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Deep Learning methodologies for diagnosis of respiratory disorders from chest X-ray images: A comparative Study

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CONTENTS

ABSTRACT

- Chest radiography needs timely diseases diagnosis and reporting of potential findings in the images, as it is an important diagnostic imaging tests in medical practice.
- A crucial step in radiology workflow is fast, automated and reliable detection of diseases created on chest radiography.
- To overcome this issue, an artificial intelligence-based algorithm such as Deep learning (DL) are promising methods for automatic and fast diagnosis due to their excellent performance analysis of a wide range of medical images and visual information.
- This paper surveys the DL methods for lung disease detection from chest X ray images.
- The common five attributes surveyed in the articles are data augmentation, transfer learning, types of DL algorithms, types of lung diseases and features used for detection of abnormalities, data augmentation, transfer learning, and types of lung diseases.
- The presented methods may prove to be extremely useful for people to ideate their research contributions in this area.

INTRODUCTION

- Deep learning (DL) methods have achieved a tremendous growth in the last decade in the area of various computer vision applications such as classification of medical and natural images [3].
- This led to the development of deep convolutional neural networks (CNNs) for the diagnosis of respiratory diseases based on chest radiography.
- The computer-based diagnosis of respiratory diseases consists of the detection of pathological abnormalities, followed by their classification.
- The challenging task is the automated abnormality detection on chest radiographs due to the diversity and complexity of respiratory diseases and their limited quality.
- On the chest radiographs, manual marking of abnormal regions needs even more labor and time than labelling it.
- Therefore, in many chest radiography data, the abnormalities are masked [4], which lead to the computer-aided diagnosis task to a weakly supervised problem by showing only the names of abnormalities in each radiograph without their locations.

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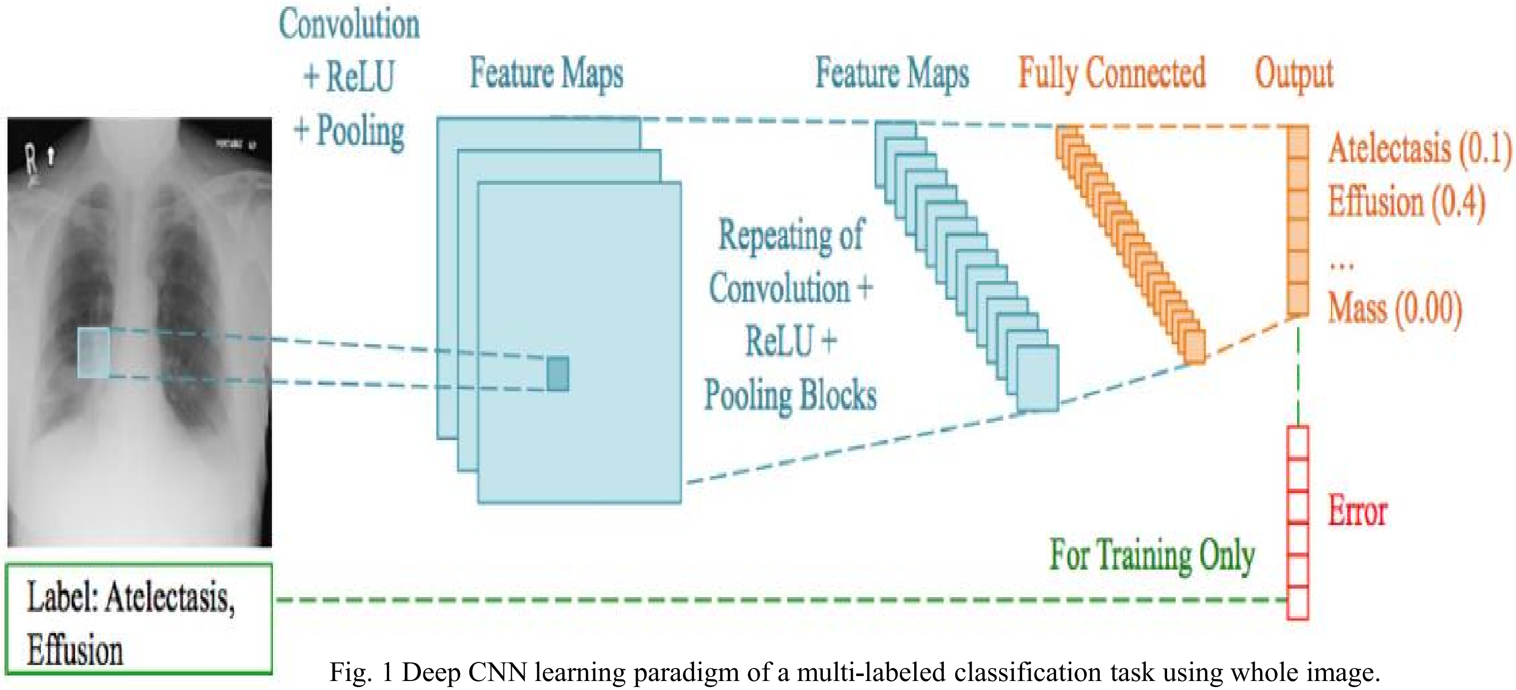

Fig. 1 Deep CNN learning paradigm of a multi-labeled classification task using whole image.

