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Research Article

The Improvement concerning Recognition Accuracy of Six Skill Levels of Flux-Cored Arc Welding Hand Welder using Convolutional Neural Network-Long Short-Term Memory

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Abstract: The shipbuilding industry in developing countries is a sector that heavily relies on manual welding methods of Shielded Metal Arc Welding (SMAW) and Flux-Cored Arc Welding (FCAW). The reliance on manual welding skills often leads to substantial rework due to inconsistencies in weld quality and variations in welder proficiency. There is an observation that many welders drop performance due to fatigue problems after a period of working or changes in working conditions. Therefore, this study aimed to develop an Artificial Intelligence (AI)-driven to monitor the changes concerning the performance of welder using wearable sensors and a Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) model in improving recognition accuracy of six FCAW welder performance levels. Data of six welder hand movements were collected during 1G, 2G, and 3G positional welding and analyzed using CNN-LSTM. During the analysis, the hand movement data of six levels of welder skills were classified by the number of discontinuity records. The model achieved a total accuracy exceeding 95%, showing its effectiveness in skill assessment and real-time welder monitoring. These results show the potential of AI-powered systems to improve welding productivity and reduce project delays in shipbuilding.

Keywords: Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM); Flux-Cored Arc Welding (FCAW); Performance; Welder

1. Introduction

Manual welding systems are methods relying heavily on the skill of welders (Moore and Booth, 2014), often leading to low production rates due to the challenging conditions of work that demand significant physical stamina (Sakuma et al., 2001). This issue has been addressed in many modern countries, particularly with the development of clean industry initiatives. As a result, industrial robots and mechanized equipment have become essential for high-volume welding production (Kahnamouei and Moallem, 2024). In highly competitive manufacturing environments, industries are increasingly pursuing alternative technologies to optimize production processes. For small to medium production volumes, robotic systems often outperform manual and automated production in terms of cost per unit (Chodha et al., 2021). Recent advancements in robotic welding systems have main benefits, including improved productivity, welding quality, worker safety, workspace

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flexibility, and reduced labor costs (Villaverde and Maneetham, 2024; Kah et al., 2015). The rise of robotic applications has also reduced operator input, enabling improved automated control over welding parameters, robotic motion paths, and fault detection as well as correction (Schwab et al., 2008)

Efforts to improve robotic systems to match human capabilities have introduced additional complexity and increased investment costs. Various sensor systems have been incorporated to improve the effectiveness of robotic welding, achieving positivity in precise and accurate movements (Kah, 2021; De Graaf and Aarts, 2013). For instance, infrared thermography methods have been adopted for real-time adaptive weld quality monitoring in robotic welding. Smart systems such as artificial neural networks (ANNs) are also used to handle complex tasks and improve how machines are controlled. These AI-powered tools help robots adjust to changes in the environments, learn how different inputs lead to certain results, and make decisions based on the present occurrence (Sudhakaran et al., 2013; Nagesh and Datta, 2010; Pires et al., 2006). Despite all the progress made, robotic sensors are still not flexible or quick to react as human senses when working in constantly welding conditions.

How fast and well Shielded Metal Arc Welding (SMAW) and Flux-Cored Arc Welding (FCAW) get done depends a lot on how skilled the welders are. When welders are not very experienced or make mistakes, it can slow down ship construction projects (Gazali and Baroroh, 2022). To solve these problems, Pribadi and Shinoda (2018) created a wearable device with motion sensor such as accelerometer and gyroscope to keep track of workers in shipyard. This device could identify common movements made by workers, which helped in starting to measure productivity. Building on this, (Pribadi and Shinoda, 2020) improved the method by using a 9-degree-of-freedom (DOF) inertial measurement unit (IMU) and a multilayer perceptron (MLP) algorithm, achieving high accuracy in classifying welder activities. Further studies (Pribadi and Shinoda, 2022) focused on monitoring wrist-hand motions during basic welder training, using wearable sensors and Support Vector Machines (SVM) to assess skill acquisition. The analysis show the potential of wearable technology and AI in improving training efficiency as well as welder performance. Relating to the discussion, this study builds on the foundation of previous findings by applying similar methods to FCAW processes.

