Employing U-NET and RBCNN to Build an Automatic Lung Cancer Segmentation and Classification System

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Abstract. The most common cancer-related cause of death globally is lung cancer. The key to effective lung cancer treatment and higher survival rates is early diagnosis. Converting a radiologist's diagnosing procedure to computer assisted results in more accurate results and an earlier diagnosis. The difficulty is that building a effective model for segmentation and classification. In this paper, we suggest a system for detecting lung cancer that makes use of a number of methods for precise and effective diagnosis. To enhance picture quality, our method pre-processes CT scan images using a Gaussian filter and contrast stretching. For the purpose of determining the borders of lung nodules with high precision, the U-Net architecture with the Adam optimizer is used. Then, a Gaussian mixture model (GMM) with EM optimisation and pixel padding is used to extract features. The rotational-based CNN (RBCNN) classifier successfully categorises the nodules as benign and malignant using these form variables as inputs

Keywords: Computer assisted system, Lung cancer detection, Lung nodule segmentation, feature extraction, RBCNN classification.

1 Introduction

Globally, lung cancer is solely to blame for a large percentage of cancer-related deaths and poses an imminent life-threatening danger. The diagnosis and management of this condition are greatly aided by the precise categorization of lung nodules. These minute, round or oval globs of tissue are capable of being benign or malignant, but because of their site and texture, diagnosing may be complicated. Because there is no discernible colour difference among lung nodules and surrounding tissue, it is hard to differentiate benign from malignant nodules on CT images. At the same time , several characteristics can be used to distinguish between benign and malignant nodules. Several forms of lung nodules can be identified by their CT scan appearance, including juxtapleural nodules, isolated lesions, cavitary nodules, calcific nodules, and ground glass nodules. Juxtapleural nodule found on the lung's pleural membranes and can be difficult to distinguish from neighbouring tissues. Most isolated nodules are solitary, solid, or appear to be fairly solid. Cavitary nodules with hollow canters are common signs of advanced lung cancer. The majority of calcific nodules include calcified tissue and are benign growths. Ground glass nodules may have an early lung cancer connection due to their hazy appearance. A nodule's uneven form, spiculated (spiky) borders, size greater than 3 cm, rapid development, and presence of a hollow are all indications of malignancy. Conversely, benign nodules often have slower growth rates, uniform shapes, and

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smooth edges. Lung nodules must be properly classified in order for lung cancer to be detected and treated early. An important challenge in the domain of medical image analysis is the segmentation and classification of lung nodules. Lung nodules are tiny, round or oval-shaped growths that can be discovered in the lungs and may be signs of lung cancer. Early identification and treatment of these nodules depend on their proper detection and categorization. In this work, we provide a technique for classifying and segmenting lung nodules. Pre-processing, segmentation, feature extraction, and classification are some of the phases in our method. Pre-processing is used to strengthen the raw image's quality and begin preparing it for further processing. One typical method is to use a Gaussian filter, which assists in removing any noise or inconsistencies in the image. The range of brightness values in the image is also be expanded by using contrast stretching, which boosts the image's overall resolution and texture. The input picture can be improved for upcoming analysis and modification by using these methods during the pre-processing step. The U-Net architecture and ADAM optimizer are used to segment the lung nodules. It is conceivable to dissect and identify lung nodules in diagnostic imaging more thoroughly and efficiently using U-Net. Pixel padding, entropy value, and other factors are used in the feature extraction process. In addition to pixel padding, entropy value, GMM, and EM partitioning are used in the feature extraction procedure. Ultimately, utilising a rotational-based CNN and the retrieved characteristics, the categorization of malignant and benign nodules is accomplished. This suggested technique offers a thorough framework for precisely segmenting and categorising lung nodules, which can help in the early lung cancer detection and therapy.

