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Colon Cancer Detection by using Transfer Learning

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Abstract: Cancer detection at early stage will provide the chance of existence of living. Using image processing techniques medical image analysis becoming easier and exact stage of cancer is also detected. In this work transfer learning technique is used to identify the Colon Cancer.

Keywords: Colon cancer, transfer learning, Convolutional Neural Networks (CNN), U-net, AlexNet, GoogleNet.

I. INTRODUCTION

Cancer is a fatal disease that accounts for over 10million deaths worldwide in 2020, according to World Health Organization (WHO). CRC refers to the cancer affecting the colon, rectum and anus, with 4-fold higher incidence in transitioned outcomes, when compared to the transitioning countries. Cancer arises due to the uncontrollable raise of the cells. The most common reasons for cancer are genetic factors, chain smoking, imbalanced diet (excessive intake of animal-source foods), biological factors [10], changes in life style (sedentary life style and excessive body weight) [9]. High death rate is mainly due to the diagnosis of cancer at later stage, thereby resulting in poor treatment planning and metastasis. Therefore, timely detection is essential for the prognosis and also for prolonging the chances of survival. In certain cases, cancer can occur because of the inherited [12]genes and the people who have this risk associated have to perform regular screening. The diagnostic techniques used are highly expensive, and hence a necessity to develop highly efficient and cost effective colon tumour detection scheme arises[11]. A new technique called electric field effect colorectal sensor (E-FECS) is developed for diagnosing colon cancer in CRC patients [11].The images, which are obtained by the digitization of the histopathological samples collected, are used in the detection process. Machine learning (ML) techniques used in the study of the histopathological images where the key features that can be easily interpreted, are extracted. ML techniques can be utilized for a variety of medical application, like diseases detection and intelligent systems that prescribe medicines based on the symptoms [10]. DL is a machine learning that finds applications in several research areas as it offers high computing power with limited hardware. Deep learning algorithms can be trained with few samples and possesses high computational power with low operation costs [9]. Deep learning employs the use of Artificial Neural Network (ANN) for improving the pattern recognition skills and has been replacing the conventional methods of diagnosis [5]. With the advent of deep learning algorithms, machines can easily analyse high dimensional medical images and then classify and predict the biological signals. Deep learning techniques employing the CNN are used in the colon cancer detection [8] [7] where the CNN is used to distinguish the images from one another depending on the significant features extracted. CNN architecture offers highly accurate detection rate for segmentation and classification. CNN can also be employed in the object detection and localization, thereby determining the exact location of the polyps present in the image. The position is accurately determined regardless of the shape, colour, size and texture of the polyps and performs well even in the conditions where the camera's viewpoint, reflection, and light conditions pose a major challenge , [13] A proposed method for detecting colon cancer with high accuracy where the ResNet is optimized using the Stochastic Gradient Descent (SGD) [12]. The method offers superior performance, but with increase in depth of the network, the network parameters tend to become more complex and hence the necessity of high accuracy and low complexity techniques arises. The primary objective of the work is to detect the colon cancer using the proposed hybrid

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optimization technique based CNN with transfer learning. Initially, the images are pre-processed, and then segmented with U-net. The weights of the neurons in the CNN are optimized using the introduced RSSOA. The introduced RSSOA is developed by transforming the weight update process of the SSOA in accordance to that of the ROA. The exploration capability of remora is augmented by the usage of SSOA algorithm leading to improvement in the performance of the classifier.