- Fig.1 describes a generalized manner in which Deep Neural Networks process data and classify images.
- In turn, these improvements support clinicians in classification and detection of certain medical conditions in a more efficient way [7].

OBJECTIVES

- To provide a comparison of the state-of-the-art DL based respiratory disease detection methods and also identifying the issues in this direction of research.

METHODOLOGY

- A total of five attributes, which the authors found to be present commonly and imminent in the majority of the articles, are identified and discussed in detail.

- These attributes are :

1. Types of DL algorithms,
2. Features used for detection of abnormalities,
3. Data augmentation,
4. Transfer learning, and
5. Types of lung diseases.

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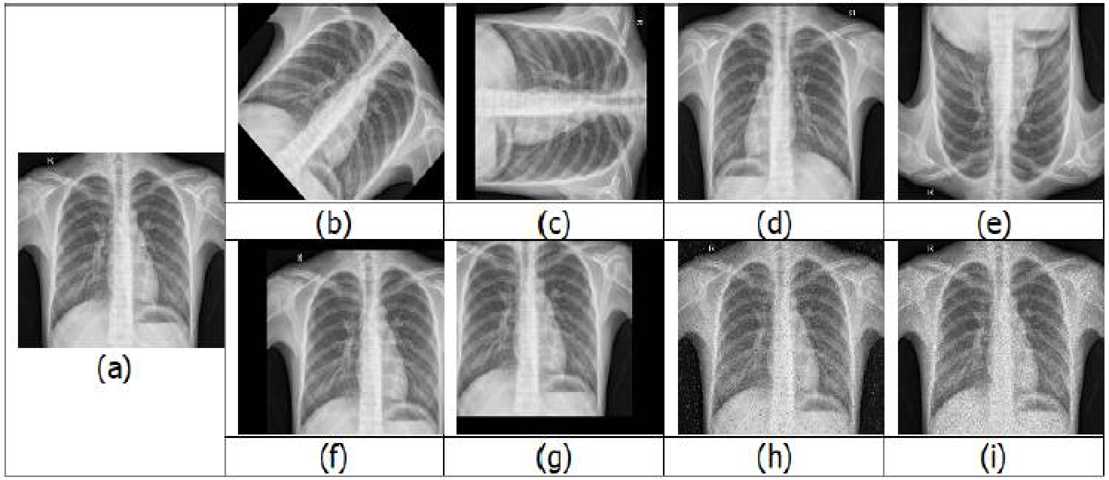

Fig. 2 Examples of image augmentation: (**a**) original; (**b**) 45° rotation; (**c**) 90° rotation; (**d**) horizontal flip; (**e**) vertical flip; (**f**) positive x and y translation; (**g**) negative x and y translation; (**h**) salt and pepper noise; and (**i**) speckle noise.

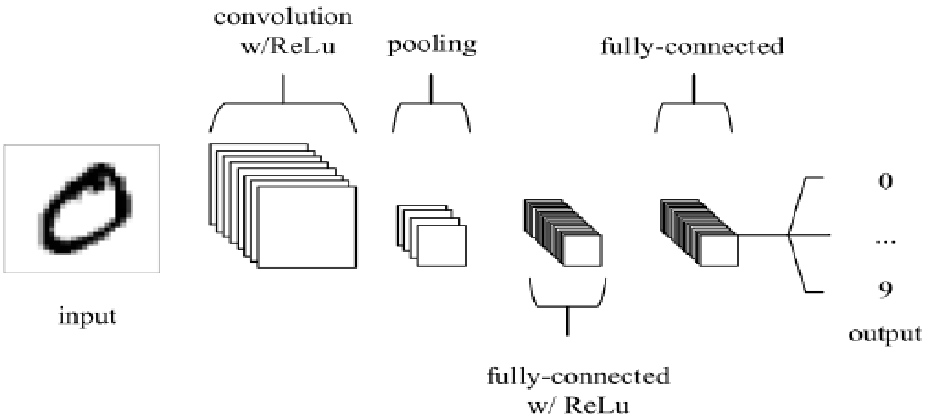

Fig. 3 Example of a CNN structure

Issues Observed In The Present Area Of Research

- The main issues that were observed during this study were: (a) data imbalance (b) handling of images with large size and (c) limitation of datasets that can be used.

(a) **Data imbalance:** It is of paramount importance that there are similar number of 1 images for each class. If this condition is not satisfied, then the trained model would tend 2 to be more biased towards the class that has more amount of data. This can be disastrous 3 in medical applications. 4

(b) **Handling of images with large size:** It is usually computationally expensive to 5 work with high resolution data. For this purpose, researchers tend to reduce the size of 6 the original images to counter this. Even with the use of powerful GPUs, training a DL 7 architecture is quite time consuming.

(c) **Limitation of datasets:** To obtain extremely accurate results, it would be desirable 9 to have thousands of images for each class that the images need to be classified into. But 10 in real life situations, the number of images available for training is less than ideal.

CONCLUSION

- The presented study is an attempt to summarize and provide, in an organized manner, the key focus and concepts used for the detection of lung diseases through DL methodologies.
- A taxonomy of the state-of-the-art methodologies for this purpose is presented.
- Along with these three issues that might hinder the progress of research in this area are also put forward, namely, data imbalance handling of images with large size and limitation of datasets.
- The authors strongly feel that in order for the research of this topic to progress in the right direction, such an investigative study would be helpful for other researchers who might be keen to contribute to this field.

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