International Journal of Computing and Digital Systems
ISSN (2210-142X)
Int. J. Com. Dig. Sys. , No. (Mon-20..)

http://dx.doi.org/10.12785/ijcds/XXXXXX

Design, Development and Evaluation of a Deep Learning-Based Personalized Healthcare System for Diagnosis of Brain Metastases

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Received Mon. 20, Revised Mon. 20, Accepted Mon. 20, Published Mon. 20

Abstract: Brain metastases (BM), which affect 10-30% of cancer patients, represent important diagnostic and therapeutic problems due to their impact on cognitive function. Traditional manual MRI interpretation methods are time-consuming and potentially inaccurate, especially for tiny or diverse tumours. Artificial intelligence (AI) tools such as deep learning (DL) and machine learning (ML) made it possible to analyse complex MRI data quickly, accurately, and automatically, which was a major factor in BM diagnosis. This paper presents a novel approach for automatic brain metastases segmentation on MRI data that makes use of a U-Net model. To improve the accuracy of BM identification, the proposed method combines numerous imaging modalities, including T1-Weighted, T2-Weighted, T1-contrast enhanced, and Fluid-Attenuated Inversion Recovery (FLAIR). The University of California San Francisco Brain Metastases Stereotactic Radiosurgery (UCSF-BMSR) MRI dataset has been utilized for this purpose. The U-Net model was trained, verified, and tested on this dataset, and it performed admirably with an overall accuracy of 99.75%, a dice coefficient of 64.49%, and an Intersection over Union (IOU) of 96.81%. The proposed technique has been compared with two baseline models, namely Convolutional Neural Networks (CNN) and Fully Convolutional Networks (FCN). The U-Net model outperformed the baselines in all important measures, demonstrating its potential for real-world clinical application. The findings highlight the U-Net model's capacity to greatly enhance BM detection accuracy, allowing for prompt treatment decisions.

Keywords: : Brain Metastasis, Brain Metastases, U Net, Segmentation, BM Detection

1. INTRODUCTION

Brain metastases (BM) is a complex process in which cancer cells enter the brain from elsewhere in the body and spread to various sections of the brain, creating difficulties with the brain's function [1], [2]. These metastases impact 10-30% of all cancer patients, with the most common causes being primary lung, breast, melanoma, kidney, and colorectal cancers [3], [4].Symptoms of brain metastases may include headaches, seizures, difficulty thinking or speaking, weakness, and changes in vision or hearing. The ability of BM spread from primary brain tumours can be through circular or lymphatic system [5]. This metastatic expansion to the brain provides a unique set of obstacles that differ from primary brain tumours, with consequences for both prognosis and treatment methods. The location of these tumors and the blood-brain barrier can make diagnosis and treatment challenging. The necessity of resolving this issue arises from its significant influence on patient health and mortality. In most cases, BM may induce cognitive deficits in the patients which lead to distress and might worsen their quality of life[6], [7].Brain metastases can be treated using various options, range from surgery to radiation therapy to chemotherapy to immunotherapy to targeted therapies. The outcome of treatment depends on several factors, such as tumor size and location, cancer progression elsewhere in the body, and patient health. Additionally, the common BM treatments such as radiation therapy and surgery may produce inflammation, healthy brain tissue damage that might culminate cognitive impairment like memory or attention issues[8], [9]. Radiation therapy is a key component of treatment for brain metastases (BM), encompassing SRS (stereotactic radiosurgery) and WBRT (whole-brain radiation therapy). Multiple brain metastases are treated with WBRT; however, because it affects healthy brain tissue, there may be considerable neurocognitive side effects. Thus, timely prediction of BM with high accuracy is crucial to reduce the neurocognitive effects. However, diagnosing BM poses various challenges such as tumor heterogeneity in shape or size, limitation of imaging techniques and risk of biopsies. Accurate detection of BM is critical for disease surveillance and response evaluation in healthcare practice. Traditional methods of diagnosing

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brain metastases rely mainly on the manual interpretation of MRI data by expert clinicians. Radiologists frequently lack detailed quantification when interpreting MRI's, making the detection and segmentation of BM's time-consuming [10], [11]. Moreover, MRI and CT scan interpretation face difficulty in detecting small lesions or differentiating primary tumor types [12]. However, with advancements in 3D imaging techniques and usage of imaging modalities such as T1 weighted, T2-weighted, T1-contrast enhanced and FLAIR (Fluid-Attenuated Inversion Recovery) have improved the detection and characterization of BM [13], [14], [15]. Over the past two decades, Artificial intelligence (AI) has played an increasingly important role in detecting and segmenting BM with machine learning (ML) and deep learning (DL) techniques[16], [17], [18], [19].

