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Research Article

Efficacy Analysis of Boosting Techniques for Road-Surface Detection Using Very High Resolution Trispectral Satellite Images

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ABSTRACT

Boosting techniques are machine-learning algorithms that combine the strengths of several weak learners to increase the accuracy of predictive models. They are invaluable for tasks involving objects, fraud, and analysis. Optimization algorithms iteratively construct models by concentrating on the errors made by earlier models, thereby increasing their overall accuracy and precision. Changing the weights of misclassified instances helps manage imbalanced data such as anomalous or fraudulent instances. Boosting techniques are resistant to noise, focusing on hard-to-classify cases and mitigating the impact of noise through weighting schemes to produce more dependable detection models. Boosting techniques can be used for many detection problems where the desired features are few compared to non-desired ones. They offer flexibility in model building, as they are not restricted to a particular type of base learner and can be used with decision trees, neural networks, and other algorithms. Updating the model and adding new data without retraining it through incremental learning is also possible. High-dimensional data can be handled effectively by boosting techniques, particularly for object detection in images and videos. In this study, the WHU dataset was used to detect road surfaces in an image. A smaller number of desired pixels than the others mimic an imbalanced binary classification problem. In this study, we tested adaptive boosting, gradient boosting, histogram gradient boosting, and light gradient boosting machines to analyze the efficacy of boosting techniques.

Keywords: Road surface detection, Machine learning, Deep learning, Digital image processing, Satellite images.

INTRODUCTION

Imbalanced classification refers to a situation in which the number of instances in a class is much greater than in other classes [1]. Boosting techniques are crucial for addressing such cases [2]. Owing to the potential bias of traditional machine learning algorithms towards the majority class, this imbalance can make it challenging to train effective models, resulting in poor performance for the minority class [3]. Boosting improves precision and recall, handles high-dimensional and complex data, focuses on misclassified instances, modifies instance weights during training, builds robust ensemble models, and is adaptable when working with decision trees and other base learners [4]. Boosting is a commonly used technique in practical applications for fraud detection in financial datasets, where fraudulent instances are uncommon compared with legitimate cases [5]. Boosting aids in the precise diagnosis of unusual conditions in medical datasets, where specific diseases or conditions are far less common [6]. Boosting approaches also improve the identification of malicious activities in network traffic, which is generally far less common than regular traffic [7]. In short, by combining several weak learners, dynamically modifying instance weights, and concentrating on misclassified instances, boosting techniques are highly effective in mitigating problems associated with imbalanced classification. This makes boosting an effective method in many applications where class imbalance is a significant problem, because it improves the overall performance and produces more trustworthy predictions in imbalanced datasets [8].

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Imbalanced or skewed datasets are frequently found in real-world situations, where one class significantly outperforms the other. Significant outcomes may result from these datasets, such as skewed model performance, erroneous forecasts, moral and societal fallouts, monetary losses, operational risks, public health and safety, customer satisfaction, and deceptive performance metrics. Biased models frequently have a bias in favor of the majority class, which hurts the minority class and raises the false-negative rate. Accurate predictions can also result from biased models that favor the majority class. Discriminatory results in criminal justice, loan approval, and hiring processes can lead to ethical and social fallout. Failure to identify infrequent but crucial events, such as cyber-attacks and system failures, can lead to operational risks and endanger the security and dependability of a system [9]–[11]. The accurate identification of uncommon diseases or adverse drug reactions is essential for public health and safety. However, models that favor more prevalent conditions may overlook early warning indicators of outbreaks or fail to identify people who are at risk, which would impede prompt interventions and responses [12], [13]. Models trained on imbalanced datasets can hurt customer satisfaction because they may be unable to identify and handle uncommon but essential issues, which can cause dissatisfaction and hurt customer retention and brand reputation [14]. Working with imbalanced datasets can also lead to misleading performance metrics such as accuracy. Several strategies can be used to address these issues, such as resampling techniques (e.g., SMOTE, Synthetic Minority Oversampling Technique [15]) to increase the number of instances of the minority class, algorithmic methods (e.g., to improve the model's sensitivity to these situations by providing the minority class with more significant misclassification costs [16]), ensemble methods (e.g., to enhance the identification of minority class instances by applying tactics such as boosting and bagging [17]), and data augmentation (e.g., producing artificial data to add diversity to the dataset, particularly when it comes to image and text data [18]). In brief, dealing with skewed datasets necessitates careful consideration of data handling strategies and suitable assessment metrics to guarantee that models function well in all classes, particularly the minority class. Strong dataset management techniques can reduce risks and improve the consistency and fairness of machine-learning applications.

This study analyzed the efficacy of boosting techniques for road surface detection using high-resolution trispectral (true color) satellite images. The problem considered was treated as an imbalanced binary classification. Here, the desired features mimic those of the minority classes. We considered four major boosting algorithms on binary imbalanced datasets, emphasizing Adaboost, gradient boost, histogram gradient boost, and light gradient boost machine classifiers, evaluation metrics, experimental findings, and conclusions.

