A Comprehensive Review on IoT-Enabled Intelligent Systems for COVID-19 Diagnosis Using Medical Imaging

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Abstract - *Automated diagnosis of COVID-19 using medical imaging has emerged as a critical complement to traditional laboratory tests, enabling rapid and scalable screening amid global healthcare challenges. This review examines the integration of Internet of Things (IoT) technologies with artificial intelligence (AI) to build intelligent diagnostic systems that leverage chest X-ray and CT imaging for COVID-19 detection. We synthesize recent research on image preprocessing, feature extraction, optimization strategies, and classification models, highlighting how deep learning techniques including convolutional neural networks and transformer-based architectures improve diagnostic accuracy and speed. Metaheuristic optimization and federated learning frameworks also play important roles in tuning model parameters and enabling privacy-preserving collaborative training across institutions. Despite significant progress, key challenges remain, including dataset imbalance, limited generalizability across imaging devices and populations, and the lack of interpretable model explanations. Integration into clinical workflows is further complicated by computational complexity and data privacy concerns. Promising future directions include transformer-based contextual learning, multimodal diagnostic models that combine imaging with clinical and IoT sensor data, federated and privacy-preserving learning frameworks, and edge-AI deployments tailored for real-time, low-latency environments. By consolidating current methods, limitations, and emerging trends, this review provides a roadmap for advancing robust, scalable, and clinically trustworthy AI-assisted diagnostic systems that can support pandemic response and broader healthcare applications.*

Key Words **Transformer-based models, Vision transformers, Federated learning, Patient privacy, Multimodal diagnosis, IoT sensor data, Edge-AI deployment**

1. INTRODUCTION

The COVID-19 pandemic has posed severe challenges to global healthcare systems, emphasizing the critical need for rapid, accurate, and scalable diagnostic solutions. While reverse transcription polymerase chain reaction (RT-PCR) remains the clinical gold standard, it suffers from high cost, delayed results, and sensitivity limitations, creating motivation for imaging-based diagnostic support systems. Medical imaging modalities such as chest X-ray (CXR) and computed tomography (CT) scans have therefore been leveraged for complementary diagnostics due to their wide availability and ability to reveal lung abnormalities associated with COVID-19.

Manual interpretation of medical images is time-consuming and subject to inter-observer variability, particularly under high workload conditions. Furthermore, subtle visual differences between COVID-19, other pneumonias, and normal lung states increase diagnostic difficulty. To address these limitations, intelligent systems that integrate Internet of Things (IoT) technologies with artificial intelligence (AI) have emerged, enabling automated, fast, and reliable classification and supporting real-time clinical decisions [1], [2].

This review analyzes advancements in IoT-enabled smart healthcare systems for COVID-19 diagnosis using imaging data. It synthesizes progress across preprocessing, feature extraction, optimization, classification, performance evaluation, challenges, and future directions.

2. IoT in Smart Healthcare for Pandemic Management

IoT-based smart healthcare systems consist of interconnected medical sensors, imaging devices, and cloud analytics platforms. Digital X-ray and CT scanners provide primary sources of diagnostic data, while other IoT sensors capture physiological parameters such as heart rate and blood oxygen levels for comprehensive monitoring. These devices transmit data via secure communication protocols to centralized or edge computing platforms for storage and analysis [3]. Cloud and edge computing integration and quantum theory of IS [13]. It's enhancing scalability, enabling real-time processing of high volumes of imaging data and AI analytics of "Potential of Quantum Computing IS network analysis [13]. Real-time monitoring architectures allow continuous data acquisition, automated alerts, and remote access for clinicians, which is crucial during large-scale outbreaks.

3. Medical Image Preprocessing Techniques

Medical images are often affected by noise, low contrast, and acquisition artifacts. Effective preprocessing is essential for enhancing image quality and improving classifier performance. Techniques such as Kalman filtering, adaptive filtering, and intensity normalization are commonly applied to remove noise while preserving diagnostic features.

