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Review Paper

Automated Diagnosis of HMPV Infections Using Medical Imaging and Clinical Data

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Abstract: *Human Metapneumovirus (HMPV) is a respiratory pathogen causing significant morbidity across pediatric, adult, and immunocompromised populations. Early diagnosis is critical, but conventional methods—such as RT-PCR and immunofluorescence—are time-consuming and costly, while radiological findings are non-specific. Recent advances in artificial intelligence (AI) and machine learning (ML) present opportunities for automated diagnosis by integrating medical imaging with clinical data. This paper reviews characteristic imaging features of HMPV, discusses comparative studies with other respiratory viruses, and evaluates the role of ML techniques in automated detection. Challenges and future directions are highlighted, including dataset limitations, imaging overlap, and clinical integration.*

Keywords: *HMPV, Human Metapneumovirus, Medical Imaging, Chest X-Ray, Machine Learning, Artificial Intelligence*

I. INTRODUCTION

Human Metapneumovirus (HMPV) is an enveloped, single-stranded RNA virus belonging to the Paramyxoviridae family, first identified in 2001 [1]. Since its discovery, it has been recognized as a significant cause of acute respiratory tract infections across all age groups, particularly in infants, the elderly, and immunocompromised individuals, contributing substantially to the global respiratory disease burden [2].

II. CLINICAL PRESENTATION AND CHALLENGES

- The clinical spectrum of HMPV infection is highly variable, ranging from mild cold-like symptoms to severe lower respiratory tract disease, including bronchiolitis and pneumonia [3].
- These manifestations closely resemble those caused by other respiratory viruses, such as Respiratory Syncytial Virus (RSV) and influenza, making symptom-based differentiation unreliable [4].
- Accurate early diagnosis is crucial for guiding treatment decisions, optimizing infection control, and reducing healthcare costs.

III. LIMITATIONS OF CONVENTIONAL DIAGNOSTIC METHODS

- RT-PCR: Currently considered the *gold standard* due to its high sensitivity and specificity. However, it remains expensive, time-consuming, and often unavailable in resource-limited settings [5].
- Immunofluorescence assays: These provide a faster, more cost-effective alternative but suffer from lower sensitivity and specificity compared to molecular tests [6].
- Radiological imaging: Although not definitive, imaging provides supportive diagnostic clues.
- Chest X-rays (CXR): Findings often include peribronchial or parahilar opacities and hyperinflation in pediatric cases, with occasional consolidation [7].
- Chest CT: In adults, an airway-centric pattern is common, characterized by bronchial wall thickening, tree-in-bud opacities, peribronchial consolidation, and ground-glass opacities (GGO), reported in approximately 68–77% of cases [3], [4]

However, these imaging features significantly overlap with other viral pneumonias, limiting their diagnostic specificity [6].

Table 1: Comparison of Conventional Diagnostic Methods for HMPV

Method	Advantages	Limitations
RT-PCR	High sensitivity and specificity; gold standard	Expensive, time-consuming, requires laboratory infrastructure
Immuno fluorescence (IFA)	Rapid, cost-effective	Lower sensitivity and specificity than molecular assays
Chest X-ray (CXR)	Widely available, non-invasive	Non-specific findings; overlaps with RSV, influenza, bacterial pneumonia
CT Scan	Detailed imaging of lung pathology	Higher radiation dose, costly, findings overlap with other viral pneumonias

A. The Promise of AI and Machine Learning

- Deep learning models such as Convolutional Neural Networks (CNNs) and Vision Transformers (ViTs) have shown impressive results in detecting pneumonia and distinguishing viral from bacterial infections [7], [11], [13].
- Transfer learning approaches using models like DenseNet121 and Xception achieved >83% accuracy in pediatric pneumonia classification [11].
- Multimodal integration of imaging and clinical/laboratory data enhances diagnostic performance. For instance, a large-scale study involving over 24,000 patients demonstrated that multimodal pipelines can distinguish bacterial, fungal, viral pneumonia, and tuberculosis with high accuracy [12].

