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A Comparative Study of Lung Nodule Classification Using Local Binary Patterns and Convolutional Neural Networks

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Motivation

- Lung cancer is the leading cause of cancer related deaths in Canada.[1]
- In 2017, 14% of new cancer cases and 26% of cancer-related death resulted from lung cancer.
- Effects both men and women.
- Disproportionately effects the lower and middle class.
- High cancer rates pose an economic burden on the healthcare system.
- Early detection and diagnosis of lung nodules can increase the 5-year survival rate of patients by approximately 50%.[2]

Objective

- Employ computational vision and machine learning techniques to design Computer-Aided Diagnostic (CAD) systems to diagnose lung nodules as malignant or benign.
- Utilize Local Binary Patterns (LBP) enhanced with oriented gradient features for k Nearest Neighbors (KNN).[3]
- Learn deep features of lung nodules using VGG 16 Convolutional Neural Network (CNN) with weights pre-trained on the imagenet dataset.[4]
- Evaluate results using accuracy (acc), sensitivity (sen), and specificity (spec) for two distinct labeling methods.[5]

Dataset

- Computed Tomography (CT) images and assessments from 4 thoracic radiologists for 1012 patients from the LIDC-IDRI database.
- Radiologists assign a grade of 1-5 to nodules of interest where 1 is benign, 5 is malignant and 3 is indeterminate. In this study a grade of 3 is considered malignant.
- Two malignant labeling schemes are considered: 1. when at least two votes (split vote) predict malignant and 2. when at least three votes (majority vote) predict malignant.

Local Binary Patterns (LBP)

Classification of lung nodules by KNN requires the extraction of image features.

- For a given CT image such as Figure 1(A), a series of thresholds and morphological operation isolates potential lung nodules as shown in Figure 1(B). The images are resized to shape 32x32 and centered at the nodule as shown in Figure 1.
- The texture features are then quantified by applying the texture operator of Figure 1(D) to each interior nodule pixel of Figure 1(C). The neighbor pixels of the texture operator, P_n are binarized relative to the central pixel, P_c according to Equation (1). The sequentially numbered pixels are arranged as a binary pattern and converted to a single scalar value according to Equation (2), which produces the mask depicted in Figure 1(E). The LBP values of Figure 1(C) are then binned by a histogram.
- Oriented gradient features are obtained by dividing the segmented nodule of Figure 1(C) into cells of 4x4 and computing the magnitude and direction of the gradient at each pixel as shown in Figure 1(F). The gradient values of each cell are are then binned by a histogram.
- Concatenating the histograms of LBP and oriented gradients yields a nodule feature vector.
- Prediction of a query feature vector x is made the feature vector x' that minimizes the Euclidean distance metric of Equation (3).

$$s(p) = \begin{cases} 1, & \text{if } p_n - p_c \geq 0 \\ 0, & \text{otherwise.} \end{cases} \quad (1) \qquad LBP_{R,N}(x,y) = \sum_{i=0}^{N-1} s(p_i - p_c)\cdot s^i \quad (2) \qquad d(x,x') = \sum_{i=1}^{N} (x_i - x_i')^2 \quad (3)$$

