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ANALYSIS ON DEEP LEARNING TO DETECT THE BRAIN MRI TUMOR SEGEMENTATION

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Abstract – In this recent scenario, brain tumour detection system through classification technique helps in the person infected with brain tumour and plays an important role to provide effectiveness in the diagnosis process and proper treatment. The above MRI classification method helps to provide effective and early-stage treatment for identifying the tumour in the brain and determine the level of tumour occurrences. As there are several classification methods related to brain tumour exists in recent days, which is associated with U-Net architecture i.e., deep learning methods related to medical classification. Based on the comparison of the feature information among low-level and high-level, in this paper the propose architecture of Residual U-NET with some enhanced local feature information as it helps to improve the medical image segmentation. Through this, propose work helps to highlight the improvement in the attention module for the segmentation of image tumour, propose the novel attention module based on the Residual U-Net model. In the modified Residual U-Net model, residual module and attention gate is addressed along with dropout and wide context layers. Here the addition of salient feature information, which helps to focus on the large sensitive scaled information but also consider the small-scale images also. In the performance analysis, modified model associated with gate attention outperforms with the existing models like, U-Net and CNN Densely models.
Keywords: Brain tumour, Local feature, Image classification, Segmentation, Residual.

I. INTRODUCTION

In the recent days, the brain tumour is so crucial disease and severe impact on the human body. As it causes to unconditional abnormal cell growth to the human body as it gives high brain tumour and more influence on the human. In the recent days, the severe brain tumour is gliomas and it can be identified as high scale [1] and low scale gliomas [2].To detect the brain tumour, there is a standard magnetic resonance imaging helps to identify and generate the improved image on brain tumour by reducing the damage and skull. By considering the brain images, there are certain feature information can be fetched as mentioned as, image diameter, volume and image quantity so that brain tumour severity can be identified and analysed [3]. This will help for the doctors to patients to provide effective diagnosis and earlier treatment to set up the plan and it will help to provide to identify the proper treatment for the patient before or after the brain tumour is affected.

Thus, the above segmentations related to brain tumour play a crucial role for the brain tumour to be diagnosis and provide treatment for the brain tumour patients. The brain tumour segmentation process plays a significant role as a component in the area of medical images for long time as it is

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needed for the medical researches and hospital and lab applications. There are certain techniques like AlexNet [4], VGGNet [5], ResNet [6] and Dense Net [7] related to deep learning as it is the effective learning domain now a days. This segmentation image will utilize the variety of computer vision and it is applicable to academic and industry. As the feature extraction, which is done automatic based on deep learning and it has an important role in the field of image processing and analysis related to medical and it will provide crucial role for the treatment of brain tumour. As brain tumour segmentation issues is integrated with medical image computing and analysis has a crucial role in 2012 [8].

[9] Discuss the improvement of deep learning related to brain tumour with the process of segmentation techniques. As the brain tumour image classification is difficult to proceed manually and to mitigate it further the automated based brain tumour segmentation method can be developed. In the brain tumour segmentation has certain image separation and data interpretation based on brain tumour related to medical field is the essential factor. Based on the improvement in the image processing related to medical field, identifying the tumour based on machine learning to process the image segmentation to make it data reliable and data sophisticated compared to the existing ones in the past. For the researchers who is working in the field of medical field can process the tumour image process follow the prediction-based techniques.

Based on the above discussion, the conclusion results in the medical experts to trust on the prediction techniques. When prediction techniques are applied in the field of image processing, deep learning, etc., will results in effective results. When deep learning is applied in various fields will provide effective real time analyses and results in better impact and improved results.

The objective of the paper is highlighted as below,

- Propose architecture of Residual U-NET with some enhanced local feature information as it helps to improve the medical image segmentation.
- Propose work helps to highlight the improvement in the attention module for the segmentation of image tumour, propose the novel attention module based on the Residual U-Net model.
- In the modified Residual U-Net model, residual module and attention gate is addressed by adding the salient feature informationof dropout and wide context layers, which helps to focus on the large sensitive scaled information but also consider the small-scale images also.
- In the performance analysis, modified model associated with gate attention outperforms with the existing models like, U-Net and Residual U-Net models and it is classified based on the image as whole, core and enhancing with the propose novel Residual U-Net.

