Paper1:

**Significant Symptoms and Non-Symptom Related Factors for Malaria Diagnosis in Endemic Regions of Indonesia**

In Indonesia there are not always available medical laboratories for health relevant tests. symptoms and non-symptom-related factors are crucial for clinical diagnosis of malaria in order to take appropriate actions for treatment.Malaria diagnosis at early stages can avoid a progression in severity of the conditions and possible transmission of the disease. With insufficient knowledge of significant malaria symptoms and non-symptom-related factors for clinical diagnosis of malaria, medical doctors may presumptively treat febrile patients, which leads to an increase in resistance to antimalarial drugs.

Methods:

1. Collect are records of patients (Malaria and other febrile diseases)
2. With 8 doctors collects interview to understand symptoms and non-symptoms
3. Collec 472 records
4. With 17 features we used three ML techniques (SVM, k-nearest and logistic regression)
5. Identify most significant symptoms and non-symptoms factors to diagnose malaria

Results:

Achive 85% Average Accuracy with 17 Features. six significant symptoms (duration of fever,

headache, nausea and vomiting, heartburn, pain and severe symptoms)

Trios malaria symptoms (fever, shivering and sweating) are shown to be less significant than other symptoms in endemic regions

Conclusion: Raise public awareness regarding symptoms and non-symptoms factors these will be very helpful for newcomers doctors (or less experienced doctors) to diagnose malaria especially in rural areas.

Paper2:

**Predicting the microbial cause of community-acquired pneumonia :**

**can physicians or a data-driven method differentiate viral from bacterial**

**pneumonia at patient presentation?**

Community-acquired pneumonia (CAP) requires urgent and specific antimicrobial therapy. However, the causal pathogen is typically unknown at the point when anti-infective therapeutics must be initiated. Physicians synthesize information from diverse data streams to make appropriate decisions. We aimed to evaluate the abilities of experienced physicians and AI to answer this question at patient admission: is it a viral or a bacterial pneumonia?

Method:

We included patients hospitalized for CAP and recorded all data available in the first 3-hour period of care (clinical, biological and radiological information) Positive likelihood ratio (LR) values >10 and negative LR values <0.1 were considered clinically relevant.

Conclusion. Neither experts nor an AI algorithm can predict the microbial etiology of CAP within the first hours of hospitalization when there is an urgent need to define the anti-infective therapeutic strategy.

Paper3:

Clinical decision support (CDS) with help to predict can also utilize machine learning to provide a diagnosis, recommendation, or therapy course. prediction of hemodynamic instability, respiratory distress, and infection within critical care settings.

Conclusion: This review showed an increasing use of Machine Learning for CDS in all three areas. Large datasets are required for training these algorithms; making it imperative to appropriately address challenges such as class imbalance, correct labelling of data and missing data. Recommendations are formulated for the development and successful adoption of CDS systems.

COPD is now becoming the 4th leading cause of death worldwide and according to WHO report it is estimated to be the 3rd leading cause of death by 2030. Due to environmThe main cause of COPD is smokingental changes and increased use of tobacco. The rate of disease progression is increased.The main cause of COPD is smoking.

Conclusion:

With SVM we got 96.9% Accuracy

With KNN we got 92.5% Accuracy

Paper4:

**Predicting post-stroke pneumonia using deep neural network approaches**

13,940 records 85% Training and 15% Testing

Conclusion

This study takes the initiative to develop new pneumonia prediction

models for patients with AIS using novel deep learning algorithms,

which combine time-insensitive features, such as disease history and

demographic information, with time series of medications and lab tests

for pneumonia prediction within different time windows. Deep learning model perform well and provide optimal result

PAPER5:

**The 4 Chest Ray CheXperts**

Chest X-rays are currently the best available method for diagnosing diseases like Pneumonia, Edema, Pleural Effusion, etc which affect millions of people throughout the world.We also propose a novel architecture combining aspects of pre-existing models.

Dataset: CheXpert.The size of the data set proved to be a challenge. It is 15GB downsampled(lower resolution images) and 236GB for regular resolution. This might be due to the trade off between false negatives and false positives. Both of these instances are bad but having false negatives could be

considered much worse as it means the patient actually has the disease

1. Edema: The likelihood of edema increases with how foggy the image is due to build up of liquid in the lungs.

2. Pleural Effusion: The likelihood of pleural effusion increases as there is build up of white towards the bottom of one of the lungs. This is representative of liquid building up in the Pleural space between the lungs and the chest cavity.

3. Lung Lesion: The likelihood of lung lesion increases if there is a small white oval on the lungs that is somewhat transparent.

4. Cardiomegaly: The likelihood of cardiomegaly increases as space between the two lobes increases.

**Conclusion**

Our models are able to detect and distinguish between different pathologies at the level of expert radiologists. With automation at the level of experts, we hope that this model can improve diagnostics especially in parts of the world where access to skilled radiologists is limited

Paper6:

Lung Opacity Prediction From Chest

X-Rays

I chose Support Vector Machine (SVM) and the Radial Basis Function (RBF) kernel as the algorithm for image classification. This was implemented in Matlab with LIBSVM. LIBSVM is an open-source, easy-to-use library for SVM learning developed at the National Taiwan University [10].

Feature extraction: SVD

Accuracy 68%

Paper7:

**A Novel Approach for Detecting Pneumonia in Machine Learning**

Dr Shankar Chatterjee

Deep Learning. Chest X-ray 14 dataset

We will use ChestX-ray14 dataset which contains 112,120 frontal-view X-ray images of 30,805 unique patients. we randomly split the dataset into training validation and test. There is no patient overlap between the sets. Before inputting the images into the network, we downscale the images to 224 × 224 and normalize based on the mean and standard deviation of images in the Image Net training set. We also augment the training data with random horizontal flipping.

Paper8:

**Computer-Aided Diagnosis of Pulmonary Fibrosis Using Deep Learning and CT Images**

Early diagnosis is crucial for making fundamental treatment decisions, particularly for IPF or nonspecific interstitial pneumonia (NSIP), whereas a misdiagnosis may lead to life-threatening complications. It is well understood that biopsy-proven NSIP cases improve under the treatment of steroids and that pirfenidone increases the survival rate of IPF patients.5,6

### Fleischner Classification

Reader 1, reader 2, and CAD demonstrated similar (no significant difference) accuracy for classifying the pulmonary fibrosis, according to the Fleischner Society Guidelines[3](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6738634/#bib3): 0.6, 0.54, and 0.56, respectively, with *P* > 0.45. The CAD system achieved an F-score (harmonic mean for precision and recall) of 0.56, whereas the 2 readers on average achieved 0.57 (*P* = 0.991).

Conclusions

We found that a computer-aided detection algorithm based on machine learning was able to classify idiopathic pulmonary fibrosis with similar accuracy to a human reader.