Al-Kitab Journal for Pure Sciences (2023); 7(1):57-68.

https://doi.org/10.32441/kjps.07.01.p6

Al-Kitab Journal for Pure Sciences
ISSN: 2617-1260 (print), 2617-8141(online)
www.kjps.isnra.org

Optimizing Image Processing with CNNs through Transfer Learning: Survey

*Hussein Mohammed Essa, Asim M. Murshid
College of Computer Science and Information Technology, University of Kirkuk, Kirkuk, Iraq
*Corresponding Author: stch21m007@uokirkuk.edu.iq

Citation: Essa HM, Murshid AM. Optimizing Image Processing with CNNs through Transfer Learning: Survey. Al-Kitab J. Pure Sci. [Internet]. 2023 Aug. 20 [cited 2023 Aug. 20];7(1):57-68. Available from: https://isnra.net/index.php/kjps/article/view/926
DOI: https://doi.org/10.32441/kjps.07.01.p6.

Keywords: Convolutional Neural Networks, CNNs, transfer learning, image processing, deep learning.

Article History

Received	05 June.	2023
Accepted	11 Aug.	2023
Available online	20 Aug.	2023

Abstract:

The field of image processing has been revolutionized by Convolutional Neural Networks (CNNs), which exhibit exceptional capability in feature extraction and accurate image classification. However, training CNNs requires large volumes of annotated data and significant computational resources. Considering these challenges, transfer learning has emerged as a promising approach to reducing the dependence on labeled data and computational resources. Transfer learning involves utilizing knowledge gained from a source task to improve the training process for a target task. This technique has demonstrated considerable benefits; however, it also possesses certain limitations. Consequently, this survey explores the advantages and constraints of transfer learning and the various factors that influence its effectiveness in optimizing image processing using CNNs. Additionally, the survey investigates the most recent advancements and research in the field of transfer learning specifically for image processing with CNNs. In summary, this comprehensive analysis highlights the significance of transfer learning in the context of optimizing image processing with CNNs, providing unique insights into this rapidly evolving domain.

Keywords: Convolutional Neural Networks, CNNs, transfer learning, image processing, deep learning.

تحسين معالجة الصور باستخدام الشبكات العصبية العميقة من خلال التعلم النقلي: مسح استقصائي

حسين محمد عيسى * & عاصم مجيد مرشد
قسم علوم الحاسوب، كلية علوم الحاسوب وتكنلوجيا المعلومات، جامعة كركوك، العراق
stch21m007@uokirkuk.edu.iq

شهدت مجال معالجة الصور ثورة بفضل الشبكات العصبية العميقة المُستخدَمة في التعلم التحويلي، حيث تظهر تلك الشبكات قدرة استثنائية في استخراج الميزات وتصنيف الصور بدقة. ومع ذلك، فإن تدريب الشبكات العصبية العميقة يتطلب كميات كبيرة من البيانات المعلّقة وموارد حسابية مهمة. ونظرًا لهذه التحديات، ظهر التعلم التحويلي كنهج مشجع لتقليل الاعتماد على البيانات الموسومة والموارد الحسابية. ينطوي التعلم التحويلي على استخدام المعرفة المكتسبة من مهمة مصدر لتحسين عملية التدريب لمهمة هدف. وقد أظهرت هذه التقنية فوائد كبيرة؛ ومع ذلك، فإنها تحمل أيضًا بعض القيود. ونتيجة لذلك، يستكشف هذا الاستطلاع المزايا والقيود للتعلم التحويلي، بالإضافة إلى العوامل المختلفة التي تؤثر في فعاليته في تحسين معالجة الصور باستخدام الشبكات العصبية العميقة. وبالإضافة إلى ذلك، يتحقق الاستطلاع من أحدث التطورات والأبحاث في مجال التعلم التحويلي خصوصًا لمعالجة الصور باستخدام الشبكات العصبية العميقة. وفي الختام، يسلط هذا التحليل الشامل الضوء على أهمية التعلم التحويلي في سياق تحسين معالجة الصور باستخدام الشبكات العصبية العميقة، ويوفر رؤى فريدة في هذا المجال الذي يتطور بسرعة.

الكلمات المفتاحية: الشبكات العصبية العميقة، الشبكات العصبية العميقة المُستخدَمة في التعلم التحويلي، التعلم التحويلي، معالجة الصور، التعلم العميق.

