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AI-Powered Diagnostic Tools for COVID-19 Pneumonia: A Unified Approach Using Deep Learning and Explainable Models

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ABSTRACT:

We're Leveraging AI to Detect COVID-19

In this review, we have provided an update on the use of artificial intelligence (AI) and computed tomography (CT) scan for COVID-19 pinpointing. The study is important as the rapid and reliable diagnosis is important for controlling the spread of the virus especially in light of the scarcity of expert radiologists.

A lot of studies are underway for AI-based tool development to support them. One study looked at deep learning (the training of artificial neural networks on large collections of images). * This study reported an AI-based pipeline that quantifies disease extent and identifies imaging biomarkers and integrate with clinical variables to predict short and long term outcomes in patients with COVID-19. With AI combined the camera chest bear scans, the made and recogn on COVID-19 and X-ray pictures using two that promising results procised performance in a multicenter set and the research where several with human the made of AI used in chest CT images. The reliability and good generalisation properties of the method make it promising for clinical use, especially if healthcare resources are not broad.

Another study focused on COVID-DeepNet, a hybrid deep learning system. Convolutional deep belief networks (CDBN) and deep belief networks (DBN) are some of the deep learning techniques on which the system is built. The x-ray images are initially pre-processed with contrast-limited adaptive histograms equalization (CLAHE) and Butterworth bandpass filter techniques to enhance contrast and reduce noise content in the input data. Adding up the results of both methods leads to the final diagnosis. AI system which amazing recognises COVID-19 in chest X-ray images using two that AI combined with chest CT images performed encouraging results, showing comparable performance to or even better than humans readers in as multicenter dataset. It proved both reliable and generalisable, thus demonstrating its potential for clinical use, particularly in situations where healthcare resources are scant.

Another study looked at a hybrid deep learning system called COVID-DeepNet. We achieve a true positive rate of 99.90% with detection accuracy rate 99.93% with this system reaccuracy. Not only that, but it also processes each image in under three seconds, making it efficient as well.

Active learning approaches are also being explored to alleviate the burden of finding large datasets. One study proposed weakly-supervised deep active learning architecture, COVID-AL, which actively selects most informative samples of data for labelling with the help of an expert medical labeller. In comparison to other active learning methods, this framework is more effective in reducing labelling costs while providing an accurate diagnosis of COVID-19.

An alternative approach, beyond deep learning, combines deep learning networks with metaheuristic algorithms to enhance accuracy and efficiency of detecting COVID-19. For purpose of detecting COVID-19, one such study developed MH-COVIDNet, a framework that employs deep learning models including ResNet, GoogleNet, VGG19, and AlexNet.

cognises COVID-19 in chest X-ray pictures using two that it AI with CT images as input achieved promising results — with performance comparable to or better than human readers in a multicenter dataset. This approach showed its potential for practical use, particularly in cases when medical resources are scarce, by demonstrating reliable performance with good generalisation properties.

Another study focused on COVID-DeepNet, a hybrid deep learning system. This system reX-ray picture feature extraction. To enhance the features by amplifying contrast and boundary descriptions, the authors pre-processed the images by the algorithm for image contrast enhancement (ICEA). Two binary particle swarm algorithms and metaheuristic algorithms

optimisation (BPSO), and binary grey wolf optimisation (BGWO) were then employed for the optimal features selection. The features were then classified using a support vector machine (SVM). Overall, this method achieves an accuracy of up to 99.38%, which demonstrates its ability to assist professionals in COVID-19 diagnostics and is an effective approach.

In another study, authors explored the feasibility of using handcrafted Q-deformed entropy features in combination with deep learning features in discriminating healthy versus CT lung images from healthy subject versus COVID-19 versus pneumonia. The researchers combined deep after pre-processing CT lung images to reduce the intensity variation,

recognizesCOVID19inchestX-rayimagesusingtwo that the authors have validated the performance of AI technology in conjunction with chestCT images and produced encouraging outcomes, demonstrating performance on par with or better than human readers on a multicenter dataset. Thisis shown to be worthy of clinical use, particularly when medical resources are scarce by being robust and exhibiting good generalisation properties.

Another study focused on a hybrid deep learning system known as COVID-DeepNet. Such a method was created to extract features is the Q-deformed entropy methods and learning. Then, a long short-term memory (LSTM) neural network was employed for classifying these properties. The study also indicated the advantages of integrating different methods of feature extraction to enhance diagnostic accuracy, which was an incredible 99.68%.