The paper is organized as follows; the existing work is discussed in section 2 and then proposed methodology of datasets to be considered; dropout and wide context layers are discussed along with the modified attention model as discussed in section 3. Then the performance analysis of high scale glioma and various datasets MRI images are analysed in Section 4 and the conclusion is discussed in section 5.

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II. RELATED WORKS

The general classification of the brain tumour related to deep learning is further classified as, Convolutional Neural Networks (CNN) [10] and Fully Convolutional Networks (FCN) [11]. The CNN considers the small image segmentation related to brain tumour. With this CNN regards, [12] discuss small 3x3 VGGNet based on CNN to deploy the automated image segmentation network. Then followed with VGGNet, [13] deploy the dual path 2-dimensional CNN based brain tumour segmentation network and it consider both the local and global path based on the size variation to initiate the different feature extraction methods. It has trained datasets with 155 times dense as compared to 2D, 3D MRI images will contain 155 sliced data. Few brains tumour segmentation address the issue in the lack of space continuity and lack of storage with low efficiency.

For the FCN related to brain tumour segmentation network [11], the encoding and decoding process initiate the process of prediction and classification the image pixel for the entire brain and then determine the efficiency of the brain. Then FCN is further getting improved as it integrates with prediction problem based on image pixel and it is the crucial role in the task of image segmentation. [12] proposed the U-Net, which has symmetric based fully convolutional Neural Networks and it is used widely for the field of medical image segmentation. This U-Net has expanded to identify the feature information and this process helps to face the feature extraction information and it helps to improve the performance related to medical image segmentation. Then U-Net is further improved with 2-dimensional image segmentation, which will address the real time segmentation to redefine the performance.

Further in [13] has proposed the U-Net architecture with feature-based pyramid module, which associate with semantic as multi scale and information location and it is helpful in effective performance accuracy. Then the U-Net can be further improved with dense block [14] and dilated convolutional [15] etc., to improve the efficiency of the segmentation based convolutional network. As the human perception on brain tumour based on segmentation will plays a role with extraction of useful information and eliminating the unwanted information. Then the brain tumour-based technique has vast significant on computerized tasks like Natural Language Processing (NLP), Image classification, image / video segmentation, etc. Based on the above domain integration, deep learning will pave the way with the integration of attention module, which helps to improve the process of image classification and segmentation.

[16] proposed U-Net architecture with the deployment of residual based attention module with change in the layer adaptively and it helps to improve the analysis efficiency. Then further the integration of dense block of squeeze and excitation is integrated with attention module [17], which focus on the relationship of the channel and perform channel feature selection dynamically with more enhancement. [18] propose the extraction of deep layer with semantics helps to convert the attention based on segmentation block and it helps to extract the improved level of performance accuracy and improved the recovery rate on image segmentation through sampling with 100 datasets of MRI images.

So far, the discussion on U-Net architecture is related to attention based neural network and it helps in identifying the context information. Apart from deep learning and modified attention module, two-dimensional and three-dimensional segmentation through slicing technique helps in identifying and analysing the brain tumour. When compared to three-dimensional based technique, MRI uses some trained with labelled data and if the trained data label is large, then it is difficult to process on 3D and results in network parameters & issues on memory to be hard to train the data.

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To overcome the above issues, [19] proposed a specific multipath Convolution Neural Network (CNN) to segment the MRI image based on data slicing. It provides unbalanced class based on input data. Then further the Full Convolutional Network (FCN) based on boundary awarehelps to improve the image segmentation efficiency. Then neural network has enhance to proposed the Non-Local Neural Networks (NL-Nets) [20] to identify the data dependencies through query based aggregation through global data context for each data position to perform image segmentation task. Then this NL-Nets associated with location sensitive module helps to provide effective image segmentation results with parsing datasets.

As the authors have focused on attention module with U-Nets or NL-Nets architecture, which classifies on attention of image segmentation.Thus U-Net has a greater excellence towards the field of image processing based on medical segmentation and it provide effective performance in the brain tumour segmentation. For the small-scale image tumour, when there is a reduce in the image dimension and ineffective performance accuracy in segmentation techniques. To overcome the above issue, there will be an enhance local feature information and complex image segmentation also. So, U-Net has reduced accuracy for small tumour segmentation. So, there is a need of modified attention model based residual based U-Net model.

