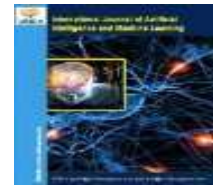




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Aneurysm Detection Using Ternary View Densenet and Shifted Window Vision Transformer on Cta Images

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Abstract

Detection and management of intracranial aneurysms (IAs) are essential to prevent deadly complexities. Artificial Intelligence (AI) can investigate medical images, like Computed Tomographic Angiography (CTA) or Magnetic Resonance Angiography (MRA), distinguishing traces or implications probably ignored by humans. Early detection smoothen timely interferences and enhances results. In addition, AI algorithms provide quantitative data on aneurysm attributes, assisting in long-term monitoring. Essentially, recent years have noticed the growth of sophisticated computational methods using deep learning algorithms. However, convolutional neural network (CNN)-based methods have an intrinsic drawback in capturing long-range spatial dependencies that accidentally trade-offs the holding of global features crucial for segmentation. In response to this challenge, we introduce an artificial intelligence (AI) application to screen aneurysm detection using Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) which incorporates three different vessel-enhanced scales into vision transformer using shifted windows to perform aneurysm detection on CTA images. Initially Lightweight Statistical Hessian-based Pre-processing incorporating skull stripping and vessel enhancement are applied to the sample images to improve noise ratio. Second the pre-processed samples are subjected to an AI-based model called, Ternary View Partial Attention DenseNet to extract relevant features. Finally the noise improved pre-processed samples and relevant features extracted forms as input to the Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection. We trained TVDN-SWViT using the CMHA dataset and noticed significant performance improvements compared to conventional method. The TVDN-SWViT method reached an accuracy of 28% showing its robustness in ascertaining the detection of aneurysm. The promising results demonstrate that TVDN-SWViT can play an important role in clearing the way for accurate diagnosis, while also exhibiting the prospective of vision transformer-based architectures in medical imaging with improved noise ratio.

Keywords: Computed Tomographic Angiography, Lightweight Statistical Hessian, Ternary View Partial Attention DenseNet, Dual Position Shifted Window, Vision Transformer

1. Introduction

Early intracranial aneurysms (IA) detection of is demanding for preventing rupture and assisting clinical interference. In spite of the computed tomography angiography (CTA) images has been extensively utilized in diagnosis of IA owing to its clear imaging and ease of use, manual location of aneurysms in CTA images is time-consuming and notably influencing efficiency. Deep learning models (DLMs) have recently manifested strong performance in segmentation, however their dependence on large amounts of labeled data has become a drawback as far as clinical application is concerned. An efficient semi-supervised learning method, called Uncertainty-guided Joint Cross Pseudo Supervision (UJ-CPS) was proposed in [1] based on a shared encoder and three decoders with identical frameworks but independent parameters. Initially an uncertainty-based joint pseudo-label generation approach weighting the two decoder output based on uncertainty to generate pseudo-labels with higher confidence was designed. Next, joint pseudo-labels were utilized to output rest decoder. Moreover, the cross-supervision mechanism avoided the error accumulation issue generated by low-quality pseudo labels. Finally, during testing, the three decoders were incorporated to generate more accurate segmentation results with improved sensitivity. In spite of improvement in terms of sensitivity the noise ratio involved in aneurysm detection was not focused. A method incorporating convolutional neural network (CNN) based Deep Learning Model (DLM) called, CNN-based DLM was proposed in [2] with the objective of assessing aneurysms stability. The DLM that integrated clinical, morphological and DL parameters of aneurysm was found to be comparatively better when assessing aneurysm stability with improved sensitivity and specificity. It also had the potentiality in preventing rupture of unstable UIAs and avoids unnecessary treatment of stable

UIAs with improved accuracy. However the false positive rate was not address involved in assessing aneurysms stability.

Over the recent few years, endovascular repair of abdominal aortic aneurysm (EVAR) has become the early treatment for aneurysm. One pivotal step for technical and clinical success is accurate planning to select the pertinent endo-prosthesis. Currently there is an inclination towards increasing use of AI and DL to analyze vascular imaging.

An image reconstruction algorithm employing DL to detect aneurysm in the early stage with improved accuracy was presented in [3]. However the error factors involved in detection process was not analyzed. A DL based method in CTA was proposed in [4] ensuring minimal segmentation errors. Yet another method to focus on segmentation error using DL U-Net algorithm was presented in [5]. A systematic review on employing DL for rupture risk prediction was investigated in [6]. Detecting and differentiating aneurysms, specifically for minimal size is predominant for assessing risk and hence treatment planning remains laborious process. Existing materials and methods fail in identifying small aneurysms. An Anatomically-guided Masked Autoencoder for reliable cerebral aneurysm analysis was presented in [7] therefore reducing false positive extensively. Accurate classification of intracranial aneurysms is demanding as far as computer-aided diagnosis is concerned. Nevertheless, prevailing point-based DL methods suffer from constrained feature representation and poor segmentation performance. A detailed surveillance for aneurysm measurement was proposed in [8] therefore meeting clinical precision thresholds. A multi-layer deep learning architecture with improved accuracy was proposed in [9] while sustaining robust cross-domain generalization. Cerebral aneurysm detection employing deep learning algorithm for multicenter study via AI was presented in [10]. Human evaluation of detecting rupture risk is error prone and treatment for IAs frequently depends on expert opinion and institutional policy. To help guide decision making procedure and generating future decision an aneurysm detection method was proposed in [11] with improved sensitivity and accuracy.

Detection and management of IAs are pivotal to prevent fatal difficulties like subarachnoid hemorrhage (SAH). AI analyzes medical images, like CTA identifying nuances probably missed by humans. Early detection smoothen timely interventions and enhanced outcomes. In addition AI algorithms, frequently employing quantitative data, on aneurysm aid in assessing rupture risks. However, manual segmentation of CTA images is labor intensive and time consuming. Therefore, there is an increasing requirement for automated segmentation that influence treatment planning. A patch-based dilated modified U-Net method manifesting effectiveness in accurately delineating AAA regions within the CTA scans was proposed in [12] with exceptional speed and minimal segmentation error. Also by using rational B-splines provided notable improvement in segmentation accuracy.

IAs is extensively identified as both prevalent and potentially lethal conditions. Ruptured intracranial aneurysms are the primary cause of spontaneous subarachnoid hemorrhage, which can result in severe consequences. Therefore, early detection of intracranial aneurysms is particularly crucial. A systematic review aiming to measure the ML and DL algorithm performance for IA rupture risk prediction was investigated in [13]. A holistic review on image based AI for IA early detection using CTA images was modeled in [14]. A three dimensional convolutional neural network for aneurysm detection on CTA images focusing on the error rate by introducing multi layer perceptron was detailed in [15].

Detection of aneurysm with CTA images is a complicated procedure necessitating scientific research and careful analysis, with precise research recommending prospective for increased diagnosis. In earlier researchers have endeavored to reveal associates between deep learning techniques with AI and CTA image analysis, nevertheless, for the most part by employing only DL techniques. Apart from above stated issues, in our study explores the association between Vision Transformer and accurate aneurysm detection prediction for clinical AI deployments. The major objective of present study is to incorporate AI and vision transformer called, Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) for evaluating and detecting aneurysm using CTA image analysis.

