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A ROBUST CT SCAN APPLICATION FOR PRIOR STAGE LIVER DISORDER PREDICTION WITH GOOGLENET DEEPLEARNING TECHNIQUE

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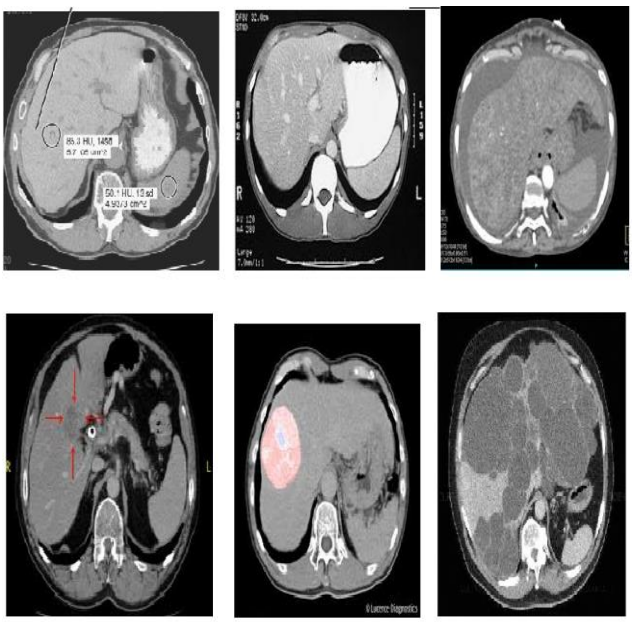
ABSTRACT

Recent technologies mainly concentrate on medical applications based on image processing tools. The medical image processing has recognized the different diseases with fast diagnoses, such as lung, heart, brain tumour and liver. The earlier stage of disease diagnosis helps to identify appropriate disease treatment. In this investigation, CT scan based liver disease or disorders have been predicted and classified based on the GoogleNetCNN(Convolutional neural networks) deep learning algorithm. At the initial stage, the local threshold (LT) segmentation model and at the classification stage Improved GoogleNet CNN deep learning model applied on selected real CT liver images. This work mainly focuses on liver disorders prediction and disease identification using CT liver medical images. The proposed LT-GoogleNet CNN deep learning model diagnosis the liver diseases with real and accurate manner. Here we used the two different algorithms to identify the black and white pixels on the given data set CT images to remove noise on the practical image to get proper and good accurate results. The performance measures such as precession, accuracy, PSNR, CC and time of diagnosis has been improved. At final implemented LT-GoogleNet CNN deep learning model compared with existed methods, conclude that this mechanism is efficient. After doing the practical values we got using the mentioned proposed method Google Net CNN prediction probability is good accuracy as 98 and precession 98.6, Recall 98.3, F1 score 98.4, PSNR 59.8, CC 99.83predection of liver disease is verified using the different database ANDI-1 and ANDI-2.

Keywords: CT scan, liver medical image, local segmentation, LT- GoogleNet CNN, niblack, sauvola algorithm.

1. INTRODUCTION

Nowadays, developing technologies have classified CT liver images for various diseases. MRI scan is a significant medical image diagnosis in radiotherapy; in this scanning, powerful magnetic resonance rays are used to scan the soft tissues. MRI scanning is an important imaging technology to identify superior soft tissues. But, this MRI imaging does not alone in radiotherapy; therefore, CT scan comes under picture [1]. The CT images, quality and accuracy, is more for diagnosis structure of the tissues. The average mean absolute error is 80%; it is more compared to traditional techniques. The mean, median and variance are 0.17, 0.18 and 0.15; respectively, these values have to be improved. The image SSIM and feasibility was achieved less accurate at CT generation method [2]. In [3], Leiy *et al*. demonstrates that MRI and CT based semantic RFO method for liver disease classification. In this research work, 14 patients datasets with B1 weighted MR and CT liver images are evaluated. S. kazemifar *et al* [4] in this work, MR images noise, has removed by using de-noise filters. The de-noise filters are used to remove the noise layers at various places selected in medical liver images. Various filters like a median filter, average filter and adaptive filters are used to improve the white additive noise in MRI liver images. W. Schneider *et al* [5] explains about impulse noise removal filter design, and LULU filter design is implemented and achieved 0.05improvment in noise density. In this work, the median filter and LULU filter non-linear designs are implemented for quality metrics like PSNR and RMSE improved to 49dB and 0.32, respectively. P. Qian [6] in this work classical entropy clustering algorithm and a fuzzy logic algorithm is implemented for CT liver scanning and classification. The clustering pattern recognition experiment has demonstrated with real-life datasets. This investigation achieves more threshold values compared to implemented methods. P. Qian *et al*. [7] explains about knowledge leveraged fuzzy C algorithm; this method can implement accurate liver diagnosis process with accurate results. Jzhou *et al* [8] describe that multiview maximum entropy model for medical images. View collaborative multi-model attribute mechanism efforts the threefold image analysis; this entire mechanism gives more accurate results. Y. jiang *et al* [9] explain that recognition of EEG data for liver diagnosis process, the fuzzy system named as takagi-sugeno-kang has evaluated the modern liver diseases with classification. This implemented model promising accurate outcomes compared to existed models.



