Explainable anomaly detection in hot rolling process

Jakub Jakubowski, *AGH University of Science and Technology*, *ArcelorMittal Poland,* Kraków, Poland
Przemysław Stanisz, *ArcelorMittal Poland*, Kraków, Poland
Szymon Bobek, *Jagiellonian University*, Kraków, Poland
Grzegorz J. Nalepa, *Jagiellonian University*, Kraków, Poland

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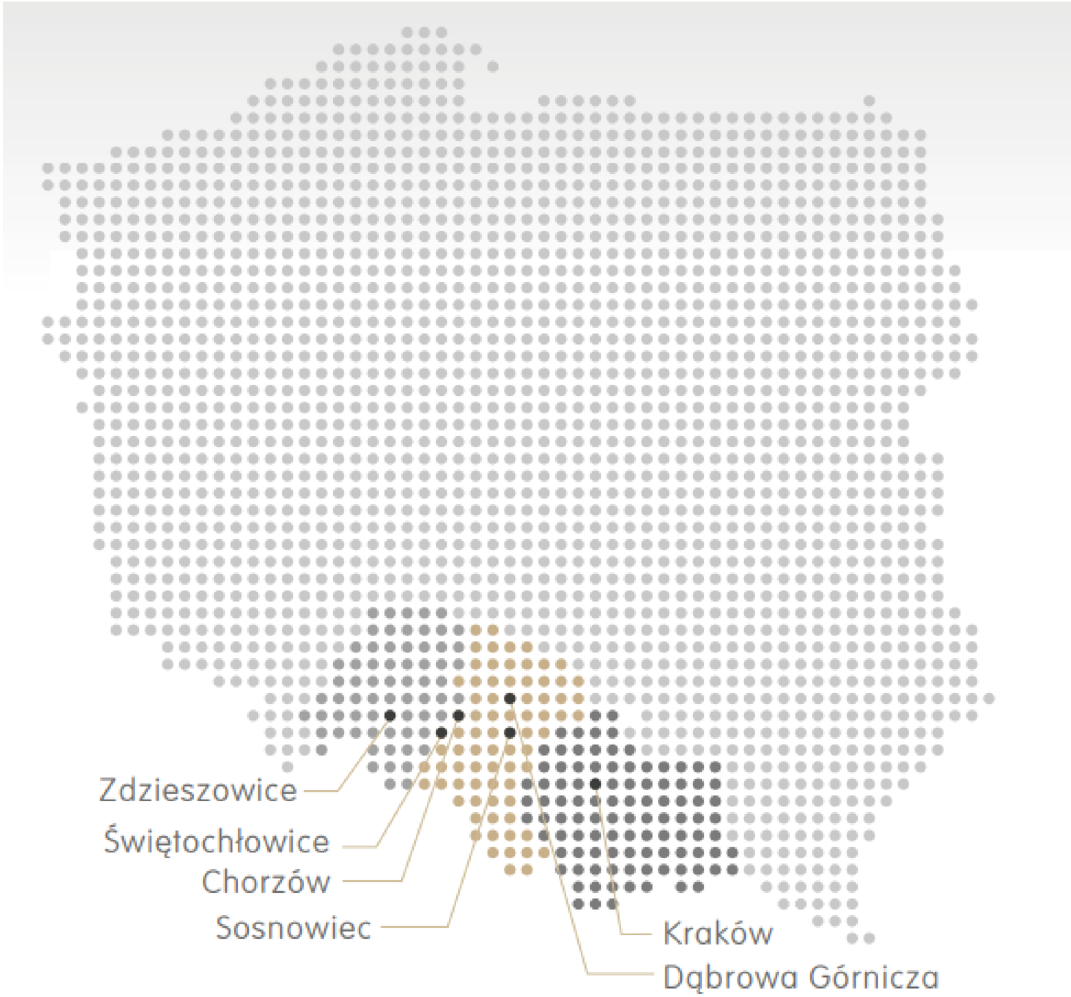
Plan of the presentation

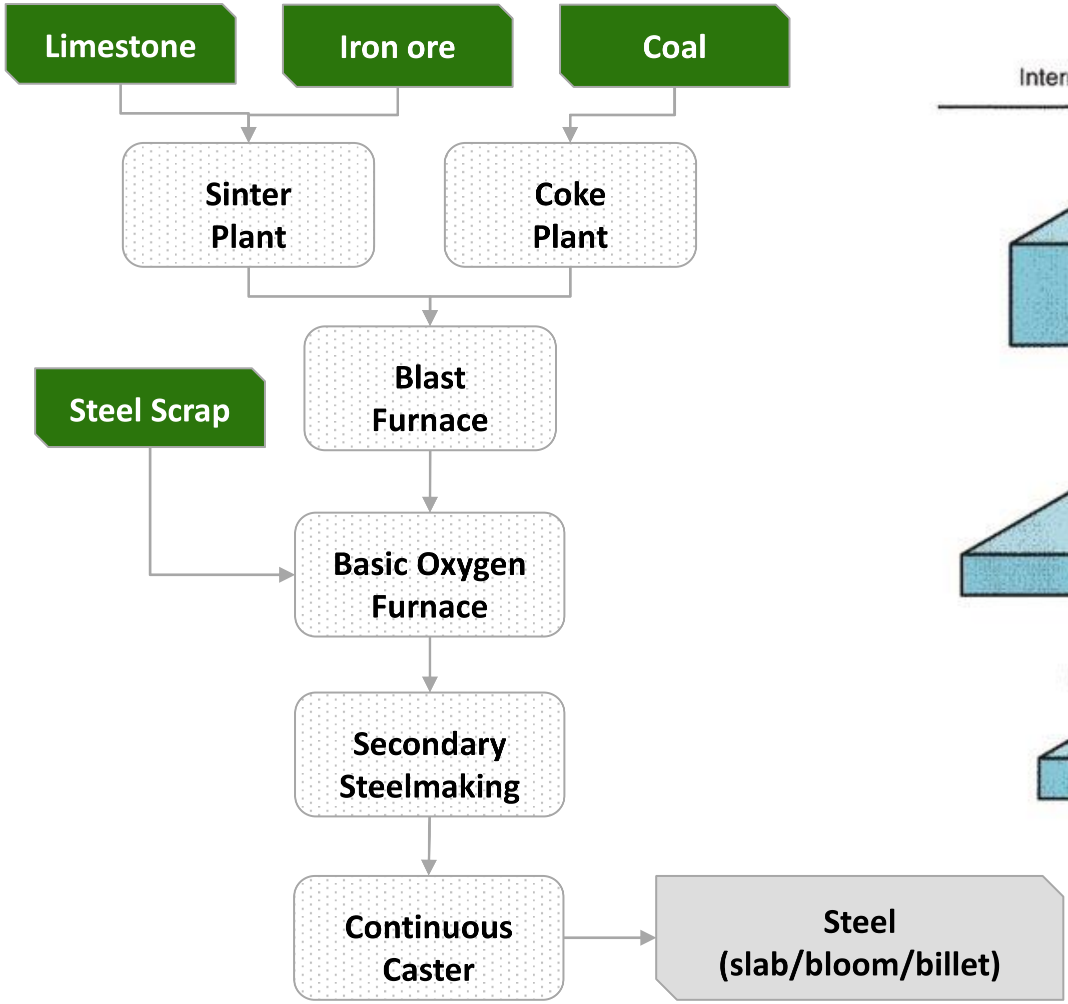
1. Steel manufacturing process
2. Anomaly detection with machine learning
3. Our research papers
4. Summary

