UAV and AI-Driven Approaches for Accurate Species Classification in Railway Trackside Vegetation Management

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Abstract—**Railway trackside vegetation management is vital for safe and reliable operations. We explore integrating UAV and AI technologies to enhance this practice. Our study developed two AI models: a Mask R-CNN-based segmentation model and a feature classifier-based classification model, both using a ResNet50 backbone. Trained on extensive UAV imagery datasets annotated by domain experts, the models achieved promising results. The segmentation model achieved 78% average accuracy while validating with the ground truth, providing insights into vegetation density. In contrast, the classification model excelled with 96% average precision with the ground truth data, particularly in identifying prevalent vegetation species. Analysis reveals strong performance for specific species despite overall segment accuracy being lower. Ground truth data validation ensured robustness and accuracy. This research demonstrates the transformative potential of UAV and AI technologies in railway vegetation management, empowering operators with advanced tools for efficiency, safety, and sustainability.**

Index Terms—**Railway trackside vegetation management, Unmanned Aerial Vehicle (UAV), Artificial Intelligence (AI), Canopy cover delineation, Vegetation species classification**

I. INTRODUCTION

Railway trackside vegetation management presents a formidable challenge for railway operators across the UK. Network Rail, as a primary custodian of the nation's rail infrastructure, annually expends significant resources on vegetation control efforts. However, traditional methodologies reliant on manual labor often prove inadequate in mitigating the proliferation of diverse plant species along railway tracks. According to Network Rail's Vegetation Management Strategy, over 2,500 miles of track are susceptible to vegetation-related issues, leading to approximately 1,500 annual delays and accounting for over 10% of all service-affecting incidents [1]. These delays have considerable economic repercussions, costing the UK economy an estimated £300 million per year [2] Moreover, the unchecked growth of vegetation poses safety hazards, with foliage encroachment contributing to over 600 signal failures annually [3]. Such failures not only disrupt rail services but also jeopardize passenger safety, emphasizing the critical need for effective vegetation management practices.

In addition to operational and safety concerns, inadequate vegetation management can have significant environmental impacts. Non-native invasive species, such as Japanese Knotweed and Himalayan Balsam, proliferate rapidly and outcompete native flora, leading to habitat degradation and loss of biodiversity [4]. The environmental cost of invasive species management in the UK exceeds £1.7 billion annually [5].

Railscape Ltd and the University of Essex have launched a joint venture to use UAVs and AI technology to revolutionise plant control tactics in response to the issues described in railway trackside vegetation management. The project, "Railway Trackside Vegetation Management using AI", automates the identification and categorization of plant species throughout railway corridors in the Anglia region by utilising cutting-edge machine learning techniques.

The segmentation and classification results demonstrate how important the built AI models are to this innovative strategy. The segmentation approach accurately distinguishes canopy cover in UAV images, offering information on the density of vegetation along railway tracks. Meanwhile, the classification model demonstrates remarkable accuracy in identifying a variety of plant species, making accurate species-level classification essential.

Railway operators stand to gain a great deal by utilising AI and UAV technology, such as better resource allocation, streamlined vegetation control procedures, and increased operating efficiency. The AI-driven strategy provides a proactive way to reduce vegetation-related dangers, which minimises service interruptions, boosts safety, and lessens environmental effects.

II. LITERATURE REVIEW

Railway trackside vegetation management has garnered attention from researchers and practitioners, with a focus on developing innovative solutions to mitigate challenges associated with vegetation encroachment along rail corridors. The utilization of Unmanned Aerial Vehicles (UAVs) for vegetation

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This work is supported by the UK Engineering and Physical Sciences Research Council through grants, EP/V034111/1 and Innovate UK (10003919).

monitoring has gained traction recently. Khoshelham and Elberink demonstrated the effectiveness of UAVs equipped with remote sensing instruments for high-resolution mapping of vegetation cover. Similarly, Anderson and Gaston highlighted the potential of UAV-based approaches for assessing vegetation health and biodiversity [6].

