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Application of Continuous Wavelet Transform and Convolutional Neural Networks for Diagnostics of Screw Wear in Wheat Extrusion

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Highlights

- Electrical signals enable diagnostics of screw wear in extrusion.
- Time–frequency analysis reveals wear-related signal patterns.
- CNN classifies screw condition using CWT scalograms.
- Current signals show higher diagnostic sensitivity than voltage.
- Method demonstrates potential for predictive maintenance systems.

Abstract

This study presents a hybrid diagnostic approach combining the Continuous Wavelet Transform (CWT) and Convolutional Neural Networks (CNN) for assessing screw wear in a single-screw extruder operating under controlled conditions. Electrical current signals from the drive motor were analyzed to identify changes associated with the degradation of working components. CWT scalograms were used as time–frequency inputs for a CNN classifier, achieving a classification accuracy of 92.3% in distinguishing between new and worn screw states. Principal Component Analysis (PCA) confirmed clear separability of operating conditions, with the first two components explaining over 99% of the total variance. The results indicate that electrical signals contain diagnostically relevant information and that their combined analysis using CWT and CNN enables automated, non-invasive condition assessment with potential applicability in predictive maintenance systems without additional sensors.

Keywords
predictive diagnostics, screw extruder, CWT, CNN, deep learning, signal analysis.

1. Introduction

Extrusion is among the most versatile processing techniques applied in the food, feed, and polymer sectors, as it enables the formation of product structure, improvement of digestibility, and modification of physicochemical properties [1]. Due to its flexibility and energy efficiency, extrusion has found broad application not only in food engineering but also in materials and chemical technologies. The overall efficiency of the process depends on multiple design and operational parameters, such as the geometry of the screw, the condition of the barrel, and the frictional interaction between the rotating screw, processed material, and the internal surface of the cylinder [2].

In single-screw extruders, material flow is mainly driven by friction and pressure gradients along the screw channel. The rheological characteristics of the processed material, together with the geometry of the screw elements, determine process stability and energy efficiency [3,4]. The presence of grooves on the inner surface of the barrel enhances friction, limits

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slippage, and improves the uniformity of material conveyance. Over time, however, wear of the screw flights and degradation of barrel grooves lead to increased clearances, backflow, and deterioration of flow conditions [5,6].

The progressive wear of the screw and barrel negatively influences both energy efficiency and operational reliability. As these components degrade, power demand, pressure fluctuations, and temperature irregularities within the plasticizing section tend to increase, resulting in higher overall energy consumption [7]. For this reason, there is a growing need for methods that enable continuous, non-invasive monitoring of the technical condition of extruder components without disrupting production.

Conventional diagnostic techniques—such as monitoring motor load or production rate—provide only indirect information and often require operator supervision. In contrast, non-destructive approaches based on electrical signal analysis allow continuous, automated assessment of machine load. Time–frequency methods like the Continuous Wavelet Transform (CWT) enable the identification of non-stationary variations in these signals, which can serve as indicators of wear in mechanical components [8]. When combined with artificial intelligence techniques, particularly Convolutional Neural Networks (CNN), such analysis allows automatic recognition of characteristic patterns associated with specific technical conditions [9,10].

Modern diagnostic strategies increasingly integrate signal analysis with machine learning, consistent with the concepts of predictive maintenance and Industry 4.0. Through the analysis of current, voltage, and power signals, it is possible to construct predictive models capable of detecting early symptoms of wear or process anomalies [11,12]. Applying CWT–CNN methods in single-screw extruder diagnostics therefore represents a significant advancement toward intelligent monitoring systems that minimize maintenance costs, enhance process stability, and improve the reliability of technological lines.

Unlike the approach presented by Danielak et al. [8], which relied mainly on wavelet-based statistical interpretation of current signals, this study introduces a hybrid CWT–CNN model that combines automated feature extraction and classification of screw wear states. This integrated methodology enhances diagnostic autonomy, scalability, and repeatability while reducing the dependence on expert-driven signal interpretation. Moreover, it fits naturally into the framework of predictive maintenance and Industry 4.0 by converting raw electrical data into diagnostic knowledge through deep learning mechanisms.

The purpose of this research is to develop and experimentally validate a method for assessing screw wear in single-screw extruders using electrical signal analysis supported by wavelet transformation and convolutional neural networks. The proposed approach enables real-time detection of component wear without interfering with process operation, thereby contributing to improved understanding of energy efficiency and system reliability.

This interdisciplinary research merges aspects of mechanical engineering, tribology, and artificial intelligence. It provides a comprehensive understanding of how mechanical degradation of the extruder's working parts affects the electrical behavior of the drive system. The Continuous Wavelet Transform offers insight into the time–frequency nature of these dynamic phenomena, while CNN-based models enable automated pattern recognition that surpasses traditional feature-engineering approaches. Consequently, the developed diagnostic framework advances condition monitoring in extrusion systems and contributes to the broader field of data-driven maintenance for industrial machinery.

2. Materials and Methods

2.1. Object of the study and extruder configuration

The study was carried out on a laboratory single-screw extruder METALCHEM E-75 (AgroFeedingTech, Polska) equipped with a 7.5 kW squirrel-cage induction motor (400 V, 50 Hz) and an intermediate gearbox ensuring stable screw rotational speed. The screw, with a length of $L = 25D$ and a nominal diameter of 75 mm, cooperated with a barrel containing twelve longitudinal grooves in the feeding zone. The grooves had a depth of 2.5 mm, a width of 4 mm, and an attack angle of 30°. Two sets of screws were used in the experiment (Figure 1):

- N (new) – a factory-new screw after 8 hours of run-in operation,
- W (worn) – an operationally worn screw with visible edge degradation, deformation of flight profile, and reduced ridge height.

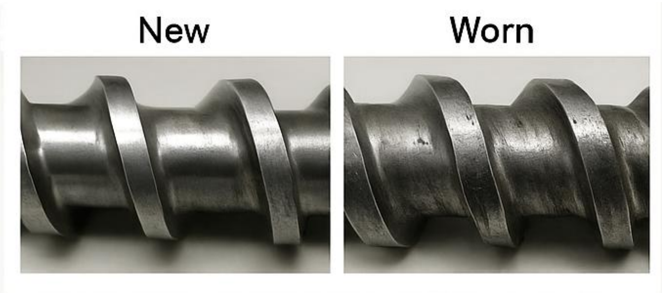

Figure 1. Comparison of the new (N) and worn (W) screw.

Photographs of the screws in both states and the wear description were used as a reference during signal interpretation.