2 Related Work

Efficient lung nodule classification using transferable texture convolutional neural network: To enhance the efficacy of pulmonary nodule classification, a transferable textured convolutional neural network was suggested. The number of learnable parameters is reduced by using the Energy level technique, which reduces memory requirements and computation complexity. Normalisation of pixels in CT images is accomplished by converting to Hounsfield scales using DICOM series header information. Then, in the first phase, they have extracted the region of interest around the nodule by acquiring the central coordinates and slicing a number of malignant and benign nodules. Then the voxel coordinates are acquired by some pixels around the central coordinates with respect to slice thickness. The patches were then extracted using voxel coordinates in the second phase. Then, after the third layer of CNN, they built a Convolutional neural network layer with an energy level.

Classification of lung cancer using lightweight deep neural network : The lung nodules are categorised using deep hybrid-based learning. The scan images are first downscaled to 11 mm for each voxel. To find nodules and masses that emerged at each voxel's border, the thresholding approach, the simplest segmentation method, is applied. Using Hounsfield units and a CT scan, the pixel-intensive tissues are segmented while the nonlung tissues are obscured. The blue pixels that are close to specific ranges are removed to produce a segment that is more relevant. The segmented nodule image is used as input by squeeze, mobile, and convolutional neural networks. Of the three, CNN regularly offers the most accurate results. because it takes longer to train the model.

Lung cancer detection and classification with DGMM-RBCNN : To detect lung cancer accurately, the DGMM-RBCNN system employs a region growing segmentation algorithm. Results from experiments show that the predicted segmentation accurately and without form distortion detects nodules of different sizes and shapes. The RBCNN classifier, which achieves middling accuracy while taking less time than traditional techniques, is trained on reduced characteristics to distinguish between non-cancerous and malignant nodules. The technique has a high sensitivity rate and is efficient in detecting lung cancer early. In order to fulfil time restrictions, the approach processes enormous volumes of data quickly and efficiently.

An efficient and robust model is created for the detecting and classification of cancer stage in CT lung images using FCM and SVM techniques : A significant advancement in the identification and categorization of lung cancer has been made with the creation of the Optimal Classification Algorithm for Cancer Practices Designed. A variety of image processing methods are used in the model to improve the categorization and precise segmentation of cancer pictures. This makes it simpler to apply the steps of effective therapy in practical contexts. Prior to extracting information from contrast, energy, homogeneity, and correlation variables, Gaussian and Gabor filters are employed to pre-process CT images. The SVM classifier split the classification process into four phases, and the fuzzy C-Mean Clustering method isolates the cancer image from the in volume cell.

Detection and classification of lung cancer using CNN and google Net : In order to automatically identify lung cancer, deep learning algorithms have proved quite helpful. Using a base network from the VGG-16 design, a unique technique has been given in this respect. Adenocarcinoma, Large Cell Carcinoma, and Squamous Cell Carcinoma can now be reliably distinguished from images of healthy lungs thanks to the algorithm. Pre-trained neural networks like Google Net and Vgg16 were compared to a CNN network with two blocks of layers in order to assess the algorithm's performance. Despite Google Net and Vgg16 having lesser and greater memory capacities, respectively, they were chosen because of their higher performance in comparison to other pre-trained neural networks. Surprisingly, the usage of just two CNN network blocks in the Google Net and VGG16 networks was sufficient to meet the necessary accuracy targets. The early identification and treatment of lung cancer, which is essential for improving patient outcomes, holds considerable potential for this novel technique.

Identifying lung cancer using image processing techniques : The Weiner filter, bit image slicing, erosion, and other techniques to extract the lung regions from the CT image. presented the use of the bit-plane slicing technique. This approach is speedier and more independent of users and data than thresholding. Segment the lung segments that acquired by applying the region-growing segmentation technique. A variety of attributes of the initially generated lung candidate nodules were evaluated in order to be integrated into the diagnostic standards. In order to locate malignant regions, the noise in the CT images was successfully reduced, and the lung sections were correctly segmented. The accuracy and productivity of the CAD system were improved by using bit-plane slicing and region expanding segmentation techniques.

A more powerful architecture for identifying lung cancer cells utilising the Gabor filter and an intelligence system : A novel approach that makes use of picture development enhances illness identification and care. Finding anomalies in the target photos takes into account time. Accuracy and image quality are crucial. Image quality is improved using low pre-processing methods based on the Gabor filter and Gaussian rules. The method segments pictures well for feature extraction. Compared to other procedures, it yields good outcomes. Mask-labelling and pixel percentage are used to accurately compare normalcy.

