Mental Stress and Overload Detection for Occupational Safety

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Ph.D. Defense

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Motivation and Background

Canada Construction-Related Accidents

Source: Association of Workers' Compensation Boards of Canada

- Due to the high number of fatalities in the construction industry, **Safety Improvement** remains a high priority.
- Among contributing factors leading to accidents, **Human Unsafe Behaviour** was the most frequent cause of accidents. *(Chua and Goh 2004; Heinrich 1950; Reason 1991)*

Presentation Outline

Presentation is organized as follows:

- Introduction
- Research Gap and Objectives
- Research Methodology
- Data Collection and Pre-Processing
- Anomaly Detection Using Deep Learning Method
- Anomaly Detection Using Adaptive Nero Fuzzy Inference System
- Conclusion

Introduction

Stress and Overload Affecting Human Behaviour

Pressure on the human nervous system

Leading to **accidents** and human **unsafe** behavior

Variations in human physiological features

Real-time data collection by wearable biosensor in form of a wristband

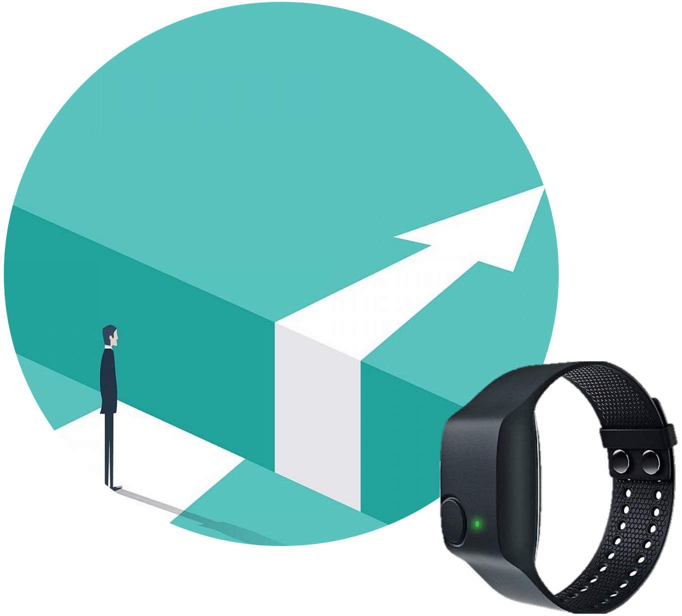
Deep learning technique to recognize distinct neurological status by assessing physiological signals.

Introduction

Research Gaps

The existing stress detection studies differ from each other in the following aspects:

1. Data Collection Method
2. Selected Features
3. Stress-Inducing Approach
4. Learning Algorithms



Introduction

Research Objectives

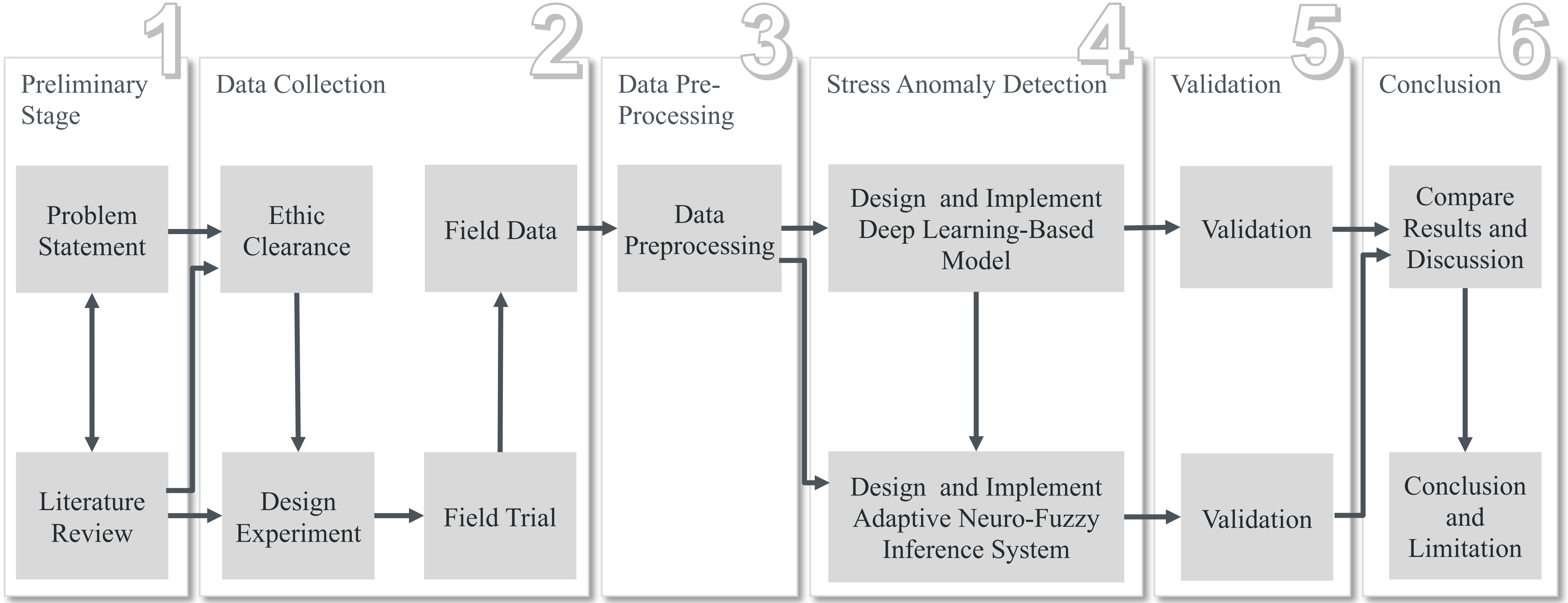
1) Design and implementation of a field experiment

