

Deep Learning Morphological Analysis of Chest Radiographs as Preliminary Predictor for Hospitalization in Patients with Chronic Cardiac Disease

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Abstract

Background: Chronic cardiac disease is characterized by slow progressive structural and functional cardiac and systemic abnormalities. The annual global cardiac disease hospitalization exceeds 65 million rate of admission. Deep learning based chest radiograph predictor of need for hospitalization is an essential decision since incorrectly discharged patients experienced increased pulmonary disorders and mortality whereas unnecessary hospitalization is associated with a risk of infection.

Objectives: This study uses deep learning to analyze morphological features of chest radiographs to predict the need for hospitalization in patients with cardiac problems.

Methods: A retrospective case-control approach was designed. A public dataset of chest x rays was used and validated. The multimodal AI model was designed to extract x-ray features at different CNN levels to classify patients into 'admission' and 'No admission' groups.

Results: Several important morphological features from patients attributes and chest radiographs were obtained to predict the need for hospitalization in patients with chronic cardiac disease. These preliminary predictors, belonging to different CNN layers: L3 (layer 3) Texton Density 61, L4 Reflection Symmetry 40, Relative Size Context may be linked to structural changes and severity.

Conclusion: There was a preliminary association between multimodal DL features and personalized hospitalization decisions in patients with chronic cardiac disease.

Keywords: Chronic cardiac disease, chest radiographs, features extraction, predictor, hospitalization, deep learning model

Introduction

Chronic cardiac disease is characterized by slowly progressive structural and functional abnormalities that distinguish it from other forms of cardiac disorders.¹

The global sample linked to heart disease hospitalization is more than 65 million with 2% rate of admission according to an updated reference study.²

Recent research showed that age over 65 years and abnormal cardiac morphology on chest radiography were the factors most highly related to hospitalization for heart disease.³⁻⁵

The cost of hospitalization for heart disease is several thousand USD per patient bed.⁶

The importance of appropriate hospitalization decisions is underscored by the consequences of errors: non-hospitalized patients face increased pulmonary disorders and mortality, while unnecessary hospitalization carries risks of infection and patient distrust.⁷

A study that yields a predictor for hospitalization of patients with chronic heart disease from chest radiograph feature is an applied study. Such a study can be implemented for personalized decisions.^{8,9}

A rational approach to deciding hospitalization can be based on the fact that severe, complicated cardiac problems trigger cardiopulmonary structural and functional alterations. These pathological events will proportionate with cardiac problem severity since hemodynamic and cardiovascular stress factors will be markedly increased. An AI-enhanced

capability to explore this pathway from plain chest x-ray features would correlate with actual severity and, hence, the real need for personalized hospitalization. This AI enhanced approach is probably much advantageous than expert based clinical decision although augmented by routine clinical features and investigations. Such advantages are attributed to the superior capabilities of well-designed AI model in being more accurate, less cost and can accelerate clinical measures.¹⁰⁻¹²

Chest radiography features from multiple deep learning layers are likely new predictors for assessing heart disease cases to guide hospitalization decisions and explore new solutions.^{13,14}

Deep Learning (DL) model for analysis of chest radiographs inputs is a good method for extracting chest x-ray features. Five convoluted neural network CNN layers (L) are powerful channels for extracting upto 512 chest x-ray features. This approach may provide extensive reviewing of any association between the structural cardiopulmonary features and the severity of cardiac problems.^{15,16}

Study Hypothesis: This study adopts the assumption that there is likely association between the actual need for hospitalization in patients with chronic heart disease and particular features in chest radiographs extracted and analyzed by AI models.

Novelty and Feasibility: This project assigns AI model for reviewing any chest x ray extracted feature throughout all 5 CNN layers and simultaneously testing its association with the classes: 'Admission' or 'No Admission'. This approach may provide method for testing any predictor that augment clinical

decision whether hospitalization is mandatory or unnecessary. On the other hand, it may ensure proper decisions and consequently save costs and avoid morbidity and mortality.

Research Aims and Objectives

1. To extract 5 CNN layers features from chest radiographs of patients with chronic heart problem in comparison with normal using multimodal DL model.
2. To analyze the importance features that may predict the severity and generate robust clinical decision for hospitalization.

Models, Materials and Methods

The study design was a retrospective case-control approach, as demonstrated in Figure 1. Findings from chest radiographs of patients with chronic heart disease who required hospitalization were compared with those from elective and normal cases.

Study Time and Place: This study was conducted from November 12, 2025, to February 10, 2026, in a private IT office in Al Najaf.

Type and Size of the Selected Dataset: Two classes were selected from the overall dataset exist in the original NIH source: Those two classes represent 54 patients with chest x-ray cardiomegaly and 69 others with normal to mild cardiac findings. The multimodal DL model uses a built-in algorithm to create a fused table. This mechanism yields single tabular dataset involves both patients attributes and chest x-ray features.¹⁷

Data Augmentation: One of the well-known methods for processing limited datasets is the data augmentation. Our multimodal DL model has built-in data augmentation mechanism. This mechanism is used to increase the reliability of the model. Such an algorithm uses accredited tabular data amplification methods, namely: Gaussian variations, jittering, SMOTE (Synthetic Minority Oversampling Technique), and min-max normalization. We used the 5 fold augmentation to increase dataset size from 123 to 615 and at the same time avoiding overfitting.¹⁸



Fig. 1 Represents the steps of our study. The study design was retrospective case control design. The used dataset included 123 cases: 54 with cardiomegaly and 69 with normal or mild findings. Key stages include preprocessing, resizing to 456x456. This set for all images and all levels of CNN feature extraction using Python 3.12 and Keras. Model 0.01 learning rate, 100 epochs whereas target column was classes.