2. Related Work

Tasnim, Z. et al [8] devisede a DLP Model by CNN. This technique employs the CNN for analysing the colon images, wherein the CNN comprises of two layers. The CNN along with MobileNetV2 was utilized to classify colon cancer. The technique was detected colon cancer in a very short time and is viable for real time application; though the model failed to train and test on a broad dataset. A large dataset was used in the colon cancer detection framework proposed by [6] Babu, T., Singh, T. and Gupta, D in which a high level features are mined by the CNN. Further, a classifier was employed in the classification of colon cancer. The technique performed exceptionally well on public datasets, and the features are extracted irrespective of the segmentation tasks; however it failed in considering the heterogeneity of the image. To overcome the drawback identified in Wang, L[3] created an Image Analysis and Earlier Cancer Prediction (IAECP) for colon cancer detection. The performance was improved by using an Adam optimizer in [6], wherein Gupta, P.et al introduced an Artificial Intelligence (AI)-based classification and localization model to determine and localize the colon cancer regions. The technique was utilized two types of training for the CNN for cancer detection where the first set was utilized for pre trained networks, and the second set was utilized to train the customised CNN. The abnormal patches were localised and hence it reduces the effort required as the pathologists can analyse the small area instead of the entire slide. However, the method considered slides collected from the population in a certain area, and hence the robustness of the method isn't analysed. Gessert, N. et al [7] developed a colon cancer detection method based on CNN with deep learning. Which performed exceptionally well without pre-training, produced a total of FP cases, by heterogeneous appearance of the cancer tissue and small dataset usage. Then count of FP cases was reduced in the segmentation and classification technique proposed by Babu, T. et al [9] for detection of the colon cancer. Here, segmentation is performed and a hybrid feature set was utilized in the classification of colon cancer. The method accurately segments epithelial cells from background resulting in high detection rate, but failed to produce any improvement in accuracy In [9], AI based IR-v2 Type 5 model was developed for the classification and localization of the colon cancer. The technique suffered a major setback where it failed to determine the tumor growth so as to determine the stages of cancer.The growth of the colon adenocarcinoma cell was considered by deep learning method used for colon cancer detection in [6], which delivers high performance even in case of small datasets but was unsuccessful in finding a single transfer strategy or optimal model for all the classification problems. The drawback in [6] was overcome by the use of an optimization process for the classification process in the segmentation and classification technique. The method produced superior performance, but failed to segment the colon gland region and overlapping cells, so as to produce significant detection. The colon cancer detection framework using BO-SVM classifier [6] offered superior performance regardless of the segmentation task, but it failed to analyze the effect of heterogeneity on the histopathological image, thereby trying to classify image as benign. Also, it failed in grading of the malignant tumors of the images. Accurate detection of colon cancer by the deep learning methods mainly depend on the classifier used, data set availability, images contained, and their magnification. Existing deep learning techniques fail to achieve high performance considering the above challenges without producing any optimal detection.

3. Proposed Work

RSSOA method , which is employed in the tuning of the CNN. The developed RSSOA is created by the incorporation of SSOA and ROA. The integration of the two algorithms is performed so as to achieve enhanced accuracy in a high dimensional search space. RSSOA based CNN with transfer learning employed in the detection of colon cancer. Early detection of colon cancer plays a crucial role in appropriate treatment planning resulting in betterment of survival chances of those affected. Detection of colon cancer with high accuracy is a challenge faced by the existing technique, considering the small datasets available. In this research work, an efficient RSSOA-based CNN is devised for detecting colon cancer. The input image is initially pre-processed using the Gaussian filter to eliminate the artifacts and noises present in the image for smoother processing and improving the quality of the image. After pre-processing, the image is segmented using U-net to identify the homogeneous regions in the image. Once the segmentation is executed, colon cancer is detected using the CNN with transfer learning. The weight of the neurons will be updated based on the introduced RSSOA algorithm, which is developed by modifying the SSOA in accordance with the ROA. Figure 1 illustrates the schematic view of the developed colon cancer detection.

