Automated Oatmeal Overflow Detection

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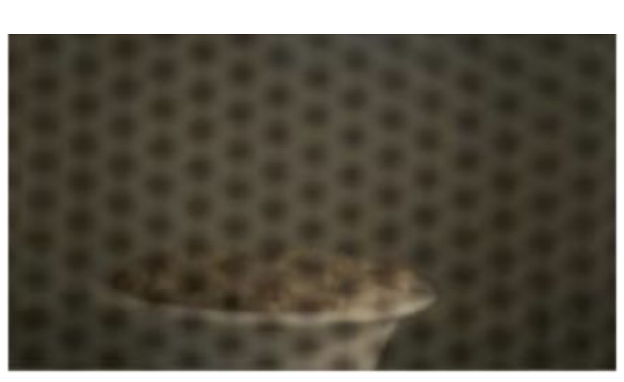
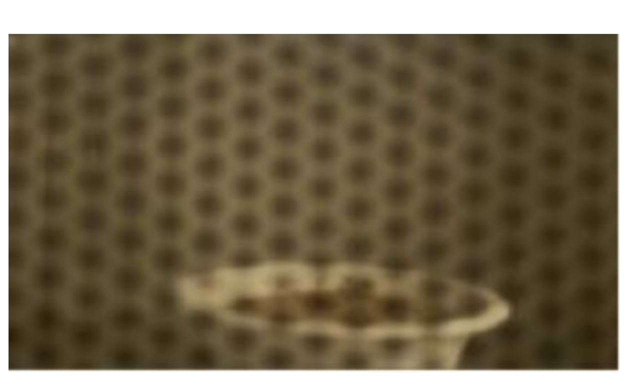
Motivation

- We want to prevent microwave oatmeal overflow with vision
- Existing approaches require camera inside microwave and regular CV fails is challenging within microwave environment

Dataset

- We collect 33 videos of oatmeal heating
- Frames are sampled every 300ms and classified as off, safe, or unsafe, for 1744 frames in total
- Since unsafe frames only occur in the last second or so before heating must stop, there is a class imbalance of only 16% unsafe images


(a)


(b)

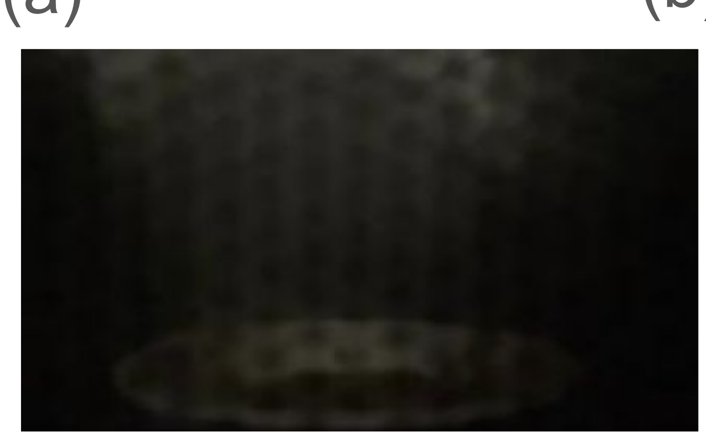

(c)

Fig 1: an of a (a) unsafe (b) safe (c) off fram unsafe frame

Fig 2: data collection and inference setup

Architecture

- We remove the last 10000 way classifier of MobileNetV3 and replace it with a 3 way linear classifier layer (the *head*)

