TPM Vol. 32, No. R2, 2025
ISSN: 1972-6325
https://www.tpmap.org/

Open Access

EVALUATING SITTING POSTURE USING PRESSURE SENSORS: A LIGHTWEIGHT CNN APPROACH WITH PSYCHOMETRIC AND ERGONOMIC PERSPECTIVES

CHAWAKORN SRI-NGERNYUANG
INSTITUTE OF FIELD ROBOTICS, KING MONGKUT'S UNIVERSITY OF TECHNOLOGY THONBURI, BANGKOK, THAILAND.

PRAKRANKIAT YOUNGKONG
INSTITUTE OF FIELD ROBOTICS, KING MONGKUT'S UNIVERSITY OF TECHNOLOGY THONBURI, BANGKOK, THAILAND

JINPITCHA MAMOM
FACULTY OF NURSING, THAMMASAT UNIVERSITY, PATHUM THANI, THAILAND

The seated posture is quite an important element of ergonomics at work and exercise. An accurate category can help in injury prevention and work-related health programs. Samples of 30 subjects in four sitting positions were collected, and data from 7200 samples were used to train a lightweight CNN. In the training epochs (20-50) and batch sizes (16-32), a systematic search was done. The model has been contrasted with the MobileNetV2 in terms of accuracy, precision, recall, training time and size. The custom CNN achieved a higher accuracy across all the batch sizes (93.83%-99.63%) than MobileNetV2. Training time per iteration reduced (4.12-13.37 seconds vs. 162.88-493.59 seconds), and storage requirements were also minimal 0.03 MB vs. 9.87 MB). The data collected was the same between trials. The findings indicate that the parameter tuning enhances psychometric robustness in classification. The compact CNN can be used to monitor sitting behaviour in real-time, direct ergonomic product design, prevent injuries and conduct psychologically relevant studies.

Keywords: Sitting Posture Classification, MobileNetV2, Custom Lightweight CNN, Pressure Sensors, Sitting psychometric reliability, Applied psychology

Correspondence concerning this article should be addressed to Institute of Field Robotics, King Mongkut's University of Technology Thonburi, Bangkok, Thailand.Email: chawakorn.sringern@gmail.com

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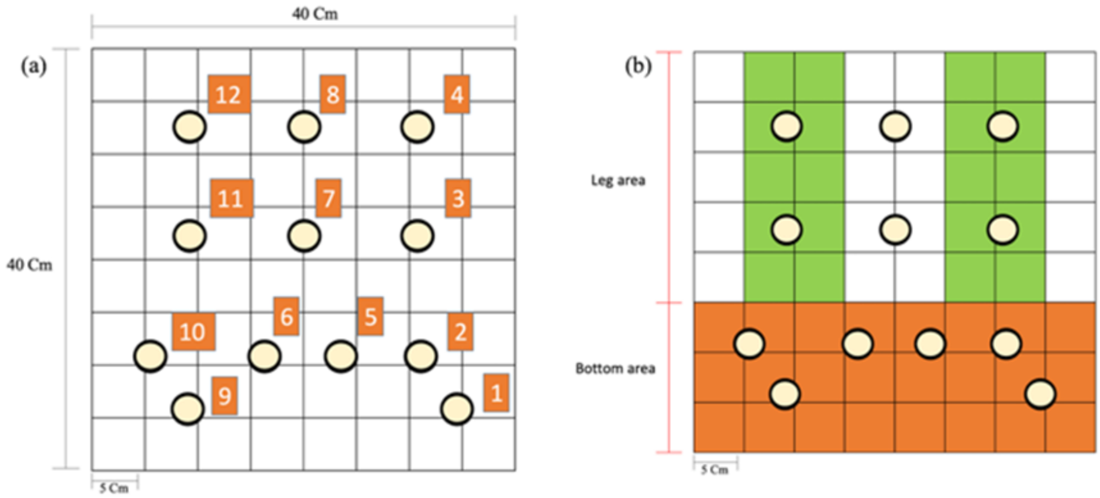
INTRODUCTION

Prolonged sitting in incorrect postures has become a significant concern in both occupational and daily settings, often leading to musculoskeletal disorders, fatigue, and long-term health issues. Many different real-time notification sensors have been developed for ergonomic chair cushions [1]. These new sensors have accurate and fast response rates for delivering posture notifications [2]. Integrated flexible pressure sensors in ergonomic cushions play vital roles in applications related to the external environment, advanced healthcare, human–machine interfaces, and contact force notification sensors [3, 4]. Studies show that prolonged sitting decreases blood circulation, especially in the lower limbs, resulting in venous thromboembolism and deep vein thrombosis [5, 6]. The diverse notifications from real-time ergonomic cushion sensors demonstrate: (a) highly sensitive detection; (b) sensitivity with low (less than 10 kPa) and medium pressure (10–100 kPa) in detecting human motions [7].

