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An Enhanced U-Net and CNN-based Tumor Edge Detection Technique in MR Images

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ABSTRACT

Tumor edge detection and segmentation are crucial in cancer diagnosis and monitoring. Existing methods are limited to detecting complex tumour edges because of their low spatial resolution. This results in inaccurate detection of tumour boundaries. Deep learning (DL) based approaches have recently emerged as a promising solution for improving the accuracy of tumour detection. We propose an ensemble DL-based U-net and CNN model for tumour edge detection, segmentation, and classification. The model uses Leaky ReLU instead of ReLU and dice loss as a function. It was evaluated on the BraTS 2020 dataset of a diverse range of MR images. It achieves an accuracy of 0.9928, precision of 0.9935, sensitivity of 0.991, and specificity of 0.9978 on BraTS 2020. The algorithm was deployed on a Linux-based embedded Edge AI system combining the processing powers of Nvidia Jetson Nano and Google Coral USB AI Accelerator for faster computation than regular desktops. It is a portable, low-powered, cost-effective, and time-efficient system. .

Keywords: Cancer diagnosis, Deep learning, Medical image processing, Spatial resolution, Tumor edge detection.

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INTRODUCTION

Magnetic Resonance Imaging (MRI) is a widely practiced medical technology nowadays due to its visible adaptation in medicine, providing a better intellectual approach; this imaging technique related to magnetic resonance allows the patient to interact with a magnetic field. MR Imaging is a result of the interaction of the magnetic field created by the magnet in an MR machine with particles that can spin and charge[1-3].

Tumor refers to the abnormal growth of cells. Meanwhile, brain tumors are abnormal brain or spinal cord cell growth. The brain is the most functional and complex part of the human body. The brain controls the functions related to memory, emotions, vision, breathing, or other processes that regulate our body. The size, shape, and contrast are different in different tumors and can appear in any part of the brain[4]. The size and shape are the other necessary types based on which the impact of tumors is predicted[5-8].

Detecting brain tumors is challenging for physicians and radiologists because every tumor has a heterogeneous nature[9-11]. The process of manual detection of tumors is time-consuming, while the treatment of brain tumors requires diagnosis as early as possible. Computer-assistive diagnosis plays a vital role in reducing the time complexity and provides a platform with the help of which early diagnosis takes place with less human intervention[12-13].

Artificial Intelligence (AI) is an approach that aims to mimic human behaviors into machines. The primary motive of AI is to make machines act like humans; introducing thinking ability into machines is an achievement in AI. An exquisite problem-solving skill is required to solve a particular problem efficiently. AI is the foundation of a program that achieves and flourishes intelligence in a machine. Algorithms are a set of rules and mathematical implementations that are used to achieve AI. Artificial Intelligence is a broader term that covers all the aspects of machine learning, deep learning, natural language processing, automation, and so on[15].

The process of ML is to make a model similar to the human brain. Deep Learning (DL) is providing a platform to promote computer-aided assistance. Deep learning-based models consist of artificial neural networks. The connection of artificial neural networks is complicated and depends on layers. The structural unit of the human brain is neurons. The DL practitioners tend to make artificial neurons that take input and predict an output. The numerous neurons are connected and initiate the layers. The traditional way of processing an image is a simple phenomenon. Now, processing an image and implementing the DL algorithm to train the model allow the detection and classification of complex objects like tumours in MR images. DL models in the field of medicine maximize the efficiency of detection procedures. Classification, Regression and Clustering problems can be solved by using deep learning[14].

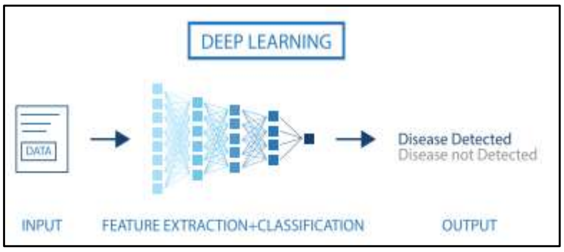

Fig.1 Machine Learning Mode
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Fig.1. shows the deep learning model feature extraction and classification process in hidden layers of the deep learning model.

