Journal of Information & Optimization Sciences
ISSN 0252-2667 (Print), ISSN 2169-0103 (Online)
Vol. 44 (2023), No. 1, pp. 97–111
DOI : 10.47974/JIOS-1298

Abnormality detection in chest diseases using a convolutional neural network

K. K. Dhar [§]
P. Bhattacharya [†]
Department of Computer Science Engineering
National Institute of Technology Agartala
Agartala
India 7990046

Nitendra Kumar *
Department of Applied Sciences and Humanities
Accurate Institute of Management and Technology
Greater Noida
Uttar Pradesh 201310
India

Asish Mitra [‡]
Department of Physical and Material Sciences
College of Engineering and Management Kolaghat
West Bengal
India

Abstract

It has developed into a new branch of medicine where doctors and researchers are continually working on numerous issues linked to lung ailments. This field of medicine studies lung abnormalities through chest pictures and classifies them using artificial intelligence and machine learning techniques. As graphics drives and data storage systems have gotten more prevalent and sophisticated, enormous amounts of medical picture data are now being produced. Despite the fact that there have been several studies in the medical profession over the past ten years, this particular area has not received enough attention because of a lack of data. Numerous researchers have employed custom feature learning algorithms, but the results have not been sufficiently useful for real-world applications. The

[§] *E-mail:* kkdhar82@gmail.com
[†] *E-mail:* pari76@rediffmail.com
* *E-mail:* nkshukla.kumar4@gmail.com (Corresponding Author)
[‡] *E-mail:* mitra_asish@yahoo.com

© Taru Publications

employed technique is advantageous in bridging the semantic gap between low-stage records obtained by imaging tools and high-stage information preserved by living things. With five layers—a convolutional layer, an activation layer, a pooling layer, an absolutely linked layer, and a softmax layer—that decide the output probability for each component, we created a far better convolutional neural network that enables accurate X-ray image type. We built our model utilizing a set of facts that are freely accessible. To be honest, our version performs a respectable job at diagnosing conditions related to the chest. Comparative observations show that the proposed model is more suited for the class of chest-related problems.

Subject Classification: *68T05, 68T09, 68T07.*

Keywords: *Deep learning, Classification, Convolutional neural network (CNN), Class-selective relevance mapping (CRM), Chest X-Ray.*

1. Introduction

Neuroscientists discovered something fascinating in the late 1990s: The brain's visual representations may actually move down two different pathways: protest and spatial. While protest data adheres to a protest manner, location, colour, differentiation, measure, and other types of data follow an uncommon way. Hubel and Wiesel investigated in 1968 whether the brain's visual cortex could respond to light detection. The first computer framework capable of learning, identifying, and recognizing transcribed letters was developed in the 1990s by LeCun and colleagues. This learning process attracted a lot of attention from analysts in the late 1920s.

The method has pulled in much consideration from analysts. Frameworks based on fake insights are as of now a well-known subject to consider. Figure 1: Haphazardly chosen illustrations based on chest X-ray information much appreciated to X-ray and capacity framework advancement. Analysts have attempted to extend the computing control

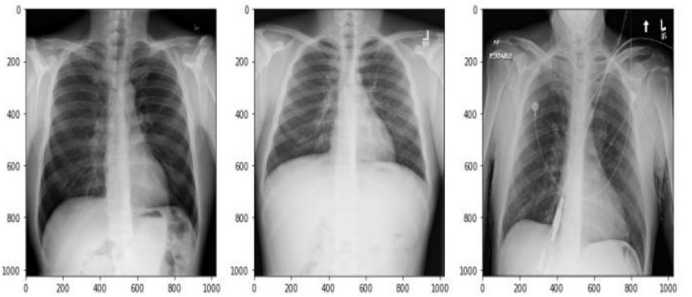


Figure 1

Proposed CNN architecture for chest ailment detection

of the therapeutic space. The 1980s was a time when analysts utilized low-level highlights to analyze therapeutic pictures. Learning frameworks based on feature extraction were well known within the 1990s. Machine learning-based approaches to include learning were utilized within the early 2000s. Profound learning-based methods, on the other hand, are progressively utilized because of their capacity to completely learn.

2. Related Work

The history of profound learning isn't later, Backpropagation (Pale et. al., 2014) was first presented within the 1980s and is still broadly utilized nowadays. One of the accomplishments of counterfeit insights has been profound learning calculations in restorative picture preparing.

