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A Comparative Study On Performance Of Pre-Trained Convolutional Neural Networks In Tuberculosis Detection

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***ABSTRACT**:*
India accounts for 26% of the words Tuberculosis population. The WHO's Global TB Program states that in India, the number of people newly diagnosed with TB increased by 74% when compared to other countries from 1.2 million to 2.2 million between 2013 and 2019. Tuberculosis was and still remains a disease that causes high death rates in the country. Many of these deaths can be easily prevented if diagnosed at an early stage. The easiest, cost-effective and non-invasive method of detecting tuberculosis is through a frontal chest x-ray (CXR). But this requires a radiologist to manually examine and analyse each of the X-ray, considering the heavy patient count this puts a great burden on the resources available. A computer aided diagnosis system can easily mitigate this problem and can greatly help in reducing the cost. In recent times deep learning has made great progress in the field of image classification and has produced remarkable outputs in terms of image classification in various domains. But there still remains a scope for improvements when it comes to Tuberculosis detection. The aim of this study is toapply three pre-trained convolutional neural networks that have proven record in image classification on to publically available CXR dataset and classify CXR's that manifest tuberculosis and compare their performances. The CNN models that are used on our CXR images dataset as a part of this study are VGG-16 ,VGG-19,AlexNet ,Xception and ResNet-50. Also visualization techniques have been applied to help understand the features whose weights played a role in the classification process. With the help of this system, we can easily classify CXR's that have active TB and even CXR's that show mild abnormalities, thus ensuring that high risk patients get the help they require on time.

KeyWords: Tuberculosis, Chest X-Rays, Deep Learning, Convolutional Neural Networks,Pre-trained Models, Image Classification.

1. INTRODUCTION

The WHO's total predicted deaths from TB in 2020 is 1.66.million deaths, TB also ranks as the sixth infections disease that leads to mortality in the world .Early diagnosis and treatment could help in preventing these untoward deaths.I recent times multiple diagnostic methods that are highly accurate such as molecular analysis and bacteriological culture that help with accurate diagnosis of the infection. But these are not cost effective and cannot be afforded by the masses in developing countries such as India, where there is a high density of population that is affected by Tuberculosis. Sputum smear is an affordable technique that can be

employed for tuberculosis diagnosis but some studies have indicated that this test exhibits sensitivity issues[2]. The alternate course for effective diagnosis of tuberculosis is through a Frontal Chest X-rays (CXR), but thedrawbackof this method is that a qualified radiologist is required on hand for quick diagnosis; this could be a problem especially in rural areas where there is a dearth of qualified personals. An automated system that is capable of detecting and diagnosing using the CXR can help easily mitigate this issue;also this automated system can be used to lessen the strain on radiologists in locations where there is a huge influx of patients. Such an automated system will be cost effective, accessible and helpful is greatly reducing the turnaround time between testing and diagnosis. Computer aided diagnostics of chest x-rays has been around for quite some time and in recent times with the advent of deep learning, a whole lot of progress has been made in this area. In this study we use two publically available tuberculosis chest x-ray image data sets. The images are of .png extension and along with the normal/abnormal labels are givento the pre-trained network model as input , the CNN model then givens as output a classification of normal/abnormal for each mage. Data on the levels of abnormality is unavailable hence we do not consider grading the level of abnormality exhibited, the study will be a strict binary classification of presence or absence of Tuberculosis infection.

2. RELATED WORKS

Commercial CADx tools like CAD4TB developed by the Image Analysis group, Netherland uses Machine Learning approaches that apply a mixture of morphological and Textural attributes, the AUC ranges from 0.71 to 0.84[3]. Another study indicates when using SVM classifier that uses texture and shape features exhibited in the CXR image for detecting of abnormalities the AUC was 0.87 to 0.90[4]. The disadvantage of these mechanisms is that they require hand crafter feature extraction.

