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# CLASSIFICATION OF ANOMALOUS REGION IN HUMAN CEREBROVASCULAR STRUCTURE USING RANDOM FOREST

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**Abstract- To predict and assess the cerebrovascular diseases anomaly detection in cerebrovasculature is a crucial job. Classification of anomalous part in human cerebrovascular structure which will lead to several vascular disease, can help to detect or predict the same. Aneurysm is one of the vascular disease which causes a number of deaths worldwide and so it is very crucial for clinicians to predict or assess it. It is reasonable to assume that rupture risk assessment can be improved by incorporating hemodynamic analysis as it is commonly thought to play an important role in the mechanisms of development, progression, and rupture of aneurysm. Hemodynamic parameter like wall shear stress(wss), velocity, static pressure information are to be developed by digital flow based model. So the comparison of the hemodynamic parameters on several cerebrovascular structures with and without aneurysm and to find some features from that for pattern classification, carries a significant role in prediction of occurrence of aneurysm and subsequently rupture risk of the same.**
**Keywords – Aneurysm, hemodynamic analysis, cerebrovascular phantoms, wall shear stress, classification, feature, rupture risk.**

## 1. INTRODUCTION

Detection of anomalous region is one of the vital job to predict some cerebrovascular disease. So analysis and study of the human vasculature and classification of anomalous part and normal part of the human cerebrovasculature signify a lot because disease like aneurysm which is caused by some anomaly in structural form and hemodynamic parameter form.

Cerebrovascular disease (CVD) is one of the leading causes of deaths in the arban area. CVD ailments are relative to atherosclerosis. Atherosclerosis is responsible for the thickening of the artery walls. Aneurysm is one of the major vascular disease is responsible for nearly 500,000 deaths a year worldwide if they burst before being treated.

An aneurysm occurs when an artery’s wall weakens and causes an abnormal out pouch which is filled with blood. This bulge can rupture and cause internal bleeding. Although the exact cause of an aneurysm is unclear, certain factors contribute to the condition. For example, damaged tissue in the arteries can play a role. The arteries can be harmed by blockages, such as fatty deposits which can trigger the heart to pump harder than necessary to push blood past the fatty buildup. This stress can damage the arteries because of the increased pressure. Atherosclerotic disease can also lead to an aneurysm. People with atherosclerotic disease have a form of plaque buildup in their arteries. This buildup is due to a hard substance called plaque that damages the arteries and prevents blood from flowing freely.

High blood pressure may also cause an aneurysm. The force of your blood as it travels through your blood vessels is measured by how much pressure it places on your artery walls. If the pressure increases above a normal rate, it may enlarge or weaken the blood vessels.

Various hemodynamic parameters are suspected to be major factors related to the genesis and progression of aneurysm. So it is of immense importance for treatment to understand the hemodynamic factors that play a role in the formation and development of disease like aneurysms [1]. The flow pattern will be changed in the vascular structure if there exits an aneurysm and also the hemodynamic parameter values differ from the one without aneurysm. So to classify the aneurysm part and normal part of the vascular structure, it is very crucial to analyze hemodynamics there in and select features form that analysis.

When a brain aneurysm ruptures, the result is called a subarachnoid hemorrhage. Depending on the severity of the hemorrhage, brain damage or death may result.

The most common location for brain aneurysms is in the network of blood vessels at the base of the brain called the circle of Willis.

In this work, we focus on the major arterial structure present in the human carotid region because carotid vasculature is the one of the major part of the human vasculature. To do the hemodynamic analysis and to select feature from that analysis, it is important to understand the carotid blood flow patterns and so structural analysis of carotid arteries are needed for determination of abnormal out pouching. Detection of possible shrinkage or blockage in the blood flow determines the causes of malformation. To describe the network of carotid arteries, knowledge about the structure of the Circle of Willis which is

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present at the base of the brain, is very much necessary. This is a circular vasculature formed by the left and right Anterior cerebral artery (left and right), Internal Carotid Arteries (ICA), Anterior Communicating Artery (ACA), Internal Carotid Artery (left and right) or ICA, Posterior cerebral artery (left and right), Posterior communicating artery (left and right). The basilar artery and middle cerebral arteries, which supplies the oxygen rich blood to the brain, are also considered as part of the circle of willis [2].

