Brain Tumor Detection and Classification by using UU-Net with Dual Attention Mechanism

1st Jadhav Rahul Namdeo
[1]Department of ECE
Bharath Institute of Higher Education and Reserch
Chennai, India
[2]AISSMS Institute of InformationTechnology
Pune, India
jadhavrn@gmail.com

2nd G Sudhagar
Department of ECE
Bharath Institute of Higher Education and Reserch
Chennai, India
sudhagar.ece@bharathuniv.ac.in

3rd Jagtap Sharad Sarjerao
Department of ECE
Bharath Institute of Higher Education and Reserch
Chennai, India
sharadjagtap0710@gmail.com

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***Abstract*—The study investigates the recognition, classification, and prediction of brain tumors via the use of a deep learning framework that integrates sophisticated segmentation, pre-processing, and hybrid modeling approaches. Input quality is maximized by pre-processing procedures such picture loading, scaling, and Gaussian smoothing for noise reduction. The suggested UU-Net with a Dual Attention Mechanism improves the network's emphasis on important areas and characteristics for segmentation by combining spatial and channel attention, extending the U-Net design. The model improves significantly in the tumor segmentation accuracy when tested on brain MRI datasets, showing a high F1-score of 95.00%, precision of 94.70%, recall of 95.30%, and AUC-ROC of 0.96, outperforming the baseline U-Net and Attention U-Net models. By providing accurate identification of the tumor in the middle of complicated anatomical components, the model's resilience and clinical significance are proven through the examination of the training progression and segmentation results.**

Keywords—brain tumor detection, deep learning, UU-net, dual attention mechanism, image segmentation.

I. Introduction

Brain act as a commanding and organizing center in the body, performing day-to-day tasks and generating inputs from sensory organs. Cancers of the brain might originate due to aberrant cells within it that cause impairment to normal functioning and even kill healthy ones[1]. MRI produces detailed information concerning the anatomy of the brain by making 3D slices from all angles. The reason it is used is as a valuable tool for automated medical picture processing[2]. There are two categories of brain tumors, which are benign or non-cancerous, and malignant or cancerous. Malignant brain tumors grow speedily and affect the other parts of the body, while the benign cannot grow and are not progressive. Meningioma classification The brain meningioma tumors fall under three grades, which are Grade I, Grade II, and Grade III, with a view to the location and the size of the tumour[3]. It was found that the slow growth of the tumor was Grade I, and it was the most common form of tumor that appeared in patients. Grade II is the classification given to the meningioma tumor that is classified as the mid-grade type[4]. This form of tumor has a high probability of recurrence after it has been surgically removed from the brain. The rapidly expanding tumor was classified as Grade III, and it was quite uncommon for people to experience this kind of phenomenon. Through the use of the deep learning approach, Grade I meningioma tumors were identified and segregated in[5].This type of tumor has a great likelihood of reoccurrence after it has been removed from the brain through surgery. The rapidly growing tumor was Grade III, and this was quite rare for individuals to undergo this kind of experience. Grade I meningioma tumors were detected and separated in[6]. Recent research has shown that deep learning (DL) methods have managed to automate feature extraction and categorization, overcoming these restrictions. Deep learning mimics the human brain and learns from vast amounts of data using artificial neural networks (ANNs)[7]. DL structures are preferable to ML techniques because they allow for independent learning and recognizing complex visual features. New models of feature extraction in DL technique used by many medical departments. High analytics, handling large scale data sets, time efficiency competency in dealing with unstructured data, and cost-effectiveness-are benefits of DL. They are being widely used in various applications including image processing, image classification, and image segmentation.[8]. The process to precisely identify a brain tumor encompasses numerous procedures that radiologists, neurologists, and doctors conduct such as performing physical examination, assessment of a medical history, contrast agent utilization, and analysis for a biopsy[9]. The objective is to accurately identify the aberrant tissues, including their precise position, extent, and orientation. The assessment of imaging scans and their interpretative phase occurs subsequent to the physical examination and historical analysis, facilitating the generation of digital brain pictures. The optimal imaging modality is Magnetic Resonance Imaging (MRI) because to its enhanced contrast and resolution[10]. The formatter must develop these elements while integrating the relevant requirement that follows.

