3. RESEARCH METHODOLOGY

The introduced model is the transfer learning approach that is the combination of VGG16 and CNN. The various phases of proposed model are explained below: -

1. Input MRI image and Pre-process: - Magnetic Resonance Imaging employed for input and Gaussian filter utilizes to pre-process it. This filter will reduce noise from the image This filter makes images non-blurry and is also known as a smoothing operator. It eradicates intrinsically available fine image details. Its impulse response refers to a Gaussian function (GF) that is used to outline the probability distribution of the noise. It efficiently removes Gaussian noise. This filter is linear and lower pass having a GF of a given standard deviation.

2. Segmentation: - The technique of snake segmentation will be applied for segmenting the brain region part from Magnetic Resonance Imaging image. The Snake segmentation technique is inspired from the raster scan due to which it will cover maximum edges of the image SAC algorithm [6-8] is employed for modelling a parameterized primary contour curve in the image space, and an energy function (EF) is put forward to characterize the shape of the area in accordance with the internal and external power. The features of curve help to determine the first one and the attributes of image assist in describing the external energy including curvature, curve length, etc. EF is diminished to converge the primary contourcurve $C(s) = (x(s), y(s), s \in [0,1])$ continuously to the boundary of the destination region in the restraints of both energies:

$$E(C) = \int_0^1 \alpha E_{int}\big(C(s)\big) + E_{img}\left(C(s) + \gamma E_{con}\big(C(s)\big)\right) ds - -(1)$$

Three portions are included in EF such as E_{int} uses to illustrate the internal energy for ensuring that the curve if smooth and regular; E_{img} is utilized to denote the image energy, assigned in accordance with the desired position attributes like edges; the constrained energy is represented with E_{con}. SAC algorithm is useful as the geometric restraints are taken in account. Avoiding the quality of image, the major focus is on extracting the closed boundaries. However, some limitations are occurred still. The challenging task is of tackling the region due to its dependence on the first contour. The position, shape and number of control points are capable of acquiring the preferred impact only in case of selecting an appropriate primary contour.

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3. Filtering: - The MRI images has special type of noise which can de-noised using parallel non-local mean filter which is the advanced version of non-local mean filter. The PNLM filter give low MSE value as compared to non-local means filter. An image contains the weighted average of all the voxel intensities which assists in computing the stored intensity value of the voxel. For discrete noisy image, $u = \{u(i) | i \in I\}$, the evaluation of the predictable value $NL[u](i)$, for a pixel denoted with i, is done as:

$$NL[u]\, i = \sum_{j \in I} W(i, j) u(j) \qquad \dots (2)$$

The resemblance among the pixels i and j is the base on which family of weights $\{w(i, j)\}j$ depends and also result in satisfying the conditions such as $0 \leq w(i, j) \leq 1$ and $w(i, j) = 1$. $u(N_k)$ represents a square neighbourhood of set size and centred at a pixel k, while on the resemblance of the intensity gray level vectors $u(N_i)$ and $u(N_j)$ denotes the base where likeness of two pixels i and j relies. For computing the resemblance, the descended function of ED is expressed as:

$$\| u(N_i) - u(N_j) \|_{2}^{2}, a \qquad \dots (3)$$

Where, 'a' specified as SD of the Gaussian kernel and is larger than 0. The application of ED to the noisy neighbourhoods leads to raise:

$$E\| u(N_i) - u(N_j) \|_{2}^{2}, a = \| u(N_i) - u(N_j) \|_{2}^{2}, a + 2a^2 \qquad \dots (4)$$

ED is employed to maintain the order of resemblance among pixels and also this similarity depicts the sturdiness of approach. Huge weight is available in the average of the pixels containing an analogous gray level neighbourhood. These weights are expressed as:

$$W(i, j) = \frac{1}{z(i)} e^{-\| u(N_i) - u(N_j) \|_{2}^{2}, a / h^2} \qquad \dots (5)$$

at which Z (i) is the normalized constant

$$Z(i) = \sum e^{-\| u(N_i) - u(N_j) \|_{2}^{2}, a / h^2} \qquad \dots (6)$$

at which 'h' behaves as a degree of filtering. This metric restricts the regression of the exponential function and h is used to illustrate the degree of filtering. It assists in controlling EF regression as regression of the weights is alike to a function of EDs.

4. Classification: To prediction the tumour type model of transfer learning is applied which is the combination of VGG16 and CNN model. The VGG16 is used as the base model over which CNN model is used for the training.

