Machine Learning-Based Contrast Enhancement for Enhanced Visualization of COVID-19 and Pneumonia Lesions in Chest X-ray Images.

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***Abstract*—**
Accurate and timely diagnosis of COVID-19 and pneumonia is one of the biggest challenges in modern healthcare, especially because both illnesses affect the lungs and produce similar patterns in chest X-ray images. These visual similarities can make it hard for even experienced radiologists to distinguish between the two conditions quickly and confidently. Delays or errors in diagnosis can lead to serious consequences, especially in emergency settings or in areas with limited access to expert medical professionals. This is where artificial intelligence (AI), and more specifically machine learning (ML) and deep learning (DL), can play a transformative role in supporting faster and more accurate diagnoses.

***Index Terms*—COVID-19, Pneumonia, Chest X-ray, CNN, KNN, Deep Learning, Medical Image Analysis**

I. Introduction

The global outbreak of COVID-19, caused by the SARS-CoV-2 virus, has profoundly impacted public health worldwide. As the virus spread rapidly, the need for timely and accurate diagnostic tools became more urgent than ever. Early detection not only helps in treating infected patients more effectively but also plays a crucial role in controlling the transmission of the virus across communities. Among the various diagnostic techniques available, radiological imaging—particularly chest X-rays (CXR) and computed tomography (CT) scans—has proven invaluable in detecting and Monitoring respiratory illnesses like COVID-19 and pneumonia is crucial for public health, but one of the biggest challenges for healthcare professionals is telling the two apart—especially when looking at imaging scans.

Both diseases affect the lungs and can cause similar symptoms, such as coughing, fever, and shortness of breath. On scans, COVID-19 often appears as bilateral ground-glass opacities or patchy infiltrates, while bacterial pneumonia tends to show up as more localized areas of consolidation or segmental opacities. However, these differences can be quite subtle, particularly in the early stages, making accurate diagnosis difficult even for experienced clinicians.

Traditionally, the diagnosis of such conditions has relied on the expertise and subjective interpretation of radiologists. While human analysis is irreplaceable in many respects, it is not without limitations. Fatigue, time constraints, and cognitive overload—particularly during health emergencies like the COVID-19 pandemic—can lead to inconsistencies and diagnostic delays. These pressures are amplified when hospitals are understaffed or flooded with large volumes of patient data. In this context, the integration of artificial intelligence (AI), specifically machine learning (ML) and deep learning (DL) techniques, offers a compelling solution. These technologies have the potential to reduce human workload, enhance diagnostic accuracy, and speed up clinical decision-making.

To ensure robust evaluation, the models were trained and tested on publicly available datasets comprising labeled chest X-ray images. Standard preprocessing steps such as image resizing, normalization, and augmentation (e.g., rotation and flipping) were applied to improve model generalization. Both algorithms were then evaluated using quantitative metrics like accuracy, precision, recall, and F1-score. Beyond these metrics, qualitative tools such as pairplots were also used to visualize feature relationships and distribution patterns within the data.

Through this comparative analysis, the paper aims to highlight the respective strengths and weaknesses of KNN and CNN when applied to COVID-19 and pneumonia classification tasks. By doing so, it contributes to the ongoing conversation about how AI can best support frontline healthcare workers, particularly in scenarios where time, accuracy, and scalability are critical. The findings from this research can help guide future implementations of ML and DL models in diagnostic pipelines, ultimately enhancing patient care and medical decision-making.