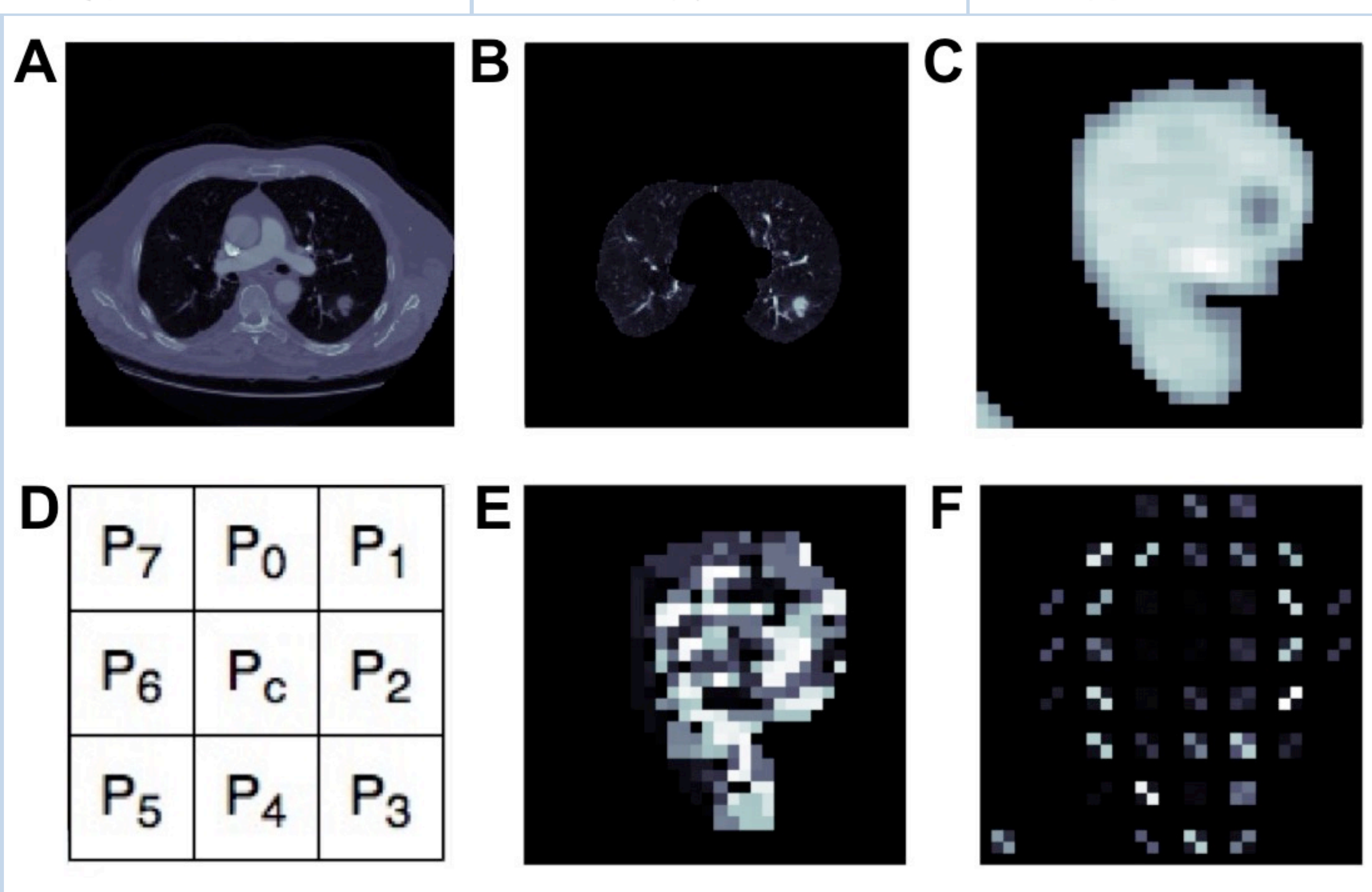

Figure 1: Summary of the preprocessing approach implemented for LBP and HOG to obtain the texture features for KNN classification. (A) shows original CT image, (B) shows the processed (A), (C) shows (B) resized to 32x32 pixels, (D) shows the LBP operator, (E) shows the resulting LBP mask of (C), and (F) shows the oriented gradient image of (C).

Convolutional Neural Network (CNN)

- The VGG 16 CNN architecture is depicted in Figure 2.[4]
- CNN architectures consist of two primary components: feature extraction and classification.
- Feature extraction is achieved by learning the weights of a series of convolution layers and pooling layers (green and red blocks, respectively) that extract simple features in the initial layers and increasing complex features in subsequent layers.
- Classification is achieved by learning the weights of a set of fully connected layers (blue blocks) that map the features to the output prediction.
- CNNs with many layers are generally better but require a large number of labeled images in order to generate adequate weight values.
- Therefore, transfer learning is employed by applying a VGG 16 network with parameters initialized by the imagenet database consisting of a variety of objects with general features.
- The initialized weights are then fine-tuned to generate a mapping for the input features and prediction classes unique to the system being studied.

