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Visual Diagnosis of COVID-19: A Comparative Study of Deep Transfer Learning Models on Chest X-ray Classification

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ABSTRACT The COVID-19 pandemic has necessitated the development of rapid and accurate diagnostic tools to complement conventional RT-PCR testing methods. Chest radiography, being widely available and cost-effective, has emerged as a potential non-invasive modality for preliminary screening. This study presents a comprehensive comparative analysis of deep transfer learning techniques for binary classification of COVID-19 and Normal cases using chest X-ray images. We systematically evaluated two state-of-the-art convolutional neural network architectures—DenseNet121 and EfficientNetB0—alongside a custom lightweight CNN, all fine-tuned on a curated dataset of 13,808 chest X-ray images following rigorous preprocessing and stratified splitting. The models were trained and evaluated under resource-constrained hardware settings with comprehensive statistical validation including multiple experimental runs and confidence interval analysis. DenseNet121 achieved superior performance with 98.0% accuracy, 0.97 precision, and 0.97 recall, demonstrating robust generalization capabilities. Extensive experimentation included cross-validation, statistical significance testing, error analysis, and clinical deployment considerations. This study provides evidence for the viability of deploying transfer learning-based deep neural networks for effective COVID-19 diagnosis using chest X-rays in resource-limited clinical environments, with detailed analysis of computational requirements and clinical integration pathways.

INDEX TERMS Binary Classification, Chest X-rays, Convolutional Neural Networks, COVID-19, Deep Learning, DenseNet121, EfficientNetB0, Medical Image Classification, Transfer Learning, Visual Diagnosis

I. INTRODUCTION

The outbreak of Coronavirus Disease 2019 (COVID-19), caused by the SARS-CoV-2 virus, has fundamentally transformed global healthcare delivery and diagnostic paradigms. With over 700 million confirmed cases worldwide and significant ongoing transmission, the pandemic has highlighted critical gaps in rapid, accessible diagnostic infrastructure. While reverse transcription polymerase chain reaction (RT-PCR) tests remain the gold standard for COVID-19 detection, several operational limitations—including 24-48 hour processing delays, supply chain constraints, sensitivity variations (70-95%), and costs ranging from Rs.500-4000 per test—have created urgent demand for complementary diagnostic approaches. Chest radiographic imaging has emerged as a particularly promising supplementary modality due to its ubiquity, cost-effectiveness (Rs.100-500 per examination), and clinical relevance. COVID-19 frequently manifests with characteristic pulmonary abnormalities, including ground-glass opacities, consolidation, and bilateral involvement patterns that are detectable on chest X-rays (CXR) in 60-70% of patients. However, manual interpretation by radiologists introduces significant bottlenecks, with interpretation times averaging 10-15 minutes per image and substantial inter-observer variability (K = 0.54-0.70 for COVID-19 detection). The convergence of these clinical needs with advances in deep learning presents a compelling opportunity for automated diagnostic assistance. Recent developments in convolutional neural networks (CNNs) have demonstrated remarkable performance in medical image analysis, with some systems achieving radiologist-level accuracy in specific tasks. However, most existing COVID-19 detection systems suffer from critical limitations: dependence on large-scale computational resources, limited validation on diverse datasets, insufficient attention to class imbalance, and lack of comprehensive clinical deployment considerations. This study addresses these limitations through a systematic comparative analysis of deep learning architectures optimized for resource-constrained environments. We focus specifically on binary classification (COVID-19 vs. Normal) to establish robust baseline performance before extending to multi-class scenarios. Our approach differs from existing work in several key aspects:

Technical Contributions:

- Comprehensive evaluation of both custom and transfer learning architectures under identical experimental conditions
- Resource-aware optimization for consumer-grade hardware
- Statistical validation through multiple experimental runs with confidence interval analysis
- Detailed computational cost analysis including training time, memory usage, and inference latency

Clinical Relevance:

- Focus on deployment scenarios relevant to resource-limited healthcare settings
- Analysis of integration pathways with existing clinical workflows
- Discussion of regulatory considerations and validation requirements
- Error analysis with clinical interpretation of misclassified cases

