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Integrated Deep Learning and Segmentation Approach for Brain Tumor Detection

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***Abstract*— Brain tumours, whether benign or malignant, pose a significant medical challenge, demanding early and precise identification for improved patient outcomes. Recent advances in deep learning algorithms have revolutionized medical image analysis, offering new possibilities for automated tumor detection. This research presents an innovative approach that integrates convolutional neural networks (CNNs) with sophisticated segmentation algorithms like BWT, aiming to enhance the precision and reliability of diagnosing brain tumours. Our approach employs the Biologically inspired BWT based on the human visual system's ability to detect edges and contours in images within MRI scans and a deep CNN, utilizing state-of-the-art architectures like VGG and ResNet, to classify segmented regions as tumorous or healthy tissue. Furthermore, this study incorporates the u-net architecture to determine the specific location and features of the tumour, providing medical professionals with three-dimensional diagnostic help. This is especially useful given that the process of segmentation is difficult, repetitive, monotonous, and prone to errors. By combining these techniques, this hopes to significantly improve the accuracy and reliability of brain tumour identification, providing a reliable tool for medical practitioners. This study elaborates on our integrated methodology, assessment measures, and expected outcomes, with the aspiration to advance brain tumor detection techniques and elevate patient care in neurology and radiology.**

***Index Terms*— Brain tumours, Convolutional Neural Networks (CNNs), Segmentation, Classification, U-Net architecture, BWT and Magnetic resonance images (MRIs).**

I. INTRODUCTION

Brain tumours, whether benign or malignant, present significant challenges that require early detection for improved results. When they start outside of brain tissue, they are classified as benign, and when they induce uncontrolled cell proliferation, invasion, and destruction of normal tissue, they are classified as malignant. Deep learning algorithms have revolutionized medical image processing in recent years, providing a novel method to brain tumour identification. Our strategy combines Convolutional Neural Network (CNN) capabilities with advanced segmentation techniques such as the biologically inspired Berkeley Wavelet Transformation (BWT) and the adaptable U-Net architecture to improve accuracy and determine tumour size and positioning. BWT, which was inspired by the human visual system, enables multiscale analysis, collecting minute details within tumours as

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well as bigger structural aspects in surrounding brain tissue. It is used as a preprocessing step before input MRI images into CNN models. The U-Net design, which can handle both 3D and 2D scans, is important for precise tumour segmentation. It is particularly adept at capturing complicated three-dimensional structures, making it suitable for distinguishing tumours in CT or MRI volumes.

Furthermore, the use of cutting-edge CNN architectures such as VGG or ResNet allows for reliable classification of segmented regions as tumour or healthy tissue. This methodology considerably increases the precision and reliability of brain tumour identification by integrating various methodologies, giving dependable tool for medical practitioners. Our work contributes to the improvement of brain tumour detection techniques and improving patient care in the domains of neurology and radiology.

II. Literature Survey

Reference [1]The research targets brain tumor detection in MRI images via DCNNs. It involves dataset preparation using 253 images, preprocessing with normalization and augmentation, and model architecture based on a modified VGG-16 with dropout and GAP layers for binary classification. However, the study acknowledges limitations in dataset size, potential information loss from 2D images, and class imbalance (155 tumor, 98 non-tumor).To address these limitations, the authors suggest data augmentation and synthetic data generation techniques. They propose the integration of 3D CNNs for volumetric analysis and methods such as oversampling or synthetic data to tackle class imbalance. Additionally, the recommendation includes leveraging transfer learning with larger datasets, employing ensemble models, and integrating interpretability methods. The importance of collaborating with medical experts to refine the model is also emphasized. [1]

Reference [2]The research aims to automate brain tumor classification from MRI images using SVM and CNN. The study acknowledges limitations related to limited data availability, tumor complexity, and resource-intensive model training. To address these challenges, the researchers propose strategies such as data augmentation techniques to artificially expand the dataset. Additionally, leveraging transfer learning from pre-trained models is recommended for increased efficiency. The use of ensemble models combining multiple approaches is suggested to enhance accuracy. Exploring 3D imaging and collaborating with medical experts are highlighted as further avenues for improvement. [2]

