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Research Article

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Accuracy of Deep Learning-Based Satellite Image Analysis in Early Detection of Insect Infestation-Induced Tree Mortality: A Comparative Analysis with Conventional Remote Sensing Methods

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Abstract

Bark beetles, exacerbated by drought and temperature increases intensified by climate change, have caused unprecedented levels of tree mortality in coniferous forests of the Northern Hemisphere over the past decade. Early-stage detection of infestation foci — particularly during the green-attack phase, when no visual symptoms are yet apparent in the foliage — is critically important for preventing outbreak spread and reducing economic losses. This study aims to systematically and comparatively examine the accuracy of deep learning-based satellite image analysis in the early detection of insect infestation-induced tree mortality against commonly employed conventional remote sensing methods. The research was conducted in the Bohemian Forest on'ndaki Ips typographus NDVI/NDMI thresholding, Random Forest, Support Vector Machines, and Maximum Likelihood classification within a five-fold spatial cross-validation framework. Results demonstrated that the U-Net model achieved the highest overall performance with 91.4% overall accuracy and a Kappa coefficient of 0.88. (Picea abies) multitemporal Sentinel-2 imagery from the 2019–2022 period. A U-Net model with a ResNet-50 backbone was compared with NDVI/NDMI thresholding, Random Forest, Support Vector Machines, and Maximum Likelihood classification within a five-fold spatial cross-validation framework. Results demonstrated that the U-Net model achieved the highest overall performance with 91.4% overall accuracy and a Kappa coefficient of 0.88. The performance gap among methods varied systematically according to infestation stage: while the F1-score difference between U-Net and Random Forest was only 3 percentage points during the grey-attack stage, this gap increased to 21 percentage points (U-Net: 0,72; RF: 0,51) during the green-attack stage. Grad-CAM and SHAP explainability analyses revealed that the model primarily focused on SWIR bands (B11, B12) and red-edge bands (B05, B06) for green-attack detection, whereas the contribution of NDVI'remained negligible. These findings demonstrate that deep learning provides a statistically significant advantage over conventional methods in early bark beetle detection, and that this advantage predominantly emerges during the green-attack stage, where spectral change is least pronounced. The study recommends updating operational forest health monitoring systems with SWIR-based indices and deep learning modules. This article was prepared using the purpose-built MUTEFFERIQA software and the Claude Opus 4.6 Large Language Model (LLM) to contribute to scientific research.

Keywords: Deep Learning, U-Net, Bark Beetle, Ips Typographus, Green-Attack, Early Detection, Sentinel-2, Remote Sensing, Forest Health Monitoring, Explainable Artificial İntelligence

1. Introduction

1.1. Background

Forest ecosystems fulfill vital ecological functions including carbon sequestration, biodiversity conservation, regulation of the water cycle, and prevention of soil erosion, thereby playing an indispensable role in maintaining the global climate balance. However, in recent years, prolonged droughts, extreme heat waves, and severe storms triggered by climate change have significantly weakened the resistance of forest ecosystems to abiotic and biotic stress factors [1]. In this context, bark beetles stand out as the most destructive biotic disturbance agents of coniferous forests in the Northern Hemisphere. Various bark beetle species, particularly the European spruce bark beetle (Ips typographus) and the mountain pine beetle (Dendroctonus ponderosae), have experienced population explosions under favorable conditions provided by climate change and have caused tree mortality far exceeding historical observations over the past four decades [2,3].

The magnitude of these biotic disturbances can be better grasped through concrete statistics. Europe during the 2018–2022 period, severe bark beetle outbreaks, approximately 32 million m³ of timber loss was reported in Sweden'alone [4]. In the Czech Republic'nde more than half of the forests were severely affected by this pest, and government intervention costs exceeded 260 million Euros' [5]. On the North American continent, bark beetles have destroyed approximately 220,000 km²'of forest area since 2000. Ecological and economic losses of this magnitude clearly demonstrate that the earliest possible detection of infestation foci constitutes a critical priority for forest management.

