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Objective: *Build machine learning models to Identify and enhance the image quality.*
Steps to perform:

1. *Attached is the set of Scanned PDF (Images)*
2. *Find image quality index*
3. *Enhance the image quality by using any relevant Deep Learning models*
4. *Recalculate the image quality index*
5. *Write a one pager on your findings (report), challenges and model you used (word/pdf or .ppt should be suffice)*

Note: it is acceptable to use any pre-build models.

1. Accessing Image Quality Assessment

Image Quality indices or measures are broadly categorised in two parts — Full-Reference Image Quality Index/Indicators (IQI) and No-reference Image Quality Index. Traditional IQIs are as follows as

- Mean squared error (MSE)
- Root mean squared error (RMSE)
- Mean absolute error (MSE),
- Peak signal to noise ratio (PSNR) etc.

are employed for reference based IQIs, i.e, when the ground truth is available (typically called paired images). Among relatively low count of No-reference based IQIs, Blind/Referenceless Image Spatial QUality Evaluator (BRISQUE**) [1] measure commonly used in the literature to compare the quality of image under the unpaired case or when the reference image is not available. Since no ground truths are available in the given problem, this work employs established no-reference image quality index measure — BRISQUE.

BRISQUE is a computationally efficient, no-reference image quality index measure which normalizes pixel intensities images using mean subtracted contrast normalization and computes the pairwise neighborhood relationship for capturing neighborhood relationship (Horizontal, vertical, left diagonal and right diagonal). Finally, it uses support vector machines (SVM), which yields quality score for a given image. In this assignment, a BRISQUE score is used which is also available in python in *imquality* module. BRISQUE score is normalized in the range of [0,100], where 0 zero represents best score and 100 as worst.

****Note:*** *BRISQUE is one of the popular metrics but while working with it I got an impression that there is some implementation issues (particularly with z-score normalization) in the imquality module which implements BRISQUE method. Nevertheless, I used this measure due o the time constraint but it needs careful attention.*

2. Image Quality Enhancement

Firsly, I applied morphological operations like erosion, dilution, opening, closing, hat etc, which are good for gray scale images but as per the assignment there is no such constraint that images will be of gray scale binary image, Further, my experience reveals that it works very well for image test1.pdf, test2.pdf and test4.pdf. Hence, I extended my experiment for robust and more advance deep learning models.

Image quality enhancement methods which attempt to address the issues with color rendition and image sharpness with the use of interactive tools and semi-automatic methods. Most of the softwares provides simple tools such as histogram equalization, color and contrast adjustment, and sharpening etc., while some adopts advanced functions such as local and adaptive adjustments. With the advent of CNNs, deep learning tools are currently state-of-the art tools for particularly unpaired image enhancement. Hence, this work focuses on two frameworks for unsupervised or unpaired image enhancements.

2.1 Super Resolution Residual Convolutional Neural Network

Considering the popularity of CNNs in various computer vision tasks, authors in [2] proposed a CNN based super resolution technique in which image quality is enhanced via super resolution techniques integrated with CNN. Amongst the various available CNNs, authors used a well know Res-Net, which effectively reduces a serious concern of vanishing gradients in CNN with more layers. The authors reported a good performance in terms of image quality enhancement via super resolution. In this algorithm, images are processed via small patches extracted from images using image based morphological operations. After that this model is trained on DIV2k data set with 800 HR images. In this work, a pre-trained model available in below link (sobel_model.h5) which is trained on DIV2k data set with 800 HR images is used.

2.2 Unsupervised image enhancement generative adversarial network (UEGAN)

Recently proposed UEGAN [3] is the first approach to employ a unidirectional GAN[4] framework to apply unsupervised learning to enhance the aesthetic quality of images. Authors have proposed a global attention module and a modulation module to construct the joint global and local generator to capture global features and adaptively adjust the local features. UEGAN uses quality loss, fidelity loss, and identity loss to train the model, to make it towards extracting quality-free features and controlling the enhancement procedure to be more robust to the quality change. In this work, a pre-trained UEGAN model available in below link (UEGAN-FiveK_rahinge_92.0) which is trained on MIT Adobe FiveK dataset (https://data.csail.mit.edu/graphics/fivek/) is used.

