Detection of Valve Stiction in Industrial Control Loops through Continuous Wavelet Transformation with a CNN*

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***Abstract*— Control valve stiction is a common equipment problem where the valve exhibits delayed response to control output and becomes stuck due to static friction, which can lead to undesired nonlinear behavior and oscillations. It is critical to identify and correct this problem to ensure consistent operation in control loops. This paper introduces the novel technique continuous wavelet transform - convolutional neural network (CWT-CNN) for non-intrusive valve stiction detection. Industrial Process data is converted to an image with continuous wavelet transformation and then fed into a deep convolutional neural network to classify stiction behavior. The CWT-CNN is fine-tuned from pre-trained models like GoogleNet and ResNet via transfer learning for better classification and faster training while requiring less data. This work uses control loops from various chemical plants for training. The best performing CWT-CNN using GoogleNet can accurately predict 95.62% loops in the validation set, and has a true positive rate of 83.9% on the test set.**

I. INTRODUCTION

Valve stiction is a prevalent equipment problem for control valves that lead to undesired nonlinear behavior. Monitoring and identifying 'sticky' valves is important to ensure consistent plant operation. In response to a change in control output, sticky valves may demonstrate a static period followed by a slip jump when the output has overcome the 'stickiness' of the valve. Stiction is due to excess static friction or other mechanical failure. One can typically diagnose valve stiction in flow control loops by looking for square waves in the process variable (PV) and saw-tooth patterns in the controller output (OP), as seen in Fig 1.

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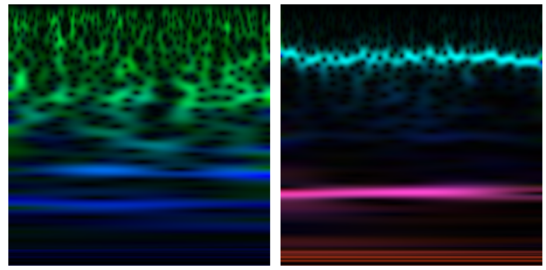

Fig. 2. CWT images produced by industrial process data. The left image is that of a nonstiction loop, while the right is for a loop with stiction behavior.

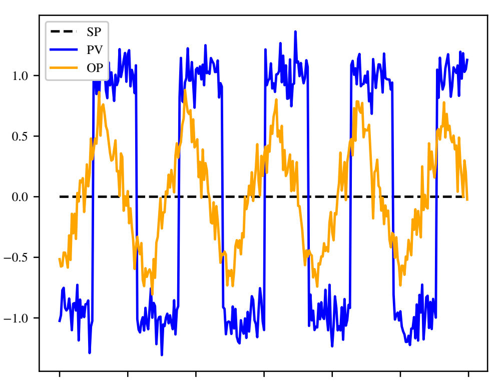

Fig. 1. Simulated process data for a flow loop with stiction. The PV does not move while the OP changes due to static friction; once a threshold is reached, the PV demonstrates a 'slip-jump'.

A collection of definitions of valve stiction can be found in [5]. Resistance to initial motion, becoming stuck in a certain position, undergoing a 'slip-jump' to a new position after static friction is overcome, and stickiness are all behaviors exhibited by valves suffering from valve stiction. It is imperative to identify and correct this undesired behavior of control loops, as inconsistent and unpredictable performance can lead to production upsets, process hazards, or further equipment damage.

While stiction can be identified through invasive tests like a bump test, this is not ideal as the valve either needs to be removed from operation or non-standard behavior would need to be introduced to the process. A non-intrusive method would be preferred, as it would allow automated screening during operation and not disturb the process. Non-intrusive methods can be difficult due to the poor quality of data, valve stiction occurring at different frequencies and process regions, or other nonlinear problems that may mask stiction behavior. The motivation of the work proposed here is to non-intrusively and accurately detect valve stiction to support chemical process operations.