Artificial Intelligence (AI) techniques have shown promise in automating species identification processes. Beery et al. showcased the feasibility of using CNNs for automated plant species recognition, achieving high accuracy levels across diverse vegetation types [7] [8]. Projects like "PlantNet" have leveraged crowd sourced image databases and AI algorithms for plant species identification [9]. Several initiatives have explored the integration of UAV and AI technologies for vegetation management. Kučera et al. proposed a UAV-based system for real-time detection and classification of invasive plant species, demonstrating significant improvements in detection accuracy compared to traditional methods [10].

The "TreeSnap" project utilized UAV imagery and AI algorithms to monitor tree health and identify tree species in urban environments [11]. Efforts to enhance vegetation management practices within the railway domain have been documented. Helmiet al. explored the use of remote sensing technologies and GIS-based approaches for assessing vegetation encroachment along rail corridors, underscoring the importance of timely vegetation monitoring for maintaining rail network integrity [12]. Despite advancements, there is a need for further research to develop tailored solutions for railway trackside vegetation management. This paper aims to address this gap by integrating UAV and AI technologies to automate plant species identification and classification, thereby enhancing vegetation management efficiency.

III. METHODOLOGY

The methodology adopted for railway trackside vegetation management using UAV and AI technologies encompassed a comprehensive series of steps, including meticulous data collection, precise image labeling, sophisticated model development, rigorous validation, and eventual deployment. Each phase was executed with meticulous attention to ensure the accuracy, reliability, and effectiveness of the developed models.

A. Data Collection and Preprocessing

UAV imagery was collected using DJI Matrice 210 RTK drones with Zenmuse P1 cameras, chosen for high-resolution capabilities ideal for vegetation mapping. The Zenmuse P1 features a full-frame 45 MP sensor, ensuring precise image capture crucial for detailed vegetation analysis. These drones operated across three Network Rail-managed ELRs: "LTN," "BGK," and "ETN." RUAS, Railscape's drone and LiDAR data provider, conducted systematic data collection across the Anglia region throughout the year. Each flight covered 200 × 30 meters at 2 cm resolution, capturing Red, Green, Blue, and NIR spectral bands. Preprocessing steps included georeferencing to OSGB 1936 datum, orthorectification, and mosaic creation to integrate data accurately with railway infrastructure. Normalization of pixel values maintained consistent image quality, essential for precise vegetation classification and management along railway tracks.

B. Image Labeling

The acquired UAV images underwent meticulous labeling to identify and annotate twelve prominent plant species prevalent along railway tracks. This critical task was executed with precision using the ArcGIS Pro deep learning framework, which facilitated efficient and accurate labeling of vegetation species within the images. Dedicated arborist team leveraged the intuitive labeling tools provided by ArcGIS Pro to annotate vegetation regions, thereby creating ground truth data for model training and validation.

C. Model Development

By utilising the ArcGIS Pro deep learning framework, two distinct models were meticulously developed to address specific aspects of vegetation management.

1) Segmentation Model (Mask R-CNN with ResNet50 Backbone): The segmentation model focused on accurately delineating canopy cover within the UAV images. Mask R-CNN, an advanced instance segmentation algorithm, was employed for this purpose. This model utilized a region-based convolutional neural network (R-CNN) framework along with a mask prediction branch to precisely identify and segment vegetation regions. The ResNet50 backbone architecture, renowned for its depth and accuracy, provided the necessary feature extraction capabilities. To accommodate the complexities of railway trackside vegetation, the input size for this model was set at 1024 × 1024 pixels, ensuring detailed analysis of vegetation patterns and structures.

2) Classification Model (Feature Classifier with ResNet50 Backbone): By complementing the segmentation model, the classification model focused on accurately classifying segmented vegetation regions into specific plant species. This model employed a feature-based classification approach, wherein extracted features from the segmented regions were utilized for species classification. The ResNet50 backbone architecture facilitated feature extraction, enabling the model to discern subtle differences between different plant species. Similar to the segmentation model, the input size for this model was maintained at 1024 × 1024 pixels to ensure consistency and compatibility.

