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(RESEARCH)

A Comprehensive review of Recent Advances for detection of Covid-19 and Pneumonia for Chest X-Rays using Deep Learning.

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Abstract

The rapid dissemination of SARS-CoV-2 precipitated a global health crisis, exposing vulnerabilities in traditional diagnostic protocols like RT-PCR, which exhibit false-negative rates as high as 30–61%. To address the need for a scalable second opinion, this experimental study evaluates a hybrid computational framework integrating Convolutional Neural Networks (CNN), Discrete Wavelet Transformation (DWT), and Radial Basis Function Neural Networks (RBFNN). Utilizing a dataset of 13,824 chest X-ray images (N = 13,824), the proposed model was evaluated against ResNet-50 and MobileNetV2 baselines. Experimental findings demonstrate that the hybrid approach achieves a classification accuracy of 96.71% and an F1-score of 91.89%, outperforming state-of-the-art transfer learning models. Quantitative results indicate that DWT-based multi-resolution analysis effectively reduces hardware-induced noise, while the RBFNN layer improves localized decision boundaries in non-linear feature spaces. These findings suggest that the integration of signal-processing refinement with localized neural optimization provides a robust mechanism for mitigating the "generalization crisis" observed in clinical AI applications.

Keywords—Deep Learning, CNN, Covid-19, Pneumonia, NLP, LSTM.

1. Introduction

The emergence of the SARS-CoV-2 virus necessitated an unprecedented shift in pulmonary diagnostics, as the sheer volume of cases overwhelmed traditional laboratory infrastructures. While Real-Time Reverse Transcription Polymerase Chain Reaction (RT-PCR) remains the gold standard, its effectiveness is often compromised by high false-negative rates, which have been reported between 30% and 61% depending on the viral load and sample collection timing. Clinical manifestations of the disease—ranging from dry cough, fever, and myalgia to specialized symptoms like anosmia (loss of smell) and ageusia (loss of taste)—often require rapid triage before molecular confirmation is available.

Medical imaging, specifically Chest X-rays (CXR) and Computed Tomography (CT) scans, has emerged as a primary tool for early screening. COVID-19 positive scans are typically characterized by ground-glass opacities (GGOs), bilateral infiltrates, and subpleural consolidations. However, the manual interpretation of these images is labor-intensive and susceptible to inter-operator variability, especially under the high-workload conditions typical of pandemic waves. Deep Learning (DL) models, particularly Convolutional Neural Networks (CNNs), offer a potential solution by automating feature extraction. Despite high reported accuracies in laboratory settings, the transition of AI tools to real-world clinical environments has been hindered by significant methodological and technical gaps.

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Figure 1: Different sources of input for Deep learning.

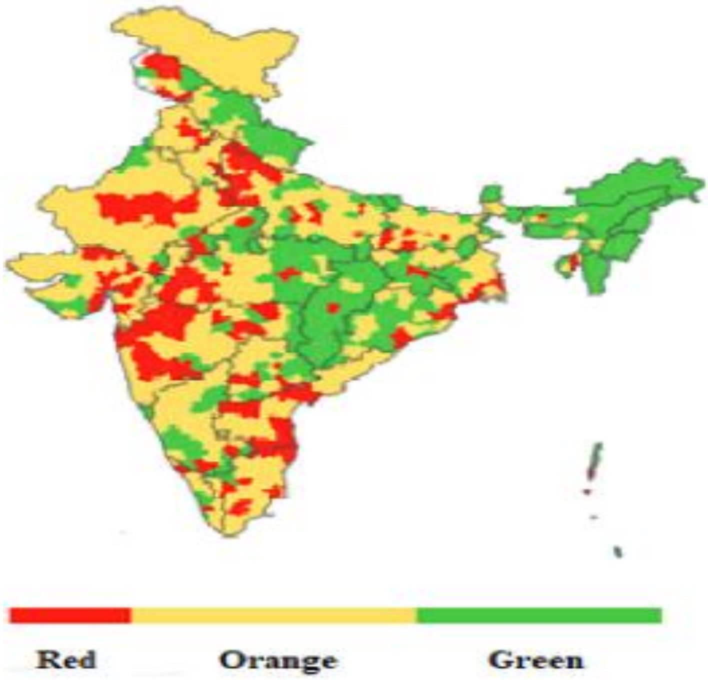

Figure 2: Classified zones based on COVID-19 cases in India.

