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# A Medical Analysis for Colorectal Lymphomas using 3D MRI Images and Deep Residual Boltzmann CNN Mechanism

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**Abstract**: In this technological world the healthcare is very crucial and difficult to spend time for the wellbeing. The lifestyle disease can transform in to the life threating disease and lead to critical stages. Colorectal lymphomas are the 3rd most malignancy death in the entire world. The estimation of the volume of lymphomas is often used by Magnetic Resonance Imaging during medical diagnosis, particularly in advanced stages. The research study can be classified in multiple stages. In the initial stages, an automated method is used to calculated the volume of the colorectal lymphomas using 3D MRI images. The process begins with feature extraction using Iterative Multilinear Component Analysis and Multiscale Phase level set segmentation based on CNN model. Then, a logical frustum model is utilized for 3D simulation of colon lymphoma for rendering the medical data. The next stages is focused on tackling the matter of segmentation and classification of abnormality and normality of lymph nodes. A semi supervised fuzzy logic algorithm for clustering is used for segmentation, whereas bee herd optimization algorithm with scale down for employed to intensify corresponding classifier rate of detection. Finally, classification is performed using Deep residual Boltzmann CNN. Our proposed methodology gives a better results and diagnosis prediction for lymphomas for an accuracy 97.7%, sensitivity 95.7% and specify as 95.8% which is superior than the traditional approach.

**Keywords**: Colorectal Lymphoma (CL), Accuracy, Sensitivity, Specificity, Convolution neural network (CNN) Deep Residual Boltzmann Convolution neural network (DRBCNN).

## I. Introduction

Uncontrolled proliferation and spread of aberrant cell types is the hallmark feature of cancer. Malignancy is a disease in which a collection of cells undergoes uncontrolled growth, incursion (invasion and destruction of neighboring tissues), and in rare cases metastasis. Oncology is a specialty of medicine that deals with cancer prevention, research, diagnosis and treatment. Malignancy may affect peoples of all ages, including infants, although the risk of most mixed bags increases with ages.This research focusses on to evolve an automated technique for calculating colon volume using three-dimensional MRI images. The purpose is assisting medical specialist in accurately identifying the numeral and location of metastatic lymph nodes. The research intent to enhance the detection rate of classifier and provide an additional classification method that can achieve high accuracy in prediction.

**Primary survey for Men-female colorectal cancer statistics**

World Cancer Research reports that colorectal cancer, also malignancy in colon which attained the 3rd position among male and 2nd common among female. The exact cause for this cancer is still unknown factor that makes the research towards this colon cancer is inevitable

- Asia carries the highest burden of colorectal cancer, with over half of all cases and deaths recorded in the region.
- Compared to Western countries, number of malignancy in colon in India is lower, and it made a position as the seventh in general analysis of cancer ratio in the country
- It was estimated the rate of colon cancer increases with lack of physical activities and high consumption of alcohol
- According to the survey regarding the new cases and death rate of cancer in male and female are estimated as 8% new cases detected comparatively with other cancer's but for the death rate there is small difference in male and female

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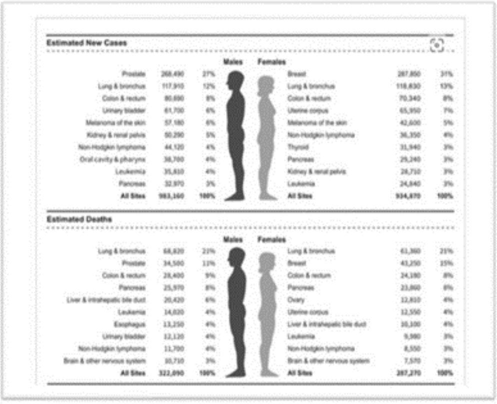


Figure 1:2021 Statistics for Men –female colorectal cancer (Source: https://www.cancer.org/cancer/colon-rectal-cancer/about/key-statistics.html)

### 1.1 An overview about Colorectal Lymphoma

Colorectal lymphomas call attention to the occurrence of malignancy in the colon and rectum, a section of the digestion system especially larger intestine. It results from the deviate growth of cells that can develop or spread to body part sooner and faster. The presence of colorectal lymphomas by two criteria: the dimension of lymph in the colon and whether the malignancy has metastasized or disseminated all over the body. Figure 2 below illustrate the refinement of colorectal lymphoma taken from polyps to dangerous stages.