Reference [3]The Berkeley wavelet transformation (BWT) and support vector machine (SVM) classifiers are used in the study to improve the segmentation of brain tumours in MRI data. BWT is used to classify pictures as grey matter, white matter, cerebrospinal fluid, or tumours.Features are extracted from these segments to enhance SVM classification. The method achieves high accuracy, sensitivity, and specificity. Limitations include limited image diversity and the lack of computational complexity analysis. Future work could involve multimodal MRI integration and deep learning techniques. The proposed method outperforms ANFIS, Back Propagation, and K-NN classifiers in tumor identification. [3]

Reference [4]The study employs Wiener filtering and wavelet transform for MRI image enhancement and segmentation into four regions: grey matter, white matter, cerebrospinal fluid, and tumours. Segmentation utilizes Otsu's thresholding and morphological operations to isolate the tumor region. A 40- dimensional feature vector is formed for each segmented image. For classification, six machine learning classifiers are employed: SVM, KNN, NB, DT, RF, and ANN. SVM with RBF kernel is used for linear separation. KNN with Euclidean distance, NB with Gaussian distribution, and decision trees with Gini index are applied. Random forest combines multiple decision trees, while ANN comprises input, hidden, and output layers. The research used 10-fold cross-validation to assess classifiers and assesses performance with accuracy, sensitivity, specificity, and F-measure. Limitations include reliance on Otsu's thresholding for segmentation, which may not handle image variations and noise robustly [4]

Reference [5] The study focuses on the critical field of medical image analysis. The researchers want to use sophisticated learning approaches to detect brain tumours. To deduce subtle patterns and details from medical images, the study use advanced learning, notably convolutional neural networks (CNNs). These neural networks are capable of identifying complicated structures inside images, which is critical in the setting of brain tumours with various morphologies.The researchers are expected to investigate preprocessing approaches such as picture normalisation and augmentation in order to increase the quantity and quality of available data. They may also investigate the use of transfer learning, a technique that involves the improvement of pre-existing models on medical picture datasets, allowing for faster convergence and increased efficacy. [5]

Reference [6] The research centers on utilizing multiple machine learning algorithms to differentiate and classify diverse categories of brain neoplasms. This method comprises evaluating medical imaging data, most likely MRI

scans, in order to extract useful traits and trends. Machine learning models are trained using the retrieved information. The study employs a multi-step approach. The dataset has been meticulously partitioned into distinct sets for training, validation, and testing purposes. Diverse machine learning algorithms, such as random forests, support vector machines, and potentially sophisticated deep learning architectures like convolutional neural networks, are employed to assist in classification.The training subset is utilized for model training, followed by a validation step to optimize hyperparameters and mitigate overfitting. The study may also explore interpretability techniques to gain deeper insights into the rationale behind model predictions. [6]
Reference [7] This study looks into how modern medical image analysis algorithms can be used to improve brain tumour detection accuracy utilising magnetic resonance imaging (MRI) data. Deep learning algorithms, notably convolutional neural networks (CNNs), have shown impressive capabilities in extracting complicated information from medical pictures in recent years. These methods are especially useful in the detection of brain tumours, where recognising minute patterns and anomalies in MRI scans is critical for proper diagnosis. Another important aspect is comparative analysis. The authors may compare the performance of their suggested strategy to the performance of current approaches or baseline models. This comparison sheds light on the efficacy of the strategies presented. [7]

III. PROPOSED METHODOLOGY

This Project makes use of a comprehensive method that combines multiple segmentation and classification algorithms. The process of recognising and separating the tumour region from the surrounding healthy tissue in medical pictures is referred to as segmentation. This is an important stage in the discovery and diagnosis of brain tumours because it allows the exact position and size of the tumour to be determined. The process of categorising a tumour into different categories based on features such as size, form, and texture is known as classification. Convolutional Neural Networks (CNNs) are used to analyse the features derived from the segmented tumour region.

