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# AI-Powered Detection of Stroke in Non-Contrast Brain CT Images

**Vikramaditya Tarai[1], Nabin Chandra Sahu[2], Sonam Pattanaik[3] , Gayatree Maharana[4]**

[1]*Department of M Sc Computer Science, Sophitorium Institute Of Technology And Lifeskills, Odisha, India*
[2]*Department of Mechanical Engineering, Sophitorium Engineering College, Odisha, India*
[3] *Department of Computer Science, Sophitorium Engineering College, Odisha, India*
[4] *Department of M Sc Computer Science, Sophitorium Institute Of Technology And Lifeskills, Odisha, India*

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**Abstract -**The identification and categorization of brain tumors represent essential components in the enhancement of human health. A range of medical imaging modalities is capable of detecting brain pathologies associated with hemorrhagic events, including nuclear magnetic resonance, ultrasound, X-ray imaging, radionuclide imaging, laser technology, electron imaging, and photonic methods. Among these modalities, magnetic resonance imaging (MRI) is preferred within the medical community due to its superior image resolution and the absence of ionizing radiation. The interpretation of MRI scans is facilitated by the application of Artificial Intelligence, which alleviates the labor-intensive and time-consuming nature of this process. The efficacy of deep learning and convolutional neural networks in the identification of brain tumors has been well established. In the present study, deep learning transfer methodologies are employed for the classification of tumors. Specifically, ResNet-50 models with pre-training on convolutional neural networks are utilized to automatically predict and categorize brain tumors. The dataset comprises head CT (Computed Tomography) images in JPG format, featuring 2,500 images from the brain window and 2,500 images from the bone window, sourced from 82 patients. The performance of the ResNet-50 models is assessed in comparison to Support Vector Machines (SVM), K-Nearest Neighbors (KNN), and You Only Look Once (YOLO) algorithms, with experimental findings substantiating the effectiveness of the ResNet-50 approach. Consequently, the application of ResNet-50 for tumor classification is affirmed and endorsed.

***Key Words*:**ResNet-50, Support Vector Machines, You Only Look Once, Computed Tomography, Artificial Intelligence.

## 1. INTRODUCTION

ResNet50 is a convolutional neural network (CNN) architecture that is part of the ResNet (Residual Network) family, which was introduced by Kaiming He et al. in their 2015 paper titled "Deep Residual Learning for Image Recognition." ResNet architectures are designed to address the problem of vanishing gradients in very deep networks, allowing for the training of networks with hundreds or even thousands of layers.

Key Features of ResNet50:

1. Residual Learning:
- The core idea behind ResNet is the use of residual connections (or skip connections) that allow the network to learn residual functions with reference to the layer inputs. This means that instead of learning the desired output directly, the network learns the difference (or residual) between the input and the output.
- This approach helps in mitigating the vanishing gradient problem, making it easier to train deeper networks.

2. Architecture:
- ResNet50 consists of 50 layers, which include convolutional layers, batch normalization layers, and ReLU activation functions.
- The architecture is built using a series of building blocks called "Residual Blocks." Each block typically contains two or three convolutional layers and a skip connection that bypasses one or more layers.
- The network starts with an initial convolutional layer followed by a max pooling layer, and then it is followed by a series of residual blocks.

