e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:03/March-2025 Impact Factor- 8.187 www.irjmets.com

COMPARATIVE EVALUATION OF SIMPLE CNN AND VGG LIKE ARCHITECTURE FOR LUNG NODULE DETECTION USING CT SCAN IMAGES

Sindhu*1, Muthumani*2

*1Post Graduate Student, Department Of Electronics And Communication Engineering, Government College Of Engineering, Tirunelveli, Tamil Nadu, India.

*2Professor, Department Of Electronics And Communication Engineering, Government College Of Engineering, Tirunelveli, Tamil Nadu, India.

DOI: https://www.doi.org/10.56726/IRJMETS68495

ABSTRACT

Lung nodule detection is a critical step in the early diagnosis and treatment of lung cancer, requiring reliable and efficient methods for analyzing CT scan images. This paper aims to present a comparative evaluation of two deep learning models: a Simple Convolutional Neural Network (CNN) and a VGG-like architecture. The Simple CNN, designed with fewer layers, focuses on computational efficiency and faster training, while the VGG-like architecture employs deeper convolutional blocks to extract more complex features, potentially improving classification accuracy. This project implements a VGG-like convolutional neural network (CNN) architecture using MATLAB for the detection of lung nodules from CT scan images. The VGG-like architecture leverages multiple convolutional layers, ReLU activations, and max-pooling layers for hierarchical feature extraction. Fully connected layers and a softmax classifier are employed for final classification. Both models were evaluated on a IQ-OTHNCCD lung dataset, where the simple CNN achieved an accuracy of 81%, and the VGG-like architecture outperformed it with an accuracy of 98%. These results suggest that while both models show promising performance, the deeper VGG-like architecture provides superior accuracy, making it a more effective choice for lung nodule detection in CT scan images.

Keywords: Convolutional Neural Network, CT Scan, Lung Nodule.

I. INTRODUCTION

The Simple CNN model is designed with fewer layers to prioritize computational efficiency and speed. This architecture consists of a series of convolutional layers followed by activation functions like ReLU, and pooling layers for down-sampling. The reduced complexity of this model allows for faster training and less resource consumption, making it ideal for scenarios where computational power is limited or real-time analysis is required. In this project, the Simple CNN is employed to detect lung nodules by learning basic hierarchical features from the preprocessed CT scan images. The model achieves an accuracy of 81% on the IQ-OTHNCCD lung dataset.

The VGG-like architecture is known for its deep and consistent use of convolutional layers. Unlike the Simple CNN, the VGG-like model employs multiple convolutional blocks, each consisting of several convolutional layers followed by ReLU activations and max-pooling layers. The depth of the architecture enables the extraction of more complex and abstract features from the CT scan images, leading to better performance in tasks that require detailed pattern recognition, such as nodule detection. This model's depth allows it to capture intricate structures within the images that simpler models might miss. The VGG-like architecture utilizes fully connected layers at the end of the network, followed by a softmax classifier for final classification. The deeper layers contribute to improved classification accuracy by learning high-level representations of the image data. In this paper, the VGG-like CNN architecture achieved an accuracy of 98% on the IQ-OTHNCCD dataset, outperforming the Simple CNN model.

II. CONVOLUTIONAL NEURAL NETWORK

Convolution Neural Networks(CNNs)area specialized type of artificial neural network designed to process data with a grid-like topology, such as images. They have gained popularity due to their exceptional performance in tasks involving image and video recognition, natural language processing, and other areas requiring pattern recognition. CNNs are inspired by the visual cortex of animals, which contains neurons that respond to specific

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:03/March-2025 Impact Factor- 8.187 www.irjmets.com

regions of the visualfield.

Key Components of CNNs

Filters/Kernels:

Small matrices that slide over the input data to perform convolution operations, extracting local features.

Stride: The step size by which the filter moves across the input data.

Padding: Adding extra pixels around the input to control the output size.

Activation Functions:

Typically, nonlinear activation functions like ReLU (Rectified LinearUnit) are applied after convolution to introduce non-linearity into the model.