Patients Criteria: Patients ages ranged from 28 to 73 years of both sexes within the used dataset. Patients ethical requirements are described within the section of dataset source below.¹⁹

Data Inclusion Criteria: We selected chest radiographs for patients who had cardiomegaly records in the attached CSV of the original data. This selection method extracted cardiomegaly records, and no findings records from the original dataset CSV table. That table contained 112120 total records. The extraction was done using the application 'Expression-Based CSV Extractor'. This app was already developed by the IT programmer Hussein A A. The application used the regular expressions to extract records that contain "cardiomegaly" and "no findings" in the column 2 (finding labels). For more valid inputs, we used additional filtering included PA view chest x-ray films, follow-up numbers of 2 or more and images dimensions of 2048 by 2048. The resultant filtered number was 106 cardiomegaly and 3406 no finding cases. Out of these 106 cardiomegaly cases we further selected only 54 by neglecting artifact containing or low-quality images. Similarly,

we obtained 69 images from the mentioned 3406. However, we selected the first 69 normal chest x-ray images that meet the above attributes. Selecting 69 normal cases is within the range that makes the ratio between the two classes acceptable.

Data Exclusion Criteria: All cases within the source dataset that had either patients data alone, chest radiographs alone or invalid dataset as well as ages other than adults age groups.

Multimodal DL Model Design: The platform elements and user interfaces are shown in Figure 2. Parts and logics of the multimodal DL model are clarified as: backend server-side package using python 3.12 and keras library to support CNN layers of deep learning algorithms. Flask for creating GUI elements and logics. This is well known approach of designing multimodal DL model.²⁰

X-ray image features extraction by CNN layers were assessed against two outcome classes i.e. 'Admission' and 'No Admission'.

Data analysis was achieved by using deep neural network algorithm specifically designed to extract computer

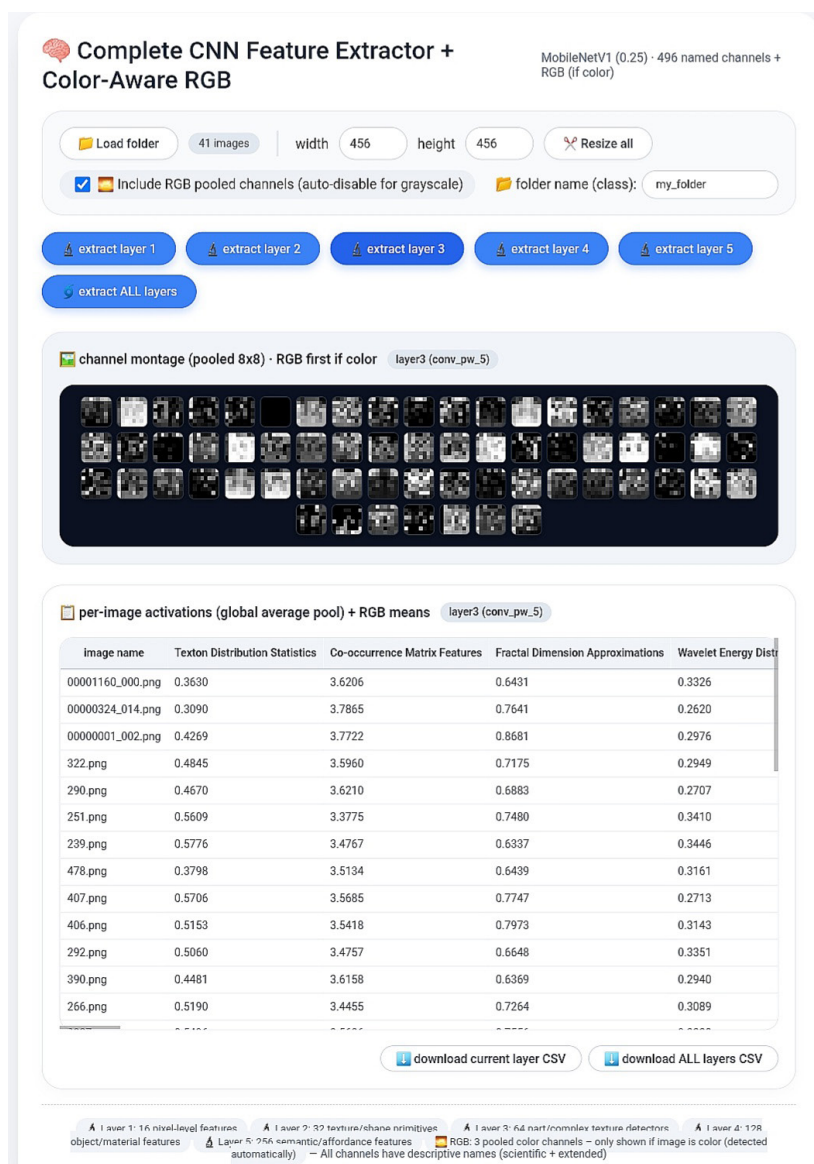


Fig. 2 The GUI panel with obvious 5 levels deep neural network algorithm that extract features from chest radiographs to be tested as hospitalization predictors displayed as channels montage.