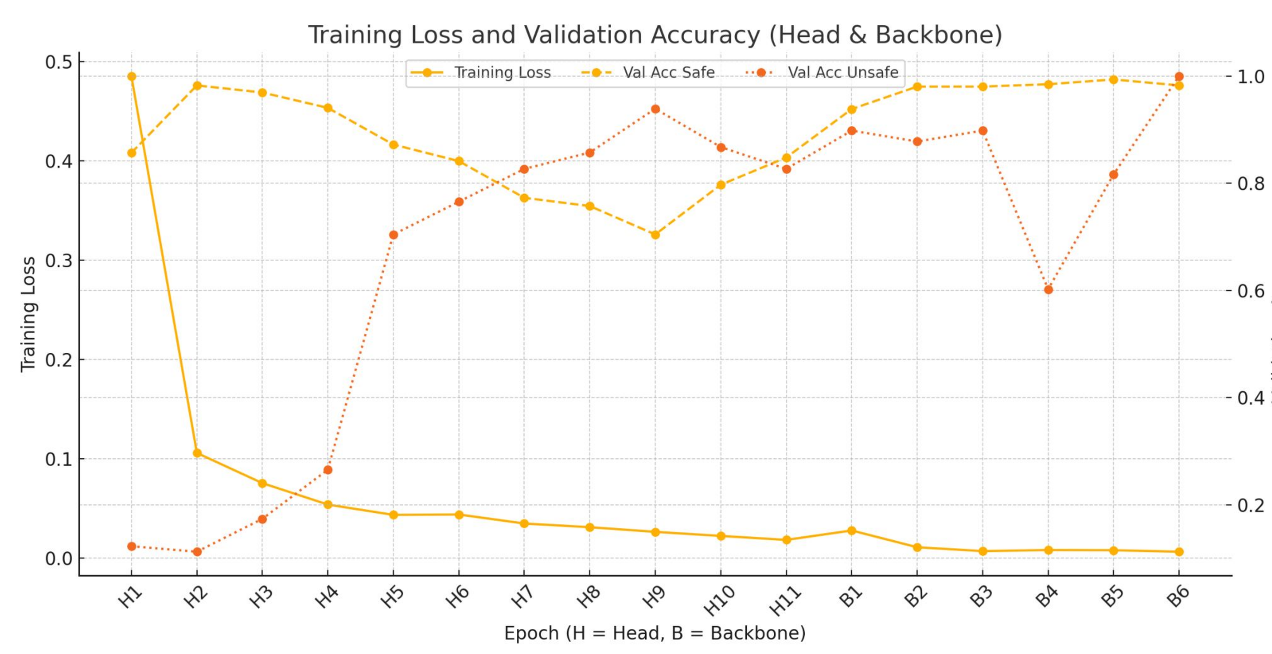


Fig 3: validation and test accuracy and loss over training

Training

- We counteract our class imbalance by sampling training frames proportional to their inverse sample count with a 10x oversampling of unsafe frames
- In addition, we use focal loss with $\alpha = 7.0$ for unsafe samples and $\gamma = 2$ for all classes
- We train the head while holding the backbone (the rest of the model) constant until 75% validation recall is achieved on all classes
- Then, we unfreeze the backbone and train the entire model until 90% validation recall is achieved on all classes

Results

- >99% recall for all classes for the backbone included model
- >90% recall for all classes for head only model

Inference

- Inference takes approximately 7ms on a CPU
- Interestingly, images must be JPEG compressed before being fed into the model, since the model trained on JPEG compressed inputs
- Currently, the model does not generalize to other cameras due to the microwave mesh
- Empirically, we find that stopping heating after a 0.7 softmax value for the unsafe class is better than simply an unsafe prediction

Prototype

- We tape a servo operated arm to the microwave controlled by a Raspberry Pi 3 B+ which our overflow detector calls over http to press the STOP button on the microwave
- We find that all overflow situations are avoided

References

[1] Andrew Howard, Mark Sandler, Grace Chu, Liang-Chieh Chen, Bo Chen, Mingxing Tan, Weijun Wang, Yukun Zhu, Ruoming Pang, Vijay Vasudevan, Quoc V. Le, and Hartwig Adam. Searching for mobilenetv3. *CoRR*, abs/1905.02244, 2019.

[2] Tareq Khan. An intelligent microwave oven with thermal imaging and temperature recommendation using deep learning. *Applied System Innovation*, 3(1), 2020.

[3] Tsung-Yi Lin, Priya Goyal, Ross Girshick, Kaiming He, and Piotr Dollár. Focal loss for dense object detection, 2018.

[4] TorchVision maintainers and contributors. Torchvision: Pytorch's computer vision library. https://github.com/pytorch/vision, 2016.

[5] Rishabh Singh. Understanding and implementing mobilenetv3, October 2024. Accessed: 2025-04-28.

[6] Rejin Varghese and Sambath M. Yolov8: A novel object detection algorithm with enhanced performance and robustness. In *2024 International Conference on Advances in Data Engineering and Intelligent Computing Systems (ADICS)*, pages 1–6, 2024.

[7] Kan Wu, Jinnian Zhang, Houwen Peng, Mengchen Liu, Bin Xiao, Jianlong Fu, and Lu Yuan. Tinyvit: Fast pretraining distillation for small vision transformers, 2022.

[8] Xu Zhao, Wenchao Ding, Yongqi An, Yinglong Du, Tao Yu, Min Li, Ming Tang, and Jinqiao Wang. Fast segment anything, 2023.