Indonesian Journal of Computer Science
ISSN 2549-7286 (*online*)
Jln. Khatib Sulaiman Dalam No. 1, Padang, Indonesia
Website: ijcs.stmikindonesia.ac.id | E-mail: ijcs@stmikindonesia.ac.id

Deep Learning in Medical Image Analysis Article Review

Media Ali Ibrahim[1*)], Shavan Askar[2], Mohammed A. Saleem, Daban Ali Qadir
[1]media.ibrahim@eup.edu.iq, [2]shavan.askar@epu.edu.iq
[1]Information System Engineering, Technical College of Engineering, Erbil Polytechnic University, Erbil, 44001, Iraq
[2]Information System Engineering, Technical College of Engineering, Erbil Polytechnic University, Erbil, 44001, Iraq

Article Information

Submitted : 20 Mar 2024
Reviewed: 25 Mar 2024
Accepted : 8 Apr 2024

Keywords

Transfer learning knowledge of, Medical image analysis, Deep learning, MRI, Convolutional neural networks

Abstract

Transfer learning, in evaluation to common deep studying strategies which include convolutional neural networks (CNNs), stands proud due to its simplicity, efficiency, and coffee education value, efficaciously addressing the venture of restricted datasets. The importance of scientific picture analysis in both scientific research and medical prognosis can't be overstated, with image techniques like Computer Tomography (CT), Magnetic Resonance Image (MRI), Ultrasound (US), and X-Ray playing a crucial function. Despite their utility in non-invasive analysis, the scarcity of categorized medical images poses a completely unique challenge in comparison to datasets in other pc imaginative and prescient domains, like facial reputation.

Given this shortage, switch getting to know has won reputation amongst researchers for medical photo processing. This complete evaluation draws on one hundred amazing papers from IEEE, Elsevier, Google Scholar, Web of Science, and diverse sources spanning 2000 to 2023 It covers vital components, which includes the (i) shape of CNNs, (ii) foundational know-how of switch learning, (iii) numerous techniques for enforcing transfer mastering, (iv) the utility of switch gaining knowledge of throughout numerous sub-fields of medical photo analysis, and (v) a dialogue at the future potentialities of transfer studying within the realm of medical image analysis. This evaluate no longer handiest equips beginners with a scientific understanding of transfer mastering applications in medical image analysis but additionally serves policymakers by means of summarizing the evolving trends in transfer learning within the scientific image domain. This insight might also encourage policymakers to formulate advantageous rules that support the continued development of Transfer learning knowledge of in medical image analysis.

ISSN 2549-7286 (*online*)

A. Introduction

Medicine, a cornerstone of worldwide properly-being, closely relies on medical image analysis. Advances in scientific research and scientific diagnoses require huge proof from this evaluation, that is supported through various image techniques consisting of CT, MRI, US, and X-rays. While each image technique has particular characteristics, deep learning algorithms display promise in successfully matching their various capabilities due to their robustness in handling photograph scale and resolution. Non-invasive image strategies, essential for assessing symptoms in essential frame parts, are surprisingly safe [1]. However, manual medical image analysis by means of skilled physicians has limitations, inclusive of an absence of skilled professionals and the potential for human errors. To deal with those demanding situations, laptop-aided diagnosis generation has an extended history, gaining momentum with the appearance of convolutional neural networks (CNNs). CNNs, with their ability to extract deep features from scientific pictures, have drastically advanced computerized medical image evaluation. Despite their fulfillment, CNNs have drawbacks, which include the need for significant schooling and reliance on large, classified datasets—demanding situations within the context of scarce and high-priced scientific image data [2] . To triumph o Fig. 1 ver these issues, researchers have introduced transfer learning into scientific image analysis. Transfer studying, derived from CNNs, leverages pre-educated networks, extensively lowering training time and data requirements. Two common techniques, best-tuning and function extractor, offer flexibility primarily based on dataset availability [3]. Transfer learning has gained popularity in latest years, demonstrating fulfillment throughout various medical image strategies and frame elements. This survey paper reviews the improvement and alertness of transfer getting to know in medical photo evaluation. It introduces the history expertise of CNNs, explores the formal definition and categories of transfer getting to know, and examines its application in distinctive components of the human body [4]. Additionally, the paper discusses the integration of transfer studying with other deep learning technology and envisions destiny tendencies, which include addressing shortcomings. The bankruptcy emphasizes the importance of knowledge CNN infrastructure and normally used optimization techniques to understand the wider utility of transfer mastering inside the scientific image area [5].

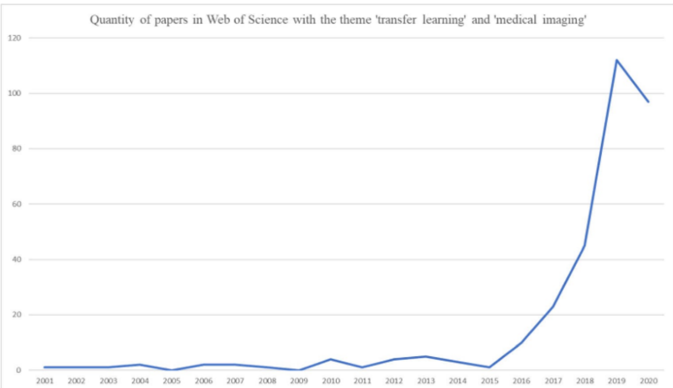

Figure 1. number of papers published on transfer learning in medical image analysis.

B. Analysis Review

This paper goals to introduce and explore the utility and development of Transfer learning knowledge of inside the discipline of medical image, with a selected cognizance on special body parts or organs. Each bankruptcy will delve into the intricacies of switch getting to know as it relates to scientific pix of diverse anatomical areas, highlighting its effect, challenges, and advancements. The discussions will include insights into the usage of transfer getting to know strategies, such as first-rate-tuning and function extraction, tailored to the characteristics and nuances of every frame component. Additionally, the combination of switch studying with different deep getting to know technologies and the anticipation of destiny developments will be addressed, offering a concise overview of switch mastering's role in improving diagnostic abilities across diverse medical image domains.