IMBALANCE ANALOGY OF USED IMAGES

Upon visual inspection, the images revealed several broad categories within the image. However, we include the road surface as the desired category among the existing objects in the images. Other possible categories were collectively considered undesired categories (background). This indicates that each considered image can be called a binary-class image (see Fig. 1). We took three images with different road-surface architectures in this context [19]. The examined images had a spatial size of 512×512 pixels, translating to 262,144 pixels. Table I lists the percentage of imbalances in the images used based on the labeled pixels in the ground truths. These images also represent true color or trispectral images, with the red, green, and blue bands representing the visual electromagnetic spectrum.

METHODOLOGY AND EXPERIMENTAL RESULTS

As shown in Fig. 2, several steps were taken to analyze the efficacy of the boosting techniques for road surface detection.

Table 1: Percentage of Imbalance in Used Images

Related Parameters	Dataset		
	Image1	*Image2*	*Image3*
Road Pixels	62,138	42,819	53,027
Percentage	23.70%	16.33%	20.23%
Imbalance	Mild	Moderate	Mild

Binary imbalanced data classification, considering the desired (road surface) and undesired (background) classes. We spatially vectorized both the images and their ground truths for the intended class, where the images used were trispectral (true color) satellite images. After vectorization, we partially chose both the desired and non-desired pixels for further analysis. The remainder rule for the smallest single-digit prime was used to select the desired pixels, whereas the largest two-digit prime was used to select the non-desired pixels. Table II lists the selected pixels.

Table 2: Selected Pixels in Used Images for Analysis

Related Parameters	Dataset		
	Image1	*Image2*	*Image3*
Desired/Road Pixels	31,070	21,408	26,507
Non-desired/Background Pixels	2,102	2,252	2,137
Imbalance	Extreme	Extreme	Extreme

The selected pixels were combined and arbitrarily divided into 70:30 training and testing pixels. The exact pixel counts are listed in Table III. The spatial locations of the partially selected pixels are shown in Fig. 3. The training and testing pixels were then applied to the four distinct boosting strategies. AdaBoost [20], Gradient Boost [21], Histogram Gradient Boost [22], and light gradient boost machines [23] are related classifier models. Overfitting of the models was then verified by comparing the testing and training accuracies, as shown in Table IV. The trained models were evaluated on an entire image to obtain a pseudo-prediction of the entire road surface in the images.

Table 3: Training/Testing Pixels in Used Images for Analysis

Related Parameters	Dataset		
	Image1	*Image2*	*Image3*
Training Pixels	21,716/1,504	14,930/1,632	18,553/1,497
Testing Pixels	9,354/598	6,478/620	7,954/640

A. Pseudo Prediction

The absence of overfitting in boosting techniques ensures a green signal for further analysis. In this sequence, the trained models were tested on all images with 1, 2, and 3 pixels to achieve a pseudo-prediction of road architectures. A pseudo-prediction map provides road architecture with the occlusion of similar pixels, such as buildings, shadows, and other associated objects that look similar in a tricolor representation. Furthermore, a logical AND operation is performed between the ground truths and pseudo-prediction maps, resulting in post-rectified prediction maps. Prediction error maps were also determined using logical XOR operations between ground truths and post-rectified maps. These outcomes are shown in Figs. 4–6 for all boosting techniques used.