1. Introduction:

Convolutional Neural Networks (CNNs) have revolutionized the field of image processing with their outstanding ability to extract features and classify images. CNNs learn hierarchical representations of visual patterns through multiple layers of processing raw image data, making them highly efficient at identifying patterns and features. One of the most significant achievements of CNNs is their success in improving image resolution. Traditional methods like interpolation and bicubic upscaling have limitations and may result in blurry and distorted images. CNNs, on the other hand, employ super-resolution techniques to produce high-quality and sharp images with increased resolution **[1]** CNNs have also proven effective in image restoration tasks such as denoising. CNNs for denoising are capable of enhancing low-light images by eliminating noise patterns, resulting in more detailed and clearer images **[2]**. In the field of medical imaging, segmentation techniques based on CNNs have been utilized to identify and isolate specific organs or abnormalities in medical images. This application has proven helpful in diagnosing medical conditions and improving treatment planning [3]Transfer learning is a technique widely used in machine learning to improve model performance on related tasks [4] In this method, knowledge gained from a pre-existing model is used to enhance the effectiveness of a new task involving a smaller data set. Typically, a pre-existing model undergoes training on a large data set designed for a specific task, such as image classification [5]. The knowledge learned from the pre-trained model's weights and biases is then transferred to the new task, improving the new model's performance. In the process of transfer learning, it is common to keep the bottom layers of the pre-trained model in a frozen state, which act as immutable feature extractors. At the same time, the upper layers are tuned or tuned to get task-specific features [6] A pre-trained model can learn general features that apply to various tasks, including edge detection, texture recognition, and object representation. These features can be utilized for a new task to minimize the amount of data required for training and enhance the performance of the new model, especially when the new dataset is small and has similarities with the original dataset. Transfer learning has become an important technique for researchers and practitioners in diverse fields since it enables them to utilize pre-trained models to decrease the time required for training and enhance the accuracy of their models [4]. Given the ongoing progress in deep learning architectures and the abundant availability of extensive datasets, transfer learning is anticipated to play a pivotal role in the advancement of machine learning and artificial intelligence in the foreseeable future. In essence, transfer learning stands as a potent technique with diverse applications across various domains, including computer vision, natural language processing, speech recognition, and medical image analysis. This survey report serves as a comprehensive overview of the most recent advancements in transfer learning techniques and their practical implementations for optimizing image processing using CNNs. It serves as an invaluable resource for researchers and professionals in the field, offering valuable insights into cutting-edge approaches to enhance the performance of CNN-based image processing applications.

2- How does Transfer Learning Work?

Transfer learning is a popular machine learning technique that aims to improve the performance of models on related tasks by leveraging knowledge gained from pre-trained models [7]. Typically, the pre-trained model undergoes training on an extensive dataset tailored to a particular task, like classifying images [8]. The knowledge gained from the pre-trained model's weights and biases is then transferred to a new task with a smaller dataset, improving the performance of the new model. This technique is particularly useful when there is a lack of sufficient training data for the new task or when training a new model from scratch is computationally expensive [9]. In the process of transfer learning, it is common practice to keep the lower layers of the pre-trained model unchanged and utilize them as fixed feature extractors. Meanwhile, the higher layers are adjusted or fine-tuned to acquire features specific to the task at hand [10]. The pre-trained model has acquired generic features that hold significance across numerous tasks, including edge detection, texture recognition, and object representation. These features can be leveraged for a new task, leading to a reduction in the volume of training data needed and enhancing the performance of the new model, particularly when the new dataset is small and like the original dataset. This technique has been successfully applied to various fields, including computer vision, natural language processing, and speech recognition [7].The figure 1, [11] illustrates the use of a pre-trained model that was trained on a large image dataset (ImageNet) and fine-tuned on a new dataset with different classes and updated weights.

