

# Predicting Tuning Harmonics in Circular Drum Membranes using Machine Learning

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Code available at:

[https://colab.research.google.com/drive/1y\\_XpOJWH0CSJWv1Y0KBRwKMGMytixh6D?usp=sharing](https://colab.research.google.com/drive/1y_XpOJWH0CSJWv1Y0KBRwKMGMytixh6D?usp=sharing)

## Introduction

The art of drum tuning is both a science and a skill, requiring careful adjustment of tension across the drumhead to achieve desired tonal characteristics. Despite the widespread use of drums in various musical genres, tuning them remains a challenging and often subjective process, influenced by the drum's construction, the player's preferences, environmental factors and a lot of trial and error. Full time drummer Rojas, F (2024, personal communication, translated), comments on the subject: "It drives me crazy, I'm trying to get the correct tuning at the first try, but it's so relative". This relativity results in drummers developing different approaches to tune their drums, some examples include the Drumeo<sup>[1]</sup>, ArtOfTuning<sup>[2]</sup>, Sweetwater<sup>[3]</sup> and Sounds Like A Drum<sup>[4]</sup> videos all featuring different techniques.

This project aims to bridge the gap between traditional tuning methods and modern machine learning techniques by developing neural network (NN) capable of inferring the sound profile of a drum from tuning tension of each bolt.

The ultimate goal of this work is to create a system capable of tuning any drum piece, including both resonator and batter heads, across various drum types. However, as a first step, this project focuses on a very simplified scenario: the range of sounds a floor tom can produce with a uniform batter head and no resonator head. By beginning with this controlled setup, the complexity of the problem is reduced, allowing for a better understanding of the relationship between drumhead tension and the resulting acoustic properties.

In this initial phase, data is collected by tightening the tuning bolts in the standard star-shaped pattern, beginning from a hand-tightened baseline and counting the amount of turns. Audio recordings are made at each tuning state using high-quality microphones. Spectral analysis is performed to extract key acoustic features. Data is used to train a NN that maps the resonance of the drum to its tuning configuration.

This foundational work lays the groundwork for future advancements, ultimately aiming to develop a robust, generalizable model that can assist musicians and sound engineers in achieving precise and consistent drum tuning for any drum type and genre.

## Methodology

### Data Gathering

The methodology was designed to simplify the problem as much as possible, considering a simple ground state problem from where to build. The experimental setup involves a single tom with the resonator head removed to isolate the behavior of the batter head. Including the resonator head would mean considering every combination of batter and resonator tuning combinations, which would make the problem considerably more difficult.

The tuning process starts with all tuning bolts hand-tightened to a baseline, or "tare state," ensuring a uniform starting point achievable by any drummer. Pressure is placed upon the drumhead using both



Figure 1: Setup for recording. Microphones at fixed positions over the floor tom.

hand as to reduce the viscoelastic relaxation, this is standard procedure for most tuning techniques. An audio sample is recorded for the drum in its tare state. From this baseline, the tuning bolts are adjusted incrementally in a uniform manner, with each bolt tightened by a an eighth of a turn. This ensures consistency and repeatability in the tuning process. To maintain balance across the drumhead, the bolts are tightened in a standard star-shaped pattern, a method commonly used by drummers, which reduces the effect of viscoelastic relaxation.

The audio recordings are captured using a Mackie EM-890 concert microphone positioned at 12cm from the center with an approximate angle of 45° and a Mackie EM-91C condenser microphone at 80cm with an approximate angle of 45°.

A hickory wood, size 5A stick and wooden acorn shaped head is used for all testing. The hits were all as centered as possible.

For each set up, different hits are tested: piano, mezzo piano, mezzo forte, forte and fortissimo for a total of 10 data points for each set up, adding up to 110 data points total. Each data point considers three identical hits as to reduce human error.

## Data Processing

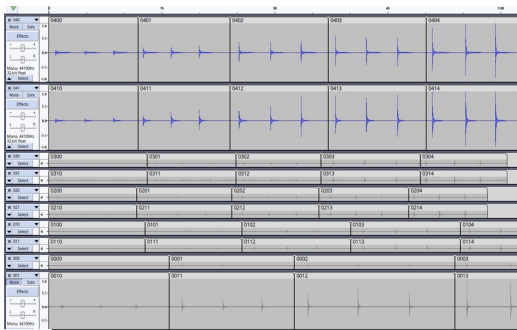


Figure 2: Data recording in Audacity.

The recorded audio is routed through a Mackie Onyx Producer 2-2 audio interface into Audacity, a digital audio workstation. To ensure the correct volumes are being played, the wave amplitude in the concert microphone is checked for every hit, ensuring dynamics are distinct and consistent. The condenser microphone is not checked because it is more heavily affected by the acoustics of the room, leading to different volumes on hits of similar intensity. Spectral analysis of each three hit trial is performed within Audacity, selecting the optimal bandwidth for each case and exporting the resulting data as CSV file. The name of the file was used to save information according to the following serial code structure:

Serial number of data	
00000.csv	Drum Head Hit
00000.csv	Tuning State
00000.csv	Microphone used
00000.csv	Dynamics (Volume)

Table 1: Serial codification of data.