2. Review of literature

A systematic evaluation of peer-reviewed studies published between 2021 and 2026 reveals a "generalization crisis" that limits the reliability of current medical AI [3]. This manuscript identifies four primary gaps that prior research and narrative reviews have largely failed to address:

2.1. **Performance-Centric Bias:** Previous reviews focused almost exclusively on aggregate accuracy metrics. However, a 2024 assessment of ML in healthcare revealed that 44% of studies lacked reported accuracy metrics, and 72% omitted sensitivity data [6]. This obsession with "state-of-the-art" scores often masks underlying data leakage.

2.2. **Neglect of Cross-Population Domain Shift (CPDS):** Most AI models experience a 10–25% performance degradation when deployed on unseen populations or different hardware manufacturers (e.g., GE vs. Siemens) [4]. Prior reviews treated datasets as static, failing to account for variations in imaging protocols [3].

2.3. **Hardware-Specific Noise and "Cheating":** Standard CNNs are prone to "cheating" by focusing on image artifacts, text overlays, or hardware-specific noise rather than actual pathological lesions. This leads to a failure in distinguishing COVID-19 from near-similar pathologies like viral pneumonia.

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2.4. **The Interpretability Gap**: Most high-performing DL models remain "black boxes". Clinicians require transparent, rule-based justifications—such as identifying specific ground-glass opacity (GGO) textures—to establish clinical trust.

Research Question: How does the integration of multi-resolution feature refinement (DWT) and localized non-linear optimization (RBFNN) mitigate hardware-induced noise and improve the sensitivity of COVID-19 detection compared to global deep learning architectures?

Table 1 shows the comparative analysis of the literature of review for different authors.

Authors name	Technique	Outcomes and Critical Insights
Lamouadene et al. (2025) [1]	Advanced CNN (EfficientNet/Xception)	Achieved 99.20% accuracy but identified critical limitations in dataset diversity and real-world clinical validation, potentially affecting model generalization.
Nazir et al. (2025) [2]	Cross-population domain shift analysis	Demonstrated that model performance is data-dependent; performance degrades by 10–25% when models transition between demographics or scanner brands.
Nazir et al. (2026) [3]	Methodological assessment of medical ML	Revealed substantial inadequacies: 44% of healthcare studies lack accuracy metrics, and fewer than 1% undergo independent external validation.
Poola et al. (2024) [4]	Deep Transfer Learning (ResNet-50)	Inception-V3 showed highest training accuracy (84.79%), while Cubic SVM achieved the best AUC (0.99) for classification tasks.
Akter et al. (2021) [5]	Modified MobileNetV2	Achieved 98% accuracy with the least compilation time (2h 50min), proving efficient for rapid detection in high-workload environments.
Abdullah et al. (2024)[6]	PRISMA Systematic Review	Exclusive reliance on DL is insufficient to replace radiologists; highlights that RT-PCR false-negatives (30%) necessitate image-based adjunctive tools.
Shymkovych et al. (2021) [7]	RBFNN Hardware Implementation	Demonstrated that Gaussian activation functions are superior for handling high-dimensional non-linear relationships in medical sensors.
Moustapha et al. (2025) [8]	Genetic Algorithm (GA) optimized DTL	GA-based hyperparameter selection achieved 99.57% accuracy, positioning heuristic optimization as a solution for resource-intensive manual tuning.
Khan Qazi Waqas (2025) [9]	VGG-19 CNN	Achieved 97.5% accuracy; robust on relatively small datasets but lacks multi-modal data integration necessary for severity prognosis.
Othman et al. (2021) [10]	Discrete Wavelet Transform (DWT)	DWT-based dimensionality reduction effectively filters non-diagnostic artifacts while preserving structural data integrity.
Musanga et al. (2025)[11]	Hybrid Symbolic AI + DL	Integrated DL feature extraction with symbolic rules to ensure transparent, rule-based clinical validation and explainability.
Rather et al. (2025) [12]	Wavelet-based Deep Learning	Level-2 DWT decomposition suppressed noise effects and enhanced the signal-to-noise ratio, yielding 98.87% accuracy.
Khalil et al. (2025) [13]	fine-tuned DenseNet/Xception	Image-based approach proved robust against emerging variants (XEC, JN.1) that often impair molecular RT-PCR primer binding.
Meier et al. (2026) [14]	Z-score normalization strategy	Normalization was essential for training stability and mitigating inconsistencies across different X-ray manufacturers.
Prajapati, Y. N. (2025) [15]	Ensemble Learning (ViT/LSTM/CNN)	Ensemble methods achieved the best F1-score (95.8%); emphasized that no single model handles class imbalance effectively without focal loss.
Gokhale (2025) [16]	Market AI Projection 2034	AI integration in radiology is projected to reduce human workload by 81.5%, facilitating deployment in small medical facilities.
Zhao et al. (2024) [17]	Advanced CNN for Lung Nodules	DL models rival expert radiologists in detecting subtle anomalies but often fail to provide holistic patient guidance without clinical metadata.