Some outstanding results in medical imaging, such as (Roth et. al., 2015; Goel, et. al., 2022) identification of diseases (Albarqouni et. al., 2016; Anthimopoulos et. al., 2016; Kumar et. al., 2017; Rajpurkar et. al., 2017) Albarqouni et. al., 2016), regression (Liao et. al., 2017), registration (Yang et. al., 2015) and so on. In spite of the fact that numerous machine learning calculations are broadly utilized in picture examination, they are ineffectual for deciphering restorative pictures. In this segment of the writing, we briefly talk about a few prior inquire on therapeutic picture investigation. Manual incorporate extraction, which needs talented ability, is one of the preeminent critical execution challenges of customary machine learning strategies. Another issue in ask almost is choosing the right classifier. Restorative pictures were analyzed utilizing straight discriminator (Stefan et. al., 1997; Xu et. al., 2014), Bayesian classifier (Uppaluri et. al., 1999; Sluimer et. al., 2003), closest neighbor Xu et. al., 2006; Lauge et. al., 2010; Korfiatis et. al., 2010; Rodríguez et. al.,

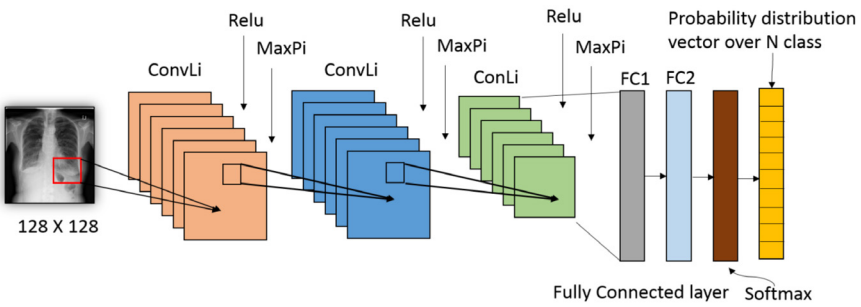


Figure 2

Proposed CNN architecture for chest diseases recognition

2012, ANN (Uchiyama et. al., 2014; 2016; Tripathi et. al., 2022), irregular woodland (Zhao et. al.,2013(,Krizhevsky et. al., 2012), geometric degree (Rodríguez et. al.,2012), histogram (Vo and Sowmya, 2010), nearby double classifier (Lauge et. al., 2010), wavelet change (Simonyan and Zisserman, 2015). Both straight and non-linear (Deng and Yu, 2014) capacities are endeavored to be spoken to in present day engineering with incredible illustrations preparing units. More profound plans (Glorot and Bengio, 2010) are too useful for maximizing execution. Anthropoulos et. al. (2016) utilized profound learning to classify interstitial lung infections. For lung CT anomalies, Moeskops et. al. (2016) utilized a confined Boltzmann device. Multilevel bits with CNN were utilized to identify diverse organs (Moeskops et. al., 2016). In CT and MR pictures were analyzed utilizing CNN-based highlight extraction calculations (Yan et. al., 2016).

The proposed demonstrate outfit appears way better execution than any other show. Our fundamental inquire about issue in this paper is to distinguish chest-infiltrating malady from sets of chest radiographs that incorporate fourteen infections: pneumonia, pneumothorax, counting atelectasis, penetration, cardiomegaly, emanation, mass, knob, union, edema, emphysema, pleural thickening, fibrosis, a hernia and onemalady that was not found. The colossal capabilities of convolutional neural arrange are moreover illustrated in this investigation.

3. Preliminary

The essential diagram of the DL strategy is secured in this segment, taken after by a see at the CNN demonstrate and the customary CNN architecture's working concept.

3.1 *Deep Learning*

One of the different methodologies to move forward engagement execution is information securing. DL methods are primarily utilized to make strides the usage of an expansive number of ML applications. With straight and non-linear change capacities, a deep engineering with trainable parameters emphasizes the next level of information deliberation (Xu et. al., 2014). The history of DL dates back to 1965, when it was begun by Lvakhnenko, and has picked up energy with the increment in GPU-supported computing control and non-linearity that gives more seriously systems for way better information utilization. Profound engineering with numerous profound layers improves the appearance of fake LV. After backpropagation was found in 1980, it has been broadly utilized to protect NN and fathom numerous real-time issues. Common backpropagation