Deep learning (DL) is a branch of machine learning technique that tutors the computers to learn from examples. Deep learning is achieving results like never before. Deep learning models can produce very high accuracy that sometimes exceeds even human performance. Neural network architectures are multi layered and models are trained by using voluminoussets data that is labelled. A Convolutional Neural Network also frequently known as ConvNet or CNN is a type of Deep Learning algorithm which takes as input images, learns the weights and biases to various aspects in the image and will be able to differentiate one from the other. ConvNet require very little pre-processing and with sufficient training they have the ability to learn these filters or characteristics by themselves. The only drawback being that it requires huge volume of data for the training process. Pre-trained DL models are trained on a very large dataset like ImageNet, that contains 15 million annotated natural photography images from over 21,000 categories[4]. These models can be used for a wide variety of image recognition problems or they can also serve as feature extractors. AlexNet was proposed in 2012[5] it uses sequential stack of convolutional layers and rectified linear units (ReLU). The model was trained using stochastic gradient descent (SGD) algorithm and handled the overfitting issue by using dropout layers. A VGG model was proposed in 2014 it uses a 3×3 sized filters throughout its length. In 2014 it won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) benchmark in object localization task. VGG- 16 and VGG-19 are variants of these networks , where the number 16 and 19 denote the number of weight layers in the network [6]. · One more model called Xception uses depth-wise separable convolutions[7] . In 2015, a model based on deep residual connections (ResNet) was proposed in 2015 its performance surpassed all other models and won the ILSVRC classification task[8].Rajkomar et al. used GoogLeNet another model pre-trained on ImageNet

along with image augmentation andto classify CXR images as either frontal or lateral with an astounding accuracy of 100%[10]. This discovery though does not have any actual clinical usage it proves that DL can be used for analysing CXR imageson concept of the use of deep learning on CXR images

3. MATERIALS AND METHODS

The dataset that has been used in this comparative analysis has been discussed in this section. All pretrained models were tested using the two public CXR datasetsShenzhen and Montgomery, published in Ref. [9]

The Montgomery dataset collected by the health department of the Montgomery County in Maryland, USA has138 labelled frontal chest x-ray images of which 80 of them are CXRs of lungs with no disease, and 58 contain lungs infected by tuberculosis[9]. The radiographs' resolutions are either 4,020 x 4,892 or 4,892 x 4,020 pixels. Manually generated lung segmentation masks for every sample in the set are a part of this dataset[9].Samples of the dataset are depicted in Fig. 1.

