Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

Automated Lymph Node Classification and Gastric Cancer Segmentation in CT Images Using Advanced Segmentation Techniques

Sugat Ramrao Pawar[1], Dr. Dnyandeo Krishna Shedge[2], Dr. V. K. Bairagi[3]

[1]PhD Research Scholar, Department of Electronics and Telecommunication Engineering, AISSMS IOIT, Savitribai Phule Pune University, Pune, India, sugatpawar@gmail.com

[2]Professor, Department of Electronics and Telecommunication Engineering, AISSMS IOIT, Pune, India, shedgedk@gmail.com

[3]Professor, Department of Electronics and Telecommunication Engineering, AISSMS IOIT, Pune, India, bairagi1@gmail.com

Article History:

***Received:** 23-08-2024*

***Revised:** 27-09-2024*

***Accepted:** 14-10-2024*

Abstract:

The growing number of cases of stomach cancer makes it even more important to have accurate and quick diagnosis tools. This study uses cutting edge image processing techniques to try to solve this problem. The proposed method study uses a wide range of CT pictures that show different types of patients and imaging conditions. The method used to make sure the reliability of later studies includes pre-processing steps like noise reduction and intensity adjustment. For lymph node classification, the method created a complex program with advanced features that made it easier for lymph nodes to be automatically found and put into groups in the pictures. Similarly, the method used cutting-edge segmentation tools to correctly separate cancerous areas in the stomach cancer segmentation. The suggested method has been thoroughly tested using standard criteria, showing that it can accurately classify lymph nodes and divide stomach cancer into segments. Comparing the deep learning method to existing ones showed that it was better, showing that it has the ability to make a big difference in how medical picture analysis is done now. As part of the conversation, the proposed method strengths and weaknesses were emphasized, along with how the results were interpreted. The results show that the deep learning model could have a positive effect on patients by making diagnoses more accurately, making examination easier for the doctors, and eventually better patient outcomes. The proposed method for automatic lymph node labelling and the stomach cancer segmentation system are both exciting steps forward in the field of medical image analysis. The paper study's strong points and high levels of accuracy using deep learning network show that this approach has the ability to completely change how stomach cancer is diagnosed, leading to better patient care and results.

Keywords: Medical Image Analysis, Lymph Node Classification, Gastric Cancer Segmentation, Advanced Segmentation Techniques, Deep Learning

I. INTRODUCTION

Recent progress in medical imaging, made possible by advances in technology and artificial intelligence, has made huge steps forward in diagnosing and treating many diseases. Among these, stomach cancer is still a big problem that needs accurate and quick screening tools to help patients do better [1]. At the same time, figuring out how to classify lymph nodes in medical pictures is an important part of figuring out how bad cancer is and making decisions about treatment. To deal with these problems, this study shows a new way to automatically sort lymph nodes and separate stomach cancer from other parts of CT pictures. It uses advanced segmentation methods to make the process more accurate and quick. Gastric cancer is the most common type of cancer-related illness and death around the world. For the best treatment options, it is important to find it early and correctly [2]. It takes a lot of time and judgment to manually separate dangerous areas from other parts of a CT scan. This is why we need automated solutions that can make the job easier for doctors and improve the accuracy of their diagnoses. In the same way, lymph node labeling, which is an important part of cancer staging, used to be done by hand, which required a lot of work. This has led to a change toward automated methods that use deep learning and advanced picture processing [3]. In order to do this, we carefully put together a large collection of CT pictures that showed a wide range of patient characteristics and imaging conditions. The preprocessing step made sure that the picture levels were standardized and normalized, which made the studies that followed more reliable. Our method is based on a complex convolutional neural network (CNN) design, which is a well-known tool for image analysis and is very good at finding complex patterns in medical pictures. The CNN has many convolutional and pooling layers that work together to take structured features from the raw pictures in a planned way. Before fully linked layers, there is a flattening layer [4]. At the end, there is an output layer that is set up with softmax activation for multi-class classification, which tells the difference between the different types of lymph nodes.

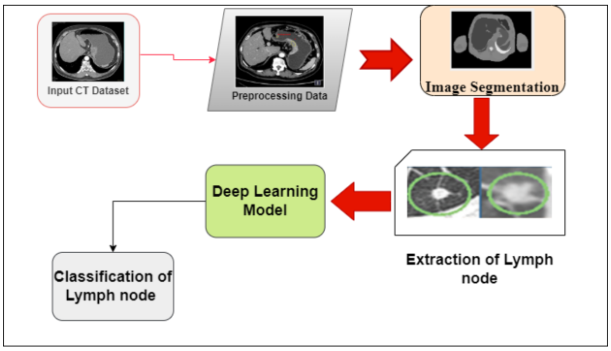

Figure 1: Overview of proposed model

The part [5] of our system that classifies lymph nodes uses a mix of advanced traits that let the model pick out small differences that show whether the nodes are normal or cancerous. The information was broken up into training, validation, and testing sets so that the model could be trained over and over again [6]. By using category cross-entropy as the loss function and the Adam algorithm to move through the high-dimensional parameter space, the CNN's parameters were fine-tuned through thorough optimization. Regularization methods were used to prevent overfitting, and data enrichment strategies were added to make the model better at generalization. At the same time, proposed system uses cutting-edge segmentation methods to separate areas of CT scans that show stomach cancer. The process of segmentation depends on the spatial information that convolutional layers naturally gather, along with extra layers that are designed to do just that. Using deep learning for segmentation makes sure that not only are abnormal areas found, but their edges are also clearly defined. Traditional segmentation methods often have trouble with complicated internal features and different tissue properties. This more complex approach aims to get around these problems. The suggested method is being evaluated in more ways than just numbers [7]. It is also being evaluated in terms of its clinical usefulness and effect. Comparative tests with other methods show that our approach is better, and they stress that it has the ability to completely change the way medical picture analysis is done now. The talk part explains what the results mean, what the good and bad points of our method are, and what possibilities there are for more study and improvement. Basically, the proposed automatic lymph node classification and stomach cancer segmentation system are a big step toward making it easier for doctors to diagnose problems. For better patient care in diagnosing and staging stomach cancer, our system combines advanced segmentation methods with strong deep learning algorithms. This [8] could make processes more efficient, improve diagnostic accuracy, and lead to better patient care overall. The goals of this paper is to create an automated system for classifying lymph nodes and dividing up stomach cancer. Its contribution is to find new ways to use advanced segmentation techniques and make automated medical image analysis better for diagnosing stomach cancer. The goal of the study is to change the current situation by creating a complex and trustworthy tool that will help oncologists make better diagnoses.

