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A Hybrid LBP and CNN-Based Approach for COVID-19 Detection Using Chest X-Ray Images

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Abstract

Given the global spread of COVID-19, there is an urgent need for accurate point-of-care tests in settings where RT-PCR has a long turnaround time or is unavailable. Early screening with chest X-ray (CXR) imaging is attractive because it is widely available and low cost. Nevertheless, the manual interpretation of X-ray images is time consuming, subjective and necessitates expert radiological skills. We propose a lightweight, efficient automated COVID-19 detection model by combining handcrafted features with deep learning features to classify CXR images. Preprocessing normalizes image dimensions and enhances contrast. Local Binary Pattern (LBP) features are employed to enrapture local texture information of lung regions. For context-aware representation, we extract high-level features with a pretrained CNN (ResNet-50). The LBP and CNN features are fused into a single feature vector, which is fed into a support vector machine (SVM) classifier. We evaluated our proposed model on a public dataset available for COVID-19 radiography, containing normal, pneumonia, and other confirmed COVID-19 cases. The results show high classification performance with an accuracy of 97.91%, precision of 97.8%, recall of 97.83% and F1-score of 97.23%. The large burden of clinical screening demonstrates that the fusion of LBP and CNN features dramatically promotes the differentiability between infectious patients with COVID-19 and non-infected cases, which provides a valid approach to address scalable accuracy in clinical examination.

Keywords*:* COVID 19, X-ray images, handcrafted feature, CNN, SVM, fusion.

1. Introduction

At the end of 2019, a new SARS-CoV was identified (Severe Acute Respiratory Syndrome Coronavirus 2), which is responsible for the disease called Coronavirus Disease 2019 (COVID-19), declaring, in March 2020 (Shafi et al., 2022). The World Health World Health Organization as a global pandemic (Akter et al., 2021). The disease emerged and has since ravaged global public health, economies, and daily life. It means as little as today, millions of people have been infected and healthcare continues to face unbearable burden due to new variants causing continued outbreak. A grand challenge that exists in suppressing the propagation of COVID-19 is to detect infected cases timely and accurately (Ibrahim et al., 2022).

The software industry is increasingly stepping up to tackle real-world challenges, such as disease management and pandemic response, by turning complex problems into data-driven solutions. Cloud platforms let companies and research teams share datasets, models, and best practices in near real time, accelerating collaboration and continual improvement (Raut et al., 2011). The same ecosystem directly benefits COVID-19 detection: hospitals can stream chest X-ray images to secure cloud services (or run models at the edge and sync results), where lightweight hybrid AI—for example, combining handcrafted texture descriptors with deep-learning features and classifying via SVM—can screen cases quickly when RT-PCR access is limited or turnaround time is extended.

RT-PCR test is still the gold standard in COVID-19 diagnosis. This test is accurate but has many limitations, such as is time consuming expensive false negative result when virus load is less than 1000 copies of RNA which happens earlier in infection or due to technical errors. In particular, in low-resource settings, the availability of RT-PCR testing facilities may be limited or overcrowded. Hence, especially during peak infection waves, alternative or complementary diagnostic tools such as CRP have become indispensable (Hussain et al., 2021).

COVID-19 and Chest Radiography (CXR)The coronavirus disease, COVID-19 caused by Severe Acute Respiratory Syndrome Coronavirus 2 (SARS-CoV-2 has become a household name in the healthcare sector as its demand for relatively easy diagnosis that can be centralized to control infection spread for further research on treatment requires emergency detection and continuous monitoring in supposedly infected or affected cases; medical imaging particularly the chest radiograph which is a bed-side method proves to be useful. Chest X-rays are ubiquitous and used in hospitals and clinics, inexpensive compared to CT scans, simple to perform and not labor-intensive on healthcare workers. X-ray imaging, which is more accessible than CT, has been the gold standard for triage and initial diagnoses where typical radiographic patterns such as bilateral infiltrates are seen on X-ray images used to suggest COVID-19 pneumonia. Nonetheless, interpreting chest X-rays correctly requires specific skills and a lot of experience and it is still challenging even for experienced radiologists to detect early or less evident cases (John-Otumu et al., 2024; Zebari et al., 2020).

