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Liver Cancer Detection and Grading using Efficient Computer Vision Techniques

Mr. Shaikh Imran Turab*, Dept. of Electronic & Telecommunication Eng. Govt. Polytechnic Osmanabad;

Dr. V. K. Kadam, Professor, Dept. of Electronics & Telecommunication, P.E.S. College of Eng. Aurangabad

Abstract: Early prediction of any kind of cancer always advantageous for on-time medical treatment to save the patient lives. The Computer Aided Diagnosis (CAD) tools using signal processing and image processing methods gained significant attentions for immediate and accurate diagnosis using patient's raw medical data like Magnetic Resonance Imaging (MRI), Chromatography (CT), etc. The liver cancer early detection and analysis of its grading is important research problem. This paper proposed the CAD system for early detection liver cancer accurately followed by its grading analysis into different stages like stage 1 (T1), stage 2 (T2), and stage 3 (T3). The proposed framework consists of stages like pre-processing, Region of Interest (ROI) extraction, features extraction, and classification. The raw CT scans of liver pre-processed to remove the noises using the filtering and contrast adjustment functions. The adaptive segmentation method designed to using binarization and morphological operations to extract the accurate ROI with minimum computational burden. For features extraction, the text and shape features extracted using Gray Level Co-occurrence Matrix (GLCM) and geometric moment methods respectively. The conventional classifiers such as Artificial Neural Network (ANN) and Support Vector Machine (SVM) applied for prediction. The experimental results shows accuracy of proposed model improved existing methods.

Keywords: Artificial neural network, computer aided diagnosis, adaptive segmentation, classification, features extraction, liver cancer detection.

I. Introduction

Cancer is the significant danger for person wellbeing and its number of patients expanding word wide because of the an unnatural weather change, regardless of whether there are new treatments and therapies proposed by research specialists, however level of cancer characterizes the capacity of its fix. There are various kinds of cancers from which individual is enduring male and female. Computers have been successfully applied to various fields of medical sciences such as biochemical analysis, drug development and recognition of diseases from medical images [1].

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Successful identification of lung cancer, brain tumor is possible with the existing CAD. However, little 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 most well-known clinical imaging reads for early discovery and analysis of liver illnesses incorporate Ultra Sonography (US), Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) [2].

Liver illnesses are paid attention to, in light of the fact that liver is indispensable critical to the existence of a patient. Liver is perhaps the biggest organ in the human body situated in the upper right bit of the midsection. The liver has numerous significant capacities, such as clearing poisons from the blood, utilizing drugs, blood proteins and produce bile which helps absorption [3]. Liver can be forever harmed because of various reasons which incorporate infection contaminations, response because of medications or liquor, tumors, genetic conditions and issue with the body's invulnerable framework. Liver sicknesses establish a significant clinical issue of overall extents. Approximately 50% of the people [4] are affected by liver diseases.

