Automatic Computer Aided Diagnosis for Liver Cancer Detection

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Abstract

Liver cancer is one of the universal diseases that cause the death. Ancient detection is important to diagnose and slash the incidence of death. Improvements in medical imaging and image processing techniques have significantly unchanged interpretation of medical images. Computer Aided Diagnosis (CAD) systems plays a dominant role in early detection of liver disease and in reducing liver cancer death rate. The liver is the second enormous organ in human body that include by metastasis disease being live cancer that cause of death worldwide. Beyond healthy liver a human cannot live. The liver cancer is life frightening disease which is particularly challenging to recognize for the medical and engineering technique. The Medical image processing technique is utilized for the non-invasive methods to recognize the tumours. The possibility of living having Tumour usually depends on early recognize of Tumour. Computers have been successfully enforced to various fields of medical sciences such as biochemical analysis, drug development and recognition of diseases from medical images.

Keywords
pre-processing, Feature Extraction, segmentation, Computer Aided Diagnosis, Noise Removal

1. INTRODUCTION

Liver is an important organ that observes vital functions such as detoxification of hormones, drugs, filter the blood from waste products, production of proteins mandatory for blood clotting. However, diseases can occur without ominous and early detection will help to reduce the cancer death becomes critical to successful treatment. Statistics about Global Cancer [1] has reported worldwide that the liver cancer was the fourth dominate diagnosed and third leading development of death by cancer for the men. While in women, it is the seventh at most frequently diagnosed and the sixth most common cause cancer death. Moreover, extent statistic's rate of liver cancer was increasing across many parts of the world where most patients who are diagnosed with liver cancer die within six months of diagnosis. There are assorted imaging modalities such as Computed tomography (CT) scan, Ultrasound, X-Ray, and Magnetic Resonance Imaging (MRI) used to diagnose liver lesions. The CT scan is generally preferred for diagnosing liver diseases, especially as being premeditated of high accurate imaging and cheaper than MRI [2], [3]. However, liver segmentation and liver lesion detection can be a very challenging task and it depends on the experience of the radiologist and that's referring to small noticeable changes between healthy liver tissue and lesion [4]. Generally, along the improvements in image processing and artificial intelligence designing and developing technique for computer-aided diagnosis (CAD) to characterize liver lesions have received considerable attention over the past years. These systems can bring diagnostic assistance to clinicians for the improvement of diagnosis and increasing the accuracy [5]. This contributes towards avoiding the imperil of liver biopsy and surgery. A general automatic/semi-automatic CAD system is supposed to bring complete assistance to doctors in diagnosis of liver cancer.

Cancer in initially starting in liver is called as primary liver cancers. The HCC (hepatocellular carcinoma) is the most common types of liver cancer and it purpose to influence on males larger than females. Soon reorganization and proper personification of liver cancer is a significance challenge in empirical radiology. Liver lesions offer that weird tissue cell present in liver. It is a in the cramp tissue region of the body due to agony by disease. Lesions can be detected in CT scan by separates in pixel force from other expanse of the livers. For perceived treat, manual

