MATH70103 - UNSTRUCTURED DATA ANALYSIS
FINAL PROJECT - NOVEL APPROACHES TO EMERGENCY FLOOD DETECTION WHEN SATELLITE IMAGES FAIL USING IMAGE SEGMENTATION

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1. INTRODUCTION AND PROBLEM STATEMENT

Water body proximity detection from images is vital in helping emergency response teams to quickly judge the extent of flooding across thousands of locations worldwide. However, as noted by Wang et al.(2021)[1], existing deep convolutional neural network methods to process these images are difficult to train, resource-intensive, and cannot meet real-time requirements. Additionally, if real-time satellite or aerial imagery is not available due to cloud cover, technical issues, or other logistical constraints, lateral camera images can provide critical supplementary information. The dataset in this case is substantially smaller than those provided by satellites, and may be provided by stationary cameras, or live video feeds from individuals at the scene.

Since Neural networks typically require large datasets to achieve high accuracy, smaller lateral image datasets may fail to produce strong accuracy levels when using neural networks, motivating the application of simpler models which work better on smaller datasets. This report compares two novel approaches to detect water body proximity, by applying three common supervised learning techniques to features derived from region-based segmented images.

Further, utilising proximity categories as opposed to exact distances brings computational advantages and may lead to greater robustness to variability in image quality as it relies on relative rather than absolute measurements. Images, especially those taken from different angles or altitudes, can present challenges in accurately determining exact distances.Categorization into proximity classes can be more reliable when dealing with ambiguous or unclear imagery. Lower resolution or blurry images can make exact distance measurement difficult or inaccurate, making classification a more achievable target.

2. DATA COLLECTION AND PREPROCESSING

The dataset consists of 60 JPEG images featuring water bodies (lakes, rivers and sea), 58 of which were taken on an iPhone 13, with 2 being taken on an iPhone 7. The images span multiple locations including Vancouver, Cornwall and Dublin and across various proximity levels, which were manually and subjectively labelled as 0 - immediate vicinity; 1 - close; 2 - moderately close; 3 - moderately far and 4 - very far. The dataset size is a limitation, however, due to the necessity of manual labelling, available images on the phone and the desire to produce a dataset which is both original and complex, this was a trade-off in this investigation.

3. DATA VISUALISATION

Figures 1-5 show a subset of the data containing one image from each of the 5 proximity categories. This provides insight into the subjective labelling process and approximate distance ranges that are associated with each category. The photos additionally provide a range of weather conditions (sunny, overcast, dull, bright), which provides greater diversity in terms of water reflections and colour, which should benefit the model in the training process. The diversity of landscapes provided by the different locations also brings greater diversity to the dataset, leading to a model more robust to overfitting, since parameters must be able to produce a sufficient level of performance across various water colours and textures. 58 of the images are high quality and 2 of the images are lower definition and blurry.