Liver diseases are mainly classified into diffused liver diseases and focal liver diseases based on the dispersion in the pathology. Diffused liver diseases are distributed throughout the whole liver volume whereas Focal liver diseases are concentrated in small spots in one or both of the liver lobes while the rest of the liver tissues remain normal [5] [6]. A doctor may diagnose a disease on the basis of symptoms, laboratory test results, patient's medical history, physical examinations and scan reports. For example, during physical examination, the doctor may notice that the liver is harder or larger than usual and order blood tests that can show whether the disease is present. The doctor can ask for a scan if it is needed. Central liver sores are as often as possible identified in patients going through stomach examinations. The liver tumors comprise a significant analytic test for radiological imaging, particularly when cancer patients are included. Most benevolent tumors are found by chance on an imaging investigation of the liver, for example, ultrasound or CT examine. Sometimes, a biopsy might be needed to make the finding of hepato cell adenoma [7]. Harmful tumors might be identified by screening high danger patients or by chance on an imaging investigation of the midsection performed for another explanation or might be distinguished on account of side effects, for example, stomach torment. In patients, who experience the ill effects of further developed hepatocellular carcinoma, weight reduction, intermittent serious agony and other summed up indications may happen. The analysis of hepato cell cancinoma is ordinarily made by liver imaging tests, for example, stomach ultraround and CT filter in mix with the estimation of blood levels of aiphafeto protein. The existing tests such as biopsy are conducted for the final diagnosis of liver cancer. Such tests are difficult and expensive as the attention of experienced doctor required to analysis the CT scan images. Therefore in recent studies, Computer aided design (Computer Aided Diagnosis) can help radiologist and doctors in identifying sores and in separating kindhearted and dangerous injuries on clinical pictures. The outcomes got from CAD can be utilized as a "second assessment" by radiologists in their understandings which improve indicative precision [8]. Various CAD plans have been produced for discovery and arrangement of sores in clinical pictures. Execution examines show that the computer yield assisted radiologists with improving their indicative precision. As, CAD can be applied to all imaging modalities, all body parts and a wide range of assessments, almost certainly, CAD will significantly affect clinical imaging and symptomatic radiology in the 21St century [9] [10]. However, the accuracy of liver cancer detection and analysis is mainly depends of accurate estimation of Region of Interest (ROI) using the effective image segmentation methods. This paper proposed the efficient CAD tool for early prediction of liver tumor detection and automatic grading of its severity. Section II presents the review of various recent methods related to the same domain. Section III presents the design of proposed model. Section IV presents the simulation results and analysis. Finally conclusion discussed in section V.

II. Related Works

Several image processing based techniques proposed using various approaches and classification techniques. The core focuses of such methods on tumor segmentation, features extraction, and classification phases. Some of the recently introduced related works described in this section.

In [11], creator proposed programmed division of liver injuries utilizing half breed division methods. Their framework depended on two distinctive datasets and test results indicated that the proposed framework was quick, strong and viable in recognizing the presence of injuries in the liver, and figure the region of liver influenced as tumors sore, and gave order precision of 93%, which could section liver and concentrate sores from stomach CT in under 0.15 s/cut.

In [12], author designed an accurate method for liver tumor segmentation, in which the noise removed liver CT image by preprocessing was employed with SVM classifier for tumor segmentation. The SVM was already trained using the manually given image sets before test image classification. One after the other, feature extractions and morphological operations were performed on the binary image for further refinement ofthe rough segmentation result of SVM classifier. Their experiment results provided an accuracy of 97.83% for dataset 1 and 95.23% for

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dataset 2.

In [13], author predicted the global shape properties and pose of liver tumor regions with a statistical shape model to study the shape features of the liver from the liver CT image. In their method, a template was used to recover local deformations by comparing the template with the original liver image. The experiment results were validated for 10 cases and obtained moderate results.

In [14], author proposed quick, conventional calculation for estimating the volume of strong, minimal tumors in CT that considers halfway volume impacts at the boundary of a given division result. It is an expansion of the division based incomplete volume examination technique.

In [15], author announced arbitrary walker based structure that can section contrast-upgraded livers CT pictures with extraordinary precision and speed. In view of the area of the correct lung projection, the liver arch consequently distinguished in this manner wiping out the requirement for manual introduction. The computational prerequisites are additionally limited using rib-confined zone division; the liver is then extricated by using irregular walker technique.

In [16], author acquainted a robotized CAD framework with characterize liver sores into Benign or Malignant. The framework comprises of three phases; initially, programmed liver division and sore recognition. The highlights are extricated from various ROIs, and afterward ordering liver sores into kind and harmful. The technique separates a divided injury into three zones, for example inside, outside and line zones.

In [17], proposed programmed liver tumor division from stomach CT check pictures. A measurable boundary based methodology is utilized to recognize liver tumor tissue from other stomach organs. The current division strategies, for example, area developing and force based thresholding techniques examined.

In [18], author proposed and assessed a novel programmed approach for Oral Squamous Cell Carcinoma diagnosis utilizing profound learning advancements on CLE pictures. The technique is analyzed against textural include based AI moves toward that address the present status of the craftsmanship.