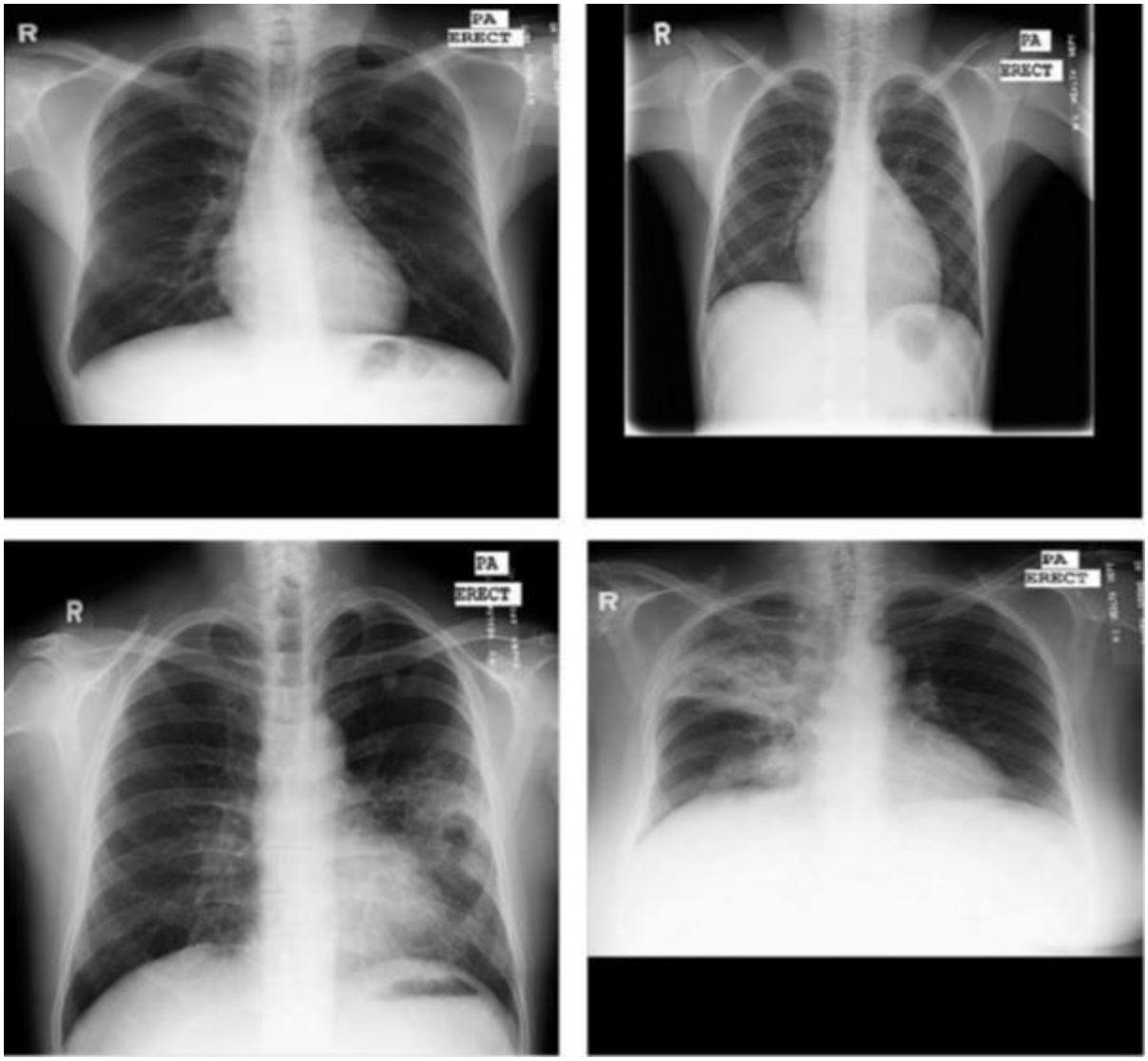

Fig. 1.Example CXRs in the Montgomery dataset.The CXRs in the topare of normal lungs and the CXR's in the bottom are with tuberculosis infection;

The Guandong Hospital in Shenzhen, China served as the source for the the Shenzhen dataset was collected. The total of 662 frontal CXRs are a part of this data set of which 336 are infected by tuberculosis, and 326 are not infected. All image resolutions are around 3,000 x 3,000 pixels. Fig. 2 Gives a snapshot of CXRs in this dataset.