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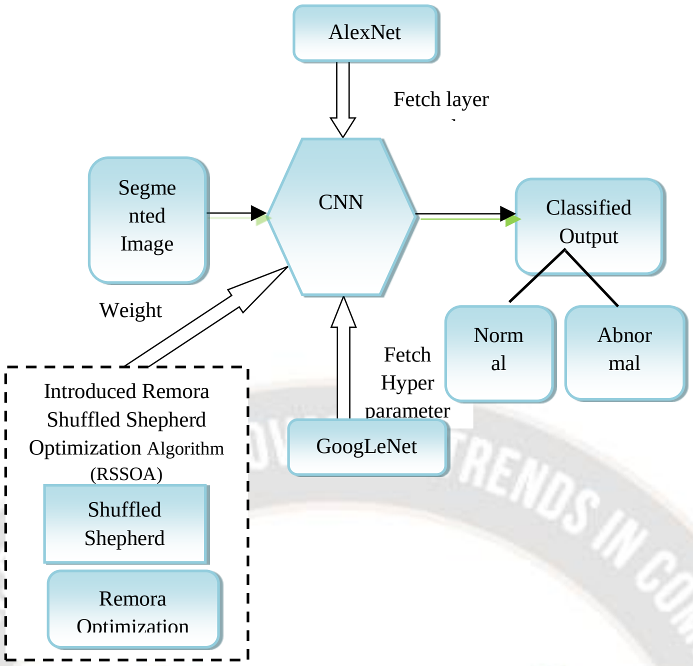

Figure 1. Proposed view of transfer learning for colon cancer detection.

3.1 Pre-processing

Assume a dataset containing a total of images and is represented by the following equation.

A=A1,A2,..,Ai,..An (1)

Represents the image present in the database. The starting step is pre-processing, used to model the image for testing and training in the classifier. The Gaussian filter provides the advantage of smoothing of the input images, thereby denoising and clarity of the image is enhanced represented by,

Gf(t)=12πσ2e-(t-μ)22σ2 (2)

3.2 Segmentation

The pre-processed image is given as input for segmenting, wherein it is segmented into multiple segments for further processing. U-net is utilized for the segmentation of the images. U-net is a fully CNN, which is developed for segmentation of medical images. The data augmentation technique provides a efficient and precise segmentation of images with a few annotated images available. In addition to this, U-net also offers the advantage of fast segmentation. U-net comprises of two paths, namely the contracting and the expansive paths. The contracting path is similar to that of the convolutional network and contains multiple application of convolutional layer, ReLu with max pooling along with stride 2 is used. The feature maps keep doubling at every down sampling step. The elaborated path contains up sampling followed by the convolutional layer, and then the ReLU. The feature maps are halved at every step of the convolutional layer. Finally, convolution is utilized in mapping the feature vector to the corresponding classes. The output thus obtained t is the segmented image and can be expressed as,

S=S1,S2,...,Sl (3)

S1,S2,…S_l represents the segmented images corresponding to the image and is used in the detection of colon cancer.

3.3 Introduced RSSOA-based CNN for colon cancer detection

The introduced RSSOA technique utilized for the optimization of the weights of the neuron present in the CNN. AlexNet offers faster training and is effective on challenging datasets. The segmented image is subjected to the colon cancer detection process where the CNN along with transfer learning is used for identifying the colon cancer in to cancerous or non cancerous. The CNN based transfer learning technique aimed at reducing the False Positive (FP) rate, which occur due to the variation in the size and appearance of the nodules. The technique is based on the principle of training a source model and then transferring the knowledge

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gained to other platforms, thereby resolving the challenges associated with the unevenly distributed data and the limited number of samples available. CNN utilizes the layer and architecture of the AlexNet and the hyper parameters from the GoogLeNet are fetched to train the CNN. The introduced RSSOA algorithm is utilized in the optimization of the weights of the hidden neuron in the CNN. Figure 2. portrays the overall schematic representation of the developed RSSOA enabled transfer learning method used in the detection of colon cancer.

3.3.1 AlexNet

AlexNet offers faster training and is effective on challenging datasets. The network build with 6, 50,000 neurons along with 60 million parameters. The output of the convolutional layer and the fully connected layer is applied with the ReLUs non-linearity. Data augmentation and dropout technique are employed in the reduction of the overfitting issue which occurs in the fully-connected layer. The layer and the architecture of the AlexNet, GoogLeNet are used in training of the CNN.