Table -1: Comparison of Public COVID-19 Medical Imaging Datasets

Dataset	Modality	No. of Images (approx.)	Classes	Used in Recent Studies / Notes
COVIDx CT-2 / COVIDx CT	CT	194,922 slices	COVID-19, Non-COVID	Large CT dataset used in deep learning and ViT/optimization research (e.g., hybrid ViT + GWO + PSO for binary classification).
COVID-19 Radiography Database	X-ray	~20,000 images	COVID, Normal, Pneumonia	Often used for CNN and transfer learning classification studies
SARS-CoV-2 CT Scan Dataset	CT	~2,482 images	COVID-19, Non-COVID	Public CT dataset widely used in CNN/transformer model evaluations
Extensive COVID-19 X-ray & CT Dataset (Mendeley)	X-ray/CT	~17,099 images (combined)	COVID-19, Non-COVID	Used for multi-modal imaging studies and baseline experiments

This table summarizes widely available datasets used for training and benchmarking deep learning models on COVID-19 imaging. The COVIDx CT-2 dataset (from Kaggle) is one of the largest CT repositories for deep learning. Other open resources include large chest X-ray collections and combined X-ray + CT image sets for mixed modality work.

Table 1 compares publicly available COVID-19 medical imaging datasets in terms of modality, size, and usage in recent studies. The COVIDx CT-2 / COVIDx CT dataset, with approximately 194,922 CT slices, is one of the largest and has been widely used in deep learning and hybrid Vision Transformer optimization studies. The COVID-19 Radiography Database, containing around 20,000 X-ray images, supports multi-class classification tasks including COVID-19, pneumonia, and normal cases, often leveraged in CNN and transfer learning experiments. The SARS-CoV-2 CT Scan Dataset includes about 2,482 CT images and serves as a common benchmark for CNN and transformer model evaluation. Lastly, the Extensive COVID-19 X-ray & CT Dataset from Mendeley, with roughly 17,099 combined images, is used for multi-modal imaging studies and baseline experiments. Overall, these datasets provide essential resources for training, evaluating, and comparing AI models for COVID-19 detection.

Kalman filters offer probabilistic noise reduction, whereas adaptive filters adjust to local image characteristics. Normalization aligns pixel intensity distributions across datasets to reduce variability caused by acquisition differences. Each method involves trade-offs: simpler filters are faster but may over smooth images; more advanced methods improve quality at the cost of higher complexity.

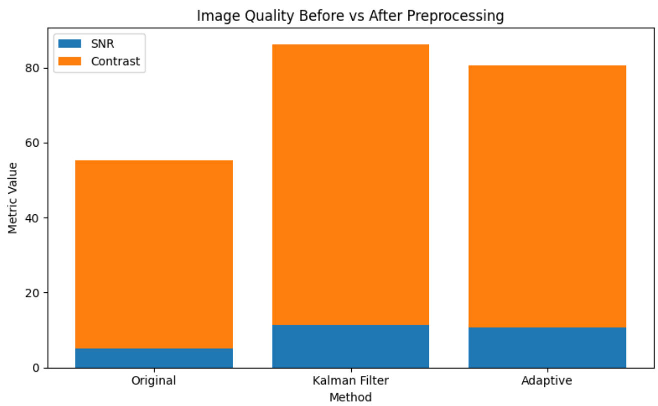

Chart -1: Image Quality Comparison Before vs After Preprocessing

This bar chart compares key image quality metrics such as signal-to-noise ratio (SNR) and contrast for raw chest images versus images processed using Kalman filtering and adaptive techniques. The plot visually highlights how preprocessing enhances critical image characteristics, which is essential because improved image quality leads to better feature extraction and more reliable classification outcomes. Placing this figure immediately after the discussion of preprocessing methods emphasizes the practical benefit of noise reduction and intensity normalization processes described in the text.