vision-based features at 5 different CNN layers. These features are demonstrated in Figures 3 and 4. These features are fused with their corresponding patients data and the hospitalization decision. This is accomplished by internal algorithm specified for data fusion (patients tables and x-ray images features). Another capability within our multimodal DL model was the dataset augmentation algorithm which is used to increase rare or difficult to be obtained dataset.²¹

Multimodal DL Model Validation and Dataset Preprocessing: This step is where the researcher adjusts according to the actual topic. Preprocessing included training setting upto 100 epochs and learning rate. Visualization of the results were accompanied via horizontal bar chart hierarchy of the important features relevant to the classes of hospitalization. As it was shown in Figure 5 dataset partitioning was set to 0.2 as default. This splitting ensures 20% test data with random



Fig. 3 Part of the chest radiographs in montage array out of the original chest x-rays images. X-ray images of patients with enlarged cardiac shadows (left) and the radiographs of mild to no cardiac problem (right) as a comparator for severity and hospitalization decision makers.

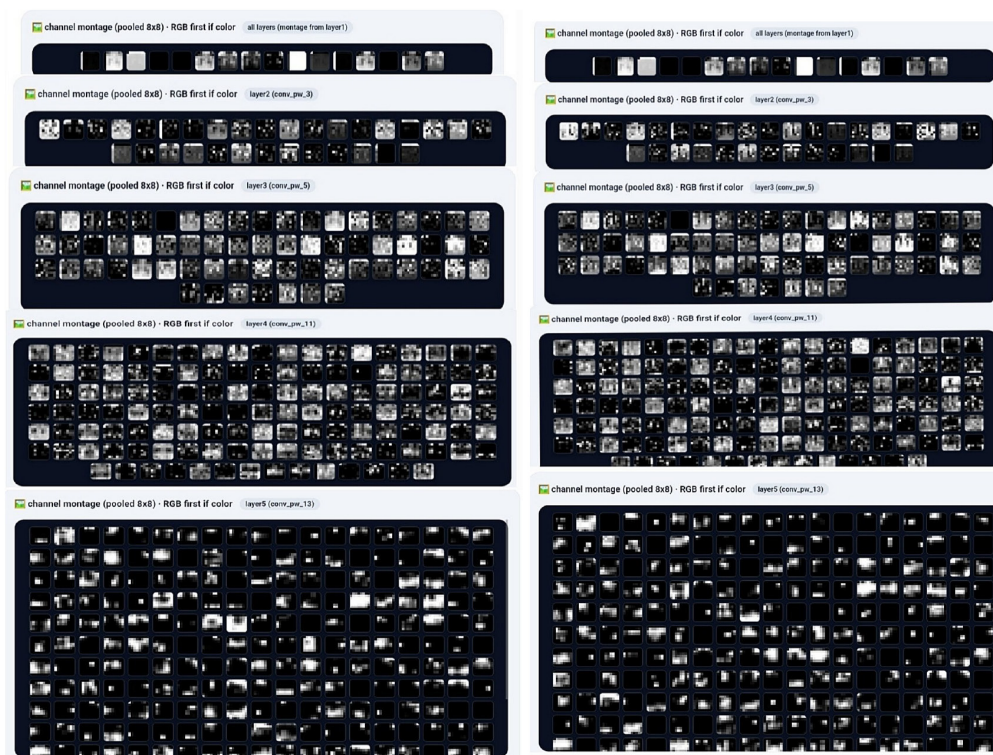


Fig. 4 Arrays from the 5 levels extracted features groups by importance of total 491, examples of the most important: 1. Critical (>80%): Count: 3, Features: L3 Texton Density 61, L4 Reflection Symmetry 40, Relative Size Context 2. High (60–80%): Count: 24 Features: Local Mean/Median, Granularity Measures, L5 Scene Type 141, L5 Spatial Layout 62 3. Medium (40–60%): Count: 80 Features: L5 Novelty Index 48, Chromatic Aberration, Horizon Position, L4 Scale Invariant 93 4. Low (20–40%): Count: 231, Features: L5 Viewpoint Fusion 204, L4 Regularity Pattern.

Fig. 5 The deep learning model settings of deterministic mode: epochs: 100, learning rate: 0.01, batch size: 32. The original dataset included 123 case, 491 feature throughout the 5 CNN layers and 2 classes.

shuffling. Model training accuracy, validation accuracy and loss throughout model training progress were selected within the ADAM optimizer.²² Moreover, model performance assessment was further presented as confusion matrix.

Equipment: An external 12 GB GPU was connected to Panasonic PC core i5 with 16 DDR ram and 512 SSD hard disk.

