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ORIGINAL

Integrated neural-hybrid system for efficient tumor detection and object reconstruction

Sistema híbrido neural integrado para la detección eficaz de tumores y la reconstrucción de objetos

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ABSTRACT

In computer vision and robotics, reconstructing multi-view 3D images is essential for accurate object representation from 2D data. In the first study, optimised weights through Adaptive School of Fish Optimisation are combined with 2D and 3D networks to introduce a Residual Network-50 model for deep learning-based 3D image reconstruction. On the ShapeNet dataset, this method demonstrates superior accuracy (0,993), F-score (0,734), and IoU (99,3 %). Using Concurrent Excited DenseNet (CED)for feature extraction and Attention-Dense GRUs for prediction, the second study introduces the Concurrent Attentional Reconstruction Network(CARN) for reconstructing point clouds from single 2D images, achieving over 99 % accuracy with low EMD and CD values. By combining convolutional layers, inception modules, and attention mechanisms with preprocessing steps like Ex_NLMF for noise reduction and Up_FKMA for accurate disease area identification, the third method,Twin Attention-aided Convolutional Inception Capsule Network (TA_CICNet), performs exceptionally well in medical image reconstruction and classification when it comes to diagnosing brain tumours.

Keywords: 3D Reconstruction; Image Preprocessing; Medical Image Processing; Segmentation; Disease Detection.

RESUMEN

En visión por ordenador y robótica, la reconstrucción de imágenes 3D multivista es esencial para la representación precisa de objetos a partir de datos 2D. En el primer estudio, se combinan pesos optimizados mediante la optimización adaptativa de la escuela de peces con redes 2D y 3D para introducir un modelo de red residual-50 para la reconstrucción de imágenes 3D basada en el aprendizaje profundo. En el conjunto de datos ShapeNet, este método demuestra una precisión superior (0,993), F-score (0,734) e IoU (99,3 %). Utilizando la red concurrente excitada densa (CED) para la extracción de características y las GRU de atención densa para la predicción, el segundo estudio introduce la red concurrente de reconstrucción atencional (CARN) para reconstruir nubes de puntos a partir de imágenes 2D individuales, logrando una precisión superior al 99 % con valores bajos de EMD y CD. Combinando capas convolucionales, módulos de incepción y mecanismos de atención con pasos de preprocesamiento como Ex_NLMF para la reducción del ruido y Up_FKMA para la identificación precisa del área de la enfermedad, el tercer método,Twin Attention-aided Convolutional Inception Capsule Network (TA_CICNet), obtiene resultados excepcionales en la reconstrucción y clasificación de imágenes médicas cuando se trata de diagnosticar tumores cerebrales.

Palabras clave: Reconstrucción 3D; Preprocesado de Imágenes; Procesado de Imágenes Médicas; Segmentación; Detección de Enfermedades.

INTRODUCTION

Appropriating representation accuracy of object from the obtained data of 2D in the fields of robotics and computer visions is very much need while reconstructing 3D image in a multi-view.[7] In this process of duration features are being extracted and are transformed into the meshes of volumetric for 3D images. However, as previous research has shown, processing the same input images in different orders frequently produces inconsistent results.

These Procedures will adequately help us to generate and helps to avail the models of 3D over 2D imaging data in medical, for research improvement, planning the treatment and the capabilities for diagnosing in a better way.[1] In medical imaging, 3D reconstruction is crucial for a few reasons. Depending on the needs of applications ranging from design and entertainment to scientific research and medical imaging, 3D shapes representation combines geometric, surface, and occasionally volumetric representations. Every component helps to produce precise, intricate, and visually appealing three-dimensional representations of environments and objects.

Table 1. Combining diverse geometric elements shapes in 3D

Geometry Representation	Physical Struture of an Object(Vertices, Edges, Faces)	Meshes	Collection of Vertices which defines surface of object
		Point Clouds	set of points in 3D space useful for capturing complex surfaces
Surface Representation	Realistic Visualization	Textures	Color, Patterns Materials
		Normals	Enhance Visual Realism
Volume Representation	Interior space or volume of objects like medical Imaging or fluid Dynamics	Voxel Grids	3D Grids of small Cubes Stores Information about presence or properties of object
		Implicit Surfaces	Set of Scalar Function Describes Smooth Surfaces or Complex Shapes.
Level of Detail(LOD)	To Maintain Levels of Details	High Detail Models	Closeup Inspection or Rendering
		Low Detail Model	RealTime Application to Optimize Performance
Animations and Deformation	Movement of Objects	Animations	Change Shape OverTime
		Deformations	Modelling in response to forces or interactions
Metadata and Semantics	Enhances Utility in Application	Classification	Based on Shapes
		Search & Retrieval	Based on Specific Criteria

Table 2. 3D reconstruction techniques and their categorization

Category	**Techniques**
Geometric Methods	Stereo Vision - Shape from Shading - Shape from Texture - Shape from Contour - Shape from Motion (Structure from Motion) - Photometric Stereo
Volumetric Methods	Voxel-based Reconstruction - Signed Distance Functions (SDF) - Marching Cubes Algorithm
Point Cloud Methods	Laser Scanning (LiDAR) - Structure from Motion (SfM) - RGB-D Cameras
Deep Learning-based Methods	Convolutional Neural Networks (CNNs) - Generative Adversarial Networks (GANs) - Autoencoders - Graph Neural Networks (GNNs)
Multi-view Stereo	Passive Stereo - Active Stereo
Tomographic Methods	Computed Tomography (CT) - Magnetic Resonance Imaging (MRI)
Hybrid Methods	Combined Approaches (e.g., integrating geometric and volumetric methods)

To enhance the care and outcomes of patient betterment by improving identity capacity, manage, issues comprehend in medical are achieved by reconstruction of 3D.A few essential components are needed for efficient 3D reconstruction from photos. To grab the expansive information approximately for a scene or an object we require high in quality images, images with multi angle and resolution in high are needed.[13]

Algorithms of sophisticated and need of software is essential to precisely create a 3D model in which we extract features in pertinent way for processing the images. Sufficient processing power is required to manage the demanding tasks. Data calibration, distortion for correct lens and accuracy is needed to ensure for geometric accuracy. By the usage of hardware in specialized way such as structured light scanners or stereo cameras we can increase the precision of reconstruction. Modelling in 3D, computer vision and for image processing proficiency is essential to enhance the process of reconstruction and to guarantee the outcomes precisely.