## Building the Framework

Data was then uploaded into Google Drive and mounted into a GPU Colab environment, using the serial number to categorize data points. A vector,  $X$ , was generated considering tuning, microphone and dynamic. The corresponding vector,  $y$ , featured the Fourier transform dictionary. Data was binned into evenly spaced intervals as spectrograms had different band widths. Bins considered the average value.

A different number of bins where tested through visual inspection as to reproduce the curve without adding noise or loosing features. The data from a recording can be seen in Table 2 below, next to it Figure 3 shows its plot in blue, and a 125 bin structure for frequency in red:

000000.csv		
	Frequency (Hz)	Level (dB)
0	5.383301	-91.172676
1	10.766602	-75.086281
...	...	...
4093	22039.233398	-135.977173
4094	22044.616699	-136.252945
[4095 rows x 2 columns]		

Table 2: Data from a three shot recording.  
Floor tom; no turns; concert microphone; piano.

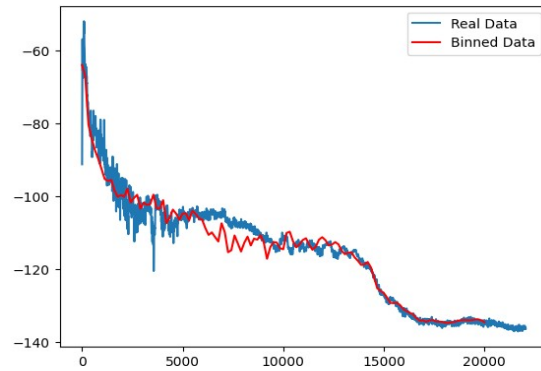


Figure 3: Fourier plot and its binned approximation.

The vector  $y$  was transformed using the sklearn library. First, a scaling was performed using the StandardScaler; then, principal components where chosen through PCA to explain 99% of the variance; finally, data was separated using the train\_test\_split using the standard 80/20 ratio.

## The Neural Network

A neural network was build using five Dense layers with increasing depth 8-16-32-64-64 using ReLu activation functions and a final linear output layer shaped as the output PCA vector. The model compiles using the mean squared error (MSE) method and Adam optimizer. Training is done with batchsize 2 and 500 epochs with Early Stopping.

## Results

Training was done with a 125 bin configuration, the maximum value before results get too noisy, and a 20 bin configuration, which offers a more user friendly information. The models perform with a 0.62 MSE and 0.28MSE respectively:

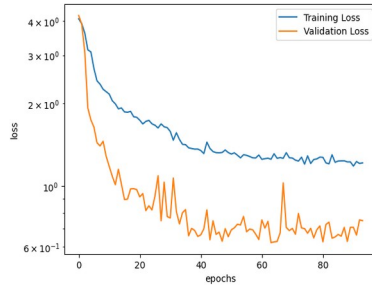


Figure 4: 125 bins. Training and Validation Loss.

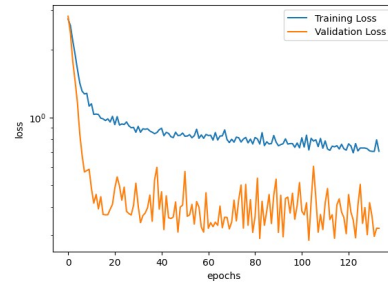


Figure 5: 20 bins. Training and validation loss

Data is transformed back from the PCA and unscaled from the Standard Scaler so that the plot shows meaningful data. In the following figure, a plot of all the test samples can be seen against each machine prediction.

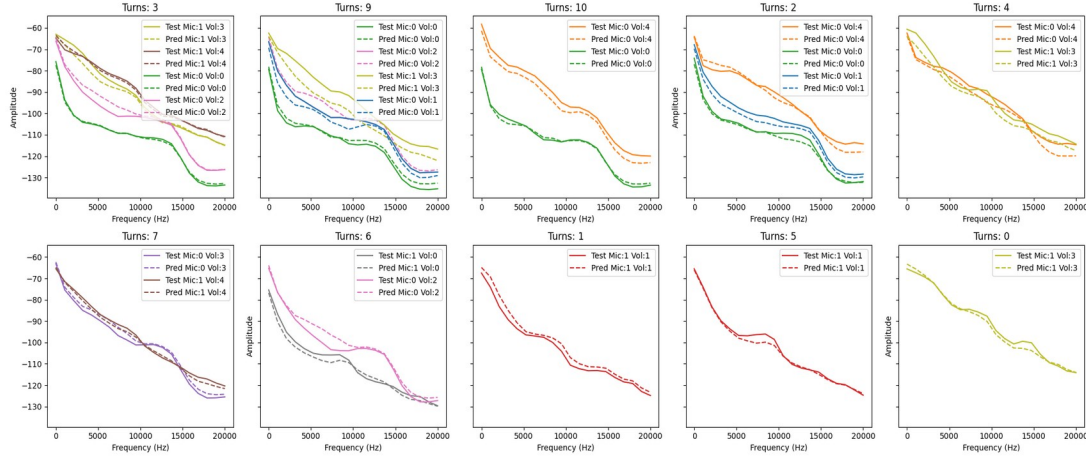


Figure 6: 125 bins. Plots showing results for every test data point in the test set.

