THE UNIVERSITY OF SYDNEY

Project Report for ENGG2112

A Machine Learning Approach for Faster Pneumonia Diagnosis in Clinical Applications

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1 Executive Summary

Pneumonia is an infectious respiratory disease leading to impaired breathing and oxygen-conversion due to the action of bacterial, viral or fungal pathogens [1]. With over 1.5 million active cases worldwide [2] and a community-acquired rate of 1.4 every 10 000 positive diagnoses [3], Pneumonia imposes significant socioeconomic burdens on healthcare systems. In Australia alone, it is the 6th leading cause of death [4] and is the largest contributor to infectious infantile deaths globally [5], claiming over 190 000 'preventable' infantile deaths globally [5]. Conventional diagnostics involve monitored CT scans managed by specialists [6], demanding larger healthcare framework of instrumentation staff, doctors, hospitals and a line of care ultimately delaying the time between scanning and diagnosis. This highlights the need for a more effective and accessible alternative pivotal for rural and remote areas where timely access to healthcare is difficult.

Our multidisciplinary team brings forth Biomedical, Civil and Software Engineering expertise to formulate a machine learning (ML) solution for the time-efficient diagnosis of pneumonia. The primary objective of improving diagnostic healthcare outcomes implements core Biomedical Engineering principles of data collection and underlying physiology complemented by the technical expertise of the Software stream members for ML implementation. A consideration of social studies and public infrastructure is enabled by the Civil angle. The report outlines the development of a low-cost, non-intrusive diagnostic tool which quickens pneumonia detection, alleviating dependence on specialists to improve time efficiency.

A dataset of 5856 infantile chest X-ray images were surveyed, implementing Gabor filters and Principal Component Analysis (PCA) for feature extraction given the numerically ambiguous nature of image data. To handle improper image formatting and augmentation, data pre-processing techniques involving normalisation and others were implemented. A 90:10 train-test split and 5 to 16-fold cross validation was used to test a variety of image-specific ML algorithms, including K-Nearest Neighbour and Convolutional Neural Networks (CNNs) respectively. Several difficulties were encountered; such as unexpected accuracy losses with pre-processing techniques and large dimensionalities, yet the high performance outcomes of testing demonstrate the novel practicality of the ML approach and the ability to reshape pneumonia detection and diagnosis. The overarching accuracies of the models are promising, though future developments may seek to improve their functionality by integrating a cloud-based approach, using higher resolution models and expanding dataset training to diagnose a wider range of respiratory pathologies. Overall, the defined ML approach aims to make pneumonia diagnosis more accurate, efficient and accessible through continuous innovation, enabling faster intervention and ultimately improving patient healthcare outcomes and quality of life.

Contents

2 Background and Motivation

This project is focused on leveraging machine learning (ML) modalities to develop a robust classification model for the diagnostic prediction of pneumonia. Pneumonia, is an infectious respiratory disease that is characterised by inflammation and fluid accumulation in the lungs, and is caused by bacterial, viral, or fungal infections. Despite advancements in the thriving healthcare systems, pneumonia remains the most prevalent cause of mortality among infectious diseases, contributing to approximately 3.2 million of the 56.4 million global annual deaths and accounting for 20% of paediatric fatalities [7]. The current diagnostic system for conventional pneumonia cases as endorsed by the World health organisation (WHO), is through computerised tomography (CT) scans which provide high diagnostic accuracy due to their high resolution cross-sectional image production.

However this requires efficient patient transportation to an accredited scan centre, sufficient equipment, highly skilled instrumentation staff, doctors, hospitals and a line of care, absent in low income regions such as rural India battling inadequate diagnostic tools and overwhelming patient volumes [8]. Seeking care for children with early pneumonia symptoms has declined in south Asia, middle East and North Africa [3]. Alternatively, widely used conventional radiographic imaging, such as chest X-rays (CXRs), which per [9] is generally a less intrusive and cost effective imaging modality, are limited in their ability to reliably detect and classify early-stage pneumonia. This limitation stems from their lower sensitivity in capturing subtle radiographic frequencies in faint lung opacities and soft tissue, which can delay accurate diagnosis and subsequent treatment. In fact as per [10] 31.8% of chest X-ray reports had inconclusive results with the overall sensitivity to detection ranging widely from 32% to 77.7%. This leads to delayed detection and preventable deaths increasing mortality rates by 6.1% [2]. The limitations of the above diagnostic approaches highlights the importance of a new method of pneumonia detection to improve diagnostic accuracy of chest radiography using feature extraction and deep learning.