FCAW offers several advantages, such as higher deposition rates and improved productivity (Mohamat et al., 2012), making it a preferred welding method for various joint configurations. Recent studies have also examined advancements in FCAW, with scientometric analyses showing developing trends and technological developments in the field (Świerczyńska et al., 2024). Following the discussion, hybrid welding methods combining FCAW and other processes have shown improved mechanical properties as well as process efficiency (Prajapati et al., 2018). Studies have also investigated the impact of welding groove configurations on the mechanical properties of FCAW joints, signifying the importance of process optimization (Çevik, 2018). Moreover, the distinct electrode handling methods in FCAW introduce unique motion patterns that fall under human activity recognition (HAR), necessitating advanced analytical methods. Several studies have explored the use of motion sensors to monitor and identify various types of movements, with AI being used for human motion classification (Genc et al., 2024; Khatun et al., 2022; Mutegeki and Han, 2020; Shiranthika et al., 2020). This study incorporates AI methods based on Convolutional Neural Network-Long Short-Term Memory (CNN-LSTM) algorithms to address these challenges, aiming to improve recognition accuracy more than the achievement of traditional SVM methods.

The incorporation of deep learning methods, particularly Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM) has significantly advanced HAR by enabling strong feature extraction and temporal sequence modeling. CNN excels in spatial feature extraction (Liu, 2018), particularly in image and sensor data. Meanwhile, LSTM captures temporal dependencies in sequential data (Malashin et al., 2024), making the models highly suitable for HAR applications comprising time-series data, such as motion tracking through accelerometers and gyroscopes (Ignatov, 2018). The workflow of CNN-LSTM models typically includes data preprocessing, feature extraction via CNN layers, temporal sequence modeling with LSTM levels, and final classification. This architecture increases the ability of the system to recognize complex activities over time, leading to improved classification accuracy compared to traditional machine learning methods (Hammerla et al., 2016).

Several studies have shown the efficacy of CNN-LSTM models in various HAR applications. For example, (Perez-Gamboa et al., 2021) developed a CNN-LSTM model for HAR with wearable sensors, achieving high classification accuracy. Similarly, (Lee et al., 2021) reviewed CNN-based deep learning applications in welding study, signifying the potential of CNN for real-time welding quality monitoring. Other studies have incorporated hierarchical deep LSTM networks for HAR using wearable sensors, further improving recognition accuracy (Wang and Liu, 2020). The growing incorporation of AI in welding and HAR applications shows the potential of CNN-LSTM models in industrial environments.

Deep learning methods including CNN and LSTM, have been successfully implemented in various machine learning applications, such as license plate recognition (Tan et al., 2022), depression detection (Tey et al., 2023), as well as violence detection (Abdullah et al., 2023). These applications show the versatility of CNN-LSTM architectures in real-time monitoring and classification tasks. The implementation of deep learning for HAR in welding is a logical extension of these methods, leveraging AI for precision monitoring and productivity improvement.

Various AI-driven applications have explored the capabilities of CNN-LSTM models outside HAR. For instance, combined CNN-LSTM models have been applied to heating, ventilation and air conditioning (HVAC) system optimization (Sari et al., 2023) and bankruptcy prediction (Pham et al., 2025), showing the effectiveness of predictive analytics. These studies reinforce the potential of AI-driven HAR models for industrial applications, such as welding skill assessment and productivity monitoring.