d) Male 35years CT liver e) Female 24 years CT liverf) Detection of noise image

Figure-1. a) Female 32 years CT liver. b) Male 28 years CT liver. c) CT output image.

Figure-1 explains about various orientations of CT liver images are collected for different investigations from ADNI-1 and ADNI-2 datasets. Using this CT liver images to diagnosis the corresponding disease based on local threshold segmentation as pre-processor and SVM is used as feature extractor, classifier. LT-GOOGLENET CNN methodology is used to trace out the diseases of the liver in an accurate manner. The above all four CT liver images are given as inputs of LT-GOOGLENET CNN method and obtain the disease identified image as output.
The multi-task fuzzy modelling system is used to identify the structural medical image analysis. L2-norms and classical fuzzy system effectively interact the common hidden layers on the medical liver images and easily identify the tumours in the liver. This analysis is useful for real-time fast diagnosis system. The experiment results for implemented multi-task fuzzy system gives an accurate real-world improvement in [10]. The artificial intelligence algorithms had utilized for training the MR images with the segmentation process. This automatic disease classification method can help the fast diagnosis and accurate results generation. The multi-task fuzzy schemes avoid the false effects caused by various noise in MR images. In this investigation, the experimental outcomes demonstrate improved performance than classical methods [11]. Recognition of EEG signals and MRI liver images have been evaluated with supervised learning fuzzy system. The machine learning approach is superimposed on classical medical images with the help of testing and training datasets. Finally classifies the liver-related disorders, this mechanism can help for seizure patients diagnosis purpose in [12]. The fuzzy clustering and collaborative fuzzy algorithm can easily handle the medical image disease diagnosis process with efficient results. This work is more suitable compared to k-means optimization; existing models cannot solve the many diagnosis issues and multi clustering parameters. The implemented multi-task algorithms were promising the accuracy and throughputs [13]. The computer-aided design has classified the existing tumours in the liver. These datasets are collected from various research organizations, utilizing these datasets compare our real-time CT medical images. This work is implemented based on sparse component analysis and artificial neural networks. Finally, results were detected and classify the various liver disorders [14]. Generally, different diagnosis process can identify the various liver disorders based on shape, location and sizes of the image. This implementation was designed by SVM classification method with the help of gliomas dataset and improved results challenging the modern technologies. But, the future extraction stage is missing before the classification, so we need to implement and future extraction and classification for liver diagnosis system [15].

In this work, explains about [23] deep learning mechanisms and object detection models clearly. This technique helps medical image processing analysis. In this work, machine learning models have investigated clearly. The CMS Edge detection process has used to identifies the digital image classifications [24]. In this work Logistic Regression Machine Learning Algorithm On MRI Liver Image for Fast and Accurate Diagnosis is examined [25]. Image denoising and its classification models are reviewed for disorders in Medical liver images [26]. This survey is most useful for identifies the many techniques supported for Liver diagnosis process. In [29] explains about liver tumor detection based on level set and chanvese segmentation models, these are more efficient in pre-processing of a medical image training. This investigation explains about a novel approach for MRI-CT based CWT techniques on medical images. These above all literature gives the better examination of medical image and its easy diagnosis process.