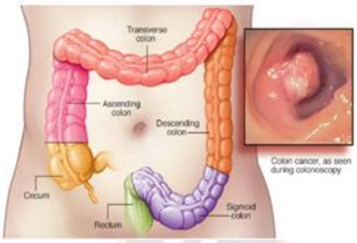


Figure 2: Colorectal Cancer (Source: https://www.mayoclinic.org/diseases-conditions/colon-cancer/symptoms-causes/syc-20353669)

Colorectal lymphoma is mainly found in individual with non-genetic history of the illness, accounting for 70% to 90% of cases. The Components that raise the risk of advancing colorectal cancer include advanced age, male gender, high-fat diet, alcohol or meat consumption, continuous smoking habit, and reduce level of metabolic activity. Colorectal tumors are detected by examining a dubious colon site for signs of lump growth, typically through a colonoscopy, while level of malignancy is determined by a Computerized tomography scan of ribs, pelvis and abdomen. Supplementary imaging test like Pets can and MRI may be used in certain cases. Staging of colorectal cancer refers to the extent to which malignancy has disseminated from its origin in the colon lymph to different biological structures in intestine area through vital fluid and lymphatic vessels at diagnosis time. The staging in accurate is critical for analyzing treatment options and determining prediction. The tumor node and metastasis system are a generally used staging system in therapeutic settings.

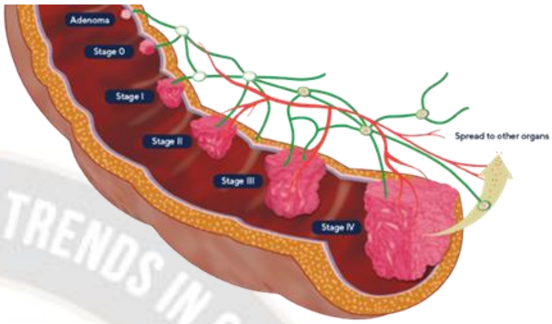


Figure 3: Different stages of Colorectal Cancer (Sources: https://www.rhythmbio.com/colorectal-cancer)

It is believed that most cases of colorectal cancer advances in a methodological manner called as the sequence of adenoma carcinoma. This process involves the transformation of normal intestinal mucosa in to an adenoma, which the progresses to become adenocarcinoma.

### 1.2 CNN (Convolutional Neural Network) for Colon cancer prediction

While the description of CNN is generally accurate, there are some technical inaccuracies in the provided components. Here is a corrected version:

A Convolution Neural Network is a kind of machine learning system which is particularly good at image processing. It takes an input image, analyzes and attributes significance to distinct parts in the picture, and then discriminates between them to perform functions such as object recognition, image classification, or segmentation. The key component of a typical CNN include:

- Input layer: The input layer takes a grayscale or color image as the input unit.
- Convolutional layer: This layer applies filter or kernels to the input images to extract features and create a feature map. Each filter produces a set of activations which constitutes the occurrence of particular pattern in the loaded image.
- Activation layer : This layer applies an activation function without linearity in particular Rectified Linear unit ,to the output of the convolution layer ,introducing non-linearity into the model and improving its ability to capture complex pattern.

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- Pooling layer: The down sampling is technique used in this layer reduces the spatial dimension of the feature maps, usually through max or average pooling. This makes the network more robust to variations in the input images, while also reduces the count of parameters and required computation.
- Fully connected layer: The special feature of this layer is the connectivity of all neurons in the previous layer to all neurons in the current layer, also enabling the network for learning mapping complex from the loaded input to the output. The terminating fully connected layer typically produces the final classification output of the connected mesh.

Overall, CNNs have shown remarkable success in different computer viewing task ,attaining state of the art performance on many benchmarks and datasets.

