Liver Cancer Detection Using Hybrid Approach-Based Convolutional Neural Network (HABCNN)

Shashi Bhushan

Abstract Liver cancer is one of the serious disease these days. Every year almost 800,000 people get detect of liver cancer and 700,000 died out of that. But it is very difficult to detect it at early stage. To detect this manually is a tedious task and cannot be perform easily as there was a serious of tests and all through which patient has to go through and still did not have any surety of detection. So CT images after applying watershed segmentation can be used to get this liver cancer detected by assessing tumor load, clinical treatment response by using the concept of deep learning. In this paper, a Hybrid Approach-Based Convolutional Neural Network (HABCNN) is proposed for liver tumor segmentation which has been mathematically modeled so that issue of cancer detection get resolved. The kidney and spleen is segmented initially. After cancer tissue segmentation, GLCM was used to extract features from tumor parts. Eventually, Hybrid Approach-Based Convolutional Neural Network (HABCNN) was used to identify the hepatocellular and metastatic carcinoma for hepatic cancer. A better 99.44% identification precision came from the suggested classifier. The modern segmentation approach should insure that the precise boundary structure of the cancer area is known so that important information can be better diagnosed. A comparison based on specificity, sensitivity, accuracy and DSC has been done with some existing techniques like Multilayer Perception [14] and C4.5 [15]. Without human intervention, the classification method allows successful cancer damage defection. So this can be used by medical practitioner for early detection of liver cancer.

Keywords Liver cancer detection · Deep learning · Hybrid approach-based convolutional neural network

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1 Introduction

Since liver cancer signs appear in late stages, it cannot be identified early such that they are challenging to detect, which causes a high mortality rate among all other cancers. The most significant cause of death among humans is liver cancer. Therefore, the detection of liver cancer is required in the early diagnosis and this early detection offers the most possibility to treat cancer patients safely and effectively. However, it is the most complicated approach to boost the likelihood for the individual to live. Segmentation and classification of liver tumors from computed tomography images are essential to the advancement of early diagnosis and treatment of liver cancer. Nevertheless, the varying morphologies, boundaries, different densities, and sizes of the lesions make this job complicated. In the second stage of the work, to design a new method for distinguishing and classifying tumors from computed tomography images using a Hybrid Approach-Based Convolutional Neural Network (HABCNN) is employed [1–11]. The findings are correlated with scientific specialists' results. The ultrasound image of liver is shown in Fig. 1. The world's most common cause of mortality is liver disease [1]. The early diagnosis of the occurrence of liver cancer via optimum therapies is vital to enhance survival chances. At present, biopsy for cancer is regarded as the golden standard, depending on the tumor's location, although it is uncomfortable, invasive, and not always a viable alternative. Noninvasive treatment of liver disorders can be performed using techniques of diagnostic imaging. Computed Tomography (CT) is the best useful imaging device for oncological and follow-up treatments. In the United States, in 2007, more than seventy million CT scans take effect in the recognition, diagnosis, and observing of liver lesions. Images are collected from a contrast agent before and during intravenous infusion. The

