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Rooftops detection with YOLOv8 from aerial imagery and a brief review on rooftop photovoltaic potential assessment

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ABSTRACT

Recent years have seen significant advancements in the switch from fossil fuel-based energy systems to renewable energy. Decentralized solar photovoltaic (PV) is one of the most promising energy sources since there is a lot of rooftop space, it is easy to install, and the cost of the PV panels is low. The determination of rooftop locations for PV installation is crucial for energy planning. With this context, this study aimed to detect the suitable rooftops of different shapes. The dataset of 5,076 building roofs used in this study was gathered by us utilizing a drone. This study identified ten distinct roof shapes accurately, including triangle, square, penta, hexa, hepta, octa, nona, deca, gabled roof, and hipped roof, using the most recent version of you only live once (YOLO), known as YOLOv8. Recent research revealed, YOLOv8 is more accurate than earlier YOLO models which is the reason of utilizing YOLOv8. Accuracy of this work of rooftops detection is 93.6%. Also, the precision, recall, and F1-score confidence curve showed good performances too. Finally, a brief review of the most recent studies on the evaluation of rooftop PV potential was conducted to provide insight into the use of solar energy.

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1. INTRODUCTION

As the demand for renewable energy rises globally, solar power has emerged as a practical and sustainable choice. Photovoltaic (PV) modules, which convert sunlight into electricity. However, locating suitable rooftop surfaces is not an easy task. In this study, automated deep learning approaches have been investigated to identify and assess rooftop zones that are suitable for PV modules from aerial images. Now more than ever, people are considering low-carbon development and the use of renewable energy. Installation of PV panels can surely reduce amount of greenhouse gas emissions. The majority of countries rely on fossil fuel-based energy production; however, this method is expensive. The high cost of this kind of energy production is a major concern for developing countries. In countries with scarce natural resources and inadequate energy management capacities, particularly in Bangladesh, there is a severe energy shortage. From this situation, it is clear that employing solar panels is now very necessary.

But the first step to install PV modules on rooftops is to find out the suitable rooftops. The search for acceptable rooftop surfaces for the installation of PV modules, however, is typically a time-consuming, expensive, and labor-intensive process that requires physical examination. In order to make it simple to install PV modules on the appropriate rooftops quickly and with minimal labor, this study aims to automatically detect rooftops and classify them into various categories. This study uses a dataset that we had collected on our own. We captured the aerial footage by using a drone to capture aerial images. Aerial photographs shot by a drone provide a bird's-eye perspective of buildings and landscapes. Aerial imaging gives spatial data that can be utilized to quickly and accurately analyze large areas, doing away with the necessity for physical inspections. With a runtime of five to seven minutes each, we recorded a total of 30 films. The videos were then converted into images.

After reviewing earlier studies [1]–[4] that indicated a greater accuracy of detection when utilizing the YOLOv8 model, we made the decision to employ it. You only look once (YOLO) is an object detection algorithm. It is a popular real-time object detection system that can identify and localize multiple objects in an image or video stream. YOLOv8 is the most updated version of YOLO right now. Recent research revealed that YOLOv8 is more accurate than earlier YOLO models. Additionally, YOLOv8's training time will likely be shorter than that of previous two-stage object detection models [5].

Following the rooftop detection phase, we conducted a brief review on the other potentialities of this rooftop detection research, including estimating mathematically the number of PV modules that can be installed on a particular rooftop, determining the shape and angle of the rooftop that is best suited for the highest solar power generation, and estimation of solar irradiance. So, the contributions of this research work can be summarized as follows:

– Creating a dataset of drone captured arial images with high resolution to get very accurate detection.
– Utilizing the most recent YOLOv8 model for detection and, further potentiality analysis of rooftop detection for PV installation.

