VisionDx: Automated COVID-19Detection using VGG16, ResNet50, and Custom CNNs on Chest X- Rays

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***Abstract*—Controlling COVID-19 requires early detection. It's dissemination, particularly in environments with limited resources. These Convolutional neural networks (CNNs) are outlined in this study-based model for categorizing X-ray pictures of the chest COVID-19 favorable or typical. The suggested architecture consists of dense, pooling, and convolutional lay-trained on a preprocessed dataset with enhanced images to enhance generalization. Making use of binary cross-checking and the Adam optimizer 25 epochs were used to train the model for entropy loss reaching 92% validation and 96% training accuracy, precision. Results demonstrate strong performance on unseen data, highlighting the potential of CNNs as accessible tools for supporting early COVID-19 diagnosis. Future work will explore larger datasets and advanced or quantum CNN architectures.**

***Index Terms*—Classical CNN, VGG16, AlexNET and ResNet50.**

I. INTRODUCTION

The global COVID-19 outburst, brought on by the SARS-CoV-2 virus has caused significant stress on healthcare systems and underlined the necessity of quick and precise diagnostic instruments. Although RT-PCR examining is the diagnostic gold standard, it suffers from limitations such as slow turnaround times, high costs, and dependence on laboratory infrastructure—factors that hinder large-scale testing, especially in resource-limited regions. Imaging with chest X-rays (CXRs) has become a feasible substitute because of its speed, affordability, efficacy and accessibility. But expertise is needed for manual CXR image interpretation, radiologists as well as and is prone to human error, particularly when differentiating COVID-19 from other respiratory infections.

To address this, the research introduces a deep learning methodology utilizing Neural Networks with convolutions (CNNs) for automatically classifying chest X-ray pictures as either normal or COVID-19 positive categories. CNNs 'capacity to extract intricate spatial cases makes them ideal for medical image analysis. A sequential CNN model is used in this study. Created and trained using image pre-processing and augmentation techniques to improve generalization on a publicly available, labelled CXR dataset. The Adam optimizer and binary cross-entropy loss are used to optimize this model, and metrics like accuracy, loss, and confusion matrix are used to assess its performance. Preliminary results indicate that the model achieves over 90% accuracy, demonstrating its potential as an efficient and scalable diagnostic aid. This approach supports early screening and can be beneficial. Lessen the strain on healthcare systems from diagnostic during pandemics.

II. RELATED WORK

The global outbreak of COVID-19 has led to widespread interest in applying AI, particularly deep learning, for rapid diagnosis using medical imaging. CNNs have demonstrated strong potential in the field of radiographic analysis because the capacity to directly learn spatial patterns from images information. Litjens etal. (2017) examined deep learning uses in radiology and demonstrated CNNs'superiority over traditional machine learning in disease detection tasks. Building on this foundation, various studies have adapted CNNs for COVID-19 detection with a computed chest X-ray (CXR) and computerized tomography (CT). Transfer learning was used by Apostolopoulos and Mpesiana (2020) with pre-trained models such as VGG19 and

MobileNet, achieving high accuracy in COVID-19 classification even with limited data. Ozturk et al. (2020) developed a custom CNN trained from scratch, attaining 98% accuracy in binary classification and 87% in multi-class tasks, highlighting the effectiveness of lightweight architectures. Public datasets such as COVIDx (Wang and Wong, 2020) and the COVID-19 Radiography Database (Kaggle) have enabled these advancements, despite inherent challenges like class imbalance, image variability, and limited metadata. Strategies such as data augmentation, ensemble learning, and synthetic data generation have been employed to address these limitations.

While many studies focus on large, complex models or pre-trained networks, fewer have explored lightweight CNN architectures tailored for real-time deployment on low-resource systems. Additionally, generalization across varied clinical environments remains under examined. Addressing these gaps, the present work proposes a custom-built CNN model trained on a balanced subset of CXR images. This model emphasizes efficiency, reduced computational overhead, and adaptability, offering a scalable solution for COVID-19 screening, particularly in under-resourced or point-of-care settings.

