Enhancing Lung Cancer Detection Using AI-Based Deep Learning Framework

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Abstract: Cancer of the lungs is considered the global supreme deadly disease that is life-threatening. However, premature diagnosis and appropriate cure are crucial for tumbling the transience rate concomitant with this ailment. Computed tomography scans have emerged as among the most prevalent imagining methods for lung cancer exposure, particularly when coupled with deep learning models. In this study, propose a deep learning framework grounded on a Deep Convolutional Neural Network for the timely exposure of lung cancer expending CT scan images. Additionally, we have analysed the enactment of supplementary models, such as Inception V3, Xception, and ResNet-50, in comparison to our proposed model. Our comparative analysis considered various metrics, including accurateness, Area beneath the Curve, recall, and loss. After appraising the models' presentation, the outcomes show that the DCNN-based approach outperforms the other models and demonstrates promising potential compared to traditional methods. Specifically, the proposed DCNN model attained an precision of 98.27%, an Area Under Curve (AUC) of 97.12%, a recall of 98.70%, and a loss of 0.328.

1 INTRODUCTION

This type of cancer is the deadliest and furthermost miserable on the planet after all the others. It is extremely complex in its nature and highly stimulating to diagnose, as its symptoms are frequently revealed only during the later and final stages. However, mortality rates from lung cancer can definitely be concentrated significantly done premature recognition and timely therapy. This disease mainly initiates in lungs but sometimes completes the entire course with a few minor noticeable symptoms before it has metastasized to the other parts of the body. There has been much on-going research and developments on different methods, and more of them, in the recent past, have produced really promising results toward an effective identification and diagnosis in the case of lung cancer. One of the best imaging modalities employed here to assist in diagnosing early medical conditions would definitely turn out to be CT scan images; however, the interpretation and detection of such scans from cancer is a very complicated and challenging practice for most medical practitioners. Early detection helps the timely intervention and thus can prove to be highly crucial for the outcome of patients. Continued research and innovation in lung cancer screening and diagnostic methods are very necessary to reduce the significant impact of this condition on individuals.

2 MATERIAL AND METHODS

Publicly available data set comprising computed tomography scan images was used in the study, which went through a whole processing pipeline beginning

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with image resizing, removing artifacts and noise, as well as advanced image segmentation techniques to cut out regions of interest. The resulting DCNN model was used to train, test and validate pre-processed CT sets with other widely recognized deep learning architectures such as Inception V3, Xception and ResNet-50, according to the normal hold-out-validation method. This performance comparison of these deep learning models was further evaluated and analysed to find the best architecture that could potentially detect different types of cancer. The DCNN model was custom trained architecture and ResNet-50, Inception V3, as well as Xception, compared with pre-trained transmission learning models that exploited their learned representations within lung cancer detection capabilities.

2.1 Dataset Collection

The study makes use of a public dataset comprising computed tomography images which had undergone an entire processing pipeline from resizing the pictures to artifact and noise elimination as well as advanced image segmentation techniques to cut out the regions of interest. Such that the resulting model of convolutional neural networks deep was used as training, testing, and validation in all the pre-processed CT sets using the mainstream pour-deep learning architectures such as Inception V3, Xception and ResNet-50, following the normal threshold method of comparison. This performance comparison of such deep learning models was also further evaluated and analyzed to find the probably best architecture that might be able to detect cancer types. Compared to the above models, the DCNN model was custom trained architecture and pre-trained transfer learning models Inception V3, Xception and ResNet-50 were used in their detection capabilities within lung cancer. As such, the study involved the consideration of a publicly available computed tomography scan image database that underwent a very rigorous pre-processing pipeline that involved the following strides: the resizing of images, removal of noise and artifacts, and requiring advanced image segmentation techniques to isolate areas of interest. The projected DCCN model was tested, verified, as well as trained on pre-processed CT scan images by the regular hold-out-validation technique along with other known DL architectures. With respect to these three models of deep learning, thorough evaluation and analysis were done to find the most suitable architecture for identifying the three included types of lung cancers.

2.2 Dataset Pre-Processing

Feature extraction pipelines a too important pre-processing step before going for a model analysis through deep learning. It has different components which together perform certain important activities on input data around the needed modelling tasks. Fist, the raw image data is read, capturing all original pixel level information. It is here that the rest of this pipeline begins. The next important pre-processing activity is resizing the images into a common format.