1.2 Contributions of the work

The major contributions of this paper are as follows:

- To propose a method called Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) by utilizing AI for early detection of aneurysm.
- To design brain skull stripping and vessel enhancement using Lightweight Statistical Hessian-based Pre-processing therefore improving noise ratio.
- To present Ternary View Partial Attention DenseNet for extracting relevant features that by concentrating on local and detailed vascular structures reduces false positive rate.

- A Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) for detecting aneurysm adopts Linear Patch Embedding to obtain computationally efficient flattened image patches. The Dual Positional Encoding on the other hand, encodes Attribute-based Positional Encoding (APE) and Topology-based Positional Encoding (TPE) results, therefore improving the precision rate extensively. Finally, Shifted Window Transformer Encoder compares distinguish subtle differences in medical images in an accurate and precise fashion required for model construction.
- The Intracranial Aneurysm containing healthy controls (i.e. normal) and containing aneurysms is utilized to conduct the experimental analysis for the proposed evaluation of aneurysm detection. The best prospective combination of image set features that aid improving the precision accuracy performance has been identified. The comparative analysis of the proposed TVDN-SWViT method has been evaluated based on normal and aneurysm samples separately.

1.1 Organization of the work

The remainder of this paper is organized as follows: Section 2 describes the recent related works related to aneurysm detection mechanisms designed using deep learning and vision transformer learning via CTA images. Section 3 provides the detailed description of proposed method for aneurysm detection analysis using Vision Transformer. Section 4 presents the case study and detailed inferences followed by experimental setup with detailed quantitative analysis in Section 5. In addition, detailed discussion is provided along with the comparison of traditional methods. Finally, Section 6 concludes the paper.

2 Related works

The exact shape of intracranial aneurysms is pivotal in diagnosing medial images and surgical planning. While voxel-based DL algorithms have been presented for this segmentation, their performance remains constrained. A two-step surface-based DL pipeline achieving notably better results with improved accuracy was presented in [16]. A method to reduce false positive employing convolutional neural network transformer was proposed in [17] via segmentation mask. However in case of robust in diverse clinical settings the accuracy factor was not facilitated. To address on this research gap an IA visualization enhancement technique improving clinical workflow efficient was presented in [18]. A systematic review of AI in aneurysm detection was investigated in [19]. However there exist drawbacks in incorporating CTA with clinical scores (PHASES) to predict IAs rupture risk. A meta-analysis measuring AI algorithm performance for predicting IAs rupture risk based on CTA was investigated in [20].

A detailed CTA scans based validation using automated DL-based segmentation pipeline to screen abdominal aortic aneurysms (AAA) was presented in [21]. An early stage validation study for IA detection using DL was proposed in [22] with improved clinical diagnostic performance. Yet another automatic detection of IA employing double blinded random controlled trial model was investigated in [23] in CT angiography patients. However lack of automation in wall weakens results. Hence, automated IA detection method is required to assist physicians make more accurate diagnoses. For this reason, 2D CNN based on network for classification in medicine was proposed in [24] with improved accuracy. A comparative study of reconstruction methods for aneurysm repair detection was investigated in [25]. Yet another automated segmentation of IA using time of flight [26] with improved accuracy.

An AI-based medical imaging technique to predict rupture risk for IA was presented in [26] therefore improving accuracy with minimal error. Nevertheless, owing to the However, due to the weakened boundaries and complicated framework of IAs [27] remains demanding. An attention residual U-Net framework using differential pre-processing and geometric post-processing for automatic segmentation of IAs was presented in [28]. This in turn resulted in the improved segmentation results. A systematic review of rupture risk prediction in IA to enhance the accuracy and reliability was modeled in [29].

From the scrutiny of related works, constrained traditional vision transformer solutions have been designed to evaluate the efficiency of aneurysm detection. With this objective an AI application to screen aneurysm detection using Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) is proposed. The elaborate description of the TVDN-SWViT method is provided in the following sections.

3 Materials and Methodology

Intracranial aneurysms (IA) are becoming gradually frequent with advancement observed in imaging technology. With regard to the aneurysms detection from several imaging modalities, the likelihood of being not noticed occurs chiefly owing to the minuscule size and complicated structure. Artificial intelligence (AI), with its unprecedented potentialities in image-based tasks has put away scholarly interest globally. The application of AI in the operation of IAs being encouraging for promoting medical research and patient care.

Employing deep learning techniques, AI evinces exceptional potentialities in precisely obtaining and segmenting aneurysms, notably improving diagnostic sensitivity and accuracy. In this work an artificial intelligence (AI) to detect aneurysm by applying Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) is designed. Figure 1 shows the architecture of TVDN-SWViT method.



Figure 1 Architecture of TVDN-SWViT method

As illustrated in the above figure, first intracranial aneurysm image were accumulated and thereafter experienced brain skull stripping and vessel enhancement processes as part of the preprocessing stage using Lightweight Statistical Hessian. Subsequently, it leads to the feature extraction from the images with the help of the AI-based Ternary View Partial Attention DenseNet Feature extraction model. Moreover, the Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection is applied for binary classification into normal and aneurysm detected cases.

3.2 Data Preparation and Pre-processing

The CMHA dataset extracted from <https://www.kaggle.com/datasets/amirmahdaviakia/cmha-control>, <https://www.kaggle.com/datasets/amirmahdaviakia/cmha-patient-1/data> and <https://www.kaggle.com/datasets/amirmahdaviakia/cmha-patient-2> comprises of comprehensive medical imaging data obtained from 99 patients and 44 healthy controls. Each patient's record consist raw CTA images, 3D models and hemodynamic analysis results for both aneurysm detection. The data for healthy controls comprises raw CTA images of healthy arteries. Also patient identifiers were coded uniformly with 'AHMU1218', denoting Anhui Medical University in addition to the data collection period between 2012 and 2018, followed by a three-digit unique patient number. Moreover, the analysis results were grouped into five different CSV files within the CMHA directory, including clinical data, morphological parameters for both patients and healthy controls along with the hemodynamic parameters for both groups.

3.3 Lightweight Statistical Hessian-based Pre-processing

The high resolution CMHA-Intracranial Aneurysm dataset employed in our work is pre-processed with the objective of isolating the brain vasculature with other and therefore reduce the noise. In our work Lightweight Statistical Hessian-based Pre-processing model is applied. The Lightweight Statistical Hessian-based Pre-processing model employed in our work for Intracranial Aneurysm CTA images is designed to improve vascular structures while suppressing noise and non-vascular tissues. By applying these functionalities via multi-scale analysis of Hessian matrix tubular structures in turn improve the contrast-to-noise ratio in the CTA volumes. Figure 2 shows the structure of Lightweight Statistical Hessian-based Pre-processing model.



