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A Review of Classifying the Hepatocellular Carcinoma using ML and Image Processing Techniques

Ankita[1] and Kamal Malik[2]
[1] Research Scholar, Department of Computer Science, CT University Ludhiana, Punjab
[2]Professor, Department of Computer Science, CT University Ludhiana, Punjab

Abstract. As a part of this study, an intricate and exhausting review has been done on classify the liver lesion using Deep Learning (DL) and Image Processing Techniques. Despite that, Computerized Axial Tomography (CAT) Scan or CT-Scan,Nuclear Magnetic Resolution Image(NMRI) or (MRI),Ultrasound (U/S),positron emission tomography-computed tomography (PET-CT) scan are most recommended techniques used for cancer testing and diagnosis. However, doctors and radiologists found difficulty in detecting and identifying cancer from these techniques. Since Computer Aideddiagnosis can be crucial for detecting cancerous cells in the body to such an extent, doctors can givethe best treatment to the patient accordingly. Various machine-learning and image-processing computer-aided techniques have been explored, tested, and also accomplished in the medical field. The primary intention of the paper is to examine the diverse Computer – Aided strategies, correlate these techniques with each other and evaluate the best technique with their limitations and shortcoming. Various types of machine learning techniques are used in the healthcare field such as Decision trees, Artificial Neural Network (ANNs), Space Invariant Artificial Neural Networks or ConvNet, Bayesian Networksetc. By using these approaches, it is to be seen that there is a lack of accuracy in classifying the liver lesion in the initial stages.

1. Introduction

One out of every two men and one out of threewomen is a Cancerous patient worldwide. Since the adjusted incident rate and death rates for liver cancer patients continue to rise, researchers are continuing to work to reduce these rates by helping radiologists find cancer at an initial stage[1]. Cancer and cancerous cells have lost the efficiency to carry out regular supervision. The human body is made up of a large number of cell structures and they carry out various activities[2]. It is a very complex process under incredibly unprecedented supervision. If these cells escape the normal control phenomena then continuously growing cells may form cancerous cells[3]. Similarly, liver cancer begins in the liver when there is a change or mutational accumulation in the DNA of those liver cells[4]. A cell's DNA is the material that provides instructions and when enough of these mutations accumulate an effect, essential genes in cells can get out of control and eventually form a tumor and a mass of cancerous cells in the liver which is commonly known as liver cancer[5], [6]. The liver has over 500 known functions. The liver performs many essential functions such as detoxification of tablets, and hormones, blood filtration and removing protein [7], [8], [9]. To achieve useful image extraction, image processing techniques are becoming leading and progressively prominent nowadays. The image processing technique is relevant in various fields, it can be in the industry to extract useful information for routine production, medical image retrieval, face recognition and machine learning interpretation [10]. There is an urgent need for a model to aid early cancer detection and diagnosis with more accurate results in medical practise that improve HCC therapy and survival rate of the infected patients [11]. Tumours grow rapidly resulting in organ malformation which is the leading cause of death worldwide [12]. These abnormal growths may be benign (non-cancerous)or malignant (Cancerous)[13]. A malignant tumour may be primary or secondary. The major difference between malignant primary and malignant secondary tumours is that a malignant primary liver tumour is infected with a cancerous tumour that starts in the liver and vice versa, while a malignant secondary liver tumour starts infected or originated elsewhere and contaminating the liver[14].It should be investigated that Hepatocellular Carcinoma (HCC) or hepatoma is most prevalent disease worldwide with a high mortality rate in men and women [15]. There are three common kinds of benign tumours, adenomas, focal nodular hyperplasia (FNH) and hemangioma. Some malignant tumor types are hepatocellular carcinoma (HCC), hemangiosarcoma, Hepatoblastoma, metastatic[16]. Various surgical treatments are available for these types of diseases, such as RFA, Radiation therapy, immunotherapy, etc[17], [18]. Easier to surgically treat patients whose disease is diagnosed at an early stage and whose liver regeneration capacity is low.Identifying malignant cancerous tissues using machine learning techniques offers a new idea for early cancer detection that may reduce the life-threatening risk of HCC patients[19].The continuous development of new technology to detect liver health can increase the patient survival time.

