Optimising Data Processing in Industrial Settings: A Comparative Evaluation of Dimensionality Reduction Approaches

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Abstract: The industrial landscape is undergoing a significant transformation marked by the integration of technology and manufacturing processes, giving rise to the concept of the Industrial Internet of Things (IIoT). IIoT is characterized by the convergence of manufacturing processes, smart IoT devices, and Machine Learning (ML) algorithms, enabling continuous monitoring and optimisation of industrial operations. However, this evolution translates into a substantial increase in the number of interconnected devices and the amount of generated data. Consequently, with ML algorithms facing an exponentially growing volume of data, their performance may decline, and processing times may significantly increase. Dimensionality reduction (DR) techniques emerge as a viable and promising solution, promoting dataset feature reduction and the elimination of irrelevant information. This paper presents a comparative study of various DR techniques applied to a real-world industrial use case, focusing on their impact on the performance and processing times of multiple classification ML techniques. The findings demonstrate the feasibility of applying DR: for a Logistic Regression classifier, minor 4% performance decreases were obtained while achieving remarkable improvements, over 300%, in the processing time of the classifier for multiple DR techniques.

1 INTRODUCTION

Industry has recently undergone its 4th major revolution, Industry 4.0, marked by the widespread adoption of technologies such as Machine Learning (ML), Internet of Things (IoT), or Artificial Intelligence (AI), and giving rise to the concept of Industrial Internet of Things (IIoT). Furthermore, as industries embrace Industry 4.0, a new industrial paradigm, Industry 5.0, is currently unfolding (Xu et al., 2021). While Industry 4.0 primarily focused on process automation and optimisation, Industry 5.0 revolves around a human-centric industrial environment, fostering seamless collaboration between technology and human resources. This collaboration strives to develop more sustainable and environmentally friendly industrial processes and solutions (Xu et al., 2021; Maddikunta et al., 2022; Nahavandi, 2019). This new paradigm, emphasising human-technology collaboration and decentralised decision-making, outlines the need for an even deeper intertwining of AI, ML and IIoT to enhance flexibility, adaptability, and efficiency in industrial operations (Xu et al., 2021; Maddikunta et al., 2022; Nahavandi, 2019).

In the pursuit for flexible and efficient industrial processes, AI has emerged as a key player within IIoT, facilitating processing tasks such as fault detection and prediction, equipment health monitoring, and predictive maintenance (Sisinni et al., 2018; Angelopoulos et al., 2020; Yao et al., 2017). However, such tasks require substantial amounts of data; consequently, the growth of IIoT has resulted in a significant increase in the amount of interconnected devices generating data, a phenomenon commonly referred to

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as Big Data (Hashem et al., 2015; Jia et al., 2022). Despite the robust capabilities of data-driven ML tools in handling large datasets, the sheer volume of generated data can become overwhelming, adversely impacting the performance of the ML algorithms, especially in time sensitive operations. The accumulation of data not only introduces more variables into the processes, but also brings in additional irrelevant and redundant information, inadvertently leading to an increasing process complexity.

In this context, Dimensionality Reduction (DR) poses as a promising solution. Particularly for data processing, having the possibility to reduce the amount of features and dimensions of a given dataset can prove advantageous for ML algorithms, reducing the amount of data that is input to a classifier or regressor. As a result, the processing technique encounters a more streamlined dataset, enabling more efficient data processing. Furthermore, integrating DR within an IIoT architecture can bring additional benefits, including data noise reduction, increased data protection, and enhanced data storage and visualisation (Chhikara et al., 2020).

DR encompasses a set of techniques aimed at reducing the dimension of a given dataset, while preserving as much information as possible (Jia et al., 2022). This reduction can be achieved through various methods, whether by employing approaches that filter and select a subset of the original features, referred to as Feature Selection (FS), or by generating a new set of features that represent a mapping of the original ones, termed Feature Extraction (FE). Using DR offers numerous benefits, including reducing the complexity of a given dataset, eliminating redundant or irrelevant information, and contributing to a faster and more efficient processing of the information for ML classifiers or regressors (Ayesha et al., 2020; Huang et al., 2019). Owing to their ability to decrease data volume and dataset complexity, DR may play a crucial role in the rapidly evolving landscape of technology-connected industries.

In light of this, the main contributions of this paper involve providing a comparative study, concerning both performance and processing time analyses, of several DR techniques applied to a dataset obtained from a real-world industrial setting. The specific use case centres around a boiler testing procedure conducted in the final stages of a boiler production line at Bosch Termotecnologia Aveiro[1]. Numerous variables are captured during the testing process, with the aim of determining the testing outcomes based on the collected data. Seven commonly employed DR approaches, namely Principal Component Analysis (PCA), Independent Component Analysis (ICA), Non-negative Matrix Factorization (NMF), Singular Value Decomposition (SVD), Random Forest (RF), Recursive Feature Elimination (RFE), and Autoencoder (AE) were analysed, employing also four classifiers - Logistic Regression (LR), k-Nearest Neighbours (kNN), RF, and Multi-layer Perceptron neural network (MLP) - for a more comprehensive evaluation. The final findings illustrate that, for the LR classifier, significant reductions in processing and fitting times (more than 300%) can be achieved at the cost of only a 4% compromise in performance, using techniques like PCA, SVD, and ICA.

The remainder of the paper is organised as follows. Section 2 provides a concise overview of DR techniques and their main families/groups. Section 3 elucidates the main techniques and steps implemented and incorporated in the comparative study. Section 4 presents and discusses the main findings of the comparative study. Finally, Section 5 provides the main conclusions drawn, accompanied by suggested future works.

[1] https://www.bosch.pt/a-nossa-empresa/bosch-em-portugal/aveiro/

2 BACKGROUND

DR techniques can be categorised into various classes and subclasses, with the most common division being between FE and FS. FE involves generating a new set of features that represents a combination of the original data, whereas FS consists of selecting a subset of the original features (Jia et al., 2022; Zebari et al., 2020). This section offers a brief introduction to DR, delineating these multiple groups, and subsequently emphasises the importance of applying DR in industrial data processing.

2.1 DR Techniques

DR encompasses a set of techniques aimed at reducing the dimensions and simplifying a dataset. Given the variety of approaches, they are commonly split into multiple categories, the two main groups being FS and FE. Some authors, such as Jia et al. (2022), propose a third group - Deep Learning (DL) methods. Those can include both FE and FS, but leverage neural network architectures to promote DR. Then, various authors propose diverse subdivisions for DR (Zebari et al., 2020; Solorio-Fernández et al., 2019; Ashraf et al., 2023). Drawing from these literature proposals, Figure 1 presents a basic taxonomy outlining the primary families and subfamilies of DR.