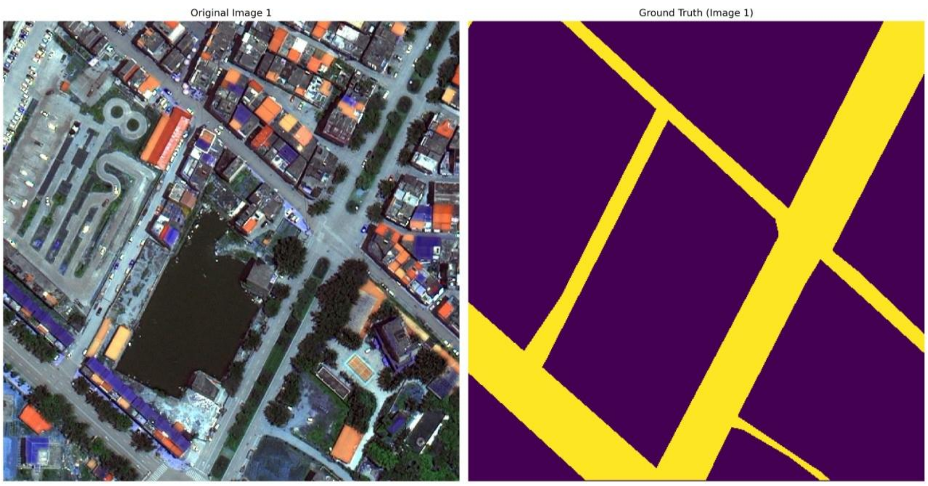


Image 1 and Associated Ground Truth

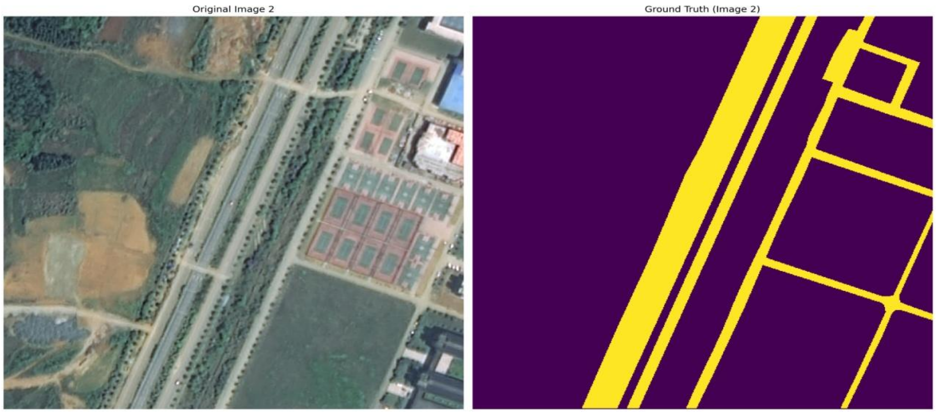


Image 2 and Associated Ground Truth

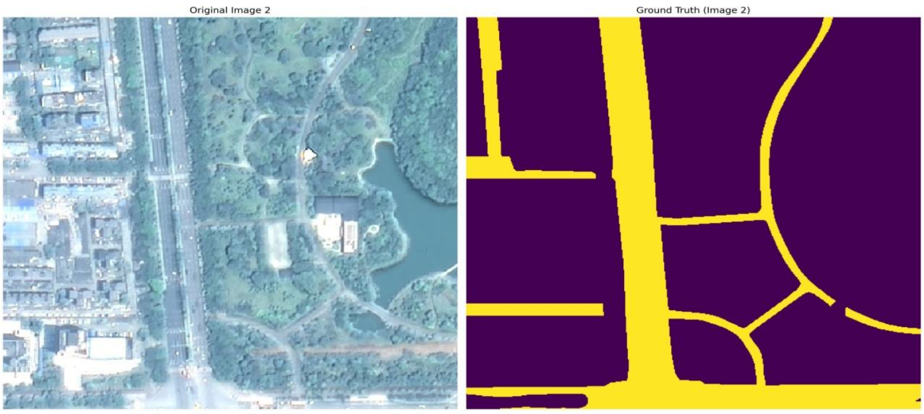


Image 3 and Associated Ground Truth

Figure 1: Images and their Ground Truths for The Road Were Considered To Be The Desired Pixels, and Others Were Considered as Background Pixels.

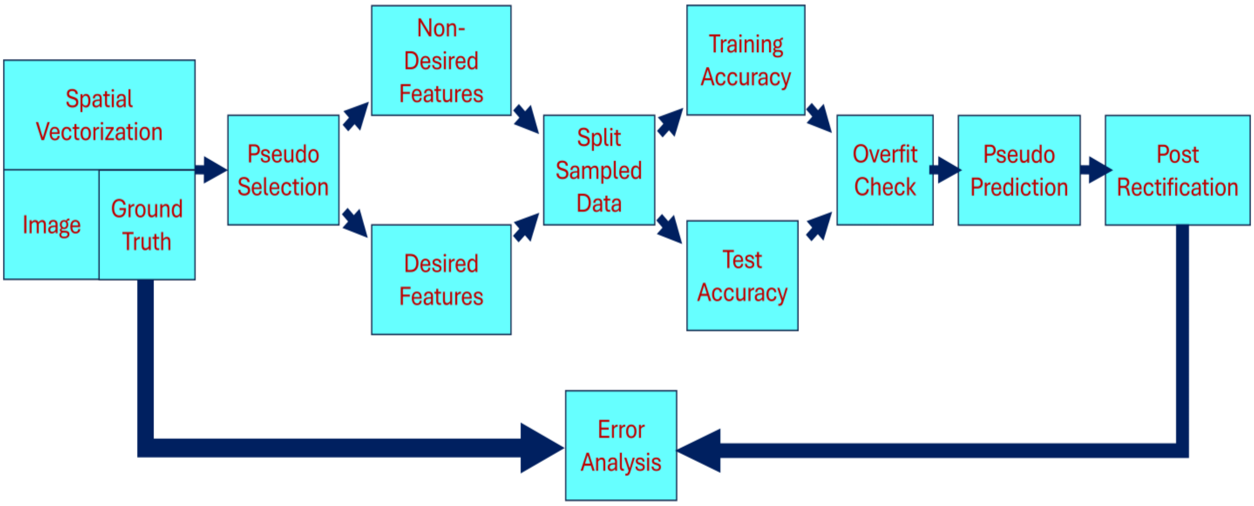


Figure 2: The following are the Sequential Steps in the Efficacy Analysis of Boosting Techniques For Road-Surface Detection.

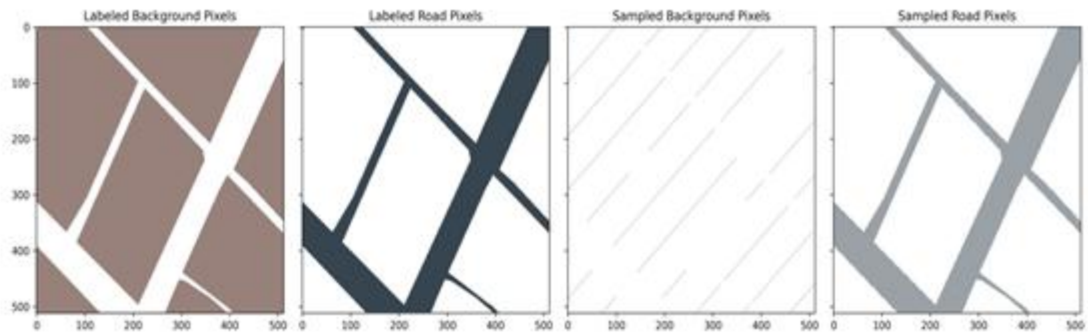
Table 4: Training and Testing Accuracies for Overfit Check