This paper introduces a novel method of valve stiction detection with advanced machine learning and signal processing concepts known as Continuous Wavelet Transform - Convolutional Neural Network (CWT-CNN). By performing a continuous wavelet transform (CWT) on a segment of process data (composing of set-point (SP), PV, and OP), an image can be generated that is characteristic of the loops frequency behavior, as seen in Fig. 2. The image is then used as an input to a deep convolutional neural network (CNN), which will then classify whether stiction is occurring or not. To leverage advanced models for faster training time and better performance, transfer learning is used on state of the art architectures like GoogleNet [24] and ResNet [11]. Industrial process data for flow loops is used to train and evaluate the CWT-CNN model. The results section shows that CWT-CNN has a higher accuracy and true positive rate compared to state of the art machine learning methods.

Both valve stiction detection and valve stiction quantification are well studied areas in literature. Akavalappil et. al [1] and Capaci et. al [3] offer in depth reviews of available methods for all studies related to modeling or detecting valve stiction behavior. A brief review focusing on detection methods only is presented below for comparison to the CWT-CNN method.

Traditionally, statistical based methods are used for early advances in valve stiction detection, and many are based on characterizing a PV-OP plot. Horch et al. [12] applied cross-correlation functions between the OP and the PV to detect stiction. Yamashita et al. [26] calculates a stiction index based on limit cycle patterns. Approaches like Srinivasan et al. [23] use waveforms to characterize the shapes of the OP and PV data, and then classify stiction behavior. Choudhury et. al [6] uses the bicoherence function from higher order statistical analysis to detect nonlinear behavior in process data, and then fit an ellipse to a filtered PV-OP plot to classify stiction behavior.

Recently, machine learning based methods have become more common in valve stiction detection. Rengaswamy et al. [19] introduces machine learning to this endeavor, using a hybrid method of a waveform shape-based approach and neural networks. Dambros et al. [7] convert simulated PV and OP data into an 8x8 pixel image based on intensity of the process data and then use an artificial neural network to classify stiction behavior.

The most recent literature has focused on advanced machine learning methods that employ CNNs. The method introduced in this paper is based on a CNN model, and is the most comparable to these approaches. Rosario et. al [20] uses a CNN method to classify a PV-OP plot using the GoogleNet model [24]. Kamaruddin et al. [13] first compose a 'butterfly' shape image from PV and OP data, which is then fed to a CNN. Zhang et al. [27] uses an advanced mixed feature learning stage combined with a CNN to classify valve stiction. Akavalappil et. al [2] introduced a CNN method trained on simulation and industrial data that directly uses the process data rather than perform a feature transformation like previous methods.

Beyond the application of valve stiction, the combination of CWT and CNN has been applied to other classification tasks. Wang et al. [25] uses CWT and CNN to classify electrocardiogram signals. Meintjes et. al [16] uses a similar method to classify heart valve problems, and shows improvement over traditional machine learning methods. Mao et al. [15] demonstrated a classification task with CWT and CNN that outperformed large CNNs like GoogleNet and Alexnet. Cheng et al. [4] developed a CWT and CNN method with local binary convolution layer for fault detection in rotating machinery.

The CWT-CNN is the first valve stiction detection method that identifies stiction based on a CWT image of SP, PV, and OP process data. As will be discussed in the results section, This approach outperforms alternative state of the art machine learning classification methods. The use of CWT allows the method to capture important signal information indicative of stiction without the need to filter for noise. Unlike other methods ([27], [7], [20]) that employ extensive feature selection, this approach is purely data driven and does not require manual input for threshold values or controller specific parameters. CWT is chosen over other image transformation methods due to its robustness to signal noise found in most chemical process data. Consequently, it is more flexible and easily be extended to other flow loops.

II. Methods

The CWT-CNN method is visually summarized in Fig. 3. Industrial process data (SP, PV, and OP) for a day is cut into smaller segments. Each of the features is then transformed with CWT and concatenated to form an red-green-blue image (each color channel representing a different feature). The image is rescaled and normalized to fit the input format required by the selected pre-trained model, which outputs a final classification.