III. PROPOSED RESIDUAL U-Net ARCHITECTURE

3.1. Bu-Net Model Datasets:

Here the discussion is related to public datasets, which will be more useful for the propose system. Here we have considered both some datasets related to BraTS, where the collection of certain images and contains 350 glioma patients and it can further segregate into glioma of low level and high-level cases. Then the datasets are validated with certain images of the patients and those datasets are labelled and are validated and it is not publicly available. As the datasets are labelled with certain classes as, tumour enhancement, tumour non-enhancement, Edema and healthy tissue.Here the two datasets are considered in Fig. 1 as it contains certain training images and has labelling procedure and classes. The data labelled are validated contained images with certain data collection. The images have truth colour, which represented with different tumour images of enhancing and non-enhancing images.

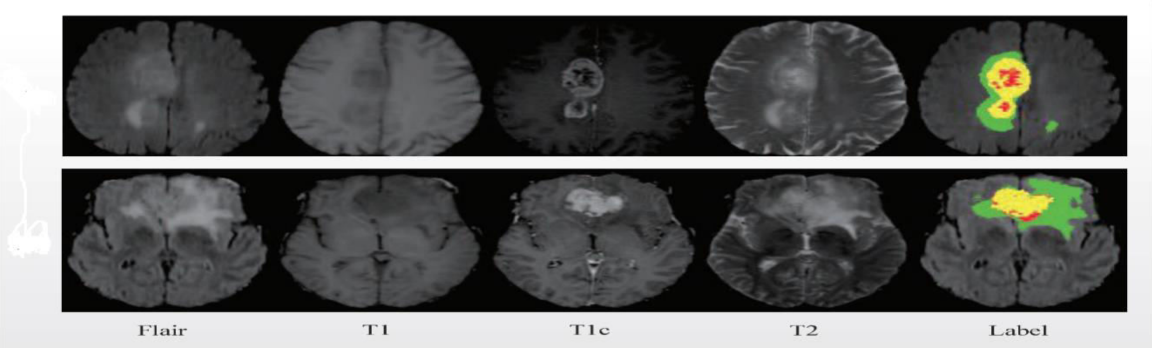

Fig. 1. Two cases of brain tumour with certain multimodal and labelled plots.

3.2. Proposed Methodology

For the proposed system, the certain raw inputs and the proposed U-Net architecture with a module integration of Residual and wide images.

A. Image Pre-processing

To avoid certain weakness by the deep learning model related to robust noise and data processing plays a significant role and it this task is being carried out earlier to the image before it is given to

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the network. To perform the image processing, N4ITK algorithm, which is a correctio bias algorithm and it is analysed on all the images and it is featured with homogenous. As there are several algorithms exist for the process of pre-processing related to brain tumour and it is suggested that N4ITK algorithm provide more reliable data and it has data collecting capability with bias field on MRI images.

B. Modified Residual U-Net

In fig. 2., the proposed U-Net architecture, which is integrates with residual and wide blocks and here the architecture built the interaction between the local and global feature extraction added in the network. It helps to enhance the performance analysis with the proposed U-Net architecture. Here the system takes the image resolution of 256 x 256 and get generate the output image.