Pooling Layers

Max Pooling: Reduces the spatial dimensions (width and height) of the input, retaining the most important features.

Average Pooling: Similar to max pooling but calculates the average value instead of the maximum.

Fully Connected Layers:

Neurons in these layers are fully connected to all activations from the previous layer, similar to traditional neural networks. These layers interpret the high-level features extracted by convolution

III. VGG ARCHITECTURE

VGG-like model employs multiple convolutional blocks, each consisting of several convolutional layers followed by ReLU activations and max-pooling layers. The depth of the architecture enables the extraction of more complex and abstract features from the CT scan images, leading to better performance in tasks that require detailed pattern recognition, such as nodule detection.This model's depth allows it to capture intricate structures within the images that simpler models might miss. The VGG-like architecture utilizes fully connected layers at the end of the network, followed by a softmax classifier for final classification. The deeper layers contribute to improved classification accuracy by learning high-level representations of the image data. In this project, the VGG-like CNN architecture achieved an accuracy of 98% on the IQ-OTHNCCD dataset, outperforming the Simple CNN model.

The motivation behind using a VGG-like architecture over a simple CNN lies in its ability to capture complex hierarchical features through a deeper and more structured design. VGG models employ small convolutional filters (3x3) stacked in a deep architecture, enabling them to learn intricate spatial patterns while maintaining computational efficiency. The consistent use of max-pooling layers aids in progressive dimensionality reduction, preserving essential features and minimizing overfitting. Unlike simple CNNs, which may struggle with scalability and feature extraction in deeper networks, VGG-like architectures excel in generalization and performance, particularly for large-scale datasets, making them a robust choice for tasks requiring high accuracy and feature discrimination

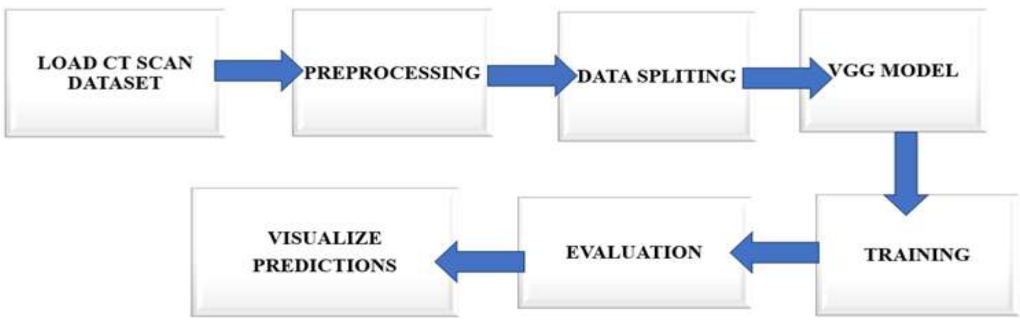


Figure 3.1: Block diagram

PROCEDURE:

Load CT Scan Dataset

The process begins with loading the CT scan images that contain lung nodules, which are the primary input data for training the model. The dataset may include images from various patients, with each image potentially

e-ISSN: 2582-5208
International Research Journal of Modernization in Engineering Technology and Science
(Peer-Reviewed, Open Access, Fully Refereed International Journal)
Volume:07/Issue:03/March-2025 Impact Factor- 8.187 www.irjmets.com

showing a lung nodule (benign or malignant). These images are stored in a structured format for easy access during training.

Preprocess Images (Resize)

CT scan images typically vary in size and resolution, and they need to be resized to a consistent dimension for the model to process them efficiently. Resizing ensures that the input images match the expected input size for the VGG-like architecture, which is commonly set to 224x224 or similar dimensions.

Split Dataset (Train/Test Split)

The dataset is divided into two main subsets: the training set (used for training the model) and the test set (used to evaluate model performance). 70-30 split is used, where the majority of the data is used for training, and a smaller portion is reserved for testing.This split helps evaluate the model's performance on unseen data, ensuring it is not overfitting to the training data.

