A Review of Image and Phylogenetic Analysis Based Techniques for Ischemic Stroke Risk Estimation

Huma Tauseef, Muhammad Abuzar Fahiem, Saima Farhan, Fahima Tahir

Department of Computer Science, Lahore College for Women University, Lahore, Pakistan
itisab@gmail.com

Abstract: One of the most communal causes of death in the world and the foremost cause of severe, long-standing disability is Ischemic Stroke. There is an imperative need for automated techniques and mechanisms to pre diagnose people at high risk of ischemic stroke. Genetics as well as phenotypes of the visible symptoms contribute highly to the risk of stroke. There is a compelling need of post analysis and follow up checkups to prevent further strokes. A lot of research is being carried out on computer based automated techniques and mechanisms for estimation of Ischemic Stroke risk evaluation. A comparative study of different Carotid Imaging Techniques is being reported in this paper. Also the Work done by different researchers to estimate the Ischemic Stroke risk by using different feature sets is also reviewed. In depth knowledge of the preprocessing involved before actual analysis to achieve the results is also covered. Carotid Artery morphology, noise and artifacts in the Carotid images can lead to false classification. Historical patterns can facilitate improvement and accuracy of the risk evaluation. Genes trees can help take into account the genetic risk factors and gene mutations. The historical patterns can be extracted using these trees from the sampled group of data. Keeping these facts in view, we have also proposed an improved classification model for estimation of Ischemic Stroke risk. This model considers the Carotid Image Features and the Genetic Features.

[Tauseef H, Fahiem MA, Farhan S, Tahir F. **A Review of Image and Phylogenetic Analysis Based Techniques for Ischemic Stroke Risk Estimation**. *Life Sci J* 2013;10(7s):1040-1049] (ISSN:1097-8135). http://www.lifesciencesite.com. 167

Keywords: Ischemic Stroke, Medical Imaging, Phylogenetic Trees, Image Analysis, Risk Estimation, Genetic Data Analysis, Computer Aided Diagnostics.

1. Introduction

Deprivation of oxygen to the brain due to blood clot causes Ischemic stroke which accounts for almost 80% of all of the stroke cases. According to the World Health Organization (2007), 15 million people suffer from stroke worldwide each year. Of these, 5 million die and another 5 million are permanently disabled. Worldwide, stroke is the third leading cause of death, responsible for 4.4 million of the total 50.5 million deaths each year. Ischemic strokes (PubMed Health; The Internet Stroke Center) occur due to thrombosis, embolism (National Stroke Association) or atherosclerosis (Goldschmidt-Clermont et al., 2012; National Heart Lung & Blood Institute). Person affected with ischemic stroke may lose the ability to move one side of the body, speak, see, eat and drink. It also increases the person's chances for heart attack and heart failure (National Stroke Association). The damage may be temporary or permanent. It is the leading cause of long-lasting disability, long lasting injury and death. Studies confirm that a person who had Ischemic stroke is at high risk of having more strokes. Studies have proven that stroke is preventable and treatable provided needful is done in time (Johnson et al., 2010). Preventive measures can preclude 80% of the strokes.

The major phenotypes for stroke are hypertension, diabetes, arterial fibrillation, smoking, heart diseases like coronary artery disease, valve defects, enlargement of one of the heart's chambers, transient ischemic attacks, cholesterol imbalance, physical inactivity and obesity. These phenotypes can be modified with medical treatment or lifestyle changes. Some other non-amendable risk factors are age, gender and race (Goldschmidt-Clermont et al., 2012). Two things that can help prevent stroke and the risk of death or disability from it are to control the factors that cause stroke and to lookout for the stroke warning signs. However in many stroke cases the phenotypes are not present. Researchers are of the opinion that strokes are strongly related to genes and are passed on in generations. Even the risk factors that contribute to strokes are passed on genetically (Goldschmidt-Clermont et al., 2012). Genetics influence the inherited predisposition for certain diseases. There is a compelling need for automatic risk evaluation and detection of Ischemic strokes.

In section 2 we have given a literature survey on Medical Image Analysis based Ischemic Stroke Risk Estimation, Genetic Data Analysis based Ischemic Stroke Risk Estimation and Classifiers. Comparison of different Carotid Artery Imaging techniques and Ischemic Stroke risk estimation approaches is discussed in section 3. An improved model for Ischemic Stroke risk estimation is proposed in section 4 followed by discussion and conclusion in section 5 and 6.

2. Literature Survey

A survey of Ischemic stroke risk evaluation is conducted. There are two types of evaluation approaches; Medical Image based approaches and Genetic Data based approaches. Both of these approaches and the steps involved are discussed in this section.

2.1. Medical Image Analysis based Ischemic Stroke Risk Estimation

Medical images are used in image based techniques for analysis. Analysis includes image segmentation for Carotid Artery and Intima Media Thickness (IMT) followed by segmentation for plaque inside the Carotid Artery. A feature set is then extracted which is used for classification purpose. Tests that provide information about the Carotid Artery structure and the blood flow information are useful in estimating the stroke risk.

2.1.1. Image Acquisition

There are different medical imaging techniques which are being practiced. The most common ones are Carotid Duplex Ultrasound, Computed Tomography Angiography, Magnetic Resonance Angiography, Cerebral Angiography and Digital Subtraction Angiography.

Carotid Duplex Ultrasound is used to observe the blood flow in the Carotid Artery. It combines the blood flow information with the traditional imaging of the Carotid vessels. This technique is the most frequently used technique for the estimation of stenosis. Computed Tomography Angiography is used to see the blood flow in the blood vessels throughout the body. It makes use of the Computed Tomography that uses x-rays and a computer system to generate the images of the blood vessels. Magnetic Resonance Angiography is based on Magnetic Resonance Imaging. It makes use of magnetic field to capture images of the blood vessels generally in the head and neck region.