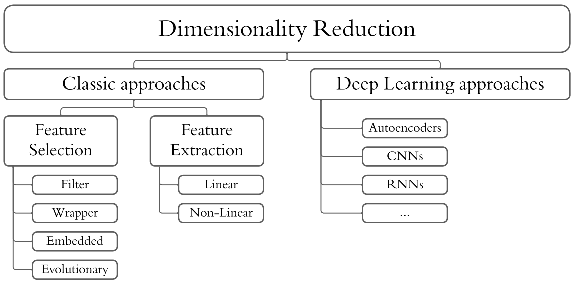


Figure 1: Taxonomy of DR techniques, based on some literature proposals (Jia et al., 2022; Solorio-Fernández et al., 2019; Zebari et al., 2020; Ashraf et al., 2023).

Feature Selection

FS techniques focus on reducing the dimensionality of a dataset by selecting a subset of the initial features, operating on the premise that these features contain all essential information (Zebari et al., 2020; Chhikara et al., 2020). FS is mainly split into 3 subclasses: filter, wrapper and embedded methods. *Filter*-based approaches rank features by importance, defining thresholds and rules determining which variables to retain and which to discard (Jia et al., 2022). *Wrapper*-based approaches are used in conjunction with a classifier, selecting a variable group that maximises the performance of the classifier (Solorio-Fernández et al., 2019). *Embedded* methods combine characteristics from filter and wrapper approaches, integrating a classifier that adjusts its parameters iteratively according to the importance of each feature (Zebari et al., 2020). An additional approach involves evolutionary methods, *e.g.*, Genetic Algorithm or Particle Swarm Optimisation, to select an optimal feature set.

FS offers advantages such as keeping the original physical significance of data (as no data transformation is applied), while preserving interpretability (Zebari et al., 2020; Jia et al., 2022). However, the trade-off between number of features and data relevance needs to be handled carefully, as large reductions may lead to loss of relevant information.

Feature Extraction

The objective of FE is to create a new set of features, or components, mapping the initial set of variables (Jia et al., 2022; Zebari et al., 2020). FE can be mainly categorised into two subclasses, linear and non-linear methods. This distinction is based on whether they consider the linearity of data. *Linear* approaches assume that the new feature set forms a linear mapping of the original one, *i.e.*, the lower-dimension representation is a linear combination of the original features (Anowar et al., 2021). However, linear methods may fail to capture true non-linear relationships within data if the original data is non-linear and exhibits dependencies between variables. Conversely, *non-linear* techniques can be employed to capture the more intricate dependencies within non-linear data (Chhikara et al., 2020).

Applying FE provides the potential for a smaller set of reduced features when compared to FS. The reduced data, being a combination of the original data, retains the dependencies of the initial dataset, facilitating more efficient removal of redundant information (Zebari et al., 2020; Jia et al., 2022). However, the application of FE comes with the drawback of data loss of interpretability and physical meaning.

DL-Based Approaches

DL-based approaches leverage neural networks, particularly in FE tasks. Various techniques can be used to extract the most relevant information and features from data. For instance, Recurrent Neural Networks (RNNs), like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), are utilised to extract sequential and time-dependent features from data. Convolutional Neural Networks (CNNs) are effective in extracting spatial features, commonly applied to process image data. Another notable DL-based approach are AEs, notable for their architecture. As illustrated in Figure 2, they consist of an encoder, a decoder, and a latent space representation. They aim at discovering a compressed representation of the original data through the encoder, and then reconstructing it back to its original state via the decoder. This design forces the AE to learn the most important features in data resulting in a lower-dimensional representation in the latent space. Additionally, depending on the scope of the problem, different neural network layers can be employed within the AE to extract temporal, sequential, spatial, among other features.

2.2 DR Importance Within Industrial Environments

As previously highlighted in Section 1, the industrial paradigm is currently shifting towards the integration of new technologies. IIoT architectures, such as the one depicted in Figure 3, are adopting a layered and block-structured design. In this evolving IIoT paradigm, key processes include data gathering, transfer, storage, processing, and visualisation. Ensuring a rapid and secure data flow between these blocks is crucial, especially for applications that demand low-latency processing and response times.

In architectures of this kind, the proliferation of

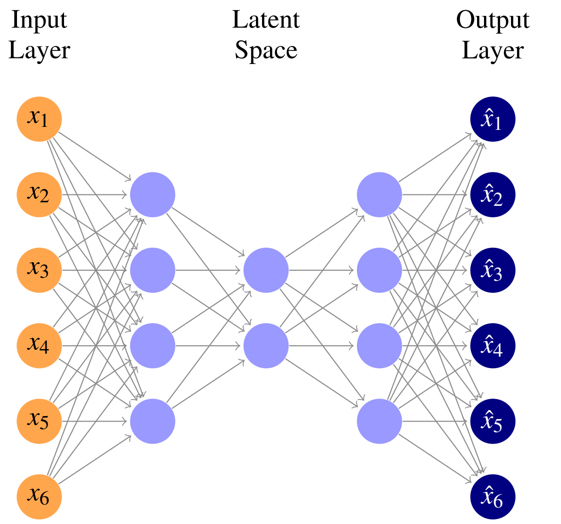


Figure 2: Base architecture of an autoencoder.

IoT sensing devices near the manufacturing processes has resulted in an impressive increase in the volume of collected data. Consequently, there is a growing need to process the data via ML algorithms. While having more data about manufacturing processes is advantageous and facilitates a more profound understanding, it also introduces challenges within the IIoT framework. The increased data quantity poses challenges in terms of data transmission, resulting in higher latencies. Data storage systems may become more congested, leading to reduced storage space. Visualising and understanding relationships among various process variables can become more challenging due to the abundance of information. Moreover, data processing is also affected, as more data inadvertently leads to more redundant and irrelevant information, possibly decreasing the performance of the algorithms. Additionally, larger amounts of data translate into larger processing times, potentially impairing response times and the ability of the architecture to promptly handle data (Ashraf et al., 2023; Jia et al., 2022).

