IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

COVID-19 Chest X-ray Classification Web App

Dr. Kavyashree N[1], Chaithra S J[2]

Assistant Professor, Department of MCA, SSIT, Tumkur[1]

IVth Sem Department of MCA, SSIT, Tumkur[2]

Abstract: COVID-19's worldwide spread has put a strain on healthcare systems, especially in recognising it quickly. Despite its time and expense, RT-PCR is the most preferred testing technique. This web-based project classifies chest X-rays as COVID-19, Pneumonia, or Normal using deep learning. Clinicians can check for COVID-19 quicker.

The project uses CNN models learned on free medical imaging datasets. This model can discriminate COVID-19 radiography indications among additional lung infections and healthy lungs. Web interfaces simplify chest X-ray submissions. After scanning the image, the backend system instantly categorises correctly.

This programme is simple and effective. This helps radiologists, doctors, and researchers make decisions. It cannot substitute for clinical examinations, but it is useful when medical competence is lacking or early detection is important. The programme shows how AI may enhance public health response and digital diagnostics can avoid pandemics.

Keywords: COVID-19, Chest X-ray, Deep Learning, CNN (Convolutional Neural Network), Medical Imaging, Image Classification, Web Application, Healthcare AI, Pneumonia Detection, Diagnostic Tool.

I. INTRODUCTION

To kerb the spread of COVID-19, fast, accurate, and easy-to-use diagnostics are needed. Reverse Transcription Polymerase Chain Reaction (RT-PCR) is the best approach to detect COVID-19, but it takes longer, isn't accessible everywhere, and requires expert personnel. However, chest radiography, particularly CXR imaging, is a cheap and easy technique to detect COVID-19-related lung pathology such ground-glass opacities and bilateral infiltrates [1]. This has increased interest in chest X-rays for early COVID-19 detection and sorting. Artificial intelligence has advanced with deep learning and CNNs. These advances allow computers to evaluate medical images as well as humans. CNNs are exceptional at extracting features and categorising photographs, making them ideal for discovering patterns in COVID-19, pneumonia, and healthy lung chest X-rays [2]. When trained on large, diverse, and well-labeled datasets, these models may generalise and perform well. However, making these models simple to use for non-experts like physicians or healthcare workers in rural or underserved regions remains a major challenge.

A deep learning model trained to locate COVID-19 will be used to construct a web-based chest X-ray sorting programme to handle this challenge. The online interface makes uploading X-ray images simple and clear. The user receives the predicted class (COVID-19, Pneumonia, or Normal) after pre-processing and running the photos via a trained CNN model [3]. This programme highlights how AI may be applied in healthcare and stresses its ease of use, making it accessible to physicians, students, researchers, and healthcare support staff. The system architecture includes the frontend interface, backend server, and AI model. Submit X-ray images and observe the front-end classification. The backend processes files, communicates with the trained model, and sends frontend predictions [4]. To train the AI model, Kaggle's COVID-19 Radiography Database is carefully selected. It can be improved using clinical data.

This programme does not replace clinical judgement or RT-PCR testing. Instead, it aids diagnosis, especially in areas where lab testing is difficult or time-consuming. Early screening may be aided by timely replies and a chest X-ray. It may also identify cases for additional testing and aid research by assessing huge medical imaging data. These technologies represent the future of AI-powered healthcare with proper validation and ethics.

II. RELATED WORKS

Smart diagnostic technologies to detect and contain COVID-19 have increased because to the epidemic. Since they are fast and simple to discover, medical imaging, particularly chest X-rays, may replace or supplement RT-PCR. Researchers are using AI to automate the interpretation of radiographs with COVID-19 lung issues such bilateral infiltrates and ground-glass opacities. One of the most promising image recognition AI systems is CNNs [5]. They categorise illnesses in medicine too.

