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Extraction of Medical Image Features with the Wavelet Transform

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ABSTRACT
For computer aided diagnosis of brain tumor problems, researchers have created different methodologies and methods. Each of the brain diseases demands a different strategy to characterize the disease depending on the type of brain tumor. Because the focus of this work is on brain tumor diagnosis and classification, one technique to anticipate aggressive behavior is to measure the properties of these tumor masses (i.e. how high is their metabolic activity). Early indications of cancer may exist, and it is important to determine if they are benign or malignant. This study discusses the major approaches to brain tumor detection and classification. The most significant tool for detecting a brain tumor is MRI. A new algorithm is being developed that combines support vector machine (SVM) and fuzzy c- means, resulting in a hybrid technique for brain tumor prediction that is more accurate and successful in classifying brain MRI data.

Keywords: - Feature Extraction, CAD, SVM, DWT, Prevention

I. INTRODUCTION

The technique of creating images of the human body for clinical reasons is known as medical image processing. It's commonly thought to refer to a group of noninvasive approaches for producing images of the body's internal anatomy. This means that cause can be deduced from effect. It is critical in improving illness diagnosis, prevention, and therapy [1]. Medical imaging, which includes radiology, nuclear medicine, investigative radiological sciences, endoscopy, thermography, medical photography, and microscopy, is a subset of biological imaging. The human eye is the judge for how well a method works when an image is processed for visual interpretation. Computed Tomography (CT) provides the finest information on denser tissue with less distortion for medical diagnosis [2]. With increased distortion, magnetic resonance imaging (MRI) provides better information about soft tissue [3,4]. With more multimodality medical pictures available in clinical applications, the concept of fusing images from several modalities has become increasingly relevant, and medical image fusion is emerging as a new potential study topic [5].

With the introduction of quicker, more accurate mass invasive equipment in recent decades, medical image processing (MIP) has undergone a revolution. This has prompted the development of related software, which has fueled the development of new signal and image processing techniques [6,7]. Many researchers in the image processing and pattern recognition fields have been interested in image analysis techniques such as segmentation, edge detection, boundary detection, classification, clustering, and texture property extraction in recent years. Medical images contain so much information that feature extraction is difficult [8]. CT and MRI medical scans display information about the inside of the patient's body in a non-invasive manner, making them very useful for doctors' diagnoses and not too uncomfortable for patients [9]. However, the raw data can only provide material to the doctor, who must select which information is significant and which is not.

Computer-aided diagnostics (CAD) is a method of extracting valuable information from medical photographs so that a doctor may make a diagnosis choice fast and simply [10]. However, because of the uneven structure of the human body, it is difficult to find issues in medical photographs if they are noisy or not in an appropriate format [11]. The use of image processing technology is critical in the processing, analysis, and formation of images. The detection of edges in an image will assist us in comprehending the picture feature. Because edges frequently appear in image places

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that reflect object boundaries [12]. In picture segmentation, edge detection is commonly employed. Acquisition of a TRUS picture of the prostate, preprocessing, segmentation, feature extraction, and classification are the five stages of the CAD system[13]. Figure 1 shows a high-level overview of the CAD system.

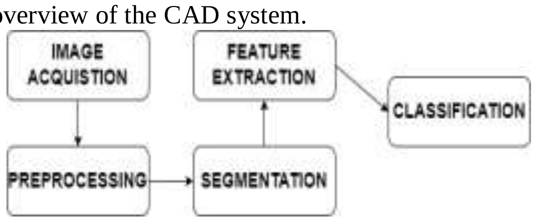

Figure 1: computer aided diagnosis system

All conventional computer vision seeks to replicate the effect of human vision by perceiving and analyzing images electronically. Giving computers the ability to see is a difficult endeavor. The specific implementation of a computer vision system is also determined by whether its functionality is pre-defined or if some parts of it can be taught or modified while in use. However, many standard functions may be found in most computer vision systems. The following are the five steps of the CAD system:

a. IMAGEACQUISITION

A digital image produced by one or more image sensors can include range sensors, tomography devices, radar, ultra-sonic cameras, and other forms of light-sensitive cameras. Depending on the type of sensor, the picture data produced is a 2D image, a 3D volume, or an image sequence. Pixel values correspond to light intensity in one or more spectral bands (grey or colour images), but they can also be linked to physical parameters like depth, acoustic or electromagnetic wave absorption or reflectance, or nuclear magnetic resonance.

b.PRE-PROCESSING

Before using a computer vision approach to extract a specific piece of information, the data must be processed to ensure that it meets the method's assumptions. Noise reduction, for example, to ensure that sensor noise does not introduce erroneous information.

