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Automated ergonomic sitting postures detection for office workstation using XGBoost method

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ABSTRACT

Sedentary office work increases musculoskeletal risk, underscoring the need for non-intrusive, real-time posture monitoring. This study presents a computer vision approach that classifies ergonomic versus non-ergonomic sitting postures using upper body key points extracted by MoveNet thunder. Images from 30 participants were captured from frontal and side views, and labeled according to SNI 9011:2021 criteria. Seventeen key points were detected, with head-to-hip landmarks retained, then normalized and centered. Three classifiers—adaptive boosting (AdaBoost), extreme gradient boosting (XGBoost), and a multi-layer perceptron (MLP)—were trained and evaluated with 10-fold stratified cross-validation. XGBoost achieved the best performance, with accuracy 93.0%±1.9%, precision 94.6%, recall 91.4%, F1-score 92.9%, and area under the receiver operating characteristic curve (ROC-AUC) 0.974±0.010, outperforming MLP and AdaBoost. The method supports privacy-preserving, on-device inference and is suitable for integration into smart office systems to reduce exposure to high-risk postures. Limitations include controlled capture conditions and an upper-body focus; future work will expand posture taxonomy and real-world deployment.

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1. INTRODUCTION

Work in contemporary offices is largely screen/desk-centered, leaving employees seated for nearly four-fifths of the workday [1]. This setting correlates with widespread health complaints, notably musculoskeletal disorders (MSDs) and computer vision syndrome; surveys report back pain in nearly half of workers and eye pain in about one-fifth, with apparent knock-on effects for productivity through both absenteeism and presenteeism (working despite illness). These patterns highlight the importance of preventive and proactive ergonomics in the workplace [2]. Although sedentary time includes all low-intensity activities, sitting dominates in office settings. Prolonged sitting is associated with various health risks, such as eye strain, obesity, type 2 diabetes, poor nutrition, high cholesterol, cardiovascular disease, certain cancers, and MSDs [3]–[5]. Targeted countermeasures include scheduling regular, brief breaks that follow ergonomic guidelines during prolonged desk work [4], [5]. Equally important is maintaining correct seated posture, as poor alignment is a known contributor to MSDs [5]–[7]. Embedding ergonomics into day-to-day work practices is therefore a central strategy for reducing sitting-related risks [4].

Assessing ergonomic sitting posture typically requires measuring multiple body segments, which is disruptive and impractical at scale. Therefore, automated systems are necessary to classify posture as either ergonomic or non-ergonomic without requiring manual measurement. Previous studies have employed sensor-based and machine learning methods for posture detection, providing accurate real-time feedback, but often relying on wearable or external devices [3], [8]–[11]. Rapid progress in computer vision, propelled by deep learning, has transformed automation across various domains [12]. Deployed applications span 3D reconstruction from 2D imagery, robot guidance, part categorization, and automated inspection [12], [13], along with facial-recognition-based attendance systems [14]–[17], traffic incident detection [18], and posture recognition for seated workers [19], [20]. By leveraging these capabilities, computer vision can replace manual measurements and reduce the need for continuous human supervision, automatically detecting and flagging risky seated postures so users can adjust in real-time [19].

A recent study proposed an anomaly-sitting posture detection model that runs on internet of things (IoT) devices. It leverages the lightweight pose estimation model, MoveNet thunder, to extract 17 key body landmarks as well as a shoe position detector as an additional feature to enhance detection. The study employed a 5,042 labeled image dataset with three distinct posture categories: normal, crossed leg, and forward head. The features were classified with a neural network model that consists of an embedding layer and several dense layers. The model achieves an overall F1-score of 97% [7].

Estrada *et al.* [20] developed a rule-based model for sitting posture classification using key body points (nose, shoulders, and spine) obtained via human pose estimation, achieving 91.5% and 97.05% accuracy on left and right camera data, respectively. OpenPose was also applied to analyze joint angles and movements from video data. Lin *et al.* [21] employed a decision tree for ergonomic assessment based on rapid entire body assessment (REBA), rapid upper limb assessment (RULA), and ovako working posture analyzing system (OWAS), identifying high-risk postures in 10.4% of working time, which is consistent with expert evaluations. A random forest model tested on the KTH dataset achieved the highest performance, with 90.48% accuracy at 15 sample rates and 15-frame sequences [22].

