UNIVERSITY OF CAMBRIDGE

DiS MPHIL

A7 Image Analysis Coursework Presentation

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Introduction

Image analysis is important because it enables...

- Object detection and segmentation
- Image classification

But it is complex because images are/can be...

- High dimensional
- Affected by noise and artefacts

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Introduction

A typical procedure for analysing images involves:

Acquiring the image

Removing noise from the image

Further processing such as object detection, segmentation, and classification

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Module 1 – Classical Image Processing

Classical image processing involves manipulating and/or analysing images using algorithms without learning from data

These can involve filtering, thresholding, and morphological transformations

We can use Python libraries such as skimage and scipy to perform these tasks

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Module 1 – Method

Ex 1.1
- RGB -> HSV converted images cropped to focus on central region and number of orange, yellow, and blue pixels in each image counted

Ex 1.2
- Sobel filter used for gradient based edge detection. Largest enclosed region assumed to be the butterfly and used to create a mask

Ex 1.3
- Collage of butterflies created by using the previous two parts and arranging the butterflies of the same colour on a blank canvas

Ex 1.4
- Outlier butterflies have different shape. Hu moments used and pairwise distances computed, enabling the outlier in each group to be identified

Module 1 – Results I

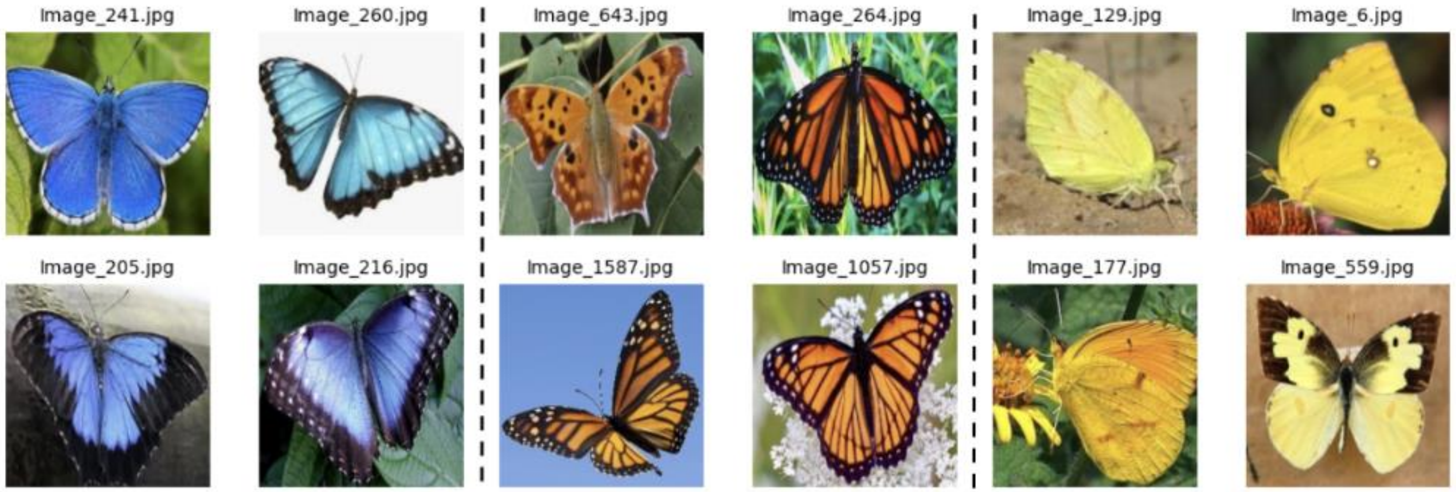

Figure 1: Butterflies grouped by colour

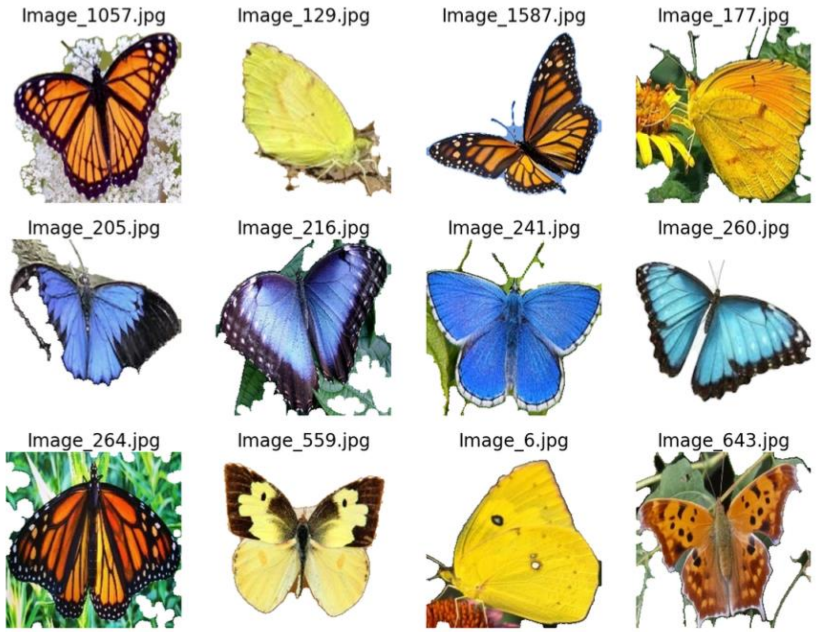

Figure 2: Background removed butterflies