International Journal of Advanced Research in Computer and Communication Engineering
Impact Factor 8.471 ⁙ Peer-reviewed & Refereed journal ⁙ Vol. 14, Issue 7, July 2025
DOI: 10.17148/IJARCCE.2025.14708

Many research have examined how deep learning algorithms can classify chest X-rays as "normal," "COVID-19," and "pneumonia." These approaches usually include training CNNs from scratch or employing transfer learning with pre-trained models [6]. Many studies emphasise the need of understanding, verifying, and testing data in a therapeutic environment. As this technology improves, adding AI models to user-friendly platforms like web applications might enhance diagnostic processes, particularly in resource-constrained areas where speedy choices are needed. Many research have advanced this discipline. CNNs were more reliable in clinical settings when Ghoshal and Tucker included uncertainty modelling to find COVID-19. Apostolopoulos and Mpesiana demonstrated VGG19 and MobileNetV2 transfer learning success. Little data didn't hinder categorisation accuracy [7]. A custom CNN by Ozturk and colleagues classified binary and multi-class chest X-rays well. COVIDX-Net, developed by Hemdan et al., compares CNN architectures and finds DenseNet201 performs best.

Wang and Wong proposed COVID-Net, a deep network trained on COVIDx. They supplied visualisation tools to demonstrate the concept. Chowdhury and others tried to distinguish COVID-19 from other pneumonias, which have similar X-ray characteristics. They emphasised strong training datasets [8]. Finally, Cohen et al.'s open-source COVID-19 chest X-ray dataset was essential to several of these projects. In the early days of the epidemic, this allowed speedy testing, empathy, and model building.

These studies demonstrate AI-assisted diagnosis's progress and the importance of open data, transfer learning, and model interpretability. Adding a web-based interface for COVID-19 chest X-ray classification builds on these foundations. We want to bridge the gap between sophisticated AI models and simple healthcare technologies.

Table 1 compares traditional and AI-based diagnostic methods in eleven key healthcare sectors [9]. From manual image interpretation and paper records to AI-driven diagnostics, automated reporting, and remote screening, technology is improving accuracy, speed, accessibility, and automation in medical diagnostics and healthcare delivery.

TABLE.1.COMPARISON OF TRADITIONAL VS. MODERN METHOD

Criteria	Traditional Method	Modern (AI-Based/Digital) Method
Image Interpretation	Manual analysis by radiologists	AI-based image classification (e.g., CNN, ResNet)
COVID-19 Detection	RT-PCR test	AI-powered chest X-ray screening tools
Medical Record Management	Physical record keeping	Electronic Medical Records (EMRs)
Image Comparison Over Time	Visual/manual side-by-side comparison	Automated temporal change detection using deep learning
Diagnostic Approach	Symptom-based clinical judgment	Data-driven predictive modeling (images + patient history)
Tool Integration	Separate systems for imaging and reporting	Unified AI-enhanced diagnostic platforms (e.g., PACS + AI)
Report Generation	Manual documentation	NLP-based automated report generation
Medical Training	Textbook-based and static image training	Interactive simulations and AI-augmented reality tools
Remote Diagnosis Accessibility	Limited to on-site specialists	Web/mobile apps for remote AI-assisted diagnosis
Severity Assessment	Subjective evaluation by physicians	AI-based severity scoring (e.g., lung opacity heatmaps)

III. PROPOSED METHODOLOGY

The suggested strategy is organised and practicable for constructing an AI-powered online application for COVID-19 identification from chest X-rays. It efficiently blends deep learning, medical imaging, and web development to facilitate early diagnosis and triage, particularly in quick and automated screening environments.

1. Overview of the Approach

Deep learning and a user-friendly online interface are used to construct a COVID-19 Chest X-ray Classification online App for automated illness identification. This system's approach includes data collection and preprocessing, model selection and training, model assessment, system integration, and deployment [10]. Each step is critical to the application's accuracy, usability, and effectiveness.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁒ Peer-reviewed & Refereed journal ⁒ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

2. Data Collection and Preprocessing

The initial stage is acquiring a high-quality, labelled dataset. This project uses Kaggle's COVID-19 Radiography Database and academic libraries' Chest X-ray Pneumonia dataset. These files comprise COVID-19, Normal, and Pneumonia chest X-rays. Preprocessing prepares pictures for model training [11]. Resized images (usually 224x224 pixels) are used to match the input size of most CNN designs. To boost training convergence, pixel values are normalised between 0 and 1. Horizontal flipping, rotation, zooming, and brightness modifications enhance dataset size and variety to reduce overfitting and improve model resilience.