In [19], author introduced comparative and various tissues in CT pictures of liver are dictated by utilizing two unique techniques; watershed and histogram thresholding. The pictures have been pre-prepared before division.

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In [20], author proposed multi-modular picture investigation for assurance of the liver and perfusion domains. They utilized the self-loader liver division approach for ROI extraction.

In [21], author proposed the a programmed approach that coordinates the versatile thresholding and spatial fluffy bunching approach for location of cancer district in CT filter pictures of liver. They assessed the proposed calculations on 123 CT examine pictures.

In [22], author proposed a staggered outfit model to identify a liver and its order utilizing highlights extricated from CT pictures. The k-overlap cross-approval applied to legitimize the vigor of the classifiers. Contrasted with the individual classifier, the staggered outfit model accomplished high exactness in both the recognition and characterization of various tumors [26-31].

III. Methodology

This section presents the design of proposed model of detecting the liver cancer and grading analysis of tumor severity using the extracted features. Optimized CAD tool for early liver cancer detection using image processing terminologies is main goal of this paper. The practical approach used for evaluating the efficiency of proposed liver cancer detection method. The methods such as bilateral filter for pre-processing, ROI segmentation using the binarization and morphological operations, hybrid features for disease grading analysis and detection designed as showing in figure 1.

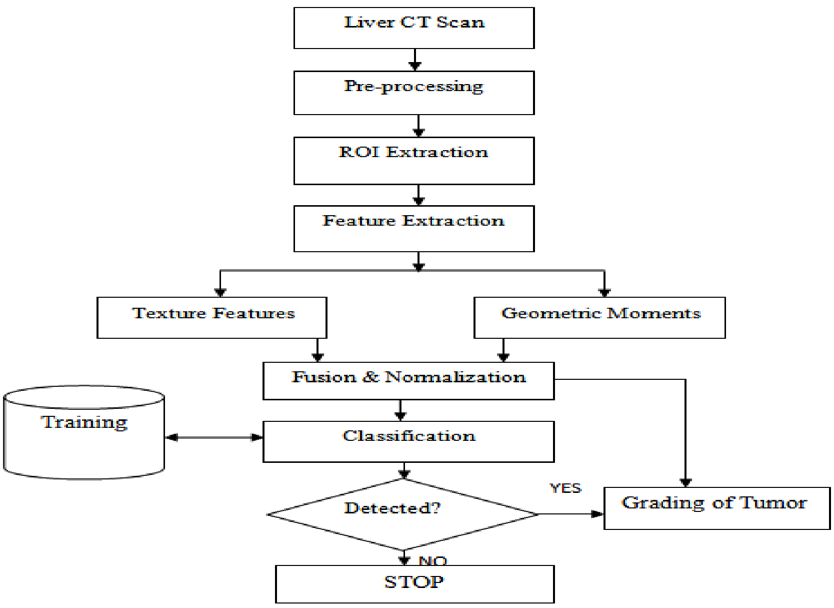

Figure 1. Proposed CAD model for liver cancer detection and tumor analysis

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Figure 1 demonstrating the functionality of detecting the liver cancer. If liver cancer detected in input CT image, tumor analysis performed to discover the stage of cancer. The functionality of each phase of proposed model elaborated in below sections.

A. Pre-processing: As the quality of input liver CT scans may contain noises, it can lead to suppressions of tumor areas and hence possibility of wrong predictions. The recent automated deep learning based techniques designed without image pre-processing. These methods may not be reliable for a longer time. The input CT image C pre-processed in the proposed model by applying techniques that work adaptively such as intensity values adjustment and median filtering. The first operation focused on adjusting the image intensity values of low contrast CT images as:

$$C^1 = imajust\ (C) \qquad (1)$$

Where, C^1 is outcome of contrast enhancement step using function $imadjust$.