Various approaches have been explored for automated detection and segmentation of intracranial metastases. Automated systems based on deep learning frameworks have demonstrated promising outcomes in detecting BM's with enhanced precision in assessing treatment success. These approaches, notably CNNs(convolutional neural networks), have shown exceptional effectiveness in a variety of medical imaging applications, including image segmentation and classification [20], [21], [22]. CNN can automatically extract information from medical images without the need for human interaction. In contrast to conventional techniques that depend on manually generated features, CNNs get hierarchical features straight from the unprocessed image data, improving BM recognition and segmentation accuracy. Through these advanced methodologies, deep learning not only boosts the accuracy of BM identification and segmentation but also decreases the time and effort required by radiologists, making it a vital tool in medical imaging and BM treatment planning. This research is proposing a groundbreaking approach utilizing U-Net model for automated segmentation of brain metastases on magnetic resonance imaging (MRI) scans.

The primary objective of the study is to develop U-Net model based on deep learning, for automated classification of brain metastasis on MRI scans. In addition, the proposed model rigorously evaluates the performance of this approach on a diverse dataset, comparing it with existing methods, including two baseline models: traditional CNN and FCN. This comparison aims to determine the model's efficacy in real-world clinical settings, thereby contributing to the advancement of diagnostic tools and improving patient outcomes through timely decision-making.

The following section summarises previous research and present methods in the field of automated brain metastasis classification using MRI data. It pays focus on the difficulties and improvements in the application of deep learning methods to medical imaging. The next section describes the methodology that includes the study of dataset, design, and implementation of the proposed U-Net model. Furthermore, the results section is presented showcasing

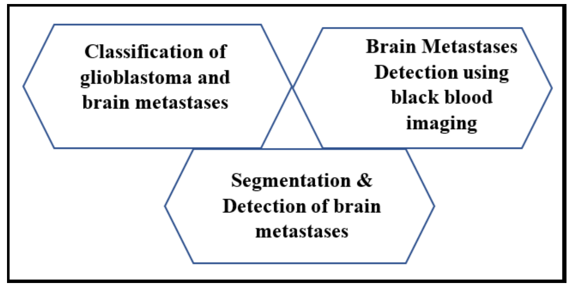

Figure 1. Literature Trio

the performance metrics and outcomes of the proposed approach, along with a detailed comparison with traditional CNN and FCN models. The discussion section delves into a thorough analysis of the proposed model's effectiveness against baseline models, emphasizing the advantages and potential limitations. Finally, the conclusion summarises the important findings, emphasises the study's contributions, and proposes future research areas.

2. Related Work

The field of brain metastasis diagnosis and prognosis has evolved rapidly, due to improvements in medical imaging, machine learning, and deep learning techniques [4], [11], [23]. This review of literature examines significant studies that have led to the understanding and application of various in addressing the challenges posed by brain metastases. The recent studies have been categorized into three parts i.e. the classification of glioblastoma and brain metastases, the detection and segmentation of brain metastases, and the specific detection of brain metastases using black blood imaging as demonstrated in Figure 1.

A. *Classification of glioblastoma and brain metastases*

Accurate classification of glioblastoma (GB) and brain metastases (BM) poses a significant challenge due to their similar appearance on conventional MRI scans. Various machine learning approaches, including SVM and LASSO regression, deep neural networks, and CNNs, have been used to distinguish glioblastoma from brain metastases, with accuracy rates ranging from 69.2% to 90%. The Table I demonstrates key studies and their findings in this domain. Research has shown high success rates in distinguishing glioblastoma from brain metastases, including sub-types like breast and lung metastases, using machine learning and deep learning algorithms.

