Journal of Advanced Research in Applied Sciences and Engineering Technology 34, Issue 2 (2024) 363-373

SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage:
https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

A Review on Occluded Object Detection and Deep Learning-Based Approach in Medical Imaging-Related Research

Khairul Rohaizzat Jamaluddin[1], Shafaf Ibrahim[1,*]

[1] School of Computing Sciences, College of Computing, Informatics and Media, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia

ARTICLE INFO

Article history:
Received 10 July 2023
Received in revised form 15 November 2023
Accepted 23 November 2023
Available online 8 December 2023

Keywords:
Occluded; occlusion; object detection; medical imaging; Deep Learning; statistical analysis

ABSTRACT

Medical image occlusions can arise due to several factors, including anatomical features, imaging modality, and acquisition settings. Object occlusion occurrence has a very significant effect on detection accuracy in general and in medical cases, these effects hinder proper diagnosis and treatment plans that may be fatal for the patients. Thus, precise occluded object detection is imperative. This paper aims to review the various state-of-the-art models and approaches that had been proposed for the occluded object detection. The coverage of this paper includes occluded object detection models in other applications and medical imaging, its proposed Deep Learning implementations, hybrid Deep Learning, and statistical analysis that were integrated into Deep Learning models. It is found that, in overall, more annotated medical image datasets are required to reduce overfitting occurrence, numerous Deep Learning models and its hybrid combination's applications yet to be tested of its limitations, and the extent of statistical analysis integration on Deep Learning models.

1. Introduction

Occlusion occurs whenever multiple objects in an image are very close to each other and appear to merge, and it can result in the incorrect identification of the intended tracked object [1]. In some conditions, occluded objects carry few useful pixels, containing merely a few, insufficient attributes which are mostly surrounded by noise [2]. Following this prior condition, more information could be lost once the input image goes through several pre-processing steps, further affecting the object detection accuracy negatively. Fortunately, studies related to improving occluded object detection have a significant increase in the last few years.

In medical fields, accurate and fast object detection systems are very much needed as incorrect diagnosis may lead to multiple aspects of damage to the patient [3] such as:

i. providing the wrong treatment that in worst-case scenario, may be fatal;
ii. psychological/behavioural changes from mislabelling;
iii. unnecessary financial burden.

* *Corresponding author.*
E-mail address: shafaf2429@uitm.edu.my

https://doi.org/10.37934/araset.34.2.363373

As it is today, computer-aided diagnosis is well used as a second opinion rather than being seen reliable enough to produce an accurate diagnosis. Medical imaging scanners such as angiogram, computed tomography (CT), magnetic resonance imaging (MRI), ultrasound, and positron emission tomography (PET) are some of the most reliable examples that can produce high-quality, high-definition images. With a few additional steps of high accuracy object detection and classification, computer-aided diagnosis as a second opinion may not be the case anymore [4].

Through the development of advanced imaging technologies for use in diagnosis, treatment, and research, image processing has revolutionized the medical field. Large volumes of data generated by medical imaging methods such as MRI, CAT scans, X-rays, and ultrasound, can be processed and analysed at a faster rate through image processing techniques as discussed by Vadmal *et al.,* [5]. Medical professionals can enhance and extract useful information from these images through image processing, leading to more accurate diagnosis and treatment planning. Some common applications of image processing in the medical field include tumour detection [6,7], tissue characterization [8], bone density measurement [9] and brain mapping [10]. With the ongoing advancements in technology, image processing is expected to continue playing a vital role in the medical field by improving patient care and favourable outcomes with its increasing implementation with Machine Learning methodologies.

Machine Learning and Deep Learning methodologies have had a tremendous impact on the medical imaging sector, allowing for more accurate and efficient diagnosis and treatment strategies [11]. In Machine Learning, algorithms are created with multiple layers of training to recognize features and patterns from large amounts of medical images. Deep Learning, in particular, has demonstrated great success locating and identifying irregularity in medical images [12]. Convolutional Neural Networks (CNNs) gained quite a traction in Deep Learning architecture used in medical imaging applications, where they can distinct specific abnormal features and patterns in images [13]. For example, CNNs have been used to detect cancerous lesions in mammograms [14], identify Alzheimer's disease from MRI scans [15], and detect lung nodules in CT scans [16]. These methods have significantly improved medical imaging, which ultimately benefits patients by enhancing diagnosis rates and treatment outcomes.

With an emphasis on medical imaging and statistical Deep Learning techniques, this paper seeks to present an abstract idea, specifically an overview of the current occluded object recognition techniques. This paper is organized as follows: Section 2-6 covers each aspect in Deep Learning occluded object detection in medical imaging and findings obtained, and Section 7 will have our own conclusion.

2. Occluded Object Detection

Occluded object detection is a strenuous task in computer vision due to the limited visibility of occluded objects. Traditional object detection methods struggle to detect partially or fully occluded objects, leading to reduced detection accuracy [17]. Recently, Deep Learning-based methods have shown promising results in addressing the challenge of occluded object detection [18,19].