2. METHODOLOGY LT-GOOGLENET

The local threshold segmentation is applied to patients CT scan liver images for pre-processing. The entire investigation generally divided into three steps such as pre-processing, feature extraction and classification. Pre-processing stage CT scan liver medical images are segmented with LT segmentation method. The segmentation is a fundamental step in any image processing applications. Computer vision applications like medical image processing, pattern generation and many spectral image classifications. In the local threshold segmentation process, CT liver image is separated into particular regions and apply the critical analysis. After the 1st phase, grey pixel and white pixels have to be differentiated from background and object image. The local thresholding is a useful tool to identify the disorders in medical images. The main functionality of the LT method is to binarize the greyscale pixels with low contrast parameter. In local thresholding, two types of algorithms are applied to the selected medical image. They

are Niblack LT and sauvola LT segmentation algorithms. After this segmentation GOOGLENET CNN feature extractor and classifier are performed. Finally calculated the accuracy PSNR SSIM, F1 score performance measures.

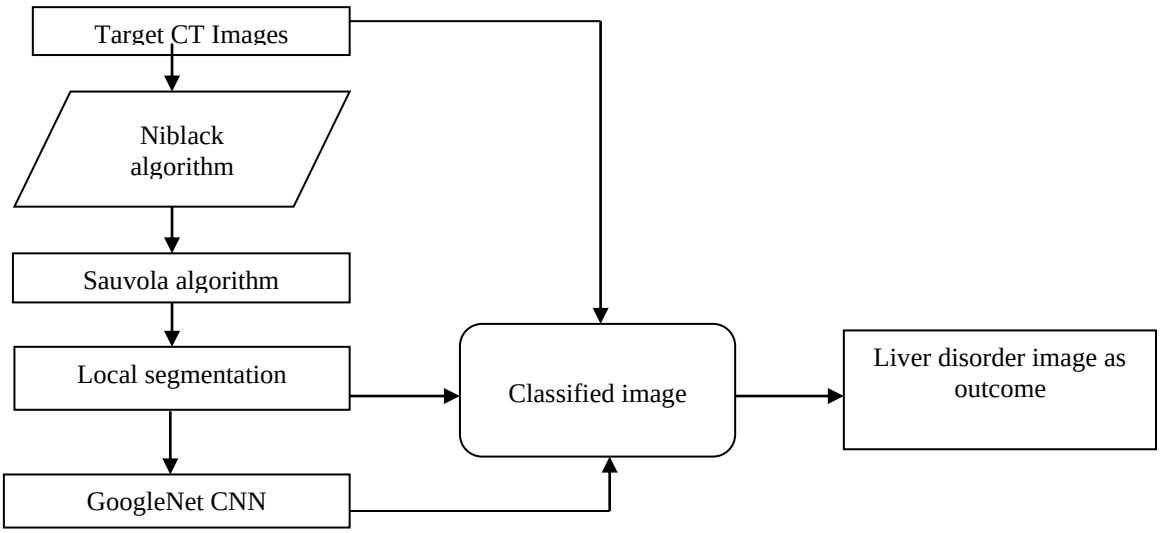


Figure-2. Training process of the proposed algorithm.

The above block diagram explains about detailed notes of pre-processing and classification on liver disorders identification system. At the 1st phase, target CT liver images are collected for pre-processing, in pre-processing image acquisition, and Local segmentations are applied for primary data collection. The classification is performed using the GOOGLENET CNN technique with this tumour is identified effectively; the overall mathematical representation is shown in equation 2 to 6

3. PREPROCESSING

3.1 LT Niblack Algorithm

This algorithm is specially designed for local threshold segmentation purpose [23], Niblack method mainly focuses on local mean and standard deviation computational step. These two statistical parameters are utilized to find out the threshold value for Niblack optimization. Using this local thresholding method find out the object in the CT scan liver image. The Tn(X, Y) demonstrate that Niblack thresholding value.

$$T_n(X,Y) = m(x,y) + k \cdot s(x,y) \quad (1)$$

Here *m(x,y)*= local averaging area.

S(x,y)= Standard deviation.

The above equation "1" is used to find out the threshold value for grey pixels of the object image. Size of the neighbour pixels should be less enough to preserve the local values. But, at the same time, suppress noise value should be substantial. In this k is the adjustment boundary value for a print object in the selected CT scan liver image.