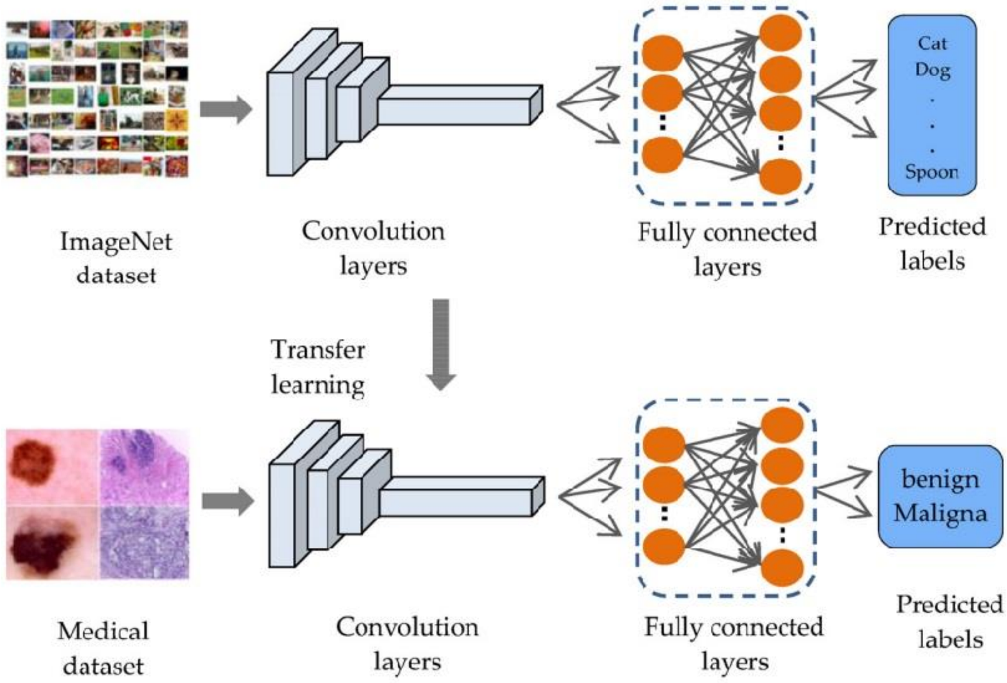

Figure 1: Transfer learning from ImageNet.

In the context of image classification, Table 1 presents an overview of the top five CNN models, each offering pre-trained weights and biases that can be effectively employed for transfer learning. To determine the parameter, count for each filter, we employ the formula (a * b * c) + 1, where a * b represents the filter dimensions, c denotes the number of filters in the preceding layer, and the additional 1 account for the bias. The models are arranged chronologically, commencing with the initial-generation LeNet [12] and AlexNet [13], which were developed in 1998 and 2012, respectively. VGG16 [14] stands out as the pioneering deep model, while GoogleNet [15] introduced the innovative concept of blocks, and ResNet50 [16] introduced residual blocks featuring skip connections between layers. ResNet effectively resolves the vanishing gradient problem, ensuring adequate updates to the weights of earlier layers during training. Notably, all models employ the SoftMax function in the classifier head, except for LeNet-5, which utilizes the hyperbolic tangent function.

Table 1: presents a comprehensive overview of five key backbone models.

Model	Released Year	Total Parameters	FE Parameters	Trainable Layers	Dataset
VGG16	2014	134.2 million	14.7 million	16	ImageNet
AlexNet	2012	62.3 million	3.7 million	8	ImageNet
LeNet5	1998	60,000 thousand	1,716 thousand	4	MNIST
GoogLeNet	2014	5.3 million	5.3 million	22	ImageNet
ResNet50	2015	25.6 million	23.5 million	51	ImageNet

Note: Abbreviations: FE stands for feature extraction, FC stands for fully connected layers. The MNIST database refers to the Modified National Institute of Standards and Technology database, which includes 60,000 training and 10,000 test images of handwritten digits. The ImageNet database is a vast collection of over 14 million hand-annotated images organized based on the WordNet hierarchy and is commonly used for research on visual object recognition.

