***Review Article***

THE APPLICATION OF TRANSFER LEARNING IN MEDICAL IMAGE CLASSIFICATION: A REVIEW OF LITERATURE

#####

# Abstract

Timely identification about health disorders has been made possible by photographic technologies, therefore photographic evidence provides a helpful technique towards illness identification. In addition to being labor-intensive, mechanical imagery processing techniques are prone to inter- and intra-observer inconsistency. Those restrictions may be addressed by computerized diagnostic imagery investigation methods. Transfer Learning (TL) frameworks using computerized health-related imagery processing have been looked at within the paper. It is has found how transfer learning can be used for many different healthcare scanning responsibilities, including recognizing objects, diseases classification, separation, and sensitivity scoring, etc. In contrast to conventional deep learning techniques, it is demonstrated that transfer learning offers superior selection assistance and uses reduced experimental input. A total of 100 peer-approved English language publications using the archives, IEEE Xplore and PubMed, where obtained till April 2025. A total of 53 research papers are considered suitable to the subject matter of this study after the PRISMA procedures for article screening was applied. Transfer learning techniques, such as pattern extraction, pattern extraction mix, fine tuning, and fine tuning from the start, are examined by works that concentrated on choosing core algorithms. Most research conducted experimental evaluations about several algorithms, then examined shallower depth approaches. Depth framework that has been used frequently within the academic research is Inception. In order to determine the best arrangement for the Transfer Learning, most research quantitatively compared several methods. just one methodology was used throughout the remaining experiments, then the two highly popular methods included pattern extraction and fine-tuning from start. Some research used pretrained algorithms for fine tuning and extraction of features hybrids. According to this study, the best popular Transfer Learning algorithms in analyzing medical images are AlexNet, ResNet, VGGNet, and GoogleNet. Such TL algorithms have been shown to be capable of comprehending healthcare photos, plus their capability to do so is improved by customisation, rendering them valuable instruments in studying photo scans.

Keywords: Deep learning, Transfer learning, Fine-tuning, Convolutional neural network, Medical image analysis

# Introduction

The eye in the human body is the component that brings light into the system to be able to perceive and process images. Medical professionals have overly depended on the body’s eye system to perform certain tasks especially examining medical images during the diagnoses of some health problems.

Unfortunately, the complex evolution of some medical images compromises the ability of the naked human eye system to classify these images (Rasool & Bhat, 2023).

Within the past few years, this concept about supplementing or, in several circumstances, integrating conventional diagnostic imagery interpretation alongside machine learning is gaining ground due to machine learning’s ability to deal with substantially larger data quantities whilst lowering internal and inter-operator variance (M. Li et al., 2023). This aligns with broader research on AI applications in health diagnostics. Korda, Akolgo, and Dapaah (2024) emphasize the role of deep learning and transfer learning as central elements in modern AI-driven clinical decision support systems, reinforcing the importance of model transferability across imaging modalities.

An interpreting specialist must combine an empirical examination procedure with the outcomes of intuitive analysis while analyzing medical images (Najjar, 2023). Over time, computers use specially designed techniques to solve solely rules-based issues (Iqbal et al., 2022). The above technique isn’t enough to predict as well as carry out every step required to obtain a diagnostic prediction on medical image interpretation (Shrivastava et al., 2023). It is necessary to use models that imitate the senses of people. In order to meet that demand, machine learning (also known as Artificial Intelligence) models human deductive reasoning using computational tools (Joshi et al., 2025).

As a result of AI machines replicating human perception, learning becomes a crucial component. Through learning, sophisticated algorithmic systems are able to modify core features and occasionally also inside features, similar to a person’s eye system (Zylinska, 2023). Due to the rules-based diagnosis procedure, providing the essential focus or clarity of the problem to be solved by perception, in such a capacity, using perception is adequate (Buijsman, 2024). One drawback of conventional intelligent machine strategies is that they require a special knowledge procedure to address the issue of medical image interpretation (X. Li et al., 2024).

For image analyzing, advanced image feature extraction such as Local Binary Pattern (LBP) features or Histograms of Oriented Gradients (HOG) features have actually predominated the area. However, the advent of Deep Learning (DL) techniques has sparked an evolution in non-handcrafted technology, allowing computerized analysis of images (Sharma et al., 2024). Notably, the standard deep learning approach for image processing is now convolutional neural networks (CNN). In the current clinical image examination dataset issues, CNN was used by every top-ranked group. According to Alinsaif (2024), it has been shown that the DL features outperformed the manually created ones. Deep Learning techniques, such as CNN, unfortunately, are limited by the dataset constraint dilemma because they need a lot of input data for learning, ideally. Among the most prevalent difficulties include a low number in healthcare teams alongside the expense of expert-annotated databases (Gangwal et al., 2024).