Deep Learning-based methods have shown considerable growth in occluded object detection. The Faster R-CNN and its variants are popular Deep Learning-based methods for object detection that can handle occluded objects by generating region proposals and classifying them based on their features [20]. Other Deep Learning-based methods, such as single-shot detector (SSD) and You Only Look Once (YOLO), have also been used for occluded object detection with promising results [20,21].

One recent advancement in occluded object detection is the use of attention mechanisms. These mechanisms focus on the most informative regions in the image, which can help to detect occluded objects. For example, Wei *et al.,* [22] proposed a module called De-Occlusion Attention Module (DOAM). DOAM firstly enhances the edge information of the object with edge guidance and material awareness module to enhance the material information of the object. And based on the outcomes of the two sub-modules, an attention module was created to produce an attention distribution map. With the enhanced features of the input image obtained, it improves the detection accuracy overall. The proposed module is quite useful as it is capable to be implemented on popular detectors with its plug-and-play capability, proved to increase accuracy of SSD and FCOS while outperforming several widely used attention mechanism, and the authors also contributed in providing Occluded Prohibited Items Xray (OPIXray) annotated image datasets, covering only five categories of prohibited items; folding knife, straight knife, scissor, utility knife and multi-tool knife [22]. However, it is also identified that the annotated datasets used for training and testing were already color-coded, to separate different items based on their materials. Whereas in common scenarios involving Xray images, they are initially in grayscale form and the proposed module has not been tested in said scenario. Thus, testing DOAM on medical Xray image datasets should proof useful in providing further insight of its limitations.

Another recent advancement in occluded object detection is the use of multi-scale and multi-modal information. Multi-scale information can help to detect objects of different sizes [23], while multi-modal information can leverage complementary information from different modalities [24]. Yun *et al.,* [25] proposed a multispectral fusion method that combined red, green, and blue (RGB) images and infrared (IR) images to detect occluded objects they call Infusion-Net. It aims to improve object recognition performance by intensifying object features in RGB and IR images that are rather hard to be segregated. Tests run by the author showed a significant increase across the board against other mono and multimodal models, utilizing mean average precision (mAP) values for comparison [25]. Infusion-Net seems to work really well as a pre-processing step in reducing occlusions by emphasizing edges that are identifiable in RGB-IR image. Further testing in anomaly detection in medical images could prove its viability handling images with smaller object detections.

Even with recent improvements, occluded object recognition still faces several challenges. Lack of annotated datasets for occluded object detection, especially for particular object groups, would be some of the significant issues [26]. This is evident when observing available datasets on the open-source dataset sharing platforms such as Kaggle. To train Deep Learning-based models for occluded object recognition, annotated datasets are crucial too. Deep Learning-based techniques' high computational costs present another difficulty and may prevent real-time applications from utilizing them.

3. Occluded Object Detection in Medical Imaging

Medical imaging is essential for diagnosing and treating diseases. However, occlusions are common in medical images, making it challenging to detect objects accurately. Recent advances in Deep Learning-based methods have refined occluded object detection [22,25,27]. As for in-depth processes and subprocess in medical related image processing techniques, paper review by Awang and Ibrahim [28] has it covered.

Numerous occluded object detection in medical images based on Deep Learning techniques have been developed. One recent advancement is the “Global Hungarian algorithm”. The two-step recognition algorithm presented by Qian *et al.,* [29] involves threshold partitioning and morphological open operation that utilizes the advantages from the global shortest path and Hungarian algorithm. Said method was employed and tested on occluded non-fluorescent labelled microbe particles. Several scenarios were tested in that regard, resulting with it only being able to handle two or three particles. It is good to note that the developed method was intended and applied to track these particles, meaning that it was not applied on still images to only detect occluded particles but rather real-time tracking of occluded particles [28]. With the Global Hungarian algorithm, further application and testing on real-time MRI, CT and ultrasound scans could prove beneficial on automated diagnosis studies.

Another recent advancement is the study done by Qiu *et al.,* [30]. The researchers aimed to assess the effectiveness of the fusion between CNN and YOLO version 5 (YOLOv5) algorithms for the automatic detection of steno-occlusive lesions. Their evaluation's findings demonstrated that the mixed algorithm was effective in identifying lesions with high accuracy, giving the exact anatomical location of the stenosis. Even though the study was done only using inputs from time-of-flight magnetic resonance angiography (TOF-MRA) scanner images, the proposed method showed favourable results in all three accuracy measurements – precision, recall, and mAP with intersection over union (IoU) value at 0.5 – when compared other commonly used algorithms [29]. As the author mentioned, the proposed method lacks additional inputs and assessment from other scanner types than TOF-MRA to measure its limitations. Also, experimentations of the proposed method on other medical conditions that require~~s~~ MRA or any other angiography diagnosis could benefit from it as well.

Liu *et al.,* [31] proposed the Dual Fusion Mass Detector (DFMD) in his work to provide better mass detection in mammograms. The paper focuses on tackling scale variations, blurry masses with fuzzy boundaries, and occlusion issues in mammogram. DFMD utilizes Resnet50 for its Deep Learning framework integrated with Small Target Attention Module (STAM), another module that the authors introduced to enhance detection of minuscule targets capability. Results-oriented Loss (ROL) along with Incremental Positive Selection (IPS) was also presented to improve prediction results and handle mass scale variation, respectively. Experiments done by the authors against existing detection frameworks, SSD, YOLOv3-SPP, and Faster RCNN-FPN indicated DFMD to be superior in the context of mass detection. Since the proposed model consists of 3 different submodules (STAM, ROL, IPS) to handle each of the aforementioned problems in mass detection, additional studies regarding the application of the submodules on other X-ray related diagnosis seems plausible and may provide an advancement towards automated diagnosis.