Step 1: Input image
Step 2: Processing
Step 3: Object image
Step 4: Output

3.2 Sauvola Algorithm

For local threshold segmentation process, this method is used. $T_{sauvola}$ is a background threshold value at a particular CT scan image of liver. By using equation 2, mean and standard deviations are measured, in this k value with positive with range from 0.5 and $T_{sauvola}$estimated threshold value. By using image region R, mean and standard deviation $T_{sauvola}$ value is calculated. If value is in between S~R, high contrast is observed and for low contrast $T_{sauvola}$ ~ m is observed. If threshold value is less than mean value, then dark region is removed successfully. Threshold value is controlled by parameter 'k', and k value is adjusted from 0.34 to 0 and they are sensitive to k.

$$T_{sauvola} = m * (1 - k * (1 - \frac{s}{R})) \quad (2)$$

Step 1: Algorithm 1 output image
Step 2: Calculate the background image
Step 3: Find out the local segmentation image
Step 4: Output image.

3.3 Feature Extraction and Classification: Improved GOOGLENET CNN

GOOGLENET CNN is a highly classified feature extractor; this can be used to identify the problems in the medical images easily. Improved support vector machine (GOOGLENET CNN) is working based on rough set theory. This optimization mechanism can decrease the feature sets at the second stage. The reduction of original results quicker and real outcomes. The GOOGLENET

CNN consists of two stages at first step conditional attributes are analysed for a set of frames. Then reduced dataset will be classified by GOOGLENET CNN classifier. The early stage is nothing but feature extractor, and the second stage is the classifier algorithm [29].

Step 1: Decision information
Step 2: Discrete the decision
Step 3: Dataset reduction
Step 4: Additional information training
Step 5: Execute the GOOGLENET CNN classifier
Step 6: Return to step 1
Step 7: Stop the process.

$$F_{F,c}(j) = \sum_{i=1}^{n} w_c\,(i)\,F_{D,c}(i,j) \quad (3)$$

Equation 3 explains about fitness function of GOOGLENET CNN and W is the weight estimator, and FD is the local function. These all parameters are helping for fitness function classification.

$$e^2 = \sum_{j=1}^{N_c}\left(F_{R,c(j)} - F_{F,c}(j)\right)^2 = \sum_{j=1}^{N_c}\left[F_{R,c}(j) - \sum_{i=1}^{n} w_c\,(i)\,F_{D,c}(i,j)\right]^2 \quad (4)$$

Equation 4 explains about local entropy value for estimating the image disease for feature extraction. Based on this we can reduce or extract the features with efficient manner, here FR, C is the region of a local function, and FC is the local fitness function statistical values. All parameters can help the calculation of entropy.

$$\frac{\partial e^2}{\partial w_c(k)} = \sum_{j=1}^{N_c} 2F_{D,c}(k,j) \times \left[F_{R,c}(j) - \sum_{i=1}^{n} w_c\,(i)\,F_{D,c}(i,j)\right] = 0 \quad (5)$$

Equation 5 demonstrates that improved entropy value for calculating the classification parameters. This equation can give the feature extraction of a dataset. Therefore, the classification is performed efficiently.

$$\begin{bmatrix} w_c(1) \\ w_c(2) \\ \dots \\ w_c(n) \end{bmatrix} = \begin{bmatrix} \sum_{j=1}^{N_c} F_{D,c}(1,j)\,F_{D,c}(1,j) & \cdots & \sum_{j=1}^{N_c} F_{D,c}(1,j)\,F_{D,c}(n,j) \\ \sum_{j=1}^{N_c} F_{D,c}(2,j)\,F_{D,c}(1,j) & \cdots & \sum_{j=1}^{N_c} F_{D,c}(2,j)\,F_{D,c}(n,j) \\ \cdots & \cdots & \cdots \\ \sum_{j=1}^{N_c} F_{D,c}(n,j)\,F_{D,c}(1,j) & \cdots & \sum_{j=1}^{N_c} F_{D,c}(n,j)\,F_{D,c}(n,j) \end{bmatrix}^{-1} \times \begin{bmatrix} \sum_{j=1}^{N_c} F_{D,c}(1,j)\,F_{R,c}(j) \\ \sum_{j=1}^{N_c} F_{D,c}(2,j)\,F_{R,c}(j) \\ \cdots \\ \sum_{j=1}^{N_c} F_{D,c}(n,j)\,F_{R,c}(j) \end{bmatrix} \quad (6)$$

Equation 6 explains about confusion weight classification matrix, and this matrix can find out the diseases by labelling the area of illness. This mathematical expression solves the disease classification issue and give accurate results [24-25]. Based on weights classifies the liver disorders with indication. Finally, this work is mainly concentrating on liver disorders and diseases classification quickly.