Our feature set contains 5856 chest X-rays images divided into three categories of normal, bacterial and viral pneumonia to detect and classify early infection. A sample of the categories can be found in Figure below.

Figure 1: Normal vs Bacterial vs Viral Pneumonia

3 Objectives and Problem Statement

Can we use ML to create a low-cost, non-intrusive alternative for Pneumonia detection?

The project aims to quicken and enhance the diagnostic capabilities of current pneumonia detection to ultimately bridge the healthcare disparity facing remote and low-resourced regions. The individual and wider socioeconomic burden of poor access is undeniable, which our model aims to counter by offering a simple, low-cost alternative. Though the imaging dependence of screening cannot be immediately replaced by our solution, the integration of machine learning (ML) classification techniques such as K-Nearest Neighbors (KNN) and Convolutional Neural Networks (CNN) aim to elevate interpretive capabilities for faster pneumonia detection via scans in populations. Features are denoted by normalised vectors of opacity, shape, colour and others, within which some extracted features may remain implicit. By comparing features of Normal cases to morbid pathologies, the binary classification problem can be solved. Unlike conventional radiographic approaches, ML-driven models allow precise analysis of X-ray imaging, leveraging layers of pattern recognition to significantly improve early diagnostic outcomes.

Thus, the primary objective of our report is to develop an ML model that is able to simply survey a chest x-ray scan and provide a preliminary diagnosis. Current methods of radiographic diagnosis achieve a maximum accuracy of about 77.7% [2]. This project targets a higher accuracy setting a minimum acceptability threshold of 85% and targeting accuracies above 90%. This high target is set to particularly achieve early detection of pneumonia to prevent complications, thereby reducing the complexity of treatments and the length of stay in the hospital. This relieves pressure on healthcare systems in low income regions where clinical resources are outnumbered by patient volume. Key sub-objectives to reach this goal include:

1. Early Detection: Analyse patterns which indicate early onset of Pneumonia, subsequently classifying them as morbid.

2. Preliminary Diagnosis: Predict whether a patient has pneumonia based on the x-ray data.

4 Methodology

4.1 Data Pre-Processing

4.1.1 The Dataset

3.1.0. The Dataset The 'chest_xray' dataset is a comprehensive collection of 5856 total images, separated into 'train', 'test' and 'val' (validation) folders, each with 'Normal' and 'Pneumonia' pathology classes. The 'train' folder presents 1314 'Normal' samples and 3875 'Pneumonia' samples, whilst the 'test' folder presents 234 and 390 samples for the two respective categories. Further detail on the precise organisation of the data

Dataset Split	Normal	Pneumonia	
		Bacterial	Viral
Train	1314	3875 total	
Test	234	242	148
Validation	8	8	0

Table 1: Breakdown of dataset composition: Normal and Pneumonia categories.