Related Parameters	Dataset		
	Image1	*Image2*	*Image3*
AdaBoost Training/Testing Accuracy	93.59/93.99	92.37/93.34	93.08/92.98
Gradient Boost Training/Testing Accuracy	93.61/94.01	92.28/92.81	93.80/93.83
Histogram Gradient Boost Training/Testing Accuracy	94.33/94.06	95.56/94.76	95.01/94.15
Light Gradient Boost Machine Training/Testing Accuracy	94.46/94.12	95.50/95.22	95.03/94.31
Overfitting	No	No	No

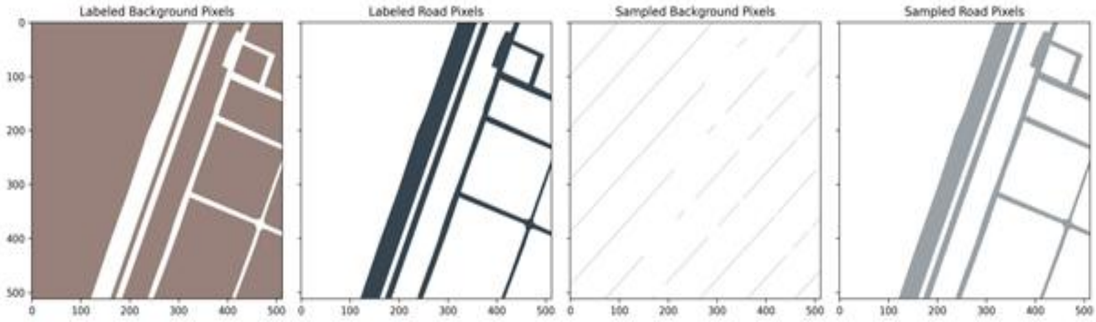
EFFICACY ANALYSIS

Several challenges arise in classifying imbalanced binary datasets, which may affect the performance of machine-learning models. As more predictions of the majority class can result in higher accuracy, machine learning algorithms tend to favor the majority class, especially those that maximize the overall accuracy. The minority class, which is frequently interested in real-world issues, performs poorly (e.g., fraud detection and disease diagnosis). Standard metrics that do not represent the model's performance for the minority class, such as accuracy, can be deceptive. Therefore, alternative metrics such as precision, recall, F1-score, ROC-AUC, and precision-recall AUC are required to accurately reflect the performance. The minority class may not have enough data points, making it harder for the model to identify distinctive characteristics and causing overfitting of examples from the minority class and underfitting of examples from the majority class. This imbalance may make it difficult for models to determine a suitable decision boundary, which could result in misclassification. As a result, there are more false positives (erroneous identification of minority classes) and false negatives (missed detection of minority classes). If models are not handled appropriately, they may also overfit the few examples from the minority class, leading to poor generalization of unseen data, particularly for the minority class.

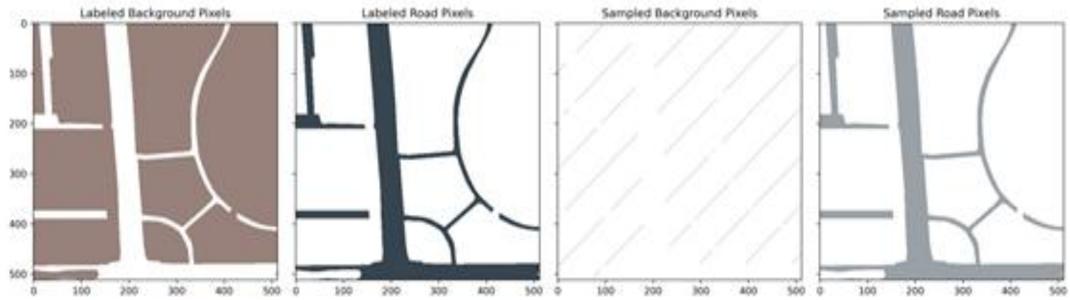
Synthetic instances for the minority class can be produced using methods such as (Synthetic Minority Oversampling Technique). The dataset can also be balanced by lowering the proportion of majority-class instances. Generating synthetic data or performing transformations to create new samples of minority classes is popularly known as data augmentation. Inaccurate predictions indicate that the minority class is penalized more significantly if given a higher misclassification cost. By emphasizing more examples that are challenging to classify, methods such as bagging, boosting (e.g., Adaboost, Gradient Boosting), or random forests can be customized to handle imbalanced data. Combining cost-sensitive learning and over- or under-sampling is another way to deal with such issues. Metrics that offer the minority class a better balance between recall and precision should be used. The precision-recall curve or area under the ROC curve was used to better understand the model's performance at various thresholds. Applying anomaly detection techniques and treating the minority class as desired also pave the way in this context. We can also utilize the already trained models on related tasks or domains to enhance performance with smaller datasets. State-of-the-art neural network architectures can also provide a better way to include data-augmentation techniques. Therefore, to improve the performance of models for imbalanced binary classification tasks, we must carefully address these issues with an appropriate strategy.