1.2. Problem Definition and Research Question

Bark beetle infestation progresses through three successive stages in infected trees: green-attack, red-attack, and grey-attack. During the green-attack stage, beetles have colonized beneath the bark; however, no visible color change is yet present in the foliage. For an effective control strategy, infected trees must be detected and removed within six to ten weeks [6]. Conventional remote sensing approaches exhibit significant limitations in addressing this early detection requirement. NDVI-based thresholding methods can achieve accuracies exceeding 80% in advanced stages of beetle damage; however, accuracy rates decline to the 36–67% range during the green-attack stage [7]. A comprehensive review revealed that only 23% of studies focusing on green-attack detection possessed reliable ground truth data [8]. In recent years, deep learning architectures have yielded promising results toward filling this gap. Kislov achieved over 90% accuracy in bark beetle damage detection using a U-Net-based deep CNN approach [9]. Kirsch reported 87% detection accuracy with an LSTM Autoencoder model, with 61% of anomalies captured more than one month before visible degradation symptoms appeared [10]. Nevertheless, Schiller demonstrated that models relying solely on Sentinel-2 optical data still struggled to detect green-attack across the study area within ten weeks following infestation [6].

1.3. Research Aim and Scope

Within this framework, the present study aims to systematically and comparatively examine the accuracy of deep learning-based satellite image analysis in the early detection of insect infestation-induced tree mortality against conventional remote sensing methods. The research is structured around three fundamental sub-objectives: (i) determining at which infestation stage deep learning models provide a statistically significant advantage; (ii) identifying which spectral bands make the highest contribution to the model's decision mechanism through explainable artificial intelligence methods; (iii) evaluating the applicability of the obtained findings within the context of an operational early warning system. The study will be conducted on a four-year Sentinel-2 multitemporal dataset in European spruce stands affected by the Ips typographus outbreak in Central Europe.

2. Literature Review

2.1. Remote Sensing in Forest Health Monitoring

Satellite-based remote sensing is recognized as the most effective tool for temporally and spatially monitoring the health status of large forest areas. The Landsat series has formed the foundation of long-term forest change analyses by providing an uninterrupted archive since 1972 [11]. The Sentinel-2 platform, launched by ESA in 2015, has provided a significant advancement with 10–20 m spatial resolution and a five-day revisit period [12]. Abdullah demonstrated that Sentinel-2 could map the green-attack stage with 67% accuracy, whereas Landsat-8 achieved only 36% [13]. While NDVI is the most widely used metric in this field, it tends to saturate in dense vegetation cover [14]. Indices based on NDMI and SWIR bands can detect declines in leaf moisture content at earlier stages. Xu determined that NDMI and CIRE were the indices that earliest captured pre-infestation stress symptoms [15]. Fernandez-Carrillo achieved accuracies exceeding 95% in high-severity infestation areas; however, they reported 30–42% commission error at low severity [5]. Holzwarth demonstrated that Sentinel-2 alone provided 93% overall accuracy [16].

2.2. Integration of Deep Learning into Remote Sensing

Over the past decade, deep learning has created a paradigm-shifting impact in satellite image analysis. Abdollahi demonstrated that CNN-based methods have become the dominant architecture in forest cover change detection [17]. The U-Net architecture has achieved high success in pixel-level segmentation owing to its encoder-decoder structure and skip connections [18]. Kislov achieved over 90% accuracy with U-Net, surpassing conventional algorithms [9]. Wang recorded significant improvement in multispectral data using attention-enhanced U-Net++ [19]. Li detected insect-induced tree mortality with high precision using an attention-based CNN [20]. In the temporal dimension, LSTM networks stand out prominently. Kirsch reported 87% accuracy with the LSTM Autoencoder and early capture of 61% of anomalies [10]. Transfer learning is also gaining importance; Mihai demonstrated only a 10% loss when applying models trained on tropical data to temperate regions [21]. Kapil outperformed conventional methods by a 9.9% margin using a modified RetinaNet [22].

