第 48 卷 第 9 期
2021 年 9 月

湖南大学学报（自然科学版）
Journal of Hunan University（Natural Sciences）

Vol. 48. No. 9.
September 2021
ISSN 1674-2974

Open Access Article

AUTOMATIC COMPUTER AIDED DIAGNOSIS FRAMEWORK OF LIVER CANCER DETECTION USING CNN-LSTM

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Abstract

Liver cancer detection using the computer vision methods and machine learning already received significant attention of researchers for accurate diagnosis and on-time medical attentions. The Computer Aided Diagnosis (CAD) preferred for cancer detection all over the world which is based on image processing functions. Earlier CAD tools were designed using conventional machine learning methods using semi-automatic approach. The recent growth of deep learning for automatic detection and classification leads to significant improvement in accuracy. This paper proposed the automatic CAD framework for liver cancer detection using Convolutional Neural Network (CNN) and Long Short Term Memory (LSTM). The input Computed Tomography (CT) scan images first pre-processed for quality enhancement. After that we applied the lightweight and accuracy Region of Interest (ROI) extraction technique using dynamic binary segmentation. From ROI images, we extracted automated CNN-based features and hand-craft features. The combination of both features formed unique feature set for classification purpose. The LSTM block is then perform the classification either into normal or diseased CT image. The CNN-LSTM model is designed in this paper to enhance the accuracy of liver cancer detection compared to other deep learning solutions. The experimental results of proposed model using CNN-based features and hybrid hand craft features outperformed the recent state-of-art methods.

Keywords: Computer tomography, computer aided diagnosis, convolutional neural network, deep learning, features extraction, segmentation, and liver cancer.

抽象的

使用计算机视觉方法和机器学习进行肝癌检测已经受到研究人员的高度关注，以实现准确诊断和及时医疗。基于图像处理功能的计算机辅助诊断（CAD）在世界范围内首选用于癌症检测。早期的 CAD 工具是使用使用半自动方法的传统机器学习方法设计的。最近用于自动检测和分类的深度学习的发展导致准确性的显着提高。本文提出了使用卷积神经网络 (CNN) 和长短期记忆 (LSTM) 进行肝癌检测的自动 CAD 框架。输入的计算机断层扫描 (CT) 扫描图像首先经过预处理以提高质量。之后，我们使用动态二进制分割应用了轻量级和准确的感兴趣区域

Received: July 02, 2021 / Revised: August 22, 2021 / Accepted: September 11, 2021 / Published: September 26, 2021 About the authors: Mr. Imran Shaikh

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(ROI) 提取技术。从 ROI 图像中，我们提取了基于 CNN
的自动化特征和手工特征。这两个特征的组合形成了用于分类目的的独特特征集。然后
LSTM 块将分类为正常或患病的 CT 图像
。与其他深度学习解决方案相比，本文设计了 CNN-LSTM
模型以提高肝癌检测的准确性。使用基于 CNN
的特征和混合手工艺特征的所提出模型的实验结果优于最近的最新方法。

关键词：计算机断层扫描、计算机辅助诊断、卷积神经网络、深度学习、特征提取、分割和肝癌。

1. Introduction

Liver is perhaps the biggest organ in the human body situated in the upper right bit of the mid-region. The liver has numerous significant capacities, such as clearing poisons from the blood, processing drugs, blood proteins and produce bile which helps absorption [1]. Liver can be for all time harmed because of various reasons which incorporate infection contaminations, response because of medications or liquor, tumours, genetic conditions and issue with the body's invulnerable framework. Liver infections comprise a significant clinical issue of overall extents. Approximately 50% of the people [2] are affected by liverdiseases.Liver diseases are mainly classified into diffused liver diseases (Table 1) and focal liver diseases (Table 2) based on the dispersion in the pathology. Diffusedliver diseases are distributed throughout the whole liver volume whereas Focal liverdiseases are concentrated in small spots in one or both of the liver lobes while therest of the liver tissues remain normal [3].

Greasy and cirrhosis are the normal diffused sicknesses. Greasy liver is a gatherer of fat cells in the liver which is basic in diabetic patients or patients experiencing overweight. Cirrhosis is a gathering of persistent liver infections where typical liver cells are harmed and supplanted by scar tissue, diminishing the measure of ordinary liver tissue. This is portrayed by fibrosis and knob arrangement. Greasy liver is profoundly weakening and acrogenic, yet cirrhosis liver has typical lessening and echogenicity [4]. Central liver sores range from kind sores to very forceful hepatic cell carcinomas and cholangio carcinomas. Liver tumour is additionally an illustration of central liver infection. Tumour is a development of tissue where the tissue cells increase in an uncontrolled style. Tumours can be either generous (non cancerous) or harmful (cancerous). The most well-known favourabletumours of the liver are haemangioma, hepatic cell adenoma and central nodular hyperplasia. The malignant tumours are hepatic cellularcarcinoma and cholangio carcinoma [5].

