Computer-assisted Diagnosis of Cancer on Medical Images: A Survey

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ABSTRACT

Objective: To evaluate the cancer classification techniques based on sensitivity, specificity and accuracy.

Method: The survey has been done on cancers which include brain tumor, breast cancer and thyroid tumor using medical images.

Results: Most of the classification techniques used on various medical images has been utilized for supervised learning approach such as support vector machine, artificial neural networks etc.

Conclusion: This survey enables the medical practitioners to have a quick look on the various cancer classification techniques using medical images. The comparison table also provides the clear picture about the classification techniques based on different parameters.

Keywords: Brain tumour, classifiers, diagnosis, mammograms neural, network, support vector

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INTRODUCTION

The significant role played by the Medical and healthcare as a giant industry in scaling up the standard of living of the human beings knows no bounds. In this regard, the image based medical diagnosis has surfaced as one of the vital service segments in this domain. Of late, a volley of consistent endeavors has been carried out in the CAD by means of the medical images to boost the morale of a clinician in the investigation of the medical images. In fact, the assessment of the medical images by a clinician is invariably qualitative in nature and is likely to change from individual to individual (1). In this connection, the automatic diagnosis is capable of extending a helping hand to the pathologists by furnishing them with second opinions, thereby considerably scaling down the workload. The automated diagnostic systems have been widely employed and have surfaced as a subject of zooming enthusiasm for a diversity of medical data embracing the medical signals and medical images (2). The diagnosing diseases concerned encompass the breast cancer, blood diseases, eye diseases, brain tumors, thyroid cancer, kidney, lung, leukemia cancer and the like. By the term "Classification" what is meant is the process of assigning a physical object or incident into one of a group of specified categories (3). The automated image classification systems with superior precision are a sine-qua-non for the real-time applications. Fundamentally, the classification can be subdivided into two distinct groups such as the unsupervised classification and the supervised classification (4). The general architecture diagram of classification is shown in Figure 1.

Classification techniques of brain tumor

The brain tumors represent the anomalous and unrestrained propagations of the cells, certain kinds of tumors originating in the brain itself and are known as the primary tumors. Other types of tumors extend to this location from some other portion in the body by means of metastasis, and are known as the secondary tumors (5, 6). Kumar et.al, (7) Fantastically flagged off an innovative automated method which utilized the textural features to explain the blocks of each and every MRI slice along with the parallel features.

The local binary patterns and the gray level co-occurrence features, gray level and wavelet features were extorted and the corresponding features were trained and categorized using Support vector machine classifier. Whereas (8) proficiently propounded a probabilistic neural network for the brain tumor classification in which Discrete Wavelet Transform was initially employed by employing the Daubechies wavelet [db4], for disintegrating the MR image into several levels of approximate and detailed coefficients. The Neural network represents a novel technique intended for the purpose of the automatic categorization of magnetic resonance images [MRI].

Further, it is home to the supervised feed-forward back-propagation neural network method which is effectively employed to categorize the normal or abnormal images. The Artificial neural networks utilized for the brain image categorization are also computationally hard and do not ensure superior precision (9). With an eye on effectively identifying the Brain Tumor cells, a novel clustering approach dependent on the FCM can be elegantly carried out (13). In this regard, the Clustering method training is efficiently performed by means of the pixel features with qualities of each and every group (14). During the course of segmentation of the image, there is a feast of roadblocks encountered as the brain structure achieved is incredibly complicated and does not represent smooth imagery.

Hence, for the purpose of the defined recognized, an appropriated algorithm has to be made use of. Thus, by employing the FCM the cluster formation is found to be very quick. Further by means of the optimization employing the particle swarm (15) there is a significant enhancement in the time-frame together with the accuracy. In this regard, special mention has to be made of the neural fuzzy techniques which gain an unsurpassable edge over the peer techniques boosted by their sterling performance.

It is established that the classification precision of the integrated neuro fuzzy classifier is relatively superior to those of the individual fuzzy and neural classifiers. To add another feather in the cap of the neuro fuzzy classifier, its convergence time period is an amazing one to the tune of (11) which can also be augmented considerably by means of integrating the Neuro - Fuzzy classifier with the Genetic algorithm, which goes a long way in scaling up the precision to a whopping (12). The techniques Presented for the Diagnosis of Brain Tumor is shown in **Table1**.

