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APPLICATION OF TRANSFER LEARNING IN METALWORKING FLUID DISTINCTION

Xiao Wei*[1], Fabian Jochmann[1], Anna Lena Demmerling[2], Dirk Söffker[1]

[1] Chair of Dynamics and Control, University of Duisburg-Essen, Duisburg, Germany

[2] Rhenus Lub GmbH & Co KG, Mönchengladbach, Germany

ABSTRACT
This contribution introduces a Transfer Learning (TL) approach for the diagnostic task to distinguish the ingredients of a typical production machine element: metalworking fluid (MWF). Metalworking fluids are oil or water-based fluids used during machining and shaping of metals to provide lubrication and cooling. Additives in MWF affect their performance in different metalworking processes. Performance evaluation of MWF is of relevance for product development as well as for condition monitoring. In this contribution, for the first time, Transfer Learning is adapted for MWF distinction. Firstly, two experiments are designed to get Acoustic Emission (AE) signals from thread forming processes using variant MWF. In the first experiment, eleven kinds of water-based MWF are applied and AE signals are saved into dataset A, while in the second experiment, other five MWF are used in the process of thread forming and AE signals are stored in dataset B. A convolutional neural network (CNN)-based data mining approach including data segmentation, Short-Time Fourier Transform (STFT) and data normalization algorithms is developed from dataset A. Performance of the proposed approach in dataset A is good. Afterwards, parameters in data processing and hyperparameters in CNN of the approach are transferred into dataset B. Results of dataset B show that Transfer Learning allows suitable MWF distinction.

Keywords: Acoustic Emission, Neural Network, Transfer Learning, Algorithms, Data mining

1. INTRODUCTION
Metalworking fluid (MWF) plays a significant role in manufacturing processes allowing to cool and lubricate the contact zone between tool and workpiece to prevent tool wear and to ensure manufacturing of required geometries and surface qualities. The type of MWF and its additives mainly affect tool wear and workpiece surface roughness or make higher machining speeds possible to decrease manufacturing time and increase the output [1]. In [1] additionally the limits of the application of existing standards (here: ASTM) are shown. According to the German Institute for Standardization (DIN) standard 51385, MWF are classified as oil-based and water-based following their formulation liquid. Furthermore, water-based MWF are subdivided into emulsions and solutions. Specific properties are achieved by adding specific substances (additives) such as fatty acid esters, phosphates esters, polysulfides, or glycols [2]. Metalworking fluid can be categorized as cutting fluid, grinding oil, forming oil etc. by the manufacturing process. Usually, the performance of MWF in metalworking processes is evaluated with respect to lubrication, cooling properties, corrosion inhibition, flushing and deforming properties, long term stability, skin and environmental compatibility by testing chemical compatibilities with different materials, conducting corrosion tests, and performing several lubrication tests e.g. tapping torque test (TTT). To recommend the best suitable MWF for each machining process, lubricant manufacturers use empirical data of similar applications as well as results from standard laboratory tests [1].

Acoustic Emission (AE) is a passive method that measures transient stress waves generated by the rapid release of energy from localized sources [3]. The elastic energy propagates a stress wave (i.e. an AE event) in the structure and is detected by sensors attached to or embedded in the structure being monitored. Such an event can be linked to the onset of new damage or to the progression of existing anomalies [4]. Besides it's wide application in materials and structures as a nondestructive testing technique, AE signals are also used in this context. Wei et al. [5] classified AE signals from different MWF in time domain with convolutional neural networks (CNN). Wirtz et al. [6] analyzed AE signals from different MWF with continuous wavelet transform (CWT) and k-mean approach. In this contribution, a new approach is applied for the given task. Besides CWT, Short-

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Time Fourier Transform (STFT) which generates frequency components of local time intervals of fixed duration might be suitable approaches for AE signals time-frequency analysis.

Thread forming is a successive action of the tap lobes, each lobe causes three-dimensions plastic flow which leads to strain hardening of work material [7]. Compared with other metalworking processes, no chips are produced in thread forming processes. As a result, impact of chips on AE signals are reduced in thread forming process. From this point of view, thread forming is a metalworking process generating more accurate AE signals in standard laboratory tests.