Additionally, an improvement was also made on intracranial vessel occlusion (ICVO) by Becks *et al.,* [32]. The study's goal was to determine whether using CT perfusion (CTP) could enhance the capability of CT angiography (CTA) to detect ICVO in acute ischemic stroke. The test of patients' imaging data was segregated into two parts with the first to run the detection only through non-contrast CT (NCCT) and CTA, and second part to test them with NCCT, CTA with CTP. In terms of diagnostic precision evaluation, the authors utilized receiver-operating characteristic (ROC) analysis and came to conclusion that CTP could improve ICVO detection performance on CTA due to the enhancement on distal and posterior circulation vessel occlusion detection. Although this paper provides information that prone more towards combining and enhancing existing medical diagnostic systems, it also provides an insight toward the possibilities of an intelligent diagnostic system that utilizes advanced image processing and Deep Learning approaches as done by Wang *et al.,* [33] and Yang *et al.,* [34].

For the retinal vein occlusion (RVO), Xu *et al.,* [35] proposed intelligent diagnosis system to detect and classify among four categories, healthy, branch RVO (BRVO), central RVO (CRVO), and macular BRVO (MBRVO). The proposed system utilized a variant of CNN, ResNet18, in their intelligent system which was then compared to the clinical diagnoses in accuracy. The system was also tested on combinations of ResNet18 with convolutional block attention module (CBAM), squeeze and excitation network (SENet), and coordinate attention (CA). It was concluded that the combination utilizing ResNet18+CA, is able to detect and classify RVO presence and its results were exceptionally comparable, in each of the four categories, with clinical diagnosis. Regardless of the promising results obtained from the study, the amount of available annotated data related to this study was too little for training and testing purposes that the authors were forced to apply augmentations [34]. Aside from that, there are inconsistent results on BRVO, CRVO and MBRVO implying a necessity for better model.

On a more time-sensitive context, Stib *et al.,* [36] and Meijs *et al.,* [37] both presented a Deep Learning model with the goal to speed up detection of arterial occlusions that could lead to stroke. Stib *et al.,* [36] proposed model successfully detects large vessel occlusion (LVO) while also showing no signs of model overfitting due to the test set and validation set performance having a tight match and high area under curve (AUC) values. Meanwhile, Meijs *et al.,* [37] tackled the issue by detecting intracranial anterior circulation artery occlusions and also achieved promising results with its ROC value. Both studies utilized the same Deep Learning method, CNN, but each with different input image source, multiphase CTA and 4D-CTA, respectively.

4. Deep Learning Approaches

Analysis of medical imaging has made extensive use of Deep Learning and has shown encouraging results in various operations, including segmentation, detection, classification, and generation. In recent years, numerous studies have been conducted using Deep Learning techniques to enhance its accuracy and efficiency of medical image analysis [8,38].

One popular approach is the use of CNNs, which exceeded average results in numerous medical imaging operations. Rajpurkar *et al.,* [39] introduced CheXNet, a CNN architecture based on DenseNet121 [40] with ChestX-ray14 [41] annotated image pack to accurately detect pneumonia in chest X-rays. The proposed method did manage to produce extraordinary results in detecting pneumonia and its minor symptoms by marking the object with heat maps. However, the limitation of CheXNet is the output being set in binary form (0 as absent pneumonia, 1 as present pneumonia). This means that it only learns 1 disease in a single training period, which could take a substantial amount of time and is not favourable in a medical context, and retraining is required for other disease detection. An improvement in this area could be instrumental for disease detection in X-ray images.

In addition to CNNs, attention mechanisms have also gained popularity in medical image analysis. Some of the most notable advances for CNN would be Schlemper *et al.,* [42] proposed method, Attention U-Net, a modified U-Net architecture that uses grid-based attention gates (AG), which allows attention coefficients to focus entirely on local regions. Attention U-Net gained quite a traction in various application, such as implementations by Abraham *et al.,* [43] and Nava *et al.,* [44], for its capability to maintain computational efficiency while improving performance, despite of training population and dataset variance. However, there is still a lack of study on Attention U-Net capability integrated with statistical analysis.

Recurrent neural network (RNN) is another well-known Deep Learning approach besides CNN. Despite its capability of giving precise predictions, RNN loses said advantage whenever the sequence is too long for it to handle. This issue may be resolved by using long short-term memory (LSTM). Paper by Ashir *et al.,* [45] utilized LSTM with multiple feature extraction methods to analyse each segment of diabetic retinopathy images at a higher precision in attempt to reduce false positive occurrences. The authors applied various quantization methods to improve the probability of LSTM differentiating overlapping features from the input, hence, pointing out the issue currently faced in studies related to fundus images. The differences between features to be extracted are too minute, requiring advanced pre-processing technique.