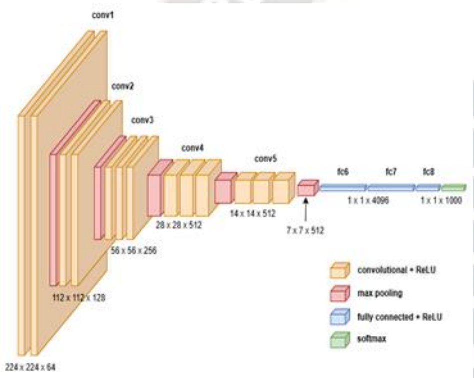


Figure 4: Convolutional neural network Architecture (Source: https://towardsdatascience.com/how-to-easily-draw-neural-network-architecture-diagrams-a6b6138ed875)

### 1.3 Colorectal detection using MRI

Colon tumor, rectal tumor, bowel tumor, and colorectal adenocarcinoma are used to describe Colorectal tumor. RI (Medical Imaging) is a method which employs electromagnetic waves and a magnetic field to generate images in depth of the heart and tissues. According to MRI, the differences between the normal and abnormal soft tissue of the body have also proved especially beneficial in identifying a range of illnesses

## II. 3D MRI images by performing volume calculation for Automated Colorectal Lymphoma

The first step involved in analyzing rectal MR image is pre-processing, which involves using the process of improving an image can involve using technique such as Weighted Adaptive Median Filtering technique also incorporated with Uplift Laplacian Partial Differential Equation. Feature extraction is then performed using Iterative Multi-linear component analysis. These extracted features are input into the Convolution neural Network based Multiscale Phase Level Set Segmentation Process, which automatically analyzes the abnormal resection margin and produces results consistent with traditional segmentation algorithm. Finally Logical Frustum Model is used for reding the medical data to created the simulation in 3D of colorectal lymphoma.

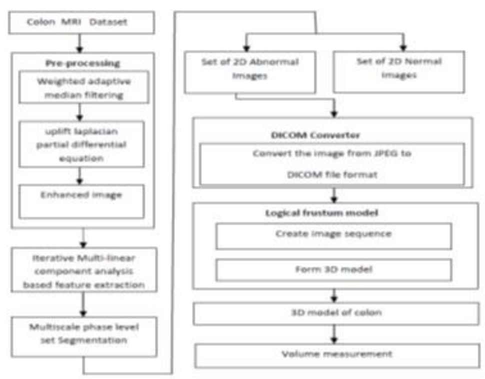


Figure 5: Schematic diagram for loaded 3D MRI images by performing volume calculation for Automated Colorectal Lymphoma [1][2]

### 2.1 Weighted Adaptive Median Filter

Weighted adaptive median filters are used to reduce noise in MR pictures. Ordering pixel approval leads to the median, and then the middle of the pixel ranking is shifted to the middle. The variation between adjacent pixels is calculated by substituting the average of nearby pixels for each pixel in the filter. The filter may be used to assess noise in original MR pictures without sharpness decrease

### 2.2 Iterative Multilinear Component Analysis

In order to explore the detection of colon lymphoma in the MRI picture, the texture features are retrieved utilizing the "Iterative multi-linear component analysis (IMCA)". Since it creates the most self-reliant component vectors, the IMCA may be classified as unrestricted learning. For this strategy, the classification issue is directly related to the distribution of input.

### 2.3 3D Reconstruction Modelling (logical frustum model's)

The MRI colon can scan a large number of pictures, but the reconstruction process is time consuming and difficult. The photos may be converted from JPEG to DICOM format before the

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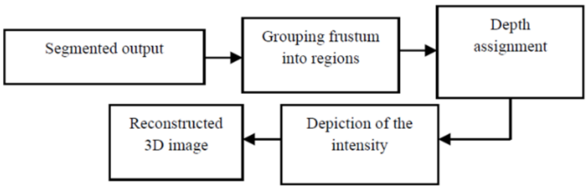


