

Laporan Penelitian



A CNN Prediction Method for Belt Grinding Tool Wear in a Polishing Process Utilizing 3-Axes Force and Vibration Data

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Abstract

Every This paper presents a tool wear monitoring methodology on the abrasive belt grinding process using vibration and force signatures on a convolutional neural network (CNN). A belt tool typically has a random orientation of abrasive grains and grit size variation for coarse or fine material removal. Degradation of the belt condition is a critical phenomenon that affects the workpiece quality during grinding. This work focuses on the identification and the study of force and vibrational signals taken from sensors along an axis or combination of axes that carry important information of the contact conditions, i.e., belt wear. Three axes of the two sensors are aligned and labelled as X-axis (parallel to the direction of the tool during the abrasive process), Y-axis (perpendicular to the direction of the tool during the abrasive process) and Z-axis (parallel to the direction of the tool during the retract movement). The grinding process was performed using a customized abrasive belt grinder attached to a multi-axis robot on a mild-steel workpiece. The vibration and force signals along three axes (X, Y and Z) were acquired for four discrete sequential belt wear conditions: brand-new, 5-min cycle time, 15-min cycle time, and worn-out. The raw signals that correspond to the sensor measurement along the different axes were used to supervisedly train a 10-Layer CNN architecture to distinguish the belt wear states. Different possible combinations within the three axes of the sensors (X, Y, Z, XY, XZ, YZ and XYZ) were fed as inputs to the CNN model to sort the axis (or combination of axes) in the order of distinct representation of the belt wear state. The CNN classification results revealed that the combination of the XZ-axes and YZ-axes of the accelerometer sensor provides more accurate predictions than other combinations, indicating that the information from the Z-axis of the accelerometer is significant compared to the other two axes. In addition, the CNN accuracy of the XY-axes combination of dynamometer outperformed that of other combinations.

Keywords: convolutional neural network; manufacturing; prediction; grinding process; vibration and force signal.

1. Introduction

In manufacturing industries, the requirements for high-quality precision parts with complex geometries have been increasing rapidly [1–3]. A workpiece generally goes through various stages such as machining, finishing and polishing to attain prescribed design specification and tolerance [4]. The development of science technology, modern control theory, and advanced machining techniques using multi-axis arm robot has enabled automated finishing and polishing for curved surfaces to achieve uniform quality.

The quality of surface finish for a complex geometry part in manufacturing processes, e.g., grinding and polishing, depends primarily on two main variables, i.e., (1) the condition of belt grinding tool and (2) the combination of operating parameters such as cutting speed, force, feed rate, polymer wheel hardness and grit size. Monitoring the condition of the belt grinding tool is necessary because if the tool deterioration is undetected, it will affect the material removal

mechanism and ultimately affect the workpiece's surface quality. In addition, the polishing process parameters are also an important aspect as they must be adaptable during the manufacturing process depending on certain scenarios or condition such as (1) the curvature shape of the workpiece, (2) the changes in abrasive tool wear condition, (3) the hardness of the workpiece, which is generally not fully uniform and (4) the area of the workpiece being manufacture, e.g., at the edges or toward the part center. This study focuses on predicting belt grinding tool condition from brand-new to wear with certain manufacturing parameters.

Several studies on tool condition monitoring found in manufacturing process literature mainly concentrate on the cutting tool and the milling process [5–9], while those on the belt grinding tool condition and prediction are still limited [10]. The abrasive belt grinding is a modification of the traditional rigid grinding process. However, the advantage of belt grinding over traditional grinding lies in its ease to uniformly machine any intricate geometries for workpieces [11,12]. The polymer wheel backing of the belt grinding tool on which the belt embedded with abrasive grains rests enables conformability with the intricate surfaces [13]. Due to the nature of the polymer backing's compliant, the process is highly nonlinear and dependent on the process parameters [11,14]. The belt grinding tool consists of three primary parts, namely the driving mechanism, the polymer wheel and the belt itself. The driving mechanism generally consists of at least two wheels in which the belt rotates. The compliance depends primarily on the type and contour of the backing material, and finally, the belt grit size and grain composition define the longevity and the material removal characteristics. Apart from the three primary components, the operating style, such as the applied force, the depth of cut, feeding direction, lubrication, the angle of feed etc., also affects the process dynamics [15].