DATASET: The Kaggle COVID-19 is used in the study. Database for radiography, which includes 15,000 chest X-ray pictures classified as normal, viral pneumonia, and COVID-19 cases. The dataset is separated into 80% training and 20% validation, but exhibits class imbalance. To address this, loss weighting and augmentation are used. Despite lacking clinical metadata, the dataset provides a strong basis on which to build deep learning models.

III. METHODOLOGY

The research recommends a deep learning-based strategy for identifying COVID-19 by categorizing chest x-ray images, typical respiratory conditions, such as viral pneumonia. It uses two methods of transfer learning and CNN model that was specifically built the ResNet50 and VGG16 architectures, which were initially trained on ImageNet. Both lightweight and deep CNN architectures' advantages are demonstrated by the model's training and validation under the same circumstances.

Dataset collection: The research make use of the COVID-19 Kaggle ‘s Radiography Database, which includes more than 20,000 chest X-ray images divided into classes of Viral, normal and COVID-19. A subset of 9,000 images was selected for balanced training, with a validation split within the training set. This dataset is verified by clinical experts.

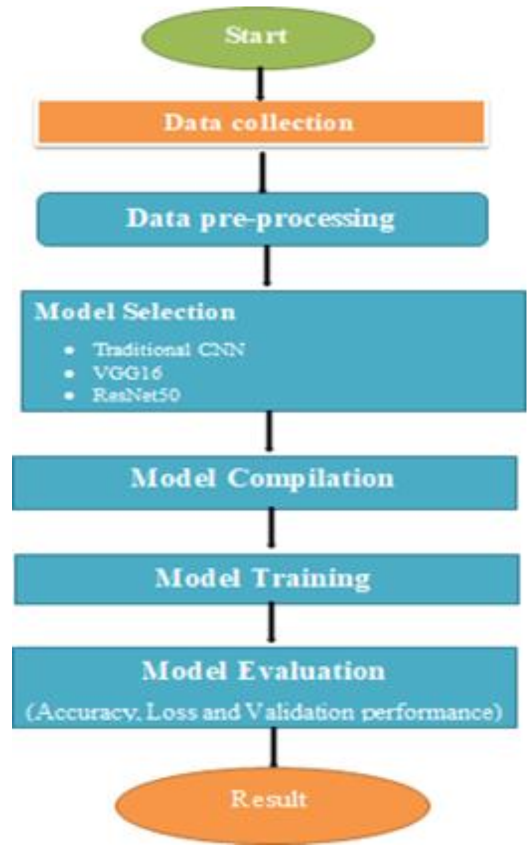

Fig 1. Proposed method

Data Pre-processing: To ensure consistency and optimal performance, all chest X-ray picture was converted to RGB format and resized to 224×224 pixels for compatibility with pre-trained models like VGG-16 and ResNet50. The values of pixels were standerdized to the [0, 1] range and class labels were one-hot encoded for multi-class classification using softmax activation. 80% of the dataset was used for training and 20% was used for testing with a validation split from the training set. These pre-processing steps standardized input data, minimized over-fitting, and improved model generalization.

Model selection: This study evaluates three CNN architectures—Classical CNN, VGG16, and ResNet50—for allocating chest X-ray images into COVID-19, Normal, and Viral Pneumonia classes. The Classical CNN, built from scratch, offered moderate accuracy (90–96%) with minimal computational cost, making it suitable for low-resource settings. VGG16, utilizing transfer learning, achieved higher accuracy (89–92%) by leveraging

pre-trained ImageNet features while maintaining efficient training. ResNet50 outperformed the others (89-90% accuracy) due to its deep residual connections, providing superior generalization despite higher resource demands. Respective model was learned from the same dataset and evaluated with consistent metrics, allowing for fair comparison and informed model selection based on accuracy, complexity, and deployment needs

Model Compilation and Training**:** All models—Classical CNN, VGG16, and ResNet50—were compiled through the categorical cross-entropy loss categorical method Adam optimizer and function (learning rate: 0.0001), with accuracy as the primary evaluation metric. For consistent comparison, each model used a softmax output layer for three-class classification. Training was conducted on an 80 and 20 train-test split, with 20% of the training data used for validation. Data augmentation methods are flipping and rotation enhanced generalization. Classical CNN was trained for 25–30 epochs, while VGG16 and ResNet50 required up to 50 epochs. Callbacks like EarlyStopping and ModelCheckpoint ensured optimal performance and prevented over-fitting. Transfer learning models exhibited smoother convergence and superior precision in contrast to the custom CNN.