Labeled and Sampled Pixels in Image1

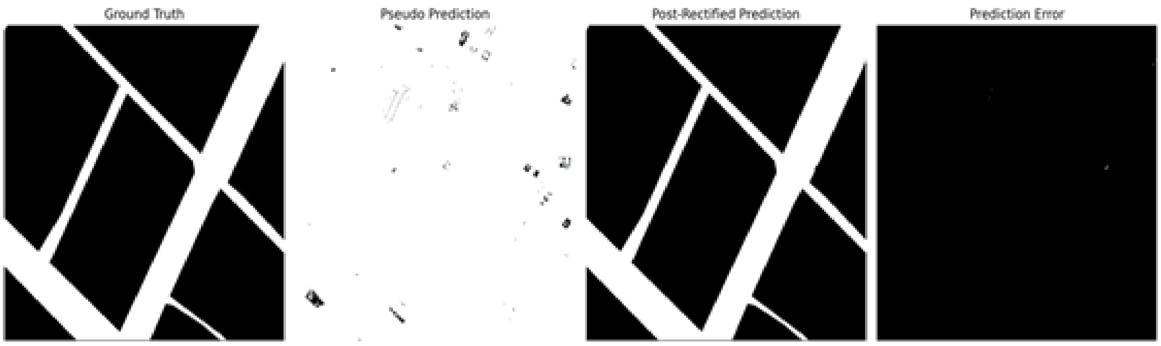


Labeled and Sampled Pixels in Image2

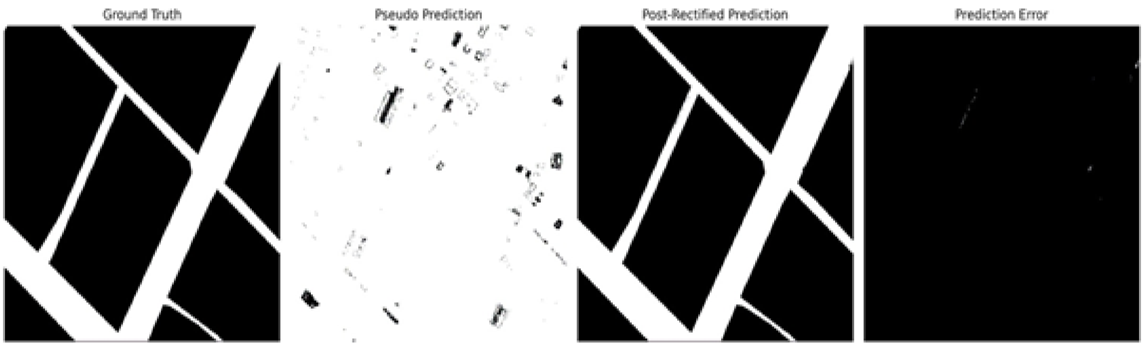


Labeled and Sampled Pixels in Image3

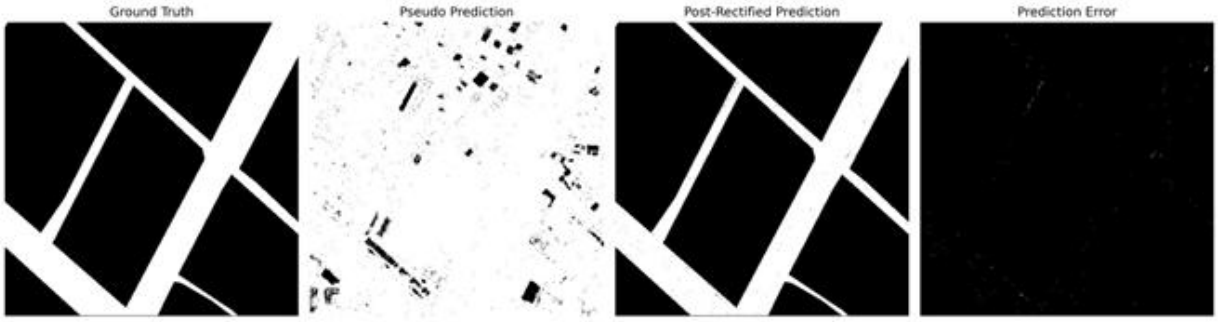
Figure 3: Spatial locations of partially sampled Pixels in Image1, 2, and 3



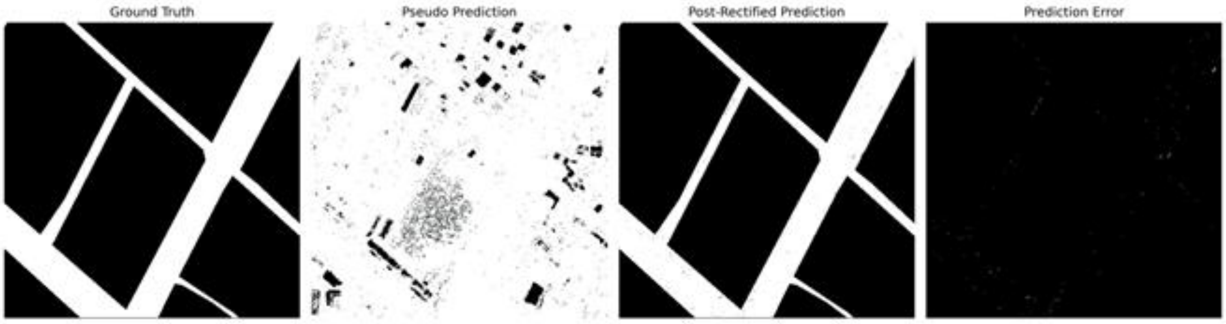
Pseudo Prediction and Prediction Error Maps for Image1 Using AdaBoost



