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REVIEW OF DISEASE IDENTIFICATION METHODS BASED ON COMPUTED TOMOGRAPHY IMAGERY

Methods and approaches to computational diagnosis of various pulmonary diseases via automated analysis of chest images performed with computed tomography were reviewed. Google Scholar database was searched with several queries focused on deep learning and machine learning chest computed tomography imagery analysis studies published during or after 2017. A collection of 39 papers was collected after screening the search results. The collection was split by publication date into two separate sets based on the date being prior to or after the start of the COVID-19 pandemic. Information about the size of the dataset used in the study, classification categories present in it, primary classification target, employed approaches and architectures, metrics used to judge the performance, and the values of those metrics were collected for each paper in the set of discovered studies. Full collected data, including the citation, on every paper was provided in two tables respective to their publication date being prior or after COVID-19. Popular methodologies with the best metrics were identified, outlined, and described. The selected methodologies were compared by their accuracies in various papers found during this study. The comparison table of the found accuracies was provided. A best-performing approach was selected based on the found accuracies. As of this review, ResNet, its variations, and the architectures built upon it have the most promising results, with VGG and Xception being close contenders. The complications with reviewing existing studies in the field are outlined, the most important of them being the diversity in the way that dataset size is described, as well as diversity in the metrics employed, making a comparison between many individual papers impossible or at least lowering the quality of such a comparison. Metrics commonly used to measure the performance of machine learning approaches used in the found studies are outlined and described. Further research direction is proposed, with an emphasis on multi-class classification, modularity, and disease progress prediction. This proposition is guided by finding that most of the studies found focus on single class classification. Additionally, almost none of the studies discuss disease progression, and almost all of the studies discuss rigid solutions which are hardly extendable for future diseases and other classification methods.
Keywords: Computed tomography image analysis, Neural networks, Deep learning, COVID.

Introduction / Вступ

A series of uncommon pneumonia cases appeared in December of 2019 in Wuhan region of China. These cases were directly tied to a novel coronavirus, named COVID-19. After a worldwide spread of this disease, it was declared a pandemic by WHO. As of early February 2024, more than 7 million cases resulting in fatal outcomes, out of approximately 770 million registered [1].

The relevance of the research – is defined by the critical need to achieve optimal medical care performance under conditions of extreme overload at times of big disease outbreaks. An increase in patient admission speed with partially automated diagnosis tools is one of perspective ways of such optimizations.

The object of the study – is the process of automated lung disease recognition.

The subject of the research – are methods of automated lung disease recognition based on computed tomography imagery processing.

The purpose of this research – is to determine the most perspective approaches towards the computed tomography based disease classification.

To achieve this purpose, the following main *research objectives* are identified:

- collect data about existing research in the field;
- determine most popular and effective methods employed;
- define requirements and parameters for disease classification systems based on chest CT imagery.

Computed tomography is a radiology method that is utilized for non-invasive diagnosis via high-quality imagery of patient's body. Using this method, imagery is obtained via scanning the patient's body with X-Ray in a gradual and layered way, and algorithmically processing the information received from X-Ray sensors on the opposite side of patient's body from the emitters.

Result of a CT scan is a three-dimensional layered image of patient's internals, with layer thickness varying from 1.5 mm to 10 mm, and level of detail varying in relation to X-Ray emitter strength used in process of making the scan. These variables are set based on the aim of the diagnosis and a particular patient – emitter strength can be reduced for children and pregnant women, resulting in a low-dose CT-scan.

Computed tomography imagery is one of the primary methods of pulmonary disease diagnosis, since it results in a three-dimensional image, the flexibility of its acquiring process for a particular disease and patient, and also gives an ability to build arbitrary projections of patient's body.

Analysis of literary sources. The search for literary sources was conducted in Google Scholar with queries "Chest CT deep learning", "Chest CT automated diagnosis" and "Chest CT prediction" with a publication time filter set from January 2017 to September 2023. A total of 39 existing works were found. For those, the target disease, employed method, dataset size, evaluation metrics achieved, and dataset classes were collected. The papers were sorted into two time buckets:

- before COVID-19;
- after COVID-19.