Define VGG-Like Architecture

The architecture used is similar to **VGG (Visual Geometry Group)**, a well-known convolutional neural network (CNN) designed for image classification tasks.The architecture typically includes several convolutional layers followed by max-pooling layers, and eventually, fully connected layers at the end for classification.For lung nodule detection, this architecture will learn to extract hierarchical features from the CT images, which may include texture, shape, and size of the nodules that are essential for distinguishing between malignant and benign nodules.

Train the Model on Training Set

The model is trained using the training set, where the network learns to minimize the loss function Training involves forward and backward passes over the data for several epochs, gradually improving the model's predictions.

Evaluate Model on Test Set

After training, the model's performance is evaluated on the test set, which it hasn't seen during training. This gives an indication of how well the model can generalize to unseen data.Common evaluation metrics include accuracy.This metric help assess how well the model distinguishes between malignant and benign lung nodules.

Visualize Predictions

Once the model has been evaluated, visualizing its predictions helps assess the accuracy of the predictions and interpret the results.This step helps clinicians and researchers understand how the model is performing and where it might need improvement, particularly in distinguishing between complex cases of benign and malignant nodules

IV. RESULTS AND DISCUSSION

VGG MODEL outperforms SIMPLE CNN in terms of training and validation accuracy, achieving higher performance metrics.. CNN is simpler and easier to train but may not capture the complexities in LUNG nodule detection as effectively asVGG MODEL.

Table 1: Comparison

METRIC	SIMPLE CNN	VGG MODEL
Training Accuracy	Reaches above 85%	Reachesabove98%
Validation Accuracy	Reaches 81.86%	Reaches98.53%
Architecture Design	Custom-designed with fewer layers; simpler structure tailored to specific tasks.	Deep and uniform design with 3x3 convolutional kernels and max-pooling layers.
Performance	Adequate accuracy for small datasets	High accuracy and robustness, especially for high-dimensional data

