

ARI 2129 - Principles of Computer Vision Group Project - Part A

Matthias Bartolo 0436103L *

Luke Cardona 0011803H *

Jerome Agius 0353803L *

Isaac Muscat 0265203L *

*B.Sc. (Hons) Artificial Intelligence (2nd Years)

Study-unit: Principles of Computer Vision for AI

Code: ARI2129

Lecturer: Dr Dylan Seychell

Q1: Writing a background about Data Augmentation

Introduction

Data Augmentation (DA) is a crucial component of Computer Vision (CV) due to its utility in reducing overfitting in Deep Learning. In most cases in the field of CV there is a lack of diversity in the training dataset, incurred by the work required to procure a reasonable number of distinct images [1,2]. DA solves this problem via the generation of more training samples through the use of techniques such as **Geometric transformations** and **Photometric distortions**, thus improving the generalisation of such deep learning models [3-5].

Historical Context

One of the first major breakthroughs in CV occurred between the 1980s and 1990s, where **Edge Detection** algorithms were constructed and implemented into industrial automation [6]. Additionally, in 2012, **Object Recognition** made a significant leap forward with the introduction of **ImageNet**, an extensive and labelled dataset that aided training classification models [7]. At the same time, **CNNs** were inaugurated to image classification in collaboration with ILSVRC Models which provided notable progression over prior approaches [8]. Moreover, in 2015 the **COCO** dataset was launched, where images were assigned multiple labels to assist in precise **Contextual Classification** of noisy images [4].

Data Augmentation Techniques

As previously mentioned, there are two main types of DA techniques, **Geometric** transformations and **Photometric distortions**:

Geometric transformations

Geometric techniques focus on changing images to different sizes, positions, and rotations, making trained models more robust due to the diversity found in objects with different geometric properties. **Rotations** geometrically transform an image on a singular central point by an angle on the z-axis. **Flipping** is a 180-degree rotation on either the x or y axis. **Scaling** resizes an image by adjusting its size with regards to its original proportions, without any change in shape or orientation. **Cropping** trims or resizes the outer borders of the image, starting from an edge. **Translation** moves the image's pixel positions from one point to another without changing its size or rotation. Finally, **Shearing** concerns moving pixels along an axis by a specified amount, distorting the image.

Photometric distortions

Photometric techniques focus on **Colour Jittering**, consisting of altering the brightness, contrast, and saturation of the image. Moreover, they also involve shifting the values in each colour channel and adding gaussian noise. This helps improve the model's robustness to deal with different image lighting and quality. Altering **Brightness** refers to adjusting the gamma channel of an image. **Contrast** is defined as the change in colour and tones, or the ratio between lighter and darker sections within an image [9]. **Saturation** involves proportionally adjusting the colour channel values in an image. Furthermore, it is also possible to adjust the values of one specific colour channel, for instance increasing the green channel's value. Finally, **Gaussian Noise** blurs the image in proportion to the distance from the centre point, thus achieving a greater blur the farther away it is from the centre point [5].

Recent Advancements

Multiple major advancements in CV have recently occurred, such as **Cutout** [10]. This technique involves randomly masking out regions of an image during training. This method can be easily implemented alongside other techniques to improve performance of **CNNs** [10]. By forcing the **CNN** to learn from incomplete data it is encouraged to consider all relevant features of the image. In comparison, **MixUp** [11] multiplies two images and superimposes them depending on various coefficient ratios, substituting labels accordingly. This encourages the model to learn smooth decision boundaries between classes. **AutoAugment** [12] searches for the most effective augmentation policy for a dataset by means of reinforcement learning methods to avoid overfitting. Thus, it produces the most accurate deep learning model.

Applications in Computer Vision

Common DA methods [5,9,13] can assist in solving the major problem of **image shortage** when it comes to developing CV models. Furthermore, combining these methods with more recent DA methods [11,14-16] is **reducing costs and time** of data collection [1,2]. Such techniques can also supply images when there is a shortage of images in an already existing dataset [17].

Generative Adversarial Networks (GANs) have been used to allow the creation of new images to train classification models to represent situations not present in the current dataset [18,19]. Furthermore, GAN's have been used to generate new labelled medical images without incurring the heavy costs of having to label large amounts of medical images [20-22]. Additionally, these are also used in the creation of autonomous vehicles [23].