Akhter *et al*. [23] have developed an event recognition system using adaptive boosting (AdaBoost) for human activity. The study employed feature representations, including movable body, optical flow, and motion data. The UCF101 and YouTube datasets were used to develop the model. These include a diverse range of activities such as cycling, swinging, and walking. The model achieved an accuracy of 75.33% on the UCF101 dataset and 76.66% on the YouTube dataset. Gao *et al.* [24] developed a Bayesian-optimized extreme gradient boosting (XGBoost) algorithm to recognize lower-limb motion intentions using combined electromyography (EMG) and inertial measurement unit (IMU) data from ten participants performing walking, squatting, and leg extension tasks, achieving an average F1-score of 95.33%. Meanwhile, Fang *et al.* [25] introduced sitting posture recognition network (SPRNet), a vision transformer model that uses OpenPose-extracted body key points to classify three student sitting postures, achieving 99.2% accuracy and surpassing other pre-trained models.

This study presents a method for assessing ergonomic sitting posture by analyzing key points of the human body extracted from images. The MoveNet pose estimation model was selected as the keypoint extractor (e.g., nose, shoulders, elbows, and spine) for generating features used by machine learning classifiers such as multi-layer perceptron (MLP), AdaBoost, and XGBoost, due to its compactness and low computational demand [20], [26], [27]. Unlike previous systems using OpenPose [21], [25] or MediaPipe [20] for multi-activity recognition or limited-angle clinical analysis, this study focuses on office sitting ergonomics with both frontal and side camera views. Using MoveNet thunder to extract 17 keypoints, the system enables real-time single-person inference on mobile or edge devices, achieving lower latency and model size than OpenPose while maintaining high pose-estimation accuracy [28]. The approach enhances cross-view generalization and classification efficiency in ergonomic posture detection, thereby reducing MSD risk and promoting workplace health.

2. METHOD

The proposed method is divided into five stages: data collection, key point extraction, data preparation, classification, and evaluation. Figure 1 displays the entire process of the proposed method. The subsequent subsection explains the specifics of each phase.

2.1. Data collection

The study used data from 30 participants, each providing 30 samples of ergonomic and non-ergonomic postures. Data were collected in a well-lit office with a plain background, capturing seated participants from side and front views (with side views mirrored for balance). Participants followed posture guidelines from an ergonomic expert, based on SNI 9011:2021. Ergonomic postures featured straight backs, flat feet, 90° knee bends, and arms on the desk, while non-ergonomic ones showed curved backs, body twists, or downward gazing. Data were collected using a digital camera with a 5472×3648-pixel resolution, an ISO of 250, an aperture of f/2.8, and a 1/30 s shutter speed. The camera was positioned 1.67 meters for the front view and 1.15 meters for the side view, measured from the person's body. The height is constant at 1.27 meters for all views. This resulted in 900 instances for each posture. Examples are shown in Figure 2.