RESEARCH BACKGROUND

Researchers have studied Brain Tumor Edge Detection extensively using machine learning and deep learning in recent years. Many robust and efficient deep-learning algorithms have already been developed. This section covers the literature review of tumour edge detection and classification using deep learning models.

In this paper, the edge detection technique is widely used to detect edges in images. Obert's cross-gradient and Prewitt's operators are mainly early edge detection methods. Sobel Operator is a modified form of Prewitt's operator. The canny edge detection algorithm has a low error rate and well-localized edge points. Watershed transform is a growing regional approach for image segmentation. Edge detection algorithms are simple but do not guarantee closed contours. Watershed transform gives closed contours but is over-sensitive for complex images[16].

This paper researched image processing and soft computing for brain tumour detection. The segmentation based on neural networks is prominent in brain tumour detection, and thus, the proposed model achieves 92% accuracy in tumour detection. The researcher also implied using morphological operations and the SFCM algorithm for segmentation. Histogram technique and edge detection approaches are used in this research for tumour detection[17.] Image processing techniques and deep learning boundary extraction methods are commonly used in medical image segmentation. Various network frameworks, such as DoubleUNet and PraNet, have shown improved segmentation performance. Techniques such as adaptive histogram equalization and contrast-limited adaptive histogram equalization are used for boundary distinction. Loss functions specialized in boundary distinction, such as Hausdorff loss and focal loss, have been researched. This paper's proposed boundary-aware loss function considers boundaries and neighbouring areas for effective Learning[18].

The comparative analysis in this paper compares the convolutional neural network (CNN) and five deep learning models for brain tumour classification. The VGG16 model outperforms others with 97.08% accuracy. MRI is the most commonly used diagnostic tool for brain tumours. The deep learning model in computer vision offers cutting-edge solutions

for image processing issues. Deep learning is ideal for modelling complex and high-dimensional data. As the segmentation of brain tumours is essential for diagnosis and treatment planning and manual segmentation is time-consuming, computer algorithms are in high demand. Thus, for feature extraction, pre-trained transfer learning models are used [19].
In the paper[20], the author presents a deep-learning framework for brain tumour classification. The proposed CNN framework achieves a classification accuracy of 99.4% and a loss of 0.0030%. This framework is compared with other state-of-the-art models for classification. The image dataset is down-sampled and normalized for better contrast in images. Automated detection of brain tumours is essential for accurate diagnostic assessment. Brain tumours can be categorized as benign or malignant. These frameworks help in the early diagnosis of brain tumours, which is crucial for saving lives.

Numerous methods for brain tumour classification based on machine learning have been reported. Machine learning-based BTC algorithms are gaining prominence, and different models and techniques have been proposed for brain tumour classification. Whereas deep learning-based approaches, such as CNN and CapsNet, have shown promising results in brain tumour classification, various datasets, such as Figshare and Radiopaedia, have been used for evaluation. Transfer learning has been used to improve classification accuracy. Genetic algorithms have been applied to modify CNN architectures for better performance. The proposed method in this paper achieves a classification accuracy of 98.95%[21].

According to the proposed research, deep learning has the potential to detect and intervene in brain tumours. Machine learning, or intense learning, is very beneficial in medical diagnosis. Computed Tomography (CT) brain scanning is a typical application of deep learning. Brain MRI images are used for brain tumour categorization research. Deep Learning-based supervised techniques can detect changes in synthetic aperture (SAR) images. Automated brain tumour classification systems based on DNN are proposed. A machine learning-based technique is used for segmenting brain tumours using MRI. Tumour segmentation aims to identify and extract metastatic tumour voxels. Deep learning techniques improve standard neural networks for tumour classification. Triangular fuzzy median filtering and Gabor characteristics are used for image improvement. The proposed approach for detecting brain cancers is based on deep Learning[22].

Various machine and deep learning algorithms are proposed for tumour detection. The author used a semiautomatic approach for tumour classification, whereas Mohsen et al. achieved 96.97% accuracy using a deep neural network. An ensemble model combining Squeeze Net and Shuffle Net outperformed base models. A hybrid Gabor filtering and DWT approach increased accuracy to 91.9%. Moreover, they used a genetic algorithm to evolve CNN architecture for tumour classification, in which a deep learning model for chronic kidney diseases achieved 100% accuracy[23].