3. Model Selection and Training

Models selection and training are the emphasis. CNNs are employed for image categorisation because to their success. Transfer learning leverages VGG16, ResNet50, and MobileNetV2 pre-trained models. After ImageNet training, these models are optimised on our chest X-ray dataset. The model's top layers are replaced with multiple classifier layers, and the soft maximal activation and category cross- Entropy loss functions train [12]. The algorithm is trained over several epochs and verified on the holdout dataset to track performance and adjust hyperparameters.

4. Model Evaluation and Performance Analysis

The model's accuracy, precision, recall, F1-score, and ROC curve region are assessed after training. A confusion matrix shows classification errors and balances performance over all three classes. The untrained test set assesses model generalisation to fresh data. Reparing or weighted loss functions may minimise class imbalance.

5. Web Application Architecture

Integration of the learned model into a web application follows. Web systems use client-server architecture. The frontend uses HTML, CSS, and JavaScript to make uploading chest X-ray photos easy. The Python-based Flask web framework processes images and communicates with the deep learning model on the backend. After uploading a picture, the backend preprocesses it, runs the model, and delivers the categorisation result. This result and the supplied picture are shown on the site for a comprehensive diagnostic experience.

6. Deployment and Accessibility

Finally, Heroku, Render, or AWS host the app for accessibility and scalability. Users may use the programme on any device that is connected to the internet. Grad-CAM visualisations for AI explanations, confidence scores, and result downloads are possible. Multilingual assistance, electronic medical record connection, and lung disease expansion are easy to add to the modular system.

COVID-19 chest X-ray categorisation app creation phases are in Table 2. AI and internet technologies are used to create a cloud-hosted, accurate diagnostic tool from gathering information and processing to model development, testing, and deployment.

Table.2. Overview of Methodology Phases

Phase	**Description**
Data Collection	Acquiring chest X-ray datasets labeled as COVID-19, Normal, and Pneumonia.
Data Preprocessing	Resizing, normalization, and augmentation to prepare images for training.
Model Selection	Choosing CNN architectures like ResNet50, VGG16, or MobileNetV2.
Model Training	Fine-tuning pre-trained models using the chest X-ray dataset.
Performance Evaluation	Using metrics such as accuracy, F1-score, and confusion matrix.
Web App Development	Designing frontend and backend using HTML/CSS/JS and Flask respectively.
Deployment	Hosting the app on cloud platforms like Heroku or Render.

DOI: 10.17148/IJARCCE.2025.14708

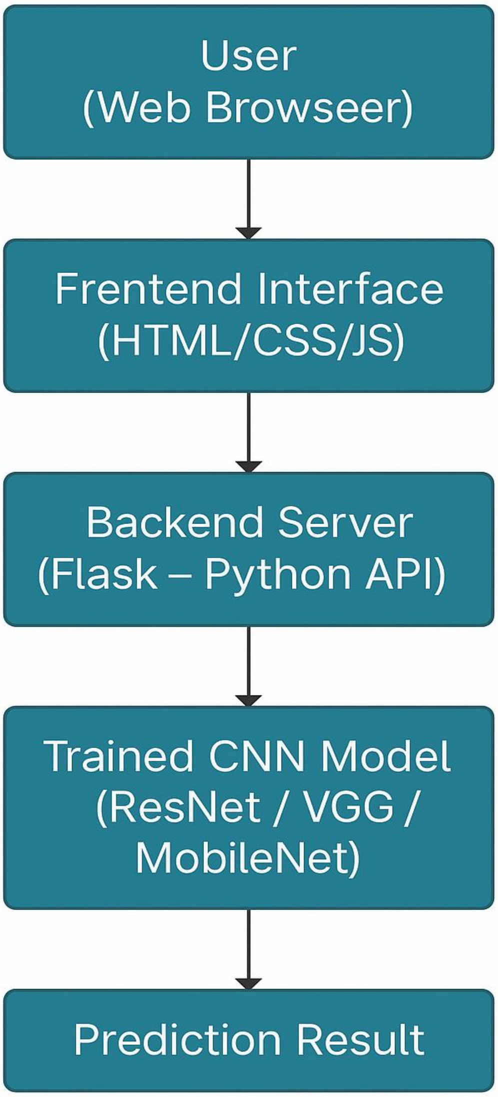

Fig.1. System Architecture of the Web Application

Figure 1 shows the COVID-19 Chest X-ray Classification Web App system design. It shows how the user interface, backend, and trained CNN model handle submitted X-ray pictures and make predictions to classify medical images automatically, efficiently, and easily.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁝ Peer-reviewed & Refereed journal ⁝ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

