2.5 Visual Applications of Machine Learning

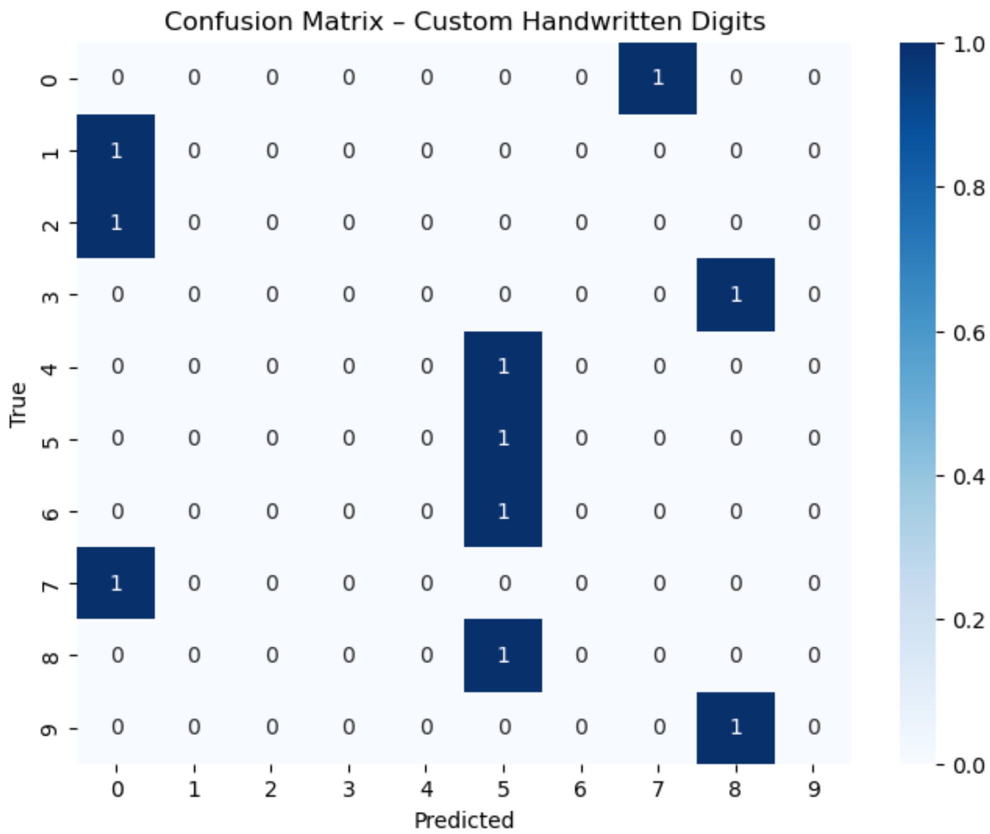
Task 1

The model correctly identified only one number, which was 5.

I uploaded handwritten digits 0–9 and a letter 'Y'. The model's predictions for each input were as follows:

- 0 → 7
- 1 → 0
- 2 → 0
- 3 → 8
- 4 → 5
- 5 → 5
- 6 → 5
- 7 → 0
- 8 → 5
- 9 → 8
- Y → 0

This resulted in an overall accuracy of 11.11%. The model attempted to classify the letter 'Y' as a digit, predicting it as 0.



