Weakly Supervised Severity Estimation of Apple Scab Using CNN and Grad-CAM

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Introduction

- **Global Importance of Apples**
  - Among the top four most cultivated fruits worldwide (>80M tons annually).
  - Vital to agricultural economies and food security.

- **Indian Significance**
  - India is a major apple producer (notably Himachal Pradesh & Jammu & Kashmir).
  - Contributes substantially to horticulture sector (≈30% of Indian agriculture GDP comes from horticulture).
  - Despite a 20% rise in apple cultivation area, production increased only 1–2% due to disease outbreaks.

- **Apple Scab: A Major Threat**
  - Caused by **Venturia inaequalis** fungus.
  - Visible as olive-green to dark lesions on leaves & fruit.
  - Leads to defoliation, reduced photosynthesis, degraded fruit quality, and yield losses.
  - Particularly damaging in Indian orchards, where scab is a recurring epidemic.

Problem Statement

- **Apple Scab Threat** – Caused by **Venturia inaequalis**; it creates spots on leaves and fruits, leading to leaf fall, less photosynthesis, poor fruit quality, lower yield, and big economic losses in apple production worldwide, including India.

- **Traditional Limitations** – Checking by hand is slow and subjective; lab methods like PCR or serological tests are costly, need experts, and cannot be used easily in farms.

- **Deep Learning Progress** – CNNs can classify apple leaves with over 95% accuracy, but they mostly only tell if a leaf is healthy or diseased.

- **Research Gap** – Current severity detection methods need pixel-level lesion masks, which take too much time, cost a lot, and require expert labeling, making them hard to scale.

- **Critical Need** – A weakly supervised and scalable method that works with only image-level labels to give fast, simple, and low-cost severity estimation for better crop management.

Literature Review

Author & Year	Title	Techniques & Model used	Remark	Dataset	Source of Publication
Vishnoi, V. K. et al. (2022)	Detection of Apple Plant Diseases Using Leaf Images Through Convolutional Neural Network	**Model**: Custom deep Convolutional Neural Network (CNN) with 3 convolutional layers (Conv-3 DCNN). **Techniques**: Data augmentation (shift, shear, zoom, flip), Adam optimization, ReLU and Softmax activation functions, random search for hyperparameter tuning.	The proposed model is designed to be **lightweight with a lower computational** burden. It achieves 98% classification accuracy and requires less storage (11 MB) and execution time than many pre-trained models, making it suitable for deployment on handheld devices. The model was trained for 1000 epochs and achieved its highest validation accuracy of 98.94% with a dropout rate of 0.4.	**Name:** PlantVillage. **Content**: 3171 RGB images of apple leaves across 4 classes (Scab, Black rot, Cedar rust, and healthy). **Details**: Images are 256x256 pixels and were captured in laboratory conditions with a simple background.	**Journal:** IEEE Access **DOI:** 10.1109/ACCESS. 2022.3232917
Sharma et al., 2022	D-KAP: A Deep Learning-based Kashmiri Apple Plant Disease Prediction Framework	Pre-trained CNNs (VGG-19, Inception-v3) + custom dense layers; Transfer learning; Data augmentation; Adam optimizer	VGG-19 achieved 92% accuracy (best), outperforming Inception-v3 (60%) and baseline (87%); trained for 220 epochs	Kashmiri Apple Leaf Dataset (500 images, augmented to 2000; 3 diseases + healthy; collected from Kashmir orchards)	TechRxiv, DOI:10.36227/techrxiv.21210320.v2