Figure 2 Structure of Lightweight Statistical Hessian-based Pre-processing

As illustrated in the above figure the Lightweight Statistical Hessian-based Pre-processing model is split into two processes. They are brain skull stripping and vessel enhancement. The pre-processing model initially performs the brain skull stripping process by applying the statistical functions like, threshold, morphological closing and distance transform. It predominantly concentrates on the brain vessels and removes non-cerebral tissue like the skull from the raw images. Next, to the results of brain skull striped images, Hessian-based Vessel Enhancement filter is applied to underscore arteries, facilitating the differentiation between blood vessels and adjacent tissue. The first step in Lightweight Statistical Brain Skull Stripping process is to eliminate high-intensity structures, primarily the skull that seem intensified in CTA images. To prove optimal separation between skull and brain region threshold of ' $\delta = 220$ ' (i.e. selected based on the intensity distribution in CTA images) is applied and is defined as given below.

$$Th(p, q) = \begin{cases} 255, & \text{if } Int[S(p, q)] > \delta \\ 0, & \text{if } Int[S(p, q)] \leq \delta \end{cases} \quad (1)$$

From the above equation (1) ' Int ' denotes the intensity of the sample images ' S ' located at coordinates ' p, q '. Also a binary mask indicating '255' (i.e. white) for skull and high intensity structures, other pixels of images were assigned '0' (i.e. black). In spite of the threshold used also eliminates the skull and dura, small gaps and a void is said to occur in the intracranial region. To focus on this aspect, morphological closing operation is carried out utilizing a ' $20 * 20$ ' kernel as given below.

$$MCK = [Int(S)]_{20*20} \quad (2)$$

By applying the above morphological closing assists in bridging fragmented brain regions and fill small holes within the mask, making certain the extracted brain region holds together. Finally to fine-tune the mask, Euclidean Distance Transform function is used to strengthen the segregation between brain and any remaining non-brain structures. The Euclidean Distance Transform-based Refinement used in our work evaluates the minimum distance from each foreground pixel to the subsequent adjacent nearest background pixel as given below.

$$Res = Dis(p, q) = \min \sqrt{(p - p')^2 + (q - q')^2} \quad (3)$$

From the above equation (3) ' $Dis(p, q)$ ' denotes the distance resultant value at pixel ' p, q '. The distance function identifies the subsequent adjacent nearest background pixel ' (p, q) ' and measures Euclidean distance. Pixels with minimal ' $Dis(p, q)$ ' resultant values are found to be closer to the background and probably belong to skull. In this manner only deeper brain regions are retained whereas the unwanted outer elements are removed from further processing. The Hessian matrix of the skull stripped image in the ' s ' scale at ' $Int(Res)$ ' or ' Res ' is defined as given below.

$$H_{Res,s} = \begin{bmatrix} \frac{\partial^2 Int(Res,s)}{\partial Res_1^2} & \frac{\partial^2 Int(Res,s)}{\partial Res_1 \partial Res_2} \\ \frac{\partial^2 Int(Res,s)}{\partial Res_2 \partial Res_1} & \frac{\partial^2 Int(Res,s)}{\partial Res_2^2} \end{bmatrix} \quad (4)$$

From the above matrix results obtained from partial derivatives is found to be sensitive to noise and hence to minimize the effects of image noise, the image intensities are initially convoluted with Gaussian filter as given below.

$$GF(Res, s) = \frac{1}{2\pi s^2} e^{\frac{-|p-q|^2}{2s^2}} \quad (5)$$

From the above equation (5) ' $|p - q|^2$ ' denotes the spatial neighborhood of ' p ' along with ' s ' as scale factor to highlight arteries. Then, the normalized Hessian-based Vessel Enhancement filter is denoted as given below.

$$PS = H_{Res,s}[GF(Res, s)] \quad (6)$$

From the above equation (6) by obtaining resultant pre-processed samples ' PS ' aids in efficiently differentiating between blood vessels and neighboring or adjacent tissues. The pseudo code representation of Lightweight Statistical Hessian-based Pre-processing is given below.

Input: Dataset ' DS ', Sample Images ' $S = \{S_1, S_2, \dots, S_N\}$ '
Output: Noise reduced and enhanced pre-processed samples
Initialize ' $N = 143$ '
Begin
For each Dataset ' DS ' with Sample Images ' S '
Evaluate threshold according to (1) for eliminating high-intensity structures
Evaluate morphological closing operation according to (2) for bridging fragmented brain regions and fill small holes
Evaluate Euclidean Distance Transform-based Refinement according to (3) for strengthening segregation between brain and non-brain structures
Return skull stripped results
Generate vessel enhancement results according to (4) and (5)
Return vessel enhanced results
Return pre-processed sample results
End for
End

Algorithm 1 Lightweight Statistical Hessian-based Pre-processing

As given in the above algorithm with the sample images obtained from the CMHA dataset are subjected to two different processes. They are skull stripping and vessel enhancement. First, by applying the Lightweight Statistical Brain Skull Stripping notably eliminates non-brain tissues or skull while preserving vascular structures for further reference. Moreover, by applying the Hessian-based Vessel Enhancement filter increase aneurysm contrast and boosts small vessels leading to higher peak signal-to noise ratio.

3.4 Ternary View Partial Attention DenseNet Feature extraction-based Artificial Intelligence model

Feature extraction helps identify small protrusions that are found to be demanding to detect. This is owing to the size of small aneurysms therefore making in difficult to differentiate between normal and aneurysm. Starting from our feature extraction pipeline, the aim of our study is to apply the methodological framework of AI and DL to extract relevant features. In our work an advanced Artificial Intelligence (AI) model incorporating DenseNet and Partial Attention mechanism is used that by selectively concentrating on the crucial parts while ignoring irrelevant information reduces false positive. Ternary View Partial Attention DenseNet Feature extraction is used for aneurysm detection in CTA images with the objective of detecting small and complex IA by improving the networks potentiality to concentrate on local and detailed vascular structures. Figure 3 shows the structure of Ternary View Partial Attention DenseNet Feature extraction model.

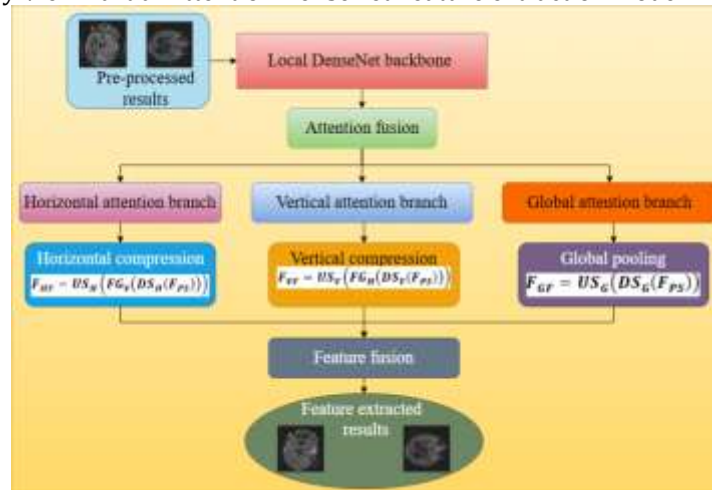


Figure 3 Structure of Ternary View Partial Attention DenseNet Feature extraction model

As illustrated in the above figure, the DenseNet feature extraction employed for aneurysm detection in CT Angiography (CTA) images directly learns to identify vascular abnormalities by reusing features across multiple layers, instead of depending on high-level features. Moreover, the Ternary View Partial Attention (TVPA) function used as feature extraction aids in improving identification of small and subtle lesion. The TVPA upon comparison to the traditional CNN by concentrating on small target lesions within complex vascular backgrounds, significantly reduce false positive.