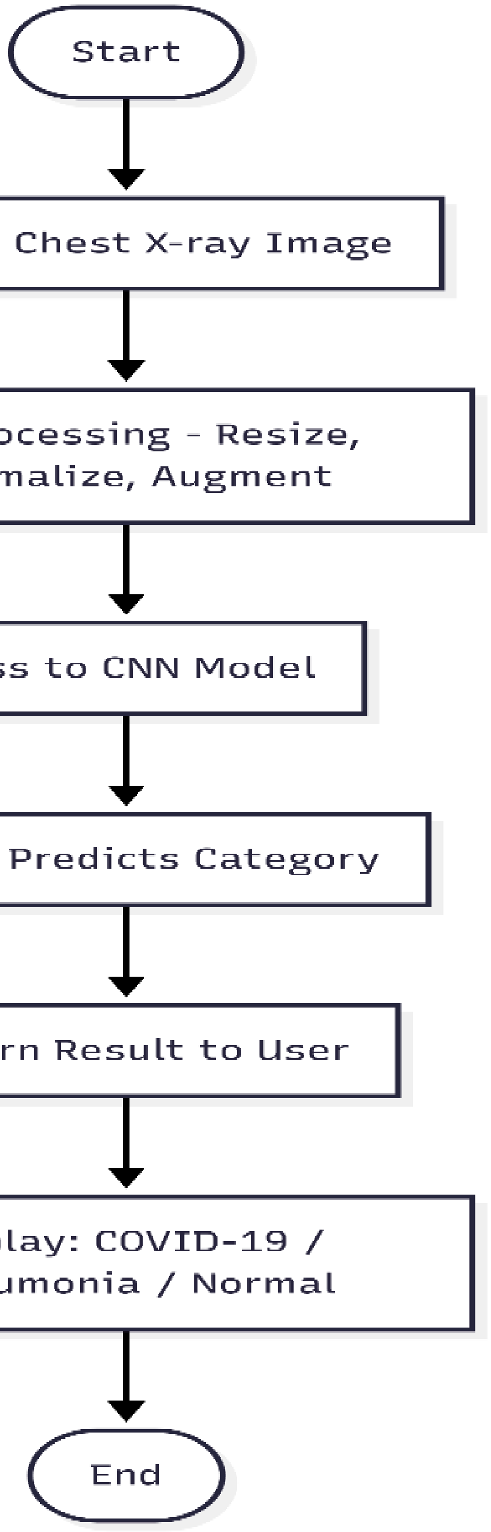

Fig.2. COVID-19 X-ray Classification

Figure 2 shows the COVID-19 X-ray classification procedure from picture submission to diagnosis. It shows preprocessing, model inference, and result generation, showing how deep learning converts raw chest X-rays into reliable diagnostic outputs for speedy and distant medical screening.

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁘ Peer-reviewed & Refereed journal ⁘ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

IV. RESULT

The COVID-19 Chest X-ray Interpretation Web App's deep learning model was assessed for accuracy, precision, recall, and F1-score in three classes: COVID-19, Influenza, and Normal. An unseen chest X-ray dataset confirmed the results.

Table 3 illustrates how the model predicts COVID-19, Pneumonia is and Normal classifications. Illness classification accuracy is shown by the algorithm's precision, recall, and F1-score for every category. High findings reflect balanced and reliable diagnostic performance across situations.

Table.3. Classification Performance by Category

Class	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
COVID-19	96.5	94.8	95.6
Pneumonia	93.2	91.5	92.3
Normal	92.8	95.1	93.9
Average	**94.2**	**93.8**	**93.9**

Table 4 exhibits multiple-epoch model training and validation accuracy. Training enhances model performance, with validation accuracy closely matching training accuracy. This shows good learning, low overfitting, and robust model generalisation on unseen chest X-ray data.