Figure 6: 3D image reconstruction

procedure begins. On a segmented output, logical frustum model is then used. The logical frustum model's (LFM's) step-by-step approach is shown in figure 6

## III. A Deep residual Boltzmann Convolution Neural Network prediction for tumor response colorectal lymph node

This approach outlines a compressive method for segmenting and classifying colon CT Images using various image processing technique and models for deep learning. A range of tools are utilized to enhance the accuracy and make classification process to be efficient which including shear let filter with curvature based and method called contrast limited savitzkvgolav histogram equalization for preprocessing the images, along with semi supervised fuzzy logic clustering segmentation, gray level cooccurrence matrix for feature extraction and Bee Herd Colony Optimization Algorithm for feature selection. Additionally, the use of Deep Residual Boltzmann CNN for classification is a cutting-edge technique in deep learning that can yields peak generalization and score for stability in actual world.

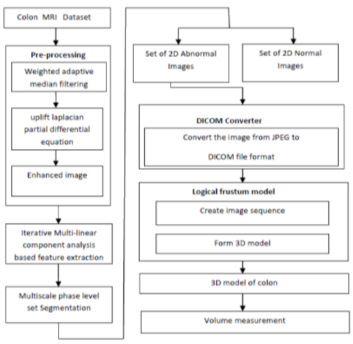


Figure 7: Schematic diagram for Deep residual Boltzmann Convolution Neural Network prediction for tumor response colorectal lymph node [2]

### 3.1 Shear let filter uses a curvature-based

To implement an advanced image processing approach, the first step is to perform image processing, which involves separating noisy pixels from their neighbors using all the pixels in the image. The method replaces the median pixel values in the surrounding area that have passed a noise labelling test. This technique utilizes a shear let filter that feature a curvature-based design to minimize distortion and eliminate impulsive noise. Following this, contrast limited Savitzky Golay histogram equalization can be applied to further improve image quality.

### 3.2 Semi-supervised fuzzy logic clustering

The initial step in the process of feature extraction involves segmentation, which refers to the division of an image into multiple segments. To achieve this, the semi-supervised fuzzy logic clustering segmentation technique is utilized to break down the colon image into various segments. This process involves identifying points, boundary lines and image curves, which can be represents as a group of sections that make up the entire object or a collection of contours derived from the image. Segmentation is akin to using topography to delineate edges in an image, which allows for easy pre-determination of image features. In this research, grayscale values are used to determine the gradient’s intensity in the process of segmentation. The gradient in image velocity is characterized by pixels with high as well as low value across the object’s boundaries. Ultimately, this approach enables process of region of interest in segmentation process.

### 3.3 Feature analysis with Gray Level Co-occurrence Matrix

GLCM is a technique involved in image processing for text analysis and feature extraction. It extracts statistical information on the relationships between pixels in an image based on their spatial relationships and gray level intensities. This method can be used to eliminate unwanted features and retain the essential texture features required for classification. By analyzing the frequency of pixel pairs in specific directions and distances, GLCM can provide texture features such as contrast, correlation, energy, and homogeneity, which can be used for further analysis and classification.

### 3.4 Bee herd Optimization

Bee colony optimization algorithm is a metaheuristic algorithm for optimization that is meant by the acquiring foods of honeybees. In this algorithm, a population of bees represents the candidate solutions and their quality is evaluated by a fitness function. The bees communicate with each other by exchanging information about their fitness, and the best solutions are gradually identified. The feature selection problem is addressed by this algorithm, where the goal is to identify the most important features from a biggest set of input features. By using the bee colony optimization algorithm, the search for the optimal subset of features can be performed more efficiently, reducing the cost of computational of the classification process. In the

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environment of colon CT image analysis, the bee colony optimization algorithm can be used to identify the most relevant texture features that can be used as resource for the classification model. The algorithm can be improving the accuracy of classification and reduce time required for computational for training as well as testing of the model by decreasing the number of features

### 3.5 Deep residual Boltzmann CNN

The classification may be done using a Deep Residual Boltzmann CNN.DRBCNN contains a number of properties, and function layers are used to obtain meaningful classification results. In order to build the DRBCNN function, the kernel is used, and the batten functionality is categorized. In this case, every layer of the kernel has been activated. A kernel technique may transform any linear model into a nonlinear template. As a result of this, greater qualities and thresholds are delivered more quickly. For the real-world application DRBCNN algorithm is used for categorizing because of its high generalization as well as high stability value. The categorization process is separated during the first stages of planning and study. Training the DRBCNN on sample datasets makes it simple to understand the retrieved features. As it is checked, the DRBCNN divides the datasets into distinct portions.