AI appears as a potential tool in diagnosis of COVID-19, particularly when coupled with deep learning and metaheuristic algorithms, as this research demonstrates.

Keywords:
Machine learning, transfer learning, viral pneumonia, ai -powered diagnostic tool, **COVID-19 Diagnosis,** COVID-19 pneumonia, **Artificial Intelligence (AI), Deep Learning, Convolutional Neural Networks (CNN), Explainable AI (xDNN), Q-Deformed Entropy, Feature Extraction, Chest X-Ray (CXR) Imaging, Computed Tomography (CT) Scans, COVID-DeepNet, Hybrid Models, Radiological Diagnostics, Medical Image Processing, Multimodal Fusion, Grad-CAM Visualization.**

Introduction:

Because of its widespread global spread, the World Health Organisation (WHO) proclaimed coronavirus disease (Covid-19), a highly contagious illness, a pandemic on March 11, 2020 [1]. The pandemic declaration also emphasised the serious concern over the COVID-19 virus's frightening severity and pace of spread

. It is among the earliest known pandemics to be brought on by a coronavirus.It is characterised as a contemporary global health problem that has spread throughout the entire world. The governments of several nations have enforced various border, flight, and social distance limitations as well as raising people's awareness of hygiene. But the infection is still growing quickly and isn't going away.

.While the majority of those infected with COVID-19 have mild to moderate symptoms of respiratory illnesses, some have even acquired pneumonia, which is extremely dangerous. There are presumptions that the majority of persons with underlying medical conditions, such as diabetes, cancer, chronic respiratory conditions, renal or hepatic illnesses, and cardiovascular disease, are more likely to experience severe illness [2].Up till March 10, 2023, 6881,955 deaths and 676,609,955 cases were documented [3]. Effective screening and prompt medical attention for infected people are essential to stopping the spread of COVID-19.The mostly used clinical screening method for COVID-19 patients which uses respiratory specimen for testing is Reverse Transcription Polymerase chain reaction (RT-PCR)

[4] The reference method for identifying COVID-19 patients is the RT-PCR test.The method is largely manual, labour-intensive, and complex, and its success rate is only 63%.

[4]. However, its supply is limited, which causes delays in efforts to manage disease [5].False positive COVID-19 case counts are a problem in the majority of nations both because test results are delayed and because test kits are scarce [6]. Due to these time delays, it is possible for infected patients to interact with healthy patients, which can lead to the infection of healthy patients.According to reports, the RT-PCR kit costs between $120,000 and $130,000, and it also needs a specialised biosafety facility to house the PCR machine, which may cost anywhere from $15,000 to $90,000 [7].Because of this extremely expensive instrument and the delay in test findings, it is causing the proliferation of

The situations are getting worse due to the coronavirus sickness.Additional techniques for diagnosing COVID-19 include clinical symptom analysis, epidemiological history, positive radiographic images (such as CT or CXR), and positive pathogenic testing.

Urgency to provide new accurate and rapid diagnostic tools, such as pneumonia, has gained even more importance during the COVID-19 pandemic. With rapid advancement of viral infections and limitations of conventional diagnostic methods, researchers are moving towards deep learning algorithms. These models are not only mini masters at fitting the naked people, make fearlessly in the diagnostics but they also do deliver explainable outputs which help us in making clinical call. Utilizing AIs potential, healthcare systems can better grasp clinical outcomes and streamline resource management during such one-of-a-kind health outbreaks. In this essay we discuss how deep learning technologies and explainability complement each other in developing diagnostic tools for COVID-19 pneumonia. ai addressing the shortcomings of manual radiological interpretation, emphasizing novel methods such as **Q-deformed entropy**[8], **COVID-DeepNet's multimodal fusion**[9], and explainable deep neural networks (xDNN)[10].

2. Literature Review: Techniques in AI-Based COVID-19 Diagnostics

In AI-based diagnostic systems, feature extraction is a crucial stage that forms the basis of precise classification. The primary technology utilised is convolutional neural networks (CNNs).

by traditional deep learning models to extract spatial characteristics from medical pictures. To improve diagnostic performance, hybrid techniques that blend deep learning descriptors with handmade features have proven to be a better option. For example, using statistical measures of pixel distribution, Q-deformed entropy, a handcrafted feature extraction method, identifies textural differences in CT scans. The heterogeneity of COVID-19-affected lungs, which are frequently distinguished by faint and diffuse patterns of ground-glass opacities, can be better understood thanks to this approach [9].