Table 1. Diffused liver disease

Number	Disease Name
1	Fatty liver
2	Cirrhosis liver
3	Steatosis
4	Hepatitis
5	Jaundice
6	Acute liver failure
7	Drug induced liver disease

Table 2. Focal liver diseases

Number	Disease Name
1	Malignant Tumour
2	Benign Tumour
3	Metastatic disease
4	Ascites
5	Cysts

Accurate diagnosis of liver diseases is important research problem. The liver cancer detection using image processing operations leads to minimum computational costs and higher detection accuracy. For example, duringphysical examination, the doctor may notice that the liver is harder or greater 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 oftentimes identified in patients going through stomach examinations [6]. The liver tumours establish a significant indicative test for radiological imaging, particularly when cancer patients are included. Most kind tumours are found by chance on an imaging investigation of the liver, for example, ultrasound or CT check. Incidentally, a biopsy might be needed to make the finding of hepatic cell adenoma. Harmful tumours might be recognized by screening high danger patients or by chance on an imaging investigation of the mid-region performed for another explanation or might be distinguished in light of side effects, for example, stomach torment [7]. In patients, who experience the ill effects of further developed hepatic cellular carcinoma, weight reduction, intermittent serious agony and other summed up indications may happen. The determination of hepatic cell carcinoma is ordinarily made by liver imaging tests, for example, stomach ultra round and CT check 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 [8] [9]. Subsequently in ongoing examinations, CAD can help radiologist and doctors in distinguishing injuries and in separating benevolent and threatening sores on clinical pictures. The outcomes got from CAD can be utilized as a "second assessment" by radiologists in their translations which improve demonstrative exactness [10]. Various CAD plans have been created for location and characterization of injuries in clinical pictures. Execution examines show that the PC yield assisted radiologists with improving their symptomatic exactness. As, CAD can be applied to all imaging modalities, all body parts and a wide range of assessments, all things considered, CAD will significantly affect clinical imaging and symptomatic radiology in the 21st century [11]. 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. Several methods presented for ROI extraction from input CT scan image of liver since from last decade [12]. It is obvious from the writing survey that the greater part of the work is done either on CT or PET pictures alone. A large portion of the division work has been finished utilizing thresholding calculations, area based calculations, edge-based calculations, watershed calculations, fluffy grouping based calculations and diagram based calculations in CT pictures. Be that as it may, these strategies have different constraints. Thresholding calculations rely upon force dissemination of picture. In CT pictures, thresholding and chart put together strategies are by and large based with respect to SUV esteems

which are touchy to volume variety in tumour or underlying/useful volumes. Edge based calculations produce disjoint edges. District based calculations require manual introduction. Watershed calculation prompts over-division and is poor in distinguishing meagre constructions in pictures. Chart based calculations give worldwide arrangements as are computationally costly. Fluffy grouping based calculations require preparing of the dataset and the precision relies upon the chose preparing tests and hence, these are duller to utilize. Recently, the automatic tumour segmentation using deep learning received the attentions [13]. However, a high computational requirement of deep learning methods leads to higher waiting time for tumour detection and classification.

This paper proposed the novel CAD tool with goal of automatic liver cancer detection and it's grading to different stages using computer vision algorithms and deep learning model. The pre-processing and ROI extraction performed before applying the CNN for features extraction. The features of CNN combined with hand-craft features followed by the normalization. Finally, the LSTM block designed for early cancer detection. SectionII(2.1) presents the brief review of various liver cancer detection techniques using deep learning approach. SectionII(2.2) presents the design of proposed methodology. Section IV presents the simulation results and discussions. Section V presents the conclusion and future work.

2. Materials and Methods

Literature Review There are significant benefits of using deep learning methods in problem domain of automatic liver segmentation and cancer detection. This received attentions of researchers since 4-5 years for automatic liver tumour segmentation and detection. This section presents the review of some recent works related to the same.

In [14], author proposed system for discovery of liver tumour applicants from CT pictures utilizing a profound CNN. They showed the proficiency utilizing profound learning contrasted with ordinary classifiers.