A. Brain Image Analysis

This phase introduces extensive studies efforts making use of Transfer learning knowledge of inside the area of brain sicknesses. Noteworthy packages consist of the differentiation of medulloblastoma tumors the usage of switch studying and CNN, reaching better accuracy and lower education costs compared to different methods [6]. Researchers have correctly employed switch getting to know for mind tumor classification, survival prediction, and Alzheimer's prognosis, demonstrating its versatility in dealing with various tasks with confined categorised records [7]. Recent research showcase ongoing advancements, together with multi-label switch feature mastering for superior reliability and using modified neural networks to detect pathological brain conditions [16, 18]. Table 1 summarizes key contributions in the application of switch studying for brain sicknesses, emphasizing various diseases, transfer strategies, and relevant years [23,42]. The constant trend in current years suggests the ongoing importance and potential of switch mastering in advancing brain medical picture processing [13] .

Table 1. Transfer learning application in Brain disease

Authors	Year	Disease domain	Transfer method	Accuracy
[10]	2015	Medulloblastoma tumor	VGG-16 as feature extractor	89.8%
[12]	2016	Brain tumor	Feature extractor	95.45%
[13]	2016	Brain tumor	Fine-tuning	99.83%
14]	2017	Glioblastoma multiforme	Feature extractor	95%
[15]	2018	Alzheimer	Fine-tuning on Inception-V2	87.2%
[19]	2019	Brain abnormality classification	Fine-tuning on ResNet	99.53%
[20]	2020	Brain tumor	Fine-tuning	99.5%
[21]	2020	Brain tumor	VGG-19 as feature extractor	99.82

B. Heart Image Analysis

This segment highlights the pivotal position of transfer getting to know in cardiology, particularly in cardiac diagnostics and image. Notable packages encompass seizure detection the usage of patient-specific ECG facts [22] and CardioViewNet, a Transfer learning knowledge of-primarily based CNN for cardiac MRI recognition. In ECG evaluation, transfer studying proves powerful for obligations like arrhythmia detection [10] and arrhythmia classification , with promising outcomes in transforming ECG sign data into spectrogram information [24]. Noteworthy achievement is discovered in making use of transfer getting to know to BCG, making it more convenient for every day tracking than ECG. Transfer learning's versatility extends to equine electrocardiogram (eECG) type [27]. In cardiovascular image, studies make use of famous CNNs like ResNet, VGG-19, VGG-sixteen, and Inception for tissue type and mitochondria segmentation. The capability of transfer mastering in cardiovascular image is highlighted, with researchers exploring packages beyond lumen segmentation. In summary, these researches underscore the massive adoption and fulfillment of transfer studying in improving diagnostic abilities and advancing cardiovascular research.

Table 2. Transfer learning application in heart disease

Authors	Year	Disease domain	Transfer method	Accuracy
[22]	2017	Epileptic seizure	Feature extractor	92%
[23]	2018	Arrhythmia	Feature extractor	98.3%
[24]	2019	Arrhythmia	Fine-tuning on GoogLeNet and AlexNet	97.8%
[25]	2019	Cardiovascular	Fine-tuning on GoogLeNet	88%
[26]	2019	Atrial fibrillation	Assembling Multi-scale-ResNet and Fast-downsampling-ResNets as feature extractor	95.3%
[27]	2020	Atrial Fibrillation	Fine-tuning	99%

C. Breast Image Analysis

Table 3 summarizes key studies on switch learning in breast ailment, emphasizing its pivotal function in laptop-aided prognosis (CADx) for breast most cancers. The technique proves effective, overcoming demanding situations like heavy annotation and restrained facts. Studies show off the flexibility of switch studying, leveraging pre-skilled models including AlexNet for characteristic extraction [28]. display advanced velocity and accuracy in breast most cancers detection using switch learning. Transfer studying handles limited classified statistics well, tested a hit pre-schooling with homemade capabilities. Multimission switch learning, complements overall performance with the aid of transferring information across datasets.[30] highlight the blessings of initializing deep networks with pre-trained values, attaining comparable performance to complex CNN systems. finding it more green than increasing education samples. [31] expand transfer mastering to breast mass class with sonography, introducing novel strategies. Researchers always discover transfer studying's capability in breast photos analysis, thinking about factors like breast cancer screening techniques, superior network architectures [31], and advantages in both supervised and unsupervised studying [32]. These efforts together underscore Transfer learning knowledge of's value in advancing CADx for breast ailment.

Table 3. Transfer learning application in Breast disease

Authors	Year	Disease domain	Transfer method	Accuracy
[28]	2016	Mammographic Tumor	AlexNet as Feature extractor	86%
[29]	2017	Masses in mammograms	Fine-tuning	95%
[30]	2018	Breast cancer	Fine-tuning	95.5% to 96.67% depending on methods
[31]	2019	Breast mass classification	Feature extractor & Fine-tuning	90%
[32]	2019	Breast histopathological images	Inception_ResNet_V2 as Feature extractor	98.74%
[33]	2019	Breast MRIs	Feature extractor	95%

D. Lung Image Analysis

Table 4 offers a concise evaluation of widespread studies on Transfer learning knowledge of packages in lung sickness, specially focusing on scientific photo analysis. Researchers are increasingly leveraging switch gaining knowledge of to decorate diagnostic accuracy and efficiency in lung-associated situations. Sawada and Kozuka [86] carried out switch studying with a multiprediction deep Boltzmann system (MPDBM), demonstrating its effectiveness in classifying lung X-ray CT photos. [34] highlighted the performance of the use of a pre-trained deep convolutional neural community (CNN) on non-medicalpix for diffuse lung illnesses (DLD) prognosis, accomplishing advanced overall performance compared to training from scratch. Transfer learning knowledge Of's advantages enlarge to texture analysis, as visible in [35] work, where a pre-skilled CNN on texture images progressed the class accuracy of lung CT scanning images. blended pre-educated CNN functions with handmade features for predicting survival time in lung cancer patients, emphasizing transfer getting to know's role in extracting deep capabilities. The fashion continues with studies like [36] excellent-tuning a pre-educated ResNet for pulmonary classification and [37] 3-D CNN structure pre-educated on non-scientific photographs for lung nodule recognition. Other fantastic applications consist of lung nodules classification the usage of transfer getting to know with 3D DenseNet and GoogLeNet, demonstrating contemporary outcomes. While lung nodule detection often focuses on CT pics, efforts to use CNN-based techniques to lung MR images are rising. [38] satisfactory-tuned a quicker R-CNN using transfer studying, showcasing its effectiveness in region-of-hobby targeting for lung nodule detection. addressing challenges like fake high-quality prices by best-tuning VGG-sixteen with transfer mastering for nodule detection, and [39] proposed a singular method combining deep transfer CNN with extreme learning system for diagnosing lung nodules based on CT images. Overall, the research underscore the developing importance of switch getting to know in advancing the accuracy and efficiency of lung ailment diagnosis via medical image analysis.