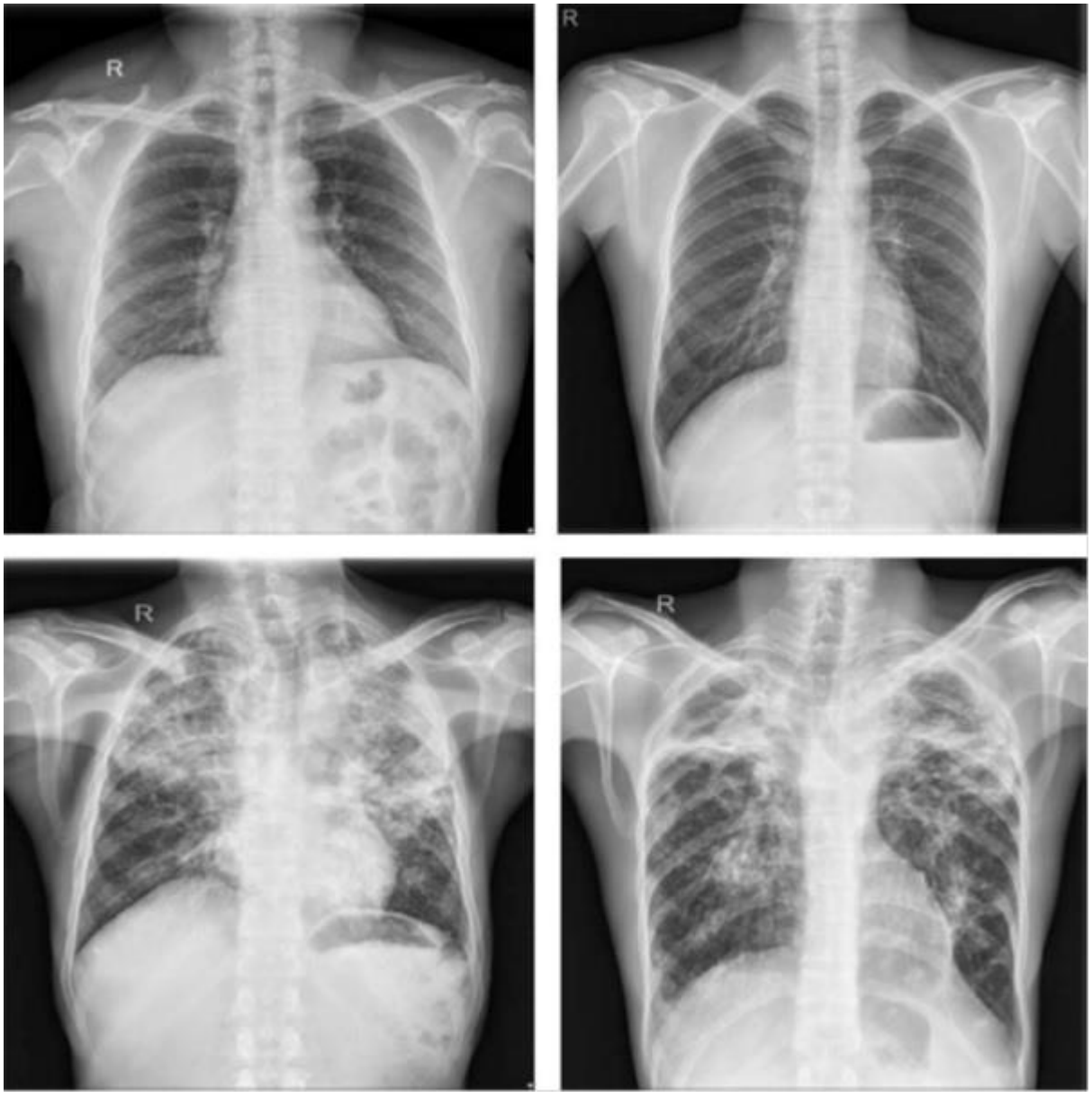

Fig.2. Examples of CRs in the Shenzhen dataset. The top left and right CXR shows no indication of TB bottom two images are cases of secondary tuberculosis.

4. PRE-PROCESSING

All images present in the datasets and are used as part of this study are frontal thoracic CXRs,which also have areas outside of the lungsthat are not used for tuberculosis diagnosis. These irrelevant features present in the image risks and may distort the final diagnosis process. To reduce this probable error segmentation of the lung regions in CXRs was performed. TheMontgomery dataset,did not require segmentation as it comes with individual

segmentation mask for all the images. Segmentation masks where generated using the SIFT flow approach [20] and graph-cuts algorithm[21] for the Shenzhen dataset. Contrast Limited Adaptive HistogramEqualization (CLAHE) was used on all the images contrast enhancement. Images from both the datasets are down-sized to 224×224 and 299×299 pixel resolutions to suit the input needs of the pre-trained CNNs

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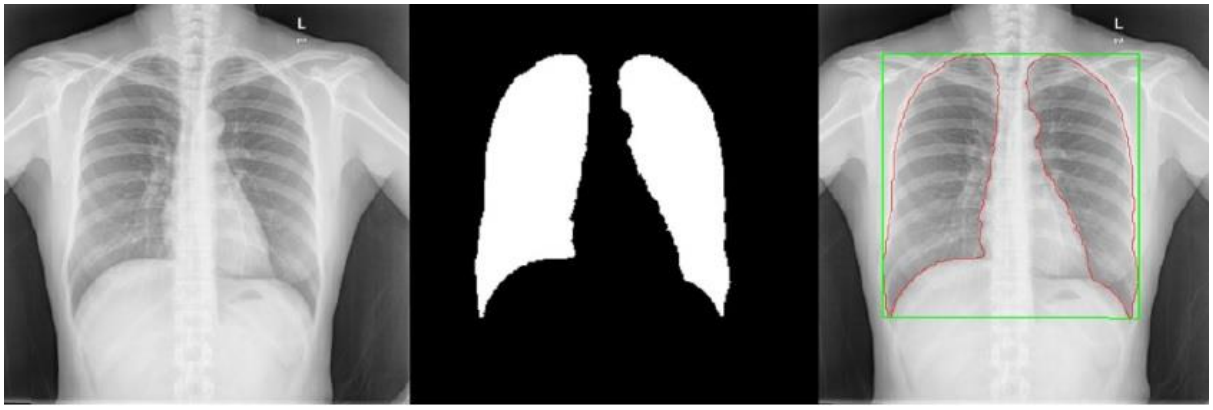