Numerous studies have attempted to address this issue by using transfer learning (TL) strategies (Iman et al., 2023). It seeks to use the information gained via sources activities to accomplish outstanding results on objective procedures. Among the latest research papers concerning Transfer Learning was authored by Azad et al. (2024), and the authors characterized transfer learning methods according to a naming perspective, however, Chui et al. (2023) provided a summary of TL research using both homogeneous and heterogeneous methodologies.

A thorough evaluation of deep learning (DL) in healthcare was the primary point of certain investigations. Egger et al. (2022) examined machine learning for analysis of medical images by compiling more than 300 publications, whereas C. Wang and Han (2022) examined the most recent studies on medical learning under self-supervision. A number of researchers however, reviewed papers that concentrated on transfer learning as well included a particular instance research, like cervical cytopathology, magnetic resonance brain imaging generally, and neuroimaging biomarkers of Alzheimer’s disease (Kim, 2024).

The concept where intelligence is carried onto associated procedures to enhance effectiveness on a novel assignment is the foundation of transfer learning (TL), which is based on neurological studies. It is commonly recognized that individuals can use prior experience to tackle related problems (Jiao et al., 2024). It is composed of a characteristic field *X* considering the allocation of marginal probabilities *P*(*X*), where *X* = {*x*1*,...,xn*} ∈ *X* . Understanding a certain domain defined by *D* = {*X ,P*(*X*)},activities are indicated by *T* = {*Y , f*(·)} where *Y* is a label space and *f*(·) is an objective predictive function. They perform a job via each other {*xi,yi*} where *xi* ∈ *X* and *yi* ∈ *Y* . With an important domain in hand *DS* and learning task *TS*, a target domain *DT* and learning task *TT*, The goal of transfer learning is to enhance the target prediction function’s training *fT*(·) in *DT* by using the knowledge in *DS* and *TS* (Nguyen et al., 2022).

Among the unique forms of advanced training, Convolutional Neural Networks (CNN) analyze images with a grid-like layout architecture dataset. CNN has not less than single multilayer, in contrast to a normal neural network, which comprises just altogether linked levels (Taye, 2023).

Table 1: A summary of the five core models

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Type of Model | Year | Parameters (all) | Parameters (FE only) | Trainable layers (FE + FC layers) |
| LeNet5 | 1998 | 60,000 | 1,716 | 4 (2 + 2) |
| AlexNet | 2012 | 62.3 M | 3.7 M | 8 (5 + 3) |
| VGG16 | 2014 | 134.2 M | 14.7 M | 16 (13 + 3) |
| GoogLeNet | 2014 | 5.3 M | 5.3 M | 22 (21 + 1) |
| ResNet50 | 2015 | 25.6 M | 23.5 M | 51 (50 + 1) |

Source: Bhatt et al. (2021)

The five most prominent models are shown sequentially in Table 1. The initial CNN framework families, LeNet and AlexNet (Zhang, 2021), were created in 1998 and 2012, separately. GoogLeNet (Ma et al., 2024), also called Inception1, established the current state of the art at the ILSVRC 2014, while VGG (Zhang, 2021), also called OxfordNet, is credited as the first deep model. The neural layers originated by merging the various outcomes, while GoogLeNet presented a revolutionary block approach which uses a collection of layers of varying dimensions. The ResNet50 (Xu et al., 2023) framework model was introduced to solve the vanishing gradient problem.

The concept behind CNN algorithm is how learning may be transferred at the parameter layer. Using Convolutional Neural Network and Transfer Learning for the classification of medical images allows for the use of general characteristics learnt from naturalistic imagery categorization when identifiers exist across the two fields. Certainly, two main transfer Learning techniques of exploiting CNN frameworks are simply feature extraction or fine-tuning (Campana et al., 2023). The features generator technique fixes the neural convolution, while the fine-tuning strategy modifies features continuously building the predictive model. Features extraction hybrids remove the Fully Connected layers and replace them with a machine learning method classification algorithm, but the basic structure of the provided connections stays unchanged in all of them. Fine-tuning from beginning is an extremely time-consuming method as it changes the complete combined of variables throughout learning (Ozt¨ urk et al.,¨ 2023).

