

A Data-Driven Multi-Configuration Parameter based Characterization of Eddy Current Inductive Sensors' Signals using Machine Learning

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Abstract—Eddy current based inductive sensors are widely used in industrial systems for non-contact material characterization, thickness measurement, and defect detection. However, their deployment typically requires extensive manual calibration of hardware and software parameters, resulting in time-consuming and error-prone configuration procedures. This paper presents a generalized data-driven characterization framework using machine learning, in which raw sensor signals are jointly processed with configuration parameters. A deep neural network learns nonlinear dependencies between sensor settings, electromagnetic responses, and target variables. Experimental validation using an industrial eddy current sensor demonstrates significant improvements in material identification and zinc layer thickness classification accuracy, enabling adaptive and task independent inductive sensing.

I. INTRODUCTION

Eddy current inductive sensors play a central role in industrial automation, quality assurance, and non-destructive testing due to their robustness, contactless operation, and suitability for harsh industrial environments. They are widely deployed in applications such as material identification, coating and layer thickness estimation, crack and defect detection, as well as position and displacement measurement. Compared to optical or mechanical sensing principles, eddy current sensors are largely insensitive to contaminants such as oil, dust, or moisture, which makes them particularly attractive for inline industrial measurements. The underlying operating principle is based on electromagnetic induction. A time-varying magnetic field generated by an excitation coil induces eddy currents in electrically conductive targets. These eddy currents, in turn, generate secondary magnetic fields that interact with the primary field, leading to measurable changes in coil impedance or induced voltage. The resulting sensor signal is strongly influenced by the electrical conductivity, magnetic permeability, geometry, and surface condition of the target material. In practical industrial systems, however, the measured sensor signal is influenced not only by the intrinsic properties of the target object but also by a large number of sensor configuration and signal processing parameters. These include excitation current amplitude and slope, pulse duration, amplification gain, signal offset, sampling rate, oversampling strategy, and digital filtering or preprocessing steps. The combined effect of these parameters introduces complex, nonlinear distortions into the measured signal. As a result, even small changes in configura-

tion can significantly alter the sensor response, making reliable interpretation challenging. Conventional calibration and characterization approach typically rely on manual parameter tuning supported by expert knowledge and empirical testing. Such procedures are time-consuming, task-specific, and difficult to scale across different measurement scenarios. In industrial environments where sensors must be rapidly reconfigured for new materials, geometries, or production conditions, this dependence on manual calibration becomes a major limitation. Furthermore, analytical modeling approaches often fail to capture higher-order nonlinearities, cross-parameter interactions, and real-world disturbances present in industrial settings. To address these challenges, data-driven methods based on machine learning have gained increasing attention in recent years. Various studies have demonstrated the potential of supervised learning algorithms, including support vector machines, random forests, and neural networks, to improve classification accuracy and robustness in eddy current sensing applications. Deep learning approaches, in particular, enable automatic feature extraction directly from raw time-domain or frequency-domain sensor signals. Despite these advances, most existing machine learning based approaches assume a fixed sensor configuration during training and deployment. Changes in excitation parameters or signal conditioning typically require retraining the model or repeating the calibration process. Consequently, generalization across varying sensor configurations remains limited, restricting the applicability of such methods in flexible industrial environments. This paper addresses this gap by proposing a generalized machine learning framework that explicitly incorporates sensor configuration parameters into the learning process. By jointly processing raw sensor signals and configuration metadata, the proposed approach enables the learning model to compensate for parameter-induced signal variations and to generalize across a wide range of operating conditions. This significantly reduces the need for manual recalibration and enables adaptive, task independent inductive sensing suitable for modern industrial applications.