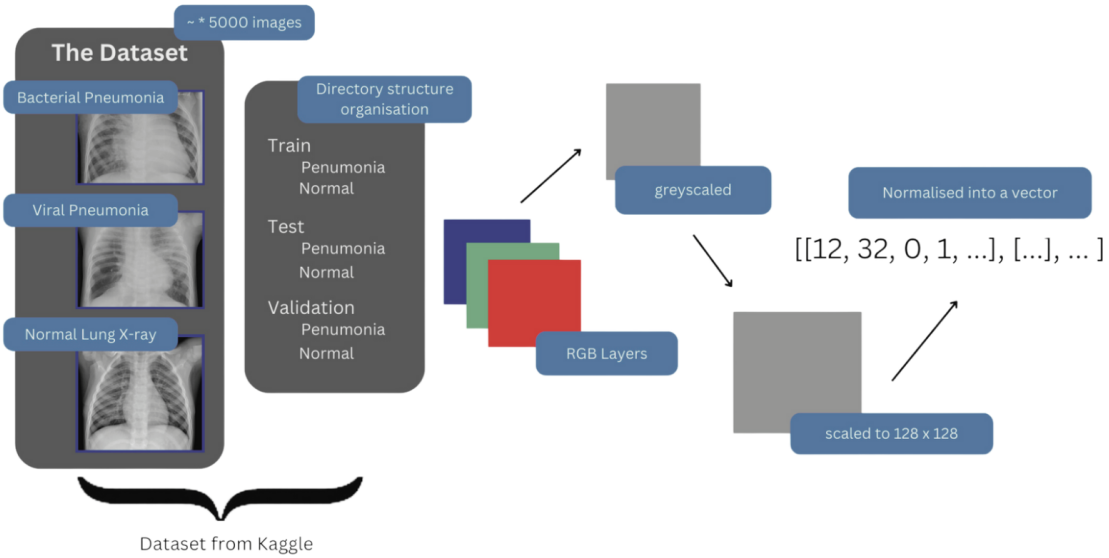

Figure 2: Data Pre Processing

Given the number and nature of images, an initial organisation split was computed:

$$\frac{totalno.pneumoniaimages}{totalno.ofimages} = \frac{624}{5189 + 624} = 90 : 10.$$

This demonstrates a 90-10 split, indicating a large training dataset which suits the requirements of image classifiers such as the KNN and CNN, as confirmed by [11]. Thus, the data organisation was deemed sufficient and further reorganisation was not undertaken.

Preliminary observation highlights several formatting issues requiring handling. The first is the varying image sizes of individual x-rays, requiring resizing to a standardised format for appropriate ML implementation. The second includes the removal of RGB colour channels to optimise streamlined pattern-recognition and reduce data size. The third is inspecting contrast and scan quality via quantitative means to ensure smoothing or sharpening of features is not required.

4.1.2 Resizing

Each chest x-ray image was of a different size, with the average pixel dimension being a 1800 x 1700 pixel vector. To obtain a standard size which could meet the computational demands of our personal computers and to finish the paper in appreciable time, we rescaled this to 128 x 128 pixels. The resizing logic was implemented within a data processing function, for which the pseudocode is outlined in Section 3.1.4.. This reduc-

tion in dimension lowered computational demands while preserving critical features for classification.

4.1.3 Grayscale Conversion

Each chest x-ray image is characterised by L (Left), R (Right), T (Top), B (Bottom) markings to indicate image orientation. Some of these markers are colour-coded for clear identification against the grayscale x-ray image, which varies across the scans. Such RGB channelling can interfere with the structure and pattern-recognition features of the implemented ML models. Thus, all images were converted to grayscale via .convert() functionalities, removing colour channels irrelevant to X-ray analysis. This eliminates potential inconsistencies which may arise from the colour variations, and further reduces data size to 33% of its original size; as the three channels of the RGB matrix are reduced to one grayscale channel.

4.1.4 Image Smoothing or Sharpening

Image smoothing and sharpening was initially considered to potentially enhance the pattern-recognition abilities of the ML models by maximising the quality of images via processing techniques. However, smoothing and sharpening were not applied after inspecting the dataset and functionalities of the intended models. The provided chest x-rays display excellent contrast with clear visible structural detail of the lung. The differences between normal and pneumonia-affected lungs are clearly visible due to distinct changes in opacity, shape and texture which are well-defined prior to filtering. The team identified the risk of losing intricate details via image processing techniques (e.g. Gaussian blurring) which could obscure diagnostically relevant details like fine lines or smaller opacities. Excessive sharpening could exaggerate boundary edges, potentially adding noise or artefacts that mislead the model rather than enhance its performance. The number of additional bodily landmarks are minimal in the x-rays, which further reduces the possibility of the model being confused. Retrospectively, deep-learning layers are designed to automatically learn feature hierarchies in images, with early convolutional layers acting as edge detectors, and contour and texture pattern recognition. This makes the application of these filters redundant for CNN.