Classification techniques of breast cancer on mammograms

A mammogram, in quintessence, represents a scrutiny of the breast for the vital objective of averting and diagnosing the breast cancer. In (16) (17)(18)(19)(20)(21)(22)(23) a flood of novel techniques have been flagged off intended for the identification of the masses. The machine learning methods are offered a red carpet welcome as the highly preferred applications devoted for the purpose of the classification (18). Standing out amongst the several classification approaches, the neural network based classifiers (20, 24) have been efficiently employed in a large majority of the applications such as the medical image analysis. Further, the Radial Basis Function Network (RBFN) has also been extensively employed in a multitude of science and engineering domains (18). The SVM classifiers (17)(21), Probabilistic Neural Networks (19), Self Adaptive Resource Allocation Network Classifier (18), K-Nearest Neighbor [KNN] (20), Fuzzy Classifier (25), SVM model employing the RBF and Polynomial kernel functions with varying arguments like the RBF_Sigma, Box Constraint & Polyorder (26) are also extensively utilized for the purpose of the classification. The existence of micro-calcification clusters is deemed as a very vital sign of the malignant categories of breast cancer, and its recognition is highly essential for the prevention and cure of the ailment. Therefore, in (27-29) have proposed effective approaches, in order to detect microcalcification clusters in digitized mammograms. The techniques Presented for the Diagnosis of Breast Cancer is shown in Table 2.

Classification techniques of thyroid tumor

The classification of papillary carcinoma and medullary carcinoma cells (30), thyroid nodules (31), thyroid lesions (32) methods in Fine Needle Aspiration Biopsy (FNAB) microscopic cytological images have been elegantly launched. In (30) at the outset, the image segmentation is carried out to eliminate the background staining data in microscopic images by means of the mathematical morphology. The Feature extraction is performed with the help of the Discrete Wavelet Transform (DWT) and Gray Level Co-occurrence Matrix (GLCM) and the classification is carried out by means of the k-Nearest Neighbor (kNN) classifier. The diagnostic precision of the GLCM is incredibly increased to the tune of a whopping 90% by effectively performing the majority voting rule. In this regard, the Ultrasound imaging appears as the finest candidate to effectively forecast the type of thyroid existing. The Ultrasound images invariably consist of the speckle noise and for the purpose of dispelling the noise several filters are employed, and further the used histogram equalization generates visual divergences and improves the contrast between images (33). Gray level co-occurrence matrix [GLCM] texture characterization methods are effectively used for the purpose of the feature extraction (33)(34). The extorted features are categorized by means of several techniques such as the Neural Network (38), scaled conjugate gradient back propagation training neural network (34)(33)(38) KNN and Bayesian (33), Linguistic Hedges Neural-Fuzzy Classifier with Selected Features (36) for the diagnosis of thyroid nodule. It is a daunting challenge to discriminate the diverse follicular derived lesions from one another (37). The techniques presented for the diagnosis of Thyroid tumor is shown in Table 3.

CONCLUSION

A host of medical image detection techniques have been extensively employed to make their significant contribution towards assisting the diagnosis of several ailments further precisely. In this regard, the image classification represents a daunting challenge which elegantly employs the image processing, pattern recognition and the classification techniques. In this regard, the automatic medical image classification emerges as a progressive region in the realm of the image classification, with the scope for added advancements in the days to come. In view of this, the automatic diagnosis is capable of extending a helping hand to the pathologists by furnishing them with second opinions, thereby going a long way in scaling down their workload.

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Table 1: Techniques Presented for the Diagnosis of Brain Tumor

Technique	**Classifier**	**Sensitivity**	**Specificity**	**Accuracy**	**Type**

DCANN(5)	ANN	NA	NA	90%	Supervised
BMMRI(6)	SVM	NA	NA	98.87%	Supervised
PATSC(7)	SVM	99.47%	99.6%	99.5%	Supervised
AMDIS(10)	ANN	80.4%	75.6%	NA	Supervised
BTCC(13)	PNN-RBF	79.27%	71.52%	NA	NA
BTDPSO(15)	FCM with PSO	NA	NA	98.57%	Unsupervised
ABTD(39)	ANN	NA	NA	96%	Supervised
CMRBNN(40)	ANN	NA	NA	95%	Supervised
BMRISVM(41)	Least Squares SVM	99.64%	95.5%	98.64%	Supervised
PLCPNN(42)	PNN	88%	83%	87%	Supervised
HTAMR(43)	DWT+PCA+ ANN	98.3%	81.8%	95.7%	Supervised
-do-	DWT+PCA+ KNN	98.4%	100%	98.6%	Supervised

