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Enhanced vegetation encroachment detection along power transmission corridors using random forest algorithm

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ABSTRACT

Vegetation encroachment along power transmission corridors poses significant risks to infrastructure safety and reliability, necessitating effective monitoring and management strategies. This study introduces an innovative methodology for detecting vegetation encroachment using a combination of manual and automatic processes integrated with the random forest algorithm. The issue of vegetation encroachment is critical as it can lead to power interruptions and safety hazards if not addressed promptly. The objective of this research is to develop a scalable and cost-effective solution for vegetation management in power infrastructure maintenance. The methodology involves manual patch extraction and labeling to ensure the accuracy of the training dataset, combined with automatic feature extraction techniques to capture relevant information from satellite imagery. Leveraging the random forest algorithm, the model constructs an ensemble of decision trees based on the extracted features, achieving robust classification accuracy. Findings from this study demonstrate that the proposed approach enables consistent and timely identification of vegetation encroachment in new satellite imagery. Stored model parameters facilitate efficient testing, enhancing the system's ability to provide proactive interventions. This scalable solution significantly reduces reliance on manual labor and offers a cost-effective method for continuous monitoring, ultimately contributing to the resilience and safety of power transmission infrastructure.

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1. INTRODUCTION

The delivery of electrical power to end users involves several crucial steps, including generation, transmission, and distribution. Among these, power transmission lines serve as the backbone infrastructure of the transmission process. However, various environmental factors pose risks to this process, including forest fires, wind storms, and vegetation encroachment [1]. Vegetation encroachment, in particular, presents a significant challenge during the installation, operation, and maintenance of transmission lines, especially in areas with dense vegetation [2]. Overgrown trees can lead to flashovers when their branches come into contact with transmission lines, as depicted in Figure 1. In Malaysia, a country with more than 60% forested terrain, approximately 17.58% of power interruptions in the state of Sarawak from 2005 to 2008 were attributed to vegetation encroachment [3]. Figure 1 shows transmission vegetation management. Monitoring vegetation encroachment traditionally involves patrol inspection, where teams of inspectors periodically visit areas of potential risk. However, this method is time-consuming and requires a large workforce [4]. Advanced optical remote sensing technologies, such as LiDAR data, synthetic aperture radar (SAR) data, and airborne photogrammetry, offer effective alternatives for monitoring vegetation encroachment, particularly in remote areas [5]. Despite their effectiveness, these methods entail high costs for data acquisition, especially concerning coverage area. To address this cost limitation, high-resolution satellite imagery presents a viable solution, offering wide geographic coverage at relatively lower costs [6].