2. LITERATURE REVIEW

Zhong *et al.* [6] proposed a framework using high-resolution satellite images available employing a deep learning-based technique for automatically extracting rooftop areas. The estimated rooftop area suitable for PV installations in Nanjing was found to be 330.36 km^2, with an impressive overall accuracy of 0.92. Mao *et al.* [7] reviews various methods for identifying PV installations, and proposes optimizations to enhance the identification process and forecast rooftop PV potential. Deep learning, exhibits superior accuracy in segmenting PV systems of all sizes, with rooftop PV segmentation achieving precision and recall rates ranging from 41 to 98.9% and 54.5 to 95.8%, respectively. Aslani and Seipel [8] aims to present a comprehensive methodology that includes automatic extraction of building footprints, segmentation of roof faces, and identification of suitable rooftop areas for solar infrastructure. The experimental results demonstrated impressive accuracy of 95% in building extraction. Mohajeri *et al.* [9] aims to enhance solar energy deployment in urban areas using PV installations. The researchers utilized a machine learning technique called support vector machine (SVM) classification to classify 10,085 building roofs in Geneva based on their solar energy potential. The SVM achieved a 66% accuracy in identifying six roof shape types. Song *et al.* [10] focuses on utilizing solar energy through the installation of solar PV systems on building rooftops. Research by Lee *et al.* [11], a novel data-driven approach to assess the solar potential of rooftops using widely available satellite images. The approach was thoroughly evaluated on an annotated roof dataset, validated by solar experts, and compared to a light detection and ranging (LIDAR)-based method. DeepRoof demonstrated high accuracy in extracting roof geometry, achieving a true positive rate of 91.1%.

Research by Zhong *et al.* [12], a computational system that uses deep learning to identify planned noise barrier sites based on local policies and recognize current noise barrier sites from street-view photos is proposed in order to estimate the solar PV potential in cities. These results demonstrate the systems' enormous potential to support urban renewable energy sources. A real-time multi variant deep learning model (RMVDM) is suggested in [13] as a method for identifying and categorizing PV problems. The suggested RMVDM performs well, reaching an accuracy of about 97%. Through identifying the tilt angle and putting PV panels in the proper orientation, Memari *et al.* [14] intends to improve the accuracy of real-time solar power generation estimation in various global regions. Chen *et al.* [15] introduces a novel approach for identifying the spatial distribution of solar power plants in large-scale areas. It detected 52 solar power plants with a recall rate of 96.30%. According to Tella *et al.* [16], various deep learning networks were used to categorize faults in solar PV cells. From 56.296% on the elpv benchmark to 91.399% on the extracted elpv datasets.

The purpose of Fakhraian *et al.* [17] is to conduct a thorough, systematic review of the various developed methodologies, identify key elements for evaluating urban rooftop solar PV potential. In order to identify suitable rooftop spaces, Castello *et al.* [18] uses a standalone convolutional neural network (CNN), which achieves an intersection over union of 64% and an accuracy of 93%. The PV system design that was placed on an Indian rooftop is the subject of this research [19]. Cadei *et al.* [20] employs satellite photography and machine learning techniques to map prospective rooftop surfaces for the installation of PV panels. In order to evaluate the rooftop area, Wiginton *et al.* [21] provides approaches that integrate geographic information systems and object-specific image recognition. The goal of the study [22] is to present a thorough analysis of geographic information system (GIS)-based rooftop solar PV potential calculation techniques used at various sizes, including national levels. The results show that large-scale spatial-temporal assessments of future energy systems with decentralized electrical grids can be performed using estimating methods based on GISs. None of the reviewed studies used YOLOv8 model yet in this sector. So, utilizing this model and analyzing its result can be a great experiment in this field.

3. METHOD

Data collection was done initially in order to locate specific building rooftops. The dataset consists of aerial photographs from drones that we have personally acquired in the form of video. The collected videos were then turned into intro pictures. Three pre-processing steps-annotation, scaling, and augmentation-were used to prepare the photos. The YOLOv8 model was then applied to the photos. We use YOLOv8, the most recent iteration of the YOLO model, which can be used for tasks including object recognition, image classification, and instance segmentation. To sort the types of building roofs in the Bangladeshi metropolis of Dhaka into groups based on their suitability for PV modules. Rooftops that were recognized and displayed inside bounding boxes in the output photos were divided into 10 different types. Last but not least, the likelihood of this rooftop discovery was then examined. Figure 1 shows the workflow diagram.

