Identifying Tree Preservation Order Protected Trees by Deep Learning in Greater London Area

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Summary

Tree Preservation Order (TPO) is used to protect specific trees from damage and destruction, which is determined in high subjectivity. This research collected and analyzed TPO data, aerial images, geographic data, and socio-economic data in the Greater London area and developed a multi-input deep learning (DL) framework to classify TPO-protected and non-TPO-protected trees. The synergy use of aerial images and GIS data with the fusion model of ResNet50 and multilayer perceptron network produced the best classification accuracy of 87.32%. The result indicated the robustness of the multi-input DL model to identify the social attributes of trees compared with the single-input DL model.

KEYWORDS: Aerial images, Deep learning, ResNet, Tree Preservation Order

1. Introduction

The definition of Tree Preservation Order (TPO) in the UK requires to meet three conditions: 1) the visibility of trees to the public; 2) the scarcity, the cultural or historical value of trees; and 3) the contribution of trees to the surrounding landscape (Wright and Slater, 2017). However, TPO-protected trees are currently managed in low capacity and efficiency because of the time-consuming field-survey and subjective classification of TPO-protected trees. The pre-trained CNN network has a wide range of applications in various image classification problems. ResNet50 model was applied to detect diseases in plant images with a final recognition accuracy of 99.80% (Mukti and Biswas, 2019). Social attributes of trees were commonly analyzed with GIS data to assess the aesthetic value, social equity, and economic benefits of individual trees (Cox et al., 2019; Vaz et al., 2019; Wyse et al., 2015). The hybrid fusion models that concatenated image-CNN model and neural network were applied to improve the prediction in daily solar radiation prediction (Ghimire et al., 2022), tea plant diseases classification (Krisnandi et al., 2019), medical diagnosis (Öztürk and Özkaya, 2021). However, there was no study to fuse deep learning and neural network to classify social attributes of trees. It is worth exploring the combination of high-resolution imagery and GIS data with a hybrid fusion neural network to classify the TPO-protected trees. The overarching goal of this research is to develop a multi-source deep learning framework to identify TPO-protected trees in a more efficient and replicable method in the greater London area.

2. Data and methods

This research selected the Greater London area as the study area, encompassing the City of London and its thirty-two surrounding boroughs. There are over eight million trees in the Greater London area (The East London Garden Society, n.d.). Other data including tree canopy coverage/location data, high-resolution aerial images with 25cm resolution, GIS (road network, building footprints, historical

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buildings, vegetation coverage, river network, and the boundary of nature reserve), and indices of deprivation were collected (The University of Edinburgh, n.d.). **Figure 1** showed the proposed workflow to classify the TPO-protected and non-TPO-protected trees. Fine-tuned ResNet50 and ResNet50V2 were employed to classify the tree image clipped from aerial images. The multilayer perceptron (MLP) and the long short-term memory (LSTM) network were applied to classify the geographical and socioeconomic features of trees. The multi-model fusion network was built by concatenating output layers of the imagery classification model (ResNet50 or ResNet50V2) and geographical and socioeconomic data classification model (MLP or LSTM) together with equal weights. As a result, eight models have been trained to identify the TPO-protected trees. All data were split into 8:2 as training and validation datasets respectively. Accuracy and area under the receiver operating characteristic (AUC) that indicates the quality of the model's predictions were used as metrics to evaluate the model performance.