When Q-deformed entropy and deep learning are combined, feature diversity is increased, increasing the classification accuracy of COVID-19 pneumonia,

both healthy patients and viral pneumonia
. Research has shown that adding manually created features can help deep learning models overcome problems like overfitting by making up for the lack of training data. Furthermore, by guaranteeing that the features extracted match clinical findings, these hybrid systems offer a superior depiction of medical imagery [9].

When identifying COVID-19
from chest X-rays (CXRs) and CT scans, deep learning models—particularly CNN-based architectures—have demonstrated impressive accuracy. Even with little medical data, pretrained models such as DenseNet and ResNet achieve good performance by utilizing transfer learning, in which models are refined on domain-specific datasets. DenseNet minimizes computing overhead while preserving accuracy by optimizing feature reuse through its densely connected layers. ResNet works well for complex image classifications because it uses residual connections to counteract the vanishing gradient issue. Globally, a coronavirus outbreak (COVID-19) has catastrophic consequences for people's daily lives and healthcare systems. There is presently no clinically licensed vaccine or antiviral medication for this recently identified virus, which is highly contagious. Controlling the virus's rapid spread requires early detection of infected people through efficient screening. A useful diagnostic and monitoring method for the COVID-19 virus is chest radiography imaging. To help skilled radiologists interpret pictures quickly and accurately, a new hybrid multimodal deep learning system called the COVID-DeepNet system is created to detect the COVID-19 virus in chest X-ray (CX-R) images.
First, to improve contrast and remove noise from CX-R pictures, the Butterworth bandpass filter and Contrast-Limited Adaptive Histogram Equalisation (CLAHE) were used. A convolutional deep belief network that was trained from scratch using a large-scale dataset and the results of two distinct deep learning techniques based on the integration of a deep belief network were then combined. Parallel design was taken into consideration since it gives radiologists a high level of confidence in their ability to differentiate between healthy and COVID-19-infected individuals.
Using a large-scale dataset, the suggested COVID-DeepNet system can achieve detection accuracy rates of 99.93%, sensitivity of 99.90%, specificity of 100%, precision of 100%, F1-score of 99.93%, MSE of 0.021%, and RMSE of 0.016%.
accurately and correctly diagnose patients with COVID-19. With less than three seconds per image to make the final choice, our technology demonstrates efficiency and accuracy and may be utilised in a genuine clinical centre for early COVID-19 viral diagnosis and monitoring of treatment.
[2][8].
Novel architectures such as **COVID-DeepNet** extend traditional CNN models by integrating multimodal learning. This system combines convolutional deep belief network (CDBN) and deep belief network (DBN),
enabling parallel processing of multiple feature sets. COVID-DeepNet's fusion of handcrafted and deep learning features ensures robust decision-making, achieving near-perfect accuracy (99.93%) in classifying COVID-19 pneumonia[10]. Such advancements underscore the potential of hybrid and ensemble methods in addressing the diagnostic challenges posed by COVID-19.
While the high accuracy of AI-based diagnostic systems is commendable, their adoption in clinical settings often hinges on explainability. Traditional deep learning models function as black boxes that don't reveal anything about how they make decisions
. This lack of transparency poses a significant barrier to their integration into healthcare, where clinicians require a clear rationale for diagnostic outcomes. Explainable deep neural networks (**xDNNs**) address this challenge by incorporating interpretability into AI systems. Regions are visualised using methods like Grad-CAM (Gradient-weighted Class Activation Mapping).
in medical images that contribute to simulate forecasts
. These heatmaps highlight abnormalities like ground-glass opacities in CXRs, providing radiologists with visual cues that align with their diagnostic expertise. This interpretability fosters trust and confidence among clinicians, ensuring AI systems complement rather than replace human decision-making[10].
Explainability is not just an academic requirement; it is essential to guaranteeing the
ethical deployment of AI in healthcare. Transparent AI models enable clinicians to verify predictions, especially in ambiguous cases where false positives or negatives can lead to misdiagnosis. For instance, an explainable system can illustrate why a specific CXR was classified as COVID-19-positive, highlighting subtle patterns that the human eye might not see right away
[9], [10].
Moreover, regulatory agencies and hospital administrators often mandate the use of interpretable AI systems to mitigate legal and ethical risks. Explainable AI ensures that decisions are auditable, reducing liability in cases of diagnostic errors. This aligns with global efforts to integrate AI into healthcare in a manner that prioritizes patient safety and clinician accountability[10].
The integration of hybrid feature extraction techniques and explainable models represents a paradigm shift in AI-driven diagnostics. By combining the precision of advanced architectures like COVID-DeepNet with the transparency of xDNNs, diagnostic systems can achieve both accuracy and trustworthiness. These systems empower radiologists by automating routine tasks while providing interpretable insights for complex cases[8], [9].
In conclusion, the convergence of deep learning, handcrafted features, and explainability is transforming COVID-19 diagnostics. Hybrid models address data limitations and improve accuracy, while xDNNs build clinician trust, paving the way for widespread adoption in real-world healthcare settings.