Transfer Learning (TL) is a machine learning method to adapt models developed for a task for reusage as the starting point for a model on a second task [8]. In addition that Transfer Learning can train deep neural networks with comparatively little data, it is also an optimization allowing rapid progress and improved performance to model the second task. Models which are transferred to the second task could be pre-trained outstanding models or models developed by users themselves. Many research institutions release models developed on large and challenging datasets like VGG-16, ResNet50, Inceptionv3, and EfficientNet etc. It is an effective way by selecting proper pre-trained models or part of models and adapt or refine them to the target task. Source data which has some relationship with the target dataset should be selected. Then, a suitable model for the source dataset should be developed. Afterwards, the new model could be tuned and reused for the target dataset.

As a class of artificial neural networks, CNN is prevalent in various tasks as a type of deep learning for processing data with grid patterns, such as images. The CNN architectures are inspired and designed to automatically and adaptively learn spatial hierarchies of features from low- to high-level pattern [9]. Typical layers in CNN are convolution, pooling, and fully connected layers. In addition to typical layers, nonlinear activation functions, batch normalization techniques, dropout layers, and softmax layers are involved in CNN to reduce calculation time and avoid overfitting.

In this contribution, TL is applied on MWFs' Acoustic Emission signals classification for the first time. Two datasets (dataset A and dataset B) which contain AE signals obtained from thread forming processes with diverse MWFs are classified. Details about the dataset are given in Section 3. In the procedure of classifying dataset A, a CNN-based model is designed. Results show that it performs well. After that, this model is reused for distinguishing data in dataset B. Good results in dataset B show that TL is a potential approach for MWF distinction.

The structure of this contribution is organized as follows: A brief introduction of TL is presented in Section 2. In Section 3, the test rig and two datasets will be introduced. Model developed from dataset A and knowledge transferred to dataset B will be introduced in detail in Section 4. Results and discussion are described in Section 5. Finally, conclusions are given in Section 6.

2. TRANSFER LEARNING

Data mining and deep learning (DL) has been successfully studied and researched in the field where patterns from training data can be extracted to predict future outcomes. Compared with traditional machine learning, in DL features are automatically deduced and optimally tuned for desired outcomes. In other words, features are not required to be a-priori extracted. Deep learning requires very large amount of data and high computational costs to perform better than other techniques [10]. Furthermore, there is no standard theory in selecting right deep learning tools [11]. Therefore, generating a related deep learning model for a target domain trained from a related source domain is a cost-effective way [12].

Transfer Learning is a machine learning technique where a model trained on source domain is repurposed on target domain. According to [13], some notations and definitions used in TL are introduced. The definition of 'domain' and 'task' is defined in the following. According to [4], a domain $\mathcal{D}$ consists of two components: a feature space $\mathcal{X}$ and a marginal probability distribution $P(X)$, where $X = \{x_1, \dots, x_n\} \in \mathcal{X}$. Given a specific domain, $\mathcal{D} = \{\mathcal{X}, P(X)\}$, a task consists of two components: a label space y and an objective predictive function $f(.)$ (denoted by $\mathcal{T} = \{y, f(.)\}$), which is not observed but can be learned from training data, which consists of pairs $\{x_i, y_i\}$, where $x_i \in \mathcal{X}$ and $y_i \in y$. the function $f(.)$ can be used to predict the corresponding label $f(x)$ of a new instance x. Given a source domain $\mathcal{D}_s$ and learning task $\mathcal{T}_S$, a target domain $\mathcal{D}_T$ and learning task $\mathcal{T}_T$, transfer learning aims to improve the learning of the target predictive function $f_T(.)$ in $\mathcal{D}_T$ using the knowledge in $\mathcal{D}_s$ and $\mathcal{T}_S$, where $\mathcal{D}_s \neq \mathcal{D}_T$, or $\mathcal{T}_S \neq \mathcal{T}_T$ [14].

Based on different situations between source and target domains and tasks, TL can be categorized in three subsettings: inductive TL, transductive TL, and unsupervised TL [13]. The inductive Transfer Learning setting, the target task is different from the source task, when the source and target domains are the same (see Table 1). In the transductive TL setting, the source and target tasks are the same, while the source and target domains are different. In the unsupervised TL setting, similar to inductive TL setting, the target task is different from but related to the source task [15]. However, the unsupervised TL focuses on solving unsupervised learning tasks in the target domain, such as clustering, dimensionality reduction, and density estimation.