strategies utilized are frequently utilized for assignments including picture investigation, and current inquire about appears that DL strategies are most commonly utilized within the field of include acknowledgment (Xu et. al., 2014). DL methods are fundamentally utilized in computer vision areas such as question location, classification, localization, variation from the norm location from therapeutic pictures (Liao et. al., 2017; Tripathi et. al., 2022; Sahoo, et. al., 2022). With the expansive sum of utilize of uninterested areas, DL procedures are also prevalently utilized within the field of Bengali and Manipuri character acknowledgment (Stefan et. al., 1997; Sluimer et. al., 2003; Li et. al., 2014; Yang et. al., 2015; Yuan et. al., 2017; Kalra, et. al., 2020; Sarin, et. al., 2022).

3.2. *Convolutional Neural Network (CNN)*

CNN may be a broadly utilized method in some ranges of computer vision and gives the foremost critical yield rate in picture classification. A CNN could be a feed-forward neural arrange, essentially upgraded with human insights. CNN is able to combine both the genealogical include and the conveyance. Standard CL acknowledges data and gives work maps to particular bit associates. Combining distinctive sets of neurons and covering them among all others makes a difference in understanding the more suitable definition of the pictures. Disseminating the weights and comparing information with regard to the input diminishes the number of restrictions within the neural arrange. In spite of the fact that CNN models flourish in picture classification, there's a probability that they will overshoot in a commonplace circumstance, which greatly undermines the victory of a Neural Arrange. Pooling could be a subsampling strategy regularly utilized to play down or maintain a strategic distance from the overfitting issue and encourage diminish parameters. In this way, one or more number of completely associated layers (FCL) upheld by Softmaxlayer (SL) highlight the classification outcome. The CNN methods are besides compelling in making learning of higher estimations and the preeminent number of spatial estimations in a convolutional organizes (Uppaluri et. al., 1999), which is calculated as:

$$Z_{out}(k) = \frac{Z_{in} - n + 2P}{S} + 1 \tag{1}$$

where, P is padding bits, S is step size, and k is the k_{th} input aspect.

We have sketched out an end-to-end preparing handle for Manipuri and Bengali character acknowledgment in this context. This paper too clarifies why the CNN demonstrate is so prevalent (Hazra, 2021).

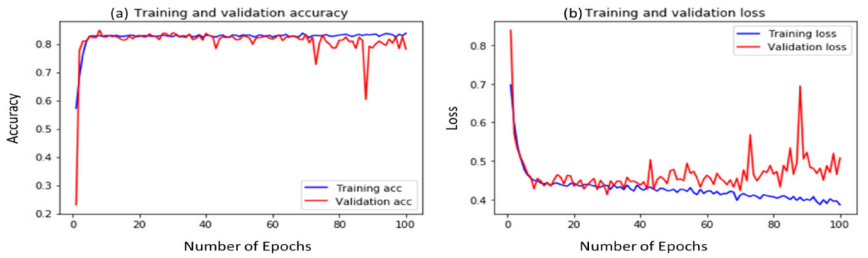


Figure 3

Training-validation accuracy and loss in different epoch's comparison

3.3. *Standard Convolutional Neural Network Architecture*

In this research, we utilize the fundamental and normal plan of CNN LeNet-5 (Xu et. al., 2006). We have carefully chosen the number of layers, optimizer, fetched work, kernel size and hyper parameters to extend the execution of the neural arrange. CL consists of a few centers that degree diverse highlight maps within the proposed demonstrate, followed by enactment layer (AL) and PL.

The primary reason of using CL is to make progressively complex designs. The system's capabilities appear to extend as the number of CLs increments. Hence, we utilized three CLs in our demonstrate since including more layers may decrease the representation of the neural network.

The highlights map $M^{n}{}_{ijk}$ can be calculated from (2), defined as follows:

$$M^{n}{}_{ijk} = (W_{k}{}^{N^{T}} XX^{N}{}_{ij}) + S^{n}{}_{k} \tag{2}$$

where $W_{k}{}^{N}$ is the weight vector and $S^{n}{}_{k}$ be each filter's bias in the n^{th} layer. The dissemination of substances in each layer gives the Neural Organize for learning more quality. To clarify the complex parts, the nonlinear actuation work (AF), indicated by λ, and is utilized. The nonlinear Re LU work is characterized by (3), (4), and (5) as:

$$\lambda^{n}{}_{ijk} = \lambda\ (M^{n}{}_{ijk}) \tag{3}$$

$$\lambda^{n}{}_{ijk} = \max(W_{k}{}^{T} X_{ij} + S_{k}, 0) \tag{4}$$

$$M^{n}{}_{ijk} = \text{pool}\ (\lambda^{n}{}_{abk}), \forall (a,b) \in U_{ij} \tag{5}$$

where U_{ij} is the position's nearest immediate neighbor (i, j) (Liao et. al., 2017).

