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Change detection and classification of satellite images using convolutional neural network

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ABSTRACT

Satellite and airborne imagery, collectively known as earth observation imagery, are images of the earth collected from spaceborne or airborne platforms such as satellites and aircraft. Over the last 100 years, with the fast development of aviation, space exploration, and imaging technologies, the coming together of these technologies has been inevitable. Earth observation imagery has many applications in regional planning, geology, reconnaissance, fishing, meteorology, oceanography, agriculture, biodiversity conservation, forestry, landscape, intelligence, cartography, education, and warfare. With the rise in the number of these airborne and spaceborne imaging platforms being deployed by government and private entities alike, the capability to sift through and analyze vast amounts of data generated by these platforms is the need of the hour. With the exponential improvement in the computational capabilities of computers over the last half a century, analysts are exceedingly moving towards the practice of artificial intelligence, machine learning (ML), and computer vision solutions to automate a large part of the processes employed in analyzing earth observation imagery. This work recommends a workflow to perceive and classify changes in earth observation imagery of a given area by utilizing the vast flexibility that convolutional neural networks (CNN) provide.

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1. INTRODUCTION

The most essential task is saving lives and protecting the infrastructure from natural disasters. The most common forms of natural disasters are landslides and earthquakes. Satellite images are used to predict the areas of earthquakes and landslides [1]. Although there are numerous uses of remote sensing (RS) satellite imagery, obtaining them is more difficult. These images are used to mine the data present in them. So, satellite images are most important for land cover analysis and an essential foundation for land use [2]–[4]. Images of the world taken from spaceborne or airborne platforms, such as satellites and aircraft, are referred to as satellite and airborne imaging, also known as earth observation imagery. With the uses of these images ranging from meteorology to intelligence and reconnaissance, the sheer number and density at which private and public organizations generate these images have posed the challenge of effectively analyzing and extracting meaningful insights from them to create actionable information.

Identifying changes on the earth's surface is the most crucial use of RS [5]. Two or more satellite photos obtained at various periods are usually compared as a part of the change detection (CD) and categorization process. The images are pre-processed and then analyzed using various techniques, such as change vector analysis, image differencing, and machine learning (ML) algorithms. The resultant categorization and change maps depict how the earth's surface has changed throughout time. CD in data is considered one of the systematic identifications over time. The CD process has profound significance across diverse fields, including healthcare, finance, environment, and the social sciences. By identifying and quantifying changes, CD helps make valuable decisions, monitor trends, and respond to evolving circumstances effectively. CD plays a vital role in RS by comparing the spectral and spatial features of the land, and vegetation. Modern techniques provide satellite images with high-resolution images, and many CD techniques depend on their accuracy [6]–[8].

CD and classification of satellite images are powerful techniques that provide valuable insights into environmental and societal changes over time. With further advancements in image processing and ML techniques, the method will continue to be an essential tool for researchers and practitioners in various fields. Satellite pictures are crucial in multiple applications, such as disaster management and environmental management. Through prior prediction, RS can save the earth from natural calamities and weather-related threats, and there is a need for human contributions in identifying the objects in the images, and the same strategies are used to represent the earth precisely [9].

Automatic CD techniques better detect multiple changes in the maps than in the 2D. CD is essential in RS CD in radar reflectivity measurements contaminated by speckle noise. Advancements in the global navigation satellite scheme are responsible for expanding the utilization of RS to proctor the atmosphere and the earth. With advanced systems, the data can be collected even from inaccessible and remote areas by offering global coverage [10]. The improvement in the RS technique has led to improved quality and clarity of the RS images and reduced the effort of obtaining these images, and humans can collect large quantities of images with different features and resolutions. The most vital information can be collected from these images, and these serve as a base for understanding the earth's system at various levels and can be used for multiple applications like urban planning, assessing climate changes, and monitoring forest resources [11].