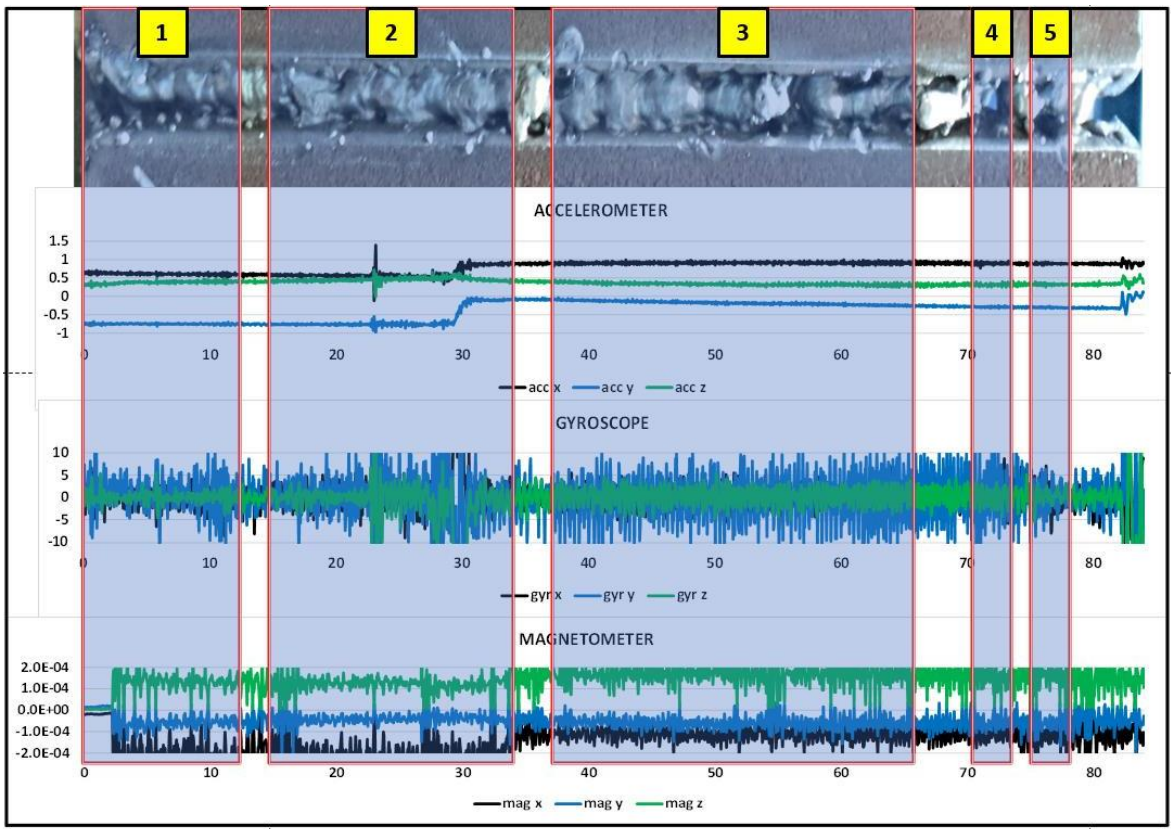
This study develops a sensor-based monitoring method for welder skill assessment as an alternative to robotic welding. By leveraging CNN-LSTM models, this study aims to improve the recognition accuracy concerning the skill levels of FCAW welders, contributing to AI-driven solutions for workforce development and quality assurance in shipyard operations. This method helps get better on jobs and gives industries in developing countries a low-cost way to improve each work.

2. Methods

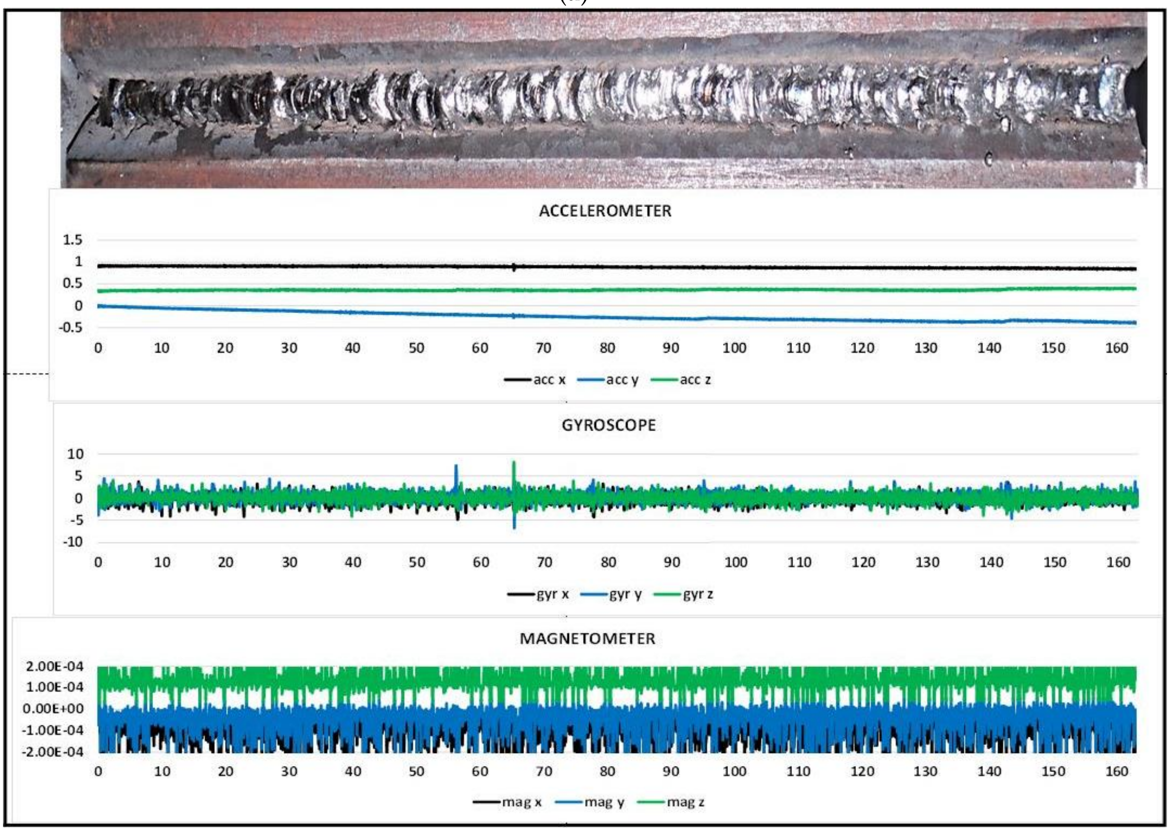
The method of this study consisted of three main stages, namely data acquisition, pre-processing, and classification. These stages were designed to analyze the hand-motion data collected during FCAW welding processes in 1G, 2G, and 3G positions using wearable sensors.