Comprehensive list of found papers including collected information is presented in Tables 1 and 2. Of 39 found papers, 12 were released before the start of COVID-19 pandemic. Of them, 7 are related to identification and classification of lung nodules and lung cancer, 2 with pneumothorax search, 1 to tuberculosis identification and 1 to emphysema. The final one is describing a method of segmenting the imagery. 27 of 39 papers were released after the start of the COVID-19 pandemic, with 25 papers regarding COVID-19 identification, 1 working on tuberculosis diagnosis and 1 on lung cancer.

Table 1. Papers published before COVID-19 pandemic / Дослідження, опубліковані до пандемії COVID-19

Year, Ref.	Target disease	Method	Dataset size	Metrics used	Data classes
2017 [2]	P.T.	AlexNet GoogLeNet	1007	AUC=99 %	Lung tuberculosis and healthy
2017 [3]	L.C.	Unknown	48	ACC=64.6 % AUC=64.6 %	Not listed
2017 [4]	Sg.	CNN	240	ACC=88 %	CT imagery in general
2018 [5]	L.N.	Modified ResNet50	Unknown	ACC=91.6 % AUC=95.7 %	Benign/malignant lung nodules
2018 [6]	L.N.	Method comparison	43 292	AUC=92–99 %	Nodules and no nodules
2018 [7]	L.N.	DetectNet YOLO	1018	ACC=93 %	Nodules and no nodules
2019 [8]	Pt.	CNN	80	Sensit.=100 % Specif.=83 %	Pneumothorax and healthy
2019 [9]	L.C.	Unknown	1139	ACC=94.4 %	Cancer/healthy
2019 [10]	Pt.	CNN YOLO	1596	ACC=86–87 %	Different pneumothorax stages
2019 [11]	L.N.	CMixNet	888	Sensit.=94 % Specif.=91 %	Benign/malignant lung nodules
2019 [12]	Em.	CNN LSTM	7143	Unknown	Different emphysema types
2019 [13]	L.C.	3DDCNN	55	ACC=98.51 %	Healthy, benign, malignant nodules

Table 2. Papers during and after COVID-19 / Дослідження, опубліковані після початку пандемії COVID-19

Year, Ref.	Target disease	Method	Dataset size	Metrics used	Data classes
1	2	3	4	5	6
2020 [14]	CVD	Unet WeakLabel	499	ACC=90 % AUC=95.9 %	COVID-19 and non-COVID-19
2020 [15]	CVD	ResNet-50 Xception Inception-v3, VGG16	3993	Sensit.=99 % Specif.=100 % ACC=99.8 %	COVID-19, other pneumonias, non-pneumonia illnesses
2020 [16]	CVD	DenseNet ResNet	812	F1=90 %, AUC=98 %, ACC=89 %	COVID-19 and non-COVID-19
2020 [17]	CVD	VGG-16 ResNet DenseNet EfficientNetCRNet.	349	F1=85 % AUC =94 %	COVID-19, other diseases, healthy
2020 [18]	CVD	2D ROI GradCam	110	AUC=94.8 %	COVID-19 and non-COVID-19
2020 [19]	CVD	Unknown	14.435	F1=97 %	COVID-19 and other pneumonias
2020 [20]	L.C.	AlexNet	Unknown	ACC=97.2 %	Not listed
2020 [21]	CVD	ImageNet	610 patients	ACC=98.5 %	COVID-19, other virus and bacterial pneumonias, pulmonary tuberculosis