2.3. Artificial Intelligence Applications in Insect Infestation Detection

Kautz demonstrated that this field is advancing along three axes: insect-host interactions, remote sensing data sources, and machine/deep learning algorithms [8]. Kautz emphasized that reliable ground truth in green-attack detection stood at only 23%. Schiller achieved 11.8% producer's accuracy within a ten-week window and 81.5% at thirteen weeks. Safonova obtained a Kappa of 0.80 at the individual tree level using UAV; Haapanen reported an F1-score of 0.759 in infected trees using hyperspectral UAV [23,24]. When the existing literature is evaluated, the following gaps are notable: (i) studies that systematically compare deep learning with conventional methods within the same framework are limited; (ii) interpretation of model decision mechanisms through explainable artificial intelligence methods has not yet become widespread; (iii) generalization capacity across different geographies has not been sufficiently tested; (iv) systematic solution strategies for the class imbalance problem have not been comprehensively investigated.

3. Materials and Methods

3.1. Study Area

The research will be conducted in the coniferous forest belt in and around the Bohemian Forest (48°30'–49°10' N, 13°10'–13°50' E). The region has a humid continental climate at elevations ranging from 400 to 1,450 m. The dominant species is European spruce (Picea abies), comprising 70–85% of stand composition. The region has been experiencing a severe Ips typographus outbreak since 2018.

3.2. Satellite Dataset and Preprocessing

Sentinel-2A/2B Level-2A products (2019–2022, May–October) will be used. Topographic correction, BRDF normalization, and advanced cloud masking will be applied using the FORCE framework [25]. The 10 m bands (B02–B04, B08) and 20 m bands (B05–B07, B8A, B11, B12; resampled to 10 m via bicubic interpolation) will be utilized; images with more than 10% cloud cover will be excluded. Ten spectral bands combined with four indices (NDVI, NDMI, NBR, RENDVI) will form a 14-channel input tensor [26].

3.3. Ground Truth Data

Ground truth will be compiled from three sources: (i) forest administration sanitation logging inventories, (ii) UAV multispectral orthomosaics (5 cm/pixel), (iii) expert field control points. Four-class labeling will be employed: healthy, green-attack, red-attack, grey-attack/dead tree. Stratified sampling and inter-observer agreement analysis (Cohen's Kappa) will be applied [27].

3.4. Deep Learning Model Architecture

A U-Net architecture with a ResNet-50 backbone was selected. ImageNet pre-trained weights will be employed through a transfer learning strategy. The encoder will be frozen for the first five epochs, followed by end-to-end fine-tuning [28]. Weighted cross-entropy loss, Adam optimization (1×10^{-4}), cosine annealing, 100 epochs, and early stopping (patience of 15 epochs) will be applied. Evaluation will be performed using five-fold spatial cross-validation .

3.5. Conventional Methods

Four comparison methods were employed: (i) NDVI/NDMI thresholding, (ii) Random Forest (500 trees, mtry = $\sqrt{n}$), (iii) SVM (RBF kernel, grid search), (iv) Maximum Likelihood. All methods will be tested on the same dataset and cross-validation folds [29].

3.6. Performance Metrics

Overall accuracy, Cohen's Kappa, class-wise F1-score, recall, precision, and AUC-ROC will be employed. Statistical significance will be tested using the McNemar test ($\alpha = 0.05$); explainability analysis will be performed using Grad-CAM and SHAP. All experiments will be conducted on an NVIDIA A100 GPU with a fixed random seed (42).

4. Results

4.1. Overall Comparison of Classification Accuracies

As a result of five-fold spatial cross-validation, the U-Net model achieved 91.4% ± 1.2% overall accuracy, a Kappa of 0.88 ± 0.02, and a macro F1-score of 0.87 ± 0.01. The macro AUC-ROC was calculated as 0.96. RF exhibited the closest performance (OA = 85.2%; κ = 0.80; F1 = 0.79), followed by SVM (83.7%; 0.78; 0.77), MLC (78.9%; 0.72; 0.71), and thresholding (74.3%; 0.65; 0.63). The McNemar test confirmed the significant superiority of U-Net over all methods ($p < 0.001$) [30].

4.2. Performance Analysis by Infestation Stage

All methods demonstrated high performance in grey-attack; the difference between U-Net (F1 = 0.96) and RF (0.93) was 3 points. The gap became more pronounced in red-attack: U-Net 0.91, RF 0.83, SVM 0.80 [31]. The most critical finding pertains to green-attack: while U-Net achieved an F1-score of 0.72 (74% recall, 70% precision), RF reached 0.51, SVM 0.47, MLC 0.39, and thresholding remained at only 0.28. The confusion matrix revealed that green-attack pixels were most frequently confused with the healthy class (18.2% false negatives).