Figure 1: Proximity: immediate vicinity. Location: Vancouver

Figure 2: Proximity: close. Location:Granada

Figure 3: Proximity: moderately close. Location: Cornwall

Figure 4: Proximity: moderately far. Location: Dublin

Figure 5: Proximity: very far. Location: Vancouver

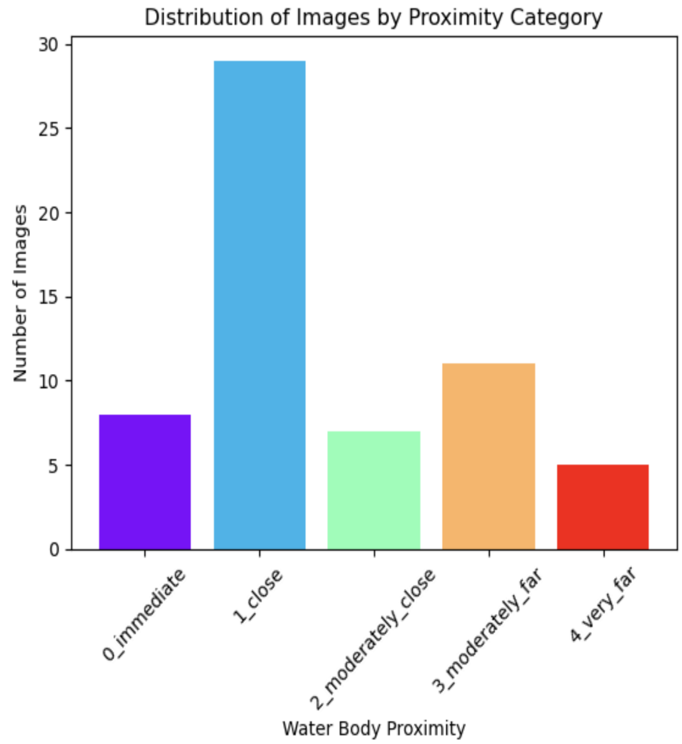

Figure 6: Dataset distribution

As can be seen in Figure 6, there is a clear bias in the distribution of images towards bodies of water in the 'close' proximity category. Whilst this is a limitation of the dataset, the problem which we are trying to address will place greater importance on detecting bodies of water which are close (i.e. flooded areas). Hence, in the presence of a biased distribution, it is at least preferable to have a larger proportion of images in the 'close' category, rather than the 'moderately far' or 'very far' categories.

The following observations were made by looking at a large subset of the images.

1. The provided camera images do not use extensive zoom features
2. Water bodies which are closer in proximity generally take up a larger proportion of the image
3. Water bodies which are further in proximity often tend towards the upper half of the image, on the horizon
4. Water bodies which are closer in proximity often tend towards the bottom half of the image, due to the typical desire for having the sky in the photo, which tends towards the top of the image
5. Water bodies which are closer in proximity have greater contrast in texture due to higher definition of texture on the water, wavelets etc

These observations form the principals on which my model is based and motivate my choice of 8 spatial/textural predictive features, which are described in Section 4.2.

4. METHODS AND ANALYSIS

4.1 Image Segmentation

4.1.1 Motivation. Image segmentation methods can facilitate easier and more direct analysis of images by dividing them into distinct, meaningful regions that can be individually analyzed and processed. In this scenario, image segmentation allows targeted examination of the body of water, from which we can create predictive features to feed into a supervised machine learning model.

4.1.2 Method. Edge-based segmentation and the unseeded region growing algotithm were tested, but there was too large a degree of variation in the optimal parameter values across different proximity categories, so instead, a colour-based segmentation method was chosen - filtering the image to identify blue tones and then applying a texture mask to help isolate the region corresponding to water, as opposed to sky or other blue regions. This was done by applying a thresholding approach to contrast and homogeneity parameters. The results were reasonably successfully as a whole across the images. An example is shown in Figures 8 and 9. Clearly, the relevant blue regions have been isolated with reasonable accuracy and the texture mask in Figure 9 further reduces the non-water regions, as indicated in white. It is clear that some non-water sections of the picture have been marked as being water (in white), however, since the parameters must be tuned to differing water colours, lighting, reflections etc, it is inevitable that there will be some level of inaccuracy in individual image segmentations. After identifying the water body region, the locations of the pixels in the water body region were stored.

4.2 Features

4.2.1 Spatial - Proportion of each image quadrant occupied by water body region. Since both the pixel-co-ordinates of the water body region and the size of the region provide insight into the proximity, I calculated the proportion of each quadrant occupied by the water body region.

4.2.2 Texture.

1. **Standard deviation of pixels**: A higher standard deviation might indicate closer proximity, as finer details and variations in the water surface, like small ripples or debris, become more apparent when the photographer is nearer.

2. **Contrast**: Greater contrast could suggest closer proximity, as near-field variations in light and shadow on the water surface are more discernible.

3. **Entropy**: Higher entropy in the texture might indicate closer proximity, revealing the intricate patterns of water movement and surface disruptions up close.

