

Detecting Cardiomegaly from CXR Images Using a 2D and 1D Convolutional Neural Network-Based Classifier

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Abstract. A disorder called cardiomegaly has no symptoms. Heart hypertrophy and ventricular hypertrophy are two subtypes of the early symptoms of cardiac hypertrophy. Blowup, include pulsations, tightness in the chest, and shortness of breath. Their fundamental causes and therapeutic approaches differ. Making decisions on when to provide drugs and execute operations can be aided by the early detection of cardiomegaly. Along with the problems with home inspection. Similar to how time-consuming it is and how visitors and mortal interpretations are needed, a supporting tool is needed to automatically detect and distinguish between a normal heart and an enlarged heart. In medical procedures Based on examinations of chest X-rays (CXR) in anterior poster anterior view, this study suggests merging Convolution neural network, 2D and 1D grounded classifiers for quick cardiomegaly detection. The initial feature extraction and pattern recognition tests were performed using the original CXR image is enhanced and undesired noises are removed using the 2D and 1D convolution methods as well as a multilayer linked classification network. The classifier's performance is validated using K-fold cross-validation after it has been trained using Using the testing dataset, the training dataset was analyzed. Recall, accuracy, precision, and F1 score of the rapid-fire cardiomegaly screening performance are demonstrated by experimental results.

Keywords: feature extraction, pattern recognition, K-fold cross validation, frontal poster anterior view.

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1 INTRODUCTION

Cardiomegaly, often known as an enlarged heart, is a benign ailment that can cause respiratory difficulty, an irregular heartbeat (arrhythmia), and oedema. While it may not cause any signs or some people's symptoms, it can do so in those who experience any of these. If you have cardiomegaly, your heart muscle will gradually degenerate or pump more powerfully than usual. Excessive blood pressure, heart valve malfunction, and cardiomyopathy can be caused by congenital cardiac abnormalities or irregular heartbeats that cause cardiac hypertrophy. Risks associated with cardiomegaly include heart failure, blood clots, and other complications [2]. Heart cardiac arrest, failure, blood clots, and murmurs of the heart are all risks associated with Cardiomegaly.

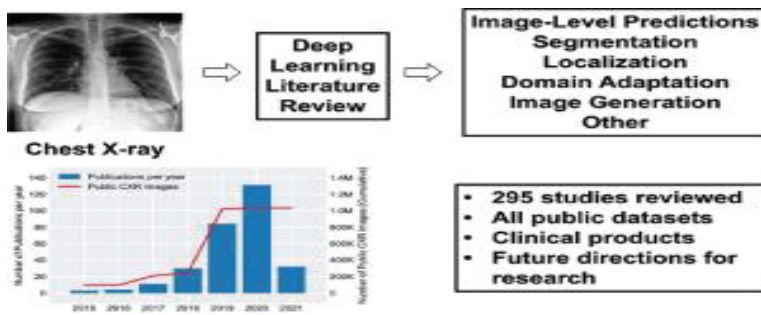


Fig.1. Cardiomegaly Chest X-ray

Cardiomegaly on demand detection on poster anterior (PA) CXR images based on classification. Therefore, by determining whether or not an aberration is present, a primary chest X-ray (CXR) image [3-6] is a straightforward examination tool for quickly determining the existence or absence of cardiopulmonary disease. This imaging approach can quickly and economically detect cardiomegaly due to its minimal radiation exposure. Low levels of ionizing radiation are typically present in the noise [10] on CXR pictures, which reduces the diagnostic accuracy of imaging for cardiopulmonary diseases. Many methods have been proposed to reduce similar noise and enhance CXR, including digital pollution, sea analysis, major factor analysis, and machine literacy techniques. However, these techniques cannot get rid of Gaussian and Poisson noise.

2 LITERATURE REVIEW

Segmentation versus classification in chest X-rays for the detection of cardiomegaly this study investigates the detection of cardiomegaly on frontal chest radiographs using image segmentation and anatomical level classification. We used the publicly available ChestX-ray[13] dataset to annotate 778 chest radiographs for the heart and lungs. In order to create the segmentation-based approach. 65 000 conventional chest radiographs that had been image-level labeled served as the training data for the classification-based technique. The top models for both strategies were identified by maximizing architectural, learning, and regularization-related parameters in hyper parameter searches. To assess the models, 367 held-out pictures with comments on cardiomegaly were manually hand-labeled by two distinct experienced radiologists. Among the parameters evaluated was area under the receiver operating characteristic curve (AUC), positive predictive value, and both

sensitivity and poor predictive ability [2] The classification-based model, which had an AUC of 0.941, was outperformed by the segmentation-based strategy. in classifying cardiomegaly. AUC of 0.978 is only seen in the segmentation-based model. area under the receiver operating characteristic curve (AUC), sensitivity, specificity, positive predictive value, and negative predictive value. The classification-based model, which had an AUC of 0.941, was outperformed by the segmentation-based strategy. in classifying cardiomegaly. AUC of 0.978 is only seen in the segmentation-based model [3] Outperformed an unbiased expert reader. We find that the segmentation-based strategy produces noticeably better results while using 100 times fewer chest radiographs and being simpler to interpret.