Continuation of the **Table 2**

1	2	3	4	5	6
2020 [22]	CVD	ResNet50	6868 images 400 patients	ACC=95.6 %	COVID-19 and healthy
2020 [23]	CVD	DenseNet3D MNas3DNet ResNet3D	3.993	ACC=87.1 %, F1=87.25 %, AUC=95.7 %	COVID-19, other pneumonias, healthy
2020 [24]	CVD	ResNet50	720	ACC=92.2 %	COVID-19 and non-COVID-19
2020 [25]	P.T.	CNN	1002	Recall=98 % Precis.=94 %	Tuberculosis and healthy
2020 [26]	CVD	Efficient Net	544	ACC=89.7 %, F1=89.6 %, AUC=89.5 %	COVID-19 and others
2021 [27]	CVD	COVID-Net, modified	13.975	ACC=94.3 %	COVID-19, other virus and bacterial pneumonias, pulmonary tuberculosis
2021 [28]	CVD	Efficient NetB3	7184	AUC=95 %	COVID-19, other virus and bacterial pneumonias, pulmonary tuberculosis
2021 [29]	CVD	CNN	3228	ACC=99 %	Available datasets SARS-CoV-2 CT-scan and COVID19-CT
2021 [30]	CVD	ResNet50	2592	Specif.=92 % Sensit.=93 %	COVID-19 and others
2021 [31]	CVD	CNN	465	Not listed	COVID-19
2021 [32]	CVD	VGG-16 ResNet50 Xception	SARS-CoV-2 CT dataset	ACC=98.79 % accuracy F1-score of 0.99	SARS-CoV-2 CT dataset
2021 [33]	CVD	Differential architecture search	3.993	ACC=88-96 % for diff. architectures	Unstated readily available datasets
2022 [34]	CVD	VGG, ResNet	757	ACC=99.35 %,96.77 %	COVID-19 and non-COVID-19
2022 [35]	CVD	Inception ResnetV2	2,471	ACC=96 %	COVID-19 and non-COVID-19
2022 [36]	CVD	SeNet154	31590	ACC=98 %	COVID-19, other pneumonias, healthy
2022 [37]	CVD	P-DenseCOVNet.	2.698	ACC=87.5 %	COVID-19, other pneumonias, healthy
2022 [38]	CVD	CVD19-Net	13216	ACC=98 %	COVID-19 and non-COVID-19
2023 [39]	CVD	DarkNet19, MobileNetV2	2482	ACC=98 %	COVID-19 and non-COVID-19
2023 [40]	CVD	RADIC	2482	ACC=99 %	COVID-19 and non-COVID-19

where:

- L.N. – lung nodule classification;
- P.T. – pulmonary tuberculosis identification;
- Pt. – pneumothorax identification;
- L.C. – lung cancer identification;
- Sg. – imagery segmentation;
- Em. – emphysema;
- CVD – COVID-19.

Research results and their discussion / Результати дослідження та їх обговорення

As would be expected, year 2020 had a peak in publications regarding automated disease recognition using chest CT images. As illustrated on Fig. 1, there has been a steady decline of interest to the topic since the peak in 2020.

All the found papers employ deep neural networks for their identification purposes, specifically – CNN's – convolutional neural networks, of such architectures:

- DenseNet – convolutional neural network architecture, that employs DenseBlocks that directly connect all convolutional layers of the network between each other's, aiding reuse of learned features between different layers of the network, and leads to generally smaller neural networks while keeping the efficiency the same [41].
- ResNet – convolutional neural network architecture, that employs jumper connections between one or several layers, aiding information pass-through to deeper layers, helping treat various phenomena that arise with deepening the neural network [42].
- VGG – convolutional neural network architecture that uses a step-by-step narrowing of the layers to achieve deeper networks while reducing the amount of parameters in the system and improve the discriminatory ability of the decision function [43].
- Xception – convolutional neural network architecture that is based on using depthwise separable convolution, that, in difference to a common convolution, separates the calculation into two steps – depthwise convolution per input channel and dot convolution to create a linear sum of convolution's output [44].