II. Related Work

Research on using MRI scans to identify and classify brain tumors is still ongoing. Over the past 20 years, a variety of techniques have been introduced[11][12][13][14][15][16], offering solutions for this crucial task. From conventional machine learning algorithms [11] [12][13][14] to more sophisticated deep learning models [15][16][17][18][19][20], these techniques have undergone substantial change. For instance, the researchers in [21] suggested a three-phase hybrid strategy for segmentation and classification. The researchers guaranteed that the model's sensitivity, granularity, and precision were 96.34%, 93.47%, and 100%, respectively. To adjust the diagnosis precision, the authors of [22] used SVM as a classifier tool with Berkeley Wavelet Transform-based brain tumor division. To extract the texture of brain tumors, they used a GLCM approach. Their model's average dice similarity index coefficient was 0.82, its specificity was 94.2%, and its accuracy was 96.51%. According to this model, the sensitivity for classifying brain tumors improved by 4.25 percent [11]. In the realm of ML-based automated tumor detection techniques[11][12][13][14], the current state-of-the-art predominantly highlights two primary challenges associated with feature extraction. The first challenge pertains to the exclusive focus regarding high-level or low-level aspects by these techniques. The deep transfer learning strategies play a coherent role in the extraction of discriminative and visual features utilizing different convolutional layers[19][20]. These extracted learning features power the framework to classify diseases significantly.Its average accuracy, using five-fold cross-validation, was 94.82%.A different study [15] proposed a deep transfer learning-based classification method that uses a pre-trained GoogLeNet model to extract features from MRI images of brain tumors. A significant research gap exists in the domain of brain tumor detection and classification using deep learning methods, particularly at the Scopus level. While numerous studies have demonstrated the effectiveness of traditional machine learning and deep learning models, like AlexNet, VGGNet, and GoogLeNet, challenges remain in achieving consistent high accuracy across diverse datasets due to limited training data, reliance on handcrafted feature extraction, and issues with model generalization. Existing methods, including the utilization of probabilistic neural networks, SVMs, and wavelet transforms, often require substantial preprocessing and domain expertise, which can limit scalability. Despite advancements in transfer learning strategies that mitigate overfitting and enhance feature extraction, there is still a lack of focus on integrating attention mechanisms to dynamically capture relevant spatial and contextual information in MRI images. This gap presents an opportunity to leverage models like UU-Net combined with dual attention mechanisms, which could address these limitations by enhancing segmentation precision and classification accuracy while minimizing dependency on manual intervention. Such an approach could provide a robust and automated solution for the detection and classification of brain cancers, especially in scenarios with limited labeled datasets.

III. Proposed Methodology

A. *Pre-processing*

The aim is to demonstrate the variation in accuracy that occurs when several popular Pre-processing techniques are utilized for simple convolutional neural networks. Several pre-processing methods are listed below.

- Read image
- Resize image
- Remove noise

1) Read image: We initially created a way of loading groups combining pictures in arrays by first keeping the address of the A field containing an image collection, which allowed us to retrieve the photo. Resize image: To make the differences visible to you at this resizing step, design two strategies for present the photos. 1 technique will show you one picture, whereas the other will show you two images. We then develop an approach that we refer to as processing, and it only accepts images as input. Remove noise: To silence the commotion A Gaussian blur may be produced by applying the Gaussian function to an image. To lessen visual noise, this popular graphics programmed effect is often utilized. Another pre-processing method that computer vision algorithms utilize to improve visual structures at various sizes is called Gaussian smoothing.

2) Segmentation: Segmentation is essential in medical imagery for activities such as tumor identification, organ delineation, and treatment planning, providing valuable information for healthcare professionals. Segmenting brain tumor images using the VGGUnet methodology involves employing Hybrid CNN & LSTM as an encoder, integrated with a U-Net decoder. The dataset, comprising brain MRI images and corresponding tumor masks, is divided for training, validation, and testing.