Comparing robust learning methods for categorizing chest X-ray pictures with multiple labels

For instance, the ChestX-ray14 dataset has improved the accessibility of tagged X-ray picture archives, igniting interest in deep learning methods. We carefully examine a powerful network architecture known as using the ResNet-50 to provide a better knowledge of the various tactics and their application to categorizing chest X-rays. We discuss transfer learning with and if no training and fine-tuning are done of a specialized X-ray network from scratch, building on past research in this area. In we also incorporate an expanded ResNet-50 design and a network that considers the high spatial resolution of X-ray data in order to benefit from the high spatial resolution of non- (Patient age, gender, and type of acquisition) Image characteristics [5-6] looked into various ResNet depths. Using ROC statistics, we evaluate the effectiveness of the various illness classification algorithms and spot discrepancies. Rank correlation is used for a systematic evaluation of the classifiers using a multi-label loss function and 5-fold resembling. The ResNet-38, which is designed for X-rays and takes into account input other than images, generates.

With application to mass screening, automatic calculation of the cardiothoracic ratio:

The cardiothoracic ratio is automatically determined by an algorithm. A permitted error of 4% was attained in 86 percent of studies utilizing 100 sheets of postero-anterior, 14 by 14-inch chest radiographs. About one second is needed for processing [7] is to give radiologists accessible technology for automated mass heart disease screening. In the experimental system, a minicomputer and a regular vidicon camera are utilized.

Postero-anterior chest radiographs showing the cardiothoracic ratio congenital heart disease in adults, a straightforward, repeatable, and independent measure of disease severity and outcome is:

Due to the large range of intracardiac architecture and repair surgical options available to persons with congenital heart disease (ACHD), measuring cardiac size and the severity of the illness is difficult. The goal of this study was to ascertain whether the outcomes in a huge group of ACHD patients could be predicted using the cardiothoracic ratio, a crucial marker of cardiomegaly [8]. Patients and the environment: Between 1998 and 2007, 113 healthy controls and 3033 ACHD patients' chest radiographs were blindly evaluated. The cardiothoracic ratio, which was determined from straightforward Radiographs of the postero-anterior chest were compared between ACHD patients and controls. Radiographs of the postero-anterior chest were compared between ACHD patients and controls. in addition to other diagnostic subgroups and functional classes. The relationship between was investigated using Cox regression [9-10] the cardiothoracic ratio and survival. In contrast to controls, patients with ACHD had an average cardiothoracic ratio of 52.07%; patients with "complex" cardiac anatomy, subgroups of Eisenmenger, and Ebstein's anomalies had the greatest cardiothoracic ratios. Asymptomatic individuals also showed high levels of the

cardiothoracic ratio, despite the fact that it was associated with functional class. 164 people died with a 4.2-year median follow-up. The cardiothoracic ratio in patients higher than 55% died eight times more frequently than those in the lowest tertile (48%). When compared to the lowest tertile, even people with a little raised Mortality was 3.6 times higher in the cardiothoracic ratio (48-55%) group.

For the purpose of machine-assisted detection and categorization of anomalies radiographs of the front of the chest, training and verifying a deep convolution neural network:

Networks of artificial neurons such as neural networks with convolutions (CNNs) have demonstrated to be incredibly effective in computer vision applications including picture classification [11]. Our hypothesis states that with enough training data, CNNs can be taught to recognize frontal chest radiographs. Tools and techniques The 35,038 adult posterior-anterior chest radiographs and final reports from a The research ethics board of our institution approved a single-center retrospective study conducted between 2005 and 2015 with a waiver for informed consent [12]. To teach the Google Net CNN to distinguish between radiographs that were normal, consolidation (n = 6788), pleural effusion (n = 11,702), and cardiomegaly (n = 9240) radiographs were used. (n = 11,702) and those that had one or more of these conditions. Pulmonary edoema in both (n = 7786) and (n = 1286) cases. On a test set of 2443 radiographs, the performance of the network was evaluated using receiver operating curve analysis, with a board-certified radiologist's interpretation serving as the standard. The network identified a study (n = 1203) as normal (using input of 256 X 256-pixel images), with an 91% overall sensitivity, 96% specificity, and a 0.964 area under the curve. Area under the curve, specificity, and sensitivity for pleural effusion (n = 782) were 91%, 91%, and 0.962, respectively. The sensitivity, specificity, and area under the curve for pulmonary edoema (n = 356) were 82%, 82%, and 0.868, respectively. Conclusions: The efficacy of current deep CNN architectures in recognizing and excluding common illness on chest radiographs can be clinically significant when trained on moderately small medical data sets.