A prime example of applications of DA techniques can be seen in the **YoloV4** [24] model which makes use of various augmentation techniques related to object detection and segmentation such as **CutOut** [10], **MixUp** [11] and **CutMix** [14]. These techniques are also used to aid the accuracy of deep learning models and reduce overfitting [25-28].

Citation and References

- [1] C. Siu, M. Wang and J. C. P. Cheng, "A framework for synthetic image generation and augmentation for improving automatic sewer pipe defect detection," Autom. Constr., vol. 137, pp. 104213, 2022. [Online]. Available: https://doi.org/10.1016/j.autcon.2022.104213. [Accessed: 05- Apr- 2023]
- [2] S. Shen et al, "A Low-Cost High-Performance Data Augmentation for Deep Learning-Based Skin Lesion Classification," BME Front, vol. 2022, 2022. [Online]. Available: https://spj.science.org/doi/10.34133/2022/9765307. [Accessed: 05- Apr- 2023]
- [3] W. Jiang et al, "MeshCut data augmentation for deep learning in computer vision," PloS One, vol. 15, (12), pp. 1, 2020 [Online]. Available: https://ejournals.um.edu.mt/login?url=https://www.proquest.com/scholarly-journals/meshcut-data-augmentation-deep-learning-computer/docview/2473412125/se-2. doi: https://doi.org/10.1371/journal.pone.0243613. [Accessed: 05- Apr- 2023]
- [4] T. Y. Lin et al., "Microsoft COCO: Common Objects in Context," 2014 European Conference on Computer Vision, Zurich, Switzerland, 2014, pp. 740-755,[Online]. Available: https://link.springer.com/chapter/10.1007/978-3-319-10602-1 48 . [Accessed: 05- Apr- 2023]
- [5] E. S. Gedraite and M. Hadad, "Investigation on the effect of a Gaussian Blur in image filtering and segmentation," in Proceedings ELMAR-2011, Zadar, Croatia, 2011, pp. 393-396, [Online]. Available: https://www.semanticscholar.org/paper/Investigation-on-the-effect-of-a-Gaussian-Blur-in-Gedraite-Hadad/6c1144d8705840e075739393a10235fcc4cd0f4b [Accessed: 05- Apr- 2023]
- [6] J. Canny, "A Computational Approach to Edge Detection," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. PAMI-8, no. 6, pp. 679-698, Nov. 1986, [Online]. Available: https://ieeexplore.ieee.org/document/4767851 doi: 10.1109/TPAMI.1986.4767851. [Accessed: 05- Apr- 2023]
- [7] O. Russakovsky, et al., "ImageNet Large Scale Visual Recognition Challenge," Int. J. Comput. Vis., vol. 115, no. 3, pp. 211-252, Dec. 2015. [Online]. Available: https://link.springer.com/article/10.1007/s11263-015-0816-y [Accessed: 05- Apr- 2023]
- [8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet Classification with Deep Convolutional Neural Networks," in Neural Information Processing Systems, vol. 25, pp. 1097-1105, 2012.[Online]. Available: https://dl.acm.org/doi/10.1145/3065386 doi: 10.1145/3065386 (Accessed: 05- Apr- 2023]