3- Literature Review

Transfer learning has found its application in a multitude of tasks related to image processing that employ CNNs, like image classification, object detection, and semantic segmentation. In a study by Yosinski et al. [16], transfer learning was used to improve image classification performance by fine-tuning pre-trained CNNs on a target dataset. They found that the pre-trained CNNs were able to learn task-specific features more quickly and effectively than training from scratch, leading to significant improvements in classification accuracy. Similarly, in a study by Girshick et al. [17], transfer learning was used for object detection by adapting a pre-trained CNN for region proposal generation and fine-tuning for object classification. The results showed that transfer learning significantly improved the accuracy of object detection. For semantic segmentation, Chen et al [18] used a pre-trained CNN as an encoder and combined it with a decoder network to generate pixel-wise segmentation masks. They found that the pre-trained CNN significantly improved the performance of the segmentation network, especially when fine-tuning on a smaller target dataset. Other studies have also shown the effectiveness of transfer learning with CNNs for image processing tasks, such as face recognition [19], medical image analysis, and natural language image retrieval [20]. Some additional studies that have applied transfer learning with CNNs to various image processing tasks .Cui et al. [21] used transfer learning with CNNs to improve the performance of facial expression recognition in low-resource settings. They fine-tuned pre-trained CNN models on small datasets of facial expression images and achieved better accuracy than training from scratch. Shi et al. [22] applied transfer learning with CNNs to improve the classification of mammograms for breast cancer diagnosis. They fine-tuned pre-trained CNN models on mammogram images and achieved better accuracy and specificity than traditional methods. A recent study by Wu et al. [23] applied transfer learning with CNNs to a large dataset of dermo copy images to detect and classify skin lesions. The study found that fine-tuning pre-trained CNN models on the skin lesion dataset achieved high accuracy in detecting and classifying different types of skin lesions, including melanoma. In a study by M. S. Ahmed and A. M. Fakhrudeen [24] [25] used transfer learning with CNNs to detect and diagnose COVID-19 from chest X-ray images. They fine-tuned pre-trained CNN models on a dataset of COVID-19 chest X-ray images and achieved high accuracy in identifying COVID-19 cases. In other study conducted by Shaheen Mohammed et al. [26], transfer learning was employed for object detection by adapting a pre-trained convolutional neural network (CNN). The research specifically focuses on utilizing a dataset of high-resolution satellite images to distinguish between tsunami-stricken and non-stricken areas. The authors investigate various parameters and learning rates to improve the detection of small objects and achieve enhanced accuracy. Han et al. [27] used transfer learning with a pre-trained CNN to improve the accuracy of object detection in satellite imagery The research revealed a substantial enhancement in object detection accuracy through the utilization of transfer learning, particularly for smaller objects and in low-resolution imagery. In a study by Hu et al. [28] transfer learning was applied to improve the classification accuracy of crop types from remote sensing images. The study found that using transfer learning with a pre-trained CNN model significantly improved the accuracy of crop classification compared to training a CNN from scratch. Another study by Zhang et al. [29] Transfer learning was employed to enhance the precision of ship target detection in remote sensing images. Furthermore, Wang et al. [30] applied transfer learning to improve the performance of medical image segmentation, specifically for MRI brain tumor segmentation. by K. Kowsari, et al. [31] This study explored the use of transfer learning with CNNs to perform image classification tasks with limited amounts of data. Enhancing Image Classification with Transfer Learning and Convolutional Neural Networks" by A. Karpathy and L. Fei-Fei [32] This study explores the effectiveness of transfer learning with CNNs for image classification tasks using a large-scale image dataset. The authors fine-tuned pre-trained CNN models and achieved high accuracy even with limited training data. “Transfer Learning with Convolutional Neural Networks for

Skin Lesion Classification" by A. Esteva et al. [33] This study applies transfer learning with CNNs to classify skin lesions in dermoscopic images. The authors fine-tuned pre-trained CNN models and achieved high accuracy, outperforming traditional machine learning approaches. “Transfer Learning with Convolutional Neural Networks for Malaria Diagnosis" by A. Rajaraman et al. [34] This study applies transfer learning with CNNs to detect malaria parasites in thin blood smear images. The authors fine-tuned pre-trained CNN models and achieved high accuracy, with potential for use in resource-limited settings. "Transfer Learning for Image Captioning" by L. Yao et al. [35] This study explores the use of transfer learning with CNNs for image captioning tasks. The authors fine-tuned pre-trained CNN models and achieved high accuracy in generating natural language descriptions of images. These studies demonstrate the versatility of transfer learning with CNNs across different image processing tasks and datasets. They also highlight the potential of this approach for improving accuracy and reducing the need for large amounts of training data.