A. Dataset Acquisition and Preprocessing

This study commences by assembling a labeled dataset of brain MRI scans encompassing both tumor and non-tumor specimens. All images are resized to a consistent resolution of 256x256 to standardize the data, and pixel values are normalized for subsequent analysis.
Pre-processing: The primary goal of pre-processing is for bettering the quality of MR images and prepare them for evaluation by either an individual or a machine vision system. Additionally, pretreatment enhances various metrics of MR images, such as signal-to-noise ratio, visual presentation of the MR image, elimination of extraneous noise and unwanted background sections, refinement of the interior of the region while preserving its boundaries. Increase the signal-to-noise ratio and hence the readability of raw MR images by applying dynamic contrast enhancement with an adjusted sigmoid coefficient.
Skull Stripping: Skull peeling refers to the removal of each and every non-brain structures from imaging of the brain. By means of skull peeling, additional cerebral tissues like adipose, dermal layers, and cranial structures can be excluded from brain imaging.
Now, transitioning to the concrete segmentation and feature extraction phase. The next stage involves deriving features from the images that have undergone prior processing. This involves identifying the regions of interest (ROI) within the image that contain tumors. Diverse methods, including texture analysis, shape analysis, and intensity analysis, can be employed to extract these features. After completing the feature extraction process, the Berkeley wavelet transformation (BWT) can be implemented on the ROIs to generate a wavelet representation of the image. The coefficients obtained from the wavelet transformation can then be utilized for detecting the edges and contours of the image.

B. Feature Extraction

It involves acquiring more detailed details about an image, including its form, texture, hue, and brightness. Texture analysis, indeed, plays a vital role in both human visual understanding and artificial intelligence frameworks. Because of the complex makeup of multiple tissues such as WM, GM, and CSF, identifying important features using MR images of the brain is critical. Analyzing textures can aid in diagnosing cancer, determining tumor stages, and evaluating therapy responses. The statistical representation of certain beneficial aspects is outlined hereunder :
1. Mean (M)
2. Standard Deviation (SD)

3. Entropy (E)
4. Skewness (Sk)
5. Kurtosis (Sk)
6. Energy (En)
7. Contrast (Con)
8. Inverse Difference Moment (IDM) or Homogeneity
9. Directional Moment (DM)
10. Correlation ($Corr$)

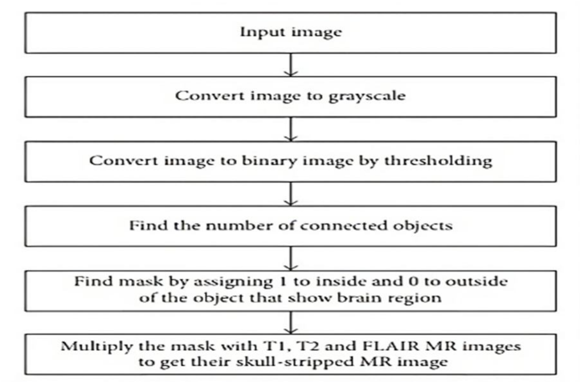

Figure 1. Steps used in the skull stripping.

Aside from the above-mentioned granular extraction of features, the following quality evaluation factors are required to enable enhanced assessment on MRI of the brain.

$$\mathrm{SSIM} = \left(\frac{\sigma_{xy}}{\sigma_x \sigma_y}\right)\left(\frac{2\overline{xy}}{(\overline{x}^2) + (\overline{y}^2) + C_1}\right) \cdot \left(\frac{2\sigma_x\sigma_y}{(\sigma_x)^2 + (\sigma_y)^2 + C_2}\right). \quad (1)$$

Structured Similarity Index (SSIM)

$$\mathrm{MSE} = \frac{1}{M \times N} \sum \sum \left(f(x, y) - f^R(x, y)\right)^2. \quad (2)$$