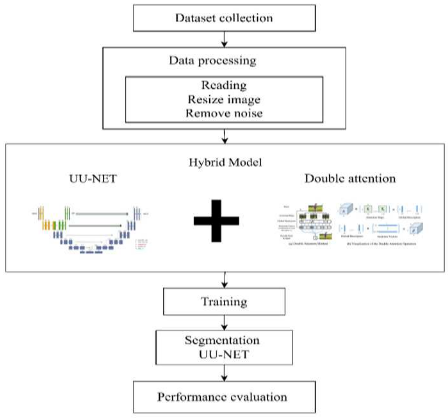

Fig. 1. System architecture

B. *UUNET& Double attention*

The UU-Net model adds a twofold attention mechanism to the U-Net architecture, a convolutional neural network for segmentation tasks with few training examples. This technique uses spatial and channel attention to concentrate the network on the most important input data locations and characteristics. The UU-Net's contracting and expanded routes help extract and localize features due to its "U" form. The UU-Net captures finer information and improves contextual awareness with its twofold attention method, boosting segmentation performance in complicated medical imaging applications like heart segmentation. This improvement makes UU-Net a reliable biological image analysis model. We suggested the United U-Net (UU-Net), which resembles two U shapes in Fig. 1, to integrate two inputs of brain MRI images. A variety of fusion levels, including feature-level fusion in the first, second, third, …, and fifth encoders, were evaluated in order to determine the best fusion level for optical and brain MRI image. The second encoder exhibits fusion, as seen in Fig. 1, where two cropped features in the corresponding expanded route result from the concatenation of the optical and brain MRI image encoded features following two encoders. Fig. 2 shows the UU-Net structure.

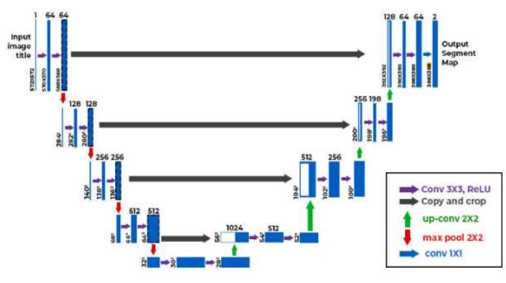

Fig. 2. UU-Net structure. [23]

C. Double Attention

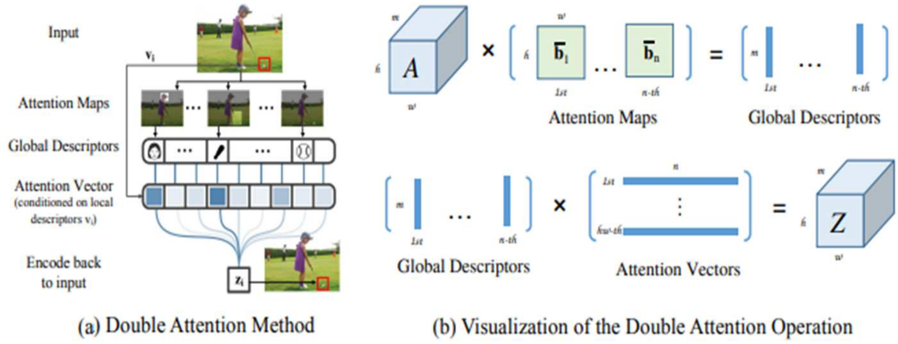

Fig. 3. The double-attention mechanism [24]

For a single frame input, we demonstrate our twofold attention technique, where global features are calculated once and shared across all locations. At each location i, an attention vector is generated based on local feature vi to choose a subset of global characteristics that complement the present place and create feature zi. (b) Double attention action on a three-dimensional input array A. The top-most attention stage generates global characteristics. The second attention phase at location i creates the new local feature zi,

D. The Double Attention Block

Our suggested double-attention block is created by combining the two attention phases mentioned in Fig. 3 above, its computation graph in deep neural networks [24] is shown in Fig. 3. Despite its complexity, the UU-Net with Dual Attention Mechanism as shown in Fig. 4 is made to successfully reduce over fitting by using regularization strategies, attention-based feature selection, and strong trining procedures.