2.1. Data Acquisition

Data was collected through hands-on experiments in a laboratory, focusing on recording the welding work done using FCAW method. The setup started with the preparation of tools and materials, checking the welding procedure specification (WPS), inspection the carbon-steel pieces to be welded, and ensure all safety rules were followed. Moreover, the welding tasks included the actual welding, slag removal, and grinding the surface. The metal pieces used were A36 carbon steel, made up of two plates with a V-groove to help with the welding. The V-groove measured 3 mm at the bottom and 32 mm at the top, with specimen dimensions of 150 mm × 300 mm × 12 mm. During the process, several welders were tasked with welding three specimens each, corresponding to the 1G, 2G, and 3G positions. The welding process was conducted using a Weiro WM350F FCAW machine with ESAB Weld 71T-1 flux-cored electrodes 1.2 mm in diameter. This experiment was conducted in the Ship Production Technology and Management Laboratory at the Institut Teknologi Sepuluh Nopember. Additionally, certified welding inspectors visually inspected the welds to identify any discontinuities. Based on Figure 1(a), the visually identified welding discontinuities were divided into several sections, labeled with numbers from 1 to 5. A more detailed explanation of the welding discontinuities was shown in Table 1.



(a)



(b)

Figure 1 (a) 3G Welding Result with discontinuities, (b) 3G Welding Result without discontinuities

An example of the obtained discontinuity analysis results from the previous discussion was used as a criterion for assessing welder performance. These criteria consisted of six performance levels classified based on the discontinuities of the welder. According to the relationships shown in Table 1 and Figure 1, poor weld quality was associated with an excessively high travel speed, as evidenced by the irregular patterns in the gyroscope sensor data and the total time used to complete one welding layer. Consequently, high-quality welds were characterized by a longer travel speed, with gyroscope sensor data showing a more stable pattern and a longer time used to complete one welding layer.

Table 1 3G Welding Discontinuity Type

No.	Discontinuity Type	Cause of Occurrence
1, 2, 3, and 5	Incomplete Fusion	the weld metal did not fully fuse with the base metal, allowing the appearance of base metal to be untouched, there was unsymmetric waving, the electrode angle was too narrow, quick travel speed, electrode speed to fast and did not fill at the edges
4	Incomplete Penetration	The electrode was not filled perfectly, causing any full penetration with a preceding weld bead because the travel speed was quick.

2.2. Data Pre-Processing

Raw data collected during the welding process were classified into three sensor types, namely accelerometer, gyroscope, and magnetometer, each with three axes (x, y, and z). The data were annotated with information on welder identification on SubID. In addition, it consisted of six welders as shown in Table 2 using the example on the sixth welder. The annotated data were imported into a database for subsequent classification.