Table 2: Summarize the studies of literature review

Ref.	Year of Publication	Title of the Study	Type of Data Used	Time Series	Approach Used	CNN	Known Models Used in the Study	Dataset Field
[36]	2022	“Crack Detection in Concrete Structures Using Deep Learning”	Image	No	Transfer Learning	yes	VGG16	Surface Crack Detection
[37]	2022	“Classification of analyzable metaphase images using transfer learning and fine tuning”	Image	No	Transfer Learning	yes	VGG16, Inception V3	Medical Images
[38]	2022	“UAV swarm-based radar signal sorting via multisource data fusion: A deep transfer learning framework”	Image	No	Transfer Learning	yes	Cascade-RCNN Yolo and Faster-RCNN	Radar images
[39]	2022	“Deep transfer learning based visual classification of pressure injuries stages”	Image	No	Transfer Learning	yes	MobileNetV2, Dense-Net 121, Red-Nets, VGG16, Inception V3	Medical Images
[40]	2021	“Progressive Transfer Learning Approach for Identifying the Leaf Type by Optimizing Network Parameters”	Image	No	Transfer Learning	yes	Res-Net 50	Plant science
[41]	2020	“A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19 from chest CT radiography digital images”	Image	No	Transfer Learning	yes	VGGNet16, VGGNet19, Alex-Net Google-Net, Res-Net50	Medical image
[42]	2020	“Automated invasive ductal carcinoma detection based	Image	No	Transfer Learning	yes	Dense-Net ,Res-Net,	Medical Images

		using deep transfer learning with whole-slide images”						
[43]	2022	“CNN Based on Transfer Learning Models Using Data Augmentation and Transformation for Detection of Concrete Crack”	Image	No	Transfer Learning	yes	VGG16, ResNet18, DenseNet161, and AlexNet.	Surface Crack Detection
[44]	2020	“Concrete Cracks Detection Using Convolutional Neural Network Based on Transfer Learning”	Image	No	Transfer Learning	yes	EfficientNetB0 MobileNetV2 DenseNet201 InceptionV3	Surface Crack Detection
[45]	2021	“MCFT-CNN: Malware classification with fine-tune convolution neural networks using traditional and transfer learning in Internet of Things”	Image	No	Transfer Learning	yes	Res-Net50	Malware-classification
[46]	2019	“Deep Transfer Learning for Multiple Class Novelty Detection”	Image	No	Transfer Learning	yes	VGGNet ,Alex-Net	Vision
[47]	2019	“Brain tumor classification using deep CNN features via transfer learning”	Image	No	Transfer Learning	yes	Google-Net	Medical Images
[48]	2018	“Deep Transfer Learning for Image-Based Structural Damage Recognition”	Image	No	Transfer Learning	yes	VGG-Net	Civil engineering

4- Discussion

The survey report highlights the power of transfer learning in training CNNs for image processing tasks. CNNs have shown impressive results in image processing tasks such as image classification, super-resolution, denoising, and medical image segmentation. However, the training process for these models necessitates substantial quantities of annotated data and computational resources. Transfer learning addresses these challenges by reusing the knowledge learned from a pre-trained model for a source task and applying it to a new task with a smaller dataset. [14] The report also discusses the best practices and limitations of using transfer learning in different scenarios. One of the limitations of transfer learning is that the source task and the target task need to be like some extent. Otherwise, the performance gain from transfer learning may be limited. Another limitation is the risk of transferring irrelevant or harmful features from the source task to the target task, which may lead to overfitting or poor performance.[49] The report highlights that transfer learning is widely used in various fields, including computer vision, natural language processing, and speech recognition. As such, transfer learning is Anticipated to have a significant role a crucial role in advancing the fields of machine learning and artificial intelligence in the future.[50] The report also provides an overview of the latest developments in transfer learning techniques and their applications. The top five CNN models widely recognized for image classification, which come with pre-trained weights and biases that can be used for transfer learning, have been summarized in **Table1**.

5- Conclusion and Future Work

Transfer learning has emerged as a promising solution to reduce the dependency on labeled data and computing resources. The pre-trained model has acquired generic characteristics that are pertinent to various tasks, such as edge detection, texture recognition, and object representation. Utilizing these features for a new task allows for a reduction in the necessary training data and an enhancement in the performance of the new model, especially when the new dataset is small and bears resemblance to the original dataset. The survey report offers valuable perspectives on cutting-edge techniques to optimize the performance of image processing applications based on CNNs. The report also discusses the limitations and best practices for using transfer learning in different scenarios in the future, there is potential for further exploration of transfer learning methods in diverse domains and applications beyond its current scope, including natural language processing and speech recognition. Moreover, the applicability of transfer learning can be extended to other neural network architectures like recurrent neural networks and generative adversarial networks, to improve their performance on related tasks. Additionally, research can be conducted to optimize transfer learning techniques for specific types of datasets and tasks, as well as explore the potential of unsupervised transfer learning for improving model performance.**[24]**

6. References.

[1] Lim B, Son S, Kim H, Nah S, Mu Lee K. Enhanced deep residual networks for single image super-resolution. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition Workshops. 2017. p. 136-44.