2) Design, develop, and evaluate anomaly detection method(s)

3) Align the model with the long-term objectives and future application in the construction

Research Methodology

Proposed Research Stages



Data Collection

Field Experiment

Fig. 7. Timeline of the experiment

Data Collection

Wearable Wristband

PPG Sensor
Measures Blood Volume Pulse (BVP), from which heart rate variability can be derived

3-axis Accelerometer
Captures motion-based activity

Event Mark Button
Tags events and link them to physiological signals

EDA Sensor (GSR Sensor)
Measures the constantly fluctuating changes in certain electrical properties of the skin

Infrared Thermopile
Reads peripheral skin temperature

Internal Real-Time Clock
5ppm high accuracy time reference

Source: https://www.empatica.com/en-int/research/e4/

Data Pre-Processing

- Data Resampling

Signal	frequency
Temp	4 Hz
IBI	1 Hz
Hr	1 Hz
EDA	8 Hz
PPG	64 Hz
Acc	32 Hz

- Data Standardization

Units: µs, °C, bpm

Eq. (3). Robust Scaler:

$$x_i^{Scaled} = \frac{x_i - Q_1(x)}{Q_3(x) - Q_1(x)}$$

- Correlation Matrices

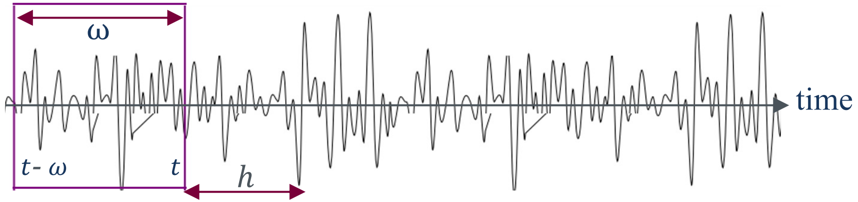


Fig. 15. Sample of a rolling window on generic data

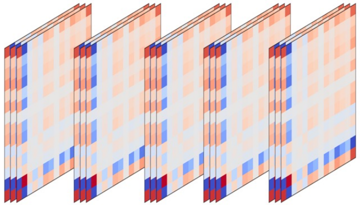
Eq. (5). Eq. (6). Eq. (7).
Inter-correlation between different pairs of features i, j:

$$X_i^{\omega} = \left(x_i^{t-\omega}, x_i^{t-\omega-1}, \dots, x_i^{t}\right),$$

$$X_j^{\omega} = \left(x_j^{t-\omega}, x_j^{t-\omega-1}, \dots, x_j^{t}\right),$$

$$m_{ij}^{t} = \frac{\sum_{\delta=0}^{\omega} x_i^{t-\delta} x_j^{t-\delta}}{\kappa},$$

