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Enhancing landslide anomaly detection in aerial imagery through pre-processing and GANomaly deployment

Amélioration de la détection d'anomalies de glissements de terrain dans l'imagerie aérienne grâce au pré-traitement et au déploiement de GANomaly

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ABSTRACT: The application of aerial imagery for landslide anomaly detection encapsulates a promising avenue for early geohazard identification. This study utilizes GANomaly, a model built upon Generative Adversarial Networks (GAN), to identify anomalies by learning to reconstruct normal data and measuring reconstruction errors to discern anomalies. Initially, a pre-processing process was developed to enhance the clarity and quality of images, thereby facilitating more effective training and testing by GANomaly. This pre-processing process encompasses several steps: image RGB channels adjustments, image slicing into tiles, tile classifications, and tile rotations. The GANomaly model is then employed, trained on a substantial dataset derived from the pre-processing stage, and tested to evaluate its efficacy in detecting landslide anomalies within the aerial imagery. The entire process involved the selection and analysis of over 120,000 tiles, each acting as a data point to feed the robust anomaly detection framework. The results highlight the potential of integrating advanced pre-processing techniques with GAN-based anomaly detection models, forging a framework for real-time geohazard monitoring and early-warning systems. The results were verified from the confusion matrix parameters to ensure the potential of integrating advanced pre-processing techniques with GAN-based anomaly detection models.

RÉSUMÉ: L'utilisation de l'imagerie aérienne pour repérer les anomalies de glissements de terrain offre une méthode prometteuse d'identification précoce des risques géologiques. GANomaly, un modèle sur les réseaux GAN, apprend à identifier les anomalies en reconstruisant et analysant les erreurs des données normales. Un prétraitement améliore la qualité des images pour un entraînement et test efficaces de GANomaly, incluant l'ajustement RGB, le découpage en tuiles, leur classification, et rotation. Testé sur un grand ensemble de données prétraitées, GANomaly évalue son aptitude à détecter les anomalies de glissements. L'analyse de plus de 120 000 tuiles démontre l'intégration réussie de prétraitement avancé et de détection d'anomalies par GAN, établissant une méthode pour le suivi des géorisques et l'alerte précoce. Les résultats, validés via la matrice de confusion, confirment l'efficacité de cette approche.

Keywords: landslide; aerial imagery; artifical intelligence; anomaly detection.

1 INTRODUCTION

Generative Adversarial Networks (GANs) represent a groundbreaking advancement in the field of artificial intelligence, particularly within the domain of deep learning. Developed by Goodfellow et al. (2014), GANs have improved the way machines understand and generate data. At their core, GANs consist of two neural networks, the generator and the discriminator, engaged in a continuous competition. The generator creates data that is indistinguishable from real data, while the discriminator evaluates this data, differentiating between the authentic and the artificial. This dynamic results in the generator becoming increasingly proficient at producing realistic data, making GANs highly effective for tasks in image generation(Salimans et al., 2016; Zhao et al., 2020), industry(Yan, 2021), and medical purposes(Skandarani et al., 2023; Struski et al., 2023).

GANomaly (Akcay et al., 2018), a variant of GAN, is specifically tailored for anomaly detection. It extends the conventional GAN architecture by introducing an additional encoder network. This setup allows the model not only to generate new data but also to reconstruct input data. In the context of anomaly detection, GANomaly works by training on a dataset of 'normal' instances. The model learns to recreate these instances, and when presented with an anomalous instance, it struggles to reproduce it accurately. This discrepancy in reconstruction is then used as a signal for anomaly detection.

Utilizing aerial imagery for detecting landslide anomalies introduces a transformative method in geohazard analysis. Traditional techniques often emphasized on the diverse appearances of landslides(Bui et al., 2020; Prakash et al., 2021; Syifa et al., 2019). Here, GANomaly's application marks a significant advancement. Unlike conventional methods that depend on labeled datasets, GANomaly excels in unsupervised learning environments. It learns from unlabeled data, detecting anomalies by their deviation from 'normal' patterns. This is especially beneficial in contexts where anomalies are infrequent or ambiguous(Ferrari et al., 2023; Han & Chang, 2023; Li et al., 2020; Madzia-Madzou & Kuijf, 2022). GANomaly's sophisticated pattern recognition abilities are adept at identifying early indicators of land shifts or unusual terrain features, enabling proactive risk mitigation and timely response in landslide management.

This study aims to apply GANomaly, an advanced variant of Generative Adversarial Networks (GANs), in the analysis of aerial imagery for detecting landslide anomalies. The approach is structured into two key phases: an extensive training phase and a subsequent testing phase. The training phase emphasized on preparing the GANomaly model to accurately identify and distinguish normal terrain from potential landslide anomalies. It began with the RGB Adjustment of the aerial images, where the color channels were tuned to enhance the consistancy on overall RGB characteristics. Following this, the images were segmented into smaller tiles. Further, these tiles were classified where they were categorized based on distinct terrain features. This step aids in training the model the various characteristics of normal terrain. To augment the dataset and enhance the model's ability to recognize patterns from different perspectives, these tiles were then subjected to rotations. This rotational variation ensures that the model is robust and can accurately identify anomalies irrespective of the orientation of the features in the imagery. The testing phase was designed to rigorously evaluate the model's effectiveness. This phase employs a smaller batch of normal tiles to ensure the model's accuracy in recognizing normal terrain patterns without raising false positives. Additionally, the model is tested with known abnormal tiles, which contain features characteristic of landslide anomalies. This step is pivotal in verifying the model's capability to detect deviations from normal terrain patterns.