An Efficient DA-Net architecture for lung cancer segmentation : In order to segregate the lung nodule from the CT scan, noise in the picture was first removed using a median filter and an anisotropic filter. The ROI from the picture backdrop is then extracted using k-means clustering for segmentation. Using these operators, morphological procedures are carried out by many structures pre-defined kernels are elements on a picture. By performing an erosion operation on a picture and a dilation operation, the faults in the photographs are eliminated. as a result of out dilation procedure over a lung mask and a structuring element of size (10, 10). The retrieved lungs mask was convolved over the structuring element of size (10, 10). The lungs' boundaries were muddled and holes were plugged with this dilation procedure. new U-Net-based architecture called DA-Net uses ground masks to separate the lung nodule from a lung ROI picture as its input.

3 Proposed Work

The optimized computer-aided diagnosis of lung cancer involves the use of the chest X-ray lung dataset. The process comprises several phases, starting with a pre-processing step that reduces noise from the original CT scan image using denoising techniques. Next, the edges are sharpened using contrast stretching, followed by the application of a Gabor filter to remove unwanted features from the image and improve the segmentation process. In the second phase, lung nodules are segmented from the pre-processed image using the U-Net architecture. In the third phase, pixel padding, Entropy value calculation and Gaussian Mixture model techniques are utilized segmented lung nodule to determine its size. The nodule is finally characterized as benign or malignant using the RBCNN architecture. In order to accurately classify the nodule, this deep learning system examines the attributes that were collected from feature extraction.

3.1 LIDC-IDRI DATASET

The LIDC-IDRI image collection, a widely available source for CAD methods, contains annotated lung cancer lesions from thoracic CT images. It includes datasets from 1018 cases with DICOM CSV, radiologist comments, nodule size lists, nodule counts, and patient diagnoses**.** The database is open to the public and is used as a resource for studying medical images. The CT images were analysed by radiologists, who noted the lesions in three categories and then independently reviewed the markings to express a judgement without being obliged to agree. The dataset used for the proposed lung cancer classification system was collected using the National Biomedical Imaging Archive (NBIA). Specifically, a dataset of 1018 cases was produced by academic institutions and medical imaging businesses. Each case contains a CT image and related XML files with annotations from two phases of thoracic radiologists. During the blinded-read phase, radiologists classified lesions into three groups: nodules under 3 mm, nodules over 3 mm, and non-nodules. This information was recorded in the XML files, which were used to train and test the proposed classification system. The dataset was obtained in manifest format in The Cancer Imaging Archive (TCIA), a freely available repository of medical pictures used in cancer research.