B. *BM detection using black-blood imaging*

In recent years, black blood imaging has emerged as a promising approach for detecting brain metastases, increasing the visibility of metastatic lesions by suppressing the signal from blood vessels and providing clearer delineation of abnormal features. Oh et al. [32] investigated brain metastasis identification using a You Only Look Once (YOLO) V2 network trained with 3D BB sampling perfection and application-optimized contrasts on various flip

TABLE I. Classification of glioblastoma and brain metastases

Reference	Methodology	Findings
[24]	SVM and LASSO regression	Accuracy: 90% .
[25]	SVC and MLP models on multimodal MRI	MLD model accuracy: of 69.2% .
[26]	Radiomics-based ML models and DNN	DNN accuracy:95.6%
[27]	Handcrafted and deep learning radiomics (HCR)(DLR)	Effective classifiers using HCR + DLR features.
[28]	Oxygen metabolic radiomics + Deep CNN	Efficient for comparing GB vs. BM.
[29]	MRI analysis with FLAIR and ADC ratios	Differentiated mGBM from BM using specific MRI and ADC values.
[30]	ResNet101 and VGG19 models	ResNet101 accuracy: 83%, VGG19 accuracy: 81%.
[31]	ML classifier and logistic regression.	ML classifier accuracy: 80% on test set.

angle evolution (SPACE) pictures. The Table II illustrates latest studies in the field of BM Detection using black-blood imaging.

C. Automated BM Detection & Segmentation using ML/DL techniques

Several studies have explored the potential of deep learning algorithms to accurately detect and classify brain metastases on medical imaging data.Recent research has revealed that applying ML (machine learning) and/or DL (deep learning) techniques to detect and segment brain metastases yields promising outcomes. Several ML and DL techniques, including SVM, Random Forest, CNN, U-Net architectures, have been assessed for their performance in segmenting brain tumours on MRI scans. Rudie et al.[35] conducted a groundbreaking study wherein they developed and validated a neural network for automated intracranial metastasis detection and segmentation on brain MRI scans, particularly those utilised for planning stereotactic radio-surgery treatment. Similarly, a study by Sommer et al. [36] developed a unique strategy to identify metastases at high risk of progression during follow-up by combining radiomics and machine learning. The Table III shows latest research along with key findings in this area.

3. Methodology

The integration of deep learning algorithms in the diagnosis and treatment of brain metastases has the potential to improve patient outcomes by facilitating early and accurate diagnosis and optimizing treatment plans. The methodology for implementing and evaluating the U-Net model for BM segmentation involves several key steps as shown in Figure 2. Initially, input images, including T1w (T1-weighted), T2w (T2-weighted), T1ce (T1-contrast enhanced), and FLAIR modalities, are gathered [41]. These images undergo data pre-processing, which includes resizing and normalization to ensure consistency and improve model performance.

Subsequently, the dataset is split into training-67%, testing-13%, and validation-20% sets to facilitate robust model training and evaluation. The core of the approach is the use of the U-Net model, a prominent convolutional

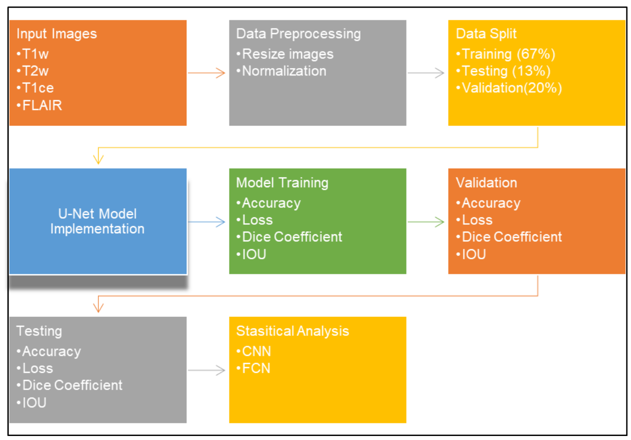

Figure 2. Proposed Research Methodology

neural network architecture built for segmentation. The model has been trained using the training dataset, and its performance is measured using measures like accuracy, loss, Dice coefficient, and Intersection over Union (IOU). Validation is conducted concurrently to tune model parameters and prevent over-fitting, using the same performance metrics. Post-training, the model undergoes rigorous testing to evaluate its final performance on unseen data, ensuring the evaluation metrics of accuracy, loss, Dice coefficient, and IOU are satisfactory. Finally, a comparative analysis is performed against other established models, including (CNN) Convolutional Neural Networks and (FCN) Fully Convolutional Networks.