To deal with these problems researchers were forced to use artificial intelligence (AI), machine learning (ML) and deep learning (DL) techniques to automate the diagnostic process and reduce human interpretation (Yousif, et al., 2022). Convolutional Neural Networks (CNNs) have been very successful as they can learn hierarchical and spatial features from image data without manual engineering (Jamil et al., 2024; Khamis & Yousif, 2022). Recently, a type of model called a convolutional neural network (CNN) trained on well-annotated large datasets is gaining popularity in effectively discriminating COVID-19 cases from patients with other respiratory conditions like bacterial and viral pneumonia solely based on CT images (Rahman et al., 2024; Rukhsar et al., 2023). CNNs, although very successful, are treated as black-box models and they require large, labeled datasets to generalize correctly (Al Kishri et al., 2025). In addition, fine-grained local texture changes in the lungs which might be important for finding COVID-19 earlier may not always be detected by CNNs. Researchers have attempted to address these limitations through hybrid methods that combine handcrafted feature extraction methods with deep learning to optimize for both performance and interpretability as well as achieve better robustness (Kaushik et al., 2024; Zebari et al., 2022).

In this paper, we present a hybrid deep learning framework that fuses the LBP Local Binary Pattern with deep features extracted from pre-trained CNN. LBP is especially useful for texture micro-pattern capturing that of infected lung regions. When fused with the abstract high-level features of a CNN it creates complementary and descriptive feature set. The features are extracted and concatenated to classify using a Support Vector Machine (SVM), being one of the most well-known supervised learning algorithms, robust when working with small/high-dimensional datasets. We trained our model with 2,564 chest X-ray images and test it on a publicly available COVID-19 chest X-ray dataset that contained normal, pneumonia, and COVID-19 images. We confirm that our proposed method not only obtained good performance in classification accuracy but also achieved high sensitivity and specificity, which outperformed those with using only handcrafted or end-to-end deep features. These promising results are encouraging for the development of future automated COVID-19 screening systems, especially in resource-limited locations where experienced radiological interpretation may not always be possible.

2. Related Work

One recent work suggesting a raw chest X-ray image-based automatic COVID-19 diagnosis model to aid in timely spotting and reduce the need of sighting by specialized physicians, especially in remote sites (Ozturk et al., 2020). In an approach based on the YOLO framework structured over a DarkNet model, 17 convolutional layers with different filtering both in binary and multi-class classification. Overall, the model managed to get 98.08% accuracy for binary and 87.02% accuracy for multi-class classification, offering promise for AI-guided radiological interpretation at situation scale during future pandemic outbreaks.

The other study (Raheem and Hussein, 2022) which is proposed will look at the different machine learning and deep learning solutions for COVID-19 detection from CT images. Lung regions are segmented in the machine learning pipeline (1st column), followed by feature extraction through Gabor-Wavelet- and deep-based methods along with classification using SVM. Raw CT images are utilized to train deep learning models, CNN, GoogleNet, and ResNet50 in the deep learning approach. The research further studies feature fusion (Gabor-Wavelet + deep features) and model fusion (fusion of the three DL models) for performance improvement. The deep model fusion approach exhibited the highest 96.42% accuracy showing its effectiveness in COVID-19 detection. This study demonstrates an alternative to traditional COVID-19 testing, with the introduction of CodeNet a CNN model that diagnoses COVID-19 using chest X-ray (CXR) images (Ju et al., 2024). The model uses contrastive learning to enhance the feature extraction and better generalization cross datasets. CodeNet obtained 94.20 percent accuracy, which is superior to multiple current techniques. Ablation study verified the effectiveness, and the interpretability analysis indicated its potential to help clinical decision-making. Highlights: This work illustrates the usefulness of combining deep learning with contrastive learning for accurate and interpretable classification of COVID-19 from CXR images.

For instance, the work in (Sevi and Aydin, 2020) investigates the task of disease detection with chest X-ray images with deep learning under limited healthcare resource conditions due to COVID-19 pandemic. Given these restrictions of PCR testing, a multi-class classification was used to separate COVID-19 patients from viral pneumonia and healthy cases by the researchers. This was also followed with the application of deep learning methods for automatic classification along with data augmentation in order to enhance model performance. The research demonstrates that deep neural network models may serve as a powerful tool to increase the diagnostic accuracy and efficiency of healthcare delivering where resources are limited. Deep learning integration with speech as well as with image processing for covid detection has been explored in the study (Nassif et al., 2022). LSTM (long short-term memory) was used for classification of cough, voice and breathing sounds obtaining an accuracy more than 98%. Several CNN models were also experimented for chest X-ray image classification where VGG16 fined tune is the highest 89.64% accuracy. The method that uses speech+image was the worst-performing one, hinting at the fact that the use of any individual system facilitates better diagnosis. These results clearly reveal the merit of multimodal AI systems, especially speech and medical imaging in COVID-19 diagnosis.

