Cutting tool wear monitoring through cutting sound classification and machine learning

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Abstract

In this work, a methodology to detect tool wear states during a milling operation through sound classification is presented. The sound was recorded during milling operations for endmills with different wear states (brand new, wear out and chipped); the wear states were determined by measuring their mass before each cutting operation. After machining, a transfer learning task was implemented for custom classification of the sound. The above, by using the VGG16 deep neural network architecture. The sound data, was represented as spectrogram images for the classification model training. Four different metrics, were used to measure the model performance, showing 97.5% in the worst result. In addition, the results showed that sound data have enough information to train classification models for cutting tools wearing. Finally, the method presented in this work can be used for the development of monitoring tools for the support of machining workshops; thus increase the efficiency of their tools, raw materials and machining time.

Keywords— CNC Machining, Machine Learning, Sound Monitoring, Tool Soundness

Introduction

Task scheduling problems are very important in today's world. It can be said that they are present in all the fundamentals of modern industry, hence the importance of these being optimal, so that resources that are associated with the problem can be saved [1]. The premature tool wear / failure, probably is the most important problem in a machining workshop. The above, since when a tool breaks or chips below its rake face during a cut, it can create defects in the finished product, wasting your shop's expensive raw materials, machine time, energy costs and labor hours [2]. Thus, currently research and technology efforts are made to identify and reduce the tool fail likelihood.

Dimla [3], presented a review of some of the methods that have been employed in tool condition monitoring. The author, points that particular attention should paid to the manner in which sensor signals from the cutting process have been harnessed and used in the development of tool condition monitoring systems (TCMSs). Similarly, Xiaoli Li [4], presented a brief review of acoustic emission method (AE) for tool wear monitoring during turning. The author, suggests that AE has been proposed and evaluated for a variety of sensing tasks as well as for use as a technique for quantitative studies of manufacturing processes. In addition, the researcher argued that AE could estimates tool wear condition by incorporating pattern classification, GMDH methodology, fuzzy classifier, neural network, and sensor and data fusion.

Sick [5], intakes a review for on-line and indirect tool wear monitoring in turning with artificial neural networks. The authors suggests that with a continuous acquisition of signals with multi-sensor systems it is possible to estimate or to classify certain wear parameters by means of neural networks. However, the development of tool wear monitoring systems is an on-going attempt.

Jurkovic et al. [6] , developed a new approach in tool wear measuring technique using CCD vision system. The presented system (light source, CCD camera, laser diod, to mention few) was characterized by its measurement flexibility, high spatial resolution and good accuracy. The authors suggests that the main advantage of their method in comparison with other techniques is that the 3D image of relief surface can be obtained without having need to employ a very complicated measuring system.

Zhu et al. [7], developed a multi-category micro-milling tool wear monitoring with continuous hidden Markov models. The authors, developed a continuous hidden Markov models (HMMs) and were adapted for modeling of the tool wear process in micro-milling for estimation of the tool wear state given the cutting force features. The results suggests, that the effectiveness and potential of such method was remarkable for the tool state estimation in the micro-milling of pure copper and steel alloys.

Castejón et al. [8], provided an on-line tool wear monitoring using geometric descriptors from digital images. In this work, a CNC parallel lathe and a computer vision system have been used to obtain 1383 flank images. Then, a binary image for each of the former wear flank images have been obtained by applying several pre-processing and segmenting operations. The result obtained using a finite mixture model approach showed the presence of three clusters using these descriptors, which correspond with low, medium and high wear level. A monitoring approach is performed using the tool wear evolution for each insert along machining and the discriminant analysis.

Vetrichelvan et al. [9], performed an investigation of tool wear using acoustic emission and genetic algorithm. In this paper, authors used the tool condition monitoring by means of acoustic emission technique (AET). The above, were real methods identified by researchers for online quality assessment of machine tools. In addition, the genetic algorithm (GA) was used to optimize the tool wear rate parameters. The practical significance of applying GA to tool wear rate was validated by means of computing the deviation between predicted and experimentally obtained process parameters. Finally, tool wear rate results were compared with online measurements and the results yielded a good correlation.

Rizal et al. [10], analyzed the cutting tool wear classification and detection using multi-sensor signals and Mahalanobis-Taguchi System. In this work, a Mahalanobis-Taguchi system (MTS) was employed as decision making and pattern recognition systems. Experimental data of end milling AISI P20+Ni tool steel is used to construct Mahalanobis space, to optimize and validate the system. The results show that the medium wear and critical wear stages of cutting tool conditions can be successfully detected in real-time

Kuntoğlu & Sağlam [11], performed an investigation of progressive tool wear for determining of optimized machining parameters in turning. This study contained experiments and optimization processes during turning of AISI 1050 material with 3 input parameters (cutting speed, feed rate, tool tip) using the Taguchi method. The results showed that cutting speed is the most effective about 45% and tool tip is the second about 35% on tool wear. On the other hand, the effect of feed rate on tangential cutting force (88%) and cutting speed on AE (80%) is remarkably higher than the other two parameters.

Kothuru et al. [12], developed an application of audible sound signals for tool wear monitoring using machine learning techniques in end milling. The researchers, explored the use of audible sound signals as sensing approach to detect the cutting tool wear and failure during end milling operation by using the Support Vector Machine (SVM) learning model as a decision-making algorithm. The results of the proposed algorithm have shown accurate predictions in detecting tool wear under various cutting conditions with rapid response rate, which provides the good solution for in-process TCM.