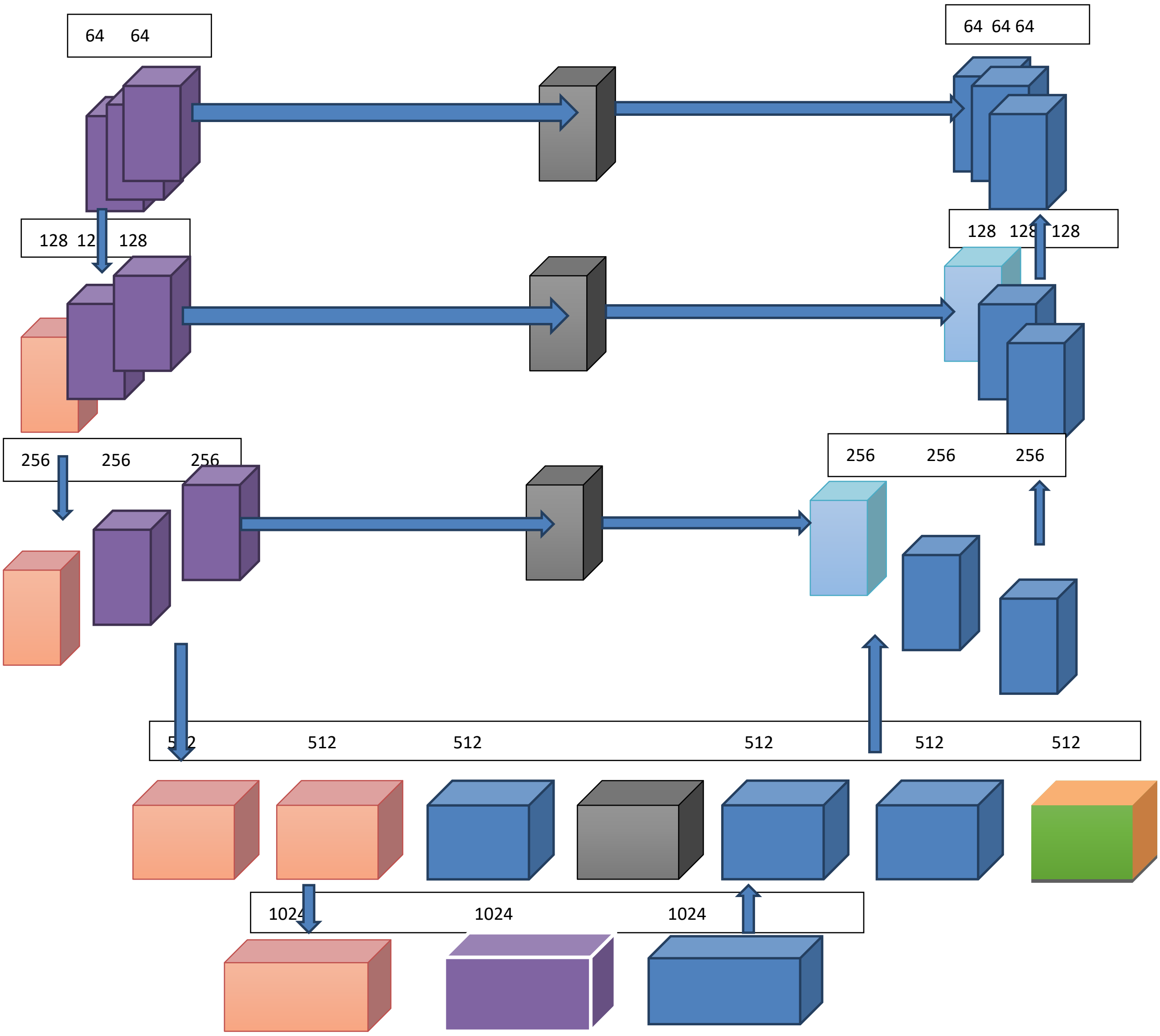

Fig. 2. Proposed Architecture of Residual U-Net with wide block (Includes Convolutional 2D; Max pooling 2D; Wide Context; Transpose 2D; Residual Block; Concatenate)

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Here the encoding and decoding process are deployed based on the block division. Then for the encoder process, each block has two convolutional layer and added with max-pooling and dropout layer. Then for the decoder process, the Conv2DTranspose is performed on each block to generate output.

i. Max Pooling Layer:

Apart from max pooling, average pooling is added and layer will provide the down feature extraction mapping, which highlighted the feature patches based on feature map method. The max pooling determines the average presence based on feature extraction and it helps to activate the feature information presence. The max pooling is used for convolutional neural networks related to computer vision field.

This convolutional layer is nothing but the neural network based convolutional layer, which is applied with filtering learning based on input images and it create the mapping feature extraction. It is analysed that the layer is more effective and data stacking for deep model with low level feature extraction. Then the convolutional layer has certain feature mapping as mentioned in algorithm1.

Algorithm 1: Max pooling in Convolutional Neural Networks

Input: Input Images

Output: Calculate the Max Pooling

1. Initially the max pooling operation is applied to output mapping feature (convolutional operations detector line)

2. Pooling line:

[0.0, 0.0, 3.0, 3.0, 0.0, 0.0]

[0.0, 0.0, 3.0, 3.0, 0.0, 0.0]

3. For the given stride, max operation is calculated as,

max(3.0, 3.0) = 3.0

3.0, 3.0

[0.0, 3.0, 0.0]

4. Max pooling operation is added with MaxPooling2D,

model = Sequential()

model.add(Conv2D(1, (3,3), activation='relu', input_shape=(8, 8, 1)))

model.add(MaxPooling2D())