TABLE 1. THREE SUBSETTINGS FOR TRANSFER LEARNING

Learning settings		Source and target domains	Source and target tasks
Transfer learning	Inductive	Identical	Different but related
	Unsupervised	Different but related	Different but related
	Transductive	Different but related	Identical

Based on 'what to transfer', approaches to TL in the above three different settings can be summarized into four cases:

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instance-transfer, feature-representation-transfer, parameter-transfer, and relational-knowledge-transfer.

3. EXPERIMENTS AND DATASETS

To obtain AE signals from different MWF in the process of thread forming, two laboratory experiments are conducted. These experiments are results from collaboration between the Chair of Dynamics and Control, University of Duisburg-Essen and Rhenus Lub GmbH & Co KG Mönchengladbach. Furthermore, measurements and data pre-processing are related to this cooperation.

The experimental test rig is shown in Figure 1. It consists of a tribometer of type Tauro®120 (Taurox e. K., Germany), a test platform made of C45E (1.1191), a thread forming tool of the type Emuge M6-6HX InnoForm1-Z HSSE-TiN-T1, different test and reference fluids, and a cleaning station with brushes and air blow system to remove chips and fluid residues. To avoid the influence of debris and chips on AE signals during these experiments, before testing, the test platform and the new tap are cleaned in an ultrasonic bath, dried in an oven at 50 °C, and cooled down to room temperature afterwards. Among different fluids, the tap is manually cleaned with a cleaning solvent. After each thread forming process, the tap is automatically cleaned in a cleaning station.

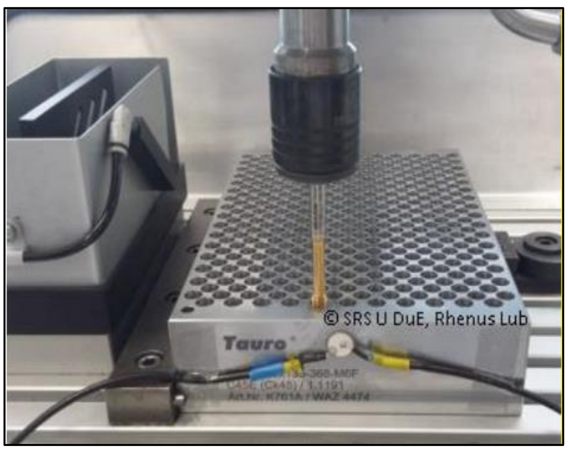

FIGURE 1. TEST RIG

A custom FPGA-based AE measurement system is used for the recording of the AE signals. At the front of the test platform (Figure 1), a disc-shaped broadband piezoelectric transducer is attached. The transducer is mounted using cyanoacrylic glue, has a diameter of 10 mm, a thickness of 0.55 mm, and a corresponding resonant frequency of 3.6 MHz. The AE measurements are acquired continuously at a sampling rate of 4 MHz.

For the first experiment, the test platform has 368 (5.6H7 mm) pre-drilled holes of 28 mm in depth, arranged in 23 columns and 16 rows (from the back to front, the holes in the first column is named hole 1 to hole 16, the holes number in the second column are 17 to 32, the third column holes are named 33 to 48, etc.). For convenience, each thread forming process is named as one measurement and measurements with one MWF is named as one series. The active tool length is 8 mm with a cutting lead of approximately 2-3 mm and a thread pitch of 1 mm. In this experiment, 11 emulsion-based (reference and 10 other fluid) fluids are filled in pre-drilled holes. Before each test fluid, the reference fluid is applied to set same initial test conditions for each fluid. This means that the first column pre-drilled holes are filled with reference fluid, the second column pre-drilled holes are filled with fluid 1, the third column holes are with reference fluid again, the fourth column holes are filled with fluid 2, …etc. In short, holes in the odd-numbered column are filled with reference fluid and holes in the even-numbered column are filled with the other 10 liquids (series 1, 3, 5, … are reference measurements while series 2, 4, 6, … are test measurements). As AE data from the last two columns are contaminated, so they are not considered in the calculation. Fluid and their additives that are applied in this experiment are listed in Table 2. Acoustic Emission signals taken from this experiment are stored in dataset A.