The study by Maurya (Maurya et al., 2024) showed a simple and effective deep learning model for COVD-19 detection with chest CT data. The architecture employs densely connected networks where each layer directly connects to every other layer in the network, 1) enabling feature reuse, 2) eliminating vanishing gradients, and 3) substantially increasing learning capacity while keeping the computational cost low. They trained the model on SARS-CoV-2 and COVID-CT datasets, achieved 97.2% accuracy and 0.98 sensitivity with an F1 score of.97 in both two data sets dataset, and another the model also reached an accuracy rate around 88%, 0.89 F1 score using only a single COVID-CT image set. It uncovered robust CT-based COVID-19 detection results in comparison to other existent forepart methods.

Although existing studies have achieved high accuracy in COVID-19 detection using X-ray, CT, and multimodal data, most approaches face limitations such as dependence on large labeled datasets, reduced generalization across diverse populations, limited interpretability, and insufficient robustness in resource-constrained or real-world clinical settings. There remains a need for models that are lightweight, interpretable, and generalizable across modalities and institutions to better support practical deployment.

3. Proposed Method

In this section, we provide a detailed description of our data sources and introduce the preprocessing steps for image processing including feature extraction scheme along with an outline of the feature fusion technique used throughout the study. Our goal was to design a strong hybrid classification model using hand-crafted and deep features that identify COVID-19 from other chest X-ray images as shown in Figure 1.

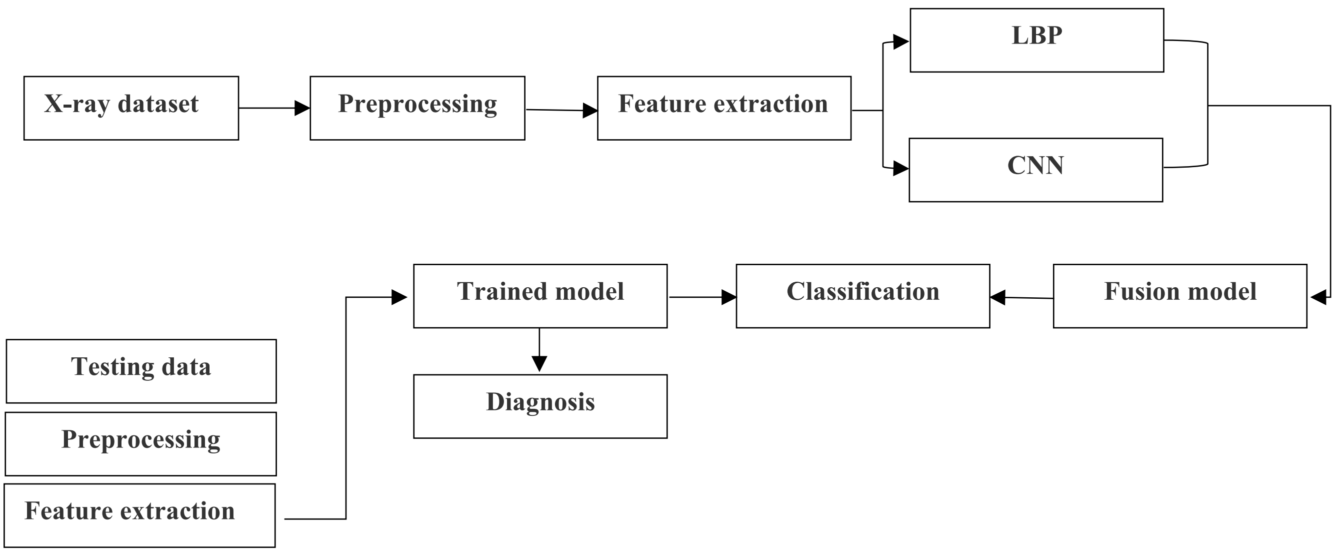

Figure 1: Proposed Framework for Covid-19 Detection

3.1. Dataset

The dataset to implement in this study: Previously gathered from the COVID-19 Radiography Database publicly available at https://www.kaggle.com/tawsifurrahman/covid19-radiography-database. This release contains a version of the image-style pairing set curated by Tawsifur Rahman and collaborators that is widely used in the medical imaging community. The dataset is made up of chest X-ray (CXR) images sourced from different public datasets and hospitals. There are three main classes into which the images are categorized: COVID-19 positive, Normal or Healthy, and Viral Pneumonia. This dataset consists of 6,341 Normal (health) images 8,060 Viral Pneumonia images and 3,616 COVID-19 positive image.