Thus, the team decided to rely on the hierarchical feature recognition of the applied ML models, without additional changes to the image quality of the scans.

4.1.5 Pseudocode

4.2 Feature Extraction

Given the nature of image data, two main steps were taken using feature extraction techniques: Normalisation, Canny Edge Detection (KNN) and Gabor filters (KNN) to 1) transform the data into notable features, and Principal Component Analysis (PCA)

Algorithm 1 Load Images from Directory

```
Set IMAGE_SIZE to (128, 128)
Initialize empty lists: images, labels
for each class label in {NORMAL, PNEUMONIA} do
  Set label_path as subdirectory path for the label
  if label_path is not a directory then
    Continue to next label
  end if
  for each file in label_path do
    if file is a valid image format then
      Open and convert image to grayscale
      Resize image to IMAGE_SIZE
      Normalize pixel values to [0,1] and add to images list
      Append 0 for NORMAL, 1 for PNEUMONIA to labels
    end if
  end for
end for
return images, labels
```

to 2) reduce data dimensionality. Normalisation involves transforming x-ray image pixel values, ranging from 0 to 255, to the [0, 1] range by dividing each pixel by 255. This process ensures that all images are scaled identically, and linearised into a single vector for better KNN and CNN reception. Canny Edge Detection was implemented to recognise infection patterns that are typically diffuse and fuzzy, as in the case with viral pneumonia. Recognition of changes in texture and density are theoretically enhanced via this method. Similarly, Gabor filters were applied to capture texture and frequency patterns in lung tissue, useful to distinguish types of infections. Additional image extraction techniques, such as Histogram of Oriented Gradients (HOG) were considered, but not implemented as they focus on sharp edges and gradients which may overlook the subtle textural patterns of infection. Retrospectively, accuracy results after extraction were disappointing (see Section 4.1), prompting us to utilise the natural architecture of the KNN and deep-learning models for better classification. Pre-trained models like VGG or ResNet can be fine-tuned to recognise specific infection patterns with little labelled data (Normal v. Pneumonia), compared to manually engineering features for KNN.

For feature extraction in the CNN, we used several of the sklearn module's functions designed for this purpose, including feature1() and feature2(). These work on the principle of correlating each feature or set of features against the target variable(s), with different ways of expressing the statistical correlation. We chose to the parameters of these modules as follows: (a) randomly, (b) linearly increasing for 0 to 100, (c) linearly decreasing from 20 to 0.

4.3 Classification

As the isolated problem is one of binary classification utilising image data, K-Nearest Neighbour (KNN) and Convolutional Neural Network (CNN) Classifier methods were

trialled. The comparison of the two models via performance metrics, including but not limited to; cross validation scores, mean accuracy, Area-Under-the-Curve (AUC) score, Receiver-Operator-Characteristic (ROC) plot and the confusion matrix, was conducted to isolate the better model.

The infantile chest x-ray image data was fed using 90-10 train-test split. The second implemented parameter included a K-fold cross-validation test, enabling the repetition of the train-test split K times. This provides a robust evaluation of the model's performance by dividing the dataset into multiple subsets and training the model multiple times on these subsets.

4.3.1 K-Nearest Neighbours (KNN) Classifier

The KNN Classifier is a distance-based ML model used for classification tasks. The model operates by identifying the 'K' nearest data points in the feature space to a given target point, which is determined by a distance metric, typically Euclidean distance. The value of K is user-set and variations in distance metrics, such as Manhattan distance or Minkowski distance, can influence the results based on data distribution and dimensionality. For the purpose of pneumonia classification based on image data, the KNN is trialled due to its simplicity, interpretability and adaptability to distance metrics. Its flexibility with varying k-values enables effective adaptation to the unique features of X-ray data, with a capability to perform well with small datasets. Additionally, KNN supports multi-class classification, suitable for the 'Pneumonia' and '!Pneumonia' categories involved in this project. However, KNNs lack computational efficiency with large datasets, making application to high-dimensionality projects challenging. It also exhibits sensitivity to noise, which can result in misclassification if given lower quality scans. CNNs are thus preferred for their ability to automatically learn relevant features and have custom software architecture to handle complex data better.