$$m_{ij}^{t} \in M^{t}$$



$h \times (14 \times 14) \times 3$

Fig. 16. A sample input

Stress Anomaly Detection

Unsupervised Deep Learning Anomaly Detection

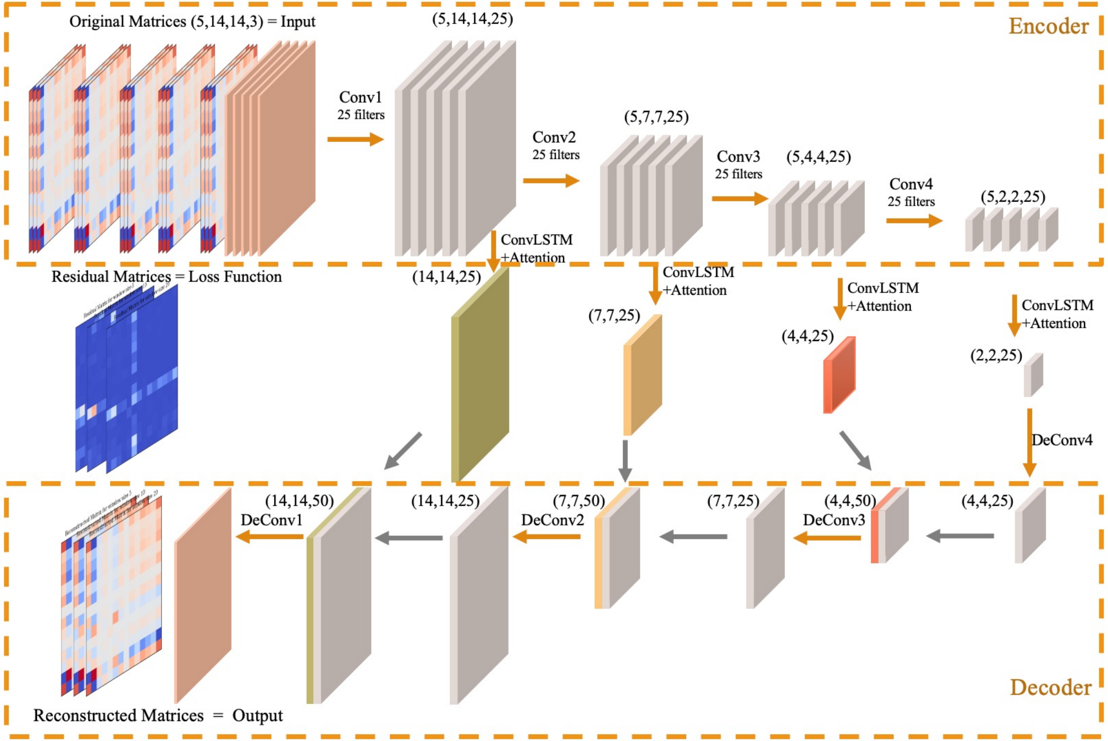


Fig. 17. Anomaly detection method architecture

Unsupervised Deep Learning Anomaly Detection

Detected Anomalies and Identified Contributing Features

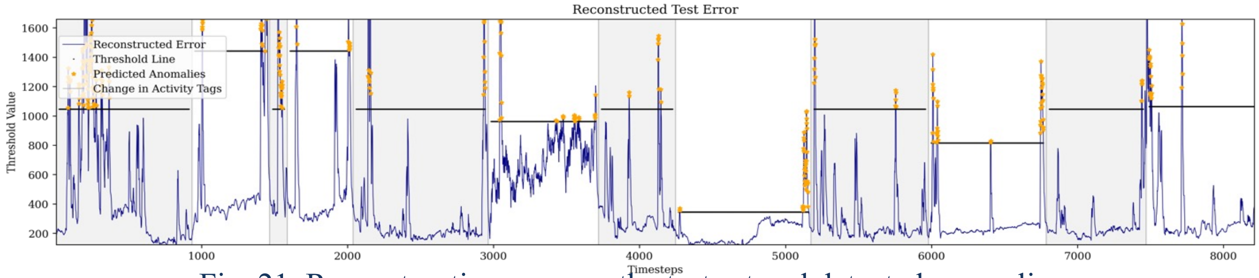


Fig. 21. Reconstruction error on the test set and detected anomalies

Eq. (8).

$$Loss = \sum_{t=1}^{5}\sum_{k=1}^{3}\left|\left| \chi_{:,:,k}^{t} - \hat{\chi}_{:,:,k}^{t} \right|\right|_{n}^{2},$$