Author & Year	Title	Techniques & Model used	Remark	Dataset	Source of Publication
Ferentinos, K. P. (2018)	Deep learning models for plant disease detection and diagnosis	CNNs: AlexNet, AlexNetOWTBn, GoogLeNet, Overfeat, VGG. Framework: Torch7. Hardware: NVIDIA GTX1080 GPU.	Developed CNNs for plant disease identification. VGG performed best with 99.53% accuracy. **Training on real-field images proved essential (field+lab mix effective**; lab-only → 33% accuracy). Very low classification time (2 ms/image) makes it suitable for mobile applications.	Open dataset (Hughes & Salathé, 2015 preliminary PlantVillage): 87,848 leaf images, 25 plants, 58 [plant, disease] classes incl. healthy. 37.3% field, 62.7% lab. Split: 80/20 (train/test).	Computers and Electronics in Agriculture, Vol. 145, pp. 311-318. DOI: 10.1016/j.compag.2018.01.009.
Barbedo, J. G. A. (2016)	A review on the main challenges in automatic plant disease identification based on visible range images	This is a review paper that analyzes various digital image processing techniques. It discusses methods for leaf segmentation, dealing with illumination issues, and symptom segmentation. It also highlights the potential of more sophisticated techniques like Deep Learning (specifically CNNs), Markov Random Fields, and Large Margin Nearest Neighbor (LMNN) classification to address the identified challenges.	The paper identifies and analyzes six main challenges affecting automatic plant disease identification: **complex backgrounds, uncontrolled image capture conditions, poorly defined symptom boundaries, variations in symptoms for a single disease, simultaneous presence of multiple diseases, and visual similarity of symptoms from different diseases**. It concludes that the lack of comprehensive public image databases is a major bottleneck for research.	As a review paper, it does not use a primary dataset for experimentation. It discusses the critical need for large, public datasets and references the PlantVillage database as a notable example.	Biosystems Engineering, Vol. 144, pp. 52-60. DOI: 10.1016/j.biosystemseng.2016.01.017.

Author & Year	Title	Techniques & Model used	Remark	Dataset	Source of Publication
Pandian, J. A. et al. (2022)	A Five Convolutional Layer Deep Convolutional Neural Network for Plant Leaf Disease Detection	**Model:** A custom Deep Convolutional Neural Network (DCNN) with five convolutional layers (Conv-5 DCNN). **Techniques:** Five types of data augmentation (**Neural Style Transfer, DCGAN, PCA, Color, and Position Augmentation), random search for hyperparameter optimization**, and GPU-accelerated training.	The study proposed a DCNN model to identify 26 plant diseases from leaf images. The best performing model (Conv-5 DCNN) achieved an average classification accuracy of 98.41%, a precision of 0.94, a recall of 1.0, and an F1-Score of 0.97. The model's performance was superior to other advanced transfer learning and machine learning techniques. **The authors highlight the significant impact of data augmentation and hyperparameter tuning on the results.**	**Original:** An open dataset of 55,448 images across 39 classes of healthy and diseased plant leaves. **Augmented:** The dataset was expanded to 234,008 images using the augmentation techniques, with each class containing 6000 images. The data was split into 224,552 images for training and 9,448 for testing.	Electronics, Vol. 11, Issue 8, Article 1266. DOI: 10.3390/electronics11081266.
Geetharamani, G. & Arun Pandian, J. (2019)	Identification of plant leaf diseases using a nine-layer deep convolutional neural network	**Model:** A custom nine-layer deep Convolutional Neural Network (Deep CNN). **Techniques:** Six types of data augmentation (**image flipping, gamma correction, noise injection, PCA color augmentation, rotation, scaling**), mini-batch gradient descent, max pooling, and hyperparameter tuning for epochs, batch size, and dropout	The proposed model was developed to identify 38 distinct classes of plant diseases plus a background class. It achieved a classification accuracy of 96.46% on the test dataset, outperforming traditional machine learning methods and popular transfer learning models (AlexNet, VGG16, Inception-v3, ResNet). **The use of data augmentation was noted to significantly increase the model's performance**. The best results were achieved after 3000 training epochs	**Name:** PlantVillage. **Content:** An open dataset with 39 classes (38 plant/disease combinations + 1 background). The original dataset had 54,305 images, which was expanded to 61,486 images using data augmentation.	Computers and Electrical Engineering, Vol. 76, pp. 323-338. DOI: 10.1016/j.compeleceng.2019.04.011