Dataset Source: The original dataset were downloaded from Kaggle as CC0. This means no citation or limitation in use is required. However, although the offering researcher work and acknowledged NIH: <https://nihcc.app.box.com/v/ChestXray-NIHCC/folder/36938765345>.²³

Licenses and Ethical Statements

Dataset license: The used dataset included patients attributes and their chest x-ray films: License type of dataset on Kaggle repository was CC0 type under the title: Heart Failure Prediction Dataset. Moreover, type of using this dataset is internal (for research purpose only). Based on these two properties, the researcher is not subject to any limitation. However, since the origin of whole dataset was NIH then we cited the authors work and acknowledged NIH: <https://nihcc.app.box.com/v/ChestXray-NIHCC/folder/36938765345>.²⁴

Ethical statements associated with the used dataset. Ethical requirements are of two types: those related to patients and those related to the dataset authors. The former is already fulfilled and described by responsibility of the team of the source dataset.²⁵

The later includes acknowledgement and meeting licenses of the source authors. We cited and mentioned dataset author work.

License requirement of the multimodal DL model also met since developer provided this model as free for research purposes.²⁶

Generative LLM models used: We used Gemini 3.5 Pro for checking the epidemiological data mentioned in the introduction. The generative AI was used only for verifying information, otherwise, we take full responsibility for the accuracy and integrity of our manuscript.

Study Feasibility and Impact: This project may save costs of unnecessary hospitalization in addition to improving outcomes of chronic heart problems. Acceleration of some clinical management steps and substituting investigations may further add advantages.

Results

Research results per sections: dataset validation, chest x-ray images features extraction, features analysis.

Discussion

The multimodal DL model yielded 491 chest radiographs extracted features throughout all of its 5 CNN layers (Figures 1–3). Although sample size was limited to 123 cases.

Data augmentation can decrease training loss, but limited augmentation should be applied to avoid over-sampling and overfitting. That was why we set the augmentation of dataset to 5. This number is within the accepted range to enhance multimodal DL model performance.²⁷

Out of the 491 extracted features, only 3 were critically associated with preliminary prediction of the need for hospitalization in patients with chronic cardiac disease as shown in Figure 4. The extracted CNN features from patients x-ray images represent just preliminary indicators for the need of hospitalization at this stage. Further evidence based confirmation is needed to detect their actual pathological and radiological lesion.

This model showed overfitting after completing training. Overfitting is clear since this DL model showed 100% training accuracy. A larger valid dataset may fix this overfitting. Deep learning model training using only 123 cases of dataset has impact to reduce its reliability of prediction. So, the extracted x-ray features at this stage of training may provide only preliminary indicators of hospitalization rather than definite predictors (Figures 5–9).

The Differences Between the Computer Vision CV and Radiological Features

Computer vision features are mathematical tensors derived from the CNN algorithm. For example, reflection symmetry, vanishing points and scene type refer to the patterns in chest x-ray pixel distribution, gradients and geometry. By themselves, they do not have built-in biological meaning, otherwise they are used by the model as temporary statistical variables. In contrast, radiological markers are clinical observations like enlarged cardiac contour with definite pathological lesion.

This study attempted to augment the radiographs markers and clinical observations by well known mechanism of dataset augmentation app as shown in Figures 10–12.

Computer vision-based terminology was accepted as temporary automatic annotations to test which features are more associated with the target classes. After this step, we can redefine the computer vision terms into their exact clinical meaning by following evidence-based detection of its corresponding cardiac pathology. One example is local pixel intensity. This might indicate coarse cardiac fibrosis.²⁸



Fig. 6 The training progress of the deep learning neural network with validation accuracy of 96% and validation loss of 0.0517 over 100 epochs.

Confusion Matrix

	Predicted admission	Predicted noadmission	Total
True admission	45 86.5%	7 13.5%	52
True noadmission	12 16.9%	59 83.1%	71
Total	57	66	123

Fig. 7 The confusion matrix for assessing performance of multimodal deep learning model. It shows green matching between model predicted 'Admission' and 'No Admission' versus the true admissions and no admissions. Most of actual/predicted results were matched.

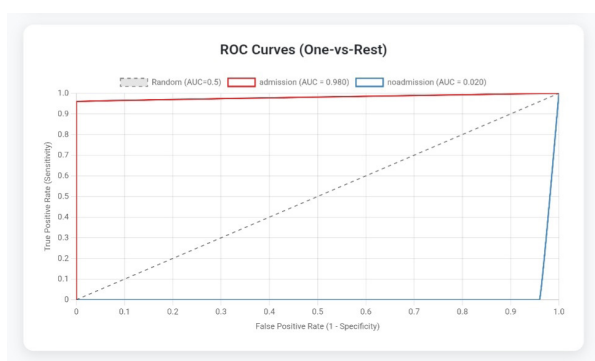


Fig. 8 ROC curve of the Multimodal DL Model illustrates the analytic capability of the multimodal DL model. The True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity). The closer to the top-left corner the higher model's capability in differentiating between patients who require 'Admission' and those who do not ('No Admission') based on extracted chest x-ray features.



Fig. 9 Bar chart provides comparison between model sensitivity and specificity for hospitalization prediction as classification accuracy. Sensitivity is the percentage of patients correctly needing hospitalization 'Admission' cases. Specificity is the percentage of patients correctly not requiring hospitalization 'No Admission' cases.