Out of all the process parameters, only the belt degradation over the cycle time cannot be controlled. The degradation of the belt happens with the abrasive grains withering out or by the grains degenerating resulting in loss of performance of the tool [16]. Several approaches have been proposed on monitoring tool states in the grinding process using the sensor data acquired during the process and state of the art machine learning (ML) algorithm [17–20]. Apart from the tool wear, Deep Learning (DL) based auto-encoder architecture has been used to perform pixel-level classification of weld seam/bead states [20]. Spectrograms computed from the sound signals with DL method have been used to classify wear states of the abrasive belt [10]. A multi-sensor fusion method of vision and sound have been used along with a light gradient boosting machine (LightGBM) algorithm to monitor in-process grinding material removal rate (MRR) [21,22].

The advancement of the manufacturing process equipped with an intelligent method opens the possibilities to answer the existing challenges. An alternate monitoring strategy using CNN and signals input from the accelerometer and force sensor is proposed in this study for monitoring the belt states. To apply ML and DL methods in tool condition monitoring, the inputs representing the dynamic condition between the abrasive grinding tool and the workpiece play an important role. It has been studied that the appearance of vibration, force and torque variable in the polishing process can be determined as the indicator of the tool wear condition [17]. To date, most of tool wear condition monitoring methods in abrasive processes, such as grinding and polishing, rely on human-interference inspection and is typically conducted as an offline measurement exercise. The

offline measurements consequently will interrupt the entire grinding and polishing process due to dismounting and re-mounting procedures of the working coupon to its reference point. This interruption leads to disruptions in the production line. This paper aims to open the possibility of using the DL method for belt tool condition prediction and the potential implementation towards online monitoring systems.

CNN is one of the DL algorithms based on the convolution sliding kernel approach [23]. CNN is usually implemented for classification and prediction methods to avoid unnecessary intermediate step of computing sparse representation such as time, frequency and time-frequency features as they can handle raw data with minimum pre-processing. The CNN algorithm has also been applied in 1-dimensional (1-D) signal, e.g., audio and vibration signal, and 2-dimensional (2-D) data, e.g., images. More details of CNN algorithm is described in Section 2. Specific to the application of CNN in the manufacturing area, especially in tool condition monitoring, CNN has been applied in tool condition monitoring such as for end milling [7]. The previous work of the authors in [13] presents the application of analysis of variance (ANOVA) combined with an adaptive neuro-fuzzy inference system (ANFIS) to model material removal. The combined ANOVA and ANFIS method is used to obtain the optimum configuration between the process parameters/variables of abrasive belt grinding such as RPM, feed, force, rubber hardness and grit size and the stock material removal rate. In the present work, the CNN method is applied to the vibration and force signal from a three-axis accelerometer and a three-axis dynamometer collected during the polishing process to monitor the belt degradation. A new belt grinding tool was used in the polishing process of the mild-steel workpiece with certain manufacturing parameters until wear. The workpiece's polishing process was performed using a customized abrasive belt grinding attached to a multi-axis arm robot. The vibration and force signals are acquired from the 4 discrete sequential conditions of the belt grinding tool from new to wear (brand-new, 5-min cycle time, 15-min cycle time, worn-out) during the polishing process of the mild-steel workpiece. The '5-min cycle time' and '15-min cycle time' mean that the belt is prepared by polishing continuously for 5 and 15 minutes, respectively. This study also aims to correlate the vibration and force sensor axes directions with the belt grinding condition.