The analysis of the satellite images can be done in real-time and is made possible because of the availability of many satellites around the earth. For RS, these classified satellite images provide many benefits in predictions [12]. The images captured by unmanned aerial vehicles (UAV) suffer from problems related to the background, reduced targets, and hidden targets, which results in reduced accuracy in detection [13]. Our work proposes a method that combines U-Net and you only look once (YOLO) strengths for CD and satellite imagery classification. We meticulously evaluate the proposed method on an openly available dataset, demonstrating its effectiveness in detecting and classifying changes in satellite imagery. This thorough evaluation instills confidence in the robustness of our approach.

2. LITERATURE REVIEW

This segment presents a detailed literature review on CD and classification in satellite imagery using deep learning (DL) techniques. This literature survey aims to understand the present advanced practices to CD better. Very high-resolution images are used in the worst climatic conditions without being worried about the spatial details. The traditional classification techniques need help to handle the complexities of combining high-resolution images with a heterogeneous landscape. The solution uses convolutional neural networks (CNN) in most computer vision applications. In addition, a viable platform for satellite sensors has boosted this growth [14].

The applications of RS can be employed under many circumstances, such as assessing damage after a natural disaster, damage to forests after a storm, and monitoring glacier melting and deforestation. The CD is done after comparing two or more images taken at dissimilar times and dates in the exact terrestrial locations. Various methods exist to collect these images, but satellite images continuously monitor the entire planet. So, the pictures of the satellites are considered a valuable source for RS and detecting changes in the photos [15].

These days, due to the increase in the quantity of earth observation satellites, there is a massive increase in the volume of the data collected, and this increases the load because of the transmission bandwidth and delays in communication. An automatic change identification system has been developed using the essential features of DL to handle massive amounts of data. The experimental result shows that the system achieved an accuracy of 91.95% [16].

For most RS purposes, detection of changes in satellite images is the most important and requires precise boundary details. Most existing methods provide better feature extraction through pixel-level comparisons but do not consider the overall impact that blurs the edges. In addition to this, they enhance the complexity of the computation. To report these topics, a method called feature enhancement and feedback network (FEFNet) is projected for CD to improve the feature extraction and provides valuable feedback. The experimental outcome achieved an accuracy of 92.32% [17].

There are various obstacles to object recognition in satellite images, including class changes, many objects in motion, a wide range of item sizes, lighting, and a busy backdrop. This research compares the effectiveness of the various DL algorithms currently used in object detection in satellite images. Using frameworks based on CNN—like YOLO, faster region-based convolutional neural network (Faster RCNN), satellite imagery multiscale rapid detection with windowed networks (SIMRDWN), and single-shot detector (SSD)—and a collection of satellite photos is constructed to conduct object recognition. According to the data, SIMRDWN has an accurateness of 97% on high-quality pictures, whereas Faster RCNN has an accurateness of 95.31% on images with a standard resolution (1,000×600). Compared to SSD, YOLOv3 has an accurateness of 94.20% at standard resolution (416×416) and 84.61% at standard resolution (300×300). YOLO is, without a doubt, the best in speed and effectiveness. SIMRDWN fails in real-time surveillance. SIMRDWN takes 5 to 103 milliseconds to complete a task that takes YOLO 170 to 190 milliseconds [18].

In RS, CD is the most critical aspect. A CD mechanism based on the unsupervised technique is proposed by optimizing the production and analyzing the different images. The weighted vector calculation method is used to differentiate between the vectors of features produced by the clustering. At last, the Markov technique is used to generate the change map by comparing it with the neighboring pixels. The proposed method achieves an accuracy of 89.9% [19].

CD of satellite images is an unavoidable step in earth observation. CD techniques are helpful when characterizing and monitoring urban growth. Even though many DL mechanisms exist for CD, many approaches fail to identify the edges and maintain the shape of the changed areas. A DL method called urban change detection network (UCDNet) based on the encoder-decoder mechanism is developed to achieve better prediction without any loss in the image information. UCDNet achieves an overall accuracy of 89.21% [20].

Due to the rapid technological revolution in computer vision, high-quality satellite images are vital for CDs. Employing the available limited resources and reducing the burden on satellite devices is also crucial. A scale-aware pruning framework (SAPF) is proposed to reduce the complexities and manage the representation quality. To initiate, the convolutional layer in object recognition is alienated into two groups: single-scale attribute depiction using single value breakdown and multiscale attribute depiction used for optimizing attributes. The experimental result found that SAPF reduced the parameters and floating point operations (FLOPs), and more importantly, the model's efficiency was greatly improved [21].