Table 4. Transfer learning application in Lugn disease

Authors	Year	Disease domain	Transfer method	Accuracy
Nishio M et al [40]	2018	Lung nodule classification	VGG-16 as feature extractor	68.0%
Hussein, et al. [41]	2019	Lung cancer	Feature extractor	84.22%
Lakshmi, et al. [42]	2019	Lung carcinoma	VGG-16 & VGG-19 as feature extractor	90%
Shi, et al. [43]	2019	Lung nodule detection	Fine-tuning on VGG-16	87.8%

C. Methodology

A. Convolutional Neural Network

In recent years, deep learning, specially Convolutional Neural Networks (CNN), has won significant use in scientific photo processing, revolutionizing image type precision. CNN serves as a fundamental aspect for transfer mastering and functions a primary structure illustrated in Fig. 2. This structure evolves thru stacking and refining primary elements, permitting the creation of an increasing number of complex and effective neural networks. Researchers, starting with VGGNet, located that deeper structures yield superior consequences. Consequently, efforts were committed to building deeper neural community architectures. Convolutional layers play a key function in characteristic extraction, and by means of incorporating extra layers, networks gain the capability to extract deeper capabilities from enter pics. The concept of a "block" emerged, comprising convolutional layers, pooling layers, and activation capabilities. Blocks, especially modern systems like Inception and Residual Blocks, have end up essential devices in contemporary CNNs, frequently surpassing conventional blocks in overall performance and finding great software in cutting-edge research [44].

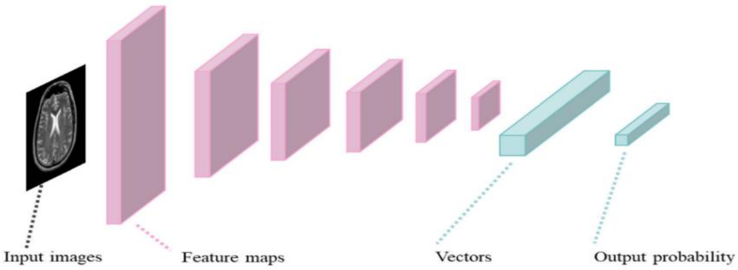

Figure 2. Basic structure of typical convolutional neural network.

In image class responsibilities, an average Convolutional Neural Network (CNN) accommodates convolutional layers, pooling, activation, and absolutely linked layers. Convolutional layers extract capabilities from enter pics, pooling reduces characteristic map decision, activation introduces nonlinearity, and fully related layers connect extracted capabilities. Convolutional layers are regularly established in multiple levels. The first layer extracts fundamental functions, while next layers extract more superior functions. For instance, while identifying a cat, the first layer may additionally capture edges, and the second may become aware of particular functions like the eyes, nose, and ears. The layer-through-layer technique lets in the CNN to learn and apprehend complicated patterns. Discussing convolution structures, vital parameters encompass kernel size (k), input photo size (t), zero-padding (p), stride (s), and output characteristic map size (u). Kernels, represented as k× k matrices, act as function extractors. Padding supplements extra pixels of value zero across the enter image, ensuring deep mastering [45]. Convolution operations contain applying kernels to the enter image little by little, with the stride generally set to one. Different strides can be used for specific overall performance necessities.

1. Convolutional Layers

In a Convolutional Neural Network (CNN), the convolution layer generally follows the input layer to extract functions from the enter records. This layer employs convolutional kernels, analogous to filters in signal processing. As the kernel slides across the image, it selectively captures unique capabilities, allowing specific convolutional layers to extract diverse functions from the input [46]. The convolutional operation involves defining parameters inclusive of kernel size (k), input photograph size (t), stride (s), and zero-padding (p). Zero-padding is mainly positive, making sure that the output continues the same length as the enter picture. This is important for keeping spatial facts in the course of deep convolutional architectures.

2. Standard Convolution

We investigate the simplest and most classic convolution structure. In this condition, the output feature map's size u could be written as:

$$u = t - k + 1 \quad (1)$$

According to Fig. 3, in this simplest example, the convolution does not have padding and set stride to one. That is to say, t = 7, k = 3, thus u = 5. We consider a more complex situation that we add a circle of zero-padding around the input image. Then the equation should be recorded in Eq (2).

$$u = t - k + 2p + 1 \quad (2)$$

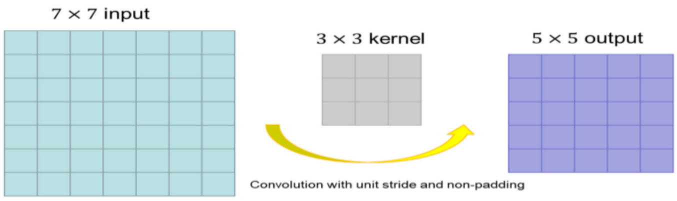

Figure 3. A simple example of convolution.

According to Fig. 4, in this more complex situation, the convolution has one zero-padding and still keep stride as one. That is to say, t = 7 , k =3 , p =1 , u =7 (3)

Moreover, we could study certainly one of maximum crucial gain of zero-padding, to get output as same size as input picture's without compressing pixels. Without 0-padding, it's far easily to imagine that when convolutional operations layer by using layer, the output function map's length gets smaller and smaller. As a result, we couldn't observe deep convolutional architecture on this circumstance. But with 0-padding, we hold output with the equal length of enter image, which equips us capability to design deep convolutional neural networks.