2. Re-sampling to ensure the image coordinate system is accurate.
3. Contrast enhancement to ensure that important information is visible.
4. Image structure enhancement via scale-space representation at locally relevant scales.

c.FEATUREEXTRACTION

When an algorithm's input data is excessively vast to analyze and it's suspected that it's infamously redundant (data with little information), the data is translated into a simplified representation of a collection of features (also named features vector). Features extraction is the process of transforming raw data into a set of features. If the features extracted are appropriately picked, the features set should extract meaningful and valuable information from the input data to execute the required task using this smaller representation instead of the full size input (example, in medical imaging, extract anatomical boundaries before comparison with normal template and diagnosis). Lines, edges, and ridges are common examples of such features. Corners, blobs, and points are examples of localized interest points. Texture, form, and motion may be associated with more complex qualities. Wavelets, statistical methods, and most of them used feature derived using image processing techniques are some of the feature extraction methods used to detect and classify anomalies in medical pictures. Other techniques include fuzzy theory and neural networks.

d.SEGMENTATION

As the name implies, segmentation is the process of dividing a digital image into many parts (which is sets of pixels also known as super pixels). The goal of segmentation is to make an image more understandable and easier to evaluate by simplifying and/or changing its representation [14]. Image segmentation is a technique for identifying objects and boundaries (lines, curves, and so on) in photographs. Image segmentation, to put it another way, is the process of giving a label to each pixel in an image so that pixels with the same label have certain visual properties. The image segmentation process yields a set of segments or contours that cover the entire image. Each pixel in a region has a similar color, intensity, or texture [15]. With respect to the same attribute, adjacent locations are drastically diverse(s).

e.Classification

At this phase, we have a tiny collection of data, usually a set of points or an image region, that is thought to contain a specific item. The remaining processing, for example, deals with:

1. Calculating application-specific characteristics such object poses and sizes.
2. Checking whether the data meets model-based and application-specific assumptions.

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3. Sorting the discovered object into different categories.

II. AVAILABLE METHODS

Because features are employed as part of a classification technique, there is a trend in the image processing field to build and implement recognition systems using tiny feature sets. However, there is a great desire to add a significant number of characteristics in order to obtain high identification rates under difficult settings. As a result, the image processing community has developed a number of algorithms for determining a "optimal" subset of features from a broader collection of available features.Sérgio et al. use single-valued functions to evaluate ranks to construct a family of feature selection methods in their work. This is based on a genetic algorithm, and it enhances the accuracy of content-based picture retrieval systems as well as the quality of ranking, which improves retrieval performance [16]. Jaba and Shanthi examined continuous feature discretization previously and established distinguishing properties of the techniques. On this foundation, a novel supervised strategy is defined, which combines discretization and feature selection to select the most relevant characteristics for classification. Associative Classifiers [17] are the classification approach employed.

H. B. Nandpuru, Dr. S. S. Salankar, and Professor V. R. Bora collaborated on using support vector machines to classify MRI images of brain tumors. Brain image classification was done using Support Vector Machines (SVM). Grey scale, symmetry, and texture features were used to extract features from brain MRI images in this work. They came up with a reasonable outcome [18].

Cancer found exploiting artificial neural network and support vector machine: A comparative study was performed on by S.H.S.A. Ubaidillah, R. Sallehuddin, and N.A. Ali. They compared the performance of SVM and ANN classifiers on four completely different cancer datasets in this research. In this study, the ANN classifier gated sensible classification performance on datasets with a larger number of input options (prostate and ovarian cancer datasets), SVM also gave sensible performance when compared to ANN on datasets with a smaller number of input features (breast cancer and liver cancer datasets), and finally, the SVM classifier gives higher growth results [19].

Feature extraction and selection are critical in neural image classification, according to Yong and Ding-gang, for identifying meaningful features and minimizing feature dimensionality. This is usually done in two parts and presented as a combined feature extraction and selection technique with two iterative steps: constrained subspace learning-based feature extraction and support vector machine (SVM)-based feature selection [20].

