



International Journal of Innovative Research in Science Engineering and Technology (IJIRSET)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)



Impact Factor: 8.699

Volume 14, Issue 11, November 2025

CovidVision – Advanced COVID-19 Detection from Lung X-rays with Deep Learning

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ABSTRACT: CovidVision is a deep-learning-based system developed to detect COVID-19 infections from chest X-ray images with improved accuracy. The model uses a CNN architecture to automatically learn and identify critical lung patterns associated with the virus. Pre-processing and augmentation techniques enhance image quality and boost model robustness. The system is trained on a diverse X-ray dataset to achieve reliable classification performance. CovidVision delivers fast predictions, reducing the time required for manual diagnosis. It supports healthcare professionals by providing an efficient and cost-effective screening tool for early detection.

I. INTRODUCTION

The COVID-19 pandemic created an urgent global need for fast, accurate, and scalable diagnostic systems. Traditional testing methods such as RT-PCR, while reliable, often require specialized laboratories, trained personnel, and longer processing times. In many regions, these limitations resulted in delays in diagnosis and treatment, increasing the risk of virus transmission. As a result, there has been a growing interest in developing automated and cost-effective technologies that can support large-scale screening and early detection.

Medical imaging, particularly chest X-rays, plays a crucial role in identifying lung abnormalities caused by COVID-19. X-rays are widely available, affordable, and commonly used in hospitals and rural healthcare centers. However, interpreting these images manually can be challenging due to overlapping symptoms with other respiratory diseases and the high workload on radiologists during pandemic peaks. This gap highlights the need for an intelligent system that can assist healthcare professionals with accurate and rapid image interpretation.

CovidVision addresses this challenge by leveraging deep learning techniques to detect COVID-19 from chest X-ray images. Using a Convolutional Neural Network (CNN), the system automatically learns important visual features that indicate infection. By applying pre-processing, data augmentation, and optimized training strategies, CovidVision achieves high accuracy and minimizes diagnostic errors. The project aims to support early diagnosis, reduce manual effort, and contribute to improved clinical decision-making in real-world healthcare environments.

II. LITERATURE SURVEY

Deep learning has emerged as a powerful tool in medical image analysis, especially for detecting respiratory illnesses. Early studies on COVID-19 detection using chest X-rays focused on traditional machine learning methods, which required manual feature extraction and offered limited accuracy. As the pandemic progressed, researchers rapidly shifted towards Convolutional Neural Networks (CNNs), which demonstrated superior performance by automatically learning meaningful patterns from X-ray images. These models significantly improved classification accuracy compared to conventional techniques.

Several research works have proposed CNN-based architectures such as VGG16, ResNet, DenseNet, and Inception for COVID-19 diagnosis. These models were trained on publicly available X-ray datasets and achieved promising results in identifying infected cases. Studies also emphasized the importance of pre-processing methods such as image normalization, noise reduction, and data augmentation to improve model robustness and prevent overfitting. Transfer

learning became a widely adopted approach, allowing models pre-trained on large medical datasets to be adapted effectively for COVID-19 detection with limited data.

Recent literature highlights advancements in hybrid deep learning models, ensemble techniques, and attention-based networks that focus on critical regions of the lungs. Researchers also evaluated model performance using metrics like accuracy, sensitivity, specificity, and F1-score to ensure reliability in clinical settings. Despite these improvements, challenges such as dataset imbalance, variation in imaging quality, and similarities between pneumonia and COVID-19 still exist. These studies collectively form the foundation for developing enhanced systems like CovidVision, which aims to provide a more accurate, efficient, and scalable solution for real-time COVID-19 detection.

