Waste Recyclability Classification

Group 21 (Ryan, Gregory, Bowei)

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Introduction

Motivations

Our only landfill, Semakau, is projected to **run out of space** by 2035.

This is partly preventable by recycling.

But we sometimes make **mistakes**!

And post-hoc sorting can be **laborious.**

Task

Learn some

$$f : \mathbb{R}^{H \times W \times C} \to \{0, 1\}$$

so that given an image of waste, a model returns if the item is recyclable (or not).

Task

This is probably novel.

Other tasks often define classes by **material type.**

No other task we know of uses **NEA's waste recyclability definitions.**

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Related Work

Zheng et. al (2021)

They introduced an **ensemble** which combines predictions from GoogLeNet, ResNet50, and MobileNetV2.

UPMWS was introduced to determine weight coefficients of the ensembled models.

EnCNN-UPMWS model achieved an accuracy of **93.50%** on TrashNet, beating EnCNN-Voting by 0.092%.

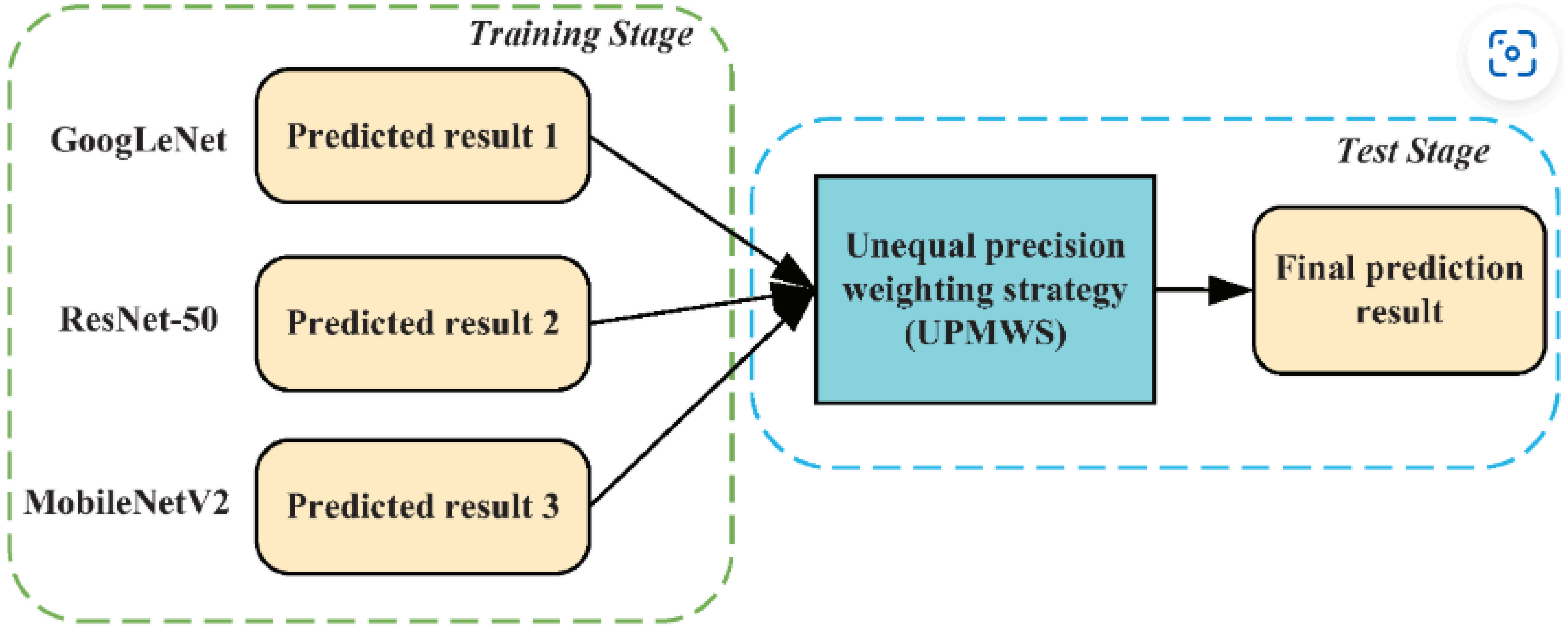

Figure: Architecture of EnCNN-UPMWS.

$$Y^*(x) = \Sigma_{j=1}^{3} w_j P_j(x)$$

Figure: Computation of final prediction.

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Dataset

Summary

1559

images of nonrecyclable waste

1559

images of recyclable waste

100%

hand-crafted from NEA guidelines

Sources

Our dataset compiled images from the following sources.

1. TrashNet.
2. RealWaste.
3. Search engines.

Figure: Examples of samples from RealWaste.