2 METHODOLOGY AND RESULTS

2.1 Description of aerial images

The aerial images utilized in this study were specifically sourced from the mountainous regions within the Fuxing District of Taoyuan City, Taiwan. This area, known for its complex terrain and susceptibility to landslides, presents an ideal location for analysing the capabilities of GANomaly in detecting terrain anomalies.

The aerial images for this study were captured using aerial remote sensing aircraft, operated by the Aerial Survey and Remote Sensing Branch of the Forestry and Nature Conservation Agency, under the Ministry of Agriculture. These aircraft were flown at an altitude of 35,000 feet. The orthophoto images obtained were corrected by ground control points, and adjusted by digital orthoimage mosaicking and toning, ensuring a consistent scale and an accurate representation of the earth's surface. Each image possesses a resolution of 25 cm, which is an essential benefit for the detailed and precise identification of potential landslide anomalies in the complex terrain of the study area.

2.2 Procedure for image pre-processing

In this study, an image pre-processing procedure was employed to prepare aerial images for the training and testing of the GANomaly model, focusing on landslide anomaly detection. The procedure commenced with an step of RGB profile adjustment. The aerial images, containing three channels, were standardized against a base image chosen for its optimal RGB balance. This involved a comparison of the RGB histograms of all images against the base image. The mean values of these histograms were then adjusted to align with those of the base image, ensuring a consistence on RGB profile representation across the dataset. This step aims to establish a consistent coloration for the accurate identification and analysis of terrain features. Figure 1 presents the base image (Image 1) along with its corresponding RGB histograms and mean values. Figure 2 and Figure 3 illustrate the images before (Image 2) and after (Image 3) RGB adjustment, respectively.

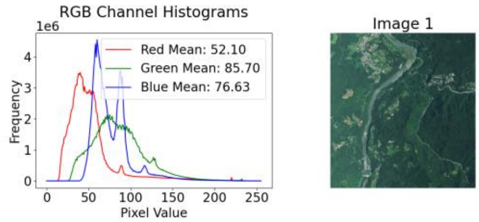

Figure 1. Plot of RGB histograms of the base image.

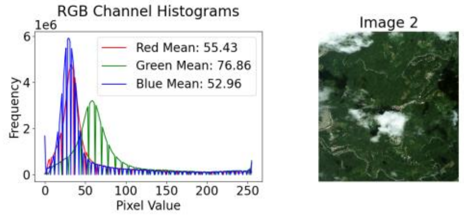

Figure 2. Plot of RGB histograms of the image required adjustment.

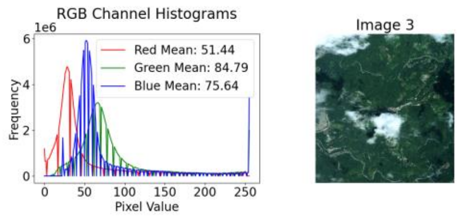

Figure 3. Plot of RGB histograms of the image after RGB adjustment.

Following the RGB profile adjustment, the images were sliced into tiles, each measuring 128×128 pixels. This slicing step allowed for a more granular examination of the terrain, enabling the GANomaly model to focus on specific areas and detect subtle anomalies that might be indicative of potential landslide risks. The smaller size of the tiles ensures that even minor variations in the terrain are captured and analysed.

To further refine the dataset, a classification of tiles was implemented. Tiles were categorized based on prominent terrain features visible in images, such as trees, agricultural land, buildings, roadways, rivers, and riverbanks. This classification allowed for a detailed characterization of normal terrain, establishing a baseline for the model to identify deviations that signify anomalies.

Figure 4. Examples of tiles classified as trees.

Figure 5. Examples of tiles classified as agricultural land.

Figure 6. Examples of tiles classified as buildings.

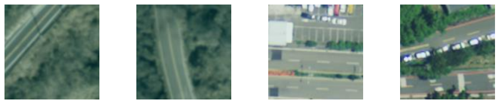

Figure 7. Examples of tiles classified as roadways.

Figure 8. Examples of tiles classified as rivers.

Figure 9. Examples of tiles classified as riverbanks.

The final step in the preparation process was the rotation of tiles. Each tile underwent rotations at angles of 90, 180, and 270 degrees, as shown in Figure 10. This step was particularly important for addressing the disparity in the number of tiles available for certain categories. Notably, the categories of agricultural land, buildings, roadways, rivers, and riverbanks were underrepresented compared to the number of tiles depicting trees. By rotating the tiles, the study effectively augmented the dataset for these less represented categories, ensuring a more balanced and comprehensive training set for the GANomaly model.