2.2. Raw material and process parameters

The raw material was wheat with a moisture content of 15%, originating from a single storage batch to minimize variability in rheological properties. The process was carried out under constant technological parameters:

- screw speed: 500 rpm,
- temperature in the final barrel zone: ~115 °C,
- die diameter: 8 mm,
- L:D ratio of the plasticizing system: 5:1.

All measurements were performed under steady-state conditions in separate sessions for the N and W screw states.

2.3. Data acquisition and recording system

Three-phase RMS current signals were recorded using a METREL MI 2883 Energy Master power analyzer equipped with A1227 current clamps (up to 1000 A, accuracy 1%). The system complies with EN 61000 4-30 Class S. The following quantities were measured:

- phase current (A),
- voltage (V),
- instantaneous power consumption (W),
- cumulative energy consumption (Wh),
- barrel temperature (°C).

Recording parameters:

- raw signal sampling frequency: 7 kHz,
- averaged data frequency: 1 Hz,
- RMS measurement accuracy: ±1.5%.

The dataset consisted of 1429 signal segments extracted from continuous electrical measurements acquired under steady-state extrusion conditions. Each sample represents a time window of the recorded signal rather than an independent experimental run. Data acquisition and subsequent processing, including statistical analysis, time–frequency transformation, and neural model development, were performed using MATLAB.

2.4. Data preprocessing

Collected data were subjected to:

- quality control,
- removal of outliers,
- z-score normalization,
- verification of sampling uniformity,
- calculation of descriptive statistics (mean, median, min, max, standard deviation).

Kolmogorov–Smirnov normality tests were performed, and the Pearson correlation matrix was calculated to assess linear relationships.

2.5. Time–frequency analysis (CWT)

For power and phase current signals, the Continuous Wavelet Transform (CWT) was calculated to obtain scalograms representing changes in signal energy as a function of time and frequency.

Equation (1) defines the continuous wavelet transform of a signal *x(t)* using a wavelet *ψ(t)*:

$$W(a, b) = \int_{-\infty}^{\infty} x(t)\, \psi^* \left(\frac{t-b}{a}\right) dt \quad (1)$$

Parameter *a* controls scale (stretching or compression of the wavelet), while *b* corresponds to time shift. The result *W*(*a, b*) represents wavelet coefficients that capture local variations in signal energy across time and frequency domains.

The Morse wavelet was used as the mother wavelet due to its good resolution properties for non-stationary mechanical signals.

Two representations were obtained:

- CWT–N – signal during operation with a new screw,
- CWT–W – signal during operation with a worn screw.

Scalograms were subsequently used as input images for the convolutional neural network.

2.6. Feature extraction and PCA analysis

Based on the normalized signals, Principal Component Analysis (PCA) was performed. Mathematically, PCA solves:

$$T = XW \quad (2)$$

where T is the score matrix and W contains eigenvectors of the covariance matrix.

The following were determined:

- eigenvalues,
- eigenvectors,
- percentage contribution of components to total variance.

The first two components (PC1 and PC2) explained more than 99% of data variance, allowing dimensionality reduction and visualization of differences between N and W classes.

2.7. Convolutional neural network (CNN) architecture

The input data for the CNN model consisted of images obtained from the CWT of current signals recorded for two extruder operation configurations:

- New screw (N) – 1429 samples,
- Worn screw (W) – 1400 samples.

From each time record, fixed-length segments were extracted and transformed into CWT scalograms (Morlet wavelet). A total of 2850 CWT images were created (1425 per class, N and W). The images were saved in .png format at 224×224 px resolution and used as CNN input data.

The CNN model (Figure 2) developed for screw condition classification (N/W) consisted of:

- input layer: 224×224×3 (RGB images),
- first convolutional layer: 32 filters 3×3, stride = 1, ReLU activation,
- second convolutional layer: 64 filters 3×3, stride = 1, ReLU activation,
- max-pooling layer: 2×2,
- fully connected (FC) layer: 128 neurons, ReLU activation,
- output layer (Softmax): 2 classes (N and W).

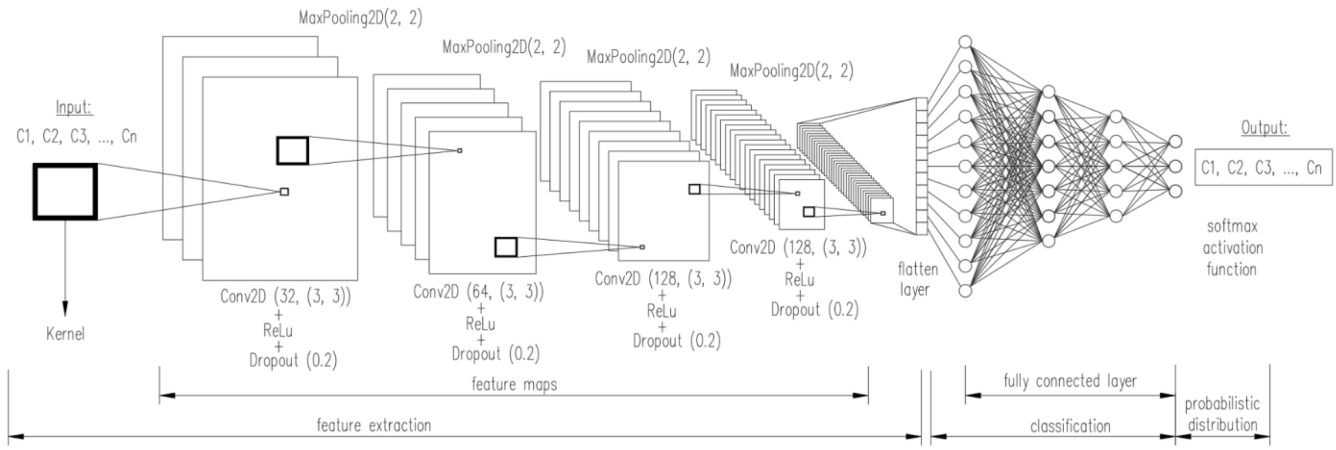

Figure 2. Architecture of the multi-layer CNN.

Dropout regularization (0.3) was applied to prevent overfitting.

Training was performed in Python (TensorFlow/Keras) using GPU (NVIDIA RTX 3060):

- number of epochs: 50,
- batch size: 32,
- loss function: *categorical cross-entropy*,
- optimizer: *Adam*,
- learning rate: 0.001,
- single iteration training time: ~45 s, total training time: ~38 min.

Data were split into 70% training, 15% validation, and 15% testing sets. Early stopping was used to prevent overtraining once the loss function stabilized.