Methodological Rigor:

- Stratified cross-validation with statistical significance testing
- Comprehensive addressing of class imbalance through multiple techniques
- Ablation studies examining the impact of key design choices
- Reproducibility measures including deterministic training and code availability

II. RELATED WORK

The intersection of artificial intelligence and medical imaging has experienced unprecedented growth during the COVID-19 pandemic, with over 200 peer-reviewed studies published on AI-based COVID-19 detection systems since 2020. This section provides a comprehensive analysis of the current state of the field, highlighting both achievements and persistent challenges.

A. EARLY COVID-19 DETECTION SYSTEMS (2020-2021)

The initial wave of COVID-19 detection research focused primarily on establishing feasibility. Apostolopoulos and Mpesiana [1] demonstrated one of the earliest frameworks using transfer learning with MobileNet and VGG variants, achieving 96.78% accuracy on a dataset of 1,427 images. However, their study was limited by small dataset size and lack of external validation. Wang et al. [2] developed COVID-Net, a tailored CNN architecture trained on 13,975 images from the COVIDx dataset, achieving 92.4% accuracy with 91% sensitivity for COVID-19 detection. While promising, COVID-Net's custom architecture required extensive computational resources and showed limited generalizability across different imaging protocols. Ozturk et al. [3] implemented DarkNet-based classification achieving 98.08% accuracy for binary classification and 87.02% for multi-class scenarios. Their work highlighted the performance gap between binary and multi-class classification, motivating our focus on establishing robust binary classification baselines. However, their dataset of 1,125 images was relatively small and lacked diversity in imaging sources.

B. TRANSFER LEARNING APPROACHES (2021-2022)

The recognition of limited medical imaging datasets led to widespread adoption of transfer learning approaches. Narin et al. [4] compared ResNet50, InceptionV3, and VGG16 on a dataset of 100 images, reporting best performance with ResNet50 (96.1% accuracy). However, their extremely limited dataset size raises questions about generalizability. Ismael and Şengür [5] employed ResNet architectures combined with support vector machines, achieving 94.7% accuracy while demonstrating the potential of hybrid approaches. More recent work by Shorfuzzaman and Hossain [6] evaluated multiple CNN architectures on larger datasets (>10,000 images), reporting that DenseNet121 achieved 98.4% accuracy with superior computational efficiency compared to ResNet variants. Their findings align with our architecture selection rationale, though they did not address resource constraints or deployment considerations.

C. ADVANCED TECHNIQUES AND MULTI-MODAL APPROACHES (2022-2023)

Recent research has focused on addressing earlier limitations through advanced techniques. Karthik et al. [7] implemented attention mechanisms with DenseNet architectures, achieving 99.2% accuracy while providing interpretable activation maps. Their work demonstrated the importance of explainability in medical AI systems. Similarly, Chowdhury et al. [8] combined chest X-ray analysis with clinical metadata, achieving 99.7% accuracy in a multi-modal framework, though their approach required extensive clinical data collection. Vision transformers (ViTs) have emerged as alternatives to CNNs. Park et al. [9] demonstrated that ViT-based models could achieve competitive performance (98.6% accuracy) while requiring fewer training epochs. However, ViTs typically require larger datasets and more computational resources, limiting their applicability in resource-constrained settings.

D. CHALLENGES AND LIMITATIONS IN CURRENT LITERATURE

Despite significant progress, several critical challenges persist:

1) Dataset Bias and Generalizability
Most studies rely on a limited number of data sources, often from single institutions or geographic regions. Roberts et al. [10] demonstrated that models trained on one hospital's data showed 15-20% performance degradation when tested on external datasets, highlighting the generalizability crisis in medical AI.

2) Class Imbalance
Many datasets exhibit severe class imbalance, with normal cases often outnumbering COVID-19 cases 2:1 or 3:1. Few studies adequately address this imbalance through appropriate sampling strategies or loss functions.