2. Methods for Diagnosis

The study proved that screening tests such as CT Scans, MRIs and Ultrasound can detect the patient at the presymptomatic stage, increase the response rate and prolong the survival time. These screening tests are discussed below.

2.1 MRI: Magnetic Resonance Imaging

Magnetic Resonance Image or MRI, for short, is the fastest adding diagnosis processor that produces superior soft tissue contrast which is non – negotiable in image testing known to medicine[20]. The image produced by the large tubes can provide crucial information aboutmany diseases. An MRI machine produces cross-sectional imaging in a specific direction[21], [22]. It can be used to visualize some information about cancerous tissue and damaged muscles. MRI images are helpful in the diagnosis of cancer cells and other diseases. MRI machine basically shows the water molecules thatalign with a magnetic field generated by the machine[23]. It is then relayed to its actual location and the power released by the processor is decoded and converted into an image.MRI images are constructed without using ionizing radiations[24]. These ionizing radiations can vandalize the cells and deoxyribonucleic acid or DNA in the body[25]. So, patients remain protected from the detrimental effect of ionizing radiation. MRI image is very useful in detecting cancer inside the body because it creates cross-section images like a slice from different angles, i.e., from the front, from the side, or from above your head[26]. It also helps in detecting the signs of cancer, i.e., it may be metastatic or not and the doctor will give their treatments accordingly.

2.2 CT scan

Computerized Tomography more commonly known as CT is a diagnosis processor that plays a wider role in identifying tumour cells[27]. It provides a crystal clear view and answers many clinical and diagnostic questions, often within seconds[28].This powerful diagnostic technique allows the slide to pick up pathological changes and characterize tumor tissue. CT-Scan can take multiple images in excess each time of different layers of the body. Computed Tomography is a technique that produced cross-sectional images. It is also known as computer axial tomography[29]. These are used to create two-dimensional sectional images in various shades of grey. It can also detect the size, location of the tumor and possible succession of the treatments. The X-Ray intended in the scannerrotates continuously and monitors each part of the liver from different angles. Organs such as liver and tissuesin the body limit X-Ray to varying degrees[29]. The beam passes through the body detector and is converted into electrical signals. This signal allows the computer to calculate the image. This will make it possible to obtain and clear image of tumour tissue in the liver. Based on these 2D and 3D images of the liver, radiologists arrive at the diagnosis[30]. This computerized axial tomography not only visualizes tissue in the body but also rapidly informs the doctors about the characteristics of the tissue. This additional information is important for deciding on the appropriate therapy. Being the most common, it is the most vigorous imaging technique for liver cancer detection[31]. CT scanner can help in providing multiple-staging consecutive scans of the whole liver. Computerized Tomography helps perform various activities like proper diagnosis treatment planning, screening, etc[32]. With the help of a tomography scan, Doctors or Radiologists can able to see the blood vessel that sustains the tumour without going into the biopsy test.

2.3 Ultrasound

Medical Ultrasound is an intra-operative diagnostic technique that can convert energy into high-frequency sound waves [33]. This high–frequency sound wave technique creates an image of internal organs and other body tissue. Diagnostic ultrasound has several advantages; it is cheaper than Computer Tomography and Magnetic Resonance Imaging. Behind this diagnostic technology is a device commonly known as a transducer[34]. This transducer device converts the electric current into sound waves, which are sent to the tissues of the human body[35]. In turn, the sound wave reproduces the structure to the transducer and converts this signal into an electrical signal. Now, the electrical signal is converted into an image and also recorded on a digital screen [36]. With its help, harmful radiation is not exposed during an ultrasound. Ultrasound video Technology requires skeletal Knowledge that helps in getting higher frequency for optical images [37].

2.4 Positron Emission Tomography (PET)

The PET scan is another diagnostic testing technique that can help to demonstrate in our body metabolic or biochemical functional tissue. PET scan creates the 3D images of the body by using radioactive tracers, which is usually administered to a patient through interventional injection. The tracers are made up of carrier molecules that are tightly bonded to a radioactive atom which is called as isotope. The carrier molecules can attract with or bind to specific proteins or sugars in the body. Carrier moleculeswill be used to monitor cancer growth using FDG, a modified form of glucose that gets absorbed by tissues.When tissues absorb a lot of glucose, it may indicate a cancerous tissue. PET scans can often detect abnormal metabolism of tracers in diseases before the disease become apparent with another imaging test. It helps detect cancer cells, heart disease and brain condition of a patient[38]. The PET scan can show areas of the body whose cells are more active than normal through radioactive medicine[39].