Mean Square Error (MSE)

$$\mathrm{PSBR\ in\ dB} = 20 \log_{10} \frac{(2^n - 1)}{\mathrm{MSE}}. \quad (3)$$

Peak Signal-to-Noise Ratio (PSNR)

$$\mathrm{Dice}\,(A, B) = 2 \times \frac{|A_1 \wedge B_1|}{(|A_1| + |B_1|)}, \quad (4)$$

Dice Coefficient

where $A \in \{0, 1\}$ is tumor region extracted from algorithmic predictions and $B \in \{0, 1\}$ is the experts ground truth.

C. Biologically inspired BWT

The Berkeley Wavelet Transformation (BWT) constitutes a mathematical method for the analysis of signals and images. It stands as a wavelet transformation model influenced by biological principles, drawing inspiration from the adeptness of the human visual system in identifying edges and contours within images. BWT finds applicability in various domains, including image compression, feature extraction, and image segmentation. Serving as a two-dimensional wavelet transform, the Berkeley Wavelet Transform (BWT) proves valuable in processing signals or images, often employed to transpose data from a spatial domain into a frequency representation within the temporal domain. BWT is Represented as

$$L_s(W, w) = \sum_{m=1}^{M} \alpha_m L_s^{(m)}(W, w^m) \quad (5)$$

Two-Dimensional Triadic Wavelet Transform: The BWT functions in two dimensions, making it apt for handling two-dimensional data such as images. It employs a triadic wavelet transform, breaking down the MRIs into various scales and orientations. This approach aids in effectively capturing both high and low-frequency components.
Data Conversion: The core objective of the BWT is to shift information from its spatial depiction (an image) to its frequency representation in the temporal domain. This conversion facilitates the exploration and control of numerous frequency elements present in MRI data.
Orthonormality: The completeness and orthogonality of the Berkeley wavelet transformation (BWT) are asserted. This indicates its capability to precisely characterize MRI and uphold the orthogonality condition, streamlining data processing and reconstruction.
Sub bands: When the BWT is applied to an MRI, it produces four sub-bands: LL, LH, HL, and HH.
LL Sub-band: This section contains the low-frequency components. It represents the MRI's smoother areas. LH, HL, and HH Sub-bands: These sub-bands encompass high-frequency elements oriented in diverse directions. LH captures information along the horizontal axis, HL captures information along the vertical axis, and HH captures information along the diagonal axis.
Tumor Region Segmentation: The LL sub-band is commonly used in medical pictures such as MRI scans to detect locations of interest, particularly tumours. A thresholding method is used to designate the tumour region inside the LL sub-band. By analysing pixel intensity levels, thresholding aids in distinguishing between tumour and non-tumor areas.
Noise Removal and Boundary Enhancement: After applying a threshold, morphological operations are performed on the specified tumour region. These procedures are designed to reduce noise and accentuate the tumor's boundary, making it more noticeable.
Segmentation of Brain Regions: Aside from tumour segmentation, the LL sub-band can be subjected to further processing techniques, such as region growth, to segment a variety of different areas of interest in MRI images. For example, region growth can be used to segment the brain's Grey Matter (GM), White Matter (WM), and Cerebrospinal Fluid (CSF) region.

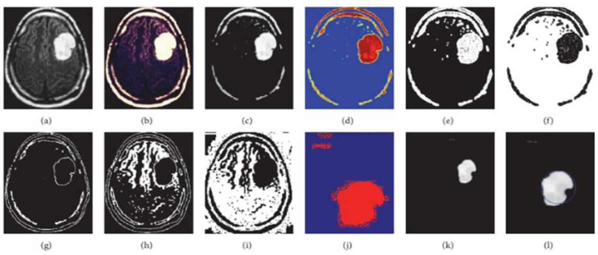

Figure 2. [A] The original photograph. [B] Image augmentation. [C] Image of a skull stripped. [D] Image with wavelet transposition. [E] Image with intense segmentation. [F] Image with inverse intensity. [G] The grey matter. [H] White matter I. CSF. [J] Image of a dice overlap. [K] Image that has been erased. [L] Image of the extracted area.