The correct ergonomic posture is necessary when sitting for prolonged periods, to reduce the negative effects of workstations during the workday [8]. Research has found that young people (aged 16–19 years) spend approximately 7.5 hours of their day in sitting behavior and older adults (60–85 years old) spend nearly 60% (8 hours a day) in this way [9]. Substantial daily sitting time is associated with a greater risk of musculoskeletal, cardiovascular, or cerebrovascular disease (strokes), type 2 diabetes mellitus, decubitus ulcers, and some malignancies. Poor ergonomic sitting posture has been demonstrated to cause a variety of physical problems, including lower back pain, neck pain, headaches, respiratory and cardiovascular diseases, and digestive issues [10]. Furthermore, people's poor ergonomic posture can be detected using novel notifications for sitting posture by sensing pressure from body segments. Recent studies indicate that poor ergonomic sitting postures are associated with several spinal musculoskeletal disorders, including structural deformity of the spine, and back pain [10, 11]. Prolonged sitting is a serious problem for both the public and clinicians, as metabolic abnormalities accelerate the development of cardiovascular illnesses. There is a clear need to develop ergonomic cushions for sitting-posture detection chair prototypes [12]. Systems for recognizing ergonomic sitting postures on chair cushions are being developed to monitor and evaluate an individual's posture with real-time notifications [13]. These ergonomic sensing chairs are especially useful in healthcare environments, since they provide a proactive strategy for minimizing posture-related illnesses in patients who are unable to freuently change their posture without assistance.

FIGURE 1 Cushion structure with FSR Sensors.

Pressure sensors have been developed to monitor posture, placed in chair cushions for ergonomic



purposes, with real-time notification. Such sensors include nanoribbon hybrids, triboelectricity, mechanoacoustic systems, and bioinspired soft sensor arrays [14, 15]. With an emphasis on applying machine learning, we have studied current developments in sitting posture notification, such as posture detection, the system architecture of cushion sensors.

In this context, our study introduces machine learning techniques for sitting posture classification, specifically through the development of a Custom Lightweight CNN designed for recognizing sitting positions based on data from pressure sensors embedded in a smart cushion shows in Figure 1. These sensors capture real-time pressure distribution patterns corresponding to various postures. By comparing the performance of the Custom CNN with MobileNetV2, the study aims to identify the most effective model in terms of classification accuracy, training time, and computational efficiency for ergonomic monitoring applications.

MATERIALS AND METHODS

General Framework

The method details how sensors apply Convolutional Neural Network (CNN) training to identify different sitting postures. Raw sensor signals are prepared by importing files, normalizing and redistributing the 2D arrays corresponding to the sensor layouts to generate training-testing-validation sets. Multi-class data catego-rization is realized through fast encoding. CNN requires convolutional and pooling layers to extract and reduce features using them, then fully connected layer and softmax output are used. Training data gets the model ready prior to verification checks. Evaluation uses new data to test the model to arrive at accuracy, precision, recall rates and confusion matrices. The model facilitates categorization with displaying postural differences in terms of ergonomics, healthcare and occupational surveillance. The framework appears in Figure 2.

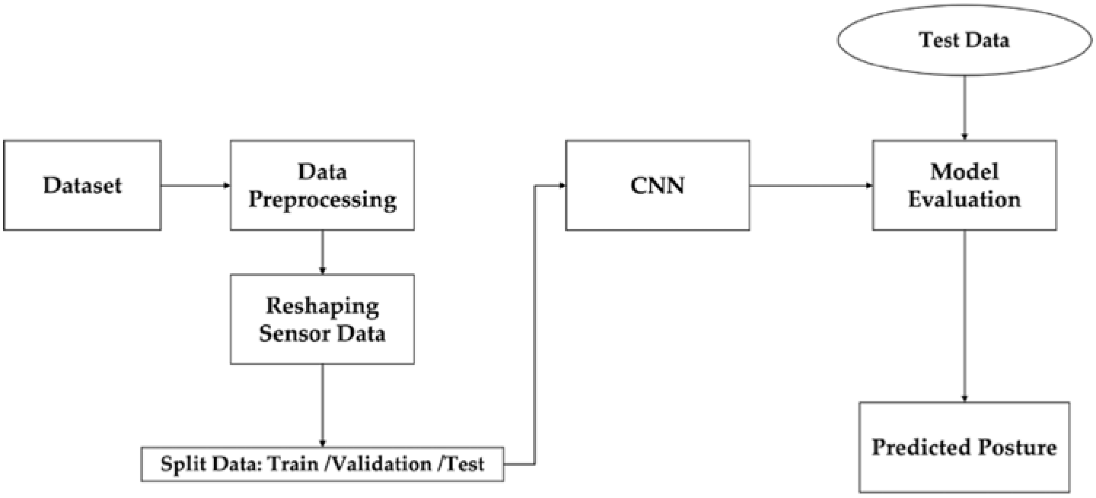


FIGURE 2 General Framework Structure.