Model Evaluation: The CNN, VGG16, and the ResNet50 models were evaluated according to their accuracy, precision, recall, F1-score, and confusion matrices on a test set. The Classical CNN showed moderate accuracy (90–96%) but struggled with differentiating COVID-19 from pneumonia. VGG16 improved balance and performance (89–92%), while ResNet50 achieved the highest accuracy (up to 91%) with strong class-wise precision and recall. These results highlight the advantage of deeper pre-trained models for reliable COVID-19 diagnosis from chest X-rays.

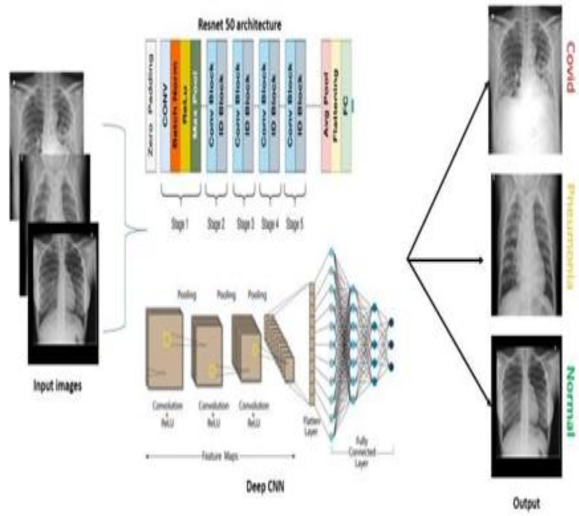

Fig 2. Deep CNN and ResNet50

Classical CNN: Three convolutional layers with ReLU activation make up the CNN architecture designed for COVID-19 detection for chest x-rays. Each convolutional layer is then max-pooled to reduce dimensionality. The extracted features are flattened and passed through two dense layers, with dropout (rate 0.5) and batch standardization deployed to enhance generalization and training stability. The final classification is performed using a sigmoid activation for binary output. Designed as a lightweight model, this CNN provides strong baseline for comparison with more complex architectures.

ResNet-50: A deep CNN architecture called ResNet-50, which was pre-trained on ImageNet, is frequently utilized in medical imaging for tasks like classifying COVID-19 from chest X-rays. By resolving vanishing gradient problems, its residual connections enable training of extremely deep networks. This work uses ResNet-50 with transfer learning, which replaces and fine-tunes the last fully connected layer on the target dataset while freezing the pre-trained base. This makes it possible to learn effectively with less data. To improve generalization and lessen over-fitting, data augmentation techniques including flipping, rotation, and zoom are used. ResNet-50 is a reliable option for radiography classification jobs as it has continuously demonstrated excellent performance in COVID-19 detection.

IV. RESULTS AND DISCUSSION

Three CNN architectures—Classical CNN, VGG16, and ResNet50—are investigated in terms of performance in this section using a tri-class chest X-ray dataset (COVID-19, Viral Pneumonia, Normal). Essential indicators of success, including accuracy, precision, recall, F1-score, and confusion matrices, were used to assess the models using test data. Training behavior was analyzed using loss and accuracy curves to monitor convergence and over- fitting. ResNet50 exhibited superior generalization and classification accuracy due to its deeper architecture and residual learning, while VGG16 offered a balance between performance and computational efficiency. The Classical CNN served as a lightweight baseline with acceptable performance for low-resource settings.