DR emerges as a promising solution to address these challenges, particularly in the context of data processing. Its main positive impact is evident when applied as a pre-processing step for ML classifiers or regressors, effectively eliminating redundant and irrelevant information, and thereby improving processing time and performance outcomes for the ML techniques. One such example is the work of Gómez-Carmona et al. (2020), who demonstrated that the application of DR techniques achieved, for their use case, an 80% reduction in computational efforts and time, with only a 3% decline in ML model performance. However, DR not only proves beneficial for data processing. Other potential advantages of its implementation may be the following:

- **Enhancing Data Storage:** reducing data entering databases alleviates communication latencies and conserves storage space;
- **Improved Data Visualisation:** by minimising variables and irrelevant information, identifying correlations in manufacturing processes variables becomes more straightforward;
- **Noise Reduction and Data Security:** DR diminishes data noise. Therefore, less information is transferred across the architecture, lowering the risk of data leaks and possible cyberattacks.

3 METHODS

As previously mentioned, this paper exposes a comparative study of multiple DR techniques applied to an industry-related dataset. The use case involves a watertightness boiler testing process, conducted at the end of the boilers' production line, aiming to identify leaks within the piping systems. This constitutes a multi-label classification problem, with the target variable indicating pass or fail outcomes for different boilers. All testing code was developed in Python, and is publicly accessible on GitHub[2]. This section is dedicated to provide the main details about the testing procedure.

3.1 Use Case and Dataset Description

Bosch Termotecnologia Aveiro, part of the Robert Bosch GmbH[3] group, specialises in the production of heat water solutions, primarily boilers and heat pumps. This factory is one of Portugal's most innovative industrial environments, focused on the digitalisation and automation of their production lines, aiming to enhance productivity and environmental efficiencies. Particularly, one of their main projects, ILLIANCE[4], focuses on developing efficient and sustainable heating technologies, particularly hybrid gas and hydrogen systems. Furthermore, there is also a major focus on the digitalisation and improvement of their productive building process.

In the final stages of boiler production, each unit undergoes a watertightness test to identify leaks and deficiencies in the piping system. The test monitors

[2]https://github.com/zemaria2000/DR_Comparison
[3]https://www.bosch.com/
[4]https://www.illiance.pt/pt-pt

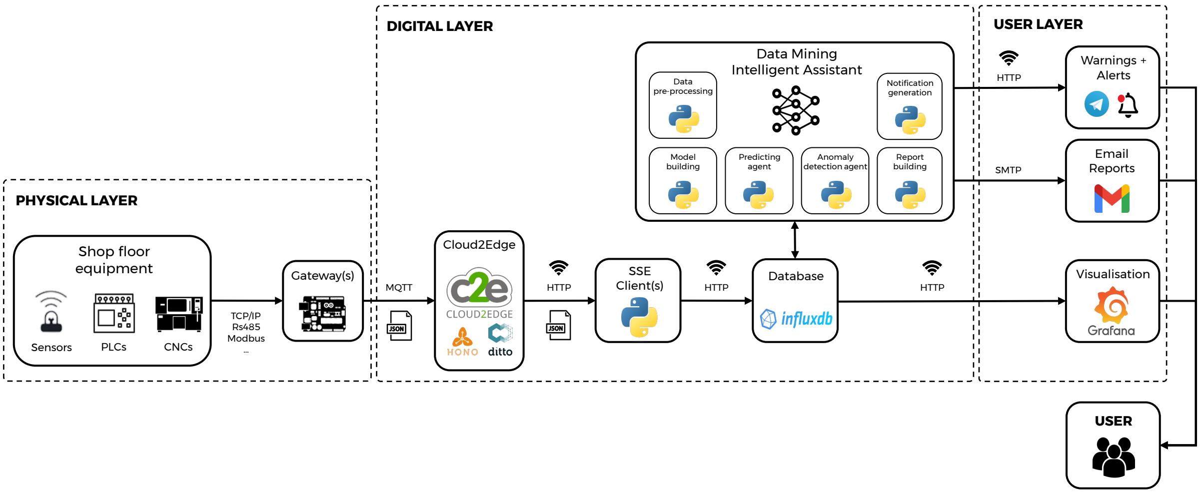


Figure 3: IIoT architecture used on a previous project (Cação et al., 2024).

variables such as gas flows, temperatures, and pressures. If the values all fall within certain appropriate intervals, the equipment passes the test, otherwise, it fails it, and inadvertently halts the production line. These test failures require manual examination, contributing to inefficiencies and production bottlenecks. Within this scenario, DR can play a crucial role in optimising the testing process, aiding in selecting relevant features, for instance, and identifying significant variables, consequently enhancing ML techniques' processing efficiency.

The main characteristics of the described process dataset are presented in Table 1. It comprises a total of 48 variables, collected during each watertightness test. The test results in a multi-label four class classification problem: two equipment classes, split into successful and unsuccessful tests. The dataset is relatively small, with 11962 samples in total, each representing the average values for each feature for a complete testing procedure.

Table 1: Dataset description.

No. of Features	No. of Classes	Classes	Samples
48	4	0: 'Equipment 1 - Failed'	410
		1: 'Equipment 1 - Passed'	6372
		2: 'Equipment 2 - Failed'	390
		3: 'Equipment 2 - Passed'	4790

3.2 Pre-Processing Steps

To prepare data for the comparative study, several pre-processing steps were employed to ensure a better testing procedure. The main ones are outlined below:

1. **Data Imputation:** the original dataset, collected at Bosch's production environment, contained missing values in some columns. To facilitate processing by both DR techniques and classifiers, data imputation was performed: NaN and Null values were replaced by the mean value of their respective column;
2. **Data Balancing:** as indicated in Table 1, the distribution of passed and failed tests is quite imbalanced, with passed tests accounting for around 93% of the dataset. This imbalance can lead to classifier overfitting during training, potentially negatively impacting testing performances. To address this, a combination of SMOTE (Synthetic Minority Oversampling Technique) and Tomek Links was employed for data balancing (Swana et al., 2022). SMOTE was used to oversample minority classes, while Tomek Links balanced the undersampling of majority classes. This synthetic data generation was carefully conducted, aiming for a balanced 4:1 ratio of successful to unsuccessful tests. The final sample amounts are presented in Table 2;

Table 2: Number of samples for each class after data balancing using SMOTE and Tomek Links.

Classes	Original Samples	Balanced Samples
0: 'Equipment 1 - Failed'	410	2124
1: 'Equipment 1 - Passed'	6372	6370
2: 'Equipment 2 - Failed'	390	1596
3: 'Equipment 2 - Passed'	4790	4790

3. **Data Normalisation:** given the substantial discrepancies in certain features' values, data normalisation was conducted using two scikit-learn[5] Python library scalers: 'StandardScaler', scaling the data to have a mean of 0 and standard devia-

[5]https://scikit-learn.org/stable/

tion of 1, and ‘MinMaxScaler’, scaling data to the 0-1 range. The latter was employed for methods like NMF, unable to handle negative values.