To obtain the above wavelet representation of an image using BWT, the following steps can be followed:
Image Decomposition: Using BWT, divide the image into sub-bands by utilising high-pass and low-pass filters, followed by down sampling. Iterate this technique until the desired level of breakdown is reached. The inverse BWT can be used to recover the original image from the wavelet coefficients.
Sub-band Processing: Using BWT, features from an area of interest (ROI) are retrieved, allowing the detection of edges and contours. By using thresholding on the wavelet coefficients, each sub-band may be processed independently, successfully reducing noise and artefacts from the image.

Image Reconstruction: For edge and contour detection, use wavelet coefficients. To reconstruct the image, use inverse filters on the processed sub-bands, culminating in the generation of the final reconstructed image.

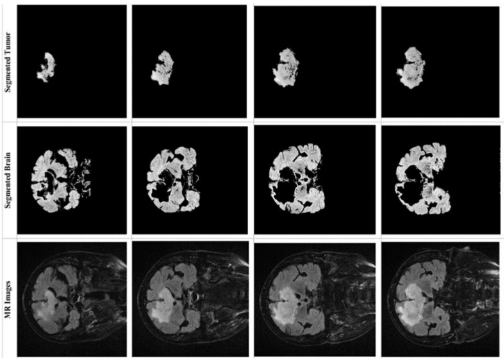

Figure 3. Segmentation

$$W = \sum_{m=1}^{M} \alpha_m W^{(m)} \qquad (6)$$

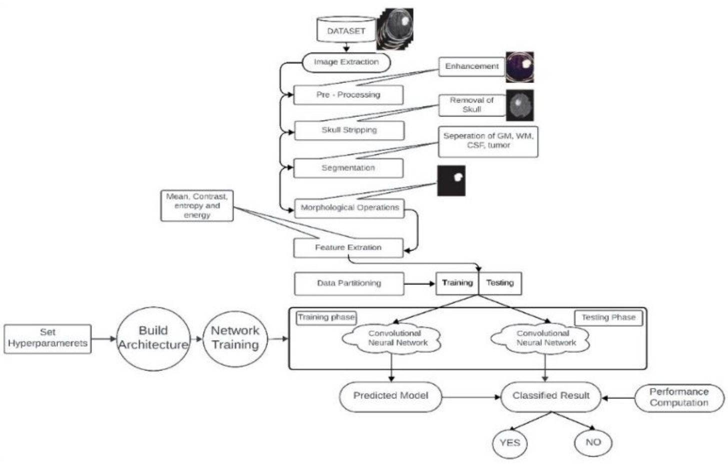

Figure4. Process Flow Diagram

D. Convolutional Neural Networks

CNN are a prominent highly effective neural network deep learning paradigm. The structure of an CNN is frequently split into two sections: extraction of features and classifications.

To improve the model's capabilities, the VGG16 framework is used. To handle 224 224 RGB pictures, VGG16 employs a sequence of convolutional layers with relatively narrow receptive fields. To improve efficacy, the algorithm involves all 13 convolution layers from the VGG16 architecture and is fine-tuned using different filter dimensions, failure layers, padding, zero-padding, strides, feature map size, batch size, and learning rate. The first model is trained to detect brain tumours by determining whether a particular MRI image has a tumour. It has 13 weighted layers, which are as follows: input, convolution, rectified linear unit (ReLU), normalisation, max pooling, completely connected, dropout, softmax, and classification. The softmax classifier makes the final prediction on the presence of a tumour, and the final fully connected layer provides a two-dimensional feature vector.