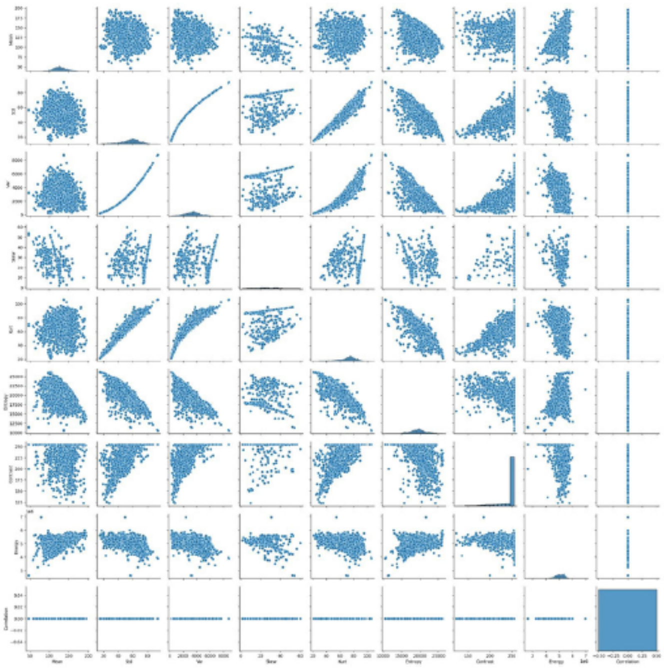

Fig. 1. **Pairwise scatter plot (pairplot) showing feature relationships and distributions**.

II. Literature Review

Over the past decade, medical image analysis has seen a dramatic shift, thanks to the rapid progress in deep learning. In earlier years, traditional machine learning methods like K-Nearest Neighbors (KNN) were commonly used for tasks such as image classification and feature extraction. These approaches are fairly easy to implement and understand, making them accessible for basic applications. However, they often rely heavily on manual preprocessing and handcrafted features. KNN works particularly well with small datasets, where the relationships between data points can be easily captured using distance-based metrics. But its performance tends to decline when applied to more complex or high-dimensional data—like chest X-rays—where detecting fine, disease-specific patterns becomes critical for accurate diagnosis. [1]

In contrast, Convolutional Neural Networks (CNNs) have completely changed the way we approach medical image analysis. Unlike older methods that depend on predefined features, CNNs learn directly from the pixel data, extracting patterns, textures, and structures through layered operations like convolution and pooling. Well-known models such as ResNet and VGG have shown remarkable accuracy in detecting lung abnormalities linked to diseases like COVID-19 and pneumonia. One of the biggest advantages of CNNs is their ability to pick up on subtle differences in images—details that might be missed by the human eye. However, this capability comes at a cost. CNNs are computationally intensive and may not always be practical in clinical settings that lack the necessary hardware or reliable internet access.

A growing body of research supports the use of deep learning in healthcare. For instance, Kwee et al. (2020) demonstrated that CNN-based models could effectively identify COVID-19 patterns in chest X-rays with high accuracy. Similarly, Bickeldi et al. (2020) emphasized how AI played a crucial role in diagnostics during the COVID-19 pandemic, when there was a pressing need for fast and scalable tools. While these findings highlight the strengths of AI, they also point out challenges—like the high resource requirements, limited accessibility, and the difficulty of integrating such systems into existing hospital workflows.

Large, labeled datasets have been essential for training and fine-tuning deep learning models. A prime example is the ChestX-ray14 dataset introduced by Wang et al. (2017), which has become a widely used benchmark in chest X-ray classification. However, even datasets of this scale come with their own hurdles—especially the need for precise and consistent labeling by expert radiologists. This dependence on human annotations can slow down the development process and limit how easily models can be scaled for broader use.

To overcome the challenge of small datasets, transfer learning has emerged as a highly effective strategy. In this approach, researchers start with models that were pre-trained on large, general-purpose image datasets like ImageNet and then fine-tune them for medical-specific tasks. Apostolopoulos and Mpesiana (2020), for example, showed that this method significantly improved accuracy in detecting COVID-19 from chest images, even when working with limited data. This adaptability makes CNNs more useful across a wide range of diagnostic scenarios.