For deep learning classification, the sensor data recorded at a frequency of 25 Hz were segmented into 10-second windows, producing 250 data points per sensor for each window. The segmented data were then prepared for training and testing in the classification stage.

Table 2 Pre-Processed Data Identification on the Sixth Welder

Elapsed Time (sec)	Acc x (g)	Acc y (g)	Acc z (g)	Gyr X (deg/s)	Gyr Y (deg/s)	Gyr Z (deg/s)	Mag X (T)	Mag Y (T)	Mag Z (T)	SubID
0	0.9	-0.12	0.363	0.915	0.183	0.244	-8.98E-05	-7.18E-05	1.23E-04	6
0.04	0.896	-0.11	0.359	2.805	0.732	1.28	-9.86E-05	-9.59E-05	1.22E-04	6
0.08	0.91	-0.111	0.361	2.439	2.683	0.671	-1.08E-04	-1.20E-04	1.38E-04	6
0.12	0.902	-0.117	0.37	1.463	1.037	0	-8.24E-05	-1.06E-04	1.28E-04	6
0.16	0.908	-0.106	0.356	-0.976	2.561	-0.244	-7.51E-05	-1.13E-04	1.37E-04	6
0.2	0.89	-0.11	0.359	-1.768	0.732	-0.61	-5.28E-05	-9.85E-05	1.42E-04	6
0.24	0.908	-0.113	0.371	-2.5	-0.61	-1.098	-7.04E-05	-7.83E-05	1.48E-04	6
0.28	0.906	-0.11	0.357	-2.805	-1.22	-0.854	-5.83E-05	-1.50E-05	1.12E-04	6
0.32	0.904	-0.111	0.356	-2.866	-1.28	-0.854	-6.85E-05	-2.78E-05	1.16E-04	6
0.36	0.912	-0.114	0.361	-2.317	-0.976	-0.488	-8.94E-05	-6.33E-05	1.20E-04	6

2.3. Data Classification

The classification process used a CNN-LSTM deep learning model to analyze motion data from accelerometer, gyroscope, and magnetometer sensors, as shown in Figure 2. Each sensor captured X, Y, and Z-axis values at 25 Hz, generating 25 data points per second along each axis. During the process, a windowing method was applied to structure the input data, where each 10-s window contained 250 timesteps per axis. The segmented data were then classified using a hybrid CNN-LSTM model, where CNN layers extracted spatial features, and LSTM levels modeled sequential dependencies, improving the classification accuracy for complex motion activities. The classification process included hyperparameter tuning, window size optimization, epoch count optimization, activation functions optimization, and loss functions to improve model performance. In addition, a confusion matrix was used to measure accuracy, precision, and recall to evaluate classification effectiveness. The testing phase validated the ability of the model to differentiate activity patterns based on sensor data, ensuring reliable classification results.

