IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

ANALYSIS OF MEDICAL IMAGE CLASSIFICATION BASED ON CONVOLUTION NEURAL NETWORK

P. Poornima M.Sc., M.Phil

Assistant Professor,

Department of Computer Applications,

KSG College of Arts and Science

Coimbatore – 641015.

Abstract: Image classification has long been a popular study topic across the world, and the advent of deep learning has aided in the advancement of this discipline. convolution neural networks (CNNs) have gradually become the dominant algorithm for image classification, and the CNN architecture used for other visual recognition tasks is generally derived from the network architecture used for image classification. The application of information and communication technologies in medical imaging to improve healthcare services is known as medical imaging informatics. The purpose of medical imaging analytics is to improve the accuracy and reliability of medical services, particularly medical image use and interchange across complicated healthcare systems. Deep learning techniques, particularly convolution networks, have swiftly emerged as the primary method for analyzing medical images. This paper is analysis medical image classification which exploits a large image dataset based on Convolution Neural Network models.

Index Terms: Medical image, Image Classification, deep learning, convolution neural network

I. INTRODUCTION

To detect local anatomical properties, several existing medical image processing algorithms depend on morphological feature representations. However, such feature representations were primarily created by humans, and the picture characteristics are frequently problem-specific and are not guaranteed to operate with other image formats. Medical imaging modalities vary depending on the anatomical component. The absence of effective computing tools significantly impedes the translation of innovative imaging techniques into the field of medical imaging [1]. Although cutting-edge approaches employ supervised learning to identify the most critical features for specific tasks, they need a large amount of manually labelled training data, and the learned features may be shallow and misrepresent the complexity of the anatomical structures.

More importantly, the learning technique is frequently limited to a specific generic domain with a limited number of predesigned features [2]. As a result, if the template or picture features change, the entire training process must be restarted. Biomedical imaging has transformed the practice of medicine by providing an unparalleled capacity to identify disease by imaging the human body and allowing for a high-resolution examination of cells and pathological specimens. Images are created in general by the interaction of electromagnetic waves of various wavelengths with biological tissues in modalities other than ultrasound, which uses mechanical sound waves.

Images created with high-energy radiation at shorter wavelengths such as X-rays and Gamma-rays at one end of the spectrum are ionizing, whereas images formed with longer wavelengths such as optical and even longer wavelengths such as MRI and Ultrasound are non-ionizing. The imaging modalities discussed in this section include X-ray [3]. Because of its low cost and rapid acquisition time, X-ray imaging is one of the most regularly utilized imaging methods. The image is created by passing X-rays generated by an X-ray source through the body and detecting the attenuated X-rays on the other side using a detector array; the resulting image is a 2D projection with resolutions as low as 100 microns and intensities that indicate the degree of X-ray attenuation.

Ultrasound uses pulses in the 1–10 MHz range to scan tissue in a non-invasive and very affordable manner. The backscattering effect of the acoustic pulse interacting with interior structures is utilized to measure the echo and create the picture. Magnetic resonance (MR) image generates high spatial resolution volumetric pictures of Hydrogen nuclei by combining an externally applied magnetic field with non-ionizing radio-frequency (RF) pulses. Images have a high signal-to-noise ratio, which necessitates augmentation, and the picture is classified to determine the region of interest. CT creates a 3D image by assembling a series of 2D axial slices of the body [3]. By gating to the ECG and breathing, 4D images are also achievable. Despite worries about radiation exposure, CT is widely utilized due to its rapid scan duration and great resolution.

II. RELATED STUDY

There has been a resource of works on medical image analysis using signal exploration and statistical modelling. Some of the most successful feature analyses include the classification based on the modalities are practiced under deep learning techniques on the earlier stage of emerging medical image analysis which is mentioned by Lo et al (1995) research-based on lung cancer analysis using the X-ray image data of 55 patients with the help of 2 layer CNN method and resulted in the classification feature of nodules detection in patch fashion which described as the first-ever attempt of medical image analysis in the CNN history. Modality of X-ray taken by Antony et al for detecting knee osteoarthritis grading with pre-trained imagenet and the fine-tune of CNN.