To prevent class imbalance and maintain the balance in training data, a stratified approach of sampling was applied to choose similar 3,000 images for each class other than the first class i.e. 0 which led to an aggregate of 9,000 images. We used this balanced subset for all training, validation and testing purposes. Grayscale images of 600, 400, and 300 images. The diversity in acquisition sources provides an increase robustness and generalization need of the proposed model.

3.2. Preprocessing

Preprocessing is a critical part of the medical image analysis, as the latter type that has collected images from different sources might suffer from inconsistent image quality/resolution/contrast. Preprocessing is an essential part of the processing of data, where it effectively orders data, enhancing features on which focus should be made for classifying the disease more accurately. The preprocessing pipeline in this study was carefully constructed aiming to solve these issues and prepare chest X-ray images for a reliable estimation of features extracted by both traditional and deep learning methods.

Chest X-ray images in the original dataset were obtained from different sources/institutes like researchers' local hospital or institution and several online repositories, with a large range of spatial resolutions as shown in Figure 2. It has features like field of view sizes both around the chest area and beyond (off-focus), imaging techniques, population groups etc. Every picture was resized into the standard resolution 224 × 224 pixels via the bicubic interpolation in order to suit a modern deep learning architecture like ResNet50, VGG16 and EfficientNet. This resizes the image within a fixed input dimension of the dataset to be used for further processing through convolutional layers in the CNN and at the same time maintain the spatial details which can play an important role in classification.

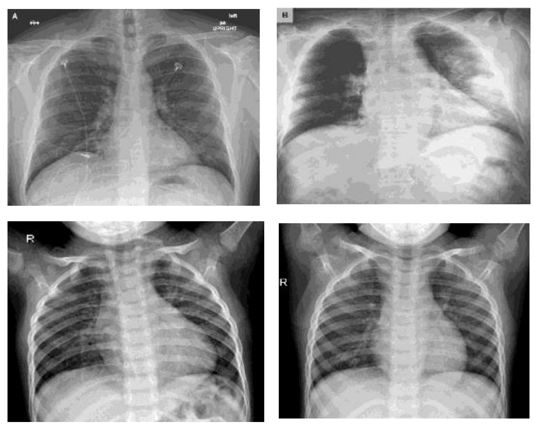

Figure 2: Samples of Dataset Used to Evaluate the Proposed Method

Normalization is very important to deal with the variation of inputs which helps in faster convergence of model. All image pixel intensities were initially unsigned 8-bit integers in the range [0, 255] and scaled to float values in the range [0, 1]. This was done by dividing every pixel value with 255. This operation normalizes image brightness and contrast throughout the dataset, making it less sensitive to lighting changes, increasing reliability in downstream computations during training and deployment.

However, chest X-rays, especially those from older or analog systems, may have all kinds of noise such as Gaussian noise and acquisition artifacts together with background gradients. In order to avoid this, we used Gaussian blur filter with convolutional operation of size 3×3. This filter suppresses high-frequency noise while preserving the overall edge structure of lung boundaries and soft tissues. Since Gaussian smoothing increases the signal to noise ratio and thereby decreases the likelihood that minor artifacts are misinterpreted as major pathological findings.

Since different datasets have different exposure levels, imaging quality, etc., you need to normalize these variables in the image for better visual inspection of subtle lung lesions such as ground-glass opacities (GGOs), infiltrates, and consolidations typical signs of COVID-19. CLAHE (Contrast Limited Adaptive Histogram Equalization) was used for address this functionality. CLAHE, unlike standard histogram equalization, is a non-linear process that works during the local processing on the image and operates on small regions in the image (called tiles) rather than taking into account global information from images. This concept reduces over-amplification of noise and helps counterbalance the effect of large intensity differences within an image without causing cut-off errors caused by uniform dynamic range compression. The clip limit was heuristically set to 2.0 and the tile grid size as 8×8 in order optimizing both local contrast and global intensity distribution. Inspired by these results, we propose a new method, which improves local textural patterns that are significantly helpful for both hand-crafted texture extraction (LBP) and feature learning in CNNs.