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Module 1 – Results II

Figure 3: Collages of butterflies with a variable number in each one

Figure 4: Outlier butterflies from each colour group

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Module 1 – Observations and Conclusions

Much easier to use HSV than RGB colour histograms

Very sensitive fine tuning for butterfly colour classification and outlier detection

Limitations of classical imaging methods can be seen with mixed performance in removing background

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Module 2 – Data-Driven Regularisation for Inverse Problems

In this PnP variant of ADMM, we replace the proximal operator with an off-the-shelf pre-trained image denoiser based on U-net architecture

This is because image denoisers are a good proxy for proximal operators and the U-net architecture offers convergence guarantees

This can be used to solve denoising problems such as inpainting and deblurring

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Module 2 – Method

Ex 2.1

- Defined a function implementing PnP-ADMM using the provided functions
- Compute MSE for reconstructed images for different blur kernel sizes with and without added Gaussian noise

Ex 2.2

- Inpainting using PnP-ADMM for varying number of missing pixels
- Implemented PnP-RED to minimise objective function and compared inpainted MSE with PnP-ADMM

Ex 2.3

- Tracked the PnP-ADMM deblurring and inpainting MSE at each iteration
- Plotted the trend to visualise performance

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Module 2 – Results I

Figure 5: Original, blurred, and deblurred butterfly

Blue kernel size, p	MSE (no noise)	MSE (noise)
7	0.0041	-
13	0.0104	0.0115
17	0.0146	-

Table 1: MSE of reconstructed (deblurred) image with and without added Gaussian noise