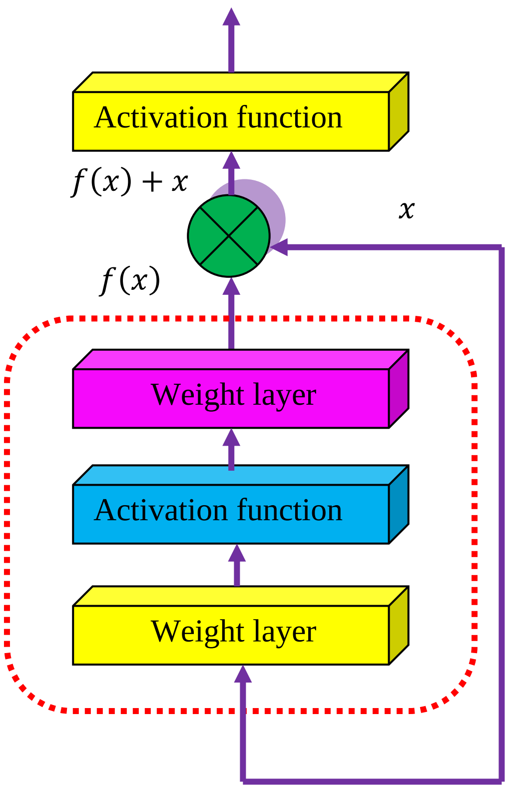


**Fig -1**: Resnet ( Residual Network ) basic block

3. Bottleneck Architecture:
- ResNet50 uses a bottleneck design, where each residual block consists of three layers: a 1x1 convolution (to reduce dimensions), a 3x3 convolution (to process the features), and another 1x1 convolution (to restore dimensions).

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- This design reduces the number of parameters and computational cost while maintaining performance.

4. Global Average Pooling:
- At the end of the network, instead of using fully connected layers, ResNet50 employs global average pooling, which reduces each feature map to a single value by averaging. This helps in reducing overfitting and makes the model more robust.

5. Output Layer:
The final layer is typically a softmax layer for classification tasks, which outputs the probabilities for each class.

Applications:ResNet50 is widely used for various computer vision tasks, including:

- Image classification
- Object detection
- Image segmentation

## 2. LITERATURE REVIEW

Here is a literature review based on the provided references, summarizing the main findings and limitations for each paper:

(Chen et al., 2024) [1]. Main Findings:- The study introduces the YOLO-NeuroBoost model, which combines the YOLO (You Only Look Once) object detection framework with a neuroboosting technique to enhance the accuracy of brain tumor detection in MRI images. The model demonstrated improved performance metrics, including precision, recall, and F1-score, compared to traditional methods and existing deep learning models.

Limitations:- The study may have limited generalizability due to the specific dataset used for training and testing, which may not represent the diversity of brain tumor cases encountered in clinical practice.

(Mithun&Jawhar, 2024) [2].Main Findings: - This research presents the YOLO NAS (Neural Architecture Search) model for the detection and classification of brain tumors in MRI images. The model achieved high accuracy and efficiency, outperforming several baseline models in both detection speed and classification accuracy.

Limitations: - The reliance on a single dataset for evaluation may limit the robustness of the findings, as variations in MRI imaging protocols and tumor characteristics could affect model performance in real-world applications.

(Basthikodi et al., 2024).[3] Main Findings:- The authors propose a method that combines Support Vector Machine (SVM) classifiers with novel feature extraction techniques to improve multiclass brain tumor diagnosis.The approach showed significant improvements in classification accuracy and reduced misclassification rates among different tumor types.

Limitations: - The study may be limited by the choice of features extracted, which could overlook other potentially relevant features that might enhance classification performance.

(Archana&Komarasamy, 2023). [4] Main Findings:- This paper introduces a Bagging ensemble method combined with K-nearest neighbor (KNN) for brain tumor detection, demonstrating improved accuracy and robustness against overfitting.The ensemble approach effectively leverages multiple models to enhance prediction reliability.

Limitations: - The computational complexity of the Bagging ensemble may limit its applicability in real-time clinical settings, where rapid diagnosis is crucial

(Abdusalomov et al., 2023) [5] Main Findings:- The authors review various deep learning approaches for brain tumor detection using MRI, highlighting the strengths and weaknesses of different methodologies. The paper emphasizes the potential of deep learning to significantly improve diagnostic accuracy and speed in clinical settings.

Limitations:- The review nature of the paper may not provide new experimental results, and the conclusions drawn may be influenced by the quality and scope of the studies reviewed.

(Biratu et al., 2021).[6] Main Findings: - The study presents an enhanced region growing algorithm specifically designed for the segmentation of brain tumors in MRI images. The proposed method improves upon traditional region growing techniques by incorporating adaptive thresholding and seed point selection, which enhances the accuracy and robustness of tumor delineation.

Limitations: - The study may be limited by its reliance on a specific dataset, which may not represent the diversity of brain tumor types and MRI imaging conditions encountered in clinical practice.The computational complexity of the enhanced algorithm could limit its applicability in real-time clinical settings, where quick decision-making is crucial.