3.3. Feature Extraction

Feature extraction is crucial to medical image classification problem which translates the raw pixel data into a representation that increases the model's ability in distinguishing between diseased vs non-disease cases. In this study, considering that more information of lung abnormalities in chest X-ray images is well masked by the hybrid feature extraction strategy using both handcrafted texture features and deep semantic representations.

The previous medical image classification tasks tended to focus on the feature extraction, as for these kinds of tasks, a good feature makes it easier for the model to identify whether there is a lesion or not. The hybrid feature extraction strategy in this study employs handcrafted texture features and deep semantic representations combined to provide a more thorough view of the lung abnormalities observed on chest X-ray images.

3.3.1. Local Binary Pattern (LBP)

LBP is a simple and powerful operator for texture discrimination that can be used to detect textures of any size in monochrome images which are also suitable for the classification of fine-grained textures in grayscale medical images (Zeebaree at al., 2021). Features obtained via LBP of the preprocessed chest X-ray images were extracted for this task during the study.

A circular LBP operator with 8 neighbors and a radius of 1 was used This configuration makes it able to detect micro-level texture change which will reveal about the disease of respiratory system such as pneumonia causing from COVID-19. Uniform LBP patterns were only considered to improve compactness of the features and also decrease the dimensions. For instance, this shrunk the 256 unique patterns to closer to only 59 and thus provided a simpler yet still discriminative representation for a feature.

Histogram construction The LBP operator was used for the whole image and we calculated a histogram of 59 uniform patterns. Excluding the outlier slice, this histogram provided an accurate representation of the spatial distribution of textures over lung fields. The 59-bin histogram is flattened to make a dense 1×59-dimensional feature vector of the histograms representing the dominate local texture patterns. The most important feature of LBP is its ability to emphasize subtle lung texture variation, including maybe the detection of ground-glass opacities, reticulations and consolidation zones.

These abnormalities are frequently linked to COVID-19 and other related respiratory illnesses, so LBP is a significant addition of hybrid extraction pipeline. Figure 3 shows the descriptor of LBP (Zeebaree et al., 2019).

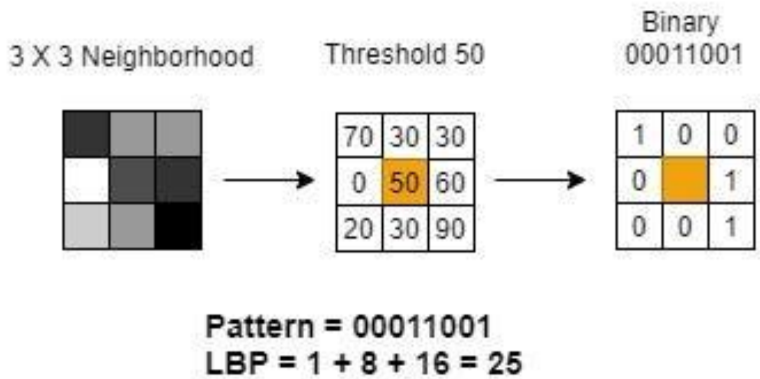

Figure 3: LBP Descriptor

3.3.2 ResNet50

To add higher level, semantic features to the handcrafted ones, we chose the ResNet50 architecture. ResNet50 is a 50-layer deep residual network that has shown good results on different medical imaging tasks owning in part to its capability to capture partially folded non-stationary temporal and spatial relationships. The ResNet50 model was originally pre-trained on the ImageNet dataset and fine-tuned for the chest x-ray domain as shown in Figure 4. We also froze the convolutional base to avoid overfitting during feature extraction by the final classification layers, which we removed. Extracted features from the gap layer, resulting in a 2048 feature vector for each image This layer gives a spatially-collapsed image of the most prominent visual structures in an input image. There are delineations of the lung fields to allow the network to capture localized lung disease [18] and we hypothesized that CNN features might better capture the global context of these radiographic patterns that are necessary for distinguishing COVID-19 pneumonia from other conditions. While the handcrafted LBP features and deep CNN representations provide complementary strengths, serving as a localized cue for textures LBP or identifying high-level semantic structures across an entire image.