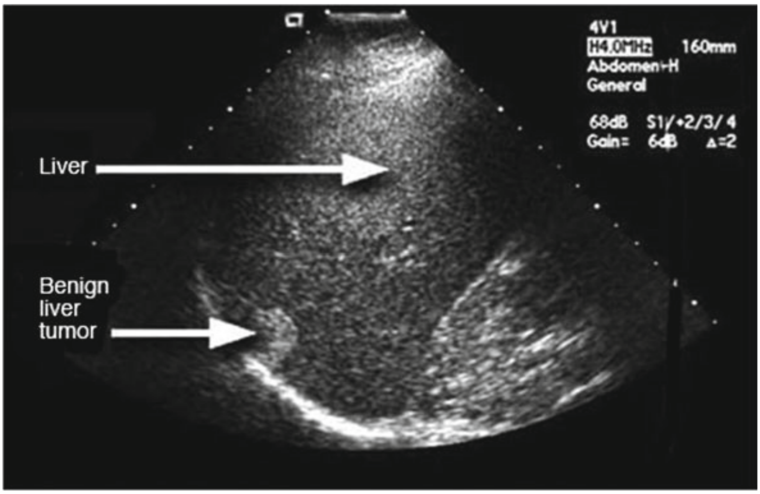

Fig. 1 Ultrasound image of liver cancer

liver is usually detected and diagnosed by radiologists [2, 3]. Lesions are based on various densities presented at specific scan time and optimal identification in the portal stage in Hounsfield Units (H.U.). A variety of cancer lesions are identified in the liver including both benign and malignant. The primary source of mortality from cancer is metastasis. Metastatic diseases usually arise from prime locations in the intestine, breast, heart, pancreas, and stomach affect the liver. In the number, size and general appearance of metastatic liver cancer lesions, there is a considerable variability, rendering computerized metastatic liver injury diagnosis a challenging one. Radiological procedure is available to evaluate the hepatitis manually [4]. This process takes time for a 3-D CT scan of several hundred slices and several lesions to be looked for by the radiologist. This is not a definitive examination. In the first time, it is especially important to identify so-called "too small to distinguish" cancer lesions. For radiology to perceive this as a demanding job it takes additional time and concentration. Over the modern years, the introduction of these methods into clinical procedures would lead to even greater information and practical evaluation and care, as well as more over depth research strategies. The development of predictive tools for computed tomography (CT) clarifications has both a significant clinical and economic value. Throughout the area of medical science and analysis photos such as MRI, X-ray, C.T, quickly evolved deep learning algorithms, mainly CNNs and FCN's, and DBN's. Comprehensive learning strategies are used to identify, classify and diagnose information for images, the segment organs and lesions. The identification, diagnosis, marking, and evaluation of CT images and X-rays have been the most challenging for medical image processing. For example, large data sets are used in the application of liver cancer research to train the model that combines deep learning methods, including CNN, DBNs for image recognition, and NLP [5, 6].

2 Medical Image Processing

Even though human experts are available to diagnose and predict the kind of diseases and cancer cells, an opinion based on machine intelligence aids the decision. In this connection, there is the applicability of various devices employed for diagnosing and computing the pathologies of human diseases (Fig. 2).

3 Proposed Methodology

In Fig. 3, a detailed description about the proposed methodology is given. First dataset in the form of images has to be taken as an input, preprocessing is done in step 2, in step 3 segmentation is done through watershed segmentation, in step 4 Features get extracted from segmented region then a training and testing set has to be generated to get the model trained and tested. After performing training and testing, in next step images will be get processed, classified and segmented using proposed