4. **Correlation**: Lower correlation might be observed when closer to the water body, as the immediate diversity in water texture and surface irregularities is more pronounced at a shorter distance.

The features were calculated and stored in a design matrix, and the proximity labels of the images stored in an array for input into the models described in the section 4.4.

Figure 7: Original image. Location: Vancouver.

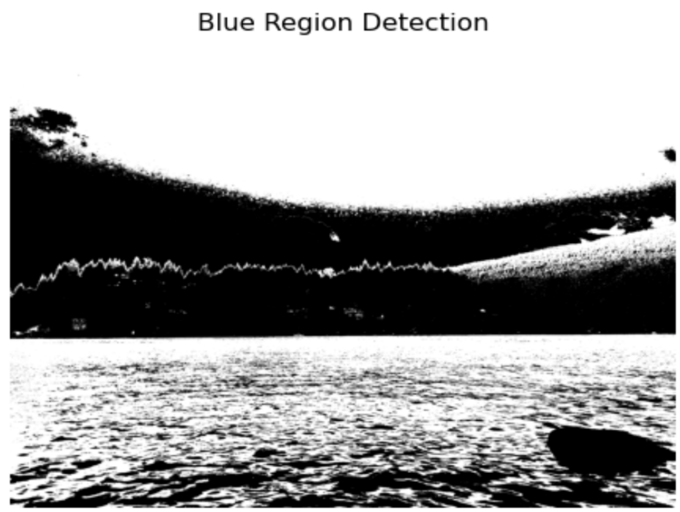

Figure 8: Image segmentation. Blue regions indicated in white.

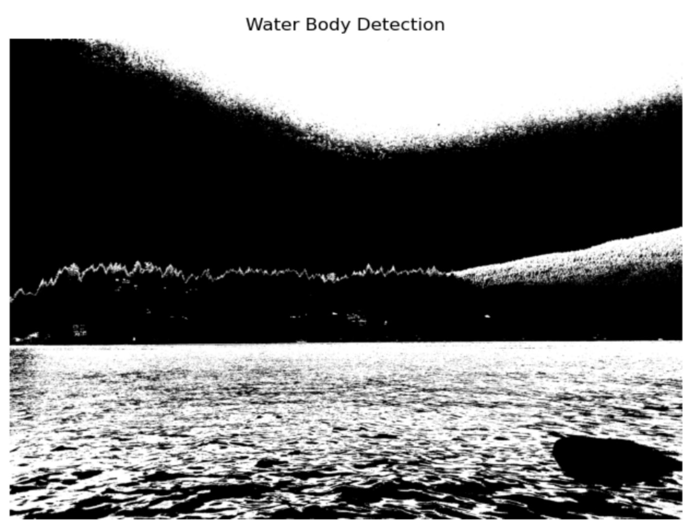

Figure 9: Image segmentation. Water body indicated in white. Some sky region has been misidentified as water.

4.3 Cross-Validation

Since the dataset is small, cross-validation was used to evaluate model performance. This involves splitting the model into 5 batches of 12 images and training the model on each subset of 4 of these batches while evaluating performance on the remaining batch, and then taking an average of the misclassification rate. This helps to produce a more robust estimate of the misclassification rate.

4.4 Models

4.4.1 Support Vector Machine (SVM). SVMs are known to be used to model water body extraction and change detection [2]. The one-vs-one classification approach extension of SVMs was used since there were more than two classes. The model was implemented using Python's *scikit-learn* package. The regularization strength parameter was tuned by performing grid search, leading to an optimal parameter value of C = 10, where the strength of the regularisation is inversely proportional to C. A linear kernel was selected for three reasons.

1. Exploratory analysis of the data suggested that the relationships between both the pixel locations and texture of the water body and water body proximity were not complex and so a simpler model could produce good performance.

2. It is computationally faster, a vital consideration due to the need to simultaneously and quickly identify any regions where the water proximity has changed, indicative of flooding.