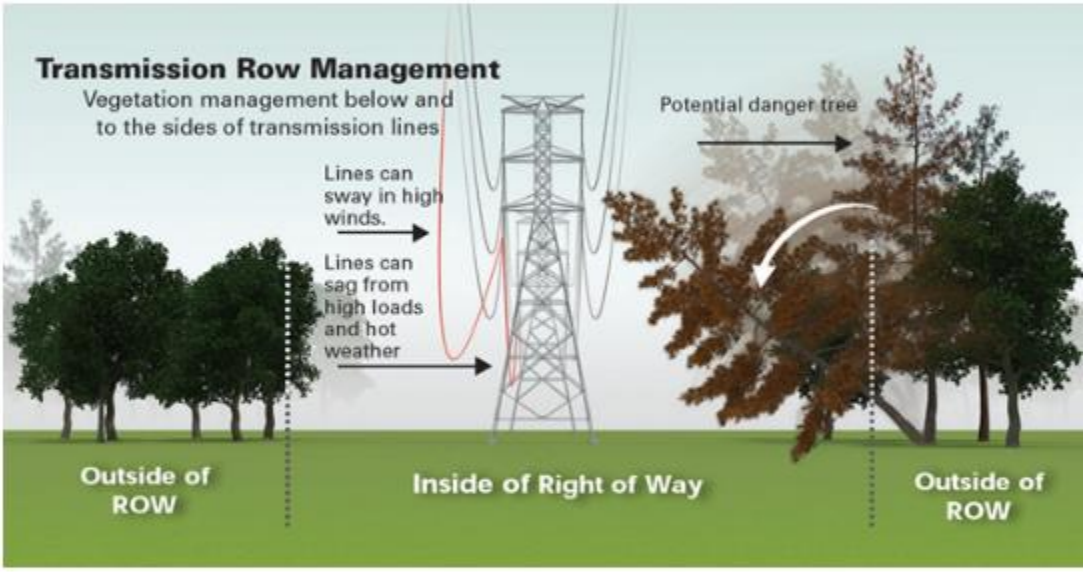

Figure 1. Shows the transmission vegetation management

Various studies have explored the feasibility of using satellite images for monitoring vegetation encroachment, broadly categorized into two groups. The first group employs vegetation index methods, such as the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), and atmospherically resistant vegetation index (ARVI), to detect vegetation activity along power line corridors [7]. Most studies in this category focus on NDVI, leveraging the natural properties of green plants to absorb red light and reflect near-infrared (NIR) light. However, the effectiveness of this method depends on the availability of multispectral satellite data for the target location [8]. The second group utilizes stereo satellite images to generate digital elevation models (DEMs), estimating the heights of objects surrounding transmission line corridors [9]. While this method offers advantages in height estimation, the availability of suitable-resolution stereo image data can be limited [10]-[13]. Additionally, visible light bands in high-resolution satellite images present a cost-effective alternative to previous methods, readily accessible through platforms such as Google Maps and Google Earth. Despite these advancements, several issues remain unresolved:

– High acquisition costs for LiDAR and SAR data.
– Limited availability of suitable-resolution stereo image data.
– Dependence on multispectral satellite data for effective NDVI application.

This paper addresses these gaps by exploring the feasibility of using visible light band spectrum and texture properties of satellite images to classify vegetation regions adjacent to power line corridors using the random forest algorithm [14]-[17]. The subsequent sections will demonstrate how this approach can be effectively implemented, providing a cost-effective, scalable solution for vegetation encroachment monitoring in power transmission lines. We will also discuss the implications of our findings and suggest directions for future research to enhance the reliability and efficiency of power transmission systems [18]-[21].

2. METHOD

The proposed vegetation encroachment detection process, as depicted in Figure 2, comprises two main steps: training and testing. In the training phase, patches are manually extracted from satellite images and labeled to indicate the presence or absence of vegetation encroachment [22]-[24]. Features are then automatically extracted from these labeled patches and used to train a random forest classifier. During the testing phase, new patches are automatically extracted from satellite images, and the trained model predicts the presence of vegetation encroachment based on the extracted features. This two-step process ensures the model can accurately identify areas of concern along power transmission lines. Figure 2 illustrates the block diagram of the proposed method [25].

Training and testing steps:

a) Manual patch extraction and labelling:

Training Phase:
- Patches are manually extracted from satellite imagery, focusing on areas along power transmission lines.
- Each patch is meticulously labeled to indicate the presence or absence of vegetation encroachment, ensuring the accuracy of the training dataset.
- This manual labeling process provides ground truth information essential for the machine learning model's training.

b) Automatic feature extraction:
- Following patch extraction and labeling, an automatic feature extraction process is employed to derive meaningful features from the satellite imagery.
- Features including statistical moments, textural properties, and spectral characteristics are consistently extracted from both training and testing patches.
- The goal is to capture relevant information that distinguishes between patches with and without vegetation encroachment.

c) Random forest training:
- The extracted features are utilized to train a random forest classifier, a robust supervised learning algorithm capable of handling complex datasets and achieving high classification accuracy.
- During training, the random forest algorithm constructs multiple decision trees based on subsets of the training data and features.
- These decision trees collectively form an ensemble model, combining their predictions to classify vegetation-encroached and non-encroached patches effectively.