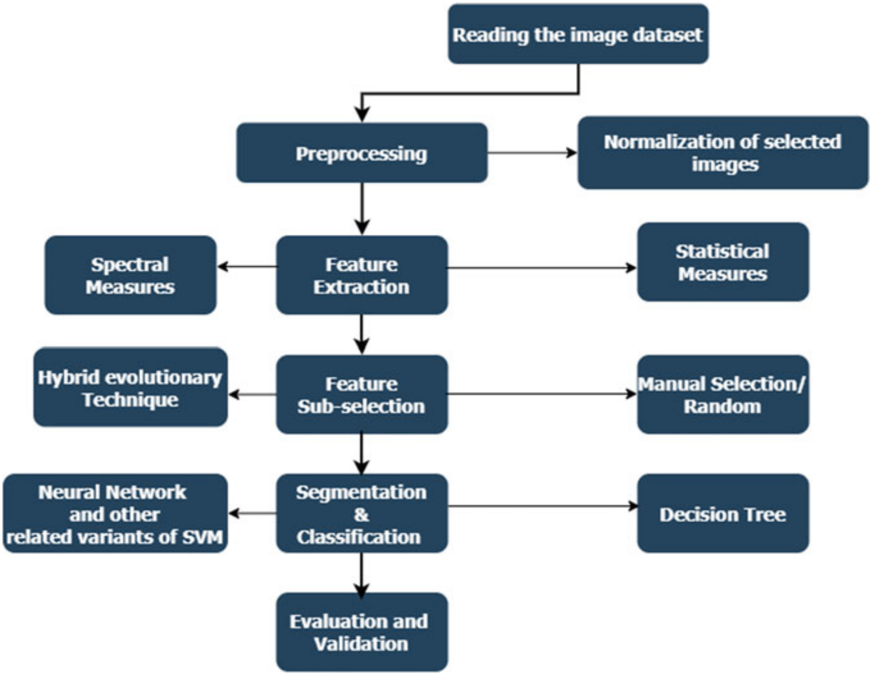

Fig. 2 Medical image processing

Hybrid Approach-Based Convolutional Neural Network (HABCNN). And at last performance analysis is done based on sensitivity, specificity, accuracy, and DSC.

Step 1: Dataset of Liver CT Images

CT scan is a noninvasive diagnostic image method in which it is the mixture of X-ray and CT to produce the horizontal or axial images of the liver. Hence, image processing-based research work facilitates liver cancer treatment. In computer tomography, X-ray beam passes in a circle movement around the body. By this, it offers the different view of similar organ. CT scan is done with or without "Contrast" (type of material that taken by mouth and/or injected into an intravenous (IV) line that cause liver organ or tissues under supervision to become clearer).

Step 2: Preprocessing

The first step of the diagnosis of liver carcinoma is preprocessing. To ensure the durability and usability of a database, preprocessing is important. For this, any step seems to be essential to the workflow of image processing. The process carries out preprocessing of unnecessary error identification using filters and histogram equalizing techniques. Here, with CT image the noises can be removed in this step. The Adaptive Median Filter (AMF) is often used as a non-linear optical filtering system to remove noise from an image or signal. A noise reduction is a typical

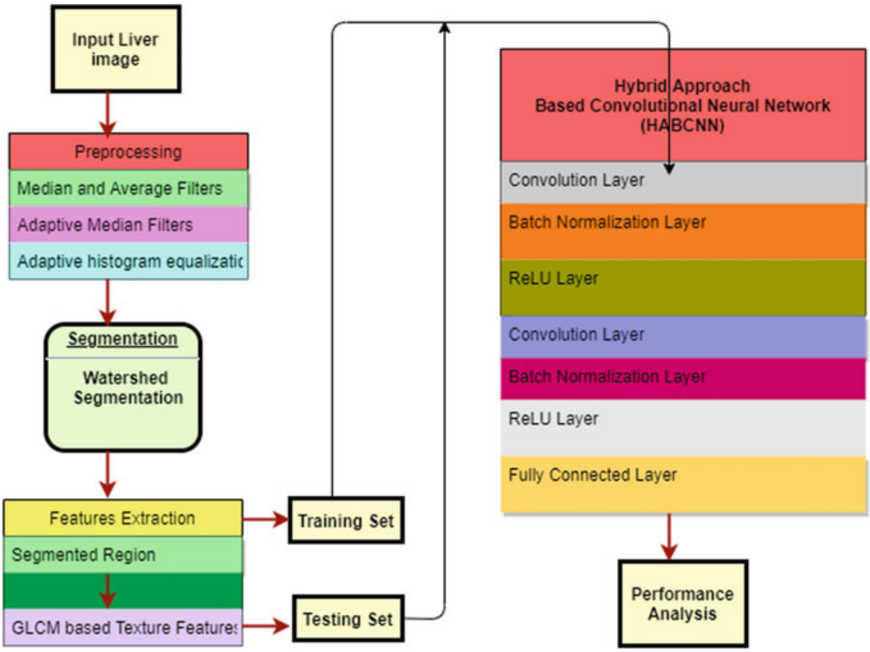

Fig. 3 Proposed methodology

preprocessing method for efficiency enhancement. Preprocessing is carried out to enhance the contrast of the image in the CT image. Typically, histogram equalization is achieved to increase image consistency. Histogram Equalization is a technique used to enhance the contrast of pictures. It is also used to improve the sensitivity values effectively, i.e., the image intensity range is broadened. In order to boost relations between regions, it allows less local contrast. Therefore, after implementation of the histogram equalization, the average contrast of the images is improved. Consider h denote the normalized histogram of an image. Hence,

$$h^x = (\text{Total number of picture element in} \times \text{intensity/total no. of pixel}) \quad (1)$$

where $x = 0, 1, \ldots, x - 1$.

