



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

IJIRSET

International Journal of Innovative Research in
SCIENCE | ENGINEERING | TECHNOLOGY



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 10, Special Issue 2, December 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.569

Classification of Lesion in 3D CT Liver Image Using 3D-CNN Based on GLRLM Feature Extraction

A.Bathsheba Parimala^{1*}, R.S.Shanmugasundaram²

Research Scholar, Vinayaka Mission's Research Foundation, Salem, Tamil Nadu, India¹

Professor, Vinayaka Mission's KirupanandaVariyar Engineering College, VMRF, Salem, TamilNadu, India²

ABSTRACT: CT imaging is considered as most reliable techniques for non-invasive diagnosis. In this paper we used 3D CT images for the classification of cancerous tumor in the liver. The dimension reduction is applied in 3D CT image using PCA(Principal Component Analysis) . Noise is reduced by 3D median filter and Data Augmentation techniques are implemented, Random Forest Algorithm gives the segmentation of the abnormal part of the liver. GLRLM features are extracted using Pyradiomics of Python and fed to 3D CNN classifier for Haemangioma and Cancer Tumor. The result is compared with other models and found that our model give better performance. The performance metrics is evaluated for our model that gives an accuracy of 98.6% for train dataset and 96.66% for test dataset.

KEY WORDS: Liver lesion, Computed Tomography, Principal Component Analysis, Augmentation, GLRLM, Pyradiomic, 3D-CNN.

I. INTRODUCTION

Liver Cancer is one of the dangerous diseases that mostly lead to death worldwide. The abnormal liver tissues starts growing rapidly without control and spread to other parts of the body (metastasis) is termed as primary Liver Cancer and the cancer tissues developed in other parts of the body conquer the liver and causes tumors [1] which is termed as secondary Liver Cancer. Liver Cancer is commonly termed as Hepatocellular carcinoma (HCC). For the detection, diagnosis and staging of liver tumors, computed tomography (CT) is the most widely used imaging method. It is also beneficial to physicians to segment the lesions so they can make the selection of treatment easier.

Data augmentation is used in this paper to increase the dataset size. This helps in machine learning algorithms to learn more features that leads to more accurate prediction. Since 3D CT images are used, Dimension reduction without affecting the originality of the features is needed and carried out by PCA. De-noising is performed by 3D Median filter. Liver image is extracted from 3D CT scan image using watershed algorithm. Random forest is the most promising algorithm that gives lesion segmentation.

3D CT images can render more features than 2D images and can be extracted using GLRLM algorithm with the help of Pyradiomics of python. GLRLM (Gray Level Run Length Matrix) measures gray value runs as the number of pixels between successive pixels with the same gray value. Convolution Neural Network is an advance network among machine learning algorithms that uses number of layers of nodes to achieve high-level functions from input information.

In the second phase of classification 3D Convolution Neural Network algorithm [2] is used to classify the tumor as cancer tumor (HCC) or ordinary lesion or Normal liver.

The remaining topics reveals the proposed work: The various work related to this proposed work are presented in section2 under the topic “Related works”. The architecture of the proposed model with dataset splitting, pre-processing, segmentation and classification are depicted under section3 and explained. Section4 discusses the result and analysis of the proposed work with confusion matrices. Finally the conclusion is made under section5.

II. RELATED WORK

Anju Krishna et.al [3]used a modified Segmentation-based Fractal Texture Analysis (SFTA) algorithm to get the features of tumor . the extracted features are employed in the classification algorithm for further classification. For the classification process support vector machine (SVM) was used. This study compares the performance of SFTA based multi SVM classifiers with modified SFTA-based multi SVM Classifiers.

T. Dhiliphan et.al [4] uses Support Vector machine for classification. Abdomen CT images are used .The tumor in the liver was classified in to normal and abnormal. In the first phase liver was segmented using morphological operations. The features were extracted using GLCM method and fed to the SVM classifier. The tumor got segmented if the liver is abnormal.

A Region growing technique is used by A.Keerthana et.al[5] to segment the ROI. The textural feature are extracted from Gray level co-occurrence matrix (GLCM) of the segmented image. Extracted textural features are given as input to the designed SVM classifier system. Performance analysis of SVM classification of CT liver tumor image is studied. This will be useful for physician in better automatic diagnosis of liver tumor from CT images.