By automatically segmenting the brain using appropriate texture features, Sasikala et al (2006) found malignant tumors in magnetic resonance imaging (MRIs). These texture properties are recovered utilizing the spatial grey level dependency approach and wavelet transform from normal and tumor areas (ROI) in brain images that are being studied [21].

III. WAVELETTRANSFORM

Any arbitrary function represented as a superposition of wavelets is referred to as a wavelet transform. These wavelets are dilation and translation functions created from a mother wavelet. It is a useful mathematical technique for decomposing a function into its time and frequency components. For non-stationary signals, it outperforms the classical Fourier transform on the condition of localization, which should be in both the time and frequency domain [22]. A signal's spatial and frequency information are both captured by the DWT. DWT decomposes the given image into a coarse approximation using low-pass filtering and in depth information using high-pass filtering. This type of decomposition is carried out recursively on low-pass approximation coefficients produced at each level, until the required number of iterations is attained. Wavelet bases are divided into two categories: orthogonal and biorthogonal. Common orthogonal bases are the Daubechies (db), Coiflets (coif), Symlets (sym), and discreteMeyer (dmey). Daubechies wavelets are the most popular and non-redundant orthogonal wavelet bases. The Symletsis wavelets are a quasi-symmetric extension of the Dubechies wavelets. Coiflets are a symmetrical extension of the classical Daubechies that has vanishing moment conditions for both the wavelets and scaling functions. Because they can preserve linear phase, have finite impulse response, and the mother wavelets have arbitrarily high regularity, biorthogonal (bior) wavelets are sometimes preferred over orthogonal wavelets. Wavelet filters are also available in a variety of lengths [23]. After the name of the basis, the length of the wavelet filter is stated. "db3" stands for the Daubechies wavelet filter, which has a length of three. Because the low pass and high pass filters in biorthogonal wavelets may not be the same length, their lengths are separated by a dot. For example, "bior3.5" refers to a biorthogonal wavelet filter with a low pass filter length of 3 and a high pass filter length of 5. Wavelet is a type of visual representation that is usually very minimal and effective.

IV. PROPOSEDMETHOD

1. The suggested methodology is divided into several stages, beginning with the grouping of brain MRI images [24]. This is a hybrid technique that includes procedures such as augmentation, skull striping, segmentation using fuzzy c-means clustering, feature extraction, and coaching or training the SVM classifier using MRI images and wavelet-based GLRLM features using 2D DWT, as well as storing and evaluating the data[25]. Begin collecting the sub-image blocks from the top left corner. 2. Using a two-level 2-D discrete wavelet transform to decompose sub-image blocks (DWT).
3. Using 1 for distance and 0,45,90, and 135 degrees for è, derive the grey level run length matrix (GLRLM) for two level high frequency sub bands of the discrete wavelet decomposed image and average it.
4. Wavelet dominant run length texture features (WDRLT) are extracted from these grey level run length matrices as the dominant run length texture features [26]. The feature values acquired are then normalized. Subtract the minimum value and divide by the highest value minus the minimum value. If a feature value is less than the minimum value, it is set to minimum value, and if it is larger than the maximum value, it is put to maximum value in the data set.
The image is upgraded using enhancement techniques including contrast improvement and mid-range stretch in this procedure [27]. Double thresholding and morphological operations are used to stripe the skull. The image is then segmented using a wavelet-based dominant grey level run length feature extraction method to find suspicious regions in brain MRI images[28]. Starting from the top left corner, we acquire sub-image blocks and then decompose sub-image blocks using two level 2-D DWT (Discrete wavelet transform). Then, for brain tumour classification, a new hybrid technique based on support vector machines (SVM) and fuzzy c-means was developed [29]. This method is a hybrid technique for predicting brain cancers that combines support vector machine (SVM) with fuzzy c-means to produce more accurate and effective results for brain MRI image categorization.