The Softmax AL allows making each class associated to that input is in (6):

$$S^{n}_{ijk} = \frac{e^{m[n]}}{\sum_{x=1}^{X} e^{m[n]}} \tag{6}$$

One of the foremost troublesome errands for analysts is to prepare neural systems whereas bringing down costs (7), characterized as takes after, can be utilized to appraise the yield of a Neural Organize.

$$\nabla = \frac{1}{X} \sum_{b=1}^{X} n(\phi; m^{(b)}, Z^{(b)}) \tag{7}$$

where ϕ is the total no. of parameters used in the Neural Network, m^{b} is objective output tag.

The loss function can be evaluated from the below equation (8):

$$q(\phi) = -\frac{1}{t}[\sum_{g=1}^{t} \sum_{v=1}^{V} \mu_{v}^{(g)} \log h_{\phi}(y^{(g)})_{v} + (1-\mu_{v}^{(g)}) \log (1-h_{\phi}(y^{(g)})_{v})] \tag{8}$$

where 't' signifies the number of preparing events, and v is the execution estimations (Wang et. al., 2017). $\mu_{v}^{(g)}$ is the gth represents the superiority of the experiment as proven by the outcome of v. $h_{\phi}(y^{(g)})_{v}$ shows the experiment's quality as evinced by the v outcome, the esteem of ϕ, and the learning execution of g.

4. Proposed Methodology

Most of the ancient strategies are either oversimplified or inaccurate. In this paper, we endeavor to build a CNN engineering utilizing basic strategies that are both computationally proficient and valuable for illness discovery. The examine dataset is used by the CNN design.

4.1. *Information of Dataset*

One of the foremost cost-effective approaches could be a chest X-ray examination (Simonyan et. al., 2015) by the by, as clinical conclusion creates, the pathology imaging records are developing. In spite of the fact that there are other datasets on chest clutters, they are all confined to a number of thousands. The genuine source of this dataset is Open-I (Wang et. al., 2017; https://openi.nlm.nih.gov/). NIH chest X-Ray dataset from kaggle (Tulder and Bruijne, 2016) was utilized to approve our show. This dataset contains 5606 case photographs with 1024x1024 pixels each of 14 unmistakable infections and one no-finding affliction. Figure 1 outlines a few of the dataset's arbitrarily picked X-Ray pictures.

4.1. *Proposed Convolutional Neural Network Architecture*

Convolutional neural networks are one of the most highly developed and powerful learning algorithms for image recognition in the field of computer vision. Three convolutional layers, two totally associated layers, and a softmax layer make up our CNN architecture. The ConvL layer is made up of three layers: a convolution layer, an interpretation layer, and a wholly dedicated layer, as shown in Figure 2. ConvLi and MaxPi are the names of the convolutional and most extreme pooling layers, respectively, where 'I' denotes the number of layers in the CNN. The convolutional layer's fundamental and immediate layers are designated FC1 and FC2, respectively. To extract information from restricted input ranges, the primary convolutional layer employs a large number of highlight maps. These highlighted cards represent additional implementation work. This will clip all negative pixels to zero, effectively removing positive pixels. A common problem is training neural placement with a large number of settings. Pooling can be a subsampling technique that solves such problems. To demonstrate this with three ConvLs, we increased the depth of the neural system. Finally, there are two fully related layers that summarize the data to train on. These fully connected layers are computationally intensive.