Motivation

In Medical imagining mostly 3D reconstruction is used to identify any disease in medical science and to enhance the care of patient. Precise diagnosis and disease tracking are made possible by detailed 3D views, especially in the early identification of minute tissue alterations.[11] Identification of tissue alterations are done in early minute are view detailed using 3D views for tracking disease and diagnosing precisely. Surgical precision improvement and treatment plans that can be individualized is supported by the treatment planning of 3D models. Long-term effects, treatment of insights efficacy and overtime the disease course can be tracked precisely which can be possible by 3D models. Advanced medical research by innovations fostering in diagnosis and treatment by including machine learning and AI for datasets are moreover very useful for reconstruction in 3D.

Table 3. Motivation from Various Techniques

Motivation	Description
Enhanced Diagnostic Accuracy	Detailed 3D views of anatomical structures improve understanding of spatial relationships and complexities, enabling precise detection, diagnosis, and monitoring of diseases.
Improved Treatment Planning	Risk reduction, precision enhancement, to resemble procedures that are complex and to plan well in advance for surgeons these 3D models are used. Some objective therapies can be effective in more as they can be treatments which are personalized plans that are developed by 3D models.
Early Disease Detection	Early detection of disease is facilitating such as tumors, profound tissue change and organs are focused .To enhance the diseases in most stage of treatable way screening is done comprehensively.
Enhanced Monitoring and Follow-up	Precise monitoring of disease progression or regression over time helps evaluate treatment effectiveness and make necessary adjustments. Continuous monitoring provides insights into long-term impacts.
Educational and Training Benefits	3D reconstructions serve as educational tools for medical training and help patients understand their conditions and treatment options through visualizations of their own anatomy.
Advancements in Medical Research	Diagnostics in medical and their treatments are further innovated which drives AI applications, machine learning to contribute for large in number of datasets, methods for treatments and new technologies in medical research are supported.

The application of 3D reconstruction in medical imaging significantly improves the accuracy of diagnosis, makes treatment planning easier, enables early disease detection, encourages continuous monitoring, and is beneficial for medical research and teaching.

3D reconstruction application in the field of medical imaging enhances the diagnosis accuracy, making planning treatment easier and monitor continuously encourages to detect disease in early stage. When taken as a whole, these innovations enhance patient outcomes and progress healthcare.

Structure of this suggested work: Section I presents an introduction followed by Section II, where an intense literature review of traditional methods is addressed. Section III addresses the proposed Neural Hybrid system model and disease detection model and describes about algorithms. Section IV handles the results and discussions of the contributed model. The conclusion of the work is summarized in Section V.

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Related Work

Table 4. Contributions of different authors and their key Findings			
Reference	**Overview**	**Key Findings**	**Contribution**
Zhang et al. (2020), "Deep Learning-Based 3D Reconstruction for Medical Imaging"	A deep learning method using CNNs to reconstruct 3D from 2D medical images.	Improved quality of reconstructed 3D images by minimizing artifacts and enhancing structural details, particularly for MRI and CT scans.	Developed a unique CNN architecture for reconstructing medical images, which performed faster and more accurately than previous algorithms.
Chen et al. (2019), "3D Reconstruction from CT and MRI Images Using Generative Adversarial Networks"	Investigates 3D reconstruction of medical images using GANs.	Produced highly realistic 3D models with better texture and detail preservation compared to traditional methods.	Demonstrated the capability of GANs to process various imaging modalities and generate high-quality 3D reconstructions from sparse or noisy input.
Lee et al. (2018), "Volumetric 3D Reconstruction Using Deep Learning for Medical Imaging Applications"	Presents a volumetric approach using deep learning to reconstruct 3D images from 2D slices of medical scans.	Improved volumetric accuracy and consistency across different slices, providing better continuity and anatomical correctness in reconstructed 3D models.	Showed how volumetric deep learning methods can integrate multiple 2D slices into coherent 3D structures.
Wang et al. (2021), "3D Reconstruction of Medical Images Using Autoencoders"	Utilizes auto encoders to enhance the robustness and detail of 3D reconstructions of medical images.	Auto encoders reliably produced accurate 3D reconstructions by effectively capturing intricate details and complex structures within the medical images.	Presented a novel application of auto encoders in medical imaging, demonstrating improvements in 3D model reconstruction quality.
Kumar et al. (2017), "Sparse Representation-Based 3D Image Reconstruction in Medical Imaging"	Explores a sparse representation approach for 3D reconstruction to improve image quality and reduce computational complexity.	Produced high-quality reconstructions with fewer data requirements, making it effective for clinical applications where data may be scarce.	Developed a sparse representation framework that balances computational efficiency and reconstruction quality, suitable for practical medical applications.
Patel et al. (2022), "Multi-View 3D Reconstruction of Medical Images Using Deep Learning"	Investigates a multi-view approach to 3D reconstruction by integrating images from various angles using deep learning techniques.	Greatly improved the accuracy and detail of reconstructed 3D images by providing better spatial resolution and anatomical accuracy.	Highlighted the benefits of deep learning multi-view integration for producing high-quality 3D reconstructions, particularly useful for complex anatomical structures.

METHOD

Problem Statement

Data related to medical imaging is complex and growing volume are the challenges that we face while monitoring, treating plan and trying to diagnosis accurately. Certain changes in pathological may be subtle in techniques of 2D imaging have comprehensive views of limitations frequently for anatomical structures.[21] So, there is a need of desperate reconstruction of 3D models which are advanced in reconstructions techniques converted from 2D images for maintaining accuracy. Ongoing disease monitoring progression, detecting disease in early stage is promoted, enable planning of treatment and to improve diagnose precision we need 3D model. Research in medical should be further increased and should be effective and reliable for the techniques which are using.[22] To provide trustworthy data and clinician useful insights in medical imaging are done by provided by handling issues, techniques of computational and deep learning utilization are the main objectives for novel 3D reconstruction and its validation.

Objectives

Many objectives which were crucial are aimed to achieve in medical imaging using 3D reconstruction. In anatomical structures we use methods which create and offer 3D views of fine-grained for precision monitoring diagnosis and to improve the capability for detection of disease is the first and foremost goal. Surgical planning and simulation are imperative to create 3D models for each patient as they have anatomical features of unique and they can plan for treatment and customize, improves surgical risk in lower rate and accuracy.[15] To identify the illness in the stages of manageable is guaranteed by thorough screenings, techniques applied to draw attention in organ and tissue alterations which can be detected in early stage will be promoted by using this.