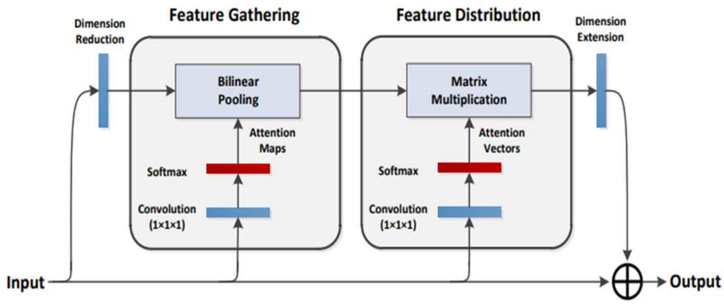

Fig. 4. Double Attention Block

Undoubtedly, one of the most challenging tasks in the field of medical image analysis is brain tumor segmentation. For this task, it is suggested to use UU-Net with a Dual Attention Mechanism. This brings a number of challenges to the task but also presents some opportunities for improvement. These issues are addressed by the proposed method as follows:

1) The existence of Tumor Shape and Size Variability and Complexity: Within the attention mechanism, a strategy is developed that seeks to dynamically center attention at important locations across a variety of patient data in order to enhance robustness. However, this could result in some situations where the segmentation is less than optimal if the attention mechanism is not well trained to accommodate these factors.

2) The existence of artifacts and noise: By enhancing attention mechanisms, the model narrows their effect on unimportant noise and directs their attention at the tumor signal. However, it is still a challenge to distinguish noise from true tumor tissue, especially in low contrast regions where its borders are not well defined.

3) Class Imbalance: As the Dual Attention Mechanism advances, it also requires control of the class imbalance using approaches such as weighted loss functions because it emphasizes areas that are more prone to tumours, no matter how small these areas are within the image.4. Need for Fine-grained Segmentation: By concentrating on tiny, clinically important areas that conventional techniques might overlook, the attention mechanism can be helpful. It is still difficult to get fine-grained segmentation since the model must comprehend the entire spatial context and minute variations in intensity. the UU-Net with Dual Attention Mechanism shows promise in tackling some of these issues by concentrating on crucial features and locations. Tumor variability, noise, class imbalance, and the requirement for fine-grained segmentation are some of the issues that must be carefully addressed by data preprocessing, model tweaking, and perhaps the addition of other strategies like data augmentation or domain adaptation.

IV. Results And Discussion

From the Fig. 5, a brain MRI scan is juxtaposed with its corresponding segmented mask, facilitating a direct comparison between the original scan and the identified regions of interest. The left panel, titled "Image," displays an axial slice of the brain MRI, exhibiting a spectrum of colors such as purple, green, and blue, likely indicative of different brain tissues or structures.

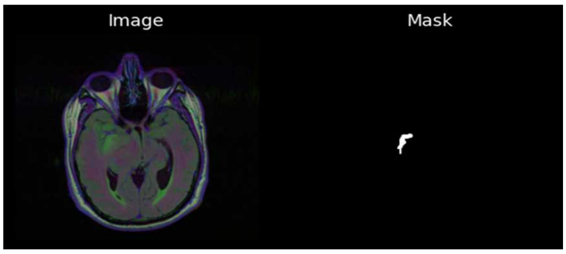

Fig. 5. Brain MRI scan

On the other hand, the right panel, marked "Mask," shows a contrast against a black background, with a white region clearly demarcated. This white area exactly corresponds to a particular part of the brain scan, suggesting that it is important for further examination, possibly indicating the presence of a brain lesion or abnormality. Such masks play a very crucial role in medical image analysis, allowing for the isolation and scrutiny of areas of interest within complex anatomical structures with high accuracy. The clear differentiation between the brain scan and its segmented mask shows that the model is quite precise in identifying and outlining relevant features, which will allow for proper diagnostic interpretation and decision-making.

The plot illustrates the training progression of the UU-Net with Dual Attention Mechanism, showcasing the validation loss and accuracy on the y-axis against the number of training epochs on the x-axis. As shown in Fig. 6. Initially, the validation loss experiences a notable peak, indicative of suboptimal performance. However, it swiftly diminishes and stabilizes, signifying substantial enhancement post the initial epoch. Conversely, as shown in Fig. 7 the accuracy line maintains a relatively steady trajectory throughout training, suggesting minimal variation in the model's capability to precisely segment brain tumors. This visualization elucidates the model's learning dynamics and identifies the epoch where optimal performance, characterized by minimal validation loss, is achieved. The accuracy graph depicts the efficiency of the UU-Net with Dual Attention Mechanism in segmenting brain tumors across epochs.