CWT is a signal processing method that has been used for image compression, electrocardiogram analysis, and acoustics [22]. CWT is comparable to the Fourier transform in that it convolves a signal with a basis function. While the Fourier transform uses sinusoids for the transform, CWT allows for a variety of customizable and mathematically complex wavelet functions. The signal is convolved with the wavelets at different scales to produce a two-dimensional output from a one-dimensional signal. Varying the scales allows CWT to capture information on signals with multiple frequencies. CWT also acts as a filter for unwanted noise, as only the periodic signals that match the chosen wavelet's shape are propagated. The mathematical definition of CWT is as follows:

$$\mathrm{X}(\tau, s) = s^{-\frac{1}{2}} \int_{\infty}^{-\infty} x(t)\psi(\frac{t-\tau}{s})dt \quad (1)$$

where X is the transformed signal, τ is the time shift, s is the scale, $x(t)$ is the original signal, ψ is the wavelet function, and $\frac{(t-\tau)}{s}$ is the scale factor. Operating at different scales allows CWT to be more robust and capture non-stationary signals, capturing a higher resolution of data compared to a discrete transform. Commonly used wavelets for CWT are the generalized morse wavelet, Morlet wavelet, Mexican Hat wavelet, and Gaussian wavelet [14].

The specific tool used for CWT in this paper is the Python package Ssqueezepy [17]. Scales are automatically generated with a log-piecewise sampling, and a time-frequency image is created by Eq. 1. The image is reshaped into

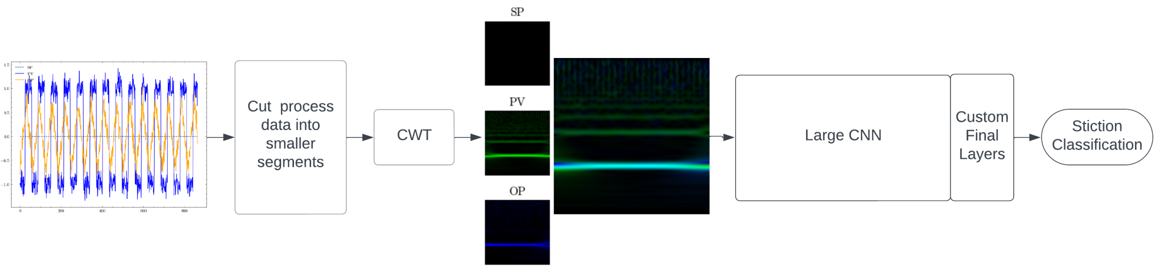

Fig. 3. The CWT-CNN Method. Process Data is divided into segments, then CWT is performed independently on the SP, PV, and OP, and stacked together into an image. A large CNN uses this image as input to make the final classification.

224x224 pixels and normalized for input into the CNN models.

CNNs are a class of deep learning models that are commonly used for image processing tasks. By learning the best filters to apply to an input image, the model can learn textures, patterns, and other image data that is useful for prediction. These models can be applied to classification, object detection, object segmentation, or any other necessary task. More complex tasks can require larger and more complex CNNs. Consequently, CNNs can become very large and computationally prohibitive to train for difficult tasks.

The best CNN models are compared in competitions on large datasets like ImageNet [21]. ImageNet is a dataset of over 14 million images with 1000 labels. As larger models are difficult to train, a method known as transfer learning can be employed to leverage the architecture and performance of pre-trained models. These large models can be trained on one task, like ImageNet classification, and then applied to a different task after calibration on new data.

For this study, deep CNN models trained on ImageNet are used for transfer learning. These models are GoogleNet [24] and ResNet-18 [11]. The full architectures are not discussed here for brevity as they are open source models. The pretrained models are downloaded and customized using Pytorch [18]. The output layers of these pretrained models are modified from a dense layer with 1000 outputs to a dropout layer and a dense layer with 2 outputs of stiction or non-stiction. The dropout layer is necessary to help regularize the model during training and prevent overfitting.

The dataset used to train these models contains a week of industrial process data, sampled every 10 seconds, from 163 flow loops. 55% of the manually labeled data exhibits stiction behavior. The CWT-CNN method segments these loops into 2.4 hour long batches, so that multiple predictions can be generated for a loop each day. Previous tests showed that increasing or decreasing the time window had no significant impact on classification performance. The dataset after segmentation results in 11410 individual images, which are randomly split into train and validations sets with a 70/30 split for model selection. An additional hold-out test set of 117 expertly labeled loops is used for final performance evaluation. This test set only had one day of data for each loop, with about 30% of the data considered stiction loops.