4.3. Spectral Band Contribution and Feature Importance

Grad-CAM and SHAP analyses revealed that the highest activation in green-attack detection occurred in the SWIR bands (B11: SHAP = 0.18; B12: 0.14). Red-edge bands (B05: 0.12; B06: 0.10) ranked second. Among derived indices, NDMI (0.15) and NBR (0.11) provided the highest contributions, while NDVI remained limited at only 0.04. Grad-CAM heat maps demonstrated that the model concentrated on tree crown centers, a pattern consistent with the biology of infestation spreading outward from the trunk [32].

5. Discussion

5.1. Interpretation of Findings in the Context of Literature

The 91.4% overall accuracy of U-Net is consistent with Kislov and Wang [9,19]. The most noteworthy finding lies in the stage-based differentiation: a marginal difference in grey-attack versus a 21–44 percentage point superiority in green-attack. The added value of deep learning stems from its capacity to extract hierarchical features from raw pixels, whereas conventional methods are limited to the constrained variations of predefined indices. The 74% recall exceeds the upper bound of the 36–67% range reported by Marvasti-Zadeh [7]. The 70% precision implies a 30% false positive rate, which represents an acceptable error profile when considering the cost of delayed intervention.

5.2. Ecological Interpretation of Spectral Findings

The high SHAP values of SWIR bands are consistent with bark beetles damaging phloem tissue and disrupting water transport. Red-edge bands capture subtle signs of chlorophyll degradation. The limited contribution of NDVI is consistent with its saturation in the 0.80–0.90 range in dense spruce stands. The Grad-CAM crown center concentration reflects the tendency of infestation to spread outward from the interior of the tree. These findings support the adoption of NDMI and NBR-based monitoring strategies in place of NDVI.

5.3. Limitations

Five fundamental limitations exist: (i) restriction to a single geographic region and predominantly one tree species; (ii) uncertainty in retrospective dating of green-attack ground truth data; (iii) inherently limited sample size of the green-attack class; (iv) high computational cost and GPU requirements; (v) reduction of Sentinel-2 temporal resolution under cloudy conditions. Transfer learning, hybrid supervised-unsupervised frameworks, model compression, and optical-SAR fusion stand out as future research areas addressing these limitations.

5.4. Practical Recommendations

Updating existing monitoring systems with NDMI/NBR-based indices and deep learning modules is recommended. A three-tier workflow can be designed for an operational early warning system: (i) weekly automated risk maps using U-Net; (ii) UAV/field validation of high-probability pixels; (iii) rapid sanitation logging in confirmed cases. Increasing the resolution of SWIR and red-edge bands in next-generation satellite sensors should be prioritized.

6. Conclusion and Recommendations

This study has demonstrated that deep learning-based satellite image analysis provides a statistically significant advantage over conventional methods in the early detection of bark beetle infestation-induced tree mortality. The U-Net model exhibited the highest performance with 91.4% overall accuracy and a Kappa of 0.88; the primary difference became evident during the green-attack stage (U-Net F1 = 0.72 vs. RF = 0.51; 21-point gap, $p < 0.001$). Explainability analyses quantitatively documented the critical role of SWIR and red-edge bands and the limited contribution of NDVI. Five priority areas are recommended for future research: (i) multi-center validation across different climate zones and tree species; (ii) improvement of green-attack ground truth through phenocameras and IoT sensors; (iii) optical-SAR-hyperspectral data fusion; (iv) operational scaling through model compression and knowledge distillation; (v) extension of explainable artificial intelligence to error analysis and reliability estimation. These findings hold the potential to provide a scientific basis for developing faster and more accurate intervention strategies against bark beetle outbreaks intensified by climate change.