The histogram equalized image can be defined as

$$H_{i,j} = \text{base}((x - 1)\sum_{x=0}^{b_{i,j}} p^x \quad (2)$$

While the result indicates that the equalization process used is exactly flat histograms, it can soften them and improve them.

Step 3: Segmentation

Segmenting both the liver and tumor regions is an important and demanding task in the recent days. For this purpose, various segmentation techniques are developed, which segment the image with the help of modalities. There are different types of techniques for segmentation which include manual segmentation, semi-automatic segmentation, and fully-automatic segmentation. In manual segmentation, the medical experts segment the image slice by slice, and the liver frontiers are recognized contrarily by a dissimilar radiologist or the same radiologist at a different time [7]. This type of segmentation explains the structure and observation of the medical images. In this category, the difficulties are mainly related to reducing image quality and increasing artifacts. The major drawbacks of manual segmentation are large amount of image slices, intensive time, and lack of results. Further, creation of distinct dataset is a highly complex process. Due to these issues, the semi-automatic segmentation is developed, which interactively identifies the seed points for extracting the boundary of liver from the selected regions. However, it has some important disadvantages such as more amount of time, inefficient segmentation results, and it needs a user interaction to segment the liver and exactly locate the tumor. In order to reduce the workload of medical experts, and avoid inaccurate measurements, the fully-automatic segmentation is developed to automatically. Segmenting the liver and tumor from the medical images without user interaction helps the radiologists to assist diagnosis. It works based on prior knowledge of the image that includes the shape and localization of liver. When compared to the semi-automatic segmentation, it has the advantages of reduced time consumption, user interaction and full automation. Thus, fully-automatic segmentation is highly preferred for liver and tumor identification during diagnosis. The class of image is distinct, and it never remains the same because the input image can vary from a scanner to scanner. It leads to the problem of automatic recognition, and so the segmentation depends on the acquired input image. Still, the extraction of liver and tumor from the abdominal images is a challenging and demanding task. Based on the contrast enhanced CT scans, the diagnosis is provided during the clinical practice for liver tumor. The contrast media reaches the liver via the hepatic artery or the portal vein if the enhancement of two vascular trees is possible. The evolution of liver tissue region is the discriminating factor of liver tumor. The visual analysis of CT scans provided by the radiologists is not enough for an accurate tumor detection and diagnosis because only the small part of information stored in the images is identified using CT scans. Here, the segmentation was done utilizing the watershed algorithm. The separation of an image into several parts is image segmentation. Segmentation of the pixel range is meant to split the CT image into segments. Frame segmentation is used to identify points and borders, image curves. The segmentation comprises of a series of parts describing the whole entity or an image contours array. The image characteristics can easily be predicted by using this process. In this study, Gray scales are used for the segmentation method. The variation between large pixels and small pixels around the object's boundaries are evaluated.

$$W^{\text{segment}} = \sum_{\{i,j\}\varepsilon Q_2}^{n} K_2\big(Z_i, Z_j\big).w.\log_{ci} + \gamma \int c_i dx \tag{3}$$