A cascaded training model was implemented by Lei Chen et.al [6] for the segmentation of liver lesions from CT volume images. The segmentation process was carried out with two stages by designing two networks. First the liver was segmented and consecutively the tumor was also segmentd. Multi plane integrated network was used to segment the liver tissue from 3D CT volumes. For segmenting the tumor, 3D DFCN(Densey connected fully convolution Network) was used.

Lu Meng et.al [7] proposed a 3D dual path multi-scale CNN (TDP-CNN) based on CNN for the segmentation of liver.A dual path was used in order to balance segmentation performance and computational requirements. At the end of the paths, the feature maps of both paths were merged. In order to improve segmentation results, CRF(conditional random fields) were used so that the over segmentations were removed thereby improving the accuracy.

R. Manjula Deviet.al[8], implemented a system for classification of liver lesion . Three stages were employed. In the first stage liver is segmented and the lesion is detected. In the second stage, the features were extracted and in the last stage classification was carried out using a new support vector machine classifier. A feature difference method based on contrast was adopted in the classification process.AHS (adaptive-hybrid segmentation), CT (contourlet transform) and the ELM (Extreme learning Machine are used by D.Selvathi et.al.[9] for diagnosis of liver tumors in computed tomography images. Adaptive threshold method with morphological methods are used to segment the liver. FCM was used for tumor extraction. CT based algorithm gives the textural and statistical features from the tumor region. Using the features, ELM gives the classification of the liver tumor.

A. Bathsheba parimala et.al.[10] improved the accuracy in the classification and staging of Liver tumor using 3D-CNN combined with GLRLM features. Segmentation based on region growing is applied to extract the tumor part. Liver 3D-CT images and 3D-US datasets are used separately and the results are analyzed. Classification in 3D-CT produce greater accuracy compared with the classification in 3D-US images.

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

III. PROPOSED MODEL

3.1 Model Architecture

The Proposed Architecture is executed in five phases. First the data set are splitted for training and testing then in the second phase, pre-processing is employed where de-noising, Dimension reduction and Liver extraction is carried out. The third phase consists of segmentation of lesion region where Random forest algorithm is implemented. In the fourth phase, feature extraction is achieved through GLRLM based on pyradiomics of python. The complete Model is depicted in Fig-1.

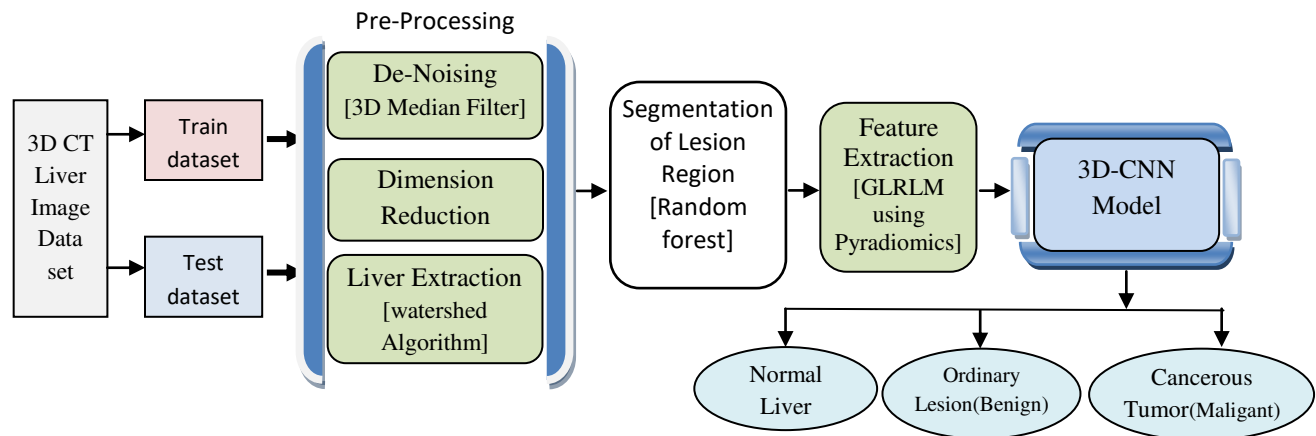


Fig-1 Architecture of proposed Model

3.2 Data Set

Data set contains 500 3D Liver CT (Computed Tomography) image and all the images are in DICOM format. Among the 500 images, 50 images correspond to Normal Liver, 150 images with Ordinary Lesion and 300 images with Cancerous tumor.

