IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

LUNG CANCER PREDICTION USING IMAGES FEATURE ANALYSIS AND CNN

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Abstract: Lung cancer is a fatal disease with a high mortality rate in diseased patients. Early diagnosis of this disease and accurately identifying the lung cancer stage can save the patients' lives. Several image processing, biomarker-based and machine automation approaches are used to identify lung cancer, but accuracy and early diagnosis are challenging for medical practitioners. In conventional methods, manual CT images are supplied to visualize whether the person has lung cancer. This research article proposes a novel method for an early and accurate diagnosis called Cancer Cell Detection using Hybrid Neural Network (CCDC-HNN). The features are extracted from the CT scan images using deep neural networks. The accuracy in feature extraction is very important to detect the cancerous cells at early stages to save the patient from this fatal disease. In this study, an advanced 3D-convolution neural network (3D-CNN) is also utilized to improve the accuracy of diagnosis. The suggested approach also enables the distinction between benign and malignant tumors. The results are evaluated using standard statistical techniques, and the results confirm the viability of the proposed hybrid deep learning (DL) technique for early diagnosis of the lung cancer.

Index terms: Machine learnin,Lung cancer, Image processing Hybrid neural network, Convolutional Neural Network, RNN

1. INTRODUCTION

In 2018 it was estimated that approximately 9.6 million deaths were claimed by lung cancer. Lung cancer tops the list if a person talks about the types and their shares. Estimated cases of lung cancer are around 2.09 million with 1.76 million deaths which account for around 84% deaths [1]. Due to this reason lung cancer has been entitled as one of the most fatal diseases. Tumor is made by multiplication of abnormal cells in lung cancer. Cancer cells tend to spread really fast due to blood streams ans lymph fluid that is present in lung tissue. In general, due to normal lymph flow, cancer cells frequently migrate to the middle of the chest. As cancer cells migrate to other tissues, metastasis occurs. It is important that cancer be detected as early as possible as it tends to spread and is beyond curable in case of a larger spread. It is difficult to diagnose lung cancer since it shows symptoms in the final stage and it is nearly impossible to save a person's life in the final stage. Images of lungs for examination are captured by imaging techniques such as Computed Tomography (CT), Positron Emission Tomography (PET),Magnetic resonance imaging (MRI) and X-ray. CT image technique is the most common out of the mentioned methods due to its ability to give a view excluding overlapping structures. Interpreting and recognizing cancer is complicated for doctors. CT photographs are accurate for the diagnosis of lung cancer. To identify lung cancer, image processing, and deep learning methods will be used. Accuracy can be improved using these approaches. Tumour detection and determination of its form, size, andlocation is a tough task. Timely detection helps in saving a lot of time. And this time can be used in providing early treatment to the patient. In this project, pre-processing (removing noise if any), post-processing (segmentation) and classification techniques will be used to classify tumors into one of the two groups i.e. Malignant and Benign. Benign refers to a non-cancerous tumor and it doesn't spread to other parts. Abnormal cells divide without control in malignant and may invade surrounding tissues.Exploring different methods to diagnose lung cancer will be a prime aim in this paper. Computed tomography can be used to capture images of lungs across various dimensions so that a 3D image of the chest can be formed. This 3D image can be used to detect tumors present. Normally a doctor or any field expert uses a CT image to detect cancer. Due to the large number of CT images, it is difficult for a doctor or radiologist to detect cancer quickly and accurately. But with the advancement in technology, Computer-Aided Diagnosis (CAD) can be utilized to complete this duty efficiently and in considerably less time. This process has two separate processes i.e. first to identify all the nodules present in the CT image and second to classify the detected lung nodules.