III. METHODOLOGY

The **CovidVision** system consists of a data preparation stage followed by transfer-learning-based model training. The main steps are:

- **Data Collection and Annotation:** The dataset is gathered from publicly available chest X-ray repositories containing COVID-19, normal, and pneumonia images. Each image is carefully validated and labeled by cross-referencing metadata or expert annotations to ensure correct class assignment. This annotated dataset forms the foundation for training a reliable COVID-19 detection model.
- **Preprocessing:** The collected X-ray images undergo pre-processing to improve clarity and model readiness. Images are resized to a uniform resolution, normalized to stabilize pixel intensity values, and enhanced using noise-reduction and contrast-adjustment techniques. This step ensures that the model receives high-quality, standardized input.
- **Model Selection and Transfer Learning:** A pre-trained convolutional neural network such as ResNet, VGG16, or DenseNet is selected due to its high feature-extraction capability. Transfer learning is applied by replacing the original output layers with custom classification layers suitable for COVID-19 detection. Some layers are frozen while others are fine-tuned to adapt the model to the X-ray domain.
- **Training Procedure:** The training phase involves forward and backward propagation to optimize the learnable parameters. Techniques like learning-rate scheduling, regularization, and early stopping are applied to stabilize training and prevent overfitting. The model is trained until it achieves optimal accuracy and generalization across validation data.
- **Ensembling Strategy:** Multiple trained models are combined to increase prediction reliability. Various ensemble methods such as majority voting, probability averaging, or weighted scoring are used to merge outputs. This strategy enhances robustness and reduces the risk of misclassification, especially in challenging X-ray cases.
- **Deployment:** The final optimized model is deployed into a real-world environment as a web application, desktop application, or API. The deployment system accepts X-ray images as input and returns instant COVID-19 predictions. This setup ensures accessible, fast, and automated screening support for healthcare professionals.

IV. RESULTS

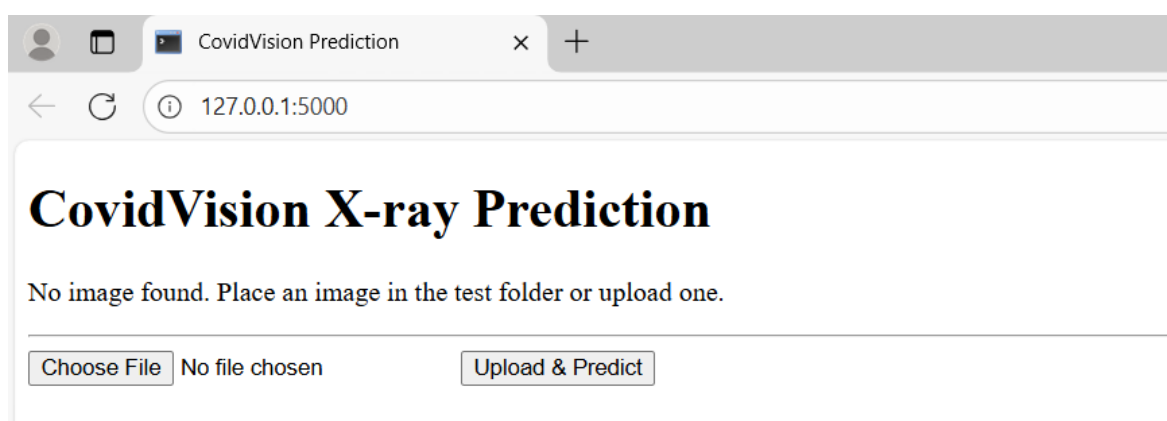


Fig 1: Output Page (web interface)