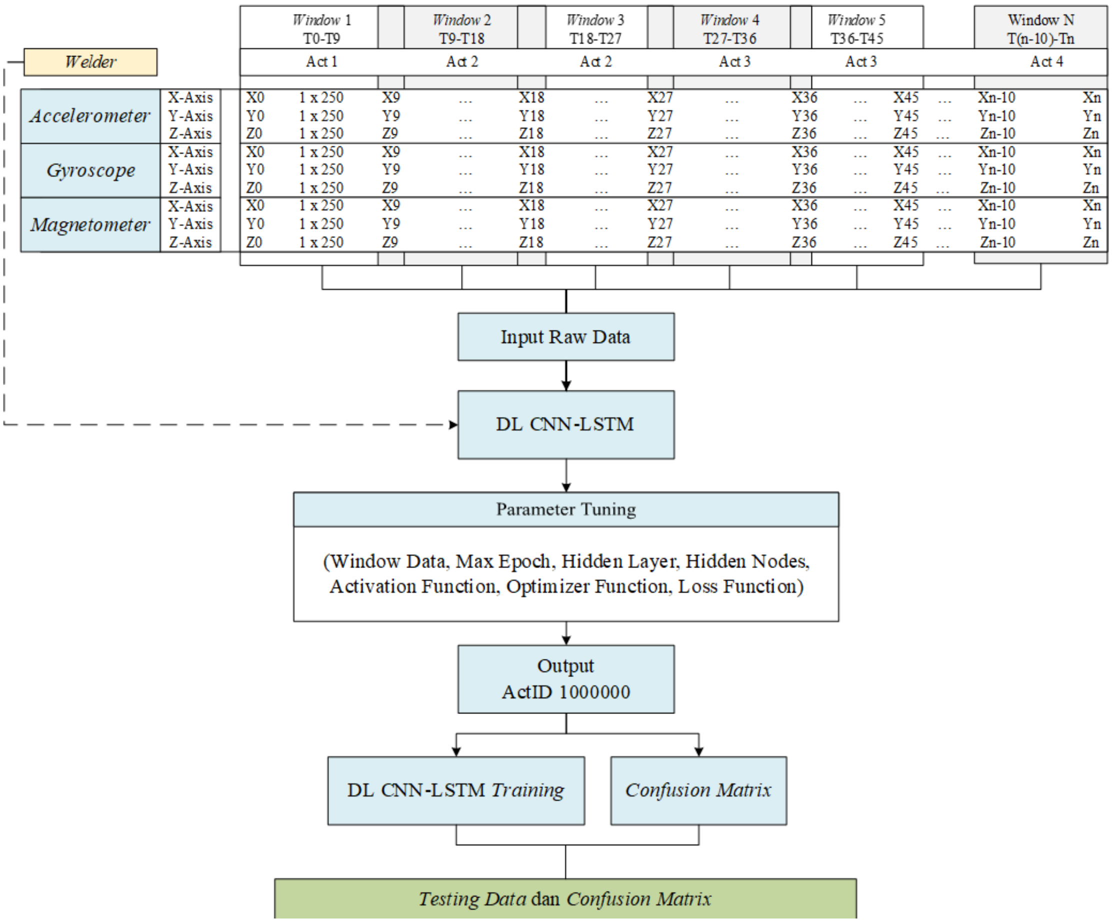


Figure 2 Flowchart of Classification using CNN-LSTM

3. Results and Discussion

The data collected during the experimental phase were processed using a CNN-LSTM algorithm to classify the welder performance during FCAW. The classification focused on six performance categories based on discontinuity analysis. CNN-LSTM model was trained and achieved the highest accuracy using a configuration of parameters consisting of three hidden layers, each containing 100 hidden nodes. ReLU activation function was applied to introduce non-linearity, while Adam optimizer was used to improve learning efficiency. The model was trained for a maximum of 1,000 epochs, ensuring extensive learning over the dataset. Following this discussion, a window size of 250 was used, signifying the input data was segmented into time-series sequences of 250 samples each. Throughout the training process, the model processed a total of 1,148 data samples. After completing all 1,000 epochs, the model achieved an impressive accuracy of 99.30%. Subsequently, testing of the model was performed with an excluded dataset from training and included outcome from training as shown in Table 3 and 4.

The confusion matrix results for the six-welder performance (W1 to W6) showed the classification accuracy of the model under different conditions. When all conditions were included, the model achieved a high true positive rate of 97.69%, with most predictions correctly associated with actual welder performance levels. During the process, misclassification was minimal as observed in W1, where 46 samples (7.86%) were correctly classified, with only a few misclassified as other levels.

However, when certain conditions were excluded, the true positive rate dropped significantly to 60.10%, showing a decline in model performance. Increased misclassification was particularly significant for W4 and W5, where multiple samples were incorrectly predicted as W6 (W4 → W6: 50 samples (7.26%)). Through these results, the model was unable to differentiate between specific welder performance levels due to changes in external influencing factors. The results showed that despite CNN-LSTM model performing well under controlled conditions, its robustness in varying conditions required improvement, potentially through further hyperparameter tuning, additional feature extraction, or data augmentation to improve generalizability.