The paper proposes a modified U-Net structure for brain tumour segmentation. Residual blocks are used to improve performance and preserve gradient information. The U-Net blocks allow for global location and context in segmentation tasks. The paper evaluates the proposed technique using the BRATS 2017 and BRATS 2018 datasets and the performance is measured using dice score, sensitivity, and positive prediction value. The pre-processing steps include scaling volumes, combining non-native volumes, and cropping. The value of the dice score ranges from 0 to 1, indicating segmentation accuracy[24].

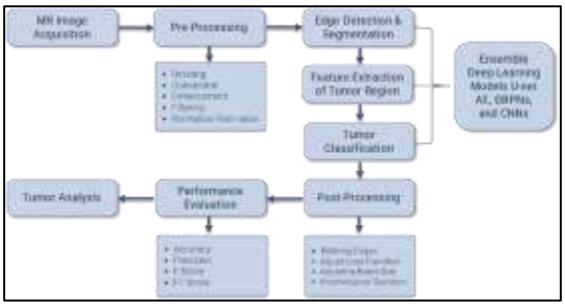

Fig.2. Block Diagram of Deep Learning Architecture

Edge detection is a challenging task in computer vision; statistical-based and deep learning-based methods are used for edge detection. Statistical-based methods exploit colour, brightness features, and clustering algorithms. Deep learning-based methods use convolutional neural networks trained on large-scale datasets. The proposed method uses scale representations to extract edges at each network block. - Authors propose a unified network based on existing feature extraction backbones. Architectures like HED, LPCB, CAFENet, RCF, and BDCN are mentioned. The proposed method focuses on multi-scale representation and high-resolution output[25].

The comprehensive literature review demonstrates that there is still a need to improve the ability of deep learning algorithms for brain tumour detection using MR images. As brain tumours can be present in different sizes, locations, and shapes in MR images, existing methods need many improvements for tumour detection and grading in enhancing and non-enhancing tumour regions through segmentation. Therefore, a careful approach is required to select the appropriate deep-learning tumour detection model with the optimal parameters to meet the requirement.

METHODOLOGY

In this section, the proposed ensemble deep learning technique using U-Net and CNN with its deployment on our specified Edge AI hardware has been described, overcoming the limitations of existing techniques. It also describes the steps of the implementation process in detail.

We employed the modified 2D U-Net. Architecture for the tumour edge detection and segmentation of MR images. It is specifically designed for the small regions of interest with complex sizes and shapes of tumours in MR images. Compared to other deep learning models, it requires less memory and is faster, making it advantageous for working with large datasets or limited computational resources. The implementation process of our deep learning technique is shown in Fig 2. It demonstrates the proposed methodology step by step in a block diagram. This methodology is followed throughout the model implantation.

A. MR Image Acquisition

The MR images dataset has been collected from the Brain Tumour Segmentation Challenge website. We acquired BraTS 2020 to evaluate our model. The BraTS 2020 training dataset has 1,251 brain MRI scans with segmentation masks of tumour regions. Skull stripping and resampling techniques were used to have MR images with 240, 240, and 155 voxels dimensions. The BraTS 2020 dataset consists of four MRI sequence scans of T1, T2, FLAIR, and T1CE in NIfTI file format, known as the Neuroimaging Informatics Technology Initiative. The MR scans are 3D, and each dimension consists of 2D images called slices. The dataset is organized in the following way, as shown in Fig.3.