Grade	Training	Testing	Total
Normal Liver	35	15	50
Ordinary Lesion	105	45	150
Cancerous Tumor	210	90	300
Total	350	150	500

Table-1 Data splitting before Augmentation

Data set has been split in to training set(70%) and testing set (30%). Nearly 350 images are allotted for training[35-Normal,105-Ordinary Lesion, 210-Cancerous Tumor] and 150 for testing [15-Normal,45-Ordinary Lesion, 90-Cancerous Tumor].

Data Augmentation is carried out to increase the number of images in the dataset. Three affine transformation(rotation, flipping, brightness change) is employed for data augmentation so that one image is transformed to three image and the data set size increased to 1500. After augmentation, 1050 images generated for training[105-Normal,315-Ordinary Lesion, 630-Cancerous Tumor] and 450 for testing[45-Normal,135-Ordinary Lesion, 270-Cancerous Tumor]. Splitting of dataset after augmentation is shown in table-2.

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

Grade	Training	Testing	Total
Normal Liver	105	45	150
Ordinary Lesion	315	135	450
Cancerous Tumor	630	270	900
Total	1050	450	1500

Table-2 Data splitting After Augmentation

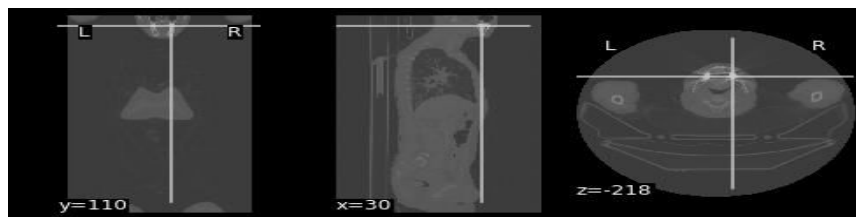


Fig-2 Sample input image

3.3 Preprocessing

3.3.1 Denoising

3D Median filter is used for De-noising the image. The edges are retained when using this filter. 3D median filter uses 3D parallelepiped window to process volume image elements (voxels). 3x3x3 mask is used to get noise free image. The median value of the neighbourhood is replaced with each voxel value. Each voxel is set to the median value of its neighbourhood. Among the 27 values from 3x3x3 filter, The median is calculated and that value is replaced.

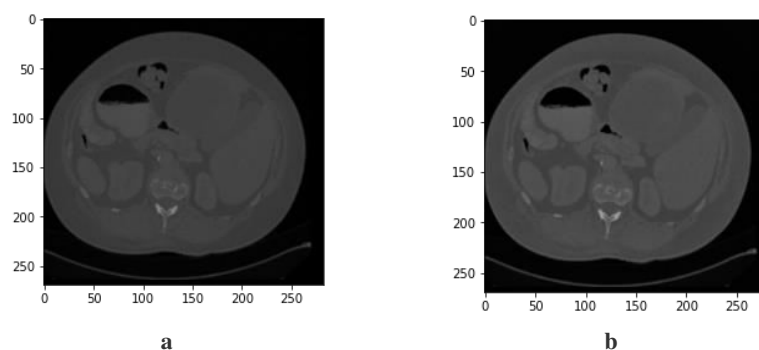


Fig-3 a-Before De-noising b- After De-noising

3.3.2 Dimensional Reduction

Since the data is having large dimension, problem will arise in inputting the image and processing it with the python program which takes very large time for execution of such large dimensional images. So it is necessary to decrease the dimension of the images by projecting it to another dimensional space. Principal Component Analysis(PCA) is used where the necessary information needed for machine learning process is retained.

