Leveraging Deep Learning and Feature Extraction Techniques for COVID-19 Detection from Chest X-Rays

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Abstract:

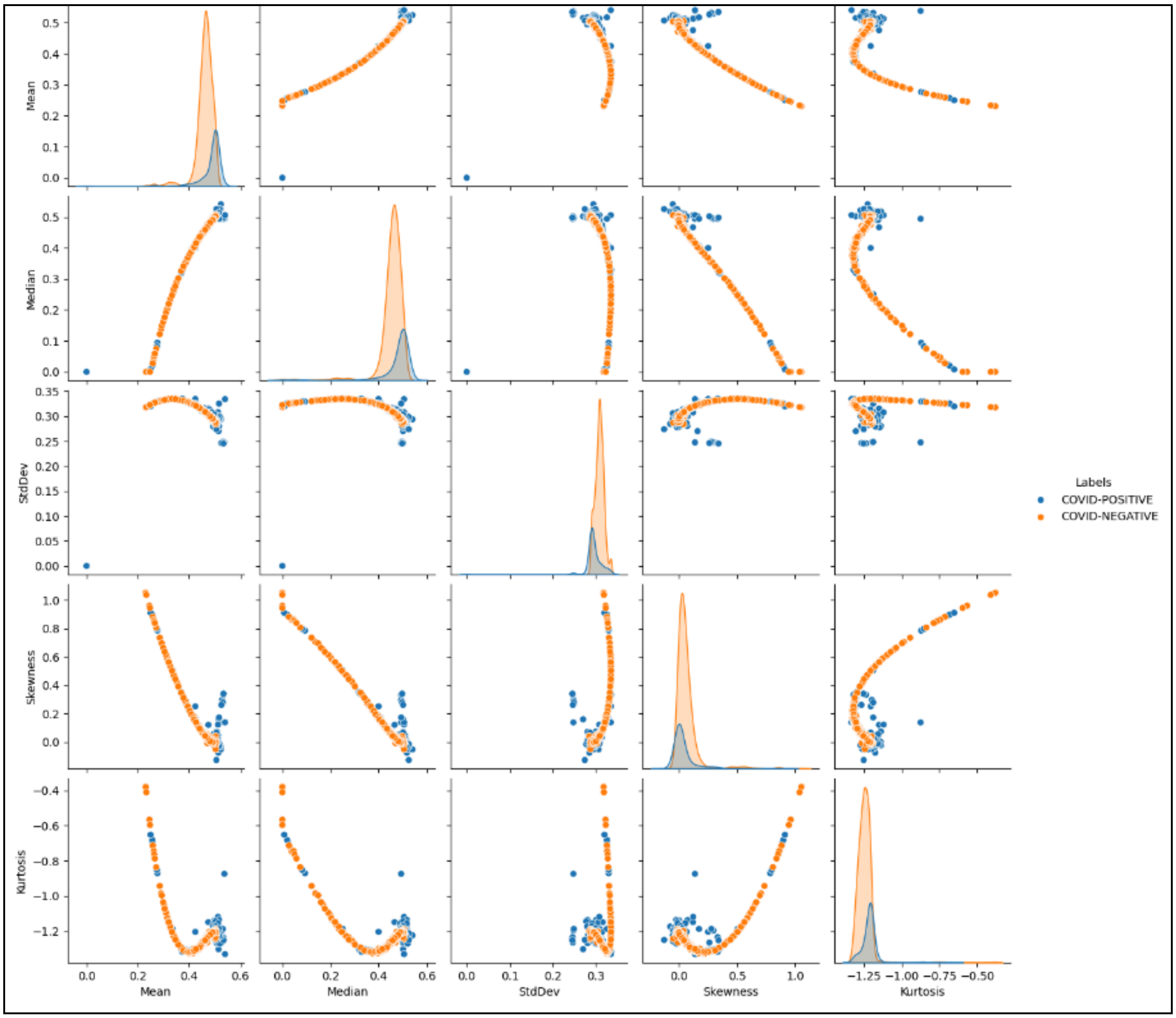
The COVID-19 pandemic has necessitated the development of efficient diagnostic tools to manage and contain its spread. This paper presents an automated system for detecting COVID-19 from chest X-ray images by leveraging a combination of Convolutional Neural Networks (CNN), Local Binary Patterns (LBP), and Histogram of Oriented Gradients (HOG). The proposed methodology integrates the powerful feature extraction capabilities of LBP and HOG with the deep learning prowess of CNN to enhance the accuracy and robustness of the detection system.