Continuous imaging process of 3D is done to look into insight effects of long-term treatment for tracking accurately and give an advancement of intimation of disease overtime is another goal for monitoring continuously to support for the goals achieved by 3D.To improve the performance of medical education and training there are two ways ,one by assisting patients by make them understand the conditions and treatment availability to support them and to aid teaching for both practice and practical study are implemented using 3D reconstruction.[19]

3D models help to drive innovations in further helps in technologies of medical field by creating a novel approach and also by providing datasets for application of artificial intelligence and machine learning as medical research is being the priority in top. In clinical workflows, conditions and modalities of image diverse is accommodated to scalability and adaptability for maintaining effectiveness and reliability which is critical to guarantee in 3D reconstruction. To validate and measure the performance of current principles 3D reconstruction will guarantee in reliability and in accuracy. Validating and measuring is compared with metrics like chamfer distance (CD), earth mover's distance, Intersection over Union (IoU), F-score and accuracy is done with state-of-art models. Potential and progress of techniques in 3D reconstruction are illustrated for collective study for enhancing the care of patient and medical diagnostics.

Proposed Methodology

3D image reconstruction is used in the first study named as Residual Network-50 (ResNet-50) which is based on deep learning model.[17] For back propagation layer the system can include 3D and 2D networks.2D features are computed for the input images in the initial stage by a dedicated network. Adaptive School of Fish Optimization which is meta-heuristic is utilized for determining ideal weights that lowers errors in classification and to improve performance of neural network.[9]

AFSO Algorithm improves the prediction performance in terms of F1 score and Iou (Intersection over Union) and Accuracy. To visualize the above metrics, it can also include of functions that are plotted.

Table 5. Function for Prediction takes 3 inputs

x	y	p
Input Data	Labels of Actual Class	Sampling Data value of percentage

Steps:

- Random samples of data are selected as percentage-(p).
- Classes are identified with occurrence which is having more than once.
- Prediction is randomly made by opting classes different from the dataset if a sample is being selected otherwise retains the value of actual by using a list of predicted values(pred).

Function for Calculating Performance

A confusion matrix is used for labels for predicted (Pred) and actual (Act) that are based on metrics of evaluating different calculations for different functions.

Metrics

True Positive (TP).
False Positive (FP).
True Negative (TN).
False Negative (FN.

True Positive (TP), False Positive (FP), True Negative (TN), False Negative (FN): Derived from the confusion matrix. IoU (Intersection over Union):

$$IoU=TP/((TP+FP+FN))$$

Accuracy:

$$Accuracy=(TP+TN)/(TP+TN+FP+FN)100$$

F1 Score

$$F1=(2.TP)/(2.TP+FP+FN)$$

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Precision

Precision=TP((TP+FP)100

Recall

Recall=TP/(TP+FN) 100

False Positive Rate (FPR)

FPR=FP/(FP+TN)

False Negative Rate (FNR)

FNR=FN/(FN+TP)

Cohen's Kappa: Agreement of two raters is measured using this

$k=(Obs_{agree}-Expec_{agree})/(1-Expec_{agree})$

Where:

- TP = True Positives.
- TN = True Negatives.
- FP = False Positives.
- FN = False Negatives.
- Obs_agree = Observed Agreement.
- Expec_agree = Expected Agreement.

Function for plt

Different views of F1 score plot across is designed using this function.

plt_iou Function for plt_iou

Similar to plt function this function will also plot the different views of IoU (Intersection over Union) across the function.

Single-or multi-view inputs are used in ResNet-50 and for Decoding the model in training a deep autoencoder is used in testing phase. Using Dataset of ShapeNet we make an experimental analysis implemented in Python leading to outperform the current models in terms of IOU,F-score and accuracy (99,3 %,0,734 and 0,993 respectively). A single 2D image is discussed which is taken from point clouds for reconstruction in the second study specifically when we have many objects within a photo. A two-tier deep learning model presenting as Concurrent Attentional Reconstruction Network (CARN) is used for facilitating for effectiveness of the process. Concurrent Excited DenseNet (CED) is used for feature extraction in CARN, and Attention-Dense Gated Recurrent Units (AD-GRU) are used for point cloud prediction. When tested in Python using the ShapeNet dataset, the model shows over 99 % accuracy with low values for the chamfer distance (CD) and earth mover's distance (EMD).

The Procedure is designed as follows:

1. An image is Loaded.
2. Using the Model named as CED_model all the features are extracted.
3. To Split the images into testing sets and training set, then we load the labels and features by using pre-trained loading process.
4. Using ADGRU model the predictions are made for the point cloud for doing the Reconstruction procedure.
5. Performance is evaluated among various metrics like Recall, F1 Score, precision, Specificity, Sensitivity and Accuracy.

Function for Calculating Performance

Accuracy

Accuracy=(TP+TN)/(TP+TN+FP+FN) ×100

F1 Score

F1=(2.Precision.Recall)/(Precision+Recall)

Precision

Precision=TP/(TP+FP)100

Specificity

Specificity=TN/(TN+FP)100

Sensitivity(Recall)

Sensitivity=TP/(TP+FN)100

The Twin Attention-aided Convolutional Inception Capsule Network (TA_CICNet), which is intended for both reconstruction and classification—with a particular emphasis on brain tumour diagnosis—is presented in the third technique. Important preprocessing procedures in the workflow include the Extended Non-Local Mean Filtering (Ex_NLMF) for noise removal and the Upgraded Fuzzy K-Means Algorithm (Up_FKMA) for precise disease area identification. TA_CICNet is a core structure in which it is an integration of inception modules and attention mechanisms and convolutional layers. Reconstructed images and reconstructing medical images are obtained while classifying different types of tumours in brain.

Deep learning fiercely improves task for medical imaging in planning for treatments, detection of area for lesion, recognition of organ, segmentation, registration of image. Thorough analysis are allowing for background key structures of distinguish for making it easier by making segmentation helps by using deep learning.

This module is designed for images of brain tumor classifying and processing the images by performing the tasks like filtering of image, segmentation of image, reconstruction of image and classifying the image.

Loading and Inputting Image

- An input image is selected by the user via the dialog file
- The loaded image is. mat data that uses scipy.io.loadmat or mat73.loadmat for extracting labels and images.
- To maintain consistency the image is resized to (256,256)

Pre-processing

- By using algorithms of Improved Non-Local Mean Filtering (INLMF) technique for reducing the noise and for enhancing the image, filtering is done for the image.
- Using matplotlib, both the filtered image and original images are depicted.