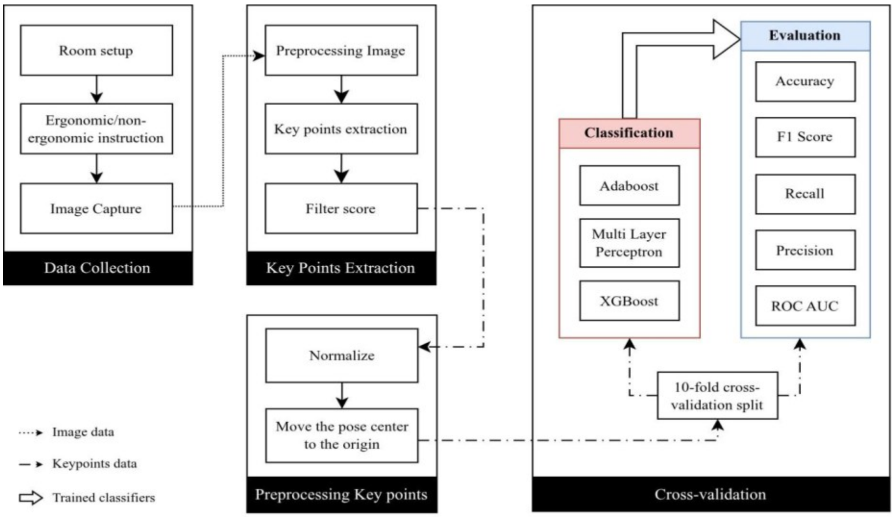


Figure 1. The process flow of the proposed sitting posture classification model

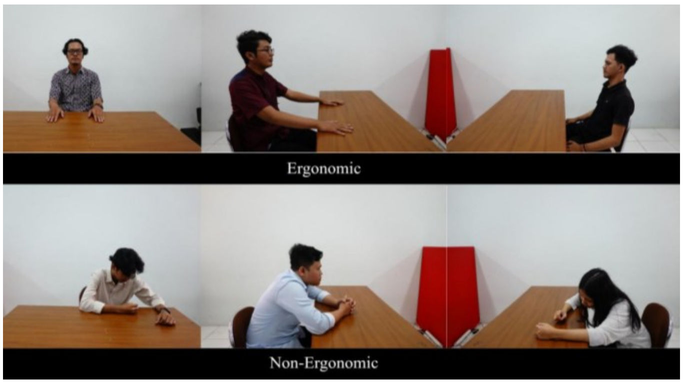


Figure 2. Examples of collected data for ergonomic and non-ergonomic postures

2.2. Key points extraction

The key point extraction phase utilizes the MoveNet pose estimation model, developed by IncludeHealth and Google in 2021, to detect human body key points in real-time [26]. MoveNet has two versions—lightning and thunder—with the latter used in this study for higher accuracy. Built on the TensorFlow object detection API and MobileNetV2, MoveNet employs the CenterNet approach, which detects center points instead of bounding boxes for efficient multi-person detection without non-maximum suppression, thereby ensuring fast and precise keypoint localization [28]. To extract the key points from an image using MoveNet, it is necessary to ensure that the image meets the specified size requirements. For MoveNet to process the image, it must be resized to a 256×256-pixel size. When the original image is resized to a 1:1 ratio, it can cause the image or the subject within it to appear squeezed. To overcome this issue, padding is added to the longer side—specifically, the top and bottom—to compensate for the reduction in pixels that occurs when resizing the image. This process ensures that the shorter side of the image is preserved, preventing a squeezed appearance. After resizing and padding the image, it is input into the MoveNet model, which detects 17 key points on the human body as shown in Figure 3 [7], [21], [27]. Each key point is represented by x and y coordinates along with a score, with a threshold of 0.1 set for validity. If all key points exceed this threshold, the image is considered valid, and the key points are stored. However, this study only considered the key points from head to hips, which represent the most critical points for determining posture [29]–[31]. This is because these body parts generally provide sufficient information for people who sit behind a desk, as only the top part of the body is visible.

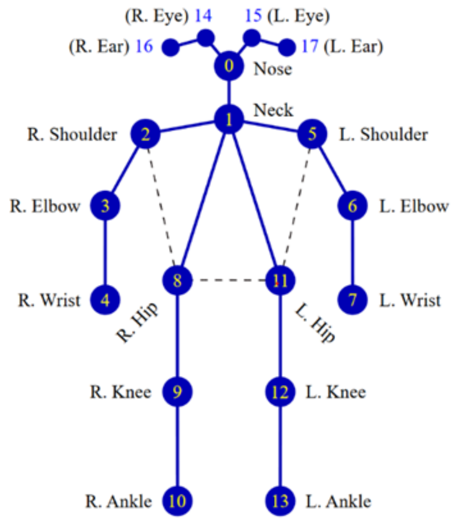


Figure 3. The 17 key points detected by the MoveNet model

2.3. Data preparation

The data preparation phase involved preprocessing and splitting the dataset. Extracted key points were normalized so that the maximum distance between them equaled one, ensuring pose comparability regardless of body size or camera distance. The key points were then centered to standardize poses and emphasize relative landmark positions. Finally, the dataset was divided into 10 stratified folds for cross-validation.

2.4. Classification

The classification phase involves training models on each cross-validation fold using AdaBoost, XGBoost, and MLP. AdaBoost is an ensemble method that combines multiple weak learners into a strong classifier [23], [32]. XGBoost optimizes decision-tree models using a second-order Taylor expansion of the objective function and incorporates tree complexity as a regularization term [24]. Meanwhile, MLP is a feed-forward neural network with input, hidden, and output layers that learns patterns through weight updates via backpropagation [12].