SIMPLE CNN

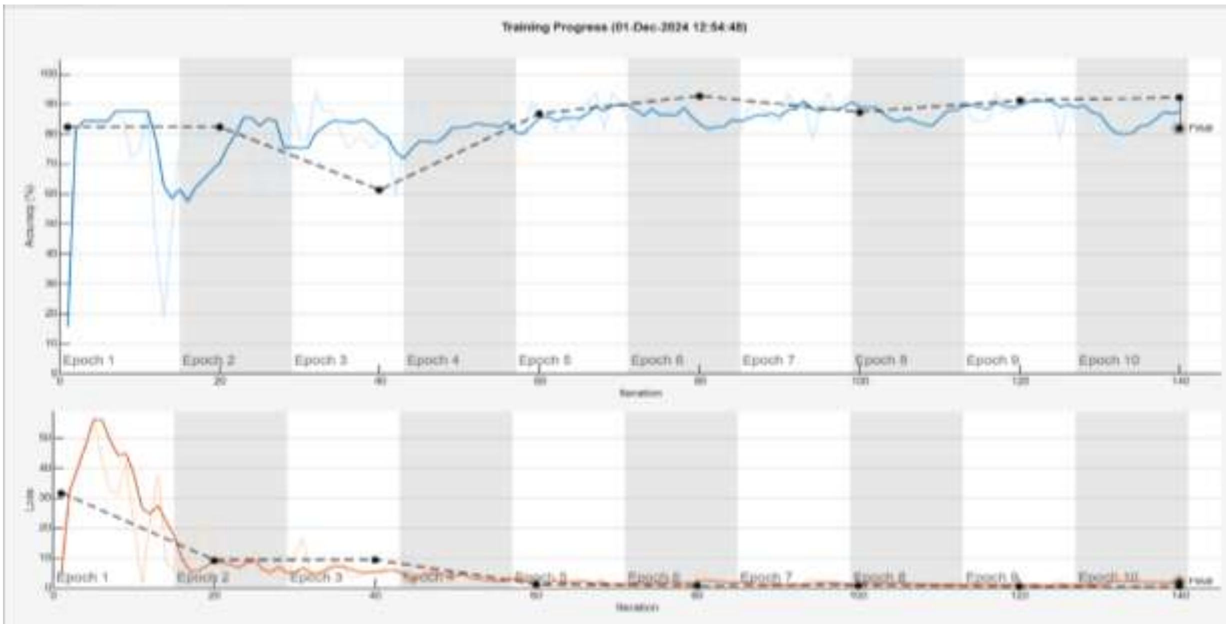


Figure 4.1: Validation result for Simple CNN

Results

Validation accuracy: 81.86%

Training finished: Max epochs completed

Training Time

Start time: 01-Dec-2024 12:54:48

Elapsed time: 4 min 37 sec

Figure 4.2; Validation accuracy for Simple CNN

Command Window

```
Training on single CPU.
Initializing input data normalization.
```

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:00:08	15.62%	82.35%	5.0653	31.7085	1.0000e-04
2	20	00:00:47	78.12%	82.35%	14.6291	9.2917	1.0000e-04
3	40	00:01:27	78.12%	61.27%	5.1077	9.4120	5.0000e-05
4	50	00:01:45	78.12%		3.0534		5.0000e-05
5	60	00:02:08	87.50%	86.76%	0.8621	1.1658	2.5000e-05
6	80	00:02:46	78.12%	92.65%	1.5375	0.7119	2.5000e-05
8	100	00:03:21	84.38%	87.25%	1.8285	0.8817	1.2500e-05
9	120	00:03:57	90.62%	91.18%	0.3114	0.5555	6.2500e-06
10	140	00:04:33	90.62%	92.16%	2.5797	0.4958	6.2500e-06

```
Training finished: Max epochs completed.
Test Accuracy: 81.8627%
```