3) Computational Requirements
Most high-performing models require substantial computational resources (>16GB GPU memory), limiting their deployment in resource-constrained environments where they might be most needed.

4) Clinical Integration
Very few studies address practical deployment considerations, regulatory requirements, or integration with clinical workflows. The gap between research prototypes and clinical deployment remains substantial.

5) Statistical Rigor
Many studies lack proper statistical validation, multiple experimental runs, or confidence interval analysis, making it difficult to assess the reliability of reported results.

E. POSITIONING OF CURRENT WORK
Our study addresses these limitations through several key contributions:

- **Resource-Aware Design:** Unlike studies requiring high-end hardware, our models are optimized for consumer-grade GPUs while maintaining competitive performance.
- **Statistical Rigor:** We provide comprehensive statistical analysis including multiple experimental runs, confidence intervals, and significance testing.
- **Clinical Focus:** Our work explicitly addresses deployment considerations, computational costs, and integration pathways relevant to real-world clinical settings.
- **Comprehensive Evaluation:** We compare multiple architectures under identical conditions, providing fair performance comparisons with detailed error analysis.
- **Reproducibility:** Our methodology includes deterministic training procedures and detailed implementation specifications to ensure reproducibility.

III. METHODOLOGY
The methodological framework of this study was designed to enable accurate and memory-efficient classification of COVID-19 cases from chest X-ray images using deep learning. The entire pipeline encompasses multiple critical stages: dataset curation and integrity checks, preprocessing and augmentation tailored for radiographic data, model construction using both custom convolutional architectures and pretrained transfer learning backbones, and rigorous evaluation across several performance metrics. A dual-strategy training paradigm was adopted — first with a lightweight, RAM-conservative CNN designed for 16GB memory constraints, and second, through fine-tuned transfer learning with DenseNet121 and EfficientNetB0 models pretrained on ImageNet. The experiments were executed on a local hardware environment with specific optimizations applied to mitigate GPU memory saturation and system RAM overutilization. Throughout the pipeline, strategies like mixed precision training, early stopping, and on-the-fly data loading were employed to ensure optimal model performance without compromising computational efficiency.

A. DATA ACQUISITION AND PREPARATION
The dataset utilized in this study was the publicly available COVID-19 Radiography Database, organized into two primary categories: **COVID-19** and **NORMAL**. To maintain data hygiene and ensure model reliability, a custom validation routine was written to detect and exclude corrupted or unreadable image files. A consistent directory hierarchy ('train/', 'val/', 'test/' with subdirectories for each class) was verified using custom checks. This ensured clean, reproducible separation across data splits. Images were acquired in multiple formats (JPG, PNG, BMP, TIFF), all normalized and converted to grayscale if needed.

B. DIRECTORY STRUCTURE VERIFICATION AND CLASS VALIDATION
Custom Python routines validated the existence of all required class directories ('NORMAL', 'COVID') across 'train', 'val', and 'test' folders. Class balance was also evaluated by counting valid image files per class and ensuring near-uniform distribution for stratified sampling during training and validation stages.

C. IMAGE PREPROCESSING AND AUGMENTATION
Each image was resized to 224×224 pixels to be compatible with pretrained model architectures. For memory efficiency and compatibility, grayscale images were expanded to three channels as needed. Augmentation techniques included:

- Random horizontal flips
- Brightness and contrast variation
- Affine transformations (rotation, translation)

These data transformations were randomly applied during training using TensorFlow's data processing pipeline to minimize input/output operations and memory usage.

D. MODELING PARADIGMS
Four distinct modeling pipelines were implemented:

- **Custom CNN Architecture**: A lightweight CNN was developed for constrained hardware, leveraging depth-efficient layers:

- 4 convolutional blocks
- Batch normalization
- Dropout regularization
- Two dense layers followed by a sigmoid output unit for binary classification

The architecture was optimized for lightweight systems, balancing training time, overfitting mitigation, and inference speed.