Pagani et al. [13], indirect cutting tool wear classification using deep learning and chip colour analysis. According to the authors, tool wear in turning is one of the biggest concerns that most expert operators are able to indirectly infer through the analysis of the removed chips. Automatizing this operation would enable developing more efficient cutting processes that turns in easier process planning management toward the Zero Defect Manufacturing paradigm.

Then, a deep learning approach, based on image processing applied to turning chips for indirectly identifying tool wear levels.

Deep learning methods have shown a superior performance on image classification tasks [14]. In [15] is shown an approach where sound classification is performed by the use of Convolutional Neural Networks processing sound signals as spectrograms; on this manner image classification algorithms can be used for sound classification tasks. Training deep neural networks for an image classification task can be a complicated specially when there is not enough data. In recent years the lack of data problem has been addressed by a technique called transfer learning. Transfer learning is used in order to reduce the need of large amounts of training data, by re-using pre-trained weights on models aimed to perform similar tasks i.e. images classification [16].

As mentioned on the paragraphs from above, the necessity of the monitoring of tool wear or damage is an important role on industrial and research activities. Thus, the aim of this work is to contribute in such efforts through the cutting sound classification taking advantage of Convolutional Neural Networks and Transfer Learning. The above, by means of an experimental try outs of two different materials (6061 T6 Al and 4041T Steel), three different cutting speeds and three different condition of cutting tool. The cutting tool conditions were categorized by their weight, based on the assumption that the tool mass represents its wear state.

Materials and Methods

In this section the materials and methods to generate data used to train a cutting tool wear state classification model are shown. For the dataset, several milling operations were performed with endmills at different wear states while the sound signal was recorded accordingly.

Materials

In this experiment, 6061T6 aluminum and a SAE 4140T bars of $80\times80\times50$ mm were employed to carry out the machining testing. Materials densities (δ) are 2.7 g.cm-3 and 7.70 g.cm-3 respectively. For the machining operations, 10 mm diameter and 4 flutes tungsten carbide endmills were employed. Three machining conditions were performed: 1) brand new, 2) wear out and 3) a chipped one endmills. The conditions mentioned before, promotes the variation in cutting endmill weight. Milling conditions were analyzed according to their soundness.

Weight measurements

As mentioned above, endmill weight was employed to classify its soundness by considering material loses. The weight, was measured by means of an Ohaus Scout compass with 0.001g of resolution and 0.003g of uncertainty. Five measurements, were carried out in each endmill and the average was reported.

Signal acquisition and processing devices

In this work, 18 experiments were performed and the propagated sound from the milling operations was recorded. For each experiment the audio signal had a duration of 130 seconds. The audio signal, was acquired with a dynamic cardioid microphone connected to a laptop, placed at fixed distance of 10 cm from machine's the hydraulic vise (see Figure 1). Audacity software was used in order to manage recorder parameters. In addition, a 32 bits resolution ADC was employed to sample the signal at frequency of 88.2 kHz.

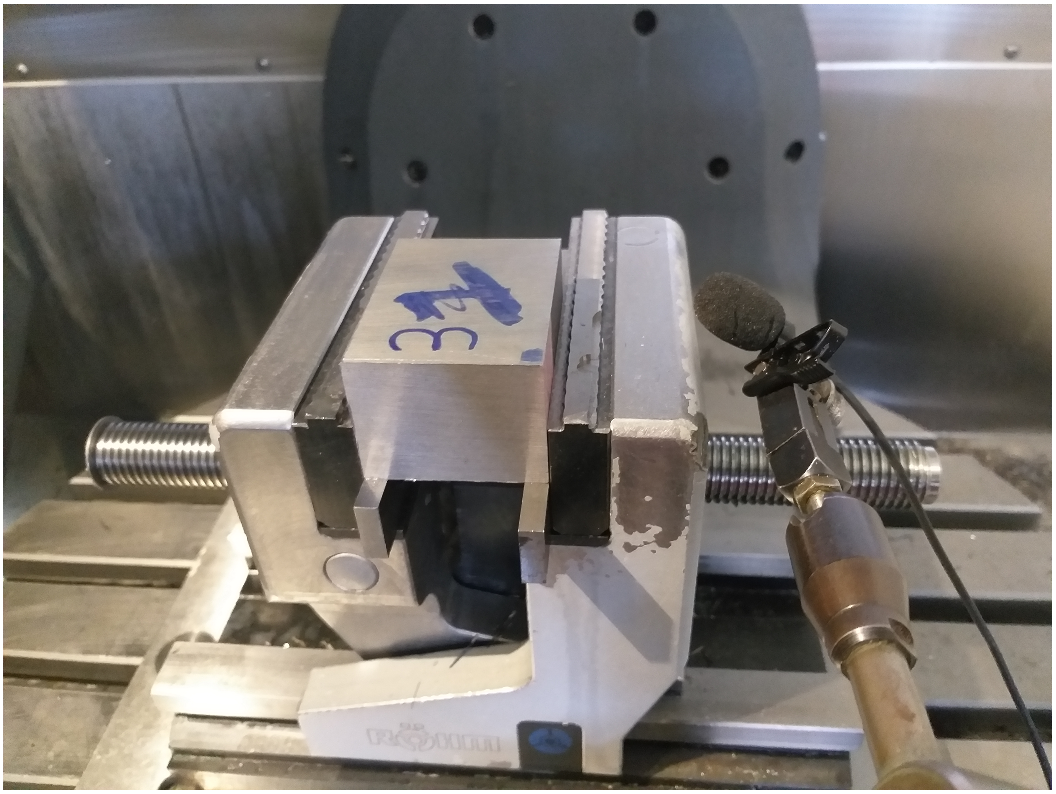

Figure 1: Experimental configuration for data acquisition.