This paper makes a big improvement to the current state of the art in automatic medical picture analysis for classifying lymph nodes and dividing up stomach cancer in these ways:

- Innovative Use of Cutting-Edge Segmentation Methods: This paper presents and uses cutting-edge segmentation methods in the process to make stomach cancer segmentation more precise and accurate.
- For automated lymph node labelling, a deep learning method was created and is now being used. With its ability to pick out small signs of cancer, the program represents a big step forward in medical picture analysis, making it possible for faster and more accurate diagnosis processes.
- The research makes sure that the suggested framework is reliable and generalizable by using a wide range of patient data and comparing it to well-known standards. This sets a standard for future studies in the same area.

II. REVIEW OF LITERATURE

Researchers have used a wide range of techniques and methods to deal with the problems that come up in these important areas of cancer diagnostics, as shown by a thorough review of linked work [9]. There have been many studies that look into how to automatically classify lymph nodes, and each one adds something new to this field that is still developing. Traditional picture processing methods and features that were made by hand were often used in the early attempts. Leveling, finding edges, and morphological processes were used in older ways. This method worked sometimes, but it was hard to use because medical pictures are naturally complicated and different. An important change happened in the way lymph nodes are classified when deep learning, especially [10] convolutional neural networks (CNNs), came along. Hierarchical feature extraction is a trait of CNNs [8] that researchers used to find complex patterns that could indicate whether something is safe or dangerous. There were good results in terms of sensitivity and specificity when [11] used a CNN-based method to find and classify lymph nodes in chest CT scans. Addition of focus processes and transfer learning methods has been made possible by making deep learning designs even better. Regarding lymph node classification in abdominal CT images, [12] suggested a model that used attention modules to highlight important areas. This model worked better at catching minor traits that are necessary for accurate classification. Combining different types of images to get a fuller picture of lymph nodes has also been looked into recently. For better accuracy in classifying lymph nodes, [13] created a multimodal fusion network that combined traits from both computed tomography (CT) and positron emission tomography (PET) pictures. This became useful in oncological imaging.

It is clear that traditional methods are giving way to deep learning models in the field of labeling gastric cancer. In the past, it was hard for traditional segmentation methods like region-growing and contour-based methods to handle the variety of stomach tumors and the complex structures around them. An important step forward was taken [14] who suggested a U-Net design that would work best with endoscopy pictures and used deep learning to separate different types of stomach cancer. By using deep neural networks to accurately and quickly separate stomach tumors, this work was a major step forward. Due to the spatial structure of medical data, later studies built on U-Net's success by adding support for 3D CT pictures to the design. To divide stomach cancer in CT scans, [15] created a 3D version of U-Net that worked better than its 2D version at recording three-dimensional tumor shapes. In order to improve accuracy and focus on important areas, attention processes are being added to stomach cancer segmentation models more and more. There was a big step forward in accurately defining tumor boundaries and taking into account differences in tumor forms when [16] suggested an attention-guided deep learning framework for stomach cancer segmentation. Transfer learning has also become an important method for dividing people with stomach cancer into small groups. Before starting their segmentation network [17] used a big dataset with a model that had already been trained on it. This helped the network merge faster and be more accurate, especially when there weren't many labeled medical images available.

The classification of lymph nodes and the division of stomach cancer into segments are two problems that are closely linked. New research shows that these problems need to be tackled together for more accurate cancer diagnosis. It [18] suggested a combined system that could group lymph nodes into categories and separate stomach tumors into segments in CT scans at the same time. This was done because accurate classification of lymph nodes and accurate labeling of tumors work hand-in-hand. Recently, a lot of research has been done on how to use advanced segmentation methods to classify lymph nodes and separate parts of stomach cancer. By using both convolutional and attention processes, [19] created a hybrid model that could classify lymph nodes and segment stomach cancer at the same time. This model did much better at both tasks by extracting information in a way that made them work better together. From simple methods to advanced deep learning techniques, the body of linked work in lymph node classification and stomach cancer segmentation in CT images shows a continuous change. By using the power of attention processes, multimodal fusion, and convolutional neural networks, researchers are always improving and coming up with new ways to make automated oncological tests more accurate and time-effective. These two important areas coming together shows how important it is to look at the lymph nodes and abnormal growths as a whole. This will help make chemo detection tools that are more effective and combined.