division of this CT scan is containing designation of this CT scan is containing and significantly time preserving work. Lesion of liver Tumors is a perception fundamental works along medical reconciliation. Proper and accurate analysis of the classification set up for the any doubt organizing and valuation of the accessible treatments that can be given to the patient. In Past years' obtrusive strategies are exploit for finding any infection like malignancy. In any case, today restorative imaging infer on non-intrusive techniques for determination of Tumor.
The CAD tools are initiate for the detection liver Tumor. Sundry sorts of imaging technique in perceive of non-intrusive model are CT filter, X-Beam, Ultrasound, X-ray and liver sweeps. These all checks not just name the size and area of the disease yet additionally designate Tumor has arrive to different parts of the body. Sundry types of image technique establish on non-harmful techniques are X-Ray, MRI, CT scan and liver scans. overhead techniques are used to recognize the size and position of threat in human body but also denoted Tumor has reach to another part of human body. Cancer is the significant threat for individual threat and its number of patients expanding word wide considering of the global warming, regardless of whether there are new treatments and medications proposed by investigate doctors, yet level of cancer characterizes the capacity of its fix. There are distinct types of cancers from which person is enduring [male and female]. Computers have been successfully adapted to various fields of medical sciences such as biochemical analysis, drug development and recognition of diseases from medical images. Visual exposition of medical images is utilized for the previous detection and evaluation diseases. The analysis in the initial level of visual interpretation gambles on the capability of doctor to recognize a definite state of the images. Diagnostic correctness can be appreciated by giving extra data, produced by computational strategies that can't be gotten by basic visual translations. Thus, Computer Aided Diagnosis (CAD) has twist out to be one of the experimental innovation topics in imaging and diagnostic radiology. Prosperous identification of lung cancer, brain Tumor is possible with the existing CAD. However, insufficient research has been focused on liver because of the difficulties in segmenting liver from other adjacent abdominal organs such as kidney, stomach and gall bladder using abdominal images due to gray level similarities of adjacent organs. The largest general medical imaging research for initially discovery and treatment of liver diseases involves US (Ultra Sonography), MRI (Magnetic Resonance Imaging) and CT (Computed Tomography) scan [1].
Liver diseases are considered important, in light of the evidence that liver is indispensable vital to the life of a patient. In human body, liver is occupying in the upper right part of the stomach area. The liver has numerous compelling functions, thus as clearing poisons from the blood, metabolizing drugs, blood proteins and create bile which helps assimilation [5]. Liver can be permanently damaged due to different inference which involves virus infection, reaction due to alcohol, hereditary conditions, Tumors and challenges with human body toxin system. A liver disease exhibits a prominent medical difficulty of world proportions. Approximately 50% of the people [6] are concerned by liver diseases.

1.1 Objective
The proposed algorithm is designed for automatic computer-aided diagnosis of liver cancer from flat contrast CT images. The idea expressed in this article is to classify the malignancy of the liver tumor earlier of liver segmentation and to locate HCC burden on the liver. The vital goal of CAD systems is to identify abnormal signs at an earliest that a human professional fails to find. In mammography, identification of paltry lumps in dense tissue, finding architectural distortion and prediction of mass type as benign or malignant by its shape, size, etc.

2. LITERATURE SURVEY
Pedro Rodrigues, et al(2011)[7] Purpose Radiological longitudinal follow-up of liver tumors in CT scans is the quality of care for disease development evaluation and for liver tumor therapy. Investigating contemporary tumors in the follow-up scan is necessary to decide virulence, to analysis the overall tumor load, and to calculate the diagnosis efficiency. Since contemporary tumors are typically small, they may be missed by analysis radiologists. Methods we investigated the contemporary method for the automatic reorganization and classification of new tumors in protensive liver CT researches for liver tumors load analysis. Its inputs are the baseline and follow-up CT scans, the baseline tumors description, and a tumor condition prior model. Its outcomes are the contemporary tumors classification in the follow-up scan, the tumor load quantification in both scans, and the tumor load modify. It consolidation data from the scans, the baseline called tumors description, and a tumor aspects model in the form of global Convolution neural network classifier. Unlike alternative deep learning-based technique, it does not necessary huge denoted training sets.

Turid Torheim et al(2014) [26]proposed a method which anticipated to develop a system that could correctly predict the cervical cancer from the Brix parameters derived from the pre-chemo radiotherapy DCE--MRI. The texture analysis was depleted by grey level co-occurrence matrix construction from the maps. The explanatory variables worn by the support vector machine classification were the first and second order features. The leave-one-outcross model validation was worn for the validation process. The first order features could not differentiate intervening cure and relapsed patients which the second order did with around 70% accuracy. The spatial affiliation within the tumor that were quantified by texture features were found to be fit for outcome prediction than first order features.