- [9] Kim, DH., Cha, EY. "Intensity surface stretching technique for contrast enhancement of digital photography." Multidim Syst Sign Process 20, 81–95, 2009, [Online]. Available: https://link.springer.com/article/10.1007/s11045-008-0049-0 doi: https://doi.org/10.1007/-008-0049-0 [Accessed: 05- Apr- 2023]
- [10] T. DeVries and G. W. Taylor, "Improved Regularisation of Convolutional Neural Networks with Cutout," in Proceedings of the 32nd Conference on Neural Information Processing Systems (NeurIPS), Montréal, Canada, Dec. 2018, pp. 8726-8737 [Online]. Available: https://arxiv.org/abs/1708.04552 doi: https://doi.org/10.48550/arXiv.1708.04552. [Accessed: 05- Apr- 2023]
- [11] H. Zhang, M. Cisse, Y. Dauphin, and D. Lopez-Paz, "mixup: Beyond Empirical Risk Minimization,"Oct. 2017, [Online]. Available: https://arxiv.org/abs/1710.09412. [Accessed: 05- Apr- 2023]
- [12] E. D. Cubuk, B. Zoph, D. Mane, V. Vasudevan, and Q. V. Le, "AutoAugment: Learning Augmentation Policies from Data," in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2019, pp. 113-123 [Online]. Available: https://arxiv.org/abs/1805.09501. [Accessed: 05- Apr- 2023]
- [13] C. Shorten and T.M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," J. Big Data, vol. 6, no. 1, p. 60, 2019, [Online]. Available: https://journalofbigdata.springeropen.com/articles/10.1186/s40537-019-0197-0 [Accessed: 05- Apr- 2023]
- [14] S. Yun et al., "CutMix: Regularization Strategy to Train Strong Classifiers with Localizable Features,"May 2019, [Online]. Available: https://arxiv.org/abs/1905.04899. [Accessed: 05-Apr- 2023]
- [15] C. Khosla and B. S. Saini, "Enhancing Performance of Deep Learning Models with different Data Augmentation Techniques: A Survey," 2020 International Conference on Intelligent Engineering and Management (ICIEM), London, UK, 2020, pp. 79-85, [Online]. Available: https://ieeexplore.ieee.org/document/9160048 doi: https://doi.org/10.1109/ICIEM48762.2020.9160048 .[Accessed: 05- Apr- 2023]
- [16] C. Lei, B. Hu, D. Wang, S. Zhang, and Z. Chen, "A Preliminary Study on Data Augmentation of Deep Learning for Image Classification," in Proc. 11th Asia-Pacific Symposium on Internetware (Internetware '19), New York, NY, USA, 2019, pp. 1-6, [Online]. Available: https://doi.org/10.1145/3361242.3361259. [Accessed: 05- Apr- 2023]

- [17] Z. Fabian, R. Heckel, and M. Soltanolkotabi, "Data augmentation for deep learning based accelerated MRI reconstruction with limited data," in Proc. 38th International Conference on Machine Learning (ICML), vol. 139, Jul. 2021, pp. 3057-3067. [Online]. Available: https://proceedings.mlr.press/v139/fabian21a.html. doi: https://doi.org/10.48550/arXiv.2106.1497. [Accessed: 05- Apr- 2023]
- [18] J. Wang and L. Perez, "The Effectiveness of Data Augmentation in Image Classification using Deep Learning," Stanford University, 2017 [Online]. Available: https://arxiv.org/pdf/1712.04621v1.pdf. [Accessed: 05- Apr- 2023]
- [19] I. J. Goodfellow et al., "Generative Adversarial Networks," in Proceedings of Advances in Neural Information Processing Systems 27, Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, Eds. Curran Associates, Inc., 2014, pp. 2672-2680. [Online]. Available: https://arxiv.org/abs/1406.2661[Accessed: 05- Apr- 2023]
- [20] F. Garcea, A. Serra, F. Lamberti, and L. Morra, "Data augmentation for medical imaging: A systematic literature review," Medical Image Analysis, vol. 70, pp. 101977, 2021, [Online]. Available: https://doi.org/10.1016/j.compbiomed.2022.106391 [Accessed: 05- Apr- 2023]
- [21] H. Tang, "GANs in medicine," AI Med, 2019. [Online]. Available: https://aimed.io/neurology/gans-in-medicine/. [Accessed: 05- Apr- 2023]
- [22] Y. Skandarani, P.-M. Jodoin, and A. Lalande, "GANs for Medical Image Synthesis: An Empirical Study," 2021. [Online]. Available: https://doi.org/10.48550/arXiv.2105.05318. [Accessed: 05- Apr- 2023]
- [23] N. Li, F. Song, Y. Zhang, P. Liang and E. Cheng, "Traffic Context Aware Data Augmentation for Rare Object Detection in Autonomous Driving," 2022 International Conference on Robotics and Automation (ICRA), Philadelphia, PA, USA, 2022, pp. 4548-4554, [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9811724 doi: https://doi.org/10.1109/ICRA46639.2022.9811724. [Accessed: 05- Apr- 2023]
- [24] A. Bochkovskiy, C.-Y. Wang, and H.-y. Liao, "YOLOv4: Optimal Speed and Accuracy of Object Detection," arXiv preprint arXiv:2004.10934, Apr. 2020 [Online]. Available: https://www.researchgate.net/publication/340883401 YOLOv4 Optimal Speed and Accuracy of Object Detection. [Accessed: 05- Apr- 2023]