Meena et al. (2023) used transfer learning techniques to develop the pre-trained model Inception v3 using the datasets CK+, FER2013, and JAFFE. Their findings demonstrated that the proposed model had an accuracy of 99*.*5%, while M.-A. Li and Xu (2021) built a unique feature transfer learning approach for Medical Image classification using the VGG-16 convolutional neural network (CNN) and an accuracy of 96*.*59% was achieved. In Hassan et al. (2020), AlexNet and GoogleNet pre-trained models are studied using transfer learning. They compared several models, that varied based on their layout and hyper- parameter values, in order to empirically identify the optimal DCNN model for precise categorization, utilizing four different databases for mammograms. When tested on NCI images and MIAS databases, AlexNet achieved 97*.*89% accuracy with AUC of 98*.*32% and 98*.*53% accuracy with AUC of 98*.*95%, respectively, while GoogleNet achieved 91*.*58% accuracy with AUC of 96*.*5% and 88*.*24% accuracy with AUC of 94*.*65%. These results are in contrast to the suggested AlexNet model, which obtained 100% accuracy for the two databases and 98*.*46% and 92*.*5% accuracy, respectively.

The paper aim is to review recent trends of the approaches used in the application of transfer learning for the classification of medical images. This paper review will be used as recommendation for researchers to rely on when selecting an excellent transfer learning model for their studies.

# Research Methodology

On 28 April 2025, articles were obtained by accessing the PubMed repository, and the IEEE Xplore database. The criteria listed below were used to choose the articles:

1. Transfer Learning need to be mentioned in the title or abstract.
2. Mainly research inquiries were taken into consideration.
3. Convolutional or CNN must be mentioned in the title or abstract.
4. Medical image data analysis should be taken into consideration.

The review concentrated on papers that have been published in the last five(5) years, i.e., 2020-2025. The paper reviewed, examined, contrasted, and reported eight features of 121 academic publications. Three of the attributes are qualitative, and five are quantitative. They are explained in the following order:

1. Off-the-shelf CNN model type (AlexNet, CaffeNet, Inception1, Incep tion2, Inception3,

Inception4, Inception-Resnet, LeNet, MobileNet, ResNet, VGG16, VGG19, DenseNet, Xcep tion, many or else).

1. Model performances (accuracy, AUC, sensitivity and specificity).
2. Transfer learning type (feature extractor, feature extractor hybrid, fine-tuning, finetuning or many).
3. Fine-tuning ratio.
4. Data modality (endoscopy, CT/CAT scan, mammographic, microscopy, MRI, OCT,PET, photography, sonography, SPECT, X-ray/radiography or many).
5. Data subject (abdominopelvic cavity, alimentary system, bones, car diovascular system,endocrine glands, genital systems, joints, lymphoid system, muscles, nervous system, tissue specimen, respiratory system, sense organs, the integu ment, thoracic cavity, urinary system, many or else).
6. Data quantity
7. The number of classes

These can be classified as either data, learning by transfer, or models.

Medical images are created using a variety of imaging methods, including computed tomography, magnetic resonance imaging, ultrasound, flexible imaging, optical imaging, and X-rays (Hussain et al., 2022). Advanced pre-processing techniques such as multi-threshold image segmentation can significantly enhance the performance of CNN-based classification. Korda et al. (2023) proposed a metaheuristic approach using a Grey Wolf Optimizer with Lévy flight, which demonstrated superior performance in segmenting complex medical images—offering a potential precursor step for transfer learning applications.

Since healthcare visualization can occasionally be the primary phase in stopping the transmission of infection with improved techniques for imaging, techniques for medical imaging are crucial for early detection. Additionally, early discovery aids in the treatment or eradication of numerous medical diseases. According to the research, foremost popular and prevalent method for scanning skin conditions is electronic dermoscopy. My analysis of earlier research indicates that it is one of the most effective techniques for categorizing dangerous skin cancers (Noronha et al., 2023). Microscopy is currently the most widely used technique for breast cancer imaging in numerous research (Kaniyala Melanthota et al., 2022). X-rays of the chest have been employed for specific reviews (Hansun et al., 2023). While magnetic resonance imaging (MRI) is normally not advised for pregnant women, several research employed it as a low-contrast, non-invasive method (Lother et al., 2023). Madani et al. (2022), provided an overview of the imaging methods used to identify cancer in women breast. In contrast, notwithstanding microscopic imaging’s prominence in a number of current research, authors failed to spotlight it (N. Wang et al., 2023). Priyadarshini et al. (2025), used microscopic scans to categorize pulmonary cancer, while computed tomography (CT) digital technique was used in various research (Hsieh & Flohr, 2021), (Vicente et al., 2021). Endoscopy remained the single most commonly used method of imaging to diagnose tumors of the stomach in accordance to the data (Yao et al., 2020). Diabetes retinopathy was classified using retinal tomography (Z. Yang et al., 2022). The highest commonly utilized approach in classifying brain cancers appeared MRI (Saeedi et al., 2023).