To start with, the Local-DenseNet used as the encoder in our work exploits DenseNet121 as the backbone network. Followed by which TVPA is added after each Dense Block to focus more on lesions. By reorganizing the input feature weights, the attention mechanism concentrates on paramount features and minimizes consideration of irrelevant information via channel attention and spatial attention. As far as the aneurysm detection in CTA images are concerned spatial attention concentrate on specific location and structural information of diseased tissues. This in turn aids in assisting the model interpretability. On the other hand, the channel attention concentrates on the channel containing the target object.

The TVPA employed in our work includes three branches for extracting local features from three different angles, namely, horizontal, vertical and global perspectives. For horizontal and vertical branches the pre-processed sample input feature ' $F_{PS} \in R^{H*W}$ ' is compressed horizontally ' $F_H \in R^{1*W}$ ' and vertically ' $F_V \in R^{H*1}$ ', respectively. Following which the branch horizontal feature ' $F_{HF} \in R^{H*W}$ ' and vertical feature ' $F_{VF} \in R^{H*W}$ ' is obtained after detail extraction. The horizontal and vertical branch feature results are obtained as given below.

$$F_{VF} = US_V \left(FG_H(DS_V(F_{PS})) \right) \quad (7)$$

$$F_{HF} = US_H \left(FG_V(DS_H(F_{PS})) \right) \quad (8)$$

From the above equations (7) and (8) ' DS_H ' denote the horizontal and vertical ' DS_V ' down sampling of feature maps are performed on the pre-processed sample input feature ' F_{PS} '. The pooling operation performs down sampling of feature maps therefore minimizing computational complexity while capturing larger and contextual features of vessel therefore highlighting the presence of suspected aneurysm or relevant features while discarding irrelevant or noisy features. On the other hand, using the up-sampling function ' US_V ' and ' US_H ' integrates high-resolution details from early layers with deeper information to differentiate aneurysm boundaries accurately. Finally, the horizontal ' FG_H ' and vertical ' FG_V ' results extract both fine-grained low-level and high-level visual structural features. Moreover with the objective of up-sampling the receptive field of local feature extraction, along with the horizontal and vertical branches a third branch is added from global perspective. This is mathematically defined as given below.

$$F_{GF} = US_G(DS_G(F_{PS})) \quad (9)$$

$$FE = F_{PS} \otimes \sigma(F_{VF} \oplus F_{HF} \oplus F_{GF}) \quad (10)$$

From the above equations (9) and (10) the three branch features i.e., horizontal, vertical along with global and pre-processed sample input feature ' F_{PS} ' are fused to obtain the output or the feature extracted results ' FE '. The pseudo code representation of Ternary View Partial Attention DenseNet Feature extraction-based Artificial Intelligence is given below.

Input: Dataset ' DS ', Sample Images ' $S = \{S_1, S_2, \dots, S_N\}$ '
Output: false positive-minimized feature extraction
Initialize ' $N = 143$ ', pre-processed sample results ' PS '
Begin
For each Dataset ' DS ' with Sample Images ' S ' and pre-processed sample results ' PS '
Generate horizontal branch feature results according to (7)
Generate vertical branch feature results according to (8)
Generate global branch feature results according to (9)
Obtain feature extracted results according to (10)
Return feature extracted results ' FE '
End for
End

Algorithm 2 Ternary View Partial Attention DenseNet Feature extraction-based Artificial Intelligence

As mentioned in the above algorithm the entire process of Ternary View Partial Attention DenseNet Feature extraction-based Artificial Intelligence is split into three parts. Initially, , by evaluating the horizontal branch feature results assists in improving the effectiveness of detecting IA specifically small ones and located at complex positions. Here, by concentrating computational attention on the most relevant features from surrounding anatomical structures in turn enhances feature extraction. Next, by evaluating the vertical branch feature by concentrating on vascular structures in specific orientations maximizes the visibility of small

aneurysms and hence reduces false positives. Finally, by combining both the AI can differentiate true abnormalities from similar looking structures, therefore reducing the overall false positive cases.

3.5 Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection

Finally, the proposed method uses a specific kind of image classification model called Dual Position Shifted Window-based Vision Transformer for performing a binary classification on aneurysm CTA medical images. It is modeled specifically with the objective of learning to classify two classes, for instance, normal versus aneurysm. The aneurysm detection process is split into three parts. They are Patch Embedding, Dual Position Encoding and Shifted Window Transformer Encoder for Aneurysm Detection. Figure 4 shows the structure of Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection.

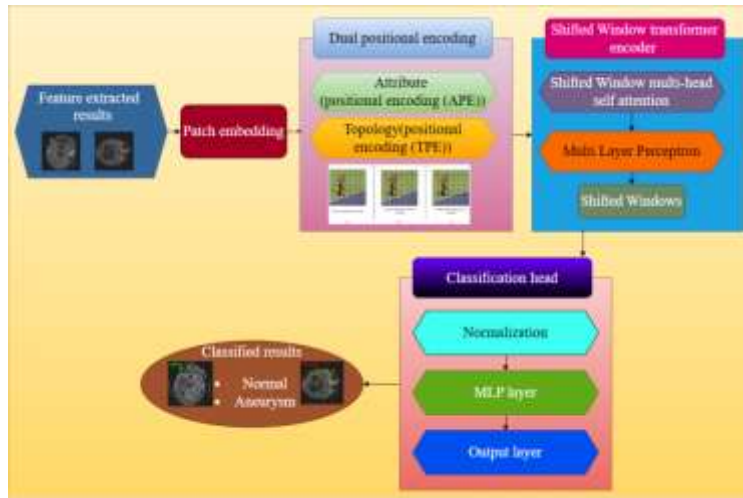


Figure 4 Structure of Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection

As illustrated in the above figure, the extracted features are flattened and converted into a sequence of embeddings or tokens and fed into the Vision Transformer. Due to the reason that the transformers do not intrinsically grasp the order, 3D sinusoidal positional encoding is added to preserve the patches spatial information. Each '16 * 16' patch is flattened and linearly projected into a '384' dimensional embedding and a classification token 'CLS' is attached along with the patch sequence to retain spatial information. The Dual Positional Encoding employed in our work is Attribute-based Positional Encoding (APE) and Topology-based Positional Encoding (TPE). On one hand, the APE integrates aneurysm-specific features into the positional representation of a voxel and on the other hand, the TPE embeds the connectivity of vascular tree or topology ensuring that the proposed method comprehends branching structure. Finally, the input is processed by the Shifted Window Transformer Encoder to obtain the classified output results (i.e. normal or aneurysm detected results).