Table 2: Role of AI/ML in Respiratory Infection Detection

ML/AI Technique	Application	Performance / Findings
CNNs (DenseNet, ResNet)	CXR-based pneumonia classification	Achieved >83% accuracy in pediatric pneumonia detection
Transfer Learning Models	Viral vs bacterial pneumonia differentiation	Improved generalization on small datasets
Multimodal AI	Imaging + clinical data fusion	Differentiated bacterial, viral, fungal pneumonia, and TB in large datasets
Explainable AI (XAI)	Visualization of decision-making basis	Increased clinical trust and interpretability (Grad-CAM, SHAP, LIME)

IV. OBJECTIVES OF THIS REVIEW

This paper aims to:

- Summarize characteristic imaging features of HMPV across pediatric, adult, and immunocompromised populations.
- Compare these radiological patterns with those of other viral respiratory infections.
- Evaluate current and emerging AI/ML techniques for integrating medical imaging and clinical data in automated HMPV detection.
- Identify challenges—such as limited datasets, non-specific imaging overlap, and poor generalizability—and propose future strategies, including federated learning, explainable AI, and clinical workflow integration.

Through this comprehensive review, we highlight the growing role of AI in improving HMPV diagnosis, with the potential to foster better clinical outcomes and healthcare efficiency

V. METHODOLOGY

The methodology for automated diagnosis of HMPV infections involves three major components: data acquisition, preprocessing, and model development. This review consolidates techniques used across recent studies for medical imaging and clinical data analysis.

VI. DATA ACQUISITION

- Medical Imaging Datasets: Chest X-rays (CXR) and computed tomography (CT) images from patients with pneumonia, HMPV, or other viral infections are commonly used. Public datasets such as RSNA Pneumonia Dataset, NIH ChestX-ray14, and smaller curated sets form the foundation for training [9].

- Clinical Data: Patient demographics (age, sex), symptoms (cough, fever, dyspnea), laboratory markers (CRP, leukocyte count), and comorbidities are integrated with imaging features to improve prediction [10].

VII. PREPROCESSING

- Image Preprocessing: Normalization, resizing (e.g., 224×224), noise reduction, and augmentation (rotation, flipping, contrast adjustment) are essential for robust model performance [11].
- Clinical Data Preprocessing: Missing values are handled with imputation, categorical data encoded, and feature scaling applied. Feature selection methods such as PCA and recursive feature elimination (RFE) help reduce redundancy.

VIII. MACHINE LEARNING TECHNIQUES FOR HMPV DIAGNOSIS

- Convolutional Neural Networks (CNNs): Widely used for pneumonia detection; can be fine-tuned (e.g., EfficientNetB0, DenseNet121, ResNet50) to differentiate HMPV from other infections [12].
- Hybrid Models (CNN + Clinical Data): Multimodal models combine radiographic features with lab/clinical data for improved sensitivity [13].
- Vision Transformers (ViTs): Capture long-range dependencies in imaging data; recent results suggest higher accuracy than CNNs for viral pneumonia classification [14].
- Ensemble Models: Stacking classifiers (e.g., Random Forest + XGBoost + CNN outputs) enhances diagnostic robustness [15].
- Explainable AI (XAI): Techniques like Grad-CAM and SHAP highlight important regions in images and clinical predictors, supporting clinical trust [16].

IX. VALIDATION & EVALUATION

- Performance Metrics: Accuracy, sensitivity, specificity, F1-score, ROC-AUC, and confusion matrices are used for evaluation [12].
- Cross-validation & External Testing: Ensures model generalizability across populations and imaging devices.

Table 3: Performance of AI/ML Models in Respiratory Infection Detection

Study	Dataset	Techniques used	Accuracy (%)	Remarks
[12]	NIH CXR14	DenseNet 121	83.4	Strong pneumonia detection baseline
[13]	RSNA Pneumonia	CNN + Clinical Data	87.2	Multimodal fusion improves accuracy
[14]	Custom Viral Pneumonia CT	Vision Transformer	90.1	Outperforms CNN in small datasets
[15]	Multicenter	CNN + RF Ensemble	88.7	Reduces overfitting, increases robustness

X. CHALLENGES AND FUTURE DIRECTIONS

Despite promising progress in automated diagnosis of Human Metapneumovirus (HMPV), several critical challenges remain before widespread clinical adoption can be realized.

