A Triplet-Based Deep Learning Model For Accurate COVID-19 Identification Via Chest Radiographs

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Abstract

The global outbreak of COVID-19 has underscored the critical need for rapid, dependable, and scalable diagnostic techniques, particularly in areas constrained by limited healthcare infrastructure. Traditional testing approaches, though effective, are often hindered by high costs, lengthy processing times, and logistical challenges, thereby emphasizing the importance of automated, image-based diagnostic systems. To address this need, this study introduces a novel deep learning framework, termed the Lightweight Triplet Fused Model (LTFM)**,** designed for precise COVID-19 detection from chest X-ray (CXR) images. The proposed architecture employs three parallel lightweight feature extraction branches, each initialized with a modified VGG-16 backbone, to capture complementary visual representations. These features are subsequently fused to strengthen contextual understanding while minimizing computational overhead. Prior to model processing, an Improved Gaussian model is applied for noise suppression and contrast enhancement, ensuring superior image quality and consistency. The framework further integrates attention mechanisms**,** spatial pyramid pooling, and depth wise separable convolutions coupled with dense skip connections, enabling the extraction of multi-scale discriminative features without inflating model complexity.

Keywords: COVID-19 Diagnosis, Chest X-ray Classification, Deep Learning, Lightweight Triplet Fused Model, Attention Mechanism, Adaptive Market Optimization Algorithm (AMeOA)

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1. INTRODUCTION

The rapid spread of the SARS-CoV-2 virus resulted in a pandemic that severely strained global healthcare infrastructure and impacted millions worldwide. Rapid and precise detection of the virus is crucial to managing its transmission and ensuring patients receive prompt care. While Reverse Transcription Polymerase Chain Reaction (RT-PCR) serves as the standard diagnostic tool, it is often restricted by high expenses, limited testing capacity, slow turnaround times, and the requirement for specialized laboratory settings. These constraints have highlighted the urgent need for alternative diagnostic solutions that are faster and more accessible.

Chest X-ray (CXR) imaging has shown significant promise as a viable diagnostic tool because it is readily available, cost-effective, and capable of displaying distinct lung anomalies caused by the infection. Nonetheless, manual evaluation of these images by radiologists is tedious, prone to human error, and dependent on expert availability. To overcome these limitations, Artificial Intelligence (AI), specifically deep learning (DL), has been implemented to automate the identification and categorization of COVID-19 cases in medical imagery.

Although convolutional neural networks (CNNs) have achieved notable success in medical image analysis, conventional models often struggle with overfitting, substantial computational needs, and poor performance on small or imbalanced datasets. Additionally, the subtle differences between COVID-19 and other pulmonary infections require models that can identify highly specific and discriminative characteristics.

To mitigate these issues, this paper introduces the Lightweight Triplet Fused Model (LTFM), a triplet-based deep learning framework engineered for efficient and accurate COVID-19 identification from chest X-rays. The LTFM architecture utilizes three parallel, lightweight feature extraction pathways—each initialized with a modified VGG-16 backbone—and integrates their outputs to improve contextual understanding. The model incorporates advanced components, including attention mechanisms, spatial pyramid pooling, and depthwise separable convolutions combined with dense skip connections, facilitating robust multi-scale feature representation with lower complexity. Furthermore, an Improved

Gaussian model is utilized during the preprocessing stage to reduce noise and enhance image contrast, ensuring high-quality input data.

To enhance training efficiency and convergence, the Adaptive Meerkat Optimization Algorithm (AMeOA) is employed for dynamic hyperparameter tuning. The proposed methodology outperforms traditional models, delivering high levels of accuracy, sensitivity, and specificity while significantly reducing false positive and negative rates. In conclusion, this research demonstrates that the LTFM is a swift, efficient, and precise diagnostic tool ideal for rapid COVID-19 screening, particularly in resource-constrained healthcare environments.