Convolutional Neural Network (CNN)

Computer vision applications benefit significantly from the convolutional neural network (CNN) which functions as a deep learning architecture destined for spatial data including pictures and video content and sensor grid outputs. The architecture and functions occurring in the visual cortex serve as inspiration for CNNs enabling them to identify and categorize visual elements. These models serve widely for three purposes that include classification and object recognition and the segmentation of objects. Model design for CNN depends on specific input data to establish autonomous spatial features independently from the data. The current research adopts CNN to function as a valuable tool that recognizes sitting postures. The system utilizes pressure sensor spatial data to extract critical features for robust classification operations which makes it suitable for posture monitoring and ergonomic evaluation and unhealthy sitting prevention.

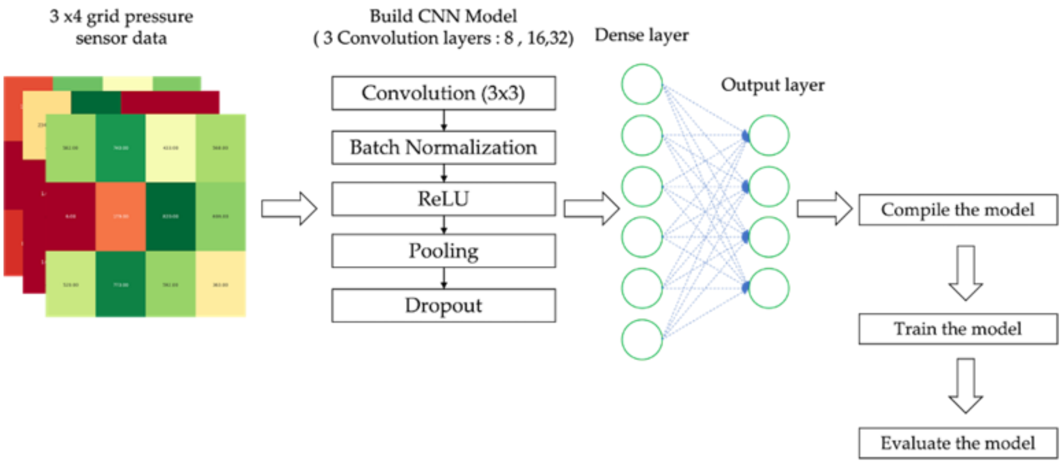


FIGURE 3 Custom Lightweight CNN model architecture.

Based on the sitting posture classification, we applied Custom Lightweight Convolutional Neural Networks (Figure 3). There are three convolutional layers on the network, the final one not containing ReLU activation or max-pooling. The layers comprise batch normalization, ReLU activations, and max-pooling, with eight, sixteen and thirty-two filters that use three-by-three kernels. The overfitting is prevented using the Dropout in the pooling and dense layers. The network recognizes features by regularization because of generalization. The full connectivity facilitates classification on the basis of convolutional features. The probabilities are optimized using Adam [15] in the softmax layer that outputs posture probability.

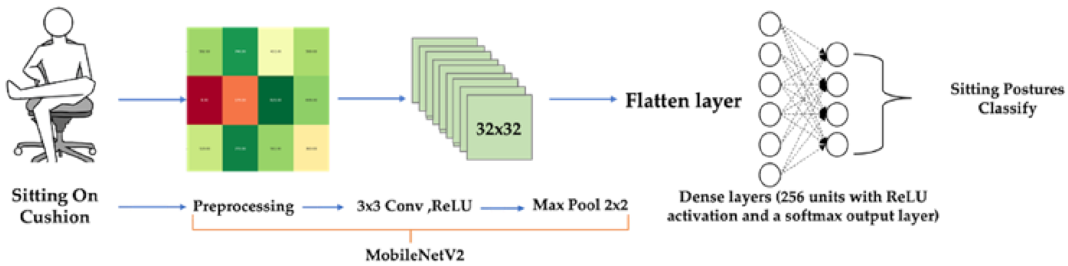


FIGURE 4 MobileNetV2 model architecture.

In multi-class classification the categorical cross-entropy loss is used. Learning procedures 16 examples, testing on validation data. There is an independent test set used to test accuracy Performance evaluation is carried out with the aid of accuracy statistics and confusion matrices. MobileNetV2 also has high power-efficiency as evident in Figure 4. The model has accuracy via the use of Inverted Residual Blocks consisting of even depth-wise separable convolutions. Convolutional networks use depth wise convolutions and point wise convolutions to optimize. The MobileNetV2 is an off-the-shelf CNN with the input size of 32x32 grayscale images, and labels four postures, and it is tested in an accuracy and speed pipeline.

Dataset

Thirty participants (12 males and 18 females) of ages 20-40 years, height 158-185 cm, body weight, 40-130 kg were selected into the study. All of them were asked to take four habitual poses: upright sitting, leaning back; the right leg being crossed on the left leg; and vice versa. These poses were chosen to reflect common ergonomic habits found in the workplace and in the daily life. The sitting observations were conducted with a pressure sensitive and 12-force sensors embedded cushion with a sampling frequency of 50 Hz. Each position was held 60 seconds to collect adequate exchange of data. The raw data of the sensor readings was then formatted to a structured form and data was ready to be extracted and trained in a model.