Figure 4.3: Test accuracy for Simple CNN

VGG MODEL

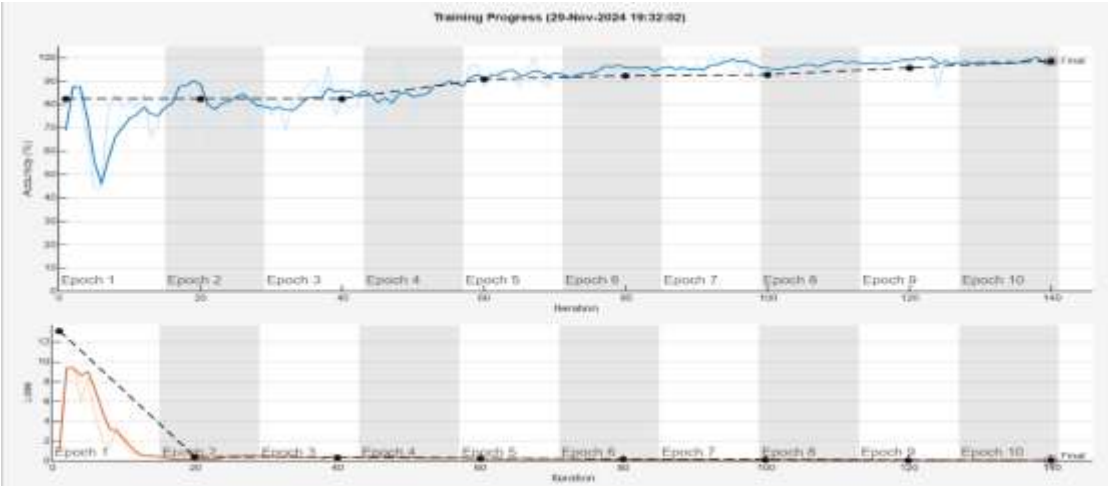


Figure 4.4: Validation result for VGG model

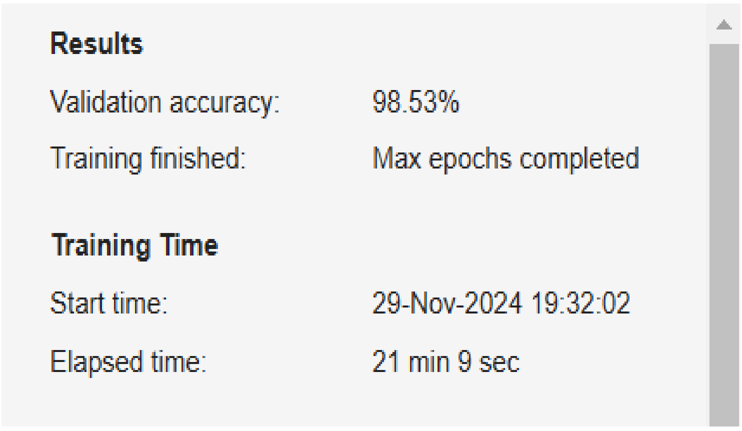
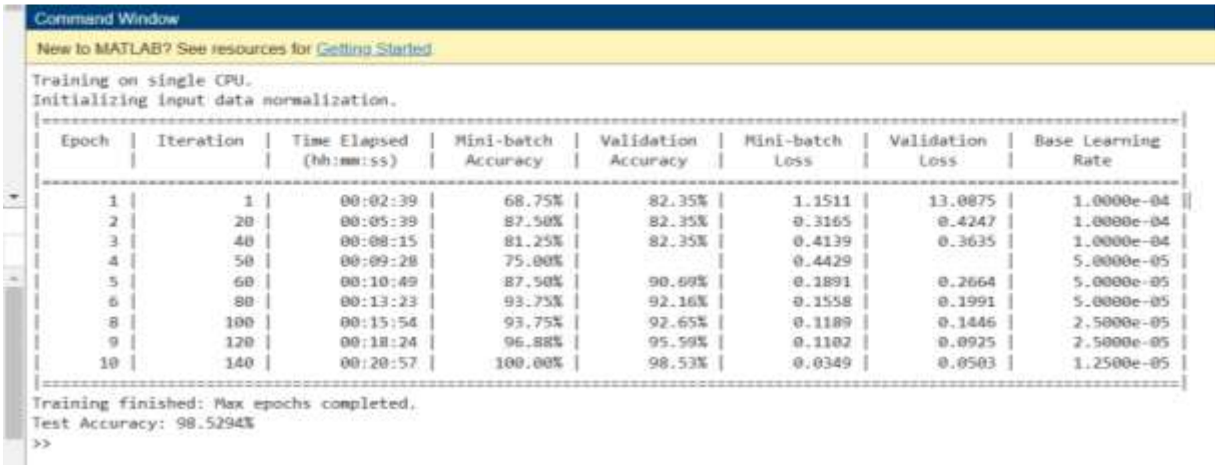


Figure 4.5: Validation accuracy for VGG model



Command Window

New to MATLAB? See resources for Getting Started

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss	Base Learning Rate
1	1	00:02:39	68.75%	82.35%	1.1511	13.0875	1.0000e-04
2	20	00:05:39	87.50%	82.35%	0.3165	0.4247	1.0000e-04
3	40	00:08:15	81.25%	82.35%	0.4139	0.3635	1.0000e-04
4	50	00:09:28	75.00%		0.4429		5.0000e-05
5	60	00:10:49	87.50%	90.69%	0.1891	0.2664	5.0000e-05
6	80	00:13:23	93.75%	92.16%	0.1558	0.1991	5.0000e-05
8	100	00:15:54	93.75%	92.65%	0.1189	0.1446	2.5000e-05
9	120	00:18:24	96.88%	95.59%	0.1102	0.0925	2.5000e-05
10	140	00:20:57	100.00%	98.53%	0.0349	0.0503	1.2500e-05

Training finished: Max epochs completed.
Test Accuracy: 98.5294%
>>

Figure 4.6: Test accuracy for VGG model

V. CONCLUSION

VGG MODEL outper forms SIMPLE CNN in terms of training and validation accuracy, achieving higher performance metrics. CNN is simpler and easier to train but may not capture the complexities in LUNG nodule detection as effectively as VGG MODEL. Both VGG MODEL and SIMPLE CNN have their strengths and weaknesses when applied to the classification of lung nodules from theIQ-OTHNCCD dataset .VGG MODEL demonstrates superior performance in accuracy and training time, making it amore effective choice for this specific application. However, SIMPLE CNN offers as impler alternative with decent performance, suitable for scenarios with limited computational resources.