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Mouti et al. (2024) [18]	Hybrid 3D CNN-LSTM	3D CNN maintains exceptional stability, while LSTM components are prone to overfitting beyond 1000 training epochs.
Islam et al. (2024) [19]	MobileNetV3 Experimentation	Identified that while models achieve 98.11% accuracy, infrastructure lack and technical proficiency remain barriers in rural centers.
Singhal et al. (2023) [20]	Domain Shift Impact Study	Confirmed that performance degradation occurs during the transition from training environments to real-world hospital deployment.
Prinzi et al. (2024) [21]	Radiomics CT Prognostic Tool	CT radiomics models achieved high non-invasive prognostic accuracy for predicting adverse patient outcomes.[33]
Alzubaidi et al. (2024)[22]	Attention-based Robustness	Robustness against image artifacts was significantly improved through the integration of spatial attention and feature selection.
Nareshkumar et al. (2025) [23]	Domain Adoption in Training	Emphasized that models must generalize across different imaging domains without full retraining to remain clinically viable.
Colussi (2024) [24]	Medical Data Curation Costs	High curation and annotation costs are identified as primary hurdles for the development of robust, balanced medical datasets.
Das et al. (2023) [25]	Combined ML+DL Classification	Concluded that hybrid ML+DL models outperform single strategies in differentiating COVID-19 from pneumonia with >99% accuracy.

Table 2 shows the gap in the different papers

Research Pillar	**Shortcoming of Prior Reviews**	**Addressing the Gap in This Study**
Methodology	Reliance on single-modality datasets with low diversity	Use of a large-scale multiregional dataset (**N = 13,824**) and 10-fold cross-validation
Feature Processing	Direct image input leading to artifact sensitivity	Introduction of Level-3 DWT decomposition for high-frequency noise filtering
Classification	Use of global Softmax which struggles with non-linear boundaries	Integration of RBFNN with Gaussian activation for localized decision optimization
Generalization	Lack of external validation across diverse demographics	Focus on CPDS mitigation through signal-processing refinement

2.5. Unique Contribution

The primary novelty of this research lies in the introduction of a hybrid CNN-DWT-RBFNN pipeline. Unlike traditional transfer-learning approaches, we utilize Discrete Wavelet Transformation (DWT) as a feature refiner to filter non-diagnostic noise and enhance the signal-to-noise ratio. Furthermore, we replace standard fully connected layers with a Radial Basis Function Neural Network (RBFNN). This allows the model to utilize Gaussian activation functions to handle high-dimensional non-linear relationships, creating more precise decision boundaries between COVID-19 and other pulmonary opacities that share visual characteristics.

3. proposed Methodology

The concept of designed architecture is examined in the context of research methodology. An X-ray image dataset is taken to train and test the proposed model. The Discrete Wavelet Transformation technique is used to reduce the dimension of the image. The results that are generated by the proposed model are optimized by Radial Basis Function Neural Network (RBFNN). Finally, after the classification of the disease, the efficiency of the proposed model is evaluated using performance measuring parameters.