Author & Year	Title	Techniques & Model used	Remark	Dataset	Source of Publication
Kandel, I. & Castelli, M. (2020)	The effect of batch size on the generalizability of the convolutional neural networks on a histopathology dataset	Model: VGG16 (ImageNet pre-trained).Techniques: Transfer learning (fine-tuning), image augmentation (flip, rotation, zoom, shift), optimizers (SGD, Adam).	The study shows that **batch size strongly influences CNN generalizability**. Large batch sizes did not consistently improve accuracy, while **small batch size (16)** with **low learning rate (0.0001)** using **Adam** gave the best performance (highest AUC). It highlights a **critical correlation between learning rate and batch size**, providing guidance for tuning CNNs: smaller batches encourage better generalization in medical image classification.	**PatchCamelyon dataset**: 220,000 binary labeled histopathology images for training and 57,458 for testing (96×96 pixels)	*ICT Express*, Vol. 6(4), pp. 312–315. DOI: 10.1016/j.icte.2020.04.010
Wspanialy, P. & Moussa, M. (2020)	A detection and severity estimation system for generic diseases of tomato greenhouse plants	Detection: ResNet-50 (transfer learning, ImageNet pre-trained).Severity Estimation: Modified U-Net with VGG16 backbone. Techniques: Transfer learning, data augmentation, semantic segmentation.	The study presents a **two-part system for generic disease detection and severity estimation**. The detection model achieved 97% accuracy but also revealed significant biases in the dataset (e.g., models trained on only the background achieved 63.5% accuracy). The severity estimation model's performance was comparable to human evaluation, with a mean error of 11.8%, working best for diseases with localized symptoms.	PlantVillage (tomato): full dataset (9 disease classes + healthy).Annotated subset: 1,800 images manually labeled at pixel level for health, disease, background.	Computers and Electronics in Agriculture, Vol. 178, Article 105701. DOI: 10.1016/j.compag.2020.105701

Author & Year	Title	Techniques & Model used	Remark	Dataset	Source of Publication
Shukla et al., 2020	Plant Disease Detection and Localization using GRADCAM	Classification: EfficientNet (5.3M parameters, efficient, mobile-suitable), ResNet (baseline, 23.5M parameters).Localization: Grad-CAM (weakly-supervised heatmaps, superior to CAM), CAM (baseline, less effective).Preprocessing: Leaf segmentation to remove background, data augmentation (rotation, flipping, noise) to balance classes.	Proposed a dual-task pipeline for **classification + localization.** Grad-CAM outperformed CAM in highlighting diseased areas. Segmented images improved accuracy. EfficientNet showed superior trade-off between accuracy and efficiency compared to ResNet. **Grad-CAM heatmaps suggested as pseudo-masks for dataset generation**. Focus on real-world deployment (smartphones).	PlantVillage dataset (Apple subset, 1902 images × 3 formats = 5706). Covers 4 classes: apple scab, cedar rust, black rot, and healthy. Strong class imbalance addressed via augmentation	International Journal of Recent Technology and Engineering (IJRTE), Vol. 8, Issue 6, pp. 3069–3075, March 2020. ISSN: 2277-3878**.**
Sattarzadeh et al., 2021	Integrated Grad-CAM:Sensitivity-Aware Visual Explanation of Deep Convolutional Networks via Integrated Gradient-Based Scoring	Proposed: Integrated Grad-CAM (**combines Grad-CAM + Integrated Gradients via path integral of gradient scores**).Implementation: Riemann sum approximation over multiple scaled versions. Models: VGG-16, ResNet-50.	**Solves Grad-CAM's weakness (averaging gradients underestimates sensitivity).** Produces more faithful visual explanations. Outperforms Grad-CAM and Grad-CAM++ in localization and faithfulness. Higher computational cost.	PASCAL VOC 2007 test set (4,952 images, 20 classes, multi-object).	*arXiv preprint* arXiv:2102.07805v1 [cs.CV]

Research Gap

<u>**From “What” to “How Much”**</u>

What We Know

- CNNs classify plant diseases with very high accuracy (>98%).
- We can reliably answer: “What disease is present?”