4.2. *Training*

One of the foremost troublesome issues is the preparing of neural systems and the determination of a driving collection of hyper metometers. This requires a few test wiring. In this segment, we clarify why we chose the perfect set of hyper parameters and compare it to a few of our past tests. To begin with, part the data into its two subsets of arrangement photographs (4484) and test photographs (1122). Each pixel is 128x128. Use a stack estimate of 16 and 100 to get the age. For ease of implementation, we use a 3 x 3 bit rate in each convolutional layer and a 2 x 2 steady value for maximum pooling. In all circumstances, the triggering work is the ReLU nonlinearity. Use 32 channels within the start level of the convolution layer, 64 levels within the moment level of the convolution layer, and 128 levels within the third level of the convolution layer. A certain amount of neurons is expelled inside the wasting layer. The illustration was prepared using the Adam Optimizer with a learning rate of 0.001, 1 = 0.9 and 2 = 0.999, and a rotation rate of the last prescription of 0.4.

Table 1

Comparison of different and models proposed work

Author	Technique	Accuracy
Lauge et. al., (2010)	KNN	0.7333
Krizhevsky et. al., (2012)	SVM-RBF	0.7152
Krizhevsky et. al., (2012)	CNN	0.7104
Li et. al., (2013)	CNN	0.6705
Anthimopoulos et. al., (2014)	RF	0.7809
Simonyan & Zisserman, (2015)	CNN	0.7800
Kumar et. al. (2017)	CNN	0.7609
Proposed Model	**CNN**	**0.8367**

4.3. *Classification Performance*

In this area, we fundamentally center on the execution of the proposed illustrate. Training-Validation-Testing may be a test method that parts the total dataset into her three sets.

We arranged the show utilizing 80% of the total picture. We utilized 20% of the planning data to check the planning exactness and the remaining 20% of the starting data to test the appear.

The normal productivity of preparing this show is 83.15%, and the normal productivity of precision checking is 83.67% Table 1. Figure 3 appears whereas the approval misfortune shifts over a certain run; the preparing misfortune diminishes as the number of epoch's increments. The execution is done on a Windows 10 PC with an Intel(R) CoreTM i7-4790 3.60 GHz processor and 12 GB Smash. The central execution system Keras (Younes, 1999) is based on the programming dialect Python.

5. Conclusion and Future Work

A robust and comprehensive end-to-end convolutional neural array for assessing breast disease with deep learning is presented in this paper. To test our demonstration, The Kaggle Chest X-Ray 14 dataset is used. Convolutional layers, pooling layers, enactment layers, and completely relevant layers are the four different types of layers in CNN. During preparation, parallel cross-entropy was minimized using the Adam optimizer. The parallel cross entropy was minimized during preparation by using the Adam optimizer. The suggested method was tested on a collection of images, and it can accurately categorise deviations from the usual in chest ailments. This paper illustrates the astounding performance

of convolutional neural systems. Our research is still in its early stages, therefore we plan to examine at 14 sets of chest radiographs for all 14 disorganized chests in the future. Additionally, we tackle the implacable problem of "Can adopting a pre-trained model for medical image processing be a superior alternative to neural network development?"

Acknowledgement

All authors acknowledge the help given by NHI:US-National Library of Medicine for providing the data.

References

[1] Albarqouni, S., Baur, C., Achilles, F., Belagiannis, V., Demirci, S. & Navab, N. (2016) Aggnet: deep learning from crowds for mitosis detection in breast cancer histology images, *IEEE Transactions on Medical Imaging*, 35(5), 1313–1321.

[2] Anthimopoulos, Christodoulidis, S., Christe, A. & Mougiakakou, S. (2014). Classification of interstitial lung disease patterns using local DCT features and random forest," 36th Annual International Conference of the IEEE Engineering Medicine and Biology Society, PMID: 25571374, 6040–6043.

[3] Anthimopoulos, M., Christodoulidis, S., Ebner, L., Christe, A. & Mougiakakou, S. (2016). Lung pattern classification for interstitial lung diseases using a deep convolutional neural network, *IEEE Transactions on Medical Imaging*, 35(5), 1207–1216.

[4] Anthopoulos, M., Christodoulidis, S., Ebner, L., Christe, A. & Mougiakakou, S. (216). Lung Pattern Classification for Interstitial Lung Diseases Using a Deep Convolutional Neural Network, *IEEE Transactions on Medical Imaging*, 35(5), 1207-1216.

[5] Chaudhary, A., Hazra, A. & Chaudhary, P. (2019). Diagnosis of chest diseases in x-ray images using deep convolutional neural network, 10th International Conference on Computing, Communication and Networking Technologies (ICCCNT), IEEE, 1-6.

[6] Choudhary, P. & Hazra, A., (2019). Chest disease radiography in twofold: using convolutional neural networks and transfer learning. Evolving Systems, 1-13.