A. Dataset

This research leveraged a comprehensive neuroimaging dataset comprising records from 413 patients collected from The University of California San Francisco Brain Metastases Stereotactic Radiosurgery (UCSF-BMSR) MRI Dataset[41]. The dataset includes 560 MRIs, encompassing diverse modalities such as FLAIR (Fluid-Attenuated Inversion Recovery) , T1w (T1-weighted), (T2w) T2-weighted, (T1ce) T1-contrast enhanced scans. This annotated dataset, collected between January 1, 2017, and February 29, 2020, supports automated detection and treatment planning, with

TABLE II. BM Detection using black-blood imaging

Reference	Methodology	Findings
[32]	DL-based detection algorithm with T1ce data	High sensitivity in detecting BM.
[21]	FDA-approved AI segmentation software	Achieved efficiency gains (55.6% in PTVs, 75.8% in OARs).
[33]	Medical Mind software	Modified accuracy:81.3% (91 from 112).
[34]	Comparison of CNN performance using BB and T1 CE MRI.	BB CNN: 92.3% accuracy, AUC 0.869; CE T1 CNN: 85.5% accuracy, AUC 0.534.

TABLE III. BM Detection & Segmentation using MLDL techniques

Reference	Methodology	Findings
[37]	3D-FCN (Fully Convolutional Network)	sensitivity: 0.96 ± 0.03, specificity: 0.99 ± 0.0002, dice ratio: 0.85 ± 0.08
[35]	3D-UNet CNN	Achieved median Dice score:0.75 with high correlations between manually segmented and projected volumes.
[36]	SVM	Improved mean AUC score from 0.53 to 0.74.
[38]	Multi-scale cascaded CNN using 3D-enhanced T1-weighted MR images.	Demonstrated robustness across internal and external datasets.
[39]	PCA, LR, SVM, RFC models	RFC model with multi-class features illustrated high efficiency with average F1 scores = 0.98.
[40]	InceptionResNetV2 network, recurrent or transformer network	Insightful outcome prediction with attention to spatial dependencies between MRI slices
[20]	3D CNN based on DeepMedic.	Automated segmentations showed good volumetric correlation with manual segmentations.
[23]	Deep Neural Network Ensemble learning model	Models trained on pooled data offer balanced predictive performance with ROC AUC=0.88±0.04.

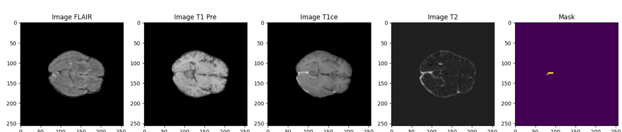

Figure 3. Dataset Sample

data and code publicly available for further research. The sample images studied with nibabel libraries (specifically designed for study of neuro imaging) have been shown in Figure 3.

The primary cancer sites mentioned in the dataset are lung cancer, breast cancer, melanoma and the pie chart for this distribution is demonstrated in Figure 4. below. The pie chart illustrates the distribution of primary cancer types among a given population. The largest segment represents lung cancer, which accounts for 39.0% of the cases. Breast cancer follows with a significant portion of 24.5%. Melanoma constitutes 16.3% of the cases, indicating its notable presence in the population. Renal cancer is less prevalent, making up 4.3% of the total cases. The remaining 15.8% are categorized under 'Others,' encompassing various fewer common types of primary cancers such as Esophogeal, Thyroid, GU Urothelial, Neuroendocrine etc.

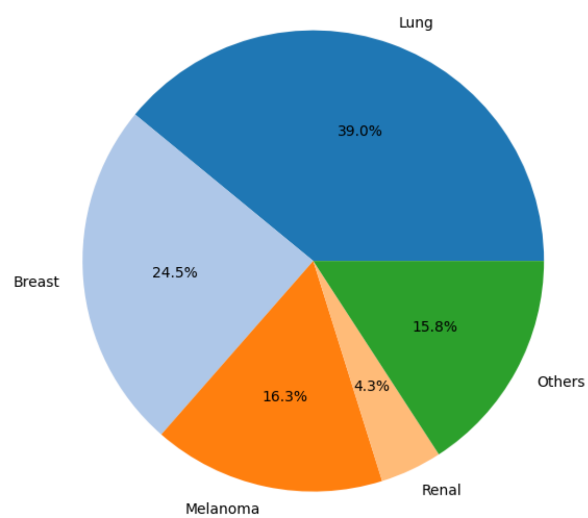

Figure 4. Primary Cancer Types

1) Data Preprocessing

The data preprocessing pipeline ensure the homogeneity and suitability of the dataset for effective model training. Each 3D volume was resized to a standardized 256x256 pixel format to ensure equal spatial dimensions, which are