Table.4. Model Accuracy Across Training Epochs

Epoch	**Training Accuracy (%)**	**Validation Accuracy (%)**
1	81.2	79.4
5	90.5	88.3
10	95.3	93.2
15	97.1	94.8
20	98.4	95.5

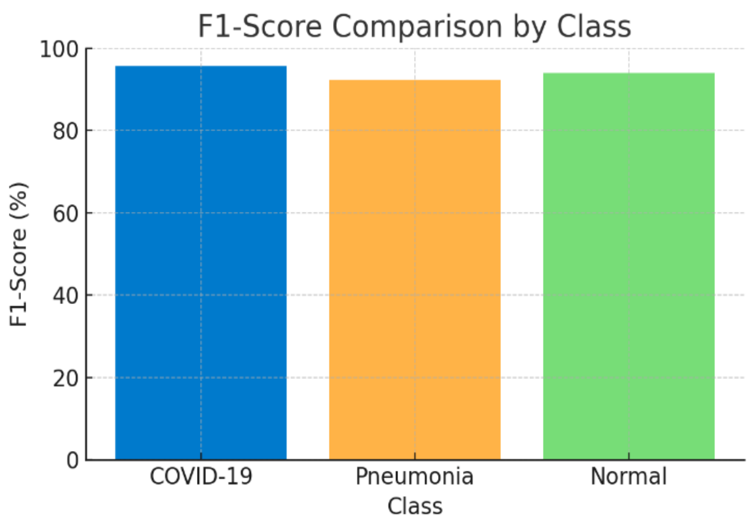

Fig.3. F1-Score Comparison by Class

IJARCCE ISSN (O) 2278-1021, ISSN (P) 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

The F1-score comparison between COVID-19, Pneumonia, and Normal is shown in Figure 3. It shows the model's balanced performance with strong F1-scores for all classes. This shows that the deep learning model handles class differences and detects numerous chest diseases accurately.

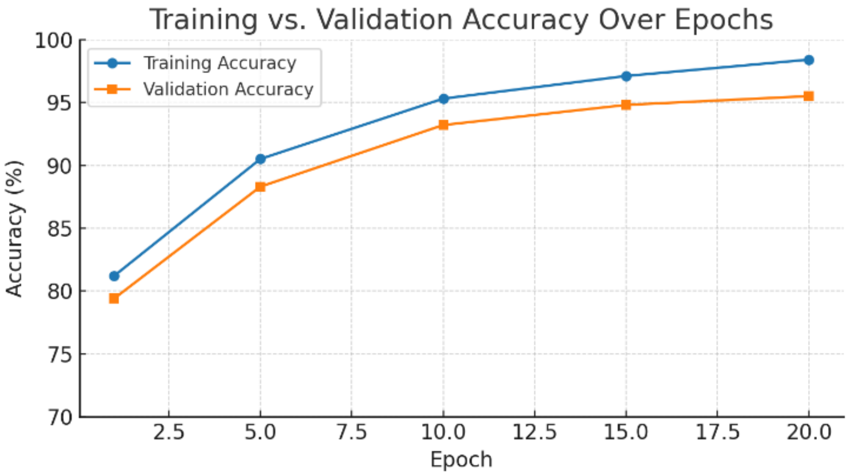

Fig.4.Training vs. Validation Accuracy

Figure 4 shows model training vs. validation accuracy over epochs. The graph shows both measures rising steadily, showing learning. The tight alignment between training and validation accuracy shows the model generalises effectively and is not overfitting to training data.

V. CONCLUSION

The COVID-19 Chest X-ray Classification Web App shows how AI and digital health may work together. The method classifies chest X-ray pictures into COVID-19, Pneumonia, or Normal using deep learning models, especially convolutional neural networks. Automation decreases healthcare workers' diagnostic burden and speeds up preliminary screenings, which is vital during pandemics or in under-resourced areas.