Module 2 – Results II

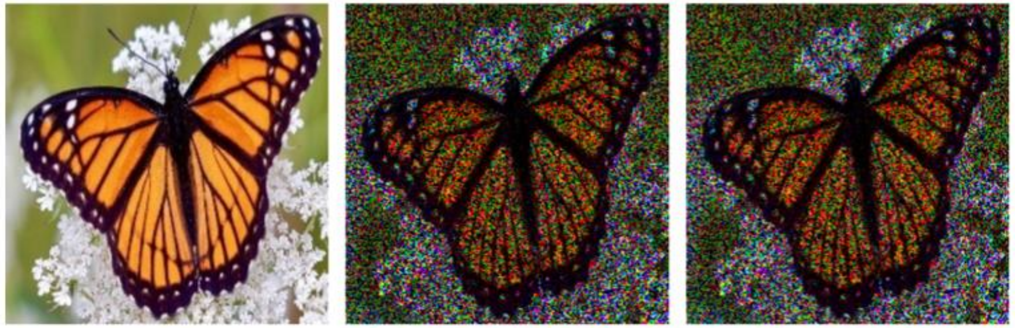

Figure 6: Original, masked, and PnP-ADMM inpainted butterfly

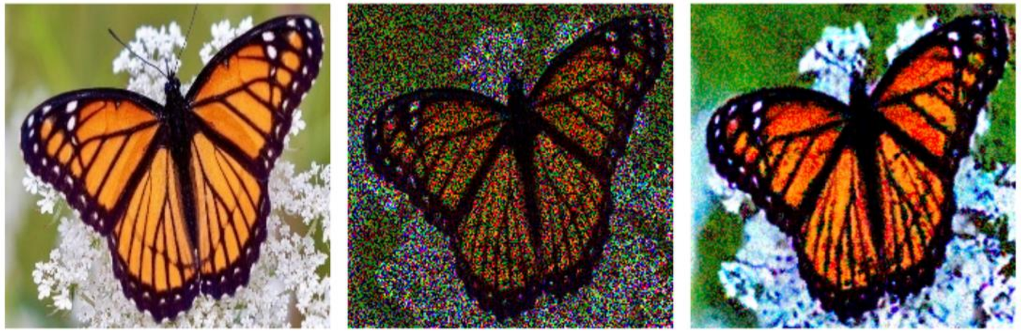

Figure 7: Original, masked, and PnP-RED inpainted butterfly

% missing pixels	MSE (PnP-ADMM)	MSE (PnP-RED)
40	0.1102	-
60	0.1740	0.0580
80	0.2319	-