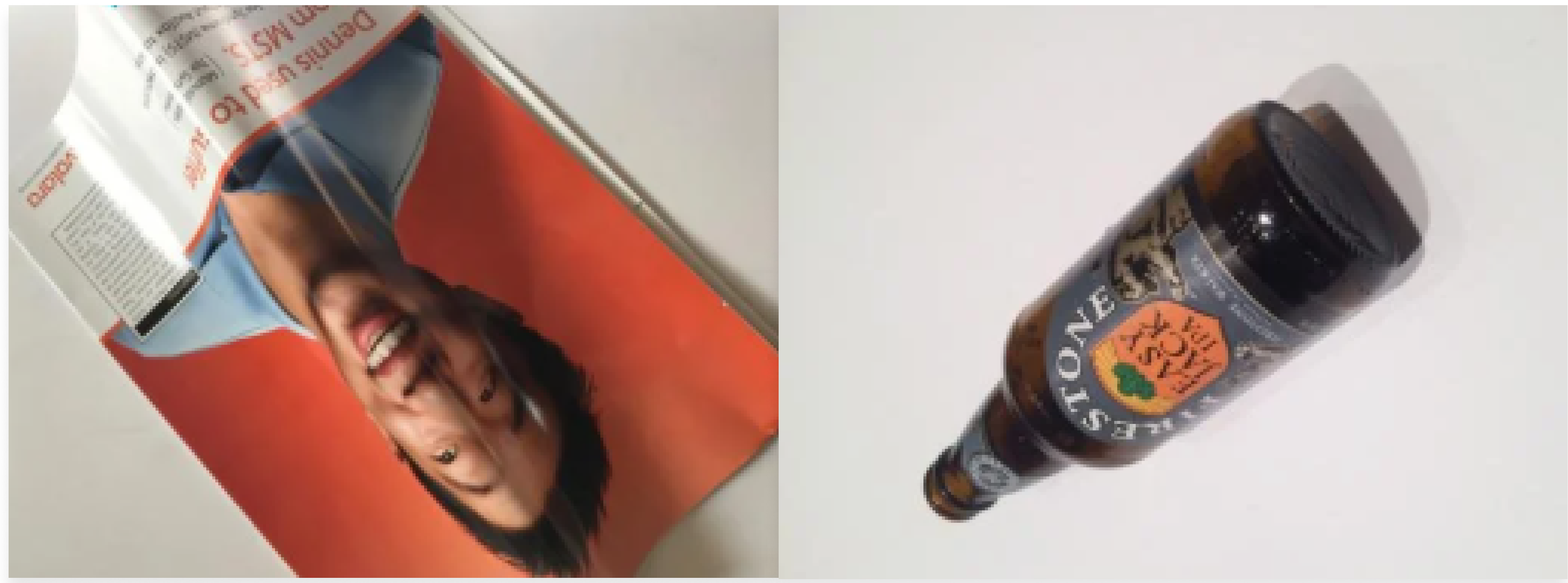

Figure: Examples of samples from TrashNet.

Figure: Examples of samples from search engines.

Balance and Split

We manually **categorised** each collected image as either nonrecyclable or recyclable.

We **supplemented** each underrepresented item category with a fixed amount of images from search engines.

We **split** the dataset into training, validation, and test sets in a ratio of **8:1:1**, respectively, in a **stratified** way.

S/N	MATERIAL TYPE	ITEM	CAN BE PLACED IN THE BLUE RECYCLING BINS	CANNOT BE PLACED IN THE BLUE RECYCLING BINS
18	PAPER	PAPER PACKAGING PRINTED PAPER BOX PAPER BOX	✓ Please flatten before recycling	
19	PAPER	EGG TRAYS	✓ Make sure it is clean before recycling	
20	PAPER	BEVERAGE CARTON - Milk carton - Drink packet - Juice packet	✓ Please empty, rinse and flatten before recycling	
21	PAPER	PAPER TOWEL TUBE TOILET ROLL TUBE	✓ Make sure it is clean before recycling	
22	PAPER	TISSUE BOX	✓ Please flatten before recycling	
23	PAPER	PAPER BAG	✓ Make sure it is clean before recycling	
24	PAPER	PAPER DISPOSABLES - Paper cup - Paper plate - Glitter paper - Crayon drawing		

Figure: NEA guidelines.

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Models

Introduction to Somnial Unit

To support our goal of accurate and efficient waste recyclability classification, we propose a **novel architectural unit** inspired by neurobiological notions of dreaming in animals.