5. The max pooling model is summarized

6. Define the vertical line detector

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7. Store the weight in the max pooling model

    model.set_weights(weights)

8. Apply the data filter

    yhat = model.predict(data)

9. Enumerate the row and then ach column to be added in the row.

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 6, 6, 1)	10
max_pooling2d_1 (MaxPooling2	(None, 3, 3, 1)	0

Total params: 10

Trainable params: 10

Non-trainable params: 0

[0.0, 3.0, 0.0]

[0.0, 3.0, 0.0]

[0.0, 3.0, 0.0]

*10.**Max pooling Calculation:*** Calculate the max and largest value of mapping feature for each patch.

ii. Dropout Layer:

It is the technique to avoid the problem of overfitting based on the convolutional neural network model. Mainly the dropout based on the setting randomly on the hidden edge units, which is nothing but the hidden layer as neurons to 0 when the training phase gets updated.

Algorithm 2: Dropout Layer in Convolutional Neural Networks
Input: Datasets
Output: Dropout model is performed with sequential and flatten / Dese with activation model.

1. Use keras to construct the neural networks

fromkeras.datasets import mnist

fromkeras.layers import Dense, Flatten, Activation, Dropout

2. Import the data and it is spitted into training and testing sets.

(X_train, y_train), (X_test, y_test) = mnist.load_data()

3. Hsowing the training data using cmap with the binary conversion.

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```
plt.imshow(x_train[0], cmap = plt.cm.binary)
plt.show()
```

4. Perform Training and Testing by normalizing and categorical

```
X_train = normalize(X_train, axis=1)
X_test = normalize(X_test, axis=1)
y_train = to_categorical(y_train)
y_test = to_categorical(y_test)
```

5. The dropout model is performed with sequential and flatten / Dese with activation model.