3.3.2 GoogLeNet

The accuracy of neural networks is generally increased by producing the depth of the networks, resulting in increase of the computational load. Increased size of the network results in higher requirement of the number of training parameters and resources. GoogLeNet solves the issue faced due to the higher requirement by the utilization of sparsely connected networks instead of the fully connected architectures, with the use of inception module, which has a parallel combination of convolutions.

3.3.3 CNN

CNN is used for classification process, because of its high accuracy. It consists of different layers, like convolution (conv) layer, max pool layer, activation layer with a softmax layer. The initial conv layers are utilized in extracting edges from the input image and the preceding layers mine the higher-level features that are subjected to pool layer, where subsampling to form feature maps by the. The activation layers can be Rectified Linear Units (ReLU) or sigmoid functions, which is used to avoid saturation and the softmax layer performs classification. The schematic representation of the proposed work for CNN is portrayed in Figure 2 and Table.1 elaborates the input and output at each layer.

Table.1 Input and Output at each layer

Layer	Input Layer	input	Output
conv2d_1_input	InputLayer	(None, 256, 256, 3)	(None, 256, 256, 3)
conv2d_1	Conv2D	(None, 256, 256, 3)	(None, 62, 62, 96)
activation_1	Activation	(None, 62, 62, 96)	(None, 62, 62, 96)
batch_normalization_1	BatchNormalization	(None, 62, 62, 96)	(None 52, 52, 256)
conv2d_2	Conv2D	(None, 52, 52, 256)	(None, 52, 52, 256)
activation_2	Activation	(None, 52, 52, 256)	(None, 52, 52, 256)
max_pooling2d_1	MaxPooling2D	(None, 52, 52, 256)	(None, 26, 26, 256)
batch_normalization_2	BatchNormalization	(None, 26, 26, 256)	(None, 26, 26, 256)
conv2d_3	Conv2D	(None, 26, 26, 256)	(None, 24, 24, 384)
activation_3	Activation	(None, 24, 24, 384)	(None, 24, 24, 384)
batch_normalization_3	BatchNormalization	(None, 24, 24, 384)	(None, 22, 22, 384)
conv2d_4	Conv2D	(None, 22, 22, 384)	(None, 22, 22, 384)
activation_4	Activation	(None, 22, 22, 384)	(None, 22, 22, 384)
batch_normalization_4	BatchNormalization	(None, 22, 22, 384)	(None, 20, 20, 256)
conv2d_5	Conv2D	(None, 20, 20, 256)	(None, 20, 20, 256)
conv2d_6	Conv2D	(None, 20, 20, 256)	(None, 20, 20, 32)
conv2d_7	Conv2D	(None, 20, 20, 32)	(None, 20, 20, 128)
activation_5	Activation	(None, 20, 20, 128)	(None, 20, 20, 128)
max_pooling2d_2	MaxPooling2D	(None, 20, 20, 128)	(None, 10, 10, 128)
batch_normalization_5	BatchNormalization	(None, 10, 10, 128)	(None, 10, 10, 128)
conv2d_8	Conv2D	(None, 10, 10, 128)	(None, 8, 8, 256)
flatten_1	Flatten	(None, 8, 8, 256)	(None, 16384)

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dense_1	Dense	(None, 16384)	(None, 4096)
activation_6	Activation	(None, 4096)	(None, 4096)
batch_normalization_6	BatchNormalization	(None, 4096)	(None, 4096)
dense_2	Dense	(None, 4096)	(None, 4096)
dense_3	Dense	(None, 4096)	(None, 4096)
activation_8	Activation	(None, 4096)	(None, 4096)
dropout_3	Dropout	(None, 4096)	(None, 4096)
dense_5	Dense	(None, 4096)	(None, 2)
Activation_9	Activation	(None, 2)	(None, 2)