Threshold = 90% reconstructed error for each activity group

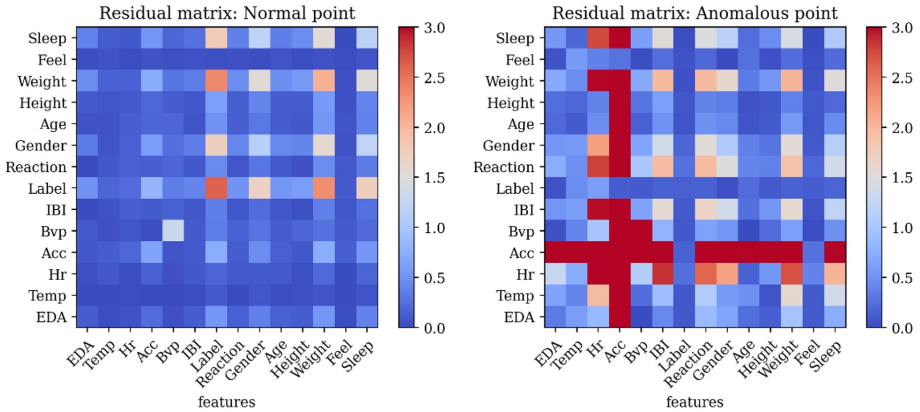


Fig. 20. Residual matrix of a normal sample vs. an anomalous sample

Unsupervised Deep Learning Anomaly Detection

Accuracy Metrics

Table 4. Unsupervised DL-based method accuracy using test dataset II

	Precision	Recall	F1-score	Support
0 Non-Anomaly	0.97	0.92	0.94	2712
1 Anomaly	0.33	0.57	0.42	183
accuracy			0.90	2895
macro avg	0.65	0.75	0.68	2895
weighted avg	0.93	0.90	0.91	2895

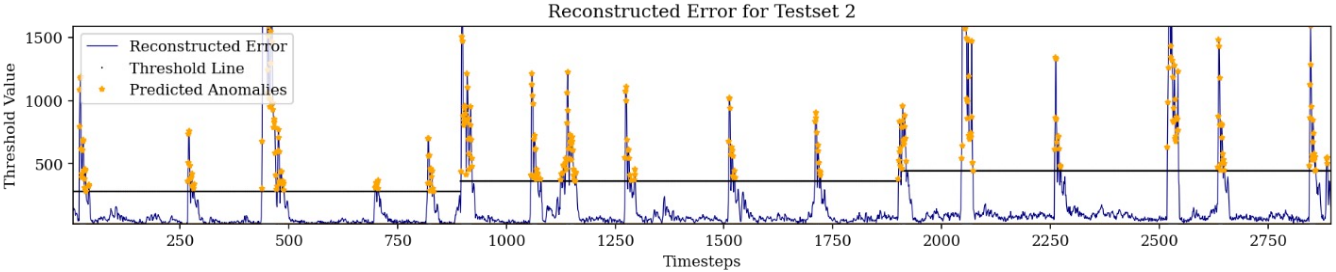


Fig. 25. Reconstruction error and detected anomalies on the test dataset II

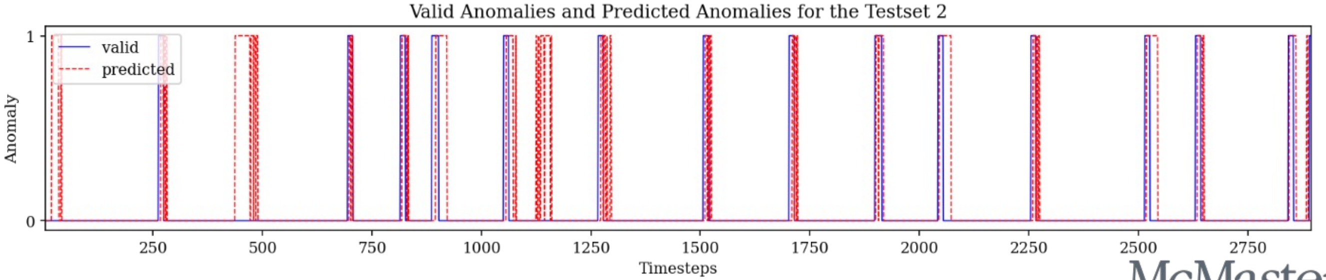
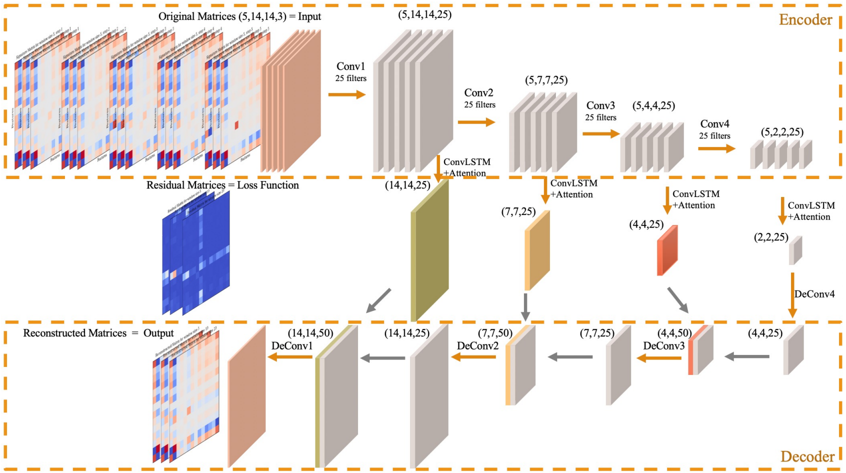