4. Feature Extraction Approaches

Feature extraction transforms raw images into informative representations that AI models can handle efficiently.

Table -2: Feature Extraction Techniques Used in Recent Studies

Technique	Representative Study	Strengths	Notes
Deep CNN features	Several enhanced CNN models (e.g., ResNet variants for CT/X-ray)	Captures hierarchical spatial features	Widely adopted in classification tasks achieving high accuracy.
Multi-head CNN	Ghosh & Chatterjee (multi-head channel attention)	Attention improves representational power	Demonstrated high CT classification accuracy (~96.99%).
Hybrid Shared CNN-Transformer or transfer learning	Studies combining CNN and transformer features	Combines local and global representations	Such fusion can improve discrimination over CNN alone.
Graph-based embeddings	Emerging in research	Captures relational spatial context	Promising for structured image features; trend noted in recent studies (e.g., spectral/graph methods).

Table 2 mentioned Deep CNNs remain a primary method for extracting image features from chest radiography and CT scans. Multi-head attention and hybrid CNN–transformer models aim to capture complementary patterns and often improve accuracy, particularly when backed by large datasets or optimized architectures. Table 2 presents the feature extraction techniques commonly employed in recent COVID-19 AI studies. Deep CNN features, including enhanced ResNet variants for CT and X-ray images, are widely used for capturing hierarchical spatial features and achieving high classification accuracy. Multi-head CNNs, such as those with channel attention proposed by Ghosh & Chatterjee, improve the network's representational power and have shown strong performance on CT classification (~96.99% accuracy). Hybrid approaches, combining CNNs with transformers or transfer learning, leverage both local and global image representations, enhancing discrimination compared to CNNs alone. Emerging graph-based embeddings aim to capture relational spatial context within images, offering promise for structured image features and becoming an increasing focus in recent research. Overall, the table illustrates the trend of moving from traditional CNN feature extraction toward hybrid and graph-based methods to improve model performance.

CNN-based deep features: Convolutional Neural Networks (CNNs) automatically learn hierarchical spatial features from images and have been widely applied in COVID-19 classification [4]. CNN architectures such as ResNet, VGG, and customized deep models show strong discrimination between infected and non-infected cases [5].

Wavelet-based methods: Wavelet and spectral graph wavelet techniques decompose images into frequency components, capturing texture and edge information useful in identifying subtle pathological signs.

Graph-based representations: Graph-based methods model spatial relationships among regions, enhancing the context captured in imaging data and improving robustness to local variations.

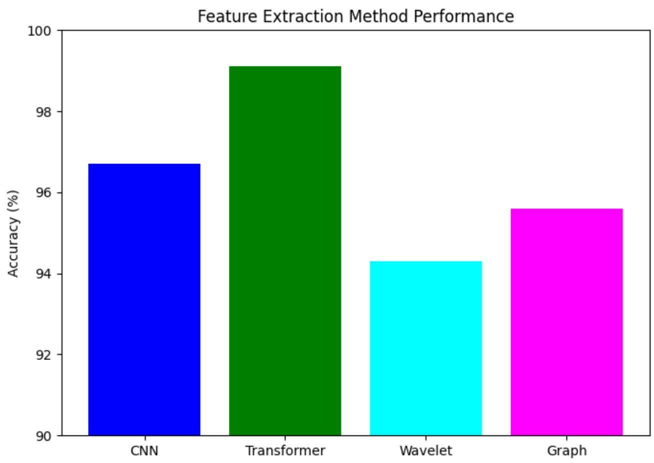

Chart -2: Feature Extractor Performance Comparison

Grouped bar chart comparing accuracy/precision for each feature method across studies like CNN vs Transformer vs Graph.