D. Model Validation

Model training and validation were conducted meticulously within the ArcGIS Pro deep learning framework. The following validation parameters were considered:

- Confusion Matrix: Confusion matrices were generated to provide a detailed breakdown of model predictions compared to ground truth labels. This facilitated the assessment of model performance across different vegetation classes.

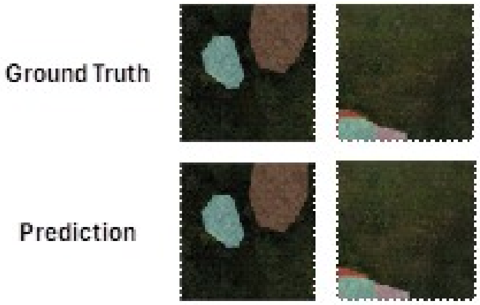


Fig. 1: Predicted output from Tree segmentation Model

Fig. 2: Predicted output from Species Classification Model

- F1 Score: The F1 score, a harmonic mean of precision and recall, served as a comprehensive metric for evaluating model accuracy. Higher F1 scores indicated robust performance in both precision and recall.
- Precision: Precision quantified the proportion of true positive predictions among all positive predictions made by the model. High precision values indicated minimal false positives in vegetation classification.
- Recall: Recall, also known as sensitivity, measured the proportion of true positive predictions captured by the model among all actual positive instances. High recall values indicated minimal false negatives in vegetation classification.

IV. RESULTS

A. Model Development

The development of the segmentation and classification models for railway trackside vegetation management involved rigorous training and evaluation processes. Both models were trained for 100 epochs to maximize accuracy, leveraging a substantial number of training chips.

1) Segmentation Model Results: The segmentation model achieved an average accuracy score of 78%, indicating its effectiveness in delineating canopy cover within UAV images.There a few reasons behind the precision score below the expected margin. Firstly, the vegetation cover alongside the railways track is too dense so it may be difficult to distinguish all the individual canopy cover even for a human eye. Secondly, the dataset considered for the model training needs to be more robust and if it were collected from different parts of the UK along with Anglia region, the precision score would have been much higher than currently it is. Approximately 22,000 training chips were utilized during the training process to ensure robust performance. The loss graph for the segmentation model depicted a gradual decrease in loss over the training epochs, indicating successful convergence of the model parameters.

Observations:

- The segmentation model exhibited satisfactory performance in delineating vegetation regions, capturing the overall canopy cover with reasonable accuracy.
- Despite achieving a moderate precision score, the model showcased consistent improvement over the training epochs, suggesting effective learning and adaptation to the dataset.

2) Classification Model Results: In contrast, the classification model yielded a significantly higher average precision score of 96%. This model utilized around 36,000 training chips, encompassing a diverse range of vegetation samples. Notably, the distribution of training samples was non-uniform, with a majority belonging to the most common plant species such as Sycamore and Common Ash. The loss graph for the classification model exhibited a similar trend of decreasing loss over the training epochs, indicating effective learning and convergence.

Observations:

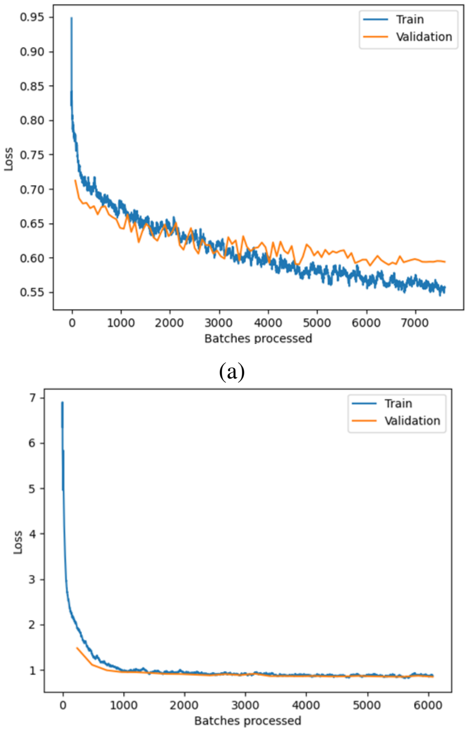
- The classification model demonstrated exceptional accuracy in classifying vegetation species, with a notably high average precision score.
- The utilization of a larger training dataset, coupled with the non-uniform distribution of samples, contributed to the model's ability to accurately differentiate between vegetation classes.
- The model exhibited robust performance, particularly in identifying prevalent species such as Sycamore and Common Ash, which constituted a significant portion of the training data.

