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Leveraging Convolutional Neural Networks for the identification of Pneumonia

Project Proposal

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CMP6228 - Deep Neural Networks

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Word count excluding figures, references and appendices: XXXX / 1500

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Introduction

In this report, a novel solution is proposed to address a significant data science problem in the medical field, in the form of a deep neural network to accurately identify the presence of pneumonia from an image of a chest X-ray. To do so, this neural network will be trained on a publicly available dataset that has been previously seen across many publications, and advanced techniques for the model will be discussed.

This proposal will specifically cover the motivation behind this project before exploring related literature and previous works in great depth. To conclude, an optimal model will be proposed based on the knowledge extracted from these related works.

Motivation and objectives

1.1 Subject area

Pneumonia is a lower respiratory tract infection (LRTI) commonly caused by viruses or bacteria wherein the alveoli of the lungs become clogged with pus and fluid, which can be life-threatening in people of any age, but especially in children and the elderly (NHS, 2017). The World Health Organisation (WHO) state that pneumonia is the single largest infectious cause of death in children, killing 808,000 children under the age of 5 in 2017 (WHO, 2025). Furthermore, even if pneumonia is survived during the initial infection, Allinson et al. (2023) studied that those who contract the condition as a child are 93% more likely to die from respiratory diseases later in life than those who did not.

It is therefore imperative that recent technological advancements are leveraged for the quick diagnosis of the infection to allow swift treatment to avoid life-threatening consequences, both in the short-term and long-term.

1.2 Dataset choice

The chosen dataset is sourced from the Mendeley data repository (Mendeley, 2025), uploaded and created by Kermany et al. (2018, p.1127) in their research of the applications of neural networks for medical diagnoses. The dataset contains 5,856 images of chest X-ray scans of children taken from the Guangzhou Women and Children's Medical Center in China, and is 1.18GB in size. Kermany et al. (2018, p.e1) state that the data was heavily screened and scrutinized for confirmation before labelling, which was done by removing low quality or unreadable images, and then consulting two expert physicians before labelling the images. The physicians' labelled set was then presented to a third expert, who confirmed their validity. Because of this, there is absolute certainty in the authenticity and validity of the data itself as well as its ground truth labels. There are only two classes of images: those with pneumonia and those without, as depicted by Figures 1.1 and 1.2.

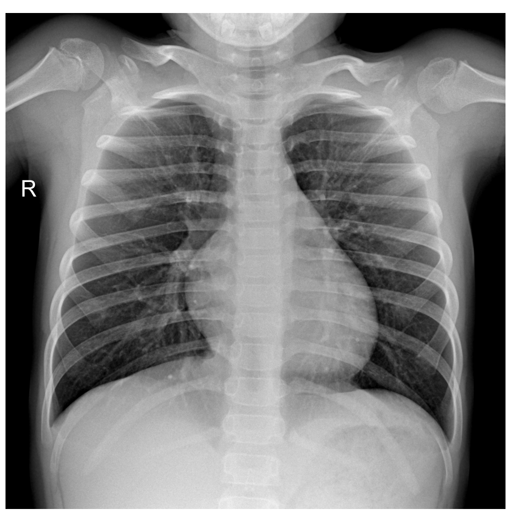

Figure 1.1: A sample image without pneumonia.

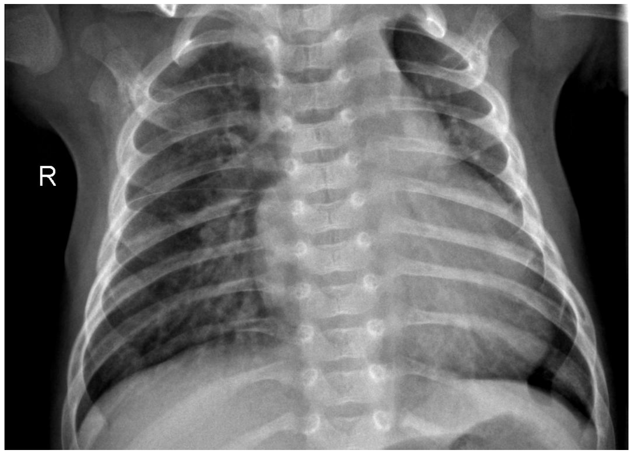

Figure 1.2: A sample image with pneumonia.