Segmentation

- Segmentation of image is done by using Upgraded Fuzzy K-Means Clustering
- Later the image which is segmented from the original image is displayed

Classification and Reconstruction of Image

- To Segment image from original image and to reconstruct we use a deep fusion algorithm.
- The loaded model is pre-trained by using Capsule Net and the image is reconstructed into four categories: Pituitary, Meningioma, Glioma or No Tumor.
- Using Plot function the visualization of the results is done for predicted vs. actual and the class of predicted is printed.

Techniques Of Conventionally compared with segmentation that are automated in effective and precise in more offers by deep learning. Identification and assignment of tissue is guaranteed accurately by registration of medical image that can be enhanced form various angles that acquire picture aligned precisely which is an additionally provided. Recognition of organ is improved by using deep learning; regular examination is required for the organs for identification which makes more accurately for providing the treatment in a proper way.[11] When considered about all the positive significant impacts deep learning has been a good brunt on medical imaging. Thorough production and accurate analysis, accuracy is planned for treatment for better improvement, registration of image and recognition of organ is enhanced, segmentation and detection areas by speeding by lesion. The challenging step is the imaging of medical component for reconstructing when its component is diseased.

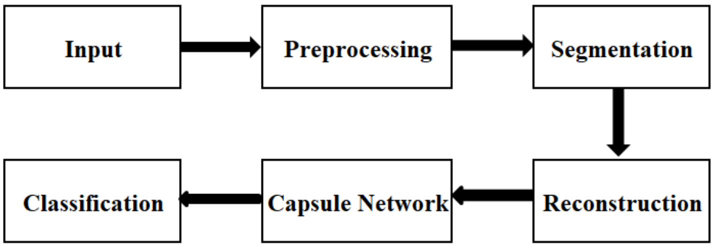

Figure 1. Block Diagram for Proposed method workflow

By using datasets of figshare we gather the input data initially and include the methodology processing in a flow as image acquisition-preprocessing-segmentation-reconstruction and then the detection is done for the disease part.pre-processing employs extended non-local mean filtering (ex_nlmf) to remove noise, and the upgraded fuzzy k-means algorithm (up_fkma) segments diseased regions. The twin attention-aided convolutional inception capsule network (ta_cicnet) then uses these segmented images to identify and classify diseases.

Algorithm for Preprocessing
Medical Image Pre-processing using Extended Non-Local Mean Filtering (Ex_NLMF)
Step 1: Image Acquisition
Collect input medical images from the figshare dataset.

Step 2: Pre-processing Initialization
- Initialize parameters for Ex_NLMF:
- α=0,35α=0,35
- Half window size =1=1
- Half patch size =2=2

Step 3: Noise Removal using Ex_NLMF
For each pixel pp in the image:
1.) Identify Similar Neighborhoods:
Locate patches in the image similar to the patch centered at pixel p.
2.) Compute Patch Variance:
Calculate the overall variance for each patch.
3.) Assign Weights:
- For each similar patch q:
- Compute the weight w(p,q) using the equation:

$w(p,q)=e-\|I(p)-I(q)\|2h2$w(p,q)=e−h2∥I(p)−I(q)∥2

- Where h is the bandwidth parameter, (p)I(p) and $I(q)$I(q) are the pixel values at p and q, respectively.

4.) Compute Weighted Average:
- Calculate the weighted average of the patches to redefine the pixel value at p:

$I^{(p)}=\sum q\in N(p)w(p,q)I(q)$I^(p)=q∈N(p)∑w(p,q)I(q)

- Where N(p) is the neighborhood of pixel p.

5.) Self-Averaging Correction:
- Apply self-averaging to enhance smoothness and preserve edges:

$I^{(p)}=\sum q\in N(p)w(p,q)I(q)\sum q\in N(p)w(p,q)$I^(p)=∑q∈N(p)w(p,q)∑q∈N(p)w(p,q)I(q)

6.) Formulate Final Image:
Combine the weighted averages to produce the denoised image.

Step 4: Output

- Generate a pre-processed image with reduced noise, enhanced contrast, and preserved image elements (size and shape).

Step 5: Result Evaluation

- Display the pre-processed images.
- Evaluate the output for reconstruction and categorization performance, checking for improved accuracy and reduced error rates.

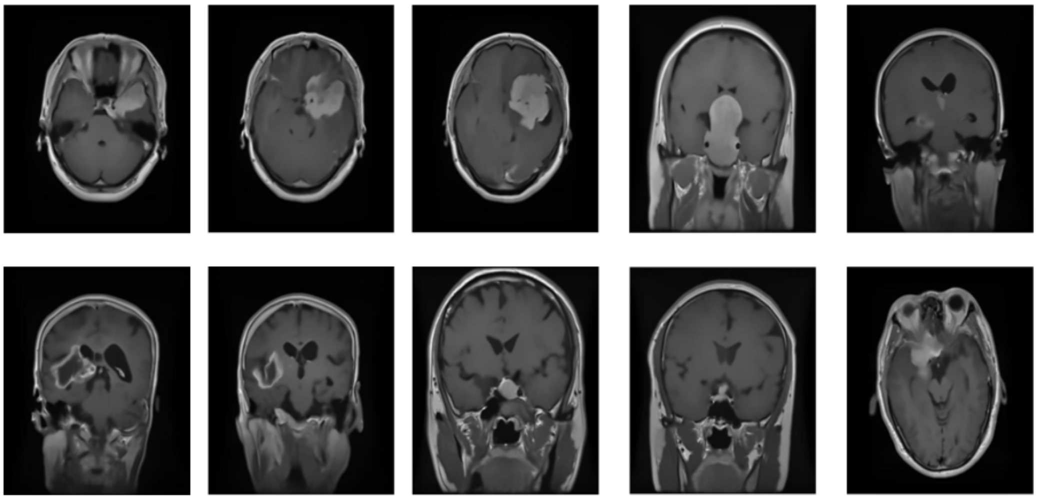

Figure 2. Samples of pre-processed images

Using the Extended Non-Local Mean Filtering (Ex_NLMF) technique, which improves image quality by reducing noise and preserving important image features, this algorithm offers a step-by-step method for preprocessing medical images. After that, the pre-processed photos are prepared for additional analysis, like illness classification and reconstruction.