2.8. Model validation and quality metrics

The classifier performance was evaluated using:

- confusion matrix,
- accuracy,
- sensitivity and specificity,
- F1-score,
- AUC ROC.

For the regression part (ANN-based power prediction):

- coefficient of determination (R^2),
- root mean square error (RMSE),
- mean absolute error (MAE).

Model evaluation was performed on both test and independent datasets.

2.9. Software and computational environment

Computations were carried out using the following environments:

- MATLAB 2023b – signal analysis, PCA, CWT, ANN,
- Python 3.11 / TensorFlow – CNN implementation,
- OpenCV + NumPy – scalogram image processing,
- Scikit-learn – classification metrics.

3. Results

3.1. Analysis of supply voltage waveforms

In the first stage of the study, the interphase voltage waveforms recorded during extruder operation were analyzed for the new (N) and worn (W) screw. Figures 3 and 4 present changes in the U12(Avg) voltage over time for both variants.

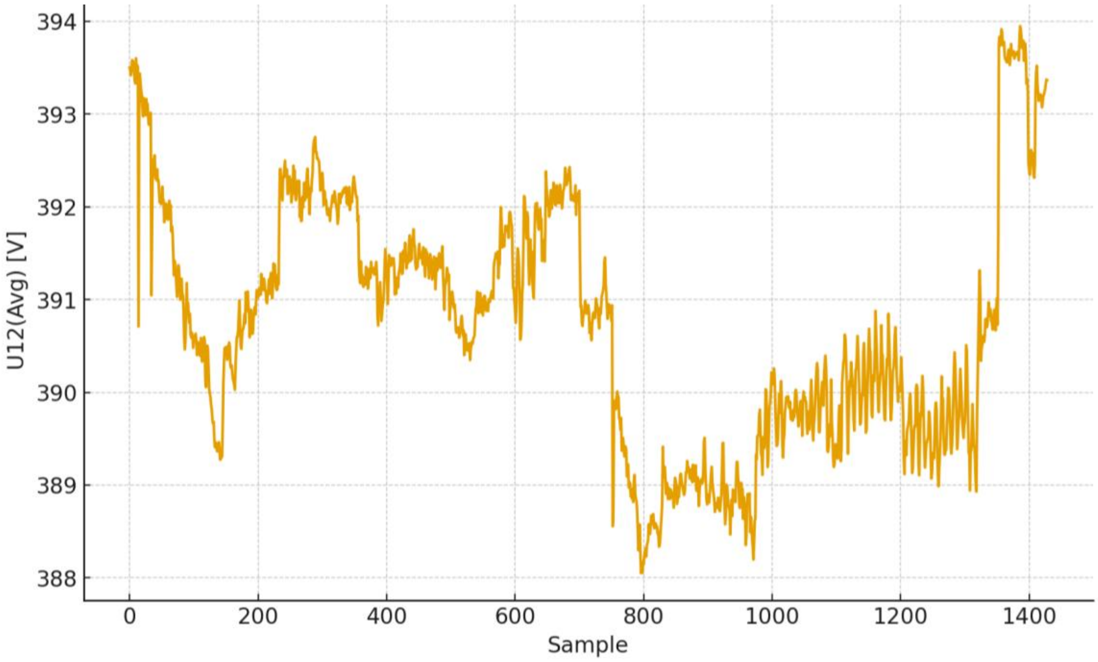

Figure 3. Time series of the interphase voltage U12(Avg) during extrusion using the new screw (N). The horizontal axis represents consecutive samples recorded at a frequency of 1 Hz.

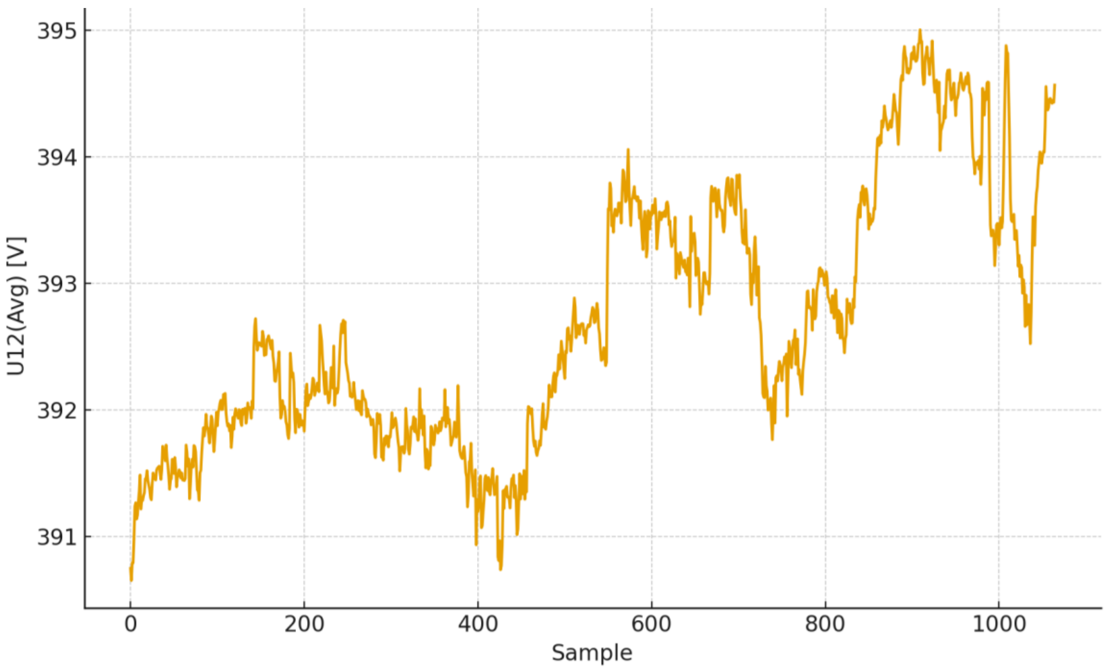

Figure 4. Time series of the interphase voltage U12(Avg) obtained with the worn screw (W). The horizontal axis represents consecutive samples recorded at a frequency of 1 Hz.

For the new screw, the voltage signal was characterized by high stability and low fluctuation amplitude. The waveform corresponds to expected behavior under nominal operating conditions and serves as a reference for evaluating extruder performance.

For the worn screw, local disturbances and slightly higher signal variability were observed, resulting from deteriorated material transport and increased frictional resistance. These effects indicate higher mechanical loading of the drive system.