3. Methods and Methodology of Research

In this research, CT Scans and MRI images are collected to analyze the liver cancer cells from professional hospitals and cognoscente. First of all, images are converted into RGB images to remove the grey level intensity which can deceive the experiment in cancer cell classification. Now, the liver part is segmented from other nearby organs using k- mean clustering. To extract the features, the threshold range was fixed which can convert the images into a binary image. Threshold makes the image easier to identify by changing the pixels of an image. Haar Wavelet transform was performed to calculate the threshold value with an attempt to minimise the input vector. These pixels are to be counted and assumed as T1. Out of this information, T2 is calculated by using the statistical formula.

$$T_2 = k * \sqrt{\frac{2*\log n*\sigma 2}{n}} \qquad (1)$$

In the above formula, 'k' indicates the number of clusters formed and 'n' indicates the total number of pixels obtained after clustering. T3 is the mean value of T1 and T2. Indeed, all their values T1, T2, and T3 are compared with each other. If the values fall in the precise range then there is liver cancer. Otherwise, there are no cancer cells in the liver. This research can achieve 82 % accuracy in identifying cancerous cells in the early stages. This research can also remove the computational complexity and it is less time-consuming[40].

The purpose of this study illustrated the classification of the hepatic lesion from the MRI images using a deep learning system.The multiphasic MRI images are reprocessed and theregion of interest in the image was automatically extracted to reveal the model whether it is a benign cyst or metastases of a colorectal tumour. This image is further examined to a resolution of 24X24X12 voxel. Four hundred ninety – four images were used for training & testing as shown in Fig 1. During the training set, images were augmented by rotating, scaling, flipping, and intensity scaling just to enlarge the number of lesion samples. The CNN model was trained consisting of three convolutional and two fully connected layers to reduce the number of parameters in the filtered image and extracted the features from the image. This study achieves 92%

accuracy and 92% sensitivity of the deep learning-based CNN model [41].

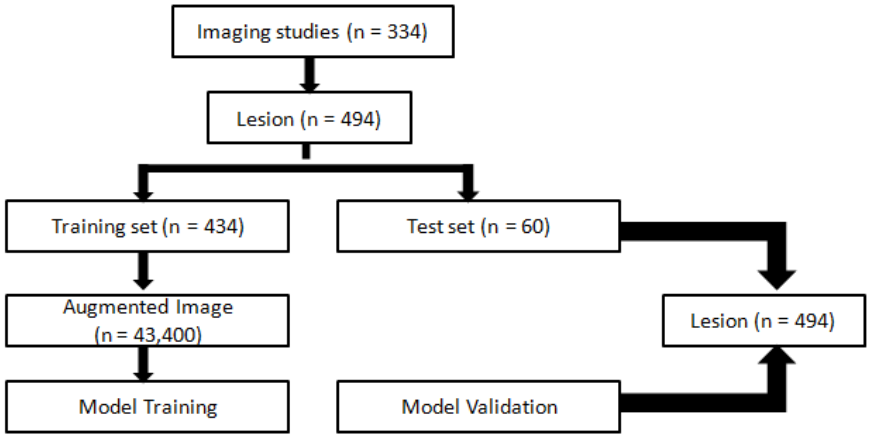

Fig. 1. The lesion segmentation approach includes four steps, namely model training, model testing, reader study and application

The main problem seen in lesion identification from CT images is obtaining the presence, fuzzy – boundaries, heterogeneous density, and variability of the size and shape of the lesion. CNN technique is adopted to solve these problems. Convolutional filter in convolutional layer are used to extracts the hierarchical features from the 2Dinput data images. Max pooling features were used to avoid the dimensionality of features and avoid overfitting as depicted in Fig 2. Under this study, five CNN layers with different input patches are adopted, in which three convolutional layers, and two fully connected layers are implemented. Data was enhanced in the form of twenty – six portals of CT Images. Test images were classified as malignant or benign with a binary number 0 or 1 respectively.To assess the rendition, the empirical result was validated with an Average Dice Similarity Coefficient of 80.06%. it is analyzed that CNN gives a satisfactory result as compared to other classification techniques because its average DSC percentage is higher than other methods [42].