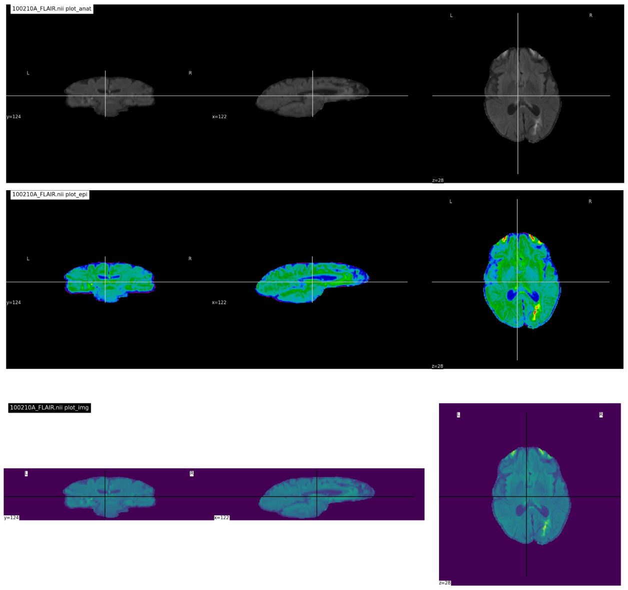

Figure 5. Resized Images

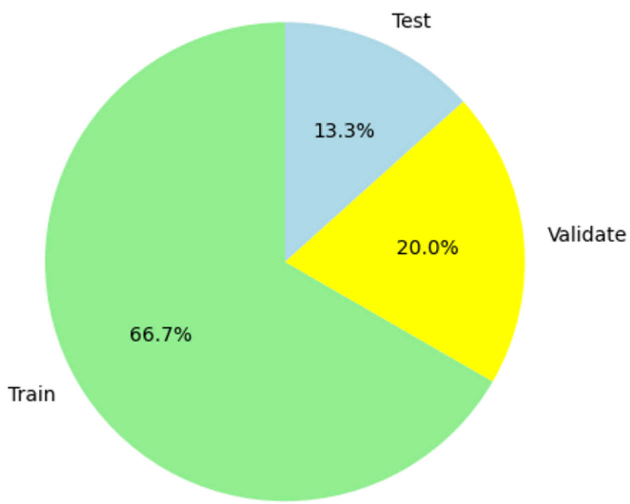

Figure 6. Data Distribution

critical for model consistency. To achieve homogeneity, intensity levels across all modalities were normalized, which facilitated convergence during training and optimized the learning process across multiple input feature sizes. Some sample resized images are visible in Figure 5

The dataset was rigorously separated into training (n=280), validation(n=83), and test (n=50) sets as shown in Figure 6 to ensure a balanced distribution of samples across all classes while also preserving representative subsets for robust model training and evaluation.

B. U-Net Architecture

The deep learning model architecture for automated BM segmentation on MRI scans utilize the U-Net architecture [35] with an attention mechanism, a well-established framework for semantic segmentation tasks as demonstrated in Figure 7. The encoder component of the U-Net employs convolutional blocks followed by max-pooling layers, with batch normalization to enhance stability during training. Attention mechanisms are strategically integrated into the encoder to focus on salient regions, improving feature capture. Dropout layers are introduced to mitigate over fitting, while a bottleneck layer condenses high-level features. The decoder, responsible for spatial reconstruction, utilizes upsampling blocks and skip connections to leverage both low-level and high-level features. The output layer generates probability maps for each class, facilitating segmentation into categories such as NECROTIC/CORE, EDEMA, and ENHANCING. In addition, the model's robustness is increased by the application of data augmentation techniques, and its optimal performance is guaranteed through hyperparameter adjustment. Custom metrics like the Dice coefficient and loss functions such as categorical cross-entropy are employed for evaluation and optimization, ensuring precise and reliable segmentation results. This comprehensive approach significantly enhances the model's ability to accurately delineate complex brain structures in MRI scans.