[7] Cun, B. B. L., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W. & Jackel, L. D. (1990). Handwritten digit recognition with a back-propagation network, NIPS.

[8] Deng, L. & Yu, D. (2014). Deep Learning: Methods and Applications, Foundations and Trends in Signal Processing: 7(3–4),197-387. http://dx.doi.org/10.1561/2000000039.

[9] Depeursinge, A., Ville, D. V. D., Platon, A., Geissbuhler, A., Poletti, P.A. & Muller, H. (2012). Near-affine-invariant texture learning for lung tissue analysis using isotropic wavelet frames, *IEEE Transactions on Information Technology in Biomedicine,* 16(4), 665–675.

[10] Foncubierta-Rodríguez A., Depeursinge, A. & Müller, H. (2012). Using Multiscale Visual Words for Lung Texture Classification and Retrieval, Medical Content-Based Retrieval, *Lecture Notes in Computer Science,* 7075, 69-79.

[11] Fu, H., Cheng, H., Xu, Y., Wong, D. W. K., Liu, J. & Cao, X. (2018). Joint optic disc and cup segmentation based on multi-label deep network and polar transformation, *IEEE Transactions on Medical Imaging*, 1-9, https://arxiv.org/pdf/1801.00926.pdf

[12] Fu, H., Xu, Y., Lin, S., Zhang, X., Wong, D. W. K., Liu, J., Frangi, A. F., Baskaran, M. & Aung, T. (2017). Segmentation and quantification for angleclosure glaucoma assessment in anterior segment oct, *IEEE Transactions on Medical Imaging,* 36(9), 1930–1938.

[13] Gangeh, Mehrdad J., Sørensen, L., Shaker, S. B., Kamel, M. S., Bruijne, M. D. & Loog, M. (2010). A texton-based approach for the classification of lung parenchyma in CT images, Medical Image Computing and Computer- Assisted Intervention (MICCAI), Springer, 595-602.

[14] Glorot, X. & Bengio, Y. (2010). Understanding the difficulty of training deep feedforward neural networks, AISTATS, 249-256.

[15] Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., Liu, T., Wang, X., Wang, G., Cai, J. & Chen, T. (2017). Recent advances in convolutional neural networks, *Computer Vision and Pattern Recognition*, https://doi.org/10.48550/arXiv.1512.07108.

[16] Hazra, A. (2021). A comprehensive survey on chest diseases analysis: technique, challenges and future research directions, *International Journal of Multimedia Information Retrieval*, 10, 83–110.

[17] Hazra, A., Choudhary, P. and Singh, M.S., (2021). Recent advances in deep learning techniques and its applications: an overview. *Advances in Biomedical Engineering and Technology,* 103-122.

[18] Hazra, A., Choudhary, P., Inunganbi, S. and Adhikari, M., (2021). Bangla-Meitei Mayek scripts handwritten character recognition using convolutional neural network. *Applied Intelligence*, 51(4), 2291-2311.

[19] https://academictorrents.com/details/e615d3aebce373f1dc8bd9d11064da55bdadede0. Bounding boxes for ~1000 images (BBox_List_2017.csv): Image Index, Finding Label, Bbox[x, y, w, h]. [x y] are coordinates of each box's top left corner. [w h] represent the width and height of each box.

[20] https://www.kaggle.com/crawford.

[21] https://www.kaggle.com/paultimothymooney.

[22] https://www.youtube.com/channel/UCjAOM-s-f2YfeLNGGZuY-Bg/featured.

[23] Hubel, D. H. & Wiesel, T. N. (1968). Receptive fields and functional architecture of monkey striate cortex, *The Journal of Physiology*, 195, 215-243.

[24] Korfiatis, P. D., Karahaliou, A. N., Kazantzi, A. D., Kalogeropoulou, C. & Costaridou, L. I. (2010). Texture-based identification and characterization of interstitial pneumonia patterns in lung multidetector CT, *IEEE Transactions on Information Technology in Biomedicine,*14(3), 675–680.

[25] Krizhevsky, A., Sutskever, I. & Hinton, G. (2012). ImageNet Classification with Deep Convolutional Neural Networks, NeurIPS Proceedings: Part of Advances in Neural Information Processing Systems, 9.