This is important in ensuring that the deep learning models will process the inputs. This is followed by the removal of noise and artefacts from the images. The model can, otherwise, be affected by those unwanted characteristics such that, eliminating them is necessary. Advanced techniques for image segmentation are applied so that the regions of interest can be isolated in the images and allow analysis focusing only on the relevant sections. Then, further, operations such as dilation and deterioration are conducted for morphological processes to make the segmented regions better. It enhances the quality and integrity of input data for the deep learning model to be used for classification or pinpointing location tasks. But by processing data through such an exhaustive feature extraction pipeline, most associated deep learning models tend to be more capable and reliable themselves. Thus, superior results can be achieved with real-world applications.

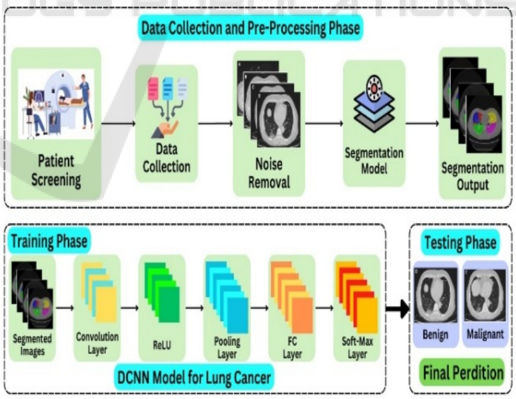

Figure 1: Deep Convolutional Neural Network Architecture.

2.3 Validation Process

These days, with increased availability for datasets of larger images, looking for an appropriate validation approach becomes crucial. One of the most used and effective ways employed for this study is a hold-out validation scheme, where we have an allocation of a

70:15:15 percent split in data for training, testing, and validating, respectively. This allows an objective evaluation of the enactment and generalizability of DL models. Furthermore, DL models were qualified for about batch size for 50 epochs is 13. This configuration was selected keeping convergence and computation efficiency in a balance. Besides, all the models were implemented with a random seed of 1000 during the execution so as to give reproducible results. This step is essential, as it mitigates the inherent variability that can arise from the random initialization of model parameters, which could otherwise lead to inconsistent outputs across different iterations. By carefully designing and executing the validation strategy, along with the appropriate training configurations and seed setting, the study was able to provide reliable and reproducible insights into the efficiency of the DL models for initial lung cancer recognition using CT scan images.

3 PROPOSED DEEP CNN ARCHITECTURE

The proposed deep CNN has a first convolutional layer that takes in the 64x64 input image. This layer has 16 filters and is expected to represent the most basic features, thus producing 62x62 feature maps. The convolutional layer served as the primary fundamental component of the DCNN. Subsequent to this, the output was conceded over a max pooling layer, which reduced the longitudinal data size by half, yielding 31x31 feature maps. Max pooling chooses the supreme features from the covered correspond with characteristics region. For further processing, the output was then fed into a second convolutional layer with 32 filters and 29x29 feature atlases. This was trailed by another max pooling layer, which halved the spatial data size to 14x14 distinctive maps. An additional set of convolutional and pooling layers was incorporated in the third stage. The pooling layer in this case contained of 5x5 distinctive maps, while the convolutional layer utilized 64 filters with 10x10 characteristics atlases. Lastly, the end results was flattened and passed through a 260-dimensional dense layer that is completely interconnected. This was then routed to the softmax activation function layer, which is usually employed for multi-class grouping tasks. Excluding for the end layer, all layers utilized the ReLU triggering utility without failure. The described DCNN architecture is represented in Figure 1. The model was accomplished, authenticated, and verified using a rate of learning is 0.02, 50 epochs, and a group size of 13. The Adam optimizer was employed to compile the model, and a Classification cross-entropy loss function was utilized, along with other evaluation indicators like accuracy, recall, and AUC.

Deep CNN Algorithm

Step 1: Convolution layer: The Initial layer serves as where the input images include are collected.
Step 2: RELU Layer: The picture passes over the RELU layer, which introduces non-linearity.
Step 3: Pooling Layer: The image is then sent to the pooling layer, where, if it is too big, the number of parameters is decreased.
Fully Connected Layer: This layer extracts the sorts of the pictures with as much as extraordinary accurateness. It is a vital layer of CNN Split data: Sort your data with labels into sets for testing, validation, and training. The model is taught by the training set, and the validation set monitors its progress, and the testing set assesses its final performance.
Loss function and back propagation: The predicted output is associated to the correct label using a loss function. After that, the error extends reluctant over and done with the network, correcting the weights and biases of each layer to minimize future errors.
Step 4: Optimization: Repeat the forward pass and back propagation for all training images, iteratively refining the model's parameters using an optimization algorithm like Adam or SGD.

