E-BOOK OF EXTENDED ABSTRACT
THE 14TH INTERNATIONAL INVENTION, INNOVATION & DESIGN COMPETITION 2025

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SEMANTICFORESTMY: A SPATIO-TEMPORAL REMOTE SENSING DATASET FOR FOREST AND NON-FOREST SEMANTIC SEGMENTATION

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ABSTRACT

Accurate classification of forest and non-forest regions in satellite imagery is vital for land monitoring. However, inconsistent annotations and limited standardised datasets hinder model comparability. SemanticForestMY addresses this issue with a high-resolution dataset derived from multi-temporal satellite data across three Malaysian regions. Annotations were produced using a hybrid method combining preprocessing, blob filtering, and manual correction. FCN32-VGG16 was used to benchmark performance, yielding 91.61% validation accuracy, a 94.52% F1-score, and an 89.60% IoU. These results validate the dataset's utility for deep learning segmentation. Future plans include multi-class expansion, seasonal coverage, and evaluation using advanced models.

Keywords: forest segmentation, deep learning, semantic segmentation, high-resolution dataset, remote sensing

1. INTRODUCTION

Semantic segmentation of forest and non-forest regions is essential for ecological surveillance, biodiversity preservation, and monitoring climate-related land changes. Although remote sensing data has become increasingly accessible, issues such as insufficient spatial resolution, variability in annotation accuracy, and inconsistent dataset partitioning protocols remain prevalent. To address these limitations, SemanticForestMY is proposed as a high-resolution dataset specifically designed for binary forest classification tasks. Developed using a structured and reproducible pipeline, the dataset ensures comprehensive spatial and temporal coverage. Building on recent advances in semi-automated and assisted labeling techniques (Md Jelas et al., 2023; Md Jelas et al., 2024), this dataset offers a reliable resource for training and evaluating deep learning-based semantic segmentation models in forest monitoring applications.

2. METHODOLOGY

The SemanticForestMY dataset was constructed to address the critical need for a high-resolution, high-quality forest and non-forest segmentation benchmark using remote sensing imagery. The dataset construction pipeline follows a multi-stage procedure, including systematic satellite data acquisition, automated ground truth annotation, manual refinement, and standardised dataset partitioning strategies.

2.1 Dataset Acquisition
Satellite images were acquired using Google Earth Pro, leveraging its extensive archive of high-resolution imagery, particularly from Landsat missions (Md Jelas et al., 2024). Three ecologically significant regions in Malaysia were selected:
  i.   Endau Rompin (2°30'42.20"N, 103°32'56.39"E) – a biodiversity hotspot,
 ii.   Royal Belum (5°47'9.93"N, 101°30'51.44"E) – a vital rainforest reserve,
iii.   Tasik Chini (3°22'32.82"N, 102°36'11.18"E) – the second-largest freshwater lake ecosystem.

Images from 1990, 2000, and 2010 were collected for each region, enabling multi-decadal analysis. Saved in PNG format at a maximum resolution of 8192 × 4883 pixels, each image covered approximately 137,500 meters, providing sufficient landscape detail.

2.2 Ground Truth Annotation

Ground truth labels were generated through a semi-automated process (Md Jelas et al., 2023) and refined in subsequent work (Md Jelas et al., 2024). The annotation procedure included:

i. Color Channel Separation: Each satellite image was decomposed into its red, green, and blue channels. The green channel was selected for analysis due to its strong vegetation signal.
ii. Gaussian Blur Application: A Gaussian filter was applied to the green channel to reduce high-frequency noise and smooth texture variations without severely distorting forest boundaries.
iii. Thresholding: Otsu's Thresholding was applied to determine an optimal global threshold. Global Thresholding based on Otsu's value was applied to generate binary masks distinguishing between forest (white) and non-forest (black) regions.
iv. Noise Reduction: The SimpleBlobDetector tool from OpenCV 4.7.0 was used to eliminate minor speckles and irrelevant blobs.
v. Manual Refinement: Final corrections were made near edges, water bodies, and cloud cover, improving overall mask accuracy.

This two-phase method ensured both efficiency and accuracy while reducing annotation bias.

2.3 Tile Generation and Dataset Partitioning

The annotated images were subdivided into uniform 224 × 224 pixel tiles, yielding 756 tiles per area per year. Dataset partitioning followed a reproducible strategy with constraints to ensure diversity (Md Jelas et al., 2024):

i. Random State Constraints: Values were selected without repetition. No more than two values were taken from the same consecutive tens group. Values were sorted to achieve a minimum sum of differences exceeding 40.
ii. Partitioning Ratios: The train_test_split function from sklearn.model_selection was used to divide the dataset as follows: 70% for training, 20% for testing, and 10% for validation.
iii. Final Tile Counts (All Areas Combined): The final dataset includes 4,761 training tiles, 675 validation tiles, and 1,368 testing tiles.