3. Implementation details:

Please go through the following instructions before running the code. (Also available in README.). Some implementation points for UEGAN:

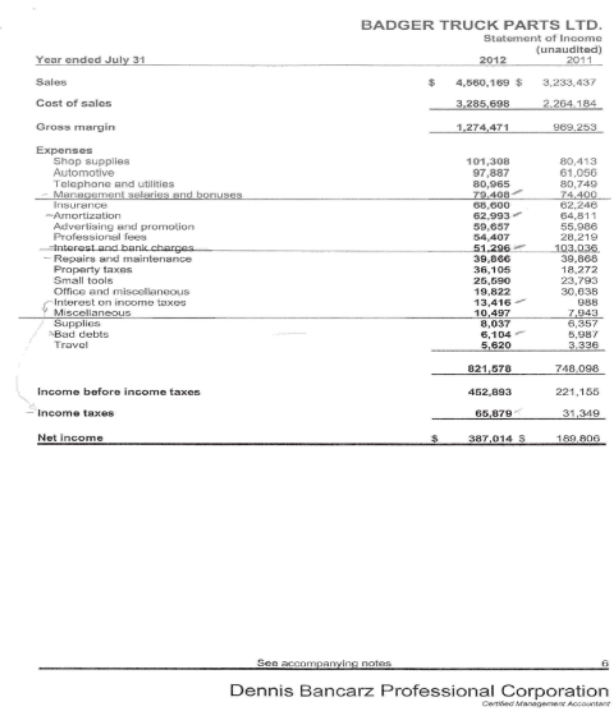
1. UEGAN is implemented using Python using PyTorch 1.4.0
2. All given input images (in pdf format) are converted into .png file (lossless compression) using fitz module.
3. Only No-Reference Metrics is considered for Image quality assessment using BRISQUE (Refer MyMetrics/Metrics.py)
4. Images are converted into pngs and copied in /data/fivek/test/raw/ folder where the algorithm fetches the images (all is handled in the main.py file)
5. Input pdf images can be found in input_pdf folder.
6. Usage: (testing the code)

(venv) Surajs-MacBook-Air:$ python main.py --mode test --version UEGAN-FiveK --pre trained_model 92 --inputpdfs input_p

--mode : Only test mode is enabled as pre-trained model is used.
--version : For creating folders
--pretrained_model 92 pre-trained model present in the folder ./results/UEGAN-FiveK/models/
--inputpds : Name of the folder which contains pdf input images

7. After testing output images can be found in ./results/UEGAN-FiveK/test/test_results/ and comparative images can be found in generated in ./results/UEGAN-FiveK/test/test_compare/

(Below figures shows images of UEGAN in comparison with original image)



BADGER TRUCK PARTS LTD.
Statement of Income
(unaudited)

Year ended July 31	2012	2011
Sales	$ 4,560,169	$ 3,233,437
Cost of sales	3,285,698	2,264,184
Gross margin	1,274,471	969,253
Expenses		
Shop supplies	101,308	80,413
Automotive	97,887	61,056
Telephone and utilities	80,965	80,749
Management salaries and bonuses	79,408	74,400
Insurance	68,600	62,246
Amortization	62,993	64,811
Advertising and promotion	59,657	55,986
Professional fees	54,407	28,219
Interest and bank charges	51,296	103,036
Repairs and maintenance	39,866	39,868
Property taxes	36,105	18,272
Small tools	25,590	23,793
Office and miscellaneous	19,822	30,638
Interest on income taxes	13,416	988
Miscellaneous	10,497	7,943
Supplies	8,037	6,357
Bad debts	6,104	5,987
Travel	5,620	3,336
	821,578	748,098
Income before income taxes	452,893	221,155
Income taxes	65,879	31,349
Net income	$ 387,014	$ 189,806