[26] Kumar, P., Grewal, M. & Srivastava, M. M. (2017). Boosted cascaded convnets for multilabel classification of thoracic diseases in chest radiographs, arXiv preprint arXiv:1711.08760.

[27] Lauge, S., Shaker, S. B. & Bruijne, M. D. (2010). Quantitative analysis of pulmonary emphysema using local binary patterns, *IEEE Transactions on Medical Imaging,* 29(2), 559-569.

[28] Li, Q., Cai, W. & Feng, D. D. (2013). Lung image patch classification with automatic feature learning, Proceedings: IEEE Annual International Conference Engineering Medicine Biology Society, 6079–6082.

[29] Li, Q., Cai, W., Wang, X., Zhou, Y., Feng, D. D. & Chen, M. (2014). Medical image classification with convolutional neural network," in 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), 844–848.

[30] Liao, R., Miao, S., Tournemire, P. D., Grbic, S., Kamen, A., Mansi, T. & Comaniciu, D. (2017). An artificial agent for robust image registration, In AAAI, 4168–4175.

[31] Liskowski, P. & Krawiec, K. (2016). Segmenting retinal blood vessels with¡? pub newline?¿ deep neural networks, *IEEE Transactions on Medical Imaging*, 35(11), 2369–2380.

[32] Moeskops, P., Viergeve, M.A., Mendrik, A. M., Vries, L., S., D., Benders, M. J. N. L. & Isgum, I. (2016). Automatic segmentation of MR brain images with a convolutional neural network, *IEEE Transactions on Medical Imaging*, 35(5), 1252-1261.

[33] Open-i: An open access biomedical search engine. https//openi.nlm.nih.gov.2,3,4.

[34] Rajpurkar, P. , Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., Ding, D., Bagul, A., Langlotz, C. & Shpanskaya, K. (2017). Chexnet: Radiologist level pneumonia detection on chest x-rays with deep learning," arXiv preprint arXiv:1711.05225.

[35] Roth, H. R., Lu, L., Farag, A., Shin, H.-C., Liu, J., Turkbey, E. B. & Summers, R. M. (2015). Deeporgan: Multi-level deep convolutional networks for automated pancreas segmentation, International Conference on Medical Image Computing and Computer-Assisted Intervention, Springer, 556–564.

[36] Simonyan, K. & Zisserman, A. (1999). Very Deep Convolutional Networks for Large-Scale Image Recognition, International Conference on Learning Representations. https://arxiv.org/pdf/1409.1556.pdf.

[37] Goel, D., Gulati, Payal, Jha, S. K., Kumar, N. K. & Khan, A. (2022). Evaluation of Machine Learning Techniques for Crop Yield Prediction, Artificial Intelligence Applications in Agriculture and Food Quality Improvement, 112-128, DOI: 10.4018/978-1-6684-5141-0.ch007.

[38] Tripathi, P., Kumar, N., Rai, M. & Khan, A. (2022). Applications of Deep Learning in Agriculture, Artificial Intelligence Applications in Agriculture and Food Quality Improvement, 17-28, DOI: 10.4018/978-1-6684-5141-0.ch002.

[39] Kumar, N., Tripathi, P. & Alam, K. (2016). Non-Negative Matrix Factorization-Based EEG Signal Classification, *Indian Journal of Industrial and Applied Mathematics*, 7(2), 212–219.

[40] Simonyan, K. & Zisserman, A. (2015). Very Deep Convolutional Networks for Large-Scale Image Recognition, International Conference on Learning Representations. https://arxiv.org/pdf/1409.1556.pdf

[41] Sluimer, C., Waes, P. F. V., Viergever, M. A. & Ginneken, B. V. (2003). Computer-aided diagnosis in high resolution CT of the lungs, *Medical Physics*, 30(12), 3081–3090.

[42] Song, Y., Cai, W., Zhou, Y. & Feng, D. D. (2013). Feature-based image patch approximation for lung tissue classification," *IEEE Trans. Med. Imaging*, vol. 32, no. 4, pp. 797–808, 2013.

[43] Stefan, D., Reichenbecher, M. A. K., Zuna, I., Schlegel, W. & Kaick, G. V. (1997). Usual interstitial pneumonia: quantitative assessment of high-resolution computed tomography findings by computer-assisted texture-based image analysis, Investigative Radiology, 32(9), 566-574.