In [15], author planned new technique to improve the effectiveness of the clinical analysis. They planned fix based CNN to play out the class forecast (ordinary or tumour) on the patches removed from the 60 liver tumour entire side pictures.

In [16], author proposed novel three-dimensional (3-D) CNN for tissue characterization in clinical imaging and applied for separating among essential and metastatic liver tumours from dispersion weighted MRI information. The proposed network comprises of four successive stride 3-D convolution layers along 3 × 3 × 3 bit size and redressed direct unit (ReLU) as actuation work, trailed by a completely associated layer with 2048 neurons and a Softmax layer for twofold order.

In [17], author introduced execution assessment, understanding, and productivity of a completely convolutional network (FCN) for liver sore discovery and division at CT assessments in patients with colorectal liver metastases (CLMs).

In [18], author designed and compared to network architectures, one that is composed of one neural network and manages the segmentation task in one step and one that consists of two consecutive FCNs.

In [19], author proposed a new system known as watershed Gaussian based deep learning (WGDL) technique for effective delineate the cancer lesion in CT images of the liver.

In [20], author formulated liver tumor segmentation of CT abdominal images as a classification problem, and then addressed using a cascaded classifier framework based on deep CNNs. Two deep encoder-decoder CNNs (EDCNN) were constructed and trained to cascade segments of both the liver and lesions in CT images with limited image quantity.

In [21], author proposed Hybridized Fully CNN (HFCNN) for liver tumor segmentation mathematically to address the current issue of liver cancer. For semantic segmentation, HFCNN has been recycled as a powerful tool for liver cancer analysis. Several other techniques reviewed during this work [22-27].

2.2 Proposed system

This section presents the design of proposed model for automatic liver cancer detection followed by the severity analysis of tumour. Fig. 1 shows the functionality of this model. As showing in fig. 1, the key steps of proposed model includes the ROI extraction, features extraction, classification, and grading. The input CT scan image first acquires into the system, then, pre-processing applied to enhance the quality of image for accurate investigation. The ROI extraction plays the significant role, thus we designed simple and robust mechanism for ROI extraction before applying the feature extraction.

The existing methods perform ROI extraction using deep learning methods; however, it is time consuming process to only segment tumour from input CT image. In this case, it is further required to automatically extract features as well. Hence, rather than applying deep learning for segmentation, we designed computationally efficient approach for ROI extraction without compromising the accuracy. For features extraction, we prefer both hand crafted features and automatic CNN features as using automatic features may not consider the tumour specific features like shape and texture. The hand crafted features and automatic features fused and normalized using min-max technique. For classification purpose, LSTM block designed where the hybrid feature vector is taken as input for classification through the LSTM layers. On the detection of cancer input CT image, its grading performed into either of three stages.

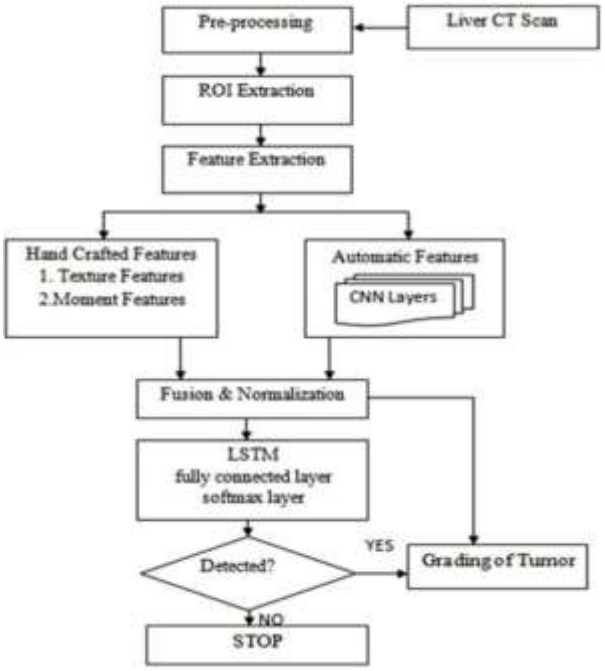

Fig. 1 Proposed automatic liver cancer detection and grading analysis

A. Pre-processing: The CT scan devices may not accurate to produce the high quality images for liver diagnosis. Thus for CAD models, the first step is to improve the quality of scanned images by removing the noises, artifacts, low contrast regions. The input CT image is pre-processed 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:

$$C^1 = imajust\,(C) \quad (1)$$

Where, is outcome of contrast enhancement step using function ?

