Villanova University

# Finding Hidden Faults in Endodontic Tools

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Mentor -

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## HYPOTHESIS

The diagnosis of faults in endodontic file instruments can accurately utilize signal processing techniques for force and vibration data collection with Fourier Transform and Wavelet Transform. With feature extraction done through MATLAB, I suspect that machine learning models trained on the features will provide very high accuracy while differentiating between normal and faulty tool behaviors, thereby improving the safety and efficiency of endodontic procedures.

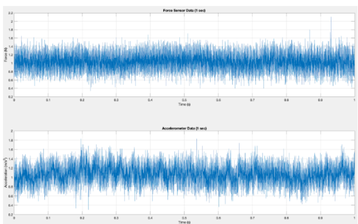
## PROBLEM

When the soft tissue inside people's teeth become infected or inflamed, root canal is necessary to fix this. This tissue gets infected or inflamed due to deep cavities, cracked teeth, trauma, or repeated dental procedures. According to the American Association of Endodontists, around 15 million root canals are performed in the United States annually. Out of those 15 million patients, around 1.11 million of these patients experience a breakage of the endodontic tool during the procedure. This breakage can result in serious complications like not being able to properly clean or shape the tooth and even the possibility that surrounding nerves and tissues get damaged. This also carries the risk that the treatment could be prolonged or even fail entirely.

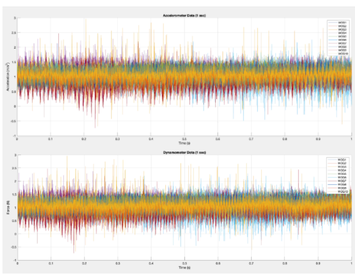
## BACKGROUND INFORMATION

**Fault detection-** determining the problem in the given system, specifically determining when, where, and what happened
**Endodontic tool-** specialized instruments used by dentists during root canal treatment to clean, shape, and fill the root canals, ultimately saving a tooth from extraction
**MatLab-** a programming language and numeric computing environment that works with matrices and arrays
**Fourier Transform-** a mathematical operation that converts a function from the time domain to the frequency domain
**Principal Component Analysis-** dimensionality reduction technique that transforms high-dimensional data into a lower-dimensional set of uncorrelated principal components keeping as much variance as possible.

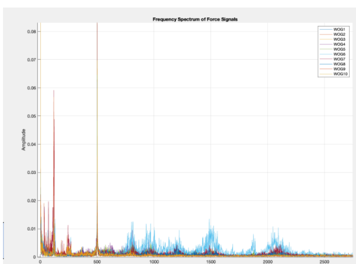
## RESULT



**1.** The graphs to the left demonstrate the 1 second interval graphs of both the dynamometer and the accelerometer to see a small interval to determine exactly when there is something irregular throughout the data. Originally, the data was a little longer than 1 second, so this also allowed both sets of data to be an equal duration to compare consistent data.



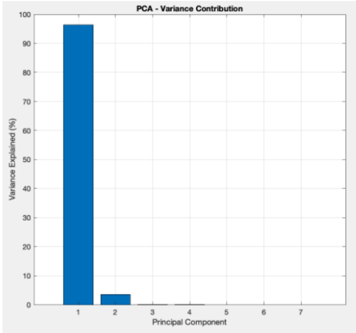
**2.** The graphs to the right demonstrate the 1 second interval graphs overlapped with the other WaveOne Gold (WOG) endodontic file data. When the data is overlapped, it makes it easier to be able to see the trends within the data and creates an easy way to identify the time of an irregular force or vibration within the data through the abnormal spikes. Using the data from both graphs, it is shown when there is a correlation between the force and vibration.



3. This graph is the frequency spectrum of force signals recorded from several WaveOne Gold (WOG) endodontic files. With a Fourier Transform, the time domain force signals are converted to

the frequency domain, and the dominant frequency components in the data are displayed. Peaks in the spectrum indicate frequencies at which force variations are most pronounced, in which patterns can be determined that can be associated with the cutting dynamics or mechanical failures impending of the file.
Interestingly, some files exhibit distinct peaks at specific frequencies (ex: in the range of 500 Hz and above), which can reflect variations in force application or vibration characteristics.