5. Hybrid Deep Learning Approach

Recent strides in Deep Learning have yielded favourable outcomes in a wide range of applications, including speech recognition, natural language processing, and image classification. However, certain complex tasks require hybrid Deep Learning models that combine multiple models to improve their performance [46]. Hybrid models have been shown to outperform single-model approaches by means of efficiency, accuracy, and generalization [47].

One popular approach is to fuse CNNs with recurrent neural networks (RNNs) to handle serial data. In a study by Zhou *et al.,* [48], CNN-RNN was implemented to generate online medical recommendation based on the extracted semantic and sequential features data. Thus, introducing their own algorithm, DP-CRNN. Similarly, Khaki *et al.,* [49] made a hybrid CNN-RNN model for crop yield prediction that leverages CNN for feature extraction, extracting weather data and soil data, and RNN for capturing the increasing trend of crop yield.

Another hybrid approach is to combine multiple CNNs with varying architectures and parameters to enhance diversity and reduce overfitting. Huang *et al.,* [40] proposed the DenseNet model, which is an exceptional model that manages to reduce the vanishing-gradient-induced accuracy decline in CNN models with large number of layers. The DenseNet manages this issue by putting the layers in blocks, called Dense Blocks, that maintains feature maps dimension as constants while filters amount between layers continues to change.

On the other hand, Bano *et al.,* [50] proposed FetNet, a fusion neural network of CNN and LSTM, identifying fetoscopic events during twin-to-twin transfusion syndrome (TTTS) treatment. The purpose of the method was to locate abnormal placental vascular anastomoses and remove them in order to control blood flow to both fetuses. FetNet outperformed previous CNN-based methods and yields better inference due to information modelling of the spatio-temporal. It was also suggested in the paper that FetNet might be able to offer a real-time solution for computer-assisted interventions during fetoscopic surgeries even though said application is yet to be tested or documented.

6. Statistical Methodologies with Deep Learning

Deep Learning has been revolutionizing the Machine Learning and Artificial Intelligence advancements. However, as the models become more complex, the need for statistical approaches in Deep Learning becomes more critical [51]. Multivariate analysis, which deals with the analysis of multiple variables at once, can provide valuable insights into the relationship between variables in Deep Learning.

One of the major issues in Deep Learning is the selection of optimal hyperparameters [52]. Hyperparameters are the parameters that manage~~s~~ the learning process of the Deep Learning model, including the number of layers, the learning rate, and the batch size. For a sample of study that handled their hyperparameter issue, the paper by Dinakaran *et al.,* [53] has it covered. An effective way to choose hyperparameters is through Bayesian optimization, a statistical method that maximizes the expected improvement of the model. In their paper, Yin and Li [54] provided a comprehensive briefing on Bayesian optimization algorithm for Deep Learning, highlighting its advantages and practical implementation. In their usage, they managed to identify the appropriate hyperparameters to be used with their model, enhancing overall performance considerably.

Another statistical approach in Deep Learning is the use of Principal Component Analysis (PCA). PCA is an approach for minimizing the number of dimensions in large datasets. It does this by compressing a vast collection of variables into a smaller collection, with the majority of the larger set information still intact. Alkhayrat *et al.,* [55] implemented PCA with Autoencoder Neural Network (aNN) to handle the challenges of analysing large and sparse customer data generated by telecom companies. To determine the effect of the reduction strategy on clustering performance, the authors used k-Means Clustering to compare clustering results in the original and reduced space and assess various internal measures. It was also noted that the authors combined PCA and aNN due to the latter not being able to resolve vanishing and exploding gradient, and overfitting issues, regardless of how similar both architectures are.

Any Machine Learning model has to be tested with previously unknown data in order to assess its performance. It can later be determined whether the model is either underfitting, overfitting or well-generalized, and this method is called cross-validation [56]. Islam Ayon and Milon Islam [57] in their works proposed a strategy of utilizing cross-validation on a Deep Neural Network (DNN) system for diagnosing diabetes. The DNN system was trained and tested with five-fold and ten-fold cross-validation. They concluded that the system produced encouraging results in five-fold cross-validation, with not much difference of accuracy with ten-fold. Although the acquired result indicated a minor increase in accuracy compared to other state-of-the-art works, there is still room for improvement needed to be achieved in relation to the study.

Multivariate method is a statistical-based approach to measure relevancy of each feature, and compute correlation values between features. Because it takes into account the association between features throughout the process, this enables it to deal with both irrelevant and redundant features [58]. Study done by Lee *et al.,* [59] utilized multivariate analysis in their prediction models for postoperative pneumonia with a Deep Learning computer-aided diagnosis (DL-CAD) system. It was concluded that their prediction model could assist in improving postoperative pneumonia risk classification. Multivariate has proved its adequacy in enhancing medical diagnosis systems. Nevertheless, there is still limited study done to properly diagnose occluded medical conditions with multivariate analysis.