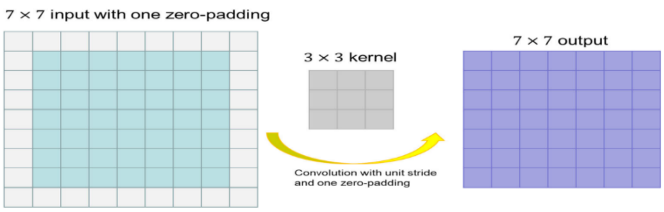

Figure 4. Convolution with zero padding

3. Strided Convolution

With the continuous development of CNN, greater and extra new convolutional layer systems were proposed. Strided convolution is primarily based on wellknown convolution, and the strided convolutional kernel is shifted through more than 2 pixels at a time. Using the definition above, the equation ought to be summarized as:

$$u = \left\lfloor \frac{t-k+2P}{s} \right\rfloor + 1 \qquad (4)$$

According to Fig. 5, the 3 × three filter stride 3 pixels each move for next calculating. In this case, t = 7, ok = 3, p = 1, s = three, as a result u = 3. In this way, we will reap smaller characteristic maps and acquire the impact much like pooling to a degree.

There is every other convolution aiming to lowering amount of parameters referred to as grouped convolution. It was first proposed in AlexNet. Grouped convolution divides convolutional kernels into several agencies with the aid of neural community segmentation [47]. The characteristic maps received are handiest a part of the original one, which can be processed in parallel with multiple GPUs.

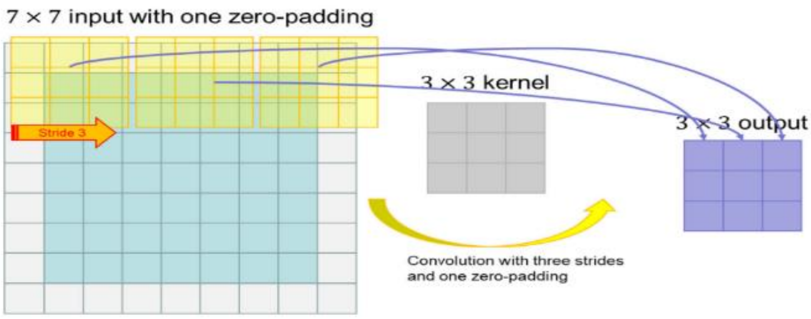

Figure 5. Strided convolution with zero-padding

4. Grouped Convolution

Figure 6 demonstrates how grouped convolution ought to lower quantity of parameters. Let us first examine wellknown convolution. The length of enter function map is

SizeInput = $E \times F \times m$ (5)

and the size of filter is

SizeFilter = $e \times f \times m$ (6)

And in everyday convolution operation, we want n filters to achieve output function map which length is

SizeOutput = $E \times F \times m$ (7)

In this progress, we need to figure out

$e \times f \times m \times n = Q$ parameters (8)

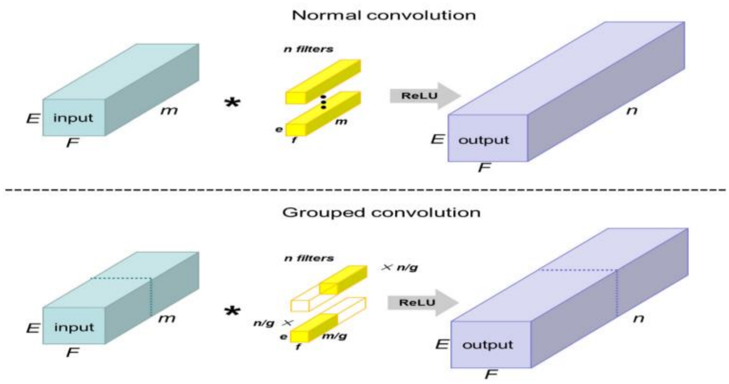

Figure 6. Comparison between normal convolution and grouped convolution

While in grouped convolution, we divided input function map into g agencies through m channels. Each institution of input characteristic map is of

SizeGroupInput = $E \times F \times m/g$ (9)

with its corresponding filter of size

SizeGroupFilter = $e \times f \times m/g$ (10)

Getting result of grouped output feature map which length is

SizeGroupFeatureMap = $E \times F \times n/g$ (11)

After concreting g agencies of grouped output feature map, we sooner or later get ultimate output function map which size is

SizeOutput = E × F × n (12)

It is easily to find that we only use

e × f × m/g× n/g× g = (e×f×m×n)/g = Q/g (13)

Parameters which is basically much less than parameter used in regular convolution operation. Taking any other element to consider this problem, all through regular convolution, every factor in output characteristic map is produced by using clear out which length is

SizeFilter = e × f × m (14)

At the same time as throughout grouped convolution every factor in output feature map is produced by way of clear out which length is simplest

SizeGroupFilter = e × f × m/g (15)

That is why grouped convolution could reduce quantity of parameters.

5. Dilated Convolution

Last, we introduce dilated convolution. The length of convolutional kernel in dilated convolution is not similar to the pixel inside the enter picture but similar to a bigger size of the enter photograph for convolution operation. The benefit of dilated convolution is to make convolution have larger receptive subject with low more computational value. In dilated convolution, a key hyperparameter written as d is proposed to symbolize dilation rate. For d = 1, which means everyday convolution. For d = 2, meaning there exists d − 1 in this situation one extra area between each factor in which kernel performs convolution operation [48]. We should take a look at its corresponding courting in Fig. 7. In dilated convolution, the corresponding location of kernel is enlarged to a wider variety.

