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Machine learning-based recognition of mental fatigue in construction equipment operators using facial features.

Imran Mehmood[1], Heng Li[1], Shahnawaz Anwer[1], Waleed Umer[2]

[1] Department of Building and Real Estate, The Hong Kong Polytechnic University, Hong Kong SAR
[2] Department of Architecture and Built Environment, Northumbria University, NE1 8ST, Newcastle upon Tyne, United Kingdom
imran.mehmood@connect.polyu.hk

Abstract
Construction equipment operators are at risk of mental fatigue, which can lead to accidents and health problems. Real-time monitoring is necessary to prevent accidents and protect operators' well-being. Previous studies have used wearable sensors to classify mental fatigue in operators, but these methods require physical sensors to be worn, causing discomfort and irritation. Therefore, a new approach is needed that allows for contactless measurements of mental fatigue. In this study, a novel approach was proposed using machine learning and geometric measurement of facial features to classify mental fatigue states during equipment operations. Video recordings were obtained during a one-hour excavation operation, and four facial features (eye distance, eye aspect ratio, head motion, and mouth aspect ratio) were extracted for analysis. The temporal increase in NASA-TLX score was used as the ground truth for mental fatigue. The results showed that the support vector machine classifier outperformed, achieving a high accuracy of 91.10% and an F1 score between 85.29% and 95.61%. These findings suggest that mental fatigue in construction equipment operators can be non-invasively monitored using geometric measurements of facial features.

Keywords
Mental Fatigue, Machine Learning, Construction Safety, Facial Features, Construction Equipment Operators.

1. Introduction

Fatigue-related human behavior is a major cause of construction equipment accidents, accounting for over 65% of incidents (Bai and Qian, 2021). Construction tasks that demand sustained effort and attention lead to mental fatigue among equipment operators, impairing their judgment and focus (Das et al., 2020, Wagstaff and Sigstad Lie, 2011). This increases the likelihood of accidents, reducing productivity and performance (Masullo et al., 2020). To improve site safety, constant monitoring of equipment operators' mental fatigue is necessary (Han et al., 2019), allowing for swift action in response to signs of inattention.

Safety is paramount in construction work, and to ensure safety, mental fatigue of construction equipment operators needs to be assessed. Initially, mental fatigue was subjectively assessed through tools like NASA-TLX, which were intrusive and not suitable for continuous monitoring (Umer et al., 2020, Turner and Lingard, 2020). Technology advancements have made it possible to use physiological measurements like the electroencephalogram (Lee and Lee, 2022), electrodermal activity (Choi et al., 2019), eye tracking (Li et al., 2020), and the electrocardiograph (Umer et al., 2022) for an objective and real-time assessment of mental fatigue. However, these techniques have limitations, such as being invasive, sensitive to harsh conditions, requiring limited physical activity, and having poor spatial resolution (Kaur et al., 2022, Chen et al., 2015). Most studies such as by Liu et al. (2021) were conducted in simulated scenarios, limiting their applicability to construction sites. There is a need for non-invasive and contact-free detection of mental fatigue during ongoing equipment operations, and an automated early warning system will enhance safety at construction sites.

Despite the widespread use of facial feature recognition in other occupations, its application in the construction industry, particularly among excavator operators, remains a knowledge gap. As per the authors' knowledge, there are no existing studies that utilize geometric measurements of facial features to monitor the mental fatigue of construction equipment operators during operations. Furthermore, it is challenging to apply findings from other occupations, such as drivers, to detect mental fatigue during excavator operations due to the significant differences in working patterns.

Liu et al. (2021) found that construction equipment operators work differently than drivers, highlighting the need for a new approach for construction industry. Hence, this study proposes a novel approach of utilizing machine learning and geometric measurements of facial features to detect and classify mental fatigue states in construction equipment operators. By using a camera to take geometric measurements of the face regions, this non-invasive, efficient, and practical approach could enable real-time monitoring of excavator operators' mental fatigue. It is anticipated that this approach will improve mental fatigue detection during equipment operations, providing safety personnel with more effective and proactive responses.