Pseudo Prediction and Prediction Error Maps for Image1 Using Gradient Boost

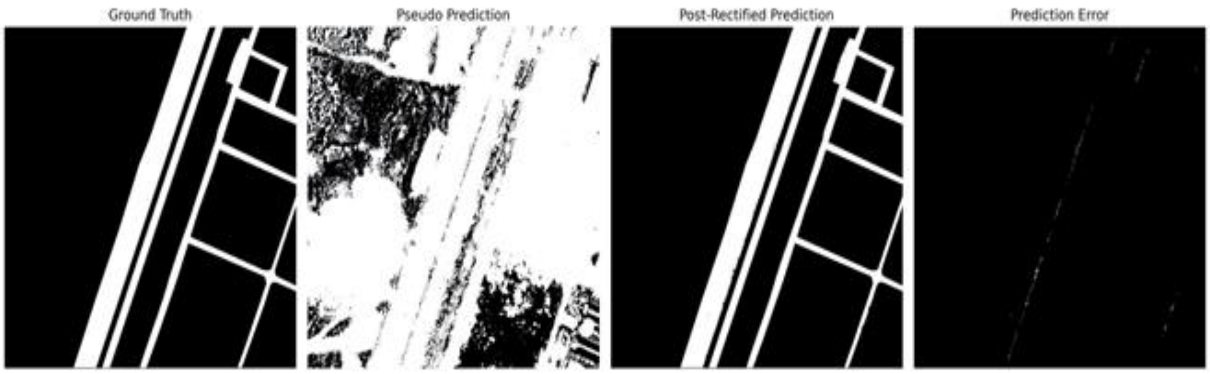


Pseudo Prediction and Prediction Error Maps for Image1Using HistGradient Boost

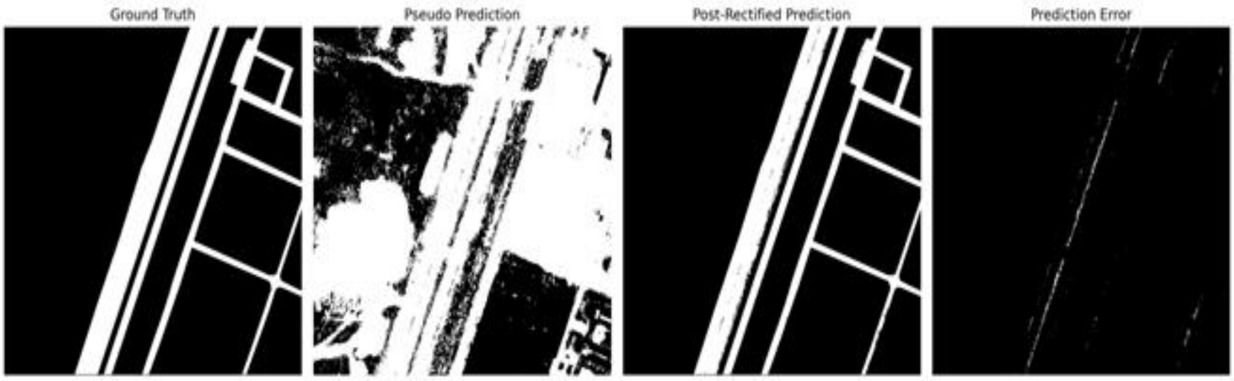


Pseudo Prediction and Prediction Error Maps for Image1 Using Light Gradient Boost Machine

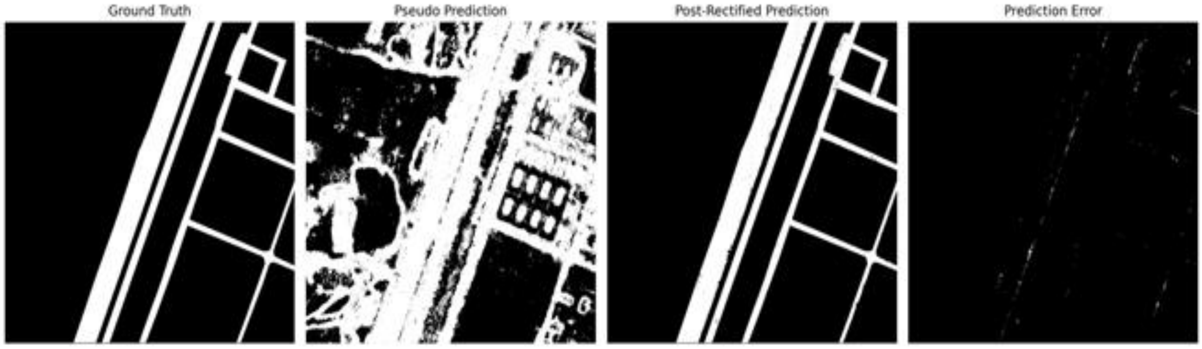
Figure 4: GroundTruth, pseudo-prediction, post-rectified prediction, and prediction error maps for Image1