Dou et al (2016a) mentioned that the same CNN technique was used in the research of MRI (magnetic resonance image) for 320 patients image data affected by cerebral micro-bleeds are trained as two stages of the process both 3D Fully convolution neural network and 3D CNN and the classification feature extraction resulted in the 3D FCN detection of micro-bleed and this process helps to reduce the false-positive rate. This image analysis, as well as MRI, was further researched for finding the features of vertebrae localization, identification, and segmentation based on initial localization of CNN by Suzani et al. (2015), and Anatomical landmark detection uses CNN for classification of slice for landmark presence by Yang et al (2015).

Setio et al (2016) used the same two-stage CNN model, but with some variations in the feature detector and the multi-view 2D, CNN for reducing the false positive rate using the CT (computed tomography) scan image of 888 scans and 1186 nodules of patients with pulmonary cancer, and this classification and feature analysis resulted in reduced false positive rate fusion with multiple 2D CNN at different views of nodules. Chen et al (2015c) used the same image modality analysis strategy to determine vertebrae localization and joint learning appearance of vertebrae dependent on CNN neighbors. Roth et al. use CNN to detect sclerotic metastases and analyze random 2D views.

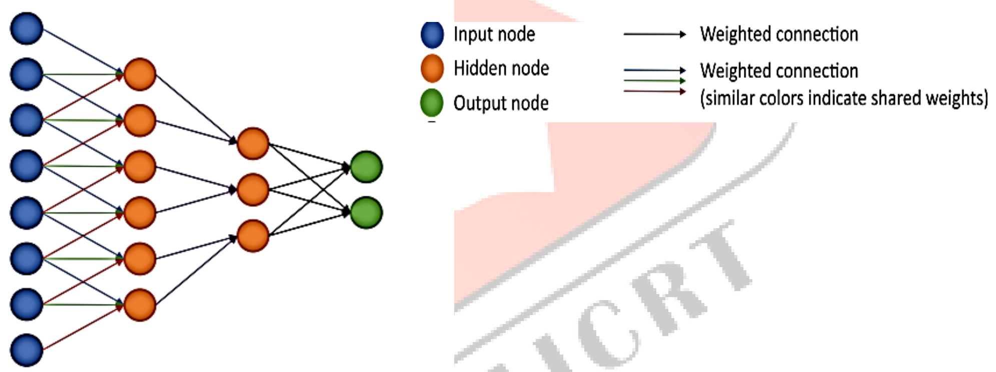
Table 1: Common Image classification dataset

Dataset	Resolution	Image type	Categories	Training dataset	Test dataset
MNIST	28 × 28	Grayscale image		60000	10000
CIFAR-10	32 x 32	RGB image	10	5000	1000
CIFAR-100	32 x 32	RGB image	100	500	100
ImageNet	256 x 256	RGB image	20000	-	-

III. CONVOLUTION NEURAL NETWORK (CNNS)

Convolution neural network (CNN) is a key topic that aids in the recognition of faces, the detection of an object, and the categorization of pictures. CNN is made up of multiple levels. These are completely linked layers, similar to neurons in a human brain. Neurons aid in the transmission of the 'message' from one cell to another. Many neurons surround a single neuron [3]. CNN is also working on a similar strategy. Because one layer is linked to many other layers, the output of one layer becomes an input for many other layers that are directly related to that layer. CNNs are made up of three layers: the input layer, the hidden layer (which is made up of completely linked layers), and the output layer.

Figure 1: Convolution Neural Network Layer nodes



The input layer accepts 2D pictures in the form of an array of pixels, and the images are represented in the form of pixel values. The main purpose is to extract characteristics from images, which may be accomplished by examining the weights of filters and assisting in determining the link between the route and neurons. CNN's get their name from the convolutional layers in their designs. Convolutional layers are in charge of recognizing certain local characteristics in all areas of their input images. Each node in a convolutional layer is linked to just a limited subset of spatially related neurons in the input picture channels to identify local features. The three connection weights are shared among the nodes in the convolutional layers to enable the search for the same local feature across all input channels.