Any CD method combining the method of feature extraction and ML can effectively amass the information compared to a manual method. Using manual methods cannot ensure accuracy. A new way for CD is proposed based on the fusion of multiple features, and the technique is called Dempster-Shafer (D-S) evidence theory. The method finds the differences in the images based on similarity in the structures. Samples are selected based on specific rules, and segmentation is applied to expand the reliability of the samples. The results are then used to obtain the result. The experimental outcomes found that the projected work achieves an accurateness of 90.76% using the average structural similarity index measure (AVE-SSIM) method [22].

The CD is the process of identifying the changes in the ground image pairs after comparing. The comparison done at the scene, object, and pixel levels is vital since it provides the semantic details and requires monitoring urban area change. The existing automatic scene-level CD uses mid-level and low-level attributes to extract changes between images and fails to uncover the hidden information. A novel automatic CD method at the binary scene level is proposed to handle the mentioned problem. The proposed method uses visual geometry group (VGG)-16 at the first level for pre-training, decision tree (DT) for pixel-level classification in the second level, training samples at the scene level are collected at the third level, and a binary scene-level change map is generated at the last. The experimental results found that the proposed method achieves an accuracy of 92.17% [23].

The CD is the most crucial technique to analyze the changes in high-definition images. Identifying the minor and the significant changes and producing an accurate CD result is vital. To handle the major and the minor changes, a deep supervised dual discriminative metric network is trained for handling the bi-temporal images. The proposed network selects the low-stage feature and converts it into global features, which are more reliable and healthier. The distance measure is used to identify the differences among the pairs. The proposed method performs better compared to many existing methods [24].

The characteristics of the RS images depend on the clouds, mist, capturing time, and weather; and will be accountable for substantial spectral modifications. The mentioned factors affect the accuracy of the CD techniques. A new scheme based on data augmentation is projected to improve accuracy. Two simulation methods, mosaic, and haze simulation, aim to create new samples to conduct data augmentation. The latest samples are mixed with the original samples and fed into DL for training. The experimental results showed that the proposed model could handle the mist region better than existing methods, with an accuracy of 84.61% [25].

CD involves a comparison of images captured at dissimilar times. Current CD techniques focus on recorded pictures and do not consider the tasks posed by unregistered pairs of images. Lack of training leads to noisy outcomes. To put an end to the mentioned issues, a new method based on CNN and generative adversarial network (GAN) is proposed, which automatically collects data from matching regions of unregistered images and applies CD on the extracted region, and CNN is used to collect information from unregistered images followed by feature mapping to identify the matching regions. From the experimental analysis, the proposed method achieves 4.46% higher accuracy than the existing methods [26].

This paper proposes a novel CNN model that ingests many multi-channel 3D data from satellite imagery and local 3D mapping data. The proposed CNN model has 43 layers. Learning has been categorized into four common types of roofing materials, and because it frequently displays patterns similar to those surrounding it, the paper exhibits the model to classify features accurately. Compared to GoogleNet, the suggested model's learning outcomes revealed a 9% improvement in material categorization accuracy [27].

Monitoring urbanization and agricultural land and updating geospatial databases through CD in satellite images is very important. DL-based CD techniques mainly focus on texture and color and face many challenges due to the background resemblance in the surrounding regions. In addition, reducing the downsampling of the images may lead to a loss of spatial data. A novel network, attention-based feature differential enhancement network (AFDE-NET), is projected to minimize data loss and uses a deep supervision model combined with an ensemble spatial channel to handle these. The projected model achieves an accuracy of 94.3% when applied to the Egypt building change detection (EGY-BCD) dataset [28].