4 RESULTS AND DISCUSSIONS

The performance results show of four DL classification models - DCNN, Inception V3, Xception and ResNet-50 - applied to the Cancer of the lungs is CT Scan Image collections need comprehensively summarized in Tables 1, with comparative insights presented in Figure 2,3,4,5. These tables provide a detailed breakdown of the training, validation, and testing show metrics for each of the respective deep learning models. The inclusion of these comprehensive performance results allows for a thorough evaluation and comparison of the capabilities of the different DL models in the task of CT scan images to find lung cancer.

Table 1: Training outcomes for various DL models for lung cancer detection.

Models	Accuracy of Training	AUC of Training	Recall of Training	Loss of Training
DCNN	98.27%	97.12	98.70	0.29
ResNet -50	95.20%	97.26	97.20	0.045
Inception V3	93.36%	95.3	93.2	1.96
Xception	95.24%	95.6	93.2	1.45

The analysis of the methods employed by the deep convolutional neural network, and other models reveals that the DCNN model surpasses the other deep learning approaches, as evidenced by the comprehensive performance results presented in Tables 1. The DCNN model was selected as the most suitable option for the proposed framework aimed at detecting lung cancer by CT scan images due to its exceptional performance metrics.

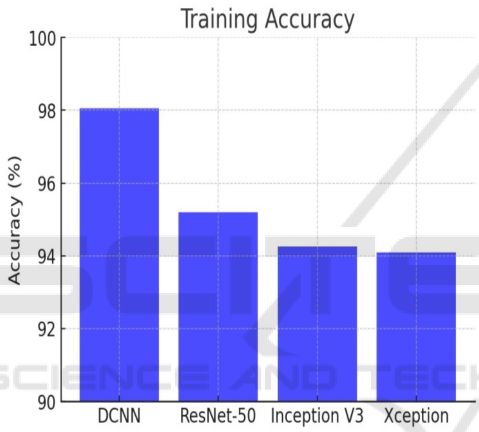

Figure 2: Comparisons for training accuracy levels.

Figure 3: Comparisons for training area under curve.

Specifically, the DCNN model achieved impressive testing results, including an accurateness of 98.27%, an area below the curve of 98.21%, a recall of 98.70%, and a loss of 0.328. These outstanding performance metrics demonstrate the DCNN model's effectiveness in accurately identifying and classifying different kinds of lung cancer as well as normal cases, from the CT scan data. The DCNN model's superior performance, compared to the other DL architectures, for instance Inception V3, Xception and ResNet-50, makes it a promising choice for the proposed framework targeting CT Scans for the preliminary credentials of lung cancer.

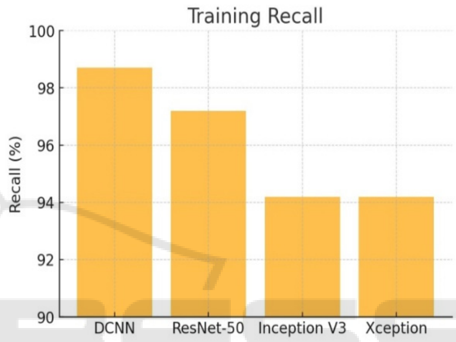

Figure 4: Comparisons for training recall.

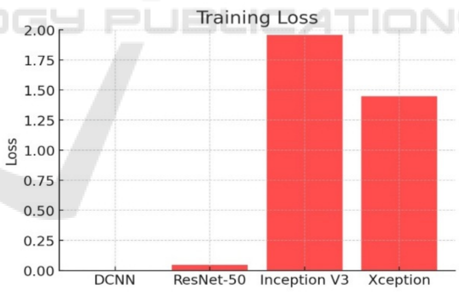

Figure 5: Training loss function.

5 CONCLUSIONS

Cancer of the lungs is a foremost reason of cancer-connected humanity global. While it cannot be fully prevented, early diagnosis and treatment can significantly improve patient outcomes and survival. This is a critical priority for healthcare suppliers and researchers, as lung cancer often goes undetected until advanced stages. Our research explored a deep learning framework founded on DCNN for primary recognition of lung cancer using CT scans. This

DCNN model outperformed other approaches like ResNet50, Inception V3, and Xception, achieving an accurateness of 98.05%, AUC of 97.32%, recall of 98.70%, and training loss function of 0.29. To further enhance early lung cancer diagnosis, we might incorporate additional datasets and explore other ML and DL frameworks in the upcoming, aiming to improve the overall performance and reliability of our detection methods.

REFERENCES

"Breast cancer statistics of american cancer socity. [online]. availabe:https://www.cancer.org/cancer.html, " [Accessed: 13- November-2022].