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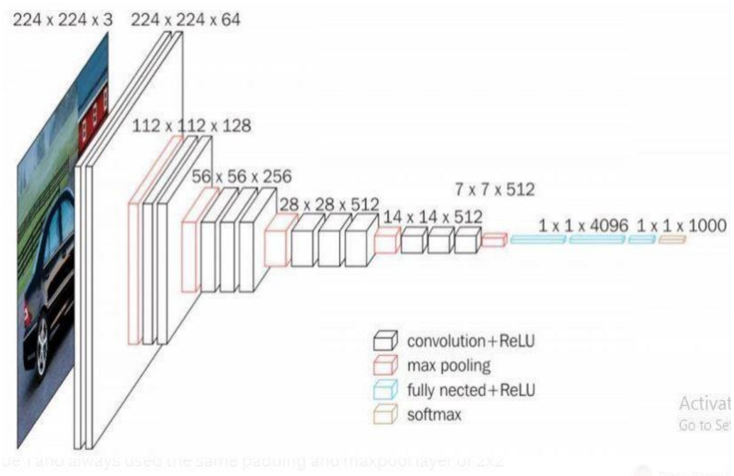

Figure 1: VGG16 Model Architecture

Following are the various specifications of VGG16 Model: -

1. This model illustrates sixteen layers with 16 and these layers contain weights. Around 13 conv layers, 5 MP layers and 3 dense layers are included. However, only 16 weight layers are there.

2. The tensor size as 224, 244 with 3 RGB channel is utilized for input in this model

3. This model does not contain a large number of hyper-parameters as it deploys conv layers of 3x3 filter with stride 1 and the same padding and max-pool layer of 2x2 filter having stride 2.

4. The arrangement of conv and max pool layers is done in consistent way in the entire framework.

5. 64 filters comprised in Conv-1 Layer, 128 in Conv-2, 256 in Conv-3, 512 in Conv 4 and Conv 5.

6. Three FC layers has a stack of conv layers: 4096 channels are included in primary two, the last leads to perform 1000-way ILSVRC classification. Therefore, one thousand channels are comprised. The last one is known as the soft-max layer.

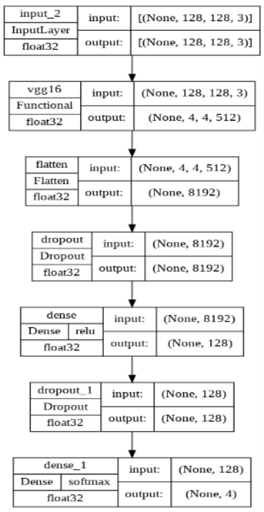

Figure 2: Proposed Transfer Learning Model

4. RESULT AND DISCUSSION

This research work is to detect brain tumour using the transfer learning approach. The data of brain tumour is collected from the Kaggle which has four classes name as Glioma, Meningioma, Pituitary and No Tumour. The data

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set has approx. 5700 images which are used for the training and testing. Accuracy, precision and recall are considered to test the models.

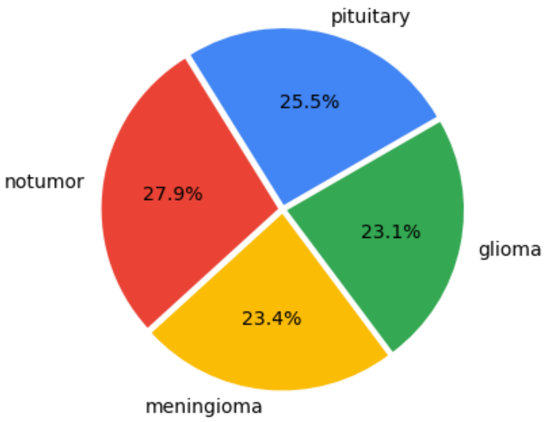

Figure 3: Dataset Class Distribution

As shown in the figure, the dataset has four classes and data is almost balanced with approx. 25 to 30 percent distribution

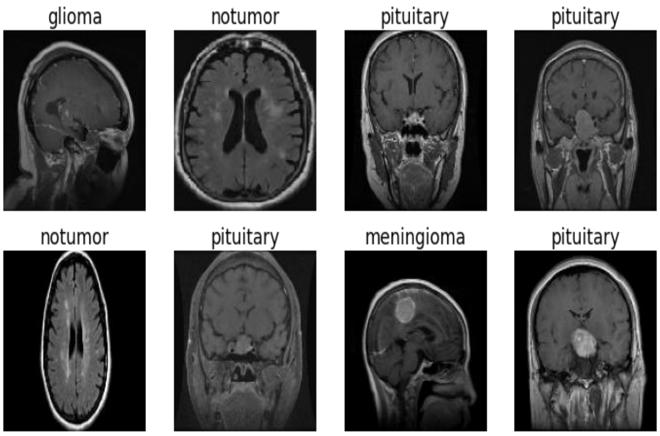

Figure 4: Sample Images

As shown in figure 4, the sample images of the brain tumour dataset. The sample image of each class is shown which are used for the training.