Collecting the medical image is really a difficult job. In vivo or ex vivo analysis of carotid arterial system is a vital job and need to be taken care very minutely by the experts. Patient permission and participation is equally important to capture and collect the in-vivo images. So construction of synthetic structures or phantoms are very necessary and important as it is important to analyze real medical data [3]. Therefore generation of the synthetic structures or phantoms are often valuable for evaluation and application of new computational techniques [4], [5], [12] at the laboratories. It also helps the patients to avoid repeated harmful cerebral scans. Due to the apparent simplicity of the design, phantom based simulation experiments are most popular. In general, there are two aspects of the study; 1) using physical vascular phantoms with and without aneurysm, generated by casting a replica of the actual vasculature, and 2) digital modeling of the vasculature, using mathematical models.

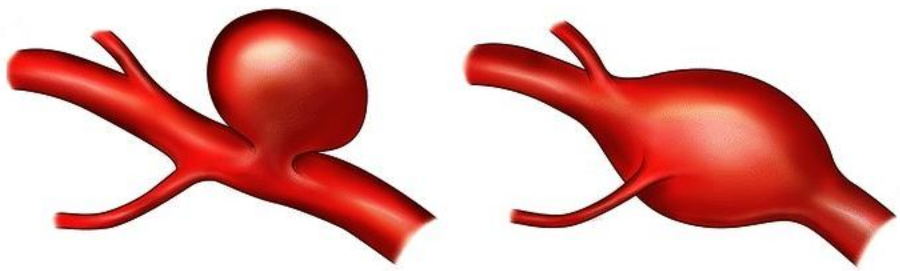


Fig.1. Different types of aneurysm

Weakness of the arterial wall is the major cause of development and progress of aneurysm. If it becomes large enough, it can be ruptured to spill blood into the surrounding tissue. Cerebral aneurysm is a bulge in the vessel wall of an artery located in the brain. There are three types of cerebral aneurysms which can be separated geometrically. A saccular aneurysm is the most common type of aneurysm. It is of rounded shape that is attached to an artery by a neck. As the shape is like berry it is also called berry aneurysm. Another less common type of aneurysm is a fusiform aneurysm. It is of spindle-shape. It is due to the widening of the vessel wall. Another type of aneurysm is a giant aneurysm which is a berry aneurysm but is large. It occurs mainly at the bifurcation of an artery.

There is no known prevention method for this vascular disease as the initiation of aneurysm is not well understood. If it is not taken care of in right time it can be ruptured and consequently patient may die. So the classification of the part which is with aneurysm from the normal vascular part is very necessary. Numerous studies have been performed to provide the detailed hemodynamic information of the artery. Many studies have attempted to identify appropriate hemodynamic properties related to the aneurysm initiation, progress and growth. Hemodynamic parameters such as the blood pressure, velocity of blood flow and the wall shear stress are performed to be linked to the progression of the aneurysm [6], [7]. Wall shear stress is considered to be highly associated with the development of the cerebral aneurysm. Furthermore, high wall shear stress magnitude or high spatial and temporal variation of wall shear stress may damage the inner wall artery [8], [9], [10].

In this connection, the purpose of the work and scope of the work are illustrated. The main purpose of the work here is to classify the normal and anomalous voxel through features extracted from the study of the flow analysis on the cerebrovascular phantoms with and without aneurysm and the comparison of the hemodynamic parameters therein. For that, at the outset we need medical data. As the real medical data collection are so troublesome and patient permission is also needed, we are not only choose the real data, but also prepared some phantom data to study the hemodynamic parameters thoroughly. The detailed need of phantom design is discussed in the introductory part of this paper. Here we have considered the aneurysm as a vascular disease as it is a very prominent and deadly disease to be taken care of. The importance and the reason of this cerebrovascular disease are already discussed briefly in introduction part of this paper. As the hemodynamics play an important role in the progression and genesis of aneurysm, we need to study hemodynamics of cerebrovasculature. As we consider brain as the most significant and essential part of human body and carotid vascular region is one of the major arterial structure of the same, we are resembling the carotid vasculature and blood flow in the same. Here we have generated digital flow to resemble the blood flow in vascular structure. Digital topology has been used for the studies related to this [14], [15], [16]. Using the digital flow based model we have generated different hemodynamic parameters like velocity, wall shear stress etc and from those hemodynamic parameter and some flow based parameter we have designed the feature set which has been used to classify the anomalous part and normal part of the cerebrovascular structure. So the present work is comprised of mainly four parts in addition with introduction and conclusion. And the organization of this work is as follows:

