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Automatic Computer Propped Diagnosis Framework of Liver Cancer Detection with Simulation using CNN-LSTM

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Abstract*— Initial prediction of any kind of cancer is always advantageous for on-time medical treatment to save the patient's life. The Computer-Aided Diagnosis (CAD) tools using signal processing & image processing methods gained significant attention for immediate & accurate diagnosis using patient's raw medical data like Magnetic Resonance Imaging (MRI), Chromatography (CT), etc. The liver cancer early detection & analysis of its grading is an important research problem. In this research, we proposed the two models semi-automatic & automatic frameworks for liver disease classification. The models perform early detection of liver cancer accurately followed by its grading analysis into different stages like stage 1 (T1), stage 2 (T2), & stage 3 (T3). The proposed framework consists of stages like pre-processing, Region of Interest (ROI) extraction, features extraction, & classification. The raw CT scans of the liver are pre-processed to remove the noises using the filtering & contrast adjustment functions. The adaptive segmentation method is designed to using binarization & morphological operations to extract the accurate ROI with the minimum computational burden. For features extraction, the text features extracted using Gray Level Co-occurrence Matrix (GLCM), shape features using geometric moment, & automatic features using Convolutional Neural Network (CNN). The hybrid form of features normalized using the min-max technique. For the classifications, we explored the classifiers such as Artificial Neural Network (ANN), Support Vector Machine (SVM), & Long Term Short Memory (LSTM). We investigated the semi-automated & automated systems using the publically available research dataset.

***Index Terms*— Computer tomography, computer aided diagnosis, convolutional neural network, deep learning, features extraction, segmentation, and liver cancer**

I. INTRODUCTION

1.1 Research Background

Computers have been successfully applied to various fields of medical sciences such as biochemical analysis, drug development & recognition of diseases from medical images. 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 & gall bladder using abdominal images due to gray level similarities of alongside organs. The most common medical imaging studies for early detection & diagnosis of liver diseases include Ultra Sonography (US), Computed Tomography (CT) & Magnetic Resonance Imaging (MRI) [1].

Liver infections are treated appropriately, in light of the fact that liver is crucial essential to the existence of a patient. Liver is conceivably 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, utilizing drugs, blood proteins & produce bile which helps processing [2]. Liver can be forever harmed because of various reasons which incorporate infection contaminations, response because of medications or liquor, tumors, innate conditions & issue with the body's invulnerable framework. Liver infections establish a significant clinical issue of overall extents. Roughly half individuals [3] are influenced by liver sicknesses.

Liver infections are predominantly arranged into diffused liver illnesses (Table 1.1) & central liver sicknesses (Table 1.2) in view of the scattering in the pathology. Diffused liver illnesses are circulated all through the entire liver volume though Focal liver sicknesses are moved in little spots in either of the liver flaps while the remainder of the liver tissues stay ordinary. Greasy & cirrhosis are the normal diffused sicknesses. Greasy liver is an aggregator of fat cells in the liver which is normal in diabetic patients or patients experiencing overweight. Cirrhosis is a gathering of constant liver illnesses where ordinary liver cells are harmed & supplanted by scar tissue, diminishing the measure of typical liver tissue. This is portrayed by fibrosis & knob development. Greasy liver is profoundly lessening & echogenic, yet cirrhosis liver has typical weakening & echogenicity [4]. Central liver injuries range from kindhearted sores to very forceful hepato cell carcinomas & cholangio carcinomas. Liver tumor is likewise an illustration of central liver sickness. Tumor is a development of tissue where the tissue cells increase in an uncontrolled style.

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Tumors can be either benevolent (non cancerous) or harmful (cancerous). The most widely recognized favorable tumors of the liver are hemangioma, hepato cell adenoma & central nodular hyperplasia. The threatening tumors are hepato cell carcinoma & cholangio carcinoma.

Table 1.1. 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 1.2. Focal liver diseases

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

A doctor may diagnose a disease on the basis of symptoms, laboratory test results, patient's medical history, physical examinations & scan reports. For example, during physical examination, the doctor may notice that the liver is harder or larger than usual & order blood tests that can show whether the disease is present. The doctor can ask for a scan if it is necessary. Central liver sores are regularly distinguished in patients going through stomach examinations. The liver tumors establish a significant demonstrative test for radiological imaging, particularly when cancer patients are included. Most favorable tumors are found by chance on an imaging investigation of the liver, for example, ultrasound or CT examine [5].