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

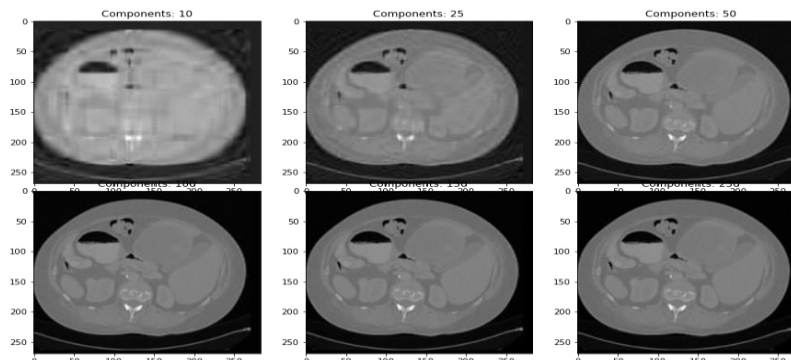


Fig-4 PCA Liver Components

3.3.3 Liver Extraction

For Liver extraction 3D watershed algorithm is used. It is possible for two seeds to grow at different rates; the one with higher values will grow faster than the one with lower values. With the seeded version implemented in 3DWatershed, voxels with a higher value will be aggregated first to the seeds. Spatial and temporal directions are considered by growing the region in both the directions. Just as a two dimension watershed represents a region boundary by a line of pixels, three dimension watersheds represents a region boundary by a surface comprised of pixels.

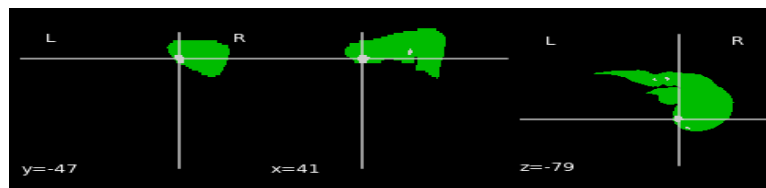


Fig-5 Liver Extraction

3.4 Lesion Segmentation

Lesion segmentation is carried out using RF (Random Forest) algorithm. RF is based on ensemble learning with supervised machine learning. In Ensemble learning, different algorithms combined or one algorithm with many times to get more accurate prediction. RF algorithm is a combination of many decision trees. It is suitable for regression as well as classification. The steps to perform the RF algorithm:

1. From the dataset choose n random records
2. Based on these n-records build a decision tree
3. The no. Of trees needed are chosen and step1 and step2 are repeated.
4. For classification, the trees predicts the category to which the new record belongs. Records are assigned to categories that receive the greatest number of votes.

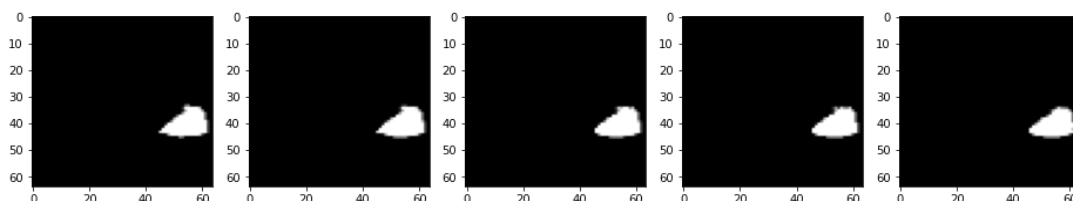


Fig-6 Segmented Image

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

3.5 Feature Extraction

This Pyradiomics package extracts radiomics information from medical images using an open-source python framework. Using SimpleITK, images are first loaded and preprocessed (e.g. cropping & resampling). After data has been loaded, numpy arrays are used for further calculation using multiple feature classes.

Pyradiomics is an open-source python package for the extraction of radiomics data from medical images. Image loading and preprocessing (e.g. resampling and cropping) are first done using SimpleITK. Loaded data is then converted into numpy arrays for further calculation using multiple feature classes. [10] GLRLM (Gray Level Run Length Matrix) measures gray value runs as the number of pixels between successive pixels with the same gray value.

For a given image, the pair (i, j) of a run-length matrix (i, j) is defined as the run-number of gray level i and run length j , as described in Figure 9. Hence, the GLRLM measures how many times there are runs of j consecutive pixels with the same value, with j going from 2 to the length of the longest in a fixed orientation. Although it is possible to define several GLRLMs for a single image, Four matrices, one for each direction, are normally computed including diagonal directions. The matrix P has the size $(M \times N)$, where M is equal to the maximum gray level and N is the possible maximum run length in the corresponding image. The typical directions are 0° , 45° , 90° , and 135° , and calculating the run-length encoding for each orientation will produce a run-length matrix.