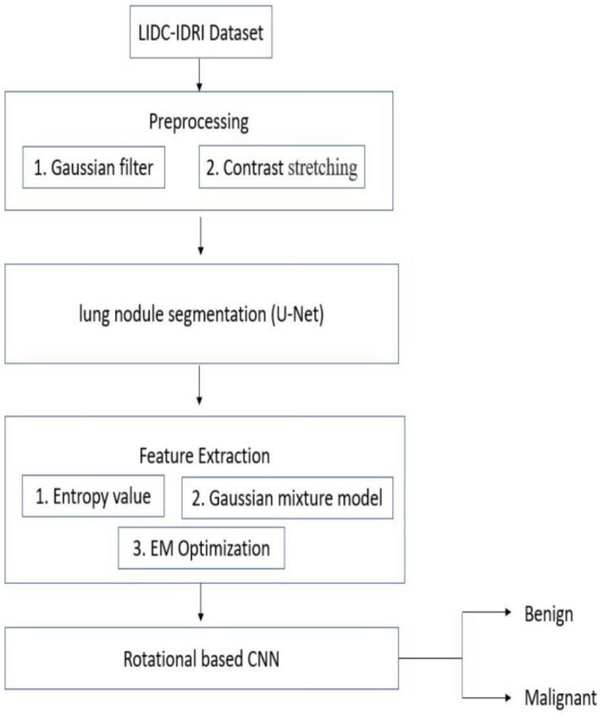

Fig. 1. System Architecture of proposed system

3.2 PRE-PROCESSING

3.2.1 Noise Reduction

The freely accessible LIDC-IDRI picture collection has a lot of noise in it. The noise reduction in the photographs reduces the high-frequency noise. The Gaussian filter is used in this case to reduce picture noise. By reducing noise and maintaining key characteristics, this filter can improve the picture quality in medical imaging applications such as the diagnosis of lung cancer from the LIDC-IDRI dataset. The LIDC-IDRI dataset contains a sizable collection of computed tomography (CT) images for lung cancer. Because of the background noise in the pictures in this dataset, it is challenging to accurately detect lung cancer. The Gaussian filter, which reduces noise in these pictures by convolving the image with a Gaussian function, is an effective technique. The CT scan image's high frequency noise is removed using a Gaussian filter. The breadth of the Gaussian function affects the filter's vitality, with wider functions having a more significant effect on the image. To obtain higher levels of noise reduction, the standard deviation of the Gaussian function is modified. This technique, which uses annotated lung cancer lesions from thoracic CT scans, is useful for successfully segmenting lung nodules as a source for CAD approaches.

$$G(i,j) = \frac{1}{2}\pi s^2 * exp^{\frac{-(i^2+j^2)}{2s^2}} \qquad (1)$$

The i and j represents the spatial coordinates of the pixel. s is the standard deviation of the Gaussian distribution. *exp* is the exponential function

3.2.2 Contrast Stretching

The output of a Gaussian filter has a limited range of intensity values. During segmentation, it is challenging to identify minute texture differences. When segmenting lung nodules, one important pre-processing step is contrast stretching. Contrast stretching is a technique that enhances the contrast between different parts of an image, making it easier to distinguish different structures within the image. This is particularly important when segmenting lung nodules, as they can be difficult to distinguish from surrounding tissue due to their small size and low contrast.

The rescaling of the pixel value of an image is done so that the lowest intensity values map to black and the highest intensity value maps to white. It reduces the impact of lighting variations and imaging artefacts, which improves the visibility of texture features.

$$I\_new = \frac{(\mathrm{I\_old} - \mathrm{I\_min}) * (\mathrm{O\_max} - \mathrm{O\_min})}{(\mathrm{I\_max} - \mathrm{I\_min}) + \mathrm{O\_min}} \qquad (2)$$

Where, I_old is the original intensity value of a pixel, I_min and I_max are the minimum and maximum intensity of original image, O_min and O_max are the minimum and maximum intensity values of desired output image. I_new is the new intensity value of pixel after contrast stretching.

3.3 LUNG NODULE SEGMENTATION

Once the image has been pre-processed with gaussian filter and contrast stretching, it is fed into the U-Net architecture for segmentation. The U-Net architecture consists of an encoder network that compresses the input image into a series of high-level feature maps, and a decoder network that reconstructs the segmentation map from the feature maps. The contracting path consists of a series of convolutional layers with max-pooling, which progressively reduces the spatial resolution of the input image. This allows the network to capture global features of the image.

$$w = encoder(u) \; ; \; v = decoder(w, u) \qquad (3)$$

where, u is the input image, w is the output of the encoder, v is the output segmentation mask. The encoder network uses convolutional and pooling layers to progressively down sample the image, while increasing the number of features captured at each level. With the help of a convolutional block and a max pooling operation, the encoder block method creates an encoder block that down-samples the input feature maps and extracts higher-level features. This allows the network to capture increasingly complex patterns and relationships within the image. After that, the decoder network up-samples the feature maps to create the final segmentation map using transposed convolutional layers. Using skip connections between corresponding encoder and decoder layers, segmentation accuracy is increased while low-level information is preserved. The optimizer used in U-Net training is typically Adam, which is a stochastic gradient descent algorithm that uses adaptive learning rates for each parameter in the model. Adam has been shown to be effective in training deep neural networks and can help speed up the convergence of the U-Net model during training. The network is trained for 25 epochs with a batch size. In the case of lung nodule segmentation, volumetric CT scan pictures have a high voxel or pixel density and make the training process computationally costly. The Adam optimizer is utilized in lung nodule segmentation because it blends quick convergence with effective memory utilization and is less likely to become trapped in local optima.