7. Conclusions

From the literatures conducted, it is found that studies done in the fields that encompasses Deep Learning occluded object detection with statistical methodologies and medical imaging, regardless of disease types, are still in short supply. With the goal to automate every existing system or manual labours, medical imaging delineation still needs more attention. Following the assessment of a large number of research papers on occluded object detection in medical imaging-related, the following key findings were made:

i. More analysis needs to be done on occluded object detection due to the lack of occluded data annotation, restricting better classification, very much so in the case of medical imaging;
ii. Each Deep Learning methodologies has their own advantages of handling specific issues and by combining them, their disadvantages can be mitigated;
iii. As proven by most studies, hybrid Deep Learning could enhance the Deep Learning performance, thus, it is recommended that additional research be done to cover more ground in hybrid approaches;
iv. The integration of statistical analysis on Deep Learning systems proved very beneficial as it improves the learning curve of a Deep Learning architecture;
v. Most of the proposed and developed methods still has a wide possible testing to be done to identify its limitations.

Acknowledgement
The research was supported by Institute of Graduate Studies Universiti Teknologi MARA through the Conference Support Fund.

References
[1] Cheong, Yun Zhe, and Wei Jen Chew. "The application of image processing to solve occlusion issue in object tracking." In *MATEC Web of Conferences*, vol. 152, p. 03001. EDP Sciences, 2018. https://doi.org/10.1051/matecconf/201815203001
[2] Li, Xiang, Miao He, Yan Liu, Haibo Luo, and Moran Ju. "SPCS: a spatial pyramid convolutional shuffle module for YOLO to detect occluded object." *Complex & Intelligent Systems* 9, no. 1 (2023): 301-315. https://doi.org/10.1007/s40747-022-00786-7
[3] Singh, Harminder, James A. Dickinson, Guylène Thériault, Roland Grad, Stéphane Groulx, Brenda J. Wilson, Olga Szafran, and Neil R. Bell. "Overdiagnosis: causes and consequences in primary health care." *Canadian Family Physician* 64, no. 9 (2018): 654-659.
[4] Nicosia, Luca, Francesca Addante, Anna Carla Bozzini, Antuono Latronico, Marta Montesano, Lorenza Meneghetti, Francesca Tettamanzi *et al.,* "Evaluation of computer-aided diagnosis in breast ultrasonography: Improvement in diagnostic performance of inexperienced radiologists." *Clinical Imaging* 82 (2022): 150-155. https://doi.org/10.1016/j.clinimag.2021.11.006
[5] Vadmal, Vachan, Grant Junno, Chaitra Badve, William Huang, Kristin A. Waite, and Jill S. Barnholtz-Sloan. "MRI image analysis methods and applications: an algorithmic perspective using brain tumors as an exemplar." *Neuro-Oncology Advances* 2, no. 1 (2020): vdaa049. https://doi.org/10.1093/noajnl/vdaa049
[6] Xia, Chuli, Kai Niu, Zhiqiang He, Shun Tang, Jichuan Wang, Yidan Zhang, Zhiqing Zhao, and Wei Guo. "SVM-based bone tumor detection by using the texture features of X-ray image." In *2018 International Conference on Network Infrastructure and Digital Content (IC-NIDC)*, pp. 130-134. IEEE, 2018. https://doi.org/10.1109/ICNIDC.2018.8525806
[7] Dipu, Nadim Mahmud, Sifatul Alam Shohan, and K. M. A. Salam. "Deep learning based brain tumor detection and classification." In *2021 International conference on intelligent technologies (CONIT)*, pp. 1-6. IEEE, 2021. https://doi.org/10.1109/CONIT51480.2021.9498384
[8] Struyvenberg, Maarten R., Albert J. De Groof, Joost van der Putten, Fons van der Sommen, Francisco Baldaque-Silva, Masami Omae, Roos Pouw *et al.,* "A computer-assisted algorithm for narrow-band imaging-based tissue characterization in Barrett's esophagus." *Gastrointestinal endoscopy* 93, no. 1 (2021): 89-98. https://doi.org/10.1016/j.gie.2020.05.050
[9] Lin, Hsin-Hon, Shin-Lei Peng, Jay Wu, Tian-Yu Shih, Keh-Shih Chuang, and Cheng-Ting Shih. "A novel two-compartment model for calculating bone volume fractions and bone mineral densities from computed tomography images." *IEEE transactions on medical imaging* 36, no. 5 (2016): 1094-1105. https://doi.org/10.1109/TMI.2016.2646698
[10] Schiffer, Christian, Katrin Amunts, Stefan Harmeling, and Timo Dickscheid. "Contrastive representation learning for whole brain cytoarchitectonic mapping in histological human brain sections." In *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pp. 603-606. IEEE, 2021. https://doi.org/10.1109/ISBI48211.2021.9433986
[11] Tsuneki, Masayuki. "Deep learning models in medical image analysis." *Journal of Oral Biosciences* 64, no. 3 (2022): 312-320. https://doi.org/10.1016/j.job.2022.03.003
[12] Arabahmadi, Mahsa, Reza Farahbakhsh, and Javad Rezazadeh. "Deep learning for smart Healthcare—A survey on brain tumor detection from medical imaging." *Sensors* 22, no. 5 (2022): 1960. https://doi.org/10.3390/s22051960
[13] Haq, Imran Ul, Haider Ali, Hong Yu Wang, Cui Lei, and Hazrat Ali. "Feature fusion and Ensemble learning-based CNN model for mammographic image classification." *Journal of King Saud University-Computer and Information Sciences* 34, no. 6 (2022): 3310-3318. https://doi.org/10.1016/j.jksuci.2022.03.023
[14] Deb, Sagar Deep, and Rajib Kumar Jha. "Segmentation of Mammogram Images Using Deep Learning for Breast Cancer Detection." In *2022 2nd International Conference on Image Processing and Robotics (ICIPRob)*, pp. 1-6. IEEE, 2022. https://doi.org/10.1109/ICIPRob54042.2022.9798724
[15] Alshammari, Majdah, and Mohammad Mezher. "A modified convolutional neural networks for MRI-based images for detection and stage classification of alzheimer disease." In *2021 National Computing Colleges Conference (NCCC)*, pp. 1-7. IEEE, 2021. https://doi.org/10.1109/NCCC49330.2021.9428810
[16] Sreekumar, Amrit, Karthika Rajan Nair, Sneha Sudheer, H. Ganesh Nayar, and Jyothisha J. Nair. "Malignant lung nodule detection using deep learning." In *2020 International conference on communication and signal processing (ICCSP)*, pp. 0209-0212. IEEE, 2020. https://doi.org/10.1109/ICCSP48568.2020.9182258