Data Preprocessing

The most important data preparations were carried out on sensor data model usage key activities. The 12 data points on the pressure sensor were summarized as a 3 x 4 table with the layout corresponding to the positions of the sensors in the CNN designs. Normalization was used to create data uniformity so as to avoid adverse effects of sensor volumes. Techniques of data augmentation were implemented to enhance resistance and application of the model. The two methods of data manipulation and augmenting noise enhanced the functionality of the model and helped avoid over fitting. Data organization and standards to model effectiveness and assessment were ensured through preprocessing methods.

Evaluation Metrics

The metrics that have been used in this paper give an extensive analysis of the predictive power of the classification algorithms. The accuracy, the precision, the recall and the F1-score were observed to address the overall correctness and the sensitivity with specificity balance. Moreover, a confusion matrix along with its analysis has been seen to present a clear picture of classification performances in regards to the four posture classes and to show possible patterns of misclassification and the robustness and generalizability of the model.

$$Accuracy = \frac{TP+TN}{TP+FN+FP+TN} \quad (1)$$

The precision is proportion of positively correctly detected/the total predicted positives. It shows how the model can minimize false positives and, thus, gauge the strength of positive predictions. That is, precision measures the proportion of the samples which identified the sitting posture were indicative of the posture.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Recall derives how successful a model is at classifying the actual positive instances as such. It tests the power of the model in covering all the cases of interest and hence its comprehensiveness. As discussed in the sitting posture classification, recall identifies the effectiveness of the model to identify the presence of each posture type without missing a real occurrence.

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

F1-score is the harmonic mean of the precision and recall and offers an average measure, weighing the trade-off between two metrics. It is useful specifically when neccessary in seme datasets or both false positives and false negatives have high importance. F1-score is the way to measure how well the model in the case of the classification of sitting posture posture corrects the accuracy of positive prediction (precision) and a complete search of potentially present posture (recall).

$$F1\,Score = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{4}$$

Confusion Matrix is a break down table because it compares the predictions of the model with the actual labels; it tells you about the true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN). In the sitting posture classification, it gives a broader perspective on the accuracy of identification of postures and the most common identification errors. This can turn it into a reliable diagnostic tool to determine the strength of a model and decide what needs to be tuned or fixed to improve the feature extraction, data augmentation, or parameter set.

Experiment Setup

The testing of Custom Lightweight CNN and MobileNetV2 followed standard training and evaluation protocols for identifying sitting postures. Training of Custom Lightweight CNN used Adam optimizer and categorical cross-entropy loss function for multi-class classification. Training ran for 50 epochs with batch size 32 when processing training samples. Model generalization was evaluated through validation data for parameter adjustments. Performance assessment used accuracy, precision and recall with confusion matrix for evaluation. The model size included parameter estimates while training efficiency measured training time and parameters. Training dynamics showed accuracy and loss trends from training and validation datasets before convergence. The four posture classes were examined through classification reports and confusion matrix. MobileNetV2 received the same training protocol, using Adam optimizer and categorical cross-entropy for multi-class classification. Training used 50 epochs with 32-batch sizes through training-validation split. Evaluation metrics measured accuracy, precision and recall using confusion matrix. Assessment monitored training time and model size to compare with Custom Lightweight CNN. The model's learning was visualized through accuracy and loss curves to understand convergence and generalization.

RESULTS AND DISCUSSION

Results of an experiment to create a model for sitting postures classification on a cushion from sitting data using four sitting postures. The researchers used Python version 3.11.5 and Keras version 3.7.0, which facilitated the development and execution of CNN model.

Data Preprocessing

An experiment has been designed to create a pressure model to identify sitting postures with the data collected in a cushion. Four sitting positions were analyzed and Python version 3.11.5 and Keras version 3.7.0 were used in the building and training of convolutional neural network (CNN) models. In the original Excel storage format, the dataset included 12 measures per sitting sample of pressure sensors, which were reshaped in the form of a 3 x 4 grid [16]. After the data reshaping, the dataset was divided into three parts: 70% of the data were assigned to training, 15% to validation, and the other 15% to testing. This division guaranteed model testing because it held out a never-before-seen dataset during training and validation [17]. The first difficulty with posture classification is the small size of the dataset of around 7,200 samples, that may lead to overfitting. To compensate this problem, the technique of dropout was adopted. Dropout adds noise to the activation of a proportion of neurons at random during training so that they cannot be co-adapted, and the performance of the generalization rises.

Dropout layers in the CNN architecture were inserted after the pooling operations in the convolutional layers, and after the dense layers in order to make the model more reliable when doing classification tasks [18]. Reliable posture classification is not only a matter of technical optimization, but it is also a question of critical interest in ergonomics and work health. Sedentary sitting has been linked closely with musculoskeletal straining, back straining, and psyche stress in the workplace and training fields. Precise identification of sitting postures may thus be employed to guide ergonomic programs, offer biofeedback in correcting postures, and prevent long-term health risks related to posture [19].