Figure 5: Training Accuracy of Proposed Model

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Figure 5 represents that the training accuracy of the introduced approach is shown which is approx. 96 percent and loss is reduced to 3 to 4 percent. The training indicates the efficiency of the introduced approach.

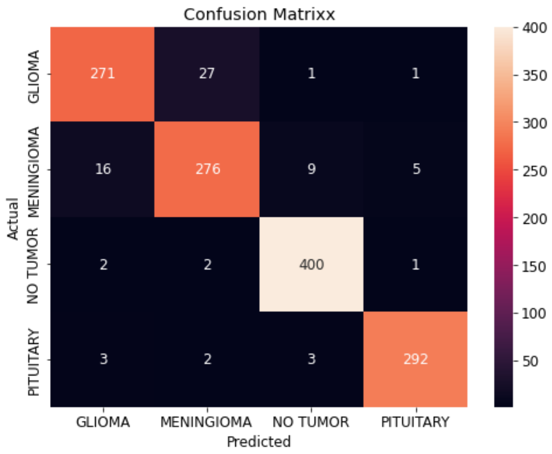

Figure 6: Confusion Matrix

Figure 6 illustrates that the confusion matrix of the introduced approach is shown with the actual value and predicted value. The classes are quite balanced and no overfitting problem is occurred at the time of prediction.

Table 1: Result Comparison

Model	Accuracy	Precision	Recall
Random Forest	66 Percent	56 Percent	66 Percent
SVM	77.59 Percent	78 Percent	78 Percent
KNN	69.88 Percent	70 Percent	70 Percent
Proposed Model	91 Percent	91.2 Percent	92 Percent

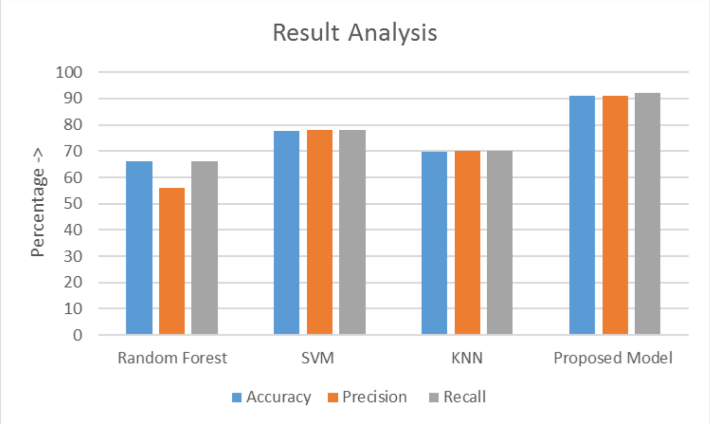

Figure 7: Result Analysis of Proposed Model

Figure 7 depicts that the results of the introduced approach are compared with the SVM, KNN and Random Forest. The proposed model achieves accuracy upto 95 percent, KNN Model, Random Forest Model and SVM Model has accuracy 69.88, 66 Percent and 77.59 percent respectively for the brain tumour detection which proves reliability of proposed model.

CONCLUSION

In this paper, it is concluded that brain tumour detection is the problem which is solved with artificial intelligence. The brain tumour detection technique has different stages such as to pre-process the data, segment it and classify the data. The technique of PNLM algorithm helps to pre-process the data which remove Rasian noise from the image. The snake based segmentation is used for the region of interest selection. In the last transfer learning is used for the

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classification which is the combination of VGG19 model with is combined with CNN model. The proposed transfer learning model achieve 96 percent of training accuracy. When the proposed model is tested it achieved accuracy, precision and recall of 95, 94, 95 percent respectively. A comparative analysis is conducted on the introduced approach against machine learning models such as RF, Support Vector Machine and KNN. The proposed model achieves upto 15 percent more accuracy as compared to machine learning models. In future hybrid transfer learning model can be designed for the brain tumour detection.

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