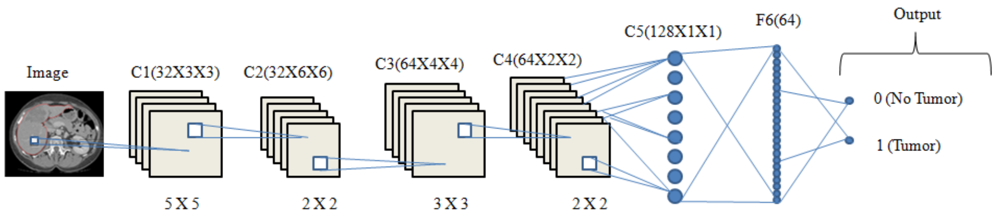

Fig. 2.A Convolution Neural Network architecture for metastasic lesion classification.

G. M. Xian[43]can diagnose liver cancer by using texture information from the ultrasound image. The proposed methods are applied to these images for diagnosis and classified the tumour cells. Five different texture features were classified, i.e., strength, entropy, data correlation, homogeneity, and dissimilarity. The combination of Support Vector Machinealong with Fuzzy Logic and Gray Level Dependence Matrix were employed for image recognition. The extracted part of image are evaluated for classify these regions.For the validation of the experiment, the most prevalent and reliable k-fold cross-validation approach was adapted to evaluate the model performance.It is to be concluded that FSVM and GLCM are realizable and better than SVM in the classification of liver ultrasonography images[43].
The method mainly deals with liver cancer cells with a filtering function, which may be able to convert a simple clinical image into an image to smooth pixels, clear edges and low noise by employing a Gaussian filter. Now, the image is ready for segmentation purposes, which can extricate the ROI (Region of Interest) part from the

image. For segmentation, a threshold technique is used which is the most popular and simpler form of image segmentation technique for creating the binary image from the grey-scale image by altering the pixels of an image. For image fissure, k means a fuzzy logistic algorithm is used. Under this method, a heuristic method is employed to initialize the centroid of the k-mean clustering. The closest pixel is selected and continues to be selected until it achieves its convergence. Now, a co-occurrence distribution matrix is taken up to measure the correlation between each pixel in the image. This matrix classifies the tumours as benign or malignant[44].In this research, the main intention is to diagnose liver lesions with high accuracy for appropriate therapy using mechanical techniques. Under this work, a method is aimed in which Gaussian filter and watershed method are used to delineate lesions from hepatic tumourimages. The Marker controlled process of watershed segmentation was to segregate the affected region and isolated the malignant neoplasm from it using GMM(Gaussian Mixture Model) algorithm. Currently, DNN classifiers come into existence to classify different primary liver cancer types, such as the most common Hepatocellular carcinoma (HCC), Metastatic Carcinoma (MCC) and Hemangioma (HEM). The strategy achieves 99.38% accuracy in classifying different lesion types and 98.18% of the statistical Jaccard Index to find diversity and similarity [45].The research is to be investigated to reflect the propensity of machine learning methods by employing combined datasets from various computer–aided technologies. At an initial stage, the six types of MRI and CT images were metamorphosed into grey-level 8-bit image format. Next, to reduce the noise from 512 X 512 size images, the Gabor filter was brought into existence for pre-processing, and "Sharpening Algorithm п" was employed to sharpen the edges of these MRI and CT images.Ostu thresholding-based region growing segmentation (OTRGS)can solve the problem in which automatic ROI is a single technique for ideal segmentation and there is a limitation in human-based extraction. Consequently, the hybrid feature selection (HFS) was employed to reduce the dimensionality of the featured images. Wavelet transfer-based feature extraction, second-order co-occurrence matrix and grey level spatial dependence matrix are parts of texture analyses applied to extract features from an image. Now for classification, four Artificial Intelligence techniques were used and Multilayer Perceptron (MLP), a well-known ML classifier was employed which gives the best result for large, noisy and complex data images.An amalgam of RF-SVM, Random Forest and Support Vector Machine were used for classification and regression problem on a huge dataset. Overall, the table depicts the accuracy levels of the four different classifiers employed on the MRI and CT-scan images.

