Signal Processing and Machine Learning as a Tool for Identifying Idling Noises of Different Circular Saw Blades

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This study examines the possible utilization of machine learning and decision-making in the woodworking sector. This refers to the recognition of certain sounds produced during tool idling. The physical and geometric properties of the circular saw blade result in different noises being generated during idling. It was assumed that the respective circular saw blades can be recognized by these noises. The noises of three different circular saw blades were examined while idling at the same speed. In order to obtain useful data for the deep learning process, the coarse signals were subjected to frequency analysis. A total of 240 noise samples were taken for each circular saw blade and later subjected to signal processing. Frequency-power spectra were created using a custom program in Matlab Campus Edition software, such as for the spectrograms. A short Fourier transform was used to create the average spectral density plot using self-made software. The input data for the deep learning network was created in Matlab using a custom program. The GoogleNet deep learning network was used as a data classifier. After training the network, an accuracy of 97.5% was achieved in recognizing circular saw blades.

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Keywords: Circular saw blade; Sound signal; Fast Fourier transform; Short-time Fourier transform; Spectral density; Deep learning network: Machine learning

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INTRODUCTION

The subjective sensation of a sound depends on its intensity and can be expressed by the following equation:

$$L = 10\log_{10}\left(\frac{I}{I_0}\right) = 20\log_{10}\left(\frac{p}{p_0}\right)\ [\mathrm{dB}] \tag{1}$$

where L present sound level or subjective sound intensity, I is sound intensity, I_0 is sound intensity at threshold of audibility, p is acoustic pressure, and p_0 is acoustic pressure at threshold of audibility. The human ear is able to detect sound intensity from 10^{-12} to 1 W/m^2 or tones with frequencies from 20 Hz up to 20 kHz. In this research, the recorded sounds ranged from 0 to 44800 Hz, which extends well above the highest level of one's ear's auditory range.

However, the difference between noise and tone is that noise consists of many different tones at different frequencies and with different intensities. For this reason, it is necessary to perform Fourier analysis or to extract recordings into individual frequencies with corresponding using the Fast Fourier algorithm:

$$F_k = \sum_{l=0}^{N/2-1} \left(g_i W^{ik} + h_i W^{(l+N/2)k} \right) \tag{2}$$

$$F_{2k} = \sum_{l=0}^{N/2-1} \left(g_i + h_i \right) \left(W^2 \right)^{lk} \tag{3}$$

$$F_{2k+1} = \sum_{l=0}^{N/2-1} \left[\left(g_i - h_i \right) W^l \right] \left(W^2 \right)^{lk} \tag{4}$$

In these equations, N is number of samples, h_i and g_i equal sets of samples, $W=e^{-j\Omega T}$ and F_k Fourier series for discrete Fast Fourier Transformation (FFT). For N/2 even and N/2 odd samples, the expressions in Eqs. 3 and 4 could be regarded as discrete Fourier transformations (DFTs). The number of iterations required for completing the process described in Eq. 3 is $N\log_2 N$. The short-time Fourier transform or short-term Fourier transform (STFT) is a natural extension of Fourier transform in addressing signal non-stationarity by applying windows for segmented analysis. In practice, the procedure for computing STFTs is to divide a longer time signal into shorter segments of equal length and then compute the Fourier transform separately on each shorter segment. The sound/noise signals thus transformed could present the starting point for alternative machining system and process monitoring, and introducing a smart machining.

The focus of this paper is on monitoring processing through sound analysis. During machining, acoustic signals that are generated can provide valuable information about the tool's condition and the efficiency of the machining process. By analyzing the noise, it is possible to detect tool wear or irregularities in the work in good time, which enables the correct adjustment of parameters or the replacement of tools before major problems or a decline in product quality occur.