After adjusting the image contrast, we applied the 2D filtering method to suppress the artifacts and noises effectively. The median filtering used to remove the noises in contrast enhanced image. The 2D median filtering works by moving via the image pixel by pixel, restoration every value with the neighboring 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:

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

Where, is outcome of median filtering and is the size of window.

B. ROI Extraction: 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 Proper accuray 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 technique. To improve the accuracy of binary segmentation, we applied morphological operations. The steps of proposed segmentation are:

- Compute dynamic threshold amount of input pre-processed image
- Apply binary segmentation using computed threshold value of
- 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
- Return

C. Hand-Crafted Features: Hand-Crafted features widely prefer in domain of pattern recognition systems. There are different types of hand-crafted features in image processing domain. The rich and unique set of features leads to accurate classification and disease analysis. Two types of hand-crafted features are extracted 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.

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 imageis computed as:

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

(11)

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)
Homogeneity	$\frac{1}{\sigma_s \sigma_y} \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i - j) Gm_{ij} - \mu_s \mu_y$	(6)
	$\mu_s = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} Gm_{ij}, \mu_y = \sum_{j=0}^{L-1} \sum_{i=0}^{L-1} Gm_{ij}$	(7)
	$\sigma^{2}{}_{s} = \sum_{i=0}^{L-1} (i - \mu_s)^{2} \sum_{j=0}^{L-1} Gm_{ij}$	(8)
	$\sigma^{2}{}_{s} = \sum_{j=0}^{L-1} (j - \mu_s)^{2} \sum_{i=0}^{L-1} Gm_{ij}$	(9)
Correlation	$\sum_{i=0}^{L-1} \sum_{j=0}^{L-1} Gm^{2}_{ij}$	(10)

Where, and are the coordinates of the object centroid. In this way, we have computed 8 moments as:

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

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

(12)

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

(13)

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

(14)

$$\mu_{11} = \sum_{i=1}^{N} \sum_{j=1}^{n} (i - \bar{i})(j - \bar{j})\, C^{3}(i, j)$$

(15)

$$\mu_{12} = \sum_{i=1}^{N} \sum_{j=1}^{n} (i - \bar{i})(j - \bar{j})^{2} C^{3}(i, j)$$

(16)

$$\mu_{21} = \sum_{i=1}^{N} \sum_{j=1}^{n} ((i - \bar{i})^{2}(j - \bar{j})\, C^{3}(i, j)$$

(17)

$$\mu_{30} = \sum_{i=1}^{N} \sum_{j=1}^{n} ((i - \bar{i})^{2}((j - \bar{j}))^{2}\, C^{3}(i, j)$$

(18)

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

(19)

The texture features and moment features fused to form total 28 features in vector X of each input CT image.

The texture features and moment features fused to form total 28 features in vector of each input CT image.

D. Automatic Features Extraction: For this case, we designed CNN to learn and extract the features from input ROI image automatically. The CNN is part of proposed deep learning block CNN-LSTM. This section presents how CNN designed to extract the features. The CNN block consists of convolution (Conv.) layer and Max

Pooling Layer (MPL) that consolidated in one squashing function via the MLP layer outcome as:

$$Y_j^S = tanh(pooling_{Nas}(\sum_j y_j^{S-1} * k_{ij}(C^3)) + b_j^S)$$

(20)

Where, Y_j^S is feature set using convolutional layer l of jth input, y_j^{S-1} represents the previous convolutional layer features maps, k_{ij} represents i^{th} trained convolutional kernels and b_j^S represents the additive bias. The function $\tanh(.)$ represents the activation function and $pooling_{Nas}(.)$ represents the operation of max pooling for features extraction. In this way, we receive the final automated feature vector as:

$$Y = mean\{Y_j^1, \ldots, Y_j^S\}$$

(21)

E. Fusion and Normalization: After extracting the hand-crafted features (X) and automatic CNN features (Y), we performed the fusion and normalization stage. As the there is significant variations in these hybrid features, features normalization applied for performance improvement. The feature normalization convert all features in range of 0 to 1 using min-max normalization technique. The fused vector $V = \{X, Y\}$ is then normalized into V^{norm} by:

$$V^{norm} = \frac{(V - min(V))}{(Nas(V) - min(V))}$$

(22)

F. LSTM for Classification: The extracted features of input CT image in V^{norm} vector are then passed to LSTM block for classification. The LSTM block consists of different layers like LSTM layer, Fully Connected Layer and Classification Layer (softmax layer). The LSTM layer layer consists of memory blocks embarrassed by memory cells such as input gate, forget gate, output gate, and peephole connections. The output of LSTM layer is then transfer to fully connected layer where the prediction task performed by mapping the outcome of LSTM layer to the particular output. Fully connected layer takes input as hidden units and output size. The outcome of fully connected layer passed to classification layer where prediction of liver cancer performed.