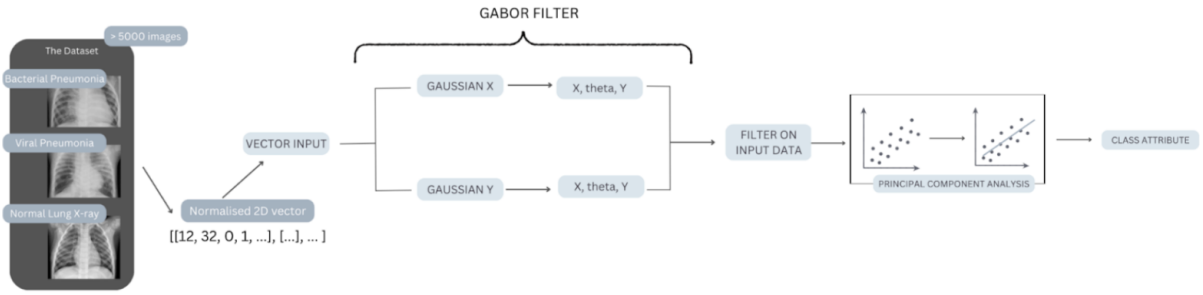

Figure 3: Sequential KNN Structure.

4.3.2 Convolutional Neural Network (CNN) Classifier

A CNN is a deep learning model specialised in processing image data by automatically detecting patterns, edges, and textures. For this pneumonia classification project, a CNN was used because it excels at analysing complex medical images, like chest X-rays, and identifying subtle features linked to pneumonia, ensuring high accuracy in diagnosis.

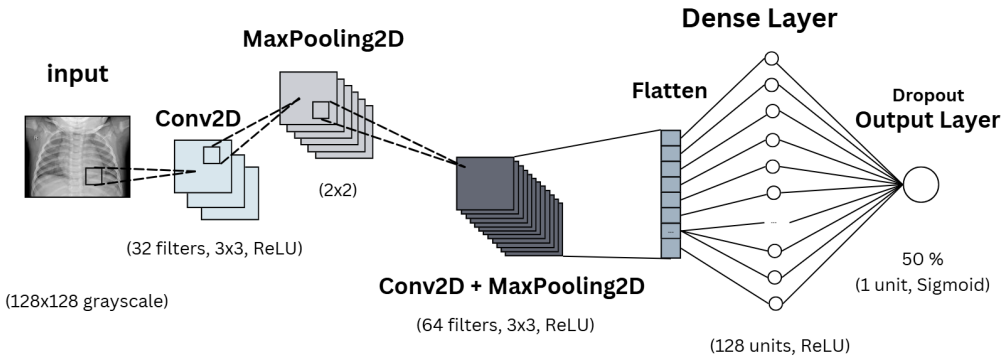

Figure 4: Sequential CNN Structure.

4.4 Simulation Environment

The simulations of the KNN and CNN were run on Microsoft Visual Studio code with a 90:10 train-test split and 5-fold cross-validation test for the KNN and 624:5189 train-test split and 16-fold cross-validation test for the CNN. The overall accuracy of each model was recorded by the accuracy score, confusion matrix, classification report and AUC/ ROC performance metrics, all generated by the sklearn.metrics module.

For the KNN, a Euclidean-distance model was used with varying K parameters (K = 5, 7, 9) to test accuracy, which assesses the classes of the K nearest neighbours and assigns the most frequent class to the target point. For the CNN, a sequential CNN was used with the ReLU activation function. A batch size of 32 and 50 epochs were used for processing. The model used a learning rate scheduler which reduced learning rate as the epochs progressed. The model also used a dropout rate of 50% to ensure robust training.