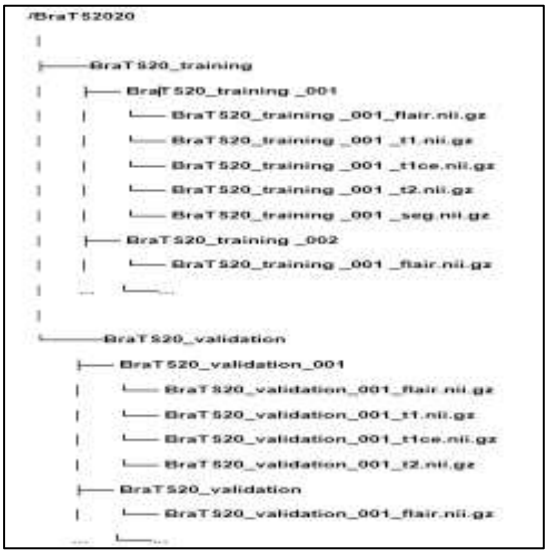

Fig-3. Organization of MR images in BraTS 2020 dataset

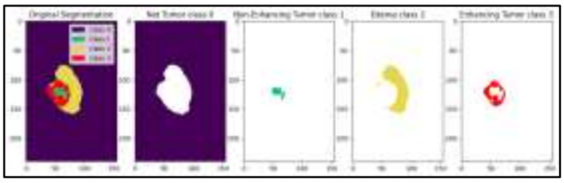

Fig.4. Four Segmentation Classes

B. Pre-processing

Data Exploration: We used only two MR modalities out of four: T1CE and T2-FLAIR. The post-contrast T1-weighted (T1ce) with a contrast agent shows better villosity of tumour regions and T2-FLAIR with suppression of fluid part for the identification of brain tumours which are not clear on T1 or T2. This approach reduced the computation and storage requirements for brain tumour segmentation using U-Net. It makes the system faster and time efficient.

One-Hot Encoding: We use the One-Hot Encoding feature engineering technique to effectively segment tumour regions denoted as classes from 0 to 3 to convert our categorical class variables into numerical data usable as input to the neural network. The four possible values of segmentation masks are classified into four classes using different colours, as shown in Fig. 4.

- **Class 0:** Not Tumor (NT) or Background in Purple Color
- **Class 1:** Non-Enhancing Tumor in Green Color
- **Class 2:** Peritumoral Edema in Yellow Color
- **Class 3:** Enhancing Tumor in Red Color

To effectively segment tumour regions represented as different classes (0 to 3), we convert classes into a numerical representation that our neural network can use. This is done using One-Hot Encoding.

Resizing: We resized each 2D MR image from 240x240 to a 128x128 shape to ensure the compatibility of MaxPooling2D and down-sampling in our convolutional neural network because it uses the power of 2 size integer. It can help maintain the spatial resolution of MR images without overlapping and leftover pooling filters to reduce the loss of spatial information.

C. U-Net Architecture

The U-Net arc is a specific type of encoder and decoder neural network model trained to regenerate a copy of its input to its output. It was developed especially for biomedical image segmentation. The contracting path of the U-Net is called the encoder, and an expansive path is called the decoder. We have implemented a few modifications to the existing U-Net architecture, as shown in Fig 5. We used a shallow supervision technique. The convolution filters at each encoder path are 32, 64, 128, 256, 512, and the depth of the U-Net decoder path is five. The convolution filters at each decoder path are 512, 256, 128, 64, and 32, and the depth of the U-net encoder path is five.

Shallow Supervision: We incorporated the supervision technique by reducing the decoder and encoder levels to 5. It enforces consistency and corrects errors earlier in the model. It helps to prevent vanishing gradient problems in deeper layers of the network. We used a convolutional neural network in the decoder and encoder path with softmax function to accurately classify and grade the different tumour regions in MR images.

Leaky ReLU: We incorporated the Leaky ReLU function as an activation function in the convolution layers instead of the ReLU function. It is the extension of the ReLU function, and it considers the negative values instead of setting them to zero. It resolves the issue of dying ReLU, where neurons show inactivity during training and fail to update the weights in backpropagation. Leaky ReLU includes a slight gradient with a non-zero value for the negative values. We use 0.1 for the slope coefficient alpha in our model, which multiplies the negative values to 0.1 for consideration in the training process and to improve performance.