Components of Somnial Unit

Memory Buffer

A **store** maintaining feature maps for recollection.

$$\mathcal{M}_t = \{\mathsf{x}_s : \max(0, t-L) \leq s \leq t\}$$

Recollector

A **convolution** of a recalled feature map.

$$\rho(\mathsf{x}) = \mathsf{x} \circledast \mathbf{W}_\rho + \mathbf{b}_\rho$$

Modulator

An **interpolation** between a current and recollected feature map.

$$\mu(\mathsf{a}, \mathsf{b}) = \sigma\left(\mathrm{sim}(\mathbf{a}_{h,w}, \mathbf{b}_{h,w})\right)_{(h,w)\in\{1,\ldots,H\}\times\{1,\ldots,W\}}$$

Training and Inference Algorithms for Somnial Unit

$$\text{Train}(\mathsf{x}_t):$$

$$\mathcal{M}_t \leftarrow \mathcal{M}_t \cup \{\mathsf{x}_t\}$$

$$\mathsf{x}_s \leftarrow \text{rand}(\mathcal{M}_t)$$

$$\hat{\mathsf{x}}_s \leftarrow \rho(\mathsf{x}_s)$$

$$\mathsf{m} \leftarrow \mu(\hat{\mathsf{x}}_s, \mathsf{x}_t)$$

$$\textbf{return } \mathsf{m} \odot \hat{\mathsf{x}}_s + (1 - \mathsf{m}) \odot \mathsf{x}_t$$

$$\text{Infer}(\mathsf{x}_t):$$

$$\mathsf{x}_s \leftarrow \mathsf{x}_t$$

$$\hat{\mathsf{x}}_s \leftarrow \rho(\mathsf{x}_s)$$

$$\mathsf{m} \leftarrow \mu(\hat{\mathsf{x}}_s, \mathsf{x}_t)$$

$$\textbf{return } \mathsf{m} \odot \hat{\mathsf{x}}_s + (1 - \mathsf{m}) \odot \mathsf{x}_t$$

Training of Models

Batch size	32
Optimiser	AdamW
Learning rate	0.001
Number of epochs	50
Patience	{10, 50}

Figure: General model settings.

Memory buffer size	{2, 5, 10, 100}

Figure: Settings for models equipped with somnial unit.