The proposed classifier method for aneurysm detection initiates the process by splitting the input image (i.e. pre-processed and feature extracted results ' $X \in PS[FE]$ ') into a fixed number of patches. Let us consider an input image ' $X \in R^{H*W*C}$ ' with ' C ', ' H ' and ' W ' denoting the channel number, image height and image width respectively. The first step is patching embedding, where the image is split into ' M ' image pieces, where ' $M = \frac{H*W}{Size^2}$ ', with ' $Size$ ' denoting the patch size. Then, these image pieces are flattened as a vector with size of ' $Size^2 C$ ' and projected to a lower dimension as given below.

$$Out_i = W \cdot x_i + b \quad (11)$$

From the above equation (11) ' W ' denotes the learnable weight matrix for the corresponding flattened input image ' x_i ' and storing their corresponding results ' Out_i ' to the image vector after projection. Given that transformers do not essentially understand the sequential ordering of patches, in our work Dual Positional Encoding is added to patch embedding results with the objective of retaining positional information about the patches. Initially ' l ' clusters ' $C = \{C_1, C_2, \dots, C_l\}$ ' based on the pre-processed and feature extracted results ' X ' are formed. Then the centroid representation ' X_i^{Cen} ' of a cluster ' C ' is evaluated as given below.

$$X_i^{Cen} = \frac{1}{|C_i|} \sum X_j \quad (12)$$

Based on the above results the APE result ' X_j^{APE} ' of ' X_j ' belonging to cluster ' C_i ' is defined as given below.

$$X_j^{APE} = \text{Cosine}(X_j, X_i^{Cen}) \quad (13)$$

From the above equation (13) result ensures that the samples within the same cluster generate more similar positional encoding representations than those in different clusters. In addition, the proposed method incorporated TPE to generate the final dual positional encoding result as given below.

$$Res = X^{DPE} = X^{APE} || X^{TPE} \quad (14)$$

From the above equation (14) the dual positional encoder results of the provided samples ' X^{DPE} ' are arrived at by concatenating '||' the results of APE ' X^{APE} ' and TPE ' X^{TPE} ' (i.e. eigen vector matrix corresponding to non-trivial eigen values) respectively. The input is then transferred to the Shifted Window Transformer Encoder for final classification. Here, the embedded and encoding sequence results are passed via multiple transformer encoder blocks consisting of normalization layer, Multi Head Attention (MHA) layer and a Multi Layer Perceptron (MLP) layer. The normalization layer is denoted as given below.

$$Norm(x) = \frac{x - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (15)$$

From the above equation (15), using ' μ ', ' σ ' and ' ϵ ' denotes the mean, variance of vector and constant serves as a mechanism to standardize data for further processing. Following which the MHA operation is performed by applying the Shifted Window function. The Shifted Window function employed in our work constrains self-attention calculations to non-overlapping patches, allowing the method to concentrate on the detailed texture and shape of prospective aneurysms without analyzing the entire 3D volume at once, hence minimizing overall training time.

$$Res^{(k+1)} = (Norm(x)(Res^k)) + (Res^k) \quad (16)$$

$$Res^{(k+2)} = MLP(Norm(x)(Res^{k+1})) + (Res^{k+1}) \quad (17)$$

$$Q = XW_Q; K = XW_K; V = XW_V \quad (18)$$

Finally the attention formula results are obtained by shifting the window partitioning between layers as given below.

$$Att(Q, K, V) = [Res^{(k+1)}, Res^{(k+2)}, \dots] softmax \left(\frac{QK^T}{\sqrt{d}} \right) V \quad (19)$$

From the above equation (19) finally the classified results are obtained by applying the scaling factor ' d ' denoting the dimension of query, key and value vectors respectively. Finally, the MHA output (i.e. the results of is Shifted Window function) is added to the initial input, followed by a layer normalization, and then fed into the MLP layer to produce the output. This procedure is repeated iteratively for ' k ' layers to generate the final output. The pseudo code representation of Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection is given below.

Input: Dataset ' DS ', Sample Images ' $S = \{S_1, S_2, \dots, S_N\}$ '
Output: accuracy aneurysm detection
Initialize ' $N = 143$ ', pre-processed sample results ' PS ', feature extracted results ' FE ' Begin For each Dataset ' DS ' with Sample Images ' S ', pre-processed sample results ' PS ' and feature extracted results ' FE ' Patch Embedding Flatten the image pieces as a vector according to (11) Dual Positional Encoding Evaluate the centroid representation ' X_i^{cen} ' of a cluster ' C ' according to (12) Evaluate the Attribute-based Positional Encoding results according to (13) Evaluate the dual positional encoding result according to (14) Return dual positional encoding result Transformer Encoder Generate normalization results according to (15) Evaluate Shifted Window function results according to (16), (17) and (18) Classification Head Generate classification head results according to (19) Return classified output End for End

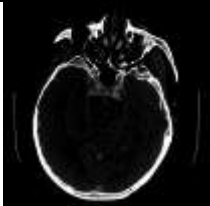
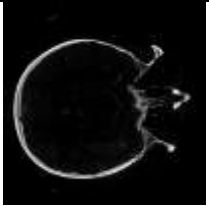
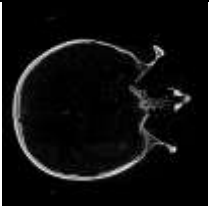
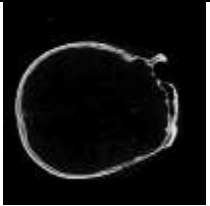
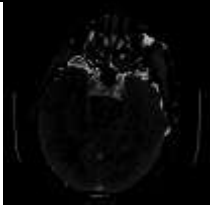
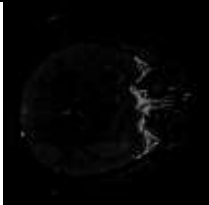
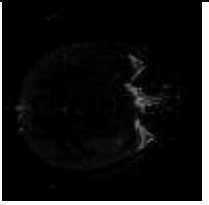
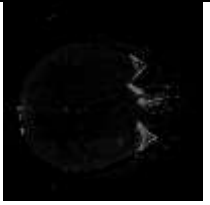
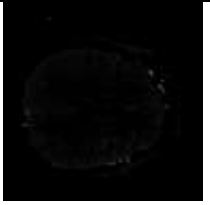
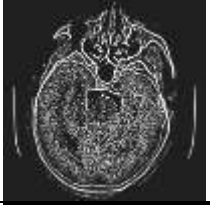
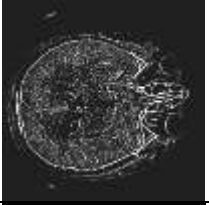
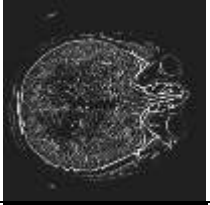
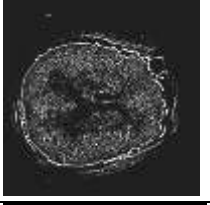
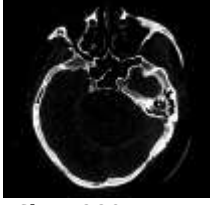
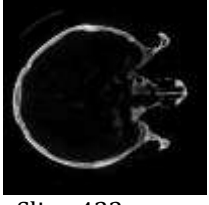
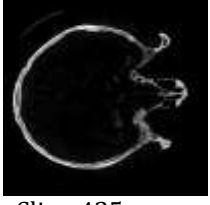
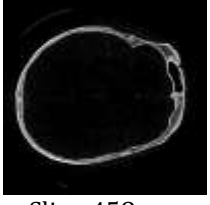
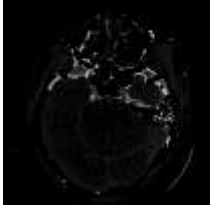
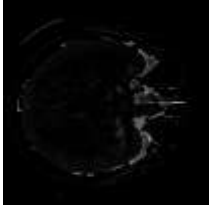
Algorithm 3 Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection