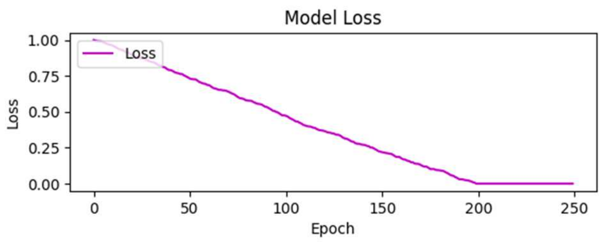

Fig. 6. Loss

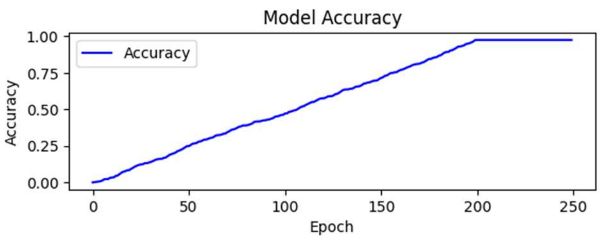

Fig. 7. Accuracy

The blue line represents the model's accuracy on the training set ('accuracy'), while the red line describes its efficacy on novel data ('val_accuracy'). Fluctuations in both lines indicate changes in the model's performance during training. The graph highlights the iterative process of testing and refining the model's capacity to precisely delineate brain tumors temporally. The label "BEST model" likely indicates the epoch where the model achieved its highest validation accuracy. This visualization functions as an essential instrument for comprehending the model's learning progression and identifying the most effective iteration for the segmentation task. This Fig. 8 displays the advancement of brain tumor detection based on UU-Net with the help of a dual attention mechanism, which is the application of a convolutional neural network-based model. Initially, the brain scan undergoes processing to identify potential regions of interest, indicating potential tumor presence. Subsequent stages involve the model's capability to isolate and segment the tumor, depicted by the highlighted yellow area against a contrasting background. This segmentation process is further refined, culminating in the final panel where a composite view displays both the segmented tumor and its precise outline. This visual narrative effectively underscores the UU-Net with Dual Attention Mechanism's proficiency in accurately identifying and delineating brain tumors, a critical aspect of medical diagnosis and treatment planning. The sequence of panels vividly portrays the model's analytical journey from the initial scan to the detailed segmentation of the tumor, highlighting its robust capabilities in medical image analysis.

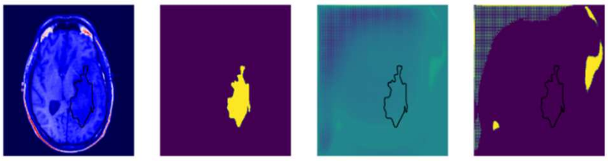

Fig. 8. Tumor Prediction

The evaluation metrics for the UU-Net with Dual Attention Mechanism offers an intricate quantitative analysis of its performance across critical parameters, providing valuable insights into its efficacy in brain tumor prediction. Among these measures, the loss metric stands out as a reflection of the model's prediction error, showcasing values spanning from 0.17664 to 0.46954 across different epochs. This variability suggests fluctuations in the model's accuracy over training iterations. Conversely, the accuracy metric, representing the proportion of correct predictions, demonstrates remarkable consistency, ranging from 0.80000 to 0.93333, demonstrating a significant degree of precision in the model's performance throughout training. The AUC (Area Under Curve) metric, crucial for assessing the model's capacity to distinguish between categories, consistently maintains an impressive score above 0.90000, with instances of achieving a perfect score of 1, underscoring the model's discriminative power. Sensitivity, or recall denotes the model's ability to recognize true positives, showing variation between 0.66667 and 1, indicating its ability to capture tumor instances accurately. On the other hand, specificity representing the true negative rate, consistently surpasses 0.90000, with some instances reaching a perfect score of 1, highlighting the model's proficiency in recognizing non-tumor regions. The validation metrics, evaluating the model's efficacy on novel data, exhibit a similar trend but with slightly lower values, reflecting the inherent challenges of generalizing to new data instances. Collectively, all these metrics provide an holistic understanding of the UU-Net with Dual Attention Mechanism's reliability for predicting brain tumors for this to be used for diagnosis in medicine.