The paper is organized into 5 Sections. Section 1 briefly reviews the belt degradation, its influence on surface quality, and the real-time monitoring strategies. Section 2 gives a brief overview of the CNN architecture used for this work. Section 3 introduces the robotized belt grinding experimental setup, processing parameters and data acquisition setup. Section 4 presents and discusses the CNN classification results on the sensor data. Finally, Section 5 summarizes this investigation's findings and future works.

2. Materials and Methods

2.1. Convolutional Neural Network (CNN)

CNN is a feed-forward neural network inspired by the brain's visual cortex and specializes in processing data with a grid or a sequential structure [24]. CNN is specifically designed for handling multiple arrays as the input. This initial input process of CNN is analogous to imitating the eyes to identify images, followed by a training process for further recognition of the scene [25].

However, to predict well on tricky scenarios, in many cases CNN must be designed with a more complicated architecture. Even though CNN takes higher computational time and hardware resources compared to traditional ML methods (support vector machine (SVM), artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) etc.), they are very efficient in processing raw data with minimum pre-processing.

CNN's are well known as a first applied method for tool wear prediction compared to other DL methods such as recurrent neural network (RNN), gated neural network (GNN) and long short-term memory (LSTM) [10,11,21,26]. CNN can have different architectures, and it depends based on the problem at hand. The model might have different layers such as VGG-16 (16 layers), LeNet, googleNet (22 layers), AlexNet (8 layers), Res-Net (152 layers), etc., and also can use different transformation such as ReLu (rectified linear unit), Dropout and batch normalization. The parameters used for the model training are primarily chosen in such a way as to reduce computational cost and hardware utilization. CNN training parameters are chosen based on exhaustive search or on trial and error [27,28].

The first modern CNN used by Tavakkoli et al. [29] has a 7-layer structure (excluding the input layer), namely LeNet-5, which has the following structures C1, S2, C3, S4, C5 and F6 output. In addition, Zhang et al. [27] reported that several layers in a CNN model are to be considered for better performance. The following layers on CNN considered in this work following [27], are as follows:

- The sub-sampling layer is usually used to reduce the dimensions coming from the input. The sub-sampling layer's goal is to reduce the number of trainable parameters needed on CNN, which can speed up the performance of CNN. The speed means computational time. By optimizing the CNN architecture, the accuracy and computational time cost could be obtained as fast as possible. The speed also means using fewer resources in identifying images.
- The convolutional layer works by imitating the properties of the visual cortex of the brain for studying the features from input images. Filters or kernels trained at this layer can identify specific shapes. For example, if it is used to study an image, the filter might learn for edge detection.

2.2. CNN Structure Used in the Present Study

The structure of CNN varies depending on the application, for example, the structure presented in [33]. The details of the CNN architecture to classify belt wear states is presented in Figure 12. The CNN architecture consists of 10 layers, namely 6 one dimensional (1D) convolution layer, 1 max-pooling layer, 1 global average pooling layer, 1 drop layer and 1 fully connected layer. Furthermore, each 1D convolution layer constitutes 200 filters, in which the filter weights have been initialized with random values before training. Additionally, the kernel length of size 4 is used in the convolution process between the signal and filter. At the first stage, the CNN receives the raw time-series 1D signals from a three-axis dynamometer sensor (X, Y and Z) and a three-axis accelerometer sensor (X, Y and Z). In the first layer (L1), each raw signal (X, Y and Z) from the dynamometer and accelerometer sensors are convolved with the filter kernels. Subsequently, the results of the convolutions at each layer are used as input to the next layers. In the fourth layer, to reduce the number of inputs, a pooling layer is applied. In this case, the max-pooling is

taken. In the next three layers (L5, L6 and L7), the values from the max-pooling layer are convolved with the filter kernels. In the eighth layer (L8), in order to reduce the number of parameters, the global average pooling layer is applied. In this case, all of the values from each filter were averaged, which results in only one value and turns the total number of the parameter to 1200 (6 inputs $\times$ 200 filters). In the ninth layer, a dropping layer is applied to prevent overfitting in the training stage. Finally, all of the nodes from the drop layer is fully connected. In layer 4 (L4), the max-pooling layer was chosen because it helps to have a high contrast feature map of the resulting convolution in the middle of the feature engineering process. On the contrary, average pooling was chosen in the last convolution (L8) to smoothen the feature maps.