B. Sample Size Distribution

The distribution of training samples per class varied, with some classes having substantially higher representation than others. For instance, Sycamore and Common Ash, being the most prevalent species, had the highest number of training samples, while other species had relatively fewer samples. This uneven distribution of samples was accounted for during model training and evaluation to ensure balanced performance across all vegetation classes.

C. Loss Graphs

The loss graphs are shown in Figure 3 and Figure 4 respectively, for both models depicted the optimization process during training, showcasing the reduction in loss over successive epochs. This trend indicated that the models effectively learned to minimise errors and improve accuracy over time. The convergence of loss indicated that the models successfully



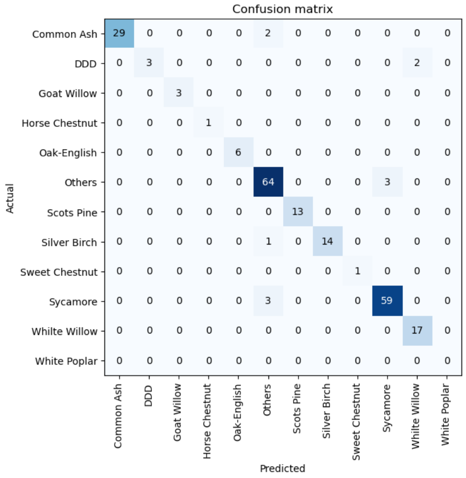
(a)

(b)

Fig. 3: Loss graph of tree segmentation model (a) and species classifier model (b).

TABLE I: Performance Metrics for Tree segmenation

Metric	**Calculation**	**Value**
True Positive (TP)	Correctly detected instances (Tree)	319
False Positive (FP)	Incorrectly detected instances (non-Tree)	124
False Negative (FN)	Missed instances (Tree not detected)	34
Accuracy	$(TP + TN)/(TP + TN + FP + FN)$	0.78
Precision	$(TP)/(TP + FP)$	0.72
Recall (Sensitivity)	$(TP)/(TP + FN)$	0.903
F1 Score	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	0.801



	Common Ash	DDD	Goat Willow	Horse Chestnut	Oak-English	Others	Scots Pine	Silver Birch	Sweet Chestnut	Sycamore	Whilte Willow	White Poplar
Common Ash	29	0	0	0	0	2	0	0	0	0	0	0
DDD	0	3	0	0	0	0	0	0	0	0	2	0
Goat Willow	0	0	3	0	0	0	0	0	0	0	0	0
Horse Chestnut	0	0	0	1	0	0	0	0	0	0	0	0
Oak-English	0	0	0	0	6	0	0	0	0	0	0	0
Others	0	0	0	0	0	64	0	0	0	3	0	0
Scots Pine	0	0	0	0	0	0	13	0	0	0	0	0
Silver Birch	0	0	0	0	0	1	0	14	0	0	0	0
Sweet Chestnut	0	0	0	0	0	0	0	0	1	0	0	0
Sycamore	0	0	0	0	0	3	0	0	0	59	0	0
Whilte Willow	0	0	0	0	0	0	0	0	0	0	17	0
White Poplar	0	0	0	0	0	0	0	0	0	0	0	0

Fig. 4: Confusion Matrix from the species classification model and ground truth

captured the underlying patterns and features of the vegetation data, enabling accurate segmentation and classification.