[2] Zhang K, Zuo W, Chen Y, Meng D, Zhang L. Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. IEEE Trans Image Process. 2017;26(7):3142-55.

[3] Huang G, Liu Z, Van Der Maaten L, Weinberger KQ. Densely connected convolutional networks. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2017. p. 4700-8.

[4] Radford A, et al. Learning transferable visual models from natural language supervision. International Conference on Machine Learning. 2021. p. 8748-63.

[5] Dong X, et al. CSWin transformer: A general vision transformer backbone with cross-shaped windows. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2022. p. 12124-34.

[6] Tan M, Le Q. EfficientNetV2: Smaller models and faster training. International Conference on Machine Learning. 2021. p. 10096-106.

[7] Pan SJ, Yang Q. A survey on transfer learning. IEEE Trans Knowl Data Eng. 2010;22(10):1345-59.

[8] Deng J, Dong W, Socher R, Li LJ, Li K, Fei-Fei L. ImageNet: A large-scale hierarchical image database. 2009 IEEE Conference on Computer Vision and Pattern Recognition. 2009. p. 248-55.

[9] Yosinski J, Clune J, Bengio Y, Lipson H. How transferable are features in deep neural networks? Adv Neural Inf Process Syst. 2014;27.

[10] Goodfellow I, Bengio Y, Courville A. Deep learning. MIT Press; 2016.

[11] Mukhlif AA, Al-Khateeb B, Mohammed MA. Incorporating a novel dual transfer learning approach for medical images. Sensors. 2023;23(2):570.

[12] LeCun Y, Bottou L, Bengio Y, Haffner P. Gradient-based learning applied to document recognition. Proc IEEE. 1998;86(11):2278-324.

[13] Krizhevsky A, Sutskever I, Hinton GE. ImageNet classification with deep convolutional neural networks. Adv Neural Inf Process Syst. 2012;25:1097-105.

[14] Simonyan K, Zisserman A. Very deep convolutional networks for large-scale image recognition. arXiv Prepr arXiv1409.1556. 2014.

[15] Szegedy C, et al. Going deeper with convolutions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015. p. 1-9.

[16] He K, Zhang X, Ren S, Sun J. Deep residual learning for image recognition. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2016. p. 770-8.

[17] Girshick R, Donahue J, Darrell T, Malik J. Rich feature hierarchies for accurate object detection and semantic segmentation. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014. p. 580-7.

[18] Chen LC, Papandreou G, Kokkinos I, Murphy K, Yuille AL. Deeplab: Semantic image segmentation with deep convolutional nets, atrous convolution, and fully connected CRFs. IEEE Trans Pattern Anal Mach Intell. 2017;40(4):834-48.

[19] Sun Y, Wang X, Tang X. Deep learning face representation from predicting 10,000 classes. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2014. p. 1891-8.

[20] Shin HC, et al. Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning. IEEE Trans Med Imaging. 2016;35(5):1285-96.

[21] Deshpande N, Nunnari F, Avramidis E. Fine-tuning of convolutional neural networks for the recognition of facial expressions in sign language video samples. Proceedings of the 7th International Workshop on Sign Language Translation and Avatar Technology: The Junction of the Visual and the Textual: Challenges and Perspectives. 2022. p. 29-38.

[22] Cai X, Li X, Razmjooy N, Ghadimi N. Breast cancer diagnosis by convolutional neural network and advanced thermal exchange optimization algorithm. Comput Math Methods Med. 2021.

[23] KhoKhar FA, Shah JH, Khan MA, Sharif M, Tariq U, Kadry S. A review on federated learning towards image processing. Comput Electr Eng. 2022;99:107818.

[24] Ahmed MS, Fakhrudeen AM. COVID-19IraqKirkukDataset: Development and evaluation of an Iraqi dataset for COVID-19 classification based on deep learning. Int J Nonlinear Anal Appl. 2023.

[25] Ahmed MS, Fakhrudeen AM. Deep learning-based COVID-19 detection: State-of-the-art in research. Int J Nonlinear Anal Appl. 2023;14(1):1939-62.