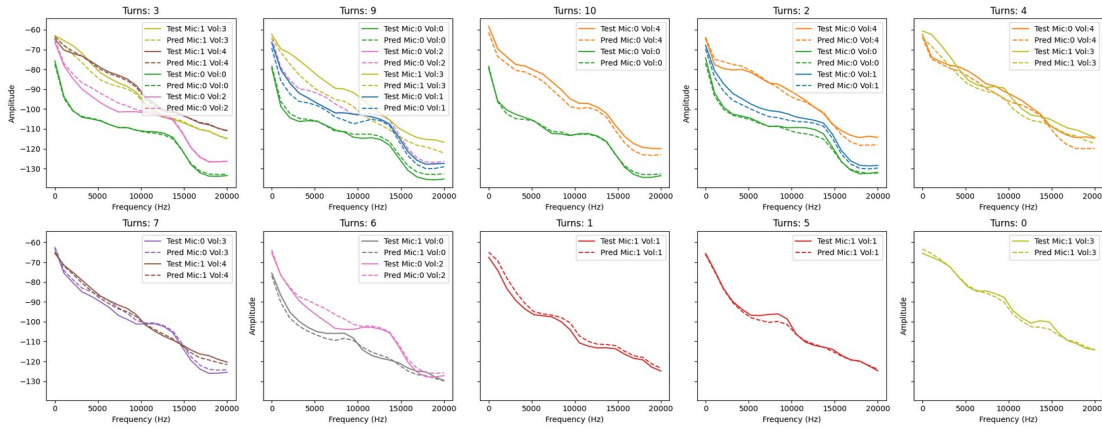


Figure 5: 20 bins. Plots showing results for every test data point in the test set

Each of the plots above shows a tuning setting. On each, pairs of solid and a dashed lines show test and predicted results respectively. Each of these trials is labeled according to microphone and volume configuration. As train\_test\_split was used, some tunings have more data points than others.

## Discussion

The results obtained from this experiment are good enough as to predict the general sound range of the studied tom and can easily be expanded to included other drums without altering the model in a

significant way. Other possible improvements are implied in the earlier simplification of the problem: testing nonuniform tuning configurations, including resonant heads, snare wires, or silencers. This complexities can be built into the model with some adjustment.

Although the model could eventually work with 125 bins, the benefit for the user does not increase much after the 20 bins, and the charts can even become more difficult to read. Less bins also come with a smaller MSE error, because the model is not trying to fit the noisy nature of a 2D membrane that is not as relevant for overall sound.

Results give one more piece of information that wasn't expected. Due to the visualization technique, it was possible to consider the dynamics of each tuning, where some frequencies become more affected than others as volume increases. This new knowledge can be harvested to provide the drummer not only with a specific sound the drum will make, but also how will the drum behave under different circumstances.

The information obtained by the use of two microphones was intended for data augmentation purposes, as to include real noise from the environment instead of synthetic Gaussian noise. It is notable that the data from the condenser microphone can be used to train a different machine to predict the sound on different spaces, which is particularly useful in live performance scenarios, for both drummers and sound engineers.

## Bibliography

\* This work was done with the help of Artificial Intelligence software as to produce code, help guide the investigation and tune the neural network.

[1] Drumeo. *How To Tune Your Drums (Jared Falk)*. (July 19<sup>th</sup>, 2019). Accessed on December 8<sup>th</sup>, 2024. [Online video]. Available: <https://www.youtube.com/watch?v=HHO-ILhESo0>

[2] ArtOfDrumming. *The Basics Of Drum Tuning*. (January 5<sup>th</sup>, 2021). Accessed on December 8<sup>th</sup>, 2024. [Online video]. Available: <https://www.youtube.com/watch?v=4p6fqIljaqE>

[3] Sweetwater. *How to Tune Your Drums Like a Pro | Drum Lesson*. (September 10<sup>th</sup>, 2019). Accessed on December 8<sup>th</sup>, 2024. [Online video]. Available: <https://www.youtube.com/watch?v=Rp-yIg8NAQE>

[4] Sounds Like A Drum. *Best Tuning Method - Don't Make it More Difficult | Season Six, Episode 10*. (August 22<sup>nd</sup>, 2023). Accessed on December 8<sup>th</sup>, 2024. [Online video]. Available: <https://www.youtube.com/watch?v=pbQv07HNKS8>