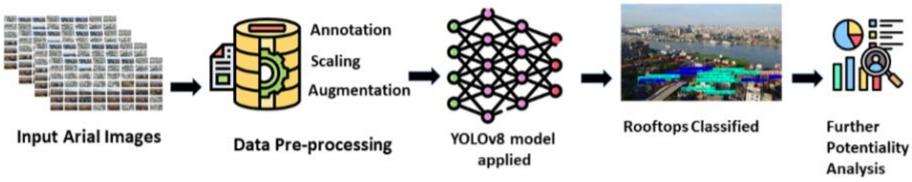

Figure 1. Workflow diagram of rooftop detection for PV installation

3.1. Data collection

The dataset utilized in this research work is our own collected dataset. We captured a few video snippets of the building's rooftop using drone footage. These films were acquired by traveling to several cities' locales. We recorded a total of 30 films, with a runtime of between five and seven minutes apiece. To obtain data of the highest quality, certain issues were preserved during data collecting.

– We made sure aerial photos are of a high enough standard to perform the detecting work because images with better resolution often provide more information for rooftop study.
– Since not all areas are ideal for solar energy installation, the zone of interest for rooftop solar energy installations has been carefully chosen for aerial imaging.
– To ensure that the annotations are reliable and correct, the dataset was checked after it was assembled. We performed quality checks and corrections as necessary.

3.2. Dataset description

After collecting video shot in the actual building, the films were transformed into frames or photographs. A frame rate of one was used to sample the videos. About 500 pictures or frames could be made by our team. We deleted some duplicate photos and had 350 frames left behind.

3.3. Data preprocessing

Preprocessing images is a great way to enhance their quality and prepare them for analysis and further processing. Through preprocessing, we can get rid of undesired distortions and enhance certain traits that are crucial for research works. Several preprocessing steps were executed for the images utilized in this study.

– Data annotation: we identified the rooftop regions in the dataset that are appropriate for PV module installation. To further leverage this for usage with deep learning models, the rooftop zones that are ideal for the installation of solar energy systems has been manually recognized.
– Image re-scaling: rescaling was done on the dataset to provide consistency during training and to standardize the size of the aerial photos.
– Data augmentation: the data augmentation techniques used in this study work include rotation, flipping, zooming, and adjusting brightness and contrast. The 350 frames were subsequently increased by 560 to yield the train, test, and validation datasets.

3.4. An overview of YOLOv8 model

The YOLO set of models has become well-known in the field of computer vision. With the introduction of YOLOv8, the most recent version of YOLO, a model that establishes a new state-of-the-art for object recognition and instance segmentation, the field of computer vision advances. According to common objects in context (COCO) and Roboflow 100 measurements, YOLOv8 has a high accuracy rate. A variety of developer-friendly features are included in YOLOv8. On COCO, YOLOv8 achieves high accuracy. For instance, when measured on COCO, the medium YOLOv8 model obtains a 50.2% mean average precision (mAP) [23].

DarkNet-53, a new backbone network introduced in YOLOv8, is substantially quicker and more precise than the one utilized in YOLOv7. A CNN with 53 layers called DarkNet-53 can classify photos into 1000 different item categories. Yolov8 generates bounding box predictions in a manner akin to pixel-wise picture segmentation. Additionally employing feature pyramid networks, YOLOv8 is more accurate overall and is able to distinguish objects of various sizes [24]. The architecture of YOLOv8 model is like the Figure 2 [25].