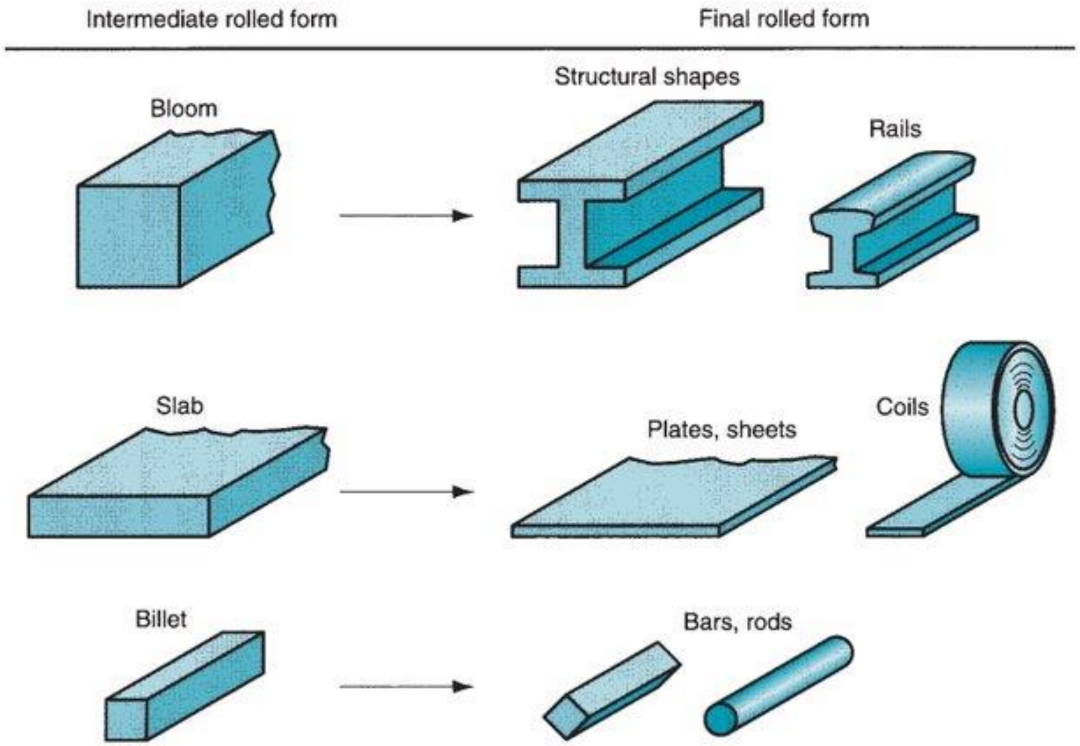
ArcelorMittal Poland

- produced over 3.8 million tons of steel in 2020, which accounts for almost 50% of total steel production in Poland.
- hires over 10,000 employees.
- is present in 6 different locations, all in southern Poland.
- sells products for automotive, appliance and construction, railway industries
- Product portfolio includes: coils (hot rolled, cold rolled, galvanized, coated), wire rod, bars, rails, heavy and medium sections as well as semi-products: billets, blooms, slabs