(Aiwale& Ansari, 2019).[7]Main Findings: - This paper explores the use of the K-Nearest Neighbors (KNN) algorithm for the detection of brain tumors from MRI scans. The authors demonstrate that KNN can effectively classify images into tumor and non-tumor categories based on features extracted from the images, achieving satisfactory accuracy rates.

**Table -1:** Literature Review

| Sl. No | Author | Algorithm | Limitation |
|---|---|---|---|
| 1 | Chen et al., (2024) [1] | YOLO | Real-time object detection, high speed |
| 2 | Mithun&Jawhar, (2024) [2] | YOLO NAS | Optimized NAS, high accuracy, efficien |
| 3 | Basthikodi et al., (2024). [3] | SVM | Good for small datasets, robust to overfitting |
| 4 | Archana&Komarasamy, (2023). [4] | KNN | Simple, works well with small datasets |
| 5 | Abdusalomov et al.,( 2023) [5] | YOLO7 | Improved YOLO accuracy, better detection |
| 6 | Biratu et al., (2021).[6] | U-Net architecture | Best for stroke segmentation, high precision |
| 7 | Aiwale& Ansari, (2019).[7] | SVM and fuzzy classifier | Hybrid approach, better classification |

## 3. PROPOSED METHOD

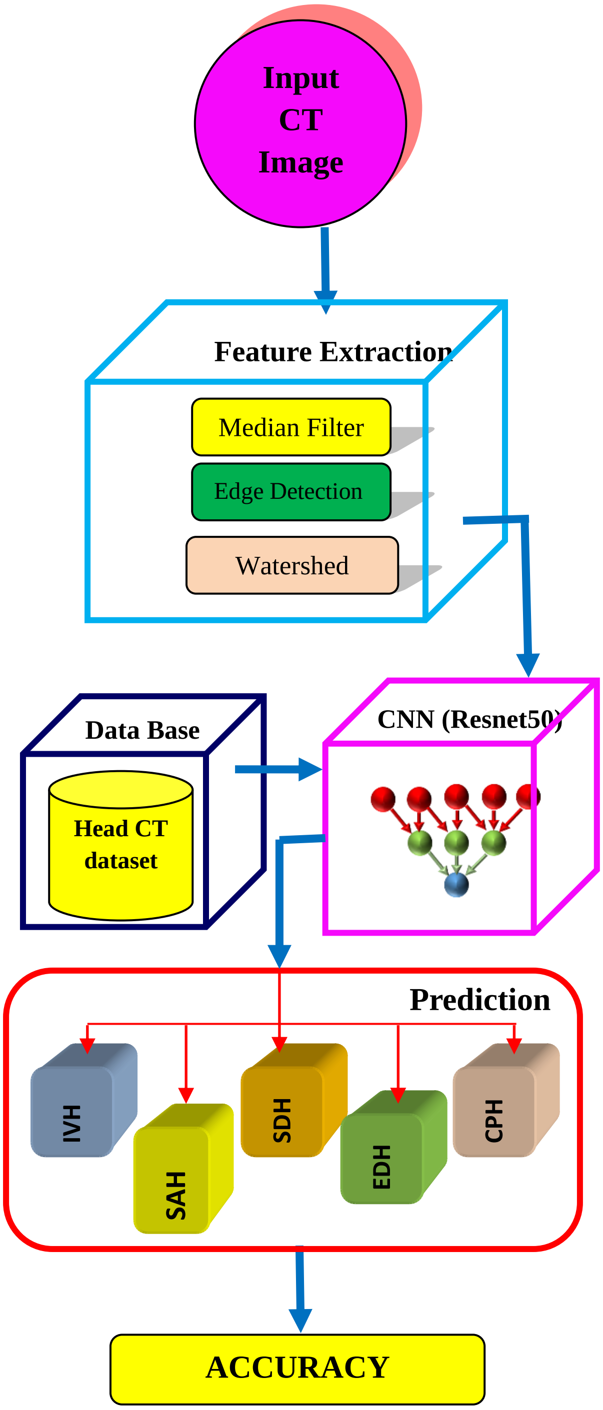


**Fig -2**: Proposed Flow Chart

The flowchart figure 2 represents a process for analyzing a CT image using various image processing and feature extraction techniques to determine accuracy. Here's a step-by-step explanation:

**Step 1:** Input CT Image:

The process starts with a CT image as input.