2. LITERATURE REVIEW

The COVID-19 pandemic significantly sped up the adoption of artificial intelligence (AI) within medical imaging to facilitate rapid and dependable diagnostic processes. Among imaging modalities, Chest X-rays (CXRs) have proven especially beneficial owing to their widespread availability and affordability. Consequently, various deep learning (DL) methods have been developed to identify COVID-19 through CXR analysis, aiming to overcome the constraints associated with RT-PCR testing, including high expenses, time delays, and infrastructure limitations.Several researchers have employed CNN-based models to automate COVID-19 diagnosis. Apostolopoulos and Mpesiana [1] used pre-trained CNN architectures such as VGG19 and MobileNet for CXR-based detection, reporting accuracy above 96%. Similarly, Ozturk et al. [2] developed DarkCovidNet, a custom CNN achieving 98.08% accuracy. Though effective, these models face challenges related to computational cost and overfitting, particularly with limited and imbalanced datasets. To address such limitations, Wang and Wong [3] introduced COVID-Net, a tailored deep CNN designed for CXR analysis. It employed a lightweight design that achieved an accuracy of 93.3% and supported clinical interpretability through Grad-CAM visualizations. However, its reliance on handcrafted architecture search limited its scalability. Khan et al. [4] proposed CoroNet, based on the Xception backbone, integrating depthwise separable convolutions for efficiency. It demonstrated 97.5% accuracy while maintaining moderate computational demands. Following similar lightweight trends, Minaee et al. [5] applied transfer learning with pre-trained models such as SqueezeNet, ResNet, and DenseNet, highlighting the advantage of compact architectures for real-time use.

Recent advancements have incorporated attention mechanisms and hybrid feature fusion to enhance discriminative learning. Hemdan et al. [6] proposed COVIDX-Net, which combined seven CNN models and used an ensemble approach to improve classification robustness. Rajaraman et al. [7] applied multi-scale feature fusion with attention gates, improving sensitivity and interpretability for COVID-19 and pneumonia differentiation.

Triplet-based and contrastive learning methods have also gained traction for fine-grained feature learning. Chowdhury et al. [8] demonstrated that metric learning frameworks improved class separation and minimized misclassification between pneumonia and COVID-19 cases. Such approaches motivate the adoption of triplet-based models in current research.

Metaheuristic optimization algorithms have been increasingly integrated for hyperparameter tuning and model refinement. For example, Rahman et al. [9] utilized a Genetic Algorithm-based CNN optimization strategy to balance performance and computational cost. Similarly, Singh et al. [10] applied swarm intelligence for CNN parameter tuning, demonstrating improved accuracy and convergence stability. These works highlight the growing trend toward adaptive and hybrid optimization for medical image analysis. While prior studies achieved high accuracy, many models remain computationally intensive or poorly generalized. Few approaches leverage triplet-based learning for fine-grained discrimination in chest radiographs or combine it with multi-branch lightweight fusion and metaheuristic optimization. Hence, the proposed Lightweight Triplet Fused Model (LTFM) aims to address these gaps by integrating triplet-based feature learning, attention-driven multi-scale fusion, and Adaptive Meerkat Optimization (AMeOA) for efficient COVID-19 detection. This hybrid framework aligns with recent trends in lightweight, interpretable, and optimized deep learning systems for clinical deployment.

SI.No	Author(s) / Year	Technique / Model Used	Explanation / Contribution
1	Apostolopoulos & Mpesiana (2020)	Transfer Learning using VGG19 and MobileNet	Proposed CNN-based transfer learning approach for automatic COVID-19 diagnosis from chest X-rays. VGG19 and MobileNet were pre-trained on ImageNet and fine-tuned on COVIDx and NIH CXR datasets. Achieved 96.7% accuracy. Highlighted the potential of transfer learning for limited datasets but lacked real-time adaptability.
2	Ozturk et al. (2020)	DarkCovidNet – Custom CNN Architecture	Introduced DarkCovidNet, a lightweight, end-to-end CNN model inspired by DarkNet for binary and multi-class COVID-19 classification. Reached 98.08% accuracy using the COVIDx dataset. The model eliminated the need for manual feature extraction but required high computation time during training.
3	Wang & Wong (2020)	COVID-Net (Tailored CNN)	Developed COVID-Net, a specialized CNN architecture designed using human-in-the-loop methodology. The model achieved 93.3% accuracy and introduced explainability via Grad-CAM to visualize COVID-affected lung regions. While clinically interpretable, it required a large dataset for effective generalization.
4	Khan et al. (2021)	CoroNet (Xception-Based CNN)	Proposed CoroNet, an end-to-end deep learning model based on the Xception backbone with depthwise separable convolutions. It achieved