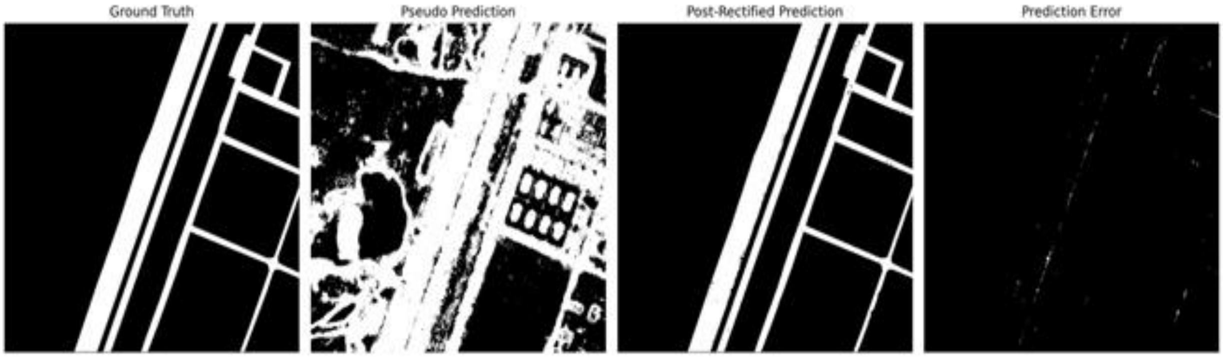
Pseudo Prediction and Prediction Error Maps for Image2 Using AdaBoost



Pseudo Prediction and Prediction Error Maps for Image2 Using Gradient Boost

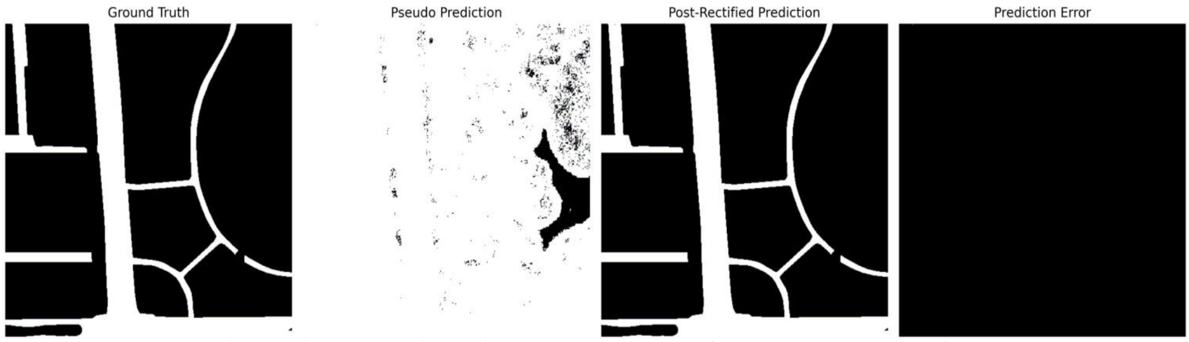


Pseudo Prediction and Prediction Error Maps for Image2 Using HistGradient Boost

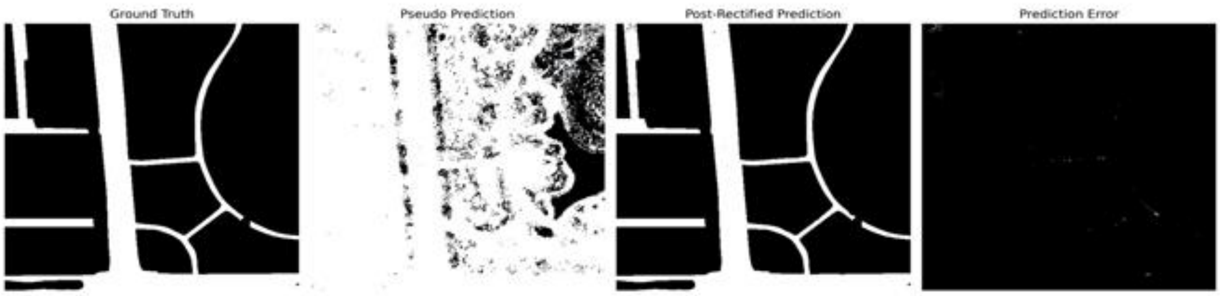


Pseudo Prediction and Prediction Error Maps for Image2 Using Light Gradient Boost Machine