Two alternative models are presented as baselines for the CWT-CNN method in the results section. The first classification model is InceptionTime [10], a CNN based model. InceptionTime is a deep CNN model based on image models like ResNet and AlexNet that uses residual connections, ensembles of convolution layers, and various filters to classify a time series. InceptionTime is comparable to the model described in [2], as the model learns directly from the process data without any additional feature engineering. The other approach is to use MiniRocket transformer [8] with logistic regression classifier. MiniRocket uses a large amount of semi-random kernels to extract features from a time series, and then classifies with a simple model like logistic regression. These models represent the state of the art time series classification methods for both deep learning and machine learning in general [9]. Because of this, they are used as a benchmark against the CWT-CNN method.

III. Results

There are many different metrics to consider when comparing the performance of binary classifiers. The accuracy represents how correctly the classifier predicts the label, regardless of class. The true positive rate (TPR) indicates how accurate the classifier is at predicting true positives, or in this case stiction events. The true negative rate (TNR) is

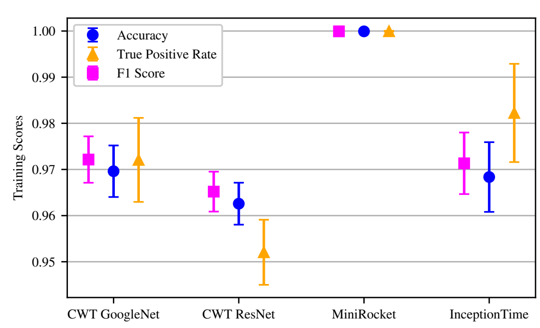

Fig. 4. Average performance scores of the four models on the training set between 5 cross validations. The training and validation data are randomly shuffled to generate the cross validations. The intervals represent the standard deviation of the 5 runs.

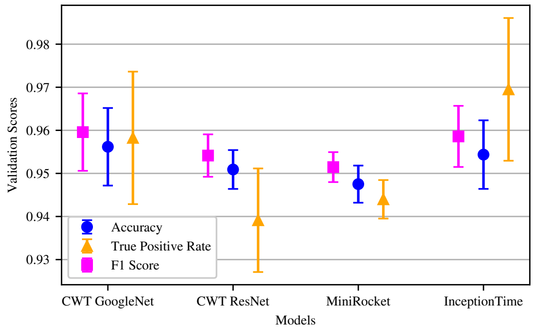

Fig. 5. Average performance scores of the four models on the validation set between 5 cross validations. The training and validation data are randomly shuffled to generate the cross validations. The intervals represent the standard deviation of the 5 runs.

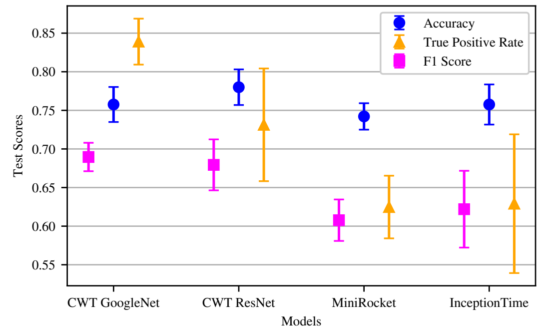

Fig. 6. Average performance scores of the four models on the test set between 5 cross validations. The training and validation data are randomly shuffled to generate the cross validations. The intervals represent the standard deviation of the 5 runs.

the same for nonstiction events. As TPR is the complement of false negative rate, and TNR is the complement of false positive rate, only TPR and TNR are presented for brevity. The F1 score combines both precision and recall to evaluate classifiers and can be a more balanced metric than accuracy. For the task of valve stiction detection, it is important to identify stiction loops that would otherwise go undetected by traditional methods; therefore, it is valuable for the classifier to have a high TPR and high F1 score.

A. Method Comparison

This section compares classification scores between different methods on industrial process data. The results are summarized in Table I. For all CWT-CNN methods, 5 epochs are used to train on the dataset; a low number of iterations is possible due to the large volume of data and the use of transfer learning. For InceptionTime [10], 50 epochs are used for training. Each model is trained 5 times on a random 70/30 split of the training and validation data. Process data batches, composed of 864 time-steps with 3 features, are scaled individually for each batch and feature. The CWT images are reshaped to 224x224 and normalized to be processed through GoogleNet and ResNet-18. The default architectures of GoogleNet and ResNet-18 as available from Pytorch are used for the base model, with the first and final layers being modified for CWT Channels and binary classification [18]. The results of the different models are plotted in Fig 4. Unless otherwise stated, all results are based on classification of individual control loop segments.