As given in the above algorithm Dual Position Shifted Window-based Vision Transformer for Aneurysm Detection is split into four parts. They are patch embedding, dual position encoding, transformer encoder and classification head. Initially the image pieces are flattened as a vector. Following which, Dual Positional Encoding using Attribute-based Positional Encoding and Topology-based Positional Encoding results are

obtained separately. The Dual Positional Encoding employed in our work by providing both geometric and structural context via APE and TPE detect even small aneurysms or those positioned near bone. This in turn improves overall precision. As already stated that the aneurysms are small in size with similar in appearance to adjacent blood vessels, the shifted window attention mechanism applied allows the network to zoom in on these fine-grained details therefore improving overall recall and accuracy.

4 Case Study and Implications

In this section case analysis of aneurysm detection using CTA images are simulated by applying Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT). As already stated the aneurysm samples can be sliced into multiple images, hence though numerous slices are present for a single subject, for reference we have used only certain slices to conduct simulation. In our work to perform simulation two aneurysm subjects with subject ID AHMU1218052, AHMU1218052 and one healthy CTA image with subject ID AHMU1218104 are used for simulation. For simulation purpose with 546 slides, 561 slides and 863 slides present in three subjects, slice number 385, slice number 415, slice number 416, slice number 417 and slice 446 are used for subject ID AHMU1218052. In a similar manner, slice number 389, slice number 423, slice number 424, slice number 425 and slice number 458 are used for subject ID AHMU1218052. Finally, five slides of subject ID AHMU1218052 including slice 529, slice 530, slice 531, slice 532 and slice 533 are used for simulation. First, Lightweight Statistical Hessian-based Pre-processing is applied to the above set of samples and their results are shown separately for skull stripping and vessel enhanced slice results.

Subject_id	Slices				
AHMU1218052					
	Slice_385	Slice_415	Slice_416	Slice_417	Slice_446
Skull Stripped results					
Vessel enhanced results					
AHMU1218053					
	Slice_389	Slice_423	Slice_424	Slice_425	Slice_458
Skull Stripped results					

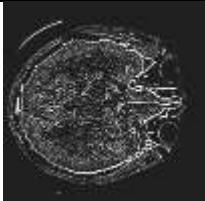
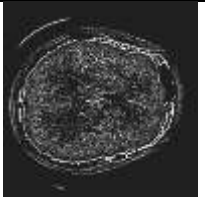
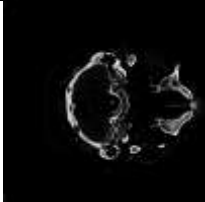
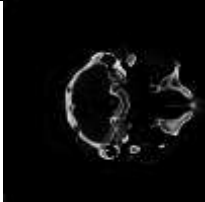
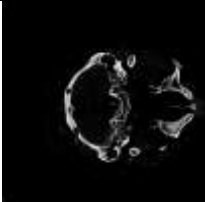
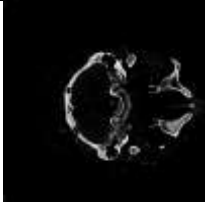
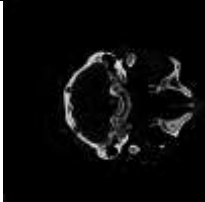
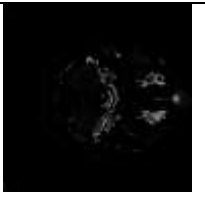
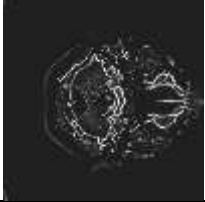
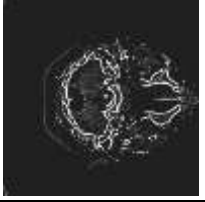
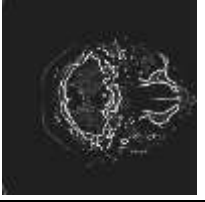
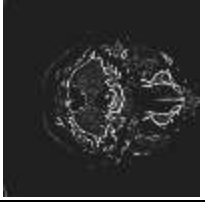
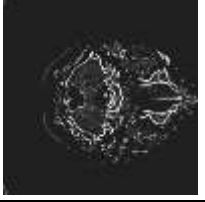
Vessel enhanced results					
AHMU1218104 (Healthy)					
	Slice_529	Slice_530	Slice_531	Slice_532	Slice_533
Skull Stripped results					
Vessel enhanced results					

Figure 5 Lightweight Statistical Hessian-based Pre-processing

As given in the above figure the results of pre-processing separately for skull stripping and vessel enhancement are applied. By applying this process improves the noise ratio. With the pre-processed samples the results are subjected to extract relevant features. Figure 6 shows the feature extracted results.

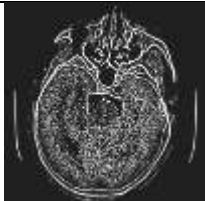
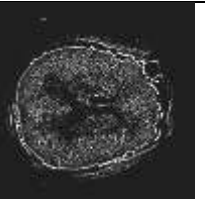
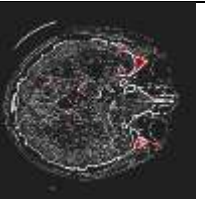
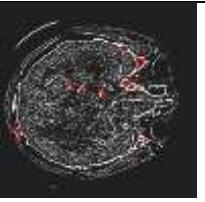
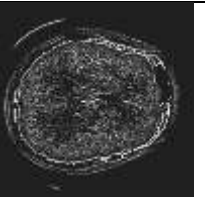
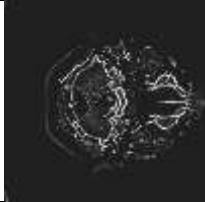
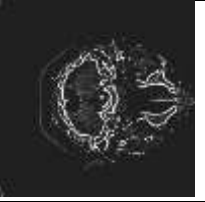
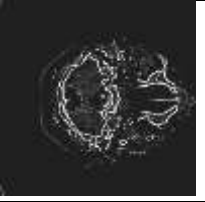
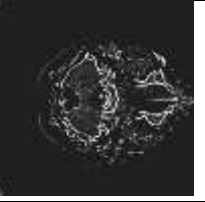
Subject_id	Slices				
AHMU1218052					
AHMU1218053					
AHMU1218104 (Healthy)					

Figure 6 AI-based Ternary View Partial Attention DenseNet Feature extraction

As given in the above figure an AI-based feature extraction model incorporating ternary view along with partial attention function are applied. By applying these functionalities as feature extraction increasing small aneurysm visibility, therefore reducing false positives. Finally, the pre-processed and relevant feature extracted results were subjected to classification. Figure 7 shows the classified results.