Model Performance

This section compares the accuracy of the posture classification models, the MobileNetV2 and the Custom Lightweight CNN designed using this work. Table 1 presents the results of this performance comparison, where the accuracy, training time and model size of both models are compared using different epochs and batch sizes. The MobileNetV2 model showed variations in accuracy between 25.65 and 99.54, and exhibited very much longer training times between 162.88 and 493.59 seconds, but still had the same static size of 9.87 MB. The Custom Lightweight CNN, by comparison, performed better than MobileNetV2 under all the experiments, recording a steady accuracy between 93.83 and 99.63%. MobileNetV2 was demonstrated to perform poorly at larger batch sizes, meaning that it was not ideal to learn the posture classification with the relatively small and domain-oriented datasets [20].

TABLE 1 Model Performance Result

Model	ID	Epochs	Batch Sizes	Acc (%)	Time (Sec)	Model Size (MB)
MobileNetV2	1	20	16	89.3	245.7	9.87
MobileNetV2	2	20	32	25.7	162.8	9.87
MobileNetV2	3	30	16	73.1	343.5	9.87
MobileNetV2	4	30	32	31.4	259.3	9.87
MobileNetV2	5	40	16	99.5	451.4	9.87
MobileNetV2	6	40	32	97.2	424.0	9.87
MobileNetV2	7	50	16	97.8	601.8	9.87
MobileNetV2	8	50	32	60.4	493.5	9.87
CNN	1	20	16	96.7	5.8	0.03
CNN	2	20	32	93.8	4.12	0.03
CNN	3	30	16	98.1	8.44	0.03
CNN	4	30	32	97.7	5.72	0.03
CNN	5	40	16	99.1	10.8	0.03
CNN	6	40	32	99.6	7.32	0.03
CNN	7	50	16	99.3	13.37	0.03
CNN	8	50	32	98.1	8.88	0.03

The Custom model was also seen to be highly efficient in that it took 4.12-13.37 seconds to complete the training process with only 0.03 MB of storage. These findings confirm the beneficial properties of lightweight CNNs in real-time monitoring systems, especially when used on resource-policed platforms, like embedded systems or IoT devices [21]. The small footprint size and rapid calculation make the model practically useful in activities that require an application of the ergonomics knowledge and feedback in time in a working or exercising environment, in conjunction with the current suggestions of using AI to monitor and schedule ergonomic dynamics [22]. Accordingly, the Custom Lightweight CNN model does not only outperform MobileNetV2 in accuracy and robustness but is also extremely optimized in speed and memory requirements, and therefore could be implemented into wearable health gadgets, smart chair furniture, and work ergonomics tracking solutions.

The strong performance of the Custom Lightweight CNN has methodological and applied implications that are beyond computational efficiency. Psychometrically, the model was proven to be reliable and stable over repeated measures, which makes it apt to be used in consistently identifying the posture-related behaviours. The findings, in an applied psychology and ergonomics context, show the potential of the model to be used in real-time in terms of posture monitoring in working and exercise settings, where sedentary behavior has been linked to musculoskeletal disorders, a decrease in productivity and psychological stress [23]. High accuracy combined with a speedy training process and limited size allows its integration into wearable devices and intelligent seating systems, where it continuously feeds back the biofeedback data needed to promote posture improvement. Such allowances add to safety protocols, work-related well-being, and enhancement of more healthy sitting habits, which syncs with recent trends in human-technology interaction within the greater study of applied psychology.

Comparative Analysis of MobileNetV2 and Custom Model Performance

The comparative analysis of MobileNetV2 and the Custom Lightweight CNN can introduce important data regarding not only methodological robustness but also the feasibility of applying the considered method to the sitting posture classification. As common knowledge, MobileNetV2 shows good results in universal image recognition tasks; therefore, in this domain-specific task, it showed an erratic result [24]. The range of the percentage scores was 25.65-99.54, and instability was highly prevalent when higher batch sizes were used. Such diversity indicates that ModelNetV2, though useful in large-scale vision applications, has a need to use large datasets to sustain performance and probably will be challenged by relatively small or targeted applications like pressure-sensor measurements. By comparison, the Custom Lightweight CNN obtained overall better results in all test variants, with an accuracy of 93.83-99.63%. Its robustness across different configurations proves both methodological reliability and psychometric soundness, with performance (e.g., F1-scores) levels remaining quite high across different runs. The reported finding is especially relevant in the field of applied psychology and ergonomics [25].

TABLE 2 Confusion Matrix - Custom Model ID-6

	Posture A	**Posture B**	**Posture C**	**Posture D**
Posture A	291	1	0	0
Posture B	3	274	0	0
Posture C	0	0	267	0
Posture D	0	0	0	244

The two models are differentiated by the aspect of efficiency. MobileNetV2 consumed significantly higher computing resources i.e., 162.88-493.59 s and an unchangeable model size is 9.87 MB. In comparison, Custom Lightweight CNN took 4.12 to 13.37 seconds per training cycle and 0.03 MB of storage space. These capabilities make the custom model a favorable solution to deploy to real-life settings where efficiency, flexibility and low-resource consumption are of essence [26]. Its size reduces the possibility of compatibility with embedded systems, wearable technologies and therefore can be used to monitor continuously in occupational and exercise settings. The speed and accuracy with which the Custom Model categorizes postures is very important in an applied psychology and an ergonomics perspective. Overextended sedentary sitting has consistently been associated with musculoskeletal discomfort, back pain, and elevated mental emphasis in working conditions [27]. Having a lightweight, stable, and psychometrically reliable model, therefore, is a starting point to the development of intelligent chairs, ergonomic feedback systems and wearable posture monitors.