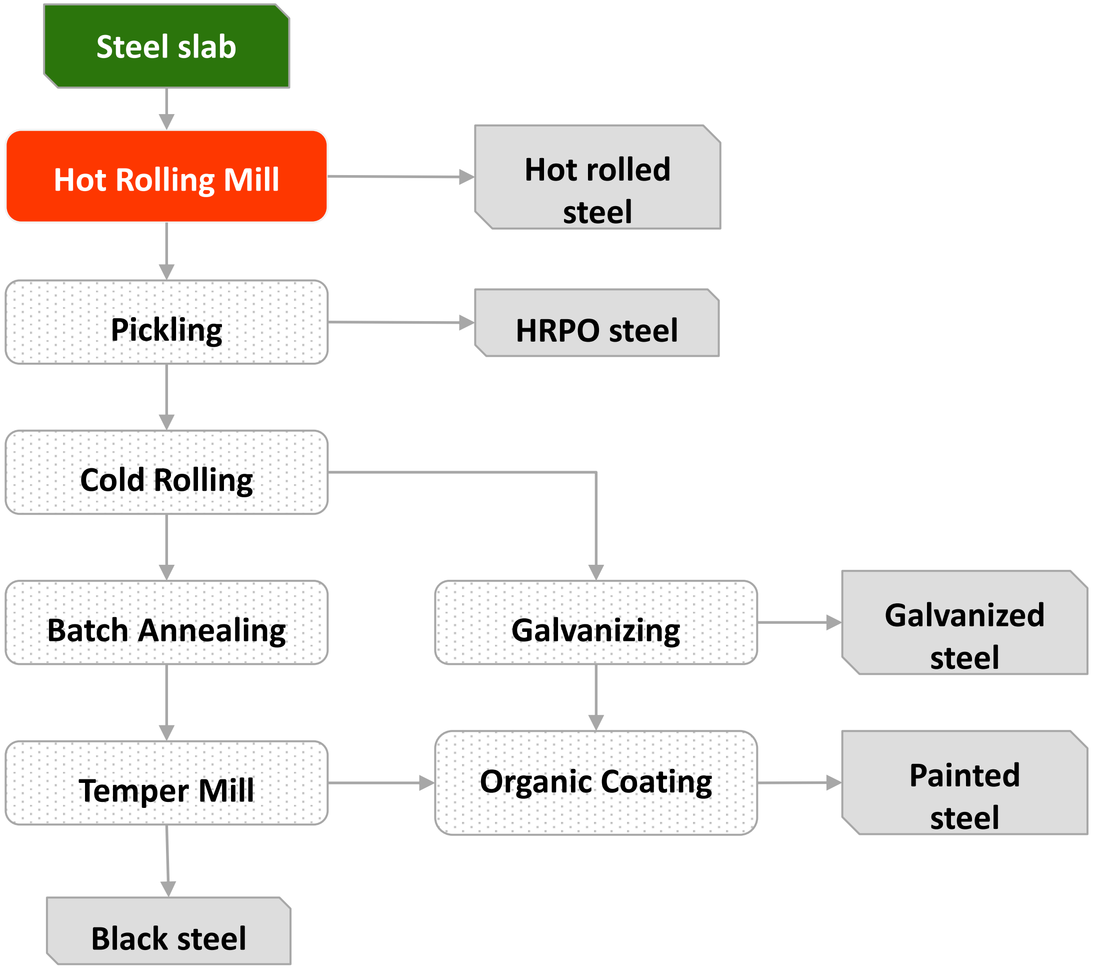


Steel manufacturing process

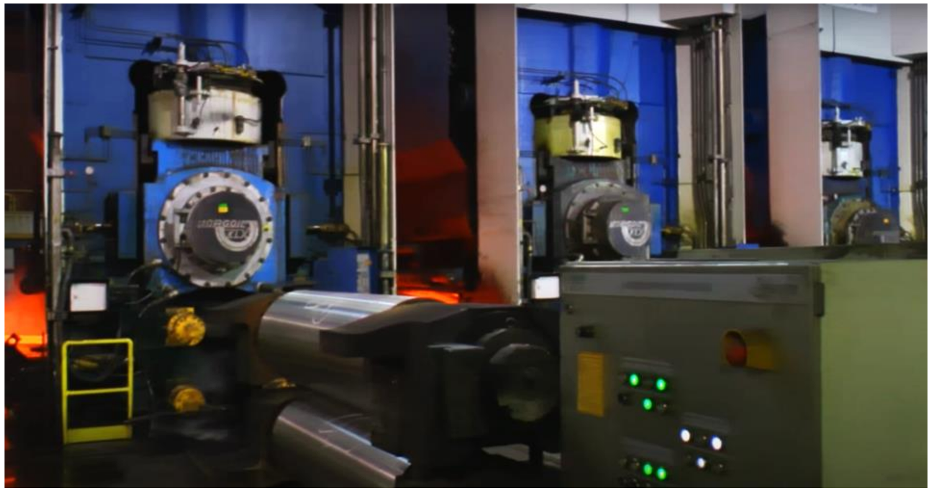




Steel manufacturing process



Hot rolling process



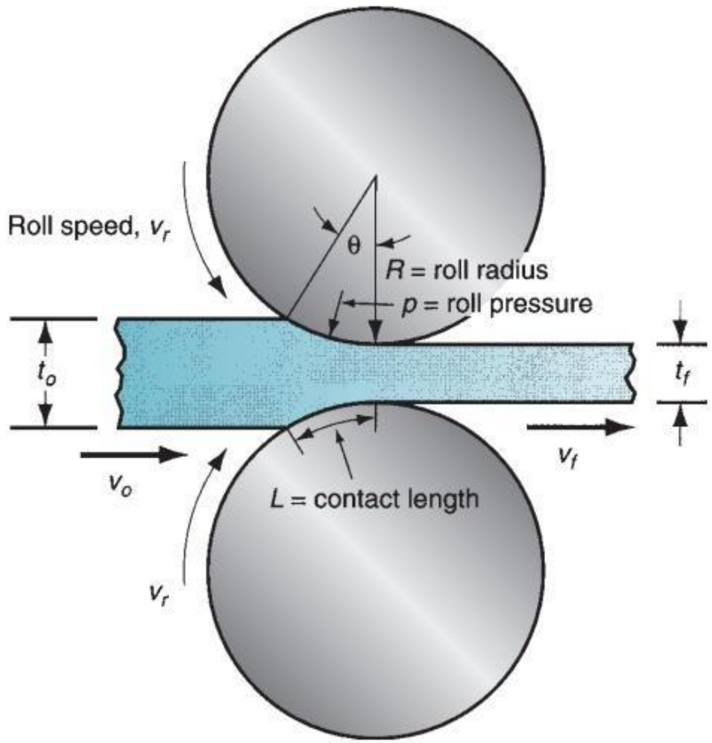
Hot rolling process

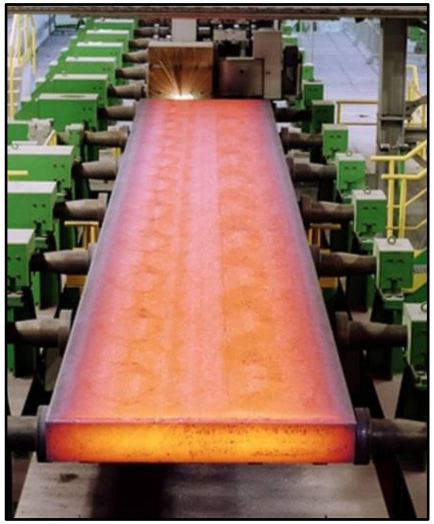
Main process parameters:

- Rolling force
- Tension
- Rolling speed
- Motor load
- Roll bending
- Temperature
- Cooling and lubrication

Main steel quality parameters

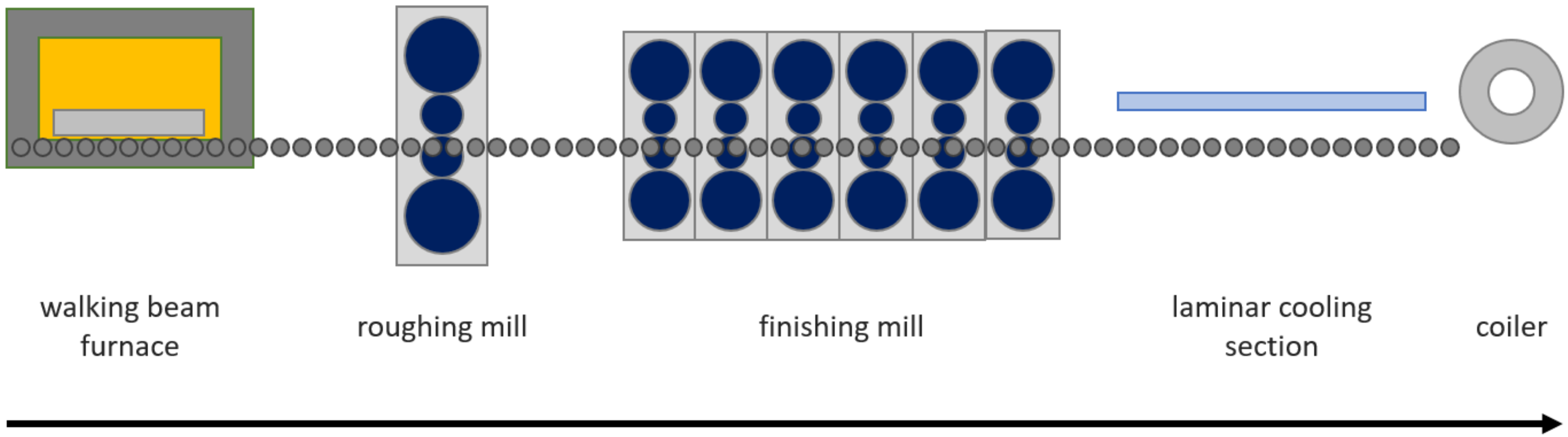
- Mechanical properties
- Thickness
- Flatness
- Visual aspects