The network's CNN weights are shared in such a way that the network may execute convolution operations on pictures. As a result, the model does not have to learn distinct detectors for the same item appearing at different locations in a picture, making the network equivariant concerning input translations. It also decreases the number of factors that must be learned significantly.

A pooling layer is added after a convolutional layer to down sample the preceding convolutional layer's feature maps. Each pooling layer feature map is linked to a convolutional layer feature map, and each unit in a pooling layer feature map is generated based on a subset of units within a local receptive field from the related convolutional feature map. The receptive field, like the convolutional layer, seeks a representative value among the units in its field. The common use of pooling layers in CNNs, is in which pixel values from neighborhoods are pooled using a permutation invariant function, generally the max or mean operation. This can result in some translation invariance and an increase in the receptive field of succeeding convolutional layers. Fully linked layers are often inserted after the network's convolutional stream, where weights are no longer shared.

3.1 CNN for image classification

One of the first areas where deep learning made a significant contribution to medical image analysis was image or exam categorization. In exam classification, one or more images (an exam) are often used as input, with a single diagnostic variable as the output. Essentially, pre-trained networks are used to try to go around the necessity of a big data set for deep network training. By implementing a feature extractor and fine-tuning with pre-trained networks on medical data. The former technique has the added advantage of not requiring any deep network training, allowing the retrieved features to be simply integrated into existing image analysis pipelines. Both tactics are well-known and regularly practiced.

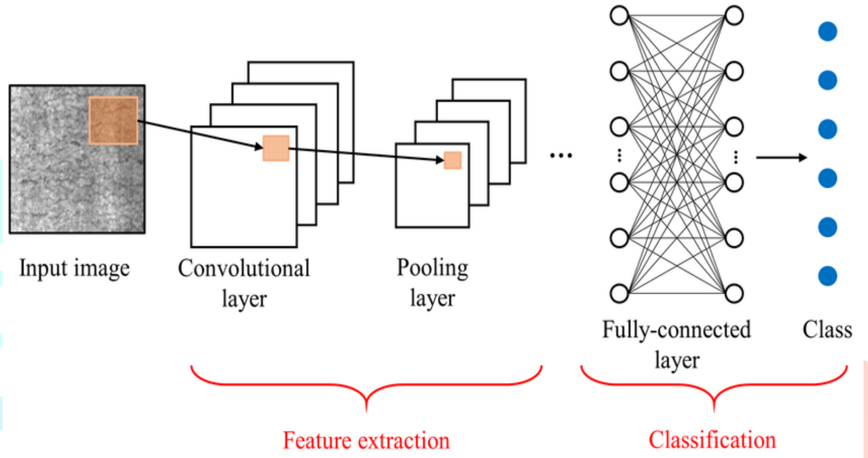


Figure 2: CNN image Classification model

3.2 CNN for Object Classification

Object classification often focuses on categorizing a small portion of a medical picture into two or more classifications (e.g., nodule classification in chest CT). For many of these tasks, successful classification requires both local information on lesion appearance and global contextual information on lesion location. In most general deep learning systems, this combination is not conceivable. The use of CNN and RNN on slit lamp pictures, with CNN filters serving as pre-trained networks [20]. This combination enables the analysis of all contextual information irrespective of image size. Incorporating 3D information is frequently required for high performance in medical imaging item categorization tasks.

The authors employed a variety of ways to effectively combine 3D with bespoke architectures. Compared to test classifications, object classification makes less use of pre-trained networks, owing to the necessity to include contextual or three-dimensional information.

The deep convolutional neural network processes the image of the item collected from the dataset, and the kind of the target object is classified [21]. In image classification, convolutional neural networks are often utilized. The learning procedure is carried out using either the traditional error back propagation approach or the stochastic gradient descent method.

3.3 Deep learning for classification

Deep convolutional neural networks (CNNs) have been proposed because they can emulate the performance of the human visual system and learn hierarchical features, allowing the model to object local invariant and resilient to translation and distortion [4]. CNNs are a form of neural network that can simulate spatial and temporal correlation while lowering signal translational variance. The size of the input pictures is used to build deep convolutional neural networks. The network architectures change depending on the picture size. Deep learning algorithms have been widely employed for illness categorization or screening, resulting in an outstanding performance in a wide range of applications [5].