Training of Models

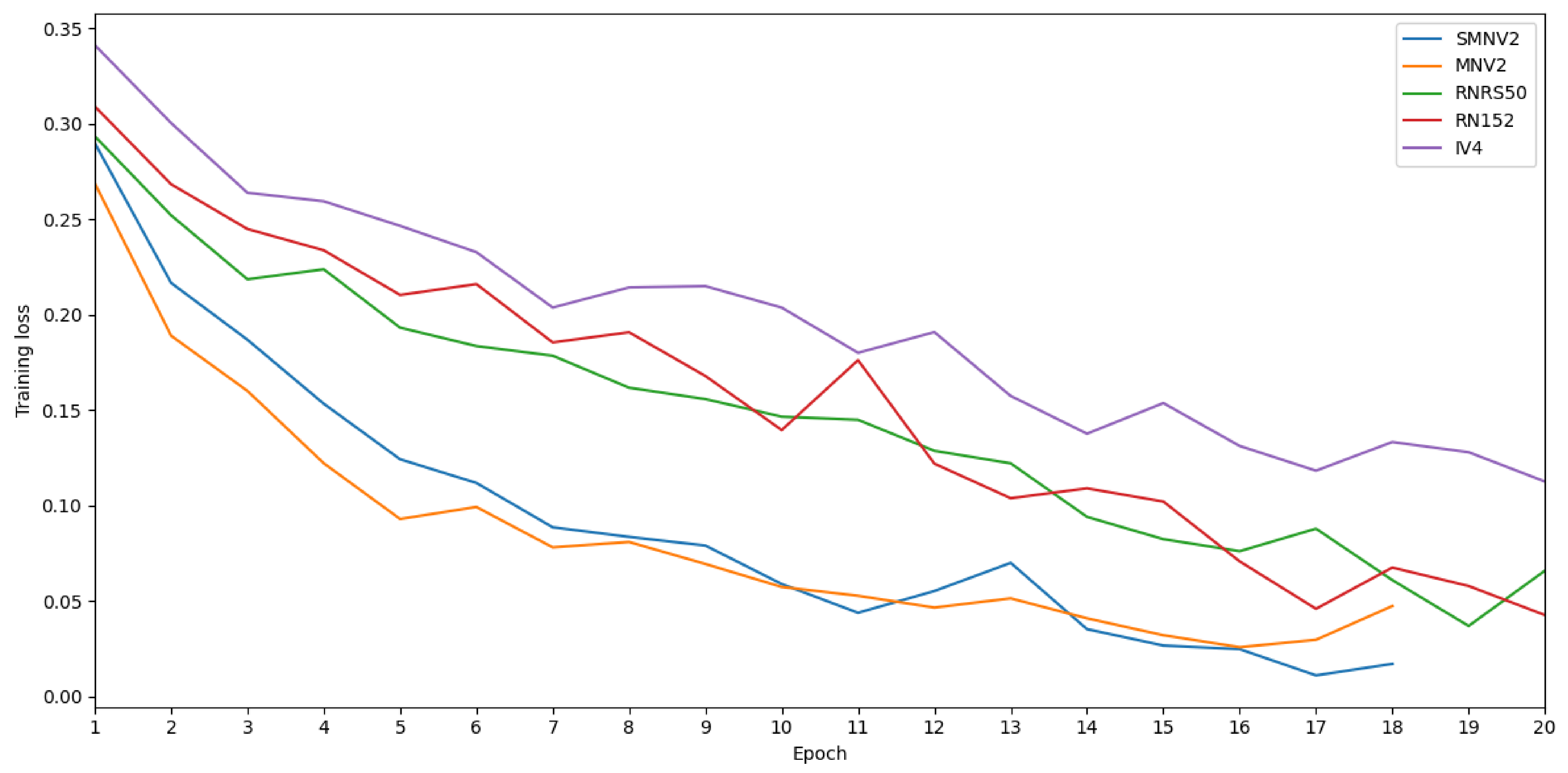


Figure: Training losses of models.