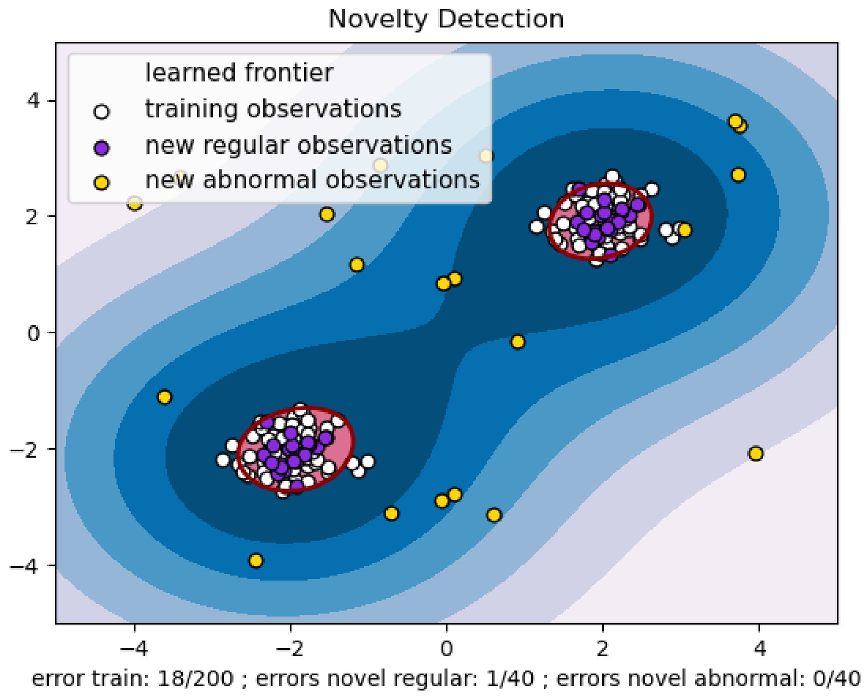
Hot rolling mill

220 mm thick slab is heated from ambient temperature to about 1200°C.
⇨
Slab is passed through a roughing mill where its thickness is reduced to about 30 mm.
⇨
Transfer bar is passed through six rolling stands to reach final thickness (1.8 – 25.0 mm).
⇨
Steel is cooled in the laminar cooling section.
⇨
At end steel is wound up to form a coil.

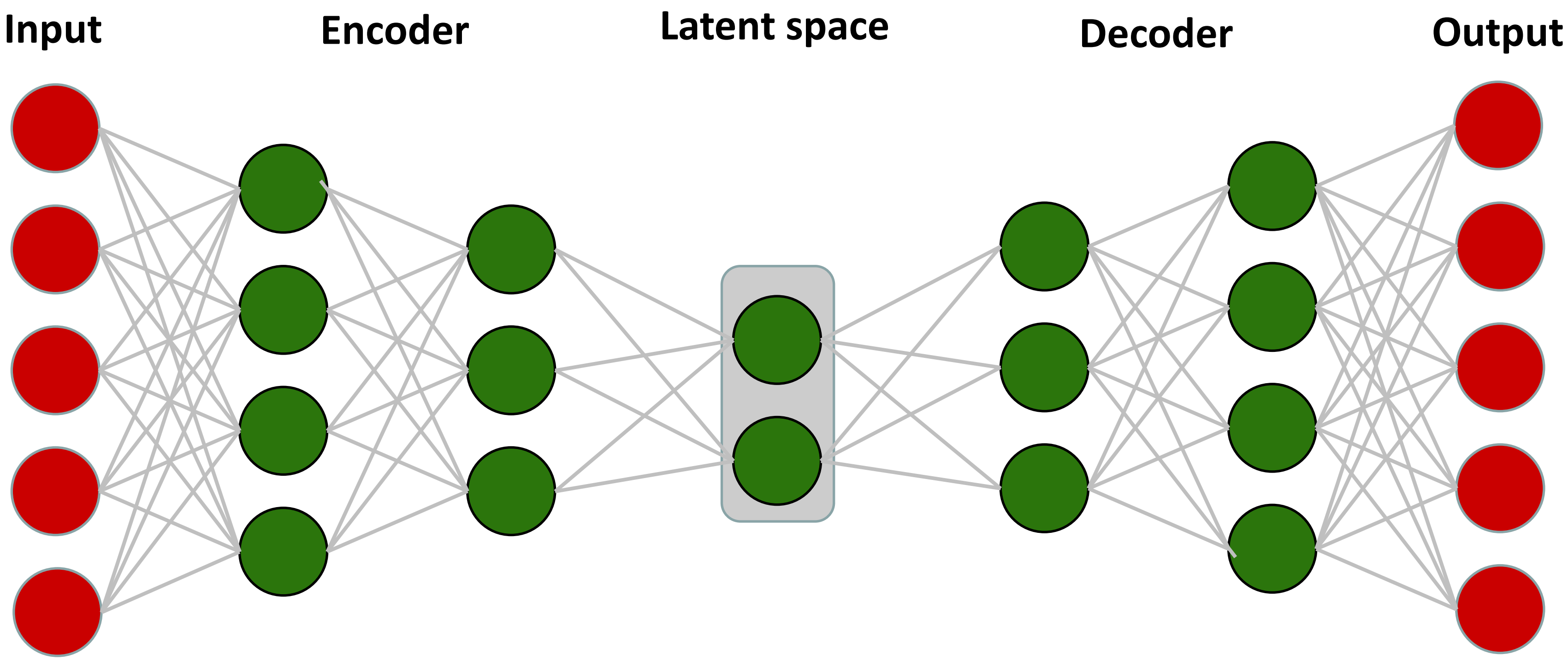


Anomaly detection

- Anomalies may be defined as the observations which do not fit to a distribution of a given process.
- They are usually a small fraction of all observations (<2%), which results in unbalanced data set.
- In industrial applications the anomalies are usually not labelled.
- Unsupervised techniques prove themselves suitable for anomaly detection tasks.
- Unsupervised algorithms for outlier detection include: Local Outlier Factor, One Class SVM, Isolation Forest, DBSCAN, Autoencoders.