2. Methodology

The proposed approach for detecting and classifying operator mental fatigue on construction sites using machine learning and geometric facial feature measurement is illustrated in Figure 1. The study was conducted on a construction site where a time-on-task experiment was performed to induce mental fatigue. The experiment involved operators performing a one-hour repetitive excavation and discharge task, which entailed excavating the ground and transporting excavated material from pits to vehicles. As this was a time-on-task experiment, the quantity of earth excavated or moved, and the number of vehicles filled were not predetermined. Furthermore, the operators did not undergo any practice sessions since they already had prior excavation operation experience. Five excavator operators participated in the research study, with a mean age of 31.25 years (SD = 2.39). All participants were experienced excavator operators, with an average of more than six years of experience in excavation operations at construction sites. They had slept for at least eight hours the previous night and had not consumed alcohol for at least 24 hours before the experiment. In addition, the temporal increase in NASA-TLX score was used to evaluate construction equipment operators' subjective feelings of mental fatigue and to establish their mental fatigue levels (alert state, mild fatigue state, and fatigue state). A color video camera placed 0.6m inside the equipment cabin was used to capture the operator's facial behavior. The camera was mounted on the windscreen to avoid visual obstruction and had a sampling frequency of 30 frames per second with a high resolution of 1440 x 1440 pixels.

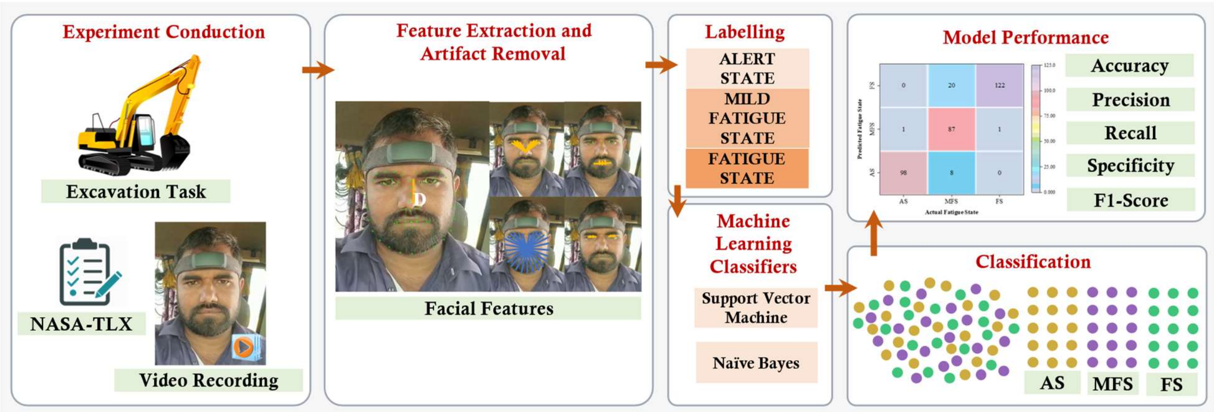

Figure 1: Framework of facial features based mental fatigue classification.

During excavation operations at the construction site, operators were recorded on video cameras for one hour. OpenCV, an open-source computer vision toolkit developed with Python, was used to convert the video footage of each operator into frames. Face recognition was then conducted on each frame using a local constrained neural field model (Baltrušaitis et al., 2016). The model was able to detect the operator's face in each frame, and the results were expressed as a vector $G = [a_1, a_2, a_3, \dots \dots \dots, a_i]^E$, representing 68 landmarks identified on the operator's face in each frame via Dlib (King, 2009). In this case, a represents a detected facial landmark at position (j_i, k_i) in any frame F, F is the number of any frame, and i is the index of detected landmarks at any frame, with values ranging from one to 68. Euclidean distance was calculated between any two desirable points, which was then used to compute the geometric measurements of four facial features investigated in this study (Mehmood et al., 2022). Four facial features were obtained individually from each frame and are outlined in Table 1 and presented in Figure 2. To eliminate artifacts in the facial feature data, nose landmarks represented by vector $D = [||a_{32} - a_{28}||]^E$ were used to create the nose line (Mehmood et al., 2022). This line's length was then employed to normalize all facial features by dividing them by D, resulting in normalized facial features for each frame.