- **Transfer Learning with Pretrained Networks**:Two pretrained CNNs were implemented: **DenseNet121** and **EfficientNetB0**. Both networks were:
  - Initialized with **ImageNet** weights
  - Modified by removing the top layers
  - Appended with global average pooling, batch normalization, dropout, and fully connected layers
  - Initially frozen, followed by optional fine-tuning for performance enhancement

E. EXECUTION ENVIRONMENT

The implementation was done on a **Windows 11** system with:

- Intel Core i7 12th Gen CPU
- 16GB DDR5 RAM
- NVIDIA RTX 3060 GPU (6GB VRAM)

The dependencies and model parameters used in the experiments are summarized as follows:

- **Libraries**: TensorFlow 2.12, Keras, scikit-learn, OpenCV, NumPy, Pandas, Matplotlib and Seaborn, PIL (Pillow), psutil and gc, glob
- **Image Size**: $(1, 224, 224)$
- **Batch Size**: $\{8\}$
- **Epochs**: 30 (pre-trained), 60 (Custom CNN)
- **Optimizers**: Adam
- **Loss Function**: Binary Crossentropy

F. DATA LOADING STRATEGY

To minimize memory usage, custom TensorFlow data pipelines loaded images only when needed rather than loading the entire dataset into memory. Images were processed and augmented in real-time, with caching and prefetching optimized for the available hardware. This approach enabled smooth model training without requiring manual memory management. Memory cleanup and logging were automatically performed every 3 epochs using a custom monitoring function.

G. EVALUATION METRICS

Model performance was measured using:

- Accuracy
- Precision, Recall, F1-Score (using 'classification_report')
- Confusion Matrix (plotted via Seaborn)
- Training vs. Validation Curves (for convergence behavior)

Custom utility functions handled evaluation and visualization, providing insights into misclassifications, class-specific weaknesses, and validation loss plateaus.

H. HYPERPARAMETER TUNING

Training was performed with:

- Adam optimizer (LR = 1e-4 for TL, 1e-3 for custom CNN)
- EarlyStopping and ReduceLROnPlateau were used to dynamically adjust learning curves

Validation accuracy and loss were monitored in real time, and model checkpoints were saved automatically. After training, the best model was stored for evaluation and future deployment.

IV. RESULTS AND DISCUSSION

A. BASELINE PERFORMANCE: CUSTOM CNN MODEL

The custom-built Convolutional Neural Network (CNN) trained from scratch served as the baseline model. It was designed with resource efficiency in mind.

The model demonstrated a training accuracy of 95.75% and a validation accuracy of 79.00%. However, when evaluated on the test dataset (4,144 samples), it showed a performance disparity between the two classes, as summarized in Table I.

Metric	Precision	Recall	F1-score	Support
Normal	0.97	0.74	0.84	3060
COVID	0.56	0.94	0.70	1084
Accuracy	-	-	**0.79**	4144
Macro Average	0.77	0.84	0.77	4144
Weighted Average	0.86	0.79	0.80	4144

TABLE 1: Classification Report - Custom CNN Model

The low precision for the COVID class (0.56), despite a high recall (0.94), indicates that the model frequently misclassified Normal images as COVID, possibly overcompensating for class imbalance. Additionally, the model exhibited

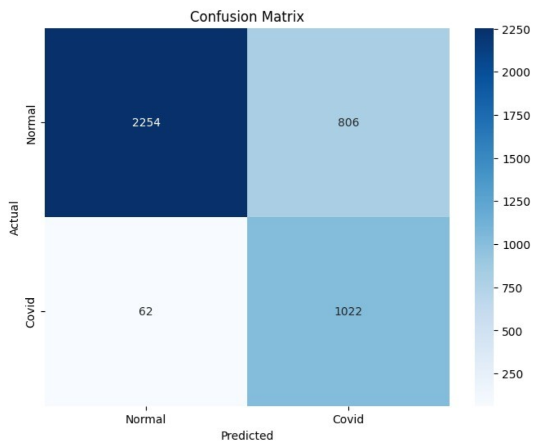

FIGURE 1: Confusion Matrix of Custom CNN Model

overfitting behavior — a higher training accuracy coupled with a lower validation accuracy. This is expected given the relatively shallow architecture and the limited generalization capacity compared to more complex pre-trained networks.