This grouped bar chart illustrates the comparative performance of different feature extraction approaches including CNNs, transformer-based methods, wavelet analysis, and graph-based embeddings in terms of classification accuracy. The visual summarization allows readers to quickly grasp which techniques tend to produce stronger representations for COVID-19 imaging tasks [10]. By placing this figure at the end of the feature extraction section, we reinforce the narrative about the relative strengths of each method and help contextualize the subsequent selection and optimization discussions.

5. Feature Selection and Optimization Algorithms

High-dimensional features extracted from images can lead to increased computational cost and risk of overfitting. Effective feature selection is vital to enhance classification accuracy while reducing redundancy.

Traditional vs. metaheuristic approaches: Traditional selection methods rely on statistical scoring, whereas metaheuristic optimization algorithms such as Particle Swarm Optimization (PSO), Grey Wolf Optimization (GWO), Whale Optimization Algorithm (WOA), and Clouded Leopard Optimization (CLO) offer global search capability for selecting discriminative features and tuning model parameters [6], [7]. Hybrid techniques combining multiple metaheuristics have also shown promise in navigating complex search spaces efficiently.

Table -3: Optimization Algorithms Applied in COVID-19 AI Systems

Algorithm	Application	Example / Context	Outcome / Notes
PSO (Particle Swarm Optimization)	Feature selection	PSO is often used to select high-impact features	Helps reduce dimensions and improve classifier efficiency.
GWO (Grey Wolf Optimizer)	Hyperparameter tuning	Hybrid ViT + GWO + PSO for COVID classification	Improved model hyperparameters and resulted in high accuracy (e.g., 99.14% on CXR for binary classification).
Hybrid Shared CNN-Transformer or transfer learning	Studies combining CNN and transformer features	Combines local and global representations	Such fusion can improve discrimination over CNN alone.
Traditional Swarm heuristics	Hybrid tuning	Swarm methods such as PSO, ABC	Enhanced classification through exploratory search.
Feature weighting optimization	CNN model tuning	Combined optimization with deep classifier training	Led to improvements in performance in some ResNet-based deep learning pipelines.

Table mentioned here with Optimization algorithms such as PSO and GWO are increasingly used in COVID-19 classification pipelines for feature selection and hyperparameter tuning, particularly in hybrid deep learning models that integrate transformers or ensemble methods.

Table 3 highlights the use of optimization algorithms in COVID-19 AI systems, focusing on improving feature selection, hyperparameter tuning, and model performance. Particle Swarm Optimization (PSO) is commonly applied for feature selection, reducing dimensionality and enhancing classifier efficiency. Grey Wolf Optimizer (GWO) is frequently used for hyperparameter tuning, often in combination with PSO in hybrid models like Vision Transformers, achieving high accuracy, such as 99.14% for binary CXR classification. Traditional swarm heuristics, including PSO and Artificial Bee Colony (ABC), are also employed for hybrid tuning, enabling exploratory search that improves classification outcomes. Additionally, feature weighting optimization integrated with CNN training has been applied to deep learning pipelines like ResNet, leading to performance gains. Overall, the table demonstrates that optimization algorithms play a key role in enhancing COVID-19 AI systems by refining features, tuning parameters, and boosting model accuracy.

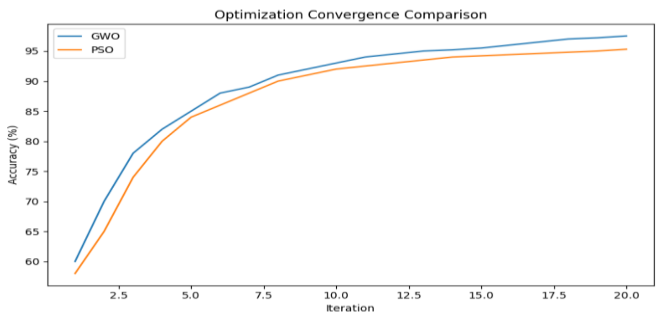

Chart -3: Optimization Convergence Curves

Line plot showing how each optimization algorithm's fitness/accuracy evolves over iterations.