Then, the features can be selected with the GLCM after the segmentation stage. The Grey Level Co-occurrence Matrix method (GLCM) is a means of obtaining second-order statistical texture properties. The technique has been used in many applications and the presence of three or more pixels is seen in the third and higher-order textures. The GLCM is an arithmetical capacity that can ordinarily dispense with the curios productively. The exactness of the picture may likewise be kept clear. For the review cycle, the picture might be extricated. GLCM might decide the recurrence of the pixels in a predefined accuracy. The single pixel is to be addressed here and another pixel is to be known as the Ø course l and the adjoining worth detachment of m. commonly, m obtains a single worth, and Ø can benefit directionally. Then, the got directional worth can dispense with the qualities of the photos used for the division cycle. The GLCM cycle may be set as continues in condition 3:

$$P(m, s) = G(m, s, 0, \emptyset) \sum_{m=1}^{H} \sum_{s=1}^{H} G(m, s, 0, \emptyset) \tag{4}$$

where G is the recurrence vector, m, s, o is the recurrence of the specific part will by and large have the pixel upsides of l and m, P addresses the 88 provisions of a picture, (m, s) was the part of the m and l, Ø addresses the standardized steady. By carrying out the GLCM, the various traits can be acquired.

Step 4: Classification using Hybrid Approach-Based Convolutional Neural Network (HABCNN)

After extracting the features, the classification process is applied in the last stage for classifying the normal tissues and liver lesions. The main intention of this stage is to apply a machine learning model for an accurate disease classification during diagnosis. Based on the feature vectors, the classifier can accurately classify the liver and tumor regions from the given image. The advantage of classification is that it separates the objects into diverse classes and identifies the healthy and the disease-affected tissues. The stage of cancer then be calculated after isolation of its characteristics whether it is mild, moderate or otherwise extreme [8]. Hybrid Approach-Based Convolutional Neural Network (HABCNN), one of the well establishing algorithms, was included in this classification. The goal is categorized as probable. It is an algorithm for pre-trained convolution. In this case, HABCNN enables measurement of discrepancies between a single variable dependency and one or more different variables. The HABCNN anticipates the possibilities and has a strategy. Statistical models occur. During this process, HABCNN reads the image first and redraws it, then measures the class likelihood for the grading process. The neural network of convolution is one of the deep neural networks of learning. In the image recognition and classification process, HABCNN represents a major breakthrough. The most widely used smash the visual meaning is the function of optics in the interpretation and characterization of images.

A HABCNN has been masterminded as the layers as ReLU layers, Convolutional layers, pooling layers, and A Fully associated layer. While contrasting other picture characterization calculations, CNNs have exceptionally less pre-preparing steps. This CNN must be utilized in different fields for a considerable length of time. Convolution the critical job of this convolution cycle is to focus the data on picture features. The underlying cycle in CNN is the convolutionary layer. During this stage the layer usefulness is recognized and the element map is made from the information picture. ReLU layer the subsequent stage is the straightforwardly rebuilt unit layer. In this review, the institution technique has been presented on the element maps to expand the organization's nonlinearity. Here, the unwanted qualities successfully can be erased.

Pooling layer: The most common way of pooling can continuously diminish the size of the info. The progression of pooling can bring down over fitting. It will quickly call attention to the vital boundaries by raising the quantity of boundaries required.

Leveling layer: It is a significant simple move whereby the surveyed work guide ought to be straightened into the numbers consecutive segment. Completely associated layer commonly the traits which can be combined with the qualities. The grouping technique should be possible with the high percentile in precision. The mistake will predominantly be estimated and recorded.

Softmax: Softmax is likewise utilized in neural frameworks to plan the un-standard organization movement over expected execution gatherings to a probabilities appropriation. The Softmax has been applied for some issues in different review fields. The likelihood of the decimal will infer 1.0. Taking the connected Softmax varieties: Full Softmax is the Softmax, which can register probability for each possible class. Softmax registers probability for every one of the positive names; but only for a self-assertive illustration of negative names. This CNN empowers the inconsistency between a solitary variable and at least one unique factors to be estimated. For CNN, chances and a capacity are determined [9]. This is the gathered administering. In this strategy, CNN would first be able to peruse and rearrange the picture and afterward utilize its class probability to gauge the characterized methodology.