After adjusting the image contrast, we applied the 2D filtering method to suppress the artefacts and noises effectively. The median filtering used to remove the noises in contrast enhanced image. It may possible that adjusting the image intensity values leads to noise and also X-ray scan also introduce the noises in image. The 2D median filtering works by moving via the image pixel by pixel, replacing every value with the neighbouring pixels median value. The neibhours pattern is decided by the size of window. The window size of 3-by-3 neighborhood is used in this work. The 2D median filter is applied on C^1 as:

$$C^2(i,j) = \ 2Dmedian\{C^1(i,j)|(i,j) \in w\} \qquad (2)$$

Where, C^2 is outcome of median filtering and w is the size of window.

B. ROI Extraction: After the task of pre-processing, image segmentation method used to extract the image ROI for further analysis. The extraction of tumor related information from the pre-processed image C^2 accurately is important research problem. The conventional techniques suffered from challenges like inaccuracy, over-segmentation, etc. In this paper, we designed the robust but accurate ROI extraction technique using binarization followed by morphological operations. The binary image segmentation is defined as the approach of classifying the intensity values of skull images into foreground regions and background regions using the threshold value. The threshold value computed dynamically for each input pre-processed skull image using Otsu's [23] technique. To improve the accuracy of binary segmentation, we applied morphological operations. The steps of proposed segmentation are:

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- Compute dynamic threshold value of input pre-processed image C^2
- Apply binary segmentation using computed threshold value of C^2
- Apply morphological structuring element operation using disk size 3 on segmented image
- The structuring element used in morphological closing operation to produce the accurate ROI image C^3
- Return C^3

C. Features Extraction and Normalization: The ROI image represented by the unique values called as the features in image processing terminology. The features extraction is another vital phase of any CAD tool. The rich and unique set of features leads to accurate classification and disease analysis. In this paper, we designed two types of features such as texture features using GLCM and moment invariant features. Both features deal with geometry, shape, and texture properties of ROI images. The well-known GLCM technique used to extract 20 features that consist of 16 GLCM features and 4 statistical features. The 4 GLCM properties such as contrast, correlation, energy, and homogeneity computed to get 16 features. We first compute the GLCM of ROI image using four offset [0 1;-1 1;-1 0;-1 -1:] as:

$$Gm = glcm(C^3, [0\ 1; -1\ 1; -1\ 0; -1\ \ -1]) \quad (3)$$

Using Gm, four texture features computed of size 1×4 of each. This builds the 1×16 feature vector for each input ROI image. Let, Gm is the GLCM matrix and L is maximum possible quantized value. Table 1 shows the texture features with equations.

Table 1. GLCM features

Texture feature	Equation	Equation Number
contrast	$\sum_{i-0}^{L-1}\sum_{j-0}^{L-1} \lvert i-j\ \rvert^2\, Gm_{ij}$	(4)
Energy	$\sum_{i-0}^{L-1}\sum_{j-0}^{L-1} \frac{Gm_{ij}}{1+\ \lvert i-j\ \rvert^2}$	(5)

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Homogeneity	$\frac{1}{\sigma_x \sigma_y}\sum_{i-0}^{L-1}\sum_{j-0}^{L-1}(i-j)Gm_{ij} - \mu_x\mu_y$	(6)
	$\mu_x = \sum_{i-0}^{L-1}\sum_{i-0}^{L-1} Gm_{ij}\ , \mu_y = \sum_{j-0}^{L-1}\sum_{i-0}^{L-1} Gm_{ij}$	(7)
	$\sigma_x^2 = \sum_{i-0}^{L-1}(i-\mu_x)^2 \sum_{j-0}^{L-1} Gm_{ij}$	(8)
	$\sigma_x^2 = \sum_{j-0}^{L-1}(j-\mu_x)^2 \sum_{i-0}^{L-1} Gm_{ij}$	(9)
Correlation	$\sum_{i-0}^{L-1}\sum_{j-0}^{L-1} Gm_{ij}^2$	(10)