Algorithm: Medical Image Segmentation using Upgraded Fuzzy K-Means Algorithm (Up_FKMA)
Step 1: Image Acquisition
Collect medical images from a source like the figshare dataset.

Step 2: Image Pre-processing

- Apply noise reduction (e.g., Ex_NLMF).
- Normalize pixel values for consistency.

Step 3: Initialization

- Set parameters: number of clusters *k*k, fuzziness parameter *m*m, stopping criterion.
- Initialize partition matrix *U*U with random values ensuring:

∑*j*=1*kuij*=1∀*i*j=1∑kuij=1∀i

Step 4: Iterative Update

- Repeat until convergence:

1.) Update Centroids:

cj=∑*i*=1(*uij*)∑*i*=1*N*(*uij*)*m*cj=∑i=1N(uij)m∑i=1N(uij)mxi

2.) Update Membership Values:

uij=(∑*k*=1*k*(*dijdik*)2*m*−1)−1uij=(k=1∑k(dikdij)m−12)−1

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3.) Calculate Distance:

$dij=\|xi-cj\|dij=\|xi-cj\|$

Step 5: Convergence Check

- Stop if changes in U or centroids are below the threshold.

Step 6: Post-processing

- Refine segmented regions using morphological operations.

Step 7: Evaluation (Optional)

- If ground truth is available, evaluate using precision, recall, and Dice coefficient.

Step 8: Visualization

- On original images the regions of overlaid segmented are displayed.

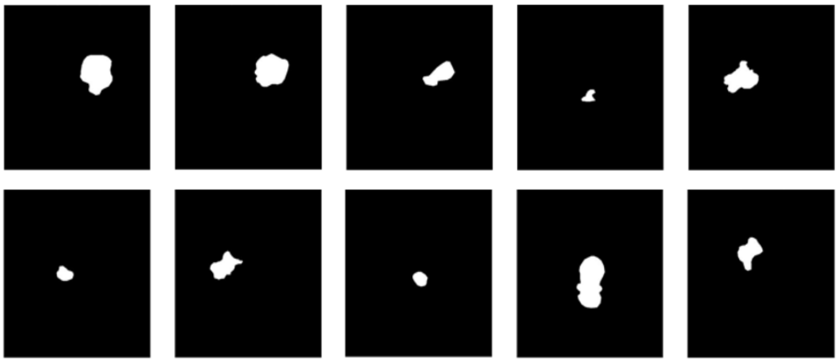

Figure 3. Samples of segmented images

Reconstruction

Classification, reconstruction, image processing and vision are essential tasks in computer handling data. Surveillance and medical imaging are the imperative process for making image reconstruction. With the data that is deteriorated or incomplete a high quality image is produced in Image reconstruction. Images are divided based on the contents that are predefined are understood with the scenes and recognition of objects is necessary for classification. Self-driving cars and recognition of facial are improved by combining the methods in image recognition.

Steps in Reconstruction

Step 1

"Obtaining Unprocessed Data: obtain signals or raw pictures."

Step 2

"Pre-processing: normalize values and remove noise and artifacts from the data."

Step 3

"Utilize methods such as super-resolution or image interpolation for data reconstruction."

Step 4

"Optional Feature Extraction: gather important features for tasks that come after."

Step 5

"Post-processing: use edge enhancement or filtering to refine data."

These procedures guarantee precise classification and high-quality image reconstruction, propelling progress across multiple domains.

Steps in Classification

Step 1

"Labelling (Supervised Learning): give data labels (e.g., add conditions to medical images)."

Step 2
"Splitting Data: separate the dataset into sets for testing, validation, and training."

Step 3
"Selecting a Model: select an appropriate model for classification (e.g., neural network, SVM)."

Step 4
"Normalise features using feature scaling to ensure consistent model training."

Step 5
"Model Training: apply cross-validation to ensure robustness while training the model on the training set."

Step 6
"Evaluate the model's performance using the validation set and adjust the hyperparameters as necessary."

Step 7
"Testing and Model Deployment: conduct tests on the test set before putting the model into practical use."

Step 8
"Interpretation and Visualisation: recognise and present the choices and results of the model."