To segment the facial feature data from the five operators, we utilized a sliding window approach with a window size segmentation of 20 seconds. Overlapping of consecutive windows was employed to ensure that no relevant data was missed, with a 50% overlap of adjacent data segment lengths in our study. As a result, a dataset of 1125 samples were generated for the five construction equipment operators. This dataset was divided into two parts, with 70% assigned for training and 30% designated for testing. To accurately classify mental fatigue using facial features data, we utilized two supervised machine learning classifiers: support vector machines (SVM) and naive bayes (NB). We evaluated the performance of the three machine learning models by using accuracy, precision, recall, specificity, and the F1-score. In addition, we plotted the confusion matrix to assess each model's performance in specific classes.

Table 1: Details of extracted facial features.

Facial Feature	Description and Computation
Eye Distance Sum (ED)	$ED = \lVert a_{31} - a_{43} \rVert + \lVert a_{31} - a_{44} \rVert + \lVert a_{31} - a_{45} \rVert + \lVert a_{31} - a_{46} \rVert + \lVert a_{31} - a_{47} \rVert + \lVert a_{31} - a_{48} \rVert$
Head Motion (HM)	$HM = \frac{1}{D} \sum_{i=1}^{E} \lvert a_{E1} - a_{E2} \rvert$
Eye Aspect Ratio (EA)	$EA = \frac{\lVert a_{44} - a_{48} \rVert + \lVert a_{45} - a_{47} \rVert}{2\lVert a_{43} - a_{46} \rVert}$
Mouth Aspect Ratio (MA)	$MA = \frac{\lVert a_{64} - a_{66} \rVert + \lVert a_{62} - a_{68} \rVert + \lVert a_{63} - a_{67} \rVert}{3\lVert a_{49} - a_{55} \rVert}$

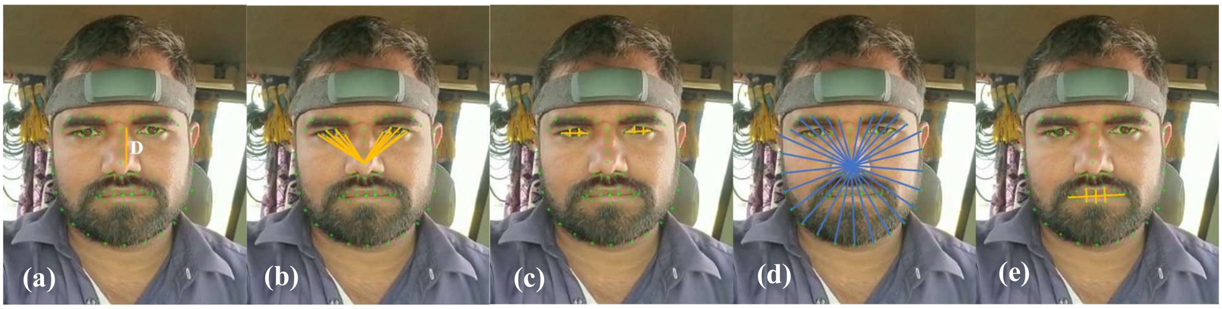

Figure 2: Extraction of facial features' geometric measurement (a) nose length (b) eye distance (c) eye aspect ratio (d) head motion (e) mouth aspect ratio

3. Results

3. 1 Ground Truth

In this study, the increase in NASA-TLX score over time served as an indicator of operators' mental fatigue. The results indicate that by the end of the experiment, participants' levels of subjective mental fatigue had increased from the baseline score of 10.20 (SD = 3.11) to a score of 61.60 (SD = 5.77), representing an increase that is statistically significant. Furthermore, the subjective scores for alert state, mild fatigue state, and fatigue state were 31.00 (SD = 2.65), 43.80 (SD = 2.95), and 61.60 (SD = 5.77), respectively. In addition, these subjective data indicate that as the excavation operation continued, the operators' mental fatigue increased.