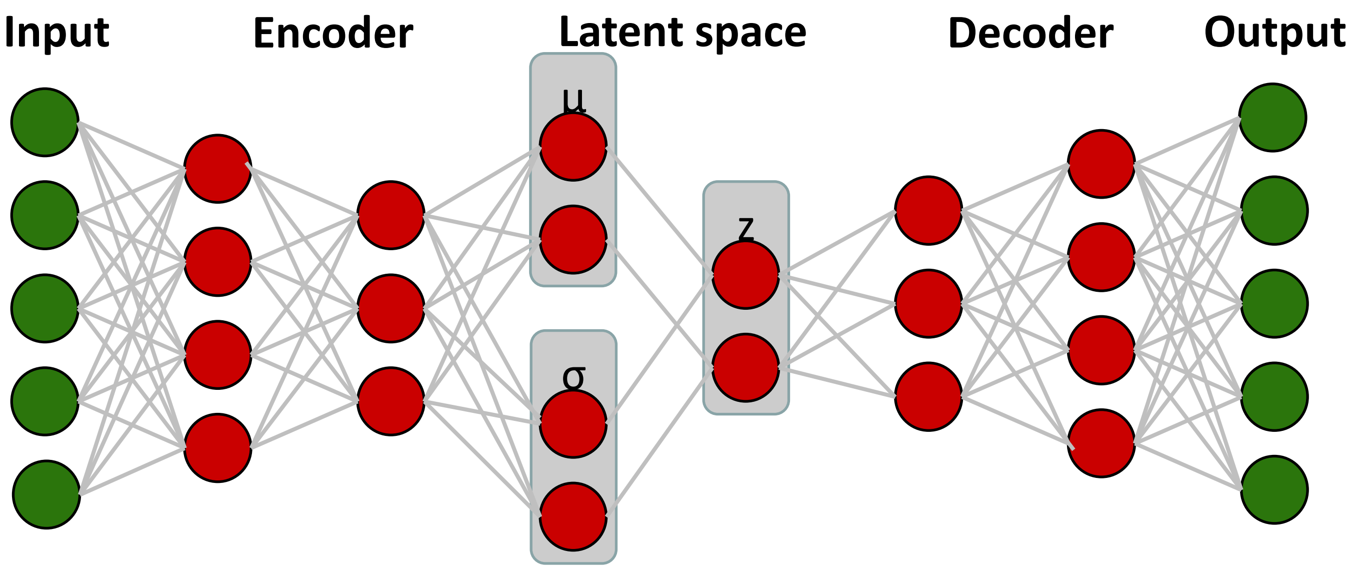


Autoencoders



$$R_{loss} = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2$$

Variational autoencoders



$$R_{loss} = \frac{1}{n}\sum_{i=1}^{n}(X_i - \hat{X}_i)^2$$

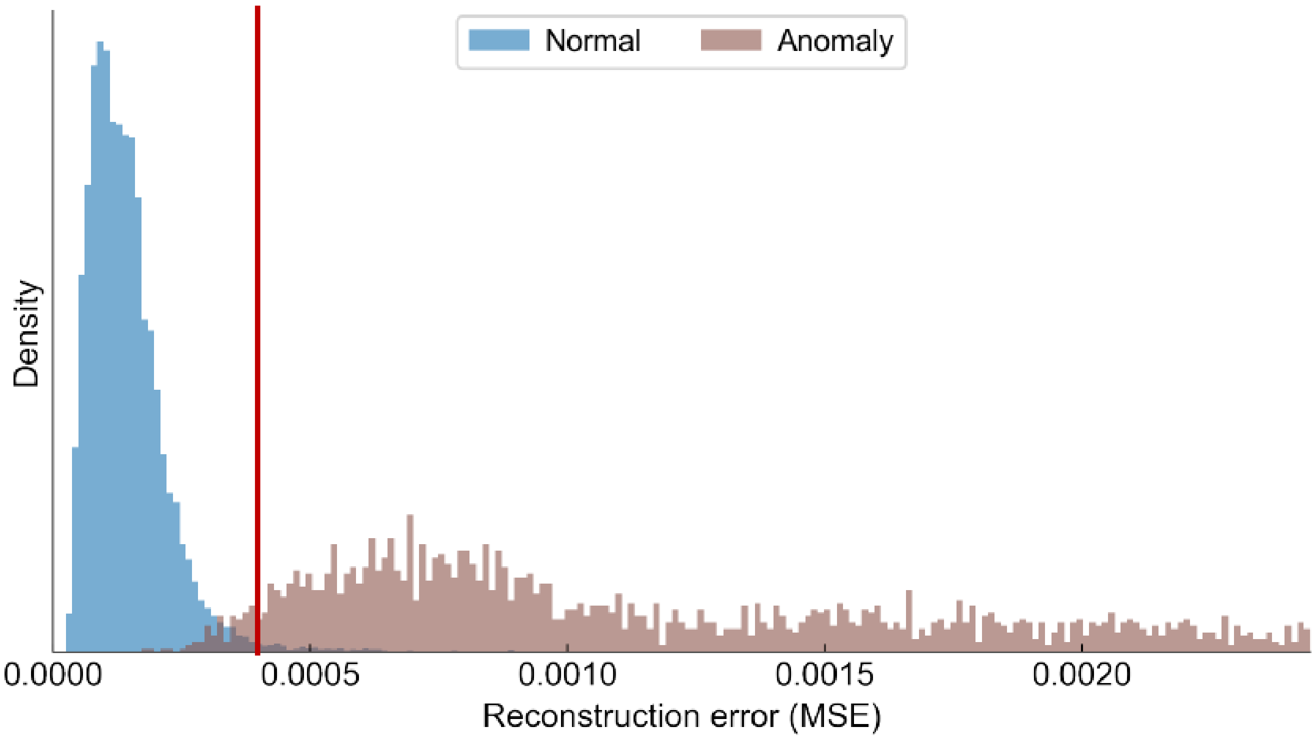
$$KL_{loss} = \sum_{i=1}^{n}(\mu_i^2 + \sigma_i^2 - \log\sigma_i - 1)$$

$$L = R_{loss} + \beta KL_{loss}$$

- Variational autoencoder during training builds a latent space in which values of neurons are sampled from a normal distribution with mean μ and standard deviation σ.
- Loss function depends not only on the reconstruction loss, but also on the structure of the latent space, which is obtained by minimizing Kullback-Leibler divergence.