In summary, the segmentation and classification models demonstrated robust performance in delineating canopy cover and identifying plant species along railway tracks. While the segmentation model provided satisfactory precision, the classification model excelled with a significantly higher average precision score, highlighting its effectiveness in accurately classifying vegetation species. The utilization of extensive training data and careful consideration of sample distribution contributed to the models' overall effectiveness in addressing the challenges of railway trackside vegetation management. These validation parameters provided invaluable insights into the models' strengths and weaknesses, guiding subsequent refinements and optimizations to ensure optimal performance in real-world scenarios.

D. Model Validation

1) Validation of the classification Model: Based on the ground truth and model rendered output for the first model with a minimum Intersection over Union (IOU) threshold of 0.1, we can calculate various accuracy metrics. Here's the calculation presented in Table I.

From Table I it is observed that:

- Accuracy: approximately 78.0% of the model's predictions match the ground truth, considering both true positives and true negatives.
- Precision: 72.0% of the instances predicted as "Tree" by the model are indeed true positives, while the rest are false positives.
- Recall: 90.3% of the actual "Tree" instances present in the ground truth.
- F1 Score: A higher F1 score indicates a better balance between precision and recall. With an F1 score of 0.801, the model demonstrates reasonable performance in capturing both precision and recall.

Overall, these metrics collectively provide insights into the model's performance in detecting trees within the given dataset. While the model exhibits a relatively high recall, indicating its effectiveness in identifying true positives, there is room for improvement in terms of precision to minimize false positives and enhance overall accuracy.

2) Validation of the classification Model: The confusion matrix presented below provides a detailed breakdown of the classification results obtained from the second model. Each row represents the actual ground truth class collected from the field, while each column represents the predicted class by the model. It can be mentioned here that about 221 ground truths were collected from different ELR's in Anglia region. The numbers in the matrix indicate the count of instances where a particular class was predicted, given the actual ground truth. The calculations of accuracy and different metrics from the confusion matrix is shown below in Table II.

Table II provides a comprehensive overview of the model's

TABLE II: Validation Metrics of Classification Model

Class	**TP**	**FP**	**FN**	**Acc.**	**Prec.**	**Recall**	**F1**
Common Ash	29	0	2	0.96	1	0.94	0.97
DDD	3	2	0	0.94	0.60	1	0.75
Goat Willow	3	0	0	1	1	1	1
Horse Chestnut	1	0	0	1	1	1	1
Oak- English	6	0	0	1	1	1	1
Others	64	3	0	0.96	0.96	1	0.98
Scots Pine	13	0	0	1	1	1	1
Silver Birch	14	1	0	0.97	0.93	1	0.97
Sweet Chestnut	1	0	0	1	1	1	1

performance across different vegetation classes based on the confusion matrix analysis. Here are some key findings:

The model demonstrates strong performance across various metrics: accuracy ranges from 93.8% to 100%, ensuring effective classification of vegetation species. Precision scores, mostly above 90%, indicate the model's ability to minimize false positives. Recall scores reach 100% for all classes, reflecting the model's capability to identify positive instances accurately. F1 scores, ranging from 75.0% to 100%, highlight a balanced performance between precision and recall, crucial for minimizing false positives and negatives. Certain classes like "Common Ash," "Others," and "Sycamore" exhibit high precision and recall, demonstrating proficiency in identifying prevalent species. Classes with fewer samples, like "DDD" and "Sweet Chestnut," show slightly lower precision due to limited training data. This comprehensive analysis underscores the model's effectiveness in vegetation classification along railway tracks.

V. SUMMARY AND FINDINGS

The integration of UAV and AI technologies for railway trackside vegetation management has shown promising results in addressing manual maintenance challenges. Key findings from this research are summarised as follows:

- Collection of a dataset comprising 500 UAV images from three ELRs managed by Network Rail, with precise dimensions and spectral information.
- Development of segmentation and classification models using advanced AI algorithms (Mask R-CNN and feature classifier) trained for 100 epochs with extensive datasets.
- Validation of models using metrics such as confusion matrices, F1 scores, precision, and recall, with average accuracy scores of 78% for segmentation and 96% for classification. Ground truth data collection ensured robust evaluation.
- The segmentation model provided insights into vegetation density, while the classification model excelled in species classification. Both models showcased effective learning capabilities and convergence, contributing to improved vegetation management along railway tracks.