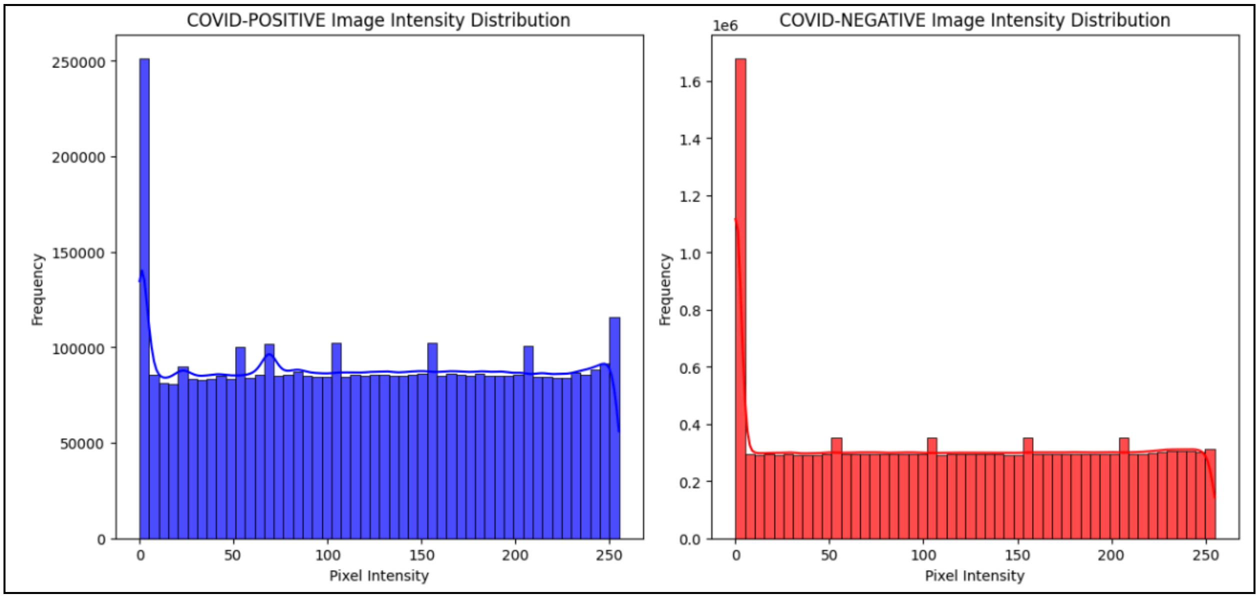
The CNN model is trained on a dataset of chest X-ray images, including both COVID-19 positive and negative cases, to learn the intricate patterns associated with the disease. LBP and HOG features are extracted to capture the texture and gradient information, respectively, which are then fused with the CNN features for improved classification performance.

Our project encompasses data preprocessing, feature engineering, model training, and deployment phases. Extensive experiments and evaluations were conducted to validate the effectiveness of the proposed system. The results demonstrate that the combined approach significantly enhances detection accuracy compared to using individual methods alone. This study highlights the importance of integrating traditional feature extraction techniques with modern deep learning methods to tackle the challenges posed by COVID-19 detection from medical imaging. The proposed system can serve as a valuable asset in

the early diagnosis and management of COVID-19, aiding healthcare professionals in making informed decisions.