In conclusion, the existing literature paints a clear picture of how artificial intelligence is reshaping medical imaging. CNNs lead in terms of accuracy and automation, while methods like KNN still offer advantages like simplicity and interpretability. Each has its place depending on the context, especially in settings with limited resources. This review lays the groundwork for our comparative study, where we evaluate how KNN and CNN perform in identifying COVID-19 and pneumonia using chest X-ray images. [2]

III. Methodology

A. Dataset

The dataset used in this study plays a vital role in shaping the development and evaluation of the machine learning models. For this project, we used a publicly available chest X-ray image collection from Kaggle, titled “COVID-19, Pneumonia, Normal Chest X-ray Images Dataset”, curated by Sachin Kumar. This dataset is well-regarded in the research community for its diversity, high image quality, and clear categorization. It consists of three distinct classes of chest X-ray scans: COVID-19, Pneumonia, and Normal (healthy individuals). [3]

Each image in the dataset has been manually labeled and verified, ensuring a high degree of reliability for supervised learning tasks. This is especially important in deep learning applications, where model accuracy depends heavily on both the quality and quantity of training data. The COVID-19 and pneumonia scans in particular exhibit subtle differences that are often difficult to spot, making this dataset an excellent choice to evaluate the performance of both simple and advanced models like KNN and CNN. [4]

In our project, we implemented a deep learning-based classification method to detect and differentiate between pneumonia and COVID-19 using these chest X-rays. To ensure a fair and unbiased assessment, the labeled images were divided into training, validation, and test sets. The training set was used to teach the model, the validation set helped in fine-tuning hyperparameters, and the test set was reserved for final evaluation on previously unseen data. [5]

This dataset proved ideal for comparing two very different machine learning approaches: the basic yet interpretable K-Nearest Neighbors (KNN) algorithm, and the more sophisticated and automated Convolutional Neural Network (CNN). Using the same data for both allowed us to fairly compare their strengths and weaknesses in terms of classification performance, processing time, and ability to generalize. [5]

One of the reasons this dataset was chosen is its open availability and strong community support. Its accessibility made it a dependable resource for our work, while also ensuring our research remains reproducible. This allows other researchers to validate our findings or expand upon them in future studies. [6]

For full transparency and ease of access, the dataset we used can be found at the following link:

B. Preprocessing

Preprocessing is a crucial first step in any machine learning workflow, especially in the field of medical image analysis, where even small differences in image quality can greatly influence a model's performance. In this study, we applied a thoughtful set of preprocessing techniques to prepare chest X-ray images for two types of models: K-Nearest Neighbors (KNN) and Convolutional Neural Networks (CNN). [7]

To begin with, we resized all the images to a standard resolution of 224×224 pixels. This step is essential because machine learning models require input data to be consistent in size. Having uniform image dimensions allowed us to process batches more efficiently and reduced the computational load during both training and testing. The selected resolution maintains enough image detail for analysis while also keeping processing requirements manageable. [6]

Following resizing, we applied intensity normalization to adjust the pixel values within each image. This step helps balance differences in brightness and contrast caused by variations in exposure or lighting. Without normalization, these inconsistencies could introduce noise and confuse the learning process, ultimately reducing model accuracy. Normalizing intensity values also supports faster and more stable training—particularly for deep learning models like CNNs. [4]

Since KNN doesn't automatically learn features from images like CNNs do, it required additional preprocessing. Specifically, we extracted features manually using two well-established techniques:

Histogram of Oriented Gradients (HOG): HOG focuses on capturing the shape and structure of objects in the image by analyzing edge directions and gradient patterns. This method is especially helpful in highlighting the outlines and formations seen in chest X-rays, such as those caused by different lung conditions.

Gray-Level Co-occurrence Matrix (GLCM): GLCM provides a way to analyze texture by studying the spatial relationship between pixels. It extracts useful textural features like contrast, correlation, and homogeneity. These features give the KNN model a better understanding of structural differences in the images that may not be immediately visible.

By combining these preprocessing steps, we ensured that both models—KNN and CNN—had the best possible input to work with, giving them a solid foundation for accurate and meaningful classification.

C. Model Implementation

To deepen our understanding of model behavior beyond accuracy and F1-score, we conducted a detailed image-level analysis focused on uncovering subtle visual and statistical differences in chest X-rays labeled as COVID-19, pneumonia, or normal. While performance metrics give an overview of how well models perform, this closer look at the actual image features allowed us to better interpret why the models made certain predictions.