3. Experimental Setup

This study employs a 3-axis accelerometer and 3-axis dynamometer sensor signature to predict the belt wear that affects the polishing quality. The following subsection presents in detail the experimental polishing setup and data acquisition procedure:

3.1. Polishing Process Equipment, Sensors and Data Acquisition

The experiments were performed using a multi-axis arm robot mounted with an abrasive belt grinding setup, as presented in Figure 13. The experimental setup consisted of ABB 6660-205-193 robot that was primarily used for imparting motion in the grinding direction. The belt grinder used in this work was electrically powered that can run at 11,000 RPM at no-load condition. The belt grinder could polish and grind with belts about 8" to 3/4" wide $\times$ 18" long. The belt grinder was coupled to a force control present in the end effector of the ABB robot with the help of a customized bracket. The force control was closed-looped into the robot controller to ensure the force input from the operator and imparted force in the normal direction (Z-axis) are equal. Normal direction is usually preferred to achieve uniform material removal. As far as the experimental trials, a force of 20 N was applied throughout this study. The experimental conditions used in this work are listed in Table 1. Four different belt condition representing four different classes of wear level in this study were prepared beforehand by performing actual grinding processes at different cycle times, as depicted in Table 2. During the polishing experiments, one variable output process parameter was the belt wear condition (four levels). Other process parameters such as feed rate, grinding speed and force control were maintained at a constant value, as presented in Table 1.

Kistler 8763A500 triaxial accelerometer sensor was attached near the tension arm of the electric belt grinder to obtain the vibration signal during polishing (i.e., contact between belt tool and workpiece), as presented in Figure 13. In addition, Kistler 9254 three-component dynamometer was placed below the mild-steel workpiece, as shown in Figure 13. NI data acquisition (DAQ) module and LabVIEW environment were used to acquire vibration signal in a digitized format with a sampling frequency of 2 kHz. In the case of the dynamometer, a DAQ device supported by the DEWESoft platform was used to acquire force signals across normal and tangential directions. The signals corresponding to the force and accelerometer sensors were synchronized offline.

ABB Robot studio was used to configure and was planned for the tool path. The tool path planning for the linear run performed in this work has five different zones, A–E, as presented in Figure 14.

The region between A–B was used to align the tool head over the machining region. Zone B–C was used to attain the force required for grinding. C–D was the zone where force control is actively applied. Finally, Zone D–E was used to decelerate the force sensor and robot motion. The whole experiments performed in this study were carried out in a non-lubricated condition on a mild steel workpiece.

3.2. Vibration and Force Data Acquisition

This paper is an extension work of the previous study that applied ML methods to sensor signatures [17,18]. The difference to the work reported by Pandiyan et al. [17] is that they used short-time Fourier transform (STFT) on acoustic emissions signal to detect the change in contact mechanisms caused by tool wear in abrasive belt grinding. However, in the present study, CNN methods are developed to predict the wear level of the belt tool using 3-axes accelerometer and 3-axes dynamometer signatures instead of the acoustic data. All accelerometer and force sparse features from the 3 axes were used as input data in the ML method [18]. However, extracting features and feeding them into the ML algorithms is a two-step procedure and is computationally expensive. In this study, the CNN algorithm evaluates which axis/axes of the sensor signature(s) are more relevant for classifying the abrasive belt wear state using raw sensor signals. An example of raw vibration and force signal from the X-axis sensor direction for different belt tool states, i.e., brand-new, 5-min cycle time, 15-min cycle time and worn-out (from top to bottom) is presented in Figure 15 a,b. For interested readers, a complete raw signals plot of Figure 15 is presented in [18].