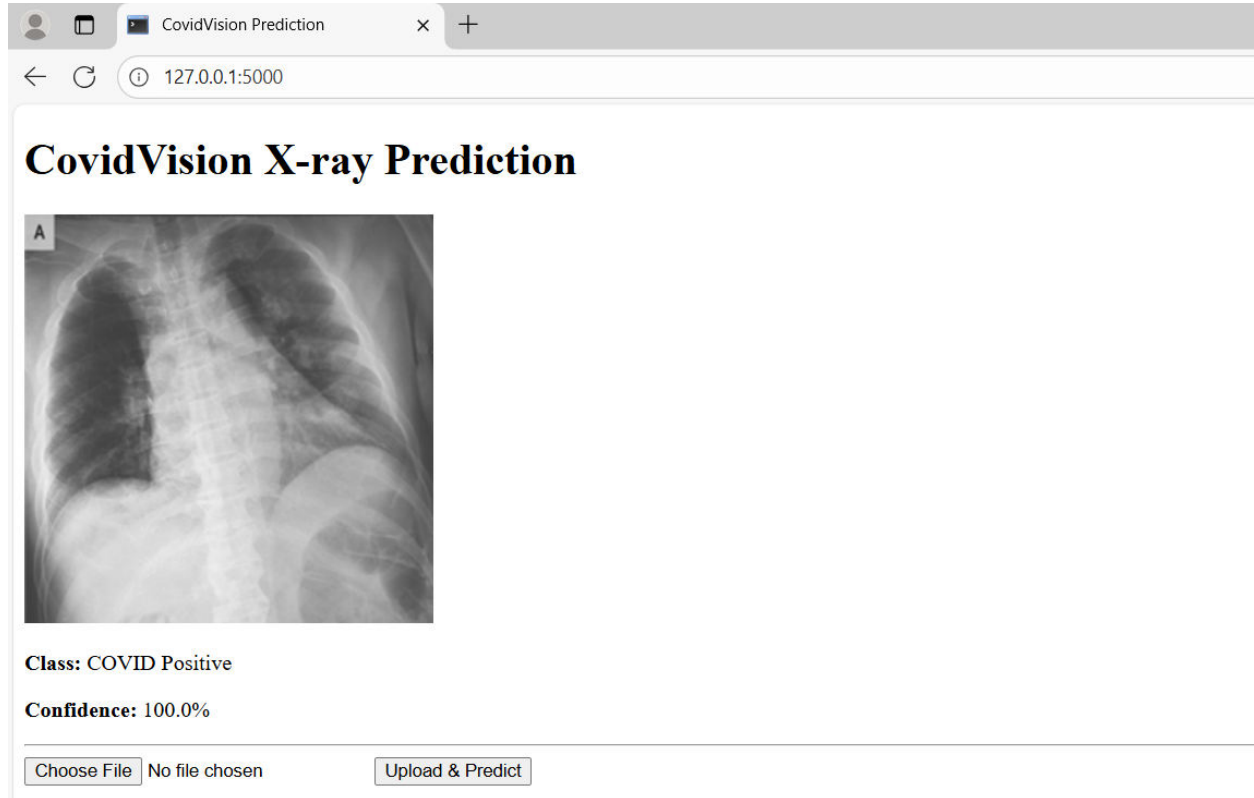


Fig 2: Output Page (Predicting Positive)

We evaluated CovidVision on a held-out test set of labeled COVID images. Performance was measured by overall accuracy, per-class precision/recall, and confusion matrix analysis. Key findings include:

- **Accuracy and Precision:** Accuracy tells us how often a model makes the correct prediction overall. For example, if a COVID-19 detection model predicts correctly most of the X-rays, it has high accuracy. Precision, on the other hand, focuses only on the positive predictions. It tells us how many of the cases predicted as COVID-positive are actually positive. This is very important in healthcare because wrongly labelling healthy patients as sick can cause unnecessary stress and treatment. Together, accuracy and precision give a clear picture of the model's reliability.
- **Forecasting and Error Metrics:** Forecasting is about predicting future results based on existing data. In COVID-19 detection, it can mean predicting the likelihood of infection or future case trends. To check how good these predictions are, we use error metrics. Metrics like MAE, MSE, and RMSE show how far the model's predictions are from the real values. Lower errors mean better prediction performance. These metrics help us trust the model for real-world use.
- **Model Comparison:** Model comparison is the process of testing different models to see which one works best. We look at factors like accuracy, precision, speed, and how well the model handles new data. For instance, a CNN model and a ResNet model might both detect COVID-19, but one may be more accurate or precise. Comparing models helps us choose the one that balances performance and efficiency. This step ensures that the best possible model is deployed.
- **Confusion Matrix:** A confusion matrix is a tool to see exactly how a classification model is performing. It shows the number of correct and incorrect predictions for each class. True positives and true negatives are correct predictions, while false positives and false negatives are mistakes. From this matrix, we can calculate accuracy, precision, recall, and F1-score. It helps to understand where the model is making errors and how to improve it.