II. RELATED WORK

Inductive [1] and capacitive [2] sensors are used for material identification and material deformation analysis. The inductive sensors work on the principle of electromagnetic induction. It applies a time-varying eddy current pulse to the target

material and performs the task of identification based on the response of the material. However, these sensors are affected by multiple parameters. In order to achieve accurate identification results, calibrations must be carried out for these parameters. Traditional eddy current signal analysis is predominantly based on analytical and semi-analytical electromagnetic models derived from Maxwell's equations. Classical approaches describe the interaction between excitation coils and conductive targets by analyzing variations in impedance, phase, or induced voltage as functions of material properties, geometry, and lift-off distance. Well-established formulations exist for simplified geometries such as infinite plates, cylindrical conductors, and layered structures, enabling thickness measurement, crack detection, and material characterization. For example, simplified inductance and impedance models for single-turn eddy current sensors were developed in [1], providing physically interpretable relations between coil parameters and conductive targets. Such analytical descriptions form the basis of many industrial inductive sensing systems. Machine learning has also been widely applied to sensor calibration problems. Neural-network-based self-calibration algorithms have been proposed for pressure sensors [3], while random forest models have been used to improve calibration accuracy in low-cost air-quality monitoring systems [4]. Data-driven calibration strategies have similarly been applied to optical and light sensors [5]. These studies demonstrate the potential of machine learning to compensate for nonlinearities, drift, and environmental effects in sensor systems. Related research in capacitive and proximity sensing further highlights the trend toward integrating intelligent data processing with physical sensor models [2], [6].

Recent advances in eddy current testing (ECT) have increasingly focused on integrating machine learning techniques to improve automation and accuracy. A comprehensive trend toward intelligent defect detection systems has been observed, where machine learning models are used to replace manual interpretation of eddy current signals. For instance, Sahu et al. demonstrated a random forest-based approach for automated flaw detection in heat exchanger tubes, achieving very high classification accuracy and highlighting the effectiveness of data-driven methods for large-scale inspection tasks [7]. Such approaches significantly reduce human dependency and enable real-time analysis.

In addition to classical machine learning methods, deep learning has gained significant attention in recent years. Convolutional neural networks (CNNs) have been successfully applied to eddy current data by treating signals or impedance trajectories as images. Niu et al. proposed a CNN-based defect recognition framework for weld inspection using ECT data, demonstrating robust performance in distinguishing defective and non-defective regions [8]. Similarly, deep learning architectures have been used for solving inverse problems in ECT, such as defect reconstruction and depth estimation, where nonlinear relationships between signals and physical properties are learned directly from data.

Further developments include CNN-based inversion and

uncertainty-aware models for eddy current testing. For example, a deep learning-based inversion model incorporating uncertainty estimation was proposed in [9], showing improved defect detection performance by combining region-of-interest extraction with CNN classification. In another study, complex-valued CNNs were utilized to reconstruct defect geometries from eddy current signals, demonstrating the ability of deep learning to extract spatial and structural information beyond traditional feature-based approaches [10].

Feature-based machine learning methods also remain relevant, particularly when interpretability is required. A notable approach is the extraction of geometric features from Lissajous impedance curves, followed by classification using multiple machine learning models. Such methods provide a balance between physical interpretability and data-driven modeling, achieving high detection accuracy while maintaining insight into signal characteristics [11].

Moreover, recent studies have emphasized the importance of reliability and evaluation frameworks when applying AI to safety-critical Non-Destructive Testing (NDT) applications. For example, sequence-to-sequence deep learning models and probabilistic evaluation frameworks have been proposed for rail inspection using eddy current testing, addressing the need for trustworthy and certifiable AI systems in industrial environments [12]. These works highlight that, beyond accuracy, robustness and explainability are critical for real-world deployment.

Despite these significant advancements, a common limitation across most existing approaches is the assumption of a fixed sensor configuration. The majority of machine learning models are trained and validated under specific excitation conditions, coil parameters, and signal processing settings. Consequently, their generalization capability across varying configurations remains limited. Even deep learning models, while powerful, typically learn implicit relationships within a fixed parameter space and require retraining when the configuration changes.

In contrast to these approaches, only limited work has explored the explicit incorporation of sensor configuration parameters into the learning process. While multi-modal learning strategies have been investigated in other domains, their application to eddy current sensing remains largely unexplored. This gap motivates the proposed work, which introduces a unified data-driven framework that jointly models sensor signals and configuration parameters, enabling improved generalization across varying operating conditions.