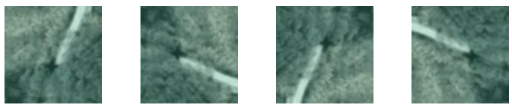

Figure 10. Examples of tiles after rotation.

2.3 Training

The training stage of the GANomaly model is designed to equip the model with the ability to accurately identify potential landslide anomalies in aerial imagery. The primary purpose of this training was to enable GANomaly to learn and differentiate between various terrain features, particularly focusing on patterns that deviate from what is typically observed in normal landscapes. For the training process, a substantial dataset comprising approximately 120,000 tiles was used in the training stage. This large number of tiles ensured that the model was exposed to a wide range of terrain features and conditions, thereby improving its learning and accuracy.

A significant portion of this dataset, about 100,000 tiles, represented areas covered with trees. Trees often dominate aerial imagery in mountainous regions, making them an component of the dataset for the model to understand and recognize as part of normal terrain. The remaining 20,000 tiles were evenly distributed among other crucial categories, namely agricultural land, buildings, roadways, rivers, and riverbanks. This equal division of the remaining tiles among these categories was strategically implemented to provide a balanced representation of various terrain types.

Among the mountainous regions, given the lower availability of tiles in these categories compared to those depicting trees, the approach of rotation tiles ensured that the model was not overly biased towards tree-covered areas and could effectively recognize and analyze a diverse range of terrain features. This balanced training approach was pivotal in preparing GANomaly for the task of landslide anomaly testing and detection, ensuring it could operate effectively across the varied landscapes present in the mountainous aerial imagery.

2.4 Testing and results

For the testing stage of the GANomaly model, a database comprising both normal and abnormal tiles was used. The normal tiles, amounting to 5,800 in total, were selected from the same aerial imagery of the mountainous areas in the Fuxing District. However, these tiles were distinct from those used in the training dataset, ensuring a rigorous testing process. In the distribution of these normal tiles, about half, or approximately 2,900 tiles, represented tree-covered areas. The remaining half was evenly divided among other categories: agricultural land, buildings, roadways, rivers, and riverbanks. This distribution was designed to mirror the diverse landscape features of the region and provide a comprehensive basis for testing the model's accuracy in differentiating normal terrain features. The number of 100 abnormal tiles were collected through visual inspections of landslide-affected areas. These tiles were used in evaluating the model's efficacy in detecting anomalies that are characteristic of landslide occurrences. Some example tiles in abnormal class are shown in Figure 11.

Figure 11. Examples of abnormal tiles in testing stage.

During the testing procedure, a receiver operating characteristic (ROC) curve was generated to determine the effectiveness of the model in distinguishing between normal and abnormal tiles, as shown in Figure 12. Two threshold determination approaches were employed: Youden's J statistic(Youden, 1950) and the closest to top-left threshold method. These approaches yielded the best threshold values of 0.0047 and 0.0048, respectively.

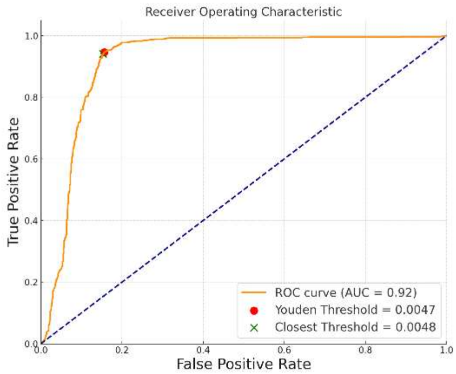

Figure 12. ROC curve in testing stage.

Adopting a threshold value of 0.00475 for the final analysis, the results were quantified using a confusion matrix. The metrics derived from this analysis were: an area under the curve (AUC) of 0.917, an accuracy rate of 0.895, an F1 score of 0.900, a precision of 0.857, and a recall of 0.947. These results indicated a high level of efficacy of the GANomaly model in detecting landslide anomalies, demonstrating its potential as a powerful tool in geohazard monitoring and risk assessment. The combination of high accuracy, precision, and recall underscores the model's reliability in identifying both the presence and absence of landslide-related anomalies in the aerial imagery.

3 CONCLUSIONS

In this study, we demonstrated the potential of employing GANomaly, an advanced Generative Adversarial Network model, for detecting landslide anomalies in aerial imagery of Fuxing District's mountainous terrain. Our methodology involved an training database of around 120,000 tiles, predominantly featuring tree-covered areas, balanced with a variety of other terrain types. This diverse dataset ensured a comprehensive and effective learning process for the GANomaly model. The testing phase, using 5,800 normal and 100 visually-inspected abnormal tiles, validated the model's precision in anomaly detection. The application of ROC curve analysis and optimal threshold determination through Youden's J statistic and closest to top-left threshold methods resulted in performance metrics: an AUC of 0.917, an accuracy of 0.895, and an F1 score of 0.900.

These results feature the potential of artifical intelligence in enhancing geohazard monitoring and risk assessment. The integration of GANomaly in high-resolution aerial imagery analysis marks a significant advancement in environmental monitoring, paving the way for more sophisticated, real-time monitoring systems.

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