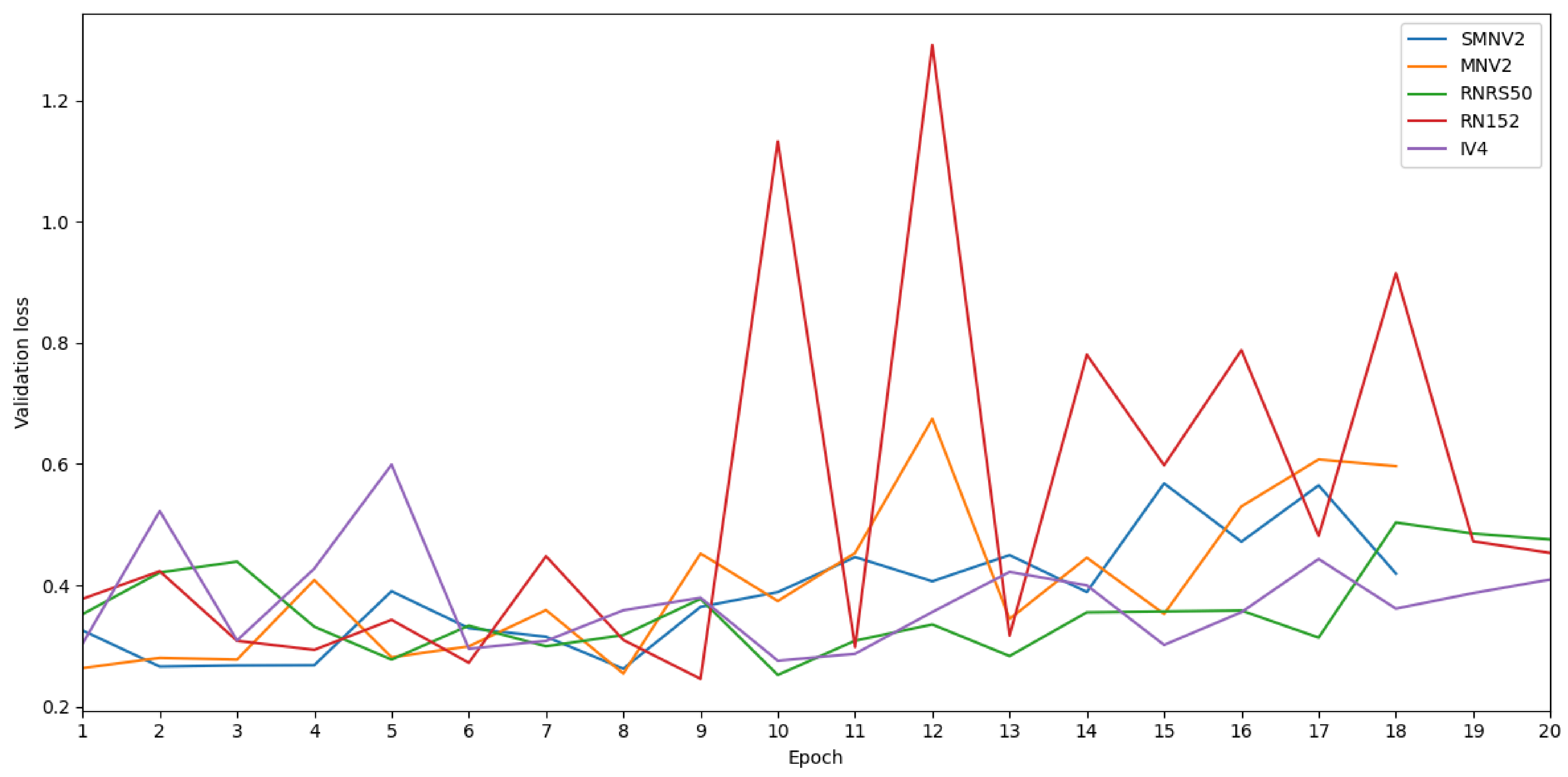
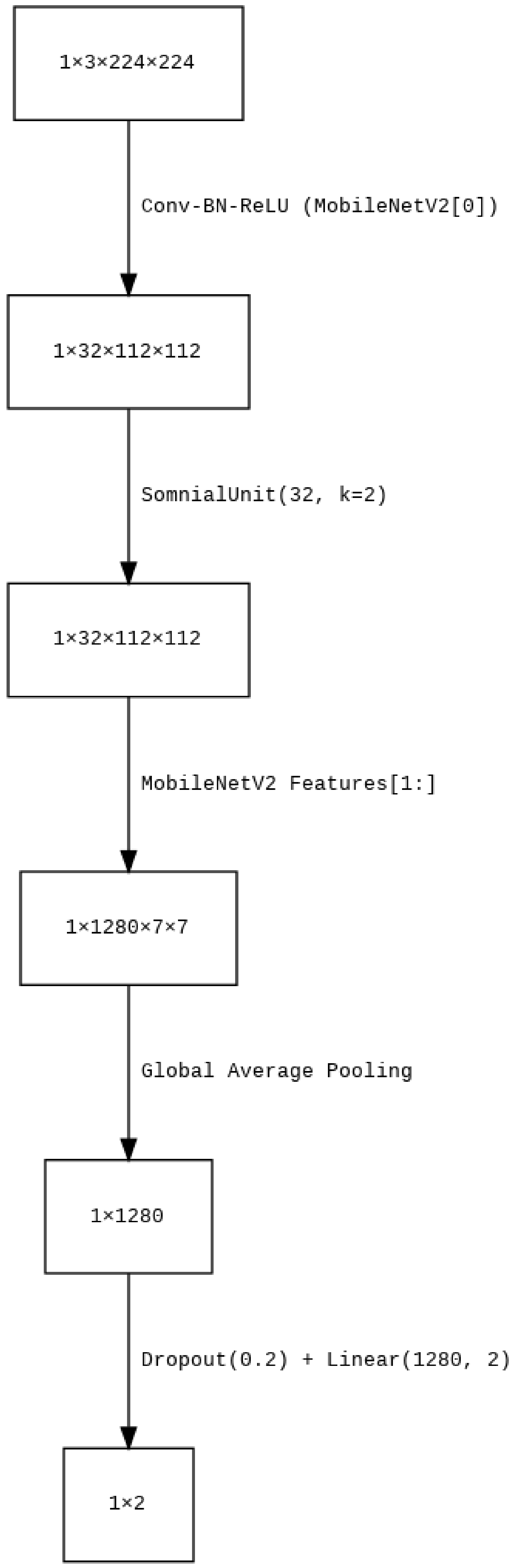