Smart machining is an inevitable step towards the design of computer-integrated manufacturing as a logical step towards Industry 4.0. In this light, the importance of monitoring the processing process is becoming more and more pronounced. There are various techniques to control the performance of the woodworking process. Some of these are non-contact and are best suited to high-speed production lines, whereas others are contact methods that are very accurate for research but not always suitable for online control (Davim 2013; Aguilera and Davim 2017). Process monitoring through the use of various types of sensors, data acquisition, and data processing creates the conditions for smart machining (Mishra *et al*. 2018.). In addition to the common methods of force measurement (Su *et al*. 2013; Li *et al*. 2018; Liu *et al*. 2018; Zhou *et al*. 2018) or vibration monitoring (Fu *et al*. 2019), sound and acoustic analysis is also of great interest for monitoring machining processes (Cao *et al*. 2017; Kothuru *et al*. 2018; Kishawy *et al*. 2018). Machine learning and its implementation are essential in novel technological processes in order to increase process performance and thus quality. So far, various techniques have been developed to accomplish these tasks, *e.g.* decision trees, support vector machine, regression analysis, Bayesian networks, K-nearest neighbor classifier, deep learning, *etc*. Deep learning itself is a part of the broader field of machine learning, which is a part of the broader field of artificial intelligence.

During the cutting process involving the circular saw blade, various parameters of the process are monitored, such as power, force, and surface quality. This article deals with the problem of recognizing a particular saw blade, which is one of the most important aspects of manufacturing. The rotation of the saw blade produces a specific sound, also known as whistling, which is generated by the geometry of the teeth and the vibrations of the blade during machining (Aguilera 2011; Kminiak and Kubš 2015; Kvietkova *et al*. 2015; Svrzic *et al*. 2021, 2023). Noise produced during machining of wood materials also can be a source of harm to workers and an environmental hazard (Özşahin and Singer 2022). An artificial neural network (ANN) model was developed to model the effects of wood species, cutting width, number of blades, and cutting depth on noise emission in the machining process. The different types of sensors as well as a microphone for noise recording were used for tool condition monitoring during chipboard drilling (Świderski *et al*. 2022). To measure the dullness of the examined drills, they tested different classification algorithms for machine learning and concluded that Deep learning is one of the best three approaches.

The difference between previous approaches and the methodology of this study is in the use of specific techniques for signal adjustment, which makes it suitable for the process of machine learning. A similar technique was proposed by Nasir and Cool (2019, 2020) (a), and Nasir *et al*. (2019) (b). There has been no such comparison between the idling noises of different circular saw blades so far. The idling noise generated by the blade itself is important for further analyses that take into account the interaction between the tool and the material.

According to Svrzic *et al*. (2023), it is possible to determine the speed of the individual selected tool at three discrete speed values (2000, 3000 and 4000 rpm) with an accuracy of 100%. The design of the optimal cutting system with respect to the saw blade factors could be achieved through sound signal analysis and decision making. When the circular saw blade is idle, the noise is generated solely by the movement of the saw blade. This noise could be recorded and analyzed, hopefully providing useful information about the circular saw blade in use. However, machining systems also generate a certain amount of noise associated with their motors and gears. This noise signal could be processed and subjected to a deep learning process that enables machine decision making and process monitoring to determine the current state of mechanical correctness of the machining system.

Thus, this research was intended to give a new perspective of process monitoring by implementation of sound signal analysis and processing and possibly provide starting point for wider base of wood machining sounds repository.

EXPERIMENTAL

Freud LU1C 0100, Freud LU2B 0500, and Freud LU2C 1200 circular saw blades were used for this study (Fig. 1). The corresponding numbers of teeth were 22, 48, and 80 respectively. The LU1C 0100 saw blade and the other two have a diameter of 250 mm, an internal diameter of 30 mm, a cutting width of 3.2 mm, and a body thickness of 2.2 mm. The carbide-tipped tooth shape on the LU1C 0100 is ATB with a 10° positive cutting angle.

According to the manufacturer, this blade is intended for longitudinal cutting and cross-cutting solid wood. The LU2B 0500 blade has ATB-shaped carbide teeth with a 10° positive cutting angle and is intended for cutting solid wood and wood-based materials. The third blade is the LU2C 1200, which has tungsten carbide (TC), ATB-shaped teeth with a 15° positive cutting angle and is designed for rip and cross-cutting softwood, hardwood, and wood-based panels.