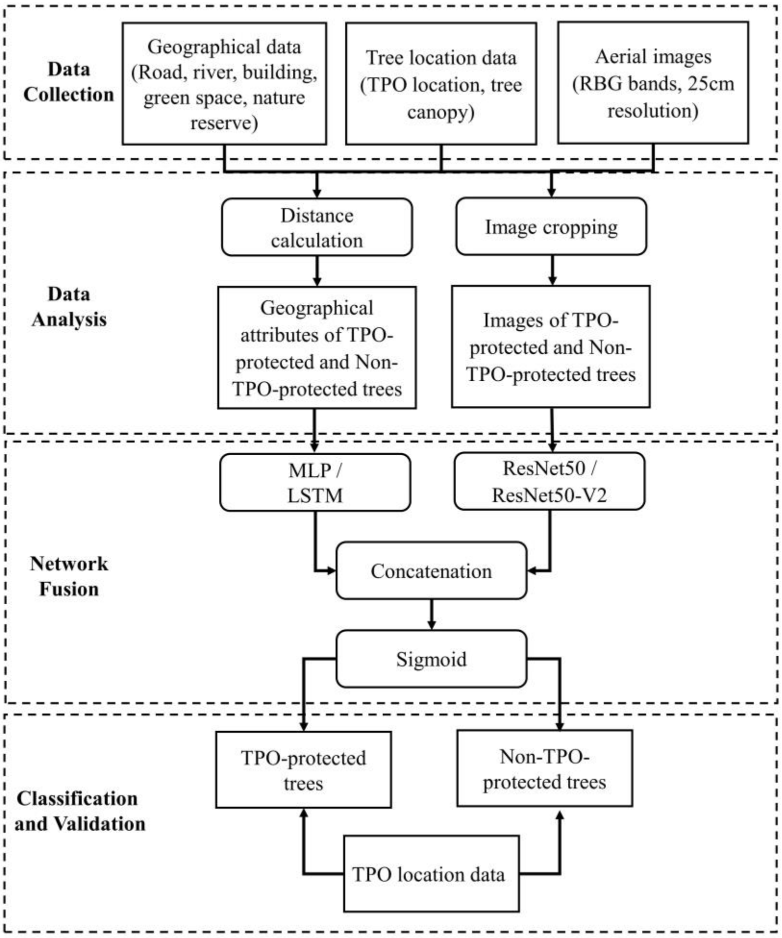

Figure 2 The Proposed Workflow to Classify the Tree Preservation Order (TPO)-protected and Non-TPO-protected Trees. (RGB: Red, Green, and Blue; MLP: Multilayer Perceptron; LSTM: Long Short-Term Memory)

3. Results and discussion

The overall accuracy of the eight models is demonstrated in **Table 1**. When using image data alone, the performance of ResNet50 and ResNet50-V2 are very similar, achieving testing accuracy over 80%. while ResNet50 acquired a slightly higher test accuracy of 0.35% and less than 8.45% in loss compared with ResNet50-V2. For using geographical variables only, the MLP network and LSTM network could achieve a testing accuracy of more than 80%. Models using geographical variables input produced much better loss score (34.93% from LSTM and 42.58% for MLP) than that using image data (52.35%

for ResNet50 and 60.80% for ResNet50V2), which implied the importance of geographical variables in TPO-protected trees recognition. This result indicated the relationship between TPO-protected trees and geographic factors, such as the distance to roads, buildings, green space, and poverty in each borough. However, we did not find a consistent trend of TPO-protected trees in either distribution and their relationship with geographic factors in each borough, which may result from a subjective determination of trees' social attributes. When using both data sources, the multi-model ResNet50+LSTM and ResNet50+MLP could slightly improve the testing accuracy results by around 2% compared to the best result of using a single source of image data with ResNet50. In addition, benefiting from the inclusion of geographical variables, the testing loss of multi-model networks is much better than that of the single image data model, with approximately a 20% decrease. This suggests that geographical variables played an essential role to adjust the model's judgment criteria and thus, reduce the error rate of the model's predictions. Furthermore, the AUC results of multi-model networks were also relatively high, and the best one was 0.944 produced by LSTM+ResNet50 (there was an approximately 94.4% chance that these models would be able to distinguish TPO-protected trees and non-TPO-protected trees), indicating a robust performance of the classifier. In this study, the output of image classification and geographical variable were considered in equal weight to concatenate together for the final determination of TPO-protected trees in the multi-model network. However, the two types of data used in this project may not be equally important in predicting TPO-protected trees. This is a factor that may affect the performance of our model and needs further study.

Table 1. Overall Results Using Models Trained on the TPO-Protected Tree Dataset. The Best Results are Highlighted in Bold. (I: Imagery Data, G: Geographical and Socio-Economic Data, and AUC: Area Under the Receiver Operating Characteristic).

Input Data	Model	Test Accuracy (%)	Test Loss (%)	AUC	Training Time (s)
G	LSTM	**84.55**	**34.93**	**0.925**	825
	MLP	80.47	42.58	0.886	**301**
I	ResNet50	**85.28**	**52.35**	**0.935**	3750
	ResNet50V2	84.93	60.80	0.929	**3735**
I + G	LSTM+ResNet50	86.66	39.91	0.944	3981
	LSTM+ResNet50V2	85.57	42.12	0.932	3749
	MLP+ResNet50	**87.32**	**39.15**	**0.935**	3759
	MLP&+ResNet50V2	85.39	45.18	0.921	**3608**

4. Conclusion

This research collected and analyzed the current status of TPO data in Greater London and built a multi-model network to identify potential TPO-protected trees. Compared with traditional survey and single-input deep learning models, this method can detect potentially TPO-protected trees with higher efficiency and accuracy. The proposed method and study results have practical application value for governments, real estate developers, and environmental organizations.

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