The raw vibration and force signals dataset were acquired with a sampling frequency of 2 kHz for 3.5 s, resulting in 7000 data points as presented in Figure 15. Prior to the convolution process, the raw datasets were segmented into a smaller data form. The raw datasets were reshaped to 200 data points with 10% overlaps. The new 200 data points were equivalent to a window of 0.1 sec of the sampling frequency of the polishing process. According to previous works [18], 200 data points can still capture the polishing process's dynamic behavior. The pre-processing of the raw dataset produced 64,000 new rows of datasets for each class and 256,000 new datasets for all four classes combined, i.e., brand-new, 5-min cycle time, 15-min cycle time and worn-out. These datasets were then divided into two sets for training and validation. The CNN model computation used 80% of 256,000 datasets (192,000 datasets) as the training set and another 20% of 256,000 datasets (64,000 datasets) for validation.

A sample of data input signals for the CNN algorithm from three directions (X, Y and Z-axes) of the accelerometer is presented in Figure 16. Based on the visualization of the vibration signals corresponding to four different belt conditions, it is evident that distinguishing them is challenging. An example of force signals from three directions (X, Y and Z-axes) of the dynamometer is presented in Figure 17. Synonymous to the vibration signals, differentiating belt conditions visually is also challenging. A detailed illustration of the data input preparation for the CNN method is presented in Figure 18. As presented in Figure 18, raw vibration and force data were collected from three axes. The raw data was then divided further into a smaller sized window for CNN training.

4. Results and Discussion

4.1. CNN Results of Vibration Data

This sub-section provides the CNN classification results of vibration signals from three categories: (1) single-axis accelerometer (X, Y and Z), (2) double-axes accelerometer (XY, XZ and YZ) and (3) triple-axes (XYZ).

This study is based on the CNN design, as illustrated in Figure 12 on the accelerometer sensor data. To provide a better understanding for the classification labels in Table 3 confusion matrix results in Tables 4–6 and Figures 19 and 20, Brand-new as Belt No.1.

5-min cycle time as Belt No.2. 15-min cycle time as Belt No.3. Worn-out as Belt No.4.

4.1.1. Vibration Signal of Single-Axis Accelerometer (X, Y and Z)

As depicted in Table 3 (a), the CNN classification result in the X-axis indicates that all 796 datasets of the “brand-new” class can be classified correctly without misclassification. In the “5-min cycle time” class, 796 datasets were classified correctly. However, 2 datasets were misclassified as “15-min cycle time”, and other 2 datasets were misclassified as “worn-out”. In the “15-min cycle time” class, all 798 datasets were also successfully classified. For the “worn-out” class, 793 datasets were classified correctly, and only 1 dataset was identified as a “15-min cycle time” class.

Additionally, Table 3 (b) shows that 795 datasets of the “brand-new” class corresponding to the Y-axis can be classified correctly, and 1 dataset was misclassified as a “5-min cycle time” class. In the “5-min cycle time” class, 798 datasets were classified correctly. However, 2 datasets were extremely misclassified as “worn-out” class. In the “15-min cycle time” class, 717 datasets were classified correctly. However, 83 datasets were classified incorrectly as “worn-out” class. The worst classification occurs in the “worn-out” class, where 670 datasets were classified correctly, but 89 datasets were classified incorrectly as “brand-new” and 16 datasets were identified as “5-min cycle time” class, while other 19 datasets were misclassified to the “15-min cycle time” class.

Table 3 (c) shows CNN results on Z-axis vibrational signals. 790 datasets of “brand new” class were classified correctly, 1 dataset was incorrectly classified as “5-min cycle time” class, and 5 datasets were misclassified as “worn-out” class. In the “5-min cycle time” class, 791 datasets were classified correctly, 3 datasets were incorrectly classified as “15-min cycle time” class, and 6 datasets were incorrectly classified as “worn-out” class. For the “15-min cycle time” class, 748 datasets were classified correctly, and there were 52 datasets classified incorrectly as “worn-out” class. Similar to the Table 3 (b) result, the poor classification result occurred in the “worn-out” class, where class 2 datasets were misclassified as “brand-new” class, 47 datasets were incorrectly identified as “5-min cycle time”, and 26 datasets were misclassified as “15-min cycle time” class.