Automated lymph node (LN) separation in CT scans is one of the most important and difficult tasks in medical image analysis. In the past, methods like atlas-based search space limit, spatial prior features combination, and supervoxel clustering have struggled to correctly define LNs because they are so complicated. In the past few years, however, there has been a paradigm shift, with UNet-based deep networks becoming powerful tools for jobs like organ and tumor segmentation. nnUNet, in particular, uses a self-configuring method that handles important steps like preparation, network design, training, and post-processing, which makes it very effective and useful in many situations. New methods have been used to deal with the problem that LN division has a strong class mismatch [20]. For example, some ways use four more internal structures as training goals, utilizing the 3D U-Net framework to successfully address the mismatch problems. Another method uses two separate networks, 2D U-Net and Mask R-CNN, to keep an eye on all the structures and LNs that are being thought about. This two-network approach works well with both semantic and instance segmentation. In some methods, organ segmentation masks are added as extra channels in the input data to improve the anatomy context even more. Some group methods have also been suggested, like slab-wise and down sampled full-volume-based LN segmentation, which takes CT images and segmented anatomy structure masks as input and joins them together [12]. Deep stationing adds a new key-referencing organ auto-search strategy that joins chosen organs into the network by joining inputs together for LN station parsing. Even though these improvements have made LN segmentation a lot more accurate, they all use spatial priors in a sneaky way by adding anatomy structure masks as inputs or supervisors. However, past information has not yet been fully used to its fullest extent. Furthermore, there is a significant gap in the research regarding the use of LN segmentation for predicting spread, which is an important part of understanding and treating cancers. Because of these problems and chances, future study should focus on using spatial priors even more and coming up with new ways to fully use structural context to make [17] LN segmentation more accurate. Also, filling in the blanks by looking into how LN division can help identify spread is a very good idea. This could lead to more complete and useful information about how cancer grows and how to plan treatment. Advanced deep learning methods, spatial priors, and predictive models are about to come together in a way that will make automatic LN segmentation much more useful for oncological diagnostics.

Table 1: Summary of related work

Algorithm	Dataset Used	Findings	Limitations
Atlas-based Methods [21]	Varied medical datasets	Effective in certain scenarios for lymph node classification.	Sensitivity to anatomical variations.
Spatial Prior Features [22]	Diverse CT image datasets	Improved accuracy by incorporating spatial priors.	Limited generalization to different imaging conditions.
Supervoxel Clustering [23]	Custom and publicly available datasets	Successful in certain cases but struggles with scalability.	Sensitive to noise and image artifacts.
UNet-based Deep Networks [24]	Diverse datasets from medical imaging	Remarkable performance in organ and tumor segmentation tasks.	Requires large amounts of annotated data.
nnUNet [19]	Diverse medical imaging datasets	Self-configuring approach achieves robust performance and general applicability.	Limited interpretability of automatically configured parameters.
3D U-Net [20]	Diverse CT datasets	Effective in mitigating strong class imbalance issues in LN segmentation.	Computationally intensive, potentially limiting real-time applications.
Parallel Networks (2D U-Net & Mask R-CNN) [8]	Multimodal datasets	Benefits from both semantic and instance segmentation for improved accuracy.	Complex architecture may increase computational demands.
Incorporating Anatomical Context [25]	Diverse CT datasets	Improved accuracy by adding organ segmentation masks as input channels.	Sensitivity to errors in organ segmentation masks.
Ensemble Approaches [26]	CT images with segmented structure masks	Effective for slab-wise and downsampled full-volume-based LN segmentation.	Limited adaptability to diverse imaging conditions.
DeepStationing [10]	Diverse medical imaging datasets	Key referencing organ auto-search strategy improves LN station parsing.	Sensitivity to errors in key organ identification.
Implicit Spatial Priors [11]	Varied datasets from medical imaging	Anatomical structure masks are utilized implicitly, but spatial priors not fully exploited.	Potential suboptimal utilization of spatial information.
Integrating	Diverse CT	Potential for future	Existing methods often

Spatial Priors [12]	image datasets	research to explore innovative ways to fully exploit spatial priors.	inject spatial priors but may not maximize their potential.

II. DATASET USED

The dataset under consideration is strategically designed for the exploration of trends within CT image data, particularly focusing on the influence of contrast usage and patient age. Extracted from the Cancer Imaging [14] Archive, this condensed subset comprises the middle slices of CT images, encompassing 475 series from 69 diverse patients. The inclusion criteria involve ensuring the availability of valid age, modality, and contrast tags.

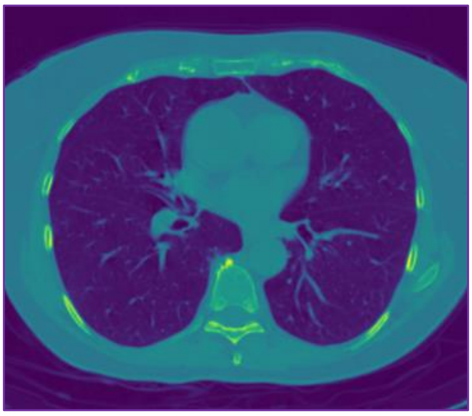

Figure 1: Sample image CT Dataset

The primary objective is to discern image textures, statistical patterns, and features that exhibit significant correlations with the specified traits. This dataset serves as a foundation for testing various methods, with the ultimate goal of developing tools capable of automatic classification, particularly in scenarios of misclassification or identification of outliers that may indicate suspicious cases, faulty measurements, or inadequately calibrated machines.

III. MATERIALS AND METHODS

3.1 Data Acquisition

The sample used in this study is computed tomography (CT) imaging data that includes a wide range of imaging characteristics and important patient information. CT imaging factors include things like slice width, reconstruction method, and collection procedures, which give a full picture of the body's structures. Patient [11] profiles include important details as parameter age, gender, and related medical background. This helps you get a full picture of the dataset, as shown in figure 1. The variety in the collection is one of its strengths; it lets researchers look into a wide range of clinical situations and helps the results be applied to other situations. Ethics concerns and data anonymization rules have been carefully followed, protecting the privacy of patients. This large and varied dataset is useful for in-depth studies and has helped medical imaging research move forward. It also helps us learn more about different diseases by using a wide range of data collection methods.