TABLE 2. METALWORKING FLUID APPLIED IN THE FIRST EXPERIMENT

MWF	Additives	Additive substance
Reference	-	
Fluid 1	Sodium sulfonate	4800 ppm
Fluid 2	Polysulfid, AS: Sulfur	1600 ppm
Fluid 3	Polysulfid, AS: Sulfur	2400 ppm
Fluid 4	Lauryl ethylene oxide phosphate	160 ppm
Fluid 5	Oleyl ethylene oxide phosphate	160 ppm
Fluid 6	Stearyl propylene oxide phosphate	86 ppm
Fluid 7	2-ethylhexylcocoate	8000 ppm
Fluid 8	Synthetic polymeric ester	8000 ppm
Fluid 9	Diethylene glycol	8000 ppm
Fluid 10	Polypropylene glycol	8000 ppm

In the second experiment, 112 threads of 28 mm in depth are formed at a speed of 1000 rpm using 5 different MWF. In this experiment, both water-based (fluid 1 and fluid 2) and oil-based (fluid 3 and fluid 4) MWF are applied. The reference fluid is different from the reference fluid in the first experiment. Basis and additives of these 5 fluids are listed in Table 3.

TABLE 3. METALWORKING FLUID IN THE SECOND EXPERIMENT

MWF	Basis	Water	Oil	Ester	Phosphorus
Reference	Water	95 %	0 %	1.25 %	50 ppm
Fluid 1	Water	95 %	1.4 %	0 %	3163 ppm
Fluid 2	Water	95 %	1.4 %	0 %	48 ppm
Fluid 3	Oil	0 %	85 %	6.5 %	80 ppm
Fluid 4	Oil	0 %	85 %	6.5 %	1600 ppm

Different from the first experiment, in the second experiment, pre-drilled holes with the same fluid are located in

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different columns. The detailed holes filled with these 5 fluid are shown in Table 4. Acoustic Emission signals in the second experiment are named dataset B.

TABLE 4. MEASUREMENTS IN SECOND EXPERIMENT

Series	MWFs	Pre-drilled holes
1	Reference	1-32
2	Fluid 1	33-40
3	Fluid 2	41-48
4	Fluid 3	49-56
5	Fluid 4	57-64
6	Reference	65-72
7	Fluid 4	73-80
8	Fluid 3	81-88
9	Fluid 2	89-96
10	Fluid 1	97-104
11	Reference	105-112

Dataset A contains more data than dataset B. Besides, all AE data in dataset A are from water-based MWF while oil-based and water-based MWF are in dataset B. Furthermore, the series of measurements for each MWF in dataset B is more complicated than in dataset A, so data processing in dataset B is more complex than in dataset A. With respect to the above considerations, dataset A is chosen as source domain while dataset B is the target domain.

4. PROPOSED APPROACH

4.1 Data processing

Except for the reference fluid, 16 measurements are realized for other MWF in both experiments, which means 16 samples for training in each class. However, the prerequisite for neural networks is to have sufficient samples. In case that there is not enough data, CNN model cannot be trained to avoid inaccurate results. In addition, the process of thread forming could be divided into air, forward, and reverse parts as shown in Figure 2. In the air part, no useful AE data as tap has no contact with platform, therefore, data in this part should be removed as preprocessing step.