The classification performances of the models become visible in Tables 2 and 3 through confusion matrices. The Custom Model (ID-6) showcases perfect classification precision through its minimal wrong identification cases. The classification of Posture C and D produced complete accuracy by avoiding any false positive or negative results. The Posture A model identified all measurements correctly except a single instance whereas Posture B made three mistakes thus indicating consistent identification for all posture types. MobileNetV2 (ID-5) demonstrated higher unpredictability when making classifications among examples. The majority of predictions were accurate yet it displayed major misinterpretations of Posture B with 18 instances mistakenly labeled as Posture C. Furthermore, Posture A demonstrated four prediction errors where two cases were assigned to Posture C and two to Posture D.

TABLE 3 Confusion Matrix - MobileNetV2 -ID-5

	Posture A	**Posture B**	**Posture C**	**Posture D**
Posture A	288	0	2	2
Posture B	1	276	18	0
Posture C	0	0	267	0
Posture D	0	0	0	244

TABLE 4 Performance outcomes - Custom Model ID-6

Posture	Precision	Recall	F1-Score
A	0.99	1.00	0.99
B	1.00	0.99	0.99

C	1.00	1.00	1.00
D	1.00	1.00	1.00

TABLE 5 Performance outcomes - MobileNetV2 ID-5

Posture	Precision	Recall	F1-Score
A	1.00	0.99	0.99
B	1.00	1.00	1.00
C	0.99	1.00	1.00
D	0.99	1.00	1.00

The performance evaluation results in Tables 4 and 5 show the divergent outcomes between these two models. The Custom Model (ID-6) produced outstanding performance in every posture type while achieving precision, recall and F1-score values between 0.99 and 1.00. The model demonstrates high precision in addition to specificity, which indicates exceptionally effective posture classification. The precision and F1-score reached 0.99 for MobileNetV2 (ID-5) across all postures except for Posture B, since it experienced increased misclassification events. The model displays dependable performance in Postures C and D, where metrics remain above 0.99, but loses reliability when trying to classify Posture B. Summarily, in spite of the usefulness of MobileNetV2 in broad-based vision applications, its inefficiency in terms of low data and targeted ergonomic applications lowers its dependability. In comparison, the Custom Lightweight CNN is methodologically rigorous, psychometrically reliable, and ergonomically applicable and, hence, suitable as a part of a continuous posture-monitoring tool in occupational and exercise science realms.

Visualization

The visualization of the performance of the presented models is demonstrated through Figures 5 and Figure 6, which show the train and validation accuracy and the loss curves of a Custom Lightweight CNN. In the accuracy curves, there is clear improvement in accuracy over epochs where the training and validation accuracy change continuously to higher levels. An interesting pattern is the fact that the validation accuracy is a little bit higher than training accuracy, which indicates that the model not only undergoes overfitting but also portrays an excellent generalisation aspect to unseen data [28]. The related loss curves support this interpretation. Both the training and validation loss decrease in a smooth and well-balanced manner until they reach minimal values. This consistency reveals that the model properly trained the features of the data without being infected by underfitting or overfitting.

The homogeneous convergence profile also validates the stability and reliability of the CNN structure, which is especially germane to applied psychology and ergonomics where robustness to variations in users and conditions is a key feature needed to achieve psychometric soundness [28, 29]. These results are a methodological confirmation of statements about the Custom Model preserving good control over the learning process that guarantees the successful classification of sitting postures in practice. In practice, these levels of stability and reliability facilitate its application into practice when postural assessments are essential in occupational and exercise environments. The MobileNetV.2 displays significant variations in its validation loss performance yet demonstrates a flat and low training loss pattern. The model exhibits overfitting and stability issues because it memorizes the training examples without gaining adequate capability to produce correct outputs on fresh data [30]. Training instability becomes apparent through the drastic validation loss spikes which stem from model complexity issues or inadequate regularization or improper hyperparameters.

This research proves the efficiency of deep learning methodologies including CNNs towards classifying sitting postures through pressure sensor information. A specifically designed Custom Lightweight CNN demonstrated better performance than MobileNetV2 in all realms of model accuracy while achieving stable training and resource-saving capabilities [20]. Domain-specific compact neural networks prove suitable for structured low-resolution sensor data prediction specifically when used with smart cushion pressure map detection. The Custom Model delivers superior results because its architecture combines pressure data spatial elements with efficient computation operations [24, 30]. The Custom Model demonstrates optimal suitability for real-time ergonomic monitoring systems and embedded devices through its efficient 0.03 MB footprint and brief training duration. This domain did not require MobileNetV2's mobile application-specific capabilities even though the architecture was originally designed for mobile needs. The extensive natural image training for its architecture surpassed the capabilities of the restricted structured dataset in this research. These issues led to inferior prediction stability and prolonged training time which negatively affected its potential for real-time posture monitoring.