## IV. Results Analysis

The suggested methodology can be corelated with existing deep learning-based algorithms and performance metric are analysed by

- Accuracy
- Sensitivity
- Specificity
- Running epoch

### 4.1 Accuracy analysis

The definition of accuracy is the proportion of properly anticipated outcomes, which includes both True positive, False Positive, False Negative and True negative, in relative to the overall number of occurrences that were investigated.

Accuracy = (True positive + True Negative)/(True positive + True Negative + False positive +False Negative )

**a) Colorectal Segmentation Method**

| No: of images | Accuracy | | | | |
|---|---|---|---|---|---|
| | MPLS 3D(Proposed ) | STVGG | TLVGG | UNET | SEGNET |
| 100 | 0.40 | 0.35 | 0.30 | 0.27 | 0.20 |
| 200 | 0.51 | 0.45 | 0.40 | 0.35 | 0.32 |
| 300 | 0.70 | 0.53 | 0.60 | 0.43 | 0.40 |
| 400 | 0.80 | 0.72 | 0.69 | 0.69 | 0.46 |
| 500 | 0.90 | 0.87 | 0.85 | 0.72 | 0.55 |
| 600 | 0.99 | 0.92 | 0.87 | 0.81 | 0.74 |

Table 1: Accuracy Vs No of Images

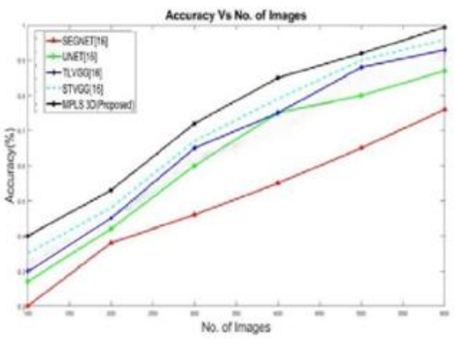


Figure 8: Prediction of accuracy

The above table and graph demonstrate that the technique that is suggested surpasses current methods in terms of efficiency.

Sectionalization based on CNNs for multiscale phase level sets.

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**b) DRBCNN Method**

| No: of images | Accuracy | | | |
|---|---|---|---|---|
| | DRBCNN(Proposed ) | Inception | Resenet 50 | Resnet 18 |
| 5 | 93.8 | 86 | 84.2 | 83.2 |
| 15 | 94 | 86.2 | 85.2 | 83.4 |
| 25 | 94.6 | 86.2 | 85 | 83.6 |
| 35 | 95 | 86.4 | 85.8 | 84.0 |
| 45 | 96 | 86.8 | 86.2 | 84.2 |

Table 2: Accuracy Vs No of Images

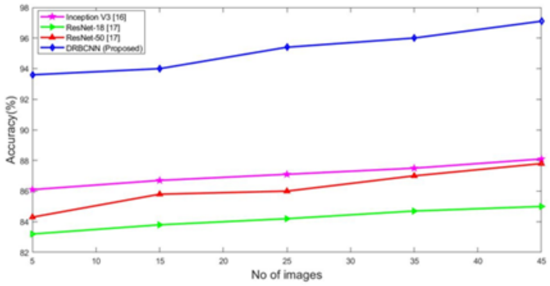


Figure 9: Prediction of accuracy

A maximum accuracy yield of 97.7 percent is shown in Figure 9 and table 2 that is superior to traditional methods.