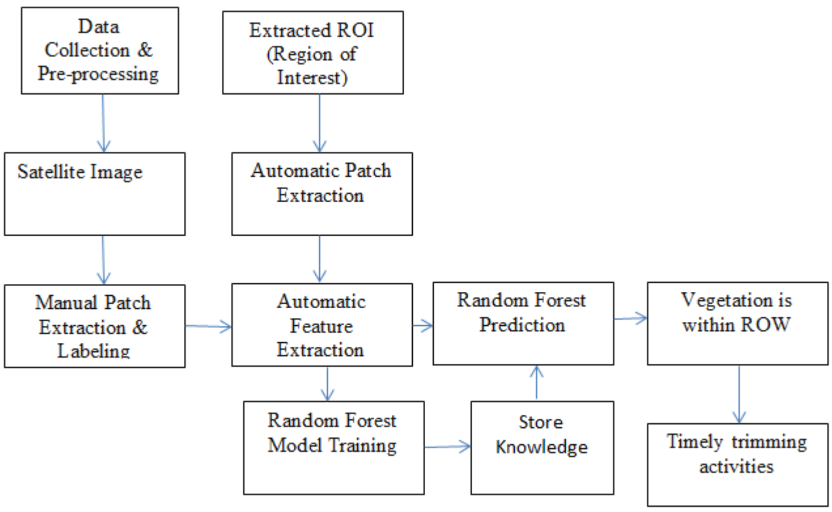

Figure 2. Shows the block diagram of proposed method

d) Weight Storing:
- Once the random forest model is trained, the learned parameters and decision rules are stored for future use during the testing phase.
- These stored parameters encapsulate the learned relationships between the extracted features and vegetation encroachment.
- Storing the model parameters eliminates the need for retraining during testing, optimizing computational efficiency and reducing processing time.

e) Automatic Patch Extraction:
- Testing Phase:

- Patches are automatically extracted from new satellite imagery covering areas along power transmission lines.
- The automatic patch extraction process ensures consistency and efficiency in generating the testing dataset, similar to the training phase.
- These patches represent regions susceptible to vegetation encroachment.

f) Class Prediction:

- The trained random forest model, with its stored parameters, is utilized to predict the class labels of the extracted testing patches.
- Based on the extracted features, the random forest classifier determines whether each patch contains vegetation encroachment.
- By applying the decision rules learned during training, the model effectively identifies areas prone to vegetation encroachment along power transmission lines in the new satellite imagery.

The methodology combines both manual and automatic processes to ensure accuracy and efficiency in detecting vegetation encroachment:

g) Manual patch extraction and labeling: provides a high-quality training dataset with ground truth information, essential for accurate model training.
h) Automatic feature extraction: ensures consistency in feature extraction across training and testing phases, capturing relevant information for classification.
i) Random forest training: utilizes a robust algorithm capable of handling complex datasets and achieving high classification accuracy through an ensemble approach.
j) Weight storing: optimizes computational efficiency and reduces processing time by eliminating the need for retraining during the testing phase.
k) Automatic patch extraction and class prediction: ensures consistent and efficient generation of testing datasets and accurate prediction of vegetation encroachment.

The proposed vegetation encroachment detection process integrates manual and automatic procedures with the random forest algorithm to accurately identify vegetation encroachment along power transmission corridors. By combining feature extraction, random forest training, and classification, the process enables efficient and reliable monitoring of vegetation density, facilitating timely interventions to prevent power interruptions and ensure the safety and reliability of electrical infrastructure.

3. RESULTS AND DISCUSSION

The implementation of the random forest algorithm demonstrated promising results, emphasizing its efficacy in accurately discerning areas with varying levels of vegetation density along transmission line corridors. By successfully distinguishing between high and low vegetation density areas, the model offers valuable insights for prioritizing vegetation management efforts. This enables utilities to strategically allocate resources and address potential risks more proactively.