```
model_dropout = Sequential()
model_dropout.add(Flatten(input_shape=(28, 28)))
model_dropout.add(Dense(128))
model_dropout.add(Dropout(0.5))
model_dropout.add(Activation('relu'))
model_dropout.add(Dense(128))
model_dropout.add(Dropout(0.5))
model_dropout.add(Activation('relu'))
model_dropout.add(Dense(10))
model_dropout.add(Activation('softmax'))
model_dropout.summary()
```

Here the Residual U-Net as numerical representation and activation function with sigmoid as mentioned as below,

$$Res\ UNet\ (R) = \begin{cases} 0 \ \ if\ R \leq 0 \\ R\ otherwise \end{cases}$$

$$Sigmoid\ (R) = \frac{1}{1 + Exp\ (-R)}$$

iii. Attention Gate with Residual U-Net:

For the brain tumour dimensional variation on varies complex structures and there exists the tumour small scale. For the effective information context, then the network will be more network capability with down sampling. The spatial information and location are mapped with high-level to get the convolutional and data transformation through non-linearities. For the small brain tumour, the attention model helps to improve the data segmentation performance accuracy. In this process, association of attention gates and residual model to propose the Res U-Net model. To address the problem of complex structure and dimensional change variation, the attention gate helps to utilize the spatial and location information based on low-scale mapping feature with process of up sampling. For the dense information feature extraction, dense will uses down sampling and able to restore the spatial and information on location using up sampling. The modified residual block is represented in Fig. 3.

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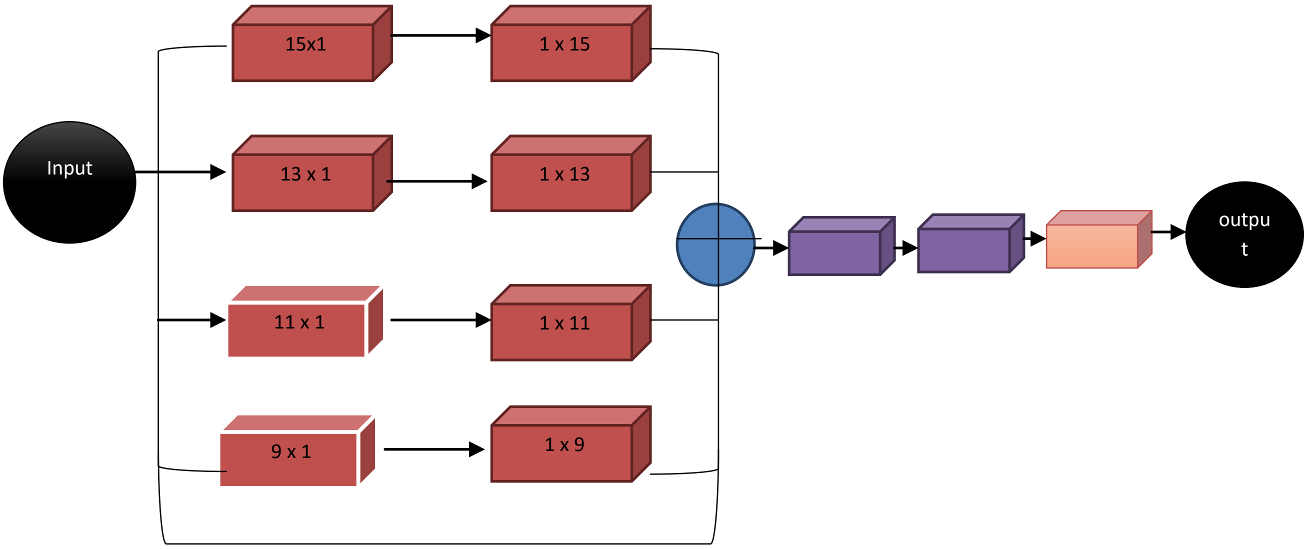

Fig. 3.Modified Residual Block with Conv2; Conv2D (3,3) and Conv2D (1,1)

iv. Wide Context Information:

In the wide context block, two parallel connections are taken as the input and it has2 convolutional layers. For the 1st connection, 1 x N and N x 1 are the layers used for convolutional model and another convolutional network connection uses 1 x N filter and then followed with another connection N x 1 filter. Based on the association of several connections will provide the effective feature information and also better performance with effective results. The information's are extracted on wide context similarity as it classifies the sub class of different convolutional network of brain cancer.

The below loss function takes the challenges of segmentation based on brain tumour on imbalance data on different class in the convolutional network. The label weight, pixel value of image segmentation and pixel value of the binary format are considered for the calculation of entropy addition and coefficient loss.

$$\text{Loss function} = \text{Entropy Addition} + \text{coefficient loss}$$

IV. PERFORMANCE ANALYSIS

In the performance analysis, the effectiveness can be determined based on the number of images it is discussed. The performance of the propose Residual U-Net is calculated based on the score dice for the existing techniques such as, U-Net, AGU-Net, ResU-Net and AGResU-Net and the propose Residual U-Net technique. By considering the two different sets R and S are identified with data similarity of score dice.