Abhir Bhandary , G. Ananth Prabhu , V. Rajinikanth , K. Palani Thanaraj , Suresh Chandra Satapathy , David E. Robbins , Charles Shasky , YuDong Zhang , Joao Manuel R.S. Tavares , N. Sri Madhava Raja , DeepLearning Framework to Detect Lung ˜ Abnormality – A study with Chest X-Ray and Lung CT Scan Images, Pattern Recognition Letters (2019), doi: https://doi.org/10.1016/j.patrec.2019.11.013

Ausawalaithong, W., Thirach, A., Marukatat, S., & Wilaiprasitporn, T. (2018). Automatic Lung Cancer Prediction from Chest X-ray Images Using the Deep Learning Approach. 2018 11th Biomedical Engineerin g International Conference (BMEiCON).

Da Silva, G.L.F.; da Silva Neto, O.P.; Silva, A.C.; de Paiva, A.C.; Gattass, M. Lung nodules diagnosis based on evolutionary convolutional neural network. Multimed. Tools Appl. 2017, 76, 19039–19055.

Deepa, R., Karthick, R., Velusamy, J., & Senthilkumar, R. (2025). Performance analysis of multiple-input multiple output orthogonal frequency division multiple xing system using arithmetic optimization algorithm. Computer Standards & Interfaces, 92, 103934.

Hany, M. (2020, August 20). Chest CT-scan images dataset. Kaggle. Retrieved November 13, 2022, from https://www.kaggle.com/datasets/mohamedhanyyy/ch est-ctscan-images

Kaur, S., Hooda, R., Mittal, A., Akashdeep, & Sofat, S. (2017). Deep CNN-Based Method for Segmenting Lung Fields in Digital Chest Radiographs. Advanced Informatics for Computing Research, 185– 194. doi:10.1007/978-981-10-5780-9_17.

M. Mamun, A. Farjana, M. Al Mamun and M. S. Ahammed, "Lung cancer prediction model using ensemble learning techniques and a systematic review analysis," 2022 IEEE World AI IoT Congress (AIIoT), 2022, pp. 187 193, doi:10.1109/AIIoT54504.2022.981 7326.

M. Mamun, M. I. Mahmud, M. I. Hossain, A. M. Islam, M. S. Ahammed, M. M. Uddin, "Vocal Feature Guided Detection of Parkinson's Disease Using Machine Learning Algorithms", 2022 IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2022,

M. Mamun, S. B. Shawkat, M. S. Ahammed, M. M. Uddin, M. I. Mahmud, A. M. Islam, "Deep Learning Based Model for Alzheimer's Disease Detection Using Brain MRI Images", 2022 IEEE 13th Annual Ubiquitous Computing, Electronics & Mobile Communication Conference (UEMCON), 2022.

Makaju, Suren, P. W. C. Prasad, Abeer Alsadoon, A. K. Singh, and A. Elchouemi. "Lung cancer detection using CT scan images." Procedia Computer Science 125 (2018): 107-114.

Naqi, S.M.; Sharif, M.; Jaffar, A. Lung nodule detection and classification based on geometric fit in parametric form and deep learning. Neural Comput. Appl. 2018, 3456789.

Nibali, A.; He, Z.; Wollersheim, D. Pulmonary nodule classification with deep residual networks. Int. J. Comput. Assist. Radiol. Surg. 2017, 12, 1799–1808.

Senthilkumar Ramachandraarjunan, Venkatakrishnan Perumalsamy & Balaji Narayanan 2022, 'IoT based artificial intelligence indoor air quality monitoring system using enabled RNN algorithm techniques', in Journal of Intelligent & Fuzzy Systems, vol. 43, no. 3, pp. 2853-2868

Senthilkumar R, Dr.P.Venkatakrishnan,Dr.N.Balaji, Intelli gent based novel embedded system based IoT Enabled air pollution monitoring system, ELSEVIER Microprocessors and Microsystems Vol.77, June 2020

Shaffie, A.; Soliman, A.; Fraiwan, L.; Ghazal, M.; Taher, F.; Dunlap, N.; Wang, B.; van Berkel, V.; Keynton, R.; Elmaghraby, A.; et al. A Generalized Deep Learning Based Diagnostic System for Early Diagnosi s of Various Types of Pulmonary Nodules. Technol. Cancer Res. Treat. 2018, 17

Xie, Y.; Zhang, J.; Xia, Y.; Fulham, M.; Zhang, Y. Fusing texture, shape and deep model-learned information at decision level for automated classification of lung nodules on chest CT. Inf. Fusion 2018, 42, 102–110.

Zhang, T.; Zhao, J.; Luo, J.; Qiang, Y. Deep belief network for lung nodules diagnosed in CT imaging. Int. J. Perform. Eng. 2017, 13, 1358– 1370