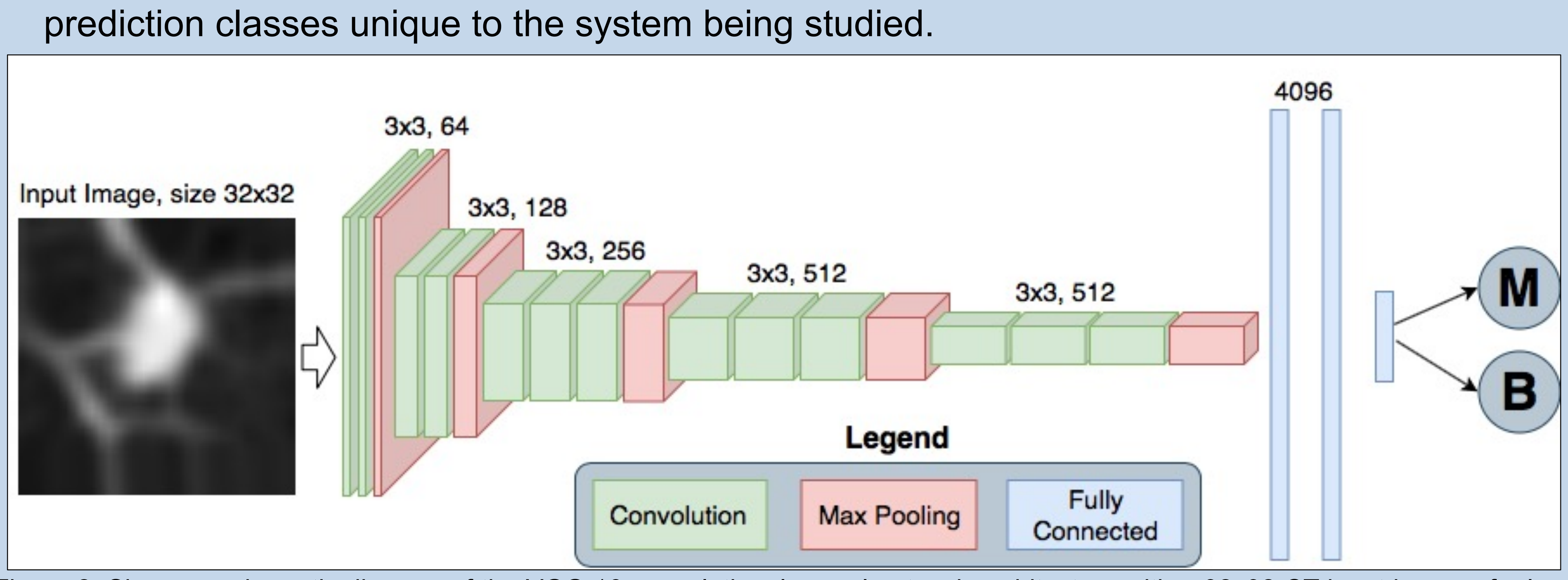

Figure 2: Shows a schematic diagram of the VGG 16 convolutional neural network architecture with a 32x32 CT input image of a lung nodule where the output circles "M" and "B" indicate either a malignant or a benign prediction.

Results

The performance measures employed are defined in terms of the quantities True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Accuracy measures the number of correct predictions according to Equation (4), sensitivity measures the number of correct malignant predictions according to Equation (5), and specificity measures the number of correct benign predictions.

$$\mathrm{acc} = \frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{TP}+\mathrm{TN}+\mathrm{FP}+\mathrm{FN}} \quad (4) \qquad \mathrm{sen} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}} \quad (5) \qquad \mathrm{spec} = \frac{\mathrm{TN}}{\mathrm{TN}+\mathrm{FP}} \quad (6)$$

- The accuracy, sensitivity, and specificity results of split vote labeling and majority vote labeling for KNN and VGG 16 CNN are summarized in Table 1. The maxim acc, sen, and spec for KNN and CNN are emphasized by green, turquoise, and orange highlighting.
- Table 1 shows that a split vote labeling method is superior for all performance measurements when employing a KNN classifier using LBP and oriented gradient features.
- Table 1 shows that a split vote labeling method is superior for all performance measurements when employing a VGG 16 CNN architecture for classification.
- The results of Table 1 appear to be counterintuitive as one might expect that a stronger malignant labeling condition would yield better agreement. The results of Table 1 are significant some lung nodule classification studies in the literature have employed a majority voting scheme for labeling.[5]
- Table1 shows that VGG yields the higher overall accuracy.

	Split Vote (at least 2 malignant votes)	**Majority Vote** (at least 3 malignant votes)
K Nearest Neighbors Classifier	Accuracy = 83.07% Sensitivity = 86.10% Specificity = 82.19%	Accuracy = 80.98% Sensitivity = 82.59% Specificity = 54.79%
VGG 16 Convolutional Neural Network	Accuracy = 86.38% Sensitivity = 85.70% Specificity = 94.52%	Accuracy = 83.00% Sensitivity = 80.11% Specificity = 83.71%

Table 1: Summary of accuracy, sensitivity, and specificity performance measures for k nearest neighbor classification and VGG 16 classification.

Conclusion

- This study shows that the preprocessing technique employed is adequate to extract LBP and oriented gradient features for KNN classification of lung nodules as malignant or benign.
- Additionally, VGG 16 using pre-trained weights can be employed to learn the image features of lung nodules.
- The accuracy, sensitivity, and specificity performance measures indicate that the best agreement is achieved using a split vote labeling scheme and CNN is the superior classifier.
- The results of Table 1 are less slightly less than those generally reported in literature, however, little tuning of the classification parameters has been implemented in this study.

Future Work

- Experiment with histogram of oriented gradients parameters such as size of cells and number of bins.
- Investigate the affects of incorporating statistical features of segmented images such as mean, standard deviation, skewness, kurtosis, 5th central moment and 6th central moment.
- Reduce noise by employing pruning techniques to eliminate outlier points or skewed points
- Investigate the affect of changing the number of layers that use pre-trained weights and the number of layers that are tuned by training on CT images.
- Additionally, study the effect of varying values of momentum and learning rate.

References

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