Machining of test samples

For the data collection, rough milling of 6061T6 aluminum and a 4140T bars were performed in a VF-6 HASS CNC machine. However, as density changes, the parameters will need an adjustment depending on the type of material. For the 4140T steel had the Feed Rate (F) values ranged from 1114 ∼ 1750 mm.min^{-1}. On the other hand, F for 6061T6 ranged 2228 ∼ 3819 mm.min^{-1} . Similarly, Spindle Speed (S) for 6061T6 aluminum ranged 891.2 ∼ 1527.6 rpm while S for 4140T were 445.6 ∼ 700 rpm. The Table 1, shows the endmill cutting parameters sets used to cut the two proposed materials .

Parameter Set		Materials	
		6160T6	4140T
1	Feed Rate (mm/min)	2228	1114
	Spindle Speed (rpm)	891.2	445.6
2	Feed Rate (mm/min)	2864	1432
	Spindle Speed (rpm)	1145.6	572.8
3	Feed Rate (mm/min)	3819	1750
	Spindle Speed (rpm)	1527.6	700.0

Table 1: Parameters sets for the experiment.

Theory / Calculations

The aim of a classification task consist on the development of a classification function that can maps patterns on data into classes. Machine learning models can be used to address this task, taking advantage of well designed datasets. One disadvantage of conventional Machine Learning is that in order to perform a model fitting, a previous pre processing of data must be done, this is a feature extraction. Deep Learning tackle these limitation with a built-in feature extractor, Deep Learning uses Neural Networks in order to fit models.

In this work, the VGG16 model is proposed to classify the wear tool condition of three different endmills based on their emitted sound during a cutting operation. The VGG16 is a convolutional neural network architecture that secured the first and second places on the ImageNet Challenge 2014 on the localization and classification tracks [17]. A Convolutional Neural Networks (CNN) architecture was selected due to their specialization in 1D or 2D data (i.e. an input image) to adjust its weights and biases to calculate class probabilities during inference. To be able to train such neural network architecture, a transfer learning task [16] was performed using weights trained with the ImageNet dataset [18]. In order to use the VGG16 model for classification, it is necessary to modify the last layer of the architecture from 1000 nodes, to 3 nodes that represent the 3 different target classes. Figure 2 depicts the diagram of the VGG16 and its association to this research. For this application, the cutting operation sound signals were represented as spectrograms, and used as input for the classification model. A sound signal is a change in pressure generated by the removed material and rotatory tool that propagates through a medium by mechanical waves, and can be captured by a microphone [19] . To represent the sound signal as a spectrogram, it was pre-processed with the Short Time Fourier Transformation (STFT) algorithm that decomposes the signal in a frequency spectrum over time windows. After processing the sound data, the result will be an image containing information about time, amplitude, and frequency at which the sound signal is propagating.

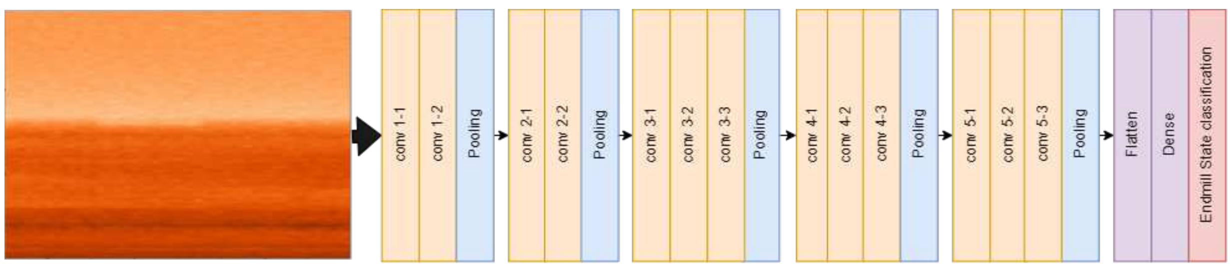

Figure 2: VGG16 CNN diagram application for this research.

There are different ways to evaluate the performance of a classification model. In this work the Accuracy, Precision, Recall and F1 score are taken into account to evaluate the proposed model. Equation 1 is used to calculate the classification model accuracy (Acc); accuracy is the measure of the number of the predictions that were correct of the total of predictions.

$$Acc = \frac{\#ofCorrectPedictions}{\#ofTotalPredictions} \tag{1}$$

Nevertheless accuracy is not enough to measure all the performance metric of a classification model. In order to properly evaluate a model performance, it is also important to understand the most likely failure mode of a classification model. A classification model may fail with false positives or false negatives depending on its failure tendency; depending on the application, some failure modes are preferred than others i.e. for health applications it preferred to fail with false positives [20]. Equation 2 shows a second performance metric known as Precision (Pr) that evaluates within all the positives predictions made with the model, which percentage are correct. A model is precise, when its predictions tend to be true positives.