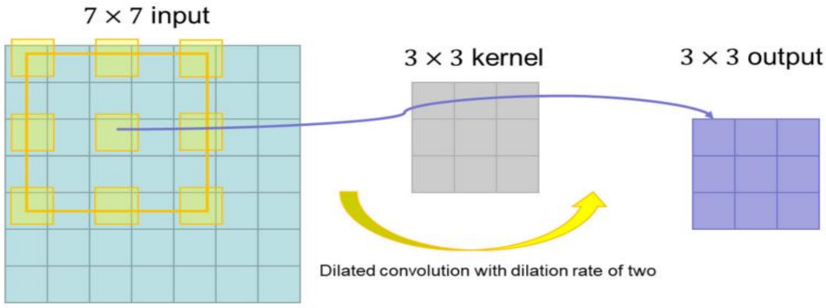

Figure 7. Dilated convolution

Therefore, we could define the size of kernel's actual corresponding area as k ′, and we give the equation of k ′:

k ′ = k + (k-1) (d-1) (16)

We applied k ′ instead of k in Eq. (3) getting:

u= [(t-k-(k-1)(d-1)+2P)/s]+1 (17)

This is the equation refers to output size in dilated convolution. In the example of Fig. 7, t = 7, k = 3, d = 2, p = 0, s = 1, thus u = 3. In the end, we summarized these various convolutions as following Table 5.

Table 5. Variety of convolution

Convolution	Zero-padding	Stride	Groups	Dilation rate	Benefits
Normal convolution	0	1	0	1	Basic and Simple
Convolution with padding	Usually more than 1	1	1	1	Ensure networks reach deep
Strided convolution	Flexible	Usually more than 2	1	1	Like pooling
Grouped convolution	Flexible	Flexible	Usually more than 2	1	Reduce quantity of parameters
Dilated convolution	Flexible	Flexible	1	Usually more than 2	Expand receptive field

6. Pooling

We recognize that the convolutional layer extracts sufficient capabilities from the input image. But in lots of cases, too many functions aren't continually a terrific thing. The extracted functions may additionally contain statistics that we do not care lots approximately, and this redundant record could make the entire network slow and bloated, so we need to get rid of the redundancy. Pooling layer is designed to perform down-sampling operation on extracted function maps, compress the decision of feature maps, and best maintain vital function records. Pooling layer is also a convolution operation mathematically. Unlike the convolution kernel of convolutional layer, the parameters of pooling layer are commonly constant [11]. The benefit of pooling layer is that, firstly, it has translation invariance. Secondly, parameters of pooling layer are constant, so the amount of parameters in complete neural networks can be reduced. In conventional CNN, there are generally two techniques: max pooling and common pooling. Max pooling is to pick the maximum value from a neighborhood domain of the photo as the consultant, that could higher preserve the feel capabilities of the image. Average pooling makes use of selection of the common price as the representative from a neighborhood domain of the photo, which could higher maintain the functions of the overall picture’s information. Both max pooling and common pooling will be regarded as convolution which stride the equal quantity pixels as its kernel’s. But some other pooling method strides much less pixels than its convolution kernel’s length, called overlapping pooling. It’s clean to understand that overlapping pooling ought to shop extra data in characteristic maps in comparison to max pooling and average pooling. What’s extra, scientists proposed spatial pyramid pooling which adopts unique scale pooling kernels and strides. With spatial pyramid pooling, function maps of exclusive sizes might be treated. And because of spatial pyramid pooling using different sclaes of pooling kernel then converging the consequences, it allows sell community structure’s accuracy and robustness. Last, we furnished Table 6 to evaluate those style of pooling methods.

Table 6. Comparison of pooling methods

Pooling	Size	Stride	Strategy	Benefits
Max pooling	Fixed	= Size	Fetch max pixel of local region	Preserve texture feature
Average pooling	Fixed	= Size	Calculate mean of local pixels	Preserve background information
Overlapping pooling	Fixed	< Size	Usually fetch max pixel of local region	Better representative ability
Spatial pyramid pooling	Flexible	= Size	Usually fetch max pixel of local region	Overcome various scales and higher accuracy

7. Activation

The feature of activation is to introduce nonlinearity into CNN. In a sensible hassle, the information is often no longer separable linearly. Without activation, it's far tough for CNN to obtain a correct effect on linearly indivisible facts. Sigmoid and Tanh are of earliest proposed activation capabilities The equation of Sigmoid could be written as:

Sigmoid(x) = [1/(1+e^(-x))] (18)

The equation of Tanh could be written as:

tanh(x) = [(e^x -e^(-x))/(e^x+e^(-x))] (19)

At present, within the subject of photograph and vision, the most typically used activation function is ReLU. Compared with

Sigmoid or Tanh, ReLU can converge more fast and efficiently alleviate the problem of gradient vanishing. The equation of ReLU can be written as:

$$ReLU(x) = \begin{cases} x, x > 0 \\ 0, x \leq 0 \end{cases} \quad (20)$$

On the basis of ReLU, a sequence of progressed activation features are derived as properly. Leaky ReLU, as compared to ReLU, when x < zero, y did no longer same to 0 but a very small poor, letting the road of characteristic maintain declining at a small gradient. The equation of Leaky ReLU may be written as:

$$LReLU(x) = \begin{cases} x, x > 0 \\ 0.01x, x \leq 0 \end{cases} \quad (21)$$

In quick, it depends which activation characteristic need to be implemented in convolutional neural networks.

8. Fully Connected Layer

In a Convolutional Neural Network (CNN), the fully connected layer acts as the "classifier," mapping the learned features to the sample space. It employs convolutional operations on characteristic maps the use of kernels, generating a one-dimensional vector. This layer assigns weights to network characteristics and reduces spatial dimensions for type possibilities. Traditional CNNs frequently function a couple of completely related layers, impacting general parameters. While global common pooling gives an alternative, absolutely linked layers, with their adjustability, regularly outperform in switch studying, making them vital for optimal effects [6].

9. Transfer Learning

In In medical image, establishing databases is often challenging and costly, leading to limited sample data. Additionally, the desire to leverage past problem-solving experiences for new tasks necessitates swift knowledge transfer [1,4]. This scenario underscores the importance of transfer learning, where existing knowledge is the source domain, and new knowledge to be acquired is the target domain. Formally, a domain (D) comprises feature space (X) and marginal distribution(P(X)).

$$D = \{X, P(X)\}$$

There are four most commonly used methods of transfer learning:

Instance Based Transfer Learning: Instance-based transfer learning compares source and target domains, emphasizing similar data in the source domain, and assigns increased weight to this subset. However, it can be unstable and relies on empirical methods, without guaranteeing a perfect match between source and target subsets.