**Step 2:** Preprocessing:

The input image undergoes preprocessing, which includes:

Median Filter (Yellow Box): Used for noise reduction while preserving edges.

Histogram (Green Box): Used for contrast enhancement or intensity distribution analysis.

Edge Detection (Beige Box): Identifies the boundaries of objects in the image.

**Step 3:** Feature Extraction:

The preprocessed image is then processed further to extract specific features. This step is represented by two connected 3D blocks, indicating transformation from raw image data to feature representation.

**Step 4:** Feature Categories:

The extracted features are categorized into different parameters:

IVH: Intraventricular Hemorrhage.

SAH: Subarachnoid Hemorrhage.

SDH:Subdural Hemorrhage.

EDH: Epidural Hemorrhage.

CPH: Cerebral parenchymal Hemorrhage.

**Step 5:** Accuracy Determination:

Finally, based on the extracted features, an accuracy value is determined, possibly indicating the reliability of classification, segmentation, or another diagnostic measure.

The flowchart describes a process for CT image analysis, beginning with preprocessing techniques (noise removal, histogram analysis, and edge detection), followed by feature extraction and classification, leading to an accuracy measure. This could be useful for medical diagnostics, such as tumor detection or tissue classification.

### 3.1 Feature Extraction

Image feature extraction is a crucial step in computer vision and image processing, enabling the identification and analysis of significant structures within an image. One effective approach involves the use of a median filter, which helps in noise reduction while preserving edges, making it ideal for preprocessing images before further analysis. Following this, edge detection techniques, such as the Sobel or Canny methods, can be applied to highlight the boundaries of objects within the image, providing a clear representation of structural features. Finally, the watershed algorithm can be employed to segment the image based on the detected edges, treating the image as a topographic surface and identifying regions of interest by simulating the flooding of basins. This combination of median filtering, edge detection, and watershed segmentation allows for robust feature extraction, facilitating tasks such as object recognition, image classification, and scene understanding in various applications.

### 3.2 Date Base

A total of 2,500 brain window images and 2,500 bone window images were collected for 82 patients, with each patient having around 30 image slices which shown in figure 3. Additionally, 318 of these images include corresponding intracranial image masks. Database link provided in ref [6].

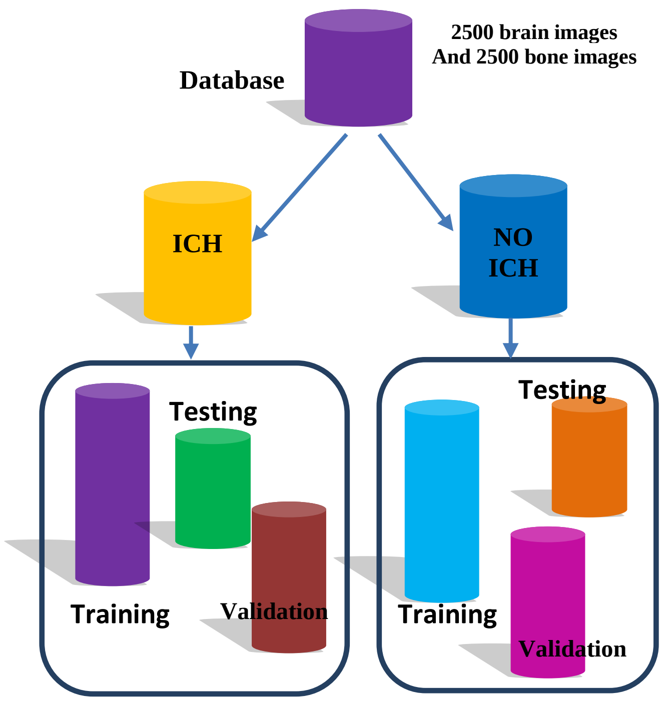


**Fig -3**: Data Base

### 3.3 Software Requirements Specification

- Matlab 2021 software
- i-3 processor
- 8GB RAM
- CNN pre-trained model
- Matlab image processing Toolbox

## 4. RESULT

### 4.1 GUI (Graphical User Interface)

The GUI (Graphical User Interface) figure 4 in the image appears to be an AI-powered system for detecting strokes in non-contrast brain CT images.