Normally four matrices are computed, for the horizontal, vertical and diagonal directions.

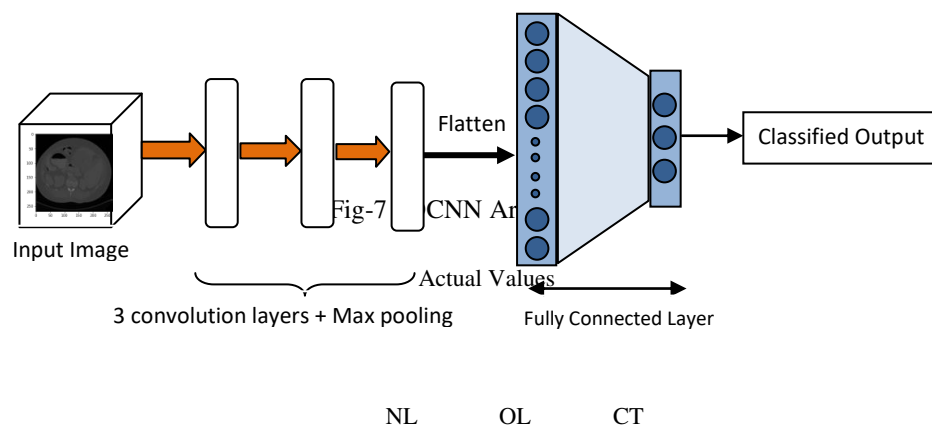
	Min	Max
radius (mean):	6.981	28.11
texture (mean):	9.71	39.28
perimeter (mean):	43.79	188.5
area (mean):	143.5	2501.0
smoothness (mean):	0.053	0.163
compactness (mean):	0.019	0.345
concavity (mean):	0.0	0.427
concave points (mean):	0.0	0.201
symmetry (mean):	0.106	0.304
fractal dimension (mean):	0.05	0.097
radius (standard error):	0.112	2.873
texture (standard error):	0.36	4.885
perimeter (standard error):	0.757	21.98
area (standard error):	6.802	542.2
smoothness (standard error):	0.002	0.031
compactness (standard error):	0.002	0.135
concavity (standard error):	0.0	0.396
concave points (standard error):	0.0	0.053
symmetry (standard error):	0.008	0.079
fractal dimension (standard error):	0.001	0.03
radius (worst):	7.93	36.04
texture (worst):	12.02	49.54
perimeter (worst):	50.41	251.2
area (worst):	185.2	4254.0
smoothness (worst):	0.071	0.223
compactness (worst):	0.027	1.058
concavity (worst):	0.0	1.252
concave points (worst):	0.0	0.291
symmetry (worst):	0.156	0.664
fractal dimension (worst):	0.055	0.208

Table-2 GLRLM Features using Radiomics

3.6 Classification using 3DCNN

A 3Dconvolution neural network (CNN) is one type of artificial neural network with more than three layers and the outputs of the neuron are applied iteratively to their own inputs. The algorithm integrally performs the classification and directly forms the decision-making function.

In this particular work, we developed a 3DCNN using the Keras that uses Tensorflow library and python programming language. The architecture of our proposed 3DCNN is presented . We have built our 3DCNN model empirically after performing various experiments. During each experiment, we have manually constructed a CNN by modifying the subsequent parameters like the number of hidden layers, the learning steps for each hidden layer, the activation function and the total number of neurons required to form the layer. During the configuration,divided the dataset into training and testing set. The classification accuracy is evaluated over the testing set. The CNN classifier used the ReLU activation function. The output layer be determined by on Softmax function relies on the cross-entropy as a cost function. The performance of the classification was evaluated using a convolution neural network (CNN).In CNN, it is required to balance the data set otherwise the classifier will produce error function. A detailed description of training and testing sets for our proposed CNN network is reported in Table 1. The entire data set was divided into 7:3 ratio and used to form the model.



Predicted Values	NL	102	2	3
	OL	2	310	4
	CT	1	3	623

NL → Normal Liver
OL → Ordinary Lesion
CT → Cancer Tumour

Fig-8 Confusion Matrix - Training

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

$$\text{Training Accuracy of the Model} = \frac{\sum \text{Right Diagonal elements}}{\sum \text{All the elements}} \times 100 = 98.66\%$$

IV. RESULT AND DISCUSSION

The proposed model is well trained up to a fair accuracy since data augmentation has been used and tested with 450 test images. In that the model predicts 435 data correctly and 15 data wrongly. The proposed model gives an accuracy of 98.66% during Testing. The error-matrix ie. confusion matrix for three classes produced by the model during testing is given in Fig-9.