4. **Label Encoding:** as exposed in both Table 1 and Table 2, the original test labels consist of strings indicating the equipment type and test result. To facilitate the reading of output results by the ML classifiers during training, label encoding was implemented, creating integer labels for each distinct class.

3.3 Testing Procedure

Following data pre-processing and preparation, a comprehensive comparative testing procedure was conducted utilising multiple DR techniques and classifiers. The study, completely implemented in Python, employed the scikit-learn and TensorFlow[6] libraries for building the DR models. All classifiers were also from the scikit-learn library, and were used with their default hyperparameters, as well as most DR techniques. Only to address convergence issues encountered during the fitting process, adjustments were implemented specifically for the ICA and NMF techniques: the convergence tolerance, initially set by default at 1×10^{-4} was changed to 5×10^{-2}. Additionally, the number of maximum iterations was adjusted from the default value of 200 to 5000 and 10000 for the ICA and NMF techniques, respectively. The AE, the only method from the TensorFlow library, had the following implementation details: a base architecture comprised of layers with 48 (input dimension), 32, 16, 8, 4, and 2 nodes, ‘swish’ as the activation function, ‘adam’ as the optimiser, and mean squared error as the loss function, evaluating the reconstruction error. Following fitting, the encoder was extracted and used to output the reduced data representation.

For both DR techniques and ML classifiers, 80% of the datasets were used for training, 10% of those for validation, and the remaining 20% to conduct the tests. All tests were ran on the same machine, whose characteristics are exposed in Table 3. Furthermore, Table 4 exposes the Python and main used libraries’ versions.

Table 3: Main characteristics of the machine where the test were conducted.

Processor	Base clock speed	RAM	Graphics card
AMD Ryzen 9 7950X 16-Core Processor	4.5 GHz	128 GB	Nvidia GeForce RTX 4090

[6]https://www.TensorFlow.org/

Table 4: Python and main used libraries’ versions.

Library	Version
Python	**3.10.8**
scikit-learn	1.3.2
TensorFlow	2.10.0
pandas	2.2.0
numpy	1.26.4
matplotlib	3.8.0
exectimeit	0.1.1

The tests conducted and discussed in Section 4 include:

- Assessing the influence of different DR approaches with varying numbers of reduced features on classifier performance;
- Evaluating classifier fitting and prediction times for different dataset dimensions;
- Assessing fitting and dataset reduction times for some DR techniques.

The primary metric for evaluating model performance was the Matthew’s Correlation Coefficient (MCC), calculated using the confusion matrix indicators - True Positives (TP), True Negatives (TN), False Positives (FP) and False Negatives (FN). The formula is presented in Equation 1,

$$\mathrm{MCC} = \frac{\mathrm{TN} \times \mathrm{TP} - \mathrm{FN} \times \mathrm{FP}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}, \quad (1)$$

with MCC ranging between -1 and 1. An MCC of -1 indicates “perfect” misclassification, an MCC of 1 perfect classification, and an MCC of 0 indicates predictions equivalent to random chance.

Finally, the measured times included fitting times for DR techniques and classifiers, prediction times for the classifiers, and dataset reduction times for the DR approaches. The exectimeit[7] library was used for time measurements, following the work from Moreno and Fischmeister (2017).

4 RESULTS AND DISCUSSION

This comparative study, as already mentioned, delved into the performance and time impacts of employing various DR techniques within an industrial real-world dataset. This section outlines the key findings from the conducted tests.

4.1 Performance Analysis

The initial test focused on evaluating the MCC for various numbers of reduced components obtained

[7]https://pypi.org/project/exectimeit/

with different DR techniques, and four distinct classifiers. For non-DL methods, reduced dimensions ranging from 2 to 47 were tested, while for the AE, the reduced dimensions corresponded to the AE architecture definition, 2, 4, 8, 16, and 32, *i.e.*, each test involved eliminating the previous last layer. Table 5 and Table 6 present the MCC results for some selected reduced dimensions and the MCC using the entire dataset, respectively.

Table 5: Performance (MCC) comparisons between the DR techniques, for all classifiers and for multiple reduced dimensions (at bold the best result for each DR technique, underlined the values that outperformed the default tests).

DR	Dim.	LR	kNN	RF	MLP
PCA	2	0.932	0.938	0.930	0.932
	5	0.931	0.936	0.935	0.939
	10	0.934	0.955	0.954	0.951
	20	0.949	0.958	0.962	0.951
	30	0.958	0.961	0.962	0.955
	40	0.968	0.961	0.970	**0.971**
ICA	2	0.929	0.936	0.933	0.936
	5	0.927	0.934	0.936	0.942
	10	0.933	0.948	0.953	0.953
	20	0.949	0.949	0.962	0.948
	30	0.956	0.951	0.964	0.952
	40	0.968	0.966	0.971	**0.973**
NMF	2	0.883	0.972	0.964	0.970
	5	0.884	0.959	0.963	0.971
	10	0.883	0.940	0.970	0.977
	20	0.861	0.936	0.964	0.974
	30	0.895	0.975	0.969	**0.978**
	40	0.884	0.959	0.976	**0.978**
RF	2	0.950	0.950	0.950	0.950
	5	0.966	0.965	0.966	0.965
	10	0.966	0.960	0.966	0.966
	20	0.971	0.962	0.978	0.979
	30	0.970	0.961	0.972	0.978
	40	0.970	0.964	0.973	**0.980**
RFE	2	0.971	0.968	0.973	0.978
	5	0.974	0.969	0.974	0.979
	10	0.970	0.951	0.974	0.979
	20	0.969	0.963	0.973	0.979
	30	0.971	0.968	0.973	0.980
	40	0.969	0.952	0.976	**0.982**
SVD	2	0.932	0.938	0.930	0.934
	5	0.931	0.937	0.935	0.941
	10	0.936	0.954	0.954	0.951
	20	0.949	0.958	0.960	0.952
	30	0.958	0.961	0.965	0.956
	40	0.968	0.961	**0.974**	**0.974**
AE	2	0.836	0.928	0.896	0.934
	4	0.919	0.965	0.920	0.973
	8	0.932	0.976	0.922	0.978
	16	0.929	0.979	0.918	**0.980**
	32	0.939	**0.980**	0.940	0.979

Table 6: MCC values for the 4 classifiers, using all available features from the original dataset.