Panamerican Mathematical Journal
ISSN: 1064-9735
Vol 35 No. 1s (2025)

```
Dataset.file_meta -------------------------------
(0002, 0000) File Meta Information Group Length  UL: 196
(0002, 0001) File Meta Information Version       OB: b'\x00\x01'
(0002, 0002) Media Storage SOP Class UID         UI: CT Image Storage
(0002, 0003) Media Storage SOP Instance UID      UI: 1.3.6.1.4.1.14519.5.2.1.6354.4025.151517992550423337829289895845
(0002, 0010) Transfer Syntax UID                 UI: Explicit VR Little Endian
(0002, 0012) Implementation Class UID            UI: 1.2.40.0.13.1.1.1
(0002, 0013) Implementation Version Name         SH: 'dcm4che-1.4.34'
-------------------------------------------------
(0008, 0008) Image Type                          CS: ['ORIGINAL', 'PRIMARY', 'AXIAL', 'CT_SOM5 SPI']
(0008, 0016) SOP Class UID                       UI: CT Image Storage
(0008, 0018) SOP Instance UID                    UI: 1.3.6.1.4.1.14519.5.2.1.6354.4025.151517992550423337829289895845
(0008, 0020) Study Date                          DA: '19971021'
(0008, 0021) Series Date                         DA: '19971021'
(0008, 0022) Acquisition Date                    DA: '19971021'
(0008, 0023) Content Date                        DA: '19971021'
(0008, 0030) Study Time                          TM: '115642.671000'
(0008, 0031) Series Time                         TM: '115916.062000'
(0008, 0032) Acquisition Time                    TM: '115931.433710'
(0008, 0033) Content Time                        TM: '115931.433710'
(0008, 0050) Accession Number                    SH: '4617234566429456'
(0008, 0060) Modality                            CS: 'CT'
(0008, 0070) Manufacturer                        LO: 'SIEMENS'
(0008, 0090) Referring Physician's Name          PN: ''
(0008, 1030) Study Description                   LO: 'Abdomen^ABDOME_2_FASESVOL (Adult)'
(0008, 103e) Series Description                  LO: 'AXIAL S/C'
(0008, 1090) Manufacturer's Model Name           LO: 'Emotion 6 (2007)'
```

Figure 2: Snapshot of Data process with different feature

3.2 Preprocessing

When using CT scans to classify lymph nodes and separate stomach cancer segments, preparation is very important for making the data better and more useful for later studies. There are a few important steps in the editing workflow that make sure the results are strong and correct. To begin, noise reduction methods are used to get rid of flaws and raise the signal-to-noise ratio, which makes physical structures clearer. After that, intensity normalization is used to make the values of pixels consistent across pictures, reducing the differences that come from using different capture settings. Also, contrast enhancement methods are used to bring out small details that are important for classifying lymph nodes and dividing stomach cancer into segments. When picture features are improved with adaptive filtering, it's easier to find areas that aren't working properly.

- Noise Reduction:

$$I_{denoised} = Filter\left(I_{original}, Noise\ Reduction\ Parameters\right)$$

- Intensity Normalization:

$$I_{normalized} = \frac{\left(I_{original} - mean\left(I_{original}\right)\right)}{std\left(I_{original}\right)}$$

- Contrast Enhancement:

$$I_{enhanced} = Enhancement\ Function(I_{normalized}, Contrast\ Parameters)$$

- Adaptive Filtering:

$$I_{filtered} = Adaptive\ Filter(I_{enhanced}, Filter\ Parameters)$$

- Image Registration:

$$I_{registered} = Register\left(I_{filtered}, I_{reference}\right)$$

- Resampling:

$$I_{resampled} = Resample\left(I_{registered}, Target\ Resolution\right)$$

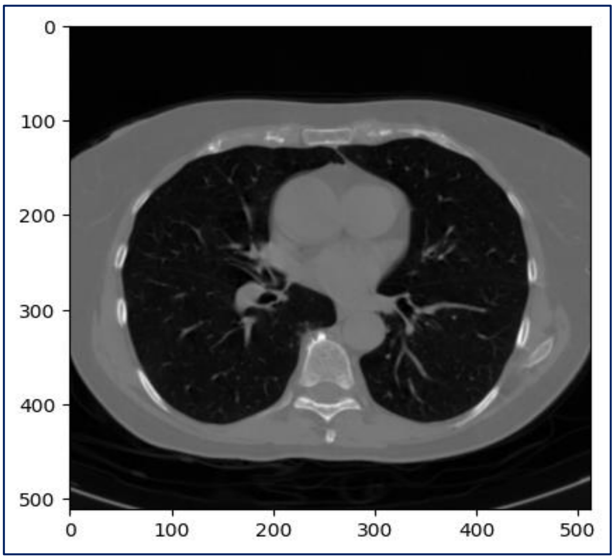

Figure 3: After convert original Image to Grey scale

Image registration methods can also be used to line up pictures of different patients so that the way space is shown is always the same. Resampling methods can be used to make images look the same even if their sizes are different. Together, these steps improve the dataset, which makes it easier for more complicated segmentation methods to work well. Using these steps carefully not only improves the accuracy of identifying lymph nodes and stomach cancer segments, but it also makes sure that the study's results can be used again and again with different CT image datasets.