- [25] C. Shorten and T. M. Khoshgoftaar, "A survey on Image Data Augmentation for Deep Learning," Journal of Big Data, vol. 6, (1), pp. 1-48, 2019. [Online]. Available: https://ejournals.um.edu.mt/login?url=https://www.proquest.com/scholarly-journals/survey-on-image-data-augmentation-deep-learning/docview/2252736881/se-2. doi: https://doi.org/10.1186/s40537-019-0197-0 .[Accessed: 05- Apr- 2023]
- [26] D. Lewy and J. Mańdziuk, "An overview of mixing augmentation methods and augmentation strategies," Artificial Intelligence Review, vol. 56, pp. 2111-2169, 2023.[Online]. Available: https://link.springer.com/article/10.1007/s10462-022-10227-z. [Accessed: 05- Apr- 2023]
- [27] J. Fonseca and F. Bação, "Research Trends and Applications of Data Augmentation Algorithms," arXiv preprint arXiv:2207.08817, 2022. [Online]. Available: https://arxiv.org/abs/2207.08817 .[Accessed: 05- Apr- 2023]
- [28] E. Vali-Betts et al., "Effects of Image Quantity and Image Source Variation on Machine Learning Histology Differential Diagnosis Models," in IEEE Journal of Biomedical and Health Informatics, [Online]. Available: https://doi.org/10.4103/jpi.jpi 69 20. [Accessed: 05- Apr- 2023]

Q2: Using ChatGPT as a writing assistant.

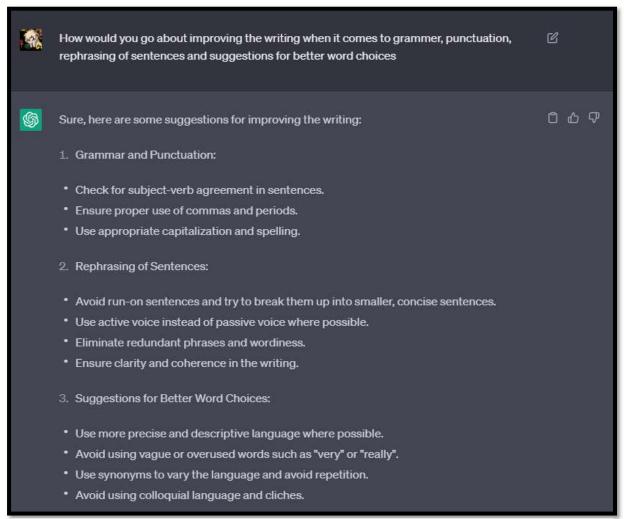


Figure 1: Prompt 1(1/2)

Here are some examples of how these suggestions could be applied to improve the original text:

Original: In most cases in the field of CV there is a lack of diversity in the training dataset, incurred by the work required to procure a reasonable number of distinct images.

Revised: In many cases within the field of CV, training datasets lack diversity due to the challenges involved in acquiring a sufficient number of unique images.

Original: Additionally, in 2012, Object Recognition made a significant leap forward with the introduction of ImageNet, an extensive and labelled dataset that aided training classification models [7].

Revised: Object recognition took a major leap forward in 2012 with the launch of ImageNet, a comprehensive and labeled dataset that greatly facilitated the training of classification models.

Original: Common DA methods [5,9,13] can assist in solving the major problem of image shortage when it comes to developing CV models.

Revised: Utilizing common DA methods [5,9,13] can help address the significant challenge of limited image availability in the development of CV models.

Overall, by implementing these suggestions, the writing can be improved for clarity, coherence, and precision.