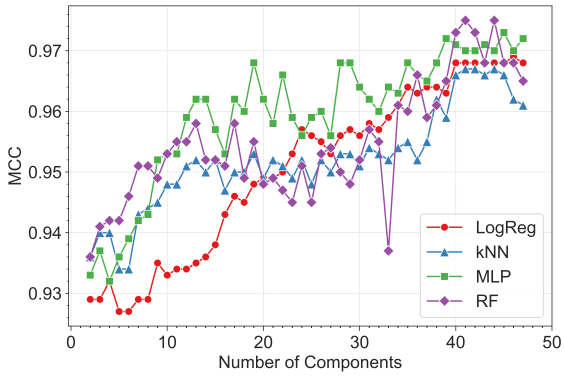
LR	kNN	RF	MLP
0.946	0.974	0.990	0.974

Analysing the MCC values for the original dataset (Table 6), all classifiers exhibited high performances, with MCC values larger than 0.9. LR had the lowest score, 0.946, with the highest belonging to the RF classifier, with 0.99.

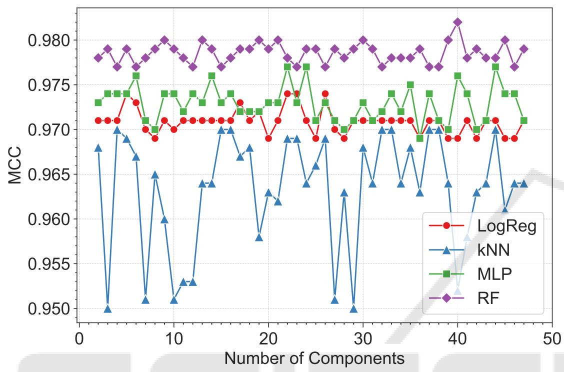
Turning to the DR techniques (Table 5), it is evident that MCC values remain consistently high, with most MCC scores above 0.9, even with very low-dimensional datasets. Apart from the RF classifier, which achieved an MCC of 0.99 with the original datasets, all other classifiers, combined with various DR techniques, achieved higher performance metrics with datasets with fewer features. Notable examples include PCA with 20 components combined with LR, resulting in an MCC of 0.949, compared to the original value of 0.946; using an AE reducing the dataset to just 16 features combined with the kNN classifier, obtaining an MCC of 0.979, surpassing the original kNN test with 0.974; or using NMF with 30 features and an MLP classifier, achieving an MCC of 0.978, opposed to the original 0.974.

For FE methods, PCA, ICA, NMF, SVD and AE, there seems to be a tendency for improved performances with a larger number of reduced components, with more components being able to encode more information and retain more data dependencies. Conversely, FS methods, RF and RFE, showcase a much more balanced performance, successfully identifying two or five features that retain essential information about the original dataset. Figure 4 visually illustrates this trend. ICA (Figure 4a) exhibits a clear performance upward trend, for all classifiers, with the MCC constantly increasing with the number of reduced components. Conversely, RFE (Figure 4b) remains more horizontally stable, achieving very high MCC values with very few features. This may suggest that FS methods can efficiently identify a very small set of features containing most essential information for classification purposes, while FE techniques struggle in creating a compact group of variables that excludes the irrelevant information.

In summary, the use of DR techniques specifically for the use case explored did not seem to significantly influence classifier performance. It was possible to achieve quite high performances with a much smaller dataset. Furthermore, in some cases, DR techniques effectively discarded irrelevant and redundant information, leading to classifier performance improvements. FS techniques, in particular, demonstrated a



(a) ICA.



(b) RFE.

Figure 4: MCC for the 4 different classifiers, in the testing dataset, depending on the number of components reduced by the (a) ICA and (b) RFE DR techniques.

notable ability to select a small set of the original features, outperforming FE techniques. Hence, for the studied use case, DR methods emerge as promising strategies, as despite utilising a significantly reduced set of features, the classifier's performance remains quite high and satisfactory. Subsequent sections will provide insights regarding the time benefits of using DR, reducing training and prediction times.

4.2 Classifiers Time Tests

As discussed earlier, an excessive number of variables in a dataset may lead to longer fitting and prediction times for ML methods. Therefore, it is relevant to assess the impact of applying DR in the fitting and prediction times of ML classifiers.

For this test, training and prediction times for the four selected classifiers were assessed with different reduced dataset sizes by each DR approach. To accurately evaluate these times, each test (*i.e.*, each reduced dataset from each DR technique, for each classifier) was conducted five times, using a dedicated Python library, exectimeit. The complete test results can be consulted in Table 10, in the Appendix section. For this particular discussion, training and prediction times for the ICA technique are presented in Table 7, with the last row representing the times for the original dataset.

Analysing the results in Table 7, particularly for the LR and RF classifiers, there is a clear tendency of increasing training and prediction times for larger datasets. Larger datasets induce more data for the models to process, resulting in longer training times. For both these classifiers, the 40-feature datasets exhibit approximately 5x longer training times compared to the 2-feature datasets, consistent with expectations. For prediction times, this growing tendency is much less evident, but that would be expected, as testing datasets are much smaller and the models are already fit.

However, for the kNN and the MLP classifiers, the time tendencies differ. For kNN, there is a notable difference between training and prediction times, with the latter being larger. This results from the kNN prediction process, which requires distance calculations for each testing point, to each of its k-nearest neighbours. Moreover, for both classifiers, the training times initially increase with the number of reduced components, and then significantly decrease with larger datasets. This behaviour might be due to possible classifier overfitting, resulting in faster convergence times. Figure 5 further illustrates this different time evolution for the MLP classifier.

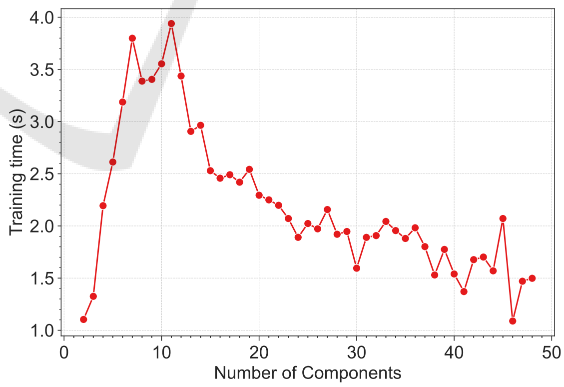


Figure 5: Training time evolution for the MLP classifier with the reduced ICA dataset.

Comparing reduced datasets with the original ones, it is evident that in general, both training and prediction times are larger for the full set of variables compared to reduced datasets, as expected. This difference is substantial in some cases, namely for LR and MLP. For LR, the fitting time with the reduced dataset is around 3x smaller than with the original

Table 7: Average training and prediction times for 5 runs, for multiple classifiers using the reduced datasets from the DR techniques.