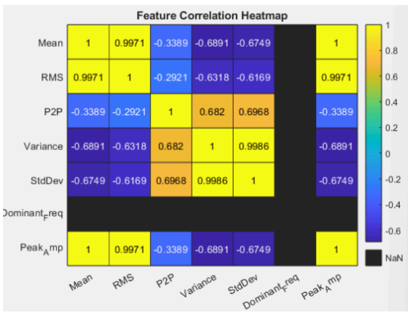
**4.** This plot displays the principal component variance contribution of a Principal Component Analysis (PCA) run on the dataset. In this case, the first principal component (PC1) explains over 90% of the variance, meaning that it contains most of the important information in the data. The second principal component (PC2) contributes only a small amount, and the remaining components contribute little variance, meaning they contain mostly redundant or less significant information. This result shows that most of the variability in the force and vibration signals is represented using just one or two principal components, and hence, one can reduce the complexity of the dataset without compromising on key features for analysis. This is helpful because it eliminates noise and redundancy, leading to easier and more interpretable results.



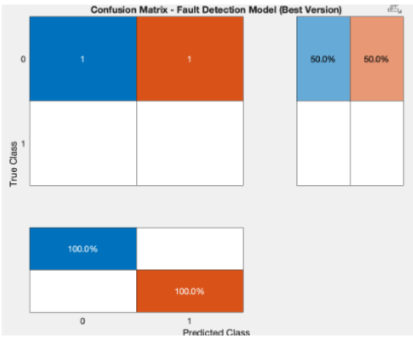

5. This table was used to analyze the dominant frequency and peak amplitude of the force signals from different WaveOne Gold (WOG) endodontic files used in the study. The aim was to identify the most significant frequency components of the force data, which could provide insights into repeating force patterns or anomalies during root canal treatment. However, the dominant frequency values are all zeros, which mean that either the force signals lack substantial periodic components, the analysis can be made to shift in the Fourier Transform process, or the signals are primarily comprised of low-frequency variations which were not sufficiently recorded. Despite this, the peak amplitude values are evidence of the maximum force exerted by any particular file and are helpful to detect uneven force application, excessive stresses, or variabilities in the cutting process. This information is helpful to aid in fault diagnosis since it indicates files that can experience unusually high forces during cutting, a situation that may lead to file fatigue, breakage, or poor cutting performance during root canal procedures. Further refining of the frequency analysis would achieve more understanding of the mechanical action of the files and allow for better detection of potential defects.

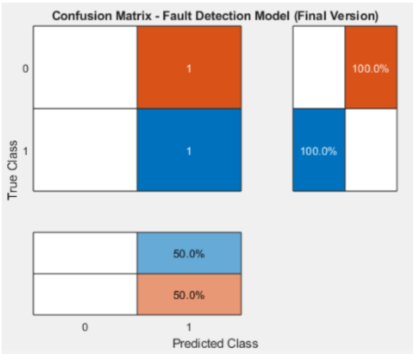
| | Dominant_Frequency_Hz | Peak_Amplitude |
|---|---|---|
| WOG1 | 0 | 1.0345 |
| WOG2 | 0 | 1.0824 |
| WOG3 | 0 | 1.0627 |
| WOG4 | 0 | 1.19 |
| WOG5 | 0 | 1.1267 |
| WOG6 | 0 | 0.93548 |
| WOG7 | 0 | 0.91447 |
| WOG8 | 0 | 1.097 |
| WOG9 | 0 | 0.94891 |
| WOG10 | 0 | 1.0812 |

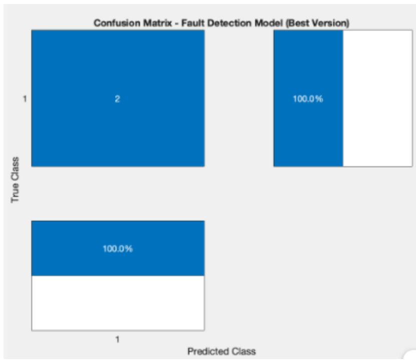
**6.** This feature correlation heatmap was used to study the correlations among the various extracted features from the project's force and vibration signals. The heatmap visually illustrates the strength of the correlation among various features, from -1 to 1. A correlation near 1 indicates a strong positive correlation where both features increase together, and a correlation near -1 indicates a strong negative correlation where one feature increases as the other decreases. Using different statistical and signal processing features extracted from the force and vibration signals, they help quantify different aspects of the signal behavior and can be used for fault diagnosis. From the heatmap, we observe that Mean and RMS (Root Mean Square) values are highly correlated (0.9971), as might be