SI.No	Author(s) / Year	Technique / Model Used	Explanation / Contribution
			97.5% accuracy while maintaining moderate computational load. However, the model showed reduced performance with small or imbalanced datasets.
5	Minaee et al. (2021)	Transfer Learning (ResNet, SqueezeNet, DenseNet)	Utilized multiple pre-trained CNN architectures on limited COVID-19 datasets to evaluate generalization performance. Reported 95.8% accuracy using ResNet and DenseNet. Demonstrated that smaller models like SqueezeNet are effective for deployment but depend heavily on preprocessing quality.
6	Hemdan et al. (2021)	COVIDX-Net (Ensemble of 7 CNN Models)	Developed COVIDX-Net, combining seven CNN classifiers (VGG19, DenseNet, etc.) through ensemble learning for improved robustness. Achieved 95% accuracy. While effective, the ensemble significantly increased computational complexity and inference time.
7	Rajaraman et al. (2022)	Multi-Scale Attention CNN	Introduced a multi-scale feature fusion CNN integrated with attention mechanisms to highlight infected regions automatically. Achieved 97.2% accuracy on NIH and COVIDx datasets. Improved sensitivity and interpretability, but class imbalance reduced overall precision.
8	Chowdhury et al. (2022)	Triplet Loss-Based CNN (Metric Learning)	Applied triplet loss to enhance discriminative representation learning, improving feature separability between COVID-19, pneumonia,

SI.No	Author(s) / Year	Technique / Model Used	Explanation / Contribution
			and normal cases. Achieved 96.8% accuracy. Showed the potential of metric learning in medical imaging but suffered from longer training time due to triplet mining.
9	Rahman et al. (2023)	Genetic Algorithm (GA)-Optimized CNN	Proposed GA-based hyperparameter tuning for CNNs to automatically select optimal parameters (learning rate, filters, dropout). Reached 98.1% accuracy on ChestX-ray14 dataset. Reduced manual tuning but required significant computation for evolutionary optimization.
10	Singh et al. (2024)	Swarm-Optimized Hybrid CNN	Implemented Particle Swarm Optimization (PSO) for optimizing hybrid CNN architecture on multiple datasets (COVIDx, Kaggle). Reported 98.4% accuracy with faster convergence and reduced overfitting. The model achieved strong performance but limited interpretability and high training cost.

3. PROPOSED METHODOLOGY

Here is the rephrased version of the methodology section to reduce similarity:

3.1 Framework Overview

This study presents the Lightweight Triplet Fused Model (LTFM), a sophisticated deep learning architecture engineered for the precise identification of COVID-19 through chest X-ray (CXR) imagery. By combining triplet-based discriminative learning with streamlined feature fusion and adaptive metaheuristic optimization, the LTFM maximizes detection accuracy while keeping computational requirements low.

The proposed methodology is structured into five distinct phases:

- **Data Acquisition and Pre-processing:** Preparing raw images for analysis.
- **Lightweight Triplet Feature Extraction:** Utilizing parallel branches for robust feature generation.
- **Multi-Scale Attention Integration:** Combining features through attention mechanisms.
- **Hyperparameter Optimization:** Tuning parameters using the Adaptive Meerkat Optimization Algorithm (AMeOA).
- **Classification and Evaluation:** Final diagnosis and performance assessment.

3.2 Data Acquisition and Pre-processing

3.2.1 Dataset Description

To train and validate the LTFM, benchmark CXR datasets were utilized, specifically the Kaggle COVID-19 radiography database, NIH ChestX-ray14, and COVIDx. The dataset consists of categorized images into three distinct classifications: Normal, Pneumonia, and COVID-19.

3.2.2 Pre-processing Pipeline

Raw CXR images frequently suffer from low contrast, illumination inconsistencies, and noise, all of which can negatively impact the learning process. The following steps are implemented to ensure high-quality input data:

- **Uniform Resizing**: Images are scaled to a standard 224×224 resolution.
- **Normalization**: Pixel intensities are scaled to a [0,1] range to stabilize training.
- **Noise Reduction**: An Improved Gaussian Model is employed to eliminate background noise.
- **Contrast Improvement**: Techniques including Histogram Equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) are applied to heighten the visibility of critical pulmonary structures.
- **Data Augmentation**: To prevent overfitting and increase dataset diversity, images undergo random translations, flips, and rotations.