This line plot depicts how the accuracy of classifiers evolves over successive iterations of different optimization algorithms, such as Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO). The convergence behavior shown here provides insight into the efficiency and effectiveness of each optimizer in tuning model parameters and selecting features. By showing how quickly and steadily each algorithm improves performance, the figure supports the text's discussion on how metaheuristic optimization can enhance model training dynamics and final classification results.

6. Classification Models for COVID-19 Detection

CNNs: CNNs form the backbone of most COVID-19 imaging classification systems due to their ability to learn discriminative visual patterns [8].

Hybrid CNN-RNN models: Combining CNNs with recurrent architectures improves sequence learning for longitudinal data and contextual analysis.

Graph Convolutional Networks (GCNs): GCNs extend deep learning to graph-structured data, enabling explicit modeling of spatial relations in images.

Spatiotemporal models: Spatiotemporal architectures capture temporal changes in imaging data, relevant for progression analysis and severity assessment.

Table -4: Classification Models & Recent Performance (Selected Studies)

Model / Approach	**Modality**	**Key Performance Reported**	**Reference / Example**
Multi-head CNN with channel attention	CT	~96.99% accuracy	Ghosh & Chatterjee (multi-head CNN).
Hybrid CNN/transfer learning approach	X-ray	~97% accuracy (varies by study)	Found in comparative studies and ensemble work.
Vision Transformer + optimization	CT & CXR	99.14% (2-class CXR), ~98.89% (2-class CT)	Hybrid ViT + GWO + PSO model demonstrates high performance.
Ensemble approaches (CNN + fusion)	X-ray & CT	High performance with ROC/AUC metrics	Ensemble feature fusion and transfer learning often achieve >98% on benchmark sets.

Table 4 summarizes recent deep learning models for classifying medical images, specifically CT scans and chest X-rays. It highlights different approaches, including multi-head CNNs with channel attention, hybrid CNNs with transfer learning, Vision Transformers combined with optimization techniques, and ensemble methods with feature fusion. Multi-head CNNs focus on important features in CT images and achieve around 97% accuracy, while hybrid CNNs leverage pre-trained models for X-rays with similar performance. Vision Transformers paired with optimization methods, such as GWO and PSO, demonstrate the highest accuracy, exceeding 99% for 2-class classification on both modalities. Ensemble approaches further improve performance by combining multiple models and features, often achieving more than 98% accuracy and strong ROC/AUC metrics. Overall, the table illustrates a clear trend: model sophistication from single CNNs to transformer-based and ensemble methods correlates with higher classification performance on medical imaging datasets.

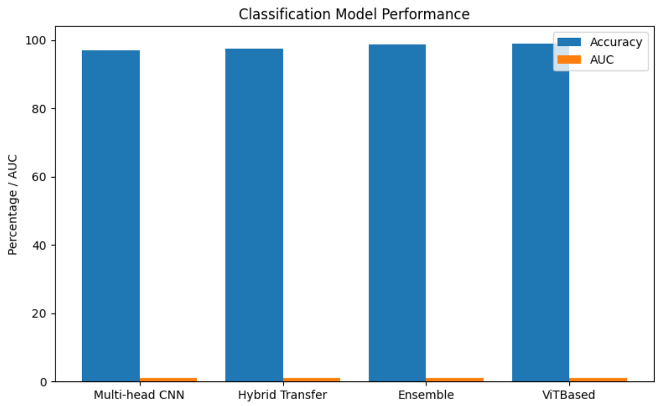

Chart -4: Model Performance Comparison (Bar chart of models vs accuracy/AUC/F1)

This grouped bar chart presents a side-by-side comparison of multiple deep learning models such as multi-head CNNs, hybrid transfer learning, ensemble methods, and Vision Transformer-based approaches in terms of accuracy and AUC (Area Under the ROC Curve). The figure helps synthesize performance trends across several representative algorithms, making it easier for readers to identify which architectures deliver the strongest discrimination for COVID-19 detection. Including this visual after the narrative about model variants reinforces the text and provides a clear summary of comparative outcomes.