See accompanying notes 6

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Certified Management Accountant

Original (BRISQUE Score = 92.236)

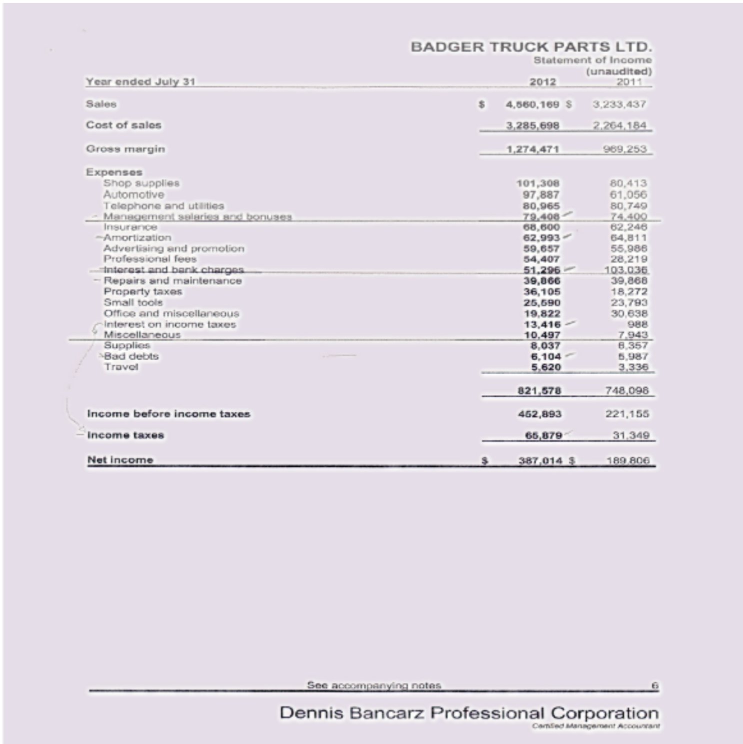

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Image Enhancement Using UEGAN (BRISQUE Score = 77.176)

Figure 1: UEGAN result for first test image (test1.pdf)

Consolidated statement of financial position
At 30 April 2019

	Note	2019 £m	2018 £m
Assets			
Non-current assets			
Intangible assets		3,211	2,043
Biological assets		9	3
Property, plant and equipment		2,993	2,396
Equity accounted investments		33	24
Other investments		12	11
Deferred tax assets		64	64
Other receivables		9	7
Derivative financial instruments		12	15
Total non-current assets		**6,343**	4,563
Current assets			
Inventories		584	543
Biological assets		6	4
Income tax receivable		18	15
Trade and other receivables		914	863
Cash and cash equivalents		382	297
Derivative financial instruments		35	44
Assets held for sale		237	–
Total current assets		**2,176**	1,766
Total assets		**8,519**	6,329
Liabilities			
Non-current liabilities			
Borrowings		(2,392)	(1,811)
Employee benefits	4	(170)	(106)
Other payables		(16)	(14)
Provisions		(16)	(4)
Deferred tax liabilities		(323)	(195)
Derivative financial instruments		(14)	(35)
Total non-current liabilities		**(2,931)**	(2,165)
Current liabilities			
Bank overdrafts		(129)	(29)
Borrowings		(233)	(162)
Trade and other payables		(1,855)	(1,705)
Income tax liabilities		(133)	(118)
Provisions		(17)	(16)
Derivative financial instruments		(16)	(24)
Liabilities classified as held for sale		(93)	–
Total current liabilities		**(2,476)**	(2,054)
Total liabilities		**(5,407)**	(4,219)
Net assets		**3,112**	2,110
Equity			
Issued capital		137	107
Share premium		2,236	1,260
Reserves		738	742
Total equity attributable to owners of the parent		**3,111**	2,109
Non-controlling interests		**1**	1
Total equity		**3,112**	2,110

Approved by the Board of Directors of DS Smith Plc on 12 June 2019 and signed on its behalf by:

M W Roberts, Director — A R T Marsh, Director

The accompanying notes are an integral part of these consolidated financial statements.