3.2 Machine Learning-based classification results

Table 2 and Figure 3(a) display the SVM model's evaluation metrics and confusion matrix, respectively. The evaluation metrics show that the SVM model performed well in identifying various levels of mental fatigue in construction equipment operators using facial features data. The SVM model achieved precision values ranging from 85.92% to 97.75%, with MFS being accurately identified in 97.75% of cases. The SVM model was less affected by AS and FS than by MFS. Additionally, the model had higher recall and precision values, indicating fewer false negatives and false positives, respectively. The specificity and F1-score measures ranged from 90.65% to 99.10% and 85.29% to 95.61%, respectively. A high specificity implies a high true negative rate, indicating that a person identified as fatigued was indeed in that state. The confusion matrix, as shown in Figure 3(a), determined whether classes were misclassified or confused with others. Correctly classified cases were represented by diagonal members of the matrix, while incorrectly classified instances were represented by nondiagonal elements. FS was more often misclassified than AS and MFS, but the misclassification rate for AS and FS was modest. Additionally, FS was confused with MFS in 20 instances.

The evaluation metrics and confusion matrix for the naive Bayes (NB) model are presented in Table 2 and Figure 3(b). The diagonal cells in the matrix provide the correct classes, allowing for a more thorough evaluation of classification performance. However, when compared to the SVM classifier, the NB classifier's evaluation metrics showed the lowest performance. Precision values for the NB model ranged from 69.77% to 84.91%, with AS achieving the highest percentage of accurately classified instances at 90.91%, while MFS had the lowest accurately categorized instances at 67.83%. Additionally, AS was confused with MFS 30 times, and MFS was confused with FS 24 times. Specificity measurements ranged from 83.61% to 92.52%, and the F1-score ranged from 71.89% to 78.94%. These findings suggest that the NB classifier was not as effective as the SVM classifier in classifying mental fatigue in construction equipment operators based on facial feature data.

Table 2: Performance assessment metrics for machine learning classifiers

Support Vector Machines (SVM) Classifier					**Naïve Bayes (NB) Classifier**				
Indicator	**Testing**	**AS**	**MFS**	**FS**	**Indicator**	**Testing**	**AS**	**MFS**	**FS**
Accuracy	91.10%				Accuracy	76.60%			
Precision		92.45%	97.75%	85.92%	Precision		69.77%	76.47%	84.91%
Recall		98.99%	75.65%	99.18%	Recall		90.91%	67.83%	73.17%
Specificity		96.64%	99.10%	90.65%	Specificity		83.615	89.19%	92.52%
F1-score		95.61%	85.29%	92.06%	F1-score		78.95%	71.89%	78.60%