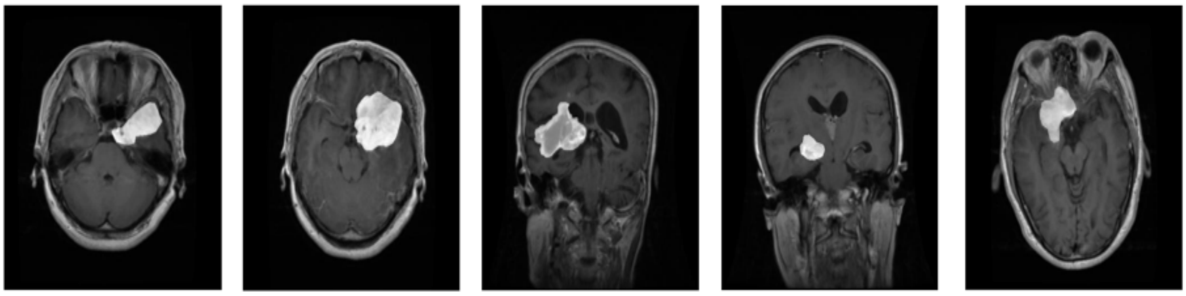

Figure 4. Reconstructed sample images

RESULTS AND DISCUSSIONS

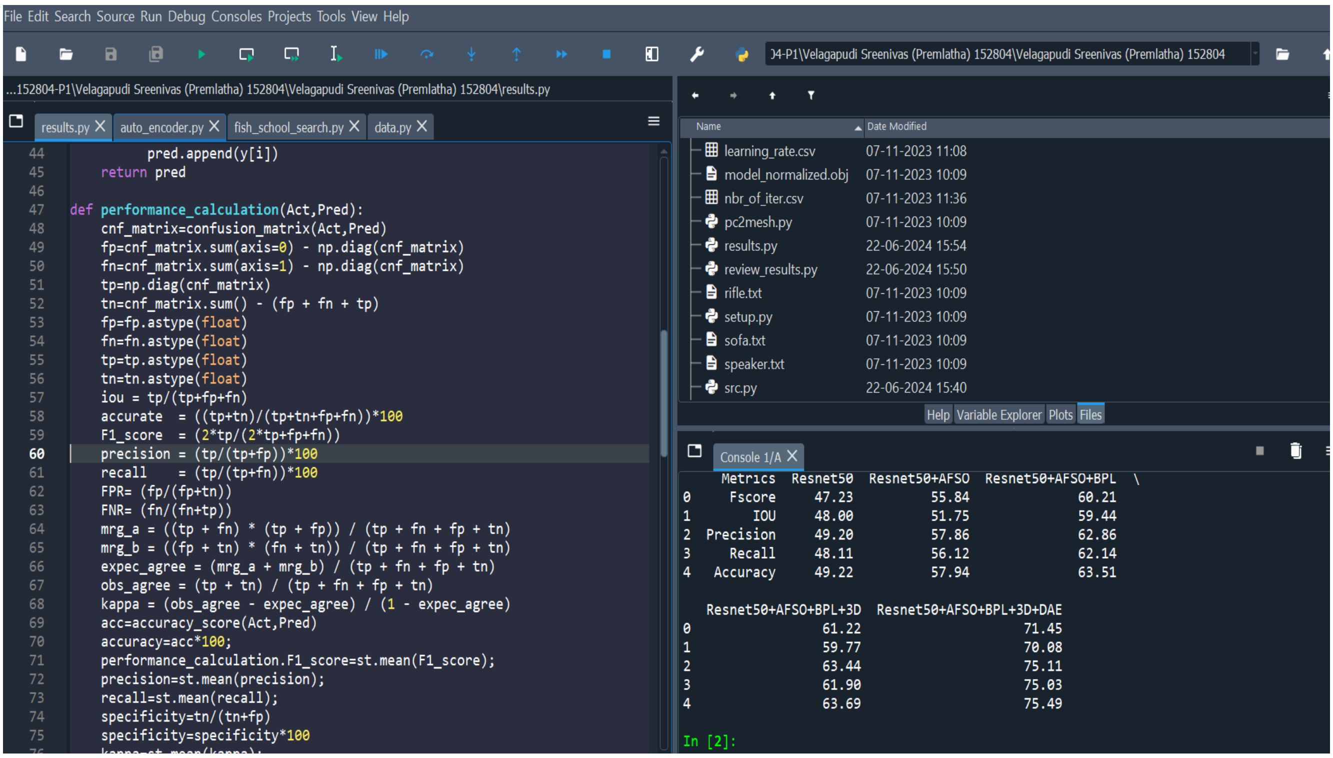

Figure 5. ResNet Algorthim Comaprision when complied with sample images

When Compared with different ResNet 50 model for variations with metrics of 5 performances i. e Accuracy, Recall, Precision, IoU (Intersection over Union) and F1 Score. The model consists of:

- ResNet50.
- ResNet50 + AFSO (Additional Feature Selection Optimization).
- ResNet50 + AFSO + BPL (Backpropagation Learning).
- ResNet50 + AFSO + BPL + 3D.
- ResNet50 + AFSO + BPL + 3D + DAE (Denoising AutoEncoder).

Table 6. Performance Evaluation for Every ResNet Model

Metrics	Resnet50	Resnet50+AFSO	Resnet50+AFSO+BPL	Resnet50+AFSO+BPL+3D	Resnet50+AFSO+BPL+3D+DAE
Fscore	47,23	55,84	60,21	61,22	71,45
IOU	48	51,75	59,44	59,77	70,08
Precision	49,2	57,86	62,86	63,44	75,11
Recall	48,11	56,12	62,14	61,9	75,03
Accuracy	49,22	57,94	63,51	63,69	75,49

We can see the improvement in a progressive way in the metrics for each and every variations and at its overall best achieved performance by the model "ResNet50 + AFSO + BPL + 3D + DAE" specifically in terms of Accuracy, recall, precision and F1 Score which shows improvement significantly over the model of ResNet50 model.