Table 3 shows the accuracy and loss curves during CNN training using the accelerometer sensor data from X, Y or Z axes. In Table 3, it can be seen that processing 7672 data for 50 epoch takes 17 to 20 s. When trained with sensors derived from the X-axis of the accelerometer, the accuracy of the CNN model results in higher accuracy (accuracy: 95.78) than the other axes (Y-axis, accuracy: 87.47%; Z-axis, accuracy: 89.43%).

4.1.2. Vibration Signal of Double-Axis Accelerometer (XY, XZ and YZ)

The sensor data from two axes were combined to examine the dynamic behavior of the abrasive process. This combined signal is inputted into the CNN algorithm. A confusion matrix from the CNN model that used two-axis (XY, XZ and YZ) from the accelerometer sensor is presented in Table 4. Table 4 (b) indicates that the result across XZ-axis shows higher accuracy with the CNN compared to other combination. Table 4 (a) indicates that all 796 datasets of “brand-new” can be classified appropriately. Additionally, in the “5-min cycle time” class, 797 datasets were classified correctly, 1 dataset was misclassified as “brand-new”, and 2 datasets were misclassified as “15-min cycle time”. For the “15-min cycle time” class, all 800 datasets were classified correctly. In the “worn-out” class, 788 datasets were classified correctly, and another 6 datasets were shifted to the “15-min cycle time” class.

Table 4 shows the accuracy and loss curves during CNN training using two inputs from sensors with a combination of XY, XZ or YZ inputs. In Table 4, it can be seen that processing 7672 data with 50 epoch takes 17 to 20 s. When trained with sensors derived from the XZ-axes of the accelerometer, the accuracy of the CNN model results in higher accuracy (accuracy: 96.40%) than the other axes (XY-axes, accuracy: 95.06%; YZ-axes, accuracy: 94.92%).

4.1.3. Vibration Signal of Triple-Axis Accelerometer (XYZ)

Figure 19 shows the confusion matrix of the CNN model that used the data from the three axes of the accelerometer sensor. Figure 19 indicates that 795 datasets of the “brand-new” class can be classified appropriately, and 1 dataset was misclassified as a “5-min cycle time” class. For the “5-min cycle time” class, 794 datasets were classified correctly, 6 datasets were misclassified to the “15-min cycle time” class. In the “15-min cycle time” class, all 800 datasets were classified correctly. In contrast to the “worn-out” class, 765 datasets were classified correctly, and 29 datasets were misclassified as “15-min cycle time” class.

Figure 19 shows the accuracy and loss model during CNN training using all accelerometer sensor inputs. Figure 8 shows that processing 7672 data with the 50 epochs take 18.2 s. When trained with sensors derived from the XYZ-axis accelerometer, the accuracy of the CNN model yields an accuracy of 94.23%.

4.2. CNN Results of Force Signals

This sub-section provides the CNN classification results of force data from three categories: (1) single-axis (X, Y and Z), (2) double-axis (XY, XZ and YZ) and (3) triple-axis (XYZ).

4.2.1. Force Signal of Single-Axis Dynamometer (X, Y and Z)

This study also utilized the CNN method for the three-axis force data, as presented in Table 5. The CNN result in the X-axis (Table 5 (a)) indicates that 793 datasets of the “brand-new” class can be classified appropriately, and 3 datasets were misclassified to the “5-min cycle time” class. In the “5-min cycle time” class, 797 datasets were classified correctly, 3 datasets were identified as “brand-new” class. In the “15-min cycle time” class, 798 datasets were classified correctly, 1 dataset was classified incorrectly to “brand-new”, and 1 dataset was classified incorrectly as “worn-out”. In the “worn-out” class, 747 datasets were classified correctly. However, 47 datasets were classified incorrectly to the “15-min cycle time” class.