$$Pr = \frac{\#ofTruePositives}{\#ofTruePositives + \#ofFalsePositives} \tag{2}$$

Recall (Rc) is another metric used to evaluate within all predictions that are actually positive, how well the model could recognize them. Equation 3 is used in order to calculate recall metric.

$$Rc = \frac{\#ofTruePositives}{\#ofTruePositives + \#ofFalseNegatives} \tag{3}$$

Finally, F1 score combines Precision and Recall in one metric. It is is the harmonic mean of the two measures. It can be calculated as shown in Equation 4.

$$F1Score = 2 \cdot \frac{Pr \cdot Rc}{Pr + Rc} \tag{4}$$

For each the metrics mentioned in Equations higher values is preferible. These metrics can be used to evaluate multi-class classification tasks, taking one class as positive and the remaining as negative classes, so that each of these metrics must be calculated for every class in our model. An average of each metric per class ca be taken a general performance metric as shown further.

Results

In this section are presented the results for data acquisition, model training and its performance. Data pre-processing and cutting tools wear state determination are also reported.

Endmill weight

The weight of the three endmills was determined as mentioned in the latter section. As supposed, older tools weighted less that newer; it is assumed, that the weight varied as the tool lost material -due to the tool integrity, and lifetime usage. The brand new endmill , had a weight about 69.396 g, while the wear out endmill 69.107 g. Finally, the chipped endmill revealed a weight of 68.873 g.

Signals preprocessing and FFT

The sound signal recordings for the three different endmills wear states with one parameter set (feed rates and spindle speeds) are shown in the Figure 3 for both materials. The signal in Figure 3a represents the sound developed by the brand new tool while cutting 4140T steel using the parameter set number 2 from Table 3. It can be noted that the sound is continuous through the analyzed range. On the other hand, a significant change can be noted for the wear out and chipped endmill (see Figures 3b and 3c). The changes mentioned before, can be inferred as a significant signal modification due the sound produced by the endmill wear condition. On the right side of Figure 3 we can see the signals for the same cutting parameter set when cutting aluminium blanks. As it happened for the steel cutting recordings, for aluminum cutting the sound produced by the brand new tool (Figure 3d) has a different aspect compared with the others two endmills (Figures 3e and 3f).