The study was conducted in the Laboratory of Machinery and Apparatus at the Faculty of Forestry, University of Belgrade (Beograd, Serbia). The machining system used for this study was a Minimax CU 410K combined machine (SCM, Rimini, Italy) equipped with a 3 kW three-phase asynchronous motor. The speed of the motor was set by a customized frequency regulator (F.R. at Fig. 3) to 4000 rpm with a corresponding frequency of 50.5 Hz. The noises that occur when the tool is idle were recorded using a dbx RTA-M measurement microphone with an electret condenser on the back (Fig. 2a). The RTA-M is an omnidirectional, flat frequency measurement microphone specifically designed to record all frequencies from 20 Hz to 20 kHz, ensuring accurate "real-time "pinking" analysis of the audio signal. It is operated with phantom power. To reduce the effects of vibration, the microphone is housed in an anti-vibration rack. The Focusrite Scarlet SOLO USB audio interface (Fig. 2b) was connected to a PC.

(a) (b) (c)

Fig. 1. FREUD (a) LU1C 0100, (b) LU2B 0500, and (c) LU2C 1200 circular saw blades

Audacity, a cross-platform open source audio software, was used to record the audio signals. The signals were sliced and trimmed using the WavePad Sound Editor developed by NCH Software. The measurements were carried out at a sampling rate of 44100 Hz.

(a) (b)

Fig. 2. (a) RTA-M Measurement microphone; (b) Scarlet SOLO audio interface

The microphone was placed 1200 mm away from the rotating tool, as shown in the test setup (Fig. 3).

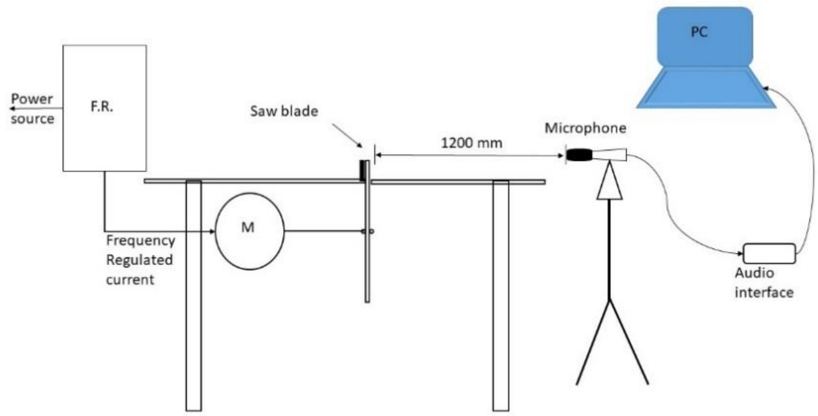


Fig. 3. Experimental setup

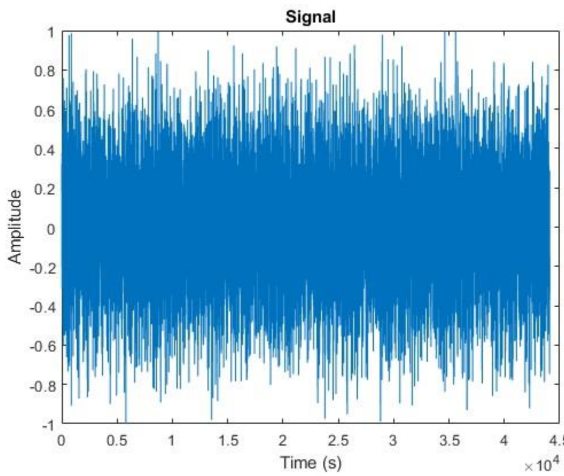
The sounds produced during the experiment came from moving machine parts (electric motor, bearings, spindles, *etc*.) and from the whistling of the saw blade. These sounds were captured with the microphone and recorded on the PC as wave files. Originally, the length of the wave files were 4 minutes for each saw blade speed. Spectral analysis was performed on these recordings using the fast Fourier transform (FFT) and the short-time Fourier transform (STFT). The use of the FFT alone was not sufficient for a detailed analysis, as the power spectra obtained contained a lot of noise or spurious frequencies. A further implementation of the STFT, using the Hann's window function with a length of 100 Hz and an overlap of 50% to obtain a spectral density plot, smoothed the spectral line considerably and thus showed which spectral regions need to be carefully observed. Self-made software was used to perform this task. This is particularly important for creating inputs to the database for deep learning networks. In general, there are some rules for preparing the raw data: 1) The data must be suitable for the network architecture; 2) The dimensionality must be reduced so that the patterns become clearer and 3) The data must be prepared to cover the entire solution space. All of these steps were performed by custom applications created with MATLAB codes, except for the STFT which was done by self-made C++ software.