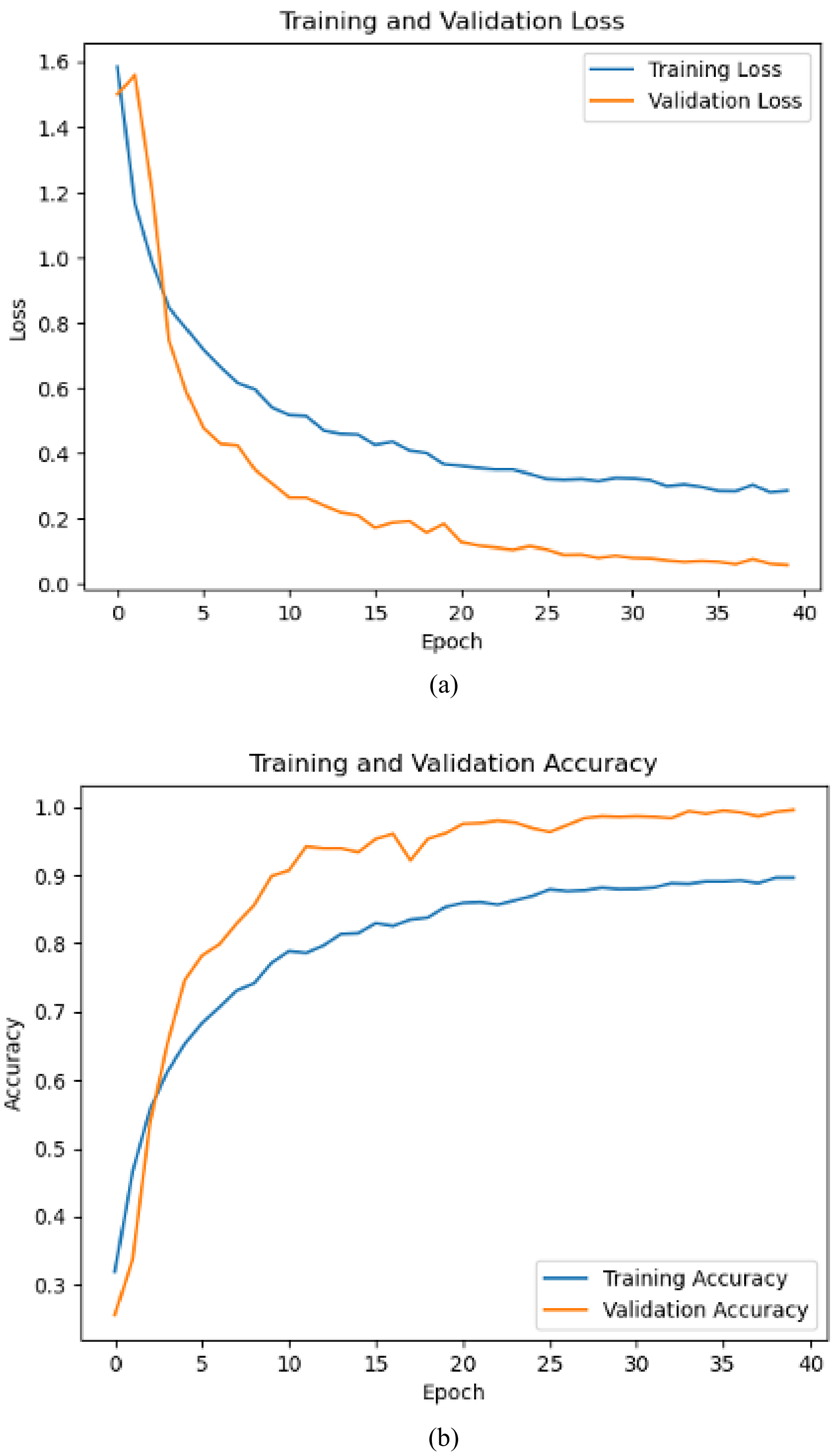
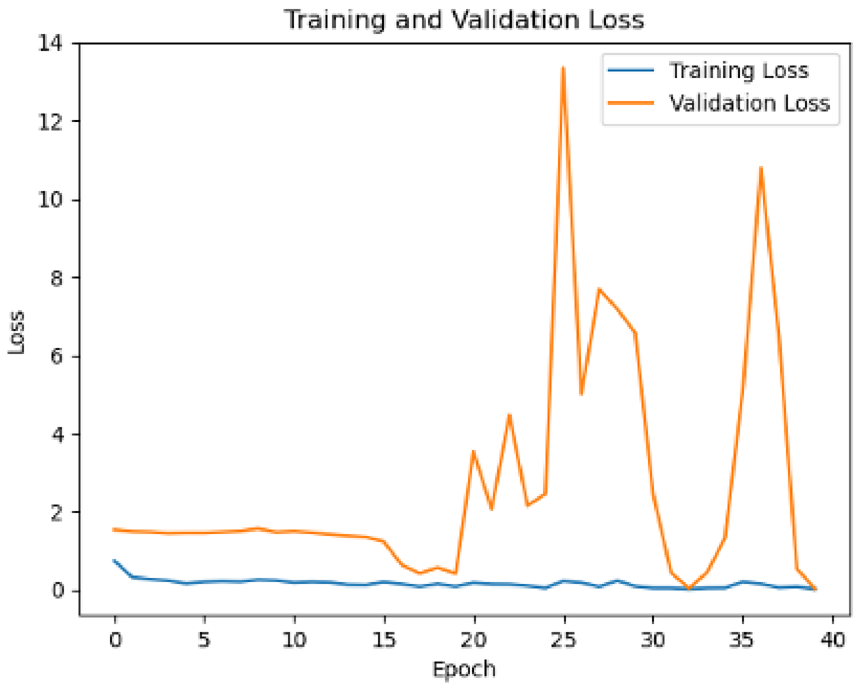
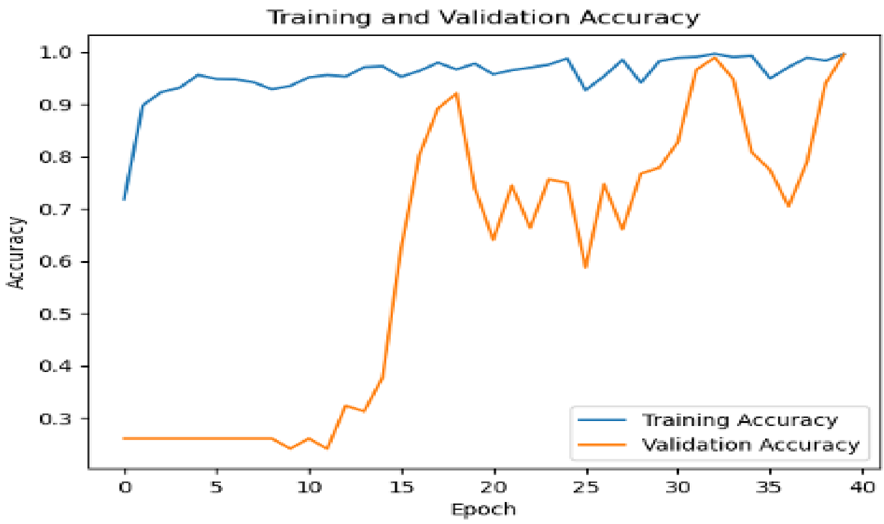