Process starts from Neuron activation by

$$a_j^1 = \sigma \sum K.W_{j,k}^1.a_K^1 + b_j^i \tag{5}$$

Equation (5) in vectored form as

$$a^l = \sigma\left(W^l a^{l-1} + b^l\right) \tag{6}$$

Training set can be merged in this as

$$C = \frac{1}{2}\left\| Y - a^{l} \right\|^{2} = \frac{1}{2}\sum_{j}\left(y_{j} - a_{j}^{l}\right)^{2} \tag{7}$$

HABCNN can be classified as

$$F = a_{j}^{1} b_{j}^{1} - \left(a_{j}^{1} b_{j}^{12}\right) \tag{8}$$

where m is empirical constant, F is the feature.

4 Results

The data sets of the liver cancer CT images were obtained from LiTS (Figs. 4 and 5).

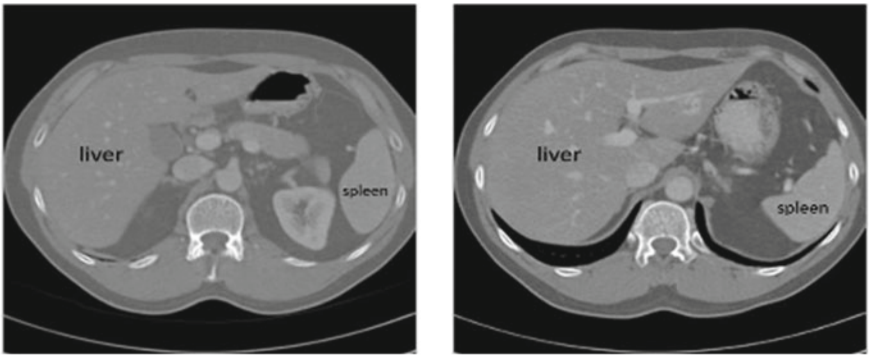

Fig. 4 Liver CT image

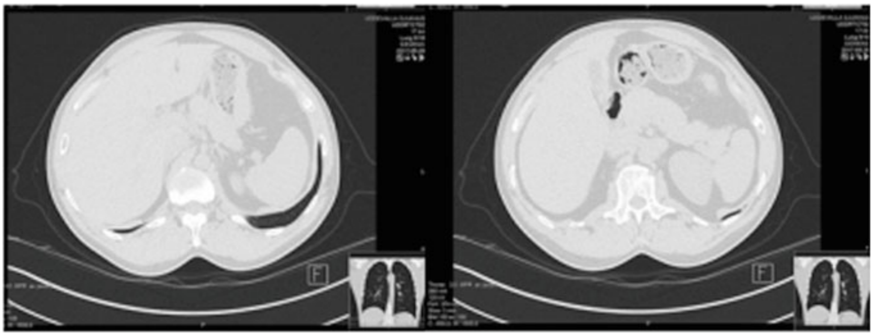

Fig. 5 Preprocessing

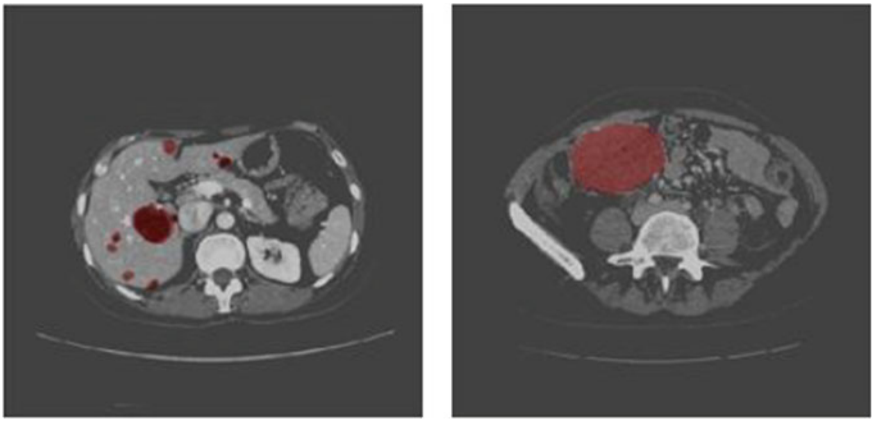

Fig. 6 Tumor detection using hybrid approach-based convolutional neural network

The process of preprocessing and segmentation can be done using histogram equalization and Hybrid Approach-Based Convolutional Neural Network will give the peak up results as shown in Fig. 6. The proposed classification methodology is simulated for the performance assessment. This analyzes was carried out using the LiTS data collection for liver cancer. The neural network training test ratio set constitutes 70% of the total data collection and the test set contains 30% of the overall results.