III. SENSOR SYSTEM AND DATA ACQUISITION

The experimental setup is based on an industrial eddy current inductive sensor system provided by Picosense Forum GmbH, designed for high-precision material characterization and thickness measurement in industrial environments. The system consists of an excitation and sensing coil unit, analog front-end electronics, and a configurable digital signal processing chain. Its modular architecture allows flexible adjustment of both hardware related and software related parameters,

making it particularly suitable for systematic investigation of parameter dependent signal behavior. A wide range of sensor configuration parameters can be adjusted through the system interface. These include the excitation current characteristics, such as amplitude and current slope, pulse length of the excitation signal, analog output signal amplification, scan depth, signal offset, and the digital oversampling factor. Each of these parameters influences the temporal shape and amplitude of the measured sensor response, either directly through electromagnetic coupling or indirectly via signal conditioning and digitization. The interaction between these parameters is highly nonlinear, motivating a data-driven analysis approach. Measurements were conducted on a set of metallic test samples representative of typical industrial use cases. The material classification dataset includes aluminum, copper, and iron samples, each with comparable geometric properties and surface conditions. To further demonstrate the capability and limits to the classification, samples with and without geometric modifications, such as holes, were included. In addition, another data set uses zinc-coated steel sheets with nominal coating thicknesses of $10\text{ }\mu\text{m}$, $21\text{ }\mu\text{m}$, and $32\text{ }\mu\text{m}$ were used to evaluate the classification of coating thickness performance. These thickness values were selected to represent realistic industrial tolerances and to challenge the sensor's sensitivity. To ensure coverage of a broad operating space, sensor configuration parameters were varied systematically within their permissible ranges. Rather than relying on a single fixed operating point, parameter combinations were selected to reflect realistic variations encountered during industrial commissioning and operation. This approach enables the acquisition of a diverse dataset that captures both material-induced and configuration-induced signal variations. Each individual measurement produces a time-domain sensor signal consisting of variable length (up to 924 sampled values, for shorter signals zero padding is applied) depending on the configuration parameters, corresponding to the electromagnetic response following excitation. The raw signal samples were directly used as input to the learning algorithm. To incorporate configuration dependency, the corresponding sensor parameter values were appended to the signal samples, forming a high-dimensional combined feature vector. This joint representation allows the learning model to explicitly associate signal characteristics with specific parameter settings. The complete dataset was divided into mutually exclusive training, validation, and test subsets. The training set was used for model parameter optimization, while the validation set supported hyperparameter tuning. The test set was reserved exclusively for final performance evaluation to ensure unbiased assessment of generalization capability.

IV. MACHINE LEARNING METHODOLOGY

To model the nonlinear relationship between raw sensor signals, sensor configuration parameters, and the corresponding target classes, a supervised deep learning approach was employed. Given the high dimensionality of the input data and the complex interactions between electromagnetic effects and configuration dependent signal conditioning, deep neural

networks were selected as a suitable modeling framework. Fully connected feed-forward architectures were chosen due to their flexibility and their proven effectiveness in handling heterogeneous input features without requiring explicit spatial or temporal assumptions.

The applied machine learning methodology is depicted in Fig. 1. To carry out experiments with all possible combinations of the 6 parameters require significant amount of time. Therefore, to simplify the setup, the configuration parameters are split to 8 unique sets and for each set 420 responses are generated as dataset for training and testing. We have chosen only 8 unique parameter sets to have quasi-random behavior for the parameters. For the sake of training, the input to the Deep Neural Network (DNN) consists of three complementary components consisting of $M = 930 + 1$ features: the time-domain sensor signal samples (response), the associated sensor configuration parameters, and the label. The raw sensor signal, comprising up to maximum 924 sampled values per measurement represents the transient electromagnetic response of the target material. The configuration parameters encode the operating point of the sensor system (6 parameters in total), including excitation, amplification, and sampling settings. Prior to training, all input features were normalized to ensure numerical stability and to prevent dominance of individual parameters due to differing value ranges. After the learning is performed, the network only get the test data consisting of the response and the configuration parameters. The network architecture is composed of multiple fully connected hidden layers with decreasing numbers of neurons, forming a bottleneck-like structure. This design enables hierarchical feature extraction, where early layers learn low-level signal characteristics and later layers capture more abstract, task-relevant representations. Rectified Linear Unit (ReLU) activation functions were employed in the hidden layers to introduce non-linearity and to mitigate vanishing gradient issues during training. The output layer uses a softmax activation function to produce normalized class probabilities. Two independent models were trained to address distinct classification tasks. The first model performs material classification, distinguishing between different metallic materials and geometric variations. The second model addresses zinc coating thickness classification, where discrete thickness classes are predicted. Model training was conducted using categorical cross-entropy as the loss function, which is well suited for multi-class classification problems. The Adam optimizer was employed due to its adaptive learning rate capabilities and robust convergence behavior. To reduce the risk of over-fitting, early stopping was applied based on validation loss, terminating training when no further improvement was observed. In addition, validation data were used to monitor generalization performance and to guide architectural and hyperparameter selection. This learning strategy enables the network to jointly model signal characteristics and configuration-induced variations, allowing it to learn compensation mechanisms that would be difficult to capture with analytical models or conventional feature-based approaches.

