

Thesis Title

Thesis Subtitle

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Forewords and Acknowledgements

Declaration of Independent Work

Figure list

Abbreviations

Abstract

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Introduction

Study Area of Interest

Research Questions

Literature Review

Remote Sensing of Informal Settlements

Deep Learning in Remote Sensing

Computer Vision and Convolutional Neural Networks

Computer Vision in Building Segmentation

Data and Methodologies

Data

Data Augmentation

Data augmentation is perhaps one of the most crucial task in training a robust neural-network. It is an economical way of increasing generalisability without increasing model complexity, data augmentation achieve this through, firstly increasing the quantity of training and validation data, secondly encompassing a greater range of textural, geometrical, and colour variability through the creation of augmented pseudo-data (Shorten & Khoshgoftaar, 2019; Kinsley & Kukiela, 2020; Howard & Gugger, 2020; Zoph et al., 2019).

Data augmentation can generally be split into 3 categories: 1. Geometric/Affine distortion, 2. Colour distortion, and 4. Noise distortion. The application of which types of distortion to the {Train and {Validation dataset is highly dependent on the context of the semantic task. Therefore, care must be taken as to not introduce mislabelling (see Figure 3.1).

Augmentation categories:

- Geometric/Affine distortion
 - e.g. Flipping, Stretching, Rotation...
- Colour distortion
 - e.g. Colour Inversion, Solarise Colour, Greyscale...
- Noise distortion
 - e.g. Blurring, Contrasting, Salt & Pepper...

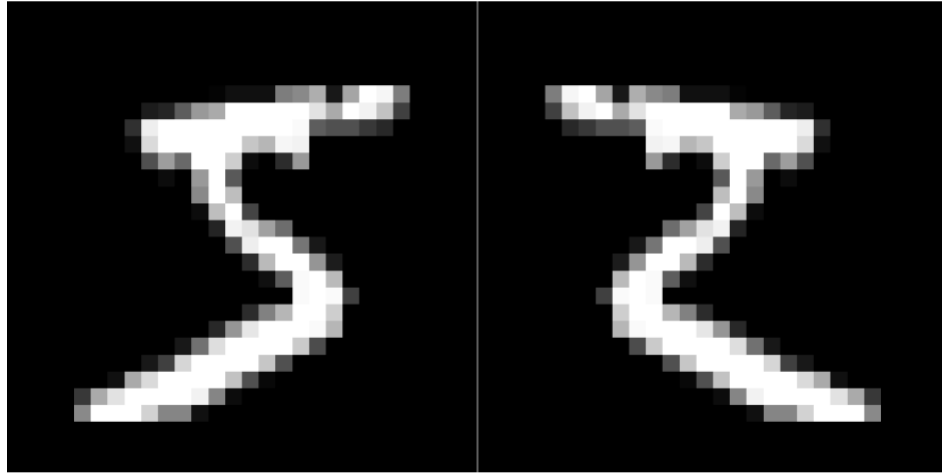


Figure 3.1: Perhaps geometric augmentation of horizontal flipping shall not be applied on the MNIST number of 5

Architecture selection

Accuracy Assessment

Detail and scrutable accuracy assessments are fundamental towards any classification based analysis. This section will introduce and break down the various lower order and higher order class-based (thematic) accuracy assessment. By explaining the characteristics of each metrics, this will provide a much more granular nature of accuracy assessment in the findings of section 4. In general, accuracy assessment in remote sensing can be divided into 2 categories: 1. Positional Accuracy & 2. Thematic Accuracy. Of which, Positional Accuracy deals with the accuracy of the location while Thematic Accuracy deals with the labels or attributes accuracy (Congalton & Green, 2019 & Bolstad, 2019). The rest of this section will consider the lower order and higher order accuracy metrics, with lower order metrics being more granular while higher order metrics more trituated but generalised.

The metrics described in this section form part of the larger family of accuracy assessment metrics that can be constructed from the confusion matrix (see Figure 3.2)

Precision, Recall, Sensitivity, and Specificity

Precision, Recall, and Specificity

Precision and **Recall**, aka. Positive-Predictive-Value and Sensitivity/True-Positive-Rate Respectively. The two metrics are often used together, another

		True condition			
		Condition positive	Condition negative	Prevalence = $\frac{\sum \text{Condition positive}}{\sum \text{Total population}}$	Accuracy (ACC) = $\frac{\sum \text{True positive} + \sum \text{True negative}}{\sum \text{Total population}}$
Predicted condition	Predicted condition positive	True positive	False positive, Type I error	Positive predictive value (PPV), Precision = $\frac{\sum \text{True positive}}{\sum \text{Predicted condition positive}}$	False discovery rate (FDR) = $\frac{\sum \text{False positive}}{\sum \text{Predicted condition positive}}$
	Predicted condition negative	False negative, Type II error	True negative	False omission rate (FOR) = $\frac{\sum \text{False negative}}{\sum \text{Predicted condition negative}}$	Negative predictive value (NPV) = $\frac{\sum \text{True negative}}{\sum \text{Predicted condition negative}}$
		True positive rate (TPR), Recall, Sensitivity, probability of detection, Power = $\frac{\sum \text{True positive}}{\sum \text{Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm = $\frac{\sum \text{False positive}}{\sum \text{Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{\text{TPR}}{\text{FPR}}$	Diagnostic odds ratio (DOR) = $\frac{\text{LR+}}{\text{LR-}}$ $F_1 \text{ score} = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}$
		False negative rate (FNR), Miss rate = $\frac{\sum \text{False negative}}{\sum \text{Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) = $\frac{\sum \text{True negative}}{\sum \text{Condition negative}}$	Negative likelihood ratio (LR-) = $\frac{\text{FNR}}{\text{TNR}}$	

Figure 3.2: The Confusion Matrix

common denomination especially in remote sensing literature are User's Accuracy and Producer's Accuracy (Congalton & Green, 2019 & Wegmann et al., 2016). To avoid further confusion in nomenclature, **Precision** and **Recall** will be used from hereon.

Precision is the measure of correctly predicted Positive class (True Positive) against all positive prediction assigned to that class (True Positive + False Positive) i.e. Given the predicted results, of those that are predicted as positive, what proportion were True. It can be expressed mathematically as:

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Positive})} \quad (3.1)$$

Meanwhile, **Recall** measures the correctly predicted Positive class (True Positive) against both the correct and incorrect prediction on the Positive reference class (True Positive + False Negative) i.e. Given the predicted results, of those that are referenced as positive, what proportion of those were True. It can be expressed mathematically as:

$$\text{Recall} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Negative})} \quad (3.2)$$

Specificity, aka. True-Negative-Rate measures correctly predicted Negative class (True Negative) against the correct and incorrect prediction on the Negative reference class (False Positive + True Negative) i.e. Given the predicted results, of those that are referenced as negative, what proportion of those were True. It can be expressed mathematically as:

$$\text{Specificity} = \frac{\text{True Negative}}{(\text{False Positive} + \text{True Negative})} \quad (3.3)$$

Therefore, higher **Recall** suggests the model is better at identifying positives and vice-versa higher **Specificity** suggests the model is better at identifying negatives. Since this is an exercise that aim to maximise the positive prediction as a binary building segmentation classifier, emphasise will be placed on maximising **Precision** and **Recall**.

Overall Accuracy, Dice Score, and Intersection-over-Union

Experimentation setup

Project workflow

Findings

Analysis

Discussion

Conclusion

Bibliography

Appendix