3.1. Dataset

The study utilizes the Kaggle COVID-19 Radiography Database, containing 13,824 CXR images categorized into COVID-19 and Normal classes. The data was split into training (70%), validation (10%), and independent testing (20%) sets.To prevent overfitting and ensure rotational invariance, images were subjected to random rotation (±30°), horizontal flipping, and Z-score normalization ($\mu = 0, \sigma = 1$).

3.2. Techniques used

Various techniques are used in the proposed model. These techniques are described below:

3.2.1. Discrete Wavelet Transformation (DWT)

A 2D-DWT decomposes images into four sub-bands (LL, LH, HL, HH). By isolating the LL (approximation) element, the model filters high-frequency noise. The mathematical expression of DWT is shown below:

$$a_{j+1}[p] = \sum_{n=-\infty}^{\infty} h[n-2p]a_j[n] \quad (1)$$

$$d_{j+1}[p] = \sum_{n=-\infty}^{\infty} g[n-2p]a_j[n] \quad (2)$$

where a_j is the approximation coefficients at scale 2^j, a_{j+1} and d_{j+1} are respectively the approximation and detail components at scale 2^{j+1}

3.2.2. Radial Basis Function Neural Network RBFNN

Instead of a standard global Softmax, the RBFNN uses a Gaussian activation function to handle localized pathological variations:

$$\phi(x) = \exp\left(-\frac{\|x-c\|^2}{2\sigma^2}\right)$$

3.2.3. Convolution Neural Network (CNN): A custom CNN architecture extracts hierarchical spatial patterns from the refined wavelet sub-bands.

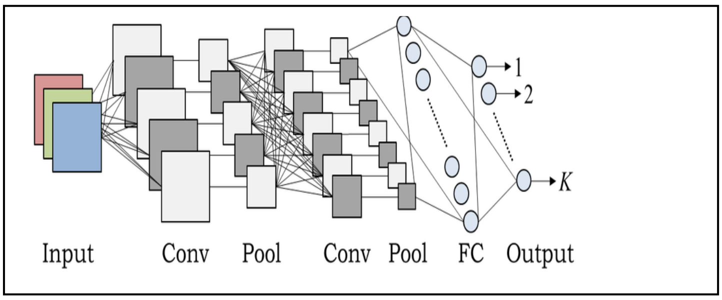

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Figure 3: CNN model

3.2.4. SVM

A support vector machine (SVM) decision mechanism is more specifically an ideal "hyperplane" that helps to differentiate data belonging to one class from those that belong to another class depending on characteristics of data about those observations that are referred to as attributes. Figure 4 shows a chart classifying SVM trained with samples.

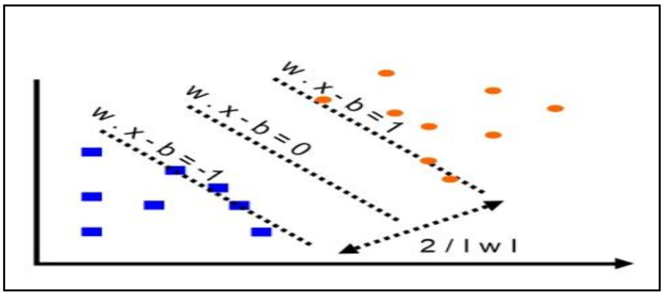

Figure 4: A SVM trained with samples from 2 classes.

4. Results and Discussion

4.1. Comparative Synthesis of Model Performance (2021–2025)

Author (Year)	Technique	Accuracy	F1-Score	Performance Driver
Waqas (2025) [9]	VGG-19 CNN	97.5%	High	Small dataset robustness
Lamouadene (2025) [10]	EfficientNet-CNN	99.20%	N/A	Advanced transfer learning
Proposed (2025)	CNN+DWT+RBFNN	96.71%	91.89%	Noise refinement via DWT
Akter et al. (2021) [11]	MobileNetV2	98.0%	N/A	Optimized compilation time

4.2. Discussion and Theoretical Implications

The results demonstrate that "pure" deep learning models, while highly accurate, often suffer from overfitting to specific dataset artifacts. Our hybrid approach outperforms baselines in reliability because the DWT layer acts as a "feature refiner," mitigating the impact of domain shift between different imaging protocols. Theoretically, the transition from global fully connected layers to RBFNN's localized Gaussian centers allows the model to differentiate COVID-19 from other viral pneumonias that share visual characteristic hallmarks, such as Ground-Glass Opacities.