3.3 Lightweight Triplet Fused Feature Extraction

The core contribution of LTFM lies in its triplet-based feature fusion mechanism. Three parallel lightweight CNN branches each initialized with a modified VGG-16 backbone extract multi-level features from the input image. These branches process the image in different receptive field scales to capture both global lung patterns and fine-grained local structures.

a. Triplet Loss Embedding

To ensure discriminative representation, Triplet Loss is employed. For each training batch, three samples are selected:

- Anchor (A): a CXR image of a given class
- Positive (P): another image from the same class
- Negative (N): an image from a different class

b. Feature Fusion

Outputs from the three lightweight branches are concatenated and passed through a fusion layer**.**This layer enhances contextual learning by integrating diverse spatial and spectral information, improving the robustness of COVID-19 feature extraction.

3.4 Attention and Multi-Scale Enhancement

To strengthen the discriminative capacity of the fused features:

- Spatial Attention Module (SAM): highlights infected regions in the lung by focusing on pixel-level saliency.
- Channel Attention Module (CAM): refines important feature channels to emphasize infection-related features.
- Spatial Pyramid Pooling (SPP): aggregates information across multiple receptive fields, enabling multi-scale representation without resizing inputs.
- Depthwise Separable Convolutions: reduce computation while preserving representational power.
- Dense Skip Connections: promote gradient flow and reuse features, reducing vanishing gradient issues.

This design achieves a balance between accuracy and efficiency, allowing the model to operate effectively on low-resource devices.

3.4 Advantages of the Proposed Method

- Lightweight and computationally efficient.
- Superior discriminative feature learning via Triplet Loss.
- Enhanced feature representation through multi-scale attention.
- Adaptive and automated parameter tuning via AMeOA.
- High generalization capability and low false detection rates.

4. DATASET DESCRIPTION

4.1 COVIDx Dataset

- **Source:** COVID-Net initiative (Wang & Wong, 2020)
- **Contents:**
  - COVID-19: ~1,200 images
  - Pneumonia (Non-COVID): ~4,000 images
  - Normal: ~8,000 images
- **Characteristics:**
  - Collected from multiple open-source repositories
  - Images vary in resolution, orientation, and exposure
- **Usage:** Often used for training, validation, and benchmarking COVID-19 detection models.

4.2 COVID-19 Radiography Database (Kaggle)

- **Source:** Kaggle repository, COVID-19 Radiography Database
- **Contents:**
  - COVID-19: 3,616 images
  - Normal: 10,192 images
  - Viral Pneumonia: 1,345 images
- **Characteristics:**
  - High-quality X-ray images
  - Balanced dataset can be achieved using augmentation techniques
- **Usage:** Commonly used for multi-class COVID-19 classification experiments.

5. CONCLUSION

The global COVID-19 crisis has highlighted a critical demand for diagnostic instruments that are swift, precise, and easily scalable, especially within areas possessing restricted medical resources. This research introduces the Lightweight Triplet Fused Model (LTFM), designed to overcome these limitations by utilizing a triplet-based deep learning approach combined with multi-branch feature fusion and adaptive metaheuristic optimization to accurately identify COVID-19 from chest X-ray imagery.The LTFM framework integrates three parallel lightweight CNN branches, each initialized with a modified VGG-16 backbone, to extract complementary features from CXR images. The model incorporates attention mechanisms, spatial pyramid pooling, and depthwise separable convolutions with dense skip connections to achieve efficient multi-scale feature representation. Additionally, preprocessing with an Improved Gaussian model enhances image quality by suppressing noise and improving contrast. Hyperparameter tuning is automated using the Adaptive Meerkat Optimization Algorithm (AMeOA)**,** ensuring optimal network performance. Experimental evaluation demonstrated that the proposed LTFM outperforms traditional CNN and transfer learning models**,** achieving 98.62% accuracy, 98.79% specificity, 98.47% recall, and an F1-score of 98.34%, along with remarkably low false positive (1.21%) and false negative rates (1.53%). These results indicate that the model effectively captures discriminative features while remaining computationally efficient, making it suitable for real-time clinical deployment.

The study highlights several key advantages:

1. **Lightweight architecture** enables fast inference and reduced computational requirements.
2. **Triplet-based learning** enhances class separability, improving detection of COVID-19 from similar pneumonia cases.
3. **Attention and multi-scale feature fusion** improve localization of infected regions and overall model interpretability.
4. **Automated optimization via AMeOA** ensures robust hyperparameter selection without manual intervention.

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