Figure 2: Prompt 1 (2/2)

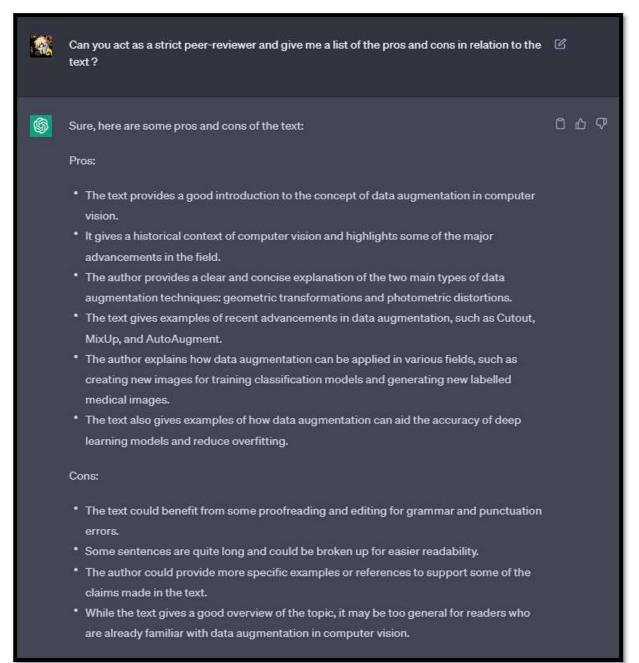


Figure 3: Prompt 2

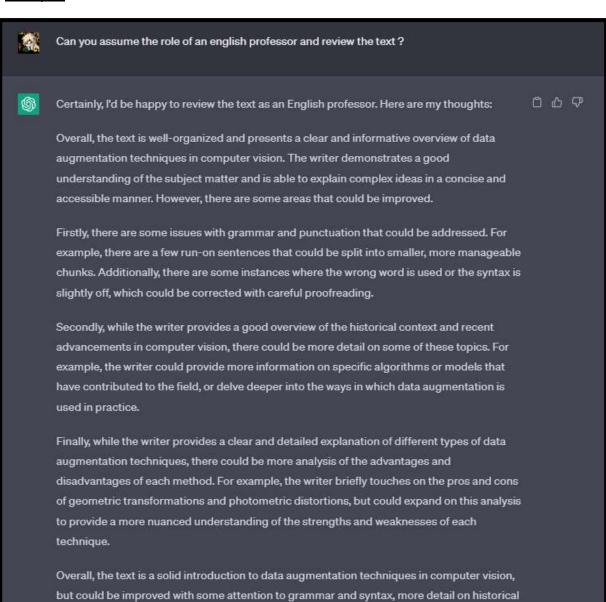


Figure 4: Prompt 3

and recent advancements in the field, and deeper analysis of the advantages and

disadvantages of different augmentation methods.

