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Advancements in Lung Cancer Diagnosis through Capsule Neural Network in CT Images

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***Abstract*—**The classification of lung cancer raises substantial difficulties because of a scarcity of training data, a large number of dimensions, intricate imaging features, and similarities within classes, frequently leading to less than optimal diagnostic precision. The Capsule Neural Network preserves the hierarchical links between distinct image components by converting scalar feature representations into vectors, providing a novel solution to these problems. This article presents an innovative deep-learning framework designed specifically for classifying lung cancer. It utilizes two convolutional neural networks to improve the extraction of spatial and spectral characteristics. We assessed the efficacy of the CapsNet model by evaluating it on the benchmark LIDC-IDRI datasets. The results indicate that LungCaps outperforms standard Capsule Networks and ConvCaps in terms of performance, highlighting its potential to enhance lung cancer diagnosis in CT imaging.

Keywords—Lung Cancer, Capsule Network, Computed Tomography, Image Classification, Deep Learning

I. INTRODUCTION

Advanced lung cancer patients survive 6-9 months and have a 5-year survival rate of 3–5% [1]. This makes lung cancer treatment innovation an urgent medical issue. Targeted therapy, on the other hand, has offered advanced lung cancer patients hope and helped clinicians treat the disease [2]. CT images are low-cost and efficient in multi-modal medical image data, allowing the detection of tumor tissue density, greyscale, and other knowledge, as well as subtle tissue differences and tumor tissue characteristics without invasive surgery [3]. Medical imaging of microscopic samples is now used for tumor diagnosis, staging, and treatment. CT lung cancer screening increases survival rates, according to the National Lung Screening Test [4]. The algorithm was chosen because increasing CNN dimensionality increases complexity [5]. The baseline capsule network's inability to capture complicated high-dimensional elements explains its efficiency drop [6]. The parallel convolution can efficiently handle high-dimensionality characteristics supplied to the primary capsule structure [7]. Increasing the number of capsule layers within a certain limit improved accuracy in detecting key features from feature location with high dimensionality. The coupling coefficient and processing capacity of capsule layers increase when they contact, preventing gradient movement reduction.

This model retrieves complex characteristics from images with large spatial dimensions, improving validation metrics [8]. Identifying proper routing numbers is also important for resolving underfitting and overfitting during training. This article suggests expanding route options and choosing the best one to optimize network performance. Key findings from this paper include identifying and classifying lung cancer using a parallel convolutional block-based capsule network. This network can interpret high-dimensional images by increasing the number of capsule layers and pathways, and incorporates more selective fine-to-coarse spatial data than typical deep learning designs.Organisation of the remaining material follows. Section 2 reviews machine learning and deep learning literature for lung cancer detection and diagnosis. The suggested model's overview and internal framework are in Section 3. Section 4 describes experiment technique and comparison outcomes. The conclusion is in Section 5.

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II. Related Works

The past decade has seen the development of lung cancer detection models to improve classification. Using deep learning to study lung cancer advances science. The Convolutional Network with Visual Geometry Group fine-tuning enhanced lung cancer categorization over deep learning models. CNN has been recognised for lung cancer diagnosis, among other deep learning and machine learning technologies [9]. Multiple studies have shown that normalisation and image processing enhance accuracy. CNN training needs lots of data to avoid overfitting. Many models used multiple datasets to avoid overfitting.

Jiang et al. [10] classified lung nodules using attentive and ensemble 3D dual-path networks. The ROI was located using spatial attention and contextual attention improved deep characteristics. Additionally, an ensemble technique improved detection robustness. A Receptive Field Regularised (RFR)V-Net deep learning network was suggested by Dodia et al. [11] for lung nodule classification. The convolutional and deconvolutional blocks use RFR to extract information. SqueezeNet and ResNet classify lung nodules. Guo et al. presented a sequential CT lung cancer detection technique [12]. CNN- and feature-based classifiers were utilised [13]. A CNN-based classifier using Harris Hawks optimizer, Haralick, and Local Binary Pattern methods. First a CNN-based classifier, then a feature-based classifier, identified lung cancer in the dataset.

Rani and colleagues developed CT lung cancer nodule detection. [14] Histogram equalisation and tophat reduced CT noise. It was novel to segment cancerous areas with superpixels and target mapping. Lung cancer was classified using enhanced Deep Convolutional Neural Network. The WOA-APSO technique by Vijh et al. [15] combined bio-inspired Whale optimisation with adaptive particle swarm optimisation. Features for convolutional neural network lung cancer nodule categorization are chosen. Wiener filter preprocessing reduces CT noise. Global thresholding separated cancer and non-cancer pictures. Following CT scan segmentation, several feature extraction methods were employed to collect data for a highly accurate suggested system.