Current earth observation data provide qualitative and quantitative information compared to earlier land-related surveys. RS offers data related to political, economic, and scientific data. Many challenges are encountered when classifying satellite images and handling these images; six ML techniques such as DT, random forest (RF), support vector machine (SVM), classification and regression trees (CART), minimum distance (MD), and gradient tree boost (GTB). Based on the experiment result it was found that an accuracy of 93% was achieved using MD [29]. This literature survey provides a solid foundation for the proposed work and serves as a guide for identifying the most promising approaches and techniques for developing a system for CD and classification using U-Net and YOLO object detection.

3. METHOD

Here, we present the work of developing a system for CD and classification using U-Net and YOLO object detection. The main objective of this research is to propose an approach that combines the strengths of U-Net and YOLO to detect and accurately classify changes in satellite imagery. By combining the strengths of these two ML models, our approach can effectively identify and classify changes between two or more images of the same area taken at different times.

The framework for the proposed work is shown in Figure 1. First, image pairs of satellite or aerial images of the exact location taken at two different time points are passed to a preprocessing node that prepares them for input into the first CNN model by performing basic image processing operations and formatting to compatible input format. Once fed into the 1st CNN, the images are compared, and the detected change is highlighted in the generated feature map, which highlights the actual change in the region within the image.

The flow of data across the proposed system is shown in Figure 2 and is managed through well-defined pipelines where the supporting functions ensure the correct data reaches the right places at the right time. Data in the proposed model is mainly transmitted in image files, NumPy arrays, and PyTorch objects such as Tensors or .pt files when temporarily storing feature maps. All outputs are stored in well-established directories to prevent the loss of results. The steps involved in preprocessing are as follows:

i) Read the input images from the disk and stores them in memory.
ii) Input images are divided into smaller patches or tiles of size 256×256.
iii) The pixel values of the input images are normalized to the range [0, 1] using min-max normalization to have a mean of 0.5 and a standard deviation of 0.5.
iv) The pixel-wise annotations are integer encoded to convert them into tensors with size [nBatch, nClass, height, width]. Pixel values ranging [0 to nClass -1].
v) Data augmentation techniques such as rotation, flipping, and zooming are applied to increase the size of the dataset and to improve the model's robustness.
vi) The patches are grouped into batches of a specified size and fed into the U-Net model for training, validation, or testing.

The U-Net model is implemented using the PyTorch neural network sub-library and has an input size of 256×256×3 and an output size of 256×256×3. It starts at its first layer with 64 convolutional filters and has 1024 filters in its deepest 5th layer. The model comprises only convolutional, maxpooling, up-convolutional, and dropout layers to prevent overfitting layers with the LeakyReLU activation function, which has a slope of 0.2. The Adam optimizer is used to optimize the model with a learning rate of 0.002, and the loss function used is the cross-entropy loss.

This work's CD aspect is implemented as a modified inferencing function for the previously trained semantic segmentation model. The function first ingests the before-instance of the bitemporal pair of input images for inference and performs the contractive phase of the network. The generated feature maps at the end of each of the five layers are then saved temporarily as PyTorch objects. The function then ingests the after-instance of the bi-temporal pair of input images and runs through the contractive phase. The newly generated feature maps are then differenced from the previously saved feature maps with an empirically calculated threshold value for each layer to provide a single difference feature map for the expansive phase of the network, after which the resultant image is a predicted semantically segmented change map.