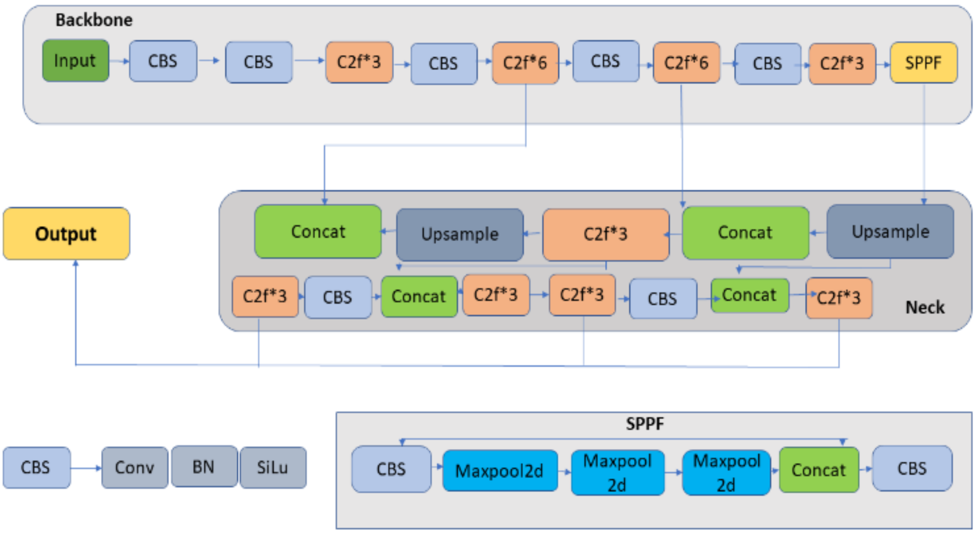

Figure 2. Architecture of YOLOv8 model

4. RESULTS AND DISCUSSION

4.1. Outcome of this research

The YOLOv8 model has successfully detected ten types of rooftops where solar panels can be installed. The outcome after utilizing YOLOv8 on the input images is shown in Figure 3.

4.2. Performance analysis in terms of accuracy, precision, recall and F1 score

Three sets-training, validation, and testing-were created from the dataset. The deep learning model is trained on training data, validated on validation data to change the hyperparameters and monitor the model's performance, and tested on testing data to determine how well the final model performs on untried data. 80% of the images were utilized for training while the rest of the images were for validation and testing purposes. Using a test dataset with 560 data points, this project's accuracy was examined. Using the pre-trained model on our dataset, we were able to detect rooftops with an accuracy of 93.6%. The precision-confidence curve plots the precision of the model's predictions against different confidence score thresholds. The precision confidence curve for this rooftop is shown in Figure 4.

The precision-recall curve is useful for understanding how different confidence score thresholds impact the performance of the object detection model. It helps in choosing an appropriate threshold that balances precision and recall based on the specific requirements of the application. Generally, models with higher areas under the precision-recall curve are considered better performers as they can achieve high precision while maintaining good recall. Precision-recall curve is shown in Figure 5.

The F1-score confidence curve is shown in Figure 6. The F1-score, which ranges from 0 to 1, is particularly useful in identifying the level of confidence that best balances the precision and recall values for a given model. The set of F1-scores for a particular model can be used to produce a single value assessment measure, which may be a reliable gauge of the performance of the model as a whole.