In Cerebral Angiography a contrast based dye is injected through a catheter in the blood vessels. The catheter is moved all the way up to the heart. X rays are used to get images of the blood vessels. This technique is invasive and usually done after some other non-invasive method confirms the stenosis. Digital Subtraction Angiography is the process in which an image is acquired before injecting the contrast dye in the blood vessels and an image is taken after injecting the dye. The pre contrast image is subtracted from the contrast image to remove the overlying structures other than the blood vessels. An image intensifier is used in this approach.

2.1.2. Carotid Artery and IMT Segmentation Techniques

In this section some of the well-known and commonly practiced segmentation techniques for Carotid Artery and IMT are discussed in detail. First one is the Balloon Snake Model segmentation is done in ultrasound images by using finite element method to calculate the continuity of the boundaries (Cohen, 1991). Dynamic Programming segments IMT from the image of Carotid Artery and outperforms maximum gradient, mathematical models and matched filter approaches in speed and continuity of boundary (Gustavsson et al., 1997). Wenddelhag et al. (1997) proposed an approach which segmented IMT from Carotid Artery images using cost function optimization in dynamic programming. In Texture Based Segmentation different tissues of Carotid Artery are segmented using texture operators and the extracted silhouettes are further refined using different morphological masks (Mojsilovic et al., 1997).

Carotid Artery can also be located in ultrasound images using optimal graph search. The drawback of this approach is that it needs an expert to make both manual and empirical values' estimates (Fitzpatrik & Sonka, 2000). The Star algorithm uses center of gravity to estimate the center of the Carotid Artery and its boundary using Kalman filter (Abolmaesumi et al., 2000).

Multiscale Dynamic Programming involves expert tracing in the training phase for cost function calculation. Cost function is the weighted sum of fuzzy terms based on geometrical features and their relationships extracted from the images. Multiscale dynamic programming is employed to segment the Carotid Artery (Liang et al., 2000). A discrete dynamic contour was modeled for Carotid Artery using entropy map and morphology of the images of the manually outlined arteries (Mao et al., 1999). Ladak, Milner & Steinman (2000) performed segmentation of artery wall for MR images to construct a 3D spline surface. Ladak et al.(2001) deformed the contour developed for segmenting the arterial wall to fit in the inner and outer walls of the artery so that an editable final contour could be obtained for the arteries for MRI images.

Gill et al.(2000) suggested an algorithm that generated a mesh from finite element triangulation for Carotid ultrasounds. Zahalka & Fenster (2001) provided an automated segmentation technique for Carotid ultrasounds based on snake method that required a single seed point. Morphology operations are also used to segment breast and heart ultrasound images (Xiao et al., 2002). Snake model is used to detect the Carotid Artery from B-Mode and sonographic images (Cheng et al., 1999, 2002).

2.1.3. Plaque Segmentation Techniques

The segmented Carotid Arteries and IMT images are further segmented to find the plaque inside the arteries. Several different algorithms are used for this purpose. In the Discrete Dynamic Contour the entropy map generated from a large database of artery images and initial seed point provided by an expert is used to generate the contour of inner Carotid Artery (Mao et al., 2000). Both temporal and spatial Kalman filters are used in this technique to extract the boundaries of the Carotid Artery and center of its walls to measure the diameter of the artery (Abolmaesumi et al., 2000). Gill et al. (2000) proposed an algorithm to detect atherosclerotic plaque in Carotid Arteries using the triangular mesh based balloon model proposed by Cohen (1991). Hamou & El-Sakka (2004) proposed an algorithm that used Canny edge detector with threshold parameters to segment Carotid Artery plaque. A multistage method was proposed by Abdel-Dayen & Sakka (2004). The proposed work generates Carotid boundaries in the form of small contours from ultrasound images. Different stages include filtering, quantization, edge detection and edge enhancement.

2.1.4. Features

Segmented images are used to extract feature sets. The features commonly used for texture analysis in medical images are Statistical Features (SF), Spatial Gray Level Dependence Matrices (SGLDM), Gray Level Difference Statistics (GLDS), Neighborhood Gray Tone Difference Matrix (NGTDM), Texture Energy Measures (TEM), Fractal Dimension Texture Analysis (FDTA) and Fourier Power Spectrum (FPS).

SF includes the mean, median, variance etc. SGLDM are the most commonly used features (Haralick, 1973) that are computed on the basis of probability density functions. These features include angular second moment (ASM), contrast, correlation, inverse difference moment (IDM), sum average, variance and entropy of the pixel values. For GLDS based features contrast, ASM, entropy and mean are calculated from difference between pairs of gray levels (Weszka et al., 1976). In NGTDM coarseness, contrast, busyness, complexity and strength were extracted as texture features (Amadasun & King, 1989). In TEM based feature extraction roughness or smoothness of a surface is calculated using Hurst coefficients (Laws, 1980; Wu et al., 1992). FDTA uses fractional brownian motion model to measure the roughness of a surface (Mandelbrot, 1983; Wu et al., 1992). FPS is used to calculate the radial and angular sum to find out the nature of the surface i.e. whether the surface is coarse or fine (Weszka et al., 1976).

2.2. Genetic Data Analysis based Ischemic Stroke Risk Estimation

Genetics play an important role in the predisposition of many diseases. Genes data analysis is conducted using different techniques. One method is to use Phylogenetic data and Phylogenetic trees.