1.2.1 Potential issues

The dataset has already been pre-emptively split into training and testing sets, which saves having to perform a manual split. However, the data itself is not immediately usable and will require further preprocessing before being used to train a model, namely due to the following issues:

- Images are different resolutions.
  - The sample images vary widely in resolution, with some being substantially higher than others. The neural network's input layer will be fixed in size, meaning all input data must be the same size or the network will be unable to process it. This can be addressed programmatically using Keras to automatically resize all images to a given resolution.
- Class imbalance
  - The training set contains 1,349 samples of patients without pneumonia, but 3,883 samples of patients with pneumonia. This will lead to the model favouring those with pneumonia rather than the underrepresented class of those without. This can be addressed using the techniques discussed in Appendix A.

1.3 Data science problem

This dataset poses a clear data science problem pertaining to the binary classification of these images which will be addressed through the development of a convolutional neural network image classification model leveraging supervised learning. The ground truth is present within the dataset through its file structure[1], shown below:

```
.
`-- chest_xray/
    |-- test/
    |   |-- NORMAL/
    |   |   |-- NORMAL-4512-0001.jpeg
    |   |   |-- NORMAL-11419-0001.jpeg
    |   |   `-- ...234 more images
    |   `-- PNEUMONIA/
    |       |-- BACTERIA-40699-0001.jpeg
    |       |-- VIRUS-4190128-0001
    |       `-- ...388 more images
    `-- train/
        |-- NORMAL/
        |   |-- NORMAL-28501-0001.jpeg
        |   |-- NORMAL-32326-0001.jpeg
        |   `-- ...1347 more images
        `-- PNEUMONIA/
            |-- BACTERIA-7422-0001.jpeg
            |-- VIRUS-12220-0001.jpeg
            `-- ...3881 more images
```

Files of the appropriate class are stored in the relevant subfolder[2]. When this dataset is loaded, it will be possible to assign the relevant label to each image based on its subfolder of origin. Note that while there are separate files for bacterial and viral pneumonia, an analysis of other works using this dataset, seen in Chapter 2, indicated that this will not be an issue.

[1]Because Kermany et al. (2018)'s work was not only on pneumonia, the Mendeley ZIP file contains two separate datasets. This proposal is only for the "chest_xray" dataset.

[2]Shown file names are given as examples, and are not in the direct order they appear in the folders.

Related work

2.1 Introduction

This section of the report aims to demonstrate the main concepts of related techniques that have been previously used to solve the problem through a thorough review of surrounding literature.

2.2 Traditional machine learning methods

Traditional machine learning methods such as Random Forests, K-Nearest Neighbours and Support Vector Machines have previously been leveraged for pneumonia classification as seen in the works of Ortiz-Toro et al. (2022). They state that leveraging these traditional approaches alongside the creation of handcrafted textural features 'offers good performance with very low computational complexity', as seen in their results wherein they attained an F1-Score of 93%.

However, leveraging traditional methods on detailed image datasets such as Kermany et al. (2018)'s relies upon manual feature engineering of textural features, which can unintentionally introduce bias. Dataset bias can significantly harm the generalisation capabilities of produced models (Selvaraju et al., 2017). This is because it is possible that the new data given to a deployed model would differ from the preset features used on the original dataset, which a biased model would be unable to accurately predict, unlike deep learning methods which can automatically interpret features without manual intervention.

Furthermore, some researchers such as Pin Wang, Fan and Peng Wang (2021) have leveraged both traditional and deep learning techniques on other unrelated datasets, wherein they discovered that the Support Vector Machine they used had an accuracy 10% lower than a convolutional neural network on a large dataset, though actually had an accuracy 3% higher on a smaller dataset. They also note, however, that deep learning methods have massively longer training times than traditional counterparts.

2.3 Deep Neural Networks

Proposed model

"This section should demonstrate the suitability of the proposed solution in solving the data science problem"

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Appendix A - Class imbalance