2. LITERATURE SURVEY

T. Sowmiya M .,et.al [1] In this paper they described Cancer as the most dangerous diseases in the world. Lung cancer is one of the most dangerous cancer types in the world. These diseases can spread worldwide by uncontrolled cell growth in the tissues of the lung. Early detection of the cancer can save the life and survivability of the patients who affected by this diseases. In this paper we survey several aspects of data mining procedures which are used for lung cancer prediction for the patients. Data mining concepts is useful in lung cancer classification. We also reviewed the aspects of ant colony optimization (ACO) technique in data mining. Ant colony optimization helps in increasing or decreasing the disease prediction value of the diseases. This case study assorted data mining and ant colony optimization techniques for appropriate rule generation and classifications on diseases, which pilot to exact Lung cancer classifications. In additionally to, it provides basic framework for further improvement in medical diagnosis on lung cancer.

Fatma Taher, et.al [6] In this paper presents two segmentation methods, Hopfield Neural Network (HNN) and a Fuzzy C-Mean (FCM) clustering algorithm, for segmenting sputum color images to detect the lung cancer in its early stages. The manual analysis of the sputum samples is time consuming, inaccurate and requires intensive trained person to avoid diagnostic errors. The segmentation results will be used as a base for a Computer Aided Diagnosis (CAD) system for early detection of lung cancer which will improve the chances of survival for the patient. However, the extreme variation in the gray level and the relative contrast among the images make the segmentation results less accurate, thus we applied a thresholding technique as a pre-processing step in all images to extract the nuclei and cytoplasm regions, because most of the quantitative procedures are based on the nuclear feature. The thresholding algorithm succeeded in extracting the nuclei and cytoplasm regions. Moreover, it succeeded in determining the best range of thresholding values. The HNN and FCM methods are designed to classify the image of N pixels among M classes. In this study, we used 1000 sputum color images to test both methods, and HNN has shown a better classification result than FCM, the HNN succeeded in extracting the nuclei and cy-toplasm regions. In this paper authors uses a rule based thresholding classifier as a pre-processing step. The thresh-olding classifier is succeeded in solving the problem of in-tensity variation and in detecting the nuclei and cytoplasm regions, it has the ability to mask all the debris cells and to determine the best rang of threshold values. Overall, the thresholding classifier has achieved a good accuracy of 98% with high value of sensitivity and specificity of 83% and 99% respectively.

Krishnaiah V et al. [4] proposed data mining classification techniques on Lung cancer diagnosis. The Rule set classifier, Decision Tree, Neural Network and Bayesian Network classification algorithms are used for Lung Cancer analysis. From the results it is identified that Naïve Bayes algorithm is produced better results than the other algorithms.

Juliet R Rajan et al. [5] proposed an unsupervised learning method is used to build an analytical model for initial detection of lung cancer. The authors used ANN technique to predict the disease. The Lung cancer was further analyzed with training resultant weight vector values.

Lynch et al., [6] Various machine learning algorithm are implemented for predicting the survivability rate of person, performance is measured based on root mean square error. Each model is trained using 10-fold cross validation, as the parameters are preprocessed by assigning default value so cross validation is used for avoiding over fitting.

Sumathipala et al., [9] proposed a model where the image data are taken from LIDC-IDRI, after collecting the image data image filtration has been implemented, filtration is done based on the patient who went through biopsy and module level is equal to 30 and then images whose module level is equal to 30 is segmented and then Logistic regression and random forest has been applied for prediction.

Fenwa et al., [3] proposed a model whether feature like contrast, brightness from the image dataset is extracted using texture based feature extraction and on that two type of machine learning algorithm are applied one is artificial neural network another one is support vector machine and then performance has been evaluated on both the algorithm to compare which algorithm is giving more accuracy.Deep learning, a subset of machine learning which in turn is a subset of artificial intelligence (AI) has networks capable of learning things from the data that is unstructured or unlabeled. The approach utilized in this project is Convolutional Neural Networks (CNN). It uses the Haar-cascade classifiers which help us in the detection of objects.

3. CONVOLUTIONAL NEURAL NETWORKS (CNN).

The convolutional neural network, or CNN for brief, could also be a specialized kind of neural network model designed for working with two-dimensional image data, although they're going to be used with one-dimensional and three-dimensional data.Central the convolutional neural network is the convolutional layer that gives the network its name. This layer performs an operation known as “convolution”.In the context of a convolutional neural network, a convolution may be a linear operation that involves the multiplication of a group of weights with the input, very similar to a standard neural network. as long as the technique was designed for two-dimensional input, the multiplication is performed between an array of input file and a two-dimensional array of weights, called a filter or a kernel.