Figures:





Approaches Tried:

1. **Histogram of Gradients(HOG) :**

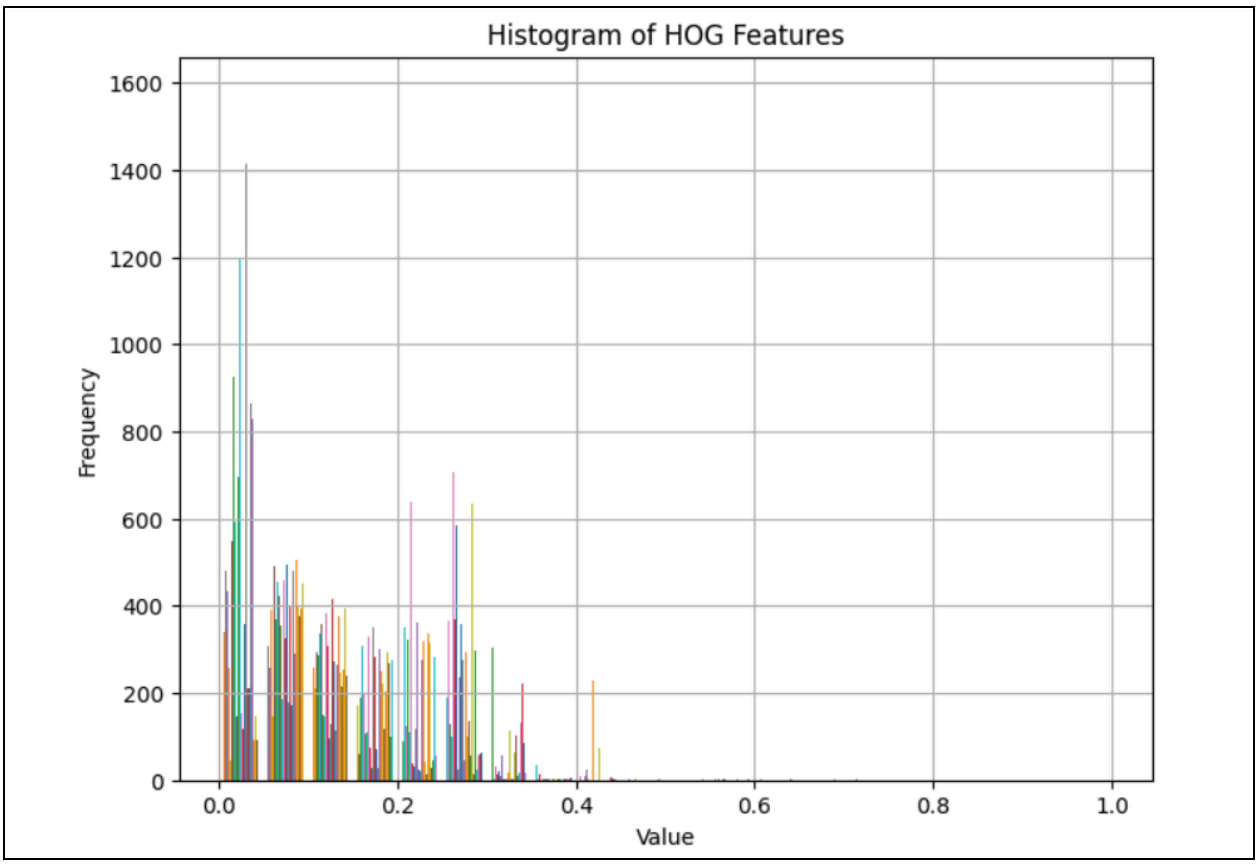
Histogram of Oriented Gradients (HOG) is a feature descriptor used extensively in computer vision and image processing for object detection and recognition tasks. Introduced by Dalal and Triggs in 2005, HOG captures the distribution of gradient orientations within an image, which helps in distinguishing different shapes and textures.

The HOG descriptor operates by dividing an image into small connected regions called cells, and for each cell, it computes a histogram of gradient directions or edge orientations. The main steps involved in computing the HOG features are as follows:

1. **Gradient Computation**: The first step involves calculating the gradients of the image. This is typically done using simple derivative filters, such as the Sobel operator, which measures changes in pixel intensity in both the horizontal and vertical directions. The result is a set of gradient vectors for each pixel in the image.
2. **Orientation Binning**: After computing the gradients, the next step is to create orientation histograms. Each pixel within a cell contributes to a histogram based on the magnitude and direction of its gradient. The

orientation binning typically involves dividing the 360-degree range of possible directions into several bins (e.g., 9 bins for 0 to 180 degrees, with each bin covering 20 degrees).