3.4 FEATURE EXTRACTION

3.4.1 Pixel padding

The portions of the image with the most information richness are highlighted using entropy filtering, which is utilized after pixel padding. By adding additional pixels all around the original image, the method known as pixel padding, makes the image larger.. This is done to ensure that the image is of a fixed size, which is important for feature extraction algorithms. In lung nodule feature extraction, pixel padding is often used to ensure that all nodules are of the same size, which allows for easier comparison of features across different nodules.

3.4.2 Entropy

The grayscale conversion of the padded images speeds up the entropy value computation. Entropy is a metric for how random or unpredictable a system is. Entropy may be used to gauge a picture's complexity in the context of image processing. Entropy is frequently utilized as a feature in lung nodule feature extraction to discriminate between various nodule kinds. For instance, compared to benign nodules, malignant nodules typically have greater entropy levels. By first determining each pixel's entropy value, it is feasible to exclude pixels with low entropy values from the image. The neighbourhood size of the entropy filter is set to 8x8 to calculate the entropy value. The pixel values in the region that is cantered on the pixel of interest are used to calculate the entropy value for each pixel in the grayscale image, the pixels with values just over the threshold are retained, and the pixel values with values below the threshold are set to zero to produce the filtered images. This step is essential because it improves the edges and textures of the image while reducing noise and unnecessary information.

3.4.3 Gaussian Mixture Model

GMM is a statistical model that represents the probability distribution of a collection of information points. The peak intensity of pixels of nodule is simulated using GMM in the procedure for obtaining lung nodule features By using a GMM to fit the energy distribution, features like the mean, variance, and deviation of the dispersion are extracted and utilised to distinguish among numerous types of nodules. Depending on the pixel intensity levels, the lung nodule image is separated into a number of parts using GMM filtering. A unique region in the image is represented by a different Gaussian distribution for each Gaussian distribution used in the GMM algorithm's model of the image. This step is crucial because it helps identify the different components of the image, such as the nodule and lung tissue, that are used to gather valuable information.

$$(y;\varphi) \; = \; \sum j \; = \; 1^\wedge J \; \omega j \; N(y;\; \eta j, \Lambda j) \qquad (4)$$

The input variable is y. The φ is variable set. The number

of elements in a composition is J. The j^{th} mixture component's weight is ωj. The Gaussian probability density function N(y; ηj, Λj) has a mean of j and a covariance of j.

3.4.4 Expectation Maximization optimization

The recovered characteristics are improved even more using the iterative optimization approach, Expectation Maximization (EM). This procedure extrapolates from the collected data the parameters of a prediction algorithm. To determine the distribution of the features in segmented lung nodule feature extraction in real time, apply the EM technique. The segmented lung nodule feature extraction can determine the distribution of the features in real time using the EM technique. This phase is significant because it aids in reducing the size of the features and catches the critical elements of the segmented picture, allowing for a quicker and more precise evaluation of the lung nodules.

$$Q(alpha|alpha^t) = \sum k = 1^X gamma_x log pi_x + 0.5 \sum k = 1^X gamma_x \big[\, log|Sigma_x| - \big(dlog(2pi) + tr(Sigma_x^{-1}(y - mu_x)(y - mu_x)^T)\big)\big] \quad (5)$$

Given the observed data *y* and the current parameter estimate alpha(t), gamma *gamma_x = p*(z = x | y, alpha* ^{t} *)* is the posterior probability of the latent variable z=x, and d is the number of dimensions in the data. The following is the update rule for the Gaussian mixture model's parameters:

1. *pi_x = N_x / N*
2. *mu_x = (1/N_k) ∑n=1*^{N} *gamma_kn x_n*
3. *Sigma_x = (1/N_x) ∑n=1*^{N} *gamma_xn (y_n - mu_x)(y_n - mu_x)*^{T}

where N is the total number of data points, N_x = ∑n=1, the effective number of data points assigned to cluster x, is N gamma_xn and y_n is the nth data point and

