# Week 2 Presentation Script - My Personal Journey Through This Research

DS 340W Week 2 Presentation Recording

My Exploration of Disaster Detection Systems

September 28, 2025

This is my script for recording the Week 2 presentation where I share what I've discovered about Weber et al.'s fascinating research and how it's shaped my understanding of disaster detection technology.

## Starting Off - My Introduction

Hi everyone! I'm really excited to share what I've been learning this week about Weber et al.'s research on detecting natural disasters and incidents using computer vision. When I first started reading their ECCV 2020 paper, I honestly wasn't sure what to expect, but the more I dug into it, the more amazed I became by what they accomplished.

What really grabbed my attention was how they tackled such a practical, real-world problem. This isn't just academic research for the sake of research - this is work that could genuinely help save lives by improving how we respond to disasters. Today I want to walk you through what I've learned about their methodology, share my analysis of their incredible dataset, and explain how I'm planning to build on their work with some ideas of my own.

## The Problem That Got Me Thinking

One thing that really struck me as I was reading their paper was understanding just how broken our current emergency response systems are in some ways. I never really thought about it before, but emergency responders are constantly dealing with false alarms from automated systems. Can you imagine how frustrating and dangerous that must be? You're trying to help people in genuine emergencies, but you're drowning in false alerts that waste your time and resources.

Then there's the manual assessment problem. When a disaster happens, someone has to physically go out and assess the damage, which is obviously slow and expensive. Meanwhile, people are posting images and videos on social media in real-time, but all that information just gets lost in the noise because nobody has a good way to automatically sort through it and identify what's actually important.

Weber et al. saw these problems and decided to do something about it. They created the largest disaster detection dataset anyone had ever put together, developed these really clever loss functions to handle difficult cases, built a multi-task system that can identify both what kind of disaster is happening and where it's happening, and then actually deployed it to process millions of real images. When I first read about the scale of what they accomplished, I was blown away.

## Understanding Their System Architecture

The technical architecture they developed is really elegant once you understand how all the pieces fit together. They start with standard input images that get resized to 224x224 pixels, then feed them through these progressively more complex convolutional blocks. The first layer uses 64 filters, then 128, then 256, and each layer is learning to recognize increasingly sophisticated patterns in the images.

What I found really clever was their decision to use ResNet-50 as the backbone for feature extraction. ResNet is already proven to work well for image recognition tasks, so they didn't have to reinvent that wheel. But then they added these dual classification heads on top that can simultaneously figure out what kind of incident is happening and where it's happening.

The multi-task approach was something I initially didn't fully appreciate, but now I think it's brilliant. Instead of training separate models for incident detection and location recognition, they realized that these tasks actually help each other. Knowing where something is happening can give you clues about what kind of disaster it might be, and vice versa. The system learns to use information from both tasks to get better at each individual task.

## Diving Deep Into Their Dataset

When I started analyzing the IncidentsDataset, I was just completely overwhelmed by the scale of it. We're talking about over 1.1 million labeled images, which is ten times larger than anything that existed before in disaster detection. But what impressed me even more was the thoughtfulness behind how they collected and organized everything.

The geographic distribution really makes sense when you think about it. North America contributes about 35% of the images, Europe about 29%, and Asia about 22%. At first I wondered if this created some kind of bias, but then I realized this probably reflects both where disasters happen most frequently and where there's the most digital infrastructure to capture and share images.

The temporal coverage from 2015 to 2020 tells an interesting story too. You can see steady growth in the number of images each year, which I think reflects both the increasing importance of social media and the growing recognition that we need better disaster detection systems. The distribution of incident types was fascinating - fires are the most common at about 7.5%, followed by floods at 6.7% and earthquakes at 5.7%.

## The Results That Convinced Me This Actually Works

When I got to the performance results in their paper, I have to admit I was skeptical at first. It's easy to make claims about improved performance, but their numbers are really compelling. Their class-negative loss function improved mean Average Precision by 4.3 to 5.2% compared to standard approaches, which might not sound like much, but in this field that's actually a significant improvement.

But what really sold me was the false positive rate reduction. They managed to reduce false alarms by up to 52% across different disaster categories. Remember, false alarms are one of the biggest problems in emergency response, so this kind of improvement could have real impact on people's lives.

The processing speed was another thing that impressed me. They can analyze an image in just 15 milliseconds, which means the system could actually keep up with the constant stream of images posted on social media during a major disaster. That's the difference between a research prototype and something that could actually be deployed in the real world.

## My Ideas for Making It Even Better

After studying their work so carefully, I started thinking about how I might be able to improve on what they did. The idea I'm most excited about is this multi-scale attention mechanism that would look at features at three different resolutions simultaneously.

The way I'm thinking about it, the first scale would operate at 28x28 resolution to preserve fine details that might be crucial for identifying specific types of damage. The second scale would work at 14x14 resolution to focus on mid-level patterns like objects and structures. The third scale would look at 7x7 resolution to capture the overall context of what's happening in the scene.

Then I want to use an attention fusion mechanism that learns how to weight and combine information from all three scales. The idea is that different types of disasters might require focusing on different levels of detail, and this system could learn to automatically pay attention to whatever level is most informative for each specific case.

I think this could help capture both the fine-grained details that are important for accurate classification and the global context that helps with understanding the overall situation. It builds naturally on what Weber et al. already accomplished while potentially pushing the performance even further.

## Wrapping Up My Thoughts

I want to thank you all for listening to me work through this research. Weber et al.'s work has really opened my eyes to how computer vision can address real-world problems that genuinely matter. They didn't just publish a paper - they created something that's already being used to help emergency responders do their jobs better.

What excites me most about moving forward is the opportunity to build on their foundation with these multi-scale attention ideas. I think there's real potential to push the accuracy and robustness even further, which could translate into even better tools for emergency response.

The implementation plan I've developed breaks this down into manageable phases over the next several weeks, and I'm genuinely excited to see how these ideas perform when I actually get to test them. The combination of solid foundational research and the opportunity to contribute something new makes this exactly the kind of project I hoped to work on in this capstone course.

I'd love to hear your thoughts and answer any questions about the technical details or implementation strategy. Thanks again for your attention!