2.2.1. Phylogenetic Trees

Phylogenetic trees (Robinsons & Folds, 1981) represent the evolutionary descent of different species or genes from a common ancestor. They represent diversity among same species or genes of a common ancestor. They are helpful for structuring classification and identifying the changes that took place in genes over the course of time. Recently genetic (Floßmann et al., 2004; Jerrard-Dunne et al., 2003) and genomic (Matarin et al., 2008) studies are greatly contributing to the study of brain and genetically transmitted diseases. Advanced studies have shown that certain genes can be mutated or deactivated (Li et al., 2008) to reduce the risks of these diseases.

2.2.2. Phylogenetic Data

Different types of data are used to construct phylogenetic trees based on the purpose for building trees (Fitch & Margoliash, 1967). Data can be phenotypes, genome gene ordered data, and nucleotide or protein sequenced data.

Phenotypes are the data which can be easily obtained by appearance. There are certain heritable factors that clearly indicate the risk for ischemic stroke (Sacco, 1995). Genome rearrangements in gene order data are used to construct phylogenetic trees (Tang & Moret, 2003).DNA or RNA data are coded using an alphabet for the four nucleotides. This data represents the genetic characters. The phylogenetic trees are constructed using these DNA or RNA sequences as these provide immense phylogenetic information (Nei et al., 1983; Rambaut & Grass, 1997). Proteins are encoded into sequences based on Amino acids. This data is also rich in phylogenetic information and thus is very commonly used nowadays for phylogenetic tree construction (Parry-Smith & Attwood, 1991).

2.2.3. Phylogenetic Tree Construction Methods

Phylogenetic data which is in any of the above mentioned forms is used to construct phylogenetic tree. Trees are most logical way to represent data for evolution representation. There are many algorithms that are used for phylogenetic tree construction (Swofford et al., 1996; Baxevanis et al., 2002). All these fall into three major classes, namely; Maximum Parsimony Methods, Evolutionary Distances based Methods and Maximum Likelihood Estimation Principle.

Maximum Parsimony method tries to estimate a tree with least mutations on the other hand the opposite i.e. Minimum Parsimony estimates the trees with most mutations during the evolution period. Distance based methods calculate genetic distances between sequence alignments and then trees are constructed. Maximum Likelihood Estimation principle tries to estimate the tree that is optimal on some function. It requires sample data on which the function is constructed.

2.3. Classifiers

Different classifiers are used based upon the application to classify the data. Well known classifiers are discussed in detail. Linear Classifiers (Sigaud & Wilson, 2007) make a classification decision based on the characteristics of the objects. These characteristics are known as feature values and are fed to the classifier. Support Vector Machines (SVM) (Kotsiantis et al., 2007) are supervised algorithms which are used to classification purpose and regression analysis for data. SVM is a non-probabilistic binary linear classifier which tries to predict the input data to be one of the two classes.

Quadratic Classifiers (Sigaud & Wilson, 2007) use quadratic discriminant analysis for classification. It assumes measurements from each class to be normally distributed. Kernel Estimation (k-nearest neighbors) (Zhu, 2005) is the most simple classification algorithm. The classification decision is based on majority voting of neighbors. Decision Trees (Kotsiantis et al., 2007) are vastly used machine learning and classification algorithm. It uses a decision tree in which the classes are represented as leaves and the feature conjunctions are labeled on the branches. Artificial Neural Networks (ANN) (Kotsiantis et al., 2007) works on the principle of human brain. It is continuously changing its design as it adapts to variations during the learning process. These are well suited for the complex datasets. Bayesian Networks (Kotsiantis et al., 2007) uses directed acyclic graph to show the conditional dependencies of the variables based on probabilities. Hidden Markov Models (HMM) (Sigaud & Wilson, 2007) assumes the problem to be classified to be unobserved and is closely related to optimal nonlinear filtering problem.

3. Comparison

A detailed comparison of Medical Imaging Techniques for Carotid Arteries is conducted as well as of the research work conducted by different researchers for Ischemic Stroke risk evaluation is done. Summarized tables of both comparisons are given.

3.1. Comparison of Different Imaging Techniques

A comparison of commonly practiced medical imaging techniques for the Carotid Artery, their advantages and limitations are given in Table 1. Different factors are being considered for comparison like invasiveness, radiation exposure, safety risks, motion sensitivity, accuracy, sensitivity, specificity, risk of allergic reaction, image quality, contrast agents, artifacts, waves / rays used for imaging, effect of metallic implants, blood flow information, operator dependency and limitations.

It is evident from the comparison that Ultrasound has many advantages; a non-invasive technique has low cost and includes no radiation exposure. Moreover it can be performed in patients with renal insufficiency and people with metallic implants. It does not need any sedative to be given to the person undergoing the test and has no safety risk. So ultrasound proves to be a safe method for analysis of stenosis.

3.2. Comparison of Different Approaches for Ischemic Stroke Risk Evaluation

Different researchers have conducted different researches for the detection of stenosis and plaque in the Carotid Arteries. A comprehensive comparison is given in Table 2. Different factors which are being considered include Input, Genetics, Segmentation technique used, Features, Classifier and Results. Input type, it's source, modality and sample size are being considered while reviewing the literature. Input can be in the form of images or signals. Image can be whole or they can be of plaque only. Input source can be from some database or from a laboratory or collected by the researcher for experimentation. Modality may include ultrasound, MRI, CT etc. Features which are being extracted for classification, their extraction techniques and methods used to reduce features are also being reviewed. Classifier and its type are also being considered. Different results achieved by different researchers are also mentioned.