After that, we computed 2D statistical features such as mean, standard deviation, entropy, and variance of ROI image. It form total 1×20 texture vector of input ROI image. To represents the shape of ROI, we extracted the 8 geometric moment features from ROI image. The geometric moment of order (p, q) for a ROI image is computed as:

$$\mu_{pq} = \sum_{i=1}^{m}\sum_{j=1}^{n}(i-\bar{\imath})^q C^3(i,j) \quad (11)$$

Where, $\bar{\imath} = \frac{m_{10}}{m_{00}}$ and $\bar{\jmath} = \frac{m_{01}}{m_{00}}$ are the coordinates of the object centroid. In this way, we have computed 8 moments as:

$$m_{00} = \sum_{i=1}^{m}\sum_{j=1}^{n} C^3(i,j) \quad (12)$$

$$m_{10} = \sum_{i=1}^{m}\sum_{j=1}^{n} i\ C^3(i,j) \quad (13)$$

$$m_{01} = \sum_{i=1}^{m}\sum_{j=1}^{n} j\ C^3(i,j) \quad (14)$$

$$\mu_{11} = \sum_{i=1}^{m}\sum_{j=1}^{n}(i-\bar{\imath})(j-\bar{\jmath})\ C^3(i,j) \quad (15)$$

$$\mu_{12} = \sum_{i=1}^{m}\sum_{j=1}^{n}(i-\bar{\imath})(j-\bar{\jmath})^2 C^3(i,j) \quad (16)$$

$$\mu_{21} = \sum_{i=1}^{m}\sum_{j=1}^{n}((i-\bar{\imath}))^2(j-\bar{\jmath})\ C^3(i,j) \quad (17)$$

$$\mu_{30} = \sum_{i=1}^{m}\sum_{j=1}^{n}((i-\bar{\imath}))^2((j-\bar{\jmath}))^2\ C^3(i,j) \quad (18)$$

$$\mu_{30} = \sum_{i=1}^{m}\sum_{j=1}^{n}\ ((i-\bar{\imath}))^3 C^3(i,j) \quad (19)$$

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The texture features and moment features fused to form total 28 features in vector V of each input CT image. As the there is significant variations in these 28 features, we opt for features normalization for performance improvement. The feature normalization convert all features in range of 0 to 1 using min-max normalization technique. The normalized features vector V^{norm} produced by:

$$V^{\mathrm{norm}} = \frac{(V - \min(V))}{(max\ (V) - \min(V))} \tag{20}$$

D. Detection and Classification: The training performed on complete dataset that consists of two categories normal and diseased CT images. For detection, we used two classifiers ANN and SVM. The performance of these classification methods are investigated by dividing the training data into the ratio of 70 % training and 30 % testing. If classification output is detected as cancer disease, then we applied the severity analysis to estimate the stage of cancer. This can be done by using the V^{norm} feature vector.

IV. Results Analysis

This section presents the simulation results and comparative analysis of proposed model using MATLAB tool. The dataset consist of 100 CT scan liver images collected from different sources from Kaggle [24] and Github [25] repositories. 50 images are normal and 50 are liver cancer of different subjects. The performance of proposed model investigated using ANN and SVM classifiers against the texture features (20 features), moment features (8 features), and normalized-fused features (28 features). The performance metrics such as accuracy, precision, recall, F1-score, and specificity parameters investigated.