DR	Dim.	LR		kNN		RF		MLP	
		Train (ms)	**Pred** (ms)	**Train** (ms)	**Pred** (ms)	**Train** (ms)	**Pred** (ms)	**Train** (ms)	**Pred** (ms)
ICA	2	14.20 ± 0.04	0.06 ± 0.01	2.22 ± 0.08	30.21 ± 0.27	1011.60 ± 12.96	13.29 ± 0.30	1103.64 ± 121.13	0.57 ± 0.04
	5	18.82 ± 0.18	0.06 ± 0.01	3.57 ± 0.06	38.52 ± 0.29	1781.73 ± 27.85	12.92 ± 0.42	2612.49 ± 1224.58	0.78 ± 0.23
	10	27.26 ± 0.10	0.06 ± 0.01	5.75 ± 0.08	111.47 ± 0.95	2773.43 ± 39.29	12.33 ± 0.26	3554.07 ± 817.27	0.82 ± 0.18
	20	70.78 ± 0.46	0.08 ± 0.02	0.39 ± 0.08	6.80 ± 2.25	3892.33 ± 82.45	12.99 ± 0.39	2294.17 ± 259.82	0.77 ± 0.11
	30	86.66 ± 1.59	0.19 ± 0.02	0.39 ± 0.11	10.25 ± 0.20	5523.99 ± 98.59	14.58 ± 0.52	1594.72 ± 358.41	0.83 ± 0.09
	40	71.82 ± 1.96	0.19 ± 0.03	0.41 ± 0.09	8.43 ± 4.28	5296.30 ± 161.25	11.53 ± 0.56	1539.47 ± 616.59	0.77 ± 0.16
Default	**48**	**283.21 ± 34.84**	**1.24 ± 0.36**	**3.24± 0.85**	**117.59 ± 74.71**	**2994.67 ± 208.77**	**16.82 ± 0.59**	**15123.26 ± 4476.46**	**2.62 ± 0.48**

data (86.66ms opposed to 283.21ms). For the MLP classifier, the training times are 4x smaller (3.55s for a 10-variable dataset opposed to more than 15s for the original data).

Overall, the implementation of DR techniques significantly reduces fitting and prediction times for classifiers. While the differences may not be substantial for this particular use case, with a small dataset comprised of less than 15000 samples and just 48 variables, it is important to note that in datasets with millions of samples and hundreds or thousands of variables, the reductions would be much more significant and with more pronounced impacts.

4.3 DR Techniques Time Tests

While testing the fitting and prediction times of classifiers is crucial for assessing the time benefits of reducing the number of variables in datasets, it is equally relevant to evaluate the time required by the DR approaches to train themselves and reduce the datasets. If the time needed for training or generating the reduced dataset is is excessively large, it becomes highly inefficient and even counterproductive to use such techniques in combination with ML classifiers. The purpose of DR techniques is to alleviate the classifiers' process times, and if DR takes too long, the resulting time impacts may offset the benefits, with the additional cost of potential loss in classifier performance. Table 8 presents, for some DR techniques, their training and reduction times for varying numbers of features.

Examining the results in Table 8, PCA stands out as the fastest technique in terms of both fitting and reduction times. The longest fitting time is just 33.37ms, with reduction times mostly below 1ms. Furthermore, NMF also showcases short training and reduction times, with the longest being for the 32 component dataset, at 92.63ms, while reduction times are in most cases smaller than 5ms. On the other hand, using the encoder from an AE for DR induces significantly longer processing times: the largest training and reduction times are 11.3s and 93.42ms, substantially higher than those for the previous two techniques. Moreover, the times tend to decrease with the increase in the number of reduced features. This is due to the base architecture and methodology used for the AE tests, with the largest autoencoder (*i.e.*, with the most layers) achieving the largest dimension reduction.

In conclusion, as highlighted earlier, it is crucial to consider both the time benefits of reducing the datasets for classifiers, and the training and reduction times of the DR techniques themselves. As shown, using DL-based techniques may lead to considerable training and even reduction times, and this factor should be considered, especially in time-sensitive operations when applying DR in conjunction with a classifier.

4.4 Overall Performance and Time Comparison

As discussed throughout this results section, the use of DR techniques can offer benefits in both performance and processing time, particularly for time-sensitive industrial processes, and it is crucial to find the right balance between performance and dataset size. This final section presents an overall comparison by evaluating the average increases in performance and processing times for the LR classifier. The comparison is based on the lowest (2) and highest (47) possible reduced datasets for each DR technique, excluding the AE. The results are summarised in Table 9, presenting average performance and classifier fitting time increases per component of the dataset and in total.

This table illustrates the trade-off relationship between performance and processing time. For example, PCA and SVD in combination with the LR classifier show that the introduction of one additional feature in the dataset yields a marginal 0.09% average performance (MCC) increase, resulting in a total increase of around 4% from 2 to 47 features. However, each additional feature introduces average fitting time increases of 13.54% and 7.32% for PCA

Table 8: Comparison, for the PCA, NMF and AE techniques, of the fitting and the reduction times.

Dim.	PCA		NMF		AE	
	Training (ms)	**Reduction** (ms)	**Training** (ms)	**Reduction** (ms)	**Training** (s)	**Reduction** (ms)
2	4.46 ± 3.63	0.07 ± 0.04	8.70 ± 0.61	0.15 ± 0.04	11.34 ± 0.28	93.42 ± 9.54
4	12.48 ± 0.70	0.07 ± 0.04	14.60 ± 3.78	0.41 ± 0.05	10.10 ± 0.11	90.69 ± 4.96
8	11.34 ± 0.98	0.07 ± 0.04	15.56 ± 0.75	0.86 ± 0.06	8.89 ± 0.15	85.27 ± 7.97
16	20.14 ± 3.64	0.33 ± 0.13	29.72 ± 1.62	2.53 ± 0.06	7.61 ± 0.06	82.36 ± 6.16
32	33.37 ± 2.09	0.20 ± 0.03	92.63 ± 1.04	5.43 ± 0.17	6.34 ± 0.14	$79{,}99 \pm 3.35$

Table 9: Performance (MCC) increases compared to the Logistic Classifier fitting time increases (per component and total).