Kernel Initialization: The kernel initializer in our U-Net model determines how the initial weights are set in the neural network. It helps to make the training process more integrated. We incorporated He-Normal Initialization, which sets the initial weights using Gaussian distribution in Leaky ReLU, where the mean is zero, and the formula follows the standard deviation.

$$\sigma = \frac{2}{(1+\alpha^2)\times No.of\ input\ units\ in\ weight\ Tensor} \quad (1)$$

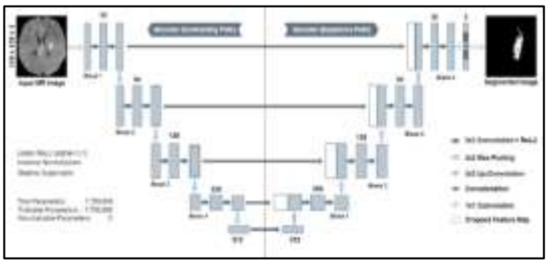

Fig.5 The Proposed Modified U-Net Architecture

D. Training and Validation

The BraTS 2020 dataset is divided into training 68%, validation 20%, and testing 12% sets, and it has been split as shown in Table I.

Table-1. Splitting Brats 2020

Dataset	Training Set	Validation Set	Testing Set
BraTS-20	250 Patients	74 Patients	45 Patients

Training Set: The training set trains our U-Net model by exposing it to the training data and adjusting its parameters to minimize the error between its predictions and the original segmentations.

Validation Set: The validation set is used to fine-tune the model's hyperparameters, which are set before training and determine the model's behaviour. The goal is to compare different hyperparameters and select the best configuration for the model.

Testing Set: After being trained, the test set evaluates the model's performance by checking how well it performs on unseen data.

Quantization Aware Training: We employed the quantization technique in building our U-Net model. It converts the continuous values into a discrete set of values using linear or non-linear scaling techniques. The reason for quantization is that high precision is required during training to achieve fine-grained weight updates. Thus, using INT8 precision is a more computationally efficient and memory-friendly approach. By using INT8 precision, the model performed faster at the cost of a very low loss in accuracy.

Data Generator: We create a data generator to feed training data to our U-Net model by combining the raw image data (X) and segmentation masks (Y). It uses an X array with all the selected slices (60-135) of two MR image modalities and a Y array with all four tumour segmentation mask class values.

Loss Function: A loss function evaluates how well the neural network models the data. It compares the predicted segmented pixels to the original segmented pixels for each patient to update the model weights at every epoch to reduce the loss and improve prediction accuracy. We use categorical cross-entropy to measure the difference in the predicted probability distribution of each pixel and one hot-encoded original segmented pixel. It resolves the multiclass-level classification issue.

Learning Rate: We set the learning rate of 0.001 for our model during training. We added the callback function to our model, which reduces the learning rate when the metric does not improve the validation loss.

Classification Activation Function: We incorporate a softmax classification function on the output layer to convolutional neural network ensemble within U-Net to compute the probability distribution for each pixel across the four classes of tumour regions in predicted and original segmentation and classify and grade them. During training, CNN modifies its weights to minimize the loss function.

System Infrastructure

The algorithm was deployed on an embedded edge AI system with two main parts: hardware infrastructure and software infrastructure.

A. Hardware Infrastructure

Hardware Infrastructure consists of a Nvidia Jetson Nano Graphical Processing Unit and a Google Coral USB AI accelerator tensor processing Unit.

1. Nvidia Jetson Nano

The Nvidia Jetson Nano is a tiny, low-powered, and powerful edge AI embedded device to train and deploy deep learning models with its CUDA cores Maxwell 128 GPU and quad-core ARM CPU. It is used to optimize the AI, ML, and DL models to bear the workload of the considerable dataset used to train data. The Jetson Nano comes pre-loaded with Jetpack 4,6,1 based on Ubuntu 18.04 OS, which provides support for Nvidia Drivers, TensorRT, CUDA 10.2, cuDNN, and Python3.6.9. Its specifications are listed below in Table II.

2. Google Coral USB AI Accelerator

The Google Coral USB tensor processing unit (TPU) is an AI accelerator that aims to bring the power for deep learning models. It is an energy-efficient device with less power drainage when used on laptops or other portable devices. It is used to improve the inference of deep learning models and implement them faster and more efficiently to reduce computational complexity and computational time. It requires Python 3.6 - 3.9 and a USB 3.0. to interface. Its specifications are described below in Table III.