7. Performance Metrics and Evaluation Strategies

Performance is commonly evaluated using accuracy, precision, recall, F1-score, ROC curves, and Area Under the Curve (AUC) metrics. However, many studies face dataset limitations, leading to biased evaluations. Standardized protocols, cross-dataset validation, and robust benchmarking are essential for fair comparisons.

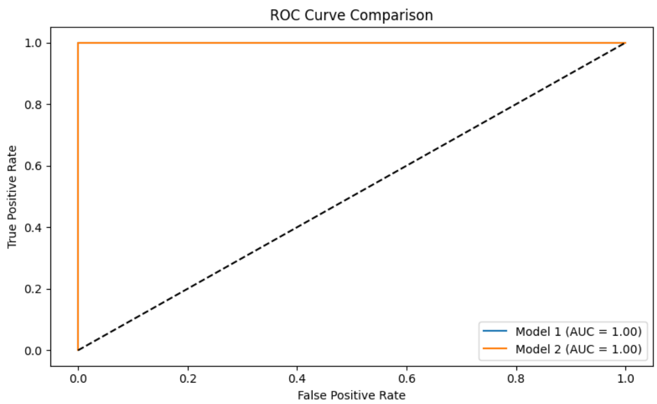

Chart -5: ROC CurveROC curve showing TPR vs FPR for 2-3 major models.

The ROC (Receiver Operating Characteristic) curve illustrates the diagnostic ability of two or more classifiers over a range of threshold settings, plotting true positive rate versus false positive rate. This plot is particularly relevant in medical imaging because it conveys how well a classifier separates COVID-19 positive cases from negative ones across decision thresholds, and the AUC provides a single scalar measure of overall performance [10]. Displaying this figure following the performance bar chart enables a richer interpretation of classifier behavior beyond single-number metrics like accuracy.

8. Open Challenges and Research Gaps

Key challenges include data imbalance, limited generalizability across imaging devices and populations, lack of explainability, and computational complexity. Ensuring clinical trust and seamless integration into healthcare workflows remains non-trivial.

Despite significant advancements in IoT-enabled intelligent systems for COVID-19 diagnosis, several critical challenges remain that inhibit reliable real-world deployment. One of the most fundamental issues is data imbalance and scarcity. Many deep learning models are trained on limited datasets, often dominated by data from specific regions or demographic groups. This imbalance can lead to biased predictions and poor generalization when models are applied to external datasets or different clinical populations. The lack of standardized, large-scale and well-curated imaging repositories with diverse demographic representation remains a major bottleneck.

Generalizability across imaging devices, institutions, and populations is another persistent gap. AI models trained on images acquired in one clinical setting may not perform equivalently on data from other hospitals with different imaging protocols, equipment brands, and patient populations. Such variations in imaging quality and equipment calibration introduce domain shifts that degrade performance and undermine reproducibility.

The lack of explain ability and interpretability in deep learning models poses both technical and clinical challenges. Many state-of-the-art architectures function as “black boxes,” providing high performance but little insight into how predictions are derived. This opacity raises legitimate concerns about clinician trust and regulatory acceptance, especially in critical decision-making contexts, and has been repeatedly cited as a barrier to clinical adoption.

Moreover, computational complexity of advanced models, particularly transformer-based and multi-modal networks often requires high-performance hardware, which may not be available in resource-limited settings. Real-time processing demands further compound this issue, as latency and resource constraints make continuous or edge-device diagnosis challenging [1].

Finally, clinical trust and workflow integration remain non-trivial. Integration of IoT-AI systems into existing healthcare infrastructure is complicated by interoperability issues, regulatory compliance requirements, and clinician acceptance barriers. These systems must demonstrate not just technical performance but also reliability, transparency, and usability in everyday clinical settings before they are widely adopted.