2.5. Evaluation

The evaluation phase assessed the model's ability to detect ergonomic posture using a 10-fold cross-validation scheme, where each fold used 90% of the data for training and 10% for testing. Model performance for each fold was evaluated using accuracy, precision, recall, and F1-score, and the results were summarized as the mean±standard deviation (SD) to assess stability and generalization. The computation of these metrics as in (1) to (4) [9].

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

$$Precission = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1 - score = 2 \times \frac{Precission+Recall}{Precission \times Recall} \tag{4}$$

TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives, respectively. TP and TN represent correctly classified positive and negative instances, while FP and FN denote misclassified negative and positive instances [9]. Model performance was also assessed using the area under the receiver operating characteristic curve (ROC-AUC), where the ROC illustrates discrimination across thresholds and the AUC measures the area under the curve; an AUC of 1 indicates perfect classification, whereas 0.5 reflects random performance [9], [32]. For visualization, out-of-fold predictions from all 10 folds were aggregated to produce a single confusion matrix and ROC curve, ensuring unbiased predictions since each sample was evaluated by a model that had not seen it during training.

3. RESULTS AND DISCUSSION

A total of 1,550 valid instances were obtained based on keypoint extraction scores, consisting of 873 ergonomic and 677 non-ergonomic samples. Figure 4 illustrates the keypoint extraction process (image not to scale). After normalization and centering, the keypoints were used to create a 10-fold cross-validation split for training and testing. Three models were trained using AdaBoost, XGBoost, and MLP classifiers, and their performance was evaluated by averaging the accuracy, precision, recall, F1-score, and ROC-AUC. Table 1 and Figure 5 summarize the results. Figure 5 provides a comparative bar plot (y-axis starting at 0.75).

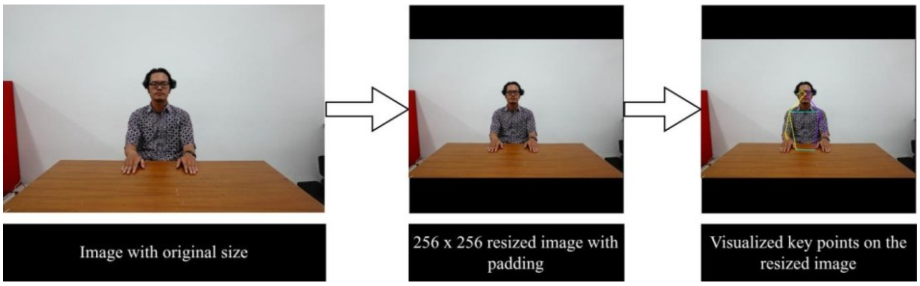


Figure 4. The process of extracting key points from an image using MoveNet

Table 1. Cross-validation performance (mean±SD)

Classifier	Accuracy	Precision	Recall	F1-score	ROC-AUC
AdaBoost	0.894±0.021	0.936±0.031	0.847±0.313	0.889±0.022	0.950±0.016
MLP	0.918±0.221	0.946±0.024	0.886±0.035	0.915±0.024	0.960±0.011
XGBoost	0.930±0.019	0.946±0.032	0.914±0.019	0.929±0.019	0.974±0.010