MiniRocket has nearly perfect scores across cross validations on the training set, while the other models hover around 96-97% for the scores, as shown in Fig. 4. For the validation set, the best performing model with an F1 score of 95.96% is the CWT-GoogleNet model, shown in Fig. 5. MiniRocket generates thousands of features with many convolution kernels, and is potentially over-fitting on the training set.

For the test set, the best model is again the CWT GoogleNet with an F1 score of 68.96%, shown in Fig. 6. This model also outperforms the other methods with a TPR of 83.9%, which is significantly greater than the other models. Signal noise is filtered out for CWT-CNN methods, but may hamper the InceptionTime and MiniRocket models. The CWT-CNN model may allow for a broader detection of stiction types, while other methods may only detect specific patterns or wave forms. The pairing of CWT and the GoogleNet architecture allow the CWT-CNN model to detect stiction behavior that other models may miss.

B. Ablative Comparisons

Most traditional valve stiction detection methods make use of only the PV and OP signals. In many loops, the SP may be flat or constant, yielding no meaningful information to the model. To test the importance of the SP feature, a study on the CWT GoogleNet model is done where the SP feature is replaced with an alternative signal, such as error (difference between SP and PV) (E), PV multiplied by OP (PV x OP), PV convolved with OP (PV*OP), or integrated error (IE). The PV x OP and PV*OP features are chosen as many traditional methods use correlations or convolutions between these signals. The error and integrated error are frequently used in control theory. The results of this study on the test set are shown in Fig. 7. When using E instead of SP, the CWT GoogleNet model's F1 score improves from 68.96% to 71.49%. The TPR and accuracy do not change much, so the improvement might not be significant and warrants further investigation. The improved performance could be due to how the error signal offers more information than the SP signal.

An important decision during the CWT pre-processing step is the choice of the wavelet. To understand the impact of this choice, the CWT GoogleNet model is evaluated with different wavelets available in the Ssqueezepy library [17]. The Morlet wavelet is used for previous studies as is considered the most general and applicable to process data. The alternatives are the generalized morse wavelets (GMW), bump wavelet, Complex Mexican hat wavelet (CMHT) and the Hilbert analytic hermitian hat wavelet (HHHT). The accuracies of these models on the test set are visualized in Fig. 8 for the CWT GoogleNet model. There seems to be no significant improvement due to the choice of the wavelet for the TPR and F1 score, the TNR does increase when using the Bump wavelet from 71.92% to 81.20%, shown in Table I. The different performance could be attributed to

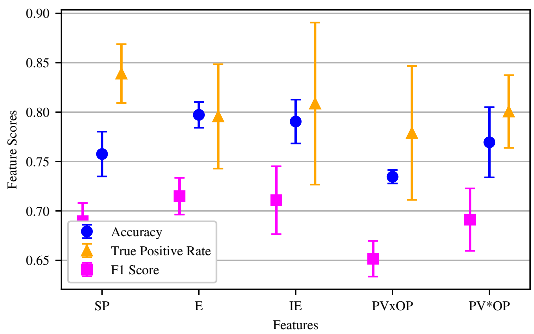

Fig. 7. Performance scores on the test set between CWT GoogleNet models using alternative features. The SP feature is replaced by another feature to produce a different image with CWT. The intervals represent the standard deviation of the 5 runs on different shuffles of the training and validation sets.

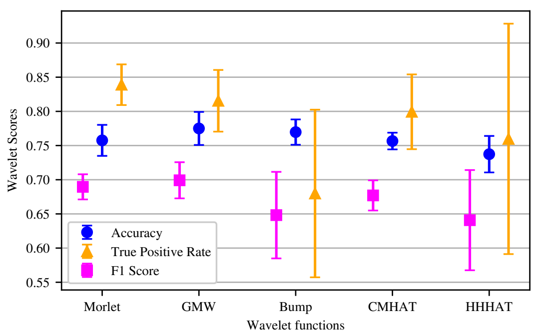

Fig. 8. Performance scores on the test set between CWT GoogleNet models using different wavelets for CWT. The default wavelet used is the Morlet wavelet. The intervals represent the standard deviation of the 5 runs on different shuffles of the training and validation sets.

how well the wavelet shape matches stiction behavior in process signals.