Xiabi Liu et al(2015)[27] proposed a new Fisher criterion and Genetic optimization based feature selection method. The feature subsets were evaluated using fisher criterion and the optimal features were selected from the set of candidates by developing a contemporary Genetic optimization algorithm. The regions of interests were selected with the benefit of the classifiers support vector machines, bagging, Naïve Bayes, K-nearest neighbor and AdaBoost and the selected features. The new method execute better than the feature selection based on classification accuracy rate and genetic optimization. It was deeply effective in the recognition process. A few additional pre-processing steps would have increased the accuracy.

Ina Singh et al(2015)[28] proposed a hybrid method combining K-Means, ACO and Level set method. This method greatly helped to treasure the match between the donor and recipient liver automatically. The K-Means algorithm was used to cluster the data. This was done in an intelligent way because different point gave different results. For optimizing the K-Means, ACO was worn. Then, the level set method was worn for the segmentation. The hybrid K-means with ACO and level set performed preferred than the existing K-means and level set on both quantitative and qualitative basis. The F-measure and sensitivity was raise to be high in the hybrid K-Means method. This method greatly sustained during surgeries.

Y. Rakesh Kumara, et al(2016)[6] Liver imaging by using CT images has been generally focus on research in this decade and is difficulty work. Segmentation of extricate expanse as an imaging physiological process disposition a necessary element of "Radio-mics". In this innovation paper represents, the automatic liver Tumor segmentation from stomach CT scan images. The statistical parameter-based system is utilized to differentiate the Tumor tissue from stomach parts. New segmentation technique, for example, zone creating and force based thresholding method are revised. The main, CT images are pre-computed by differentiates to extract out clamor from the image. At that lead the statistical mean-based thresholding is enabling to recognize the tumor. Behind empower middle sifting, isolates edge is used to transform the picture into double with Tumors as dark focuses on white foundation. Finally, post calculation as sifting strategies comparable mean channel and middle channel and morphological work are trying to remove residues. In this innovation task, Liver Tumor segmentation analysis is ability to imaging biomarker for "Personalized cancer imaging".

Hussein Alahmera, et al(2016)[1] The liver is an important part of human body that accomplishes conduit functions. Yet, diseases can occur without causation and introductory reorganization will employ to minimize the cancer death becomes too vigorous to complete diagnosis. There are different imaging techniques thus are CT-scan, Ultrasound, X-Ray, and MRI, all these technique are utilized for analysis of liver cancer. CT scan tools are worn for the detection of the cancer threat in human body and its less cost than MRI2. However, liver threat detection and segmentation on can be an extremely difficult errand and it relies upon the knowledge of the X-rays and that exhibit to small recognize change among the lesion2 and solid liver. Old medical image processing technique is as yet developing; despite the permanence that examination on computer aided segmentation of reference. Commonly, alongside the changes in picture preparing for extricating highlights and computerized reasoning utilized as a factor of classifies to recognize liver disease. Outlining and creating computer aided design frameworks to arrange liver injuries has gotten impressive consideration across the completion years, since these approach can provided analytic support to physician to the enhanced the diagnosis and raising correctness.

Marc Aubreville, et al(2017)[2] In this paper the image sequences obtained by the CLE image are divergent to other created of medical images, researcher denoted that small horizontal layer, up to 100μm beneath the surface of the probe15. In this performance, images are acquired by using a standalone probe-based CLE system(Cellvizio, Mauna Kea Technologies, and Paris, France). The probes apply for image were ColoFlex UHD and CystoFlex UHD R, both having same size of view as well as perforation depth. The analysis region is around 250μm in width and height, and pixel is 576 PX. The automatic classification using the CLE imaging technique has previously investigated to specific outcomes in clinical research in the year 2016-18. Although, the investigation branch, the CLE images deviate as the tissue under the recognition also divergent. The researcher André et al. In the two cases, the quality of images utilized as a part of the acknowledgment errand was slightly restricted; calling for corroboration of the model with a general added the willing of image. Recently, researcher used the machine learning algorithm, DNN (deep artificial neural networks) for analysis the content of image. The classical, feature-based models combine data about the order errand, intense learning strategies regularly are exclusively ascertained on the vital input data. The degree of obscure aspects is analysis higher for DNN algorithm, differentiates with the initiated work procedure, each necessary a significantly higher resolve of training data.