**4.2 Sensitivity analysis (SN)**

The fraction of real True positive predictions to the overall no: of positive predictions is known as sensitivity. In binary classification, sensitivity and recall are the same

Sensitivity = True positive / (True positive + False Negative)

**a) Colorectal Segmentation Method**

| No: of images | Sensitivity | | | | |
|---|---|---|---|---|---|
| | MPLS 3D(Proposed ) | STVGG | TLVGG | UNET | SEGNET |
| 100 | 0.45 | 0.35 | 0.33 | 0.25 | 0.20 |
| 200 | 0.50 | 0.40 | 0.38 | 0.34 | 0.32 |
| 300 | 0.65 | 0.57 | 0.55 | 0.40 | 0.38 |
| 400 | 0.75 | 0.70 | 0.65 | 0.53 | 0.51 |
| 500 | 0.85 | 0.78 | 0.71 | 0.65 | 0.52 |
| 600 | 0.97 | 0.79 | 0.78 | 0.70 | 0.65 |

Table 3: Sensitivity Vs No of Images

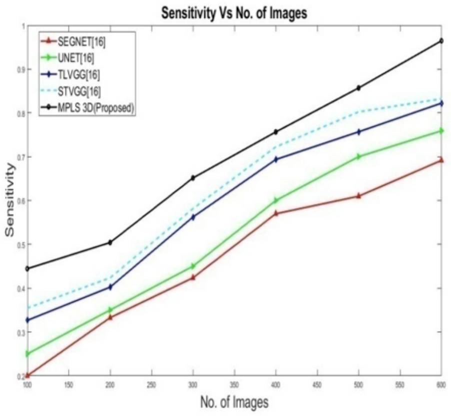


Figure 10: Prediction of Sensitivity

The suggested "Multiscale phase level set segmentation" technique classifier is shown in Figure 10 and table 3. Colorectal cancer may be accurately predicted using the suggested technique, which has Classification sensitivity of 98.9%.

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**b) DRBCNN Method**

| No: of images | Sensitivity | | | |
|---|---|---|---|---|
| | DRBCNN(Proposed ) | Inception | Resenet 50 | Resnet 18 |
| 5 | 92.0 | 87.0 | 86.0 | 80.4 |
| 15 | 93.0 | 87.0 | 86.0 | 81.1 |
| 25 | 94.0 | 87.2 | 86.1 | 82.0 |
| 35 | 93.8 | 87.0 | 86.2 | 82.1 |
| 45 | 94.2 | 87.0 | 86.1 | 82.4 |

Table 4: Sensitivity Vs No of Images

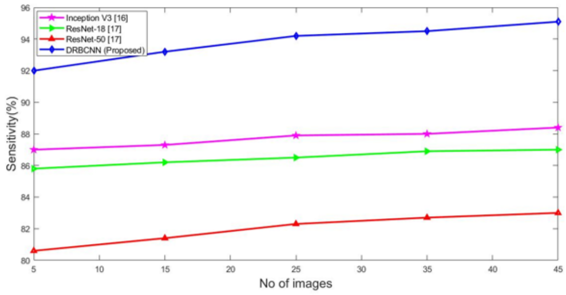


Figure 11: Prediction of Sensitivity

The suggested system, shown in Figure 11 and table 4, has a maximum sensitivity (95.7 percent) than the currently used technique.

### 4.3 Specificity analysis (SP)

The proportion of the overall number of accurate negative forecasts to the entire number of forecasts that are negative is the definition of specificity

Specificity = True positive / (True positive + False Positive )

**a) Colorectal Segmentation Method**

| No: of images | Specificity | | | | |
|---|---|---|---|---|---|
| | MPLS 3D(Proposed ) | STVGG | TLVGG | UNET | SEGNET |
| 100 | 0.40 | 0.35 | 0.30 | 0.28 | 0.20 |
| 200 | 0.54 | 0.48 | 0.35 | 0.30 | 0.29 |
| 300 | 0.73 | 068 | 0.38 | 037 | 0.33 |
| 400 | 0.82 | 0.78 | 0.53 | 0.51 | 0.42 |
| 500 | 0.93 | 0.88 | 0.88 | 0.57 | 0.51 |
| 600 | 0.99 | 0.98 | 0.98 | 0.97 | 0.97 |