5 Simulation Results

5.1 Key Findings and Significance

5.1.1 K-Nearest Neighbours (KNN) Classifier

The KNN Classifier was run using three Euclidean-distance models with k = 5, 7 and 9 and one Cosine Similarity-distance measure with k = 5, 7. Thus, five variations of the model were trialled in total. S. Goyal and R. Singh extract "...visual, shape, texture and entensity features..." from each region-of-interest area in their 2021 study, Detection and classification of lung diseases for pneumonia and COVID-19 using machine learning and deep-learning techniques [12]. Similarly, N. Gianchandani et. al. [13] uses pre-trained classification models to extract deep hierarchical features from chest X-ray images to extract '...patterns, shapes and textures..' required for diagnosis of COVID-19.

Similarly, we implemented a modified architecture incorporating Gabor filter to extract features, though, even after optimising parameters this produced a test accuracy of 78% with a strong cross validation accuracy of 93.23%. Rather, following iterations

were conducted by relying on the natural KNN software architecture to achieve a classification outcome. Whilst the [12] and numerous other Pneumonia classification studies [1], [3], [4], [5] specifically focuses on viral strains, our KNN model is able to novelly classify both viral and bacterial pathologies. The K=7, Cosine-similarity-distance KNN model provided the highest classification accuracy (92.58%) with an AUC value of 0.97. We too implemented Principal Component Analysis (PCA) to reduce the dimensionality of the dataset similar to the methodology of the [1] team. A summary of findings can be found in Figure 5 below.

5.1.2 Convolutional Neural Network (CNN) Classifier

C.Y. Effah et. al. implement a pneumonia classification model using biomarkers, laboratory parameters and physical anatomical landmarks on chest x-rays to assist in ML prediction via several models [14]. They implement six techniques for feature selection, including L1 (lasso)- and L2 (ridge)-regularisation and univariate feature selection which reduce feature weights to prevent overfitting. Keeping this research in mind, we also used relied on similar techniques to prevent overfitting, namely; regulsarisation, random dropout, adjusted learning rate and loss check for epochs. In the final simulation there were 50 epochs with a total runtime of 6 hours. The accuracy will vary with everyrun because of the random dropout of 50% however the highest accuracy over 3 runs with similar settings was 92.95%.

	KNN K = 5, Eucl.		KNN K = 7, Eucl.		KNN K = 7, Cosi.		KNN K = 9		CNN
Test Accuracy	0.8852		**0.9043**		0.8995		0.8947		0.9295
K-Fold Scores	0.8982		0.9102		0.9222		0.9222		Table excludes individual scores as there are 16 folds of validation.
	0.9102		0.8862		0.9222		0.8922		
	0.9401		0.9281		0.9401		0.9222		
	0.9222		0.9281		0.9341		0.9222		
	0.9222		0.9042		0.9102		0.8982		
Mean Train Accuracy	**0.9185**		0.9114		0.9258		0.9102		-
	Normal	Pneumonia	Normal	Pneumonia	Normal	Pneumonia	Normal	Pneumonia	
Precision	0.85	0.90	0.89	0.91	0.87	0.90	0.87	0.90	0.918
Recall	0.70	0.95	0.73	0.97	0.71	0.96	0.71	0.96	0.97
f1-score	0.76	0.92	0.80	0.94	0.78	0.93	0.78	0.93	0.95
Area Under Curve (AUC)	0.95		0.96		**0.97**		0.95		-

Figure 5: Summary of results

5.2 Issues Faced

Given our dataset was already cleaned and organized on Kaggle, images were pre-processed using various feature extraction techniques, but the application of the Gabor filters unexpectedly reduced detection accuracy, leading to confusion in feature representation and an accuracy drop to 76.63%. Additionally, prior to implementing PCA, the explained variance ratio was plotted to identify the optimal number of principal components, following the plateau point for variance retention. However, this step only increased accuracy by

1.58%, falling short of our target. This was eventually rectified by removing Gabor filters and PCA and running the standard KNN architecture, giving a final KNN with a mean test accuracy. Additionally, the group would have liked to experiment more when it came to tuning hyper-parameters for our models; however, to run a training iteration on the CNN and the KNN, a lot of computational resources were spent, because of which, given the timeline constraints, we could only run a limited number of runs and had to determine ideal distributions based on external research instead of personal experimentation.