Sporadically, a biopsy might be needed to make the analysis of hepato cell adenoma. Threatening tumors might be distinguished by screening high danger patients or by chance on an imaging investigation of the mid-region performed for another explanation or might be recognized due to manifestations like stomach torment. In patients, who experience the ill effects of further developed hepatocellular carcinoma, weight reduction, occasional serious agony & other summed up indications may happen. The determination of hepato cell cancinoma is commonly made by liver imaging tests, for example, stomach ultraround & CT filter in mix with the estimation of blood levels of aiphafeto protein. The current tests, for example, biopsy are led for the last conclusion of liver cancer. Such tests are troublesome & costly as the consideration of experienced specialist needed to investigation the CT check images [6].

Consequently in late examinations, CAD (Computer Aided Diagnosis) can help radiologist & doctors in identifying sores & in separating amiable & dangerous injuries on clinical images. The outcomes receive from CAD can be utilized as a "second assessment" by radiologists in their translations which further develop indicative exactness [2]. Various CAD plans have been created for discovery & characterization of injuries in clinical images. Execution contemplates show that the PC yield assisted radiologists with working on their indicative exactness.

As CAD can be applied to all imaging modalities, all body parts & a wide range of assessments, all things considered, CAD will significantly affect clinical imaging & analytic radiology in the 21st century [7-10]. Be that as it may, the precision of liver cancer identification & investigation is predominantly depends of exact assessment of Region of Interest (ROI) utilizing the compelling image segmentation techniques. In this examination, we introduced novel mechanized liver cancer discovery utilizing effective techniques for image pre-preparing, segmentation, highlight extraction, & characterization over the CT & MRI images.

1.2 Liver Cancer

In human body after skin the biggest organ is liver. The heaviness of the liver of a grown-up is roughly three pounds. Liver is situated at the right side under the right lung & is ensured by rib confine. It is isolated into both ways projections. It resembles a substance processing plant. The human liver is among the most intricate & significant organ in the human body. It is both the biggest inside organ & the biggest organ in the human body. It is situated in the right upper quadrant of the stomach hole, resting just beneath the stomach. It is associated with two enormous veins, in particular hepatic corridor & entryway vein. The hepatic conduit conveys blood from the aorta, though the entry vein conveys blood containing processed supplements from the whole gastrointestinal parcel & furthermore from the spleen & pancreas. The liver has two flaps, a right projection & a left flap. Two significant sorts of cells populate the liver projections: parenchymal & non-parenchymal cells. Of these 80% of the liver volume is involved by parenchymal cells generally alluded to as hepatocytes.

II. 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

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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.

A. Pre-processing

Liver tumor images are created because of oppressing the human liver under filtering. At this stage, the commotions are added to the checked image through different reasons like inductive misfortunes, low quality which would influence the clinical images. This is the most widely recognized issue & it tends to be redressed by pre-handling procedures. Image pre-preparing is utilized predominantly for procedure on images at the least degree of reflection. The point of pre-handling method is improvement of the image information that smothers undesired bends or upgrades some image highlights significant for additional preparing & examination of segmentation & characterization. Rather than genuine pixel esteems, pixels in the image show diverse force esteems. Clamor evacuation procedure is the way toward eliminating or decreasing the commotion from the image. Denoising lessens or eliminates the perceivability of commotion by smoothing the whole image leaving regions close to differentiate limits.

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 work, 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 & 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 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 three on segmented image
- The structuring element used in morphological closing operation to produce the accurate ROI image C^3
- Return C^3

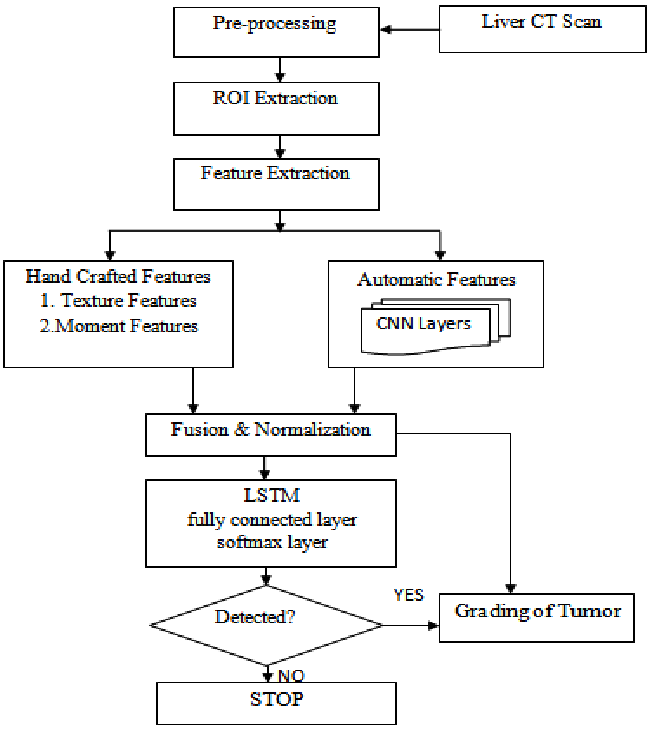

Fig. 3.1 Proposed automatic liver cancer detection and grading analysis

C. Features Extraction & 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 & unique set of features leads to accurate classification & disease analysis. In this work, we designed two types of features such as texture features using GLCM & moment invariant features. Both features deal with geometry, shape, & texture properties of ROI images. The well-known GLCM technique used to extract 20 features that consist of 16 GLCM features & 4 statistical features. The 4 GLCM properties such as contrast, correlation, energy, & 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:

$$Gm = glcm(C^3, [0\ 1; -1\ 1; -1\ 0; -1\ -1]) \quad (3.3)$$

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 & L is maximum possible quantized value.

E. Detection & Classification

The training performed on complete dataset that consists of two categories normal & diseased CT images. For detection, we used two classifiers ANN & SVM. The performance of these classification methods are investigated by dividing the training data into the ratio of 70 % training & 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.

F. Disease Grading

After detecting the liver disease using the classifiers, the final task of proposed model is to perform the disease grading for accurate medical analysis. The handcrafted feature helps for accurate grading analysis as compared to the automatically extracted features. Therefore, in this work we considered both handcrafted & automatic features extraction schemes. Next contribution presents the design of automatic features extraction. For the liver disease grading, we utilized the V^{norm} that contains the features in range of 0 to 1. We take the mean of V^{norm} & apply the rules for grading classification as:

$$grade = \begin{cases} 1, & if\ mean(V^{\text{norm}}) < 0.25 \\ 2, & if\ (mean(V^{\text{norm}}) > 0.25\ \&\&\ mean(V^{\text{norm}}) < 0.7) \\ 3, & if\ mean(V^{\text{norm}}) > 0.7 \end{cases} \quad (3.21)$$

The outcome of features value depends on the size of tumor, therefore, maximum tumor size leads to higher features value. This simplify the disease grading process either of three grades (1, 2, & 3). The grade 1 indicates the initial level cancer & grade 3 indicates the severe cancer.

CNN-LSTM Model

The combination that can boost the performance of the driver's action anticipation is CNN with LSTM model. RNNs & CNN face the problem of limited contextual information moreover the Back-Propagation, or Feed-Forward networks does not work suitably through time & generate either vanishing or exploding outputs of the network, which are an incorrect representation of data. This classical problem is termed as *vanishing gradient problem exploding gradient*. When the network is learning to bridge long time lags, it takes a huge amount of time or does not work at all, because of the vanishing gradient problem, which affects the quality of the network. Because of the inadequate error backflow, it takes a time to train. When a recurrent network or CNN tries to store information over much more long-time intervals, an important piece of information is getting lost over time. The LSTM is introduced here to minimize the error backflow difficulties in their network units. The LSTM improves the performance of RNN & CNN with the ability to generate all contextual information by bridging time intervals that too, with the low computational complexity of $O(1)$.