Accuracy: It is a measure of arithmetical predisposition; the accuracy is the proportion of true results (both true positive and true negative) in the total data.

$$\text{Accuracy}(A) = (TP + TN)/(TP + TN + FP + FN)$$

Sensitivity: Sensitivity, which is also called the true optimistic rate, the recall, or possibility of detection in some fields, measures the proportion of actual positives that are correctly identified.

$$\text{Sensitivity} = TP/(TP + FN)$$

Specificity: Specificity, which is also called the true positive rate, measures the amount of the actual negatives that are correctly identified.

$$\text{Specificity} = TP/(TP + FP)$$

Dice Similarity Coefficient: The Sørensen Dice Similarity coefficient is a mathematical method that calculates the correlation of two datasets.

$$DSC = 2TP/(2TP + FP + FN)$$

Table 1 Comparison table: proposed versus existed

Performance metrics	Multilayer perceptron [14]	C4.5 [15]	HABCNN (Proposed)
Specificity	88.02	96.02	97.1
Sensitivity	90.38	93.78	95.99
Accuracy	89.20	95.01	99.44
DSC	89.04	94.40	98.1

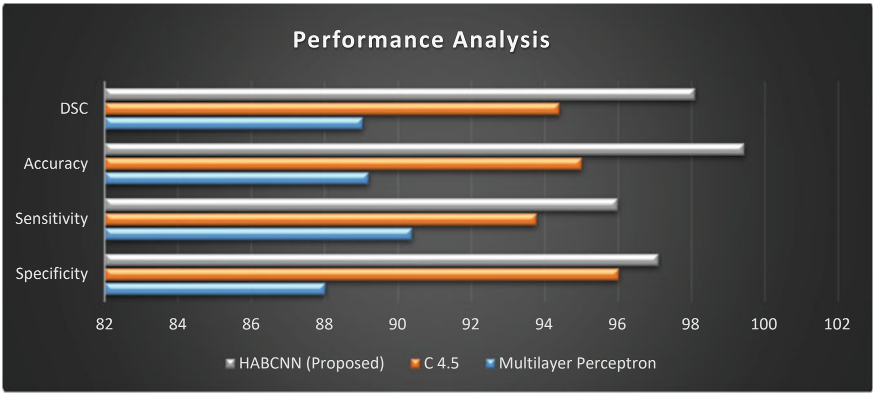

Fig. 7 Performance analysis

The comparison table of the proposed vs the existing detection mechanisms is shown in Table 1. From the Fig. 7. It can be inferred that the diagnosis and classification of hepatocellular carcinoma and liver cancer form metastasis can be effectively accomplished by using improved residual Google net CNN classifier. The proposed classifier HABCNN perform better than existing methodologies in all aspects.

5 Conclusion

Therefore the CT image segmentation is a critical operation during the second step of the study to determine the picture representing some portion of the renumber, spleen, etc. Contour and clustering methods have been used extensively for the segmentation of the medical image. This chapter therefore concentrates on the watershed segmentation of liver cancer. The kidney and spleen is segmented initially. After cancer tissue segmentation, GLCM was used to extract features from tumor parts. Eventually, Hybrid Approach-Based Convolutional Neural Network (HABCNN) was used to identify the hepatocellular and metastatic carcinoma for hepatic cancer. A better 99.44% identification precision came from the suggested classifier. The modern segmentation approach should insure that the precise boundary structure of the cancer area is known so that important information can be better diagnosed. Without human intervention, the classification method allows successful cancer damage defection. This technique may be particularly valuable for the early detection of cancer by physicians and nurses in patients.

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