3 METHODOLOGY

Cardiomegaly is a condition without symptoms. Shortness of breath, tightness in the chest, and palpitations are some of the early symptoms of cardiac hypertrophy. Also known as ventricular enlargement or cardiac hypertrophy. Their fundamental causes and therapeutic approaches differ. Early diagnosis of cardiomegaly can have an impact on the choice of medication and surgical therapy. In addition, physical inspection requires human judgments and experiences, takes time, and requires a helper tool to automatically generate and distinguish between small and large hearts [13] For quick cardiomegaly screening in clinical applications, this study provides Convolution neural networks based on a combination of 2D (two-dimensional) and 1D (one-dimensional) classifiers. Using frontal poster anterior chest X-ray (CXR) scans. The original CXR image is improved and undesirable noise is removed using the 2D and 1D convolution methods as well as a multilayer linked classification network to improve the accuracy of tasks involving feature extraction and pattern recognition. The National Institutes of Health CXR image collection serves as the training and testing datasets, which are used to train the classifier and assess its performance. Using K-fold cross validation.

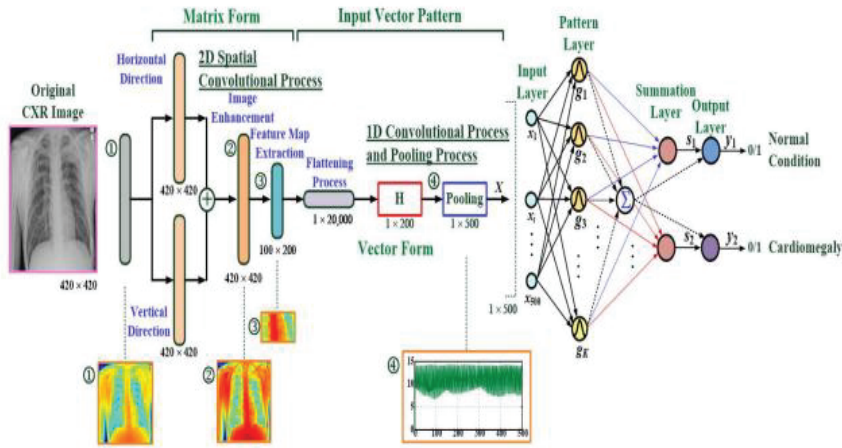


Fig.2 System architecture

Modules:-

- To execute the afore mentioned project was, we produced the aforementioned modules
- **Data investigation:** By using this module, we will load data into the system.
- **Image processing of:** We will be read data for processing using of particular module.
- **Data splitting into train and test:** The data will be split into train and test using this module.
- **Model construction:** Model building - InceptionV3 - DenseNet121 - MobileNet - MobileNetV2 - Inception + MobileNet Ensemble Model - Xception + LSTM (2D + 1D). Calculated algorithmic accuracy.
- **User registration and login:** Using this module will result in registration and login.
- **User contribution:** This module provides input for predictions

4 IMPLEMENTATION

4.1 Algorithms

4.1.1 InceptionV3:

On the Image Net dataset, it has been demonstrated that the image recognition model InceptionV3 achieves greater than 78.1% accuracy. The prototype is the outcome of years of research by several academics into a variety of ideas. In Inception V3, transfer learning has become one of the most popular methods for categorizing images. In order to shorten training time and boost performance, it is the adoption of an existing a trained model that has been used to create a new model using a limited amount of data.

4.1.2 DenseNet121:

Each layer in the Dense Net convolution every layer beneath the neural network is linked to it. Contrarily, the first layer is connected to the second, third, fourth, and so forth, and each of these layers is connected to the third, fourth, fifth, and so forth. Next is Mobile Net.

4.1.3 Mobile Net:

The mobile net is a condensed architecture that efficiently creates light-weight deep convolution neural networks using depth wise separable convolutions, making it a useful model for mobile and embedded vision applications.

4.1.4 MobileNetV2:

53-layer deep convolution neural network called MobileNet-v2. More than one million images from the An already pretrained network can be loaded using the ImageNet database. The pretrained network can classify images into more than a thousand other object categories in addition to keyboards, mice, pencils, and various animals.