Table 2**:** Techniques Presented for the Diagnosis of Breast Cancer

Technique	Classifier	Sensitivity	Specificity	Accuracy	Type
BCDTM(19)	PNN	90.3%	100%	92.3%	Supervised
AADCM(20)	ANN	100%	93%	97%	Supervised
-do-	KNN	100%	91%	95%	Unsupervised
MCMMN(21)	Fuzzy K-Nearest Neighbor Equality	94.46%	96.81%	96.52	Unsupervised
DMMI(22)	SVM	80%	85.68%	84.62%	Supervised
ENNBS(23)	NN	96%	99.12%	97.51%	Supervised
DMBAR(24)	SVM	100%	85.37%	90.26%	Supervised
SVMABC(26)	SVM-RBF	96.5%	98.36%	97.13%	Supervised
CCMANN(28)	SVM	NA	NA	90.16%	Supervised

Table 3: Techniques Presented for the Diagnosis of Thyroid Tumor

Technique	Classifier	Sensitivity	Specificity	Accuracy	Type
MVCC(30)	K-NN	94.28%	97.14%	95.71%	Unsupervised
TNSW(31)	FNAC	79.27%	71.52%	NA	NA
DAFN(32)	FNAC	92.8%	94.2%	93.6%	NA
TATU(34)	Feed Forward Neural Network	98.08± 1.77%	97.37± 2.76%	97.72± 1.69%	Supervised
CCTUI(35)	SVM	80%	100%	84.61%	Supervised
-do-	KNN	75%	0%	46.15%	Unsupervised
-do-	Bayesian	0%	100%	38.46%	Supervised
ESBNF(36)	Linguistic Hedges Neural- Fuzzy Classifier	NA	NA	97.67%	Unsupervised
TNSC(38)	ANN	93.33%	70%	87.50%	Supervised
-do-	SVM	96.66%	80%	92.50%	Supervised

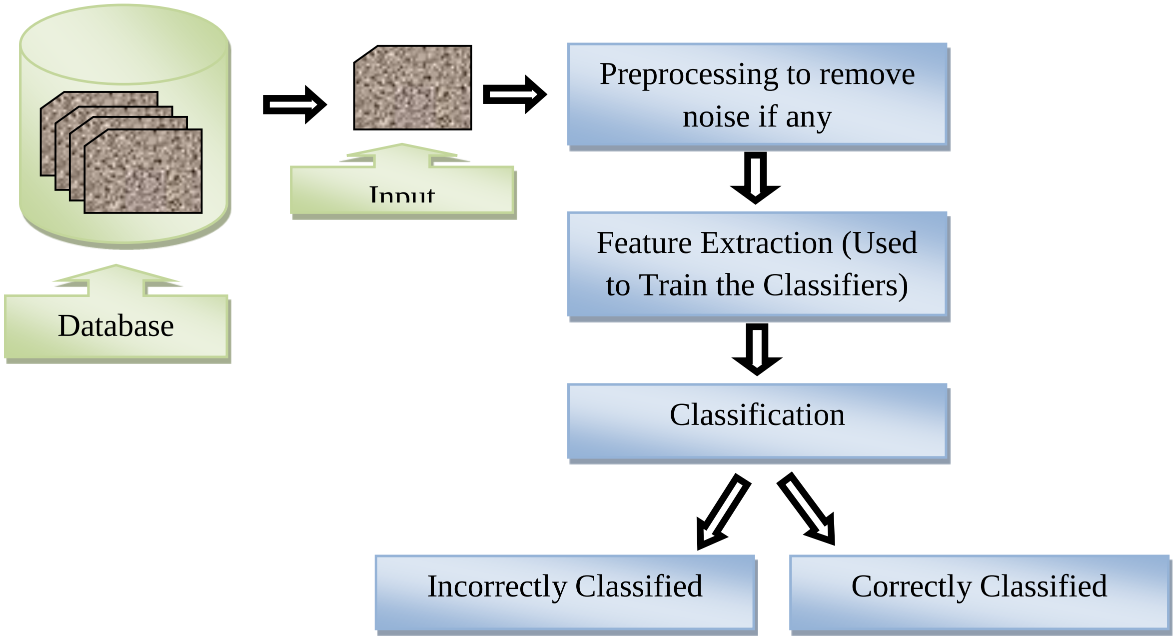

Figure: General Architecture Diagram of Classification.