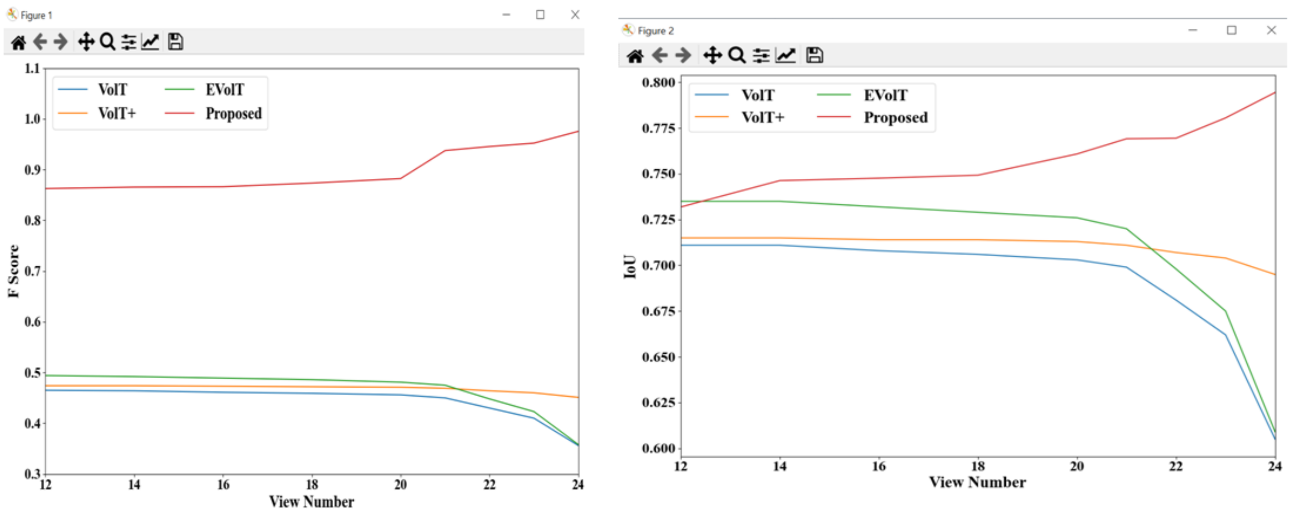

Figure 6. Performance of Each Metrics in terms of F1 Score and IoU

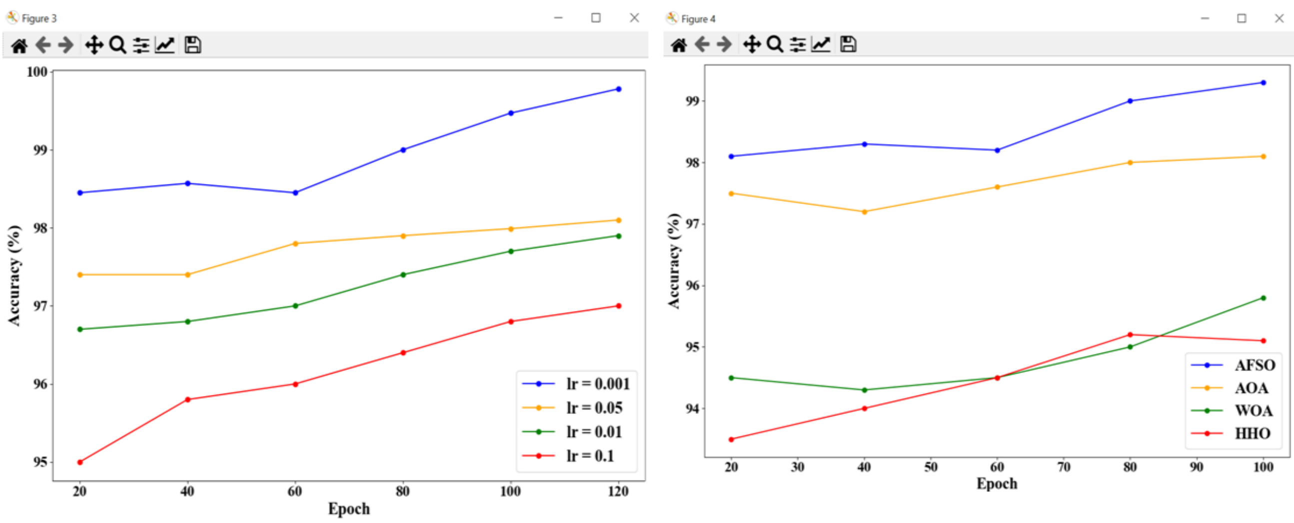

Figure 7. Performance of Each Metrics in terms of Accuracy

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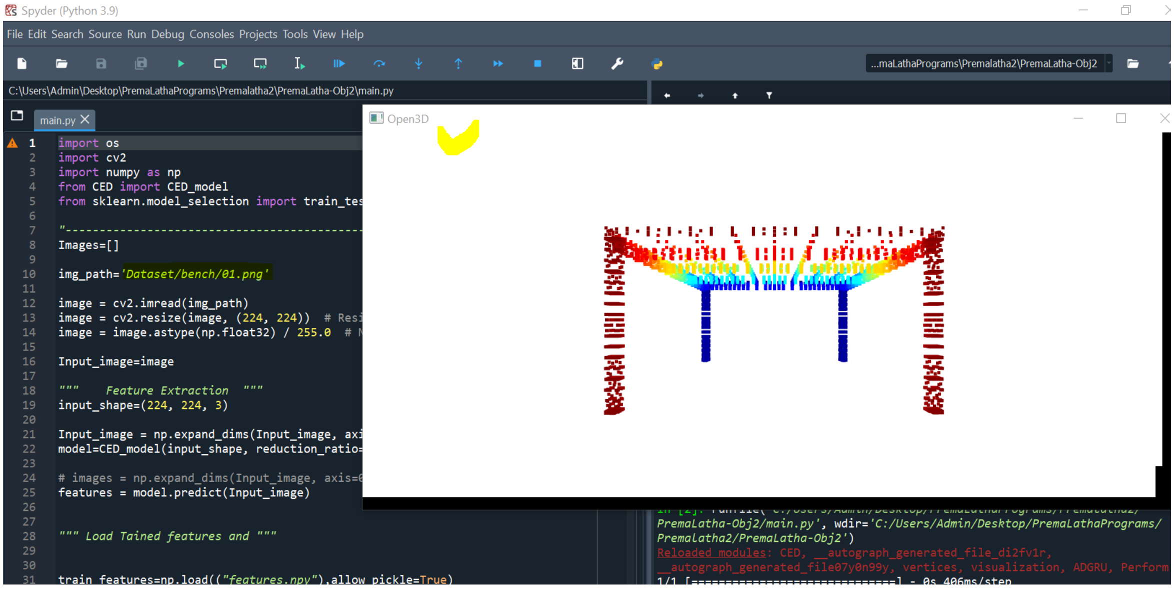