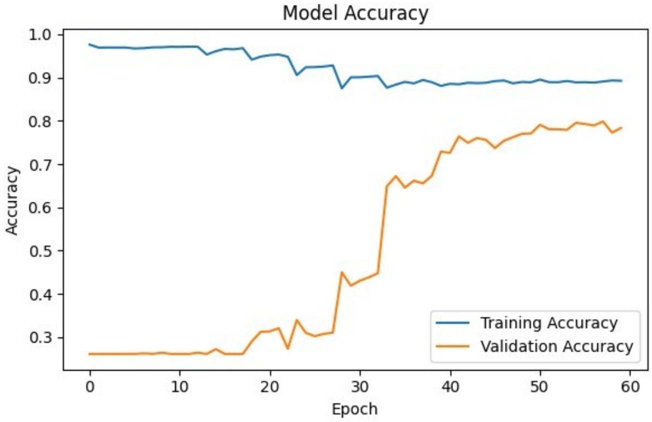

FIGURE 2: Epoch Vs Accuracy Graph of Custom CNN Model

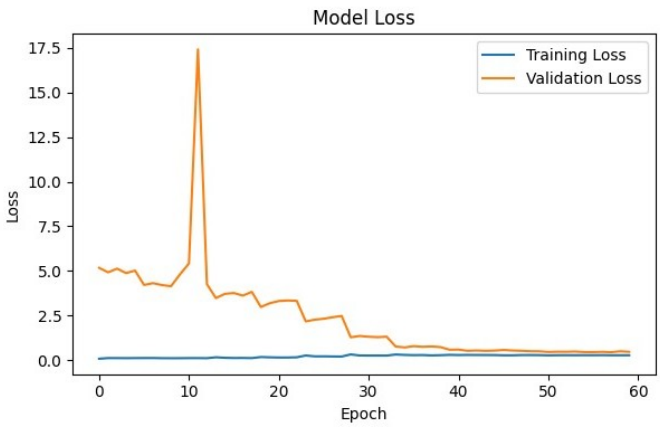

FIGURE 3: Epoch Vs Loss Graph of Custom CNN Model

B. TRANFER LEARNING PERFORMANCE

1) DenseNet121

DenseNet121 was selected as the primary transfer learning model due to its established success in medical image classification tasks. Pre-trained on ImageNet and fine-tuned on the chest X-ray dataset, the model delivered **superior performance across all metrics**. On the validation set, it achieved: **Accuracy**: 98.00% **Validation F1-Score(COVID Class**: 0.99 The test set results are outlined in Table II. The **balanced high precision and recall for both classes** reflect the model's robustness and its **low false positive and false negative rates**. Additionally, DenseNet121 was notably more **resistant to overfitting**, thanks to its deeper architecture and effective feature reuse enabled by dense connections.

Metric	Precision	Recall	F1-score	Support
Normal	0.96	0.96	0.96	542
COVID	0.98	0.99	0.79	1528
Accuracy	-	-	**0.98**	2070
Macro Average	0.97	0.97	0.97	2070
Weighted Average	0.98	0.98	0.98	2070