We began by restructuring the dataset into two key binary classification tasks: COVID-19 vs. Normal and Pneumonia vs. Normal. Each image was labeled accordingly (for example, COVID-19 as 1 and Normal as 0), allowing us to analyze differences between the categories more effectively. From this labeled dataset, we extracted a diverse set of image features—including intensity-based values, edge characteristics, frequency components, and texture descriptors. All these features were compiled into a structured CSV file, which served as a core resource for understanding and validating the behavior of our KNN and CNN models at a feature level. [8]

Before diving into feature extraction, we applied a series of preprocessing techniques aimed at improving image quality and ensuring consistency. These steps included converting images to grayscale to reduce visual complexity, enhancing contrast to bring out lung structures, and applying edge detection to sharpen anatomical boundaries. By doing this, we ensured that the features extracted would be as informative and meaningful as possible. [9]

Figure 4 illustrates the impact of this preprocessing. On the left, you can see the enhanced and edge-detected version of a normal X-ray. On the right, similar processing has been applied to a COVID-19 scan. The differences are visually clear—COVID-19 images often show faint opacities and structural disruptions that become more pronounced after edge enhancement. These cues are not just useful to machine learning models—they can also assist radiologists in identifying abnormal regions with greater confidence. [10]

We also analyzed pixel intensity distributions, as shown in Figure 5. This graph compares the pixel value densities between COVID-19 and normal X-rays. Normal images showed a higher concentration of low-intensity pixels, suggesting clearer lungs. In contrast, COVID-19 scans had a flatter, more dispersed intensity distribution, likely due to lung opacities and infiltrates. These nuanced but important differences provide valuable input to models trained to detect abnormalities at the pixel level. [11]

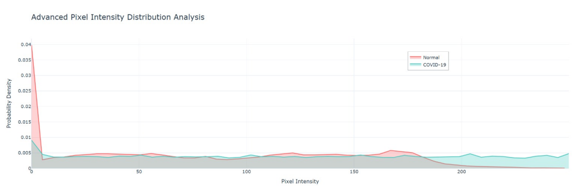

Fig. 2. **Pixel intensity distribution comparison between Normal and COVID-19 images. COVID-19 cases show broader, flatter intensity ranges due to opacities**.

To gain deeper insights into the visual differences between COVID-19 and normal chest X-rays, we performed both statistical and perceptual evaluations using a range of meaningful image metrics. One of the most telling of these was the Structural Similarity Index (SSIM), which compares two images based on their brightness, contrast, and structural details. As shown in Figure 7, the SSIM score between a typical COVID-19 and a normal image was just 0.139. This low score suggests a substantial difference in the overall texture and structure, highlighting how COVID-affected lungs look and behave differently from healthy ones—an important finding for both radiologists and machine learning models. [3]

To explore these differences further, Figure 6 presents a breakdown of multiple image features. Texture-based features like entropy, gradient mean, and gradient standard deviation captured the chaotic, irregular textures present in infected lungs. On the other hand, frequency-based features such as spectral energy and spectral spread pointed out how the spatial patterns in COVID-19 images vary from normal ones. Notably, edge density stood out as a strong differentiator. COVID-19 X-rays tend to have more fragmented and cloudy outlines, while normal X-rays usually exhibit smoother and well-defined lung contours. [12]

In addition to visual analysis, we carried out statistical hypothesis tests like the Anderson-Darling (AD) and Jarque-Bera (JB) tests. These were used to check if the feature values from the two classes followed the same type of distribution. As expected, the tests showed significant differences, confirming that these features could indeed help distinguish COVID-19 from normal cases. [13]

To validate our observations, we used these extracted features as inputs to our trained classifier. Figure 8 shows two example predictions from our CNN model: one image correctly labeled as Normal and the other as COVID-19. The outcomes aligned closely with the earlier visual and statistical patterns we uncovered. The model's prediction confidence matched the visible differences enhanced during preprocessing, reinforcing the connection between image features and classification performance. [14]