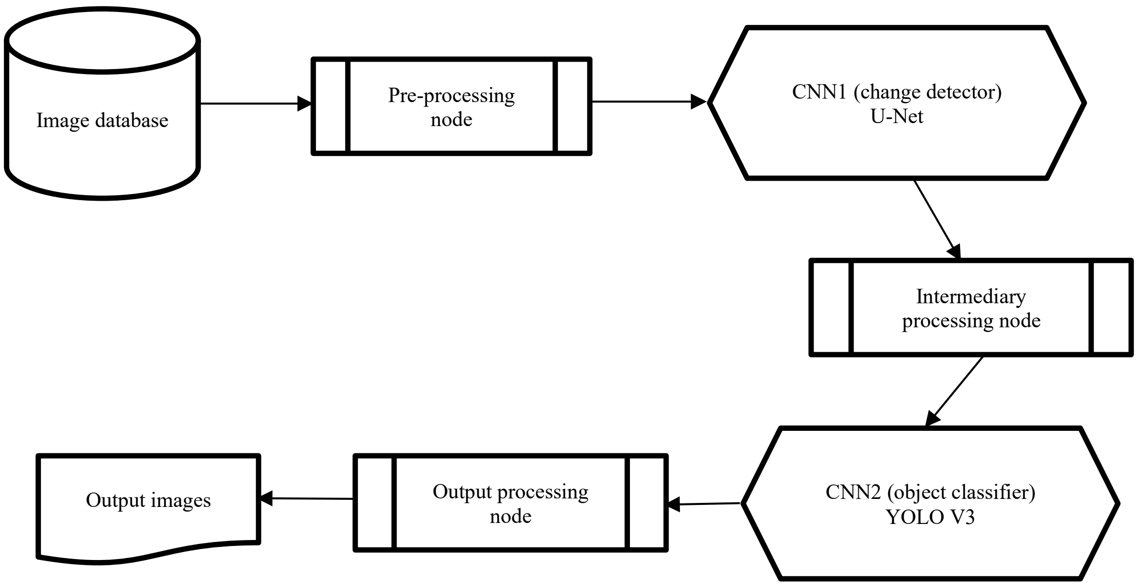

Figure 1. Framework of the proposed method

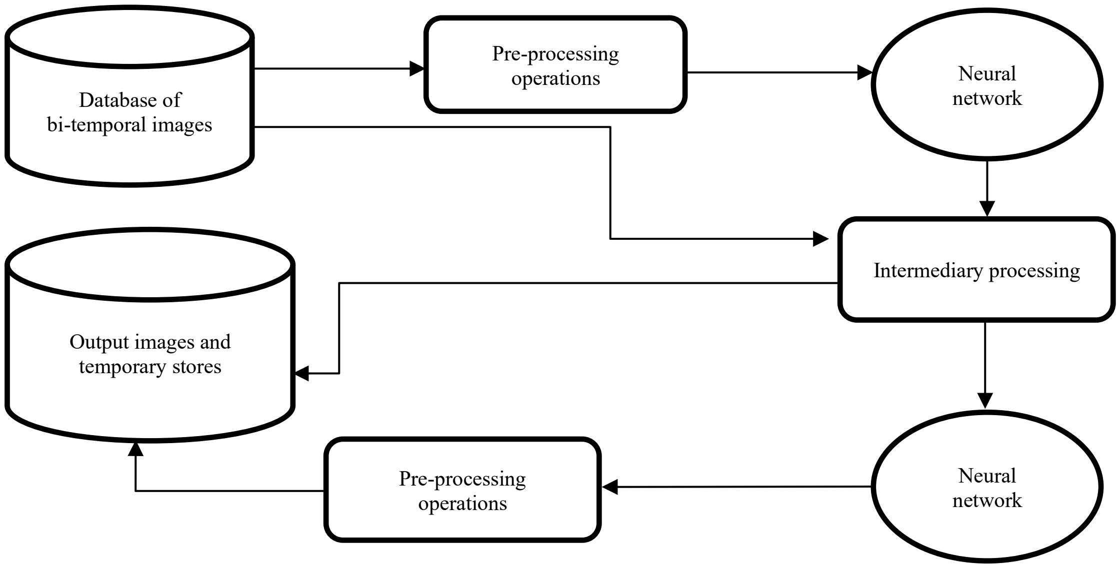

Figure 2. Data flow diagram

4. RESULTS AND DISCUSSION

The semantic segmentation model used in this work was trained using a 6-label and a 3-label version of the semantic segmentation of aerial imagery dataset. The semantic segmentation of the proposed method is shown in Figure 3. When trained on the 3-label version of the dataset, the same model generated a slightly lower performance metric, likely due to class imbalance. The model trained with the 6-label dataset achieved an accuracy score of over 85% and a mean intersection over union of 0.620. The model training metrics for the 6-label version, as seen in Figure 4, indicate slightly overfitting at play.