The Problem

- Disease management requires severity estimation (% area infected).
- Traditional approach = **fully-supervised segmentation with pixel-level masks**.
- Annotation is expensive, time-consuming, and expert-dependent.

The Opportunity

- Weakly-supervised methods (e.g., Grad-CAM) localize diseased regions using only image-level labels.
- Prior work (Shukla et al., 2020) proved feasibility but stopped at visual localization.

The Gap

- No validated method exists **to convert Grad-CAM heatmaps into quantitative severity estimates**.

Our Contribution

- Bridge this gap by transforming Grad-CAM heatmaps into pseudo-masks.
- Derive severity scores from these masks to provide actionable insights.
- Deliver a low-cost, scalable, and deployable framework for plant disease severity estimation.

Dataset

Source:

- Extracted from **PlantVillage dataset (Apple category)** available on Kaggle.
- Two classes: *Apple Scab* (diseased) & *Apple Healthy*.

Kaggle Links:

- https://www.kaggle.com/datasets/shankaraditya0693/plantvillage
- https://www.kaggle.com/datasets/kolo3allaallah/new-updated-dataset003

DATASET 1(ORIGINAL)

	Apple Scab	Apple Healthy	Total
Train	2,166	2,008	4,174
Test	504	502	1,006
Total	2,670	2,510	**5,180**

Applescab

Applehealthy

DATASET 2 (REMOVED BACKGROUND)

Class	No. of Images
Apple Scab	1,219
Apple Healthy	1,661
Total	**2,880**

Applescab

Applehealthy

COMBINED DATASET

Split	Apple Scab	Apple Healthy	Total
Train (Original + 80% BG-Removed)	2,166 + (975) ≈ 3,141	2,008 + (1,329) ≈ 3,337	**6,478**
Test (Original + 20% BG-Removed)	504 + (244) ≈ 748	502 + (332) ≈ 834	**1,582**
Total	≈ 3,889	≈ 4,171	**8,060**

BG-Removed split: Apple Scab = 1,219 → 975 train, 244 test; Apple Healthy = 1,661 → 1,329 train, 332 test)