DR	Performance increase (p/ comp.)	Time increase (p/ comp.)	Total performance increase	Total time increase
PCA	0.09%	13.54%	4.37%	622.85%
ICA	0.09%	6.67%	3.94%	306.98%
NMF	0.21%	1.78%	9.63%	81.92%
SVD	0.09%	7.32%	3.94%	336.70%
RF	0.04%	7.06%	2.02%	324.86%
RFE	-0.03%	0.16%	-0.15%	7.34%

and SVD, respectively, translating to total time increases of 622.85% and 336.70%, respectively. NMF, in comparison to all other DR techniques exposed in Table 9, demonstrates the worst performance, with a total performance decrease of around 10% between using 47 and 2 features, respectively. However, it is also the technique that exhibits the smallest average increase in fitting times, around 82%. Interestingly, for the RFE FS technique, there is an average tendency for performance drops from 2 to 47 features, which corroborates what was verified in Subsection 4.1, where RFE is able to effectively identify a very small subset of features retaining the most relevant information of the dataset.

Overall, PCA appears to be the DR technique with the most favourable trade-off between performance and fitting time increases. There is only around a 4% drop using the LR classifier with just 2 features, which is counter-balanced by an approximately 623% time decrease. Additionally, techniques such as ICA and SVD experience similar positive results, where 4% performance drops are counter-balanced by approximately 300% time decreases when utilising smaller sets of features.

In conclusion, the overall comparison underscores the benefits of using DR techniques, especially in time-sensitive industrial processes. The results suggest that, by carefully choosing the number of features in the reduced dataset, it is possible to achieve significant improvements in processing times with acceptable compromises in performance.

5 CONCLUSIONS

In the current dynamic and evolving industrial landscape, the integration of new technologies is crucial to ensure enhanced process quality and efficiency. AI and ML algorithms are increasingly being applied for various tasks, including fault detection, predictive maintenance, and automated decision-making. As the volume of collected data from IoT interconnected devices continues to grow, handling Big Data poses challenges, with ML algorithms processing higher volumes of data, containing many irrelevant and redundant information. This may lead to a simultaneous performance drop and processing time increase. As discussed in this paper, a viable solution to address this challenge may be the use of DR techniques, which reduce the amount of variables in a problem, thus potentially accelerating processing times with minimal performance loss.

This study focused on various common DR approaches applied to a real-world multi-label classification problem. These techniques included classical FE approaches, PCA, ICA, NMF and SVD, FS techniques, RF and RFE, as well as a DL-based approach, AE. The results proved the benefits of employing DR for the industrial use case. DR approaches like SVD and ICA, combined with the LR classifier, with a reduced dataset of just 2 features, lead to minor performance decrements (around 4%) while yielding substantial reductions in classifier fitting times, more than 300%. Furthermore, employing the PCA DR technique under identical conditions results in an approximate 620% reduction in classifier fitting times, also at the cost of just 4% in classifier performance. In applications demanding low-latency operations, and fast decision-making, these time reductions are of considerable importance, facilitating efficient information processing. Furthermore, for larger and more complex datasets, reducing dataset size could enhance the efficiency of processing algorithms by eliminating irrelevant data.

For future research, it is recommended to explore

(1) more complex and larger datasets to assess the scalability and generalisability of the findings, (2) compare more complex DR techniques, such as some proposed in the literature, and (3) investigate the impact of hyperparameter optimisation for the DR techniques, considering a multi-objective function optimising both performance and processing times.

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APPENDIX

Table 10: Average training and prediction times for 5 runs, for multiple classifiers using the reduced datasets from the DR techniques.