A further step consisted of cutting the entire 4-minute recording into smaller, even parts of 1 second in length, which was done using the WavePad software. Now it was possible to create a database for training the deep learning network. The first step was to import all 240 short-time recordings of the sound signal for each saw blade speed and convert them into 2D images of 3D spectrograms. Spectrograms are reported as 3D plots (frequency-time-power) obtained by STFT or wavelet transform of the original sound signals. In the 2D representation, an RGB scale is used to represent the power of specific peaks or spectral regions. These 2D spectrograms were saved in the JPG format and served as training data for the deep learning network GoogleNet Transfer Learning Network, which was developed specifically for image recognition. Some adjustments were made in terms of the number of classes, the initial learning rate, which was set to 0.0001, the validation frequency, the maximum number of epochs, and the percentage of data used for validation.

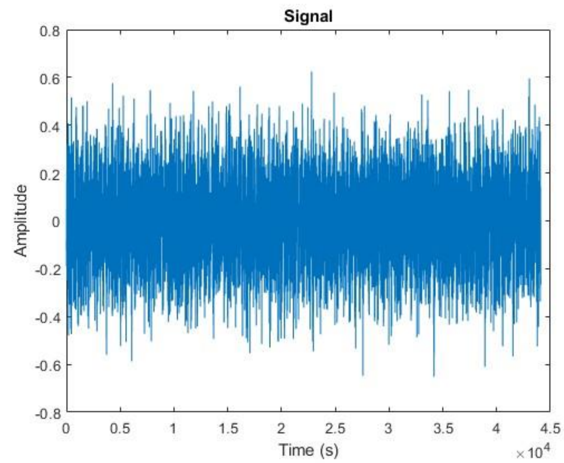
RESULTS AND DISCUSSION

Examples of the raw audio signals that were recorded throughout the experiment and saved as a wave file are shown in Fig. 4. Based on the signals obtained during the recording, it is impossible to predict the behavior of the guide frequencies or to identify a reasonable causality of their performance. The only conclusion that can be drawn is that the amplitude of the recorded signals is higher in the case of the LU1C blade compared to the other two blades.

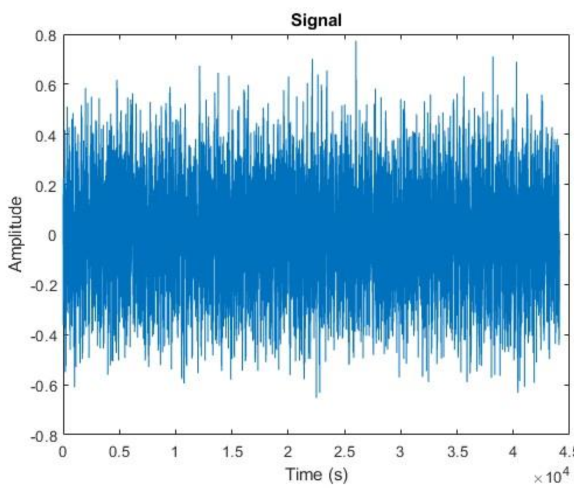
To look for a regularity in the sound signals obtained, further steps were taken in terms of an FFT application. This procedure should make it possible to resolve the complex signal into a certain number of frequencies with the corresponding amplitude values. The power spectra determined using FFT are shown in Fig. 5.