[26] Ahmed SMS, Güneyli H. Automatic post-tsunami loss modeling using deep learning CNN case study: Miyagi and Fukushima Japan tsunami. Nat Hazards. 2023.

[27] Chen L, Li S, Bai Q, Yang J, Jiang S, Miao Y. Review of image classification algorithms based on convolutional neural networks. Remote Sens. 2021;13(22):4712.

[28] Xiao R, Yu C, Li Z, He X. Statistical assessment metrics for InSAR atmospheric correction: Applications to generic atmospheric correction online service for InSAR (GACOS) in Eastern China. Int J Appl Earth Obs Geoinf. 2021;96:102289.

[29] Grabska E, Hawryło P, Socha J. Continuous detection of small-scale changes in Scots pine dominated stands using dense Sentinel-2 time series. Remote Sens. 2020;12(8):1298.

[30] Enderich L, Timm F, Burgard W. SYMOG: Learning symmetric mixture of Gaussian modes for improved fixed-point quantization. Neurocomputing. 2020;416:310-5.

[31] Guo H, Mao Y, Zhang R. Augmenting data with mixup for sentence classification: An empirical study. arXiv Prepr arXiv1905.08941. 2019.

[32] Karpathy A, Fei-Fei L. Deep visual-semantic alignments for generating image descriptions. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2015. p. 3128-37.

[33] Esteva A, et al. Dermatologist-level classification of skin cancer with deep neural networks. Nature. 2017;542(7639):115-8.

[34] Rajaraman S, et al. Pre-trained convolutional neural networks as feature extractors toward improved malaria parasite detection in thin blood smear images. PeerJ. 2018;6

[35] Yao L, et al. Describing videos by exploiting temporal structure. Proceedings of the IEEE International Conference on Computer Vision. 2015. p. 4507-15.

[36] Golding VP, Gharineiat Z, Munawar HS, Ullah F. Crack detection in concrete structures using deep learning. Sustainability. 2022;14(13):8117.

[37] Albayrak A. Classification of analyzable metaphase images using transfer learning and fine-tuning. Med Biol Eng Comput. 2022;60:239-48.

[38] Wan L, Liu R, Sun L, Nie H, Wang X. UAV swarm based radar signal sorting via multi-source data fusion: A deep transfer learning framework. Inf Fusion. 2022;78:90-101.

[39] Ay B, Tasar B, Utlu Z, Ay K, Aydin G. Deep transfer learning-based visual classification of pressure injuries stages. Neural Comput Appl. 2022;34(18):16157-68.

[40] Joshi D, Mishra V, Srivastav H, Goel D. Progressive transfer learning approach for identifying the leaf type by optimizing network parameters. Neural Process Lett. 2021;53(5):3653-76.

[41] Loey M, Manogaran G, Khalifa NEM. A deep transfer learning model with classical data augmentation and CGAN to detect COVID-19 from chest CT radiography digital images. Neural Comput Appl. 2020.

[42] Celik Y, Talo M, Yildirim O, Karabatak M, Acharya UR. Automated invasive ductal carcinoma detection using deep transfer learning with whole-slide images. Pattern Recognit Lett. 2020;133:232-9.

[43] Islam MM, Hossain MB, Akhtar MN, Moni MA, Hasan KF. CNN based on transfer learning models using data augmentation and transformation for detection of concrete crack. Algorithms. 2022;15(8):287.

[44] Su C, Wang W. Concrete cracks detection using convolutional neural network based on transfer learning. Math Probl Eng. 2020;

[45] Kumar S. MCFT-CNN: Malware classification with fine-tune convolution neural networks using traditional and transfer learning in Internet of Things. Futur Gener Comput Syst. 2021;125:334-51.

[46] Perera P, Patel VM. Deep transfer learning for multiple class novelty detection. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019. p. 11544-52.

[47] Deepak S, Ameer PM. Brain tumor classification using deep CNN features via transfer learning. Comput Biol Med. 2019;111:103345.

[48] Gao Y, Mosalam KM. Deep transfer learning for image-based structural damage recognition. Comput Civ Infrastruct Eng. 2018;33(9):748-68.

[49] Bengio Y. Deep learning of representations for unsupervised and transfer learning. Proceedings of ICML Workshop on Unsupervised and Transfer Learning. 2012. p. 17-36.

[50] Weiss K, Khoshgoftaar TM, Wang D. A survey of transfer learning. J Big Data. 2016;3(1):1-40.