Fig. 26. Valid anomalies and predicted anomalies for the test dataset II

Unsupervised Deep Learning

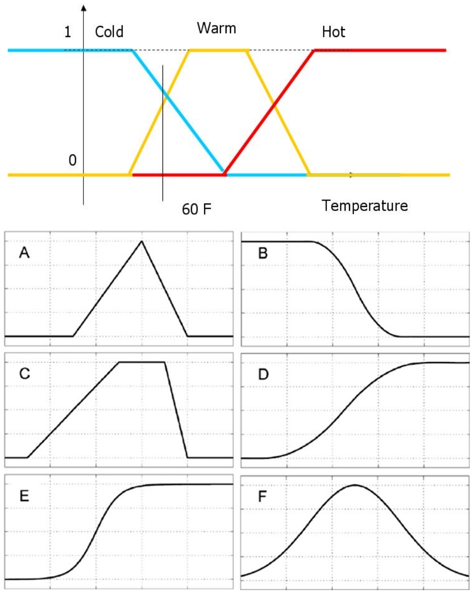
Shortcomings

Deep Learning



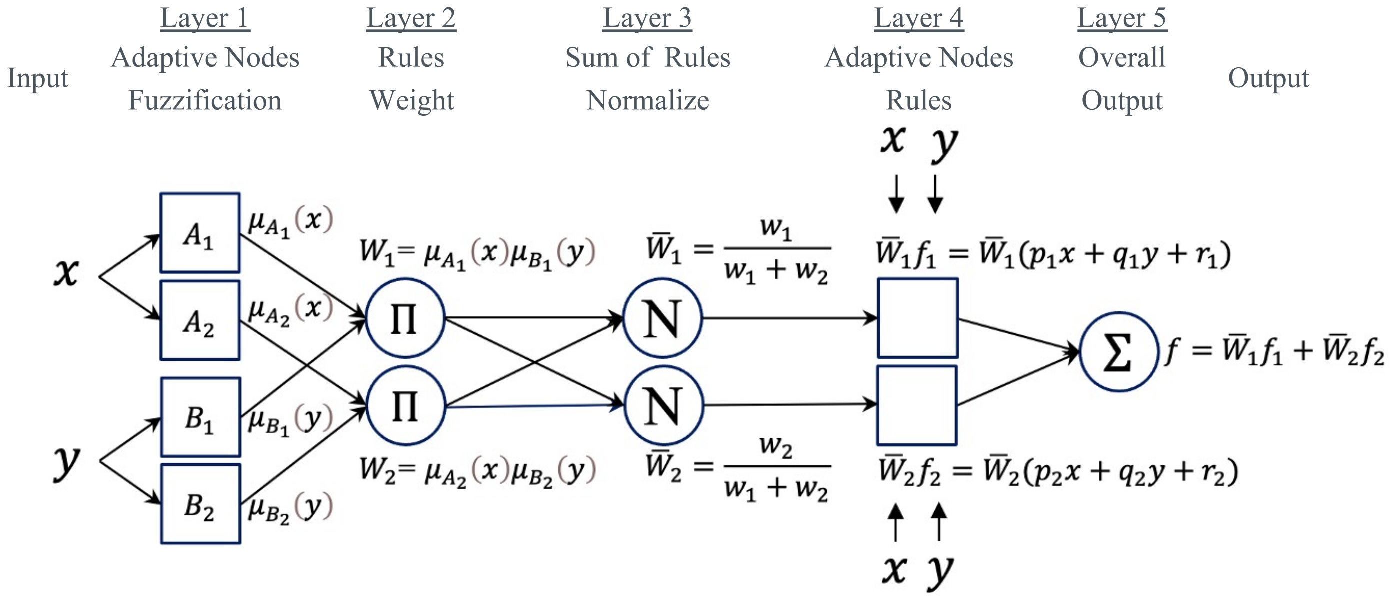
Vs

Fuzzy Logic Inference System (FIS)



An Adaptive Neuro-Fuzzy Inference System (ANFIS)

ANFIS Architecture



Premise parameters (nonlinear):