Software Infrastructure

It includes the Integrated Development Environment (IDE) and the ThingSpeak cloud by MATLAB and Proteus.

1. Nvidia Jetson Nano JetPack 4.6.1

IDE The JetPack SDK from NVIDIA is an all-inclusive solution for constructing a complete accelerated AI system. It comes with the Linux operating system's Jetson Linux Drivers (L4T), CUDA 10.2 accelerated libraries, APIs for deep learning; parallel AI accelerated computing and multimedia. JetPack 4.6.1 supports the Jetson Nano developer kit. It has cuDNN 8.2, TensorRT 8.2, DLA 1.3.7, Python, and L4T 32.7.1. TensorRT and CUDA toolkits support parallel AI-accelerated computing on GPUs.

2. TensorFlow GPU

TensorFlow-GPU is a specified open-source deep learning library for AI-based numerical computations with the help of data graphs. The graph nodes denote mathematical operations, while graph edges describe tensors. TensorFlow helps in the deployment of numerical.

Table-2. DL Supported specifications of Jetson Nano

Specification	Description
GPU	NVIDIA Maxwell architecture with 128 NVIDIA CUDA® cores
CPU	Quad-core ARM Cortex-A57 MPCore processor
Clock Speed	1.43 GHz
Memory	4 GB 64-bit LPDDR4, 1600MHz 25.6 GB/s
Storage	16 GB eMMC 5.1
Camera	12 lanes (3x4 or 4x2) MIPI CSI-2 D-PHY 1.1 (1.5 Gb/s per pair)
Connectivity	Gigabit Ethernet, M.2 Key E
Display	HDMI 2.0 and eDP 1.4
USB	4x USB 3.0, USB 2.0 Micro-B
Others	GPIO, I2C, I2S, SPI, UART
Deep Learning	CUDA architecture for parallel computing. Tensor Cores for accelerated tensor operations. Support for popular deep learning frameworks Accelerated GPU for deep learning tasks

Table-3 Specified DL specifications of Google Coral USB

Specification	Description
Neural Network Chip	Google Edge TPU (Tensor Processing Unit)
USB Compatibility	USB 3.0 Type-C
Maximum Power Usage	2.5 Watts
Supported Frameworks	TensorFlow Lite, TensorFlow, and other deep learning frameworks
Supported Models	Quantized TensorFlow Lite models
Performance	Up to 4 trillion operations per second (TOPS)
Operating Systems	Linux, macOS, Windows

Computation models on CPUs or GPUs. It performs deep learning model computations directly on Nvidia GPUs without changing the code.

TensorFlow Lite

The TensorFlow Lite is a TensorFlow variant optimized for mobile and embedded devices. It works at a very low latency rate inference in a compact binary size by converting 32-bit data into 8-bit representations through quantization, which the Edge TPU requires. It is necessary to convert TensorFlow architecture from a file format of .pb extension to a TensorFlow Lite file format such as .tflite. It is shown in Fig.6.

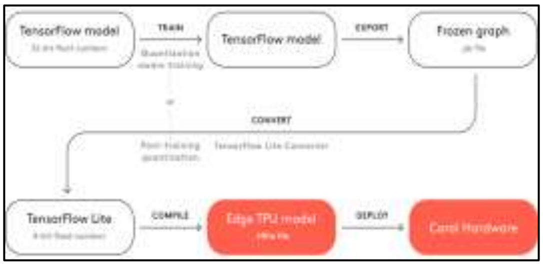

Fig-6. Conversion of TensorFlow to TensorFlow Lite

RESULTS

We compared our U-Net model with the same parameters on the BraTS 2020 datasets. We deploy the model on the embedded edge AI system of Jetson Nano and Google Coral USB AI accelerator. The comparison was based on computation resources, the number of trainable parameters, feature maps and the different performance metrics. The learning rate was set to 0.001 and adjusted using the ReduceLROnPlateau callback function. We trained our model for 35 epochs on BraTS 2020. The training and validation accuracy, loss, and mean IoU of the proposed U-Net model on BraTS 2020 for 35 epochs are shown in Fig 7. We compared the results before and after the post-processing. After conducting multiple experiments, we selected the optimal parameters for the size of the input MR image, feature maps, and learning rate. The configuration and results based on performance metrics are shown in Table IV.