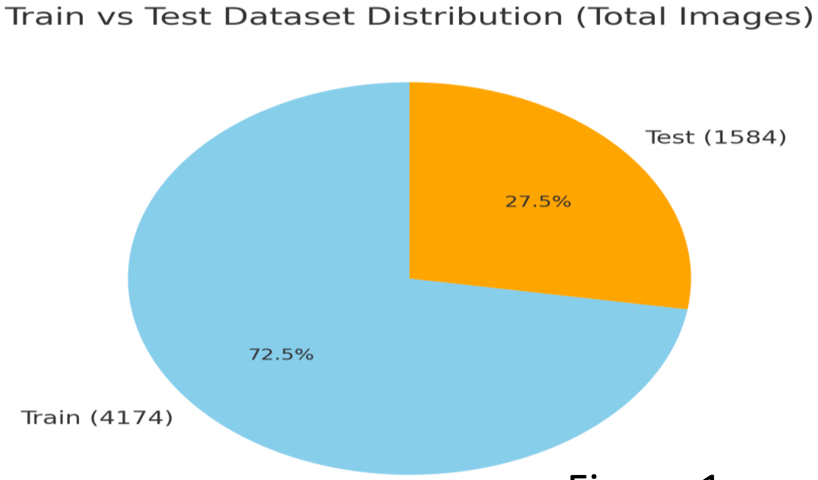


Figure 1

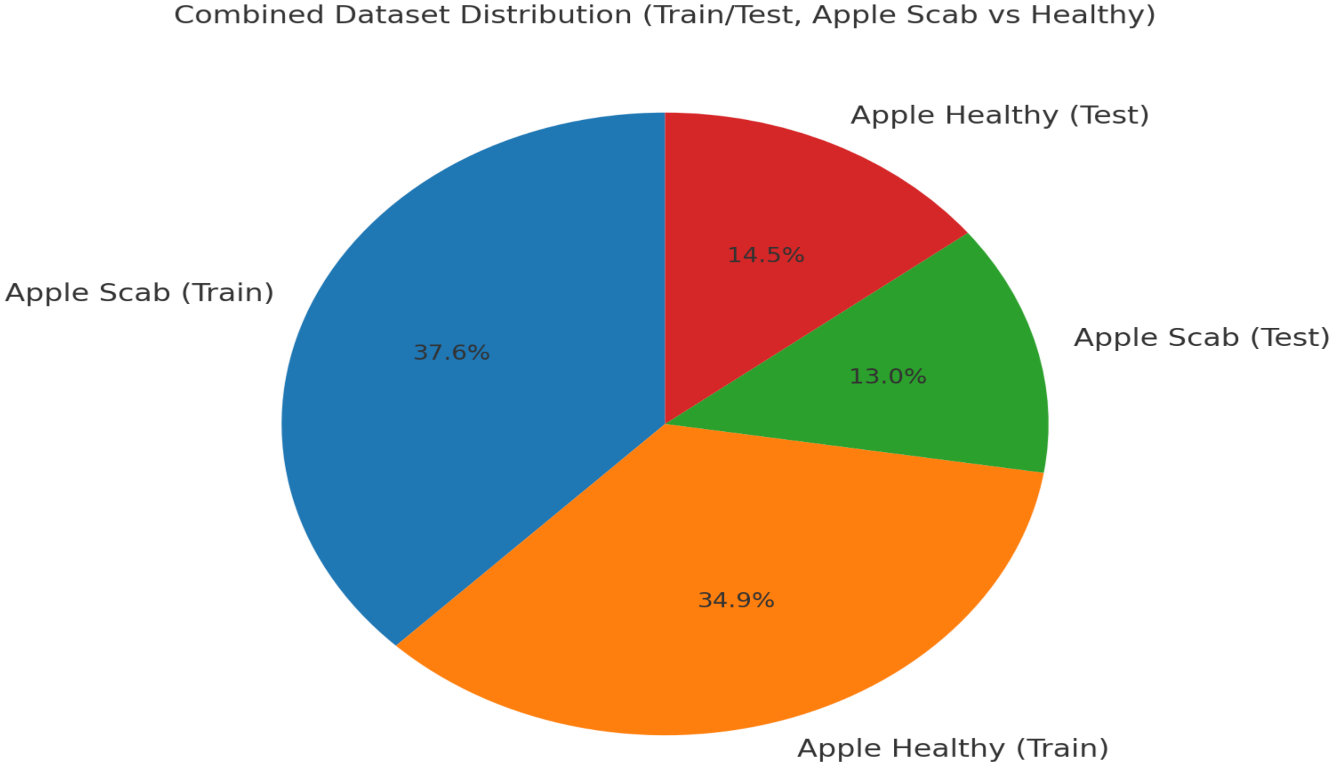


Figure 2

Remarks

- Balanced dataset across classes.
- Mixed Test set improves generalization.
- Resized to 256×256 px for CNN training efficiency.

Proposed Algorithm & workflow

Data Preprocessing → CNN Training (Sigmoid) → Grad-CAM Heatmap → Binary Mask → Severity Estimation → Results