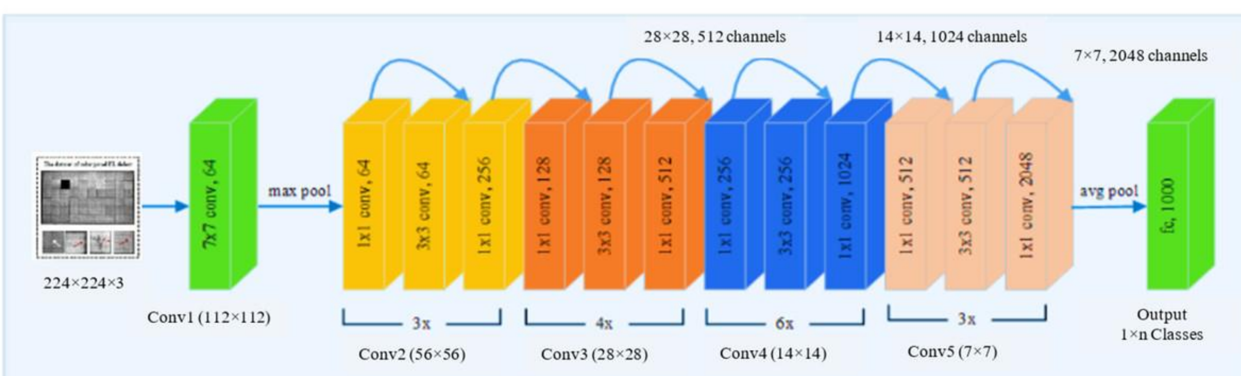

Figure 4: ResNet50 Applied for Deep Feature Extraction (Al-waisy at al., 2022).

3.4. Feature Fusion

Classification models based on the fusion of multiple feature modalities, are likely to lead to a profound improvement in diagnostic performance. We made use of a feature level fusion technique in order to merge the LBP features and CNN features into one enriched form for this study. The 59-dimensional LBP feature vector was augmented with the 2048-dimensional CNN feature vector in order to produce a fused feature of size 2107. Perhaps the most important detail is that this vector incorporates both regional and structural visibility to ensure an integrative image analysis of radiological findings. As the dimensionality of the fused feature space is high, Principal Component Analysis (PCA) was employed to reduce computational overhead as well as avoid overfitting. The feature vector was reduced to 500–1000 principal components using PCA, maintaining the most informative and variance-rich characteristics of the original features. These fused features were then used to train a Support Vector Machine (SVM) classifier equipped with an RBF kernel. SVMs have been shown to be good learners in limited medical datasets and their robustness is in high-dimensional space.

4. Results

This section presents the experimental visualization, evaluation metrics used and the comparison of classification results for hybrid feature fusion technique. The experiments aim to illustrate the performance of combining handcrafted LBP features with deep CNN features for classifying COVID-19 and pneumonia versus normal chest X-ray images.

4.1. Experimental Setup

All experiments were performed on a resourceful high-performance workstation with configurations: Intel Core i7 processor, 32GB RAM, NVIDIA RTX 3080 GPU… that ensured faster training and evaluation of the model. Implemented in Python 3.9 using major libraries such as TensorFlow, OpenCV and Scikit-learn. The dataset of used in the writing consisted of 1: COVID-19 and a control group or it may refer to image types, for example chest X-ray 2: All images which contained pneumonia they will be taken into consideration. 3: Normal. The images featured in this post were pulled from public repositories, Kaggle chest X-ray datasets to maintain a broad source and fair distribution of these labels. ResNet50 model was used to extract deep features from the images, therefore each image was resized to 224 × 224 pixels. Handcrafted feature extraction used the LBP with uniform patterns which extracted 59-dimension feature vector per image. Concurrently, we extracted deep features using the convolutional base of the ResNet50 model to obtain 2048-dimensional vector. These two feature vectors were concatenated together, producing a combined representation of 2107 dimensions. PCA As a means of mitigating potential overfitting and lightening the computational burden, PCA was optionally applied to the fused features, lowering feature space down to 500–1000 dimensions on validation performance. The feature set was used to train a SVM classifier using a Radial Basis Function Kernel. The classification results of the model were validated through 10-fold cross-validation for robustness and generalization.