6 Potential Applications and Extensions

The model is designed for low-resource settings to alleviate the strain on rural and overburdened healthcare systems. An ML-based diagnostic tool provides a low-cost, accessible alternative for pneumonia screening, especially where advanced imaging like CT scans is unavailable. In regions lacking specialists, it can aid medical students and general practitioners in learning pneumonia detection. Additionally, in overburdened systems, automated ML solutions streamline initial diagnostics, prioritizing urgent cases and reducing radiologists' workload, optimizing patient management during peak times like flu season or pandemics. Other potential adoption scopes are outlined below.

COVID-19 and Other Respiratory Infections: The similarity between pneumonia and COVID-19 symptoms and chest imaging findings allows this model to be retrained or fine-tuned for detecting COVID-19 and other respiratory infections. Previous research, such as Gianchandani et al. [13], achieved a highest accuracy of 95.3% using ensemble deep learning models on X-ray images for COVID-19 detection. Likewise, Goyal and Singh [12] demonstrated efficient classification between viral and bacterial pneumonia. These extensions could further subcategorize infection types within the proposed model framework, enhancing its flexibility and effectiveness during respiratory health emergencies.

Potential for Multi-Organ Diagnostics: Although designed for pneumonia screening, this model structure can be generalized for examining other organs, such as detecting kidney stones or abdominal masses from abdominal X-rays or CT scans. The convolutional layers in CNNs, which identify patterns, textures, and densities, are applicable across various anatomical settings. Thus, this framework could assist radiologists beyond respiratory diseases, offering broader diagnostic support.

7 Project Impact and Ethics

7.1 Patient Privacy and Data Security

Managing medical images, including OMR data, requires strict privacy measures. Our system complies with data protection laws, anonymizes information, and ensures secure storage through encryption and restricted access. Regular audits and compliance checks maintain data security and prevent misuse.

7.2 Informed Use and Decision Support

While ML models are effective for diagnosing health conditions, they are not flawless and should assist, not replace, doctors. Medical practitioners need training on the tool's strengths, limitations, and best practices. Combining model outputs with healthcare expertise ensures more accurate diagnoses.

Industry interest in this technology is strong, as shown by a Deloitte study [15]. To our knowledge, no commercial software currently addresses this problem. By overcoming identified challenges using proposed methods, we aim to build a prototype for demonstration to potential investors, including government departments, colleges, and universities.

8 Conclusion

Our project findings meet our aim by developing two successful, low-cost, non-intrusive classifiers using KNN and CNN, both achieving over 90% accuracy in distinguishing pneumonia cases from non-morbid instances. We recommend the CNN model for its adaptability and slightly higher accuracy score, which can be robustly optimized through additional neural layers and the methods discussed in Section 4.2. The KNN classifier, with K=7, Cosine Similarity, and 5-fold cross-validation, achieved a mean train accuracy of 92.58%, although test accuracy was lower. In contrast, the CNN classifier, using a batch size of 32 and 16-fold cross-validation, achieved the highest train accuracy of 92.95%. While marginally higher than KNN, the CNN model provides more functionality due to its neural network structure. Both models currently lack the ability to differentiate bacterial from viral pneumonia cases, requiring further data integration and expanded testing to achieve this.

Patient privacy and data governance must be prioritized for responsible use, as the model's application across training, resource optimization, and multi-organ diagnostics increases the risk of data breaches and consent violations if not carefully managed. Over six weeks, our team worked productively, holding 15-minute sprint meetings to address issues and track progress. We coordinated individual contributions via an Instagram group chat and collaborative Google documents for comprehensive documentation. In the future, we aim to develop an application for hospitals, allowing trained individuals to optimize the model to commercial standards. We plan to conduct integration testing in smaller healthcare regions before broader implementation.

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