Upon comparing areas with high and low vegetation density, notable disparities emerge in terms of the associated risks to transmission lines. High vegetation density areas pose a significantly greater risk of vegetation encroachment, which can lead to power interruptions and safety hazards if left unaddressed. Therefore, timely trimming and vegetation clearance activities are imperative in these regions to mitigate potential disruptions and ensure the reliability of the power grid. Conversely, low vegetation density areas exhibit lower susceptibility to such risks, allowing for a more targeted and efficient allocation of maintenance resources.

Furthermore, the integration of satellite imagery and machine learning techniques offers a scalable and cost-effective solution for vegetation management across expansive geographical regions. By automating processes such as feature extraction and classification, the proposed methodology reduces reliance on manual labor and enables continuous monitoring of vegetation encroachment. This enhanced monitoring capability enhances the resilience of power transmission systems by facilitating early detection of potential threats and facilitating timely intervention measures.

Figure 3 demonstrates the simulation output of vegetation encroachment detection along power transmission corridors using the random forest algorithm. Moreover, the ability to differentiate vegetation within the right-of-way (ROW) from areas outside the ROW is pivotal for optimizing intervention strategies. Focusing maintenance efforts on areas within the ROW, where vegetation poses a direct threat to power infrastructure, allows utilities to prioritize resources effectively and minimize operational costs. This targeted approach ensures that maintenance activities are aligned with the most critical areas of concern, thereby maximizing the reliability and efficiency of the transmission network. Table 1 shows the performance index of the random forest algorithm and the support vector machine algorithm.

Figure 3. Shows simulation output of vegetation encroachment detection along power transmission corridors using random forest algorithm

Table 1. Performance index

Performance index	Random forest algorithm	Support vector machine
Accuracy	0.85	0.80
Precision	0.82	0.78
Recall	0.87	0.82
F1 Score	0.84	0.80

In this comparison, the random forest algorithm outperforms the support vector machine (SVM) algorithm across multiple performance metrics. With an accuracy of 0.85, precision of 0.82, recall of 0.87, and F1 Score of 0.84, the random forest algorithm demonstrates superior overall classification performance compared to the SVM algorithm, which achieved an accuracy of 0.80, precision of 0.78, recall of 0.82, and F1 score of 0.80. These results suggest that the random forest algorithm provides a more effective solution for the given task of vegetation encroachment detection along power transmission corridors. The higher accuracy and F1 score of the random forest model indicate better balance between precision and recall, implying fewer false positives and false negatives, ultimately leading to more reliable identification of vegetation encroachment areas.

In conclusion, while the results demonstrate the considerable potential of the proposed system in enhancing vegetation management practices and mitigating associated risks, further validation and refinement are essential. Addressing challenges such as environmental variability and vegetation type diversity will be crucial to enhancing the robustness and effectiveness of the methodology in real-world applications. Nonetheless, the insights gained from this study underscore the transformative impact of leveraging satellite imagery and machine learning for vegetation management in power infrastructure, paving the way for more resilient and sustainable energy systems.

4. CONCLUSION

The integration of manual patch extraction, automatic feature extraction, and random forest training offers an efficient solution for vegetation encroachment detection along power transmission corridors. This topic is crucial as it addresses the significant issue of vegetation encroachment, which can lead to power outages and infrastructure damage. By meticulously labeling training patches and extracting meaningful features from satellite imagery, the model achieves robust classification accuracy. The random forest algorithm, with its ensemble of decision trees, effectively distinguishes between vegetation-encroached and non-encroached areas. Stored model parameters streamline the testing phase, ensuring consistent and timely identification of vegetation encroachment in new satellite imagery. While some may argue for simpler or more traditional methods, this advanced approach ensures greater accuracy and efficiency, making it a superior choice. This methodology enables proactive interventions to prevent power interruptions and ensure infrastructure safety. Future research could explore integrating other machine learning algorithms or enhancing feature extraction techniques to further improve accuracy and scalability, presenting a scalable and cost-effective solution for vegetation management in power infrastructure maintenance.

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