Contains four processed CT images:

- Query Image: The original input image.
- Median Filtering: A noise reduction technique applied to the image.
- Histogram Equalization: Enhances contrast to highlight stroke-affected areas.
- Wavelet CNN Output: The AI-processed output identifying stroke regions.

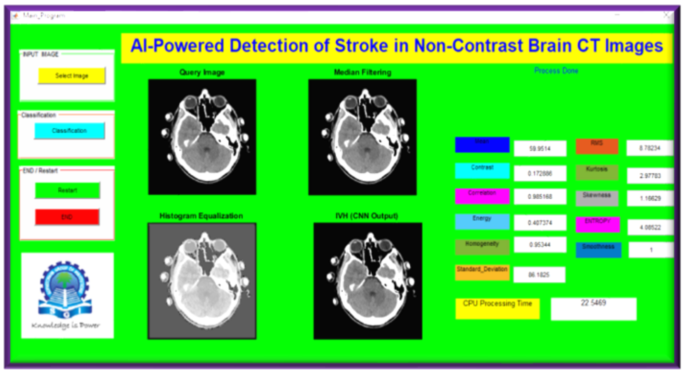


**Fig -4:** GUI

### 4.2 ROC (Receiver Operating Characteristic)

The Receiver Operating Characteristic (ROC) curve as shown in figure 5 is a graphical representation used to evaluate the performance of a binary classification model. It illustrates the trade-off between sensitivity (true positive rate) and specificity (false positive rate) across various threshold settings. By plotting the true positive rate against the false positive rate, the ROC curve provides a visual tool for assessing how well a model distinguishes between the two classes. The area under the ROC curve (AUC) quantifies the overall ability of the model to discriminate between positive and negative classes, with a value of 1 indicating perfect classification and 0.5 suggesting no discriminative power. ROC curves are particularly useful in scenarios where class distribution is imbalanced, allowing practitioners to select optimal thresholds based on their specific needs for sensitivity and specificity.

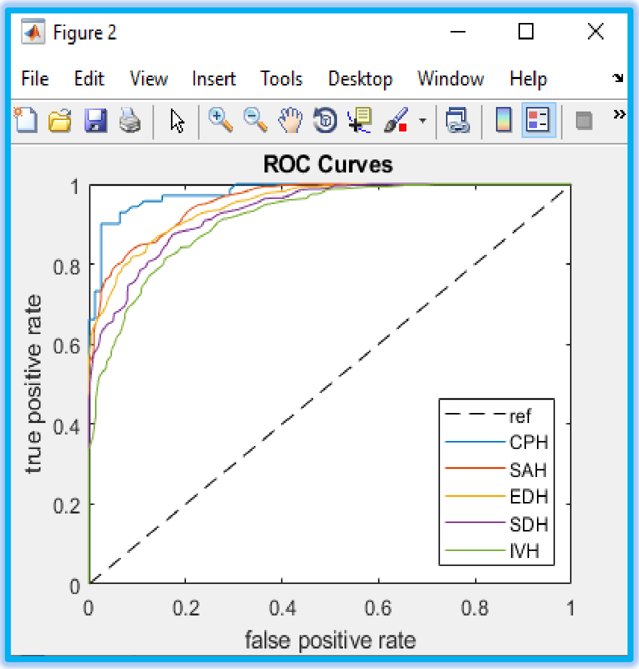


**Fig -5:** ROC Curve

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### 4.3 Comparison of Precision, Recall and F1 score