VI. REFERENCES

[1] Ferlay, J.; Shin, H.; Bray, F.; Forman, D.; Mathers, C.; Parkin, D.M. Estimates of worldwide burden of cancer in 2008: GLOBOCAN 2008. Int. J. Cancer 2010, 127, 2893–2917.

[2] Siegel, R.L.; Miller, K.D.; Jemal, A. Cancer statistics, 2018. CA-Cancer J. Clin. 2018, 68, 7–30.

[3] R.; Gatta, G.; Dal Maso, L. Life expectancy of colon, breast, and testicular cancer patients: An analysis of US-SEER population-based data. Ann. Oncol. 2015, 26, 1263–1268.

[4] Ning, J.; Zhao, H.; Lan, L.; Sun, P.; Feng, Y. A Computer-Aided Detection System for the Detection of Lung Nodules Based on 3D-ResNet. Appl. Sci. 2019, 9, 5544.

[5] Saleem, M.; Farid, M.S.; Saleem, S.; Khan, M.H. X-ray image analysis for automated knee osteoarthritis detection. Signal Image Video Process. 2020.

[6] Thomson, J.; O'Neill, T.; Felson, D.; Cootes, T. Automated shape and texture analysis for detection of osteoarthritis from radiographs of the knee. In International Conference on Medical Image Computing and Computer-Assisted Intervention; Springer: Cham, Switzerland, 2015; pp. 127–134.

[7] Das, D.; Mukherjee, R.; Chakarborty, C. Computational microscopic imaging for malaria parasite detection: A systematic review. J. Microsc. 2015, 260, 1–19.

[8] Fatima, T.; Farid, M.S. Automatic detection of Plasmodium parasites from microscopic blood images. J. Parasit. Dis. 2019.

[9] Mehanian, C.; Jaiswal, M.; Delahunt, C.; Thompson, C.; Horning, M.; Hu, L.; Ostbye, T.; McGuire, S.;Mehanian, M.; Champlin, C.; et al. Computer-Automated Malaria Diagnosis and Quantitation Using Convolutional Neural Networks. In Proceedings of the IEEE International Conference on Computer Vision Workshops (ICCVW), Venice, Italy, 22–29 October 2017.

[10] Nasrullah, N.; Sang, J.; Alam, M.S.; Mateen, M.; Cai, B.; Hu, H. Automated LungNodule Detection and Classification Using Deep Learning Combined with Multiple Strategies. Sensors 2019, 19, 3722.

[11] Castellino, R.A. Computer aided detection (CAD): An overview. Cancer Imaging 2005, 5, 17–19.

[12] McCarville, M.B.; Lederman, H.M.; Santana, V.M.; Daw, N.C.; Shochat, S.J.; Li, C.-S.; Kaufman, R.A. Distinguishing benign from malignant pulmonary nodules with helical chest CT in children with malignant solid tumors. Radiology 2006, 239, 514–520.

[13] Singh, S.; Maxwell, J.; Baker, J.A.; Nicholas, J.L.; Lo, J.Y. Computer-aided Classification of Breast Masses: Performance and Interobserver Variability of Expert Radiologists versus Residents. Radiology 2011, 258, 73–80.

[14] Giger, M.L.; Karssemeijer, N.; Schnabel, J.A. Breast image analysis for risk assessment, detection, diagnosis, and treatment of cancer. Annu. Rev. Biomed. Eng. 2013, 15, 327–357.

[15] Joo, S.; Yang, Y.S.; Moon, W.K.; Kim, H.C. Computer-aided diagnosis of solid breast nodules: Use of an artificial neural network based on multiple sonographic features. IEEE Trans. Med. Imaging 2004, 23, 1292–1300.