Table 5 (b) shows that 794 datasets of the “brand-new” class can be classified, and 2 datasets were incorrectly classified as “5-min cycle time” class. In the “5-min cycle time” class, 796 datasets were classified correctly, and 4 datasets were identified as “worn-out”. In the “15-min cycle time” class, 771 datasets were classified correctly, and 29 datasets were classified incorrectly to the “worn-out” class. Meanwhile, in the “worn-out” class, 764 datasets were classified correctly, and 30 datasets were classified incorrectly to the “15-min cycle time” class.

Table 5 (c) shows that 794 datasets of the “brand-new” class can be classified correctly. However, 2 datasets were misclassified as “5-min cycle time” class. In the “5-min cycle time” class, 798 datasets were classified correctly, and 2 datasets were incorrectly classified as “15-min cycle time”. In the “15-min cycle time” class, 788 datasets were classified correctly. However, 12 datasets were classified incorrectly to the “worn-out” class. In the “worn-out” class, 785 datasets were classified correctly, and 9 datasets were misclassified as “15-min cycle time” class.

Table 5 shows the accuracy and loss curves during CNN training using force data input from X, Y or Z axes. In Table 5, it can be seen that processing 7672 data with 50 epochs took nearly 17 to 20 s. When trained with sensors derived from the X-axis of the dynamometer, the accuracy of the CNN model resulted in higher accuracy (accuracy: 93.07%) than the other axes (Y-axis, accuracy: 92.14%; Z-axis, accuracy: 92.94%).

.2.2. Force Signal of Double-Axis Dynamometer (XY, XZ and YZ)

The force signature across two directions were combined to examine the dynamic behavior during the abrasive process. This combined signal was input into the CNN algorithm. The confusion matrices from the CNN model that used two-axis (XY, XZ and YZ) is presented in Table 6. According to the CNN results presented in Table 6, Table 6 (a) indicates that the CNN model results show highest than other combinations. In detail, Table 6 (a) indicates that all 796 datasets of the “brand-new” class can be classified perfectly. For the “5-min cycle time” class, 797 datasets were classified correctly, 1 dataset was identified as “brand-new” class, and 2 datasets were incorrectly classified as “15-min cycle time” class. In the “used” class, all 800 datasets were also classified perfectly. Furthermore, in the “worn-out” class, 788 datasets were classified correctly, and 6 datasets were incorrectly identified as “15-min cycle time” class.

Table 6 shows the accuracy and loss curves during CNN training with inputs from axes combinations such as of XY, XZ or YZ. In Table 6, it can be seen that processing 7672 data with the number of 50 epochs takes 17 to 20 s. When trained with sensors derived from the XY-axis of the dynamometer, the accuracy of the CNN model results in higher accuracy (accuracy: 99.80%) than the other axes (XZ-axes, accuracy: 95.53%; YZ-axes, accuracy: 96.47%).

5. Conclusions

A methodology for abrasive belt grinding condition monitoring and worn state prediction is presented. The methodology is focused on understanding the effect of the directions of vibration and force signatures with respect to the belt wear rate. This proposed methodology also responds to the open question, i.e., opening the possibility of applying DL for tool condition monitoring and its potential application. From the presented result, the methodology revealed that the

accelerometer and dynamometer's direction has a certain relation to the physical behavior of the belt grinding process, especially on the dynamics in the contact between the belt tool and workpiece. In vibration signal analysis, XZ and YZ direction combination have more accuracy than the others. In contrast, in force signal analysis, the combination of XY gives the most accurate results in comparison to the others. Another outcome of this study is also attributed to our future work that the DL model can be embedded into a monitoring measurement system to monitor the belt state during the abrasive process without interrupting the ongoing grinding process. Even though the DL method has potential application in tool wear prediction of mild steel, this study needs further investigation if the proposed DL prediction can be generalized and translated across different materials during grinding, which is the research direction in progress.

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