1. Design of phantoms of cerebrovascular structure are depicted in section II.
2. Generating 3D digital flow in some cerebrovascular structures is discussed in section III.
3. Classification of anomalous region and normal region of vascular structure after designing the feature set, is described in section IV.
4. Discussion of result and analysis of classification are depicted in section.

**2. DESIGN OF SOME CEREBROVASCULAR STRUCTURE WITH AND WITHOUT ANEURYSM**

Some cerebrovascular structure like ICA, BA with and without aneurysm are shown in Fig.2 and Fig.3 respectively.

In first step original CT image is taken as input and converted into fuzzy distance transform(FDT) image. One can find a vast and rich literature on FDT and its application [11], [12], [13]. Recently Guha et al. proposed a FDT based geodesic path propagation algorithm for reconstruction of cerebrovascular phantom which required least user interaction [5].

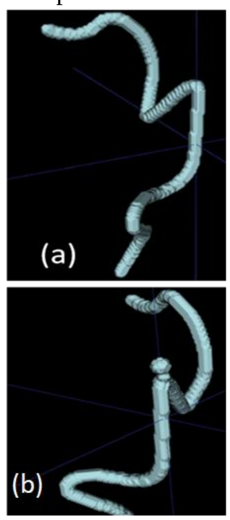


Fig.2. (a) ICA (internal carotid artery) without aneurysm (b) ICA with aneurysm

In next step start and end input seed points are taken from user and geodesic path is found between those two points. Next sphere is drawn at each point on the geodesic path with radius equal to the FDT value of that point. If generated phantom needs further modification user can give more seed points and followed same steps described before.

Fluid dynamics of blood flow which is referred to as hemodynamics explains the physical laws that govern the flow of blood in the blood vessels. Hemodynamic response continuously monitors and adjusts to conditions in the body and its environment. Due to viscosity, flow of blood engenders on the luminal vessel wall a frictional force per unit area known as hemodynamic shear stress.

To do the hemodynamic analysis through the finite element modeling we need synthetic 3-D phantom which will resemble human carotid arteries. Here we have designed 2 cerebrovascular phantom with and without aneurysm which are explained above.

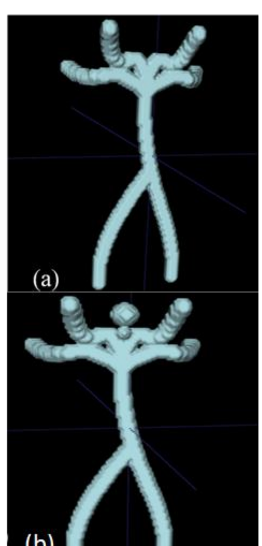


Fig.3. (a) BA (Basilar artery) without aneurysm (b) BA (Basilar artery) with aneurysm

## 3. 3-D DIGITAL FLOW MODEL

A three dimensional (3-D) cubic grid, is represented by $z^3$ $|z$ is the set of integers. A grid point is referred to as a voxel, is an element of $z^3$ and is represented by a triplet of integer coordinates. Standard 26-adjacency is used here, i.e., two points $p = (x_1, x_2, x_3)$, $q = (y_1, y_2, y_3) \in z^3$ are adjacent if and only if $max_{1\leq i\leq 3}|x_i - y_i| \leq 1$, where $|.|$ returns the absolute value. Two adjacent voxels are referred to as neighbors of each other; the set of 26-neighbors of a voxel $p$ excluding itself is denoted by $N^*(p)$.