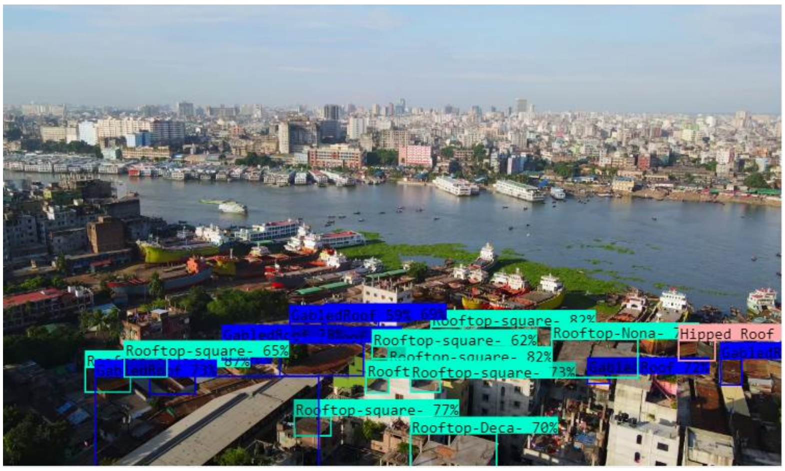

Figure 3. Rooftop's detection utilizing YOLOv8 algorithm

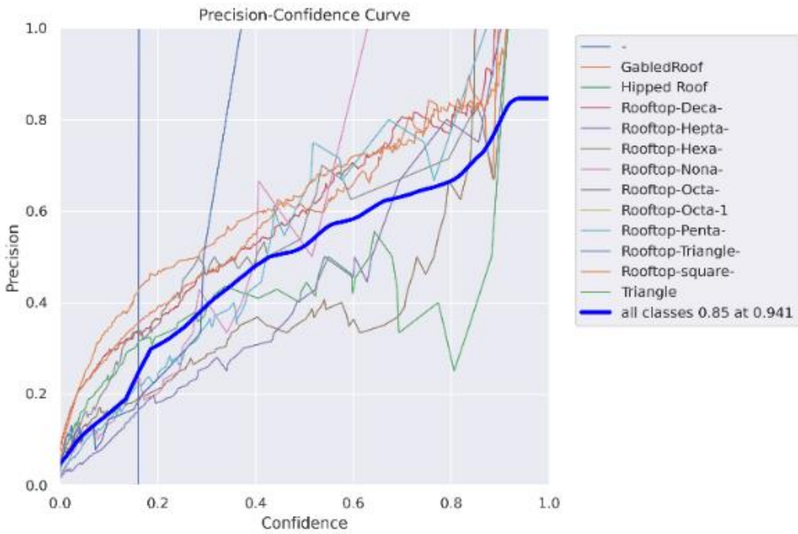

Figure 4. Precision confidence curve

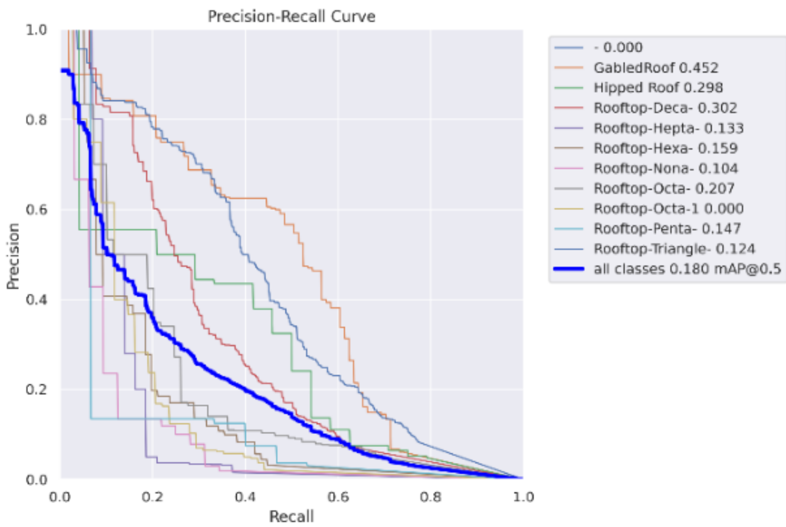

Figure 5. Precision recall curve

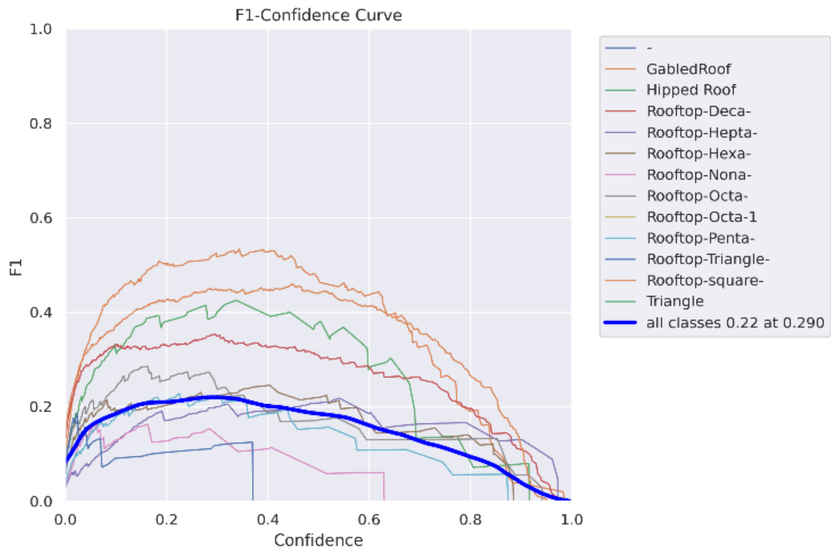

Figure 6. F1 score confidence curve

5. A SHORT REVIEW ON ROOFTOP PHOTOVALTIC POTENTIAL ASSESSMENT

Following the identification of rooftops for the installation of PV modules, there are numerous more possibilities, including measuring the rooftop's area, power generation capabilities and determining the number of PV modules that can be installed there. Once more, estimating solar irradiance is an essential phase in determining how energy-efficient PV modules are. Many studies have already been conducted to do so. This section will provide information on studies that have discovered potentialities that can be used after rooftop detection to ensure proper utilization of solar energy.

5.1. Quantifying suitable rooftop area for assessing the potentialities of solar power generation

It is necessary to deduct the area occupied by barriers from the total area when calculating a rooftop's effective area. Therefore, an effective area can be mathematically determined as the difference between the entire area and the obstacle area in pixels, which should be then translated into square meters. The necessary number of PV modules for a specific rooftop can then be determined by dividing the rooftop's overall area by the area of the PV panel that will be installed there. A significant number of studies have revealed the rooftop's potential for electricity generation. Some of these studies are summarized in Table 1.

Table 1. Summary of rooftop electricity generation potential from previous studies

Ref	Objective	Utilized method	Findings
[18]	Quantification of the suitable rooftop area.	Convolutional neural network.	Segment suitable rooftop areas with an accuracy of 93.0%.
[24]	Estimating the spatial distribution of solar PV power generation potential	Deep learning	Utilized U-net model got an accuracy of 92%
[25]	Providing estimation of rooftop PV power generation	Deep learning	The findings indicate that the province's rooftop resources have a potential installed capacity of 245.17 GW.
[26]	Estimating utilizable areas and solar energy potential of rooftops	Deep learning, morphological operation, segmentation	Accuracy: 93% for rooftop extraction and 99% for plane segmentation

5.2. Solar irradiance estimation for the assessment of energy efficiency of PV power plants based on roof shape and angle