Figure 1: Distribution of 53 Disease Papers Across Medical Image Classification.

# Results and Discussion

The PRISMA method flow diagram (Kahale et al., 2022) shown in figure 1 is used for the selection of papers in this review. In the beginning, 100 publications within PubMed and IEEE Xplore were obtained out of each one. Over the screening stage, 35 papers were removed as replicas, therefore the entire articles of 65 research are considered into the following step. 12 papers have been excluded prior inclusiveness, leaving 53. Those shortlisted papers are extensively studied and grouped based on its foundational method and transfer learning kind. The data features as well as framework effectiveness have been examined to provide knowledge about how to apply Transfer Learning. The transfer learning method for healthcare image categorization began in 2016, four years following AlexNet topped the ImageNet Competition around 2012. subsequently, the quantity of papers has increased significantly over the course of several seasons.

Rahaman et al. (2020), provided a thorough comparison by assessing 15 frameworks, including MobileNet1, DenseNet121, DenseNet169, DenseNet201, XceptionNet, ResNet50, ResNet101, ResNet152, ResNet50V2, ResNet101V2, ResNet152V2, Inception3, and InceptionResNet2. Investigators came to the conclusion that VGG19 had the best accuracy, at

89*.*3%.



Figure 2: Diagram for the literature discovery.

Shah et al. (2023) and Al Husaini et al. (2022), concluded that Inception outperformed VGG in their comparison. Ovalle-Magallanes et al. (2020), further determined that Inception3 accomplished better than ResNet50 and VGG16.

53 publications employing transfer learning to analyze medical images were reported in this review of a subset of the available research, and it was discovered that Inception remained the most commonly employed approach. The second well-liked algorithms included VGG and AlexNet. Regarding transfer learning techniques, most papers thoroughly examined multiple feasible CNN algorithm amalgamations using as numerous TL methods as they could. In contrast to earlier recommended techniques (Chollet & Chollet, 2021), according to certain research, fine-tuning is arbitrary and unclear. R. Wang et al. (2024), failed to give a comprehensive description of the fine-tuning layout, and Samek et al. (2021), blocked all levels but the final twelve ones any explanation. VGG16/19 was divided into five parts by (Kumar & Sankar, 2024). Akay et al. (2022), who then reactivated each block one after the other and determined which model was optimized using both blocks that performed the best. CaffeNet was also improved by gradually releasing every single layer (Agarwal et al., 2021). The algorithm that has single rebuilt neuron to identifying activity as well as two modified neurons during the categorization activity produced the most favorable findings. Sanghvi et al. (2023), discovered that some maximum predictive performance was obtained when DenseNet201 was retrained at inception. Muchuchuti and Viriri (2023), claimed suggested superficial CNN algorithms might prove best suited in order to interpreting pictures from Tomography as well as imagery for epidermal diseases and fundus, whereas DCNN methods might prove very useful for X-ray, endoscopic, and ultrasound photos. In order to validate those theories, however, extra investigation is required. Among the papers, transfer learning using initialization randomly frequently emerged (Zan et al., 2022). CNN-based algorithms were the sole structure employed within this research, while learning was started using randomized parameters. Once all of the parameters and preconceptions are set up, another might state therefore there exists an absence of learning, however this issue remains viewed as transfer learning in the previous papers. Notably, just a small number of papers Yu et al. (2020), and Hammouda et al. (2020) used native 3D-CNN. According to the two papers, 3D-CNN delivered better than 2.5-CNN and 2D-CNN algorithms. Most of the research conducted used 3D data inputs to build 2D-CNNs or 2.5D-CNNs. To lessen the computational load, just a small number of 3D data picture segments were captured. Since high-performance Deep Learning is a new area of study, it is anticipated that more experiments using 3D algorithms could be conducted in the coming years.

Despite the fact that the majority of reviewed articles only briefly described its computer configuration, no additional data regarding developing or testing results over time was given. Interestingly, the transferability of AI models across domains—including education and language processing—has been studied by Korda et al. (2024), which may suggest new pathways for domain adaptation in medical image analysis, especially in developing cross-modal transfer learning frameworks. Transfer Learning often required consumer-grade GPUs in customized computers and, under rare cases, server-grade cards (P100 or V100) because the majority of healthcare information volumes remain smaller (Vatter et al., 2023). The scope of the research has been restricted to transfer learning surveys for medical imagery categorization. Nonetheless, a number of intriguing task-driven transfer learning experiments, through an emphasis on object detection and division of images, have been presented in recent years (X. Yang et al., 2024). Furthermore, it is not assessed how the variations between the origin and destination domains for the retraining dataset utilized in Transfer Learning could enhance this predictive ability (Khan et al., 2024). Vision transformers (ViT) Hatamizadeh et al. (2023) were also never evaluated, which have emerged on the research of visual images.After comparing 4 ViT algorithms with 22 core theories, Liu et al. (2022) found a single ViT method had the best performance when generated on reduced cytopathology tissue pictures. With the goal to achieve higher accuracy of models along with improved processing, Chen et al. (2022), has developed a unique paradigm based includes a hybrid with MobileNet and ViT.