Task 2

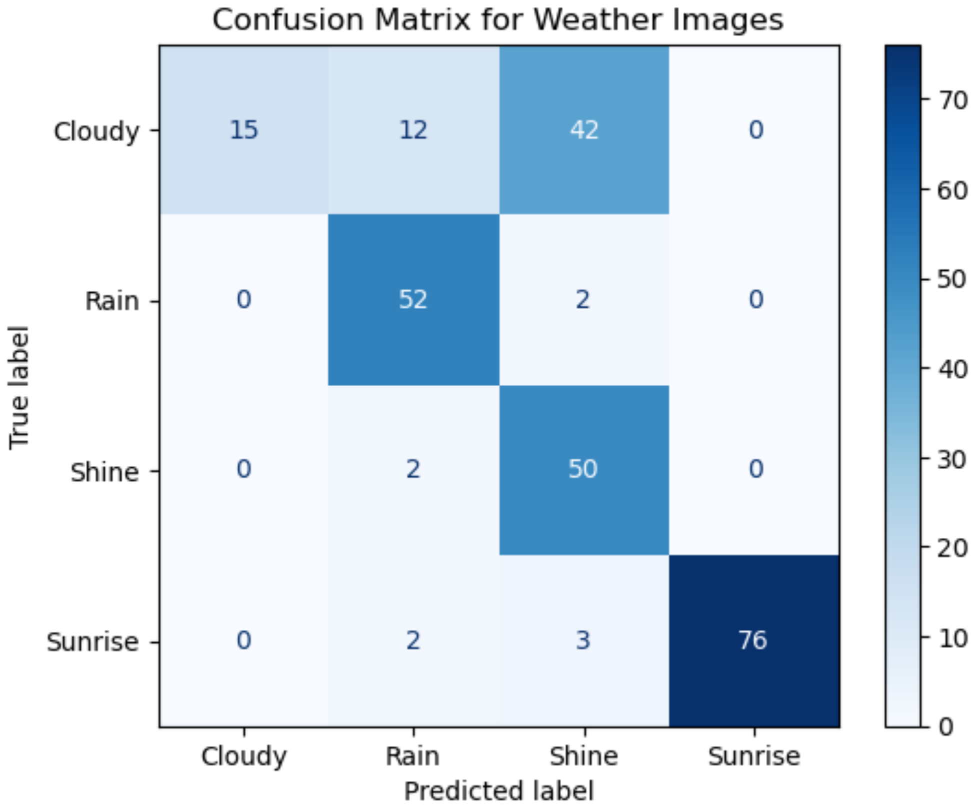
I trained the CNN on the four-class weather dataset (Cloudy, Rain, Shine, Sunrise) using ImageDataGenerator with an 80/20 split (901 training images, 224 validation images; batch size = 32). The model was compiled with Adam and categorical_crossentropy, and trained for 15 epochs.

I define convergence as the point at which validation loss stops decreasing (or changes by < ~0.01 over consecutive epochs), and validation accuracy plateaus. In this run, performance had stabilised by the end of training, so I record 15 epochs as the convergence count for this proof-of-concept.

Final metrics (epoch 15):

- Training accuracy: 0.883
- Validation accuracy: 0.759
- Training loss: 0.292
- Validation loss: 0.602

These results indicate good learning on the training set with some generalisation gap (expected for a small CNN and modest dataset). The confusion matrix confirms the model's ability to separate classes while highlighting residual confusion between visually similar conditions.



Proposal: Using GANs for Weather Prediction

Generative Adversarial Networks (GANs) present powerful opportunities to enhance weather prediction through synthetic image generation, resolution enhancement, and intuitive visualisation. Here are three promising use cases:

1. Weather Condition Translation (Image-to-Image)

Idea: Develop a GAN that can convert everyday scene images between different weather conditions—for instance, turn a "sunny" image into a "rainy" one, or a "cloudy" scene into "sunrise."
Why it matters: This could help simulate how a location might appear under alternate weather, providing intuitive visual forecasts or aiding training in low-data weather scenarios.
Related research: The "Weather GAN" tackles this exact problem by learning to transfer among multiple conditions (sunny, cloudy, foggy, rainy, snowy) using attention and weather-cue segmentation to preserve important features

Link: https://arxiv.org/abs/2103.05422?utm_source

2. Super-Resolution & Downscaling of Weather Maps

Idea: Utilise GANs to enhance the spatial resolution of coarse weather maps—say from satellite or radar data—producing high-resolution imagery that better captures local weather patterns.
Why it matters: High-resolution forecasts are critical for local decision-making, such as storm tracking or flood risk. GAN-driven downscaling models can effectively upgrade low-res data into detailed visuals.
Related research: Leinonen *et al.* proposed a stochastic super-resolution GAN that generates ensembles of high-resolution, time-evolving atmospheric images, preserving uncertainty and temporal consistency.

Link: https://arxiv.org/abs/2005.10374?utm_source

3. Predictive Video Generation for Short-Term Nowcasting

Idea: Build a GAN that predicts the next few frames in a weather image sequence—such as radar or satellite frames—to forecast short-term atmospheric changes (e.g. cloud movement, precipitation).
Why it matters: This allows nowcasting—predicting what the weather will look like in the near future (minutes to hours ahead)—in the form of realistic image sequences.
Related research: The UA-GAN model combines U-Net and attention mechanisms for precipitation nowcasting, achieving sharper and more accurate radar echo predictions than traditional deep-learning methods.

Link: https://www.mdpi.com/2072-4292/14/23/5948?utm_source