3. With a smaller dataset (as is the case here and may be the case when lateral camera images are relied upon) a linear model is less prone to overfitting, making it more robust.

4.4.2 Random Forest. Random forest models have been used to model urban flood mapping [3], and their underlying algorithm, decision trees, can capture non-linear relationships between features and classes. This provides an alternative to the linear kernel SVM and hence was selected as the alternative supervised learning model for this task. The model was also implemented using Python's *scikit-learn* package. Grid Search was used to find optimal parameter values, which are shown in Table 1, below.

Parameter	Optimal value
Number of Trees	50
Maximum tree depth	7
Min number of samples per leaf	4
Min number of samples for splits	10

Table 1: Optimal parameter values for the Random Forest Classifier, as given by grid search

5. RESULTS

The misclassification rates for the two models are very similar, as can be seen in Table 2. Given that there are 5 proximity categories, a model which picked a proximity class at random would be expected to produce an average misclassification rate of 80%. Hence, the support vector machine model performs almost 30% better and Random Forest around 27% better, respectively, than a random model. Typical object proximity studies using computer vision focus on distance as opposed to proximity categories, some reaching misclassification rates as low as 2-3% [4]. Conversely, studies predicting distance 'categories' are difficult to find and hence, a suitable benchmark for lateral images could not be found.

Model	Misclassification Rate
Support Vector Machine	50.00%
Random Forest	53.33%

Table 2: Misclassification rates for the two models in predicting the correct proximity class out of 5.

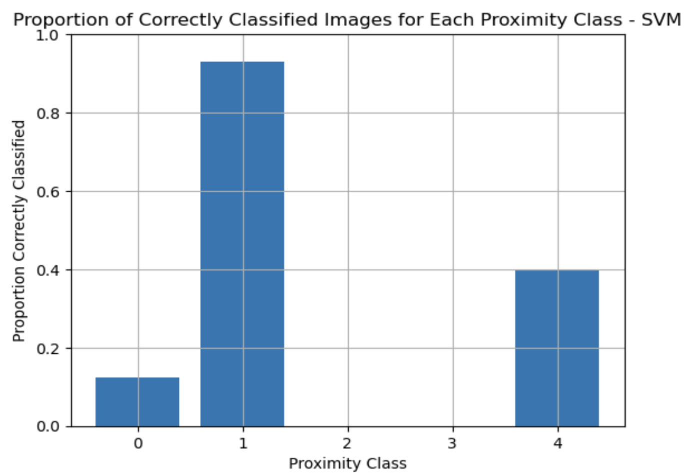

Figure 10: Classification accuracy across proximity classes for the random forest model

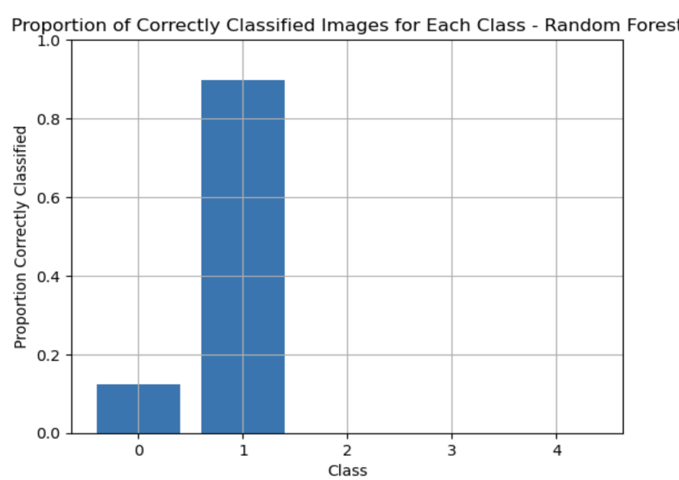

Figure 11: Classification accuracy across proximity classes for the random forest model