Most commonly used classifiers for Ischemic Stroke risk evaluation are ANN and SVM as apparent from Table 2. Tsiaparas et al. (2012) have used B mode ultrasound images of plaque to achieve an accuracy rate of 79.3% using SVM for Texture features. Stoitsis et al. (2004) achieved classification accuracy of 84% based on texture features combined with motion features using Fuzzy c-means clustering. Contours based classification using ANN and Multilayer Back Propagation Network (MBPN) is used by Santhiyakumari et al. (2007) to achieve the highest accuracy of 96%. Contours, Texture and Motion features prove to give best classification results.

Table 1: Comparison of Different Medical Imaging Techniques for the Carotid Artery

Imaging	**CDU**		**CTA**	**MRA**	**CA**	**DSA**
Invasive	×		×	×	√	√
Radiation Exposure	×		√	×	√	√
Expensive	×		×	√	√	×
Safety Risk	None		Minimal	Minimal	Significant	Significant
Repetition Frequency over Short Duration of Time	Often		Often	Rare	Rare	Rare
Motion Sensitive	×		√	√	√	√
Sedative	×		×	√	Sometimes	Sometimes
Stenosis	50-69%	≥ 70%	≥ 70%	≥ 70%	-	≥ 70%
Sensitivity	93%	99%	95%	93%	-	92.9%
Specificity	68%	86%	98%	97%	-	81.9%
Accuracy	85%	95%	97%	95%	-	-
Overestimation of Degree of Stenosis	√		√	√	×	×
Hair line Lumen Detection	×		√	×	√	√
Risk of Allergic Reaction	×		√	√	√	√
Contrast Agents	×		√	×	√	√
Contrast Dosage	NA		High	NA	High	Low
Image Quality	Low		High	High	High	High
Artifacts	• Image Speckle • Shadowing • Poor definition of artery boundaries		• Motion artifacts	• Turbulent flow • Phase wrapping • Maxwell terms • Laminar flow • Venetian blinds	• Motion artifacts	• Motion artifacts • Larynx artifact
Technology	Sound Waves		X-Rays	Magnetic Field and Radio Frequency Waves	X-Rays	X-Rays
Usage	• Blood Flow velocity • Severity of Stenosis • Carotid Index		• Arterial & Venous blood flow • Anatomic image of CA Lumen • Image of soft tissue & bony structure	• Evaluation of Extra cranial Carotid Artery	• Image Carotid Arteries • Information about disease process • Assess collaterals	• Arterial and Venous occlusions • Arterial Stenosis • Cerebral aneurysms
Effected by Metallic Implants	×		√	√	√	√
Performed in people with Renal Insufficiency	√		×	×	×	×
Procedure Duration	Short		Short	Long	Long	Short
Views of Carotid Bifurcation	Limited		Seen	Seen	Limited	Limited
Operator Dependent	√		×	×	√	√

Table 1: Comparison of Different Medical Imaging Techniques for the Carotid Artery (Contd.)

Image	Usually 2D	3D/4D	3D/4D	3D	3D
Blood Flow Information	√	×	√	√	√
SNR	Low	High	High	High	High
Accuracy effected by Carotid Calcification	√	√		×	×
Limitations	• Cannot assess intracranial Carotid artery.	• Superimposed jugular veins and arteries may hide stenosis.	• Evaluation of small vessels is difficult.	• Risk of stroke. • Bones and muscle tissue are present in images.	• Larynx artifact. • External Carotid or vertebral artery overlying the internal Carotid Artery. • Poor Arterial contrast density.