With a learning rate of 0.001, the Adam optimizer [42] is used during training to provide effective convergence and stability. Callbacks for adaptive learning rate change the learning rate dynamically in response to performance measurements, and early training termination stops overfitting by interrupting training when gains reach a plateau. Furthermore, logging callbacks keeps a close eye on the training process, recording important data and displaying performance trends to help with optimisation and debugging. Together, these tactics provide a strong training program that adjusts to the specifics of the task and guarantees the best possible model performance.

The training procedure involves data handling through a custom data generator to efficiently manage large datasets without memory overflow. This generator ensures continuous and balanced data feeding, maintaining diverse and representative batches throughout training. The model is trained over multiple epochs, with callbacks ensuring optimal learning rate adjustment, early stopping, and logging. This iterative process allows the model to progressively learn and adapt to the complexities of brain metastases segmentation. The architecture and training procedure enable accurate delineation of tumor regions and subsequent classification, significantly enhancing the accuracy of segmentation tasks. Personalised prognostic assessments are supported by this foundation, which incorporates patient-specific data to enhance clinical outcomes and guide treatment decisions. In addition, the model's generalizability is enhanced by the integration of sophisticated data augmentation and regularisation approaches, rendering it an effective

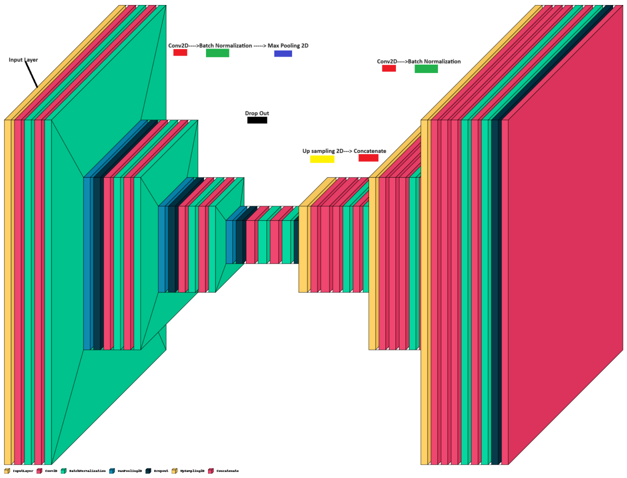

Figure 7. U-Net Model Architecture

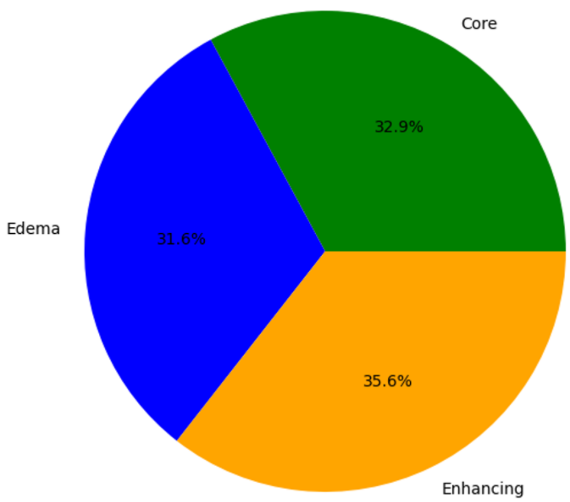

Figure 8. U-Net predicted Segmentation

tool in the field of medicine.

4. Results and Analysis

The total time taken for training the U-Net model was approximately 20 hours. The model exhibits distribution of predicted BM segmentation i.e. shown in Figure 8 categorizing different regions into three segment classes i.e. core/ necrotic, edema and enhancing [43]. The 'Enhancing' region constitutes the largest portion, accounting for 35.6% of the segmentation followed by the 'Core' region, which makes up 32.9% of the segmentation. The 'Edema' region represents 31.6% of the total segmentation. These outcomes demonstrate how well the model can distinguish and detect different tumour regions. Furthermore, evaluation metrics such as the Dice coefficient were employed to assess the segmentation performance, which showed excellent accuracy and consistency throughout the test set.