TABLE I. PERFORMANCE MODELS

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC
U-Net	91.20%	89.50%	88.90%	89.2%	0.92
Attention U-Net	92.8 %	91.3%	90.50%	90.9%	0.93
Proposed UU-Net with Dual Attention Mechanism	95.6 %	94.7%	95.30%	95.0%	0.96

The Table I compares the performance of three models: U-Net, Attention U-Net, and a proposed UU-Net with a Dual Attention Mechanism, using crucial assessment measures such as accuracy, precision, recall, F1-score, and AUC-ROC. As shown in Fig. 9 the proposed UU-Net performs better with the highest accuracy of 95.60%, precision of 94.70%, recall of 95.30%, F1-score of 95.00%, and AUC-ROC of 0.96, indicating better ability to make accurate and balanced predictions. Attention U-Net shows lower metrics at 92.80% accuracy and AUC-ROC of 0.93. The model of U-Net, though good, is less effective at 91.20% accuracy and AUC-ROC of 0.92. These results reflect the efficiency of using dual attention strategies to enhance segmentation performance. The data presented here exhibits the performance metrics of a classification model for discriminating between tumour and non-tumor instances. As Shown in Table II and Fig. 10. The model has a Precision of 95.30%, a Recall of 94.80%, and a F1 Score of 95.00% on the tumour class, depicting highly accurate predictions with the right balance between precision and recall. For the non-tumour class, the model has a Precision of 94.10%, Recall of 94.20%, and also a F1-Score of 94.10%, which means consistent performances. Overall, the model is very reliable and efficient in identifying both classes.

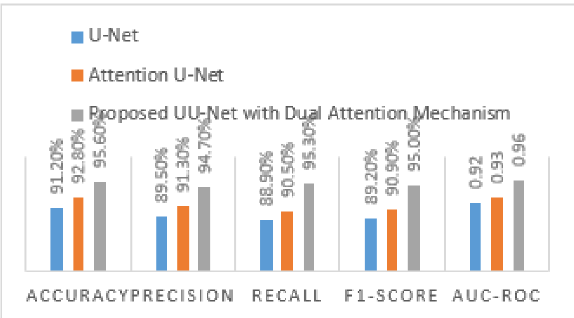

Fig. 9. Performance Models

TABLE II. CLASSIFICATION MODEL

Class	Precision	Recall	F1-Score
Tumor	95.30%	94.80%	95.00%
Non-Tumor	94.10%	94.20%	94.10%