Feature Based Transfer Learning: Feature-based transfer learning assumes common characteristics between the source and target domains. By transforming them into the same space, their data distributions become similar, allowing the use of machine learning techniques. While effective, this method can be challenging to compute.

Parameter Based Transfer Learning: parameter-based transfer learning assumes that source and target domain names share model parameters, specifically whilst the issues are correlated. It includes either initializing the new version with supply version parameters and fine-tuning or the usage of the supply version's layers as function extractors for the brand new version, lowering schooling fees and leveraging previous knowledge.

Relation Based Transfer Learning: relation Based Transfer Learning assumes similarity between source and target domains, focusing on transferring logical relationships from the supply area to the goal area.

Classic Pre-Trained Models: Classic pre-trained models, like AlexNet, VGGNet, Inception, ResNet, and MobileNet, marked milestones in deep learning, shaping the field's evolution. They remain influential, serving as foundations for transfer learning applications today [49].

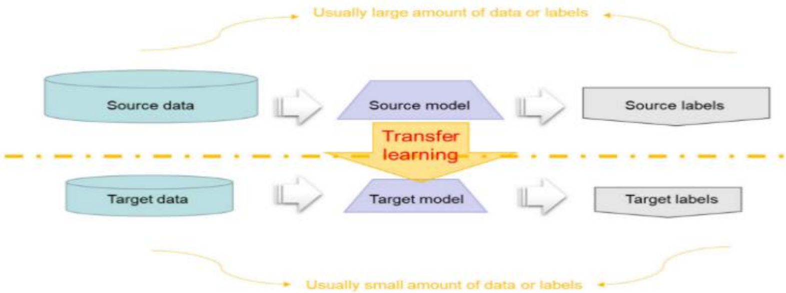

Figure 9. How transfer learning works from source domain to target domain

D. Discussion and Results

In latest years, the application of transfer learning in medical image evaluation has marked large development, providing promising results across various domain names and duties. The integration of pre-educated fashions has proven wonderful success, improving the performance and accuracy of diagnostic procedures. These improvements, however, are not with out challenges. One generic undertaking lies within the various nature of scientific photograph datasets, regularly restrained in length and plagued via problems of class imbalance. While switch getting to know alleviates the want for extensive annotations, adapting pre-educated models to specific medical contexts remains a nuanced assignment. Fine-tuning parameters and optimizing model architectures turn out to be important steps in ensuring the efficacy of transfer getting to know in these eventualities. Moreover, the heterogeneity of scientific image modalities, consisting of X-rays, MRIs, and CT scans, presents a undertaking for switch getting to know fashions aiming for generalized applicability. The edition of pre-educated fashions across these modalities necessitates a deeper expertise of the area shift, requiring tailored techniques to make certain strong performance. Ethical considerations surrounding patient privacy and facts protection add any other layer of complexity. Transfer mastering models trained on numerous datasets need to be scrutinized for capability biases and generalization troubles, in particular whilst deployed in real-world medicalsettings. While transfer learning undeniably contributes considerably to medical photo evaluation, the adventure toward seamless integration into scientific practice entails addressing those demanding situations. Ongoing research and collaborative efforts will be pivotal in refining switch learning techniques, fostering their widespread adoption, and in the long run enhancing diagnostic abilities inside the realm of medical image.

E. Conclusions

This survey delves into key studies components of scientific image analysis, tracing the evolution of switch mastering in the discipline. It comprehensively explores the foundational concepts of convolutional neural networks and transfer studying. Focusing on distinguished medical image domain names including mind, coronary heart, breast, lung, and kidney, the survey highlights representative papers and their methodologies. The article concludes with the aid of thinking of the destiny trajectory of switch gaining knowledge of in medical image, envisioning synergies with meta-learning, records augmentation, self-supervised mastering, and domain adaptation. It shows capacity integration with reinforcement learning and other models to enhance neural network overall performance. While acknowledging capability omissions, the survey goals to offer a treasured review of switch getting to know's improvement and potentialities in scientific image.

F. Research Method

The research method explains briefly and clearly about the stages of research, including research design, instruments used, data collection techniques, analysis techniques, system design, and several other things related to research problem solving strategies. [Cambria 12, space 1]

Research methods can be supplemented by tables, graphs (pictures), and/or charts. The table does not contain vertical (upright) lines. Horizontal (flat) lines in the table are only found at the beginning and end of the table. Example of table format:

Table 1. Title [Cambria 12, space 1]

No	Identity	*Type*	*Size*
1	Username	Varchar	15
2	Password	Varchar	15
3	Name	Varchar	35
4	Email	Varchar	50
5	Phone	Varchar	15

[Table content writing format: cambria 10, space single]

Giving color to the graph or chart (picture) must be accompanied by a description of the meaning of each color. Example of image format:

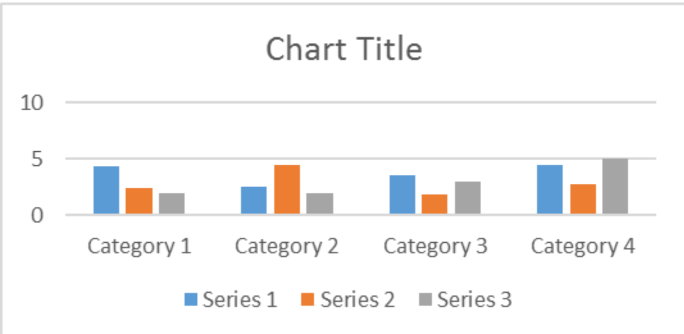

Figure1. Title [Cambria 12, space single, format png/jpg]

G. References

[1] Media Ali Ibrahim; Shavan Askar, "An Intelligent Scheduling Strategy in Fog Computing System Based on Multi-Objective Deep Reinforcement Learning Algorithm", IEEE Access, Volume 11, 2023.

[2] Shin H-C et al (2016) Deep convolutional neural networks for computer-aided detection: CNN architectures, dataset characteristics and transfer learning, 35, 5, 1285–1298.

[3] Armato SG et al (2011) The lung image database consortium, (LIDC) and image database resource initiative (IDRI): a completed reference database of lung nodules on CT scans. Med Phys 38(2):915–931.