(a) (b) (c)

Fig. 3.(a) Original Image before Segmentation , (b) Lung Mark, (c) CXR after segmentation

The study was run on Google Colab in a Tesla K80 GPU. Google Colaboratory is a free cloud-based on line Jupyter notebook environment that allows us to train our machine learning and deep learning models on CPUs, GPUs, and TPUs.

5. RESULTS AND DISCUSSION

We evaluate the performance of pre-trained DL models that include AlexNet, VGG-16 and VGG-19, Xception and ResNet-50 (winners of ILSVRC 2012, 2014 and 2015 respectively) in the process of classifyingthe presented CXR's as normal and TB-positive categories. Table 1 describes the number of parameters extracted from the pre-trained CNNs and are used in this study.

Models	**Number of Parameters Extracted**
AlexNet	60,110,000
VGG-16	148,356544
VGG-19	146,667,240
Xception	24,911,482
ResNet-50	26,632,724

Table 1: Pre-trained Models and Number of Parameters Extracted

Each layer of the pre-trained CNNs usedgenerates an activation map for the given image. The outer part layers of the CNN capture primitive features such as edges, colour and blobs. These features are abstracted by the deeper layers to form higher level image representation. The Features are extracted after passing through all the convolutional layers, right before the final classification layer which happens at the fully connected layer and are fed to a SVM classifier. SVM is a linear classifier, that uses the features extracted to predict if the CXR presented exhibits tuberculosis or not. The second fully connected layer has been identified for feature extraction in VGG-16 , VGG-19 and AlexNetmodels. For Xception and ResNet-50 models the final layer, before the classification layer, has been identified for extracting the features.

Table 2 and Table 3 depicts the results obtained by using pre-trained CNNs as feature extractors.

Datasets	**AlexNet**	**VGG-16**	**VGG-19**	**Xception**	**ResNet-50**
Shenzhen	**0.843**	0.814	0.779	0.732	0.817
Montgomery	**0.727**	0.710	0.658	0.610	0.681

Table 2: Accuracy Exhibited by the pre-trained models

Datasets	**AlexNet**	**VGG-16**	**VGG-19**	**Xception**	**ResNet-50**
Shenzhen	**0.913**	0.880	0.866	0.863	0.891
Montgomery	**0.801**	0.732	0.723	0.671	0.619

Table 3: AUC exhibited by the pre-trained models

AlexNet obtained the best accuracy of 0.843 and AUC of 0.913 for the Shenzen dataset and obtained the accuracy of 0.727 andAUC of 0.801. Alex Net's accuracy is superior to that of the of the other pre-trained models under consideration. It has also been identified that by adding dropout layer the classification accuracy is enhanced in shallow, sequential networks such as AlexNet, VGG-16, and VGG-19 but conversely the performance of deep CNNs that include Xception andResNet-50 took a hit. Thus we can clearly observer that among all the pre-trained CNNs evaluated in this study, AlexNet outdid the other models for the datasets under consideration. One would have expected that ResNet-50 would outperform all other architectures since it has been found to perform outstandingly in ImageNet but contrary to popular belief, in this study it did not perform well. ResNet-50 is deep architecture, and this may have influenced it performance, as it is complex for the task we have in hand which is a simple binary image classification. In the case of Xception and ResNet-50 the top layers of pre-trained are probably too specialized and progressively more complex so they are not suitable for the task we want them to perform. This explains the difference in performance in our case.