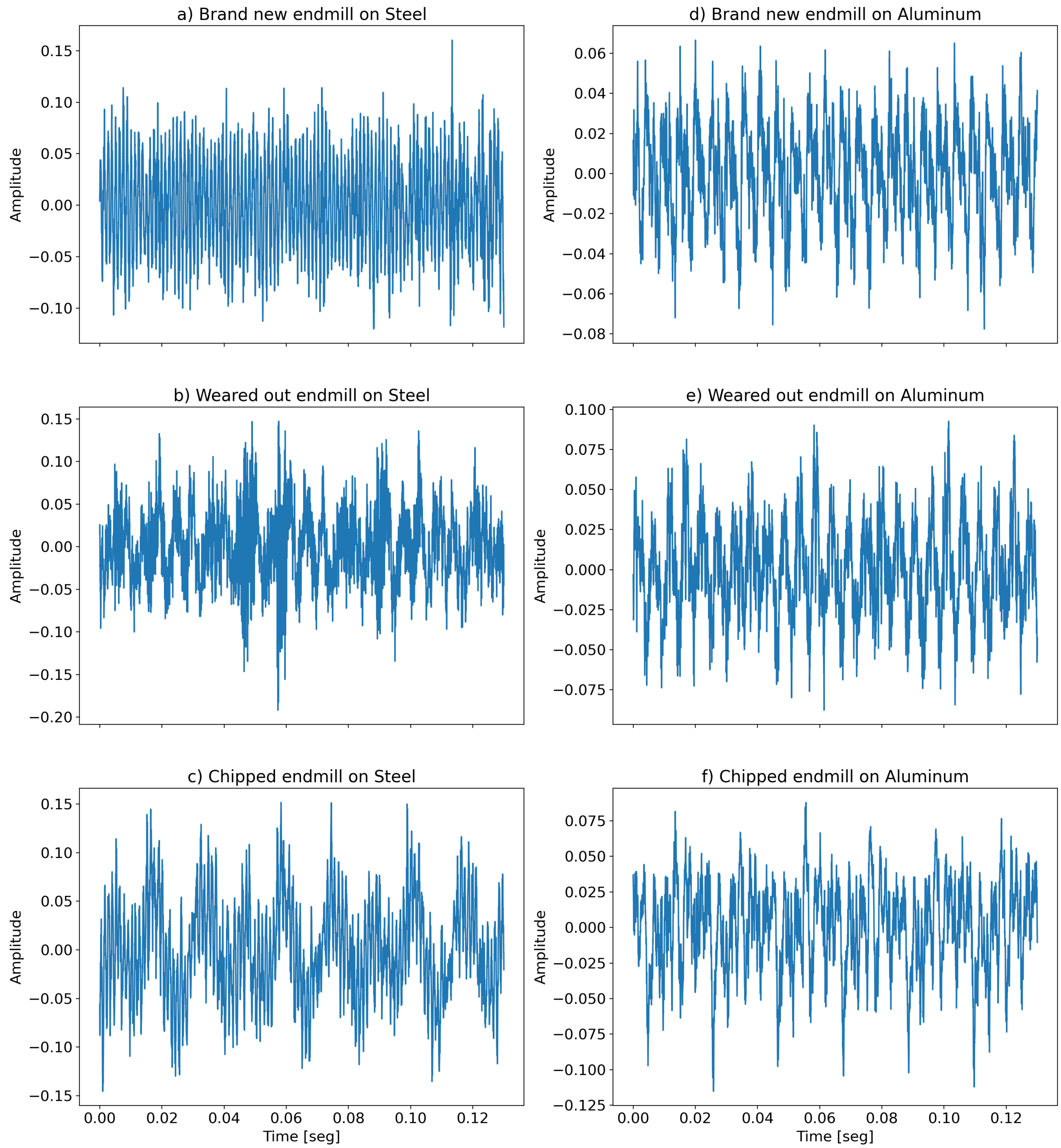

Figure 3: Sound Signals in Time Domain for brand new tool (Top), wear out tool (Middle) and chipped tool (Bottom) for Steel (Left side) and Aluminum (Right side) with parameter set number two.

In order to obtain more prediction features from the sound signals, a frequency domain analysis was performed on every signal by applying the Fast Fourier Transformation (FFT). After the transformation, the frequency spectrum can be taken as a new feature from which the predictive model can take advantage of to discriminate sound signals between all the cutting operations. The frequency spectrum for each signal shown before in Figure 3 are displayed in the Figure 4.

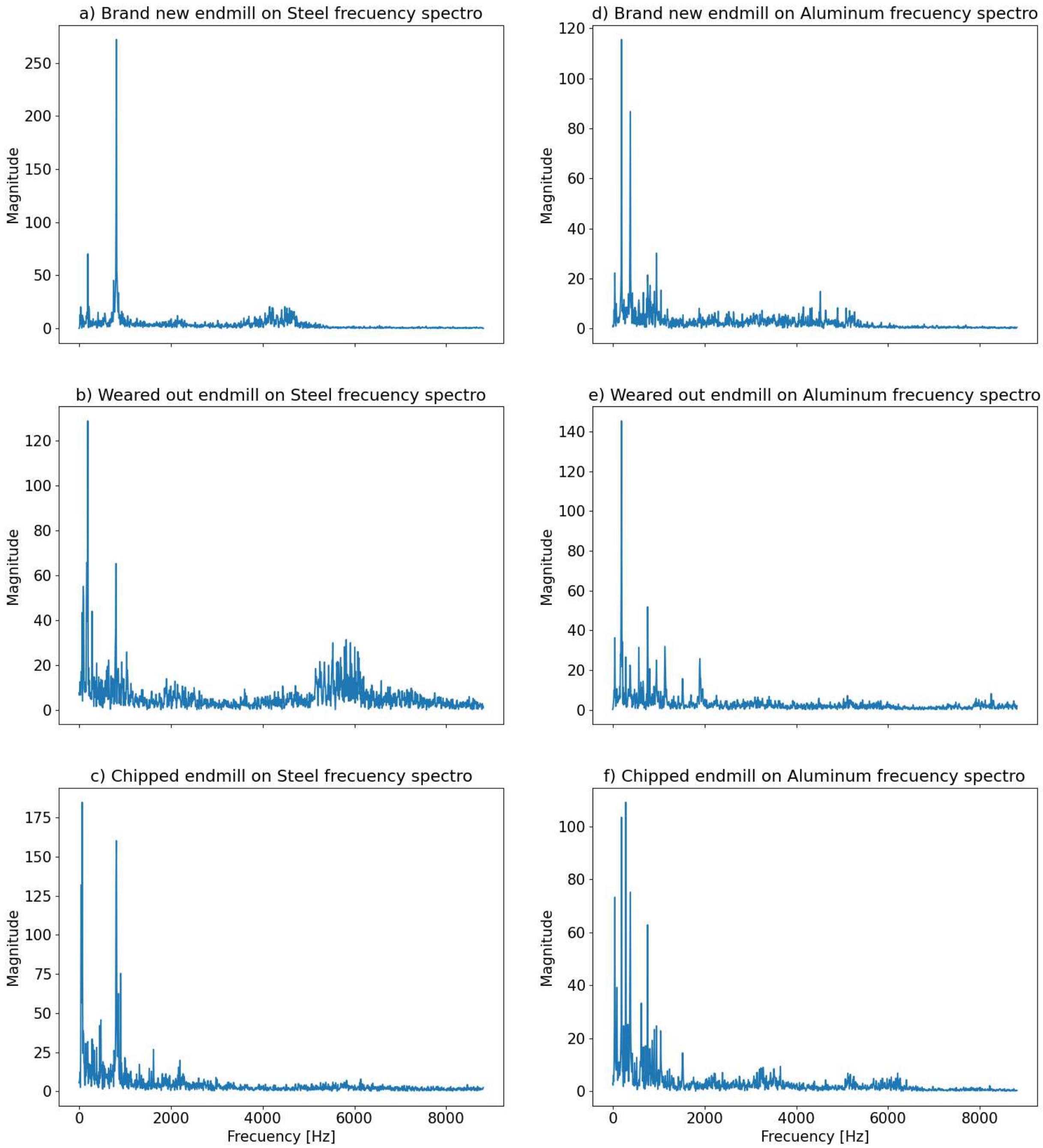

Figure 4: Frecuency espectro for brand new tool (Top), wear out tool (Middle) and chipped tool (Bottom) for Steel (Left side) and Aluminum (Right side) with parameter set number two.