The filter is smaller than the input file and therefore the before the sort of multiplication applied between a filter-sized patch of the input and the filter may be a scalar product. A scalar product is that the element-wise multiplication between the filter-sized patch of the input and filter, which is then summed, always leading to one value. Because it leads to 1 value, the operation is conventionally represented and mentioned because the “scalar product”.

Using a filter smaller than the input is intentional because it allows an equivalent filter (set of weights) to be multiplied by the input array multiple times at distinct points on the input. Specifically, the filter is applied systematically to every overlapping part or

filter-sized patch of the input file, left to right, top to bottom.

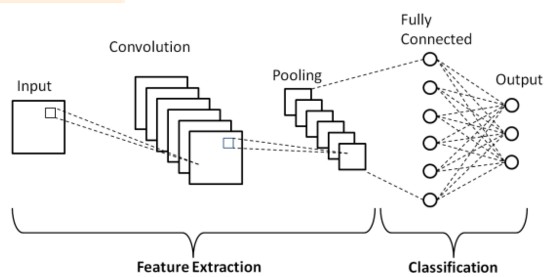


Fig 1.1 Sample block diagram indicating the flow of image processing using CNN

This systematic application of an equivalent filter across a picture may be a powerful idea. If the filter is meant to detect a selected sort of feature within the input, then the appliance of that filter systematically across the whole input image allows the filter a chance to get that feature anywhere within the image.

This capability is usually represented and mentioned as translation invariance, e.g. the total altogether concern in whether the feature is present instead of where it should had been present.

4. PROPOSED METHODOLOGY

CNN–RNN can be employed to evaluate digital histopathology images since they contain many pixel data. This study presented a combination CNN–RNN system that concentrated on visuals to give a broad context. The suggested approach first converts a histological picture’s regional representation into a higher-dimensional characteristic and then aggregates the feature by assessing its spatial organization to allow the final forecasts. The images from formalin-fixed, paraffin-embedded diagnosed blocks of malignant skin conditions were taken from the Genome Sequencing and utilized as the database. This suggested model analyses histological pictures to evaluate melanoma tumors using CNN- RNN.

4.1 FEATURE EXTRACTION

The most significant data from the image gives a more thorough picture of knowledge. The definition of a function is one or more measuring functions that target some calculated qualitative real estate values that object to the characteristics necessary for the function to represent. Finally, the statistical characteristics based on geometry and intensity are retrieved. This measurement data may help in determining if a lung nodule is cancerous or not. A physical aspect used to describe an object’s geometry is shape measurements. Perform training and testing on the extracted pictures after the retrieved feature. When fitting a model during training, the method incorporates a classification classifier, and the variable is the performance prototype, which is only evaluated when test data is utilized.

The test data must be anticipated since it is unknown, yet the outcome of the training examples may be simulated. The retrieved photos are evaluated, learned on, and classified using data.

4.2 TRAINING MODEL

Pre-trained convolutional neural system layer, RNN layer, Merging layer, and utterly connected surface with Softmax output make up the proposed model. For training the model back propagation is mainly preferred.

4.2.1. PRE-TRAINED CONVOLUTIONAL NEURAL NETWORK LAYER

The system uses the feature weights obtained from pre-training on the ImageNet database as the starting weights for CNN architecture. Convolution operation and max pooling are components of convolutional networks.

4.2.2. CONVOLUTIONAL LAYER

The primary method for calculating this layer is the most crucial component of the convolutional network. It is to employ convolution windows of various sizes to execute convolutional filters with the extracted features from the previous layer. Sequentially convolutional windows are slid onto the last layer. Typically, the convolutional layer has three or five feature weights depending on the time window, which is 3×3 or 5×5. The activation function utilized in the layer is used to achieve the result in the convolution operation twisted through matching windows.