3. Simulation Results

The simulation results and comparative analysis of proposed model CNN-Fused Normalized-LSTM (CNN-FN-LSTM) using MATLAB tool are presented in this section. The dataset consist of 100 CT scan liver images collected from different sources from Kaggle [28] and Github [29] repositories. 50 images are normal and 50 are liver cancer of different subjects. The performance of proposed model investigated using ANN, SVM, and CNN-FN-LSTM classifiers against the texture features (20 features), moment features (8 features), and normalized-fused features (28 features). The performance compared with proposed automated model CNN-FN-LSTM (we represented as CNN in graphs). In FN block, we varied the texture, moment, and normalized fused texture + moment features for performance investigation. The performance metrics such as accuracy, precision, recall, F1-score, and specificity parameters analyzed.

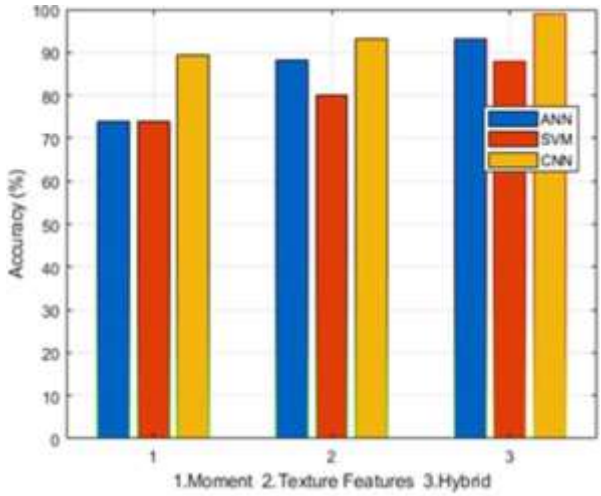

Fig. 2 Accuracy analysis of proposed model

Fig. 2 demonstrates the outcome of accuracy using different classifiers with different set of features. For ANN and SVM, only hand-crafted features were used such as moment, texture, and hybrid. In CNN, the hand-crafted features combined with automatic CNN extracted features. This leads to improvement in accuracy performance compared to both ANN and SVM outcomes significantly. The accuracy of proposed CNN-FN-LSTM using all hand-crafted features is higher compared to all other configurations.