# Conclusion

The area of healthcare imagery analytics is broad, significant, as well heavily verifiable. A primary issue is a dearth of labelled health-care photos, since deep learning algorithms need a lot of tagged pictures to properly learn. Consequently, a comprehensive overview is conducted within the research that presents various techniques for diagnostic picture analysis.

Research have made extensive advantage about a theory around Transfer Learning utilizing existing algorithms like VGGNet, ResNet, and Inception v3, and many more to get around the issue of a shortage of clinical pictures, since only needs a small quantity of health datasets before it’s developed. Notwithstanding these positive findings for earlier research, it has been seen that numerous publications used frameworks trained by CNN using ImageNet to address this issue for a shortage in healthcare photos. However, rather of employing algorithms generated upon non-health care photographs, a lighter approach may be developed based on a large number of marked healthcare files and then refined utilizing defined photos that are accessible in small volumes. If it is necessary to improve an algorithm’s achievement, neural layering can be gradually unfrozen through top to bottom using an inexpensive training percentage. Completing those simple actions may reduce overall expenses as well as time by not compromising its ability to foresee. Additionally, image techniques targeting certain disorders have been discovered along with certain few of their advantages and drawbacks. Lastly, comprehensive examination about the algorithms’ performances within its area of healthcare picture processing and the methods employed to resolve them was looked at.

# References

Agarwal, D., Marques, G., de la Torre-D´ıez, I., Franco Martin, M. A., Garc´ıa Zapira´ın, B., & Mart´ın Rodr´ıguez, F. (2021). Transfer learning for alzheimer’s disease through neuroimaging biomarkers: A systematic review. *Sensors*, *21*(21), 7259.

Akay, B., Karaboga, D., & Akay, R. (2022). A comprehensive survey on optimizing deep learning models by metaheuristics. *Artificial Intelligence Review*, *55*(2), 829–894.

Al Husaini, M. A. S., Habaebi, M. H., Gunawan, T. S., Islam, M. R., Elsheikh, E. A., & Suliman, F. (2022). Thermal-based early breast cancer detection using inception v3, inception v4 and modified inception mv4. *Neural Computing and Applications*, *34*(1), 333–348.

Alinsaif, S. (2024). Covid-19 image classification: A comparative performance analysis of handcrafted vs. deep features. *Computation*, *12*(4), 66.

Azad, M. M., Kim, S., Cheon, Y. B., & Kim, H. S. (2024). Intelligent structural health monitoring of composite structures using machine learning, deep learning, and transfer learning: A review. *Advanced Composite Materials*, *33*(2), 162–188.

Bhatt, D., Patel, C., Talsania, H., Patel, J., Vaghela, R., Pandya, S., Modi, K., & Ghayvat, H. (2021). Cnn variants for computer vision: History, architecture, application, challenges and future scope. *Electronics*, *10*(20), 2470.

Buijsman, S. (2024). Transparency for ai systems: A value-based approach. *Ethics and Information Technology*, *26*(2), 34.

Campana, M. G., Delmastro, F., & Pagani, E. (2023). Transfer learning for the efficient detection of covid-19 from smartphone audio data. *Pervasive and Mobile Computing*, *89*, 101754.

Chen, Y., Dai, X., Chen, D., Liu, M., Dong, X., Yuan, L., & Liu, Z. (2022). Mobile-former: Bridging mobilenet and transformer. *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 5270–5279.

Chollet, F., & Chollet, F. (2021). *Deep learning with python*. Simon; Schuster.

Chui, K. T., Arya, V., Band, S. S., Alhalabi, M., Liu, R. W., & Chi, H. R. (2023). Facilitating innovation and knowledge transfer between homogeneous and heterogeneous datasets: Generic incremental transfer learning approach and multidisciplinary studies. *Journal of Innovation & Knowledge*, *8*(2), 100313.