III. SIMULATION RESULTS

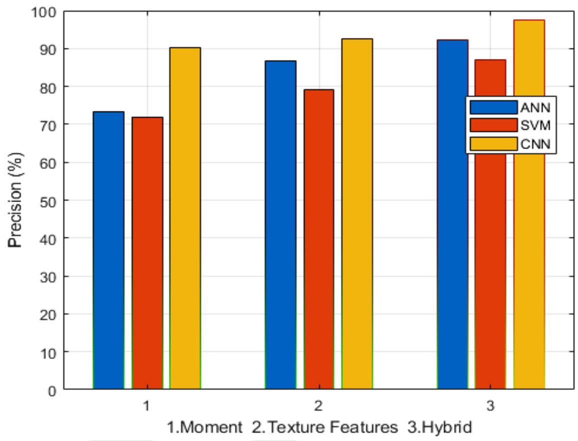

Figure 4.1 Precision analysis of proposed model

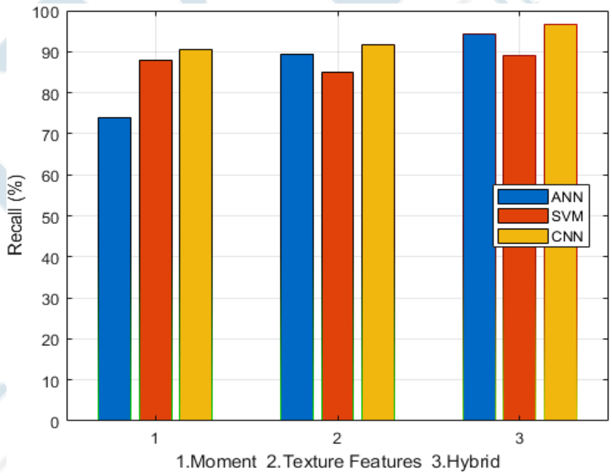

Figure 4.2. Recall analysis of proposed model

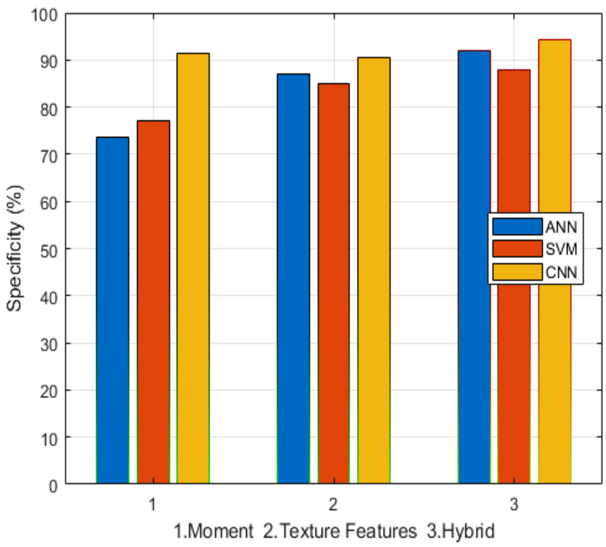

Figure 4.3 Specificity analysis of proposed model

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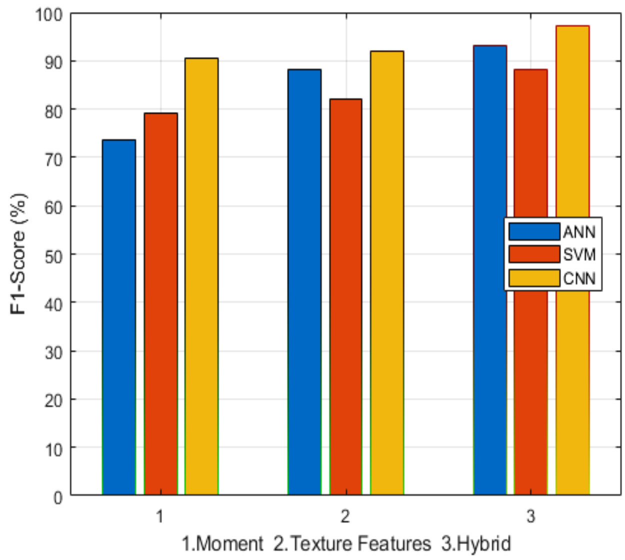

Figure 4.4 F1-score analysis of proposed model

Figure 4.1 & 4.2 demonstrates the outcome of precision & recall rates respectively. The precision & recall are important parameters for efficiency analysis of recognition systems. Both precision & 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 figures 4.3 & 4.4 demonstrate other important parameters such as specificity & 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.

4.1 Summary

This section presents the summarization of results & its comparative analysis with similar methods. Table 4.1 presents the comparative study among the different semi-automated techniques. Table 4.2 presents the comparative study among the automated methods.

In table 4.1, we investigated the performance of proposed model with recent techniques introduced in [16], [18], & [19]. All three methods similar to proposed model, thus included for comparative study. Table 2 shows the comparative analysis in terms of accuracy & average detection time. The proposed model shows the efficiency & robustness compared to all existing recent techniques. This is mainly because of using simple & accurate technique of ROI extraction & features extraction.

Table 4.1. Semi-automated state-of-art methods analysis

Methods	Accuracy (%)	Avg. detection time (seconds)
[16]	86.71	1.93
[18]	88.99	3.41
[19]	91.05	1.43
Proposed	92.67	1.13

Apart from this, we compared the performance of proposed model CNN-FN-LSTM with recently deep learning based models such as WGDL [31], EDCNN[32] & HFCNN [35] in terms of overall accuracy & average detection time in table 4.2. The exiting methods implemented using dataset mentioned used. From these results, it shows that proposed model improved the accuracy of classification & reduced the detection time as well.

Table 4.2. 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- LSTM	**98.67**	**4.78**

IV. CONCLUSION

The main scope of this research work was to design the optimized CAD tool for early liver cancer detection using image processing terminologies. This research study is considering the practical approach for evaluating the efficiency of proposed liver cancer detection method. In this research work, highly efficient & optimized CAD system development had proposed for liver cancer detection in its initial stage of configuration. The methods such as bilateral filtering for pre-processing, automatic ROI segmentation using the binary technique, hybrid features extraction (using hand-crafted & CNN features), features normalization, & classification.

V. FUTURE WORK

Design & investigate the different transform domain features for disease classification & grading. To investigate the hyperparameters using machine learning & deep learning classifiers. To extend this work for other types of cancers like brain tumor using the similar methodology.

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