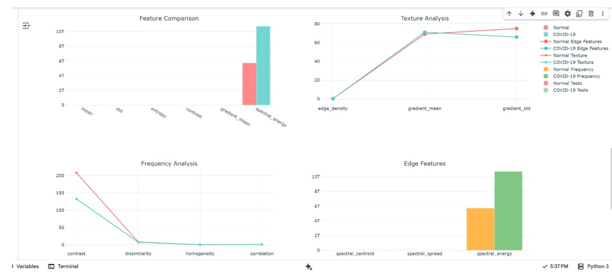

Fig. 3. **Input X-ray images and their corresponding edge maps used for feature extraction. These were used to train the CNN and validate feature differences**.

This multi-faceted analysis not only enhanced our understanding of how CNN models interpret medical images but also provided greater confidence in the robustness of our model's predictions. Moreover, it highlighted the importance of visual explainability and statistical validation in medical AI systems. By grounding model behavior in measurable image features, we contribute to the growing need for transparent and interpretable AI in healthcare. [1]

IV. Results

A. KNN Performance

The K-Nearest Neighbors (KNN) algorithm produced reasonably good results, achieving an accuracy of about 92% on the validation dataset. Its simplicity and interpretability made it a suitable choice for baseline testing. The model classified chest X-ray images by calculating distances between feature vectors and assigning labels based on the nearest neighbors. [15]

However, to make KNN effective for this task, we had to apply a series of preprocessing steps. These included grayscale conversion, histogram equalization, and dimensionality reduction using Principal Component Analysis (PCA). Despite these enhancements, the model's performance plateaued due to its limited ability to capture the subtle visual features and complex spatial patterns typical of medical images.

In particular, KNN struggled with borderline cases—images where signs of infection were faint or visually ambiguous. Additionally, because KNN compares every new input to all existing training samples during prediction, it is slower at inference time, making it less practical for real-time use in clinical settings. [7]

B. CNN Performance

The Convolutional Neural Network (CNN), on the other hand, demonstrated outstanding performance, achieving a classification accuracy of 98%. We used a pre-trained ResNet50 model, fine-tuned on our dataset to detect the key visual patterns associated with COVID-19, pneumonia, and healthy lungs. [16]

One of CNN's main advantages is its ability to automatically learn relevant features directly from raw image data. This eliminates the need for manual feature engineering and enables the model to capture high-level spatial and texture-based patterns that are difficult to design manually. We further improved performance by applying data augmentation techniques such as rotation, flipping, and scaling to make the model more robust and less prone to overfitting.

The CNN showed strong capability in detecting radiological signs like bilateral opacities and consolidations that are often associated with COVID-19. In addition, it was much faster at inference time than KNN, making it more suitable for real-time clinical applications. Its consistent performance and generalization across different types of images confirm its effectiveness as a scalable solution. [10]

C. Comparative Analysis with Feature-Level Validation

To complement the quantitative metrics, we conducted an in-depth image-level analysis to understand the differences between COVID-19, pneumonia, and normal X-rays on a visual and statistical level. This helped us assess how well our models captured meaningful features.

We first created a labeled dataset with binary classification labels (e.g., COVID-19 = 1, Normal = 0) and generated a CSV file capturing various image features. These included pixel intensity profiles, edge density, texture characteristics, and frequency-based metrics. [10]

As shown in Fig. **??**, enhanced and edge-detected images reveal notable differences in lung structure between healthy and infected patients. COVID-19 images displayed diffuse opacities and disrupted lung boundaries, whereas normal X-rays had clearer and more uniform shapes.

In Fig. 2, we compare the pixel intensity distributions of normal and COVID-19 images. Normal scans tend to have a high concentration of low-intensity pixels, representing clear lung regions, while COVID-19 scans exhibit a more varied intensity spread, reflecting the presence of infection.