(a)

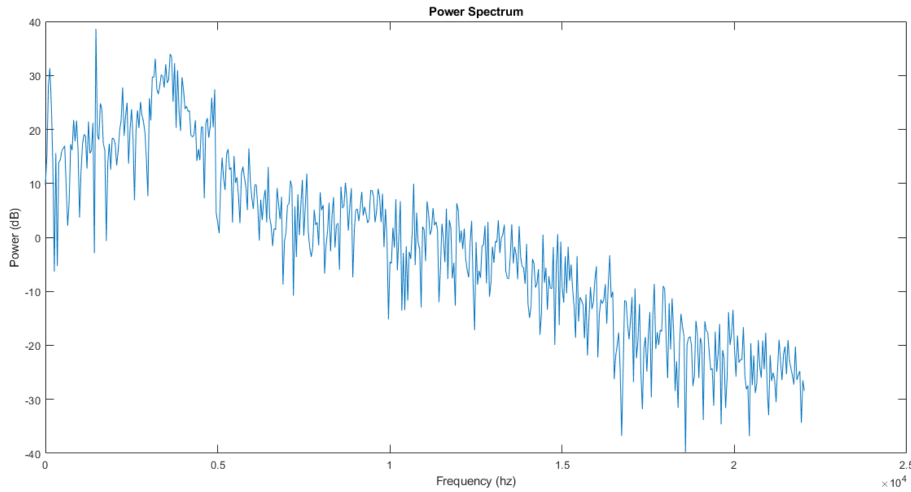


(b)

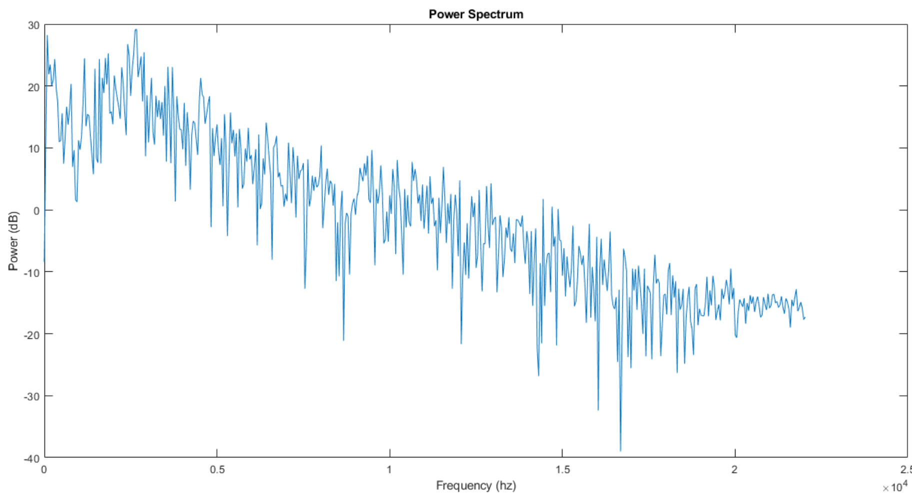


(c)

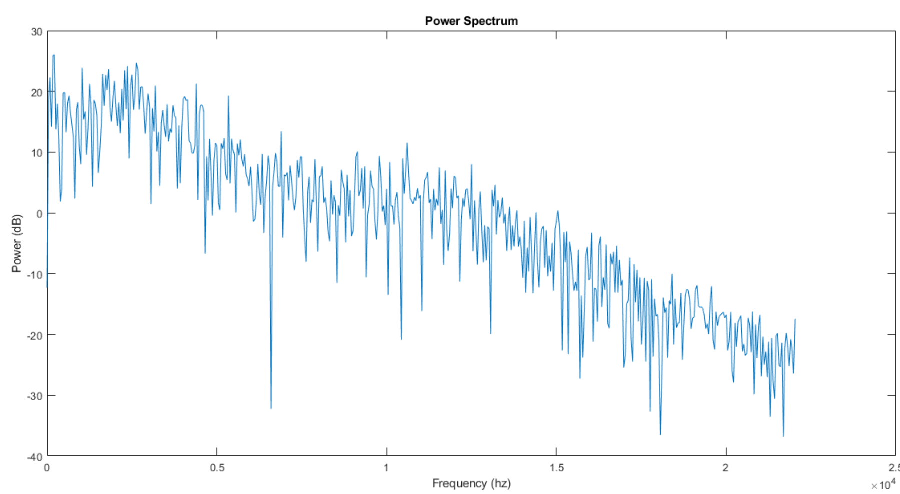
Fig. 4. Sound signal recorded for: (a) LU1C, (b) LU2B and (c) LU2C circular saw blades



(a)



(b)



(c)

Fig. 5. Power spectra for (a) LU1C, (b) LU2B. and (c) LU2C circular saw blades

The presented power spectra did not attain satisfactory data for further analysis. The reason for this lies in the obvious presence of parasitic noise frequencies. The data presented in this form did not fulfill requirements for machine learning process. So further steps in data processing were done such as obtaining average spectral density by means of STFT. After performing that procedure, the graph presented in Fig. 6. gave a much clearer picture as to how to extract data in proper form for deep learning network training. The distinct amplitude peaks and their corresponding frequencies are also presented in Table 1.