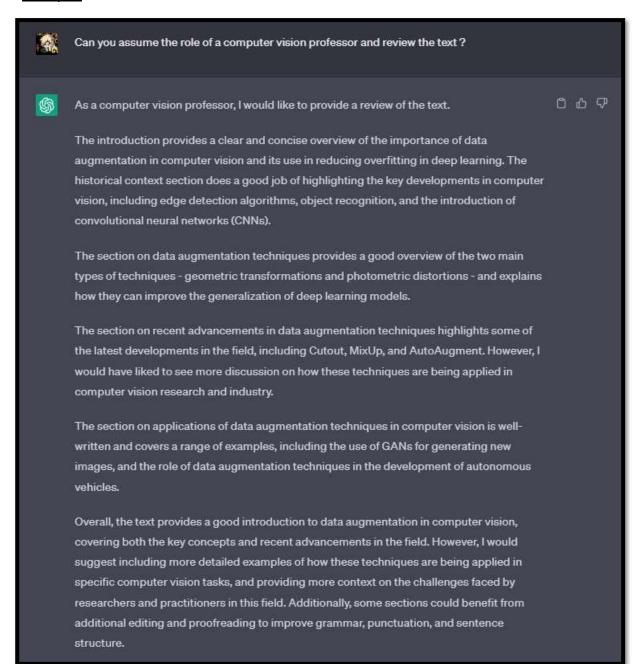


Figure 5: Prompt 4

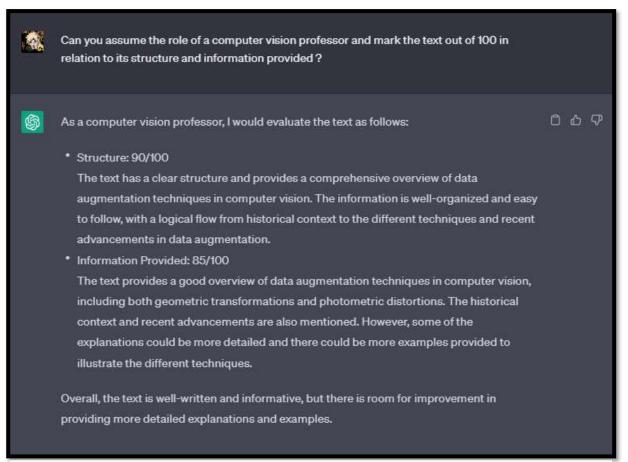


Figure 6: Prompt 5



Can you rewrite the text in a more formal manner?



Data Augmentation (DA) is a crucial component of Computer Vision (CV) due to its utility in reducing overfitting in Deep Learning. In many cases in the field of CV, there is a dearth of diversity in the training dataset, which is often attributed to the challenges associated with procuring a substantial number of distinct images [1,2]. DA resolves this problem through the generation of more training samples via the use of techniques such as Geometric transformations and Photometric distortions, thereby improving the generalisation of such deep learning models [3-5].

One of the earliest major breakthroughs in CV occurred in the 1980s and 1990s, when Edge Detection algorithms were constructed and implemented into industrial automation [6]. Additionally, Object Recognition made significant progress in 2012 with the introduction of ImageNet, an extensive and labelled dataset that aided in the training of classification models [7]. Around the same time, CNNs were introduced to image classification, in collaboration with ILSVRC Models, which demonstrated notable improvements over previous methods [8]. Moreover, in 2015, the COCO dataset was launched, where images were assigned multiple labels to aid in the precise Contextual Classification of noisy images [4].

As previously mentioned, there are two main types of DA techniques, Geometric transformations and Photometric distortions:

Figure 7: Prompt 6 (1/3)

Geometric transformations

Geometric techniques focus on changing images to different sizes, positions, and rotations, making trained models more robust due to the diversity found in objects with different geometric properties. Rotations geometrically transform an image on a singular central point by an angle on the z-axis. Flipping is a 180-degree rotation on either the x or y axis. Scaling resizes an image by adjusting its size with regards to its original proportions, without any change in shape or orientation. Cropping trims or resizes the outer borders of the image, starting from an edge. Translation moves the image's pixel positions from one point to another without changing its size or rotation. Finally, Shearing involves moving pixels along an axis by a specified amount, distorting the image.

Figure 9: Prompt 6 (2/3)

Photometric distortions

Photometric techniques focus on Colour Jittering, consisting of altering the brightness, contrast, and saturation of the image, furthermore, shifting the values in each colour channel and adding gaussian noise. This helps improve the model's robustness to deal with different image lighting and quality. Altering Brightness refers to adjusting the gamma channel of an image. Contrast is defined as the change in colour and tones, or the ratio between lighter and darker sections within an image [9]. Saturation involves proportionally adjusting the colour channel values in an image. Furthermore, it is also possible to adjust the values of one specific colour channel, for instance increasing the green channel's value. Finally, Gaussian Noise blurs the image in proportion to the distance from the centre point, thus achieving a greater blur the farther away it is from the centre point [5].

Multiple major advancements in CV have recently occurred, such as Cutout [10]. This technique involves randomly masking out regions of an image during training. This method can be easily implemented alongside other techniques to improve the performance of CNNs [10]. In comparison, MixUp [11] multiplies two images and superimposes them depending on various coefficient ratios, substituting labels accordingly. AutoAugment [12] searches for the most effective augmentation policy for a dataset, by means of reinforcement learning methods, to produce the most accurate deep learning model.

Common DA methods [5,9,13] can assist in solving the major problem of image shortage when it comes to developing CV models. Furthermore, combining these methods with more recent DA methods [11,14-16] is reducing costs and time of data collection [1,2]

Figure 8: Prompt 6 (3/3)

Reflections

Matthias

Throughout the various interactions and prompts with ChatGPT, it was interesting to notice how this software took on different roles while suggesting different improvements. A key observation was that the "English professor scenario" led to more grammatical and structural errors being highlighted, whereas the "Computer Vision professor scenario" resulted in more technical errors being highlighted. I also found ChatGPT's rating of my work on a scale of 100 to be a very helpful prompt for accurately assessing the calibre of my performance. Nevertheless, some of the ChatGPT feedback was unusable, as it dictated delving into various areas of study, a task that would have exceeded the prescribed limited word count. The ability of ChatGPT to rewrite text, on the other hand, also piqued my interest because it can be helpful in laying out various textual structures and conceptual frameworks.