Figure 8. Performance Evaluation for Cloud Point when complied

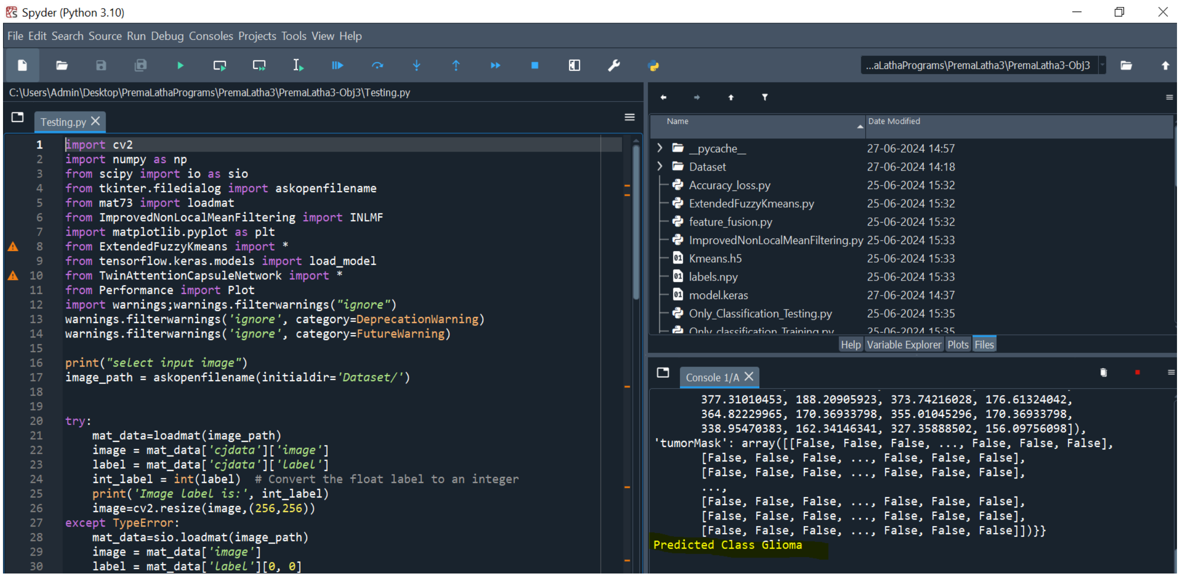

Figure 9. Performance Evaluation for Cloud Point when complied

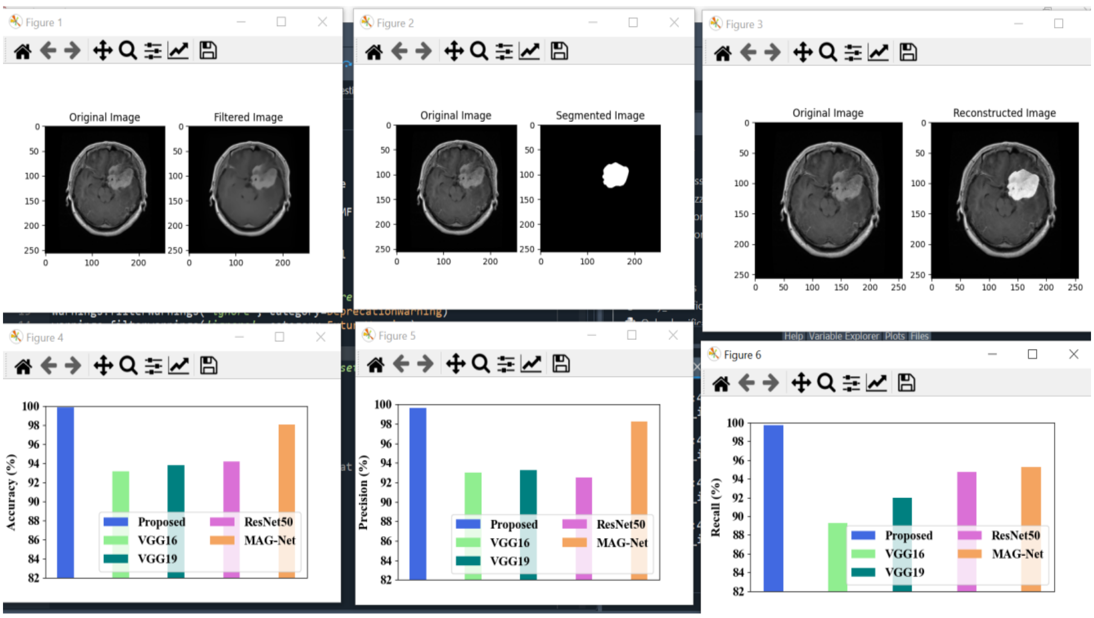

Figure 10. Performance Evaluation for Cloud Point for original image and filtered image

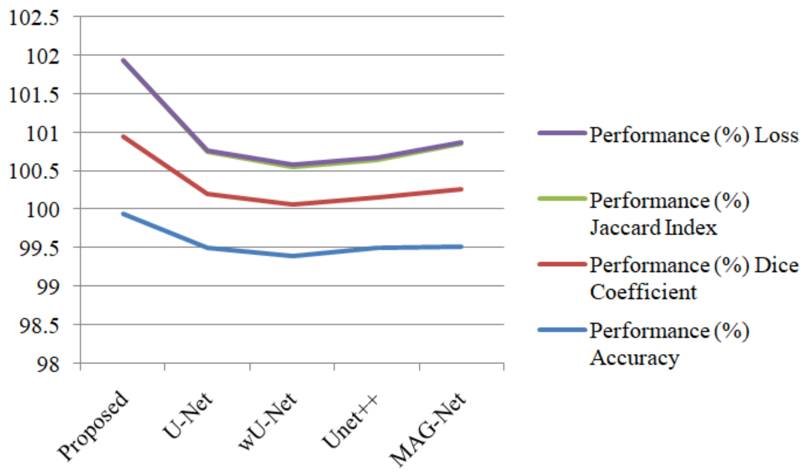

Figure 11. Performance comparison of the segmentation process

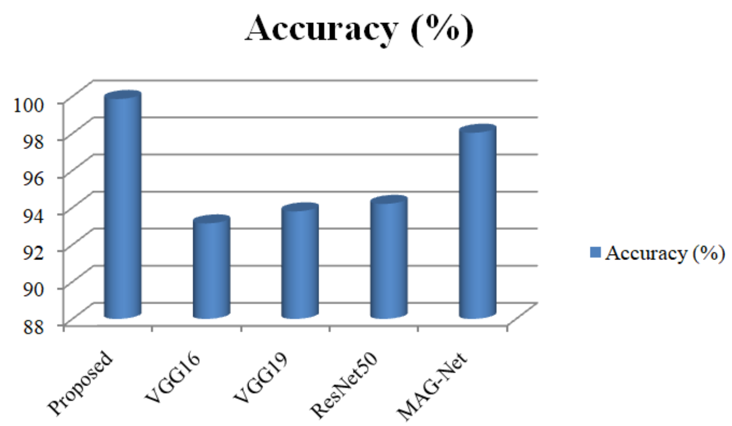

Figure 12. Proposed method accuracy comparison

The proposed Neural Hybrid System Model is implemented and is aimed to implement to detect disease. The efficiency of the Neural Hybrid System work is being compared with the conventional strategies in terms of comparison of performance for segmentation process and it is compared with accuracy methods also. Moreover, it is assessed by parameters evaluation like U-Net, wUNet, UNet++, Mag-Net and so on for performance. It is assessed by evaluation of parameters like VGG16, VGG19, ResNet50,Mag-Net.Dataset: The data set considered for our work is taken form koggle sets.

CONCLUSIONS

Brain tumor diagnosing in which frequently we find fatal cancers are processed critically in medicine are done by reconstruction and classification of image. Both reconstruction of image is reconstructed and classification has been improved by the proposed method called as hybrid TA_CICNet.To eliminate noise from images a method called Ex_NLMF is used first for pre-processing by using dataset of Figshare. Up_FKMA-based segmentation is used to identify the regions of disease. Non-tumor, pituitary, glioma and meningioma are the four categories that are used for classification of tumor in brain that are used for image segmentation in the capsule network. Dataset is available in Figshare for the procedure and is required for the information for making image reconstruction. Classification and reconstruction of image are outperformed over all the previous approaches by using this proposed method. Data collection for facilitating evaluation is easier and stages of tumor analysis and their classifications needs to be incorporating will be focused on the future work.

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None.

CONFLICT OF INTEREST
Authors declare that there is no conflict of interest.

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