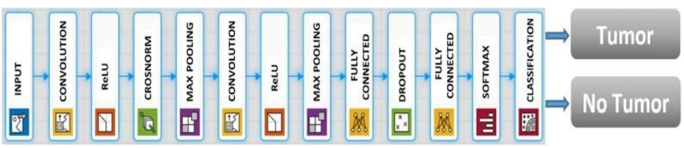

Figure 5. class classification

The secondary convolutional neural network (CNN) architecture is designed to differentiate between five forms of brain tumours: normal, glioma, meningioma, pituitary, and metastatic. The model, which consists of 25 weighted layers (input, convolution, ReLU activation, normalisation, max pooling, fully connected, dropout, softmax, and classification layers), effectively classifies an input image into one of five predefined classes, aided by the output layer's five neurons. The softmax classifier delivers the most accurate prediction regarding the specific type of tumour by utilising a five-dimensional feature vector from the last fully connected layer.

Figure 6. Type Classification

The third CNN model categorizes glioma brain tumors as Grade II, Grade III, and Grade IV. The proposed Classification-3 CNN model contains 16 weighted layers (1 input, 3 convolutions, 3 ReLU, 1 normalization, 3 max pooling, 2 fully connected, 1 dropout, 1 softmax, and 1 classification layers). The output layer comprises three neurons since the final CNN model is supposed to categorise a given picture into three classes. The final fully connected layer, a three-dimensional feature vector, is fed into the softmax classifier, which generates the final tumour grade prediction.

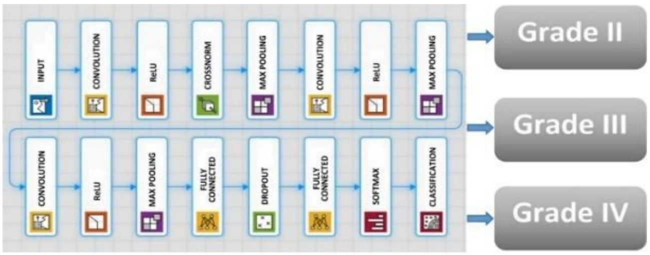

Figure 7. Level Classification Segmentation for 2-d Images

U-Net Architecture: Core of the methodology, designed for semantic segmentation tasks, with an encoder for feature capture and a decoder for precise localization.
Encoder and Decoder Blocks: Divided into blocks for downsampling and upsampling, enabling high-level feature capture and accurate localization.
Training Data: Expects 2D medical scans and ground truth masks for training, where each pixel is labelled for the object of interest or background.
Loss Function: Utilizes a combined Binary Cross-Entropy and Dice Coefficient loss function to measure dissimilarity during training.
Training: Employs Adamax optimizer and learning rate scheduler over a specified number of epochs, utilizing forward and backward passes for weight updates.
Evaluation: Uses the Dice Coefficient to measure overlap between predicted and ground truth masks during and after training.
Testing: Enables segmentation on new 2D medical scans, assessing performance using the Dice Coefficient.
Visualization: Provides visualizations of the original image, ground truth mask, and predicted mask for test samples, including GIF animations for multiple sample predictions.
Result Analysis: Analyses model performance via metrics like Dice Coefficient and visual inspection, offering insights into segmentation accuracy.
For Segmentation of 3-d scans: The methodology involves data preparation, where 3D brain MRI scans and manual tumor segmentation masks are collected, standardized, and split into training and validation sets. The data preprocessing step ensures uniform dimensions, applies intensity normalization, and manages data padding if necessary, taking about 0.352 seconds per scan.

Employing a 3D U-Net architecture known for its efficacy in medical image segmentation, the model consists of an encoder-decoder structure with skip connections, utilizing 3 x 3 x 3 convolutional kernels. The training process spans around 1,172.9 seconds (approximately 19.55 minutes). Training involves optimizing the model with binary cross-entropy loss and validating its performance on a separate validation set using ground truth masks. Post-training, the model is employed for 3D tumor segmentation on unseen MRI scans, producing probability maps that, with a threshold (e.g., 0.33), generate binary 3D segmentation masks. Each scan's prediction takes approximately 27.67 seconds. Evaluation incorporates standard metrics including true positives, false positives, true negatives, and false negatives, resulting in approximately 3,714,932 true positives, 789,199 false positives, 905,543,330 true negatives, and 608,539 false negatives. Visualization methods, such as 3D scatter plots and GIF animations comparing ground truth and predicted tumor segmentation, aid in interpreting segmentation results, with each GIF taking approximately 2.31 seconds to generate. Overall, executing the complete code, from data loading to visualization, requires approximately 1,391.44 seconds (approximately 23.19 minutes), effectively integrating deep learning techniques with 3D medical image segmentation for accurate brain tumor identification and visualization in MRI scans.