E. Keerthika, et al(2018)[29] This paper presents an automated CAD system consists of three stages; firstly, automatic liver segmentation and lesion's detection. Secondly, extracting features. The liver lesions are classified as malignant and gently based on feature difference approach. Several types of intensity, texture feature snare extracted from both; the lesion expanse and its surrounding normal liver tissue. The variation between the features of both areas is then used as the new lesion descriptors. Machine learning classifiers are then trained on the contemporary descriptors to automatically classify liver lesions into benign or malignant. Moreover, the proposed approach can affected the problems of varying ranges of intensity and textures between patients, demographics, and imaging devices and setting.

3. METHODOLOGY

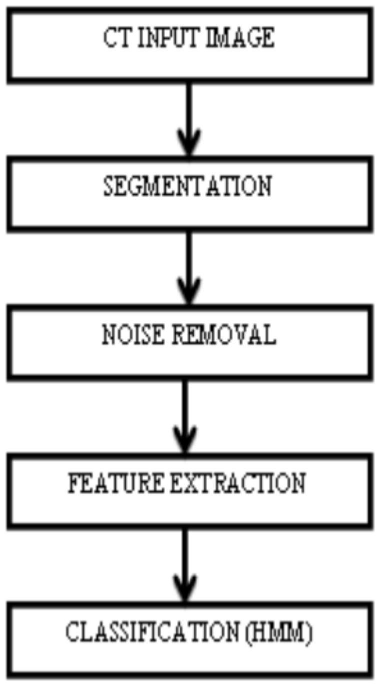

Figure 1: Block Diagram of Automatic Liver Cancer Detection

CT scan: A computerized axial tomography scan (CT scan or CAT scan) is an x-ray procedure that combines legion x-ray images with the aid of a computer to generate cross-sectional view and three-dimensional images of the internal organs and structures of the body. A CT scan is used to represent normal and abnormal structures in the body and/or assist in procedures by helping to accurately oversee the placement of instruments or treatments. It is a medical imaging technique that employs tomography [11]. Tomography is the system of generating a two-dimensional image of a slice or section through a 3-dimensional object (a tomogram) (Figure 1). CT scans of the abdomen are extremely accessible in defining body organ anatomy, including visualizing the liver, gallbladder, pancreas, spleen, aorta, kidneys, uterus, and ovaries.

Segmentation: subsequently the primary noise removal, the segmentation has to be carried out. The ambition of the segmentation is to simplify and/or change the representation of an image into something that is further meaningful and easier to analyses. Image segmentation is typically used to detect objects and boundaries (lines, curves, etc.) in images. The segmentation of medical images of soft tissues into regions is a difficult problem because of the huge variety of their characteristics [8]. All connected components in the eroded image are labelled and sum of connected components is computed. The labelled components are segmented depending on zone of interest. Here the region growing techniques is used (Figure 1). This technique is sufficient for segmented the lung region. Moreover it will take subordinate time. Here from a kernel it starts growing. It will compare their neighbor-hood values and grows up. The segmentation process will consequence in separating the liver tissue from the rest of the image and only the liver tissues under examination are considered as the candidate region for detecting tumor in liver portion.

Noise Removal: The ultimate important technique for removal of blur in images due to linear motion and also due to vibrations. Normally an image is considered as the collection of information and the occurrence of noises in the image causes degradation in the aspect of the images. So the information associated with an image tends to disaster or damage. It should be important to refurbish the image from noises for acquiring maximum information from images. Since CT images contain further Gaussian noise, a Gaussian filter is used for noise removal. Gaussian filters are a fine of linear smoothing filters [10]. The weights are elect according to the shape of Gaussian function. The Gaussian smoothing filter is a good filter to remove noise drawn from a normal distribution.