3.4 Performance Metrics

These mentioned performance measures calculated the designed model efficiency and throughput. Mean Square Error (MSE), PSNR (Peak to signal ratio), F1 Score, SSIM structural simulation index and standard deviation mathematical computations are illustrated below.

$$\mathrm{MSE} = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

$$\mathrm{PSNR} = 10\,\log_{10}\left(\frac{R^2}{\mathrm{MSE}}\right)$$

$$\text{F1 Score} = 100 \times \frac{\mathrm{PSNR} \times \mathrm{SSIM} \times \mathrm{Contrast}}{\mathrm{Std.\,Dev} \times \mathrm{MSE}}$$

$$\sigma = \sqrt{\frac{1}{N \times M}\sum_{i=0}^{N-1}\sum_{j=0}^{M-1}\left(x_{ij} - \mu\right)^2}$$

σ =standard deviation

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x + \mu_y + C_1)(\sigma_x + \sigma_y + C_2)}$$

4. RESULTS AND DISCUSSIONS

The medical image processing and applications differentiate the healthy and disorders in the diagnosis process. The diagnosis process decides the treatment with efficient, filters and image acquisition methodologies already in usage. Along this segmentation and classification outperform the diagnosis process. In this mechanism, the local segmentation and improved GOOGLENET CNN classification have performed for better diagnosis process.

Using the two different methods like Niblack and Sauvola methods to find the black and white pixels for predicting the affected area. We gathered data sets from medical websites like ANDI-1 and ANDI-2 and also some real time based images. by using the GoogleNet CNN classification technique I got more accurate results when compare to existing method using this proposed technique whereas F1 score, accuracy, PSNR etc. The CT scan images we got from Brats website and the outcome results that are explained in the table below based on the parameter values.

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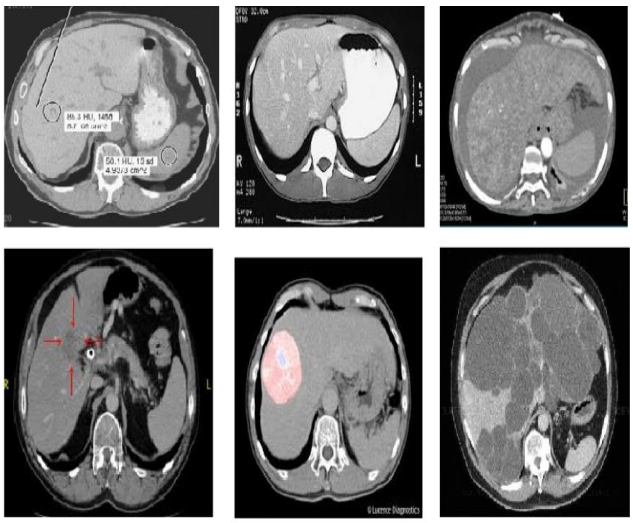

Figure-3. Input CT image.

These are the CT scan-images, which are collected from BraTS 2019 liver data sample, and this is a free dataset available at BraTS website. It is a combination of many CT scan Liver images consists of various orientations. In this oriented images, some of having a healthy liver, and some of have tumour content images. The Female -32, Male-28, Female- 60…… such variant images are collected from the available dataset. CT scan liver images consist of tumours and diseases. Figure-3 is applied to the proposed LT-GOOGLENET CNN optimization model; this technique segments the input images and classify the tumours.

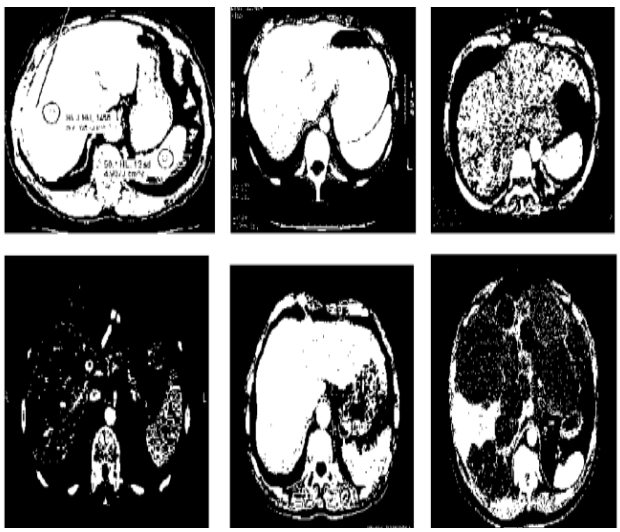

Figure-4. Local segmented images.