	MRI	CT
MLP	95.88%	97.44%
SVM	95.78%	96.89%
RF	94.44%	96.8%
J48	94.44%	96%

Table 1. Accuracy level of four Machine learning classifiers

An auspicious result is seen in the level of accuracy. The CT-Scan images indicate more valid outcomes than MRI images. The proposed system can help radiologists diagnose liver tumours as the system can verify the result of image datasets [46].A system is suggested that derives tumour features from CT – images for liver cancer diagnosis. For the evaluation, 71 histological proven liver tumour were evaluated of which 49 were benign and 22 were malignant lesions. The Region Growing method is used for image segmentation as it can separate regions in the image even if they have similar properties as illustrated in Fig 3.

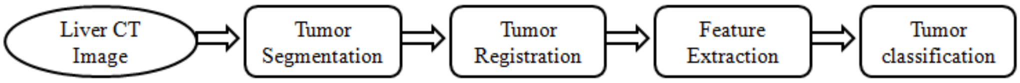

Fig. 3. Flow chart of Computer-Aided system

Texture, the shape of the tumour, and kinetic curve features were acquired for classification from this segmented image.R. M. Haralick[47] firstinitiates the GLCM feature texture set in the 1970s. GLCM can probe the spatially dense dependency by the co-occurrence matrix. Tumours have different shapes and structures oval, lobular, round or irregular, with the help of these shapes and margin smoothness, a tumour may identify whether it's benignor malignant. The kinetic curve was composed to evaluate the density of the contrast medium[49-59]. The most famous and commonly used fuzzy c- means technique was accustomed for clustering. Logistic regression was successful in distinguishing between malignant and benign. The key point of this study, analyzed in this study, is that the regional development technique is based on semi-automated tumour segmentation rather than a computerized selection of a high-quality electromagnetic image. Subsequently, researchers make use of the image registration method to achieve automatic tumour alignment[48].

Table 2. Current method and modality of liver Cancer

Reference	Methodology	Modality	Result
P. R. Anisha[40]	Haar – wavelet transform, k – mean clustering	MRI/CT/USG Scan	Accuracy – 82%
C. J. Wang *et al.*[41]	ConvNet	Multi-phasic Magnetic Neural Network(MRI) technique	Accuracy – 92% Sensitivity – 92% Specificity – 98% True positives – 93.5%
W. Li, F. Jia[42]	ConvNet, SVM Random Forest (RF-SVM)	Computerized Tomography (CT)	DSC – 80.06% Precision – 82.67% Recall – 84.34%
G. M. Xian[43]	Fuzzy Support Vector Machine (FSVM)	Ultrasonography, CT	Accuracy – 96.05% Sensitivity – 96% Specificity – 95.47% PPV – 88.54% NPV – 99.48%
V. Hemalatha and C. Sundar[44]	Watershed algorithm, Fuzzy k – mean algorithm	CT	Accuracy – 91.6%
A. Das, U. R. Acharya [45]	Watershed for segmentation, Gaussian Mixture algorithm	CT	Accuracy – 99.38% Jaccard Index – 98.18%
S. Naeem *et al.*[46]	Gabor Filter, Ostu-based thresholding segmentation, CNN based on deep learning	CT	Accuracy – 71.82% Sensitivity – 68.18%
C. C. Chang *et al.*[48]	Medium Filter, Fuzzy c – means technique, Logistic Regression (LR)	CT	Accuracy – 71.82% Sensitivity – 68.18%

4. Conclusion

In this review, various methods and algorithms that have been used for liver cancer detection are compared using various parameters. A complete literature review has prevailed on different machine learning methods used in detecting and classifying tumour cells. Some researchers have proposed an automatic approach that can expedite the procedure but are unable to get a higher accuracy level and reliability.Various image processing techniques such as decision trees, Random forests, ANNs, and SVM are demonstrated in this paper. These cancer detection techniques' performance was shown and an analysis of the potential level for improving liver Cancer detection. To identify the HCCs at an early stage, researchers make use of various intelligence retrieval methods to segment and classify liver lesions. But there is a lack of accuracy in identifyinghepatocellular carcinoma in an early stage. These techniques have some limitations and challenges which need to be conquered by researchers in the future.

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