A final study to consider is the impact of data volume on the models. Transfer learning can allow models to learn more with less required data. 11410 images may not be necessary for future applications or recalibration of the model. Fig. 9 shows the impact of data volume on the CWT GoogleNet model on the test set by randomly removing input data from the training set. As expected, more data leads to better classification performance. Interestingly, the TPR is higher when 25% of the data is used compared to the 50% and 75%. This could be because of how the data is randomly split or due to the balance of the dataset and warrants further investigation.

IV. Conclusions

The CWT-CNN is a novel contribution to the valve stiction detection community that relies on advanced signal processing and deep learning approaches. The comparison results show that the proposed method outperforms state of the art time series classifiers on real chemical process data. Of the models evaluated, the CWT Googlenet method performed the best on a hold-out test set. The CWT Googlenet model had a much greater TPR 83.9 % compared

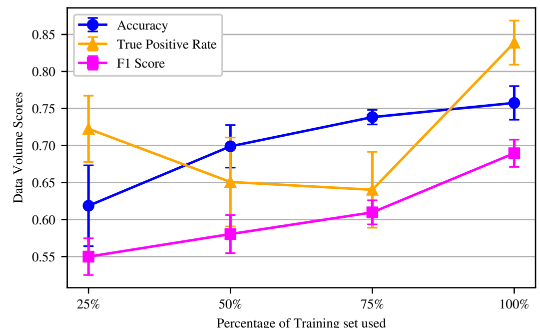

Fig. 9. Performance scores of a CWT GoogleNet when trained on different volumes of data. The intervals represent the standard deviation of the 5 runs on different shuffles of the training and validation sets.

to other methods. Using a different input feature like error instead of SP can improve the F1 score as well. A primary benefit of using data driven models like the CWT-CNN over traditional models is the ability to retrain and recalibrate on new data with relative ease. The use of CWT captures important frequency information from process data without undesired noise, allowing better performance than other machine learning methods.

The CWT-CNN method can be expanded and improved for better predictions and better understanding. The proposed method is difficult to interpret, unlike traditional statistical methods, and may perform poorly on process data dissimilar to the training data. Future work involves developing an explanation or interpretation of the models with a feature attribution method like layer-wise relevancy propagation or Shapley values. Although the CWT-CNN is used for binary detection, the method can be extended to severity quantification or categorization with improved labeling of process data. This effort is difficult as there is no established standard for quantifying stiction behavior and requires further study. One important area that this work needs to be expanded to is stiction detection for temperature and level loops, which would necessitate a larger dataset of labeled loops, and allow the method to be applied in more settings. A larger study and comparison of time series to image transformations, such as Gramian angular field (GAF), Markov transition field (MTF), or Discrete wavelet transform (DWT) is left for future work. A full comparison of the CWT-CNN method with previous methods such as [6] and [12] on a standard dataset would help establish the improvements made by this work.

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References

[1] Vijoy Akavalappil and T. K. Radhakrishnan. Comparison of current state of control valve stiction detection and quantification techniques. *Transactions of the Institute of Measurement and Control*, 44(3):562–579, February 2022. Publisher: SAGE Publications Ltd STM.

TABLE I

A summary table comparing all of the models trained for the model comparison study, feature study, and CWT wavelet study. Scores that are bold are the best in that column and underlined are the second best.