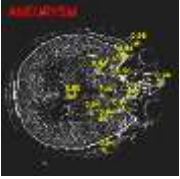
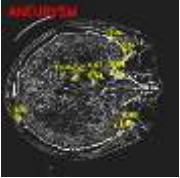
Subject_id	Slices				
AHMU1218052					
AHMU1218053					
AHMU1218104 (Healthy)					

Figure 7 Classified results

As illustrated in the above results by applying performs separate Attribute-based Positional Encoding and Topology-based Positional Encoding. By applying these functions along with the Shifted Window Transformer Encoder improves the overall precision and accuracy in an extensive manner. The quantitative analysis involved in the process of aneurysm detection is detailed in the following subsections.

5 Experimental Setup and Discussion

The proposed artificial intelligence (AI) application to screen aneurysm detection using Ternary View DenseNet and Shifted Window Vision Transformer (TVDN-SWViT) is evaluated employing Python working on MS Window platform on computer with i3-2350 processor and 2 GB RAM. The results are compared with the previous two existing methods, Uncertainty-guided Joint Cross Pseudo Supervision (UJ-CPS) [1] and Convolutional Neural Network based Deep Learning Model (CNN-based DLM) [2]. Moreover the results are analyzed and validated on the basis of five metrics, such as, PSNR, false positive rate, precision, recall and accuracy using CMHA dataset extracted from <https://doi.org/10.6084/m9.figshare.26965450>.

5.2 Performance analysis of Peak Signal to Noise Ratio

Peak Signal-to-Noise Ratio (PSNR) is a pivotal performance metric utilized in the detection of aneurysm. By using the PSNR values the quality of CTA images are said to be evaluated post pre-processing. Higher PSNR values represent lower noise with better image quality, therefore facilitating enhanced diagnostic accuracy, like increasing aneurysm detection and vice versa.

$$PSNR = 10 * \log_{10} \left(\frac{Max_s^2}{MSE} \right) \quad (20)$$

$$MSE = \frac{1}{m*n} \sum_{p=1}^m \sum_{q=1}^n [GT(p, q) - NI(p, q)]^2 \quad (21)$$

From the above equations (20) and (21) the results of peak signal to noise ratio 'PSNR' and mean square error 'MSE' results are arrived at based on the maximum possible pixel value of sample image 'Max_s²', ground truth image 'GT', noisy image 'NI' with respect to 'm' rows and 'n' columns respectively. Table 1 given below lists the results of PSNR by substituting the values in equations (20) and (21) using the three methods, TVDN-SWViT, UJ-CPS [1] and CNN-based DLM [2].

Table 1 PSNR results

Image size (KB)	PSNR (dB)		
	TVDN-SWViT	UJ-CPS [1]	CNN-based DLM [2]

26.1	28.25	23.15	21.55
26.5	27.35	22.55	20.35
34.9	25	20.25	18.55
36.3	24.15	19.55	17.35
36.8	23	18.15	16.55
37.4	22.45	17.35	15.25
37.8	21	16.55	14.15
63.8	20.85	15.35	13.25
65.3	19.35	14.25	12.15
65.9	18.15	13.55	11.55

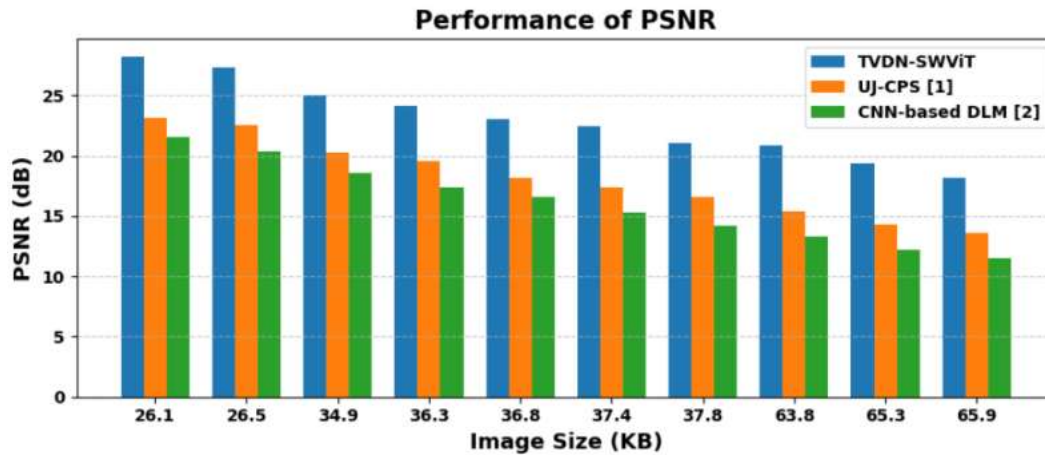


Figure 8 PSNR versus image size

Figure 8 given above illustrates the graphical representation of PSNR using three methods TVDN-SWViT, UJ-CPS [1] and CNN-based DLM [2]. Ten different subjects with image sizes ranging between 26.1KB and 65.9KB were used to analyze the results of PSNR. Also increasing the image size causes a decrease in PSNR rate. But comparative analysis show improved PSNR results for TVDN-SWViT upon comparison to [1] and [2]. The reason was by incorporating skull stripping using Lightweight Statistical function and Hessian-based pre-processing notably improves the Peak Signal-to-Noise Ratio (PSNR) of Computed Tomography Angiography (CTA) images for detecting intracranial aneurysm. Also by combining lightweight statistical functions like thresholding, morphological closing operations efficiently eliminate non-brain tissues, whereas the Hessian filters, based on eigenvalue analysis suppress noise. This incorporation of skull stripping with filter boosts the PSNR crucial for identifying aneurysms using TVDN-SWViT by 22% compared to [1] and 31% compared to [2].

5.3 Performance analysis of False Positive Rate

The false positive rate in the detection of aneurysm denotes cases where CTA imaging incorrectly identifies a normal vascular structure or anatomical variant as an aneurysm. This is mathematically defined as given below.

$$FPR = \frac{FP}{FP+TN} \quad (22)$$

From the above equation (22) the false positive rate 'FPR' is evaluated based on the false positive rate 'FP' and true negative rate 'TN' respectively. Table 2 given below lists the results of PSNR by substituting the values in equation (22) using the three methods, TVDN-SWViT, UJ-CPS [1] and CNN-based DLM [2].