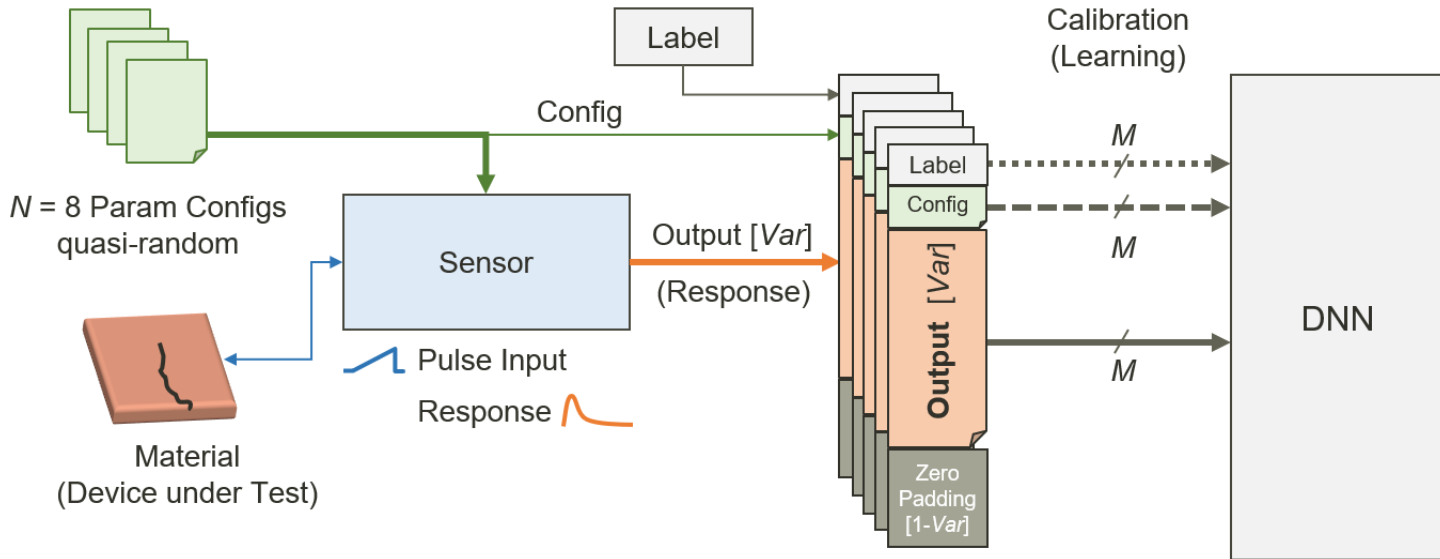


Fig. 1: Machine learning methodology for the calibration learning

V. EXPERIMENTAL RESULTS

A. Material Classification

The performance of the proposed framework was evaluated using two representative classification tasks: material identification and zinc coating thickness classification. These tasks were selected to assess both the sensor's ability to discriminate between materials with different electromagnetic properties and its sensitivity to subtle variations in coating thickness. The proposed neural network architecture is a fully connected feed-forward model designed for multi-class classification. The network accepts an input vector consisting of 930 (924 raw data samples and 6 values for parameters) features that represent the processed signal samples used for classification. The six parameters included as input to the machine learning algorithm are the pulse length (sample count), current slope (slope of the excitation pulse), offset (reference), gain (amplification of the feedback resistor, oversampling rate and, a range extending the value of the second capacitor (1 bit) used for long pulses. The input layer is followed by a sequence of three dense hidden layers with 32, 16, and 8 neurons, respectively. Each hidden layer employs the Rectified Linear Unit (ReLU) activation function to introduce non-linearity and enable efficient learning of complex feature representations while maintaining computational efficiency. This progressively decreasing layer size forms a compact architecture that reduces dimensionality and encourages the extraction of discriminative features. The final layer is a dense output layer with a number of neurons equal to the total number of target classes and uses the softmax activation function to produce normalized probability distributions over all classes. Model performance is evaluated using test accuracy, which measures the proportion of correctly classified samples on an unseen test dataset and provides an overall indication of the generalization capability of the proposed network.