Table 3 Testing Included Data of Welder's Performance with six level of criteria Result

Confusion Matrix (Include)						
	W1	W2	W3	W4	W5	W6
W1	46 (7.86%)	0 (0.00%)	5 (0.85%)	0 (0.00%)	3 (0.51%)	2 (0.34%)
W2	2 (0.34%)	55 (9.40%)	4 (0.68%)	8 (1.37%)	3 (0.51%)	3 (0.51%)
W3	9 (1.54%)	5 (0.85%)	62 (10.60%)	1 (0.17%)	4 (0.68%)	3 (0.51%)
W4	7 (1.20%)	1 (0.17%)	5 (0.85%)	106 (18.12%)	5 (0.85%)	5 (0.85%)
W5	2 (0.34%)	3 (0.51%)	1 (0.17%)	5 (0.85%)	112 (19,15%)	3 (0.51%)
W6	2 (0.34%)	2 (0.34%)	3 (0.51%)	6 (1.03%)	4 (0.68%)	98 (16.75%)

Data Length: 173
True Positive: 97.69%

Table 4 Testing Excluded Data of Welder Performance with six levels of criteria Result

Confusion Matrix (Exclude)						
	W1	W2	W3	W4	W5	W6
W1	15 (2.18%)	3 (0.44%)	10 (1.45%)	8 (1.16%)	12 (1.74%)	7 (1.02%)
W2	11 (1.60%)	26 (3.77%)	18 (2.61%)	16 (2.32%)	18 (2.61%)	9 (1.31%)
W3	19 (2.76%)	16 (2.32%)	36 (5.22%)	5 (0.73%)	11 (1.60%)	18 (2.61%)
W4	16 (2.32%)	7 (1.02%)	10 (1.45%)	35 (5.08%)	23 (3.34%)	50 (7.26%)
W5	6 (0.87%)	6 (0,87%)	10 (1.45%)	23 (3.34%)	39 (5.66%)	40 (5.81%)
W6	18 (2.61%)	8 (1.16%)	10 (1.45%)	48 (6.97%)	32 (4.64%)	50 (7.26%)

Data Length: 203
True Positive: 60.10%

In the previous study (Pribadi and Shinoda, 2021), this finding conducted a comparison to classify data using SVM and CNN-LSTM. Table 5 showed a comparative analysis of CNN-LSTM and SVM algorithms for welder performance classification. As SVM indicated faster processing times for data training and testing, CNN-LSTM outperformed SVM in terms of total training and test data accuracy. On the other hand, SVM showed better generalizability on the excluded test data.

CNN-LSTM model showed superior spatial and temporal learning capabilities due to its incorporation of convolutional as well as sequential layers, which enabled effective feature extraction and forecasting. Despite the longer processing times, higher training accuracy and the included test data of the model signified its suitability for applications requiring strong performance classification in complex datasets.

Table 5 Comparison of SVM and CNN-LSTM

No.	SVM (*Support Vector Machines*)	CNN-LSTM (*Convolutional Neural Networks-Long Short-Term Memory*)
1	Shorter duration for total data processing	Longer total data processing duration
2	Lower accuracy of training data compared to CNN-LSTM	Higher accuracy of training data compared to SVM
3	Similar accuracy results were obtained for the test data.	Similar accuracy results were obtained for the test data.
4	Higher accuracy for excluding test data compared to CNN-LSTM	Lower accuracy for exclude test data compared to CNN-LSTM

4. Conclusions

In conclusion, the experimental results showed that CNN-LSTM model effectively classified the welder performance in FCAW based on discontinuity analysis, achieving a high true positive rate of 97.69% in controlled conditions. The ability of the model to capture spatial and temporal dependencies contributed to its superior classification accuracy. However, when external conditions were excluded, the performance significantly declined to 60.10%, showing its sensitivity to varying environmental factors and potential overfitting to specific training conditions.

A comparative analysis with SVM showed that while the model offered faster processing times and better generalizability for excluded test data, CNN-LSTM outperformed SVM in training accuracy as well as total classification performance. The results signified that CNN-LSTM was well-suited for applications requiring detailed and accurate performance classification, despite the required improvements in model robustness. Future improvements, such as hyperparameter optimization, additional feature extraction, and data augmentation, could further increase the generalizability as well as reliability of the proposed model across diverse operating conditions.

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Author Contributions

TWP developed the theoretical formalism, performed the analytic calculations, and performed the numerical simulations. Both TWP and TS authors contributed to the final version of the manuscript, as TS supervised the project.

Conflict of Interest

The authors declare that there is no conflict of interest concerning the publication of this paper. No financial, personal, or professional relationships exist that could influence or bias the work presented in this manuscript. All sources of funding for the study have been disclosed, and there are no competing interests that might be perceived as affecting the objectivity or integrity of the study.

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