6. CONCLUSIONS

In this study, we have compared the performance of five pre-trained Deep Learning models forthe purposeof improving the accuracy in TB screening from frontal Chest X-rays. We have observed that the performance AlexNet pre-trained models is notably better than the other models taken for consideration in the study. It was also identified that deeper layer of the CNN did not give better results when compared to features extracted from the higher or shallow layers. It has also been noted that the volume of data available for the study directly impacts the performance of the models used, reiterating the fact that CNN's perform better when they are able to learn from larger datasets. With respect to TB detection using CNN the study also has identified the need for more larger biomedical datasets. The results obtained in the present study, proves that pertained networks can be a very useful and powerful tool for medical image classification and can be used in diagnosis of other disease types too.

7. REFERENCES

[1] Global Tuberculosis Report 2020 – World Health Organization
[2] C.C. Leung, Re-examining the role of radiography in tuberculosis case finding, Int. J.
[3] Tuberc. Lung Dis. Official J. Int. Union AgainstTuberc. Lung Dis. 15 (2011) 1279.

[4] Pande, T., Cohen, C., Pai, M. and Ahmad Khan, F., "Computer-aided detection of pulmonary tuberculosis ondigital chest radiographs: A systematic review," Int. J. Tuberc. Lung Dis. 20(9), 1226–1230 (2016).
[5] Candemir, S., Jaeger, S., Palaniappan, K., Musco, J. P., Singh, R. K., Xue, Z., Karargyris, A., Antani, S., Thoma. G. and McDonald, C. J., "Lung segmentation in chest radiographs using anatomical atlases with nonrigidregistration," IEEE Trans. Med. Imag.33(2), 577–590 (2014).
[6] Krizhevsky, A., Sutskever, I. and Hinton, G. E., "ImageNet Classification with Deep Convolutional Neural
[7] Networks," Proc. NIPS 1, 1097–1105 (2012).
[8] Simonyan, K. and Zisserman, A., "Very Deep Convolutional Networks for Large-Scale Image Recognition,"
[9] arXivPrepr. arXiv:1409.1556 (2014).
[10] Chollet, F., "Xception: Deep Learning with Separable Convolutions," arXivPrepr. arXiv1610.02357 (2016).
[11] He, K., Zhang, X., Ren, S. and Sun, J., "Deep Residual Learning for Image Recognition," Proc. CVPR, 770–778 (2016).
[12] S. Jaeger, S. Candemir, S. Antani, Y.-X.J. W_ang, P.-X. Lu, G. Thoma, Two publicchest x-ray datasets for computer-aided screening of pulmonary diseases, Quant.Imaging Med. Surg. 4 (2014) 475–477
[13] Alvin Rajkomar, Sneha Lingam, Andrew G. Taylor,Michael Blum, and John Mongan. High-Throughput
[14] Classification of Radiographs Using Deep ConvolutionalNeural Networks. Journal of Digital Imaging,30:95–101, Feb 2017
[15] LeCun, Y., Bengio, Y. and Hinton, G., "Deep learning," Nature 521(7553), 436–444 (2015).
[16] Schmidhuber, J., "Deep Learning in neural networks: An overview," Neural Networks 61, 85–117 (2015).
[17] Deng, J., Dong, W., Socher, R., Li, L. J., Li, K. and Fei, L. F., "ImageNet: a Large-Scale Hierarchical Image Database," Proc. CVPR, 248–255 (2009).
[18] Chen, Y., Lin, Z., Zhao, X., Wang, G. and Gu, Y., "Deep Learning-Based Classification of HyperspectralData,"IEEE J. Sel. Topics Appl. Earth Observ. in Remote Sens. 7(6), 2094–2107 (2014).
[19] Szegedy, C., Vanhoucke, V., Ioffe, S., Shlens, J. and Wojna, Z., "Rethinking the Inception Architecture for
[20] Computer Vision," arXivPrepr.arXiv:1512.00567 (2015).
[21] C. Liu, J. Yuen, A. Torralba, J. Sivic, W.T. Freeman, Sift flow: dense correspondence across different scenes, in: European Conference on Computer Vision, Springer, 2008, pp. 28–42.
[22] Y. Boykov, G. Funka-Lea, Graph cuts and efficient nd image segmentation, Int. J.Comput. Vis. 70 (2006) 109–131..