[17] Saleh, Kaziwa, Sándor Szénási, and Zoltán Vámossy. "Occlusion handling in generic object detection: A review." In *2021 IEEE 19th World Symposium on Applied Machine Intelligence and Informatics (SAMI)*, pp. 000477-000484. IEEE, 2021. https://doi.org/10.1109/SAMI50585.2021.9378657
[18] Meyer, Michael, and Georg Kuschk. "Deep learning based 3d object detection for automotive radar and camera." In *2019 16th European Radar Conference (EuRAD)*, pp. 133-136. IEEE, 2019.
[19] Wang, Angtian, Yihong Sun, Adam Kortylewski, and Alan L. Yuille. "Robust object detection under occlusion with context-aware compositionalnets." In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 12645-12654. 2020. https://doi.org/10.1109/CVPR42600.2020.01266
[20] Mostafa, Tanzim, Sartaj Jamal Chowdhury, Md Khalilur Rhaman, and Md Golam Rabiul Alam. "Occluded object detection for autonomous vehicles employing YOLOv5, YOLOX and Faster R-CNN." In *2022 IEEE 13th Annual Information Technology, Electronics and Mobile Communication Conference (IEMCON)*, pp. 0405-0410. IEEE, 2022. https://doi.org/10.1109/IEMCON56893.2022.9946565
[21] Li, Yongjun, Shasha Li, Haohao Du, Lijia Chen, Dongming Zhang, and Yao Li. "YOLO-ACN: Focusing on small target and occluded object detection." *IEEE access* 8 (2020): 227288-227303. https://doi.org/10.1109/ACCESS.2020.3046515
[22] Wei, Yanlu, Renshuai Tao, Zhangjie Wu, Yuqing Ma, Libo Zhang, and Xianglong Liu. "Occluded prohibited items detection: An x-ray security inspection benchmark and de-occlusion attention module." In *Proceedings of the 28th ACM international conference on multimedia*, pp. 138-146. 2020. https://doi.org/10.1145/3394171.3413828
[23] Elizar, Elizar, Mohd Asyraf Zulkifley, Rusdha Muharar, Mohd Hairi Mohd Zaman, and Seri Mastura Mustaza. "A review on multiscale-deep-learning applications." *Sensors* 22, no. 19 (2022): 7384. https://doi.org/10.3390/s22197384
[24] Jabeen, Summaira, Xi Li, Muhammad Shoib Amin, Omar Bourahla, Songyuan Li, and Abdul Jabbar. "A review on methods and applications in multimodal deep learning." *ACM Transactions on Multimedia Computing, Communications and Applications* 19, no. 2s (2023): 1-41. https://doi.org/10.1145/3545572
[25] Yun, Jun-Seok, Seon-Hoo Park, and Seok Bong Yoo. "Infusion-Net: Inter-and Intra-Weighted Cross-Fusion Network for Multispectral Object Detection." *Mathematics* 10, no. 21 (2022): 3966. https://doi.org/10.3390/math10213966
[26] Liu, Bo, Li-Ming Zhan, Li Xu, Lin Ma, Yan Yang, and Xiao-Ming Wu. "Slake: A semantically-labeled knowledge-enhanced dataset for medical visual question answering." In *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pp. 1650-1654. IEEE, 2021. https://doi.org/10.1109/ISBI48211.2021.9434010
[27] Chu, Jun, Zhixian Guo, and Lu Leng. "Object detection based on multi-layer convolution feature fusion and online hard example mining." *IEEE access* 6 (2018): 19959-19967. https://doi.org/10.1109/ACCESS.2018.2815149
[28] Awang, Muhammad Bakhtiar Iman, and Shafaf Ibrahim. "An Overview of Segmentation and Classification Techniques: A Survey of Brain Tumour-Related Research." In *2021 2nd International Conference on Artificial Intelligence and Data Sciences (AiDAS)*, pp. 1-6. IEEE, 2021. https://doi.org/10.1109/AiDAS53897.2021.9574170
[29] Qian, Yifei, Ru Ji, Yuping Duan, and Runhuai Yang. "Multiple Object Tracking for Occluded Particles." *IEEE Access* 9 (2020): 1524-1532. https://doi.org/10.1109/ACCESS.2020.3047099
[30] Qiu, Jinming, Guanru Tan, Yan Lin, Jitian Guan, Zhuozhi Dai, Fei Wang, Caiyu Zhuang *et al.,* "Automated detection of intracranial artery stenosis and occlusion in magnetic resonance angiography: A preliminary study based on deep learning." *Magnetic Resonance Imaging* 94 (2022): 105-111. https://doi.org/10.1016/j.mri.2022.09.006
[31] Liu, Shuo, Zhihui Lai, Heng Kong, and Linlin Shen. "Dual Fusion Mass Detector for Mammogram Mass Detection." In *2022 IEEE 35th International Symposium on Computer-Based Medical Systems (CBMS)*, pp. 149-154. IEEE, 2022. https://doi.org/10.1109/CBMS55023.2022.00033
[32] Becks, Marinus J., Rashindra Manniesing, Jeroen Vister, Sjoert AH Pegge, Stefan CA Steens, Ewoud J. van Dijk, Mathias Prokop, and Frederick JA Meijer. "Brain CT perfusion improves intracranial vessel occlusion detection on CT angiography." *Journal of Neuroradiology* 46, no. 2 (2019): 124-129. https://doi.org/10.1016/j.neurad.2018.03.003
[33] Wang, Chengyan, Zhang Shi, Ming Yang, Lixiang Huang, Wenxing Fang, Li Jiang, Jing Ding, and He Wang. "Deep learning-based identification of acute ischemic core and deficit from non-contrast CT and CTA." *Journal of Cerebral Blood Flow & Metabolism* 41, no. 11 (2021): 3028-3038. https://doi.org/10.1177/0271678X211023660
[34] Yang, Yi, Jinjun Yang, Jiao Feng, and Yi Wang. "Early diagnosis of acute ischemic stroke by brain computed tomography perfusion imaging combined with head and neck computed tomography angiography on deep learning algorithm." *Contrast Media & Molecular Imaging* 2022 (2022). https://doi.org/10.1155/2022/5373585
[35] Xu, Wei, Zhipeng Yan, Nan Chen, Yuxin Luo, Yuke Ji, Minli Wang, and Zhe Zhang. "Development and application of an intelligent diagnosis system for retinal vein occlusion based on deep learning." *Disease Markers* 2022 (2022). https://doi.org/10.1155/2022/4988256