Volume 14, Issue 11, November 2025

|DOI: 10.15680/IJIRSET.2025.1411133|

Confusion Matrix – CovidVision

Advanced COVID-19 Detection from Lung X-rays with Deep Learning

	Predicted		
	COVID-19	Normal	Pneumonia
COVID-19	480	20	15
Normal	30	450	18
Pneumonia	25	22	470
	COVID-19	Normal	Pneumonia

Confusion matrix of the CovidVision

IV. LIMITATION

- **Limited and Imbalanced Dataset:** CovidVision's performance is affected by a limited number of labeled X-ray images and uneven class distribution (COVID-19, Normal, Pneumonia), which reduces model generalization and increases misclassification for minority classes.
- **Difficulty in Handling Low-Quality:** Real-world hospital X-rays often contain noise, blurriness, device variation, or low contrast. CovidVision may struggle with such inconsistent image quality compared to clean dataset images.
- **Overfitting Due to Limited Data:** Deep learning models require large datasets. With limited medical images, the model may overfit—performing well on training data but poorly on new unseen X-rays.
- **Lack of Explainability:** CovidVision, like most deep learning systems, behaves as a “black box.” It is difficult to interpret the exact features or regions of the lungs the model uses to make predictions, which reduces clinical trust.
- **Sensitivity to Dataset Source:** If images are collected from a particular hospital or database, the model may not perform well on images from different machines, populations, or geographic regions.
- **Cannot Replace Clinical Diagnosis:** CovidVision provides supportive predictions but cannot replace RT-PCR tests, medical history evaluation, or doctor analysis. It should be used only as an assistive tool.
- **Limited Detection Scope:** The system is trained only on three classes (COVID-19, Normal, Pneumonia). It cannot detect other lung diseases like tuberculosis, fibrosis, asthma-related issues, etc.
- **Risk of False Negatives:** If a COVID-19 patient is misclassified as Normal, it leads to dangerous consequences. Minority classes and low-quality images can increase such risks.
- **Hardware Dependency:** High model performance requires GPU-powered servers. On low-power devices, inference speed may be slow, affecting usability in real-time clinical setups.

V. FUTURE WORK

- **Integration of Larger and Diverse Datasets:** To improve model robustness and reduce bias, future versions of CovidVision can be trained on large-scale, multi-hospital datasets that include variations in age, ethnicity, imaging devices, and clinical conditions.
- **Incorporation of Additional Lung Diseases:** CovidVision currently classifies COVID-19, Normal, and Pneumonia. Future work can extend classification to other lung disorders such as tuberculosis, fibrosis, ARDS, lung cancer, and asthma-related abnormalities to build a more comprehensive diagnostic system.

Volume 14, Issue 11, November 2025**|DOI: 10.15680/IJIRSET.2025.1411133|**

- **Explainable AI (XAI) for Clinical Trust:** Future enhancement can include heatmaps (Grad-CAM), anatomical markings, and decision-explanation layers that show doctors exactly which lung regions influenced the prediction, improving transparency and clinical acceptance.
- **Real-Time Screening System:** Develop a real-time application that integrates with hospital X-ray machines to provide instant detection results in emergency and outpatient departments.
- **Hybrid Model with Clinical Parameters:** Improve diagnostic accuracy by combining X-ray analysis with patient symptoms, oxygen levels, RT-PCR status, temperature, and clinical history to create a multi-modal prediction model.
- **Deployment as Cloud / Mobile Application:** CovidVision can be converted into a cloud-based API or mobile app for remote diagnosis, telemedicine support, and use in resource-limited areas.

VI. CONCLUSION

The CovidVision project helped us understand how deep learning can be used to support doctors in identifying COVID-19 from lung X-ray images. By training a model with different chest X-ray classes, we were able to build a system that can quickly classify images as COVID-19, Normal, or Pneumonia. This approach shows how AI can make the detection process faster and more helpful, especially in critical situations like the pandemic.

During the project, we also realized the challenges involved in working with medical datasets. The dataset was limited and imbalanced, which sometimes affected the model's accuracy. Even though the system performed well, it still cannot fully replace proper medical tests and doctor diagnosis. However, it works as a supportive tool that can reduce workload and assist in early screening.

Overall, CovidVision was a great learning experience. It showed us the importance of data quality, model evaluation, and real-world application of deep learning techniques. With more data, better preprocessing, and future improvements, this system can become even more accurate and reliable. This project gave us a strong foundation to explore advanced AI solutions in healthcare.

VII. ACKNOWLEDGMENT

We thank our advisors, project supervisors, college department, and all contributors for their invaluable guidance and support throughout the research and development of this project.

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