Table 2: MSE of reconstructed (inpainted) image using PnP-ADMM and PnP-RED

Module 2 – Results III

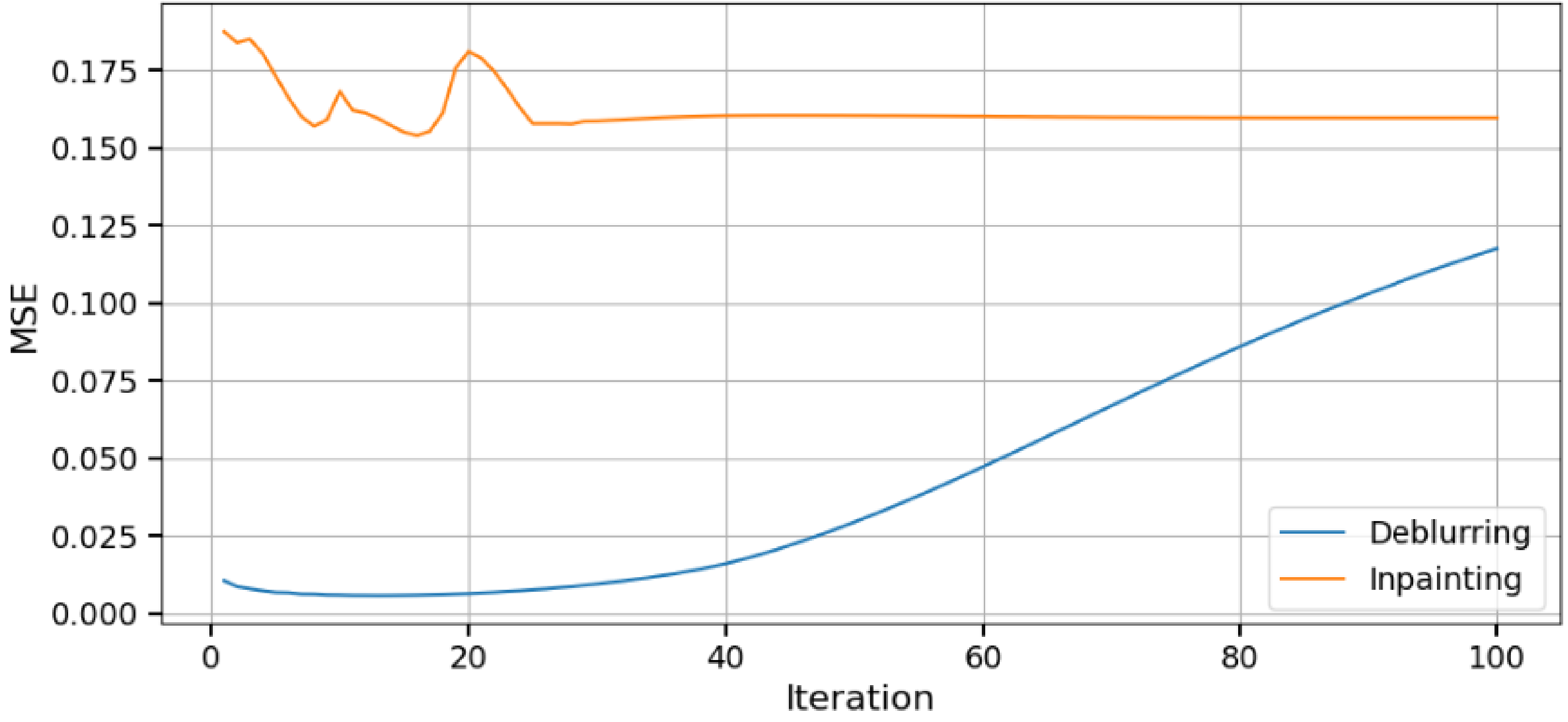

Figure 8: MSE as a function of iterations of PnP-ADMM deblurring and inpainting

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Module 2 – Observations and Conclusions

As the blur kernel size increases or when adding Gaussian noise, the final MSE increases

- Due to a larger degradation of the original image

PnP-RED is better at inpainting than PnP-ADMM

- But it is incorrect to use the gradient of the regulariser formula

Deblurring MSE reaches a minimum then increases

- As iterations continue, denoiser oversmooths the image
- Implement an ‘early stopping’ criterion

Inpainting MSE oscillates between different plausible images before converging

- Due to updates driven by denoiser in masked areas

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Module 3 – Pitfalls and Challenges

We can use IQA measures to evaluate the quality of images after reconstructing them

- IQA measures can be full reference or no reference
- Examples include PSNR (FR) and NIQE (NR)

ML/DL can be applied for image analysis

- Using Fully Connected Neural Networks or Convolutional Neural Networks

Module 3 – Method

Ex 3.1

- Computed PSNR, SSIM, LPIPS (FR), and NIQE (NR) for deblurred and inpainted images
- Created one degraded image using blurring and another using masking such that they had the same PSNR/SSIM
- Removed background and repeated the above

Ex 3.2

- Visualised data and made the following changes: mask square, grayscale, shuffle data, remove softmax, change tanh activation functions to ReLU
- Showed confusion matrices
- Repeated for the CNN

Module 3 – Results I

IQA	Deblurring	Inpainting
PSNR	19.82	7.610
SSIM	0.6325	0.1820
LPIPS	0.3971	1.083
NIQE	7.922	21.95

Table 3: IQA measures for deblurring and inpainting. NB: original image's NIQE=6.760

IQA	Blur	Masked	Blur (no bkg)	Masked (no bkg)
PSNR	15.08	15.08	18.28	20.47
SSIM	0.2637	0.2637	0.5218	0.6855

Table 4: Blurred and masked PSNR and SSIM IQA metrics for the fill image and with the background (bkg) removed