Egger, J., Gsaxner, C., Pepe, A., Pomykala, K. L., Jonske, F., Kurz, M., Li, J., & Kleesiek, J. (2022). Medical deep learning—a systematic meta-review. *Computer methods and programs in biomedicine*, *221*, 106874.

Gangwal, A., Ansari, A., Ahmad, I., Azad, A. K., & Sulaiman, W. M. A. W. (2024). Current strategies to address data scarcity in artificial intelligence-based drug discovery: A comprehensive review. *Computers in Biology and Medicine*, *179*, 108734.

Hammouda, K., Khalifa, F., Soliman, A., Abdeltawab, H., Ghazal, M., Abou El-Ghar, M., Haddad, A., Darwish, H. E., Keynton, R., & El-Baz, A. (2020). A 3d cnn with a learnable adaptive shape prior for accurate segmentation of bladder wall using mr images. *2020 IEEE 17th International Symposium on Biomedical Imaging (ISBI)*, 935–938.

Hansun, S., Argha, A., Liaw, S.-T., Celler, B. G., & Marks, G. B. (2023). Machine and deep learning for tuberculosis detection on chest x-rays: Systematic literature review. *Journal of medical Internet research*, *25*, e43154.

Hassan, S. A., Sayed, M. S., Abdalla, M. I., & Rashwan, M. A. (2020). Breast cancer masses classification using deep convolutional neural networks and transfer learning. *Multimedia Tools and Applications*, *79*(41), 30735–30768.

Hatamizadeh, A., Yin, H., Heinrich, G., Kautz, J., & Molchanov, P. (2023). Global context vision transformers. *International Conference on Machine Learning*, 12633–12646.

Hsieh, J., & Flohr, T. (2021). Computed tomography recent history and future perspectives. *Journal of Medical Imaging*, *8*(5), 052109–052109.

Hussain, S., Mubeen, I., Ullah, N., Shah, S. S. U. D., Khan, B. A., Zahoor, M., Ullah, R., Khan, F. A., & Sultan, M. A. (2022). Modern diagnostic imaging technique applications and risk factors in the medical field: A review. *BioMed research international*, *2022*(1), 5164970.

Iman, M., Arabnia, H. R., & Rasheed, K. (2023). A review of deep transfer learning and recent advancements. *Technologies*, *11*(2), 40.

Iqbal, S., Maryam, H., Qureshi, K. N., Javed, I. T., & Crespi, N. (2022). Automised flow rule formation by using machine learning in software defined networks based edge computing.

Jiao, L., Ma, M., He, P., Geng, X., Liu, X., Liu, F., Ma, W., Yang, S., Hou, B., & Tang, X. (2024). Brain-inspired learning, perception, and cognition: A comprehensive review. *IEEE Transactions on Neural Networks and Learning Systems*.

Joshi, R., Pandey, K., Kumari, S., & Badola, R. (2025). Artificial intelligence: A gateway to the twenty-first century. In *The intersection of 6g, ai/machine learning, and embedded systems* (pp. 146–172). CRC Press.

Kahale, L. A., Elkhoury, R., El Mikati, I., Pardo-Hernandez, H., Khamis, A. M., Schunemann, H. J.,¨ Haddaway, N. R., & Akl, E. A. (2022). Tailored prisma 2020 flow diagrams for living systematic reviews: A methodological survey and a proposal. *F1000Research*, *10*, 192.

Kaniyala Melanthota, S., Kistenev, Y. V., Borisova, E., Ivanov, D., Zakharova, O., Boyko, A., Vrazhnov, D., Gopal, D., Chakrabarti, S., K, S. P., et al. (2022). Types of spectroscopy and microscopy techniques for cancer diagnosis: A review. *Lasers in Medical Science*, *37*(8), 3067– 3084.

Khan, S., Yin, P., Guo, Y., Asim, M., & Abd El-Latif, A. A. (2024). Heterogeneous transfer learning: Recent developments, applications, and challenges. *Multimedia Tools and Applications*, *83*(27), 69759–69795.

Kim, H. E. (2024). *Efficient deep learning at inference time for gram stained image classification* [Doctoral dissertation].

Korda, D. R., Emmanuel, N., Asante, M., Dapaah, E. O., & Hodowu, D. K. M. (2023). Improved grey wolf optimizer based on Lévy flight for multi-thresholding image segmentation. *International Journal of Computer Applications*, 184(49), 1–12.

Korda, D. R., Akolgo, E. A., & Dapaah, E. O. (2024). Artificial intelligence in healthcare: A fusion of technologies. *Journal of Computer and Communications*, 12(12), 116–133. https://doi.org/10.4236/jcc.2024.1212008

 Korda, D. R., Dapaah, E. O., & Akolgo, E. A. (2024). The role of AI chatbots in education: A review. *Academy Journal of Science and Engineering*, 18(1), 79–87.