I. Dataset Preparation & Preprocessing

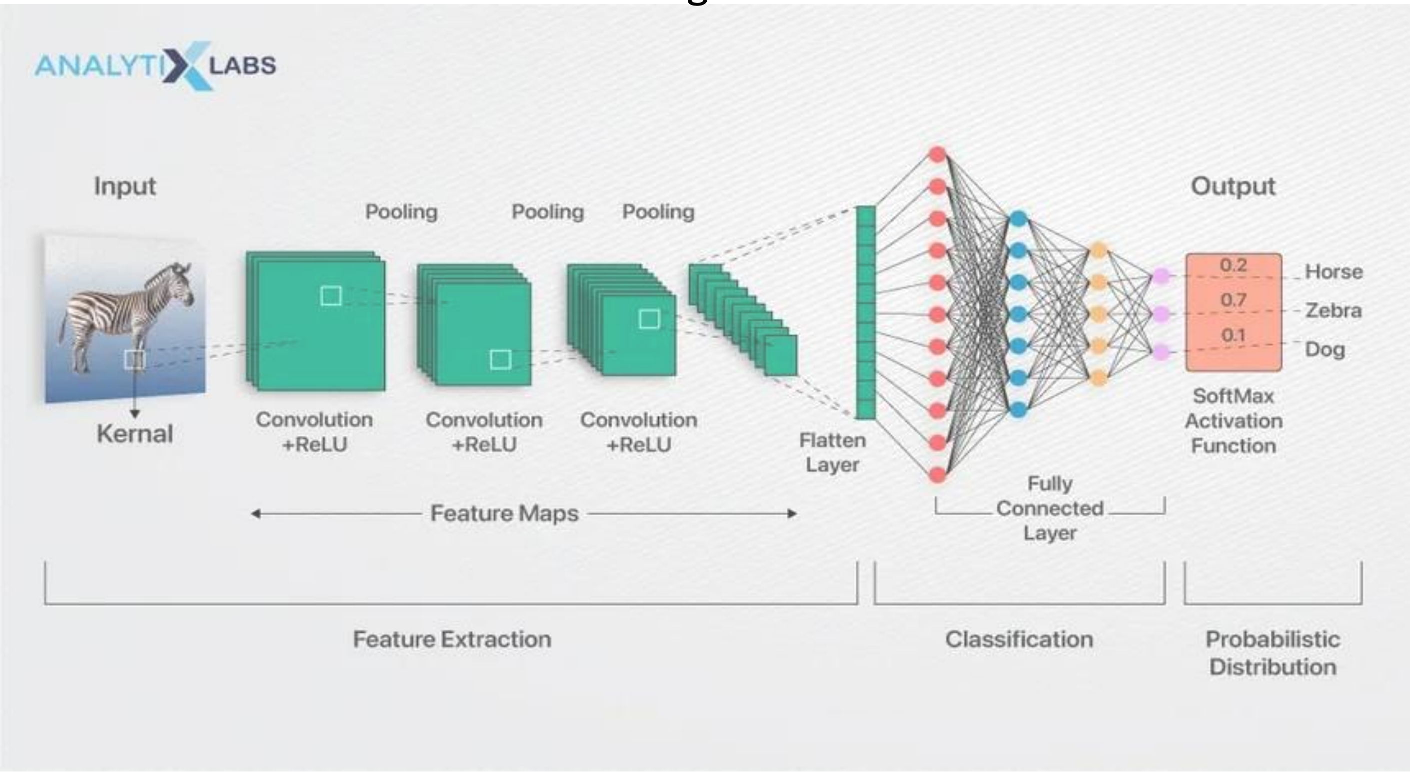
- Labels: Weak supervision (image-level only).
- Resize: All images resized to 256×256 px.
- Augmentation: Rotation, flipping, brightness/contrast, noise.

II. Custom CNN Model (Classification)

- Feature Extraction: Convolution + ReLU + Pooling layers.
- Regularization: Dropout layers to prevent overfitting.
- Classifier Head:
  - Flatten → Dense layers → 1 output neuron
  - Sigmoid activation → outputs probability of "Scab"

- Training Setup:
  - Optimizer: Adam
  - Loss Function: Binary Cross-Entropy (BCE)
  - Performance tracked on validation set.

Figure 3



III. Weakly Supervised Severity Estimation (Core Innovation)

- Grad-CAM Heatmap Generation: Localizes diseased regions.
- Post-processing: Upsample + threshold → binary lesion mask.
- Severity Calculation:

Severity (%) = (Number of Pixels in Thresholded Heatmap / Total Number of Pixels in Leaf Area) × 100

IV. Evaluation & Validation

- Classification Metrics: Accuracy, Precision, Recall, F1-score.
- Severity Validation: Compare predicted severity vs manual ground-truth.