Figure: Validation losses of models.

Evaluation of Models

Identifier (ID)	Family	Macro F1
SMNV2	CNN	0.945387
MNV2	CNN	0.935832
RNRS50	CNN	0.922874
RN152	CNN	0.926111
IV4	CNN	0.919354
ViTB32	ViT	0.869007
ViTB16	ViT	0.836259

Best-Performing Model



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Discussion

Spurious Background Texture Correlation

MNV2 seems to base its prediction more on **background textures** (e.g. floor backgrounds), than on **foreground objects**.

We suspect MNV2 **overfit** during training as positive and negative samples came mostly from TrashNet and RealWaste, respectively, and each dataset mostly collects photos taken on **similar-looking background surfaces**.

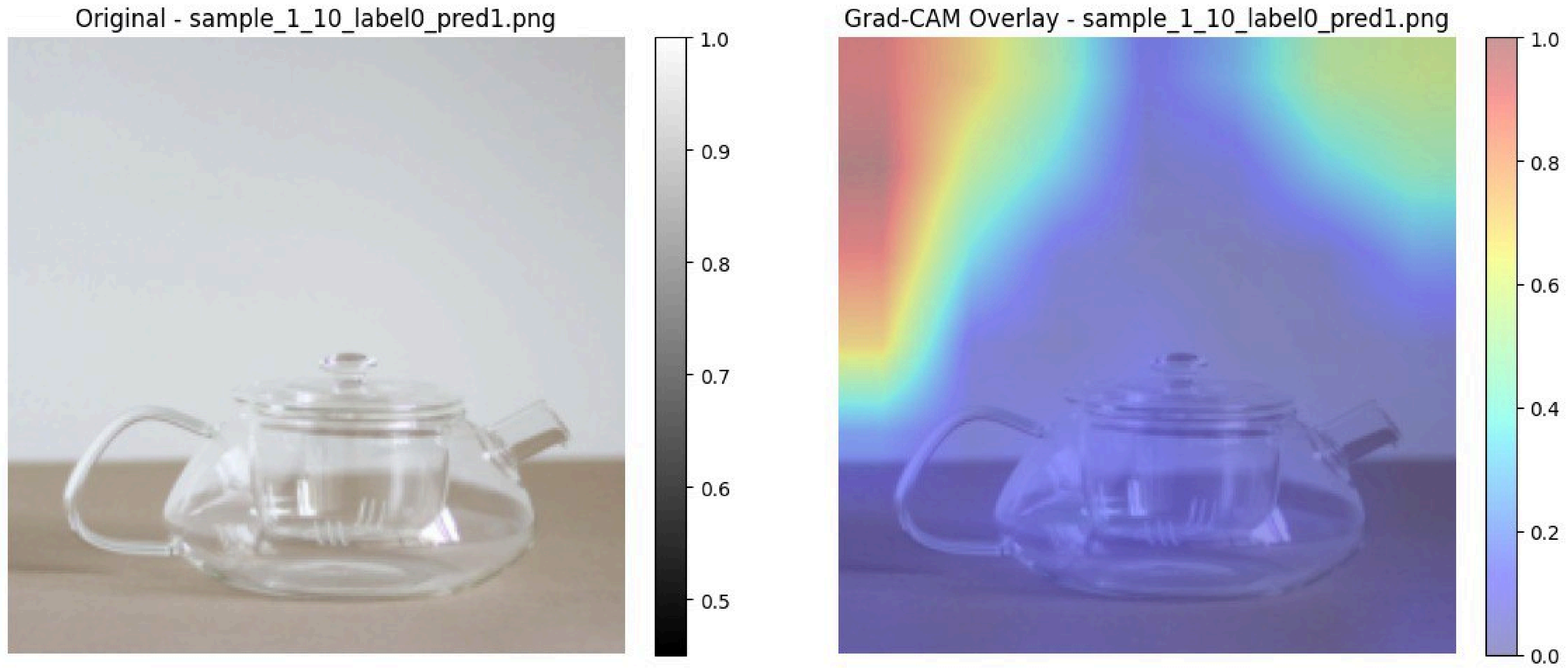

Figure: Grad-CAM Heatmap for MNV2 False Positive.