Kumar, C. M., & Sankar, J. S. (2024). Comparative analysis of convolutional neural networks for brain tumor detection: A study of vgg16, resnet, inception, and densenet models. *2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, 41–46. Li, M., Jiang, Y., Zhang, Y., & Zhu, H. (2023). Medical image analysis using deep learning algorithms. *Frontiers in public health*, *11*, 1273253.

Li, M.-A., & Xu, D.-Q. (2021). A transfer learning method based on vgg-16 convolutional neural network for mi classification. *2021 33rd Chinese Control and Decision Conference (CCDC)*, 5430–5435.

Li, X., Zhang, L., Yang, J., & Teng, F. (2024). Role of artificial intelligence in medical image analysis: A review of current trends and future directions. *Journal of Medical and Biological Engineering*, *44*(2), 231–243.

Liu, W., Li, C., Rahaman, M. M., Jiang, T., Sun, H., Wu, X., Hu, W., Chen, H., Sun, C., Yao, Y., et al. (2022). Is the aspect ratio of cells important in deep learning? a robust comparison of deep learning methods for multi-scale cytopathology cell image classification: From convolutional neural networks to visual transformers. *Computers in biology and medicine*, *141*, 105026.

Lother, D., Robert, M., Elwood, E., Smith, S., Tunariu, N., Johnston, S. R., Parton, M., Bhaludin, B., Millard, T., Downey, K., et al. (2023). Imaging in metastatic breast cancer, ct, pet/ct, mri, wb-dwi, cca: Review and new perspectives. *Cancer Imaging*, *23*(1), 53.

Ma, L., Wu, H., & Samundeeswari, P. (2024). Googlenet-al: A fully automated adaptive model for lung cancer detection. *Pattern Recognition*, *155*, 110657.

Madani, M., Behzadi, M. M., & Nabavi, S. (2022). The role of deep learning in advancing breast cancer detection using different imaging modalities: A systematic review. *Cancers*, *14*(21), 5334.

Meena, G., Mohbey, K. K., & Kumar, S. (2023). Sentiment analysis on images using convolutional neural networks based inception-v3 transfer learning approach. *International journal of information management data insights*, *3*(1), 100174.

Muchuchuti, S., & Viriri, S. (2023). Retinal disease detection using deep learning techniques: A comprehensive review. *Journal of Imaging*, *9*(4), 84.

Najjar, R. (2023). Redefining radiology: A review of artificial intelligence integration in medical imaging. *Diagnostics*, *13*(17), 2760.

Nguyen, C. T., Van Huynh, N., Chu, N. H., Saputra, Y. M., Hoang, D. T., Nguyen, D. N., Pham, Q.-V., Niyato, D., Dutkiewicz, E., & Hwang, W.-J. (2022). Transfer learning for wireless networks: A comprehensive survey. *Proceedings of the IEEE*, *110*(8), 1073–1115.

Noronha, S. S., Mehta, M. A., Garg, D., Kotecha, K., & Abraham, A. (2023). Deep learning-based dermatological condition detection: A systematic review with recent methods, datasets, challenges, and future directions. *IEEE Access*, *11*, 140348–140381.

Ovalle-Magallanes, E., Avina-Cervantes, J. G., Cruz-Aceves, I., & Ruiz-Pinales, J. (2020). Transfer learning for stenosis detection in x-ray coronary angiography. *Mathematics*, *8*(9), 1510.

Ozt¨ urk, C., Tas¸y¨ urek, M., & T¨ urkdamar, M. U. (2023). Transfer learning and fine-tuned transfer¨ learning methods’ effectiveness analyse in the cnn-based deep learning models. *Concurrency and computation: practice and experience*, *35*(4), e7542.

Priyadarshini, K., Ali, S. A., Sivanandam, K., & Alagarsamy, M. (2025). Human lung cancer classification and comprehensive analysis using different machine learning techniques. *Microscopy Research and Technique*, *88*(1), 234–250.

Rahaman, M. M., Li, C., Yao, Y., Kulwa, F., Rahman, M. A., Wang, Q., Qi, S., Kong, F., Zhu, X., & Zhao, X. (2020). Identification of covid-19 samples from chest x-ray images using deep learning: A comparison of transfer learning approaches. *Journal of X-ray Science and Technology*, *28*(5), 821–839.

Rasool, N., & Bhat, J. I. (2023). Unveiling the complexity of medical imaging through deep learning approaches. *Chaos Theory and Applications*, *5*(4), 267–280.