The Figure-4 explains about segmented images by using Sauvola & Niblack local segmentation. This method differentiates the input image for the identification of tumours in the liver. After CT scan, scanned liver image does not provide actual information in the liver. Therefore, apply a segmentation and image acquisition models such that complete information is obtained such as tumours or diseases.

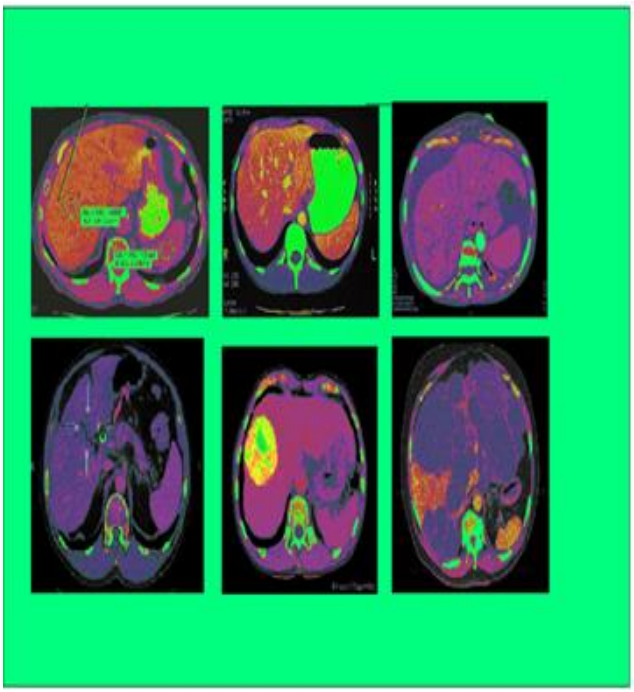

Figure-5. GOOGLE NET CNN classifier.

The improved GOOGLENET CNN is a machine learning algorithm; it can solve the medical image processing issues accurately. After the segmentation process, the segmented image has processed to improved entropy and improved entropy mathematical computations. Which are shown in the above equations 4, 5, 6 clearly.

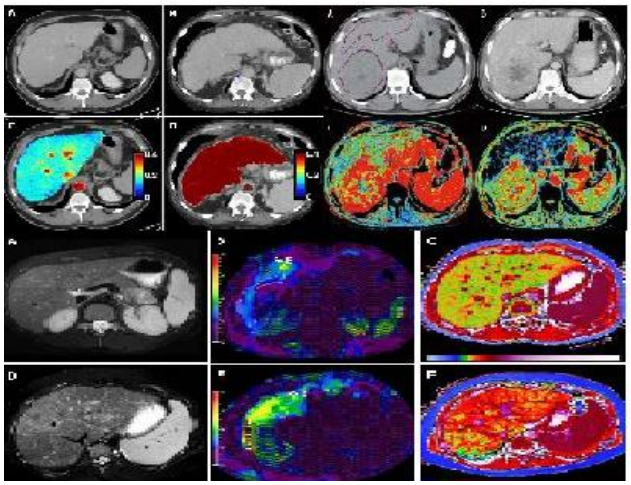

Figure-6. Data set final GOOGLENET CNN classifier

This above Figure-6 represents a transparent model of GOOGLENET CNN classification technique, in this work tumour and disorders are identified with colour indication. In the above picture, 3 -types of liver tumours are identified with the help of LT-GOOGLENET CNNmodel. The GOOGLENET CNN machine learning model achieves more performance improvement by using the above mathematical equations.

Table-1. GOOGLENET CNN prediction.