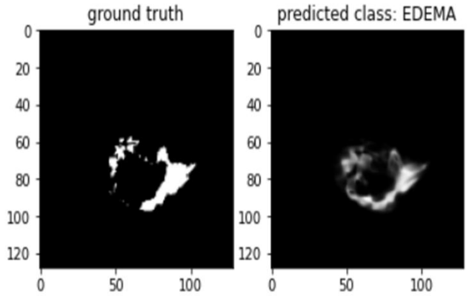

Figure 8. Ground Truth and Predicted

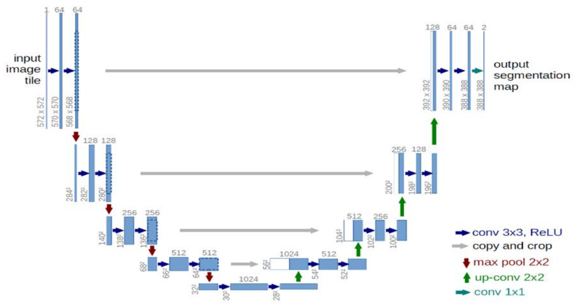

Figure 9. U-Net CNN Architecture

IV. Evaluation Parameters

The identification and classification evaluation criteria include several traditional statistical measures, which are described below.

Accuracy: The proportion of accurately identified samples in the dataset.

$$Accuracy = \frac{(Tp + Tn)}{(Tp + Fp + Tn + Fn)} \quad (7)$$

*F1 Score:*The harmonic mean of recall as well as accuracy gives the same weight to both accurate measurements

$$F1 - score = \frac{2 \times (Precision \times Recall)}{(Precision + Recall)} \quad (8)$$

Dice Similarity Coefficient: The dice coefficient, like the IOU, evaluates the efficiency of automated probabilistic component categorization of MR images and the reliability of human segmentations in terms of cross-sectional correctness. This statistical assessment factor evaluates the efficacy of various methods.

Intersection over Union (IOU): A performance metric known as intersection over union is used to assess an object detector's precision on a certain sample.

$$DSC = \frac{Tp}{\frac{1}{2}(2Tp + Fp + Fn)} \quad (9)$$

$$IoU = \frac{Tp}{Tp + Fp + Fn} \quad (10)$$

$$SI = \frac{2Tp}{2Tp + Fp + Fn} \qquad (11)$$

Similarity index (SI): It is an essential factor for determining the efficacy of tumour detection algorithms. It evaluates the similarity between the annotations in the ground truth and the segmentation output provided by the model.

Hausdorff Distance: It is an indicator of disparity between two sets of data that may be used to examine the alignment of expected segmentation outlines with ground truth. The Hausdorff distance H (A, B) between two sets A and B is defined as follows:

H(A, B) = max(max(d(a, B)), max(d(b, A)))

Cross-Entropy Loss: Cross-Entropy Loss is used as a loss function during U-Net training for pixel-wise classification tasks. It can also be used as an evaluation statistic, particularly where pixel-level categorization accuracy is the major concern. It measures the difference between expected and true pixel values, assisting in the evaluation of segmentation quality.