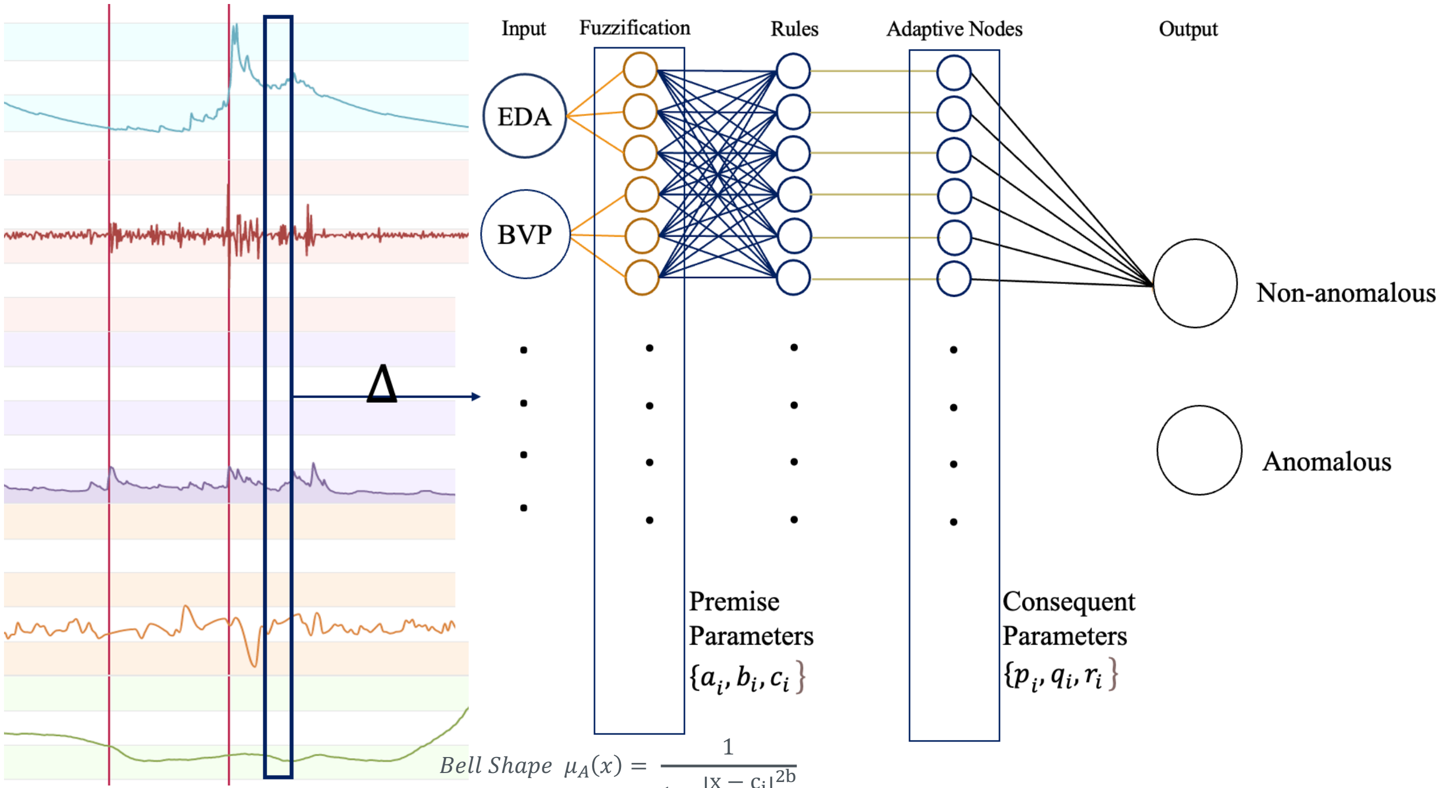
$$Bell\ Shape\ \ \mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}}$$

Consequent parameters (linear):

$Rule1{:}\ if\ \ x\ is\ A_1\ and\ y\ is\ B_1 then\ f_1 = p_1 x + q_1 y + r_1$

$Rule2{:}\ if\ \ x\ is\ A_2\ and\ y\ is\ B_2 then\ f_2 = p_2 x + q_2 y + r_2$

Proposed Adaptive Neuro-Fuzzy Inference System (ANFIS)



$$\text{Bell Shape } \mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b}}$$

McMaster University

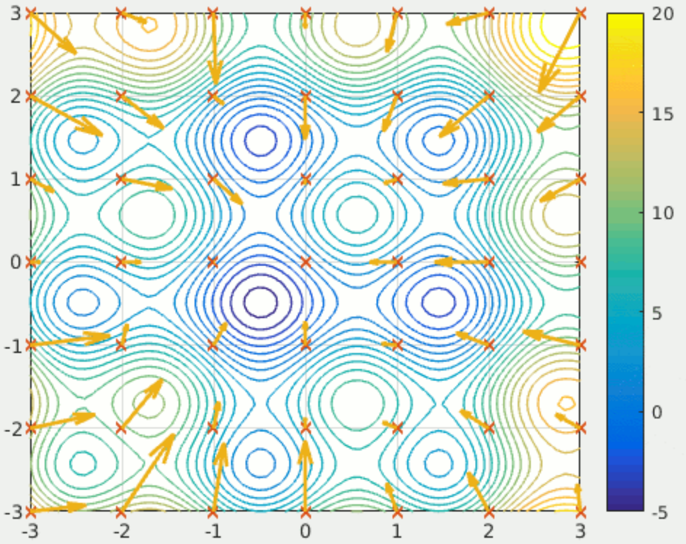
Adaptive Neuro-Fuzzy Inference System (ANFIS)