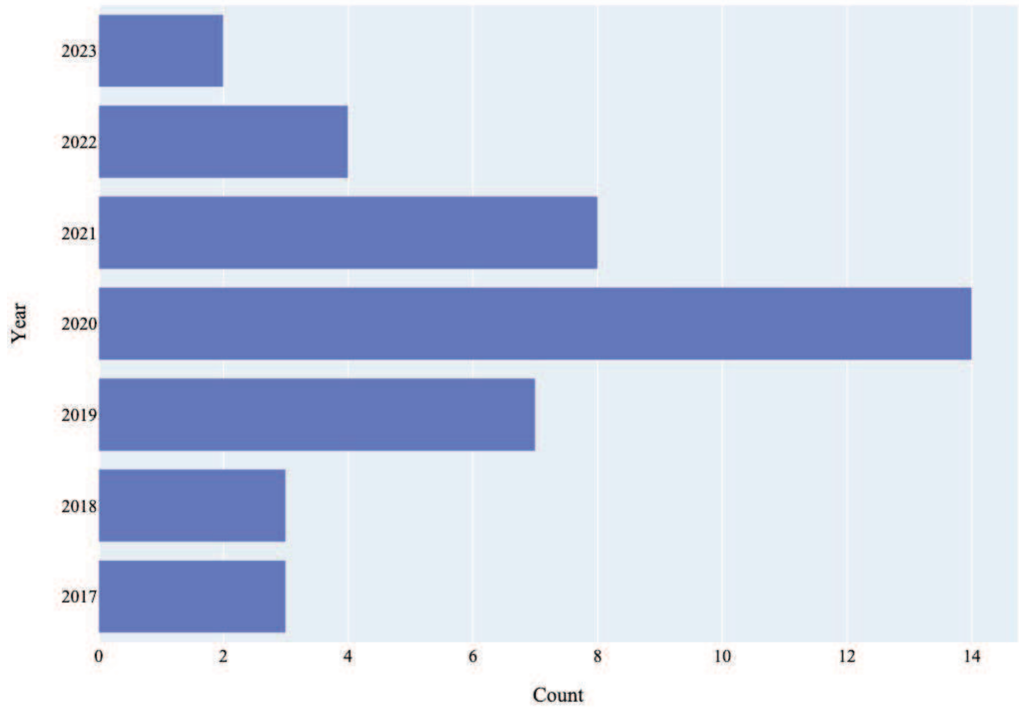

Fig. 1. Amount of works on the topic of chest CT based disease recognition per year / Кількість знайдених робіт на тему розпізнавання захворювань за знімком КТ, розподілена за роками

- EfficientNet – convolutional neural network architecture and method of scaling networks that is scaling depth, width and resolution using a compound coefficient. This architecture differs from common ones with scaling the parameters not in an arbitrary way, but with fixed coefficients [45].

Found accuracies for the above architectures are displayed in Table 3. Of discovered methods, 8 used exclusively or in combination with other architectures, the ResNet architecture, with mean AUC of 95 % and mean accuracy of 93 %, that marks this architecture as worthy of interest

Table 3. Accuracies, achieved with most popular neural network architectures across found works / Точність, досягнута найпопулярнішими архітектурами нейронних мереж згідно із виявленими статтями

Method	DenseNet, %	ResNet, %	VGG, %	Xception, %	Efficient Net,%
Achieved accuracies	88; 83	93; 97; 92.2; 86; 87; 99	87; 98; 76; 99	97; 90; 96	89; 77; 79;

An additional paper, not mentioned in search results, but deserving special attention nonetheless is a letter by Elyas Mahjoub et al. [46], that describes a simple hand-calculated scoring method that provides a remarkably reliable (odds ratio 44.243, 95 % CI 8.609-227.365, $p<0.001$) way of predicting 5-day outcome of COVID-19 pneumonia.

Direct comparison between the found works is complicated by two factors. Works may employ either 2D or 3D analysis – looking at specific slices of CT image, or looking at the image in it's entirety. Thus, the dataset sizes are described either as amount of 3D images overall, the amount of patients in the study, or the amount of individual slices used to train and evaluate the neural networks.

The articles also employ a variety of metrics to evaluate their network, which makes direct comparison between network performance across some works impossible. Of 39 works, 20 are using accuracy (1) as their metric, 11 are using AUC (area under Receiver Operating Characteristic curve) [47], 4 are using sensitivity (2) and specificity (3), 5 are using F1-score (4) and only one is using precision (5) and recall (6).

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN}, \tag{1}$$

$$sensitivity = \frac{TP}{TP+FN}, \tag{2}$$

$$specificity = \frac{TN}{TN+FP}, \tag{3}$$

$$F1 = 2 \times \frac{precision \times recall}{precision + recall}, \tag{4}$$

$$precision = \frac{TP}{TP+FP}, \tag{5}$$

$$recall = \frac{TP}{TP+FN}, \tag{6}$$

where TP – true positive, FP – false positive, TN – true negative, FN – false negative.

Most of works found were aimed at binary classification for COVID-19 pneumonia presence or absence, employing a dataset consisting of images only with either healthy lungs, or lungs damaged by COVID-19 pneumonia.

Discussion of research results. As a result of the analysis of found works the following problems were identified:

1. Lack of a singular classification quality metric;
2. Omittance towards methods other than neural networks in the discussion in general;

3. Varying methods of dataset composition and size description.

Thus, based on the performed analysis, to facilitate classification quality and statistical significance of results we can define such requirements and parameters for disease classification systems:

1. Minimum dataset size should be at least 200 patients (as 3-dimensional DICOM images, or equivalent sequential 2-dimensional slices amounting to no less than 30 per patient);
2. For multiclass classification, all the classes should be fairly represented in the dataset;
3. Prominent and common metrics should never be omitted so that the results are comparable to existing studies.