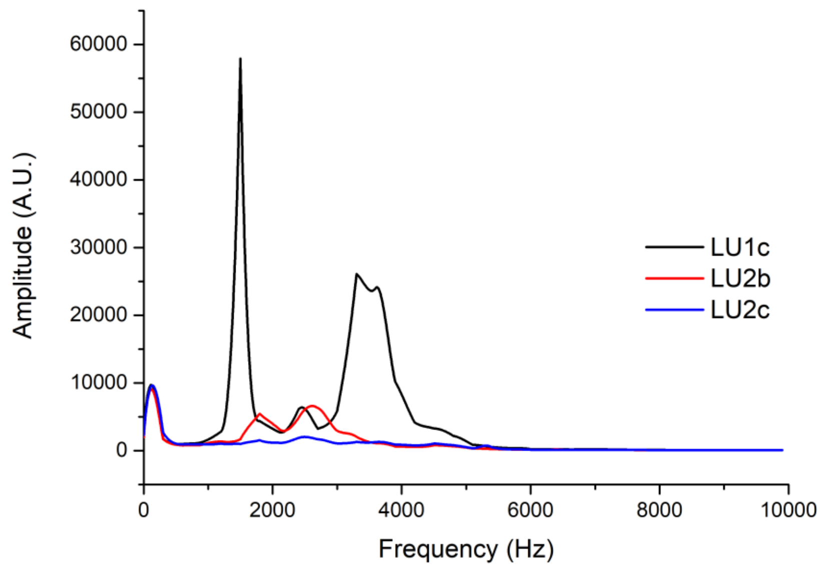


Fig. 6. Average spectral density for three circular saw blades

Table 1. Distinct Amplitude Peaks and their Corresponding Frequencies According to STFT

	Frequency (Hz)	100	1500	1800	2500	2600	3300	3700
Amplitude (A.U.)	LU1C	15900	57900	/	7300	/	26100	25400
	LU2B	15000	/	5450	/	7030	/	/
	LU2C	13920	/	1525	2226	/	/	/

According to Fig. 6, it was possible to extract two spectral ranges that were of interest for further analysis. The first spectral range extended from 0 to about 700 Hz with a peak at 100 Hz. The curves for all three saw blades observed overlapped in this range. As previously mentioned (Svrzic *et al.* 2023), this spectral range could be related to the noise generated by the machine itself. Since the speed was the same for all saw blades, the curves overlapped completely. The second spectral range of interest is from about 1000 Hz to about 5000 Hz. The spectral density curves for all three saw blades showed different behavior in this range and resulted in different peak values, especially in the case of the LU1C saw blade.