Particle Swarm Optimization algorithm (PSO)

Objectives:

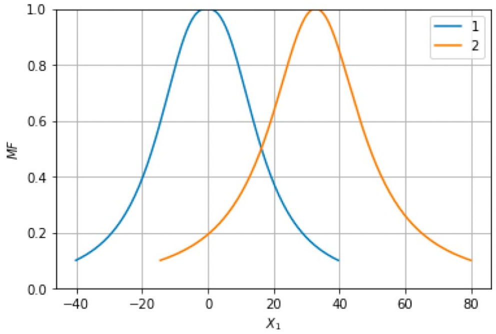
(1) Searching for optimal premise/consequent parameters

(2) Minimizing the cost function (i.e., RMSE)

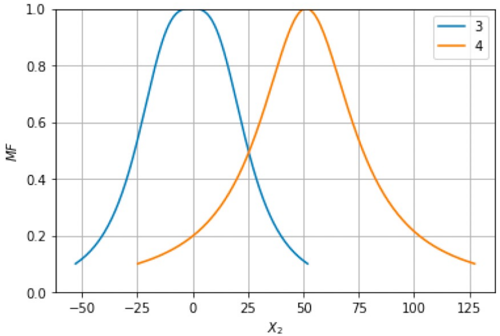


Adaptive Neuro-Fuzzy Inference System (ANFIS)

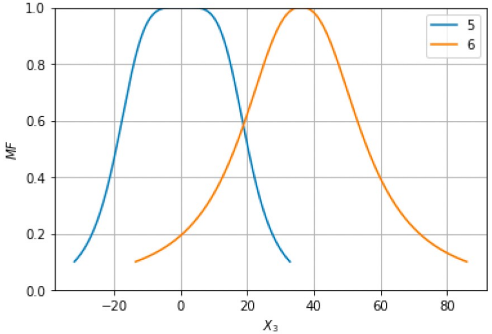
Calculated Membership Functions



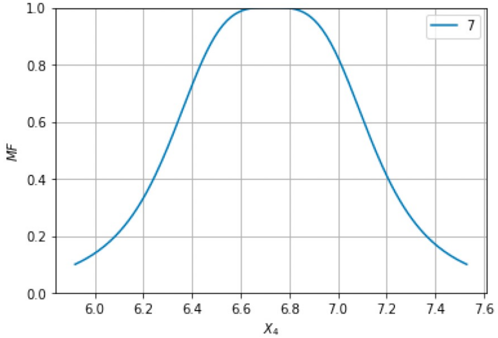
1. EDA



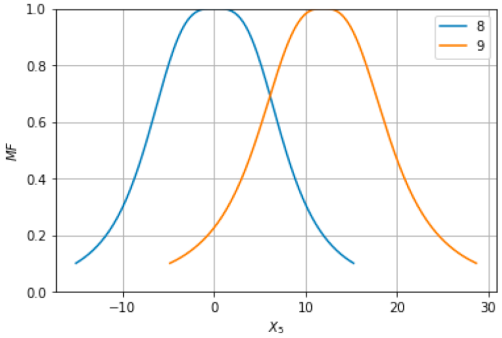
2. Temp



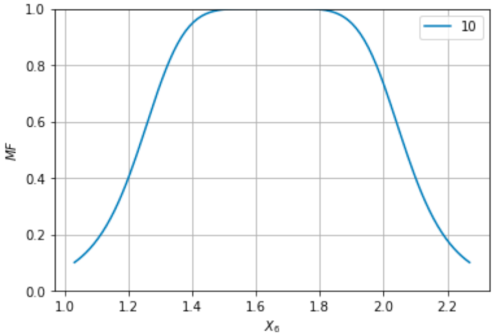
3. Hr



4. Acc



5. Bvp



6. IBI

Compare Results and Discussion

- Methods Efficiency and Training Cost

Methods	Parameters	Processing Time
1-Unsupervised DL-Based	116028	1d 5h 16min 26s
2-ANFIS	807	1h 49min 49s

- Methods' Performance Metrics

	Anomaly Detection Method					
	1-Unsupervised DL-Based			2-ANFIS		
Classes	Precision	Recall	F1-score	Precision	Recall	F1-score
Non- Anomalous	1.00	0.98	0.99	0.80	0.69	0.74
Anomalous	0.35	1.00	0.52	0.73	0.83	0.77
Accuracy			0.98			0.76
Macro avg	0.68	0.99	0.76	0.76	0.76	0.76
Weighted avg	0.99	0.98	0.99	0.76	0.76	0.76

Table 13 Unsupervised DL-based and ANFIS anomaly detection accuracy

Conclusion, Limitation, and Future Work

- Research Contribution
  - Field Experiment
  - Unsupervised deep learning-based
  - Adaptive neuro-fuzzy inference system
  - Safety in Workplaces
- Limitations and Future Work
  - Experiment design and data collection
  - Social factors and their influence
  - Expert inputs and specialists (e.g., Cardiologists)

Publications

- Eskandar, S., Wang, J., Razavi, S. "A Review of Social, Physiological, and Cognitive Factors Affecting Construction Safety" *in 36th International Symposium on Automation and Robotics in Construction, Banff, 2019, 317-323*.