Feature Extraction: When the input data to an algorithm is too huge to be processed and it is suspected to be notoriously redundant (much data, but not much information) then the input data will be transformed into a reduced representation set of features (also named features vector). Transforming the input data into the set of features is known feature extraction. If the appearance extracted are carefully chosen it is expected that the appearance set will extract the relevant information from the input data in order to perform the desired task using this abbreviated representation instead of the full size input[5],[12]. Feature extraction involves simplifying the lot of resources vital to describe a large set of data accurately. Analysis with a total number of variables generally requires a large amount of memory and computation power.

Classification: analyses the numerical properties of distinct image features and organizes data into categories [6]. The classification algorithm employs two phases of processing specially training and testing. In the initial training phase, characteristic properties of typical image appearance are isolated and based on these, training class is created. In the subsequent testing phase, these feature-space partitions are worn to classify image features.

4. PROPOSED SYSTEM

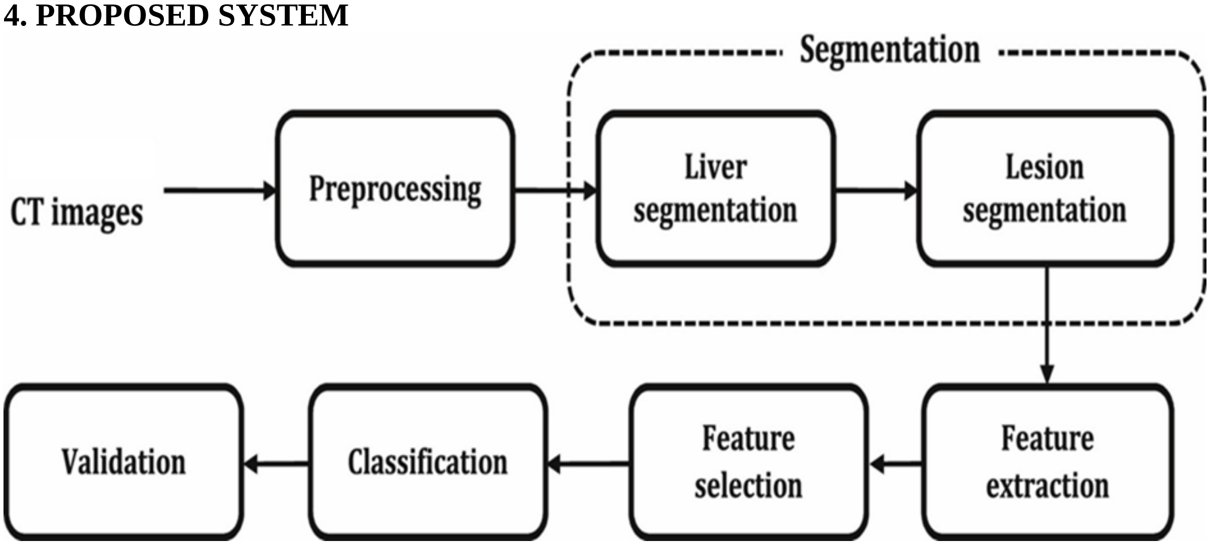

Figure 2: Proposed CAD system architecture

The classification of CT in liver lesion into one of the two major classes which are Benign or Malignant that are granted in Fig. 2 is the main goal of our CAD system. First of all lesion is detected automatically and all liver is then segmented secondly. Regions of Interest (ROIs) that reflect lesion on CT images and surrounding expanse from normal liver tissue are extracted. Three different texture feature sets are secure using Harr Wavelet, Tamura (Coarseness, Contrast, and Directionality) and Gabor Energy, and seven intensity features are calculated through Histogram, Mean, Variance, Skewness, Kurtosis, Energy, and Smoothness. The variation in features values from lesion of normal liver tissues are combined and then fed up into a machine learning classifier as final process. The proposed CAD system consists of three main stages that are carried out all of succession: (I) liver and lesion segmentation in each proposed system defines the lesion as first one is ROI in normal liver tissues surrounding the lesion of the second one ROI (II) featuring extraction stage to extract intensity and texture all features from lesion to the surrounding areas to treasure one difference between them, and lesion of classification as to classify lesion into as a Benign and Malignant tumor.