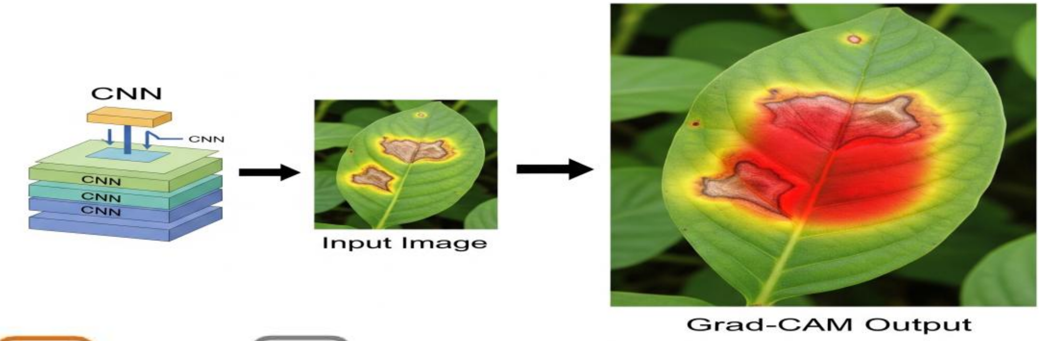


Figure 4

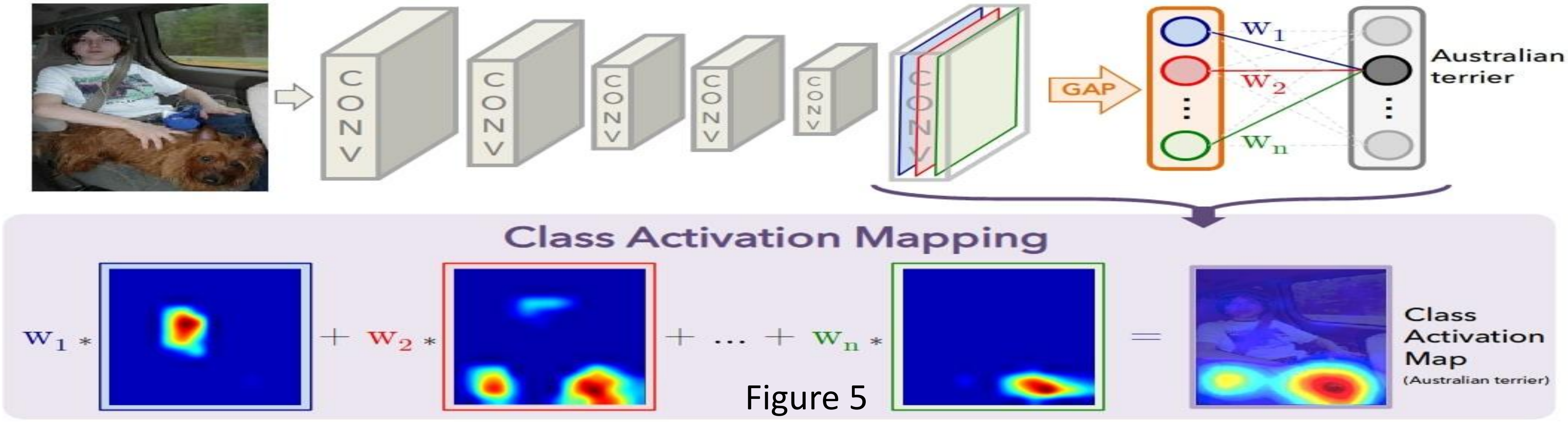


Figure 5

Figure 2. Class Activation Mapping: the predicted class score is mapped back to the previous convolutional layer to generate the class activation maps (CAMs). The CAM highlights the class-specific discriminative regions.

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