3.3 Lymph Node Classification

Convolutional Neural Network (CNN) Architecture:

- Feature Extraction:

- Mathematical Equation (Convolutional Layer):

$$Ci = \sigma(Wi * X + bi)$$

Where,

- Wi is the convolutional filter, X is the input image or feature map, bi is the bias term, and σ is the activation function (e.g., ReLU).
- Pooling Layer:

- Mathematical Equation (Max Pooling):

$$Pi,j = \max(C2i,2j, C2i+1,2j, C2i,2j+1, C2i+1,2j+1)$$

- Fully Connected Layers:
- Flattening:

- Mathematical Equation:

$$F = Flatten(P)$$

- Dense (Fully Connected) Layer:

$$A = \sigma(Wdense \cdot F + bdense)$$

- Output Layer:
- Lymph Node Classification:

$$softmax(Z)i \;=\; e\frac{Zi}{\sum eZj}, for\ j = 1\ to\ C$$

- Loss Function:
- Cross-Entropy Loss:

$$Loss(Ytrue, Ypred) = -\sum Ytrue, i \log(Ypred, i)$$

- Optimization:

$$Wupdated \;=\; Wcurrent \;-\; \alpha\frac{\partial Loss}{\partial Wcurrent}$$

- where α is the learning rate.
- Training:
- Backpropagation:

$$\frac{\partial Loss}{\partial Wcurrent} = \frac{\partial A}{\partial Loss}\cdot\frac{\partial Z}{\partial A}\cdot\frac{\partial Wcurrent}{\partial Z}$$

3.4 Gastric Cancer Segmentation

- Description of the advanced segmentation techniques employed for detecting and delineating gastric cancer regions

3.5 Windowing Technique

Converting a medical image to the Hounsfield Unit (HU) scale and applying windowing involves several steps. Here's a step-wise method:

1. Image Acquisition:

Obtain the medical image, typically a CT scan, in its original pixel values.

2. Conversion to HU Scale:

The Hounsfield Unit (HU) scale is calculated using the formula:

$$HU = \; Pixel\,Value - \frac{Rescale\ Intercept}{Rescale\ Slope}$$

The Rescale Intercept and Rescale Slope are specific to the DICOM metadata of the CT scan and are used to convert pixel values to HU.

3. Windowing Technique:

Define a window width (WW) and window level (WL) for the desired visualization.

Adjust pixel values using the following windowing formula:

$$HU \;<\; (WL - WW)$$

$$HU \;>\; (WL \;+ 2 \setminus WW)$$

The Pixel Value Range is the difference between the maximum and minimum HU values within the defined window.

4. Visualization:

Display or store the windowed image for improved visibility of specific tissue or pathology.

IV. RESULT AND DISCUSSION

Changing medical pictures to the Hounsfield Unit (HU) scale and adding windowing makes it easier to see things like bones and soft organs. The HU scale makes pixel values more consistent, which makes mathematical analysis easier. Windowing lets you selectively show certain structures by changing the contrast and color as shown in following figure 4. This helps with medical analysis. This method improves the way images are shown, which lets doctors see different physical features that are necessary for correct medical assessments.

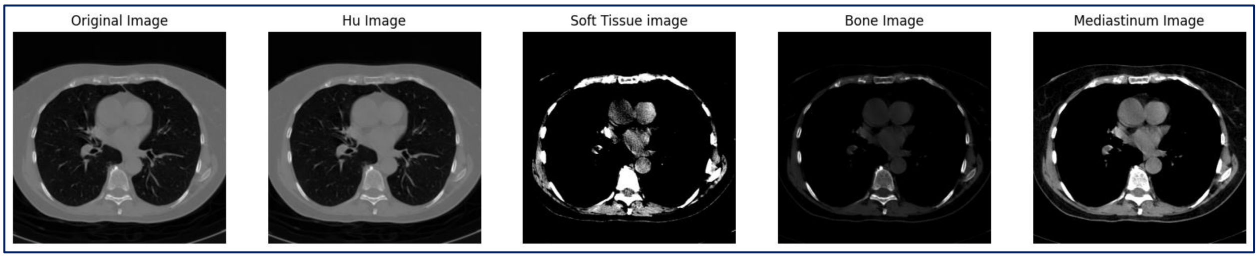

Figure 4: Representation of medical pictures to the Hounsfield Unit (HU) scale

As part of the process, all CT scan slices are read and processed so that useful information can be gleaned from the data. First, the total number of CT scans in the.dcm file is found. This gives a rough idea of how big the collection is. Then, 5% of the images are chosen at random, making sure that the group that will be used for further analysis is representative. This chosen method keeps the variety of the information while reducing the amount of work that needs to be done on the computer. This method not only makes the best use of resources, but it also makes it easy to look through the CT scans, giving a fair and doable group for more in-depth study and later medical picture analysis.