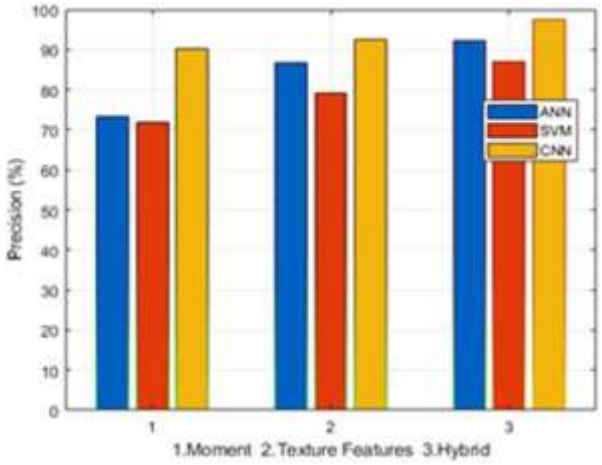

Fig.3 Precision analysis of proposed model

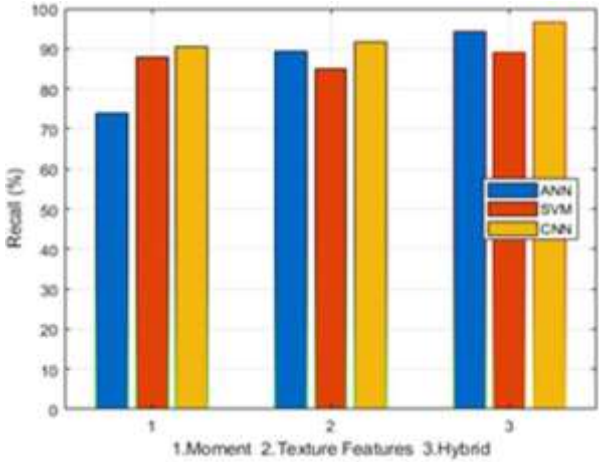

Fig.4 Recall analysis of proposed model

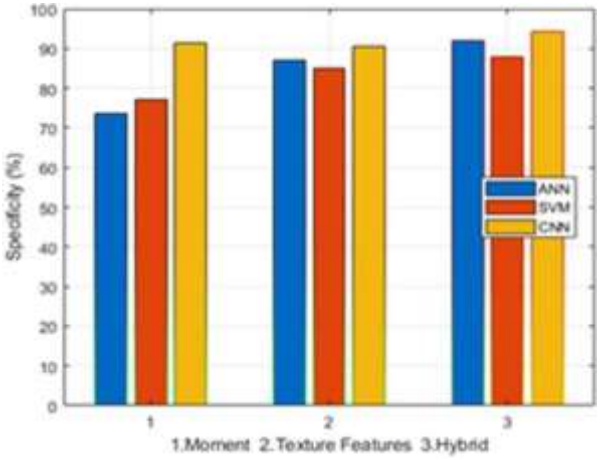

Fig.5 Specificity analysis of proposed model

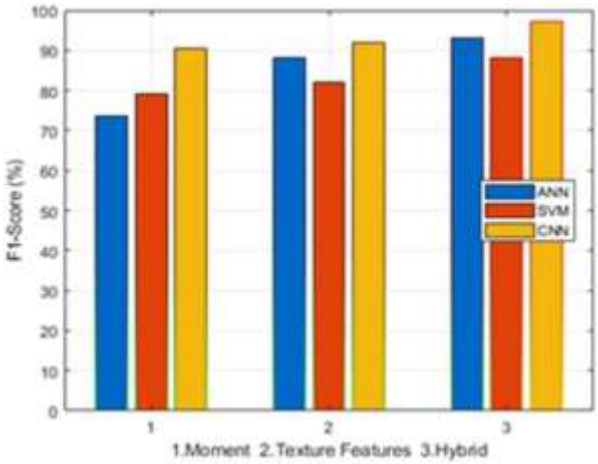

Fig.6 F1-score analysis of proposed mode

Fig. 3 and 4 demonstrates the outcome of precision and recall rates respectively. The

precision and recall are important parameters for efficiency analysis of recognition systems. Both precision and recall rates shows the higher performance for proposed CNN-FN-LSTM model compared to conventional classifiers because of superiority of deep learning model to introduce the deep features of input ROI images which helps to produce the 99 % accurate predictions.

The Fig. 5 and 6 demonstrate other important parameters such as specificity and F1-score performances. The specificity performance is minimum compared to above three results for all the cases as it represented as the actual negatives (called as true negative). For this parameter also, proposed model achieved higher performance compared to all other combinations. The F1-score outcome of proposed model is 98 % which is higher compared other methods investigated. Apart from this, we compared the performance of proposed model CNN-FN-LSTM with recently deep learning based models such as WGDL [19], EDCNN [20], and HFCNN [21] in terms of overall accuracy and average detection time in table 1. The exiting methods implemented using dataset mentioned used in this paper. From these results, it shows that proposed model improved the accuracy of classification and reduced the detection time as well.

Table 1. State-of-art methods analysis

Methods	**Accuracy (%)**	**Avg. Detection Time (Seconds)**
WGDL	97.89	6.93
EDCNN	96.15	8.12
HFCNN	97.99	7.45
CNN-FN-LSTM	**98.67**	**4.78**

4. Conclusion and Future Work

The automated CAD model for liver cancer detection and its grading designed in this paper using optimized computer vision techniques and deep learning methods. The detailed design of proposed CNN-FN-LSTM model presented and evaluated. The model consists of pre-processing, ROI extraction, hand-crafted features extraction, automatic CNN features extraction, and LSTM-based classification phases. The design of each phase discussed during this paper. The experimental results shows that CNN-FN-LSTM is improved the performance with respect to parameters such as precision, recall, specificity, accuracy, and F1-score compared to conventional methods. For future work, we suggest to investigate the proposed model with different datasets of other cancers like brain tumour, lung diseases, etc.

Acknowledgment

I would like to express my sincere gratitude towards my guide Dr. V. K. Kadam Department of Electronics and Telecommunication for the help, guidance and encouragement, provided during the work. This work would have not been possible without his valuable time, patience and motivation. I thank him for making my study thoroughly pleasant and enriching.

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