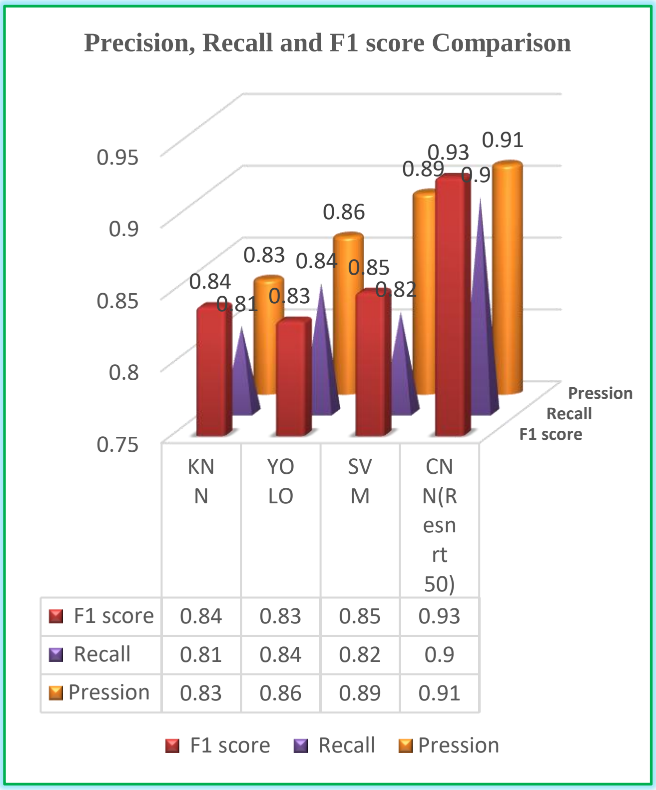



**Fig -6**: 3D bar chart of Precision, Recall and F1 score Comparison

This 3D bar chart compares the Precision, Recall, and F1-score of different machine learning models for stroke detection (or another classification task). The models being compared are: KNN (K-Nearest Neighbors), YOLO (You Only Look Once), SVM (Support Vector Machine) and CNN (ResNet 50 - Convolutional Neural Network with ResNet-50 architecture)

Key Observations from the Chart:

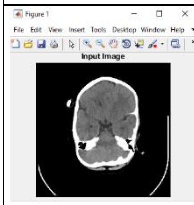
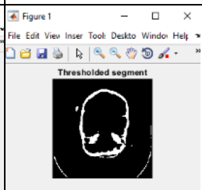
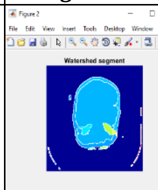
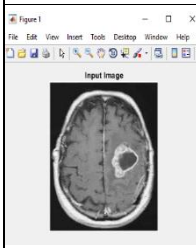
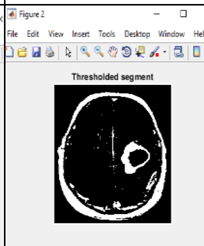
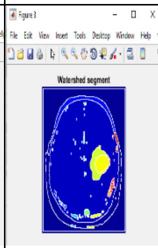
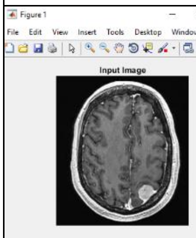
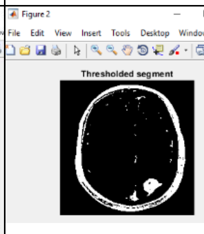
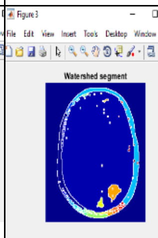
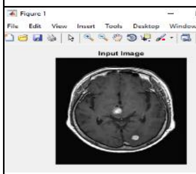
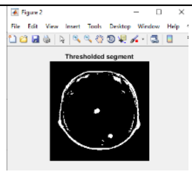
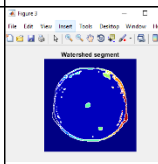
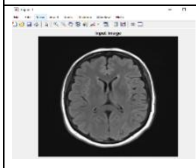
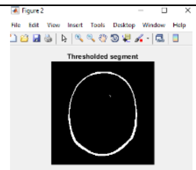
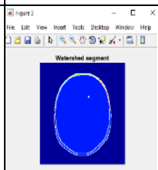
CNN (ResNet-50) Outperforms Other Models: Highest scores across all metrics: F1-score (0.93), Recall (0.90), and Precision (0.91). This indicates CNN is the most effective for the given task.

SVM Performs Well but Lower Than CNN: F1-score: 0.85, Recall: 0.82, Precision: 0.89. Good balance but slightly weaker recall compared to CNN.