3.2. Statistical characteristics of process parameters

To quantitatively assess the changes in extruder operation, statistical analysis of the recorded process parameters was performed. The results are presented in Table 1.

Temperature signals exhibited the lowest variability (SD = 4.93 °C), whereas power and energy consumption showed the widest range of values. The most significant difference between the N and W conditions was observed for power consumption, whose large amplitude variations indicate a dynamic effect of screw wear on the energy efficiency of the system.

The correlation matrix (Table 2) revealed a strong positive relationship between power and energy ($r > 0.99$), confirming their functional interdependence.

Table 1. Descriptive statistics of recorded extrusion process parameters.

Variable	Mean	Standard deviation	Min	Max	Median
Temperature [°C]	115.68	4.93	105.45	124.22	115.58
Power consumption [W]	5339.20	1223.80	26.21	9046.30	5179.00
Energy consumption [Wh]	1.4831	0.3400	0.007	2.513	1.439

Table 2. Correlation matrix of process parameters.

	Temperature	Power	Energy
Temperature	1.00000	0.65075	0.65074
Power	0.65075	1.00000	1.00000
Energy	0.65074	1.00000	1.00000

A moderate correlation between temperature and energy-related parameters ($r \approx 0.65$) reflects increased friction and mechanical load associated with deteriorated material transport typical of worn components.

The Kolmogorov–Smirnov (KS) test confirmed that all analyzed variables deviate significantly from the normal distribution ($p < 0.001$), justifying the use of nonlinear and time–frequency methods in subsequent analyses.

3.3. Time–frequency analysis of load signal (CWT)

To capture non-stationary patterns resulting from frictional and flow-related changes, the power-consumption signal was analyzed using the Continuous Wavelet Transform (CWT). Scalograms are shown in Figures 5 (new screw) and 6 (worn screw).

The dominant frequency bands in the current signal were found in the range of 60–300 Hz, corresponding to mechanical vibration harmonics related to screw rotation and material compression. The scalogram for the new screw exhibits dominance of the low-frequency spectrum and a uniform energy distribution, indicating stable operation of the system.

Compared to the new screw condition, the worn screw exhibited an increased concentration of signal energy in the 60–300 Hz frequency range, indicating elevated dynamic load and friction-related phenomena. In this case, more intensive mid- and high-frequency components, local energy peaks, and increased signal irregularity were observed. These distinct differences confirm that the CWT enables effective separation of extruder operating states and provides a suitable data representation for CNN-based classification.

3.4. Dimensionality reduction using PCA

Principal Component Analysis (PCA) showed that the first two components (PC1 and PC2) explained over 99% of the total variance. PCA was applied to RMS values of three-phase interphase voltages (U12, U23, U31). The first principal component (PC1) represents the combined variance associated with the overall electrical load of the drive system, while the second component (PC2) reflects secondary thermo-mechanical variations.

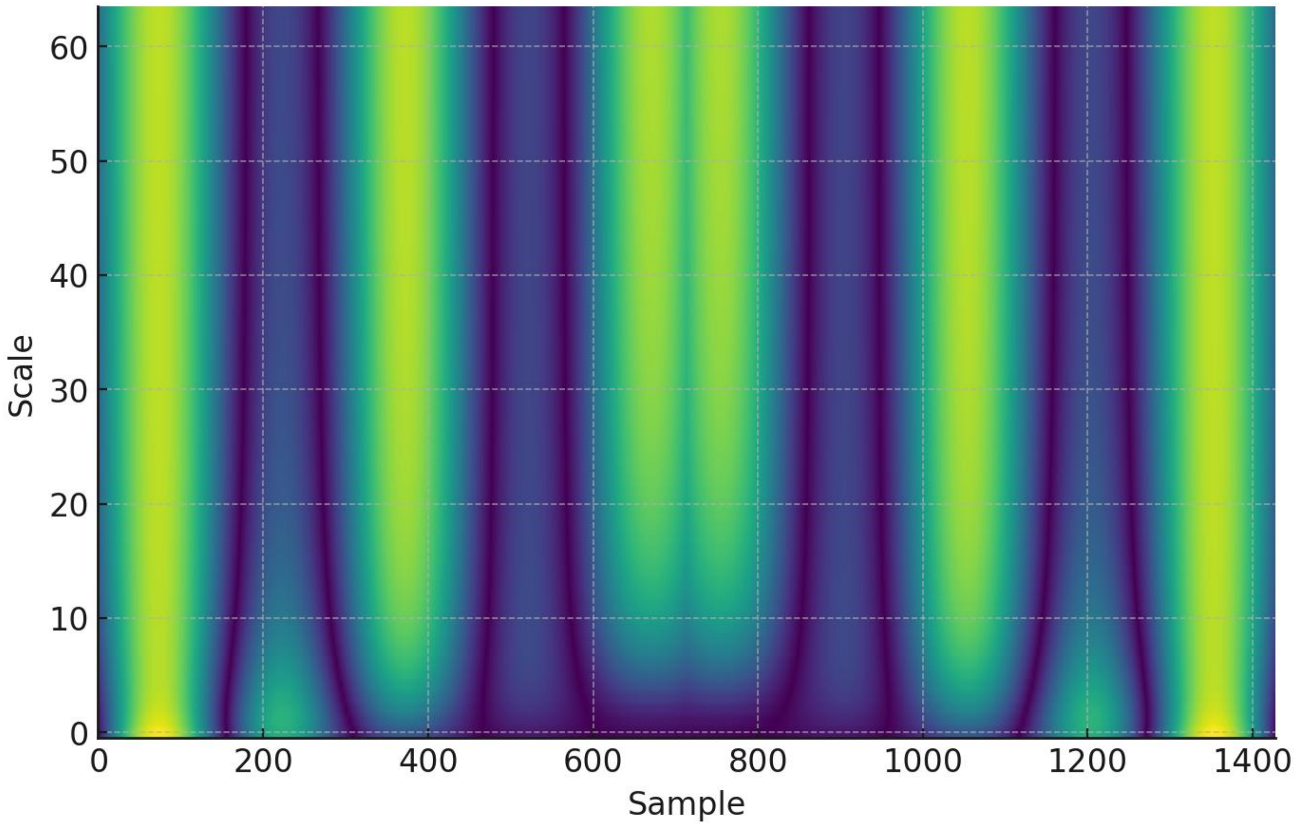

Figure 5. CWT scalogram of the power consumption signal for the new screw (N).