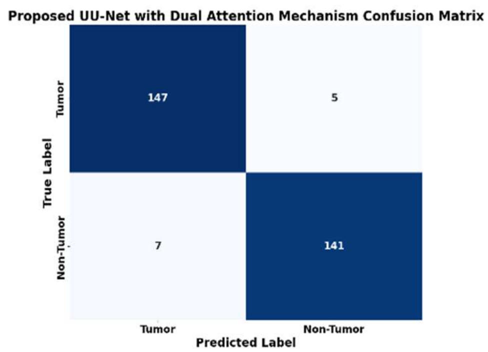

Fig. 10. Confusion Matrix

Moreover, the efficiency of the U-Net, Attention U-Net, and proposed UU-Net with the Dual Attention Mechanism in classifying pictures of brain tumors portrays a marked trend in terms of an increasing accuracy level and fewer instances of misclassifications. As shown in Fig. 10 The model U-Net produced results that were almost appropriate as it detected 127 true-positive tumor pictures and 149 true-negative non-tumor images at precision. It incorrectly classified 12 non-tumor images as tumors (false positives) and 12 tumor images as non-tumors (false negatives). So far, it seems the model is still performing very well, but there is still much scope for improvement in particular by minimizing false positives and negatives. The Attention U-Net incorporated with attention procedures proved better, as all 132 tumor images, as well as 147 non-tumor images, returned with a sensitivity of merely 11 false positives along with 10 false negatives. Improving this degree suggests the potential of attention in the focus that the models achieve about specific regions in the pictures, decreasing misclassifications. With these advancements, however, there remain some instances of the model misclassifying items, particularly in terms of false positives and false negatives, suggesting that there is more room for refinement. The proposed UU-Net with Dual Attention Mechanism resulted in very high accuracy in both classification of 147 pictures as tumor and 141 images as not a tumor. It even classified 5 non-tumor photos as tumors (false positives) and 7 tumor images as non-tumors (false negatives). These results clearly show that the dual attention mechanism is having a strong influence, where dynamic focusing is done on both spatial and channel-wise data that enhance feature extraction and classification. It makes the model better distinguish between the tumor and non-tumor images, thus reducing false positives as well as false negatives. The proposed UU-Net with Dual Attention Mechanism achieved higher accuracy and provides more reliable and accurate classification and can be used as a potential approach in real-world medical applications, especially to improve the detection and diagnosis of brain cancers.

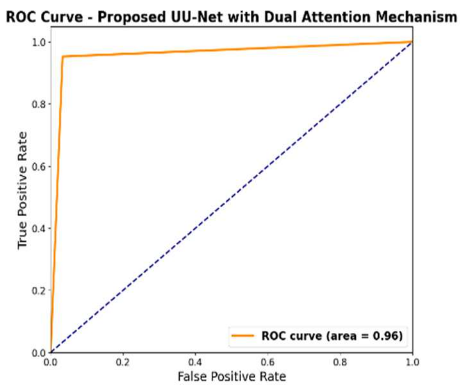

Fig. 11. ROC Curve

The Receiver Operating Characteristic (ROC) curve evaluates the ability of the models to differentiate between tumour and non-tumour images as shown in Fig. 11. U-Net's AUC is 0.92, indicating its strong performance in detecting the presence of a tumour image. From the ROC curve, it is clear that the model is quite efficient at detecting tumours (true positives) but has a tendency towards false positives. The U-Net's high AUC shows that the predictions are trustworthy, but it may improve further by minimizing false positives and maximizing accuracy. Attention mechanisms enhance the U-Net architecture, thus letting the model focus more on important visual features. The AUC is slightly enhanced to 0.93, thus it depicts a more sophisticated categorization of tumour images.