S. No.	Parameter	LT-GoogleNet Proposed Method	HOG-SVM [1]	SVM [17]	PSO [11]
1	GOOGLENET CNN Prediction Probability	[[3.95673555e-04 1.36897920e-19 9.00998259e-11 5.52006615e-78 9.99604326e-01]]	-	-	
2	Accuracy	98.33516483516482	85.61	71.52	78.12
3	Precision	98.63516483516483	92.25	63.72	52.78
4	Recall	98.33516483516482	92.21	64.63	63.54
5	F1 Score	98.43516483516483	92.23	64.17	63.78
6	PSNR	59.83516483516482	XX	XX	52.15
7	CC	99.83516483516484	88	0.85(SVM seg net)	98.22

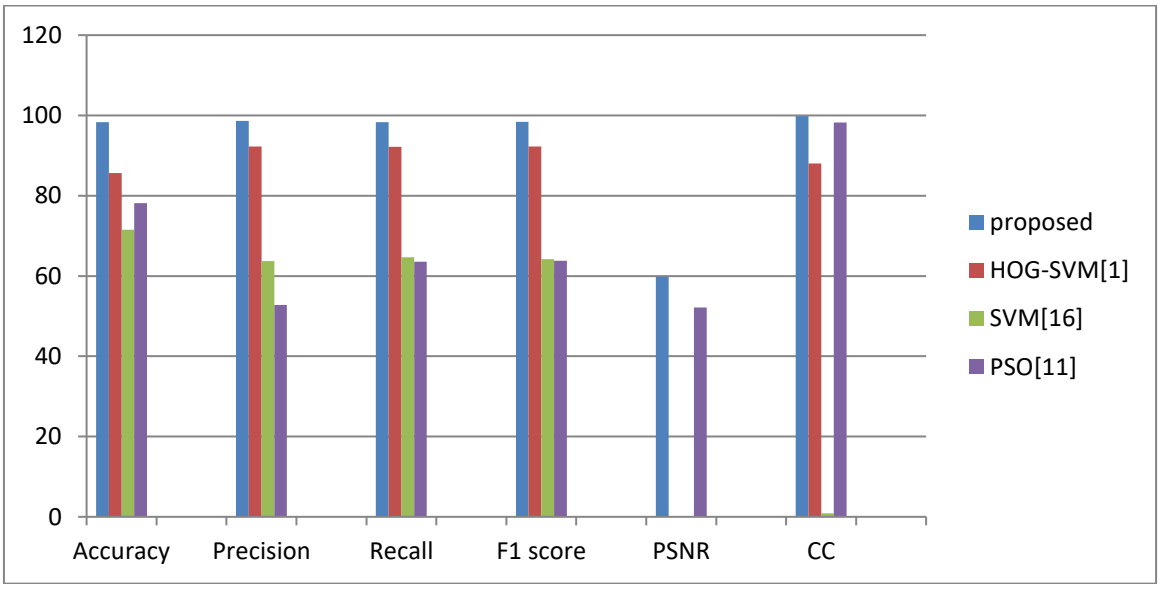

Figure-7. Comparisions of results.

Figure-7 explains about the overall comparison of PCA-KNN, PCN-RBF and LT-GOOGLENET CNNmodel. At every stage, the PSNR, SSIM, F1 score, CC and accuracy have attained more compared to existed methods. The graphical representation of results demonstrates that implemented LS-GOOGLENET CNN more efficient.

5. CONCLUSIONS

In this paper, the liver tumours and disorders have identified with fast diagnosis process using LT-GOOGLENET CNNtechnique. The proposed method not only solves the liver disorders and tumours diagnosis process. But, also deals with treatment fast up process, this investigation helps researchers, doctors and diagnostic centres. The data collected from the BraTS Live datasets from 2019 historical data and the source available in the same website, collected data and applied proposed method LT-GOOGLENET CNN model is useful to identify the tumours based on the input given and classify the results. The methods that we are sued in this two threshold limits niblack and sauvola method to identify the affected area based on the white and black pixels. let us say example Female-32 and Male-28 and Female 60 years different types of age groups images are collected and find out the more accurate observations using the available datasets. accurate results based on the affected area. The above graph shown how much accurate giving after using the proposed method. The performance measure decides the efficiency of the system, i.e. PSNR, CC, SSIM & efficiency. The peak to signal noise ratio 59.8%, correlation coefficients 99.83%, structural simulation index 97.8 and accuracy 98.33% achieved. This result outperforms the existed methods and LT_GOOGLENET CNN challenging modern technologies.

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