anticipated since RMS is influenced by the signal's overall magnitude. Similarly, Variance and Standard Deviation (StdDev) share an almost perfect correlation (0.9986), since they both quantify signal dispersion. On the other hand, Peak-to-Peak (P2P) values are moderately correlated (0.682) with Variance and StdDev, suggesting that large fluctuations in force result in higher variance in the data. Interestingly, the Dominant Frequency feature is missing (NaN), in line with the observation that no dominant frequency was able to be detected in the force signals. Within the project, this correlation analysis helps in machine learning model feature selection. Highly correlated features provide redundant information, and therefore only one of them may be needed to train a fault detection model. Additionally, weakly correlated features may have unique information useful for fault classification in the WaveOne Gold (WOG) files. By being aware of these correlations, the feature set can be optimized for improving fault diagnosis accuracy and model efficiency.




7. The confusion matrices presented are the output of a fault detection model, which was trained to distinguish between healthy and faulty cases using derived features from force and vibration sensor measurements. The model is trained with an 80-20 train-test split, where 80% of the data available was used for training and the remaining 20% was reserved for testing. This split ensures that the model is validated on unseen data to estimate its real performance. However, due to the small size of the dataset, different runs of the model produce different results, as the random selection of test examples heavily affects classification outcomes. In the first confusion matrix, we find that there is a 50% accuracy rate, which indicates that the model correctly classified one normal and one defective case but failed in another case. The second matrix shows the same division, indicating that the model is struggling to generalize. The final matrix registers a 100% accuracy, but the test set consisted solely of faulty cases and not normal ones, suggesting the model was never tested against the normal ones. This suggests there could be a bias in data partitioning and emphasizes how important it is to have even representation of normal and faulty cases in the test set. The method used in the current research, principal component analysis (PCA) to extract features and ensemble learning for classification, is a well-structured strategy, but optimization of dataset size and train-test consistency is required for an improved performing model.


## ABSTRACT

This study aimed to advance the automatic fault detection system for the endodontic file using MATLAB signal processing. Unexpected tool failures during root canal treatments

complicate procedures and increase patient risk, making early fault detection essential for safer and cost-effective dental procedures.

The research's purpose is to reduce visual inspection and instead use data-based real-time feedback for dentists. Automated monitoring would increase patient safety with the sense of prolonging tools and diminishing costs in saving failures. Moreover, early detection improves efficiency of procedures and diminishes risks with more reliable root canal treatments. For data collection, dynamometer and accelerometer sensors were exploited. Fourier Transform and Wavelet Transform were used to process the signals toward the goal of delivering frequency and energy-based features.

The FFT highlighted that if the dominant frequency was small, its magnitude varied greatly between trials, suggesting that variations in tool resistance and stress in the tool. Similarly, wavelet energy levels fluctuated in various layers of decomposition, indicating a non-uniform application of force and possible degradation of the tool over time. Statistics demonstrated that a lot of standard deviation values were high in energy and dominant frequency, indicating the presence of abnormal force patterns and stress fluctuations. These findings show MATLAB signal processing can diagnose device faults before failure.

Frequency magnitude and wavelet energy variability are strong predictors of wear, microfractures, or loss of stability. Future work needs to expand the database out, enhance learning models, and add real-time feedback to practice to enhance the endodontic treatment safety and accuracy.