4.2.3. POOL LAYER

This layer operates similarly to the convolutional layer in terms of calculation. The distinction is that the lowest layer's sliding window is typically 2×2, and the slipping step is 2. Because of this, the width of the last layer's feature space is typically cut in half. That effectively reduces the convolutional weights within the neural system parameters, which helps accelerate the network training phase. Additionally, it enables the system to be more adaptable to the size of the picture modifications at the exact moment.

This study applies the pre-trained network and the Linear Rectification Function. Another enhanced version of Google's Inception v3 is called Xception. It primarily provides depth-wise separated Convolution to swap out the convolution technique seen in the initial model. As an upgraded version of Inception v3, Xception includes depthwise separable compression, which enhances the model's performance without adding to the system's intricacy.

4.2.4. RNN LAYER

An input level, a hidden surface, and an output surface are present in both RNN and CNN. The most crucial aspect of RNN is how these hidden layers are connected. The concealed layer is sent to the output nodes by connecting the input level nodes and the concealed layer vertices. Even for the concealed state, neighboring nodes to one another are included in the node outputs data sent back to the concealed layer node. RNNs are depicted as nearer to the natural neural networks, which are cyclic systems that can comprehend serial communication [2].

This method can learn on long-term reliance. LSTM differs from RNN by including a “processor” to judge whether the data is helpful or not. Input gates, a memory gate, and the gate of output are the three doors positioned in a cell. A message joins the LSTM model and is subject to rule evaluation. The inconsistent data is erased via the Oblivion Gate, leaving only the data that has been certified by the program. A memory cell plus three multiplicative gates namely input, outputs, and forget gates. The LSTM features a more intricate structure than the typical RNN module.

4.2.5. MERGE LAYER

The merger layer function combines the characteristics received from the RNN and those acquired from the CNN using a particular technique. The merge layers function combines the data received from the RNN and the characteristics acquired from the CNN using a particular technique. A neural network that can pick particular input and concentrate on it (or its characteristics) is said to have a neural network learning algorithm. For feature merging, the system applies the appropriate element-wise multiplying procedures [7].

4.2.6. FULLY CONNECTED LAYER WITH A SOFTMAX OUTPUT

The probability distributions of all categories result from the densely integrated Softmax level, which receives the features produced by the RNN and CNN after they have been combined. The cross-entropy is also used as an error function to calculate the discrepancy between the actual and desired output.

4.2.7. NETWORK TRAINING

The RNN branch initializes the variables arbitrarily, while the values in the CNN node use values that have been pre-trained on the ImageNet database. Through the slope of the cross-entropy error function, these values are continuously adjusted during the training phase. First, the CNN layer is locked. The optimizer then calculates the training data, which takes ten iterations. The CNN level is defrosted, the Adam optimizer is used throughout the system to compute training data, the development rate is set to 0.001, and 10 epochs are needed for training. After a specified number of intervals, the training procedure ends. The version with the smallest value of validation loss was selected as the final network.

5. ARCHITECTURE DIAGRAM OF THE PROPOSED WORK

The workflow of the proposed framework is shown in Fig. 5.1. The necessary images for the analysis are accessed from the dataset, and the images are preprocessed. The dataset is segmented into training and testing samples using the hybrid neural network, and the proposed method is trained and tested. Dataset examples were originally preprocessed in the segmentation method to identify the photos' basic features. The training and evaluation sets were then created from the dataset. The validation data were classified using an RNN decoder and a pre-trained CNN structure.

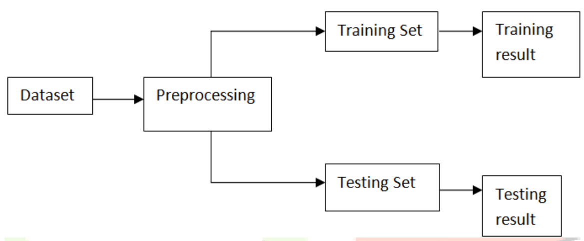


Fig 5.1 Workflow of the proposed method.