Table 2: Review of Different Stenosis and IMT Estimation Approaches

Reference	Input Type	Input Source	Modality	Sample Size	Genetics	Automated/ Semi Automated System	Segmentation Technique	Features extracted	Features: Feature Selection Technique	Features: Feature Reduction Technique	Machine Learning Algorithm / Classifier	Classifier Type	Accuracy	Positive Predict Value	Sensitivity	False Positive	False Negative	Specificity	Other
Tsiaparas et al. (2012)	Image	-	B mode ultrasound of plaque	20	×	-	-	Texture Features	DTCWT: 36	Z score	SVM	Supervised	67.6	-	68.9	-	-	72.1	-
									FRIT: 6	Z score	SVM	Supervised	71.5	-	75.2	-	-	72.6	-
									FDCT: 44	Z score	SVM	Supervised	79.3	-	78.2	-	-	84.3	-
								Frequency Features	WP	-	SVM	-	70.9	-	71.9	-	-	75.2	-
Kemény et al. (1999)	Color-coded power spectra of the audible Doppler shift	Self	Transcranial Doppler Ultrasound	282	√	Automatic	-	FFT	-	-	ANN	Supervised	-	56.7	73.4	-	-	-	-
Kyriacou et al. (2010)	Carotid plaque images	Irvine Lab	Ultrasound images	274 images	×	Semi automatic	Manual	Morphological Features	Multilevel binary morphological model	PCA	SVM	Supervised	73.72	-	83.94	36.5	16.06	63.5	Acoustic shadows are excluded
									Direct Gray scale morphology model	-	SVM	Supervised	66.79	-	54.01	20.44	45.99	79.56	
Stoitsis et al. (2004)	Static images, image sequences	Irvine Lab	B- mode ultrasound	19 patients	×	Automatic	ANALYSIS (s/w for interpretation of medical images)	Texture features: 99	FOS, SOS, law's TEM, FDTA	ANOVA	Fuzzy c-means	Unsupervised	74	-	-	-	-	-	Atheromatous plaques were predicted.
								Motion feature : 2	MSV, MRSV	ANOVA	Fuzzy c-means	Unsupervised	79	-	-	-	-	-	
								Texture + Motion feature	FOS, SOS, Law's TEM, FDTA, MSV, MRSV	ANOVA	Fuzzy c-means	Unsupervised	84	-	-	-	-	-	
Christodoulou et al. (2003)	Carotid plaque u/s image	Irvine Lab	B mode Ultrasound	230 images		Semi automated	Manual	Texture + Shape : 61	FOS, SGLDM (mean), SGLDM (range), GLDS, NGTDM, SFM, TEM, FDTA, FPS, Shape Parameters	Majority Vote	SOM	Un supervised	66	-	-	-	-	-	-
											KNN	Supervised	65.1	-	-	-	-	-	-
										Averaging confidence Measures	SOM	Un supervised	73.1	-	-	-	-	-	-
											KNN	Supervised	68.8	-	-	-	-	-	-
										All	SOM	Un supervised	68.8	-	-	-	-	-	-
											KNN	Supervised	69.7	-	-	-	-	-	-
Kyriacou et al. (2006)	Gray scale Carotid plaque images	Irvine lab	Ultrasound	274	×	Semi automated	Manual	Morphological feature	Gray Scale Morphological Analysis	-	PNN	Supervised	62.04	-	59.85	35.77	40.15	64.23	Acoustic shadows are excluded
											SVM	Supervised	63.14	-	62.77	36.5	37.23	63.5	
										PCA	PNN	Supervised	60.58	-	57.66	36.5	42.34	63.5	
											SVM	Supervised	66.79	-	54.01	20.44	45.99	79.56	
Kyriacou et al. (2005)	Clinical data + ultrasound images	EU BIOMED II ACSRS + Irvine Laboratory	Longitudinal scans using duplex scanning and color flow imaging	Clinical data: 1298 cases + U/S: 274 images	×	Semi automated	Manual	340 clinical factors + 54 Texture Features	SF	-	PNN	Supervised	65.3	-	-	-	-	-	Acoustic shadows are excluded
											SVM	Supervised	69.3	-	-	-	-	-	
										PCA	PNN	Supervised	65.3	-	-	-	-	-	
											SVM	Supervised	70.1	-	-	-	-	-	
									SGLDM	-	PNN	Supervised	71.2	-	-	-	-	-	
											SVM	Supervised	69.7	-	-	-	-	-	
										PCA	PNN	Supervised	70.8	-	-	-	-	-	
											SVM	Supervised	68.6	-	-	-	-	-	
									SF + NGTDM	-	PNN	Supervised	62.8	-	-	-	-	-	
											SVM	Supervised	71.2	-	-	-	-	-	
										PCA	PNN	Supervised	62.4	-	-	-	-	-	
											SVM	Supervised	69.3	-	-	-	-	-	
									SF + SGLDM + TEM + NGTDM	-	PNN	Supervised	65.3	-	-	-	-	-	
											SVM	Supervised	70.8	-	-	-	-	-	
										PCA	PNN	Supervised	64.2	-	-	-	-	-	
											SVM	Supervised	70.1	-	-	-	-	-	
Kyriacou et al. (2007)	Clinical risk factors + ultrasound images	ACSRS, Irvine Lab	Longitudinal scans using duplex scanning and color flow imaging	18 clinical factors, 274 images		Semi automated	IMT segmentation: Williams and Shah. Atherosclerotic plaque segmentation: Lai and Chin snake.	Texture Features	SF+ SGLDM+ GLDS+ NGTDM+ SFM+ Law's TEM + Fractals	PCA	PNN	Supervised	72.3	-	75.9	31.4	24.1	68.6	-
											SVM	Supervised	73	-	82.5	36.5	17.5	63.5	
											PNN	Supervised	69.7	-	74.4	35	25.5	65	
											SVM	Supervised	73.4	-	81	34.3	19	65.7	
Santhiyakumari et al. (2011)	Ultrasound Carotid Artery images	-	Ultrasound	100 images	×	Automated	Contour extraction using energy minimization process.	Contours	-	-	ANN, MBPN	Supervised	Normal : 96%, Cardiovascular Disease: 90%, Cerebrovascular Disease: 92%	-	-	-	-	-	-
Abdolmaleki et al. (2005)	Longitudinal view	-	High resolution B-mode ultrasound, color Doppler images	128	×	Semi Automated	-	Quantitative features: 10	Ultrasonic measurement	-	Logistic Regression Model	Supervised	-	.94	-	-	-	-	-
Lambrou et al. (2012)	Ultrasound images of Carotid plaque	Irvine Lab	-	274	×	Semi automated	Manual	Texture : 7 feature sets	SF, SGLDM, GLDS, NGTDM, SFM, TEM, FDTA, FPS, RUNL	Confidence Predict Value	ANN	supervised	71.53	-	-	-	-	-	-
											k-NN	supervised	70.8	-	-	-	-	-	
								Morphological	Multi level approach, gray scale morphological analysis	Confidence Predict Value	ANN	supervised	72.26	-	-	-	-	-	
											SVM	supervised	73.72	-	-	-	-	-	
Christodoulou et al. (2010)	Carotid plaque image	Irvine Lab	Ultrasound	274	×	Semi automated	Manual	Multi region Histogram	-	-	SOM	Un supervised	64.8	-	-	-	-	-	-
											k-NN	Supervised	63.1	-	-	-	-	-	

4. Proposed Model for Improved Ischemic Stroke Risk Evaluation

An improved model for risk evaluation and prediction of Ischemic Stroke is hereby proposed, keeping in view the analytical understanding and critical analysis of the research being conducted in the field. The methodology will consist of the ultrasound image analysis and phylogenetic analysis. For the medical image based data analysis the input will be ultrasound images. These images will be used to analyze the plaque in the artery which is the major reason for thrombosis.