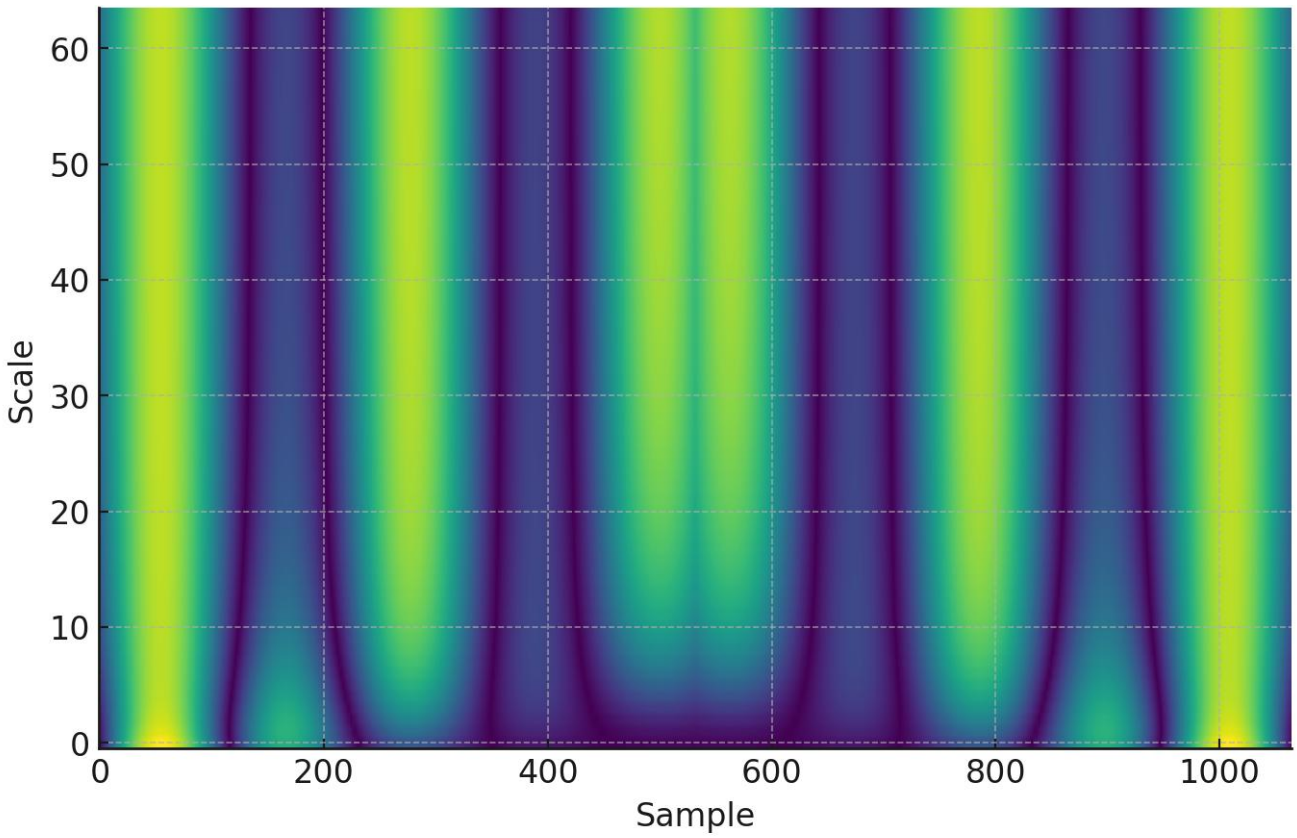

Figure 6. CWT scalogram of the power consumption signal for the worn screw (W).

PCA performed on three-phase voltages (U12, U23, U31) for both screw conditions (N and W), with projection onto the PC1–PC2 plane, is shown in Figure 7.

Visualization in the PC1–PC2 space revealed clear separation of the N and W clusters, indicating notable structural differences in the signals. Quantitatively, PC1 explained 98.2% and PC2 1.3% of total variance, confirming that over 99% of the information about system dynamics was retained in the two-dimensional feature space.

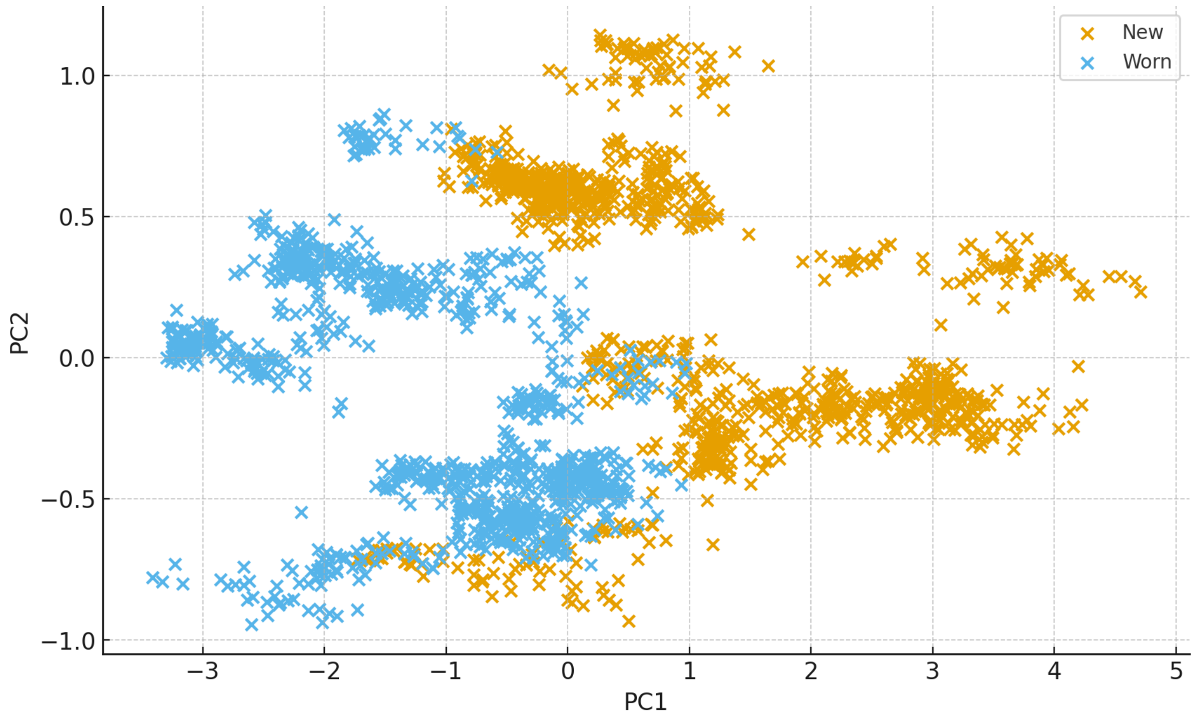

Figure 7. Projection of the data onto the first two PCA components.