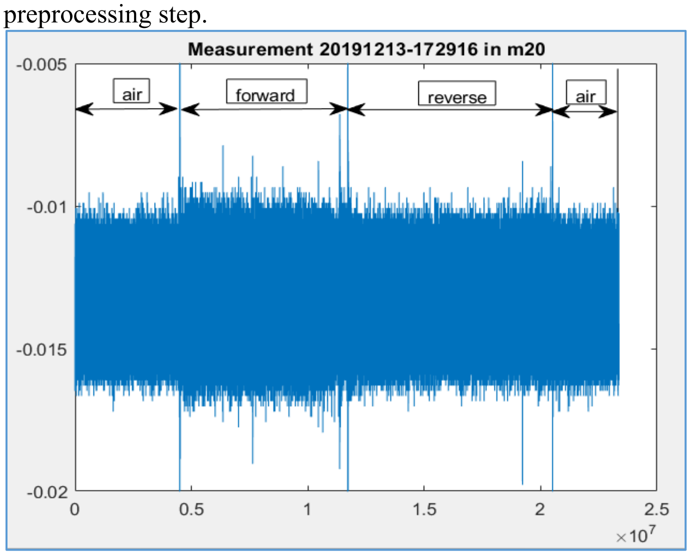

FIGURE 2. ORIGINAL AE SIGNAL

The procedure of data processing can be divided into data selection, segmentation, transformation, and normalization. To make sample numbers equivalent in each class, the first series data of reference fluid in both experiments is chosen. Afterwards, the forward part of each measurement is picked out from the whole measurement data. Each measurement forward part data is divided into proper segments according to tap speed. By adjusting parameters in STFT, segments are transformed from time domain to time-frequency domain and generating spectrograms. In Figure 3, one segment spectrogram is shown. Finally, to get rid of a number of anomalies making analysis of the data more complicated and reducing database space, spectrograms are normalized by Z-Score and Min-Max techniques. To get better results, parameters in each step are optimized by exhaustive sweep algorithm.

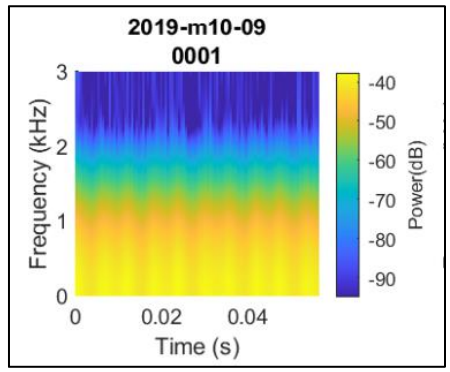

FIGURE 3. SPECTROGRAM OF ONE SEGMENT

4.2 CNN model based on dataset A

For spectrogram-based distinction a deep learning approach based on CNN is used. Hyperparameters determining the network structure and variables determining how the network is trained have significant effects on classification.

The structure of the proposed model considered for training is a basic CNN with six convolutional layers denoted as Basic6. The first layer of the Basic6 model is the image input which have been normalized by Min-Max, so every input is normalized in the range [0-1]. Feature extraction is done by six convolution (con) layers which are individually followed by batch normalization (norm), ReLU (relu) activation function, and max pooling (pool) layers. To prevent the model from overfitting, three dropout layers are used between convolutional layer 2 to 5. The classification is realized by a fully connected (fc) layer which has as many neurons as class numbers and softmax layer. Final results are presented by the classification output layer. All layers of the Basic6 network are shown in Figure 4.

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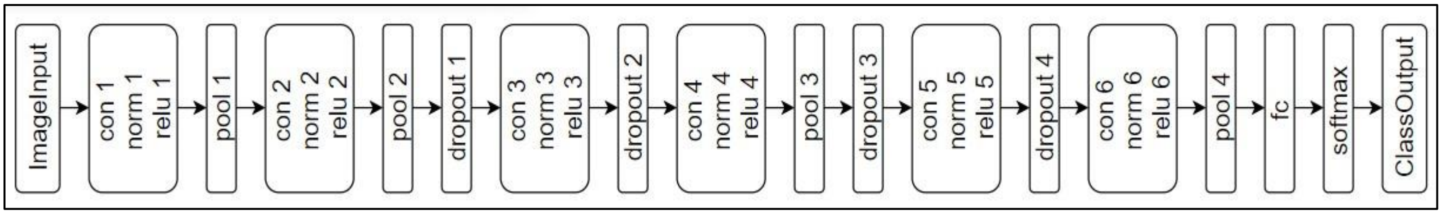

FIGURE 4. CNN STRUCTURE FOR DATASET A

Hyperparameters tuning on training algorithm is time-consuming. Many hyperparameters have to be tuned like optimizer, mini batch size, initial learn rate, max epochs etc. To define proper hyperparameters, exhaustive sweep and Bayesian optimization techniques are applied for the proposed CNN model. Firstly, an exhaustive sweep algorithm is used to sweep all possible combinations of hyperparameters values. In this step, a rough review of good parameter ranges is obtained. Afterwards, Bayesian optimization is applied to minimize the distance of the evaluation metric from its optimal value by changing the initial hyperparameters values in a given ranked sequence. After hyperparameters optimization, the best value of every hyperparameter and best combination among them are settled down.