		Actual Values		
		NL	OL	CT
Predicted Values	NL	42	3	4
	OL	2	130	3
	CT	1	2	263

Fig-9 Confusion Matrix - Testing

Accuracy for Test dataset = 96.66%.

Prediction analysis for individual classes (NL, OL and CT) are given in table-3. For class NL (Normal Liver), the model gives 42 correct prediction and three wrong prediction (one misclassified as CT and two as OL) with an accuracy of 93.3 percent. For class OL (Ordinary Lesion) the model Gives 130 correct prediction and 5 wrong prediction (three misclassified as NL and two as CT) with an accuracy of 96.29 percent. For class CT (Cancer Tumor) 263 correct prediction and 7 wrong prediction (four misclassified as NL and three as OL) having accuracy 97.4 percent.

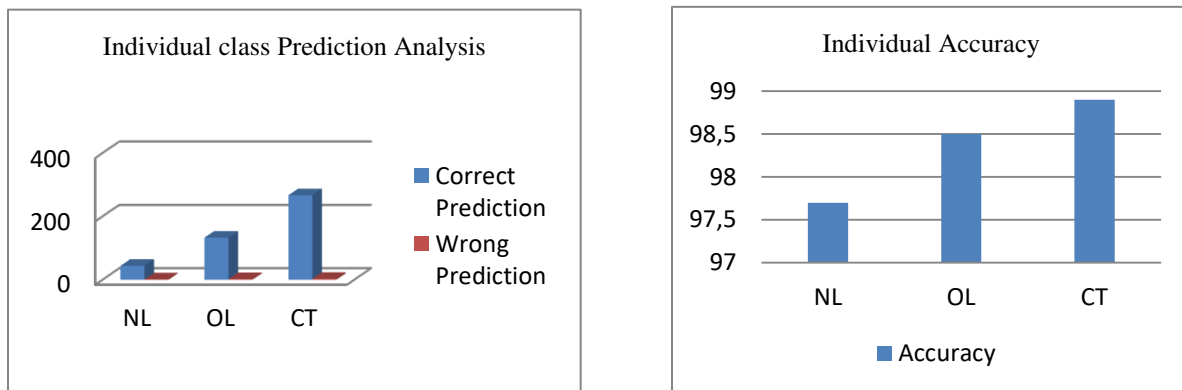
Total Test dataset = 270			
Class	Correct Prediction	Wrong Prediction	Accuracy
NL (Normal Liver)	42	3	93.30
OL (Ordinary Lesion)	130	5	96.29
CT (Cancerous Tumor)	263	7	97.40

Table-3 Individual Class Accuracy

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India



Accuracy Comparison

Model	Accuracy	Ref
3DCNN (proposed)	96.66	Our Model
CNN	93.10	[11]
KNN	90.7	[12]
SVM	92.2	[13]

V. CONCLUSION

In this paper Data augmentation is used to increase the size of the dataset there by increasing the training accuracy of the 3D CNN model. GLRLM is implemented through Radiomics of python to get the complex features of the segmented region. With the proposed 3DCNN along with GLRLM features, the model gives 99.05 percentage accuracy during training and 98.6 percentages during testing. The individual accuracy of the classes (NL, OL, CT) are also calculated and found to be 97.7, 98.5, 98.9 percentage. Our proposed model is compared with 2DCNN, KNN and SVM and found that the proposed model for 3D CNN gives more accuracy than other three algorithms.