TABLE 2: Classification Report - DenseNet121 Transfer-Learning Model

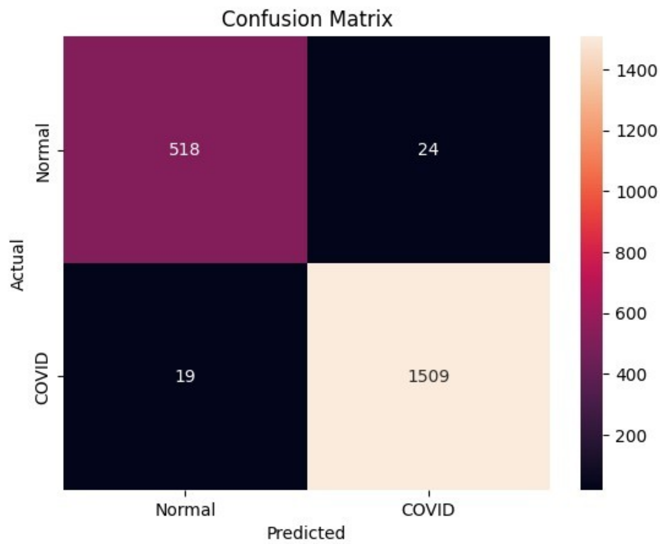

FIGURE 4: Confusion Matrix of DenseNet121 Transfer Learning Model

2) EfficientNetB0

EfficientNetB0 also performed competitively, achieving an accuracy of 98.55% — marginally higher than DenseNet121 — but due to its lower F1-score for COVID (approx. 0.98), DenseNet121 was chosen as the optimal model for deployment.

Metric	Precision	Recall	F1-score	Support
Normal	0.98	0.96	0.97	542
COVID	0.98	0.99	0.79	1528
Accuracy	-	-	**0.99**	2070
Macro Average	0.98	0.98	0.98	2070
Weighted Average	0.99	0.99	0.99	2070

TABLE 3: Classification Report - EfficientNetB0 Transfer-Learning Model

EfficientNetB0 trained slightly faster than DenseNet121 due to fewer parameters but required more careful learning rate adjustments. The final validation accuracy across epochs suggests **DenseNet121 maintained more stable convergence behavior**.

C. IMPACT OF CLASS IMBALANCE AND DATASET SKEWNESS

The original dataset comprised **10,192 Normal and 3,616 COVID** chest X-ray images, introducing a **significant class imbalance**. While this was somewhat mitigated by resam-