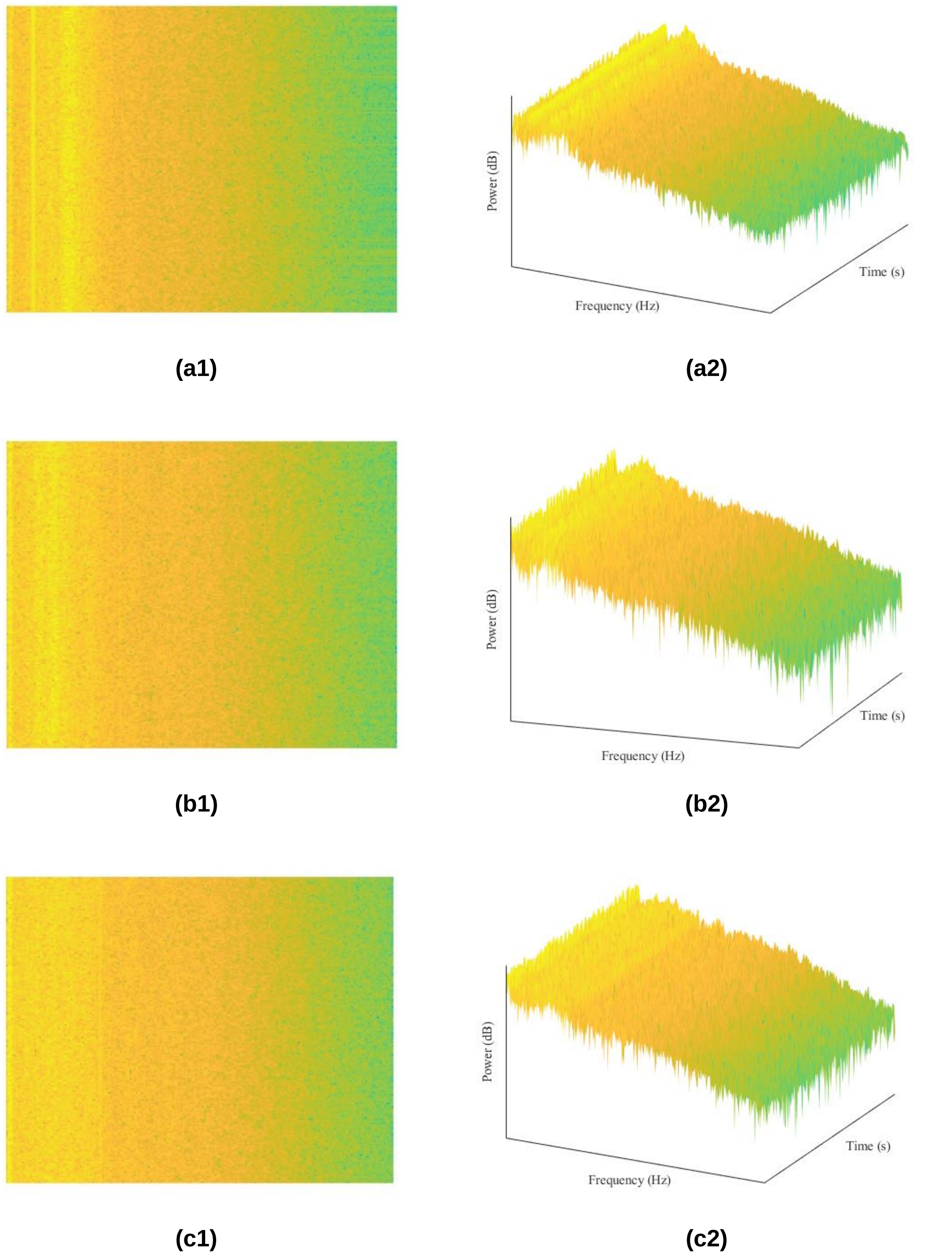


Fig. 7. (a1) 2D spectrogram without tick and axes for processed sound signal for the LU1C circular saw blade; (a2) 3D spectrogram for processed sound signal for the LU1C circular saw blade; (b1) 2D spectrogram without tick and axes for processed sound signal for the LU2B circular saw blade; (b2) 3D spectrogram for processed sound signal for the LU2B circular saw blade; (c1) 2D spectrogram without tick and axes for processed sound signal for the LU2C circular saw blade; (c2) 3D spectrogram for processed sound signal for the LU2C circular saw blade

This spectral range was associated with the noise generated when the observed circular saw blades were idle. The information about the spectral range associated with the rotation of the saw blades provided information about to which part of the spectrum attention should be paid. For this purpose, a band pass filter in the range of 600 to 6000 Hz was applied to all recordings. The filtered signal was subjected to an STFT, which analyzed the spectrograms of the signal with a time l second each. The spectrograms shown in Fig. 7 are a 2D representation of the 3D time-frequency-power diagram, where the power is represented as a color on the RGB scale (the warmer the color, the higher the power).

The purpose of removing ticks, axes, and labels from 2D spectrograms corresponds to the mentioned rules for data preparation, which provide only the essential information for the deep learning process. The 3D spectrograms shown in Fig. 7 only serve to illustrate and explain the 2D spectrograms obtained.