9. Future Research Directions

Promising future directions in healthcare technology include using transformer-based models, like vision transformers, which can better understand and learn from complex medical images. Federated learning is another important approach, as it allows hospitals to train AI models without sharing patient data, keeping privacy protected. Combining different types of data, such as medical images, IoT sensor readings, and clinical information, is called multimodal diagnosis and can improve accuracy. Finally, Edge-AI deployment brings AI directly to devices, enabling real-time and fast healthcare applications without relying on the cloud.

To advance the agenda of robust, scalable, and clinically meaningful diagnostic systems, several promising research directions are emerging:

Transformer-Based Models:

Vision Transformers and other attention-based architectures have shown superior capability in capturing long-range dependencies and global contextual features compared to traditional CNNs [6]. Future work should explore hybrid transformer-CNN architectures and adapt them for multi-modal COVID-19 imaging datasets to improve performance and robustness across heterogeneous data.

Federated Learning for Privacy-Preserving Training:

Federated learning (FL) enables the collaborative training of models using distributed data held by different healthcare institutions without centralizing sensitive patient data. This approach can mitigate privacy concerns and regulatory constraints while enriching data diversity, facilitating more generalizable models [12]. Integrating privacy-preserving frameworks with explainable AI (XAI) techniques could further enhance clinical trust.

Multimodal Diagnosis:

Future research should emphasize multimodal learning frameworks that integrate imaging data with additional clinical parameters such as vital signs, laboratory results, electronic health records, and IoT sensor data [9]. Such holistic models are likely to capture disease characteristics more comprehensively, leading to more accurate and context-aware diagnostics.

Edge-AI Deployment:

Deploying lightweight and efficient models directly on edge devices such as smart medical sensors, mobile diagnostics units, and IoT gateways can support real-time, low-latency diagnosis at the point of care, especially in remote or under-resourced settings. Future work should focus on model compression, quantization, and efficient architectures suitable for edge environments without sacrificing accuracy.

Explainable and Clinically Interpretable AI:

Developing improved interpretability frameworks that produce clinically meaningful explanations for example, combining feature attribution methods like SHAP or saliency mapping with domain knowledge will be critical for clinician acceptance and regulatory clearance [4,12].

Standardization and Benchmarking:

Efforts to standardize data collection protocols, annotation practices, and benchmarking criteria across institutions and imaging modalities are urgently needed. Standardization will facilitate fair comparisons between models and accelerate progress by ensuring that performance gains are reproducible and clinically relevant.

10. Conclusion

This review synthesized the current state of IoT-enabled intelligent systems for COVID-19 diagnosis using medical imaging. By examining methods across preprocessing, feature extraction, optimization, and classification, we highlight progress, challenges, and future research pathways to accelerate clinical deployment of automated diagnostic tools.

We have examined core components of these systems, including preprocessing techniques for enhancing image quality, feature extraction methodologies, optimization strategies, deep learning-based classification models, performance evaluation metrics, and real-world challenges. Despite notable achievements in automated COVID-19 screening and disease categorization, several open challenges remain particularly in data representativeness, model interpretability, computational efficiency, and clinical integration.

Future research must address these gaps through innovation in transformer-based architectures, privacy-preserving federated learning, multimodal diagnostic frameworks, edge-AI deployment strategies, and improved explainability mechanisms. Bridging the divide between algorithmic performance and clinical utility will require rigorous validation, standardized benchmarking, and multidisciplinary collaboration among researchers, clinicians, policymakers, and healthcare stakeholders.

By charting the technical advancements and persisting challenges, this review aims to provide a comprehensive roadmap for researchers and practitioners seeking to advance the deployment of robust, scalable, and clinically trustworthy AI-assisted diagnostic systems for pandemic response and beyond.

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