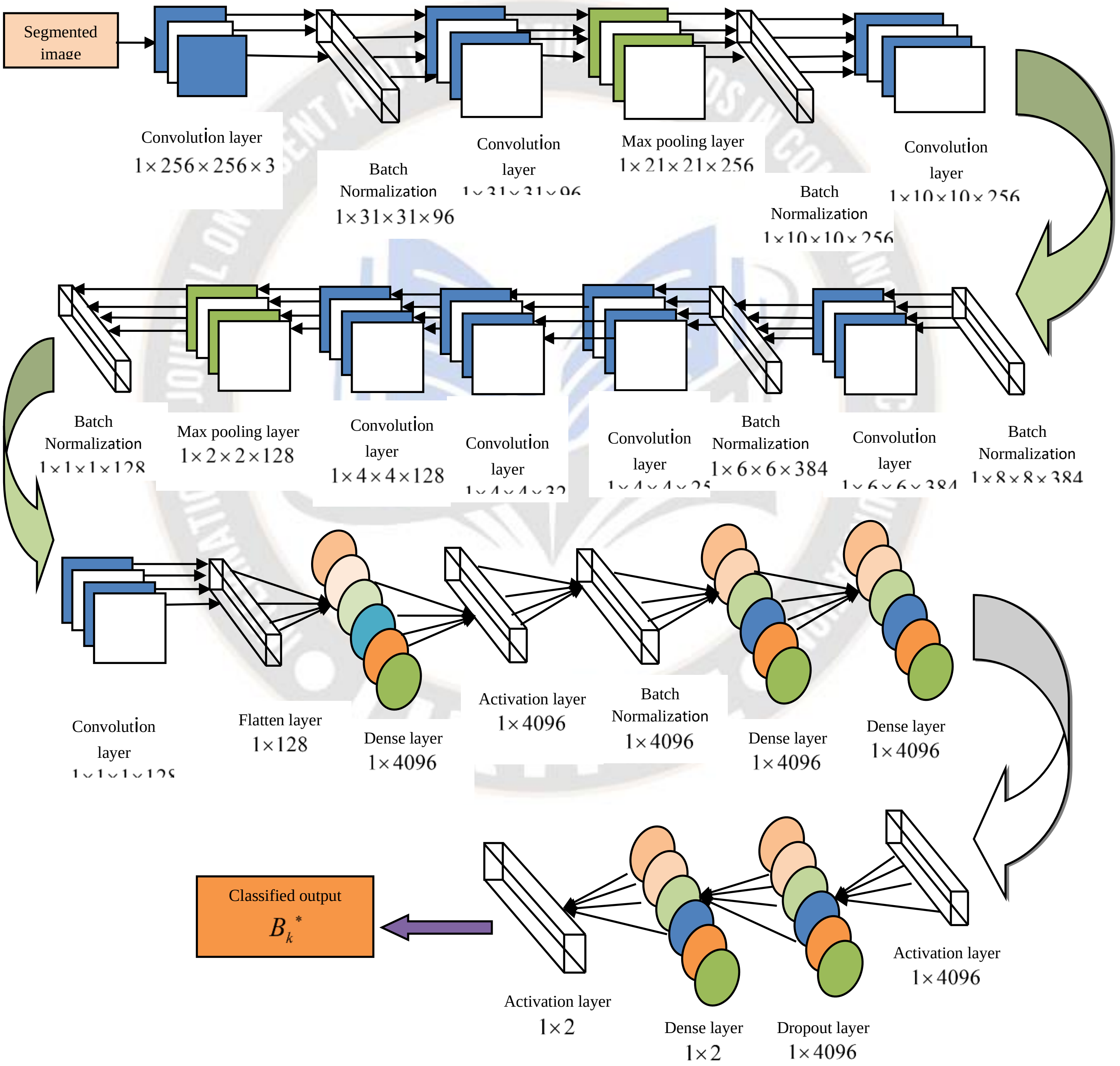

Figure 2. Proposed CNN Architecture

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Layer (type)	Output Shape	Param #
Convolutional_1	(None, 62, 62, 96)	34944
activation_1 (Activation)	(None, 62, 62, 96)	0
(Batch	(None, 62, 62, 96)	384
Convolutional_2	(None, 52, 52, 256)	1204480
activation_2 (Activation)	(None, 52, 52, 256)	0
max_pooling2d_1 (MaxPooling2	(None, 26, 26, 256)	0
(Batch	(None, 26, 26, 256)	1024
Convolutional_3	(None, 24, 24, 384)	885120
activation_3 (Activation)	(None, 24, 24, 384)	0
(Batch	(None, 24, 24, 384)	1536
Convolutional_4	(None, 22, 22, 384)	1327488
activation_4 (Activation)	(None, 22, 22, 384)	0
(Batch	(None, 22, 22, 384)	1536
Convolutional_5	(None, 20, 20, 256)	884992
Convolutional_6	(None, 20, 20, 32)	73760
Convolutional_7	(None, 20, 20, 128)	36992
activation_5 (Activation)	(None, 20, 20, 128)	0
max_pooling2d_2 (MaxPooling2	(None, 10, 10, 128)	0
(Batch	(None, 10, 10, 128)	512
Convolutional_8	(None, 8, 8, 256)	36896
activation_6 (Activation)	(None, 8, 8, 256)	0
flatten_1 (Flatten)	(None, 128)	0
dense_1 (Dense)	(None, 4096)	15863808
activation_7 (Activation)	(None, 4096)	0
batch_normalization_6 (Batch	(None, 4096)	16384
dense_2 (Dense)	(None, 4096)	16781312
dense_3 (Dense)	(None, 4096)	16781312
activation_8 (Activation)	(None, 4096)	0
dropout_1 (Dropout)	(None, 4096)	0

dense_4 (Dense)	(None, 2)	8194
activation_9 (Activation)	(None, 2)	0
Total parameters: 53,940,674		
Trainable parameters: 21,284,866		
Non-trainable parameters: 32,655,808		

Table.2 provides the Summary of Proposed RSSOA-based CNN with Transfer Learning

4. Experimental Results