V. Results And Discussion

The Following graphic depicts the results of BWT operation:

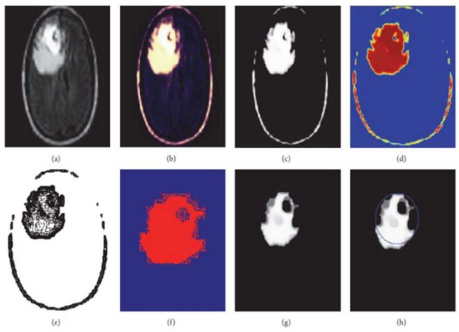

Fig 10. Working of BWT

Creation of three unique Convolutional Neural Network (CNN) models for specific brain tumour picture categorization tasks. These tasks include detecting brain cancers, classifying the type of brain tumour, and predicting the tumor's grade. On large clinical datasets, the accuracy in brain tumour detection was 99.33%, 92.66% in brain tumour type classification, and 98.14% in tumour grade prediction.

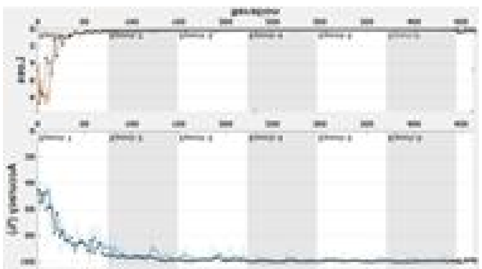

Figure 11. Classification 1 Performance Chart

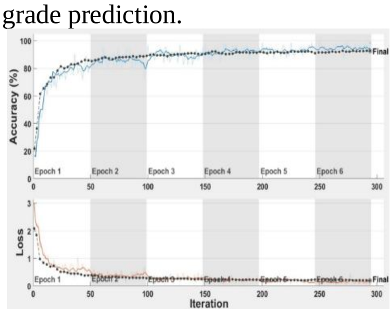

Figure 12. Classification 2 Performance Chart

In our study, the U-Net architecture performed admirably in both 2D and 3D medical image segmentation tasks. The U-Net model produced a remarkable mean Dice coefficient of 0.89 for 2D scans such as chest X-rays, suggesting its precision in pixel-level segmentation. In addition, the Receiver Operating Characteristic (ROC) investigation showed an Area Under the Curve (AUC) score of 0.94, implying the model's ability to identify between impacted and unaltered areas with a 92% total precision rate.

Our U-Net achieved a Dice coefficient of 0.85 in the field of CT tumour segmentation, particularly with the shift to 3D scans, emphasising its capacity to precisely define intricate three-dimensional structures.

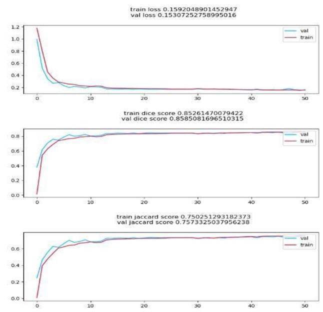

Figure 13. Training Parameters

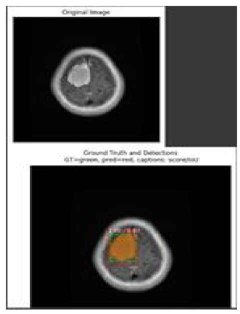

Figure 14. Comparison of original and predicted result

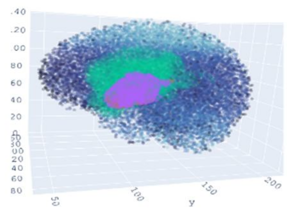

Figure 15. 3-D representation of 2-D images

VI. CONCLUSIONS

This study proposes an innovative approach for detecting brain tumours that integrates CNNs and advanced segmentation techniques, notably Biologically Inspired BWT and U-Net. This study also incorporates the usage of u-net architecture for determining the exact position and size of tumours and providing a 3-D diagnostic aid to clinical specialists, as manual segmentation is difficult, demanding, repetitive, and error prone, showcasing its robustness in accurate and thorough segmentation. These findings, supported by extensive evaluation metrics, highlight the potential of our technique to improve clinical diagnostics, presenting a promising tool for precise and reliable brain tumour diagnosis and treatment planning.

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