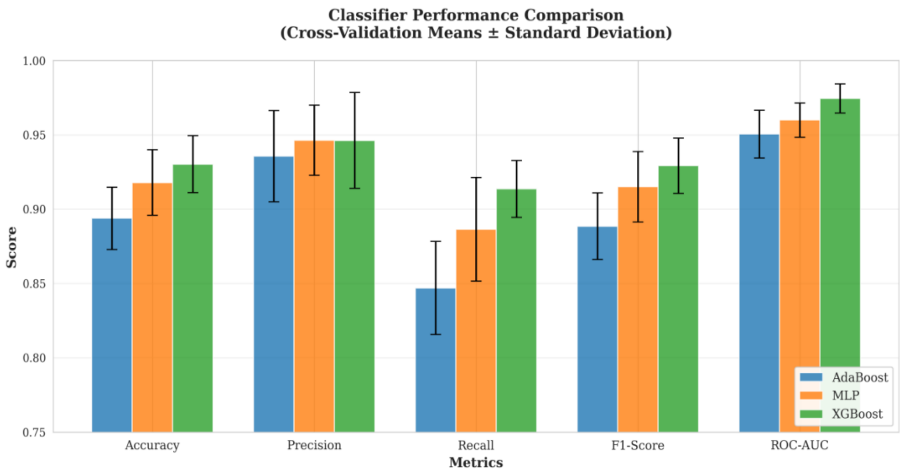
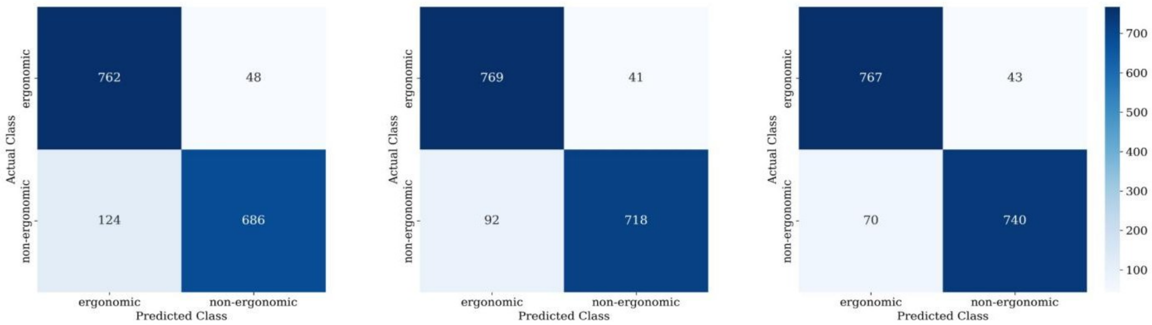


Figure 5. Multiple bar plot for metrics visualization across classifiers

The results show that XGBoost achieves the best overall performance, with the highest average accuracy (93.0%), precision (94.6%), recall (91.4%), F1-score (92.9%), and the top ROC–AUC value of 0.974±0.010, indicating stable class separation under cross-validation. MLP ranks second, performing competitively (accuracy 0.918±0.221, precision 0.946±0.024, recall 0.886±0.035, F1-score 0.915±0.024, and ROC–AUC 0.960±0.011), though its large accuracy variance suggests fold-to-fold instability. AdaBoost yields the weakest results (accuracy 0.894±0.021, precision 0.936±0.031, recall 0.847±0.313, F1-score 0.889±0.022, and ROC–AUC 0.950±0.016), with notably unstable recall.

The confusion matrices shown in Figure 6 illustrate the classification performance of each model. Figure 6(a) presents the AdaBoost classifier, which exhibits the highest number of false negatives for ergonomic postures and overall weaker performance. Figure 6(b) shows the MLP classifier, which produces the highest number of true positives for ergonomic postures and performs better than AdaBoost. Finally, Figure 6(c) depicts the XGBoost classifier, which achieves the truest negatives and the fewest false positives for non-ergonomic postures, indicating the best overall performance among the three classifiers.

Correspondingly, the ROC curves in Figure 7 show that XGBoost has the highest AUC, MLP is second, and AdaBoost is lowest. All matrices and curves are derived from combined out-of-fold predictions across 10-fold cross-validation, ensuring an unbiased evaluation.



(a) (b) (c)