CNN's have also improved in classification problems. Many of the network architectures demonstrated on the ImageNet image classification challenge have been repurposed for medical imaging applications by fine-tuning previously trained layers.

The results of pre-training a model on natural pictures and fine-tuning its parameters for a new medical imaging task were outstanding. However, when the goal is tissue categorization of 3D image data, this transfer learning technique is not simple [6]. Transfer learning from natural photos is not possible in this case without first reducing the 3D data to two dimensions. Practitioners have presented a plethora of options for dealing with this issue, many of which have proven to be highly beneficial.

Alternative techniques use architectures that conduct 3D convolutions and then train the network from scratch using 3D medical pictures to directly use the 3D data. Other famous strategies include splitting 3D data into distinct 2D perspectives and then combining the results to achieve a final classification score.

Learning image nodule features with a 2D auto encoder and then using a decision tree to distinguish between benign and malignant nodules are common classification tasks in medical imaging [7]. These tasks are often dominated by some formulation of a CNN – with fully-connected layers at the end to perform the final classification. CNN may frequently attain state-of-the-art performance when given a large amount of training data; however, deep learning methods usually underperform when given a little amount of training data.

Table 2: Basic CNN models for image classification

Model	Layers	Remarks
LeNet	7 Layer	The capacity to interpret higher resolution pictures necessitates larger and more convolutional layers, hence this technology is limited by computational resources.
AlexNet	8Layer	This network won the ILSVR 2012 by a wide margin. It demonstrated for the first time that learnt features can outperform manually constructed features, thereby shattering the prior state of computer vision research in one fell stroke.
ResNet	12 Layer	Residual neural network (ResNet) is a form of deep learning model that has skip connections. The network has connections that span several tiers. This is helpful in avoiding the vanishing gradient problem. The Inception architecture benefits from faster training times because to residual connections.
GoogLeNet	22 Layer	Increasing network depth and breadth is the most straightforward technique to enhance network performance.
MobileNetV1	22 Layer	This convolution converts a conventional convolution into a depth wise and a point wise convolution.
ZfNet	5 shareable Layer	The network activity visualization was designed to track CNN performance by analyzing neuron activation.

Highway Network	50 Layer	Depth was employed in Highway Networks to learn superior feature representation and create a unique cross-layer connection mechanism.
Wide ResNet	3 x 3 convolution layer	Wide ResNet has demonstrated that spreading the layers may be a more effective way of boosting performance than making residual networks deep.
Inception v2	33 Layer	This minimizes calculation time and hence increases computation speed.
Inception v3	48 Layer	The purpose of inception-V3 was to reduce the computational cost of deep networks without losing generalization.
DenseNet	7 x 7 stride 2 convolutin Layer	The network's information flow increases when each layer has direct access to the gradients through the loss function.
Pyramindal Net	3 x 3 convolution Layer	ResNet's learning capabilities are aided by the Pyramidal Net.
Xception	71 Layer	It improves performance by making learning more efficient.
VGGNet	19 Layer	Small filter size, Blocks of layers
NIN(Networkin Network)	Multiple Layer	Instead of the typical convolution layer, the combination of NIN and MLP employs a more complicated structure of the micro neural network.

3.4 Limitation

Convolution Neural Network image classification methods do have some limitations from their early stage of implementation in both Deep learning and CNN which has to improve by the advanced CNN models and their parameters.

- CNNs require a significant quantity of labelled training data, which may be challenging to satisfy in the medical sector, where the expert annotation is costly and ailments are uncommon in datasets. This is a crucial concern because, given the scarcity of labelled data in medical imaging, training deep CNNs from scratch may be impractical.
- Deep CNN training necessitates a large amount of processing and memory resources, without which the training process would be exceedingly time-consuming.
- The low amount of training samples available to develop deep models without overfitting is a major barrier in applying deep learning to medical images
- Overfitting and convergence difficulties typically hinder deep CNN training, and their resolution frequently necessitates repeating modifications to the network's design or learning settings to guarantee that all layers learn at equal speeds.
- The research community is failing to fully realize the promise of the quantity of data currently available at the individual patient level, which underpins precision medicine.
- The difficulty is determining how to probe the features of data emanating from numerous modalities in a reliably.
- One of the most difficult challenges is figuring out how to manage relatively large-scale, multi-dimensional data sets that will continue to grow over time, because it is impractical to exhaustively compare query data with each sample in a high-dimensional database due to practical storage and computational bottlenecks.
- Object classification often focuses on categorizing a small portion of a medical picture into two or more classifications. For many of these tasks, successful classification requires both local information on lesion appearance and global contextual information on lesion location. In most general deep learning systems, this combination is not conceivable.