It should also be noted that interest should be taken in reproducing and improving upon works by Hoon Ko et al. [15], Xuehai He et al. [17], Qianqian Ni et al. [19], Min Fu et al. [21], Xin He et al. [23], Matthias Fontanellaz et al. [27], Mehdi Yousefzadeh et al. [28]. These works employ data, that includes other lung diseases aside the target disease – most often the third class in the study is community acquired pneumonia. Networks, trained on such datasets are, arguably, more stable and more applicable real-life use and augmentation for other diseases, including future ones.

So, based on the results of the work performed, it is possible to formulate the following scientific novelty and practical significance of the research results.

The scientific novelty of the obtained research results – constituted by drawn attention to main problems of research result comparison, and outlined necessity for research result unification to aid in research reproducibility and further studies.

The practical significance of the research results – is the defined state of the art, as well as the result generalization in the field of disease recognition based on CT imaging, and the ascertainment of lack of unified result metrics and lack of multi-class classification studies.

Conclusions / Висновки

Review results lead us to conclude that research direction of automated analysis of CT imagery is quite a developed one. A big flow of attention was given to it after COVID-19 pandemic started, provoked by a big deficit of virus presence test systems. Nonetheless, a notable marker of direction's development is the availability of systems that reliably discriminate between different illnesses.

As simple classification is a well-researched topic, it is deemed perspective to approach disease progression prediction, also considering factors like patient age, presence of chronic diseases, etc. Also, a perspective direction would be building ensemble systems to achieve a complete diagnosis and scoring system.

Another interesting note is that methods other than convolutional neural networks are not present in the discourse, which may show either their non-expediency or that there is space for further research with non-CNN methods.

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ОГЛЯД МЕТОДІВ ІДЕНТИФІКАЦІЇ ЗАХВОРЮВАНЬ ЗА ДОПОМОГОЮ ЗНІМКІВ КОМП'ЮТЕРНОЇ ТОМОГРАФІЇ

Розглянуто методи та підходи до комп'ютерної діагностики різних захворювань легень на підставі автоматизованого аналізу знімків комп'ютерної томографії. Виконано пошук в базі даних Google Scholar за кількома запитами на тему аналізу знімків комп'ютерної томографії за допомогою глибокого навчання та машинного навчання серед статей, опублікованих протягом або після 2017 р. Після відсіювання результатів пошуку сформовано набір із 39 статей. Набір даних розділено за датою публікації на дві категорії: до та після початку пандемії COVID-19. Для кожного дослідження в отриманому наборі зібрано інформацію про розмір використаного набору даних, захворювання, які містяться у ньому, основну ціль класифікації, застосовані підходи та архітектури, метрики, використані для оцінювання результатів, та значення цих метрик. Надано повну інформацію про кожну зі статей у наборі, разом з посиланням. Інформацію наведено в двох таблицях, залежно від публікації до чи після появи COVID-19. Визначено, описано та порівняно популярні методології із найкращими показниками. Вибрані методології порівняно за отриманим показником точності, наведеним у відповідному дослідженні. Надано порівняльну таблицю одержаних показників точності. Вибрано найперспективніші з досліджених у розглянутих статтях методологій за показником точності. На момент укладання цього огляду ResNet його варіації та архітектури, побудовані на його основі, мають найкращі результати, а VGG та Xception є близькими конкурентами. Описано складнощі з оглядом наявних досліджень у цій галузі, найважливішими з яких є різноманітність у способі опису розміру набору даних та виборі метрик оцінювання результатів, що ускладнює порівняння багатьох окремих статей або принаймні погіршує якість такого порівняння. Описано та розглянуто метрики, які часто використовують для вимірювання результативності методів машинного навчання, застосованих у знайдених дослідженнях. Запропоновано напрям подальших досліджень з акцентом на класифікацію з багатьох класів, модульність та прогнозування прогресу захворювання. Запропонований напрям обґрунтовано тим, що більшість виявлених досліджень зосереджені на класифікації за одним класом. Також практично жодне з досліджень не аналізує прогрес захворювання, а майже всі дослідження розглядають жорсткі рішення, малопридатні для розширення з метою підтримки майбутніх захворювань та інших методів класифікації.

Ключові слова: аналіз знімків комп'ютерної томографії, нейронні мережі, глибоке навчання, коронавірус, COVID.

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