CNN architectures are hard and overfit. Many lung cancer detection and classification models use CNN subnetworks to simplify the design by dividing categorization into basic tasks. The CNN-based lung cancer classification models' pooling layer[16], which ignores rotational invariance data, needs further research. After its development, CapsNet examined rotating pictures. To improve lung cancer classification, many image analysis models use CapsNet with spatial features [17], feature polymerization, and target reconstruction loss as a superior regularisation term. Capsule networks have been studied for CT analysis and lung cancer diagnosis [18]. Deep Learning's capsule networks are new [19]. Their better performance than CNN in the tasks above deserves commendation. This study explored capsule network architectures, resources, and procedures. Adu et al. created a CapsNet model for lung and colon cancer diagnosis using histopathology scans [20]. The suggested method squashes vectors to extract valuable information from images with different backgrounds. The efficacy of DHS-CapsNet was shown by histopathological images. CapsNet was updated to classify lung nodules by Mobiny et al. [21]. Afshar et al. [22] developed a CapsNet lung nodule cancer malignancy model. Bo Tange et al. [23] analysed lung cancer survival with a Capsule Network.

Using CT scans from the Lung Image Database Consortium (LIDC) datasets, a Capsule Network (CapsNet) with a dynamic routing algorithm classified lung cancer as benign or malignant [24]. Capsule Network-based frameworks created in this research addressed rotational consistency in lung cancer classification. enhanced feature extraction enhanced classification accuracy. These models used complex feature extraction to improve precision. The proposed approach improves LungCaps by extracting efficient traits without advanced methodologies.

III. . Materials and Methods

A. Datasets

The template is designed for, but not limited to,The LIDC-IDRI dataset [25] from the Lung Image Database Consortium is used for the training and testing of the proposed approach. In total, 4335 CT pictures were evaluated by this model. If a nodule's diameter is three millimetres or less, it is classified as benign; if it is three millimetres or more, it is classified as malignant.

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Figure 1 displays samples of benign and malignant data from the LIDC databases.

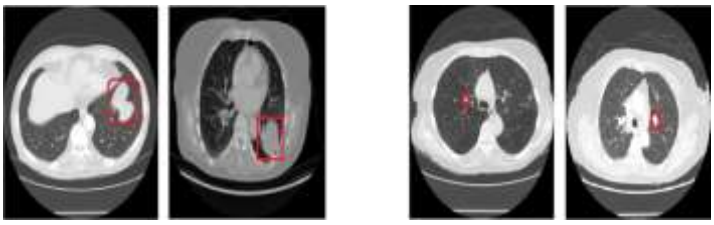
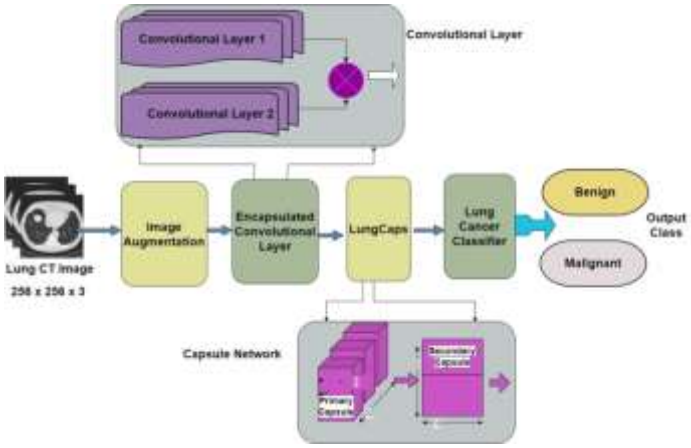


Fig.1: Sample Lung Images (a) Malignant nodule (b) Benign nodule (Courtesy: LIDC- IDRI Dataset)

They are divided into three categories: training, testing, and validation datasets. Twenty percent (867) of the photos in the LIDC collection are test cases. The model is trained using the remaining datasets (2,774), and the best model is determined by using 20% of the remaining pictures (694 total) for validation.

B. Proposed Capule network for Lung Cancer Detection



F*ig.2: Lung Cancer Classification pipeline of the proposed Capsule Net method*

Figure 2 shows a schematic illustration of the capsule network that is used to identify lung cancer. The primary capsule layer and the secondary capsule layer are the two separate layers that make up the block of capsule networks. First, the leading principal capsule layer is built using a reshaped layer. This layer consists of 32 channels with 8-dimensional convolutional capsules, making it a convolutional capsule layer. The main capsule produces a tensor of 32 × 8 × 8 capsules, each of which is represented by an 8-dimensional vector. The result of the first capsule layer is then passed on to the second capsule layer. Finally, the classification capsule layer receives the resultant vectors that are obtained from the secondary layer capsules.

C. Experimental Results and Discussion

Using the LIDC-IDRI benchmark data sets, an experimental evaluation is conducted to compare the proposed LungCaps Network with the baseline Capsule Network and ConvCaps Network. In this dataset, the original lung CT images are resized to 256 × 256 pixels in order to standardise the augmentation processes and training process, which increases the number of datasets. The simulations are run using Keras and TensorFlow backend on a 64-bit Windows PC with an i5-1135G7 CPU and an NVIDIA MX450 GPU. The models are trained with a starting learning rate of 0.001 and a learning rate decay of 0.9 over 50 iterations. There can be two to ten routing iterations, and error is computed using a margin loss function.