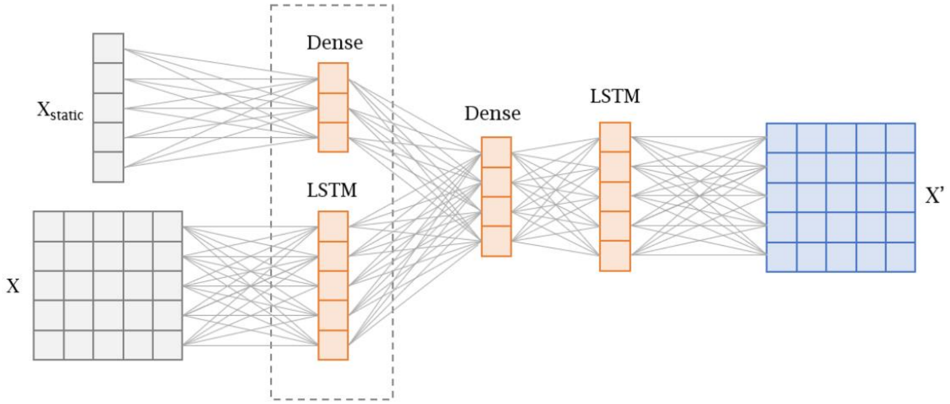
Anomaly detection with autoencoders

- Anomalous observation have higher reconstruction error than normal samples.
- Based on the value of reconstruction error sample may be classified as normal or abnormal.



Paper 1: Explainable anomaly detection for hot-rolling industrial process

- In this research we have focused on a rolling process in six-stands finishing mill.
- The production data was grouped by product (one slab = one observation).
- For each observation 20 sequential features (which vary with the length rolled) were recorded together with 34 static features (non-varying).
- Key process variables are rolling force, torque, speed, motor current, temperature.
- For detection of anomalies we have build a quasi-autoencoder architecture, which has two inputs (sequential and static data) and one output (sequential data).
- To understand the root cause of the anomalies we have engaged a SHAP method.



Paper 1: Explainable anomaly detection for hot-rolling industrial process

- The aim of the research was to build an AI model for anomaly detection in hot rolling process.
- We have extracted data from research from an industrial line of ArcelorMittal located in Kraków, Poland.
- Dataset was not labelled, which entails usage of unsupervised learning methods.
- We have proposed solution based on LSTM autoencoder architecture and used SHAP method for explanations

Paper 1: Explainable anomaly detection for hot-rolling industrial process

- We have transformed original dataset into equal length sequences and divided it into train and test datasets.
- We have trained our quasi-autoencoder and computed anomaly score as mean absolute error between original data and reconstruction
- To speed-up SHAP explanations we have built a surrogate model (XGBoost), which was used as input to the SHAP.
- The anomalies found by quasi-autoencoder were explained with SHAP and manually labelled to estimate precision on industrial data

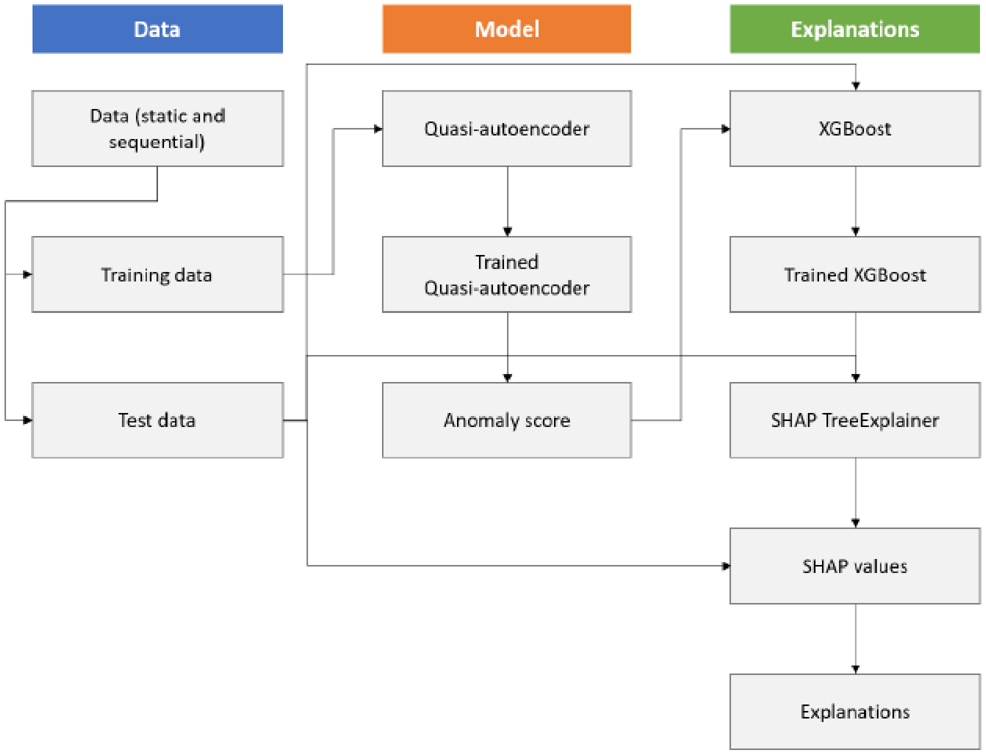


Fig. 5. Summary of the proposed solution. Process flow from input data to model explanations.

Results and discussion

- R^2=0.88 for training and R^2=0.89 for test dataset.
- In the test dataset 35 observations (1.4% of all) were classified as anomalies.
- The accuracy of surrogate model was R^2=0.98.
- Each observation labelled as anomaly was manually revised to validate its label.
- Based on this we have assigned each anomaly to one of the following categories: *anomaly*, *potential (slight) anomaly* and *normal (no anomaly)*.

TABLE VII
MANUAL CLASSIFICATION OF SAMPLES SELECTED BY MODEL AS ANOMALIES

Class	Observation	Share
Anomaly	11	31.4%
Potential anomaly	14	40.0%
Normal	10	28.6%