Upon fusing chest radiograph features with their corresponding patient attributes, the model identified features with different levels of association: Critical (>80%) score, namely L3 Texton Density 61 and L4 Reflection Symmetry 40. Findings are shown in Figures 13–16.

Other x-ray features that are still important although not critically indicate the hospitalization or cardiac disease severity. These second line important predictors included local mean/median, granularity measures, L5 scene type 141 and L5 spatial layout 62 which scored between 60–80%.

Further validation of such multimodal features may offer good clinical implementation and enhance hospitalization decision. On the other hand, such study may provide feasible and applicable clinical management method.

Although our deep learning model achieved 100% training accuracy and 96% validation accuracy based on training options settings above. These values are still in need for larger sample size to extend generalizability and confirm accuracy. When we augmented the dataset size upto 5 times (615 cases), there was interesting decline in validation accuracy and increase in loss. From deep learning model point of view this decline may indicate the original (123 cases) overfitting. Due to limited classes (hospitalizations) and limited variations, overfitting may occur. Further increasing the dataset may achieve plateau level validation accuracy.²⁹

Several studies that uses machine learning attempted somewhat similar approaches to recruit predictors, our study is partially in alignment with their outcomes. Such attempts were to link abnormal cardiac morphology in radiography with the severity of cardiac disease and its need for hospitalization although such studies adopt the conventional image processing mechanisms.^{30,31}

Interpretation of the Extracted Features

Our multimodal DL model yielded large number of features, namely 491 x-ray extracted features against classes of 'admission' and 'no admission' as shown in Figure 11. This means impractical to annotate all their corresponding pathological lesions. A narrowing method used within this study is by filtering only the top significantly associated CV features against hospitalization. Then it will be possible to interpret their real radiological and pathological facts based on evidences.³²

The results can be summarized as follows: Critical features have an importance score above 80%. There are 3 features at this level. These features are L3 texton density 61, L4 Reflection Symmetry 40 and the Relative Size Context. Features with a high score (60–80%) collectively are 24 features. The top ten out of these 24 included: Local Mean/Median, Granularity Measures, L5 Scene Type 141, L5 Spatial Layout 62, Prewitt-like Filter Responses, L4 Color Distribution 129, L3 Saliency Map 40, L4 Internal Structure 66, L4 Context Co-occurrence 115, L5 Vanishing Point 64.

Medium level score is between 40–60% which included 80 features like L5 Novelty Index 48 and Chromatic Aberration.

Low level score is between 20–40% which included 231 features like L5 Viewpoint Fusion 204 and L4 Regularity Pattern 45.



Dataset Augmentation · Gauss · Jitter · SMOTE · MinMax

accurate logic

↓ load CSV → select mechanisms → set amplification → generate → save augmented file

📁 SOURCE CSV (FIRST ROW = HEADERS)

Choose File
 allCombined2.csv

☒ 📢 Gaussian noise
 ☒ ⚡ Jitter (uniform)
 ☒ 🌱 SMOTE (k=1 neighbor)

☒ 📏 MinMax sample

🔄 amplification factor
 5

⚡ Run augmentation

Local Brightness Contrast	Oriented Edge Gradients	Color Channel Opponency	Local Mean/Median	Local Variance
0.161641	0.942447	1.016396	2.473052	2.445232
0.176238	1.010964	1.010572	2.845187	1.968933
0.160607	0.939375	1.016863	2.425047	2.5044
0.166808	0.967816	1.014043	2.602487	2.279062
0.170124	0.982201	1.013049	2.68604	2.17142
0.167511	0.970091	1.014001	2.617172	2.259752
0.162162	0.946224	1.016049	2.479856	2.435537
0.160842	0.938746	1.01655	2.439746	2.486674
0.158885	0.930579	1.017508	2.382286	2.56008
0.165458	0.961803	1.014688	2.570001	2.321544

rows: 615 (original: 123)

📄 Save augmented CSV

⚡ SMOTE uses Euclidean distance (normalized numeric columns). For large data (>500 rows) it may be slower; keep factor moderate.

Fig. 10 The panel of the tabular data augmentation. It displays the well known mechanisms of tabular data augmentation i.e. gaussian, jittering, SMOTE and minMax methods. These methods are recommended to be included upon limited number of datasets. Rows amplification was set as 5. The resultant total cases were 615 case from the 123 original case. Augmentation number is preferred not to exceed 10 to avoid overfitting.



ML Feature Importance Analyzer

Deterministic & Reproducible Machine Learning Analysis



Data Upload

 **Drop CSV file here or click to upload**
Supports tables with up to 500 attributes and 120 rows

TOTAL ROWS
615

TOTAL FEATURES
491

CLASSES
2

TARGET COLUMN
class



Model Configuration

Deterministic Mode

Model Type
Deep Neural Network (Gradient ▾)

Target Column (Class)
class ▾

Training Iterations
20

Learning Rate
0.001

Batch Size
32

Random Seed (Reproducibility)
42

 **Start Training & Analysis**

Fig. 11 The deep learning model. After dataset being augmented. Training settings: epochs: 100, learning rate: 0.01, batch size: 32. The augmented dataset yielded 615 case, 491 feature with 2 classes.