The first evaluation task focused on material classification, and the respective results are provided in Fig. 2 and Fig. 3. Six distinct classes were defined, corresponding to three metallic materials: aluminum, copper, and iron, each measured in two geometric variants with and without geometric modifications. This setup introduces both material-related and geometry-related signal variations by making holes in the materials. The class with holes is denoted by appending H, e.g. for copper without holes we have Cu and with holes we have CuH. Measurements are taken at the target material at defect-free spots and at spots with holes. When the neural network was trained using only raw sensor signals as input features, the model achieved an average classification accuracy of approximately 83% on the test dataset as shown in Fig. 2. Analysis of the confusion matrix revealed that most misclassifications occurred between materials with similar electromagnetic characteristics, particularly in cases where geometric modifications altered the effective eddy current distribution. These results indicate that raw signal information alone is insufficient to fully disentangle material-specific features from configuration-induced distortions. When sensor configuration parameters were included as additional input features, classification performance improved significantly as shown in Fig. 3. The average classification accuracy increased to approximately 94%, representing a substantial relative improvement. Confusion matrix analysis showed a marked reduction in systematic misclassification, particularly for material pairs previously affected by overlapping signal characteristics. This demonstrates that the neural network successfully learned to compensate for variations introduced by different sensor configurations, enabling more reliable material discrimination across multiple operating points.

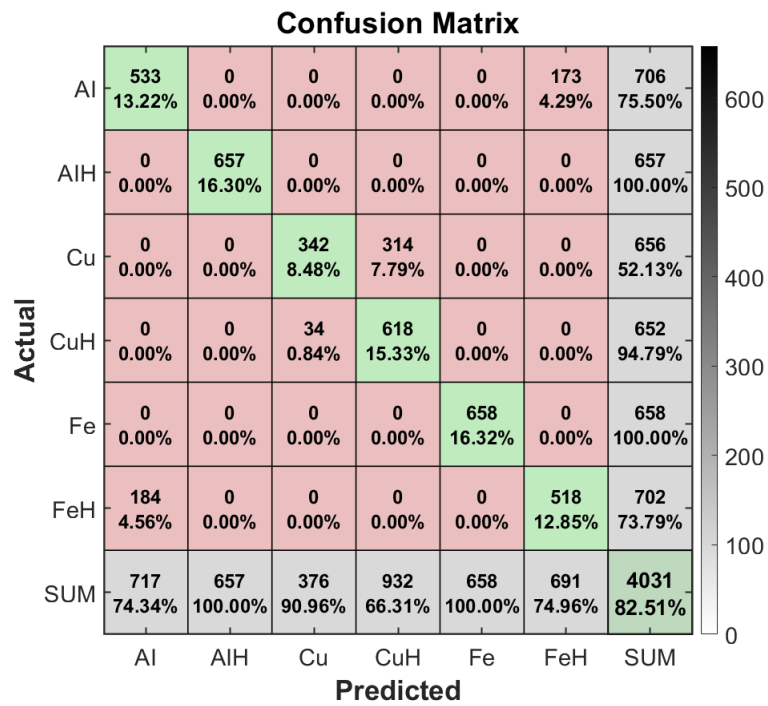


Fig. 2: Confusion matrix for the classification of the metallic materials based on raw signals without inclusion of the calibration parameters in the learning process