In a nutshell, the research underscores the effectiveness of UAV and AI technologies in enhancing vegetation management practices, offering valuable tools for proactive monitoring and maintenance in railway operations. Continued research and refinement hold the potential for further optimization and sustainability in railway infrastructure management.

VI. CONCLUSION

The convergence of UAV and AI technologies in railway trackside vegetation management offers a transformative opportunity to revolutionize traditional maintenance practices. By leveraging UAV imagery for high-resolution spatial data acquisition, detailed insights into vegetation density and species composition are gained. This dataset serves as the basis for developing AI-driven models, including segmentation and classification algorithms, which demonstrate remarkable capabilities in delineating canopy cover and accurately classifying vegetation species. Validation and evaluation of these models in real-world scenarios, supported by ground truth data collection, ensure robustness and accuracy. This research marks a pivotal shift towards data-driven vegetation management, enhancing operational efficiency, safety, and sustainability along railway corridors. Harnessing the synergies between UAV and AI technologies allows railway operators to proactively monitor and manage vegetation encroachments, mitigating risks and ensuring uninterrupted operations. Ongoing research and innovation promise further optimization of vegetation management strategies, guiding the railway network towards a safer, greener, and more connected future.

REFERENCES

[1] Network Rail, "Vegetation management strategy." https://www.networkrail.co.uk/who-we-are/how-we-work/vegetation-management/.

[2] Rail Delivery Group, "Delay attribution study." https://www.raildeliverygroup.com/.

[3] Rail Safety and Standards Board (RSSB), "Railway incident fact sheet." https://www.rssb.co.uk/.

[4] Environment Agency, "Non-native species secretariat." https://www.nonnativespecies.org/.

[5] F. Williams and R. Eschen, "The economic cost of invasive non-native species on great britain," *CABI*, 2020.

[6] K. Anderson and K. Gaston, "Lightweight unmanned aerial vehicles will revolutionize spatial ecology," *Frontiers in Ecology and the Environment*, vol. 11, pp. 138–146, 03 2013.

[7] L. Kouadio, M. El Jarroudi, Z. Belabess, S.-E. Laasli, M. Z. K. Roni, I. D. I. Amine, N. Mokhtari, F. Mokrini, J. Junk, and R. Lahlali, "A review on uav-based applications for plant disease detection and monitoring," *Remote Sensing*, vol. 15, no. 17, 2023.

[8] J. Su, D. Yi, M. Coombes, C. Liu, X. Zhai, K. McDonald-Maier, and W.-H. Chen, "Spectral analysis and mapping of blackgrass weed by leveraging machine learning and uav multispectral imagery," *Computers and Electronics in Agriculture*, vol. 192, p. 106621, 2022.

[9] S. M. Woods, M. Daskolia, A. Joly, P. Bonnet, K. Soacha, S. Liñan, T. Woods, J. Piera, and L. Ceccaroni, "How networks of citizen observatories can increase the quality and quantity of citizen-science-generated data used to monitor sdg indicators," *Sustainability*, vol. 14, no. 7, 2022.

[10] M. Kučera and Z. Dobesova, "Analysis of the degree of threat to railway infrastructure by falling tree vegetation," *ISPRS International Journal of Geo-Information*, vol. 10, no. 5, 2021.

[11] E. Crocker, B. Condon, A. Almsaeed, B. Jarret, C. Nelson, A. Abbott, D. Main, and M. Staton, "Treesnap: A citizen science app connecting tree enthusiasts and forest scientists," *Plants, People, Planet*, vol. 2, 06 2019.

[12] W. Helmi, R. Bridgelall, and T. Askarzadeh, "Remote sensing and machine learning for safer railways: A review," *Applied Sciences*, vol. 14, no. 9, 2024.