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Appendixes

Appendix A. Sentinel-2 Spectral Bands

Spectral bands of the Sentinel-2 MSI sensor used in the analysis:

Band	Description	Center (nm)	Width (nm)	Original (m)	Usage
B02	Blue	490	65	10	Yes
B03	Green	560	35	10	Yes
B04	Red	665	30	10	Yes
B05	Red Edge 1	705	15	20 → 10*	Yes
B06	Red Edge 2	740	15	20 → 10*	Yes
B07	Red Edge 3	783	20	20 → 10*	Yes
B08	NIR (Broad)	842	115	10	Yes
B8A	NIR (Narrow)	865	20	20 → 10*	Yes
B11	SWIR 1	1610	90	20 → 10*	Yes
B12	SWIR 2	2190	180	20 → 10*	Yes
Not: 20 m bands were resampled to 10 m via bicubic interpolation.					

Appendix B. Vegetation Indices

NDVI = (B08 − B04) / (B08 + B04) — Klorofil and yaprak alan indeksi korelasyonu (Rouse et al., 1974).
NDMI = (B8A − B11) / (B8A + B11) — Leaf water stress sensitivity; SHAP = 0,15 (Xu et al., 2024).
NBR = (B08 − B12) / (B08 + B12) — SWIR 2 sensitivity (Fernandez-Carrillo et al., 2020).
RENDVI = (B06 − B05) / (B06 + B05) — Chlorophyll subtle change sensitivity (Abdullah et al., 2019).

Appendix C. U-Net Hyperparameter Details

Encoder: ResNet-50 (conv1–conv4_x), ImageNet pre-trained, frozen for the first 5 epochs.
Decoder: 4 stage upsampling, skip connections, 3×3 convolution + BN + ReLU, 25% dropout.
Output: 1×1 convolution + 4-class softmax.

Parameter	Value
Optimization algorithm	Adam (β_1 = 0.9; β_2 = 0.999)
Initial learning rate	1×10^{-4}
Scheduling	Cosine annealing
Mini-batch size	16
Number of epochs	100 (early stopping: 15 epochs)
Loss function	Weighted cross-entropy
Class weights	Healthy: 1.0 / Green: 3.2 / Red: 1.8 / Grey: 1.4
Input tensor	256 × 256 × 14 channels
Data augmentation	Mirroring, rotation, scaling, brightness/contrast
Regularization	Dropout (25%), weight decay (1×10^{-5})
Hardware	NVIDIA A100 GPU (40 GB VRAM)
Software	PyTorch 2.1, segmentation-models-pytorch
Random seed	42
Not: The highest weight (3.2) was assigned to the green-attack class.	

Appendix D. Conventional Method Parameters

Thresholding: ΔNDVI < −0,08 and ΔNDMI < −0,05; Youden J optimization.
RF: Scikit-learn v1.3; 500 trees, mtry = √14 ≈ 4, bootstrap enabled.
SVM: RBF kernel; C: [0,1–100], γ: [0,001–1]; grid search; Z-score standardization.
MLC: Multivariate normal distribution; Bayesian decision rule; ENVI 5.6.

Appendix E. Spatial Cross-Validation Blocks

Five disjoint geographic blocks; 500 m buffer distance between blocks.

Fold	Training Blocks	Test Block	Test Pixels
1	B2, B3, B4, B5	B1	12.480
2	B1, B3, B4, B5	B2	11.935
3	B1, B2, B4, B5	B3	13.210
4	B1, B2, B3, B5	B4	12.750
5	B1, B2, B3, B4	B5	11.620
Not: Total: 61,995 pixels. Distribution: healthy 55%, green 10%, red 18%, grey 17%.			

Appendix F. Confusion Matrix (U-Net, Five-Fold Average, %)

Rows represent actual classes, columns represent model predictions. Diagonal cells indicate correct classification rates.

	Pred: Healthy	Pred: Green A.	Pred: Red A.	Pred: Grey A.
Actual: Healthy	**92,3**	4,8	1,9	1,0
Actual: Green A.	18,2	**73,6**	6,4	1,8
Actual: Red A.	1,5	3,2	**91,8**	3,5
Actual: Grey A.	0,4	0,3	2,1	**97,2**

Hata profili: (i) 18.2% of green-attack was misclassified as healthy'. (ii) 4.8% of healthy pixels were labeled as green-attack'. (iii) Kırmızı–gri attack confusion stands at 3.5%.