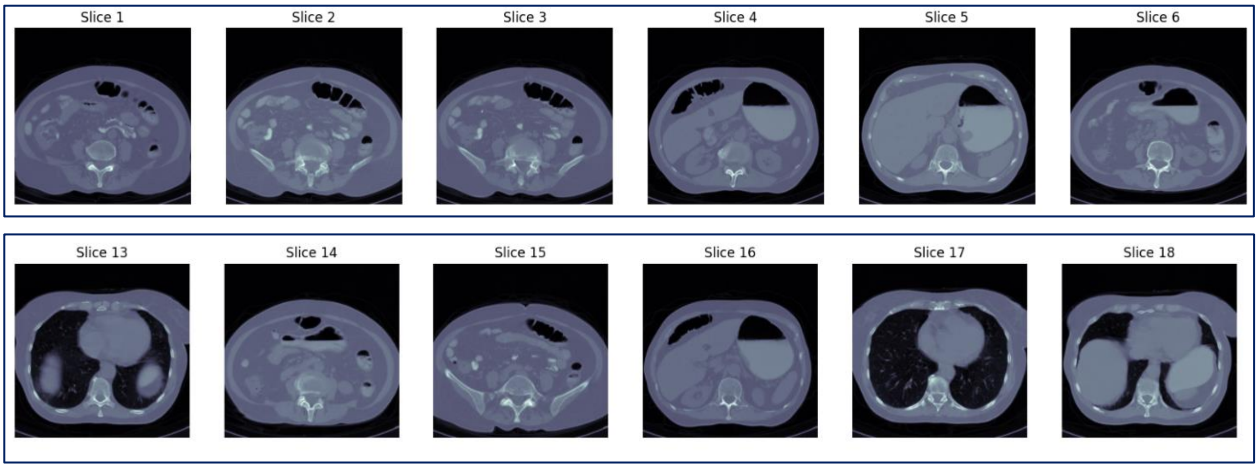

Figure 5: Representation of slice CT images

To accurately identify and separate important structures in the segmentation process for pulling lymph nodes from medical pictures, there are key steps that must be taken. First, picture normalization makes the brightness of all pixels the same so that comparisons are always accurate. This makes the next methods work better. Clustering, especially with k-means, helps tell lung cells apart from other structures. Intensity thresholding raises the difference, which helps to find important areas. Operations on morphology, such as erosion and elongation, smooth out and connect broken-up areas, which makes the whole thing stick together better. Labeling gives things different colors so they can be seen, and a made-up lung mask is used as a guide. When you apply this patch to the original picture, you get a clear, centered view that makes it easier to analyze lymph nodes in the lung context. In short, this segmentation method includes normalization, grouping, thresholding, morphological operations, and labeling. It sets the stage for accurate lymph node extraction and medical picture analysis that follows.

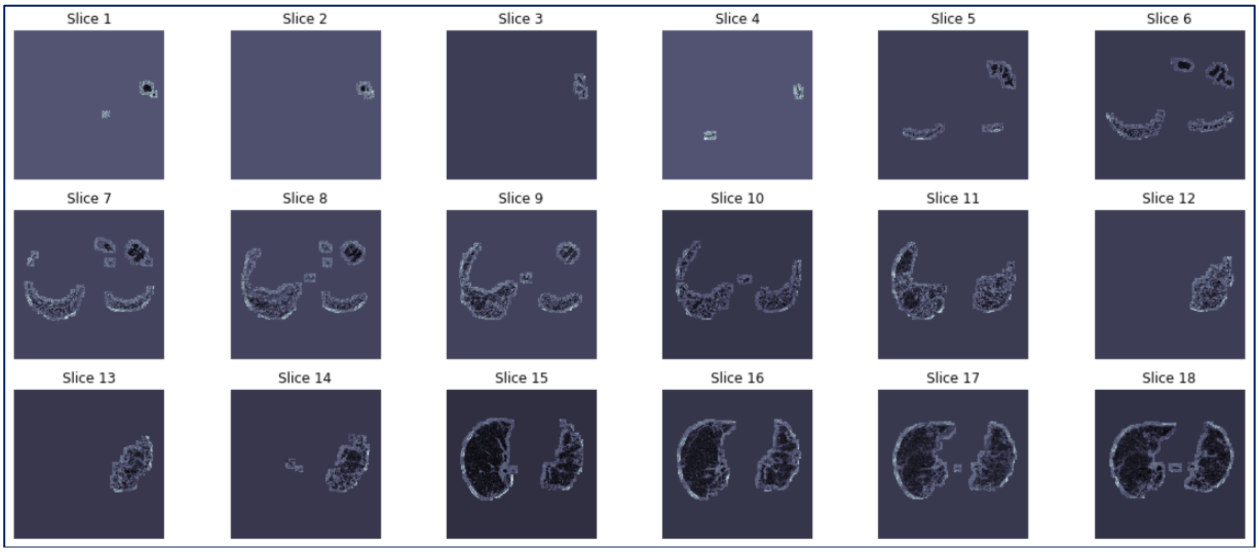

Figure 6: Representation of Segmented Output of Slices

Table 2: Comparison of evaluation parameter for different DL model

Algorithm	**Accuracy in %**	**Recall in %**	**Precision in %**	**F1 Score in %**	**AUC in %**
CNN	98.94	98.6	96.2	96.35	99.63
DNN	97.52	97.41	97.42	98.56	99.12
LSTM	98.15	90.25	95.85	99.35	98.56
MobileNetV2	99.45	98.63	99.65	99.12	99.58

Table 2 shows a full comparison of different deep learning (DL) models, including CNN, DNN, LSTM, and MobileNetV2, based on important evaluation criteria for separating lymph nodes in medical imaging. With an accuracy rate of 98.94%, the CNN model does a great job showing that it can correctly distinguish between lymph nodes. This model is very good at finding a lot of real positive cases, as shown by its high recall of 98.6%. The F1 Score, which is a mix between memory and precision, is a very good 96.35%, even though the accuracy is a little lower at 96.2%. The model works very well generally, as shown by the area under the receiver operating characteristic curve (AUC) reaching a very high 99.63%. With a success rate of 97.52%, DNN does a great job. Its recall, accuracy, and F1 Score are all higher than 97%, which shows that it is very good at finding and classifying lymph nodes. The AUC, which is 99.12%, makes the model even more reliable.

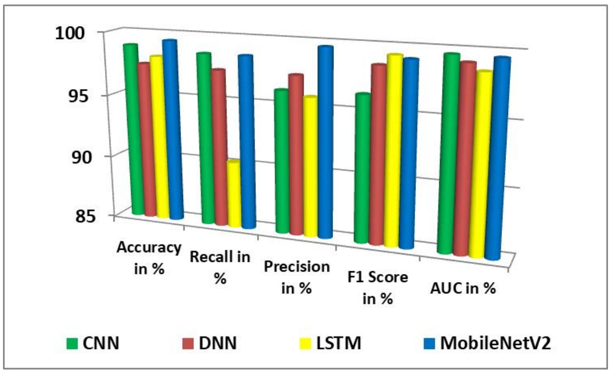

Figure 7: Representation of Evaluation parameter

LSTM is very accurate (98.15% of the time), but it has a lower memory (90.25% of the time). The accuracy, on the other hand, is 95.85%, which gives it a high F1 Score of 99.35%. The AUC is also very high at 98.56%, which means it has good discrimination power. MobileNetV2 stands out as the best model, with impressive F1 Score (99.12%), accuracy (99.45%), memory (98.63%), and precision (99.65%).