3.5. Classification of screw condition using CNN

The CWT scalograms were used as input images for the convolutional neural network. The model achieved high classification accuracy for the two classes: N (new screw) and W (worn screw).

The confusion matrix (Figure 8) shows a high true-positive rate for both classes, with only a small number of misclassifications between N and W. Most errors occurred near the transition between partial and advanced wear.

The quantitative evaluation of the CNN classifier showed an overall classification accuracy of 92.3% on the independent test dataset, with an F1-score of 0.91, indicating good generalization performance of the model under the considered experimental conditions. Additionally, a comparative analysis of current- and voltage-based inputs revealed that the model trained on current-based CWT scalograms achieved higher accuracy (92.3%) than the model based on voltage signals (88.7%). This result indicates that current signals more effectively reflect dynamic changes associated with tribological wear of the screw and barrel elements.

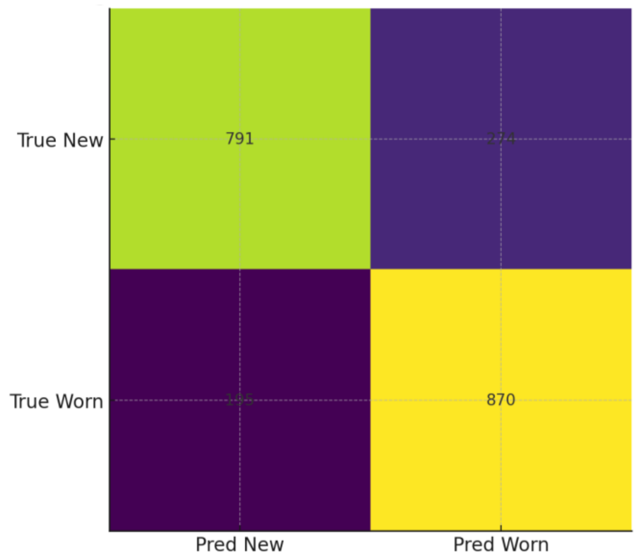

Figure 8. Confusion matrix of the CNN classifier for distinguishing between new (N) and worn (W) screw conditions.

A complete list of the obtained performance metrics is provided in Table 3.

The CNN effectively distinguished between the two operating states, and misclassifications were rare, occurring mainly for borderline signal patterns between classes. Compared with the model proposed by Danielak et al. (2023), which achieved 89.5% accuracy using statistical features, the CWT–CNN approach improved classification performance by approximately 3 percentage points. This result indicates the potential advantage of combining time–frequency analysis with deep feature extraction for screw-wear diagnostics based on electrical signals.

Table 3. Quantitative evaluation metrics for the CNN classifier.

Metric	Training	Validation	Test
Accuracy [%]	94.8	92.3	92.3
Precision [%]	93.7	91.5	91.0
Recall [%]	94.1	92.0	91.2
F1-score	0.94	0.91	0.91

3.6. Prediction of energy load — ANN model

To complement the analysis, the prediction of instantaneous power consumption was performed using an artificial neural network (ANN). Model evaluation was conducted on the test dataset, yielding a determination coefficient of $R^2 = 0.71$. This result indicates a moderate yet practically useful predictive quality.

The plot (Figure 9) illustrates the correlation between estimated and measured data points, confirming that the developed ANN model effectively captures the main trends in energy-load variation, despite local deviations resulting from the nonlinear dynamics of the extrusion process.

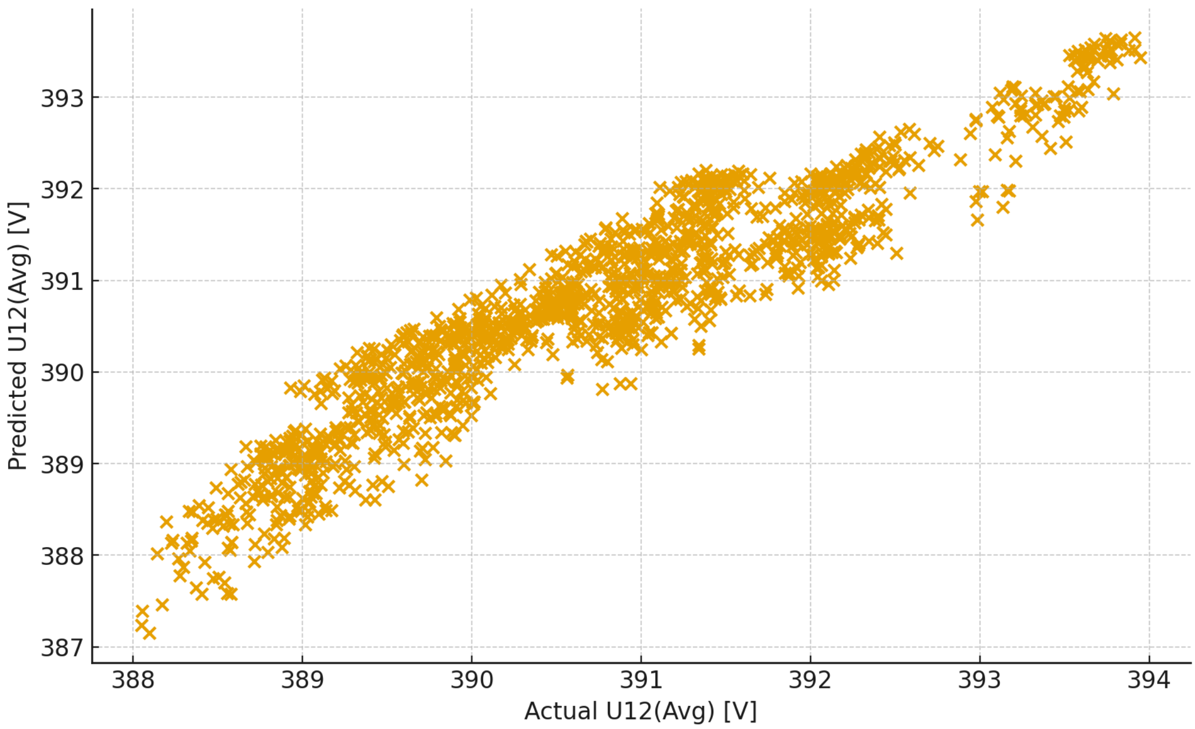

Figure 9. Correlation between predicted and measured power consumption values for the test dataset obtained from the ANN regression model.