The random 200 out of a total of 240 2D spectrograms for each of the three circular saw blades studied were used for training GoogleNet deep learning network. The remaining 40 were used to test the trained network. At the end of the training process, the recognition accuracy was highly satisfactory at 97.50%, as shown in Fig. 8.

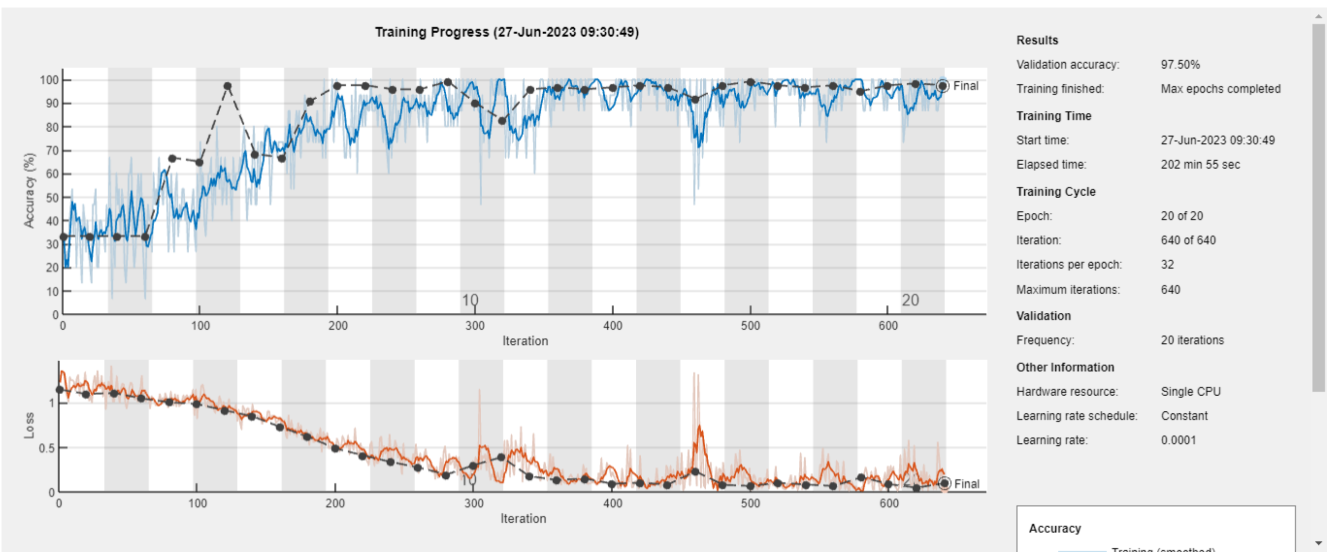


Fig. 8. Deep learning network report

In the study, 40 spectrograms were used for each circular saw blade to test the trained network. The results showed a recognition accuracy of 100%, which means that the trained network could accurately predict which saw blade was used. Such high accuracy may be due to the number of testing samples, meaning that the higher number could possibly give less accurate results, but certainly not below the achieved 97.50%. The accuracy shown in the learning network report is considered sufficient for machine learning and decision-making. Further research in this area will include the interaction of a tool (circular saw blade) with materials commonly used in woodworking with different cutting conditions and different bluntness states of the tool.

CONCLUSIONS

1. The sound signal examined in this investigation proved to be a satisfactory data carrier for this type of investigation.
2. The processing of the sound signal provided fairly good information, consistent with certain circular saw blades.
3. From the average spectral density plots, it was quite clear which spectral regions were of interest for training the deep learning network.
4. The spectrograms provided a sufficiently good basis as data for the deep learning process.
5. According to the results of the deep learning network, a validation accuracy of 97.5% was achieved, which indicates that this approach can be used for monitoring cutting processes in terms of decision making.
6. It is quite obvious that different circular saw blades with a specific tooth geometry produced recognizable noise patterns, resulting in the creation of specific sound repositories which could be used by the manufacturers of machining systems and their users. The findings of this research implicate the possible use of sound sensors in machining systems for monitoring purposes.
7. However, the results presented refer to the particular environmental conditions. No reverberation noise was taken into account.

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