5. RESULT

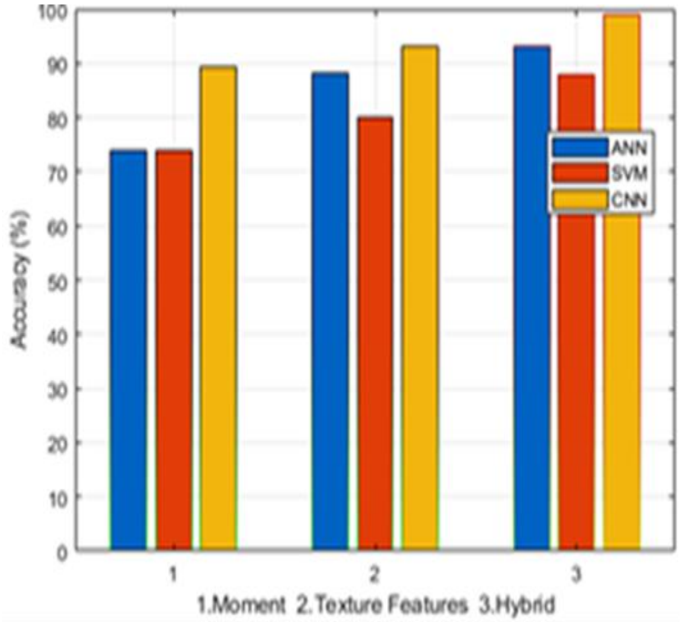

Figure 3. Accuracy analysis of proposed model

The automated CAD model for liver cancer detection and its grading designed in this paper using optimized computer vision techniques and deep learning methods. accuracy using distinct classifiers with different set of features. For ANN and SVM, apart hand-crafted features were used such as moment, texture, and hybrid. In CNN, the hand-crafted features connected with automatic CNN extracted features. This leads to improvement in accuracy performance compared to twain ANN and SVM outcomes significantly. The accuracy of proposed CNN-FN-LSTM using all hand-crafted features is higher compared to full other configurations.

6. CONCLUSION

There are distinct types of cancers to cause the death, among them liver cancer is stands on third place. The hepato-cellular carnoma (HCC) is most common liver cancer type and it tends to affect males candidates. There is significant problem in previous prediction and proper presentation of liver cancer practically. The abnormal tissues begin in liver are nothing but the liver lesions. Such lesions are basically recognize through the CT scan process. Early Tumor detection accurately is authentic significant for liver cancer diagnosis and treatment. There are sum of computer aided diagnosis solutions presented based on image processing terminologies. However hush their concerns of simple, accurate, less processing time and efficient method for liver cancer detection. This research proposal attempts to solve the progression problems and presents the framework to effectively detect and analysis the liver cancer. The CAD system is used to use the radiologists to interpret the medical images like mammography, X-ray, ultrasound, MRI, etc. It used as a second judgment by the radiologists. Improving CAD accuracy increases the treatment benefit and a cure is more likely. All of these commercial CAD systems perform preferred at detecting calcifications than the masses. Architectural distortions become the challenging function to all the commercial CAD system. One cannot make a direct comparison among these systems and their work because there is no same clinical dataset to study and compare the performances. The proposed CAD model is further suitable for mass detection and classification.

FUTURE SCOPE The usage of the proposed system can be further improved by increasing the CT image feature set to include the distinct orientations of the CT scan and also 3D CT scans. This will greatly improve the laboratory results. Better segmentation and classification algorithms will highly upgrade the accuracy of the automated system. The process can further be speeded up by keeping the factor set as small and concise as possible.

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