3. **Descriptor Blocks**: To account for variations in illumination and contrast, the histograms are normalized. This is achieved by grouping cells into larger blocks (e.g., 2x2 cells) and normalizing the histograms within each block. The blocks overlap, meaning that each cell contributes to multiple blocks, enhancing the robustness of the descriptor.
4. **Feature Vector Formation**: Finally, the normalized histograms from all blocks are concatenated to form a single feature vector that represents the entire image. This feature vector is then used for further processing, such as classification.



The HOG descriptor is particularly effective in capturing local shape and appearance information, making it a powerful tool for identifying objects within an image. Its robustness to changes in illumination, scale, and small deformations makes it suitable for various applications, including human detection, face recognition, and in this case, COVID-19 detection from chest X-rays.

In the context of this study, HOG features are extracted from chest X-ray images to capture the gradient and texture information associated with COVID-19 related lung abnormalities. These features are then combined with those extracted by Convolutional Neural Networks (CNN) and Local Binary Patterns (LBP) to form a comprehensive feature set, which enhances the accuracy and reliability of the COVID-19 detection system.

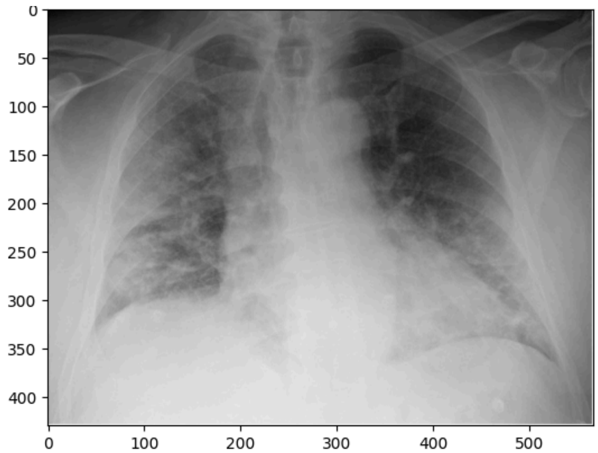
2. **Local Binary Patterns(LBP) :**

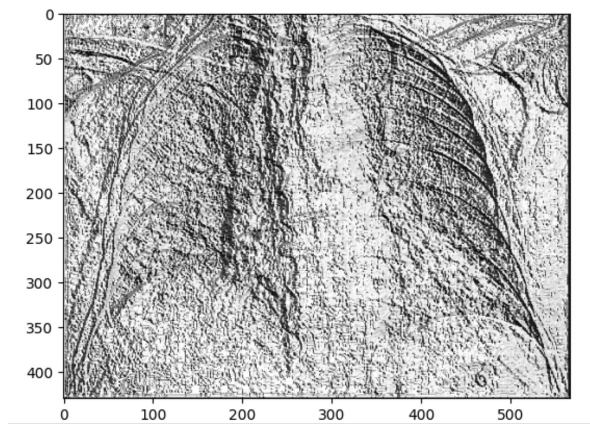
Local Binary Patterns (LBP) is a simple yet powerful texture descriptor used in image processing and computer vision for various tasks, including texture classification, face recognition, and medical image analysis. LBP is particularly effective in capturing local texture information by encoding the spatial structure of pixel intensity patterns.

The LBP operator works by comparing each pixel in an image with its surrounding neighbors and encoding this relationship into a binary pattern. The main steps involved in computing LBP features are as follows:

1. **Thresholding**: For a given pixel in the image, the LBP operator compares the pixel's intensity value with the intensity values of its neighboring pixels. A typical neighborhood consists of 8 pixels around a central pixel, forming a 3x3 grid. Each neighbor's intensity is compared with the central pixel's intensity. If the neighbor's intensity is greater than or equal to the central pixel's intensity, a value of 1 is assigned; otherwise, a value of 0 is assigned.
2. **Binary Pattern Formation**: The binary values obtained from the thresholding step are arranged in a clockwise or counterclockwise order to form an 8-bit binary number. This binary number is then converted into a decimal value, resulting in a unique LBP code for the central pixel.
3. **LBP Histogram**: The LBP codes for all pixels in an image or a region of interest are calculated, and a histogram of these codes is constructed. The histogram represents the frequency of each LBP code in the image, capturing the texture information in a compact form.