- To be efficient, lightweight models frequently lose precision. Currently, the efficiency of employing CNN in embedded and limited systems is being investigated.
- Although certain models have had considerable success in semi-supervised learning, the majority of CNN models have not moved to semi-supervised or unsupervised learning to manage data. The NLP field is doing better in this regard.

To overcome this limitation the CNN, need more efficient approach for medical image analysis with strong decision making which can quickly realise the image classification model and categorize the training and test dataset which provide the accurate result.

IV. DISCUSSION

Valuable information in medical image analysis is not just included within the pictures themselves. Physicians frequently use a variety of data on patient history, age, demography, and other factors to make better diagnoses. Many deep learning algorithms in medical imaging are still based on patch classification, where the network is frequently unaware of the patch's anatomical position. One option is to input the complete image to the deep network and utilize a different sort of assessment to drive learning. The utilization of enormous volumes of training data more than one million annotated photos in ImageNet a huge, publicly accessible data collection of medical images from which deep models may uncover more generic characteristics would lead to enhanced performance resulting in breakthrough gains.

Although data-driven feature representations, particularly unsupervised representations, have helped improve accuracy, a new methodological architecture including domain-specific knowledge would be preferable. It is necessary to formulate algorithmic strategies to effectively process images collected using various scanning procedures so that modality-specific deep models are not required. Some stereotypical components of CNN, like activation functions, dropout, or batch normalization, may become impediments to progress. Various research has obtained extraordinary outcomes by violating the rules, and such concepts are likewise deserving of future research development.

V. CONCLUSION

In this paper, we suggested a category of convolutional network-based efficient medical image classification networks. We proposed a medical image classification study based on deep learning and CNN models, as well as their convolution layers, for categorizing medical image modalities from distinct case histories. Many deep learning systems in medical imaging, are still based on patch classification, where the anatomical location of the patch is frequently unknown to the network. This research study also includes a common image classification dataset together with training and test dataset values that are important for classification and feature extraction analyses. Essentially, classification extracts the primary elements from the medical image, whereas CNN captures the in-depth features and creates patterns in a creative method. As a result, it can produce more accurate results than any other classification system.

REFERENCE

[1] Dou, Q., Chen, H., Jin, Y., Yu, L., Qin, J., Heng, P.-A., 2016a. 3D deeply supervised network for automatic liver segmentation from CT volumes. IEEE Transactions on Biomedical Engineering 64 (7), 1558–1567.

[2] Suzani, A., Rasoulian, A., Seitel, A., Fels, S., Rohling, R., Abolmaesumi, P., 2015. Deep learning for automatic localization, identification, and segmentation of vertebral bodies in volumetric MR images. In: Proceedings of the SPIE Medical Imaging, 9415, p. 941514.

[3] Setio, A.A.A., Ciompi, F., Litjens, G., Gerke, P., Jacobs, C., van Riel, S., Wille, M.W., Naqibullah, M., Sanchez, C., van Ginneken, B., 2016. Pulmonary nodule detection in CT images: false positive reduction using multi-view convolutional networks. IEEE Trans. Med. Imaging 35 (5), 1160–1169.

[4] Yang, X., Kwitt, R., Niethammer, M., 2016d. Fast predictive image registration. In: Proceedings of the Deep Learning in Medical Image Analysis (DLMIA). In: Lecture Notes in Computer Science, 10008,

[5] Chen, H., Dou, Q., Yu, L., Heng, P.-A., 2016a. Voxresnet: deep voxelwise residual networks for volumetric brain segmentation.