For the below analysis, various number of datasets are considered as it is discussed 3.1 by comparing the Low Level and High-Level Glioma. Here the various techniques are based on image of Whole, Core and Enhancing images related to brain tumour images.From the Fig. 4. Residual U-Net propose will gain some high-scale data value with 7 % to 9 % compared to existing U-Net and CNN Densely architecture.

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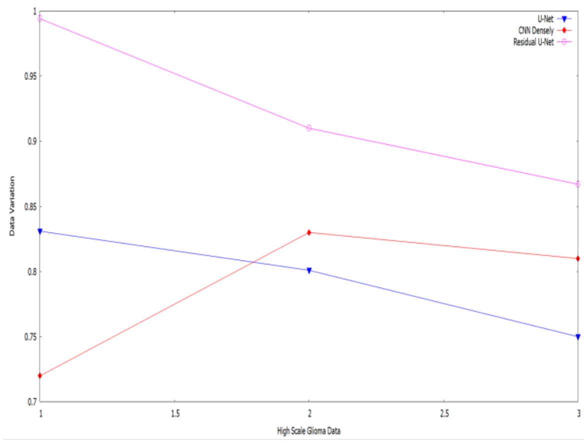

Fig. 4. High Scale Glioma Data based on the variation of 1: Whole Image; 2: Core Image and 3: Enhancing Image.

From the Fig. 5, some 100 MRI scan images are considered to calculate the images classification based on whole, core and enhancing images. Here the High Scale Glioma Data based on the varies datasets of MRI images are used based on variation of Whole Image, Core Image andEnhancing Image and to calculate the performance efficiency based on small space tumour regions.

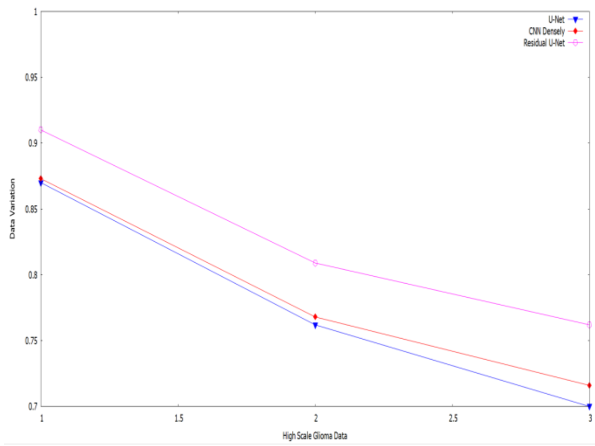

Fig. 5. High Scale Glioma Data based on the varies datasets of MRI images based on variation of 1: Whole Image; 2: Core Image and 3: Enhancing Image

In the Fig. 6, the DSC Scores are determined with image segmentation results with baseline based on the validation of the datasets. Here the datasets variation of MRI images based on Whole Image; Core Image and Enhancing Image.

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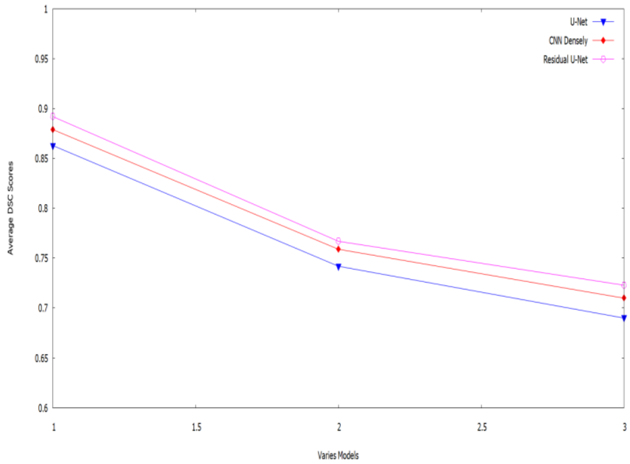

Fig. 6. Dice Similarity Coefficient (DSC) based on variation of 1: Whole Image; 2: Core Image and 3: Enhancing Image

In the Fig. 7, we have determined the Dice Similarity Coefficient (DSC) and able to provide the optimal image segmentation performance. Here the datasets are validated based on 150 patients with DSC Scores.

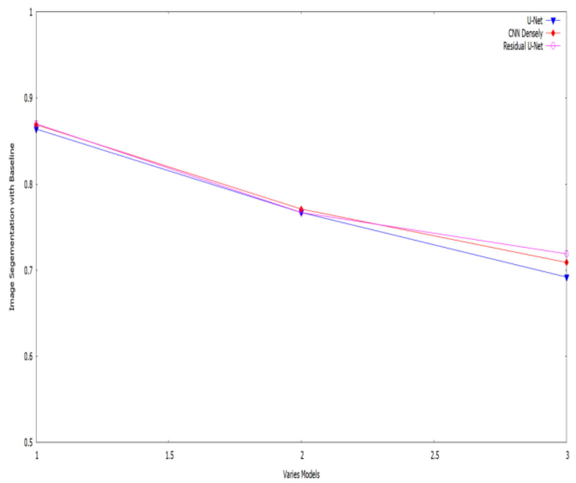

Fig. 7. Image Segmentation performance with baseline based on variation of 1: Whole Image; 2: Core Image and 3: Enhancing Image

Thus, the research work is associated with image segmentation as the data prediction and truth table region are calculated based on the propose residual U-Net architecture compared to the existing U-Net and CNN Densely architecture.

V. CONCLUSION

In the recent era, the brain segmentation related to brain tumour is getting difficult to process based on the complexity of the MRI images datasets and the segmentation helps to perform prediction against brain tumour through learning models. The propose Residual U-Net architecture help to segment the data and classify the image related to brain tumour. To perform the segmentation for brain tumour, the encoding and decoding is performed on the propose Residual U-Net architecture. Address the problem of complex structure images and low / high scale images and it includes max pooling and wide context along with attention model for residual. It helps to perform data pre-processing and

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proposed encoding / decoding process based on the datasets of MRI images. The analysis is done based on the high scale glioma for image segmentation based on image as whole, core and enhancing. Then the images are segmented based on the various datasets of MRI images also and propose Residual U-Net will perform better when compared to the existing U-Net and CNN densely architecture.

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