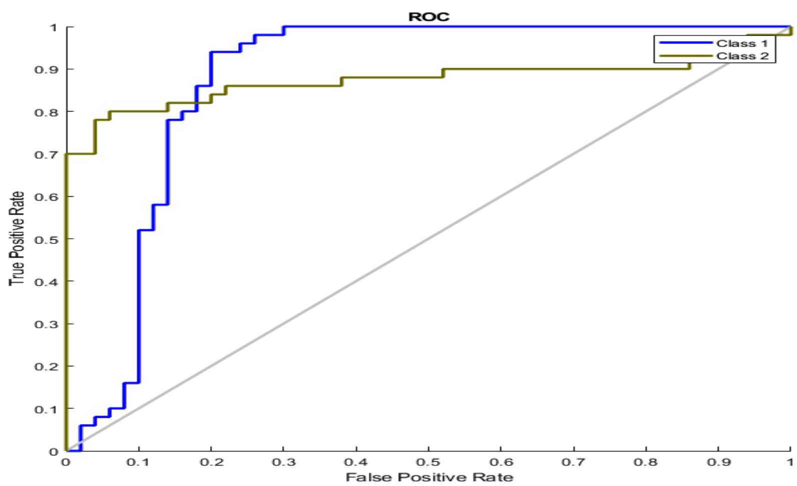

Figure 2. ROC representation of proposed model

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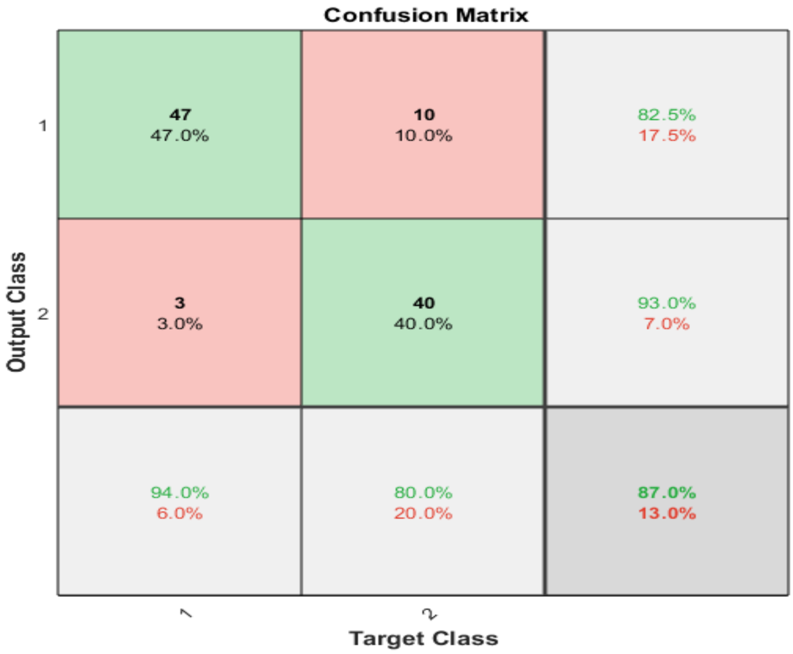

Figure 3. Confusion matrix representation of proposed model

A figure 2 and 3 demonstrates the Receiver Operating Characteristics (ROC) curve and confusion matrix respectively using ANN classifier for proposed model. It shows the 87 % overall accuracy considering both classes achieved using techniques designed for pre-processing, segmentation, and features extraction.