4.3 Transfer Learning to dataset B

Like data processing in dataset A, AE data in dataset B are also selected, segmented, transformed, and normalized. The threading process of one thread consists of 27 tap spins that can be divided into segments due to one tap round. Tap speed in the first experiment is 1061 rpm while tap speed in the second experiment is 1000 rpm. Considering sampling rate for both experiments is 4 MHz, each round contains 226200 data in the first experiment while each round contains 240000 data in the second experiment. When selected part (forward) of each measurement are partitioned into segments, segment's length is designed based on data number in each round. As result segment length in the second experiment is different from the first experiment. To keep the main properties of each segment, overlap among adjacent segments is needed. In dataset A and B, the overlap among adjacent segments is similar but not identical. Other parameters related to the processes of data segmentation, STFT, and normalization are equal. From this point of view, in the data processing step, parameters in each step are transferred from dataset A to dataset B.

Although different data in dataset A and B, the task for both datasets is MWF classification. Convolutional neural network model that are trained using dataset A for the classification task could be transferred into dataset B. Hyperparameters related to network structure are equal in both datasets. In dataset A, eleven MWF should be distinguished. So in the last layer, the class number should be eleven. In dataset B, five different MWF need to be differentiated, so the class number is five. Briefly, the class number needs to be changed. According to the subsettings of these two datasets, transductive TL is applied to them. Furthermore, as just the last classes number are different, other hyperparameters in CNN model are the same, so parameter-transfer is also applied for the proposed approach.

5. RESULTS AND DISCUSSION

Different metrics can be used to evaluate training and test. In many recent contributions [5, 9, 16], accuracy as the metric denoting the ration between the total number of correct predictions and the total number of predictions for a dataset is applied. However, as performance measure, accuracy is inappropriate for imbalanced classification problems. Precision and recall are alternatives. Precision quantifies the number of positive class predictions that actually belong to the positive class while recall quantifies the number of positive class predictions made out of all positive examples in the dataset. F-score provides a suitable step that balance both the concerns of precision and recall in one number [16]. In most classification problems, imbalanced class distribution exists, so F-score is a suitable alternative metric. For the proposed approach, both F-score and accuracy are used for evaluation.

4-fold cross validation is applied to evaluate trained models. Cross validation is a resampling procedure used to evaluate machine learning models. Generally, results from cross validation have a lower bias than other methods [17].

Detailed results of both datasets are shown in Table 5. For dataset A, F-score for each fold ranges from 98.15 % to 98.92 % and the mean F-score is 98.61 %. The accuracy for dataset A is 98.58 %. When the CNN model is transferred to dataset B, the mean F-score is 86.85 % and accuracy is 86.20 %. In contribution [5], AE signals of the same kinds of MWF are also classified by CNN trained by dataset B itself. In [5], Acoustic Emission signal features are extracted in time domain. Here five kinds of MWF are firstly divided into three categories and then water-based and oil-based MWF are subdivided. The best classification accuracy is 79.87 % and the worse result is 67.54 %. Compared with results in [5], the results from TL for dataset B are improved.

TABLE 5. RESULTS FOR BOTH DATASETS

Data sets	Results (%)					
	F-score					Accuracy
	1	2	3	4	mean	
A	98.58	98.80	98.15	98.92	98.61	98.58
B	70.30	91.30	94.51	91.30	86.85	86.20

From results and calculation process, the following conclusions can be given.

1) The preprocessing of AE signals has a significant impact on MWFs classification results improving the extracting process of signals features.
2) The best classification result comes from segments containing 5 round data.

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3) Comparing parameters and hyperparameters tuned manually in data processing and CNN, optimization techniques can be applied to save time.
4) The structure and other hyperparameters of trained models from dataset A could be transferred to dataset B.

Although results in dataset B are not as good as dataset A, but improved in relation to previously published best results [5], which demonstrates that knowledge and parameters in data processing as well as hyperparameter in convolutional neural networks could be transferred to dataset B. As a concluding result it can be stated that the proposed approach trained from water-based MWF distinction could be transferred to other kinds of MWF classification.

6. SUMMARY AND CONCLUSION

To differentiate MWFs, two thread forming experiments which apply different kinds of MWFs in pre-drilled holes are conducted. In the first experiment, eleven water-based MWFs are used while five water-based and oil-based MWFs are applied in the second experiment. By data selection, segmentation, transformation, and normalization, AE signals data are processed. Via CNN structuring and hyperparameters optimization, an approach is raised and eleven MWFs are well distinguished in the first experiment by the proposed approach. Afterwards, knowledge and parameters in data processing as well as hyperparameters in CNN are transferred to the AE signal distinction on the second experiment. The good classification results in the second experiment show that transfer learning can be successfully applied for MWF distinction.

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