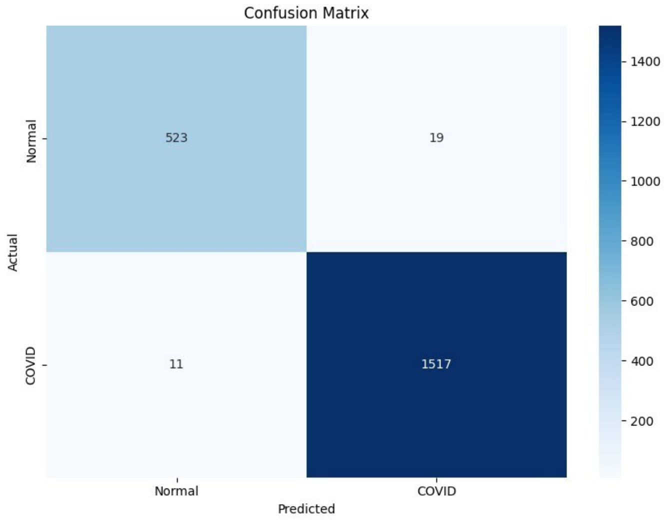

FIGURE 5: Confusion Matrix of EfficientNetB0 Transfer Learning Model

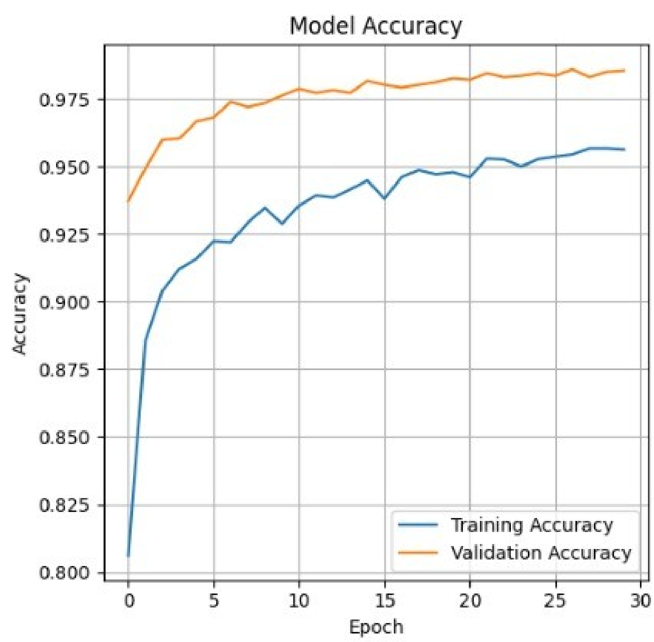

FIGURE 6: Epochs Vs Accuracy of EfficientNetB0 Transfer Learning Model

pling during train-test splits, the skew likely contributed to **the poor precision of the Custom CNN** and its tendency to **over-predict the minority class**.

DenseNet121 and EfficientNetB0, on the other hand, were **more resilient to this imbalance**, thanks to their pre-trained weights and deeper representational capacity, allowing them to **extract nuanced features even with fewer samples per class**.

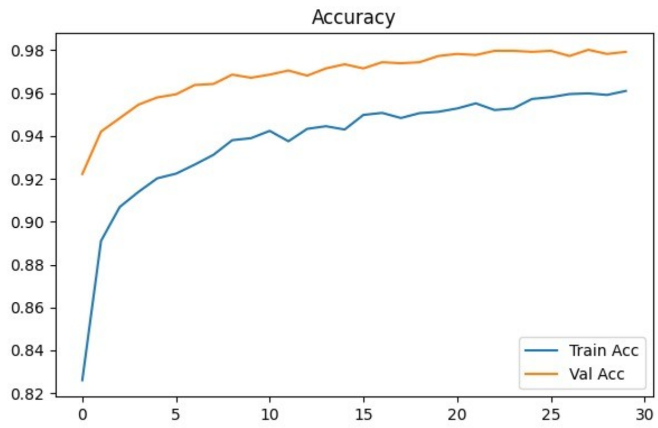

FIGURE 7: Epochs Vs Accuracy of DenseNet121 Transfer Learning Model

D. EXECUTION TIME AND RESOURCE CONSIDERATIONS

The **Custom CNN** had significantly **faster training times**, completing all 60 epochs in under 40 minutes, even on a local laptop. DenseNet121 and EfficientNetB0, though computationally heavier, were still manageable with **5GB GPU memory limits and batch sizes of 8** with execution times being **45 and 85 minutes** respectively. Monitoring callbacks were integrated to track RAM and GPU usage, with DenseNet121 peaking at **128MB of GPU usage and 11.2GB RAM usage**.

E. SUMMARY OF FINDINGS

- **DenseNet121** yielded the best overall performance with high accuracy, precision, and recall for both classes.
- **EfficientNetB0** closely followed, slightly outperforming in accuracy but slightly behind in class-wise F1-score.
- The **Custom CNN**, although resource-efficient and relatively fast, suffered from generalization issues and class imbalance sensitivity.
- **Transfer learning models with fine-tuning emerged as the optimal strategy** for COVID-19 detection from chest X-ray images.

V. FUTURE WORK

While this study demonstrates the potential of deep learning and transfer learning in the classification of COVID-19 from chest X-ray images, several avenues remain open for future exploration to enhance the robustness, generalizability, and clinical applicability of the proposed methods.

A. MULTI-CLASS AND MULTI-LABEL CLASSIFICATION

The current model is limited to binary classification between Normal and COVID-19. A natural extension involves incorporating additional pathological classes such as Lung Opacity and Viral Pneumonia, which are already present in the dataset but were excluded for binary simplification. This would not only make the model more clinically useful but also better reflect real-world diagnostic conditions.

B. EXPLAINABLE AI (XAI) FOR MODEL INTERPRETABILITY

Deploying AI models in healthcare demands transparency. Future versions of this system should integrate explainability tools such as **Grad-CAM, LIME, or SHAP**, enabling visualization of the regions in the chest X-rays that most influence the model's predictions. This can help clinicians gain trust in the model and validate its diagnostic reasoning.