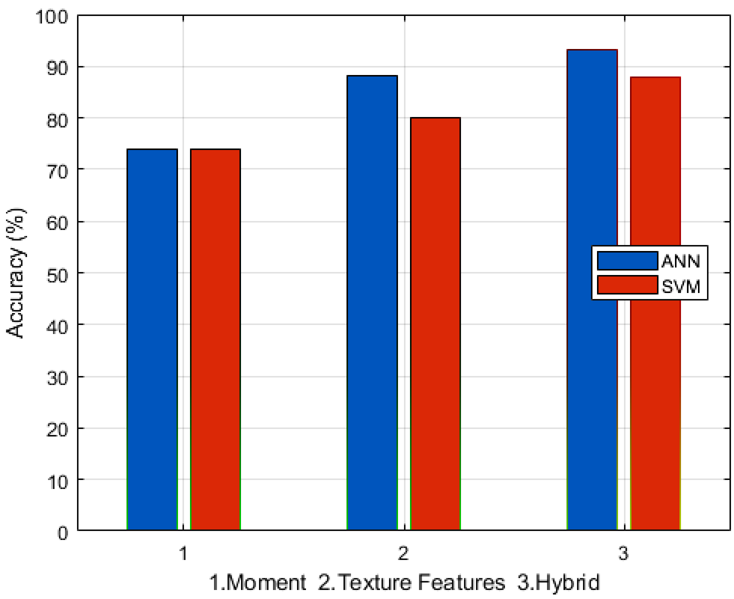

Figure 4. Accuracy analysis using different classifiers

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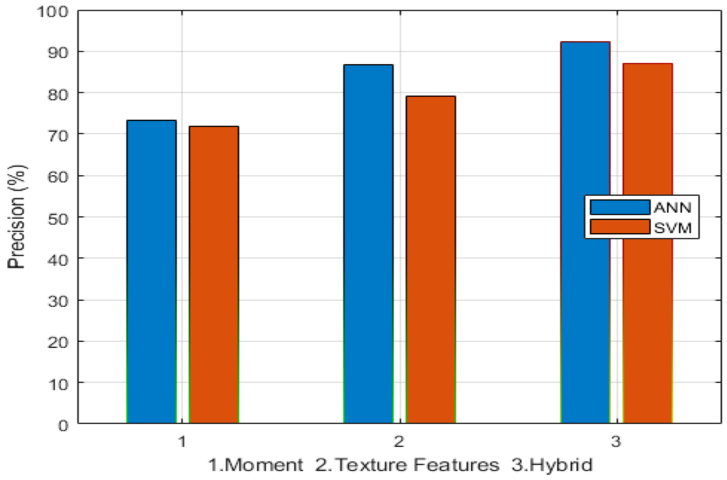