Figure 6. Confusion matrix of (a) AdaBoost, (b) MLP, and (c) XGBoost classifiers

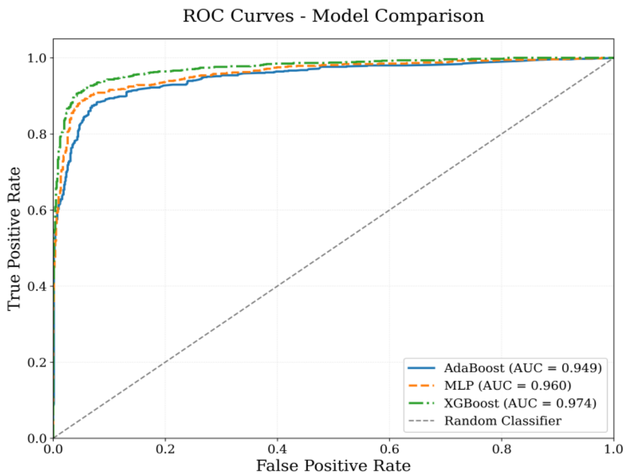


Figure 7. ROC curves for he proposed sitting posture detection model

A comparison of the proposed model with other studies is presented in Table 2. The proposed model, highlighted in bold, which implements the XGBoost classifier, demonstrated an accuracy of 93.02±1.91% in classifying ergonomic postures. The proposed model demonstrated superior performance compared to the deep recurrent hierarchical network [19], which achieved an accuracy of 91.47% in spine posture recognition while sitting. Furthermore, the proposed model demonstrated superior performance compared to the MediaPipe+decision tree model [20], which achieved accuracy of 91.5 and 97.05% in recognizing proper sitting postures from the left and right, respectively. Although the improvement over previous studies are modest, the proposed model benefits from using images captured from three angles. In contrast, the deep recurrent hierarchical network and MediaPipe+decision tree models rely on a single viewpoint (left, right, or front). Moreover, the proposed model outperforms the OpenPose+random forest approach [21], which reported an accuracy of 90.64% in human activity recognition. This highlights the model's effectiveness in classifying ergonomic postures and its potential for integration into systems designed to reduce MSDs in sedentary workplaces.

The system integrates with smart-office platforms using a lightweight client–server architecture. Posture is inferred on-device, and only anonymized features and risk scores are transmitted for centralized aggregation, index computation, and ergonomic alerts. User feedback is delivered through desktop notifications or collaboration tools, and the modular design supports easy deployment within existing wellness systems while preserving privacy through minimal data sharing.

Long-term exposure metrics (e.g., minutes per hour spent in moderate or high-risk postures) enable ongoing monitoring of musculoskeletal risk and support early ergonomic intervention. Reducing high-risk exposure may help lower musculoskeletal complaints and prevent productivity loss. Team dashboards can summarize key performance indicator (KPI) such as exposure rate, alert-resolution time, and ergonomic-compliance levels, linking them to operational outcomes for return on investment (ROI) assessment. However, the study is limited by its small, controlled sample of 30 participants, its reliance on upper-body keypoints that are sensitive to viewpoint changes, occlusion, lighting, and pose-estimation errors, its omission of lower-limb cues, and its restricted and imbalanced posture classes. The work also does not evaluate resource demands on embedded devices or address privacy considerations for on-device processing.

Table 2. Comparison of the proposed model with other studies

Method	Task	Accuracy (%)
Deep recurrent hierarchical network [19]	Spine posture recognition while sitting	91.47
MediaPipe+decision tree [20]	Recognition of proper and improper sitting postures	91.5 and 97.05
OpenPose+random forest [21]	Human activity recognition	90.64
MoveNet+XGBoost (this work)	Ergonomic sitting posture classification	93.02

4. CONCLUSION

This study successfully developed and evaluated a method for detecting and classifying ergonomic postures using computer vision and machine learning classifiers. The MoveNet pose estimation model was employed to extract key points from images, which were then processed for classification using AdaBoost, XGBoost, and MLP classifiers. Among the classifiers tested, XGBoost established the highest accuracy, precision, F1-score, and ROC-AUC, making it the most reliable for overall performance. MLP classifier followed by AdaBoost underperformed across all metrics. The results indicate that XGBoost is effective for posture classification and can support health and safety efforts in sedentary workplaces. The model could be integrated into smart office systems using webcams or small edge-device cameras to deliver ergonomic feedback and trigger alerts for non-ergonomic postures. Future work may refine the model and expand its application in various work settings, including continuous health-monitoring systems, to help reduce musculoskeletal risks and improve productivity.

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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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Farida Djumiati Sitania	✓	✓				✓	✓		✓					✓
Anindita Septiarini		✓				✓		✓	✓	✓	✓	✓		
Hamdani Hamdani	✓	✓	✓	✓	✓		✓			✓	✓		✓	✓

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

The data that support the findings of this study are available on request from the corresponding author, [TAP].

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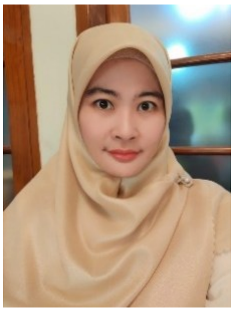

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