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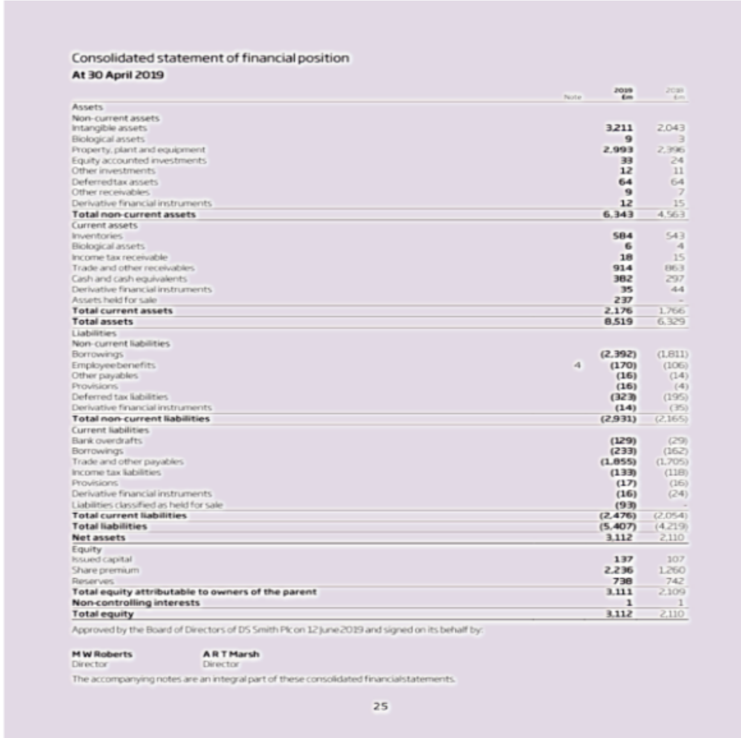
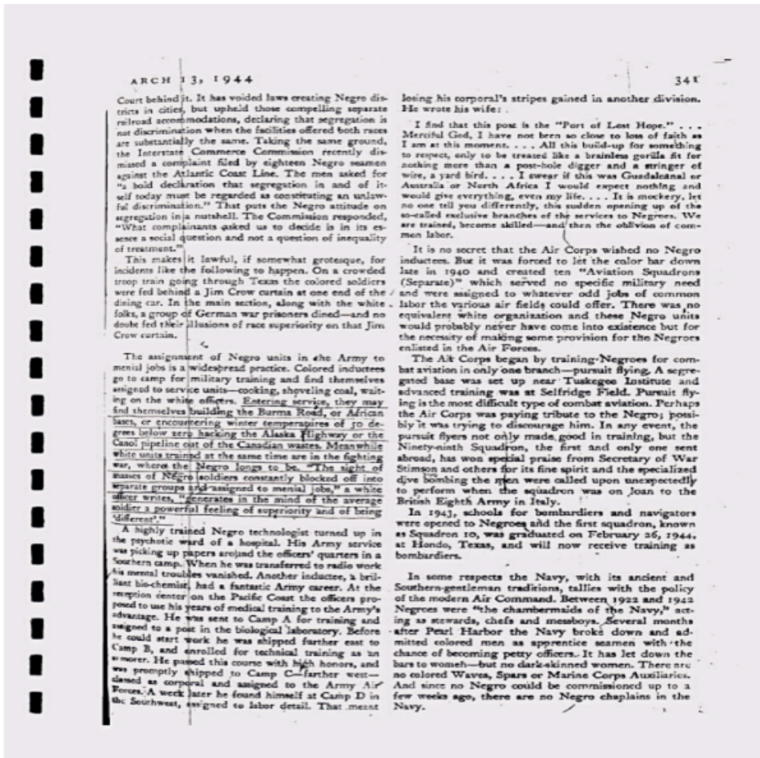