The amount of electromagnetic radiation that is emitted from the sun per unit area, which is typically square meters, is known as solar irradiation. The sun irradiation and cell temperature have the biggest effects on how much electricity PV sources can generate. Here are some researches which have studied on this topic in Table 2.

Table 2. Solar irradiance estimation for rooftop from previous studies

Ref	Objective	Utilized method	Findings
[27]	Finding out the optimum tilt angles of maximum solar irradiance	Mathematical calculation	The maximum solar radiation can be found with the tilt angle between 0° to 64°
[28]	Finding out the effect of tilt angle and orientation of solar surface for solar power generation	Solar panels and sensors	The energy harvesting capacity of each solar panel is strongly influenced by the inclination
[29]	Estimation of annual solar irradiation	Machine learning (random forest)	Accuracy 92% at estimating solar irradiation
[30]	Estimating solar irradiance and PV power	Long short-term memory and gated recurrent unit	With 0.96%, machine learning models produced very unbiased estimations.

6. CONCLUSION

In this research work, a system for detecting rooftops suitable for installation PV modules in aerial images using deep learning techniques is presented. The study sought to address the drawbacks of manual inspections and traditional methods by applying deep learning algorithms for accurate and successful rooftop identification. The most recent YOLOv8 model, built and used to detect potential installation sites, showed promising results in terms of accuracy, precision, and F1-score when trained on a carefully selected collection of aerial photographs with annotated rooftop surfaces. The system's automated detection process, which reduces the time and money associated with manual inspections, can enable the faster integration of solar power. Once more, a potentiality analysis of this study revealed the enormous potential for solar energy use. The policymakers, energy planners, and building owners can leverage its simplicity in energy planning and decision-making processes to make the best use of solar energy, which is a crucial need for this century.

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AUTHOR CONTRIBUTIONS STATEMENT

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

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Nusrat Tasnim	✓		✓	✓			✓		✓	✓	✓		✓	
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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

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the first author, [MSA]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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