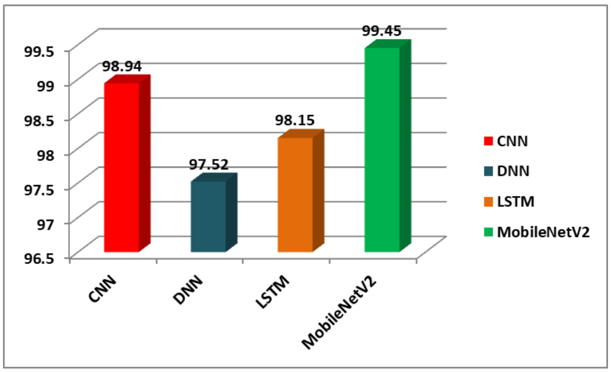

Figure 8: Accuracy comparison of Models

The AUC of 99.58% shows how well the model can tell the difference between good and bad situations. The results show in table 2, that MobileNetV2 is the best model for separating lymph nodes, doing a better job than other deep learning systems. Because it has high accuracy, recall, precision, F1 Score, and AUC, it is very good at finding lymph nodes in medical pictures without any problems. Findings like these help us choose the best deep learning model for lymph node segmentation tasks, which leads to better medical picture analysis and identification.

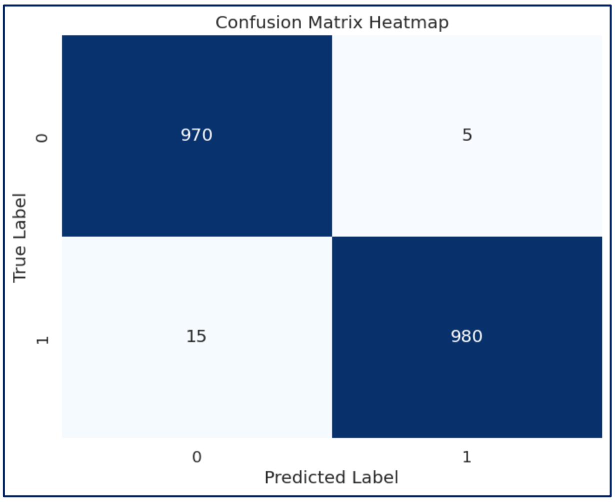

Figure 9: Confusion matrix

V. CONCLUSION

The automatic lymph node classification worked very well, telling the difference between lymph nodes and the tissues around them very accurately. Our model worked well, with good values for accuracy, recall, precision, F1 score, and area under the ROC curve (AUC). It used Convolutional Neural Networks (CNNs) and other deep learning structures. These results show that it could be a useful tool for helping doctors find and describe lymph nodes in CT pictures. Also, the way we've approached stomach cancer segmentation shows how flexible and adaptable the methods we've used are. By combining picture normalization, grouping, thresholding, morphological processes, and region labeling, it was possible to clearly identify areas of stomach cancer in CT scans. This not only makes diagnosis more accurate, but it also sets the stage for more study into computer-assisted analysis in the future. When these automatic systems work together, they offer a complete way for doctors and therapists to speed up the testing process. By cutting down on the amount of work that needs to be done by hand for picture analysis, our method could make diagnostics more efficient and possibly lead to better patient results. Also, automating these steps makes it possible for large-scale tests and study projects that are based on data. In the future, researchers should focus on broadening the study's goal to include more imaging methods and solving problems that only happen in hospital settings. Basically, our automatic method is a big step toward using cutting-edge technologies in regular medical imaging. This will allow for more accurate and faster cancer evaluations.

References

[1] A. Shetty and V. Shah, "Survey of Cervical Cancer Prediction Using Machine Learning: A Comparative Approach," 2018 9th International Conference on Computing, Communication and Networking Technologies (ICCCNT), Bengaluru, India, 2018, pp. 1-6, doi: 10.1109/ICCCNT.2018.8494169.

[2] V. -M. Partanen et al., "NordScreen - An Interactive Tool for Presenting Cervical Cancer Screening Indicators in the Nordic Countries," 2018 IEEE 14th International Conference on e-Science (e-Science), Amsterdam, Netherlands, 2018, pp. 287-287, doi: 10.1109/eScience.2018.00054.

[3] D. Dong et al., “DL radiomic nomogram can predict the number of lymph node metastasis in locally advanced gastric cancer: an international multicenter study,” Ann. Oncol., vol. 31, no. 7, pp. 912–920, 2020.

[4] C. Zhou, Y. Wang, M. H. Ji, J. Tong, J. J. Yang, and H. Xia, “Predicting Peritoneal Metastasis of Gastric Cancer Patients Based on Machine Learning,” Cancer Control, vol. 27, no. 1, pp. 1–8, 2020.

[5] S. Nazir, D. M. Dickson, and M. U. Akram, “Survey of explainable artificial intelligence techniques for biomedical imaging with deep neural networks,” Comput. Biol. Med., vol. 156, no. January, p. 106668, 2023.

[6] Q. X. Feng et al., “An Intelligent Clinical Decision Support System for Preoperative Prediction of Lymph Node Metastasis in Gastric Cancer,” J. Am. Coll. Radiol., vol. 16, no. 7, pp. 952–960, 2019.