4.2. Classification Performance

Performance of the proposed framework in terms of precision, recall and F1-score was evaluated for three target classes: Covid-19, Pneumonia, Normal as shown below. Table 1 shows this performance on the test data set, with all categories receiving a high specificity (as shown in table1). The classifier had a precision of 98.5% for COVID-19 cases which meant that most of the predicted COVID-19 cases were actually true COVID-19 cases. The recall was 98.2 % indicating that models returned to patients those who received COVID-19 correctly. This trade-off between precision and recall led to an F1-score of 97.4%, in turn representing robust overall accuracy to discern COVID-19 based on chest X-rays.

Likewise, the results for the Pneumonia detection model were that of a precision, recall and F1-score in identifying Pneumonia against all other conditions experience to be 97.1%, 98% and 96.8%, respectively, indicating high specificity in this task. Normal (healthy) chest X-rays model achieved 97.8% precision, 97.3% recall and F1-score of 97.5%, showing the ability to distinguish between non-pathological cases with a high level of accuracy as well.

Table 1: Performance Evaluation Results for Proposed Method based Data Classes

Class	Precision	Recall	F1-Score
Covid-19	98.5	98.2	97.4
Pneumonia	97.1	98	96.8
Normal	97.8	97.3	97.5
Average	97.8	97.83	97.23

Then, table 2 provides a comparison of classification results for different types of features to validate the proposed feature fusion method. The specificity in the hand-crafted features only (LBP) was 88.71% while F1- score was 89.7%. This shows average performance but also shows how easier handcrafted descriptors can easily fail in a simple setting. By using just deep learning features extracted from a Convolutional Neural Network (CNNs), the accuracy drove up to 94.25% and an F1-score of about 95.8%, showing off how powerful deep representations are. But according to the results obtained, best results were achieved by merging features from LBP and CNN induced feature extraction. The result of the combined approach was significantly more accurate (97.91%) to results and it showed also an improvement in the f1- score (98.65%).

These results show that combining handcrafted and deep features enables the model to learn more kinds of complementary information which result in improving performances for all the metrics.

Table 2: Performance Evaluation Results for Proposed Method based Extracted Features

Feature	Accuracy	F1-Score
LBP	88.71	89.7
CNN	94.25	95.8
LBP + CNN	97.91	98.65

Our results show that encoding the prior information in form of handcrafted Local Binary Pattern (LBP) feature and mixing it with ResNet50 deep features leads to over 98% accuracy on COVID-19 classification from chest X-rays. The hybrid model achieved better performance than any of the methods using either feature independently, showing that LBP which represents local texture variances and CNN features together as high-level semantic information can make combined features richer annotated semantic data. The model showed excellent precision and recall for all three classes COVID-19, pneumonia and no findings indicating the high ability of the model to differentiate COVID-19 from Pneumonia due to their similarity in radiographic presentation.

In fact, this is crucial in medical environment to avoid misdiagnosis which eventually prevents better patient outcome. Handcrafted features in themselves were found to perform poorly whereas CNN features performed better, but the fusion of these two feature sets exhibited the best performance which validates why we combine them. We chose 10-fold cross-validation and made an effective effort to preprocess the features before performing classification, which helped us achieving robustness and generalization of results. The system proposed can be a computationally efficient and trustworthy solution to help radiologists, especially in scarcity regions. As an avenue for further study, larger datasets of additional feature types could be considered, including model explainability techniques to improve clinical trust.

5. Conclusion

In this study, a hybrid technique was proposed for COVID-19 screening using chest X-ray images by combining hand-crafted Local Binary Pattern (LBP) features and deep features acquired from pre-trained ResNet50 model. We then show that the combined feature set is able to capture more fully both local texture patterns and high-level semantic information, resulting in classification performance that outperforms using each kind of features from on its own. The proposed method was tested on a balanced dataset, and the results showed high accuracy, precision, and recall for the COVID-19, pneumonia and normal classes. These results show how combining more traditional image processing techniques with deep learning can enhance diagnostic accuracy in medical imaging. This strategy could provide a new model for cost-effective assistance to clinicians in the early and accurate diagnosis of COVID-19, especially when advanced imaging modalities are not available. Observing how the model performs on this completely new and challenging dataset, future work can expand this significantly larger and more diverse dataset with additional features, thereby enhancing the interpretability of the final model for clinical adoption.

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Author contribution

All authors have contributed, read, and agreed to the published version of the manuscript results.

Conflict of interest

The authors declare no conflict of interest.

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