Original (BRISQUE Score = 95.178) Image Enhancement Using UEGAN (BRISQUE Score = 67.385)

Figure 2: UEGAN result for first test image (test2.pdf)



Original (BRISQUE Score = 64.923) Image Enhancement Using UEGAN (BRISQUE Score = 63.58)

Figure 3: UEGAN result for first test image (test3.pdf)

Original (BRISQUE Score = 63.189) Image Enhancement Using UEGAN (BRISQUE Score = 63.716)

Figure 4: UEGAN result for first test image (test4.pdf)

Original (BRISQUE Score = 70.249) Image Enhancement Using UEGAN (BRISQUE Score = 66.561)

Figure 5: UEGAN result for first test image (test5.pdf)

4 Results and Discussions

Table 1 shows the comparative study of both the models with original image with respect to BRISQUE measure. UEGAN achieves better performance than SR-ResCNN over the given samples. However, for sample 4 (test4.pdf) performances of both the models are not upto the mark, i.e., both the models are not able to reduce the BRISQUE scores. However, surprisingly aesthetically, test sample 4 does look better than the original.

Sample ID	File-name	Original Image (BRISQUE Score)	SR-ResCNN (BRISQUE Score)	UEGAN (BRISQUE Score)
1	test1.pdf	92.236	84.276	**77.176**
2	test2.pdf	95.178	83.541	**67.385**
3	test3.pdf	64.923	64.721	**63.58**
4	test4.pdf	**63.189**	68.137	63.716
5	test5.pdf	70.249	68.232	**66.561**

Table 1: Comparison of BRISQUE scores achieved by both the algorithms and original image

** Best results are shown in Bold*

5. Conclusions

This preliminary study, suggests UEGAN is certainly a candidate model to consider for the image enhancement task. It will be interesting to see the performances of both these models when they are trained on the images of documents and varieties of other natural images. For both architectures, (UEGAN and SR-ResCNN), pre-trained models are used which is trained on the natural images. Due to the lack of computational resources (GPUs) and time constraint unfortunately it is not carried out in this work. But fine tuning the hyper-parameters of the models over documents image data is certainly a future scope of this study. Finally, during the literature survey, I found that there are modified versions of BRISQUE measures which can be employed for the same task but needs implementation from scratch.

Other promising architectures which can be explored for the given task:

1. CycleGAN[5]
2. PixtoPix[6]
3. Wasserstein GAN (https://arxiv.org/abs/1701.07875)

References

1. *Mittal, A., Moorthy, A. K., & Bovik, A. C. (2012). No-reference image quality assessment in the spatial domain. IEEE Transactions on image processing, 21(12), 4695-4708.*

2. *Lee, P. Y., & Tseng, C. C. (2019, May). Image Super-Resolution Using Residual Convolutional Neural Network. In 2019 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW) (pp. 1-2). IEEE.*
3. *Ni, Z., Yang, W., Wang, S., Ma, L., & Kwong, S. (2020). Towards unsupervised deep image enhancement with generative adversarial network. IEEE Transactions on Image Processing, 29, 9140-9151.*
4. *Chen, Yu-Sheng, et al. "Deep photo enhancer: Unpaired learning for image enhancement from photographs with gans." Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition. 2018.*
5. *Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In Proceedings of the IEEE international conference on computer vision (pp. 2223-2232).*
6. *Isola, P., Zhu, J. Y., Zhou, T., & Efros, A. A. (2017). Image-to-image translation with conditional adversarial networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1125-1134).*

Attachments:

1. UEGAN Folder.
2. Report