4.1.5 Ensemble Model - Xception + LSTM (2D + 1D):

By using a range of modeling techniques or training data sets, several different models are created as part of the ensemble modeling process in order to predict a result. In order to provide a single final assessment for the unobserved data, the ensemble model also combines the predictions of each base model.

5 EXPERIMENTAL RESULTS

The user must first register on the registration page and then login using their credentials. After entering the chest x-ray image, the main page will appear and display the results.

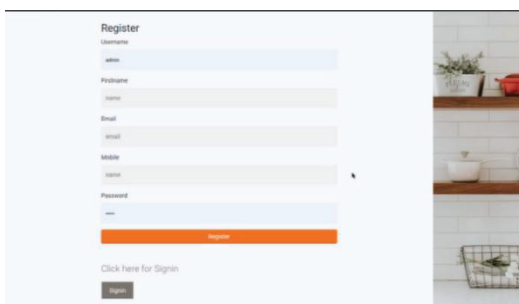


Fig.3. User registration

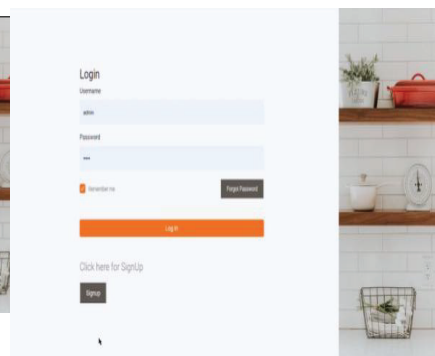


Fig.4. User login

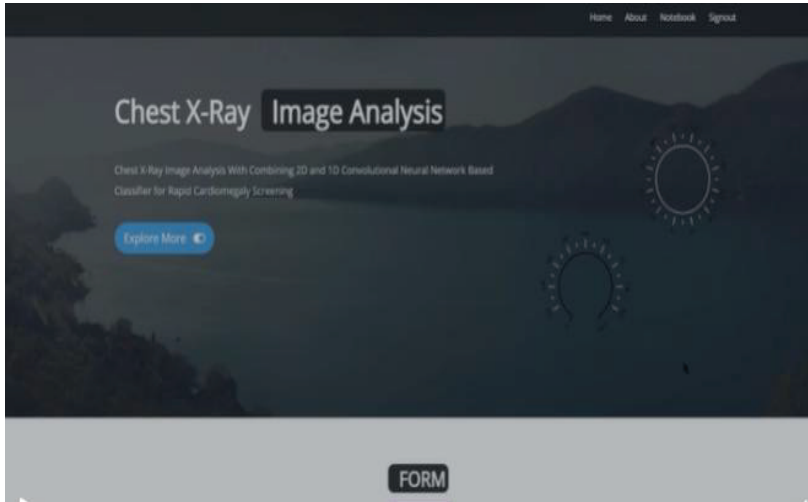


Fig. 5. Main page

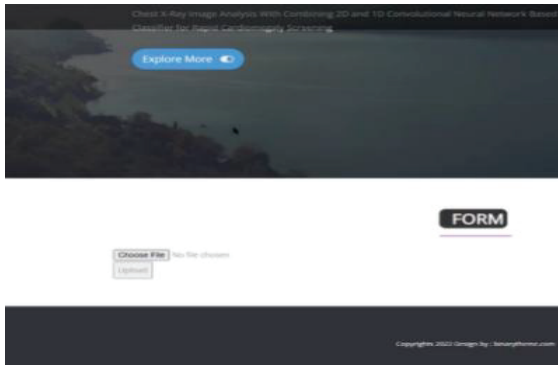


Fig.6. User input



Fig.7. Prediction result

6 CONCLUSION

We developed a classifier that combines a utilizing a 2D and 1D CNN-based model and CXR images detect diseases present in either a healthy state or cardiomegaly at initial assessment The recommended classifier's performance was also verified. Convolution layer:, the image was improved and unwanted noise was eliminated using a number of 1D kernel, fractional 2D order, and convolution processes. This could help with the extraction of the 2D feature maps with specialized for BB and their transformation into 1D feature signals for additional classification tasks. 1D pooling and flattening techniques scan is used to shrink the feature map's dimension for applications that require of real-time digital image's processing and pattern recognition. To differentiate between normal and cardiomegaly, randomly generated untrained feature maps were fed into the classifier using

10-fold cross-validation. The pattern recognition system demonstrated promising results, with screening abnormalities, the averages for recall, precision, accuracy, and F1 score are all above 95%. The outcomes of the trial showed that the automatic screening, computational efficacy, and training model were superior to the manual method in clinical applications.

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