No augmentation techniques such as flipping, rotation, or color jittering were applied to maintain data authenticity.

3. FINDINGS

The performance of the SemanticForestMY dataset was assessed using a Fully Convolutional Network (FCN32) architecture with a VGG16 backbone, a widely recognised configuration for early semantic segmentation benchmarks. The model was trained on 4,761 image-mask pairs and validated on 675 samples. The training process used a 224×224×3 input size, binary cross-entropy loss, and the Adam optimiser with a learning rate of 0.001 for 100 epochs. Evaluation results are presented in Table 1.

Table 1 FCN32-VGG16 segmentation performance on SemanticForestMY dataset.

Metric	Accuracy	Loss	Precision	Recall	F1 Score	IoU	Runtime
Training (%)	95.09%	11.17%	96.18%	97.21%	96.68%	93.62%	2h 55m 35s
Validation (%)	91.61%	30.09%	92.80%	96.31%	94.52%	89.60%	

The FCN32-VGG16 model demonstrated strong training performance, achieving an F1-Score of 96.68% and an IoU of 93.62%, indicating effective learning of the spatial patterns in forest and non-forest regions. On the validation set, the model achieved an accuracy of 91.61%, a high F1-Score of 94.52%, and a robust IoU of 89.60%, confirming that SemanticForestMY provides a reliable basis for pixel-wise segmentation tasks.

Despite this, a notable increase in validation loss (30.09%) compared to training loss (11.17%) suggests overfitting, highlighting the importance of future enhancements such as regularisation techniques, architectural tuning, or augmentation strategies. The model's high recall on both training (97.21%) and validation (96.31%) further supports its strength in capturing forest class boundaries—critical in minimising false negatives in deforestation monitoring.

Overall, the findings validate that SemanticForestMY effectively supports deep learning-based semantic segmentation. FCN32-VGG16, although a foundational architecture, performs competitively and sets a strong baseline. Future work may consider extending experiments with deeper encoders, attention mechanisms, or lightweight variants to improve generalisability while maintaining computational efficiency.

4. CONCLUSION

This study introduces SemanticForestMY, a high-resolution remote sensing dataset tailored for forest and non-forest semantic segmentation. Using a Fully Convolutional Network (FCN32) with a VGG16 backbone as the baseline model, the dataset achieved validation accuracy of of 91.61%, F1-Score of 94.52%, and an IoU of 89.60%, validating its effectiveness for spatially complex segmentation tasks. These results affirm the capability of SemanticForestMY to support classical deep learning architectures while revealing areas for improvement in generalisation. The observed discrepancy between training and validation loss underscores the importance of incorporating regularisation techniques or exploring advanced architectures to mitigate overfitting. Nonetheless, the high recall and precision values validate the dataset's annotation quality and diversity across spatial and temporal dimensions.
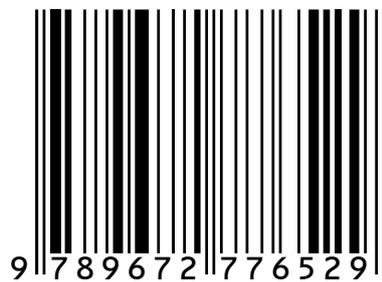
SemanticForestMY thus offers a reproducible, well-structured, and ecologically diverse foundation for developing and benchmarking forest segmentation models. Moving forward, expanding the dataset to support multi-class land cover segmentation, integrating seasonal variability, and applying augmentation techniques will further enhance its value for deep learning-based environmental monitoring. Additionally, future evaluations with transformer-based architectures and hybrid segmentation models may uncover new directions for improving segmentation robustness across diverse forest conditions.

REFERENCES

Md Jelas, I., Zulkifley, M. A., & Abdullah, M. (2023). Automated Ground Truth Annotation for Forest and Non-Forest Classification in Satellite Remote Sensing Images. *2023 4th International Conference on Artificial Intelligence and Data Sciences: Discovering Technological Advancement in Artificial Intelligence and Data Science, AiDAS 2023 - Proceedings*, 331–336. https://doi.org/10.1109/AiDAS60501.2023.10284683

Md Jelas, I., Zulkifley, M. A., & Abdullah, M. (2024). Forest Segmentation: Spatio-Temporal Ground Truth Labelling via Assisted Annotation. *2024 IEEE 8th International Conference on Signal and Image Processing Applications, ICSIPA 2024*. https://doi.org/10.1109/ICSIPA62061.2024.10686968

Md Jelas, I., Zulkifley, M. A., Abdullah, M., & Spraggon, M. (2024). Deforestation detection using deep learning-based semantic segmentation techniques: a systematic review. In *Frontiers in Forests and Global Change* (Vol. 7). Frontiers Media SA. https://doi.org/10.3389/ffgc.2024.1300060

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