<u>Luke</u>

In regards to the ChatGPT conversations, it clearly identified possible improvements by highlighting missing topics or areas where more emphasis was required. When assuming different roles, ChatGPT offered different perspectives and feedback on the text, aiding in separating grammatical and technical feedback and allowing ChatGPT to go further in depth with the critiques. The critiques offered on English writing were possible weaknesses present in my current writing, which I will keep in mind for future writing. Most of the recommendations offered, however, were focused around adding information, which was not possible due to the 600-word limit. Potentially, we could have been more concise and avoided minor repetitions throughout the text. Nevertheless, ChatGPT was a helpful gauge for assessing our own work, allowing for immediate, easy to digest feedback and improvements.

<u>Jerome</u>

The use of ChatGPT proved to be a useful tool in determining areas where our text needed improvement, as can be seen in Figures 1-3. However, the effectiveness of ChatGPT varied in accordance with the persona that it assumed. In the "English professor scenario" (Figure 4) ChatGPT gave greater importance to grammatical and structural errors whereas in the "computer vision professor scenario" (Figure 5) more technical errors were pointed out. This showcases that by customising the prompts given to ChatGPT a more tailormade response can be provided to the user. In continuation, ChatGPT can also rewrite text as can be seen in Figures 2 and 7-9 which can prove useful in outlining different ways in which text can be structured and ideas outlined. Finally, as seen in Figure 6, ChatGPT can provide a numerical score in relation to the text which can prove useful in conceptualising the quality of the text overall. Overall, ChatGPT proves to be a valuable tool in aiding students/researchers to produce work which has a greater degree of cohesion but is also accurate in the information provided.

<u>Isaac</u>

To evaluate our work, we prompted ChatGPT to assume two different roles and to review our work. When given the English Professor role, ChatGPT provided guidelines on how to strengthen the structure of our text such as utilising punctuation appropriately and phrasing sentences in a more legible manner. However, it also highlighted issues which could not be solved due to the word limit such as adding information about the limitations of Data Augmentation techniques, which was not required in this assignment. When given the Computer Vision professor role, ChatGPT offered insights on which sections of the text could be improved to explain Data Augmentation better. Additionally, we also queried ChatGPT to assign an overall mark to our work. This helped us obtain an idea of the quality of our work if it had to be reviewed by a Computer Vision professor. Furthermore, when queried, ChatGPT was also able to rewrite the entire text in a more formalised manner, further showing how powerful ChatGPT can be when generating a response suitable for the user. To conclude, this section of the assignment helped me understand how to prompt ChatGPT to review and correct my work in multiple ways.

Plagiarism Declaration Form:

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY

Declaration

Plagiarism is defined as "the unacknowledged use, as one's own work, of work of another person, whether or not such work has been published" (Regulations Governing Conduct at Examinations, 1997, Regulation 1 (viii), University of Malta).

- +/ We*, the undersigned, declare that the [assignment / Assigned Practical Task report / Final Year Project report] submitted is my / our* work, except where acknowledged and referenced.
- †/ We* understand that the penalties for making a false declaration may include, but are not limited to, loss of marks; cancellation of examination results; enforced suspension of studies; or expulsion from the degree programme.

Work submitted without this signed declaration will not be corrected, and will be given zero marks.

* Delete as appropriate.

(N.B. If the assignment is meant to be submitted anonymously, please sign this form and submit it to the Departmental Officer separately from the assignment).

Matthias Bartolo	Westate
Student Name	Signature
Jerome Agius Student Name	Signature Jus
Student Name	Signature O
Luke Cardona Student Name	lake Coeff
Student Name	Signature
Isaac Muscat	IAuscat
Student Name	Signature
ARI2129	Principles of Computer Vision for Al Assignment (Part A)
Course Code	Title of work submitted
23/04/2023	
Date	