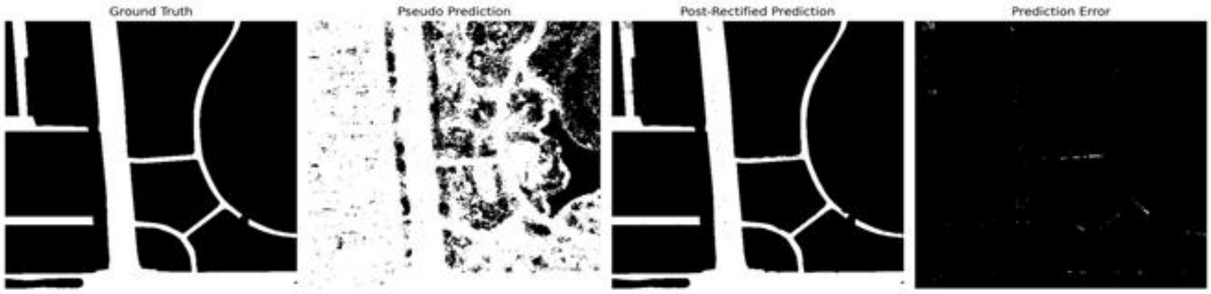
Figure 5: GroundTruth, pseudo-prediction, post-rectified prediction, and prediction error maps for Image2



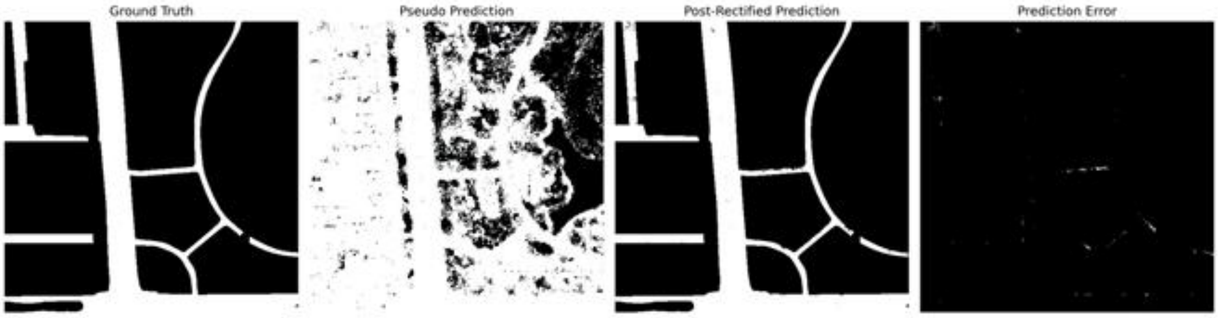
Pseudo Prediction and Prediction Error Maps for Image3 Using AdaBoost



Pseudo Prediction and Prediction Error Maps for Image3 Using Gradient Boost



Pseudo Prediction and Prediction Error Maps for Image3 Using HistGradient Boost



Pseudo Prediction and Prediction Error Maps for Image3 Using Light Gradient Boost Machine

Figure 6: Ground truth, pseudo-prediction, post-rectified prediction, and prediction error maps for Image3

Table 5: Actual Misclassified Pixels/Percentage Error Using Considered Boosting Techniques For Road Surface Detection

Related Parameters	Dataset		
	Image1	*Image2*	*Image3*
AdaBoost	21/0.0337	227/0.5301	1/0.0018
Gradient Boost	75/0.1206	1034/2.4148	138/0.2602
Histogram Gradient Boost	167/0.2687	541/1.2634	397/0.7486
Light Gradient Boost Machine	197/0.3170	440/1.0275	375/0.7071
Effective Boosting Technique	AdaBoost	AdaBoost	AdaBoost

DISCUSSION

Table 5 shows that AdaBoost performs better for all three considered images. These images were taken to generalize the methodology by cross verifying the experimental outcomes, which differed from the viewpoint of the covered landscape (as shown in Fig. 1). Detecting road surfaces is challenging because of the spectral limitations of trispectral satellite images. In addition, the similar spectral characteristics of several structures, such as buildings and shadows, occlude detection. An AdaBoost classifier, a meta-estimator, first fits a classifier on the original dataset. It then fits additional copies of the classifier on the same dataset, modifying the weights of incorrectly classified instances to focus the subsequent classifiers on complex cases. This class was responsible for implementing the multiclass AdaBoost algorithm. For Image 1, AdaBoost outperformed all subsequently used boosting techniques, for example, Gradient Boost, Histogram Gradient Boost, and Light Gradient Boost Machine. Image 2 was found to be effective in extracting road surfaces using AdaBoost. Similar to the previous ranking of boosting performers, it was changed for Image2. AdaBoost outperformed, followed by a light gradient-boost machine, histogram gradient boost, and gradient boost. An almost perfect road-surface detection was achieved for Image 3, where AdaBoost faced only one misclassification. However, the ranking list of outperformers can be seen in Table V, which is as follows: AdaBoost, gradient boost, histogram gradient boost, and light gradient boost machines.

CONCLUSION AND FUTURE SCOPE

The proposed study on the efficacy analysis of boosting techniques for road surface detection in trispectral satellite imagery suggests the outperformance of AdaBoost over its peers. The subsequent boosting techniques are gradient boost, histogram gradient boost, and light gradient boost machines. Apart from the study on boosting techniques, this study explores a novel way to handle imbalanced datasets. The road surface pixels are a minority of the complete landscape shown in the considered images. Subsequently, sampling was performed using the concepts of single-digit lowest prime and double-digit highest prime to select a subset of pixels for further analysis. This sampling approach interchanges the minority and the exact subset is used to train the four boosting techniques and check for overfitting. Complete images were tested and analyzed without overfitting the trained models. In short, the outcomes prove the effectiveness of boosting approaches for this purpose. Our novel approach paves the way for evaluating other sampling techniques capable of interchanging minorities.

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