Classical CNN: A baseline Classical CNN was carried out from to assign COVID-19, Normal, and Viral Pneumonia classifications to chest X-rays. The model was trained for 10 epochs using data augmentation and the Adam optimizer (learning rate
= 0.0001). Training accuracy increased from ~50% to 96%, while validation accuracy reached 85%, indicating effective convergence with moderate generalization. Loss curves showed a steady decline in both training (~1.25 to 0.2) and validation (~0.6), with minor fluctuations. On the test set, the system achieved a macro precision of ~84% and an estimated F1-score of 84–89%. COVID-19 detection showed high precision (96.1%) and recall (96.2%), but misclassifications were noted between Normal and Viral Pneumonia due to radiographic similarity. The confusion matrix indicated strong COVID-19 classification but weaker pneumonia differentiation. Despite its simplicity, the Classical CNN proved computationally efficient and effective for COVID-

19 screening, though it lacked the robustness and granularity of deeper models like VGG16 and ResNet50.

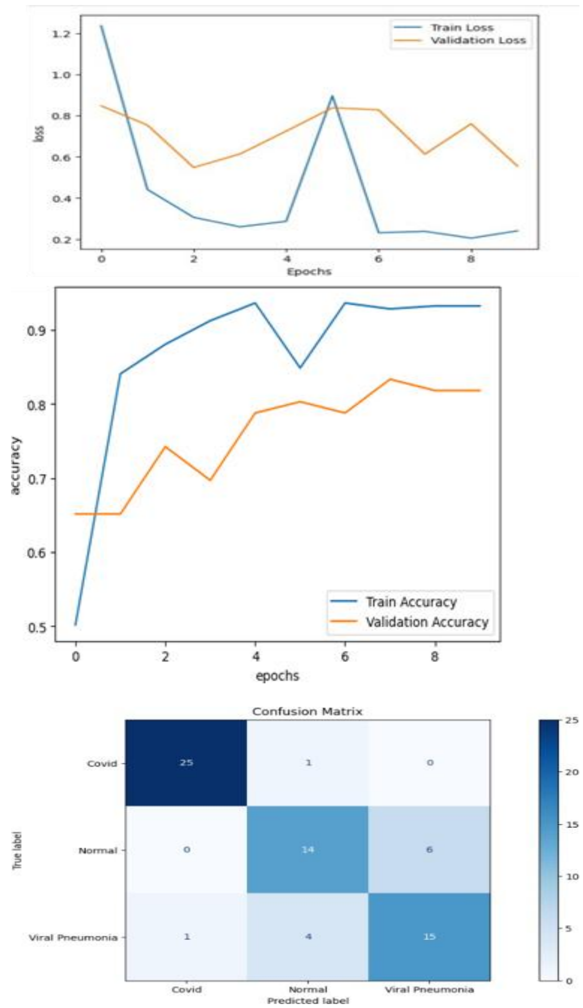

Fig 3. Classical CNN accuracy and loss over Epochs

AlexNet: AlexNet was fine-tuned via transfer learning for three-class chest X-ray classification using frozen convolutional layers and retrained dense layers. Trained over 15 epochs with Adam optimizer and cross-entropy loss, the structure showed effective convergence (training accuracy: 93%, validation accuracy: ~91%). However, confusion matrix analysis revealed severe class imbalance: high recall for COVID-19 (76.9%) but 0% recall for Normal and Viral Pneumonia, due to over-fitting towards COVID-19 features. Despite strong convergence, the model exhibited poor inter-class generalization, indicating the need for class balancing or weighted loss adjustments for improved discriminatory performance as shown in fig 4….