[44] Tulder, G. V. & Bruijne, M. D. (2016). Combining Generative and Discriminative Representation Learning for Lung CT Analysis with Convolutional Restricted Boltzmann Machines, *IEEE Transactions on Medical Imaging*, 35(5), 1262-1272.

[45] Uchiyama, Y., Katsuragawa, S., Abe, H., Shiraishi, J., Li, F., Li, Q., Zhang, C.-T. , Suzuki, K. & Doi, K. (2003). Quantitative computerized analysis of diffuse lung disease in high-resolution computed tomography, Medical Physics, 30(9), 2440–2454.

[46] Uppaluri, R., Hoffman, E., A., Sonka, M., Hartley, P. G., Hunninghake, G. W. & McLennan, G. (1999). Computer recognition of regional lung disease patterns, *American Journal of Respiratory and Critical Care Medicine*, 160(2), 648–654.

[47] Vo, K. T. & Sowmya, A. (2010). Multiple kernel learning for classification of diffuse lung disease using HRCT lung images, IEEE Conference Proceedings Engineering Medicine Biology Society, 3085–3088.

[48] Wan, J., Wang, D., Hoi, S. C. H. & Wu, P. (2014). Deep learning for content-based image retrieval: A comprehensive study, Proceedings of the 22nd ACM international conference on Multimedia, 157-166.

[49] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M. & Summers, R. M. (2017). ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly- Supervised Classification and Localization of Common Thorax Diseases, IEEE CVPR, 3462-3471.

[50] Wang, X., Peng, Y., Lu, L., Lu, Z., Bagheri, M. & Summers, R. M. (2017). Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases," arXiv preprint arXiv:1705.02315.

[51] Xu, Y., Mo, T., Feng, Q., Zhong, P., Lai, M., Eric, I. & Chang, C. (2014). Deep learning of feature representation with multiple instance learning for medical image analysis, Acoustics, Speech and Signal Processing (ICASSP), IEEE International Conference, 1626–1630.

[52] Xu, Y., van Beek, E. J. R., Hwanjo, Y., Guo, J., McLennan, G. & Hoffman, E. A. (2006). Computer-aided Classification of Interstitial Lung Diseases Via MDCT: 3D Adaptive Multiple Feature Method (3D *AMFM Academic Radiology*, 13(8), 969–978.

[53] Y. Song, W. Cai, Y. Zhou, and D. D. Feng, "Feature-based image patch approximation for lung tissue classification, *IEEE Transactions on Medical Imaging*, 32(4), 797–808.

[54] Yan, Z., Zhan, Y., Peng, Z., Liao, S., Shinagawa, Y., Zhang, S., Metaxas, D. N. & Zhou, X. S. (2016). Multi-Instance Deep Learning: Discover Discriminative Local Anatomies for Bodypart Recognition, IEEE transactions on medical imaging, 35(5), 1332-1343.

[55] Yang, D., Zhang, S., Yan, Z., Tan, C., Li, K. & Metaxas, D. (2015). Automated anatomical landmark detection ondistal femur surface using convolutional neural network, IEEE 12th International Symposium Biomedical Imaging (ISBI), 17–21.

[56] Younes, Y. (1999). On the convergence of markovian stochastic algorithms with rapidly decreasing ergodicity rates, Stochastics: *International Journal of Probability and Stochastic Processes*, 65(3-4), 177–228.

[57] Yuan, Y., Chao, M. & Lo, Y.-C. (2017). Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance, *IEEE Transactions on Medical Imaging*, 36(9):1876-1886.

[58] Zhao, W., Xu, R., Hirano, Y., Tachibana, R. & Kido, S. (2013). Classification of diffuse lung diseases patterns by a sparse representation based method on HRCT images, IEEE Annual International Conference Engineering Medicine Biology, 5457-5460.

[59] Kalra, S. & Leekha, A. (2020). Survey of convolutional neural networks for image captioning, *Journal of Information and Optimization Sciences*, 41(1), 239-260.

[60] Sarin, N., Chug, A. & Singh, A. P. (2022). An image based prediction system for early blight disease in tomato plants using deep learning algorithm, *Journal of Information and Optimization Sciences*, 43(4), 761-779.

[61] Sahoo, D. K., Das, A., Mohanty, M. N. & Mishra, S. (2022). Brain tumor detection using inpainting and deep ensemble model, *Journal of Information and Optimization Sciences*, https://doi.org/10.1080/02522667.2022.2091094.