Table 2 False Positive Rate results

Sample (slices)	False Positive Rate		
	TVDN-SWViT	UJ-CPS [1]	CNN-based DLM [2]
500	0.37	0.58	0.72
1000	0.41	0.6	0.74
1500	0.48	0.62	0.76
2000	0.55	0.65	0.78
2500	0.59	0.68	0.79

3000	0.65	0.72	0.8
3500	0.55	0.68	0.75
4000	0.48	0.65	0.72
4500	0.45	0.67	0.7
5000	0.4	0.6	0.68

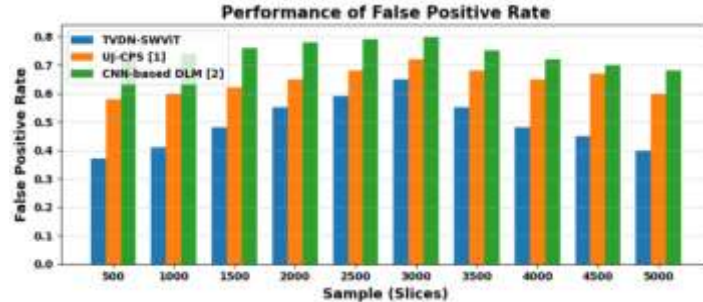


Figure 9 False Positive Rate versus sample slices

Figure 9 illustrates figurative representation of false positive rate using proposed TVDN-SWViT and two existing methods, UJ-CPS [1] and CNN-based DLM [2]. Samples of slices ranging between 500 and 5000 were used for evaluating the false positive rate using the three methods. In spite of false positive rate being higher for first six iterations whereas for the rest of four iterations found a minimizing of false positive rate using all the methods. But simulation results for 500 slices observed false positive rate of 0.37 when applied with TVDN-SWViT whereas 0.58 and 0.75 using [1] and [2]. The reason was with the Partial attention mechanisms employed in our work allow the DenseNet to concentrate selectively on subtle aneurysmal protrusions that are easily missed. Also, by using a partial attention the feature extraction model filters out non-aneurysmal vascular structures that often results in false detections in automated CAD systems. Finally, the ternary view along with partial attention boosts the models sensitivity by filtering out irrelevant background noise missed out during pre-processing. Therefore by focusing on relevant regions of the vessel the proposed methods reduces the False Positive Rate of TVDN-SWViT by 33% compared to [1] and 54% compared to [2].

5.4 Performance analysis of Precision, Recall and Accuracy

Precision refers to the potentiality of a classifier method to not label a negative sample as positive. Recall on the other hand defines the potentiality of a classifier method to identify all positive samples. To be more specific, it is defined as how many actual positive cases were correctly identified. Finally, accuracy refers to the ratio of correctly predicted aneurysm observations to the total observations.

$$Pre = \frac{TP}{TP+FP} \quad (23)$$

$$Rec = \frac{TP}{TP+FN} \quad (24)$$

$$Acc = \frac{TP+TN}{TP+FP+TN+FN} \quad (25)$$

From the above equations (23), (24) and (25) precision 'Pre', recall 'Rec' and accuracy 'Acc' is evaluated based on the true positive rate 'TP' (i.e. normal samples detected as normal), false positive rate 'FP' (i.e. normal samples detected as aneurysm), true negative rate 'TN' (i.e. aneurysm samples detected as aneurysm) and false negative rate 'FN' (i.e. aneurysm samples detected as normal). Table 3 given below lists the results of Precision, Recall and Accuracy by substituting the values in equations (23), (24) and (25) using TVDN-SWViT, UJ-CPS [1] and CNN-based DLM [2].

Table 3 Precision, Recall and Accuracy results

Sample s	Precision			Recall			Accuracy		
	TVDN-SWViT	UJ-CPS [1]	CNN-based DLM [2]	TVDN-SWViT	UJ-CPS [1]	CNN-based DLM [2]	TVDN-SWViT	UJ-CPS [1]	CNN-based DLM [2]
500	0.96	0.94	0.91	0.98	0.97	0.96	0.96	0.92	0.89
1000	0.94	0.81	0.76	0.95	0.83	0.77	0.93	0.85	0.75
1500	0.92	0.79	0.74	0.93	0.81	0.75	0.91	0.83	0.73
2000	0.9	0.74	0.69	0.91	0.79	0.73	0.88	0.8	0.7
2500	0.88	0.75	0.7	0.84	0.72	0.66	0.85	0.77	0.67

3000	0.85	0.72	0.67	0.82	0.7	0.64	0.82	0.74	0.64
3500	0.83	0.7	0.65	0.8	0.68	0.62	0.8	0.72	0.62
4000	0.86	0.73	0.68	0.84	0.72	0.64	0.84	0.76	0.66
4500	0.89	0.76	0.71	0.86	0.74	0.68	0.87	0.79	0.69
5000	0.92	0.79	0.74	0.89	0.77	0.71	0.9	0.82	0.72

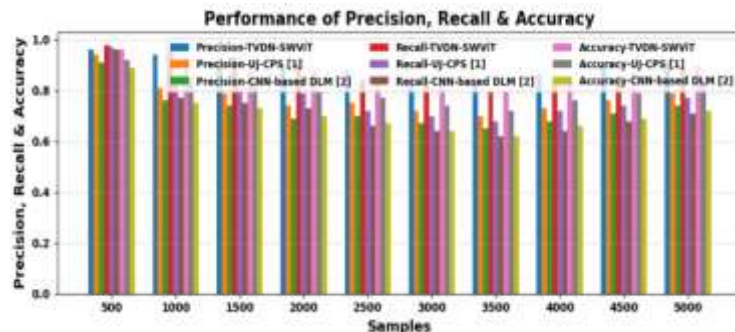


Figure 10 Precision, Recall and Accuracy versus sample slices

Finally figure 10 given above shows the precision, recall and accuracy results of the three methods, TVDN-SWViT, UJ-CPS [1] and CNN-based DLM [2] for samples ranging between 500 and 5000 performed over a simulation of ten runs. Though increasing sample slices causes a decrease in the precision, recall and accuracy, however comparative analysis found better results when applied with TVDN-SWViT upon comparison to [1] and [2]. First by applying TPE that incorporating anatomical structure directly enhances the anatomical abnormality identification. Moreover by using the APE helps the method concentrate on areas where aneurysms are probably to occur. This in turn aids in maintaining high precision. APE improves overall segmentation resolution, while TPE provides critical understanding of vessel structure. Together, they accurately distinguish vascular abnormalities in CTA images, resulting in higher precision using TVDN-SWViT by 14% compared to [1] and 19% compared to [2]. Next, the application of Shifted Window-based Vision Transformers upon comparison to normal transformer in aneurysm detection for CTA images by exploiting self-attention within local windows and shifting these windows between layers, significantly capture both long-range dependencies and local vascular details. This in turn improves recall of TVDN-SWViT method by 13% compared to [1] and 19% compared to [2]. Moreover, by shifting the window partitioning between consecutive layers, the method enables communication between adjacent windows, ensuring it captures interactions beyond a local region. This in turn therefore improved overall accuracy of TVDN-SWViT method by 9% compared to [1] and 19% compared to [2].

6 Conclusion

Aneurysm detection is a demanding task owing to drawbacks in imaging technology and demanding anatomical locations. In this paper, we propose the TVDN-SWViT, an AI application to screen aneurysm detection using Ternary View DenseNet and Shifted Window Vision Transformer for aneurysm detection. The TVDN-SWViT adopts a Lightweight Statistical Hessian-based Pre-processing model therefore facilitating difference between blood vessels and adjacent tissue with improved noise ratio. Next, a Ternary View Partial Attention DenseNet Feature extraction algorithm is designed to concentrate on local and detailed vascular structures with minimal false positive. Finally Dual Position Shifted Window-based Vision Transformer algorithm using Attribute-based Positional Encoding (APE) and Topology-based Positional Encoding (TPE) along with Shifted Window function in Transformer Encoder results in improved accuracy. Experiments on the CMHA dataset show that the TVDN-SWViT method outperforms all baselines in terms of PSNR, false positive rate, precision, recall and accuracy.

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