Let S denotes a set of voxels, a flow $\omega$ in $S$ from $p \in S$ is defined by a set of parameters$\{p, \alpha, \beta\}$, where $\alpha$ is the direction of the flow from $p$, $\beta$ is the flow angle. When flow is projected from a particular voxel with a definite divergence angle, it forms conical structure. The voxels inside the conic are the wetted voxels. Shape of the conic changes with the change of flow divergence angle because number and position of wetted voxels change.

The experimental results are shown on ICA and BA structures. Two types of phantom data are used: one is with aneurysm and another is without aneurysm.

Six different colors are used to denote flow in six different directions. Complementary colors are used to indicate opposite direction. Fig. 4 shows color code used for six different directions. For 3D rendition of the phantoms, we have used popular ITK-SNAP software [19].

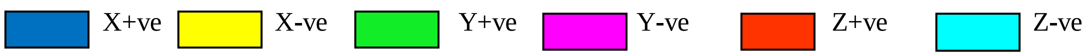


Fig. 4. Color code for six different flow directions.

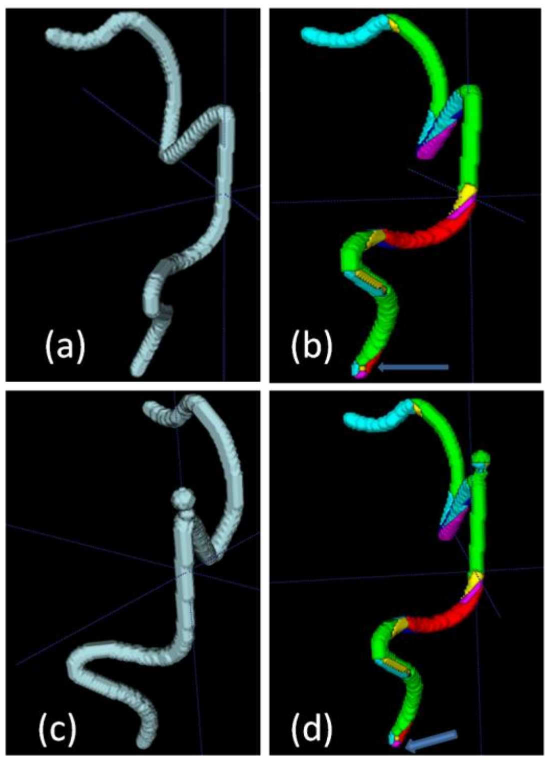


Fig.5. (a) ICA (internal carotid artery) without aneurysm (b) flow in ICA without aneurysm (c) ICA with aneurysm (d) flow in ICA with aneurysm

The approach of hemodynamic analysis which we applied here uses digital topology. All these phantoms of Fig.2 and Fig.3 are designed for flow analysis or very specifically for hemodynamic analysis. And from those analysis some important features for classification are to be extracted.

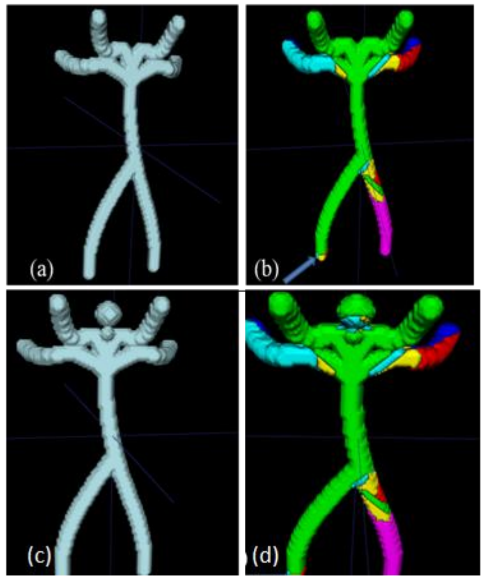


Fig.6. Flow nature in phantom of human BA (Basilar Artery) (a) BA phantom before flow (b) Flow nature in BA phantom after flow from left extreme end (c) BA phantom with aneurysm (d) BA phantom with aneurysm after flow from left extreme end

In the present work, flow based hemodynamic analysis is performed and we have classified the anomalous part specifically aneurysm part from the normal arterial structure using some flow based and hemodynamic parameter based feature.