Different steps that need to be done before plaque analysis are Carotid Artery Segmentation, Intima Media Thickness Segmentation and Carotid Plaque Segmentation as in Figure 1. Carotid Artery ultrasound images will be analyzed and further segmented for identification of Carotid Artery in the image. Then Intima Media i.e. the inner wall of the Carotid Artery will be segmented. After segmentation we need to make an estimate of the Intima Media Thickness. The Carotid Plaque also needs to be analyzed so that it could be used for further estimation and image based feature extraction. Next steps include Arterial Stenosis Estimation, Image based Feature Extraction and finally Carotid Plaque analysis and Intima Media Thickness will be used to estimate the arterial stenosis. These features will help in estimating the risk for Ischemic stroke.

Phylogenetic data will be used to extract the sequence and align it. This data will be used for Sequence Retrieval, Sequence Alignment, Phylogenetic Analysis and Gene based feature extraction. The features extracted from ultrasound images and phylogenetic data will be fed to an analyzer that will give an estimate about the Ischemic stroke risk.

5. Discussion

The real-time analysis of the phylogenetic trees and ultrasound imaging provides a quick means by which to qualitatively analyze the hierarchical data and draw meaningful interpretation which subsequently helps in analyzing the risk factors and take into account the preventive measures for the stroke. The tree can be used for the representation of multi-dimensional data sets and ultrasound imaging helps further elucidate the diagnostics. In Genetic Analysis the Gene sequence retrieval and alignment are important steps to detect the mutations that have occurred over the course of time. Phylogenetic analysis is very helpful in extraction of the gene hereditary and mutations related data.

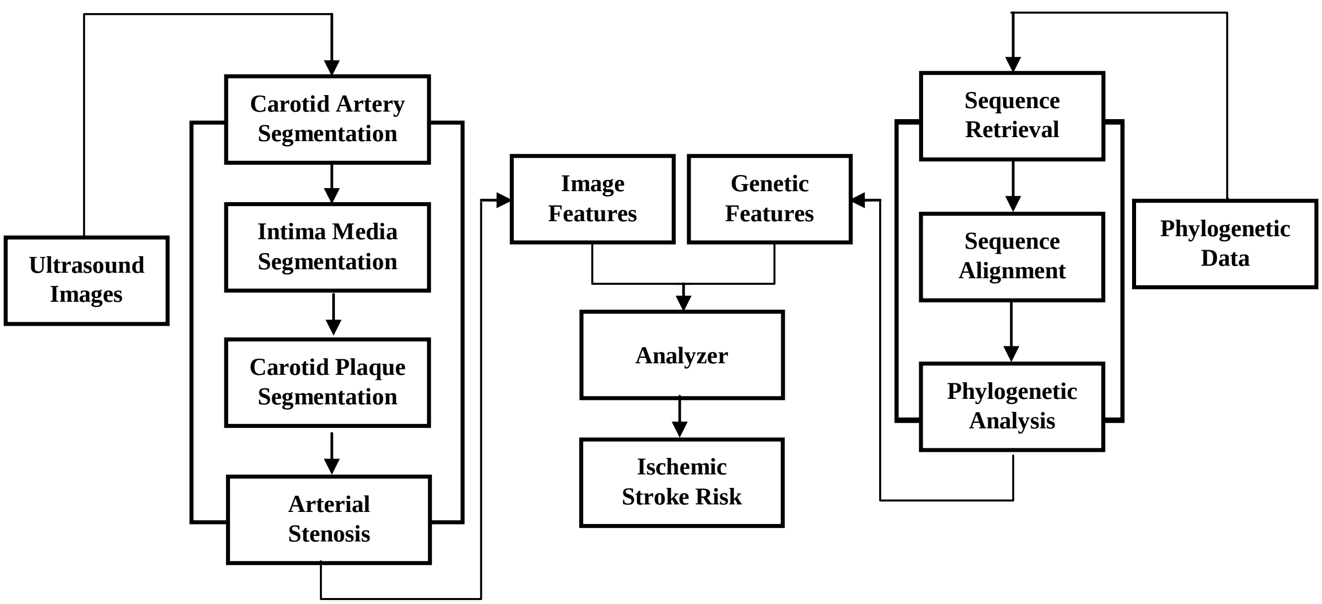

Figure 1: Proposed Model for Ischemic Stroke Risk Evaluation

6. Conclusion

There is an impelling need to design a classifier that will make use of multi-dimensional feature sets – Image and Genetic features for the early diagnosis and assessment of the stroke risk. Moreover research should be conducted so that the process of correct identification of people at high risk of ischemic stroke should improve and contribute in the visual assessment procedure conducted by the medical personals. It will not only facilitate the medical personals but also the community at large by elucidating the risk factors well in time. The proposed model may play an important role by contributing to the area of Computer Aided Diagnostics and Preventive Studies. The proposed model facilitates in meaningful interpretation of genetic and image based data that ultimately helps in critical analysis of the risk factors and the preventive measures for Ischemic Strokes.

Corresponding Author:
Dr. Muhammad Abuzar Fahiem
Department of Computer Science
Lahore College for Women University,
Lahore, Pakistan
E-mail: itisab@gmail.com