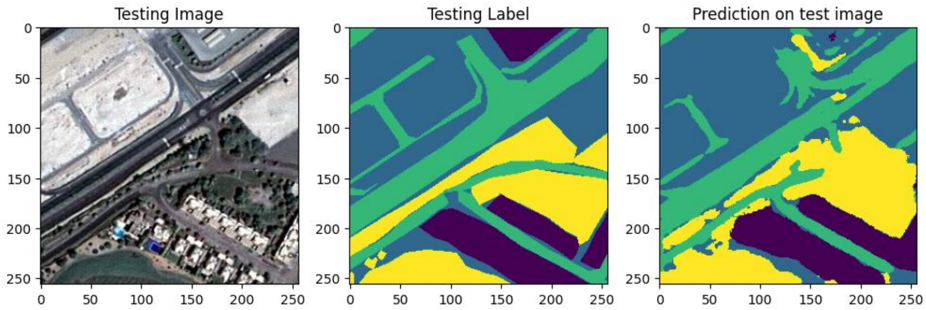

Figure 3. Semantic segmentation result

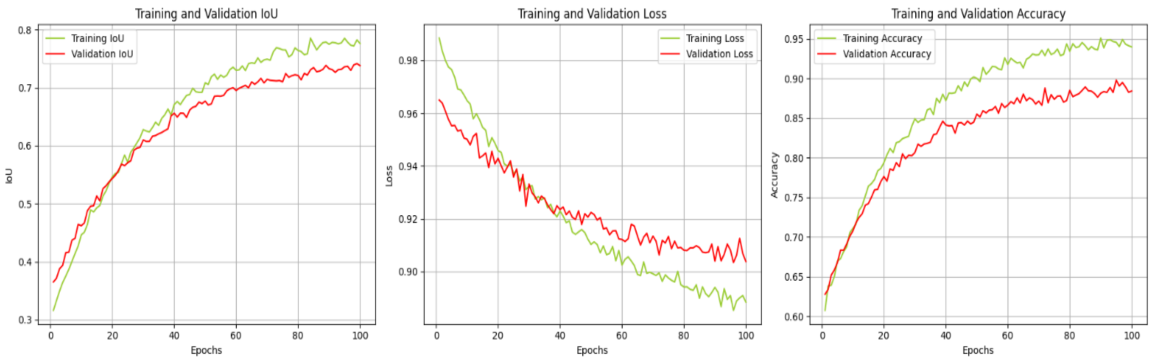

Figure 4. Semantic segmentation training metrics

The CD operation performed by the previously discussed Semantic segmentation model generated a change map due to the difference in feature maps of the two input images, as shown in Figure 5. Due to the absence of multiclass bi-temporal photos in the training dataset, manually augmented change is introduced into the test images, and the PCC2 score of around 0.90 quantifies the model's performance. Figure 6 depicts the results of the object detection model using YOLOv3 by highlighting the square box where it detects the labeled object.

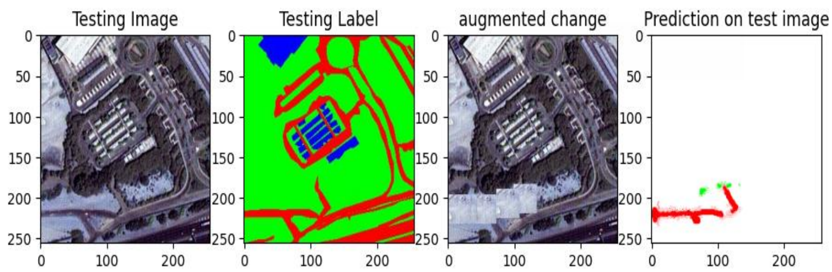

Figure 5. Change map

Figure 6. Object detection result

5. CONCLUSION

Based on the results of this study, it is inevitable that multiclass semantic segmentation is a complicated computer vision problem. This work achieves CD as a result of careful feature extraction and feature difference calculation from the semantic segmentation process with a decent level of certainty up to a certain percentage of pixels having change. The more significant the change, the larger the threshold values were likely to induce false positives. There is also the issue of class imbalance introduced to the reduction in labels, thereby creating an imbalance in the total number of pixels of a particular class. The label reduction was performed in the best interest of the model's performance concerning its primary objective of CD.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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