The total number of images considered is 1000 in that 700 employed for training and 300 for testing.

(i) Segmentation Results

Analysis of the proposed method for detecting colon cancer is depicted using Table 3 considering various parameters, such as sensitivity, accuracy and sensitivity for.

Database	Metric	Introduced RSSOA-CNN based transfer learning
Using training percentage	Accuracy (%)	97.41
	Sensitivity (%)	97.60
	Specificity (%)	96.58

Table 3. Segmentation Results

(ii)Confusion Matrix

Table 4 provides the Confusion matrix value with epoch values from 0 to 140 the loss curve is depicted in Figure 3.

	Predicted Output	
Actual Output	TN = 110	FP = 10
	FN = 7	TP =100

Table 4. Transfer learning Confusion Matrix values

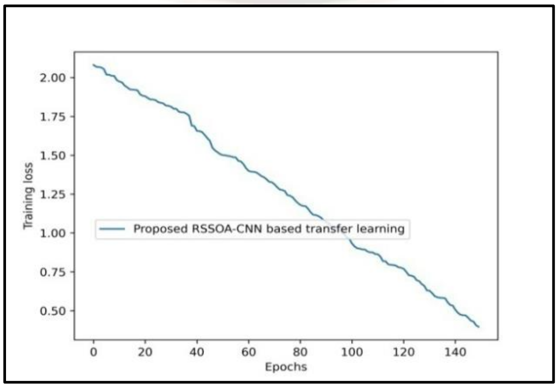

Figure 3. Loss curve for the proposed method

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5. Conclusion

This paper provides an efficient colon cancer detection scheme, using a optimization technique based on CNN with transfer learning. The Gaussian filtered input image is segmented using U-net, which is subjected to the CNN. The CNN employed uses the principle of transfer learning to acquire knowledge from the prior-trained networks, namely AlexNet and GoogLeNet. The weights of the hidden neurons in the CNN are updated using the novel RSSOA method, which is newly created by modifying the exploration capability of ROA in accordance with the SSOA technique to achieve better performance. CNN with transfer learning classifies the images obtained from the segmentation phase as cancerous or normal.

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