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Module 3 – Results II

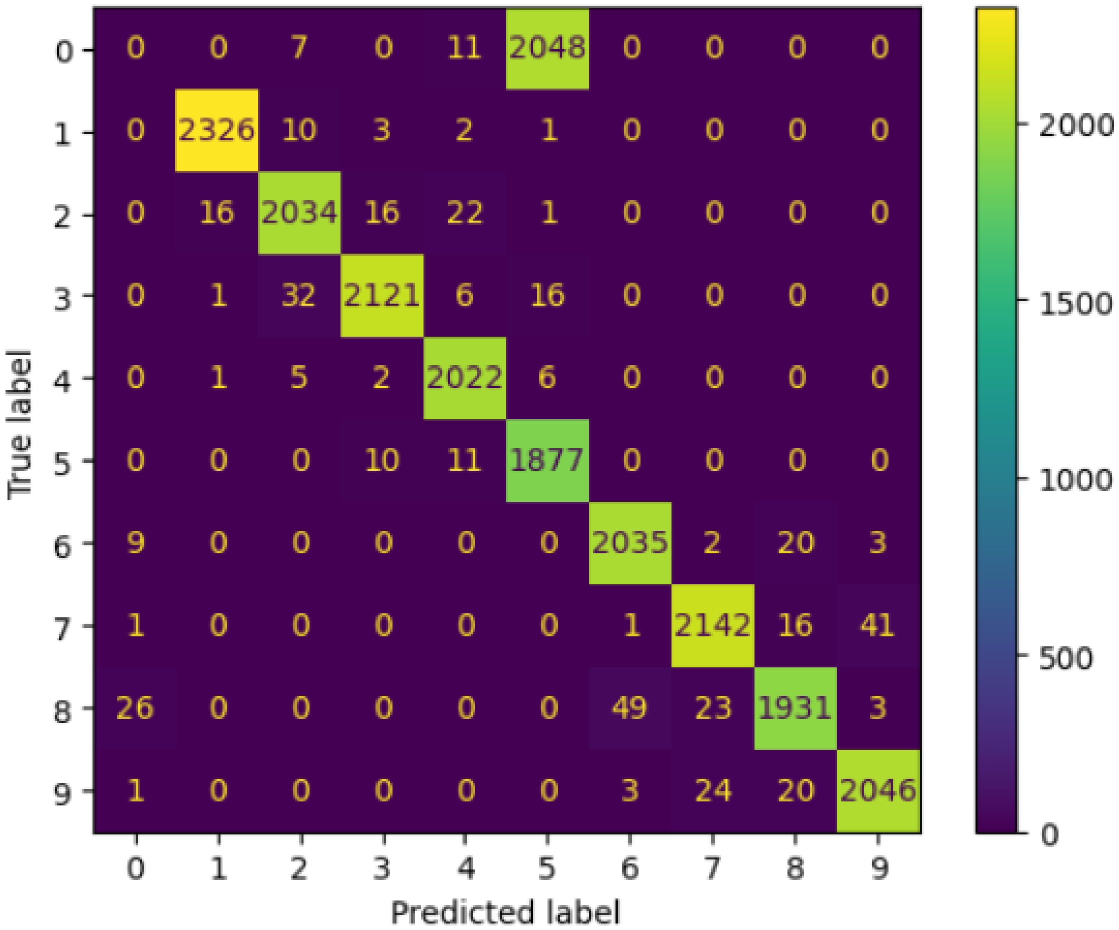

Figure 8: Confusion matrix of the original deep neural network

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Module 3 – Results III

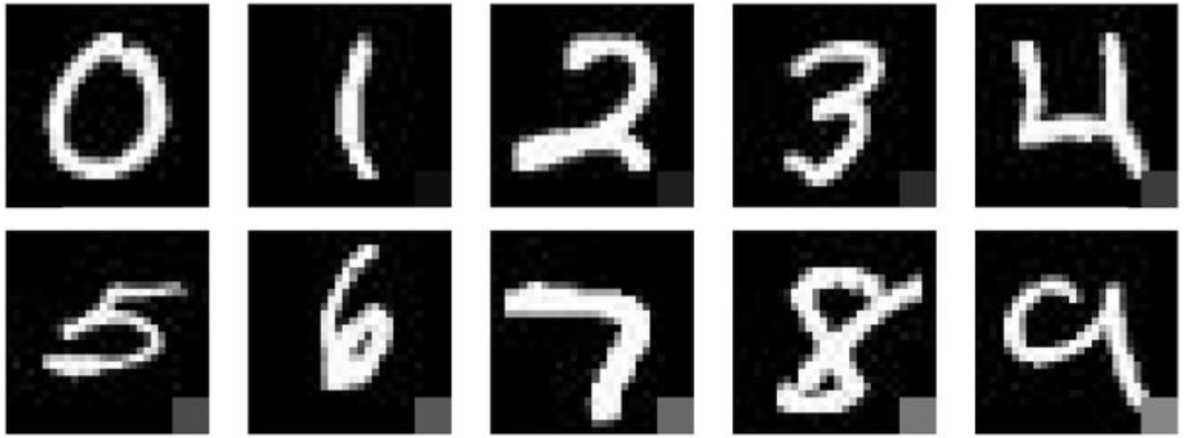

Figure 9: Examples of data from each class showing the white square

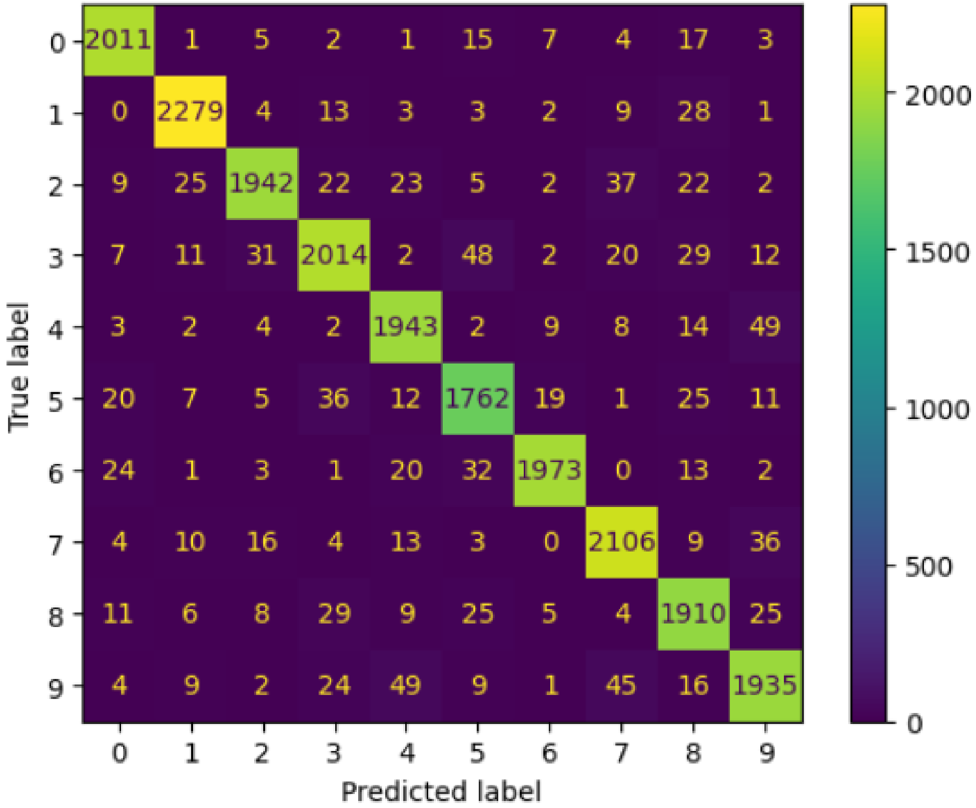

Figure 10: Confusion matrix after implementing the suggested changes

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Module 3 – Results IV

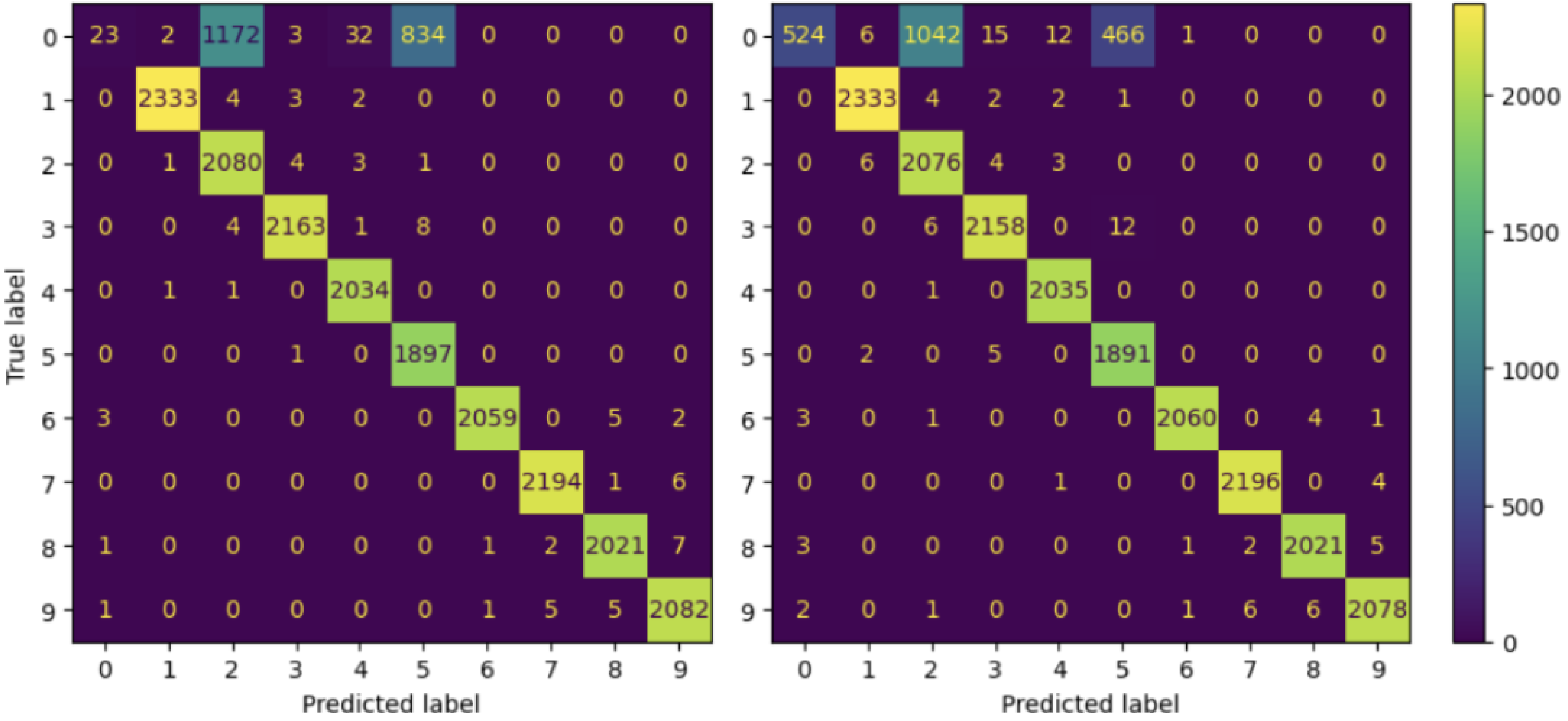

Figure 11: Confusion matrix of the original CNN and after implementing the suggested changes

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Module 3 – Observations and Conclusions

The IQA measures agree with each other

- For deblurring, PSNR is high, SSIM close to 1, NIQE similar to original image, LPIPS close to 0
- For inpainting, low PSNR and SSIM, higher NIQE and LPIPS
- PSNR and SSIM indicate reconstructed image quality when background is removed

The original model's confusion matrix shows it performs poorly for class 0

- Data corruption can affect models

The original CNN initially performs slightly better than the original neural network but the same changs do not give the same improvements

- Modify optimiser and tune hyperparameters

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Summary

We have stepped through typical image analysis problems such as

- Image classification and segmentation
- Denoising images (such as blurry or masked images)
- Data corruption when using ML/DL models

We have seen these problems in different contexts

- Using classical methods
- Using ML

For further details, please consult the repository and the accompanying report

- Thank you for listening!

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