REFERENCES

- [1] M. Rela, N. R. Suryakari And P. R. Reddy, "Liver Tumor Segmentation And Classification: A Systematic Review," 2020 IEEE-Hydcon, 2020, Pp. 1-6, Doi: 10.1109/Hydcon48903.2020.9242757.
- [2] Sultan Almotairi, Ghada Kareem, "Liver Tumor Segmentation in CT Scans Using Modified SegNet", US National Library of Medicine, National Institute of Health, doi: 10.3390/s20051516.
- [3] A. krishna M, D. Edwin and S. Hariharan, "Classification of Liver Tumor using Modified SFTAbased Multi Class Support Vector Machine," 2017 International Conference on Current Trends in Computer, Electrical, Electronics and Communication (CTCEEC), 2017, pp. 854-859, doi: 10.1109/CTCEEC.2017.8455031.
- [4] T. Dhiliphan Rajkumar, "Automatic Diagnosis of Liver Tumor in Ct Images", International Journal of Engineering and Advanced Technology (IJEAT), ISSN: 2249 – 8958, Volume-9 Issue-1S4, December 2019
- [5] A. Keerthana, "Classification of Liver Tumor on Ct Images using Machine Learning", International Journal of Recent Technology and Engineering (IJRTE), ISSN: 2277-3878, Volume-8 Issue-4, November 2019.
- [6] Lei Chen, "Liver tumor segmentation in CT volumes using an adversarial densely connected network", Chen et al. BMC Bioinformatics 2019, 20(Suppl 16):587; <https://doi.org/10.1186/s12859-019-3069-x>.

15th & 16th September 2021

Organized by

Department of Computer Science, Parvathy's Arts and Science College, Dindigul, Tamilnadu, India

- [7] Lu Meng, "Liver tumor segmentation based on 3D convolutional neural network with dual scale", J Appl Clin Med Phys, 2020 Jan;21(1):144-157. doi: 10.1002/acm2.12784. Epub 2019 Dec 2.
- [8] R.Manjula Devi, Seenivasagam, V. Automatic segmentation and classification of liver tumor from CT image using feature difference and SVM based classifier-soft computing technique. *Soft Comput* **24**, 18591–18598 (2020). <https://doi.org/10.1007/s00500-020-05094-1>.
- [9] D. Selvathi, C. Malini and P. Shanmugavalli, "Automatic segmentation and classification of liver tumor in CT images using adaptive hybrid technique and Contourlet based ELM classifier," 2013 International Conference on Recent Trends in Information Technology (ICRTIT), 2013, pp. 250-256, doi: 10.1109/ICRTIT.2013.6844212.
- [10] A. Bathsheba Parimala, R. S. Shanmugasundaram, "An Enhanced Liver Stages Classification In 3D-CT And 3D-US Images Using GLRLM And 3D-CNN" International Journal of Electrical Engineering and Technology (IJEET), Volume 12, Issue 2, February 2021, pp. 171-184, Article ID: IJEET_12_02_016, DOI:10.34218/IJEET.12.2.2021.016.
- [11] Fengxin Pan, Qinghua Huang, Xuelong L I, "Classification of Liver tumors with CEUS based on 3DCNN", IEEE 4th international conference on advanced robotics and mechatronics, 2019, DOI:978-1-7281-0064-7/19/\$31.00.
- [12] GeetaKadu, RanjanaRaut, SurajS.Gawande, " An automated Liver disease using KNN", IJCRT, International Journal of Creative research Thoughts , Vol.6, issue-2, Apr 2018, ISSN:2320-2882.
- [13] J. Baek, T. A. Swanson, T. Tuthill and K. J. Parker, "Support vector machine (SVM) based liver classification: fibrosis, steatosis, and inflammation," 2020 IEEE International Ultrasonics Symposium (IUS), 2020, pp. 1-4, doi: 10.1109/IUS46767.2020.9251611.

BIOGRAPHY



A. Bathshebaparimala, has received M.Sc. He is currently a research scholar working toward the PhD degree in the Department of Computer Science, VMKV Arts and Science College, Salem. Her research interests are in Medical image processing, Medical image analysis and Image Classification.



Dr. R. S. Shanmugasundaram, has received the BE degree in Electronics and Communication Engineering from the university of Madras of India in 1996, ME degree from Bharathidasan University of India in 2001 and Ph.D degree from Anna University of India in 2015. His research interests are in medical image processing, deformable models and segmentation. He is a life member of ACS and ISTE. Currently he is working as Director (Students Welfare) of Vinayaka Mission's Research Foundation (Deemed to be University), Salem, TamilNadu,



**Impact Factor:
7.569**



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 **9940 572 462**  **6381 907 438**  **ijirset@gmail.com**



www.ijirset.com

Scan to save the contact details