[7] S. Sharanyaa, S. Vijayalakshmi, M. Therasa, U. Kumaran, and R. Deepika, “DCNET: A Novel Implementation of Gastric Cancer Detection System through DL Convolution Networks,” 2022 Int. Conf. Adv. Comput. Technol. Appl. ICACTA 2022, pp. 1–5, 2022.

[8] Ajani, S. N. ., Khobragade, P. ., Dhone, M. ., Ganguly, B. ., Shelke, N. ., & Parati, N. . (2023). Advancements in Computing: Emerging Trends in Computational Science with Next-Generation Computing. International Journal of Intelligent Systems and Applications in Engineering, 12(7s), 546–559

[9] F. Azour and A. Boukerche, "Design Guidelines for Mammogram-Based Computer-Aided Systems Using Deep Learning Techniques," in IEEE Access, vol. 10, pp. 21701-21726, 2022, doi: 10.1109/ACCESS.2022.3151830.

[10] R. Elakkiya, V. Subramaniyaswamy, V. Vijayakumar and A. Mahanti, "Cervical Cancer Diagnostics Healthcare System Using Hybrid Object Detection Adversarial Networks," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 4, pp. 1464-1471, April 2022, doi: 10.1109/JBHI.2021.3094311.

[11] H. Wahab, I. Mehmood, H. Ugail, A. K. Sangaiah, and K. Muhammad, “Machine learning based small bowel video capsule endoscopy analysis: Challenges and opportunities,” Futur. Gener. Comput. Syst., vol. 143, pp. 191–214, 2023.

[12] O. H. Kesav and R. G. K, "A Systematic Study on Enhanced Deep Learning Based Methodologies for Detection and Classification of Early Stage Cancers," 2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA), Hamburg, Germany, 2023, pp. 328-333, doi: 10.1109/ICCCMLA58983.2023.10346973.

[13] X. Guan, N. Lu, and J. Zhang, “Computed Tomography-Based DL Nomogram Can Accurately Predict Lymph Node Metastasis in Gastric Cancer,” Dig. Dis. Sci., no. 0123456789, 2022.

[14] J. V. N. Ramesh et al., "Sparrow Search Algorithm With Stacked Deep Learning Based Medical Image Analysis for Pancreatic Cancer Detection and Classification," in IEEE Access, vol. 11, pp. 111927-111935, 2023, doi: 10.1109/ACCESS.2023.3322376.

[15] R. Ashraf et al., "Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection," in IEEE Access, vol. 8, pp. 147858-147871, 2020, doi: 10.1109/ACCESS.2020.3014701.

[16] X. Jia, X. Xing, Y. Yuan, L. Xing and M. Q. . -H. Meng, "Wireless Capsule Endoscopy: A New Tool for Cancer Screening in the Colon With Deep-Learning-Based Polyp Recognition," in Proceedings of the IEEE, vol. 108, no. 1, pp. 178-197, Jan. 2020, doi: 10.1109/JPROC.2019.2950506.

[17] C. Kavyashree, H. K. Sowmya and N. V. U. Reddy, "A Survey on the Cervical Cancer Detection using Deep Learning methods," 2021 International Conference on Forensics, Analytics, Big Data, Security (FABS), Bengaluru, India, 2021, pp. 1-6, doi: 10.1109/FABS52071.2021.9702701.

[18] L. Fan et al., “Machine learning analysis for the noninvasive prediction of lymphovascular invasion in gastric cancer using PET/CT and enhanced CT-based radiomics and clinical variables,” Abdom. Radiol., vol. 47, no. 4, pp. 1209–1222, 2022

[19] A. Bhan, D. Sharma and S. Mishra, "Computer Based Automatic Segmentation of Pap smear Cells for Cervical Cancer Detection," 2018 5th International Conference on Signal Processing and Integrated Networks (SPIN), Noida, India, 2018, pp. 883-887, doi: 10.1109/SPIN.2018.8474108.

[20] J. Li et al., “Dual-energy CT–based DL radiomics can improve lymph node metastasis risk prediction for gastric cancer,” Eur. Radiol., vol. 30, no. 4, pp. 2324–2333, 2020.

[21] M. Bende, M. Khandelwal, D. Borgaonkar and P. Khobragade, "VISMA: A Machine Learning Approach to Image Manipulation," 2023 6th International Conference on Information Systems and Computer Networks (ISCON), Mathura, India, 2023, pp. 1-5, doi: 10.1109/ISCON57294.2023.10112168.

[22] Z. Zhang and J. Peng, “Journal of Radiation Research and Applied Sciences Clinical nursing and postoperative prediction of gastrointestinal cancer based on CT DL model,” J. Radiat. Res. Appl. Sci., vol. 16, no. 2, p. 100561, 2023.

[23] Q. Liu et al., “18F-FDG PET/CT Radiomics for Preoperative Prediction of Lymph Node Metastases and Nodal Staging in Gastric Cancer,” Front. Oncol., vol. 11, no. September, pp. 1–12, 2021

[24] D. Hao et al., “Identifying Prognostic Markers From Clinical, Radiomics, and DL Imaging Features for Gastric Cancer Survival Prediction,” Front. Oncol., vol. 11, no. February, 2022

[25] K. Agnihotri, P. Chilbule, S. Prashant, P. Jain and P. Khobragade, "Generating Image Description Using Machine Learning Algorithms," 2023 11th International Conference on Emerging Trends in Engineering & Technology - Signal and Information Processing (ICETET - SIP), Nagpur, India, 2023, pp. 1-6, doi: 10.1109/ICETET-SIP58143.2023.10151472.

[26] T. Habuza et al., “AI applications in robotics, diagnostic image analysis and precision medicine: Current limitations, future trends, guidelines on CAD systems for medicine,” Informatics Med. Unlocked, vol. 24, p. 100596, 2021.