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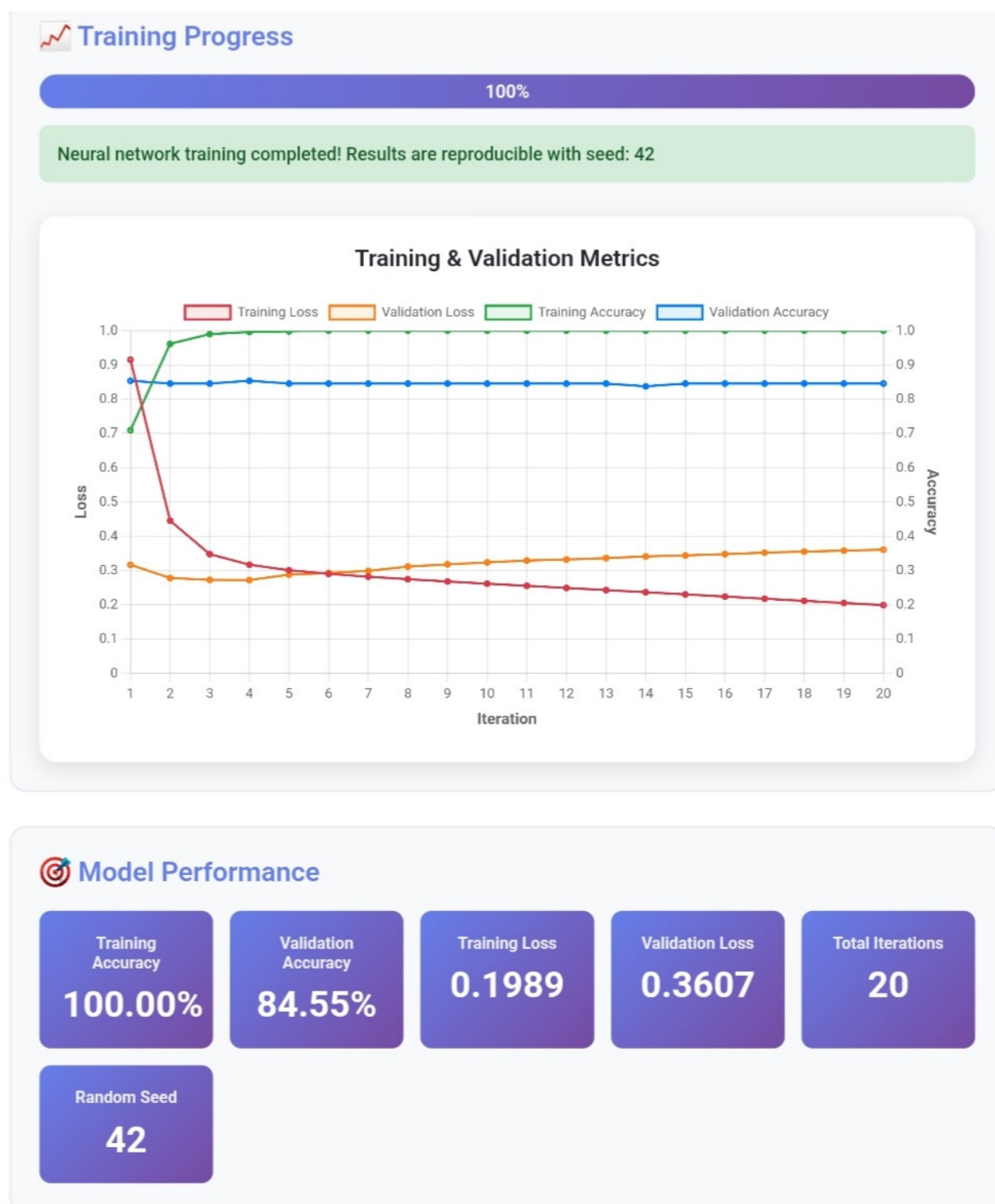


Fig. 12 Deep learning model training progress. It displays the training accuracy, validation accuracy and loss upon being trained on 615 case. Although training accuracy remained 100%, loss increased and validation accuracy declined from 96.00% to 84.55% compared to the results with the original 123 cases. This may indicate actual validation since upon increasing cases validation decrease. Validation accuracy may then pass to real plateau with increasing sample size.