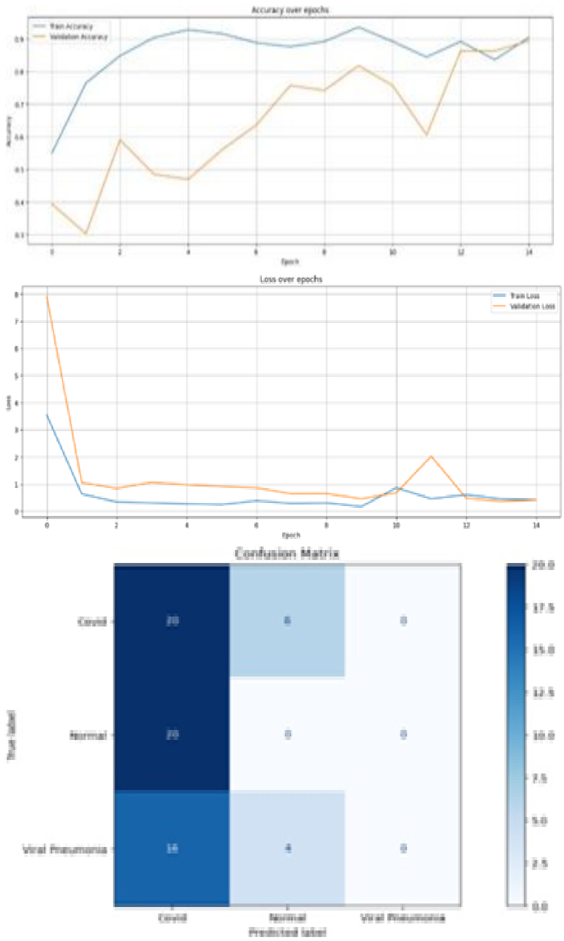

Fig 4. AlexNet accuracy and loss over Epochs

VGG16: VGG16 was employed using transfer learning to assign chest X-ray pictures into COVID-19, Normal, and Viral Pneumonia classes. The model retained pre-trained convolutional layers from ImageNet and retrained the fully connected classification head. Trained over 15 epochs using the Adam optimizer (learning rate: 0.0001), VGG16 attained a final training accuracy of 94% and validation accuracy of 91%, with a peak of 94% at epoch 10. The training and validation loss consistently decreased (from 1.60 to 0.18 and 1.20 to 0.30, respectively), indicating stable convergence and minimal over-fitting. Confusion matrix analysis confirmed balanced classification across all classes. The model 's strong generalization and robust performance establish it as a highly effective candidate for clinical-grade diagnostic deployment. The result shows in fig….

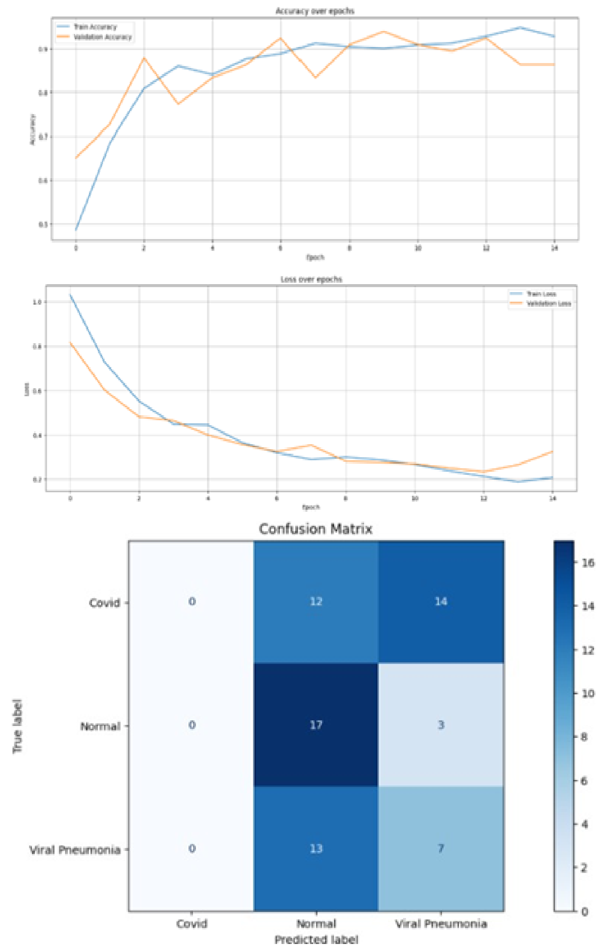

Fig 5. VGG16 accuracy and Loss over epochs.