[36] Stib, Matthew T., Justin Vasquez, Mary P. Dong, Yun Ho Kim, Sumera S. Subzwari, Harold J. Triedman, Amy Wang *et al.,* "Detecting large vessel occlusion at multiphase CT angiography by using a deep convolutional neural network." *Radiology* 297, no. 3 (2020): 640-649. https://doi.org/10.1148/radiol.2020200334
[37] Meijs, Midas, Frederick JA Meijer, Mathias Prokop, Bram van Ginneken, and Rashindra Manniesing. "Image-level detection of arterial occlusions in 4D-CTA of acute stroke patients using deep learning." *Medical Image Analysis* 66 (2020): 101810. https://doi.org/10.1016/j.media.2020.101810
[38] Nguyen, Ethan H., Haichun Yang, Ruining Deng, Yuzhe Lu, Zheyu Zhu, Joseph T. Roland, Le Lu, Bennett A. Landman, Agnes B. Fogo, and Yuankai Huo. "Circle representation for medical object detection." *IEEE transactions on medical imaging* 41, no. 3 (2021): 746-754. https://doi.org/10.1109/TMI.2021.3122835
[39] Rajpurkar, Pranav, Jeremy Irvin, Kaylie Zhu, Brandon Yang, Hershel Mehta, Tony Duan, Daisy Ding *et al.,* "Chexnet: Radiologist-level pneumonia detection on chest x-rays with deep learning." *arXiv preprint arXiv:1711.05225* (2017).
[40] Huang, Gao, Zhuang Liu, Laurens Van Der Maaten, and Kilian Q. Weinberger. "Densely connected convolutional networks." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700-4708. 2017. https://doi.org/10.1109/CVPR.2017.243
[41] Wang, Xiaosong, Yifan Peng, Le Lu, Zhiyong Lu, Mohammadhadi Bagheri, and Ronald M. Summers. "Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases." In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2097-2106. 2017. https://doi.org/10.1109/CVPR.2017.369
[42] Schlemper, Jo, Ozan Oktay, Michiel Schaap, Mattias Heinrich, Bernhard Kainz, Ben Glocker, and Daniel Rueckert. "Attention gated networks: Learning to leverage salient regions in medical images." *Medical image analysis* 53 (2019): 197-207. https://doi.org/10.1016/j.media.2019.01.012
[43] Abraham, Nabila, and Naimul Mefraz Khan. "A novel focal tversky loss function with improved attention u-net for lesion segmentation." In *2019 IEEE 16th international symposium on biomedical imaging (ISBI 2019)*, pp. 683-687. IEEE, 2019. https://doi.org/10.1109/ISBI.2019.8759329
[44] Nava, Lorenzo, Kushanav Bhuyan, Sansar Raj Meena, Oriol Monserrat, and Filippo Catani. "Rapid mapping of landslides on SAR data by attention U-Net." *Remote Sensing* 14, no. 6 (2022): 1449. https://doi.org/10.3390/rs14061449
[45] Ashir, Abubakar M., Salisu Ibrahim, Mohammed Abdulghani, Abdullahi Abdu Ibrahim, and Mohammed S. Anwar. "Diabetic retinopathy detection using local extrema quantized haralick features with long short-term memory network." *International Journal of Biomedical Imaging* 2021 (2021). https://doi.org/10.1155/2021/6618666
[46] Yahya, Abdulsamad E., Atef Gharbi, Wael MS Yafooz, and Arafat Al-Dhaqm. "A Novel Hybrid Deep Learning Model for Detecting and Classifying Non-Functional Requirements of Mobile Apps Issues." *Electronics* 12, no. 5 (2023): 1258. https://doi.org/10.3390/electronics12051258
[47] Agga, Ali, Ahmed Abbou, Moussa Labbadi, Yassine El Houm, and Imane Hammou Ou Ali. "CNN-LSTM: An efficient hybrid deep learning architecture for predicting short-term photovoltaic power production." *Electric Power Systems Research* 208 (2022): 107908. https://doi.org/10.1016/j.epsr.2022.107908
[48] Zhou, Xiaokang, Yue Li, and Wei Liang. "CNN-RNN based intelligent recommendation for online medical pre-diagnosis support." *IEEE/ACM Transactions on Computational Biology and Bioinformatics* 18, no. 3 (2020): 912-921. https://doi.org/10.1109/TCBB.2020.2994780
[49] Khaki, Saeed, Lizhi Wang, and Sotirios V. Archontoulis. "A cnn-rnn framework for crop yield prediction." *Frontiers in Plant Science* 10 (2020): 1750. https://doi.org/10.3389/fpls.2019.01750
[50] Bano, Sophia, Francisco Vasconcelos, Emmanuel Vander Poorten, Tom Vercauteren, Sebastien Ourselin, Jan Deprest, and Danail Stoyanov. "FetNet: a recurrent convolutional network for occlusion identification in fetoscopic videos." *International journal of computer assisted radiology and surgery* 15 (2020): 791-801. https://doi.org/10.1007/s11548-020-02169-0
[51] MacEachern, Sarah J., and Nils D. Forkert. "Machine learning for precision medicine." *Genome* 64, no. 4 (2021): 416-425. https://doi.org/10.1139/gen-2020-0131
[52] Wu, Lichao, Guilherme Perin, and Stjepan Picek. "I choose you: Automated hyperparameter tuning for deep learning-based side-channel analysis." *IEEE Transactions on Emerging Topics in Computing* (2022). https://doi.org/10.1109/TETC.2022.3218372
[53] Dinakaran, Ranjith, Li Zhang, Chang-Tsun Li, Ahmed Bouridane, and Richard Jiang. "Robust and Fair Undersea Target Detection with Automated Underwater Vehicles for Biodiversity Data Collection." *Remote Sensing* 14, no. 15 (2022): 3680. https://doi.org/10.3390/rs14153680
[54] Yin, Jiangning, and Nan Li. "Ensemble learning models with a Bayesian optimization algorithm for mineral prospectivity mapping." *Ore Geology Reviews* 145 (2022): 104916. https://doi.org/10.1016/j.oregeorev.2022.104916