[6] Anthimopoulos, M., Christodoulidis, S., Ebner, L., Christe, A., Mougiakakou, S., 2016. Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. IEEE Trans. Med. Imaging 35 (5), 1207–1216. doi:10.1109/ TMI.2016.2535865.

[7] Anthimopoulos, M., Christodoulidis, S., Ebner, L., Christe, A., Mougiakakou, S., 2016. Lung pattern classification for interstitial lung diseases using a deep convolutional neural network. IEEE Trans. Med. Imaging 35 (5), 1207–1216. doi:10.1109/ TMI.2016.2535865.

[8] Cicero, M., Bilbily, A., Colak, E., Dowdell, T., Gray, B., Perampaladas, K., Barfett, J., 2017. Training and validating a deep convolutional neural network for computer-aided detection and classification of abnormalities on frontal chest radiographs. Invest Radiol. 52 (5), 281–287.

[9] Ciompi, F., de Hoop, B., van Riel, S.J., Chung, K., Scholten, E.T., Oudkerk, M., de Jong, P.A., Prokop, M., van Ginneken, B., 2015. Automatic classification of pulmonary peri-fissural nodules in computed tomography using an ensemble of 2D views and a convolutional neural network out-of-the-box. Med.

[10] Esteva, A., Kuprel, B., Novoa, R.A., Ko, J., Swetter, S.M., Blau, H.M., Thrun, S., 2017. Dermatologist-level classification of skin cancer with deep neural networks. Nature 542, 115–118.

[11] Han, X.-H., Lei, J., Chen, Y.-W., 2016. HEp-2 cell classification using K-support spatial pooling in deep CNNs. In: Proceedings of the Deep Learning in Medical Image Analysis (DLMIA). In: Lecture Notes in Computer Science, 10008, pp. 3–11.

[12] Huynh, B.Q., Li, H., Giger, M.L., 2016. Digital mammographic tumor classification using transfer learning from deep convolutional neural networks. J. Med. Imaging 3, 034501.

[13] Jamaludin, A., Kadir, T., Zisserman, A., 2016. SpineNet: automatically pinpointing classification evidence in spinal MRIs. In: Proceedings of the Medical Image Computing and Computer-Assisted Intervention. In: Lecture Notes in Computer Science, 9901, pp. 166–175.

[14] Li, W., Cao, P., Zhao, D., Wang, J., 2016a. Pulmonary nodule classification with deep convolutional neural networks on computed tomography images. Comput. Math. Methods Med. 6215085. doi:10.1155/2016/6215085.

[15] Malon, C.D., Cosatto, E., 2013. Classification of mitotic figures with convolutional neural networks and seeded blob features. J. Pathol. Inform. doi:10.4103/ 2153-3539.112694.

[16] Rezaeilouyeh, H., Mollahosseini, A., Mahoor, M.H., 2016. Microscopic medical image classification framework via deep learning and shearlet transform. J. Med. Imaging 3 (4), 044501. doi: 10.1117/1.JMI.3.4.044501.

[17] Roth, H.R., Lee, C.T., Shin, H.-C., Seff, A., Kim, L., Yao, J., Lu, L., Summers, R.M., 2015a. Anatomy-specific classification of medical images using deep convolutional nets. In: Proceedings of the IEEE International Symposium on Biomedical Imaging, pp. 101–104. doi:10.1109/ISBI.2015.7163826

[18] 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, 4712.

[19] Panayides, Andreas & Amini, A. & Filipovic, Nenad & Sharma, Ashish & Tsaftaris, Sotirios & Young, Alistair & Foran, David & Do, Nhan & Golemati, Spyretta & Kurc, Tahsin & Huang, Kun & Nikita, Konstantina & Veasey, Benjamin & Zervakis, Michalis & Saltz, Joel & Pattichis, C. (2020). AI in Medical Imaging Informatics: Current Challenges and Future Directions. IEEE Journal of Biomedical and Health Informatics. PP. 1-1. 10.1109/JBHI.2020.2991043.

[20] Zhou, J.; Zhao, Y. Application of convolution neural network in image classification and object detection. Comput. Eng. Appl. 2017, 53, 34–41.