The obtained results demonstrate that:

1. Power-consumption signals can serve as a sensitive indicator of screw condition.
2. CWT methods enable graphical identification of wear-related signal patterns.
3. PCA confirms the separability of new (N) and worn (W) screw states in the feature space.
4. CNN enables effective classification of screw condition based on CWT scalograms.
5. ANN allows prediction of the extruder's energy load.

Overall, the findings indicate the feasibility of using electrical signals in combination with deep learning methods for condition monitoring of working components in single-screw extruders.

The moderate prediction accuracy reflects the nonlinear and multi-factor nature of the extrusion process and indicates the need for extended datasets in future studies.

4. Discussion

The results obtained in this study demonstrate that electrical signal analysis provides an effective foundation for diagnosing wear of the working components in single-screw extruders. The observed variations in voltage and power waveforms between the new and worn screw states correspond closely to the physical mechanisms described in earlier research. Progressive deterioration of screw flights and barrel grooves increases flow resistance, alters pressure and temperature profiles in the plasticizing section, and amplifies dynamic loads on the drive system [3-6]. These effects manifest as larger amplitude fluctuations and irregular energy variations in the electrical signal spectra.

The distinct patterns observed in the CWT scalograms for new (N) and worn (W) screws confirm that wavelet-based analysis is highly effective in detecting non-stationary behavior associated with frictional and impact phenomena in the screw–barrel assembly. The predominance of low-frequency components in the N condition, contrasted with the higher share of mid- and high-frequency bands in the W state, reflects the transition from stable to unstable flow regimes. Such spectral changes are consistent with findings from studies on polymer and food extrusion processes [8,13,20]. Comparable effects have also been documented in rotating machinery and induction motors, where mechanical wear, rotor imbalance, or bearing degradation cause transient disturbances and local increases in spectral energy [17,18].

Principal Component Analysis (PCA) offered both qualitative and quantitative validation of the separability of operating conditions. The first two principal components (PC1 and PC2) accounted for more than 99% of total variance, confirming strong correlations among measured parameters. This aligns with prior research that applied PCA for process monitoring and early fault detection in manufacturing systems [10,17,19]. The visualization in the PC1–PC2 plane revealed distinct clustering of data corresponding to the N and W conditions, illustrating that even reduced-dimensional representations can effectively capture machine-state information.

The convolutional neural network (CNN) used for classification of CWT scalograms demonstrated high classification performance, achieving over 90% accuracy. This confirms that deep learning can autonomously extract discriminative features associated with different wear levels. Similar outcomes have been reported for the diagnostics of tribological systems and industrial drives, where CNN models have shown higher classification performance and accuracy than traditional methods such as SVM or k-NN [9,11,12,16]. The superior performance of CNNs results from their capacity to model complex, nonlinear dependencies and to capture hidden time–frequency structures within signals [17,18,19].

Although the dataset employed in this study was relatively small (1429 samples), the achieved classification accuracy highlights the practical applicability of the proposed approach. Further improvement could be achieved by enlarging the dataset or employing hybrid architectures such as CNN–LSTM or Autoencoder–CNN, which integrate spatial and temporal feature extraction [17,19]. The regression analysis based on an artificial neural network (ANN) further confirmed the feasibility of predicting power consumption from current signals. The determination coefficient of $R^2 = 0.71$ indicates satisfactory predictive capability and aligns with other studies emphasizing the nonlinear influence of temperature, friction, and material rheology on process energy demand [12,19]. Importantly, the CNN and ANN address different diagnostic objectives: binary wear-state classification versus continuous power prediction. Their performance measures (accuracy/F1 vs. R^2) quantify different aspects, and the moderate R^2 reflects the multi-factor and nonlinear nature of the extrusion energy load.

From an industrial perspective, the proposed CWT–CNN diagnostic framework is fully compatible with predictive maintenance and the Industry 4.0 concept. Because it relies solely on electrical data available through standard control systems (PLC or SCADA), it allows for low-cost, non-invasive implementation without additional sensors. Similar sensorless approaches have been effectively used in the diagnostics of pumps, gearboxes, and electric drives [8,10].

Integrating signal-processing techniques (CWT, PCA) with deep-learning models (CNN, ANN) provides a comprehensive and scalable platform for monitoring the technical condition of extrusion machinery. This integration enables automatic feature extraction, classification, and energy-load prediction, forming the basis for an intelligent diagnostic ecosystem.

To position the proposed CWT–CNN model relative to other machine learning approaches, a comparative overview is presented below.

Table 4. Comparison of selected machine learning methods applied in machinery diagnostics (classification and regression tasks).

Method	Task	Input Features	Main Advantage	Limitation	Reported performance
SVM (Support Vector Machine)	Classification	Statistical indicators (RMS, kurtosis, skewness)	Simple, interpretable, and computationally efficient	Requires manual feature extraction	80–85% (typ.)
LSTM (Long Short-Term Memory)	Classification	Time-domain sequences	Captures temporal dependencies and dynamic behavior	Demands large datasets and long training time	85–90% (typ.)
CNN (Convolutional Neural Network, this study)	Classification	CWT scalograms (time–frequency images)	Automatic feature learning, robust to noise	Moderate data requirement	Accuracy = 92.3% (F1 = 0.91)
ANN (Artificial Neural Network, this study)	Regression	Current-based electrical features	Predicts energy-load trends	Moderate accuracy; sensitive to process variability	$R^2 = 0.71$

As shown in Table 4, the proposed CWT–CNN model achieves high classification accuracy and automation level while maintaining moderate computational complexity. The regression task addressed with ANN is evaluated using different metrics ($R^2 = 0.71$) and is therefore reported separately, as it is not directly comparable to classification accuracy.

Compared with the study by Danielak et al. [8], which achieved 89.5% accuracy using statistical features, the current CWT–CNN approach improved classification performance by approximately three percentage points, confirming the advantage of deep time–frequency feature extraction for precise screw-wear diagnostics.

Future development should focus on incorporating transfer learning techniques and digital twin solutions to enhance the adaptability of this method and support the evolution of intelligent diagnostic and predictive maintenance systems for extrusion equipment [11,12].