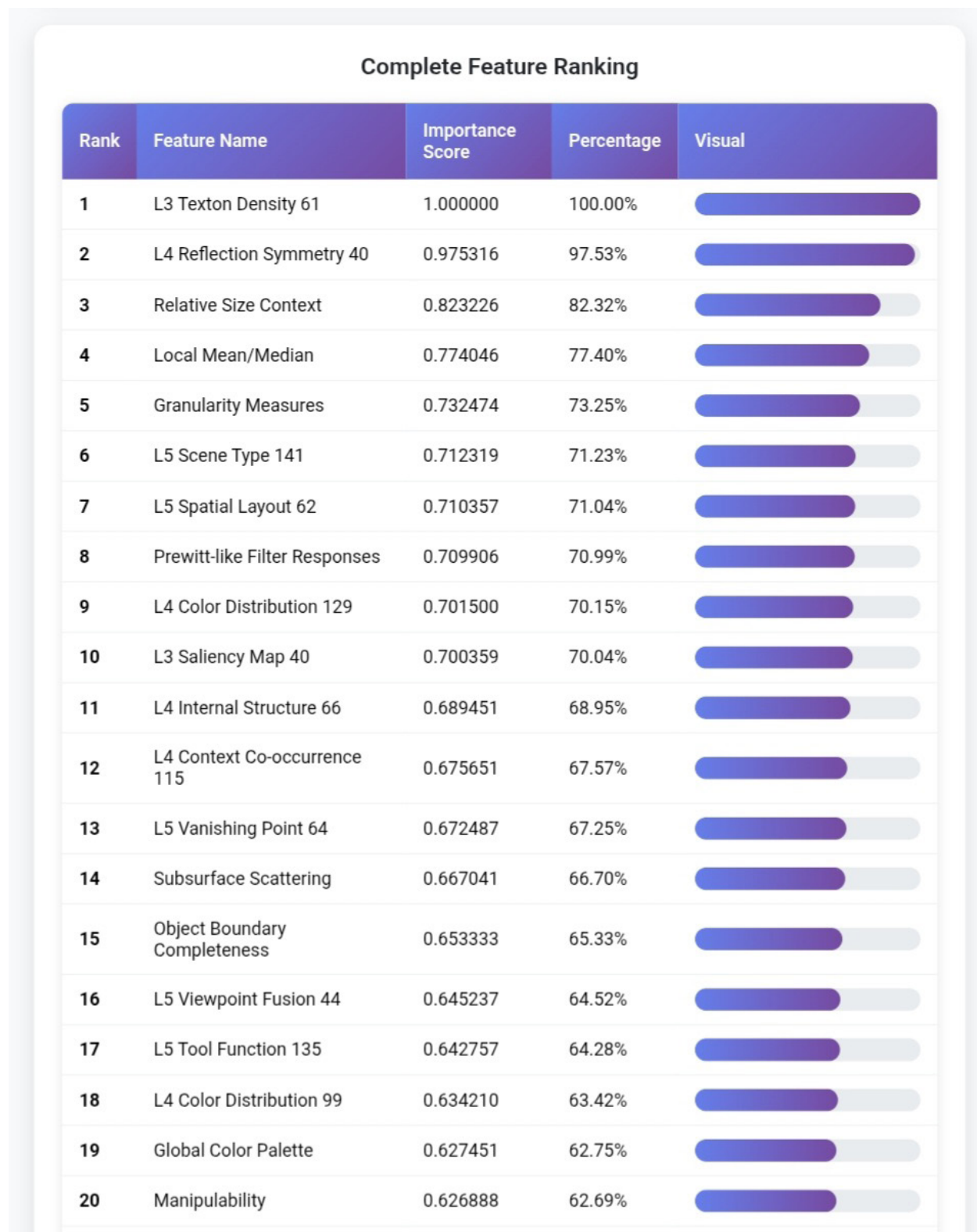


Fig. 13 Hierarchy of the chest x-ray extracted features. The top are the most critical and important predictors of the chronic cardiac disease need for hospitalization. Namely these critical predictors are: Critical (>80%): Count: 3, Features: L3 Texton Density 61, L4 Reflection Symmetry 40, Relative Size Context 2. High (60-80%): Count: 24 Features: Local Mean/Median, Granularity Measures, L5 Scene Type 141.



Fig. 14 Hierarchy of the important chest x-ray predictors but here is by the number or count of the total predictors features per each grade of importance.