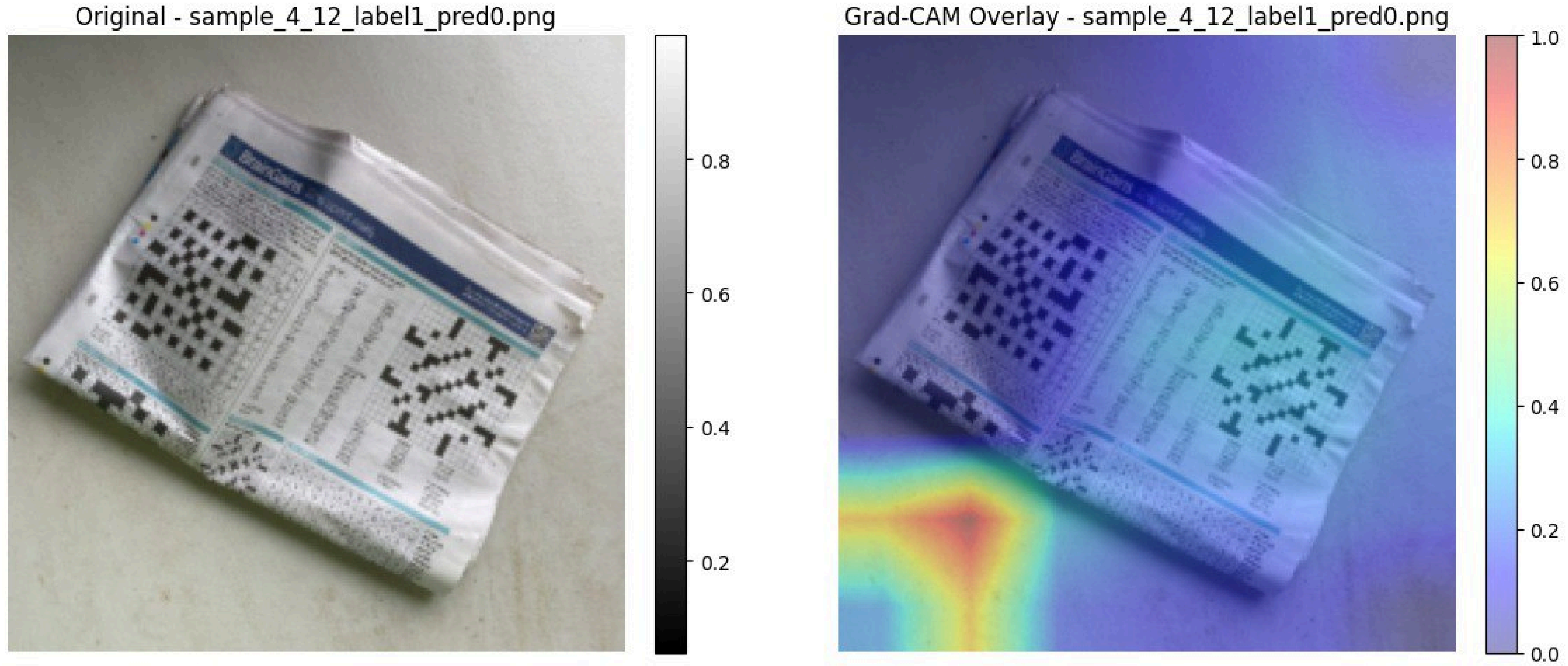

Figure: Grad-CAM Heatmap for MNV2 False Negative.

Spurious Background Texture Correlation

With a somnial unit, the model seems to look **more closely** at the objects!

The feature-level **regularisation** introduced could have helped mitigate overfitting to the spurious correlation.

Background texture features could have also been **down-weighted** if they did not (persistently) give a high enough similarity with recollected features.

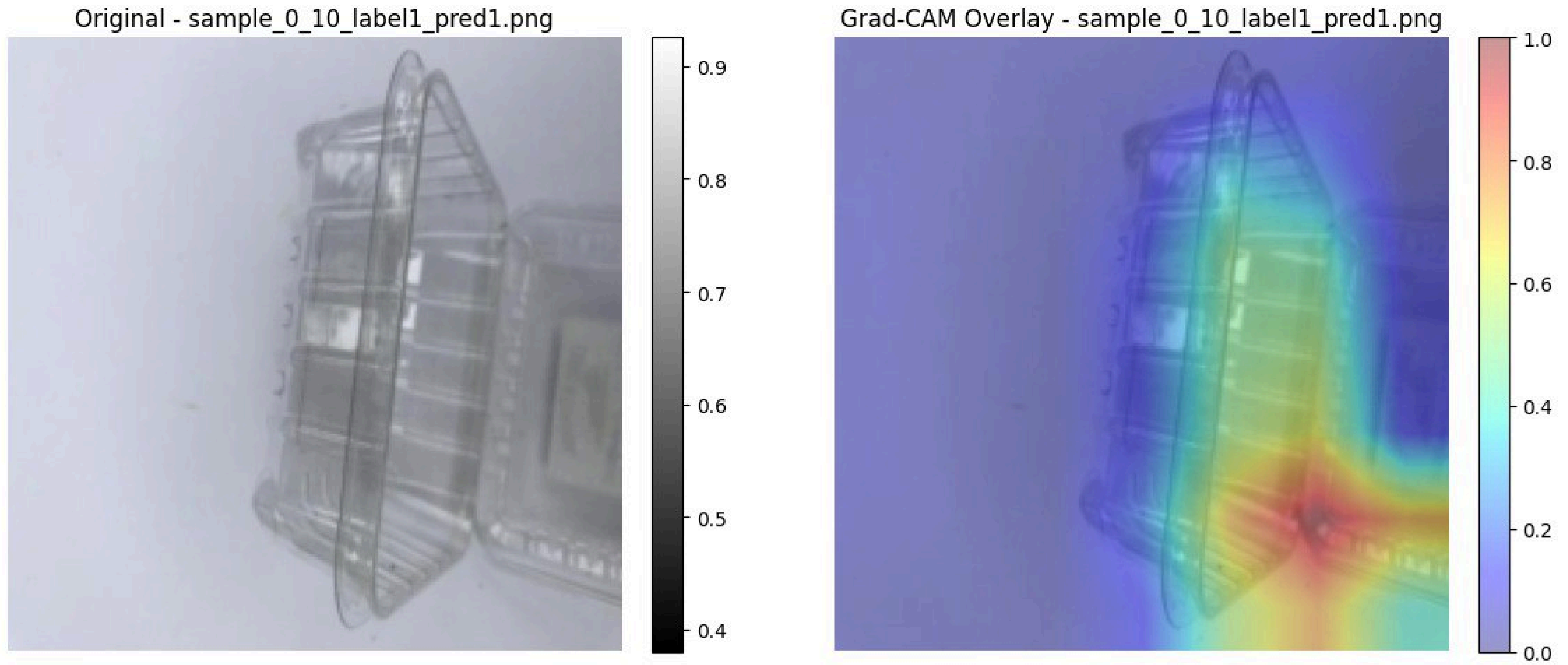

Figure: Grad-CAM Heatmap for SMNV2 True Positive.