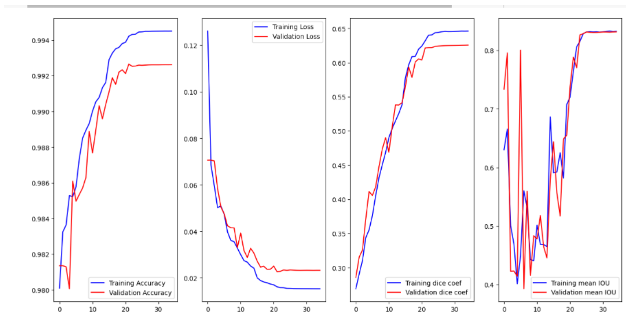

Figure 9. Evaluation Metric Curves using U-Net CNN

A. *Evaluation Metrics*

A comprehensive set of performance metrics, including accuracy, mean Intersection over Union (IoU), and class-specific dice coefficients, were calculated to assess the model's segmentation capabilities thoroughly. These metrics provided a nuanced understanding of the model's proficiency in delineating different tumor regions.

- Overall Accuracy: Demonstrating a remarkable accuracy of 99.75%, the model showcases its proficiency in distinguishing between tumor and non-tumor regions.
- Average Loss: The model achieved an impressively low average loss of 0.0052, indicative of its robust learning during the training phase.
- Average Intersection over Union (IOU): The average IOU of 96.81% attests to the model's precise segmentation capabilities.
- Average Dice Coefficient: A noteworthy average Dice Coefficient of 64.49% underscores the model's proficiency in capturing the intricate details of tumor boundaries.
- Average Precision: The model exhibits high precision at 99.75%, emphasizing its ability to minimize false positives.
- Average Sensitivity: With an average sensitivity of 99.70%, the model demonstrates its effectiveness in capturing true positives.
- Average Specificity: The model's high specificity of 99.90% highlights its capacity to accurately identify true negatives.

The results illustrated in Figure 9 revealed that the developed U-Net model shown incredibly low average loss of 0.0052, showing strong learning during training. The overall accuracy was very high at 99.75%, demonstrating the model's ability to discriminate between tumour and non-tumor regions. The average Intersection over Union (IOU) was 96.81%, demonstrating the model's accurate

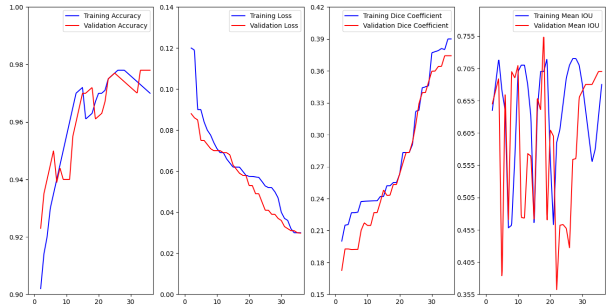

Figure 10. Evaluation Metric Curves using Traditional CNN

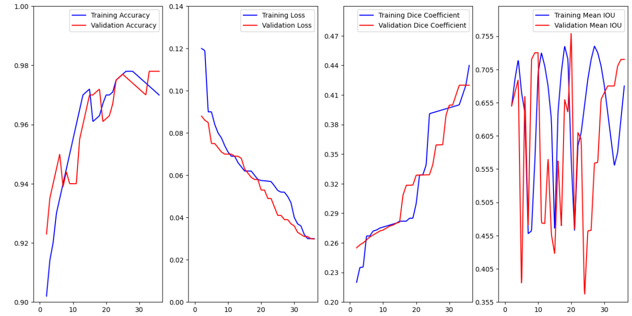

Figure 11. Evaluation Metric Curves using FCN

segmentation capabilities. Furthermore, the average Dice Coefficient was an impressive 64.49%, demonstrating the model's ability to capture the complex intricacies of tumour boundaries.