[21] Cire¸san, D.C.; Meier, U.; Masci, J.; Gambardella, L.M.; Schmidhuber, J. High-Performance Neural Networks for Visual Object Classification. arXiv 2011, arXiv:1102.0183.

[22] Krizhevsky, A.; Sutskever, I.; Hinton, G. ImageNet Classification with Deep Convolutional Neural Networks. Neural Inf. Process. Syst. 2012, 25, 1097–1105.

[23] Cheng, G.; Yang, C.; Yao, X.; Guo, L.; Han, J. When deep learning meets metric learning: Remote sensing image scene classification via learning discriminative CNNs. IEEE Trans. Geosci. Remote Sens. 2018, 56, 2811–2821.

[24] Marmanis, D.; Datcu, M.; Esch, T.; Stilla, U. Deep learning earth observation classification using ImageNet pretrained networks. IEEE Geosci. Remote Sens. Lett. 2015, 13, 105–109.

[25] Li, E.; Xia, J.; Du, P.; Lin, C.; Samat, A. Integrating multilayer features of convolutional neural networks for remote sensing scene classification. IEEE Trans. Geosci. Remote Sens. 2017, 55, 5653–5665.

[26] Wang, Q.; Liu, S.; Chanussot, J.; Li, X. Scene classification with recurrent attention of VHR remote sensing images. IEEE Trans. Geosci. Remote Sens. 2018, 57, 1155–1167.

[27] Liu, Y.; Zhong, Y.; Qin, Q. Scene classification based on multiscale convolutional neural network. IEEE Trans. Geosci. Remote Sens. 2018, 56, 7109–7121.

[28] Wang, W.; Yang, Y.; Wang, X.; Wang, W.; Li, J. Development of convolutional neural network and its application in image classification: A survey. Opt. Eng. 2019, 58, 040901.

[29] Lin, Y.; Lv, F.; Zhu, S.; Yang, M.; Cour, T.; Yu, K.; Cao, L.; Huang, T. Large-scale image classification: Fast feature extraction and SVM training. In Proceedings of the CVPR 2011, Colorado Springs, CO, USA, 20–25 June 2011; pp. 1689–1696.

[30] Perronnin, F.; Sánchez, J.; Mensink, T. Improving the Fisher Kernel for Large-Scale Image Classification. In ECCV 2010—European Conference on Computer Vision; Daniilidis, K., Maragos, P., Paragios, N., Eds.; Lecture Notes in Computer Science; Springer: Heraklion, Greece, 2010; Volume 6314, pp. 143–156.

[31] Rastegari, M.; Ordonez, V.; Redmon, J.; Farhadi, A. XNOR-Net: ImageNet Classification Using Binary Convolutional Neural Networks. In Computer Vision—ECCV 2016; Leibe, B., Matas, J., Sebe, N., Welling, M., Eds.; Springer International Publishing: Cham, Switzerland, 2016; pp. 525–542.

[32] Roth, H.R., Yao, J., Lu, L., Stieger, J., Burns, J.E., Summers, R.M., 2015c. Detection of sclerotic spine metastases via random aggregation of deep convolutionalneural network classifications. In: Proceedings of the Recent Advances in Computational Methods and Clinical Applications for Spine Imaging. In: Lecture Notes in Computational Vision and Biomechanics, 20, pp. 3–12.

[33] Shen, W., Zhou, M., Yang, F., Yang, C., Tian, J., 2015b. multi-scale convolutional neural networks for lung nodule classification. In: Proceedings of the Information Processing in Medical Imaging. In: Lecture Notes in Computer Science, 9123, pp. 588–599.

[34] Suk, H.-I., Shen, D., 2013. Deep learning-based feature representation for AD/MCI classification. In: Proceedings of the Medical Image Computing and ComputerAssisted Intervention. In: Lecture Notes in Computer Science, 8150, pp. 583– 590.

[35] Zhang, R., Zheng, Y., Mak, T.W.C., Yu, R., Wong, S.H., Lau, J.Y.W., Poon, C.C.Y., 2017. Automatic detection and classification of colorectal polyps by transferring lowlevel CNN features from nonmedical domain. IEEE J. Biomed. Health Inf. 21, 41– 47.