	Training Set				Validation Set				Test Set			
Method	Accuracy	TPR	TNR	F1	Accuracy	TPR	TNR	F1	Accuracy	TPR	TNR	F1
CWT GoogleNet SP, Morlet	96.96	97.21	96.67	97.21	95.62	95.82	95.37	95.96	75.76	**83.9**	71.92	68.96
CWT ResNet	96.26	95.21	97.52	96.52	95.09	93.91	96.48	95.41	78.0	73.13	80.29	67.94
MiniRocket	**99.99**	**100.0**	**99.99**	**99.99**	94.75	94.4	95.17	95.15	74.21	62.48	79.74	60.77
InceptionTime	96.84	98.22	95.18	97.13	95.44	**96.95**	93.58	95.86	75.76	62.91	**81.81**	62.2
CWT-GN E	97.2	97.5	96.85	97.44	95.66	96.09	95.14	96.02	**79.72**	79.57	79.8	**71.49**
CWT-GN IE	96.17	97.55	94.5	96.52	94.74	96.07	93.16	95.22	79.05	80.87	78.19	71.08
CWT-GN PVxOP	96.57	96.99	96.08	96.86	94.75	95.17	94.23	95.18	73.46	77.89	71.37	65.16
CWT-GN PV*OP	96.27	96.89	95.52	96.59	94.78	95.52	93.92	95.22	76.95	80.06	75.48	69.12
CWT-GN GMW	97.14	97.87	96.28	97.4	95.66	96.45	94.7	96.04	77.5	81.55	75.6	69.92
CWT-GN Bump	97.54	96.96	98.23	97.72	**96.15**	95.55	**96.86**	**96.43**	76.97	67.99	81.2	64.82
CWT-GN CMHAT	96.66	96.65	96.67	96.92	95.28	95.25	95.3	95.65	75.66	79.94	73.64	67.7
CWT-GN HHHAT	96.56	96.92	96.15	96.85	95.18	95.69	94.55	95.58	73.74	75.98	72.68	64.08

[2] Vijoy Akavalappil, Thota K. Radhakrishnan, and Sanjay K. Dave. A convolutional neural network (CNN)-based direct method to detect stiction in control valves. *The Canadian Journal of Chemical Engineering*, 101(7):3963–3981, 2023. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/cjce.24767.

[3] Riccardo Bacci di Capaci and Claudio Scali. Review and comparison of techniques of analysis of valve stiction: From modeling to smart diagnosis. *Chemical Engineering Research and Design*, 130:230–265, 2018.

[4] Yiwei Cheng, Manxi Lin, Jun Wu, Haiping Zhu, and Xinyu Shao. Intelligent fault diagnosis of rotating machinery based on continuous wavelet transform-local binary convolutional neural network. *Knowledge-Based Systems*, 216:106796, March 2021.

[5] M. A. A. S. Choudhury, N. F. Thornhill, and S. L. Shah. A Data-Driven Model for Valve Stiction. *IFAC Proceedings Volumes*, 37(1):245–250, January 2004.

[6] M. A. A. Shoukat Choudhury, S. L. Shah, N. F. Thornhill, and David S. Shook. Automatic detection and quantification of stiction in control valves. *Control Engineering Practice*, 14(12):1395–1412, December 2006.

[7] Jônathan W. V. Dambros, Marcelo Farenzena, and Jorge O. Trierweiler. Oscillation Detection and Diagnosis in Process Industries by Pattern Recognition Technique. *IFAC-PapersOnLine*, 52(1):299–304, 2019.

[8] Angus Dempster, Daniel F. Schmidt, and Geoffrey I. Webb. MINIROCKET: A Very Fast (Almost) Deterministic Transform for Time Series Classification. In *Proceedings of the 27th ACM SIGKDD Conference on Knowledge Discovery & Data Mining*, pages 248–257, August 2021. arXiv:2012.08791 [cs, stat].

[9] Johann Faouzi. Time Series Classification: A review of Algorithms and Implementations. In Ketan Kotecha, editor, *Machine Learning (Emerging Trends and Applications)*. Proud Pen, 2022.

[10] Hassan Ismail Fawaz, Benjamin Lucas, Germain Forestier, Charlotte Pelletier, Daniel F. Schmidt, Jonathan Weber, Geoffrey I. Webb, Lhassane Idoumghar, Pierre-Alain Muller, and François Petitjean. InceptionTime: Finding AlexNet for Time Series Classification. *Data Mining and Knowledge Discovery*, 34(6):1936–1962, November 2020. arXiv:1909.04939 [cs, stat].

[11] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep Residual Learning for Image Recognition, December 2015. arXiv:1512.03385 [cs].