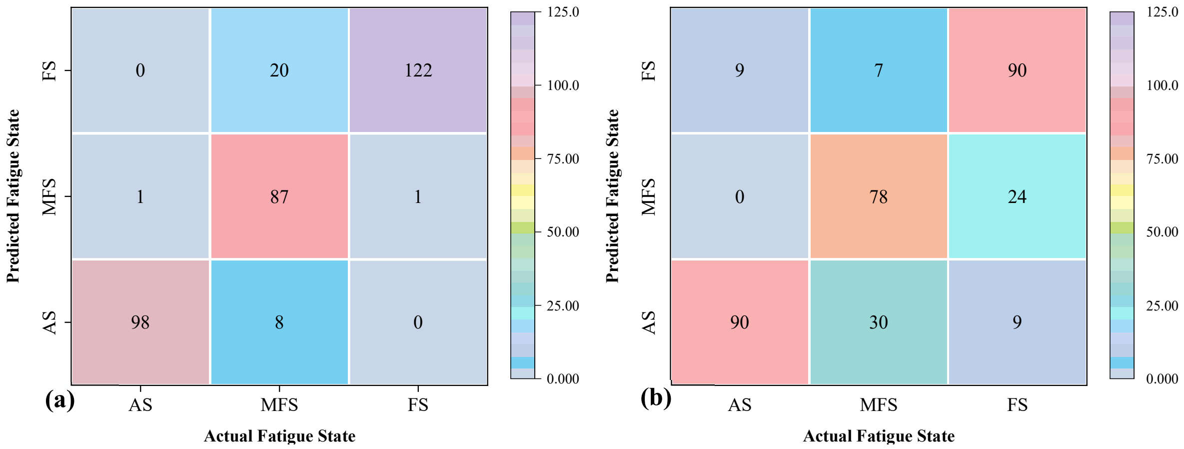

Figure 3: Confusion matrix (a) support vector machine (b) naïve bayes

4. Discussion

Construction equipment operators must remain alert and focused for extended periods, which can lead to mental fatigue and increase the risk of accidents on construction sites. This study proposes a machine learning-based approach that uses geometric measurements of facial features to recognize and classify different types of mental fatigue states during equipment operation. Four facial features were gathered during on-site operations, and the performance of two machine learning classifiers, support vector machines (SVM) and naïve bayes (NB), were compared. This study is the first to propose a machine learning-based approach for recognizing and classifying mental fatigue states in construction equipment operators using contactless measurements from video cameras. The results show that mental fatigue can be accurately classified in construction equipment operators with varying levels of mental fatigue using this approach.

Our study compared the performance of two machine learning classifiers, and we found that the SVM classifier outperformed the NB classifier. Using facial features as input data, the SVM classifier achieved an overall accuracy of 91.10%, with precision, recall, specificity, and F1-score values ranging from 85.92% to 97.45%, 75.65% to 99.18%, 90.65% to 99.10%, and 85.29% to 95.61%, respectively. Additionally, the SVM classifier had a lower misclassification rate for the three mental fatigue states than the NB classifier. These findings suggest that geometric measurement of facial features is an effective approach for identifying and classifying mental fatigue in equipment operators.

Our study's approach, which utilized machine learning and facial features data, achieved higher classification accuracy compared to previous studies in the construction domain that only used wearable sensors as input data. For instance, Jeon and Cai (2022) used a two-step ensemble approach with single-modal EEG data to classify hazard recognition and cognitive states and achieved 82.3% accuracy with the LightGBM classifier. Similarly, Jebelli et al. (2018) employed non-linear support vector machines to classify construction worker stress with 71.1% accuracy using EEG data on a construction site. Additionally, Jebelli et al. (2019) used deep learning neural networks to classify mental stress with 86.62% accuracy. However, comparing our results directly with these studies can be challenging due to differences in experimental setups, task nature, number of subjects, and individual differences.

5. Conclusions

This study presents a novel approach to classifying mental fatigue in construction equipment operators using supervised machine learning and geometric measurements of facial features. The experiment involved five equipment operators who performed an excavation task on a construction site, with the temporal increase in the NASA-TLX score serving as the ground truth for assessing mental fatigue. Facial features of the operators were recorded through video to measure their geometric changes during the task. The monotonous and prolonged nature of the excavation task induced mental fatigue, and four distinct facial features were extracted and labeled into three mental fatigue states: alert state, mild fatigue state, and fatigue state. Two supervised machine learning classifiers, SVM and NB, were utilized to classify the three mental fatigue levels. Evaluation metrics such as accuracy, precision, recall, specificity, and F1-score were used to measure the performance of the models. The results indicated that the SVM classifier outperformed the NB classifier, achieving an overall accuracy of 91.10%. The findings suggest that the SVM classifier can effectively classify mental fatigue states during construction equipment operations, enabling the development of a real-time system of video cameras and machine learning to classify mental fatigue in operators, to enhance safety and health management on construction sites.

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Author(s): Imran Mehmood, Heng Li, Shahnawaz Anwer, Waleed Umer

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Prof. Syed M. Ahmed
Chair, CITC-13
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