DR	Comp.	LogReg		kNN		RF		MLP	
		Train (ms)	**Pred (ms)**	**Train (ms)**	**Pred (ms)**	**Train (ms)**	**Pred (ms)**	**Train (ms)**	**Pred (ms)**
PCA	2	17.80 ± 0.43	0.06 ± 0.01	2.35 ± 0.18	30.56 ± 0.23	1025.23 ± 4.16	13.70 ± 0.37	826.23 ± 198.78	0.57 ± 0.04
	5	24.84 ± 0.19	0.06 ± 0.01	3.54 ± 0.08	38.90 ± 0.10	1755.75 ± 29.52	13.34 ± 0.43	2638.49 ± 537.58	0.76 ± 0.25
	10	34.26 ± 0.12	0.06 ± 0.01	5.82 ± 0.11	92.67 ± 0.61	2693.10 ± 27.83	12.78 ± 0.20	3345.69 ± 444.13	0.76 ± 0.27
	20	66.13 ± 0.52	0.07 ± 0.03	0.39 ± 0.08	9.44 ± 0.79	3609.45 ± 167.31	13.60 ± 0.42	2153.62 ± 261.25	0.78 ± 0.21
	30	98.84 ± 2.32	0.18 ± 0.03	0.41 ± 0.11	6.27 ± 4.25	4708.19 ± 133.52	13.96 ± 0.44	1989.78 ± 441.16	0.76 ± 0.26
	40	83.69 ± 0.98	0.19 ± 0.03	0.40 ± 0.14	6.68 ± 4.40	5029.11 ± 108.52	11.90 ± 0.35	1650.48 ± 290.36	0.79 ± 0.24
ICA	2	14.195 ± 0.036	0.055 ± 0.006	2.216 ± 0.076	30.214 ± 0.271	1011.559 ± 12.955	13.285 ± 0.299	1103.642 ± 121.134	0.565 ± 0.043
	5	18.815 ± 0.182	0.058 ± 0.007	3.569 ± 0.06	38.518 ± 0.29	1781.731 ± 27.854	12.916 ± 0.416	2612.49 ± 1224.582	0.782 ± 0.234
	10	27.258 ± 0.099	0.06 ± 0.01	5.749 ± 0.076	111.471 ± 0.949	2773.432 ± 39.294	12.327 ± 0.256	3554.071 ± 817.273	0.822 ± 0.179
	20	70.784 ± 0.462	0.075 ± 0.019	0.388 ± 0.079	6.803 ± 2.245	3892.333 ± 82.448	12.991 ± 0.392	2294.172 ± 259.823	0.774 ± 0.105
	30	86.664 ± 1.591	0.188 ± 0.02	0.394 ± 0.106	10.252 ± 0.202	5523.992 ± 98.588	14.578 ± 0.523	1594.723 ± 358.413	0.83 ± 0.091
	40	71.818 ± 1.959	0.194 ± 0.03	0.409 ± 0.086	8.428 ± 4.281	5296.296 ± 161.245	11.525 ± 0.563	1539.471 ± 616.594	0.77 ± 0.163
NMF	2	22.21 ± 0.803	0.055 ± 0.007	2.117 ± 0.203	30.448 ± 0.492	356.69 ± 15.297	8.178 ± 0.337	1981.707 ± 93.031	0.597 ± 0.055
	5	45.883 ± 0.835	0.057 ± 0.007	4.105 ± 0.063	34.304 ± 0.317	1002.733 ± 22.98	10.128 ± 0.17	2208.785 ± 189.321	0.757 ± 0.162
	10	44.309 ± 0.448	0.05 ± 0.012	7.173 ± 0.145	55.184 ± 0.671	1138.271 ± 101.014	9.577 ± 0.197	2240.937 ± 248.423	0.751 ± 0.238
	20	53.978 ± 0.559	0.063 ± 0.016	0.374 ± 0.077	7.173 ± 1.041	1670.726 ± 53.712	10.563 ± 0.215	3374.89 ± 719.199	0.75 ± 0.259
	30	56.724 ± 0.739	0.166 ± 0.028	0.361 ± 0.056	7.239 ± 2.01	2242.331 ± 44.628	10.351 ± 0.186	1435.853 ± 365.025	0.745 ± 0.19
	40	50.634 ± 1.621	0.185 ± 0.041	0.309 ± 0.187	9.579 ± 1.664	2187.754 ± 86.437	10.551 ± 0.583	1719.936 ± 267.23	0.752 ± 0.216
RF	2	17.277 ± 0.65	0.053 ± 0.016	1.905 ± 0.062	75.692 ± 0.201	94.945 ± 1.726	5.951 ± 0.056	481.975 ± 20.377	0.602 ± 0.036
	5	28.989 ± 0.116	0.06 ± 0.006	3.752 ± 0.035	39.792 ± 0.312	175.014 ± 5.353	7.85 ± 0.08	405.184 ± 90.626	0.767 ± 0.295
	10	31.12 ± 0.353	0.069 ± 0.041	5.888 ± 0.048	59.669 ± 0.304	441.919 ± 17.592	7.994 ± 0.059	570.014 ± 31.866	0.779 ± 0.235
	20	50.08 ± 0.519	0.062 ± 0.024	0.657 ± 0.047	34.743 ± 0.654	632.849 ± 43.792	8.302 ± 0.049	1680.587 ± 680.808	0.787 ± 0.237
	30	69.706 ± 2.22	0.066 ± 0.029	0.77 ± 0.064	40.353 ± 4.526	987.304 ± 25.129	8.405 ± 0.208	1634.69 ± 254.387	0.789 ± 0.29
	40	80.911 ± 1.74	0.063 ± 0.033	0.898 ± 0.059	35.937 ± 1.685	1303.774 ± 67.364	8.814 ± 0.173	1596.277 ± 540.497	0.788 ± 0.285
RFE	2	28.804 ± 0.113	0.063 ± 0.011	5.939 ± 0.053	61.98 ± 1.807	648.776 ± 15.305	8.848 ± 0.133	1091.54 ± 439.532	0.749 ± 0.289
	5	28.819 ± 0.728	0.062 ± 0.01	5.948 ± 0.046	60.965 ± 1.435	1100.095 ± 20.131	8.965 ± 0.164	1191.758 ± 377.225	0.752 ± 0.293
	10	28.867 ± 0.194	0.063 ± 0.005	0.618 ± 0.021	37.164 ± 8.504	845.686 ± 82.853	9.019 ± 0.079	1293.92 ± 764.612	0.926 ± 0.455
	20	40.167 ± 0.205	0.064 ± 0.012	4.999 ± 0.118	44.216 ± 0.187	907.881 ± 42.903	9.287 ± 0.169	1458.321 ± 186.419	0.762 ± 0.283
	30	29.007 ± 0.26	0.063 ± 0.008	5.969 ± 0.033	61.535 ± 0.492	1144.507 ± 91.934	9.07 ± 0.17	1597.606 ± 526.896	0.769 ± 0.19
	40	75.451 ± 0.682	0.069 ± 0.026	5.018 ± 0.044	44.195 ± 0.13	316.835 ± 14.744	8.71 ± 0.106	1158.654 ± 345.438	0.904 ± 0.097
SVD	2	16.687 ± 0.052	0.055 ± 0.008	2.267 ± 0.109	30.309 ± 0.448	1019.606 ± 20.166	13.81 ± 0.282	1103.378 ± 211.48	0.589 ± 0.05
	5	21.082 ± 0.136	0.059 ± 0.008	3.619 ± 0.041	39.698 ± 0.55	1730.519 ± 27.588	12.927 ± 0.26	3020.047 ± 675.675	0.809 ± 0.22
	10	32.578 ± 0.917	0.06 ± 0.012	5.781 ± 0.036	91.957 ± 0.284	2634.194 ± 63.621	12.411 ± 0.69	3286.687 ± 520.198	0.795 ± 0.256
	20	68.226 ± 0.618	0.071 ± 0.013	0.335 ± 0.088	9.32 ± 0.179	3691.914 ± 79.885	13.242 ± 0.462	2368.007 ± 554.351	0.721 ± 0.303
	30	97.761 ± 2.36	0.196 ± 0.036	0.363 ± 0.084	7.439 ± 2.737	4776.744 ± 117.107	14.217 ± 0.519	1866.58 ± 559.185	0.842 ± 0.129
	40	78.684 ± 1.564	0.179 ± 0.03	0.401 ± 0.134	8.537 ± 5.374	5038.901 ± 139.325	12.15 ± 0.231	1578.538 ± 420.986	0.833 ± 0.244
AE	2	179.523 ± 2.746	0.218 ± 0.033	0.35 ± 0.204	NaN	5963.516 ± 79.114	12.719 ± 0.36	1105.482 ± 447.803	0.39 ± 0.211
	4	163.848 ± 1.759	0.231 ± 0.042	0.318 ± 0.21	7.027 ± 1.999	4195.705 ± 175.332	10.489 ± 0.306	936.009 ± 411.111	0.498 ± 0.024
	8	172.314 ± 4.547	0.235 ± 0.051	0.35 ± 0.213	7.254 ± 2.076	2798.748 ± 83.084	8.898 ± 0.234	1250.442 ± 261.1	0.412 ± 0.141
	16	189.145 ± 2.155	0.242 ± 0.089	0.338 ± 0.211	9.903 ± 3.23	2749.043 ± 59.909	8.827 ± 0.176	1151.68 ± 334.608	0.463 ± 0.162
	32	160.161 ± 1.063	0.225 ± 0.046	0.387 ± 0.248	11.794 ± 4.785	2694.393 ± 92.23	8.514 ± 0.189	1058.16 ± 213.592	0.442 ± 0.188