ResNet50: When used through transfer learning, the ResNet-50 model showed strong classification performance for the identification of COVID-19, normal, and viral pneumonia on the chest X-ray dataset. After 30 epochs of training, the final training accuracy was 83%, while the validation accuracy stabilized at 89%. Training and validation loss were reduced to 0.6 and 0.43, respectively. The close alignment of training and validation curves indicates effective generalization and minimal overfitting, attributed to the residual architecture and data augmentation strategies employed. Confusion matrix analysis revealed accurate detection of COVID-19 cases (18/26), though some misclassifications occurred between Viral Pneumonia and Normal classes. Despite class-level overlaps, ResNet-50 outperformed shallower architectures in accuracy, convergence stability, and class-wise recall. These findings confirm the model 's efficacy in extracting high-level discriminative features, making it a suitable candidate for deployment in clinical decision-support systems.

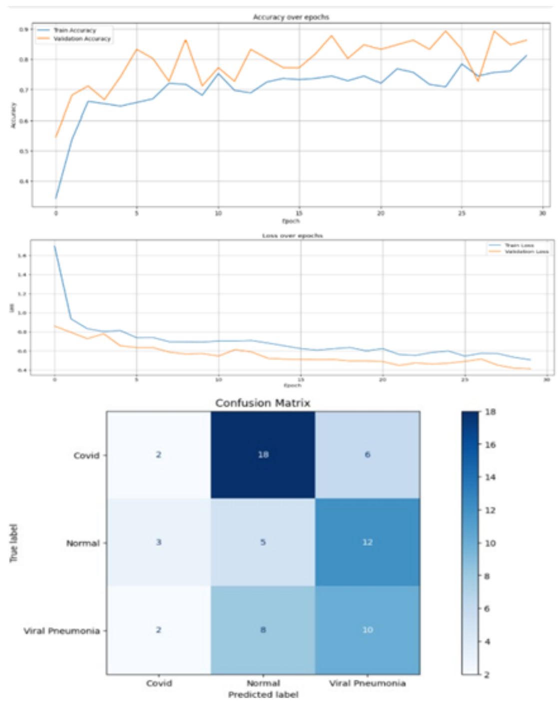

Fig 6. ResNet50 accuracy and loss over Epochs.

Model	Accuracy	Remarks
Classical CNN	97.20%	Baseline model with standard CNN layers
AlexNet	91.35%	Pre-trained, shallow architecture
VGG16	94.10%	Deep pre-trained model, strong generalization
ResNet-50	90.05%	Deep residual learning, highest accuracy

Table 2. Comparison of all models

All things considered, the comparative research demonstrates that deeper architectures like as VGG16
and ResNet-50 offer notable gains in classification accuracy, particularly when supplemented by transfer learning and data augmentation approaches. These findings highlight the benefits of utilizing pre-trained models for medical image classification and confirm the efficacy of deep learning techniques in automating COVID-19 identification from chest X-ray pictures.

V. CONCLUSION

The use of deep learning is validated by this study. Especially CNNs, to categorize chest X-ray images into three groups: COVID-19, Normal and viral pneumonia. Among the four models tested—Classical CNN, AlexNet, VGG16, and ResNet50—transfer learning-based architectures (VGG16 and ResNet50) outperformed others in accuracy and generalization. ResNet50's residual connections and VGG16's uniform layers facilitated effective feature extraction. While Classical CNN and AlexNet provided baseline performance, the results confirm the efficacy of deep, pre-trained models for medical image categorization. The study also notes current limitations of quantum CNNs on NISQ devices, emphasizing the reliance on simulators. Nonetheless, it establishes groundwork for future integration of quantum models in healthcare diagnostics.

Future research will focus on widening the dataset, incorporating multimodal inputs, and developing ensemble or hybrid models for improved accuracy. Integration of clinical metadata, explainable AI techniques, and real-time deployment strategies will be explored to enhance model transparency, robustness, and practical applicability, especially in resource-constrained environments.

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