[4] Saman M. Omer, Kayhan Z. Ghafoor & Shavan K. Askar , “Lightweight improved yolov5 model for cucumber leaf disease and pest detection based on deep learning” Journal of Signal, Image and Video Processing, 2023.

[5] Caravagna G, Giarratano Y, Ramazzotti D, Tomlinson I, Graham TA, Sanguinetti G, et al. (2018) Detecting repeated cancer evolution from multiregion tumor sequencing data. Nature Methods vol. 15, pp. 707–714.

[6] Chollet F (2017) and Ieee, Xception: Deep Learning with Depthwise Separable Convolutions. In: 30th Ieee conference on computer vision and pattern recognition (IEEE Conference on Computer Vision and Pattern Recognition, pp 1800–1807.

[7] Du Y et al (2018) Classification of tumor epithelium and stroma by exploiting image features learned by deep convolutional neural networks, 46, 12, 1988–1999.

[8] Cruz-Roa A, Arévalo J, Judkins A, Madabhushi A, González F (2015) A method for medulloblastoma tumor differentiation based on convolutional neural networks and transfer learning. In: 11th International Symposium on Medical Information Processing and Analysis, vol 9681, p 968103: International Society for Optics and Photonics.

[9] Dezheen H. Abdulazeez; Shavan K. Askar, “Offloading Mechanisms Based on Reinforcement Learning and Deep Learning Algorithms in the Fog Computing Environment” IEEE Accesss Volume 11, 2023.

[10] Xu Y et al (2015) Deep convolutional activation features for large scale brain tumor histopathology image classification and segmentation. In: 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp 947–951: IEEE [24]

[11] Saha B, Gupta S, Phung D, Venkatesh S (2016) Transfer learning for rare cancer problems via discriminative sparse gaussian graphical model. In: 2016 23rd International Conference on Pattern Recognition (ICPR), pp 537–542: IEEE.

[12] Lao J et al (2017) A deep learning-based radiomics model for prediction of survival in glioblastoma multiforme, 7, 1, 10353.

[13] Cruz-Roa A, Arévalo J, Judkins A, Madabhushi A, González F (2015) A method for medulloblastoma tumor differentiation based on convolutional neural networks and transfer learning. In: 11th International Symposium on Medical Information Processing and Analysis, vol 9681, p 968103: International Society for Optics and Photonics.

[14] Xu Y et al (2015) Deep convolutional activation features for large scale brain tumor histopathology image classification and segmentation. In: 2015 IEEE international conference on acoustics, speech and signal processing (ICASSP), pp 947–951: IEEE

[15] Liu R, Hall LO, Goldgof DB, Zhou M, Gatenby RA, Ahmed KB (2016) Exploring deep features from brain tumor magnetic resonance images via transfer learning. In: 2016 International Joint Conference on Neural Networks (IJCNN), pp 235–242: IEEE

[16] Saha B, Gupta S, Phung D, Venkatesh S (2016) Transfer learning for rare cancer problems via discriminative sparse gaussian graphical model. In: 2016 23rd International Conference on Pattern Recognition (ICPR), pp 537–542: IEEE

[17] Lao J et al (2017) A deep learning-based radiomics model for prediction of survival in glioblastoma multiforme, 7, 1, 10353

[18] Puranik M, Shah H, Shah K, Bagul S (2018) Intelligent Alzheimer's Detector using Deep Learning and IEEE (Proceedings of the 2018 Second International Conference on Intelligent Computing and Control Systems). IEEE, New York, pp 318–323

[19] Wong KCL, Syeda-Mahmood T, Moradi M (2018) Building medical image classifiers with very limited data using segmentation networks (in English). Med Image Anal 49:105–116

[20] Cheng B, Liu M, Zhang D, Shen D (2019) Robust multi-label transfer feature learning for early diagnosis of Alzheimer's disease. Brain Imaging Behav 13(1):138–153

[21] Lu S, Lu Z, Zhang Y-D (2019) Pathological brain detection based on AlexNet and transfer learning. J Comput Sci 30:41–47

[22] Talo M, Baloglu UB, Yıldırım Ö, Rajendra Acharya U (2019) Application of deep transfer learning for automated brain abnormality classification using MR images. Cogn Syst Res 54:176– 188

[23] Dar SUH, Özbey M, Çatlı AB, Çukur T (2020) A transfer-learning approach for accelerated MRI using deep neural networks. Magn Reson Med 84:663–685

[24] Saba T, Sameh Mohamed A, El-Affendi M, Amin J, Sharif M (2020) Brain tumor detection using fusion of hand crafted and deep learning features. Cogn Syst Res 59:221–230

[25] De Cooman T, Varon C, Van de Vel A, Ceulemans B, Lagae L, Van Huffel S (2017) Semi-supervised one-class transfer learning for heart rate based epileptic seizure detection, in 2017 Computing in Cardiology (CinC), pp. 1–4: IEEE

[26] Al Rahhal MM, Bazi Y, Al Zuair M, Othman E, BenJdira BJJOM (2018) Convolutional neural networks for electrocardiogram classification. B. Eng 38(6):1014–1025

[27] Alquran H, Alqudah A, Abu-Qasmieh I, Al-Badarneh A, Almashaqbeh SJNNW (2019) ECG classification using higher order spectral estimation and deep learning techniques, vol. 29, no. 4, pp. 207–219

[28] Tadesse GA et al (2019) Cardiovascular disease diagnosis using cross-domain transfer learning, In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp. 4262–4265: IEEE

[29] Cao X-C, Yao B, Chen B-QJIA (2019) Atrial fibrillation detection using an improved multi-Scale decomposition enhanced residual convolutional neural network, vol. 7, pp. 89152–89161

[30] Van Steenkiste G, van Loon G, Crevecoeur G. JSR (2020) Transfer Learning in ECG Classification from Human to Horse Using a Novel Parallel Neural Network Architecture, vol. 10, no. 1, pp. 1–12