## 4. CLASSIFICATION

In this present study our main outlook is to classify the anomalous region and normal region of carotid arterial structure and predict about some arterial disease. A vast and rich literature are available for different classification model [17], [18]. As we stated earlier that mainly the aneurysm disease is considered here, some of the vascular structure with aneurysm and some of the vascular structure without aneurysm are taken as training data. The aneurysm part is actually anomalous part and remaining part is normal. By labelling the aneurysm part as anomalous we have trained the classifier and using some unknown sample cerebrovascular structure we have tested the classifier to identify the anomalous region and normal region of the same. For the classification purpose the first step is to design the feature set.

### *4.1 Design of Feature set*

To design the feature set we have tried to classify the anomalous region and normal region with several combination of features extracted from flow analysis. But the classification performance is not equally likely for each combination of feature set. So feature selection is needed as it is a significant task in data mining and machine learning applications which eliminates irrelevant and redundant features and improves learning performance. However, here we are extracting features from flow analysis. We are considering a 3X3X3 neighbourhood information. For each voxel, there are 26 neighbourhood voxel. The first two features are the number of different directional flow in 3X3X3 neighbourhood and number of background voxel associated in 3X3X3 neighbourhood. The next six features are the - number of flow in each direction (Xpositive, Xnegative, Ypositive, Ynegative, Zpositive, Znegative). The standard deviation of these six features is calculated and selected as the next feature. The next three features are velocity, mean, standard deviation of the velocity in corresponding neighbourhood voxel. In this paper, we have used total 12 features for training and test purposes. Here we have used random forest classifier.

### *4.2 Random forests classifier*

A random forest multi-way classifier consists of a number of trees, with each tree grown using some form of randomization. Here for the classification purpose the Random Forest classifier has been used. The leaf nodes of each tree are labeled by estimates of the posterior distribution over the image classes. Each and every internal node contains a test that best splits the space of data to be classified. Here we have the image of some vascular structure. Each voxel of this image is classified by sending it down every tree and aggregating the reached leaf distributions. Randomness can be injected at two points during training: in subsampling the training data so that each tree is grown using a different subset; and in selecting the node tests. The trees here are binary and are constructed in a top-down manner. The binary test at each node can be chosen in one of two ways: (i) randomly, i.e. data independent; or (ii) by a greedy algorithm which picks the test that best separates the given training examples. “Best” here is measured by the information gain $\Delta E = -\Sigma i|Qi| \, |Q| \, E(Qi)$ caused by partitioning the set Q of examples into two subsets Qi according the given test. Here E(Q) is the entropy. The process of selecting a test is repeated for each nonterminal node, using only the training examples falling in that node. The recursion is stopped when the node receives too few examples, or when it reaches a given depth. Suppose that T is the set of all trees, C is the set of all classes and L is the set of all leaves for a given tree. During the training stage the posterior probabilities (Pt,l(Y(I) = c)) for each class c∈C at each leaf node l ∈L, are found for each tree t∈T. These probabilities are calculated as the ratio of the number of images I of class c that reach l to the total number of images that reach l. Y(I) is the class-label c for image I. The test image is passed down each random tree until it reaches a leaf node. All the posterior probabilities are then averaged and the argmax is taken as the classification of the input image.

## 5. RESULT & DISCUSSION

To analyse the performance of classifier for some specific feature set, we have done 10 fold cross validation of 35913 samples. Here the samples are comprised of features associated with each image voxel. The following evaluation metrics, based on the true positives(TP), true negative(TN), false positive(FP), false negative(FN) measures are used to assess the performance of the model.