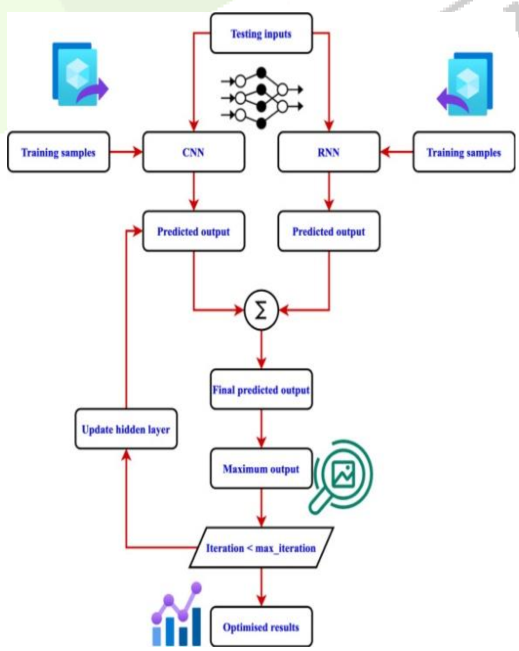
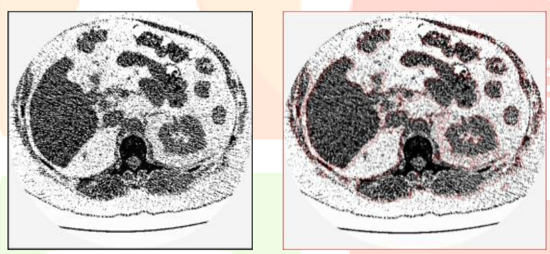


Fig 5.2 Hybrid neural network-based cancer detection framework.

6. PSEUDOCODE

Input –Sample image
Output- Cancer detection
Procedure
For every image X
Compute using 3D-CNN
Preprocess the image
Segment the image for the cancer cell area
Extract the features from the image I
Compute using 3D-CNN
Preprocess the image
Segment the image for the cancer cell area
Extract the features from the image I
Combine the results of 3D-CNN and RNN
Final Classification results(normal or malignant)

The input and output of the CT images are plotted in Fig.6.1 respectively. The cancer cell image is taken as the input and processed with the hybrid neural network, which contains 3D CNN and RNN model to detect cancer in the cell. The simulation outcomes are evaluated using training and testing samples from the dataset. The proposed framework with a hybrid neural network enhances the detection and classification process, and the combined results enhance the overall efficiency and outcomes of the system.



Sample Input **Predicted Output**

Fig 6.1 Results

The simulation outcomes such as accuracy, precision, specificity, sensitivity, are evaluated for both training and testing samples. The samples are trained with 3D CNN and RNN samples, the testing outcomes are evaluated using the training system, and the outcomes are merged to find the optimum results. The proposed framework exhibits higher outcomes in all the metrics for both training and testing samples.

Fig 6.2 Simulation based outcomes from the proposed work.

7. CONCLUSION

Lung cancer is a very fatal disease which needs an attention from the medical practitioners and researchers to find innovative solutions for early diagnosis of this disease to save the lives of the patients. Early detection of lung nodules aids in diagnosing illness and averts disease-related mortality. With the assistance of medical professionals, computer diagnosing methods have been devised to shorten diagnostic times, increase effectiveness and accuracy, and decrease disease-related mortality. The approach in this research suggests a sophisticated CNN with an RNN algorithm for classifying cancerous lung nodules. The system makes use of the LUNA 16 database. The proposed novel technique in this article is able to process the CT scan images with high accuracy by devising an innovative method for feature extraction from the CT scan images and then by employing the hybrid DL method for classification of images. The empirical results obtained from the proposed mechanism demonstrate that the proposed improved model provides single CNN and RNN classifications with 90% accuracy. In future, the efficiency of the proposed work can be enhanced by using big-data analytics and cascaded classifiers.

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