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# Comparative Evaluation of Computationally Efficient and Explainable 1D Brightness Profiles from Axial Projections for Lung Ultrasound Frame Classification

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## Introduction/Background

Analyzing lung ultrasound (LUS) data to identify pneumonia in pediatric patients is crucial for providing timely and accurate patient care. Automated solutions developed in this regard are mostly CNN-based methods; while effective, offer high computational complexity, limiting their wide application in resource-constrained environments. Their lack of transparency leads to clinician distrust. To address the aforementioned challenges, a computationally efficient yet explainable method to evaluate LUS data is our research focus.

## Methods/Intervention

Lung consolidations in ultrasound images appear as dark, wedge-shaped areas with mixed textures, characteristic patterns to be observed in pneumonia patients. We hypothesize that the compressed 1D data representation of the 2D frames can retain the characteristic features of lung consolidations. In the presence of lung consolidations, the intensity values across the axes plummet, as darker regions have lower pixel values. This drop in intensity values adds a valuable characteristic feature to the 1D BP vector that allows the MLP to discriminate between frames with/without consolidations. Classification of such representations can lead to the development of a computationally efficient and explainable automated solution. As a proof of concept, this study explores a novel LUS frame classification method using 1D Brightness Profiles (BP). These are obtained by summing pixel values along the y-axis and x-axis. Three types of BP were extracted from LUS frames: fy (sum of pixel values along the y-axis), fx (sum of pixel values along the x-axis), and fy+x (concatenation of fy and fx). These are then fed to separate Multilayer Perceptron Models (MLP) which perform the binary classification task (Figure 1).

## Results/Outcome

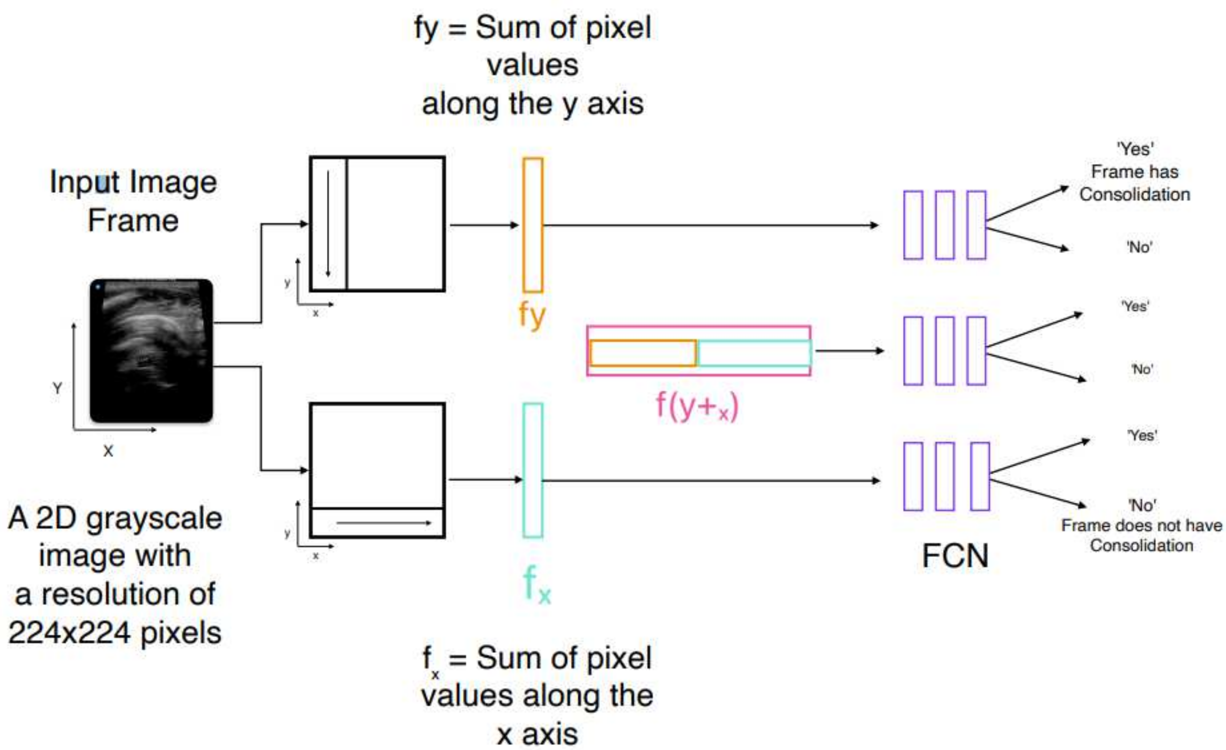
Our findings reveal that fy+x projections give better classification metrics than fy and fx projections (Figure 2). We now have a robust perspective on how different projection axes capture information.

## Conclusion

The Brightness Profiles, derived from pediatric pneumonia patients, are tested for their reliability in capturing frame patterns. The study demonstrates that the 1D arrays offer a compressed representation of LUS frames, outperforming existing CNN-based methods in terms of explainability yet offering reliable classification metrics.

## Statement of Impact

Brightness Profiles is a simplistic yet powerful information capture data type that is computationally efficient and contributes towards AI Explainability.




Our dataset comprised of LUS videos from 57 pediatric pneumonia patients. From these videos, individual frames were extracted and converted into three types of BP: fy (sum of pixel values along the y-axis), fx (sum of pixel values along the x-axis), and fy+x (concatenation of fy and fx). The flow diagram represents a process for analyzing a 2D grayscale image to determine if it contains a particular feature, referred to as "Consolidation." The process starts with an input image frame, which is a 2D grayscale image with a resolution of 224x224 pixels. The image's pixel values are summed along the x-axis and y-axis and a corresponding Brightness Profile - fy, fx, and fy+x - is obtained. These profiles are then normalized and fed into a Fully Connected Network (FCN) to check if the network can detect the presence of Consolidation. The model performance achieved is a testament to the hypothesis that brightness profiles could be used as an alternative to 2D images as they are able to retain the information from a 2D frame in a 1D array after projection along the axes. For each brightness profile, a total of six FCNs are built to make sure that all the data points in the dataset form a part of the test set once. Average evaluation metrics across these six models are recorded for all three Brightness Profiles.

Table 1

| MLP (Average Metrics) | fy | $f_x$ | $fy+_x$ |
|---|---|---|---|
| F1 Score | 61.17% | 67.21% | 69.08% |
| Balanced Accuracy | 60.58% | 62.56% | 64.21% |
| Accuracy | 60.33% | 68.45% | 70.09% |
| AUC | 0.6358 | 0.6644 | 0.6844 |

Figure 2

For each of the three Brightness Profiles, six models were built, ensuring that each patient's frames were included in the test set once across the six folds. The average evaluation metrics were reported to provide a robust perspective on the reliability and explainability of using Brightness Profiles for classification. The three profiles - fy, fx, and fy+x - showed comparable performance when averaged across the six models. The hyperparameters for all eighteen models (six models per Brightness Profile) are as follows - Epochs:100, Batch Size: 64, Gaussian Noise Standard Deviation: 0.1, Learning rate schedular decay rate: 96% after every 10 epochs, K for Train-Validation Stratified K Fold Model Training:10


## Keywords

Brightness Profiles; 1D Projections; Multilayer Perceptron; Computational Efficiency; Pediatric Pneumonia