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+FN+TN}$$

$$\text{Precision} = \frac{TP}{TP+FP}$$

$$\text{Recall} = \frac{TP}{TP+FN}$$

$$\text{F1 Score} = 2\times\frac{(\text{Recall}\times\text{Precision})}{(\text{Recall}+\text{Precision})}$$

$$MCC = \frac{(TP\times TN - FP\times FN)}{\sqrt{(TP+FP)\times(TP+FN)\times(TN+FP)\times(TN+FN)}}$$

Table1

Performance Gain of Random forest classifier using 10 fold cross validation

| TP Rate | FP Rate | Precision | Recall | F-Measure | MCC | ROC Area | PRC Area | Class |
|---|---|---|---|---|---|---|---|---|
| 0.996 | 0.652 | 0.981 | 0.996 | 0.988 | 0.486 | 0.916 | 0.997 | Normal |
| 0.348 | 0.004 | 0.706 | 0.348 | 0.466 | 0.486 | 0.916 | 0.453 | Anomaly |
| Weighted Avg. | | | | | | | | |
| 0.977 | 0.634 | 0.973 | 0.977 | 0.973 | 0.486 | 0.916 | 0.982 | |

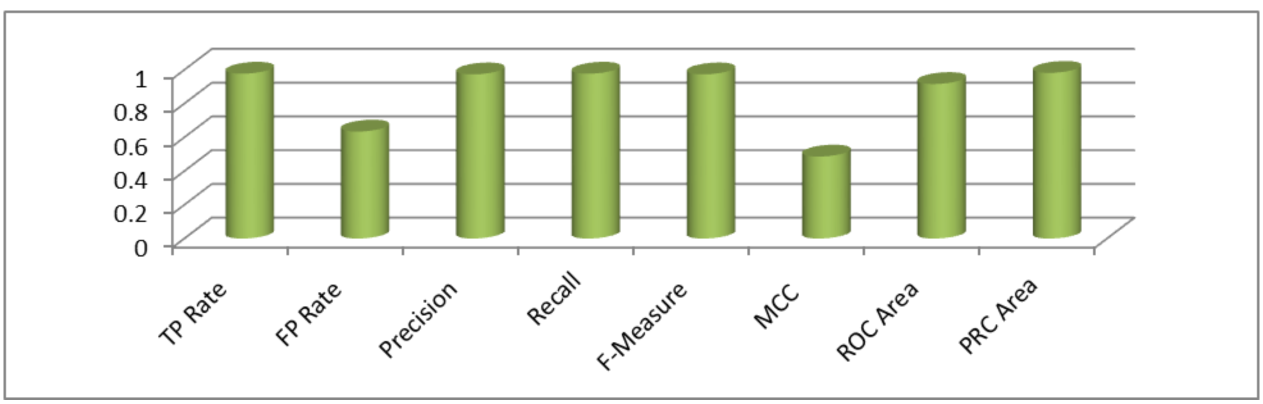


Fig.7. Graphical representation of different evaluation metrics of classification

In the above study 34735 samples are classified correctly as normal voxel out of 35913 and 149 samples are misclassified as anomalous which are normal. 358 samples are correctly classified as anomalous. And 671 samples are misclassified as normal which are actually anomalous. The accuracy of the classification model is 97.7167 %. In this present study we are resulted with quite good performance of true positive rate, precision, recall, accuracy.

## 6. CONCLUSION

In this present work we have classified the abnormal and normal voxel of the cerebrovascular phantom. This classification emphasized on the comparison of cerebrovascular phantom with and without aneurysm and hemodynamics therein.

In the flow analysis of the phantom with aneurysm we have found that there is a turbulent nature in the flow which differs from the flow in the phantom without aneurysm. These results are useful for extracting feature from understanding of fluid flows through cerebral vasculature with and without aneurysm. These computational studies on digital flows on phantom with and without aneurysm are novel and important for feature extraction as well as classification. 2-D digital flows have already been used successfully for the study of structural/plastic changes in hippocampal dendritic spines [20]. Here in this present study we have used 3D digital flow based model. The classification accuracy of the present work is 97.716%. The work presented may be included in the future study on the 3-D digital flow based hemodynamic analysis in both patients' CTA images with different anomalous signature as well as on complex mathematical phantoms. Future direction of the present study is to compare the different classification model to find the anomalous region in human cerebrovasculature.

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