5. Conclusions

1. The developed hybrid diagnostic approach integrating the Continuous Wavelet Transform (CWT) and Convolutional Neural Networks (CNN) enables accurate identification of screw wear in single-screw extruders based on motor electrical signals under the investigated operating conditions. The proposed model achieved a classification accuracy of 92.3%, indicating the diagnostic usefulness of time–frequency representations for wear assessment.
2. Analysis of CWT scalograms revealed distinct differences between operating states. The new screw condition was characterized by a stable, low-frequency energy distribution, whereas the worn screw exhibited intensified mid- and high-frequency components associated with disturbed material flow and increased mechanical load.
3. Current-based CWT analysis demonstrated higher diagnostic sensitivity compared to voltage-based signals, indicating that motor current is a more suitable indicator for assessing wear-related changes in extrusion systems.
4. Principal Component Analysis (PCA) confirmed clear separability between new and worn screw conditions, with the first two components explaining over 99% of the total variance. This result demonstrates that reduced-dimensional representations of electrical parameters can effectively differentiate machine operating states.
6. The Artificial Neural Network (ANN) regression model achieved a coefficient of determination of $R^2 = 0.71$, indicating the feasibility of predicting power consumption trends from current signals and reflecting the nonlinear relationship between energy load and wear

progression.

7. The proposed integration of signal analysis and deep learning methods enables non-invasive condition monitoring of extrusion systems without the need for additional sensors, supporting potential implementation within standard PLC or SCADA-based industrial control environments.
8. Compared with traditional diagnostic approaches based on statistical signal features, the CWT–CNN framework demonstrated improved classification performance and a higher level of automation, indicating its potential applicability in predictive maintenance systems.
9. The methodology developed in this study may contribute to improved reliability, reduced unplanned downtime, and enhanced energy efficiency of extrusion processes. Future research should focus on extended datasets and hybrid model architectures (e.g., CNN–LSTM) to support advanced diagnostic tasks, including Remaining Useful Life (RUL) prediction of working components.

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References

1. Mościcki L., Mitrus M. (2011). Extrusion-Cooking of Starch. In: Mościcki L. (ed.) Extrusion-Cooking Techniques. Wiley-VCH. ISBN 9783527634088.
2. Janssen L.P.B.M., Mościcki L., Mitrus M. (2002). Energy aspects in food extrusion-cooking. International Agrophysics, 16, 191–196.
3. Ekielski A., Osiak J. (2003). Wpływ stopnia zużycia elementów ekstrudera na wybrane parametry ekstruzji. Inżynieria Rolnicza, 7(49), 39–46.
4. Ekielski A., Żelaziński T., Durczak K. (2017). The use of wavelet analysis to assess the degree of wear of working elements of food extruders. Eksploatacja i Niezawodnosc – Maintenance and Reliability, 19(4), 560–564. https://doi.org/10.17531/ein.2017.4.9.
5. Żelaziński T., Ekielski A., Siwek A., Durczak K. (2018). By-products from brewery industry as attractive additives to the extruded cereals food. Carpathian Journal of Food Science and Technology, 10(5), 83–97.
6. Leonard W., Zhang P., Ying D., Fang Z. (2020). Application of extrusion technology in plant food processing by-products: An overview. Comprehensive Reviews in Food Science and Food Safety, 19(1), 218–246.
7. Ekielski A. (2006). Analiza energetyczna procesu ekstruzji z wykorzystaniem metod empirycznych. Inżynieria Rolnicza, 9(84), 45–52.
8. Danielak M., Witaszek K., Ekielski A., Żelaziński T., Dudnyk A., Durczak K. (2023). Wear detection of extruder elements based on current signature by means of a continuous wavelet transform. Processes, 11(11), 3240. https://doi.org/10.3390/pr11113240.
9. LeCun Y., Bengio Y., Hinton G. (2015). Deep learning. Nature, 521, 436–444. https://doi.org/10.1038/nature14539.
10. Zhang J., Kong X., Cheng L., Qi H., Yu M. (2023). Intelligent fault diagnosis of rolling bearings based on continuous wavelet transform–multiscale feature fusion and improved channel attention mechanism. Eksploatacja i Niezawodnosc – Maintenance and Reliability, 25(1). https://doi.org/10.17531/ein.2023.1.16.
11. Polychronopoulos N.D., Moustris K., Karakasidis T., et al. (2025). Machine learning for screw design in single-screw extrusion. Polymer Engineering and Science, 1–17. https://doi.org/10.1002/pen.27170.
12. Delvar E., Oliveira I., Brito M.S.C.A., Silva C.G., Santamaria-Echart A., Barreiro M.-F., Santos R.J. (2025). Literature Review on Single and Twin-Screw Extruders Design for Polymerization Using CFD Simulation. Fluids, 10(1), 9. https://doi.org/10.3390/fluids10010009.
13. Pakhomov V., Braginets S., Rudoy D. (2020). Effect of extrusion on nutritional composition of feed containing mussel meat: Experimental study results. Engineering for Rural Development, 19, 306–312. https://doi.org/10.22616/ERDev.2020.19.TF073.
14. Lachuga Y., Pakhomov V., Braginets S., Bakhchevnikov O., Rudoy D., Maltseva T. (2021). Study of extruded feed from wheat ears during early harvest. IOP Conference Series: Earth and Environmental Science, 937, 032003. https://doi.org/10.1088/1755-1315/937/3/032003.
15. Zhang G., Sun Z., Wang T., Liu L., Zhao J., Zhang Z. (2024). Effects of extrusion on the available energy and nutrient digestibility of

soybean meal and its application in weaned piglets. Animals, 14(23), 3355. https://doi.org/10.3390/ani14233355.

16. Shah R., Sridharan N.V., Mahanta T.K., Muniyappa A., Vaithiyanathan S., Ramteke S.M., Marian M. (2023). Ensemble deep learning for wear particle image analysis. Lubricants, 11(11), 461. https://doi.org/10.3390/lubricants11110461.
17. Xue Z., Yang J., Chen L. (2023). Tool wear state recognition based on one-dimensional convolutional neural networks with attention mechanism. Sensors, 23(9), 4321. https://doi.org/10.3390/s23094321.
18. Yang P., Wang H., Zhu M., Ma Y. (2020). Evaluation of extrusion temperatures, pelleting parameters, and vitamin forms on vitamin stability in feed. Animals, 10, 894. https://doi.org/10.3390/ani10050894.
19. Deokar S., Lin J., Xu Y. (2025). Hybrid CNN–LSTM architecture for mechanical fault detection in rotating machinery. Journal of Industrial Information Integration, 49, 101017. https://doi.org/10.1016/j.jii.2025.101017.
20. Cho J.H., Park J.W., Lee B.J., Kim K.W., Hur S.W. (2023). Low extrusion pressure and small feed particle size improve the growth performance and digestive physiology of rockfish. Aquaculture, 566, 739199. https://doi.org/10.1016/j.aquaculture.2022.739199.