Figure 5. Precision analysis using different classifiers

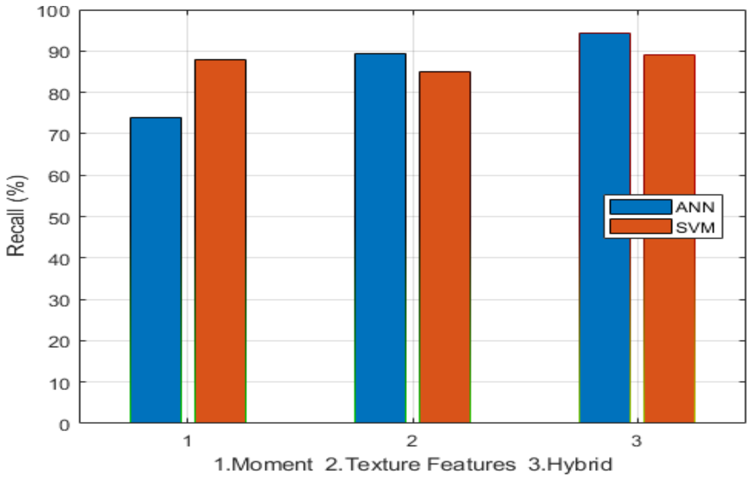

Figure 6. Recall analysis using different classifiers

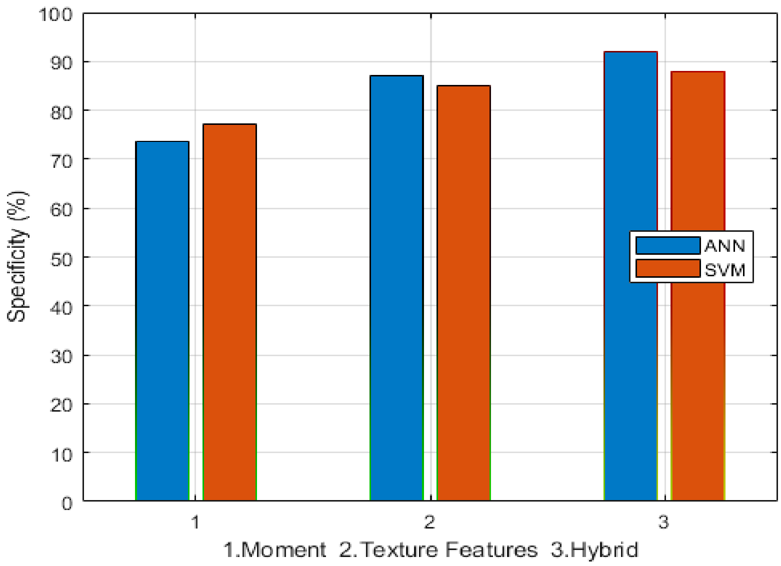

Figure 7. Specificity analysis using different classifiers

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Figures 4-8 demonstrates the analysis of accuracy, precision, recall, specificity, and F1-score parameters. As discussed earlier, the individual moment and texture features investigated against the proposed fused and normalized features vector using SVM and ANN classifiers. The accuracy results show that proposed features extraction technique achieved higher accuracy compared to moment and texture features. The similar trend observed for precision, recall, specificity, and F1-score parameters. Among the SVM and ANN classifiers, the ANN classifier achieved higher accuracy of detection compared to SVM. The F1-score and accuracy of proposed model using ANN is approximately 92 % and using SVM is approximately 88 %.

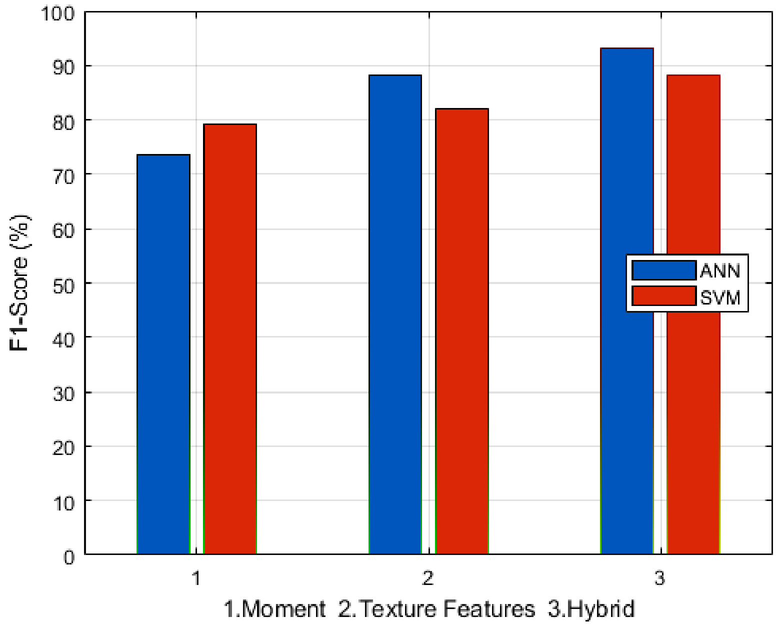

Figure 8. F1-score analysis using different classifiers

Furthermore, we investigated the performance of proposed model with recent techniques introduced in [19], [21], and [22]. All three methods similar to proposed model, thus included for comparative study. Table 2 shows the comparative analysis in terms of accuracy and average detection time. The proposed model shows the efficiency and robustness compared to all existing recent techniques. This is mainly because of using simple and accurate technique of ROI extraction and features extraction.

Table 2. State-of-art methods analysis

Methods	**Accuracy (%)**	**Avg. detection time (seconds)**
[19]	86.71	1.93
[21]	88.99	3.41
[22]	91.05	1.43

Proposed	92.67	1.13

V. Conclusion and Future Work

This paper proposed the CAD model for liver cancer detection and automatic cancer severity analysis using the similar set of normalized hybrid features. In this regards, we applied the median filtering for pre-processing, then dynamic threshold-based binary segmentation followed by morphological functions used for ROI extraction. From ROI image, texture and moment features extracted, fused, and normalized. For classification purpose, ANN and SVM classifier applied. The simulation results prove that proposed model improved the accuracy of detection with minimum computational overhead. For future work, we suggest to introduce the deep learning technique for automatic detection and accuracy improvement.

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