3.5 LUNG NODULE CLASSIFICATION

A machine learning system determines the malignancy or benignity of such a lung nodule using GMM feature extraction attributes. The expectation maximisation (EM) approach has been used to further improve these properties. It is now possible to tell if a lung nodule is benign or cancerous thanks to rotational based CNN (RBCNN), a type of neural network. The model initially pulls characteristics from the pictures of the nodules when a rotational-based CNN is used to classify lung nodules. This is done using a series of convolutional layers that are designed to identify important patterns in the image, such as edges, corners, and other distinctive features. It is made up of a number of layers that work together to classify the nodules and extract pertinent information by using the provided data. The edges, corners, and textures of the input data are all represented in these feature maps. The network becomes more nonlinear when the convolutional layer's output is sent through the ReLU activation function. The RBCNN's pooling layer, which is the next layer, applies a pooling function, such as maximum pooling or average pooling, to each sub-region of the feature maps. The network gets more efficient as a consequence, and the feature maps become less dimensional. The main advantage of using a rotational based CNN for lung nodule classification is that it is able to learn and recognize patterns in the images that are not immediately obvious to the human eye. For example, the model is able to detect subtle changes in the shape or texture of the nodule that can indicate whether it is benign or malignant. The output of the pooling layer is then sent via one or more fully connected layers, which apply a nonlinearity using the ReLU activation function and perform a linear transformation on the input features. These layers aid in the identification and refinement of significant properties from the supplied data. The RBCNN's output layer, which comes last, is responsible for classifying lung nodules as benign or malignant. In general, a SoftMax activation function is used to generate a probability distribution over the two classes, with the highest chance being the predicted class for the input nodule chance

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$$h(a,b) = g(U * (a \circ b) + c) \qquad (6)$$

The output feature map at rotation b of the input feature map is called h(a,b). An activation function, such as the sigmoid or ReLU, is a g. The layer’s filter weight is U. $\circ$ is the rotation operation, which rotates the input a by the angle b, and c is a bias term. U is the filter weights of the layer.

4 Experimental Result

The proposed method begins with a pre-processing method that uses a gaussian filter and contrast stretching to remove noise and unwanted features. The downloaded LIDC-IDRI dataset is in DICOM format, thus we used the pydicom package to load the pictures from the dataset. The picture is transformed to a floating-point representation and normalised to a range of [0, 1]. Using the np.random.normal() method and a standard deviation of 0.0001, Gaussian noise is introduced to the picture shown in Fig 3. To prevent values that are outside of the range, the noisy picture is cropped to the range [0, 1]. With a kernel size of 5x5 and a standard deviation of 0, the cv2.GaussianBlur() function applies a Gaussian filter to the noisy picture.

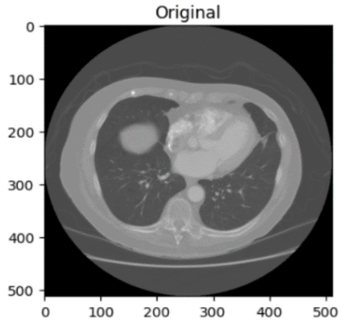

Fig. 2 Original CT scan image

The percentile() function is then used to calculate the first and 99th percentiles of the filtered image. These percentiles will be used to determine the lowest and highest pixel values for the stretched image. The calculated percentiles are stored in the variables "p5" and "p95." The NumPy. Clip function is used to clip the pixel values of the filtered image between 0 and 1 in the case that there are values outside of this range. The filtered image is stretched or normalised by subtracting the first percentile value, p1 and dividing the result by the difference between the 95th percentile value, p95 and p5 to avoid the stretching to be too extreme, the stretched pixel values are then clipped to a range between 0 and 1.5 using the np.clip() function. This means that pixel intensities below the 1st percentile will be set to 0 and pixel intensities above the 99th percentile will be set to 1.5. As a result, a normalised image with pixels ranging from 0 to 1 is produced, as shown in Fig 4.