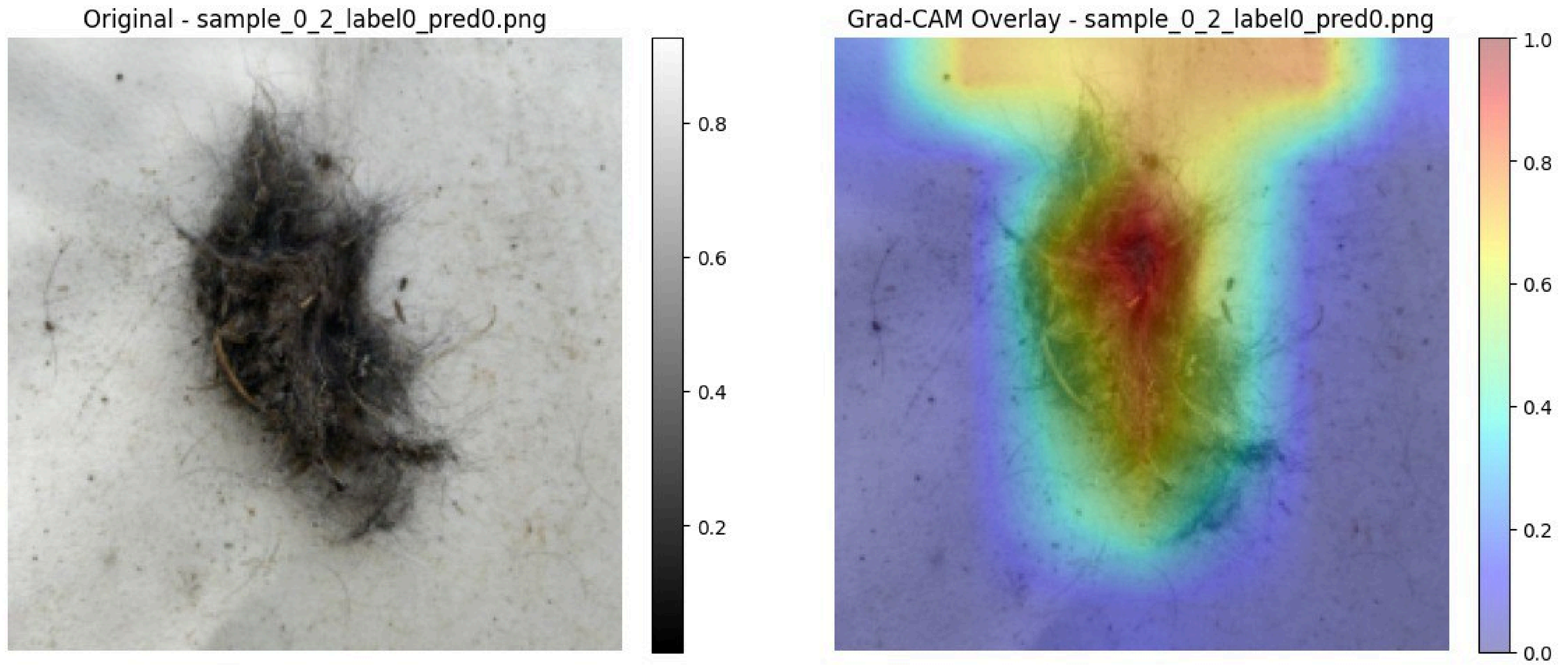

Figure: Grad-CAM Heatmap for SMNV2 True Negative.

Spurious Background Texture Correlation

We think data augmentation, masking, or segmentation could also mitigate the overfitting.

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Future Work

Foregone Explorations of Somnial Unit

1. Fourier neural operator (FNO).
2. Kolmogorov–Arnold layers.
3. Cyclic topologies.
4. Fourier feature mapping.
5. Adversarial boundary refinement.

Other Foregone Explorations

1. Other models (e.g. ConvNeXt, EVA02, DINOv2, CoaT, MobileViT, and NeXt-ViT).
2. Weighted (e.g. class-weighted, focal) variations of the loss function.
3. Mixup data augmentation.
4. Feature fusion between best models.
5. Addition of squeeze-and-excitation block to MNV2 and RN152.
6. Self-distillation of MNV2.
7. Curriculum learning using Laplacian variance as difficulty measure.

Suggested Explorations

1. More labelled features (e.g. weight).
2. Reinforcement or online supervised learning to improve model sustainably over time.
3. Data augmentation or segmentation to avoid the spurious ground texture correlation.

Demonstration