[31] Huynh BQ, Li H, Giger MLJJOMI (2016) Digital mammographic tumor classification using transfer learning from deep convolutional neural networks, vol. 3, no. 3, p. 034501
[32] Dhungel N, Carneiro G, Bradley APJMIA (2017) A deep learning approach for the analysis of masses in mammograms with minimal user intervention, vol. 37, pp. 114–128
[33] Chougrad H, Zouaki H, Alheyane OJCM (2018) Deep convolutional neural networks for breast cancer screening. P. I. Biomedicine 157:19–30
[34] Byra M et al (2019) Breast mass classification in sonography with transfer learning using a deep convolutional neural network and color conversion, vol. 46, no. 2, pp. 746–755
[35] Xie J, Liu R, Luttrell IV J, Zhang CJFIG (2019) Deep learning based analysis of histopathological images of breast cancer, vol. 10, p. 80
[36] Zhu Z et al (2019) Deep learning analysis of breast MRIs for prediction of occult invasive disease in ductal carcinoma in situ, vol. 115, p. 103498
[37] Shavan Askar, "Deep Forest Based Internet of Medical Things System for Diagnosis of Heart Disease", ARO Journal, 2023.
[38] Sawada Y, Kozuka K (2015) Transfer learning method using multi-prediction deep boltzmann machines for a small scale dataset, In 2015 14th IAPR International Conference on Machine Vision Applications (MVA), pp. 110–113: IEEE
[39] Christodoulidis S, Anthimopoulos M, Ebner L, Christe A, Mougiakakou SJIJOB (2016) H Informatics, Multisource transfer learning with convolutional neural networks for lung pattern analysis, vol. 21, no. 1, pp. 76–84
[40] Saman M. Omer, Kayhan Z. Ghafoor, Shavan K. Askar, "Plant Disease Diagnosing Based on Deep Learning Techniques" ARO journal, 2022.
[41] Nibali A, He Z, Wollersheim DJIJOCAR (2017) Pulmonary nodule classification with deep residual networks. Surgery 12(10): 1799–1808
[42] Kosrat Dlshad Ahmed & Shavan Askar, 2021. "Deep Learning Models for Cyber Security in IoT Networks: A Review," International Journal of Science and Business, IJSAB International, vol. 5(3), pages 61-70
[43] Hussein S, Cao K, Song Q, Bagci U (2017) Risk stratification of lung nodules using 3D CNN-based multi-task learning, In International conference on information processing in medical imaging, pp. 249–260: Springer
[44] Li Y, Zhang L, Chen H, Yang NJIA (2019) Lung nodule detection with deep learning in 3D thoracic MR images, vol. 7, pp. 37822– 37832
[45] Huang X, Lei Q, Xie T, Zhang Y, Hu Z, Zhou QJAPA (2020) Deep Transfer Convolutional Neural Network and Extreme Learning Machine for Lung Nodule Diagnosis on CT images.
[46] Nishio M et al (2018) Computer-aided diagnosis of lung nodule classification between benign nodule, primary lung cancer, and metastatic lung cancer at different image size using deep convolutional neural network with transfer learning, vol. 13, no. 7
[47] Hussein S, Kandel P, Bolan CW, Wallace MB, Bagci UJITOMI (2019) Lung and pancreatic tumor characterization in the deep learning era: novel supervised and unsupervised learning approaches, vol. 38, no. 8, pp. 1777–1787

[48] Shavan Askar & Chnar Mustaf Mohammed & Shahab Wahhab Kareem, 2021. "Deep Learning in IoT systems: A Review," International Journal of Science and Business, IJSAB International, vol. 5(6), pages 131-147.
[49] Lakshmi D, Thanaraj KP, Arunmozhi MJIJOIS (2019) Technology Convolutional neural network in the detection of lung carcinoma using transfer learning approach
Shi Z et al (2019) A deep CNN based transfer learning method for false positive reduction, vol. 78, no. 1, pp. 1017–1033
[50] Chnar Mustaf Mohammed & Shavan Askar, 2021. "Machine Learning for IoT HealthCare Applications: A Review," International Journal of Science and Business, IJSAB International, vol. 5(3), pages 42-51.
[51] Ertosun MG, Rubin DL (2015) Automated grading of gliomas using deep learning in digital pathology images: a modular approach with ensemble of convolutional neural networks. In: AMIA Annual Symposium Proceedings, vol 2015, p 1899: American Medical Informatics Association
[52] Al Rahhal MM, Bazi Y, Al Zuair M, Othman E, BenJdira BJJOM (2018) Convolutional neural networks for electrocardiogram classification. B. Eng 38(6):1014–1025
[53] Diker A, Cömert Z, Avcı E, Toğaçar M, Ergen B (2019) A Novel Application based on Spectrogram and Convolutional Neural Network for ECG Classification," In 2019 1st International Informatics and Software Engineering Conference (UBMYK), pp. 1–6: IEEE
[54] Vu CC, Siddiqui ZA, Zamdborg L, Thompson AB, Quinn TJ, Castillo E, Guerrero TM (2020) Deep convolutional neural networks for automatic segmentation of thoracic organs-at-risk in radiation oncology - use of non-domain transfer learning. J Appl Clin Med Phys 21(6):108–113
[55] Salah M. Saleh Al-Majeed, Shavan K. Askar, Martin Fleury, "H.265 Codec over 4G Networks for Telemedicine System Application", UKSIM, Cambridge, UK, March, 2014.
[56] da Nóbrega RVM, Reboucas PP, Rodrigues MB, da Silva SPP, Dourado C, de Albuquerque VHC (2020) Lung nodule malignancy classification in chest computed tomography images using transfer learning and convolutional neural networks. Neural Comput Applic 32(15):11065–11082
[57] Byra M et al (2019) Breast mass classification in sonography with transfer learning using a deep convolutional neural network and color conversion, vol. 46, no. 2, pp. 746–755
[58] Tua Halomoan Harahap, Sofiene Mansouri, Omar Salim Abdullah, Herlina Uinarni, Shavan Askar, Thaer L. Jabbar, Ahmed Hussien Alawadi, Aalaa Yaseen Hassan, An artificial intelligence ap-proach to predict infants' health status at birth, International Journal of Medical Informatics, Volume 183, 2024, 105338, ISSN 1386-5056,