Key Methods	**Description**	**Source**
Q-Deformed Entropy	Handcrafted texture descriptors for CT scan classification	[8]
COVID-DeepNet System	Hybrid fusion of DBN and CDBN for CXR image classification	[9]
Explainable DNNs (xDNN)	Transparent AI systems for radiological decision-making	[10]

3. Proposed Framework

Stage	Details
Preprocessing	Image enhancement techniques like CLAHE and Butterworth bandpass filters[9].
Feature Extraction	Integration of Q-deformed entropy features[8] and deep learning descriptors (ResNet/DenseNet)[9].
Classification	Use of multimodal fusion (e.g., DBN, CDBN, LSTM) for improved accuracy[8], [10].
Explainability	Incorporate xDNN techniques to enhance model interpretability and clinician trust[10].

Workflow

1. Input: Preprocessed X-ray or CT images.
2. Feature Extraction Combining Q-deformed entropy with
 and CNN-based features.
3. Classification: Use of hybrid fusion models (COVID-DeepNet).
4. Explainability: Employ heatmaps (Grad-CAM) and xDNN for transparent decision-making.

4. Experimental Results

Table: Performance of Models on Test Datasets

Model		Accuracy	Sensitivity	Specificity	F1-Score	Source
COVID-DeepNet		99.93%	99.90%	100%	99.93%	[9]
Q-Deformed Entropy + LSTM		99.68%	99.5%	99.7%	99.6%	[8]
DenseNet201 (Pretrained)		98.9%	98.3%	99.0%	98.6%	[9]

5. Discussion

Significance of Results

- Hybrid models (e.g., COVID-DeepNet) provide robust performance with improved generalizability.
- Explainability with xDNN builds trust among clinicians, enabling safer deployment in hospitals[9], [10].

Challenges

Dataset limitations: Smaller datasets can lead to overfitting[8], [9]
Integration with existing hospital workflows. The suggested frameworks make an effort to get beyond these obstacles by utilising strategies like explainable models, multimodal fusion, and sophisticated preprocessing. To fully solve these issues, future research should concentrate on lightweight models, larger, standardised datasets, and encouraging cooperation between healthcare professionals and AI researchers.

6. Conclusion

It has been shown that incorporating cutting-edge AI techniques into COVID-19 diagnostic procedures can greatly enhance the reliability, COVID-19's precision and speed pneumonia detection and classification. In order to achieve high diagnostic accuracy, the research investigated hybrid techniques that mix deep learning architectures like DenseNet and ResNet with manually created features like Q-deformed entropy. By using fusion techniques to differentiate between COVID-19, other forms of pneumonia, and healthy cases, multimodal systems like COVID-DeepNet have significantly improved categorisation.
Explainable AI models (xDNN) give clinicians logical and visual insights into AI predictions while addressing important issues of interpretability and trust. Fostering the integration of AI technologies into healthcare settings and guaranteeing their dependability as decision-support systems depend on this transparency.
Even with state-of-the-art performance, problems like small datasets, inefficient processing, and integration obstacles still exist. Larger, more varied datasets, real-time deployment model optimisation, and extending the framework to identify more respiratory and systemic disorders should be the main goals of future research. To guarantee the safe and equitable application of AI in healthcare, ethical and legal issues also need to be taken into account.

This study emphasises how AI is revolutionising modern healthcare by showing how it can reduce radiologists' workloads, enhance patient outcomes, and open the door to more robust healthcare systems.

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