V. CONCLUSION

In this research, many medical picture feature extraction strategies were investigated, as well as the proposed method. It is necessary to build a medical image processing system that is both time efficient and effective. These findings show that the created technologies can assist radiologists in making accurate diagnoses and reduce the frequency of missed malignant spots or wasteful biopsies. A computer-assisted diagnosis system must be created to serve as a supplemental tool for radiologists in diagnosing cancer. In addition, a public medical database should be created where categorized medical photos can be made available to researchers testing systems. Brain MRI pictures proven to be a significant technique of detecting a brain tumour in the system described. The brain tumor is accurately identified using a hybrid technique that combines support vector machine and fuzzy c-means clustering for classification. After segmentation with Fuzzy c-means clustering, feature extraction is performed using a two-level 2-D Discrete wavelet transform, which is the most essential method in picture segmentation. A hybrid SVM method is proposed for future work in order to achieve better results in terms of accuracy rate and error rate. Alternative data mining approaches can be utilized to train by employing different kernel functions in the future to improve the performance of the classifiers and expand the data sets.

REFERENCES

[1]. Ghantasala, G. P., Kumari, N. V., & Patan, R. (2021). Cancer prediction and diagnosis hinged on HCML in IOMT environment. In Machine Learning and the Internet of Medical Things in Healthcare (pp. 179-207). Academic Press.
[2]. Pradeep Ghantasala, G.S., Nageswara Rao, D., Patan, R. (2022). Recognition of Dubious Tissue by Using Supervised Machine Learning Strategy. In: Deepak, B.B.V.L., Parhi, D., Biswal, B., Jena, P.C. (eds) Applications of Computational Methods in Manufacturing and Product Design. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-19-0296-3_35
[3]. Ghantasala, G. P., & Kumari, N. V. (2021). Breast Cancer Treatment Using Automated Robot Support Technology ForMri Breast Biopsy. INTERNATIONAL JOURNAL OF EDUCATION, SOCIAL SCIENCES AND LINGUISTICS, 1(2), 235-242.
[4]. Ghantasala, G. P., Reddy, A., Peyyala, S., & Rao, D. N. (2021). Breast Cancer Prediction In Virtue Of Big Data

Analytics. INTERNATIONAL JOURNAL OF EDUCATION, SOCIAL SCIENCES AND LINGUISTICS, 1(1), 130-136.

[5]. Reddy, A. R., Ghantasala, G. P., Patan, R., Manikandan, R., &Kallam, S. Smart Assistance of Elderly Individuals in Emergency Situations at Home. Internet of Medical Things: Remote Healthcare Systems and Applications, 95.

[6]. Krishna, N. M., Sekaran, K., Vamsi, A. V. N., Ghantasala, G. P., Chandana, P., Kadry, S., ... &Damaševičius, R. (2019). An efficient mixture model approach in brain-machine interface systems for extracting the psychological status of mentally impaired persons using EEG signals. IEEE Access, 7, 77905-77914.

[7]. Patan, R., Ghantasala, G. P., Sekaran, R., Gupta, D., & Ramachandran, M. (2020). Smart healthcare and quality of service in IoT using grey filter convolutional based cyber physical system. Sustainable Cities and Society, 59, 102141.

[8]. Ghantasala, G. P., Kallam, S., Kumari, N. V., & Patan, R. (2020, March). Texture Recognization and Image Smoothing for Microcalcification and Mass Detection in Abnormal Region. In 2020 International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-6). IEEE.

[9]. Ghantasala, G. P., Reddy, A. R., &Arvindhan, M. Prediction of Coronavirus (COVID-19) Disease Health Monitoring with Clinical Support System and Its Objectives. In Machine Learning and Analytics in Healthcare Systems (pp. 237-260). CRC Press.

[10]. G. S. Pradeep Ghantasala, Nalli Vinaya Kumari. Mammographic CADe and CADx for Identifying Microcalcification Using Support Vector Machine. Journal of Communication Engineering & Systems. 2020; 10(2): 9–16p.

[11]. "A survey on Microcalcification identification and classification using CAD System", International Journal of Emerging Technologies and Innovative Research (www.jetir.org), ISSN:2349-5162, Vol.2, Issue 5, page no.186-190, MAY-2015, Available :http://www.jetir.org/papers/JETIR1805783.pdf

[12]. Chandana, P., Ghantasala, G. P., Jeny, J. R. V., Sekaran, K., Deepika, N., Nam, Y., &Kadry, S. (2020). An effective identification of crop diseases using faster region based convolutional neural network and expert systems. International Journal of Electrical and Computer Engineering (IJECE), 10(6), 6531-6540.