- Eskandar, S., Razavi, S., "Using Deep Learning for Assessment of Workers' Stress and Overload " in 37th International Symposium on Automation and Robotics, *2020*

- Eskandar, S., Wang, J., Razavi, S. "Human-in-the-Loop Cyber-Physical Systems (HiLCPS) for Safer Construction Sites" *in "Cyber-Physical Systems in Built Environment", Springer*.

- Eskandar, S., Razavi, S., "Using Deep Learning for Assessment of Workers' Stress and Workload" *Submitted in International journal of occupational safety and ergonomics*

- Eskandar, S., Razavi, S., "Stress Detection Using Adaptive Neuro-Fuzzy Inference System: Toward Automation in Construction Safety" *Submitted in Automation in Construction, Elsevier*

Thank You!

Unsupervised Deep Learning Anomaly Detection

Processing time for different window sizes

Training Set Size : (33659, 5, 14, 14, 3)
Processing time using Tesla P100-PCIE-16GB GPU

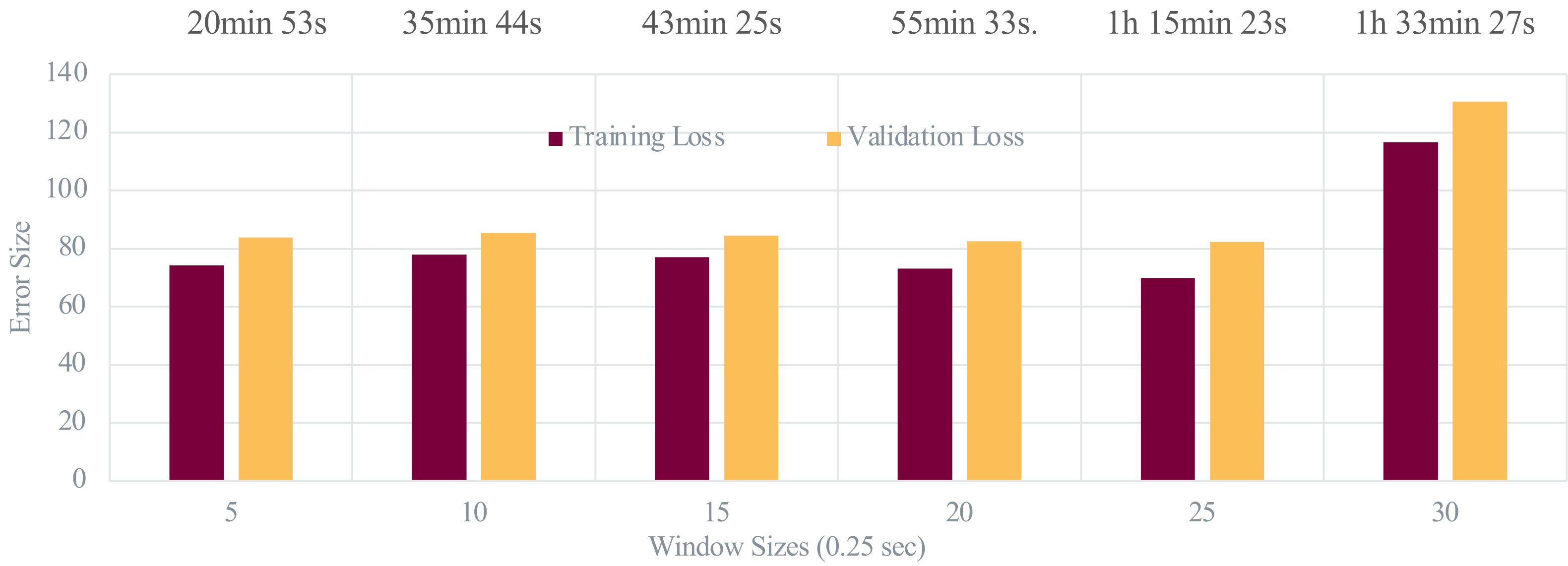


Fig. 30. Anomaly detection method training loss and validation loss for different window sizes