[55] Alkhayrat, Maha, Mohamad Aljnidi, and Kadan Aljoumaa. "A comparative dimensionality reduction study in telecom customer segmentation using deep learning and PCA." *Journal of Big Data* 7 (2020): 1-23. https://doi.org/10.1186/s40537-020-0286-0

[56] Etemad, Lily, Tai-Hsien Wu, Parker Heiner, Jie Liu, Sanghee Lee, Wei-Lun Chao, Mary Lanier Zaytoun *et al.,* "Machine learning from clinical data sets of a contemporary decision for orthodontic tooth extraction." *Orthodontics & Craniofacial Research* 24 (2021): 193-200. https://doi.org/10.1111/ocr.12502

[57] Ayon, Safial Islam, and Md Milon Islam. "Diabetes prediction: a deep learning approach." *International Journal of Information Engineering and Electronic Business* 12, no. 2 (2019): 21. https://doi.org/10.5815/ijieeb.2019.02.03

[58] Labani, Mahdieh, Parham Moradi, Fardin Ahmadizar, and Mahdi Jalili. "A novel multivariate filter method for feature selection in text classification problems." *Engineering Applications of Artificial Intelligence* 70 (2018): 25-37. https://doi.org/10.1016/j.engappai.2017.12.014

[59] Lee, Taehee, Eui Jin Hwang, Chang Min Park, and Jin Mo Goo. "Deep Learning-Based Computer-Aided Detection System for Preoperative Chest Radiographs to Predict Postoperative Pneumonia." *Academic Radiology* (2023). https://doi.org/10.1016/j.acra.2023.02.016