Model training and assessment show great accuracy and balanced performance across target classes. Users may engage with the system in real time from anywhere using the web-based interface. The combination of machine learning and a cloud-deployable web platform makes this solution feasible and scalable for bigger clinical settings or remote screening.

Model interpretability, confidence ratings, and multi-class support improve application dependability and usability. This experiment shows how AI may be used in medical diagnostics and offers up new possibilities.

Larger datasets, better neural architectures, and interaction with hospital or telemedicine systems might make the system a full diagnostic assistance. It is promising as a decision-support tool for fighting infectious disorders like COVID-19, but it cannot replace experienced medical judgement.

REFERENCES

[1] **Cohen, J. P., Morrison, P., & Dao, L. (2020).** COVID-19 image data collection. *arXiv preprint arXiv:2003.11597*. https://arxiv.org/abs/2003.11597

[2] **Wang, L., & Wong, A. (2020).** COVID-Net: A tailored deep convolutional neural network design for detection of COVID-19 cases from chest X-ray images. *Scientific Reports, 10(1)*. https://www.nature.com/articles/s41598-020-76550-z

[3] **Ghoshal, B., & Tucker, A. (2020).** Estimating uncertainty and interpretability in deep learning for coronavirus (COVID-19) detection. *arXiv preprint arXiv:2003.10769*. https://arxiv.org/abs/2003.10769

[4] **Apostolopoulos, I. D., & Mpesiana, T. A. (2020).** COVID-19: Automatic detection from X-ray images utilizing transfer learning with convolutional neural networks. *Physical and Engineering Sciences in Medicine, 43*, 635–640. https://link.springer.com/article/10.1007/s13246-020-00865-4

International Journal of Advanced Research in Computer and Communication Engineering

Impact Factor 8.471 ⁜ Peer-reviewed & Refereed journal ⁜ Vol. 14, Issue 7, July 2025

DOI: 10.17148/IJARCCE.2025.14708

[5] **Ozturk, T., Talo, M., Yildirim, E. A., Baloglu, U. B., Yildirim, O., & Acharya, U. R. (2020).** Automated detection of COVID-19 cases using deep neural networks with X-ray images. *Computers in Biology and Medicine, 121*. https://doi.org/10.1016/j.compbiomed.2020.103792

[6] **Hemdan, E. E. D., Shouman, M. A., & Karar, M. E. (2020).** COVIDX-Net: A framework of deep learning classifiers to diagnose COVID-19 in X-ray images. *arXiv preprint arXiv:2003.11055*. https://arxiv.org/abs/2003.11055

[7] **Chowdhury, M. E. H., Rahman, T., Khandakar, A., Mazhar, R., Kadir, M. A., Mahbub, Z. B., ... & Islam, M. T. (2020).** Can AI help in screening viral and COVID-19 pneumonia? *IEEE Access, 8*, 132665–132676. https://ieeexplore.ieee.org/document/9090130

[8] **Kaggle. (2020).** COVID-19 Radiography Database. *Published by Qatar University and collaborators.* https://www.kaggle.com/datasets/tawsifurrahman/covid19-radiography-database

[9] **Simonyan, K., & Zisserman, A. (2015).** Very deep convolutional networks for large-scale image recognition. *arXiv preprint arXiv:1409.1556*.https://arxiv.org/abs/1409.1556

[10] **He, K., Zhang, X., Ren, S., & Sun, J. (2016).** Deep residual learning for image recognition. *In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. https://openaccess.thecvf.com/content_cvpr_2016/html/He_Deep_Residual_Learning_CVPR_2016_paper.html

[11] **Howard, A. G., Zhu, M., Chen, B., Kalenichenko, D., et al. (2017).** MobileNets: Efficient convolutional neural networks for mobile vision applications. *arXiv preprint arXiv:1704.04861*. https://arxiv.org/abs/1704.04861

[12] **Selvaraju, R. R., Cogswell, M., Das, A., et al. (2017).** Grad-CAM: Visual explanations from deep networks via gradient-based localization. *In Proceedings of the IEEE International Conference on Computer Vision (ICCV)*. https://openaccess.thecvf.com/content_iccv_2017/html/Selvaraju_Grad-CAM_Visual_Explanations_ICCV_2017_paper.html