After obtaining the frequency spectrum, time and frequency analysis were carried out and spectrograms where developed for each signal. The spectrograms, are used as input for the CNN and are depicted in the Figure 5.

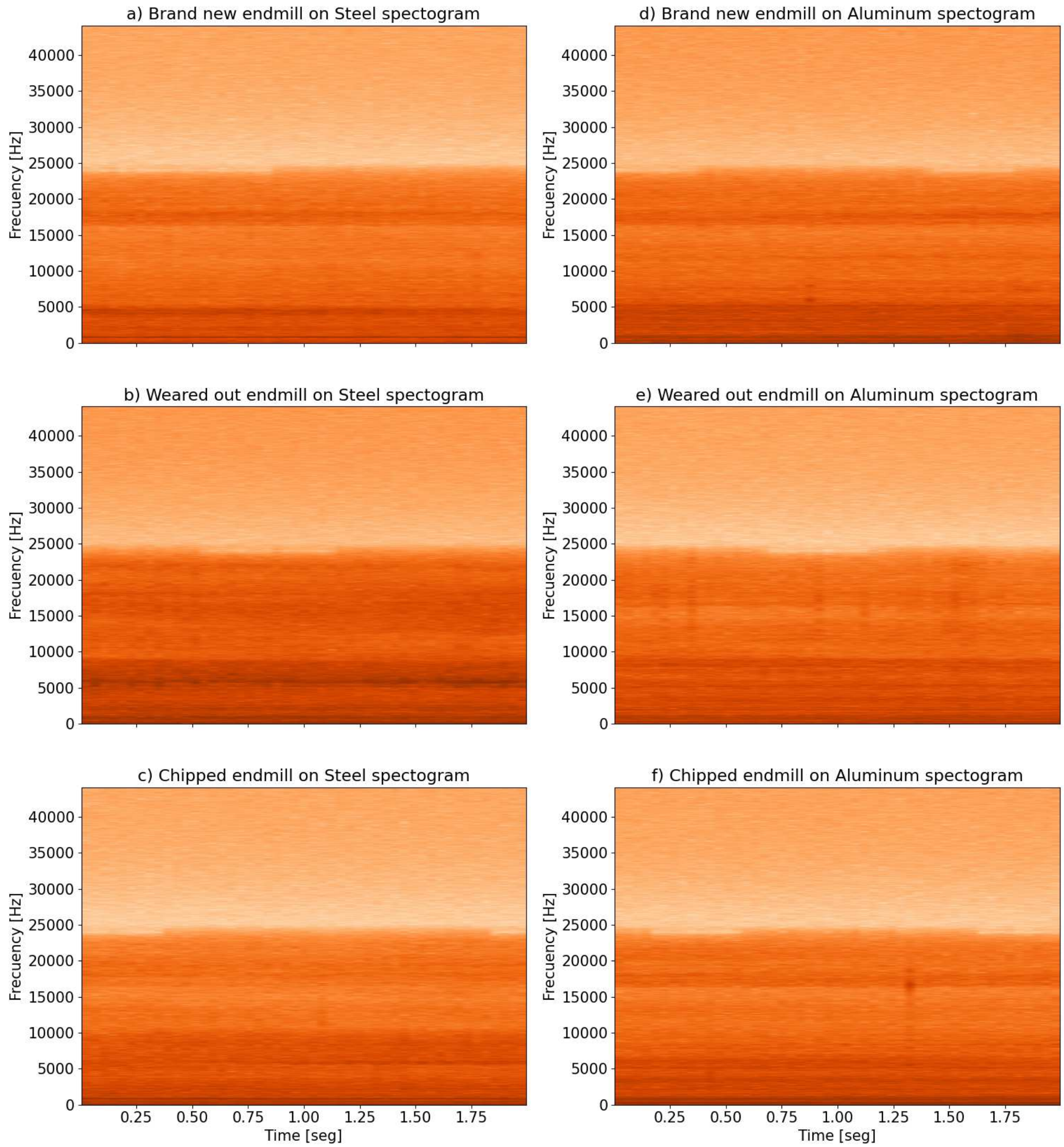

Figure 5: Spectograms for brand new tool (Top), wear out tool (Middle) and chipped tool (Bottom) for Steel (Left side) and Aluminum (Right side) with parameter set number two.

Convolutional network training, validation and test

To generate the dataset, recorded signals for each experiment were divided in time windows of 0.26 seconds, then the spectrogram for each window was obtained; on this manner 9,000 spectrograms were produced. The complete dataset is divided in training and testing sets where the latter is used to test the model on "never seen data"; the training set can be further divided to obtain a validation set used to test the model during training. There is no a general rule to divide the dataset into the training and testings sets; a common segmentation consist in a 70/30 or 80/20 ratio where the training data represents the larger set [21] . The data for our purposes was segmented on 85% for training and validation of the model, and the last 15% for testing from the 9,000 spectrograms dataset. For this work, the Keras library [22] was used to perform the transfer learning task on the VG166 model since Keras provide a complete interface to build and train Neural Networks. Keras allows users to download pre-trained VGG16 model, once with the original model the last layer is removed and the remaining weights are frozen. A new layer with the 3 required nodes is added, the weights of this last layer are trainable. The Adam algorithm [23] was selected as optimizer and a Categorical CrossEntropy was selected as the loss function [24] to train the network. Two stop conditions were set during training in order to stop the process, the first one, a maximum number of 500 epochs as training limit, and second, if after 30 consecutive training epochs the loss function does not improve, then the training process stops.