References

1. Abdel-Dayem AR, Ei-Sakka MR. A novel morphological-based Carotid Artery contour extraction. Electrical and Computer Engineering, Canadian Conference, IEEE, 2004; 4: 1873-1876.
2. Abdolmaleki P, Mokhtari-Dizaji M, Montazeri, M, Saberi H, Nikanjam N. Applying the logistic regression model to predict the carotid artery stenosis using the sequential color Doppler ultrasound image processing. Proceedings of Third Iranian Conference on Machine Vision and Image Processing and Applications (MVIP), Tehran, Iran, February 2005; 1: 312-317.
3. Abolmaesumi P, Sirouspour, MR, Salcudean SE. Real-time extraction of Carotid artery contours from ultrasound images. Computer-Based Medical Systems Proceedings, 13th IEEE Symposium, 2000; 181-186.
4. Amadasun M King R. Textural features corresponding to textural properties. Systems, Man and Cybernetics. IEEE Transactions, 1989; 19(5): 1264-1274.
5. Baxevanis AD, Davison DB, Page RDM, Stormo G, Stein L. (eds.). Current Protocols in Bioinformatics, Wiley and Sons, New York, USA, 2002.
6. Cheng DC, Schmidt-Trucksäss A, Cheng KS, Burkhardt H. Using snakes to detect the intimal and adventitial layers of the common Carotid artery wall in sonographic images. Computer methods and programs in biomedicine 2002; 67(1): 27-37.
7. Cheng DC, Schmidt-Trucksass A, Cheng KS, Sandrock M, Pu Q, Burkhardt H. Automatic detection of the intimal and the adventitial layers of the common Carotid artery wall in ultrasound B-mode images using snakes. In Image Analysis and Processing International Conference, IEEE, 1999; 452-457.
8. Christodoulou CI, Pattichis CS, Kyriacou E, Nicolaides A. Image retrieval and classification of carotid plaque ultrasound images. Open Cardiovasc Imaging, 2010; 2: 18-28.
9. Christodoulou CI, Pattichis CS, Pantziaris M, Nicolaides, A. Texture-based classification of atherosclerotic carotid plaques. Medical Imaging, IEEE Transactions, 2003; 22(7): 902-912.
10. Cohen LD. On active contour models and balloons. CVGIP: Image understanding, 1991; 53(2): 211-218.
11. Fitch WM, Margoliash E. Construction of phylogenetic trees. Science, 1967; 155(760): 279-284.
12. Fitzpatrick JM, & Sonka M. Handbook of Medical Imaging, Volume 2: Medical Image Processing and Analysis, SPIE Press, 2000.
13. Floßmann E, Schulz UG, Rothwell PM. Systematic review of methods and results of studies of the genetic epidemiology of ischemic stroke. Stroke, 2004; 35(1): 212-227.
14. Gill JD, Ladak HM, Steinman DA, Fenster A. Segmentation of ulcerated plaque: A semi-automatic method for tracking the progression of Carotid atherosclerosis. Engineering in Medicine and Biology Society, Proceedings of the 22nd Annual International Conference of the IEEE, 2000; 1: 669-672.
15. Goldschmidt-Clermont PJ, Dong C, Seo DM, Velazquez OC. Atherosclerosis, Inflammation, Genetics, and Stem Cells 2012 Update. Current atherosclerosis reports, 2012; 1-10.
16. Gustavsson T, Abu-Gharbieh R, Hamarneh G, Liang Q. Implementation and comparison of four different boundary detection algorithms for quantitative ultrasonic measurements of the human Carotid artery. Computers in Cardiology, IEEE, 1997; 69-72.
17. Hamou AK, El-Sakka MR. A novel segmentation technique for carotid ultrasound images. Acoustics, Speech, and Signal Processing 2004, IEEE, 2004; 3: iii-521.
18. Haralick RM, Shanmugam K, Dinstein IH. Textural features for image classification. Systems, Man and Cybernetics, IEEE Transactions, 1973; 6: 610-621.
19. Jerrard-Dunne P, Cloud G, Hassan A, Markus HS. Evaluating the genetic component of ischemic stroke subtypes a family history study. Stroke, 2003; 34(6): 1364-1369.
20. Johnson H, Turke TL, Grossklaus M, Dall T, Carimi S, Koenig LM, Aeschlimann SE, Korcarz CE, Stein JH. Detection of subclinical atherosclerosis by office-based carotid ultrasound increases prescription of preventive