[12] Alexander Horch. A simple method for detection of stiction in control valves. *Control Engineering Practice*, 7(10):1221–1231, 1999.

[13] B. Kamaruddin, H. Zabiri, A. A. A. Mohd Amiruddin, W. K. Teh, M. Ramasamy, and S. S. Jeremiah. A simple model-free butterfly shape-based detection (BSD) method integrated with deep learning CNN for valve stiction detection and quantification. *Journal of Process Control*, 87:1–16, 2020.

[14] J. M. Lilly and S. C. Olhede. Higher-Order Properties of Analytic Wavelets. *IEEE Transactions on Signal Processing*, 57(1):146–160, January 2009. Publisher: Institute of Electrical and Electronics Engineers (IEEE).

[15] W.-L. Mao, H. I. K. Fathurrahman, Y. Lee, and T. W. Chang. EEG dataset classification using CNN method. *Journal of Physics: Conference Series*, 1456(1):012017, January 2020. Publisher: IOP Publishing.

[16] Andries Meintjes, Andrew Lowe, and Malcolm Legget. Fundamental Heart Sound Classification using the Continuous Wavelet Transform and Convolutional Neural Networks. In *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 409–412, July 2018. ISSN: 1558-4615.

[17] John Muradeli. ssqueezepy. *GitHub. Note: https://github.com/OverLordGoldDragon/ssqueezepy/*, 2020.

[18] Adam Paszke, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, Zeming Lin, Natalia Gimelshein, Luca Antiga, Alban Desmaison, Andreas Kopf, Edward Yang, Zachary DeVito, Martin Raison, Alykhan Tejani, Sasank Chilamkurthy, Benoit Steiner, Lu Fang, Junjie Bai, and Soumith Chintala. PyTorch: An Imperative Style, High-Performance Deep Learning Library. In *Advances in Neural Information Processing Systems 32*, pages 8024–8035. Curran Associates, Inc., 2019.

[19] R. Rengaswamy, T. Hägglund, and V. Venkatasubramanian. A qualitative shape analysis formalism for monitoring control loop performance. *Engineering Applications of Artificial Intelligence*, 14(1):23–33, February 2001.

[20] Napoli Rosario, Dan Fernandes, and Daniel Chen. Control Valve Stiction:Experimentation,Modeling, Model Validationand Detection with Convolution Neural Network. *International Journal of Chemical Engineering and Applications*, 10, October 2019.

[21] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *International Journal of Computer Vision*, 115(3):211–252, December 2015.

[22] John Sadowsky. The continuous wavelet transform: A tool for signal investigation and understanding. *Johns Hopkins APL Technical Digest*, 15:306–306, 1994. Publisher: JOHN HOPKINS UNIV APPLIED PHYSICS LABORATORY.

[23] Ranganathan Srinivasan, Raghunathan Rengaswamy, and Randy Miller. Control Loop Performance Assessment. 1. A Qualitative Approach for Stiction Diagnosis. *Industrial & Engineering Chemistry Research*, 44(17):6708–6718, August 2005. Publisher: American Chemical Society.

[24] Christian Szegedy, Wei Liu, Yangqing Jia, Pierre Sermanet, Scott Reed, Dragomir Anguelov, Dumitru Erhan, Vincent Vanhoucke, and Andrew Rabinovich. Going Deeper with Convolutions, September 2014. arXiv:1409.4842 [cs].

[25] Tao Wang, Changhua Lu, Yining Sun, Mei Yang, Chun Liu, and Chunsheng Ou. Automatic ECG Classification Using Continuous Wavelet Transform and Convolutional Neural Network. *Entropy*, 23(1):119, January 2021. Number: 1 Publisher: Multidisciplinary Digital Publishing Institute.

[26] Yoshiyuki Yamashita. An automatic method for detection of valve stiction in process control loops. *Control Engineering Practice*, 14(5):503–510, 2006.

[27] Kexin Zhang, Yong Liu, Yong Gu, Jiadong Wang, and Xiaojun Ruan. Valve Stiction Detection Using Multitimescale Feature Consistent Constraint for Time-Series Data. *IEEE/ASME Transactions on Mechatronics*, 28(3):1488–1499, June 2023. Conference Name: IEEE/ASME Transactions on Mechatronics.