UU-Net with dual attention mechanism outperformed U-Net and Attention U-Net models by attaining an AUC of 0.96, which means the improved categorization of tumour and non-tumour. The model achieved a higher true positive rate and less false positive rate than other models, and its ROC curve is better. The dual technique integrates spatial and channel-wise to aid the model in identifying relevant locations and features in pictures of tumors, hence its more accurate diagnosis and less error or false positives. Thereby, the model identifies and distinguishes between tumors and non-tumors. This is because the model considerably improves its classification ability; that is, 0.96 AUC. As model complexity increases, starting from U-Net and then to Attention U-Net and further to UU-Net with Dual Attention Mechanism, the discrimination power of the model increases; the proposed UU-Net has the highest classification accuracy and reliability. Advanced designs increase the performance of models to be used for applications like detecting brain tumors, as inferred from the AUC trend. This paper presents a study identification and classification of brain tumors synthesizing current research findings in the literature to highlight recent developments and address existing gaps. The conventional methods of machine learning used extensively for medical image analysis are hampered by reliance on handcrafted feature extraction, extended processing times, and vulnerability to human error. For example, methods like probabilistic neural network with Discrete Wavelet Transform achieved notable accuracy up to 98% but involved massive preprocessing and domain expertise as discussed by Shree & Kumar[12]. Similarly, Bahadure et al. [22]This paper presents a study identification and classification of brain tumors synthesizing current research findings in the literature to highlight recent developments and address existing gaps. The conventional methods of machine learning used extensively for medical image analysis are hampered by reliance on handcrafted feature extraction, extended processing times, and vulnerability to human error. For example, methods like probabilistic neural network with Discrete Wavelet Transform achieved notable accuracy up to 98% but involved massive preprocessing and domain expertise as discussed by Shree & Kumar. On the other hand, deep learning techniques have demonstrated great potential in automatically learning features and enhancing classification accuracy. VGG-16, GoogLeNet, and AlexNet are several models that have been used to classify brain tumors extensively by applying transfer learning, even with small datasets for high accuracy Swati et al. [14] reported a classification accuracy of 98.69% using VGG-16, while Deepak and Ameer [15] Achieved 98% accuracy with GoogLeNet with deep CNN features and five-fold cross-validation. Such studies therefore highlight the importance of deep architectures in feature extraction tasks autonomously, getting over the limitation of dependency on manually crafted features. Attention mechanisms improve the performance of deep learning models by allowing them to focus on significant regions within medical images. Chen et al. [24]Introduced double attention networks that use both spatial and channel-wise attention to dynamically capture relevant contextual and spatial features. The proposed study extends this by incorporating dual attention mechanisms shown in Fig. 4 into the UU-Net architecture, which is demonstrated to be effective in the task of brain tumor segmentation. The UU-Net with Dual Attention Mechanism achieved superior performance with an accuracy of 95.60%, a recall of 95.30%, and an AUC-ROC score of 0.96. These results surpass the baseline U-Net and Attention U-Net models by significant margins, which reached accuracies of 91.20% and 92.80%, respectively. With all these developments, however, there are still gaps that remain in the literature; some of which include lack of models that generalize well to diverse datasets and that minimizes manual intervention during feature extraction. Most approaches do not dynamically capture spatial and contextual information, hence their failure to scale and be robust. This paper presents a model named UU-Net with multi-level fusion and double attention mechanisms, leading to better segmentation precision and accuracy in classification. This corresponds to previous research work, such as Kalaiselvi et al.[19], which stressed the need for hybrid CNN architectures in the detection of glioma, and Pattanaik et al.[17], which emphasized the requirement of models that can deal with the complexity of medical imaging tasks. In summary, the study benefits from existing research to develop identification and classification of brain tumors. This would integrate dual attention mechanisms with robust segmentation frameworks to better overcome the current limitations that exist in these approaches. This work, therefore, paves the way for much more accurate and scalable solutions for medical diagnostics. Advancement in precision diagnosis will allow more real-world applications in neurology and oncology.

V. Conclusion

The results obtained by utilizing the UU-Net along with Dual Attention Mechanism for brain tumor segmentation detail deep, nuanced understanding regarding performance within various critical parameters that include both the quantitative and the visual representation. Through a critical analysis in either or both these visual representations and quantitative representations, it hence, renders comprehensive insight pertaining to how effective is that specific model in medical imaging tasks. Fig. 1. presents the training evolution of the model; the learning dynamics of the model over epochs can be seen. The first peak in validation loss followed by a steep drop suggests an adjustment phase of the model while it learns about the complexities of the dataset. Then, stabilization of validation loss indicates that the model has learned to decrease the errors of predictions and optimize the accuracy of segmentation. Fig. 7. Plots Accuracy of the model showing consistent and accurate brain tumour segmentation over epochs. The oscillations in training and validation accuracies represent model training's iterative optimisation process. The "BEST model" epoch marks peak validation accuracy and the model's ability to obtain optimum segmentation results across training repetitions. Fig. 7. shows the model's analytical path in brain tumour identification, showing its accuracy in MRI images. The consecutive tumour segmentation phases show the model's ability to isolate and emphasise regions of interest in complicated anatomical systems. This evolution shows the model's technical capability and clinical promise in diagnostic interpretation and therapy planning. Fig. 6 shows detailed evaluation metrics of model performance along the axes. The loss measure is not constant with epochs because it is changing as the model is learning and adapting to the training data, hence changing prediction error. The accuracy of the model in segmenting brain tumour is constantly very high, which ensures reliability and effectiveness. The robustness of the model in AUC, sensitivity, and specificity ensures its discriminative nature and the ability to well discriminate between tumour and non-tumor region in MRI images. It clearly proves the effectiveness and trustworthiness of the brain tumour segmentation data with UU-Net with Dual Attention Mechanism. The results show the model's promise as a tool in medical image analysis and improvement of neurology and cancer patient care and treatment outcomes.

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