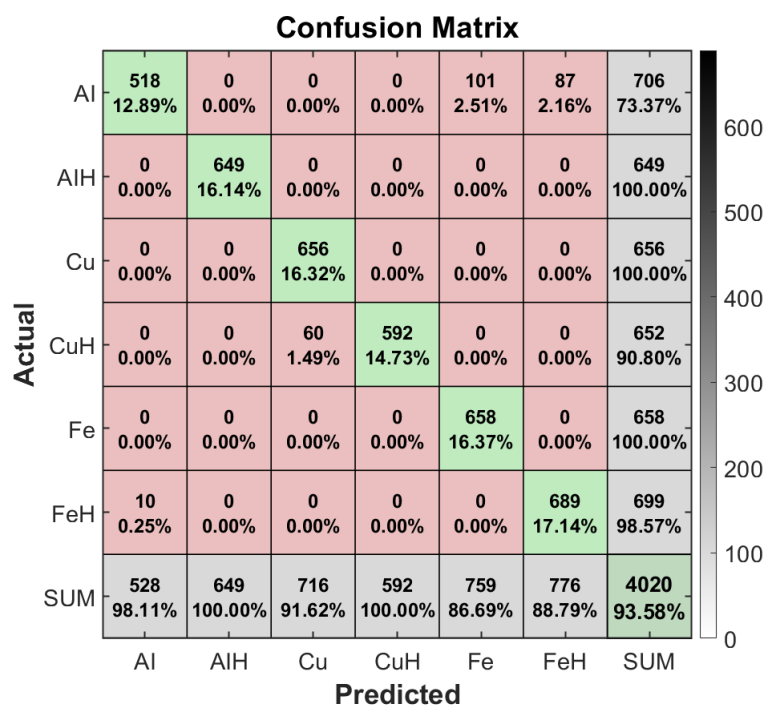


Fig. 3: Confusion matrix for the classification of the metallic materials based on raw signals with inclusion of the calibration parameters in the learning process

B. Zinc Coating Thickness Classification

The second evaluation task addressed zinc coating thickness classification for three nominal thickness values of 10 μm , 21 μm , and 32 μm . This task evaluates the sensor's sensitivity to comparatively small variations in coating thickness, which are of high practical relevance in industrial quality control. Using only raw sensor signals, the neural network already achieved a high classification accuracy exceeding 99% on the test dataset as shown in Fig. 4. This indicates that the eddy current sensor provides strong discriminatory information for thickness estimation under controlled conditions. Nevertheless, minor classification inconsistencies were observed for measurements acquired under differing configuration settings. By incorporating sensor configuration parameters into the input representation, classification robustness was further improved. The resulting model achieved 100% classification accuracy on the test dataset, with no observable misclassifications as shown in Fig. 5. This highlights the benefit of explicitly modeling configuration dependent effects, even in scenarios where baseline performance is already high.

C. Discussion and Results

Overall, the experimental results clearly demonstrate that incorporating sensor configuration metadata significantly enhances model generalization across varying sensor settings. While raw sensor signals contain rich information about material properties, the inclusion of configuration parameters enables the learning model to disentangle material-induced signal characteristics from configuration-induced variations. This leads to more stable and reliable performance across a wide range of operating conditions, which is essential for deployment in flexible industrial measurement systems

VI. CONCLUSION

This paper presented a generalized data-driven characterization framework for eddy current inductive sensors. By integrating raw sensor signals with configuration parameters, a machine learning model was able to achieve robust and task-independent classification performance. Experimental results demonstrated significant improvements in material identification and coating thickness classification accuracy.