The segmentation results for the random sample MR images acquired from BraTS 2020 using the proposed U-Net model after post-processing are displayed in Fig.9. A closed similarity can be observed for the original segmented mask and predicted segmented images. This comparison shows the efficiency of the proposed algorithm.

Table-4 Results of the proposed modified U-Net Model

Dataset	**BraTS 2020**
Image Size	128 × 128
Trainable Parameters	7,759.908
Batch Size	250
Epochs	35
Loss	0.0213
Accuracy	0.9928
Precision	0.9935
Sensitivity	0.991
Specificity	0.9978
Average Test Time	71 m/s

DISCUSSION

We observed that the proposed U-Net technique outperformed the larger dataset of BraTS 2020 in terms of increasing accuracy, precision, specificity, sensitivity, and loss. It concluded that the performance of the model could be enhanced by increasing the size of the dataset and the number of epochs. We observed a few false positives in the testing results, which can result in a false prediction of tumours. These false positives are eliminated using the post-processing technique of argmax encoding. We have used quantization-aware training to perform faster training and time-efficient inference of predictions on unseen data.

CONCLUSION

We proposed a modified implementation of the U-Net architecture to segment brain tumours in MR images using BraTS 2020 datasets. We deployed this model on specified Edge AI hardware of Jetson Nano and Google Coral USB AI Accelerator. We incorporated several modifications in the U-Net model to minimize the number of trainable parameters and quantitation for the model optimization to reduce computation complexity to meet the required computational resources. We have determined that our proposed implementation is effective with a significantly reduced number of parameters and shallow supervision. It achieved higher results of accuracy.

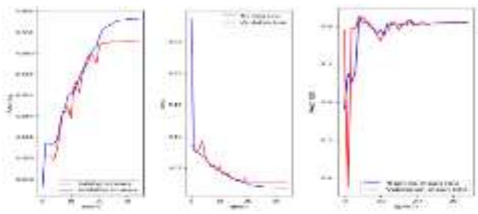

Fig..7. Training and validation accuracy, loss, and mean IoU on BraTS 2020

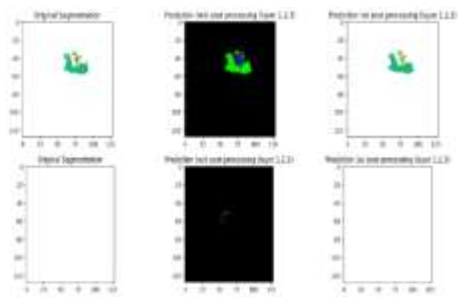

Fig. 8. Results on BraTS 2020 Dataset after post-processing

0.995, precision 0.995, sensitivity 0.9957, specificity 0.9982, and loss 0.0156. The proposed model was able to perform high inference on a portable, low-powered, and cost-effective Edge AI system and achieved an 84 m/s average test time for brain tumour segmentation in MR images.

FUTURE SCOPE

The previous methods have shown better results when training and testing are conducted on similar intensity and resolution acquisition characteristics. However, even slight variations in the images can affect their robustness. In future research, accurate patient data from any MRI modality can be used to detect brain tumours more accurately. Furthermore, two or more sophisticated DL models can be fused.

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Author Contributions
Muhammad Faris contributed to the conceptualization, methodology, formal analysis, and drafting of the manuscript. **Tariq Javid** supervised the study, validated the findings, and critically revised the manuscript. **Khalid Mahmood** was responsible for data curation, literature review, and statistical analysis. **Danish Aziz** handled software development, implementation of the U-Net and CNN models, and data preprocessing. **Mir Farooq Ali** contributed to experimental design, results interpretation, and manuscript editing. **Muhammad Mansoor Mughal** oversaw funding acquisition, project administration, and provided final approval of the manuscript.

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Conflict of Interests
None.

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