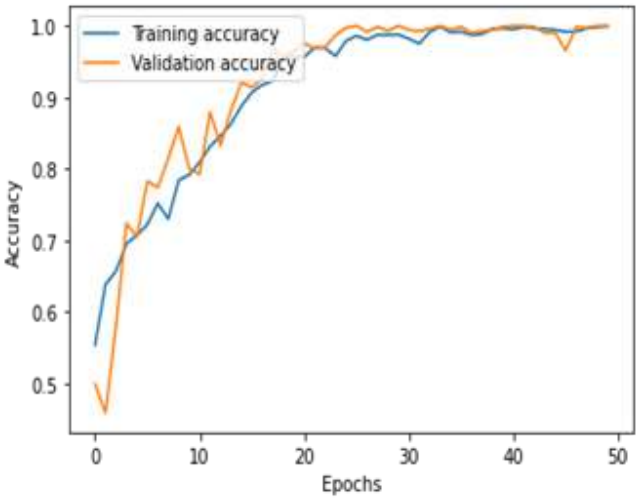


Fig.3: Training and Validation Accuracy of the Capsule Network

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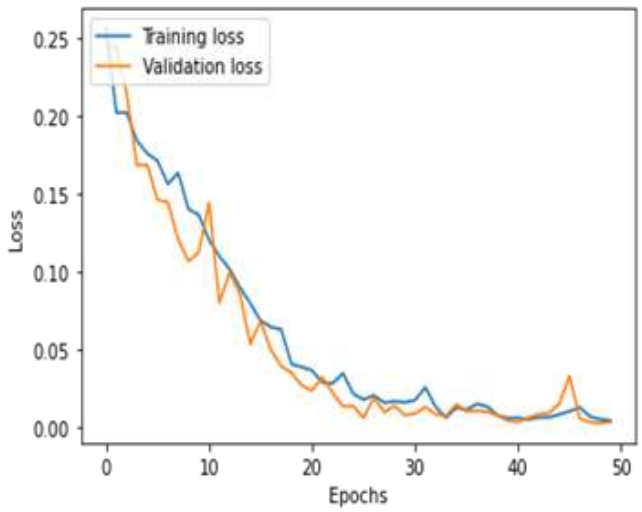

Fig. 4: Training and Validation Loss of the Capsule Network

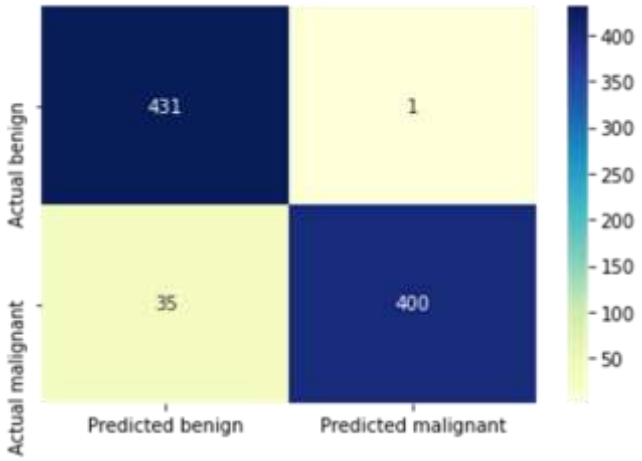

Fig. 5: Confusion Matrices of the Capsule Network

The training and validation accuracy and loss of the Capsule Network are depicted in Figures 3 and 4, respectively. These figures demonstrate the model's capacity for efficient learning and its ability to generalise across multiple epochs. Confusion matrices are shown in Figure 5, offering comprehensive insights into the model's classification accuracy across several lung cancer classifications as well as pinpointing specific instances where the algorithm might mistake one class for another. Together, these visualisations highlight the accuracy and dependability of the Capsule Network's lung cancer diagnosis capabilities.

Table 1. Quantifying Parameters of the proposed Capsule network Architectures

Model	Accuracy (%)	Recall (%)	Precision (%)	Specificity (%)
Capsule Network	**95.85**	**91.95**	**99.75**	**99.76**

The performance indicators for the suggested Capsule Network architecture designed for the categorization of lung cancer are shown in Table 1. With an accuracy of 95.85%, the Capsule Network model demonstrates its efficacy in accurately diagnosing cases of lung cancer from CT images. With a recall rate of 91.95%, the model demonstrates its ability to correctly identify a significant portion of real positive lung cancer cases. The algorithm yields relatively few false positives, as evidenced by the exceptionally high precision of 99.75%; nearly all patients labelled as lung cancer are indeed lung cancer. Furthermore, the model's specificity of 99.76% shows that it is also very good at correctly recognising negatives, or cases that are not lung cancer.

D. Conclusion

The diagnosis and categorization of lung cancer has drawn a lot of interest to the use of computer vision or human-computer interaction techniques. Because CNNs can learn distinct picture features, empirical evidence shows that they perform better as classifiers than other machine learning approaches in the context of lung cancer detection tasks. The capacity of CNNs to encode positional and orientational interdependencies between features is limited. To improve feature extraction from images, a new encapsulated CNN method has been proposed. After undergoing rigorous testing on the LIDC-IDRI datasets, the LungCaps model's performance was compared to that of the ConvCaps Network and the standard Capsule network.

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