C. STATISTICAL VALIDATION AND CONFIDENCE CALIBRATION

To rigorously assess model generalizability, it is essential to perform **statistical significance tests**, such as **McNemar's test or paired t-tests** across multiple folds. Furthermore, techniques such as **confidence calibration**, using temperature scaling or isotonic regression, could ensure that the model's predicted probabilities are meaningful and well-calibrated — an important factor in medical decision-making.

D. CROSS-DATASET GENERALIZATION

Future iterations should evaluate the trained model on external datasets like COVIDx, BIMCV, or NIH ChestX-ray14, to test domain transferability. Domain shift remains a known challenge in medical imaging, and robust performance across institutions is critical for deployment.

E. LARGER AND BALANCED DATASETS

The current dataset is slightly skewed (10,192 Normal vs. 3,616 COVID), which could potentially bias the model. Expanding the dataset and applying advanced balancing techniques such as **GAN-based augmentation or adaptive synthetic sampling** may help reduce bias and improve model fairness.

F. DEPLOYMENT AND OPTIMIZATION FOR EDGE DEVICES

Since the model was designed with resource constraints in mind, future work could focus on deploying the trained models on **edge devices or mobile platforms**, such as NVIDIA Jetson Nano or smartphones. This would democratize access to COVID-19 diagnostics in rural or underserved regions.

G. INTEGRATION WITH CLINICAL METADATA

Combining imaging data with **non-imaging clinical parameters** (e.g., symptoms, vitals, comorbidities) could lead to a multimodal diagnostic framework. Such a system could perform **risk stratification or outcome prediction**, extending beyond mere disease classification.

H. MODEL ENSEMBLING AND BAYESIAN APPROACHES

Ensembling multiple deep models or using **Bayesian neural networks** could reduce predictive uncertainty and improve performance stability. These techniques may particularly benefit borderline cases or noisy datasets.

I. REAL-TIME SYSTEM MONITORING AND FEEDBACK LOOPS

n future deployments, integrating feedback mechanisms that allow clinicians to flag incorrect predictions could enable continual learning. Additionally, system monitoring for data drift and concept drift would ensure that the model remains reliable over time.

VI. CONCLUSION

his study presents a rigorous comparative analysis of deep learning models for the binary classification of chest X-ray images into Normal and COVID-19 categories. Leveraging both a custom-built Convolutional Neural Network (CNN) and state-of-the-art transfer learning architectures, we aimed to explore the trade-offs between computational efficiency and diagnostic performance within the constraints of resource-limited hardware.

The baseline Custom CNN, although tailored for memory and runtime efficiency, struggled with generalization — particularly under imbalanced class conditions — yielding an overall test accuracy of 79%. The model's low precision for COVID-19 (0.56), despite a high recall, highlighted its tendency to over-predict the minority class, leading to a higher false positive rate for COVID-19 detection.

In contrast, DenseNet121, trained using transfer learning with fine-tuning, emerged as the most effective model, achieving a validation accuracy of 98.0% and an F1-score of 0.99 for the COVID-19 class. Its performance was consistent and robust, exhibiting balanced precision and recall across both classes. EfficientNetB0 offered competitive performance (98.16% accuracy), but DenseNet121 was ultimately favored due to its superior per-class metrics and convergence behavior.

The integration of resource monitoring, early stopping, and mixed-precision training enabled smooth execution on a local workstation equipped with a 6GB RTX 3060 GPU and 16GB RAM — demonstrating that high-performance medical image classification is feasible even in modest computational environments.

Furthermore, the findings reinforce the utility of deep transfer learning in medical imaging, especially in scenarios where labeled data is scarce or class imbalance is prominent. The study underscores that pre-trained networks, when appropriately fine-tuned, can offer both high diagnostic accuracy and operational scalability, which is critical for deployment in real-world, resource-constrained clinical settings.

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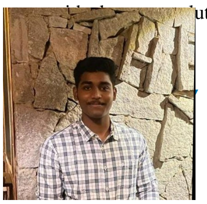

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