The training task has shown that 88 epochs were required to achieve an acceptable accuracy of classifying tool wear from sound signals. The process of validation and training of the proposed model are shown in Figure 6 (left). As validation accuracy follows the same trend as the training accuracy, we can assume that the model is not overfitted and a better performance on new data can be expected. Accuracy reached a 98% and 99% for validation and training, respectively. The Loss (error) evolution during the training task, shows the same characteristic as for the accuracy metric with values of 0.07 for validation and 0.01 for training - Figure 6 (right).

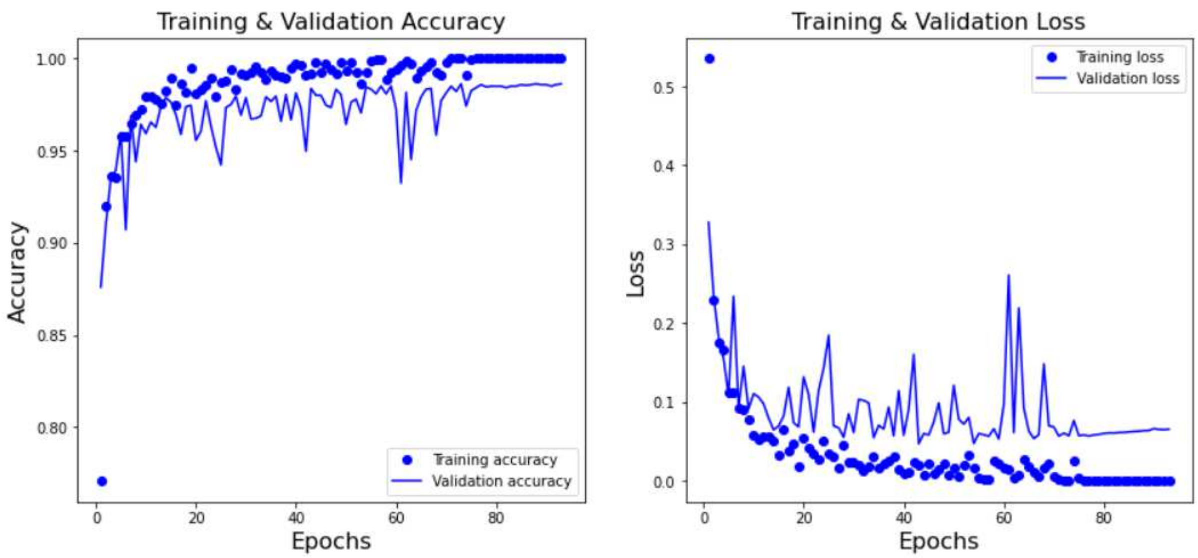

Figure 6: Left: Training and validation Accuracy. Right: Training and Validation Loss.

After the process of training has finished, the test batch which contains new data for the model is given in order to evaluate its performance. To make a prediction, the CNN will infer a probability on every output node that represent every tool wear state class. The class with the higher probability is taken as the result. The test dataset split, was composed of 1,188 spectrograms belonging to the 3 tool classes, resulting on 396 for each class. Classification results are reported in the confusion matrix in Figure 7, where the brand new, wear out and chipped tool are labeled as 1, 2 and 3, respectively. The confusion matrix shows how many spectrograms for each (Y-axis) class were classified as which class (X-axis). The principal diagonal of the matrix contains the correct matches for the classifying task.

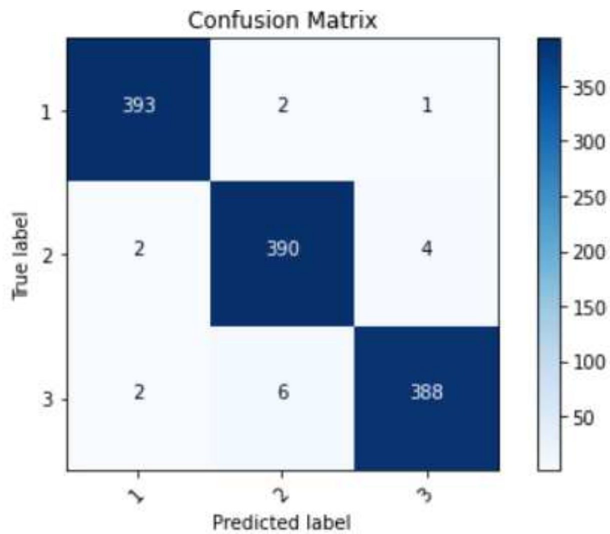

Figure 7: Confusion Matrix.

The obtained results for all metrics discussed in past sections are presented in Table 2. From the Table 2, it can be noted that the VG166 model trained for the tool wear state application has a general performance above 97.5 % for most cases. The Chipped tool achieved the worst results of the three different endmills, and in between metrics, precission reveal the worst value for all the endmills; precission is a metric to evaluate how many of a certain predicted label are actually of that label.These metric is used where False Positives concerns more than False Negatives. Even though these insights, the general results of the model are very height an can be labeled as a good classificator for the pourposes of this article.