FIGURE 5. Outcome of testing model ID-6 of Custom Lightweight CNN (a) Training and Validation Loss and (b) Training and Validation Accuracy.



(a)



(b)

FIGURE 6. Outcome of testing model ID-5 of MobileNetV2
(a) Training and Validation Loss and (b) Training and Validation Accuracy

CONCLUSION

This study aimed to improve the classification of sitting position by the utilization of pressure sensor data and machine learning, with particular emphasis on practical applications in ergonomic contexts, including office situations and exercise settings. A low-weight convolutional neural network (CNN) works with the pressure sensor data of 30 participants in four sitting postures and shown to be effective in identifying ergo-nomic sitting postures. With its high validity accu-racy (up to 99.63%) and an F1-score of 0.999-1.000, the model performed reliability throughout the different bodies and seating patterns. The tailored CNN per-formed better in generalization and less overfitting than Mo-bileNetV2 and requires fewer computing re-sources (0.03 MB model size and 4.12 seconds to train). The systematic machine learning architecture fosters consistency in a classification endeavor, which is applied in the field of psycholo-gy. The performance of the CNN is high enough to be applied to practical, limited means, environments. Real-time implementation will be explored with the microcontrollers having the module Bluetooth or Wi-Fi. Use cases: incorporation in pillows that are intelligent to assist the person to have a comfortable sleeping posture to maintain and prevent musculoskeletal contact and injuries, integration on seats that are ergonomical so that one can sit on them to avoid musculoskeletal pain and injuries or put on as a wearable device monitoring posture and giving impulse when there is poor posture to prevent discomfort and injuries. In a future study, the dataset will be extended to include the broader categories of the demographic and hence reinforcing the external validity and to test the feasibility of applying the model to a microcontroller and a low-power device with wireless connectivity in real-time. These steps will also enhance psychometrically sound machine learning methods into occupational health, ergonomics and applied practice in the field of psychology.

FUNDINGS

This research study was reviewed and approved by the Institutional Review Board (IRB) of Maejo University under research project code MJUIRB ST003/68 and conducted in compliance with ethical standards on research involving human subjects.

ACKNOWLEDGEMENTS

The authors gratefully acknowledges the financial support provided by the Petchra Pra Jom Klao Ph.D. Research Scholarship, King Mongkut's University of Technology Thonburi, which made this study possible. Sincere appreciation is also extended to the Institute of Field Robotics (FIBO), King Mongkut's University of Technology Thonburi, for providing laboratory facilities and technical resources essential for data collection and model development. The author further thanks Maejo University for ethical approval and logistical support during participant recruitment. Finally, heartfelt gratitude is expressed to the study participants for their valuable time and cooperation, without whom this research would not have been accomplished.

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