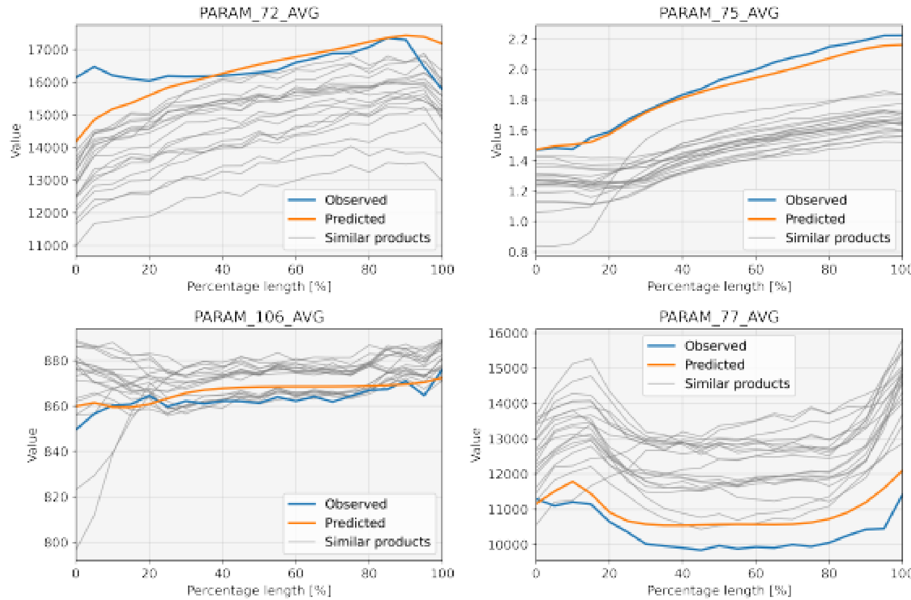
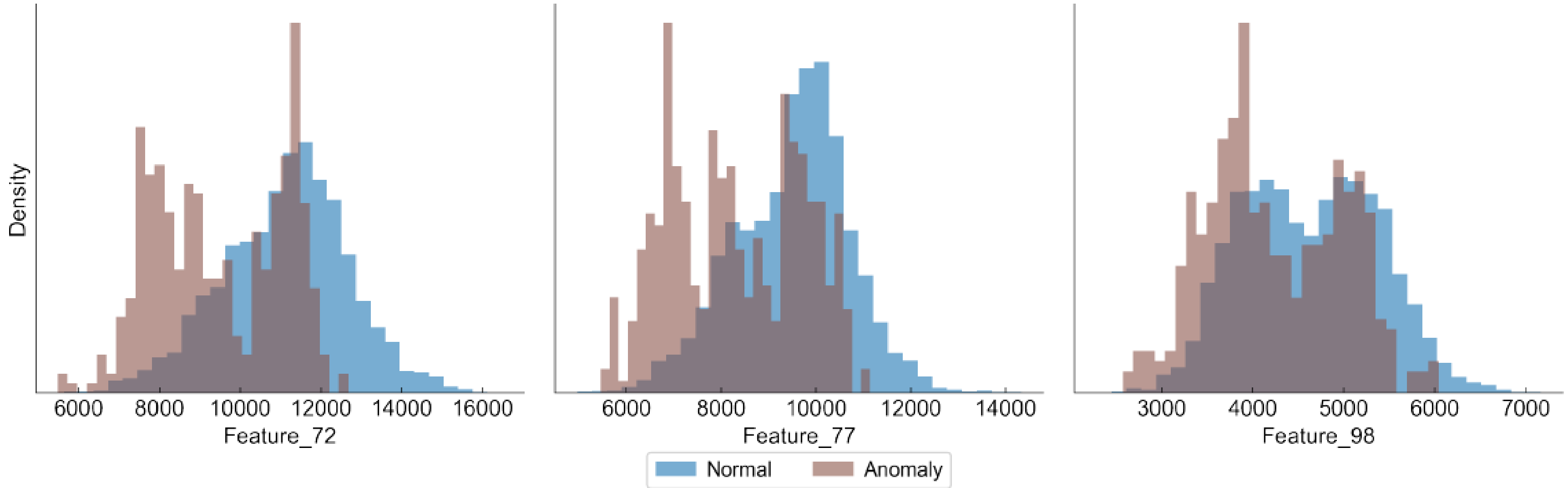


Fig. 13. Exemplary plot of 4 features with the highest SHAP value for a selected anomaly. The blue line represents the real observation, the orange line is the quasi-autoencoder reconstruction and the grey lines show the sequences observed for similar products.

Paper 2: Anomaly detection in asset degradation process using variational autoencoder and explanations

- This research is a continuation of previous works.
- Instead of sequence analysis, we have focused on average measurements per coil.
- Variational autoencoder was used for anomaly detection.
- We have labelled observations as normal or anomalous based on the wear of work rolls in the finishing mill.



Paper 2: Anomaly detection in asset degradation process using variational autoencoder and explanations

- The hyperparameter tuning was done using Bayesian optimization.
- Due to inbalanced data set, we have used F1 score as metric for evaluation of the models, which is the harmonic mean of precision and recall.

$$F_1 = \frac{2}{\frac{1}{r} + \frac{1}{p}}$$

$$p = \frac{TP}{TP + FP}$$

$$r = \frac{TP}{TP + FN}$$

Table 5. The obtained hyperparameters form HRM data set.

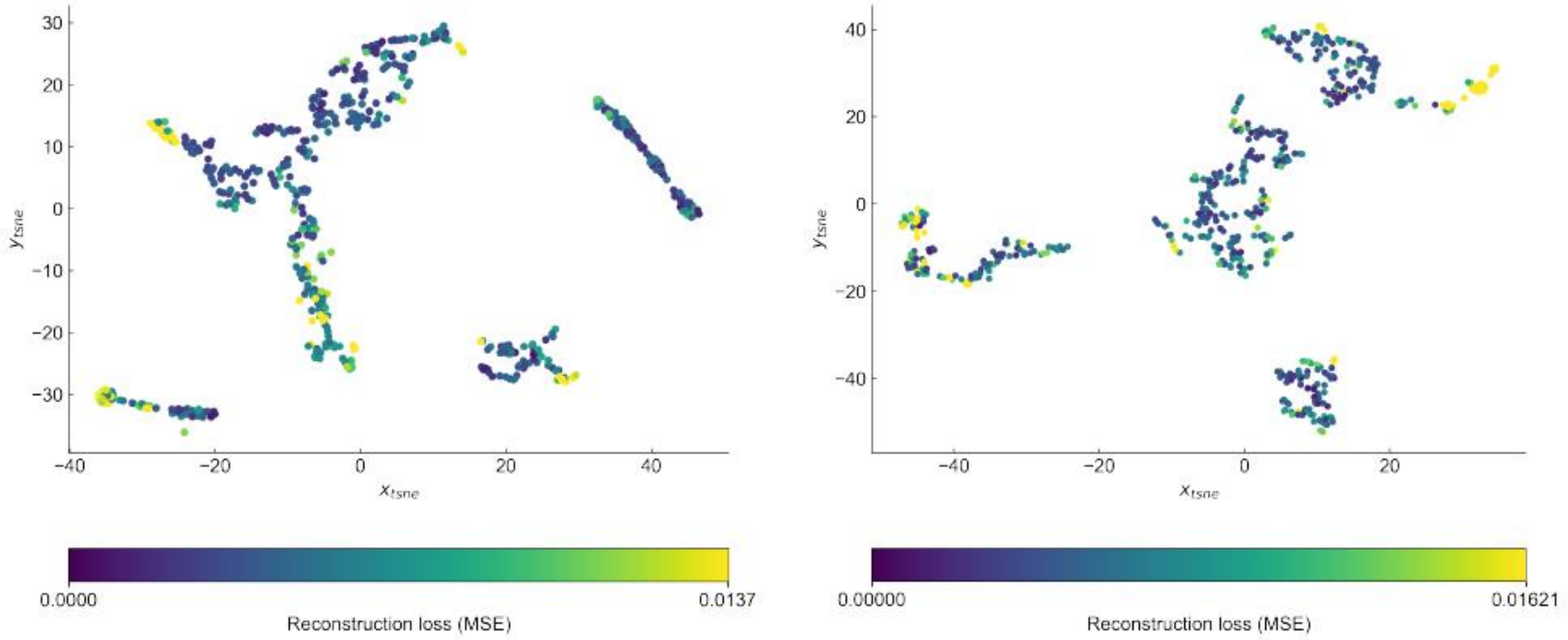
Hyperparameter	AE	VAE
Layers	3	4
Latent size	7	10
Activation	relu	relu
Dropout	0.102	0.115
Batch size	32	32
Epochs	45	34
Quantile threshold	0.930	0.916
Beta max		0.0081
Epochs Beta		8