Metric \Tool	Brand New (1)	Weared Out (2)	Chipped (3)	Average
Accuracy (%)	99.2	98.4	97.9	98.5
Precission (%)	98.9	97.9	96.2	97.67
Recall (%)	99.2	98.4	97.9	98.5
F1 Score (%)	99.1	98.2	97.1	98.13

Table 2: Metrics results.

Discussion

In past sections we have shown how sound data can be used to identify the wear state of endmills during cutting operations. The results suggests, that the information contained on post-processed sound data was enough to train the classification model a (for both steel and aluminum) and obtain good prediction performance. It means that there are good correlation between sound and tool condition.

Similar results, were obtained by Seemuang et al[25] since their results showed that there is no relationship between the frequency of spindle noise and tool wear, but varying cutting speed and feed rate have an influence on the magnitude of spindle noise and this could be used to indicate the tool wear state during the process. In addition, Charoenprasit et al[26] performed a monitoring tool wear in Drilling process using spindle noise features. A microphone was used to record the machining operation sound of S50C steel, which was drilled using a computer numerical control (CNC) milling machine in wet conditions where the results suggested the magnitude of spindle noise significantly increased in accordance with tool wear progression.

As mentioned on the previous paragraphs, the machine learning models had a good fit with the experimental data. However, since the sound signal during cutting is the result of the removed mass during the machining operations, different sound waves may be expected when using other cutting tools or parameters. As the emitted sound may be related to the mass amount removed from the blank material, other than the endmill wear state, the model may be predicting the removed mass during the cutting operation.

For this reason, further investigation is recommended in order to determine whether the model is capable of predicting wear state, removed mass, or any other cutting operation characteristic. For this reason, the results presented in this work should be considered an heuristic solution for cutting tools wear detection, that may be useful exclusively for the methodology and experimental setup presented in past sections; in despite of this possibility, the methodology described in this document can be used for different experimental setups, as long as enough data samples are used for the training task.

For implementation purposes on "live monitoring" operations the model inference latency should be taken into account. This is due to the pre-processing pipeline that is needed for the model inference. This pipeline will be responsible of transforming the sound signal into a spectrogram, then an inference operation will calculate the probabilities for each class. The pre-processing stage, may require extra processing time, that will impact on the monitoring latency in a real production implementation; thus further research on prediction latency optimization shall be done.

Conclusion

Based on the results exposed on previous sections, the following conclusion can be drawn:

The VGG16 neural network fits well for this purpose due its ability in recognize patterns in images and classyfy it with those. It yielded, that the four metrics used to evaluate its performance were up to 97.5%, thus the model fits well for this specific case (for both materials). Altough, the results had similarity with other published in the literature, care must be take and some other considerations should be observed. The avobe, opens other lines for the research of the optimization of latency optimization and the influence of other parameters such as tool geometry and cutting parameters.

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Statements and Declarations

a. Funding: No funding was received.

b. Conflicts of interest/Competing interests: We the authors, Carlos A. Catalán-Catalán. Horacio Canales- Siller, Celso E. Cruz-González and Mauricio Torres-Arellano, declare that we have not conflict/competing of interest with any institution and this is an original research. All personal and affiliations data listed in this article are true and can be used for the International Journal of Advanced Manufacturing Technology.

c. Availability of data and material (data transparency): The data of this article are available upon reasonable request to Mr. Carlos A. Catalán Catalán.

d. Code availability: The code of this article is available upon reasonable request to Mr. Carlos A. Catalán-Catalán.

e. Ethics approval: We the authors, Carlos A. Catalán-Catalán. Horacio Canales-Siller, Celso E. Cruz-González and Mauricio Torres-Arellano designate Mr. Carlos A. Catalán-Catalán as corresponding author and he will be the link between the International Journal of Advanced Manufacturing Technology and those for the article "Cutting tool wear monitoring through cutting sound classification and machine learning" submitted as JAMT-D-22-00442. In this paper, a methodology to detect tool wear states during a milling operation through sound classification is presented. The above, by using machine learning and VF-6 HASS CNC machine. As ethical approval, all authors declares that animals, humans and living beings were not used in this article.

f. Consent to participate: We the authors, Carlos A. Catalán-Catalán. Horacio Canales-Siller, Celso E. Cruz-González and Mauricio Torres-Arellano designate as corresponding author to Mr. Carlos A. Catalán-Catalán; thus we give our consent to participate in the review process, evaluation and publication of the article “Cutting tool wear monitoring through cutting sound classification and machine learning” submitted as JAMT-D-22-00442.

g. Consent for publication: We the authors, Carlos A. Catalán-Catalán. Horacio Canales- Siller, Celso E. Cruz-González and Mauricio Torres-Arellano designate as corresponding author to Mr. Carlos A. Catalán-Catalán; thus we give our consent for publication the article “Cutting tool wear monitoring through cutting sound classification and machine learning” submitted as JAMT-D-22-00442.

h. Authors’ contributions: Carlos A. Catalán-Catalán: Data acquisition and signal analysis.

Horacio Canales-Siller: Signal analysis and technical review.

Celso E. Cruz-Gonzalez: Conceptualization, paper structure, first withdrawn and manufacture advisor.

Mauricio Torres-Arellano: Technical review and materials specialist.

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