4. **Block-Based Histogram Normalization**: Similar to the HOG descriptor, LBP features can be further normalized by dividing the image into blocks and computing histograms for each block. This helps in making the descriptor invariant to changes in illumination and contrast.





The LBP descriptor is computationally efficient and robust to monotonic gray-scale changes, making it suitable for various real-time applications. It effectively captures micro-patterns such as edges, spots, and flat areas, which are essential for texture analysis.

In the context of this study, LBP features are extracted from chest X-ray images to capture the local texture patterns associated with COVID-19 related abnormalities in lung tissue. These features are combined with those extracted by Convolutional Neural Networks (CNN) and Histogram of Oriented Gradients (HOG) to create a comprehensive feature set. The integration of LBP with CNN and HOG enhances the diagnostic accuracy of the COVID-19 detection system by leveraging the complementary strengths of these feature extraction techniques.

3. Convolutional Neural Network(CNN):

Convolutional Neural Networks (CNNs) are a class of deep learning models designed specifically for processing and analyzing visual data. CNNs have revolutionized the field of computer vision, achieving state-of-the-art results in tasks such as image classification, object detection, and medical image analysis. Their ability to automatically learn and extract hierarchical features from raw pixel data makes them particularly well-suited for image-based applications.

The key components and architecture of a CNN are as follows:

1. **Convolutional Layers**: The core building block of a CNN is the convolutional layer, which applies convolutional filters (kernels) to the input image. These filters slide over the image and perform element-wise multiplication, followed by a sum to produce feature maps. Each filter detects specific patterns, such as edges, textures, or shapes, at different spatial locations. The learned filters in the early layers capture low-level features, while deeper layers capture more complex, high-level features.
2. **Activation Functions**: After each convolution operation, an activation function (typically ReLU - Rectified Linear Unit) is applied to introduce non-linearity into the model. This helps the network learn more complex patterns and improve its representational capacity.
3. **Pooling Layers**: Pooling layers, such as max pooling or average pooling, are used to down-sample the feature maps, reducing their spatial dimensions and computational complexity. Pooling helps in making the network invariant to small translations and distortions in the input image, enhancing its robustness.
4. **Fully Connected Layers**: After several convolutional and pooling layers, the feature maps are flattened into a one-dimensional vector and passed through fully connected (dense) layers. These layers perform high-level reasoning and decision-making based on the extracted features. The final layer typically uses a softmax activation function for classification tasks, providing the probability distribution over the class labels.
5. **Training Process**: CNNs are trained using large labeled datasets through supervised learning. The training process involves minimizing a loss function (e.g., cross-entropy loss for classification) using optimization algorithms like stochastic gradient descent (SGD) or Adam. Backpropagation is used to compute gradients and update the network's weights iteratively.

In this study, we employ a CNN to automatically extract features from chest X-ray images for COVID-19 detection. The CNN is trained on a dataset of chest X-rays, including both COVID-19 positive and negative cases. The network learns to identify patterns and anomalies indicative of COVID-19, such as ground-glass opacities and consolidations in the lung regions.

To enhance the performance of the COVID-19 detection system, the CNN features are combined with traditional feature extraction methods, namely Local Binary Patterns (LBP) and Histogram of Oriented Gradients (HOG). This hybrid approach leverages the strengths of CNNs in learning complex features from raw images and the robustness of LBP and HOG in capturing local texture and gradient information.

The integration of CNN with LBP and HOG leads to a comprehensive and robust feature set, improving the accuracy and reliability of COVID-19 diagnosis from chest X-rays. Extensive experiments demonstrate that the combined approach outperforms individual methods, highlighting its potential as a valuable diagnostic tool in clinical settings.

Experiments and Results:

Approach	Accuracy
HOG	74.56%
LBP	95.56%
CNN	91.66%