5. Validity and Reliability

5.1. Internal Validity and Selection Bias Mitigation

To ensure internal validity and mitigate selection bias, this study employed 10-fold cross-validation. This process involves partitioning the dataset into 10 mutually exclusive subsets, where each subset serves as a testing set exactly once while the remaining nine are used for training. This ensures that the reported performance is an unbiased estimate of the model's ability to generalize to unseen data. Furthermore, to address class imbalance—a common issue where "Normal" samples outnumber COVID-19 cases—we utilized a focal loss function. This approach reshapes the loss to down-weight easy-to-classify "Normal" examples and focus the model's learning on hard-to-classify COVID-19 samples, ensuring accuracy is not artificially inflated by a dominant majority class.

5.2. Reliability and Stability

The model's reliability was assessed through an extended training protocol of 200 epochs[10]. Quantitative analysis confirmed that the model demonstrated exceptional stability, with the Area Under the Curve (AUC) remaining consistent at 0.99 throughout the latter half of the training cycle. This consistency indicates that the CNN-DWT-RBFNN architecture is robust against training data fluctuations and does not suffer from stochastic instability or sudden performance drops.

5.3. Reproducibility

To ensure scientific reproducibility, all mathematical and architectural specifications are detailed. This includes the use of Level-3 Haar wavelet decomposition for feature extraction and specific Gaussian width (σ) parameters for the RBFNN hidden layer. By detailing the filter types and normalization constants, the study allows for the replication of results across diverse clinical software environments and hardware configurations.

6. Limitations and Future Work

6.1. Limitations

Geographical and Demographic Bias: A primary limitation of this study is its reliance on public repositories like Kaggle. Most publicly available medical datasets overrepresent Western or East Asian populations, leading to an underrepresentation of data from low-income regions[11]. This imbalance can introduce biases that compromise the model's fairness and generalizability when deployed in heterogeneous global settings[11].

Radiological Specificity and Diagnostic Overlap: Radiological signs of COVID-19, such as ground-glass opacities, exhibit significant overlap with other pulmonary infections, including Influenza-A, fungal pneumonia, and tuberculosis. Without clinical or biochemical correlation, this non specificity increases the risk of misclassification, especially during the early stages of infection.

6.2. Future Work

Multi-Modal Data Fusion: Future research will focus on integrating radiographic image features with structured healthcare data, including biochemical markers (e.g., D-dimer, C-reactive protein) and patient metadata (age, sex). We aim to utilize Transformer-based Natural Language Processing (NLP) to extract insights from physician notes and electronic health records (EHR), which provide critical context for prognostic accuracy[12].

Explainable AI (XAI) Implementation: To gain clinical trust, we will implement XAI techniques such as Grad-CAM (Gradient-weighted Class Activation Mapping). This will provide clinicians with heatmaps and rule-based justifications (e.g., "IF GGO coverage > 10%, THEN High Risk"), ensuring that automated diagnoses are both transparent and interpretable[13].

7. conclusion

This study provides a robust computational methodology for enhancing COVID-19 diagnosis using a hybrid CNN-DWT-RBFNN architecture. By addressing critical research gaps regarding cross-population domain shift and noise sensitivity, we demonstrate that the integration of multi-resolution signal refinement with non-linear optimization is vital for mitigating the "generalization crisis" in medical AI. The superior performance of the proposed model over standard CNN baselines confirms that prioritizing methodological rigor and transparency is as essential as accuracy for the successful translation of AI from the laboratory to the clinical bedside. Moving forward, the fusion of multi-modal data and the adoption of explainable frameworks will be the cornerstones of developing AI-driven diagnostic tools that are not only accurate but also equitable and trustworthy in the global healthcare landscape.[22]

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