VII. ACKNOWLEDGMENT

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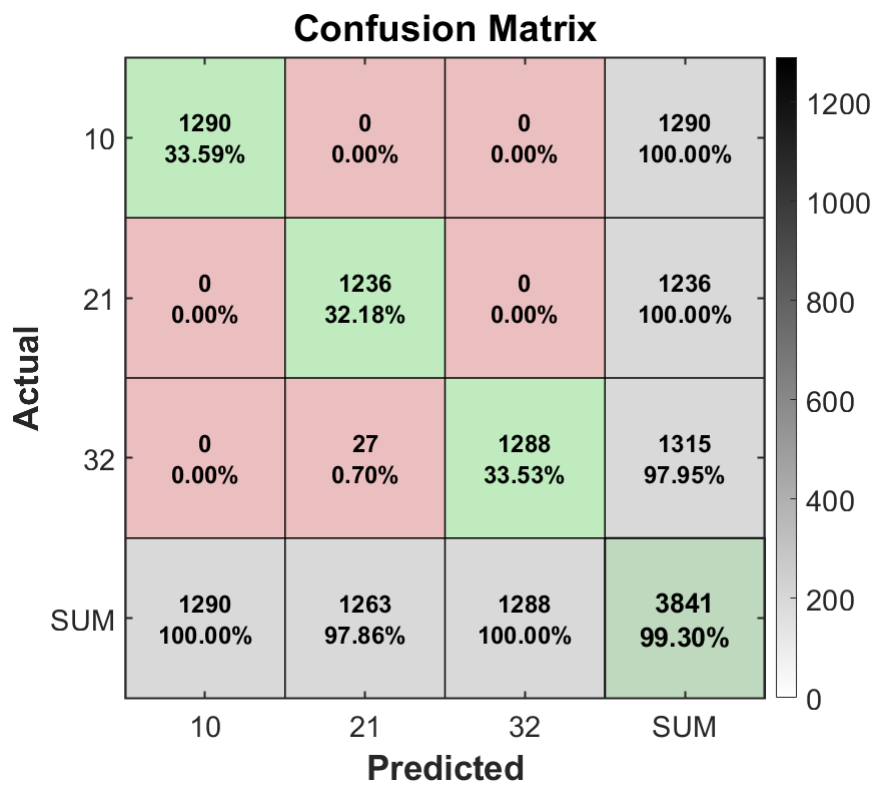


Fig. 4: Confusion matrix for the classification of zinc coating thickness based on raw signals without inclusion of the calibration parameters in the learning process

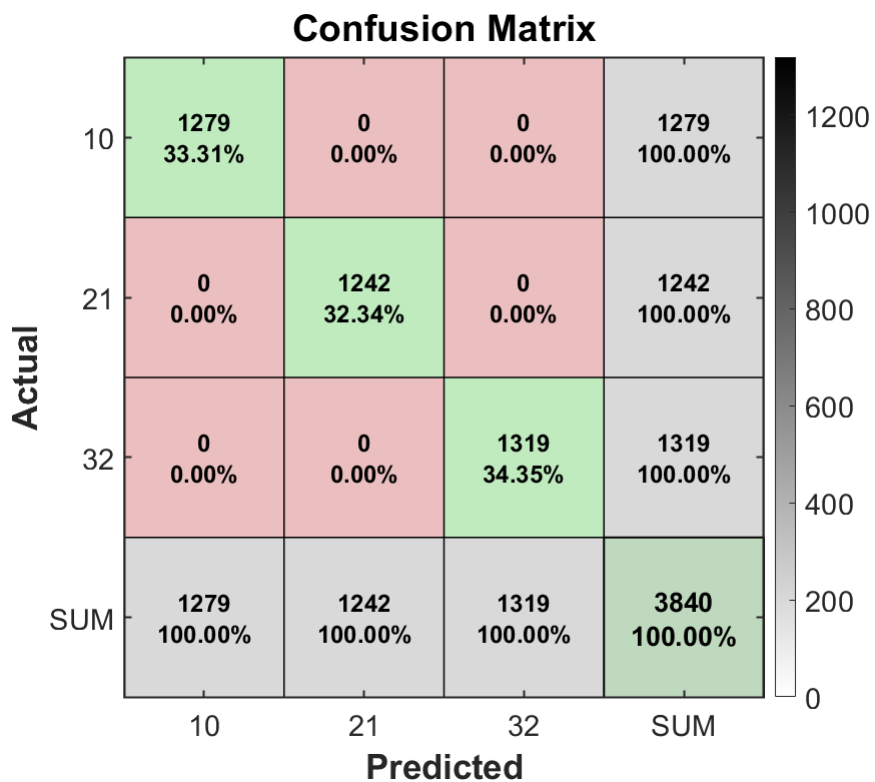


Fig. 5: Confusion matrix for the classification of zinc coating thickness based on raw signals with inclusion of the calibration parameters in the learning process