[13]. Bhowmik, C., Ghantasala, G. P., &AnuRadha, R. (2021). A Comparison of Various Data Mining Algorithms to Distinguish Mammogram Calcification Using Computer-Aided Testing Tools. In Proceedings of the Second International Conference on Information Management and Machine Intelligence (pp. 537-546). Springer, Singapore.

[14]. Sreehari, E., &Ghantasala, P. G. (2019). Climate Changes Prediction Using Simple Linear Regression. Journal of Computational and Theoretical Nanoscience, 16(2), 655-658.

[15]. Kishore, D. R., Syeda, N., Suneetha, D., Kumari, C. S., &Ghantasala, G. P. (2021). Multi Scale Image Fusion through Laplacian Pyramid and Deep Learning on Thermal Images. Annals of the Romanian Society for Cell Biology, 3728-3734.

[16]. Sérgio Francisco da Silva , Marcela Xavier Ribeiro , JoãodoE.S.BatistaNeto,CaetanoTraina-Jr.,AgmaJ.M.Traina, (2011). Improving the ranking quality of medicalimage retrieval using a genetic feature selection method.MedicalImaging,1012-1017.

[17]. Jaba S. L. and Shanthi V., (2009), International Journal ofComputerTheoryandEngineering, 1(2),154-158.

[18]. Ling C., Bolun C., and Yixin C., (2011). Image FeatureSelection Basedon Ant ColonyOptimization.

[19]. Deris, A. M., Zain, A. M., &Sallehuddin, R. (2011). Overview of support vector machine in modeling machining performances. Procedia Engineering, 24, 308-312.

[20]. YongF.andDinggangS.,(2009).IntegratedFeatureExtractionandSelectionforNeuroimageclassification.ProcofSPIEof Medical Imaging,7259,1-8.

[21]. Abhijit Smnathe, Ujjwal Harode, “A Novel Approach ofImage Fusion based on Wavelet Transform and CurveletTransform”,InternationalConference&WorkshoponRecent Trends in Technology, (TCET) 2012 ProceedingspublishedinInternationalJournal ofComputerApplications®(IJCA)

[22]. MANDAL, K., GHANTASALA, G. P., KHAN, F., SATHIYARAJ, R., & BALAMURUGAN, B. (2020). Futurity of Translation Algorithms for Neural Machine Translation (NMT) and Its Vision. Natural Language Processing in Artificial Intelligence, 53.

[23]. Ghantasala, G. P., & Kumari, N. V. (2021). Identification of Normal and Abnormal Mammographic Images Using Deep Neural Network. Asian Journal For Convergence In Technology (AJCT), 7(1), 71-74.

[24]. G S Pradeep Ghantasala, D. Nageswara Rao, Mandal K (2021) MACHINE LEARNING ALGORITHMS BASED BREAST CANCER PREDICTION MODEL. Journal of Cardiovascular Disease Research, 12 (4), 50-56. doi:10.31838/jcdr.2021.12.04.04

[25]. Kumari, N. V., &Ghantasala, G. P. (2020). Support Vector Machine Based Supervised Machine Learning Algorithm for Finding ROC and LDA Region. Journal of Operating Systems Development & Trends, 7(1), 26-33.

[26]. Ghantasala, G. P., Tanuja, B., Teja, G. S., & Abhilash, A. S. (2020). Feature Extraction and Evaluation of Colon Cancer using PCA, LDA and Gene Expression. Forest, 10(98), 99.

[27]. Kishore, D. R., Suneetha, D., Ghantasala, G. P., & Sankar, B. R. Anomaly Detection in Real-Time Videos Using Match Subspace System and Deep Belief Networks. Multimedia Computing Systems and Virtual Reality, 151.

[28]. Ghantasala, G. P., Sudha, L. R., Priya, T. V., Deepan, P., & Vignesh, R. R. An Efficient Deep Learning Framework for Multimedia Big Data Analytics. Multimedia Computing Systems and Virtual Reality, 99.

[29]. Gadde, S.S., Anand, D., Sasidhar Babu, N., Pujitha, B.V., Sai Reethi, M., Pradeep Ghantasala, G.S. (2022). Performance Prediction of Students Using Machine Learning Algorithms. In: Deepak, B.B.V.L., Parhi, D., Biswal, B., Jena, P.C. (eds) Applications of Computational Methods in Manufacturing and Product Design. Lecture Notes in Mechanical Engineering. Springer, Singapore. https://doi.org/10.1007/978-981-19-0296-3_36