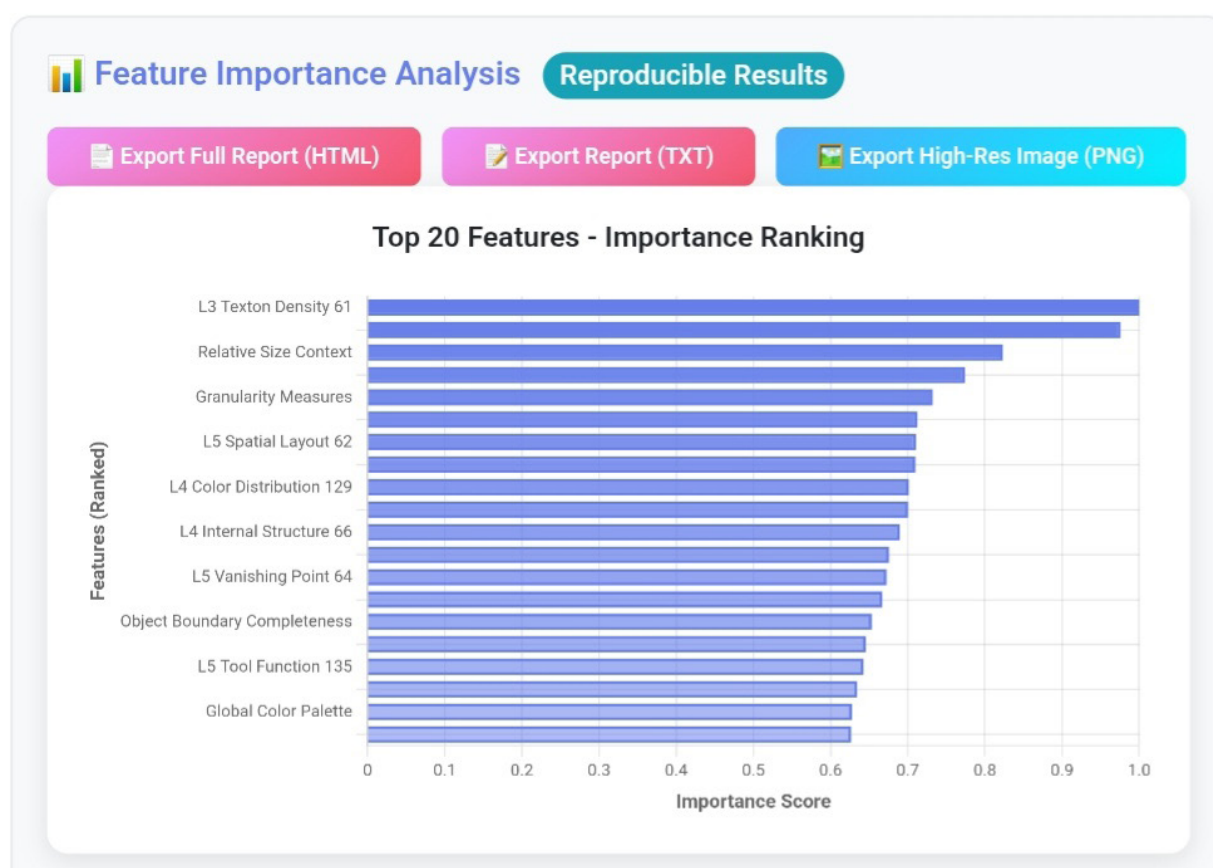


Fig. 15 The top 20 chest radiographs features according to their score of importance.

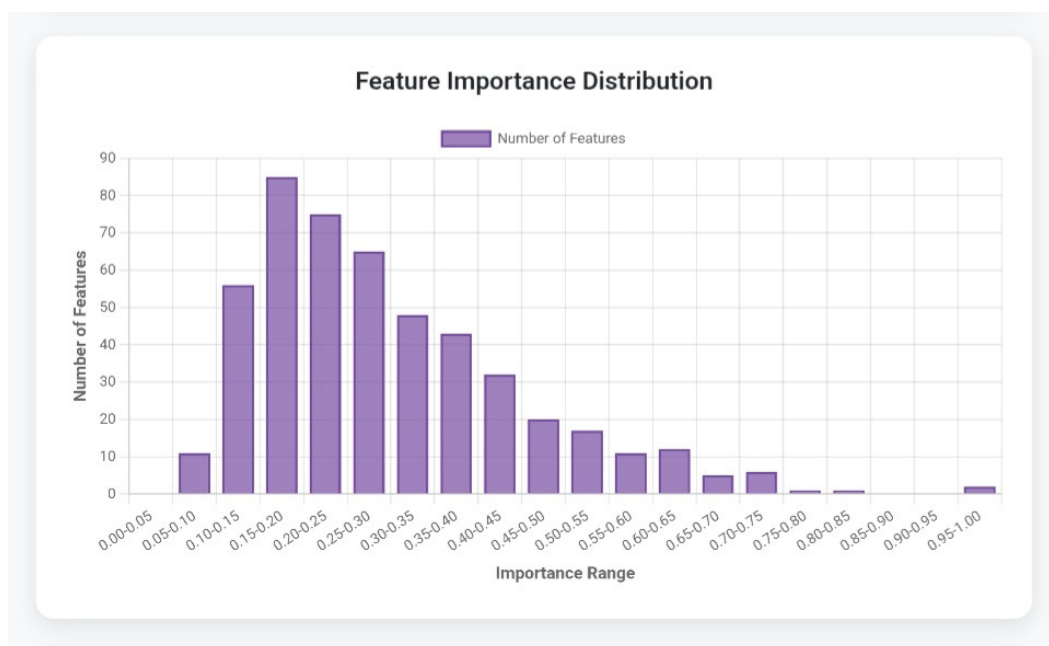


Fig. 16 Bar chart representation of the sum of important chest x-ray features. This graph explain the available options of predictors in each level of reliability so that the closely indicative feature for chronic heart disease need for hospitalization being the least available reliable features.

Conclusions

There are preliminary associations between specific set of extracted x-ray features and the need for hospitalization in patients with chronic cardiac disease. The score of this association is: critical (>80%) including three features namely L3 Texton Density 61, L4 Reflection Symmetry 40, Relative Size Context, in addition to another 24 high score associated features.

Limitations

Study sample size was in total 123 as available CC0 dataset on Kaggle repository. This was a small data size upon training Decision Tree model. This influences the model accuracy. Generalizability mandates sufficient sample size much more than 124 cases. Dataset size can be extended in further study.

The small dataset caused overfitting of the trained model and reduced reliability of our DL model predictions.

Recommendations

Future work should focus on increasing the dataset size and adopting real-world clinical testing of the chronic cardiac disease severity score for hospitalization.

Acknowledgement

We would like to acknowledge the National Institutes of Health (NIH) as the original source of the chest radiographs for providing the original 'Heart Failure Prediction Dataset' and appreciation is also extended to Kaggle team for hosting the public CC0 repository used in this study. Finally, we recognize the Tensorflow team for offering Keras library to develop our DL model.

Conflicts of Interest

None. ■

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