therapies. Journal of the American College of Cardiology, 2010; 55(10 Supplement 1): A58-E557.
21. Kemény V, Droste DW, Hermes S, Nabavi DG, Schulte-Altedorneburg G, Siebler M, Ringelstein EB. Automatic embolus detection by a neural network. Stroke, 1999; 30(4): 807-810.
22. Kotsiantis SB, Zaharakis ID, Pintelas PE. Supervised machine learning: A review of classification techniques. Frontiers in Artificial Intelligence and Applications, 2007; 160: 3.
23. Kyriacou EC, Pattichis CS, Karaolis MA, Loizou CP, Christodoulou CI, Pattichis MS, Kakkos S, Nicolaides A. An integrated system for assessing stroke risk. Engineering in Medicine and Biology Magazine, IEEE, 2007; 26(5): 43-50.
24. Kyriacou E, Pattichis CS, Pattichis MS, Mavrommatis A, Panagiotou S, Christodoulou CI, Kakkos S, Nicolaides A. Classification of atherosclerotic carotid plaques using gray level morphological analysis on ultrasound images. Artificial Intelligence Applications and Innovations, Springer US, 2006; 737-744.
25. Kyriacou E, Pattichis C, Christodoulou C, Karaolis M, Nicolaides A. An Integrated Teleconsultation System for the Evaluation of the Risk of Stroke. Proceedings of the 5th International Network Conference INC, 2005.
26. Ladak H M, Thomas JB, Mitchell JR, Rutt BK, & Steinman DA. A semi-automatic technique for measurement of arterial wall from black blood MRI. Medical physics, 2001; 28: 1098.
27. Ladak HM, Milner JS, Steinman DA. Rapid Three-Dimensional Segmentation of the Carotid Bifurcation from Serial MR Images. Journal of Biomechanical Engineering, 2000; 122: 96-99.
28. Lambrou A, Papadopoulos H, Kyriacou E, Pattichis CS, Pattichis MS, Gammerman A, Nicolaides A. Evaluation of the risk of stroke with confidence predictions based on ultrasound carotid image analysis. International journal on artificial intelligence tools, 2012; 21(04).
29. Laws KI. Rapid texture identification. IMAGE PROC. FOR MISSILE GUID, 1980; 238: 376-381.
30. Li J, Lang J, Zeng Z, McCullough LD. Akt1 gene deletion and stroke. Journal of the neurological sciences, 2008; 269(1): 105-112.
31. Liang Q, Wendelhag I, Wikstrand J, Gustavsson T. A multiscale dynamic programming procedure for boundary detection in ultrasonic artery images. Medical Imaging, IEEE Transactions, 2000; 19(2): 127-142.
32. Mao F, Gill J D, Fenster A. Technique for evaluation of semiautomatic segmentation methods. In Medical Imaging, International Society for Optics and Photonics, 1999; 1027-1036,
33. Mao F, Gill J, Downey D, Fenster A. Segmentation of carotid artery in ultrasound images: Method development and evaluation technique. Medical physics, 2000; 27.
34. Matarin M, Brown W M, Singleton A, Hardy JA, Meschia JF. Whole genome analyses suggest ischemic stroke and heart disease share an association with polymorphisms on chromosome 9p21. Stroke, 2008; 39(5): 1586-1589.
35. Mojsilović A, Popović M, Amodaj N, Babić R, Ostojić M. Automatic segmentation of intravascular ultrasound images: a texture-based approach. Annals of biomedical engineering, 1997; 25(6): 1059-1071.
36. National Heart Lung and Blood Institute. What is Atherosclerosis?. Retrieved from http://www.nhlbi.nih.gov/health/health-topics/topics/atherosclerosis/
37. National Stroke Association. What is stroke?. Retrieved from http://www.stroke.org/site/PageServer?pagename=TYPE
38. Nei M, Tajima F, Tateno Y. Accuracy of estimated phylogenetic trees from molecular data. Journal of Molecular Evolution, 1983; 19(2): 153-170.
39. Parry-Smith DJ, Attwood T K. SOMAP: a novel interactive approach to multiple protein sequences alignment. Computer applications in the biosciences: CABIOS 1991, 1991; 7(2): 233-235.
40. PubMed Health. Stroke. Retrieved from http://www.ncbi.nlm.nih.gov/pubmedhealth/PMH0001740/
41. Rambaut A, Grass NC. Seq-Gen: an application for the Monte Carlo simulation of DNA sequence evolution along phylogenetic trees. Computer applications in the biosciences: CABIOS 1997, 1997; 13(3): 235-238.
42. Robinson DF, Foulds LR. Comparison of phylogenetic trees. Mathematical Biosciences, 1981; 53(1): 131-147.
43. Sacco RL. Risk factors and outcomes for ischemic stroke. Neurology, 1995; 45(2 Suppl 1), S10.
44. Santhiyakumari N, Rajendran P, Madheswaran, M. Medical decision-making system of ultrasound carotid artery intima–media thickness using neural networks. Journal of Digital Imaging , 2011; 24(6): 1112-1125.
45. Sigaud O, Wilson SW. Learning classifier systems: a survey. Soft Computing, 2007; 11(11): 1065-1078.

46. Stoitsis J, Golemati S, Nikita KS, Nicolaides AN. Characterization of carotid atherosclerosis based on motion and texture features and clustering using fuzzy c-means. Engineering in Medicine and Biology Society, IEMBS'04. 26th Annual International Conference of the IEEE, 2004; 1: 1407-1410.
47. Swofford DL, Olsen GJ, Waddell PJ, Hillis DM. Phylogeny reconstruction. In Hillis, D. M., Moritz, C. and Mable, B. K. (eds.), Molecular Systematics, Sinauer Associates, Sunderland, Massachusetts, Second edn, 1996; 407–514.
48. Tang J, Moret BM. Scaling up accurate phylogenetic reconstruction from gene-order data. Bioinformatics, 2003; 19(suppl 1), i305-i312.
49. The Internet Stroke Center. Ischemic Stroke. Retrieved from http://www.strokecenter.org/patients/about-stroke/ischemic-stroke/
50. Tsiaparas N N, Golemati S, Andreadis I, Stoitsis J, Valavanis I, Nikita KS. Assessment of carotid atherosclerosis from B-mode ultrasound images using directional multiscale texture features. Measurement Science and Technology, 2012; 23(11): 114004.
51. Wendelhag I, Liang Q, Gustavsson T, Wikstrand J. A new automated computerized analyzing system simplifies readings and reduces the variability in ultrasound measurement of intima-media thickness. Stroke, 1997; 28(11):, 2195-2200.
52. Weszka JS, Dyer CR, Rosenfeld A. A comparative study of texture measures for terrain classification. Systems, Man and Cybernetics, IEEE Transactions, 1976; (4): 269-285.
53. World Health Organization. World Health Report – 2007, 2007; Geneva.
54. Wu CM, Chen YC, Hsieh KS. Texture features for classification of ultrasonic liver images. Medical Imaging 1992, IEEE Transactions, 1992; 11(2): 141-152.
55. Xiao G, Brady M, Noble JA, Zhang Y. Segmentation of ultrasound B-mode images with intensity inhomogeneity correction. Medical Imaging 2002, IEEE Transactions, 2002; 21(1): 48-57.
56. Zahalka A, Fenster A. An automated segmentation method for three-dimensional carotid ultrasound images. Physics in medicine and biology, 2001; 46(4): 1321.
57. Zhu X. Semi-supervised learning literature survey. Computer Sciences Technical Report 1530 , 2005; University of Wisconsin–Madison.

6/27/2013