Table 6. Confusion matriices for HRM data set.

		AE		VAE	
		Predicted			
		Normal	Anomaly	Normal	Anomaly
Actual	Normal	435	6	431	10
	Anomaly	45	41	40	45

Paper 2: Anomaly detection in asset degradation process using variational autoencoder and explanations

- Comparison of AE and VAE latent space

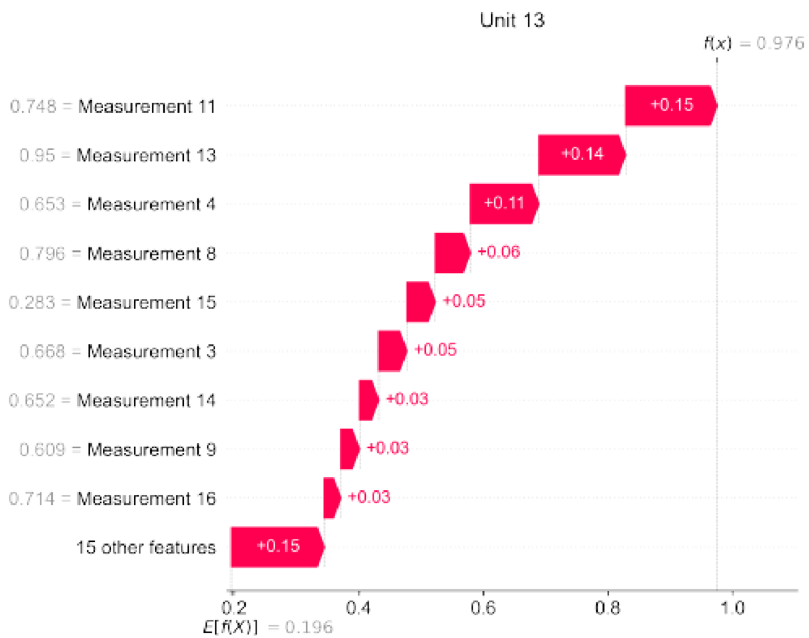


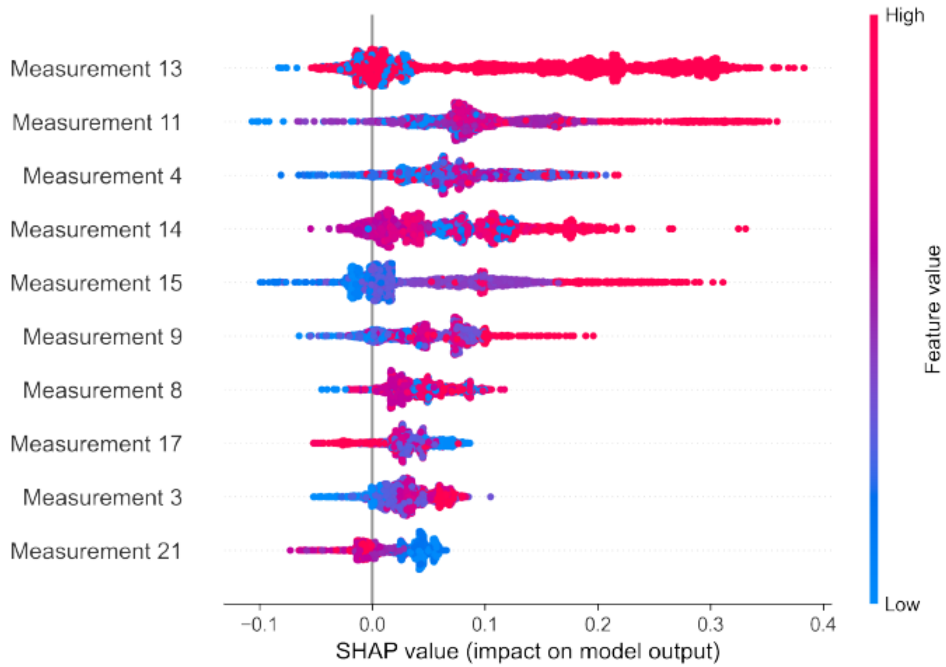
(a) AE (b) VAE

Figure 16. Latent space of the autoencoders in the HRM data set reduced to 2D with use of t-SNE

Paper 2: Anomaly detection in asset degradation process using variational autoencoder and explanations

- SHAP explanations were used to check feature imapct on model output.
- Explanations ease the debugging of the model during development and increase the reliability of the results.





Summary and future works

- The research had shown a potential way to detect anomalies in hot-rolling process in an unsupervised manner.
- Knowledge about anomalous events may be beneficial for a manufacturing company as it allows to spot the very first signs of problems with production.
- Apart from having good anomaly detection model, from business perspective it is crucial to have also an explanations in order to find the root cause of the problem and increase model reliability.
- The research was our first step in modelling anomaly detection solutions for rolling process, in future works we plan to furtherly develop such models in order to make them available for production environment.

Thank you!

Questions & Answers

References

1. J. Jakubowski, P. Stanisz, S. Bobek and G. J. Nalepa, "Explainable anomaly detection for Hot-rolling industrial process*," *2021 IEEE 8th International Conference on Data Science and Advanced Analytics (DSAA)*, 2021, pp. 1-10, doi: 10.1109/DSAA53316.2021.9564228.
2. Jakubowski, Jakub, Przemysław Stanisz, Szymon Bobek, and Grzegorz J. Nalepa. 2022. "Anomaly Detection in Asset Degradation Process Using Variational Autoencoder and Explanations" *Sensors* 22, no. 1: 291. https://doi.org/10.3390/s22010291