It is important to point out that the aim of the problem is to be able to identify flooding via water body proximity and hence, the prediction of the 'immediate vicinity' and 'close' bodies of water is of greater importance than correctly predicting those bodies of water further away. Figures 10 and 11 show the classification accuracy for each proximity class for the SVM and Random Forest models, respectively. The classification accuracy for images in the 'close' proximity category is over 90% for SVM and random forest, which shows that the models have learned the features of this class very well, which is important, and also expected, since the dataset is heavily imbalanced towards this class. However, the classification accuracy for immediate vicinity water bodies is very low, around 12.5%, which is also significant, since it is reasonable to expect that immediate vicinity pictures will be common in a real-life dataset. It is hence clear that the imbalanced dataset is a limitation of this analysis.

The analysis was repeated after reducing the size of the '1-close' category to be similar to the other class sizes, however, the misclassification rate increased by over 20%. One clear inference that we can therefore make is that further data is needed in order to produce better classification accuracy across classes. The accuracy level of 0% for proximity classes 2 and 3 across both models is also surprising, even given the imbalanced dataset, implying that the spatial and textural features are more diverse across the photos in these classes in the dataset.

The marginally better performance of the SVM model, together with the fact that it uses a linear kernel and so is a simpler model makes this model more favourable, however further testing on a larger dataset is necessary to determine if their performances diverge in larger samples.

CONCLUSION

Imagery can be used to monitor and detect instances of flooding across millions of locations worldwide. When real-time satellite or aerial imagery is not available, due to cloud cover, technical issues, or other logistical constraints, lateral camera images can provide critical supplementary information in the affected zones. Due to the computational costs of neural networks in a situation where fast responses are required, and the huge datasets required, this motivates this investigation of simpler novel machine learning methods to detect flooding via identifying the proximity category of the water body in the image. Both spatial and textural features of the water body region were identified as differentiating features in proximity categories of the water body by an exploratory analysis of a dataset of 60 iPhone camera images of water bodies. Colour and texture-based image segmentation was used to identify the pixels corresponding to the water region in the image, and spatial and textural features were calculated from the isolated region. These features were then used in support vector machine and random forest models to classify the images into proximity categories. Both models produced similar levels of accuracy, around 30% better than a random model. Both models were also more accurate in correctly classifying the 'immediate vicinity' and 'close' water bodies from the images, an important point since flooded regions will typically be closer in images.

Whilst the misclassification rate is around 50% for both models, it is important to recognise the limitations of this investigation; namely, the small dataset used, the subjective labelling of the proximity class of the images, and the lack of sustained model improvement and iteration over a long period of time, which would permit enhancements such as further parameter tuning, removal of redundant features adn feature engineering and modifications to the model. Further research may also expand the dataset to more locations whcih would help to make the model more robust.

REFERENCES

[1] Y. Wang et al. "Lightweight Deep Neural Network Method for Water Body Extraction from High-Resolution Remote Sensing Images with Multisensors". In: *Sensors* 21.21 (Nov. 2021). PMID: 34770701; PMCID: PMC8587285, p. 7397. DOI: 10.3390/s21217397. [2] G. Sarp and M. Ozcelik. "Water body extraction and change detection using time series: A case study of Lake Burdur, Turkey". In: *Journal of Taibah University for Science* 11 (2017), pp. 381–391. DOI: 10.1016/j.jtusci.2016.04.005. [3] Q. Feng, J. Liu, and J. Gong. "Urban flood mapping based on unmanned aerial vehicle remote sensing and random forest classifier—A case of Yuyao, China". In: *Water* 7 (2015), pp. 1437–1455. DOI: 10.3390/w7041437. [4] K. Karthika, S. Adarsh, and K. I. Ramachandran. "Distance Estimation of Preceding Vehicle Based on Mono Vision Camera and Artificial Neural Networks". In: *2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT)*. IEEE. Kharagpur, India, 2020, pp. 1–5. DOI: 10.1109/ICCCNT49239.2020.9225406.