Table 5: Specificity Vs No of Images

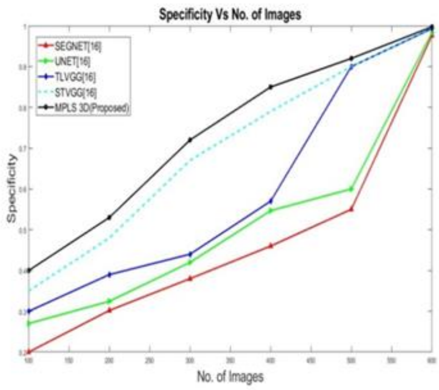


Figure 12: Prediction of Specificity

The genuine negative rate refers to the specificity of the individual negative measurements. Figure 12 and table 5 reveals that the proposed “CNN-based Multiscale phase level set segmentation” exhibits well when compared to other current approaches, achieving 99.9% specificity

**b) DRBCNN Method**

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| No: of images | Specificity | | | |
|---|---|---|---|---|
| | DRBCNN(Proposed ) | Inception | Resenet 50 | Resnet 18 |
| 5 | 91.5 | 91.0 | 89.0 | 80.5 |
| 15 | 92.0 | 91.5 | 89.1 | 81 |
| 25 | 92.5 | 91.4 | 89.1 | 81.5 |
| 35 | 93.0 | 91.5 | 89.3 | 83.0 |
| 45 | 93.5 | 91.0 | 89.2 | 83.1 |

Table 6: Specificity Vs No of Images

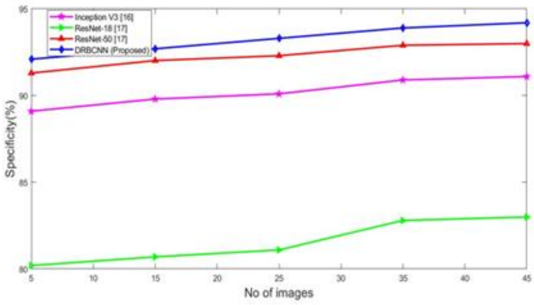


Figure 13: Prediction of Specificity

The novel approach's specificity values are compared to the approaches shown in Figure 13 and table 6. The graph shows that the suggested technique has a greater specificity than the currently used methods (95.8 percent).

**Correlation of learning curves of the training and validation**

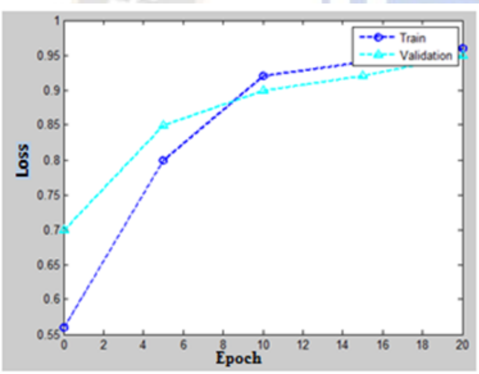


Figure 14: Comparison of the learning curves of the training and validation

The graph shows are no severe over-fitting as the performance loss falls continuously and the formation loss diminishes. This contrasted in SVGG(Self placed transfer visual Geometry Group ) for effectiveness of proposed method Multiscale phase level set segmentation

## V. Conclusion and Future scope

The article discussing about the key points which focusses on the use of advanced image processing technique and deep learning algorithm to segment and classify colon CT images for the prediction of colorectal lymphoma. The article presents a compressive methodology that include several steps to enhance the image processing workflow, starting from preprocessing technique, segmentation, feature extraction, feature optimization and classification. The study shows that the proposed methods is more efficient and effective compared to other conventional methods in terms of consistency and runtime metrics. The outcome of the study is expected to aid clinicians in developing a consistent treatment strategy for colorectal lymphoma, which is a life-threatening condition with a high mortality rate.

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