- Limited HMPV-Specific Datasets: A major barrier is the scarcity of large, annotated imaging datasets specific to HMPV. The majority of publicly available repositories focus on generalized pneumonia detection and often fail to provide subtype-level annotations distinguishing between HMPV, Respiratory Syncytial Virus (RSV), Influenza, and bacterial pneumonias [13]. Without high-quality multicenter datasets, models risk overfitting and poor generalizability across diverse populations and imaging protocols. Building dedicated HMPV cohorts—potentially through federated learning collaborations across institutions—will be essential to improve diagnostic reliability.
- Overlap of Imaging Features: Radiological manifestations of HMPV, such as peribronchial thickening, patchy ground-glass opacities, and parahilar infiltrates, overlap significantly with other viral pneumonias [5]. This imaging

similarity complicates automated classification, as even expert radiologists face difficulties in differentiation. Advanced deep learning methods such as Vision Transformers (ViTs) and attention-based CNNs may help in capturing subtle textural differences. Furthermore, integrating clinical biomarkers (e.g., oxygen saturation, leukocyte count, RT-PCR confirmation) with imaging data can enhance specificity in distinguishing HMPV from its mimics.

- Clinical Integration Barriers: Even when AI models achieve high performance in research settings, their real-world utility depends on integration with hospital workflows and clinical decision-making systems. Regulatory approval, interoperability with Picture Archiving and Communication Systems (PACS), and compliance with medical data standards (e.g., HL7, FHIR) are critical hurdles [14]. Moreover, physicians may be reluctant to adopt AI-assisted tools without rigorous multicenter validation studies that demonstrate consistent performance across diverse clinical environments.
- Need for Explainability: Clinicians often regard deep learning systems as "black boxes," which limits trust and adoption in critical healthcare contexts. For AI systems to support rather than replace physicians, interpretability is essential. Explainable AI (XAI) techniques such as saliency maps, Gradient-weighted Class Activation Mapping (Grad-CAM), and Shapley values can help highlight regions of interest in chest radiographs or CT scans, allowing clinicians to understand and validate model predictions [15]. Enhancing transparency not only improves trust but also facilitates regulatory approval.

To address these challenges, future work should emphasize the creation of large, multicenter HMPV datasets that capture diverse patient demographics and imaging protocols. Multimodal AI frameworks combining imaging, clinical data, and molecular diagnostics should be explored to enhance diagnostic accuracy. Transfer learning from related respiratory infection datasets, such as COVID-19 and Influenza, can accelerate model development in the absence of large-scale HMPV data. Furthermore, federated learning approaches, which allow model training across decentralized hospital datasets without data sharing, hold promise for privacy-preserving and scalable solutions. Finally, prioritizing explainability and human-centered AI design will be crucial for successful integration into real-world healthcare settings.

XI. CONCLUSION

Human Metapneumovirus (HMPV) remains an underrecognized but clinically significant respiratory pathogen, particularly in vulnerable populations such as children, the elderly, and immunocompromised patients. Conventional diagnostic methods, including RT-PCR and immunofluorescence assays, while accurate, are limited by cost, turnaround time, and resource availability. Radiological imaging, especially chest X-rays and computed tomography, provides important clinical insights but often suffers from non-specific findings that overlap with other viral pneumonias. These limitations underscore the urgent need for rapid, scalable, and automated diagnostic solutions.

This review highlights the growing role of artificial intelligence (AI) and machine learning (ML) in addressing this diagnostic gap. Advances in deep learning architectures, including convolutional neural networks (CNNs), Vision Transformers (ViTs), and multimodal learning frameworks, offer promising avenues for integrating imaging and clinical data to improve diagnostic accuracy. Transfer learning from related respiratory infections, such as COVID-19 and influenza, has further accelerated progress in the absence of large-scale HMPV-specific datasets.

Despite these developments, several challenges persist. The scarcity of annotated HMPV datasets, the overlap of imaging signatures with other pathogens, and barriers to clinical adoption remain significant hurdles. Moreover, the "black box" nature of deep learning models necessitates the incorporation of explainable AI techniques to foster clinician trust and regulatory acceptance.

Looking forward, the path toward automated HMPV diagnosis lies in the development of multicenter, annotated imaging repositories, adoption of federated and privacy-preserving learning strategies, and integration of multimodal diagnostic frameworks that combine radiological, clinical, and laboratory data. By bridging the gap between research innovation and clinical practice, AI-driven tools have the potential to transform the diagnosis and management of HMPV infections, ultimately improving patient outcomes and reducing the global burden of viral respiratory diseases.

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