YOLO and KNN Have Comparable Performance but Lower Scores: KNN: F1-score (0.84), Recall (0.81), Precision (0.83). YOLO: F1-score (0.83), Recall (0.83), Precision (0.86).

Both models are relatively close in performance but perform worse than CNN and SVM.

**Table -2:** Sample Table format

| Input | Edge Detection | Watershed segment | Output |
|---|---|---|---|
|  |  |  | Intraparenchymal |
|  |  |  | Intraventricular |
|  |  |  | epidural |
|  |  |  | subdural |
|  |  |  | Normal |

## 5. CONCLUSIONS

This research work aims to improve the existing pre-trained deep convolutionalneural networks with transfer learning architectures to identify tumours in the brain using MRI images. This study considers five different classes, IVH: Intraventricular Hemorrhage. SAH: Subarachnoid Hemorrhage. SDH:Subdural Hemorrhage. EDH: Epidural Hemorrhage. And CPH: Cerebral parenchymal Hemorrhage.. The dataset, taken from Kaggle, consists of 2,500 images. In order to carry out the research, the authors have used pre-trained transfer learning CNN architectures, namely, SVM, YOLO,KNN and ResNet-50, for classification.

The experiment was carried out to perform comparative analysis, and during the simulation,it was observed that ResNet-50 achieves an accuracy of 99.93% and a validation accuracyof 97.86%, outperforming SVM, YOLO and KNN. This research work can be furtherextended by using CNN-based models that have already been trained, such as the VGG-19, ResNet-104, and Efficient Net-based CNN-based models, in the prediction analysis of brain tumours

## REFERENCES

1. Chen, Aruna, Da Lin, and QiqiGao. "Enhancing brain tumor detection in MRI images using YOLO-NeuroBoost model." Frontiers in Neurology 15 (2024): 1445882.
2.Mithun, M. S., and S. Joseph Jawhar. "Detection and classification on MRI images of brain tumor using YOLO NAS deep learning model." Journal of Radiation Research and Applied Sciences 17.4 (2024): 101113.
3.Basthikodi, Mustafa, et al. "Enhancing multiclass brain tumor diagnosis using SVM and innovative feature extraction techniques." Scientific Reports 14.1 (2024): 26023.
4.Archana, K. V., and G. Komarasamy. "A novel deep learning-based brain tumor detection using the Bagging ensemble with K-nearest neighbor." Journal of Intelligent Systems 32.1 (2023): 20220206.
5.Abdusalomov, AkmalbekBobomirzaevich, MukhriddinMukhiddinov, and TaegKeunWhangbo. "Brain tumor detection based on deep learning approaches and magnetic resonance imaging." Cancers 15.16 (2023): 4172.
.6.Biratu, ErenaSiyoum, et al. "Enhanced region growing for brain tumor MR image segmentation." Journal of Imaging 7.2 (2021): 22.
7. Aiwale, P., and Saniya Ansari. "Brain tumor detection using KNN." International Journal of Scientific & Engineering Research 10.12 (2019): 187-193.
6. database https://www.kaggle.com/vbookshelf/computed-tomography-ct-images

## BIOGRAPHIES

Vikramaditya Tarai having 8 years of experience in freelancer. He did her B.Tech in ECE from Aarupadai Veedu Institute of Technology (2010) and Diploma in ETC (2006) , GATE (2013) qualify.

Nabin Chandra Sahu is an Assistant Professor Sophitorium Engineering College of Mechanical department. M.Tech (2009) in Mechanical Engineering from ITER Bhubaneswar, SOA University and B-Tech (2001) in Mechanical Engineering from GIET Gunpur, Berhampur University, India

Sonam Pattanaik is an Assistant Professor Sophitorium Engineering College of CSE Department, Odisha, India. She did her M.Tech in Computer Science Department from Veer Surendrasai University Of Technolgy (2024) and B.Tech In Computer science (2022), GATE (2022) qualify.

Gayatree Maharana is an Assistant Professor in Sophitorium Institute Of Technology And Lifeskills, Odisha, India, She did MCA in Computer Science Department of NIIS INSTITUTE OF ADMINISTRATION Of Technolgy (2017) and BCA In NIIS INSTITUTE OF INFORMATION SCIENCE & MANAGEMENT (2015).