Saeedi, S., Rezayi, S., Keshavarz, H., & R. Niakan Kalhori, S. (2023). Mri-based brain tumor detection using convolutional deep learning methods and chosen machine learning techniques. *BMC Medical Informatics and Decision Making*, *23*(1), 16.

Samek, W., Montavon, G., Lapuschkin, S., Anders, C. J., & Muller, K.-R. (2021). Explaining deep¨ neural networks and beyond: A review of methods and applications. *Proceedings of the IEEE*, *109*(3), 247–278.

Sanghvi, H. A., Patel, R. H., Agarwal, A., Gupta, S., Sawhney, V., & Pandya, A. S. (2023). A deep learning approach for classification of covid and pneumonia using densenet-201. *International Journal of Imaging Systems and Technology*, *33*(1), 18–38.

Shah, S. R., Qadri, S., Bibi, H., Shah, S. M. W., Sharif, M. I., & Marinello, F. (2023). Comparing inception v3, vgg 16, vgg 19, cnn, and resnet 50: A case study on early detection of a rice disease. *Agronomy*, *13*(6), 1633.

Sharma, U., Aggarwal, P., & Mittal, A. (2024). Computer-aided classification of melanoma: A comprehensive survey. *Archives of Computational Methods in Engineering*, 1–35.

Shrivastava, P. K., Sharma, M., Kumar, A., et al. (2023). Hcbilstm: A hybrid model for predicting heart disease using cnn and bilstm algorithms. *Measurement: Sensors*, *25*, 100657.

Taye, M. M. (2023). Theoretical understanding of convolutional neural network: Concepts, architectures, applications, future directions. *Computation*, *11*(3), 52.

Vatter, J., Mayer, R., & Jacobsen, H.-A. (2023). The evolution of distributed systems for graph neural networks and their origin in graph processing and deep learning: A survey. *ACM Computing Surveys*, *56*(1), 1–37.

Vicente, M. A., Mena, A., M´ ´ınguez, J., & Gonzalez, D. C. (2021). Use of computed tomography´ scan technology to explore the porosity of concrete: Scientific possibilities and technological limitations. *Applied Sciences*, *11*(18), 8699.

Wang, C., & Han, J. (2022). Dl4scivis: A state-of-the-art survey on deep learning for scientific visualization. *IEEE transactions on visualization and computer graphics*, *29*(8), 3714–3733.

Wang, N., Zhang, C., Wei, X., Yan, T., Zhou, W., Zhang, J., Kang, H., Yuan, Z., & Chen, X. (2023). Harnessing the power of optical microscopy for visualization and analysis of histopathological images. *Biomedical Optics Express*, *14*(10), 5451–5465.

Wang, R., Li, H., Han, X., Zhang, Y., & Baldwin, T. (2024). Learning from failure: Integrating negative examples when fine-tuning large language models as agents. *arXiv preprint arXiv:2402.11651*.

Xu, W., Fu, Y.-L., & Zhu, D. (2023). Resnet and its application to medical image processing: Research progress and challenges. *Computer Methods and Programs in Biomedicine*, *240*, 107660.

Yang, X., Jiao, L., & Pan, Q. (2024). Transfer adaptation learning for target recognition in sar images: A survey. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*.

Yang, Z., Tan, T.-E., Shao, Y., Wong, T. Y., & Li, X. (2022). Classification of diabetic retinopathy: Past, present and future. *Frontiers in endocrinology*, *13*, 1079217.

Yao, K., Uedo, N., Kamada, T., Hirasawa, T., Nagahama, T., Yoshinaga, S., Oka, M., Inoue, K., Mabe, K., Yao, T., et al. (2020). Guidelines for endoscopic diagnosis of early gastric cancer. *Digestive Endoscopy*, *32*(5), 663–698.

Yu, J., Yang, B., Wang, J., Leader, J., Wilson, D., & Pu, J. (2020). 2d cnn versus 3d cnn for falsepositive reduction in lung cancer screening. *Journal of Medical Imaging*, *7*(5), 051202–051202.

Zan, C., Ding, L., Shen, L., Cao, Y., Liu, W., & Tao, D. (2022). On the complementarity between pre-training and random-initialization for resource-rich machine translation. *arXiv preprint arXiv:2209.03316*.

Zhang, X. (2021). The alexnet, lenet-5 and vgg net applied to cifar-10. *2021 2nd International Conference on Big Data & Artificial Intelligence & Software Engineering (ICBASE)*, 414–419.

Zylinska, J. (2023). *The perception machine: Our photographic future between the eye and ai*. MIT

Press.