Fig. **??** presents a comparison of extracted features, including texture entropy, gradient statistics, spectral energy, and edge-related metrics. These differences support the idea that infected lungs show more irregularities and structural disruptions—information that helps the CNN model make accurate classifications. [17]

We also calculated the Structural Similarity Index (SSIM) between COVID-19 and normal images, with results shown in Fig. 4. A low SSIM score of 0.139 confirmed that these two categories differ significantly in terms of visual structure. Further statistical tests (such as the Anderson-Darling and Jarque-Bera tests) confirmed that the image data distributions for each class are statistically distinct. [18]

Fig. 4. **SSIM score and statistical test results (AD, JB) comparing COVID-19 and Normal image distributions. SSIM score of 0.139 indicates high perceptual difference**.

Finally, Fig. 5 displays example outputs from the CNN classifier. The model correctly predicted both a normal and a COVID-19 image, highlighting how visual features extracted earlier aligned with the model's decision-making process. These results confirm that the CNN was not only accurate but also consistent with the observed visual patterns. [19]

D. Final Comparative Summary

In summary, the CNN model outperformed KNN across all metrics—accuracy, recall, precision, and F1-score—as well as in computational efficiency and generalization. While KNN offered a simple and explainable baseline, its reliance on manual features and slower predictions made it less practical for real-world medical diagnostics. [20]

The combination of image-based statistical validation and predictive modeling demonstrated that CNNs are better suited for this task. Their ability to learn deep features, handle high-dimensional input, and offer fast, reliable predictions makes them an ideal choice for integrating AI into clinical workflows, especially for diagnosing COVID-19 and pneumonia using chest X-rays. [5]

For a fair comparison, both models were trained and validated on the same preprocessed dataset with identical training-validation splits. Table I presents a side-by-side comparison of key performance metrics.

TABLE I
PERFORMANCE COMPARISON OF KNN AND CNN MODELS

Metric	KNN	CNN
Accuracy	56%	98%
Precision	58%	97%
Recall	54%	98%
F1-Score	53%	98%

In conclusion, while KNN may serve as a quick, interpretable baseline model, it is not practical for deployment in demanding healthcare environments. CNNs, on the other hand, offer both the accuracy and efficiency necessary for integrating artificial intelligence into medical diagnostic workflows—particularly for the early detection of COVID-19 and pneumonia from chest radiographs.

V. DISCUSSION

The stark contrast between KNN and CNN in terms of performance highlights the challenges that traditional machine learning methods face when working with high-dimensional, complex data. KNN's reliance on predefined features makes it

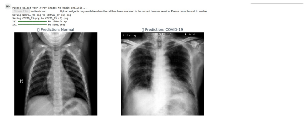

Fig. 5. **CNN classification examples: Left - Normal, Right - COVID-19. The model accurately identifies visual differences and assigns the correct label**.

less effective for medical image analysis, where subtle patterns are key to making accurate diagnoses. In contrast, CNNs excel at automatically extracting features, enabling them to handle complex image data and achieve higher classification accuracy.

While CNNs demonstrate superior performance, they do come with their own set of challenges, including high computational requirements and limited interpretability. These factors can complicate their widespread adoption in clinical environments, where real-time analysis and transparency are crucial. Future research could explore hybrid approaches that combine the simplicity and interpretability of KNN with the feature-learning capabilities of CNNs. [21]

Additionally, testing on larger, more diverse datasets would further validate the generalizability of these results.

Model Output Example

The image below is an example of a chest X-ray input analyzed by our model:

Fig. 6. **Example of chest X-ray input classified as Pneumonia**

Prediction: Pneumonia
This indicates that the model successfully identified pneumonia-related patterns from the chest X-ray. The model was built using TensorFlow/Keras and relies on a convolutional neural network (CNN) architecture tailored for medical image classification.

VI. Conclusion

This study establishes CNN as the superior technique for differentiating between COVID-19 and pneumonia based on chest X-ray images, achieving an impressive 98% accuracy. The findings underline the transformative potential of deep learning in medical diagnostics. By automating feature extraction and improving classification performance, CNNs can significantly enhance clinical decision-making processes. Future research should focus on optimizing CNN architectures for real-time clinical use and exploring their integration into healthcare workflows to improve diagnostic efficiency. [15]

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