B. Comparative Analysis

To benchmark the proposed methodology, a comparative analysis is conducted against existing state-of-the-art segmentation models i.e. CNN (Convolutional Network) and FCN (Fully Convolutional Network) on the same dataset. The comparison focused on key performance metrics such as accuracy, Intersection over Union (IoU), Dice Coefficient, and computational efficiency. The Table IV shows that the U-Net CNN model demonstrates better performance compared to both the Traditional CNN and the Fully Convolutional Network (FCN). In terms of accuracy, the U-Net CNN outperforms the other models on both the training (0.9975) and validation (0.993) datasets. Moreover, the loss values for the U-Net CNN are also the lowest (0.0052 for training and 0.0025 for validation), which suggests that its predictions are closer to the true values. Furthermore, the U-Net CNN significantly outperforms the other models in the Dice Coefficient, with scores of 0.6449 for training and 0.631 for validation, which reflects its superior ability in handling imbalanced datasets by measuring the overlap between predicted and true regions. Similarly, the U-Net CNN maintains the highest Intersection over Union (IOU) values (0.9681 for both training and validation), indicating its effectiveness in accurately segmenting the data.

The Traditional CNN and FCN models show lower accuracy, higher loss, and substantially lower Dice Coefficient and IOU values, particularly highlighting the Traditional CNN's weaker performance in segmentation tasks compared to the more specialized U-Net architecture.

The traditional CNN model shown in Figure 10 achieved an accuracy of 96.76% with a loss of 0.038, a Dice Coefficient of 38.8%, and an Intersection over Union (IOU) of 70.7%. During validation, the model maintained a high accuracy of 97.78%, with a slightly reduced loss of 0.036. The Dice Coefficient and IOU during validation were 37.2% and 70.5%, respectively. Similarly, Figure 11 demonstrated the performance metric curves for Fully Convolutional Network (FCN) that achieved an accuracy of 96.99%, with a loss of 0.035, a Dice Coefficient of 44%, and an Intersection over Union (IOU) of 69.99%. In the validation phase, the model maintained a high accuracy of 97.00%, with a slightly higher loss of 0.32. The Dice Coefficient and IOU during validation were 42.3% and 70.3%, respectively.

The performance metric curves, illustrates that the U-Net CNN model shown in Figure 9 demonstrates superior performance compared to both the Traditional CNN shown in Figure 10 and the Fully Convolutional Network (FCN) shown in Figure 11. The U-Net CNN consistently achieves higher accuracy and Dice Coefficient values, as well as lower loss values, indicating more precise and reliable predictions. Additionally, the Intersection over Union (IOU) scores for the U-Net CNN are notably higher, further highlighting its effectiveness in segmentation tasks. The performance curves visually reinforce these findings, showing a clear distinction in the performance trends of the U-Net CNN over the other models.

5. Conclusion

This study presents a comprehensive approach for the automated BM segmentation using the U-Net CNN model, demonstrating its superior performance compared to Traditional CNN and Fully Convolutional Network (FCN) models. The U-Net CNN model achieved remarkable results, with the highest accuracy, lowest loss, and superior metrics in Dice Coefficient and Intersection over Union (IOU) across both training and validation datasets. The performance curves further validate these findings, illustrating the model's consistency and reliability in segmenting brain metastases. The study highlights the importance of accurate segmentation in improving clinical outcomes, as precise delineation of tumor regions is crucial for effective treatment planning and prognosis. The U-Net CNN's ability to handle imbalanced datasets and its enhanced precision in assessing treatment success underscores its potential for real-world clinical applications. Moreover, the study's methodology, which includes a detailed data preprocessing pipeline and a robust training and evaluation strategy, ensures the model's generalizability and applicability to diverse datasets. The rigorous comparative analysis with Traditional CNN and FCN models emphasizes the U-Net CNN's advanced capabilities, making it a valuable tool in the diagnostic arsenal

TABLE IV. Comparative Performance Metrics of U-Net CNN, Traditional CNN, and FCN

Model		Accuracy	Loss	Dice Coefficient	IOU
U-Net CNN	Training	0.9975	0.0052	0.6449	0.9681
	Validation	0.993	0.0025	0.631	0.9681
Traditional CNN	Training	0.9676	0.038	0.388	0.707
	Validation	0.9778	0.036	0.372	0.705
FCN	Training	0.9699	0.035	0.44	0.6999
	Validation	0.97	0.32	0.423	0.703

for brain metastases. In conclusion, the U-Net CNN model offers a significant advancement in the automated detection and segmentation of brain metastases, contributing to the enhancement of diagnostic tools and ultimately improving patient outcomes through timely and accurate decision-making. Future research should focus on further refining the model, exploring additional imaging modalities, and validating its performance in larger, more diverse patient cohorts to ensure its widespread clinical adoption.

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