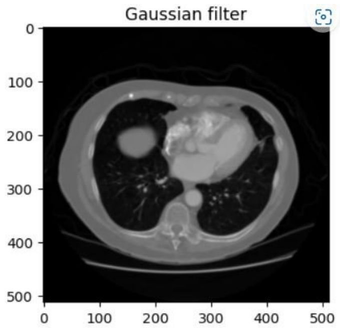

Fig. 3 Application of Gaussian Filter for Noise Removal

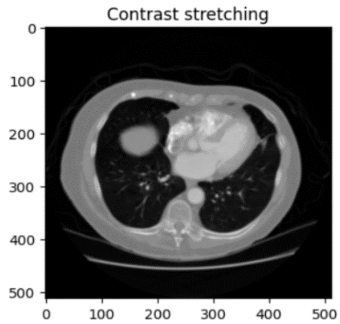

Fig. 4 Contrast stretching applied to enhance image contrast

Once the pre-processing is over, the output image is given as input for the constructed U-Net architecture. The U-Net input shape parameter is modified to suit the input picture data's dimensions. The U-Net model demands input photos with a resolution of 224x224 pixels and three colour channels, and this parameter is set to (224, 224, 3) in the code. The build U-Net function in the script is used to design the U-Net model architecture. Moreover, it defines measurements like recall, accuracy, and intersection and union over the dice coefficient. The model is built using the supplied metrics, optimizer (Adam), and loss function (dice loss) and learning rate as 0.0001. The program specifies a number of call-backs to track the progress of the training, including saving the best model, lowering the learning rate, logging the data, visualizing the data in Tensor Board, and blocking the initial training if the validation loss does not decrease for a predetermined number of epochs. Training the model using the above setup helps to improve the learning rate and accuracy of the model. In our experimental work, the use of the entropy value, GMM filter, and EM optimization lung nodules was 81.8% after 500 samples were used to train the model.

We employed a variety of carefully chosen feature extraction methods, such as entropy values and GMM filters with EM optimization, to produce these findings. To attain the optimum results, we also tweaked the model's hyperparameters. We utilized a learning rate of 0.1 and adjusted the rotating angle to 45 degrees. According to the findings of our study, a promising method for classifying lung nodules is the rotational-based convolutional neural network approach using extracted characteristics. This technique has the potential to assist in the early diagnosis of lung cancer and enhance patient outcomes by obtaining high levels of accuracy in the classification task.

5 Conclusion

The proposed system for computer-assisted diagnosis, which combines Gabor filtering, contrast stretching, U-Net with Adam for segmentation, entropy filtering, GMM with KM optimisation for feature extraction, and RBCNN for classification, represents a significant advancement in the early detection of malignant and benign tumor. Utilizing a computer-aided diagnostic tool that incorporates cutting-edge image processing and machine learning methodologies significantly improves the efficiency and accuracy of lung cancer detection and categorization. In lung nodule segmentation, the Adam optimizer in U-Net employs a momentum-based update, which enables it to approach the loss function's minimum more quickly and achieve faster convergence. Compared to other optimizers like Adagrad or RMSprop, the Adam optimizer utilizes memory more effectively. Using U-Net architecture instead of patch-based region growing segmentation can segment lung nodules from raw image data without relying on handcrafted features or patch-based region growing algorithms. It is highly flexible and can be trained on various lung imaging types, is robust to noise and artifacts, and can adapt to new data with minimal retraining, making it useful for clinical practice. This was attributed to U-Net's ability to gather global information and discover hierarchical representations of the image, allowing it to recognise subtle patterns and structures that individual vision might not detect A system like this can aid radiologists in spotting aberrant lung tissue in patients, leading to early lung cancer identification and diagnosis. The incidence of missed diagnoses is decreased by using a computer-aided diagnosis method for early lung cancer segmentation and classification, which can enhance patient outcomes.

The accuracy of our suggested computer-aided diagnostic method may be increased in the future by including additional imaging modalities like MRI or PET, which might give supplementary data. Moreover, we may use reinforcement learning (RL) to the system to data-driven refine the settings, which might result in a more effective and precise diagnosis.

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