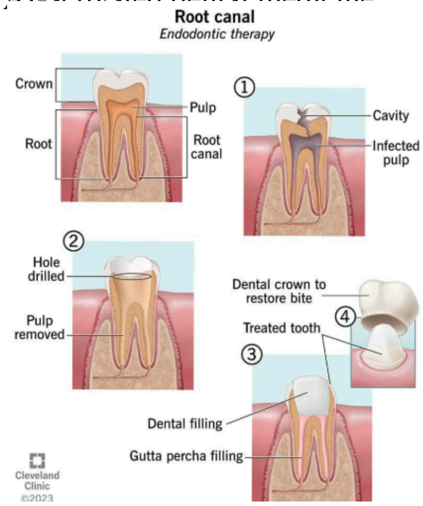
## IMPACT

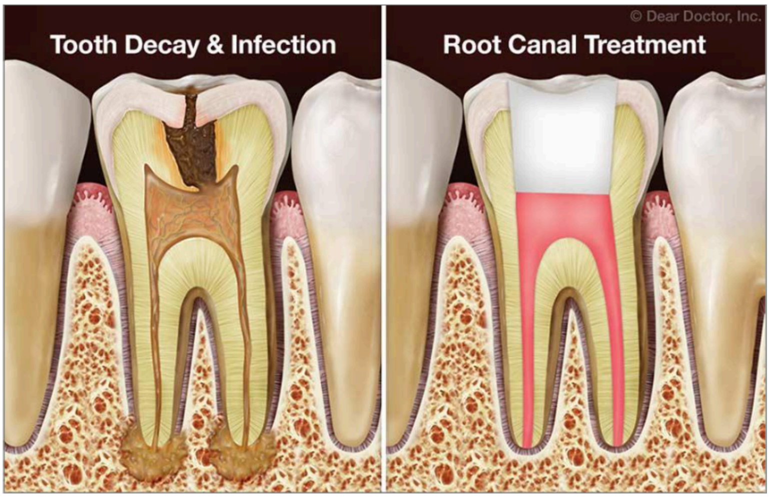
The scope of this project extends far beyond simple technical innovation in machine learning—it has significant implications for dentistry, endodontics, and medical device reliability. Root canal treatments (RCTs) are among the most common dental procedures worldwide, with an estimated 15 million root canals per year in the United States alone and over 40 million worldwide.

The procedure involves removing the infected or damaged pulp from inside the tooth, disinfecting the canal, and closing to prevent infection. The endodontic file is a crucial element of the procedure, a type of instrument for cleaning and preparing the root canal. However, one of the most serious hazards of RCT is file fracture, which in approximately 7% of cases are based on instrument type, technique, and patient anatomy. When a file fractures inside the canal, it can lead to incomplete cleaning, persistent infection, and even failure of the whole procedure, which in some instances requires surgical removal or tooth extraction.

This project envisions overcoming this risk through the development of a machine learning-based fault detection system capable of identifying early subtle signs of instrument fatigue and possible failure prior to their occurrence, thus improving patient safety and clinical outcomes. Utilizing high-frequency force and vibration sensor data, the system has the potential to improve quality control during dental tool manufacturing, assist clinicians with real-time monitoring, and reduce complications due to RCT failures.

If this technology were maximized to its optimum, it might be used in smart endodontic handpieces, which would alert practitioners to potential issues before a file reaches a failure point. At over $1.3 billion spent on endodontic treatment annually in the U.S. alone, extending the life of instruments and reducing failure rates would equate to cost savings and better patient care on a significant level, a revolutionary leap towards the future of AI-activated dental medicine.




## RESULT


**1. Data Collection:**

- Collect 10 recordings each of the dynamometer for force signals and the triaxial accelerometer for vibration signals for every sensor during experimentation of root canal treatment (RCT).

**2. Data Preprocessing:**

- Extract force signals only out of the dynamometer data.
- Extract vibration signals from the accelerometer data.
- Segment each signal into 1-second windows.

**3. Signal Processing and Feature Extraction (Using MATLAB)**

- Conduct FFT analysis on each 1-second segment for determination of dominant frequency and magnitude of the dominant frequency.

**4. Feature Engineering and Selection**

- Combine the frontier frequency-domain and time-frequency features.

**5. Machine Learning for Fault Diagnosis**

- Train machine learning models with these extracted features.
- Evaluation in terms of performance.

**6. Fault Detection and Diagnosis**

- Put the trained model through new experimental data for prediction of faults of the tool.

- Compare the outputs of machine learning against the existing tool conditions to validate the effectiveness.

**Independent Variables**

- Force signals from the dynamometer.
- Vibration signals from the triaxial accelerometer.
- Condition of the endodontic file

**Dependent Variables**

- Dominant frequency magnitude
- Wavelet energy levels
- Statistical variations in force and vibration signals
- Predicted fault classification from the machine learning model

**Constants**

- Type of endodontic file
- Sampling frequencies:
  Force signals: 71 kHz
  Vibration signals: 51.2 kHz
- Data collection method
- Experimental conditions
- MATLAB processing techniques
- Machine learning models

**Control Group**

- Data from nondamaged endodontic tool

## CONCLUSION

Currently, the fault detection model is at a level where it is practically reliable, accurately labeling buggy files and classifying some regular files as buggy. This is a significant improvement over the past iterations, when answers were highly unstable, plummeting amazingly from run to run. By some of the finetuning along the way, including optimizing for feature selection and experimenting with alternative sensitivity levels, the model has reached sufficient stability to detect faults at a high rate of confidence, though some remaining refinements need to be performed to minimize false positives. The most daunting challenge in working through the exercise was finding the optimal balance of sensitivity.

Originally, the model was either over-conservative and flagged too many files as defective or too lenient and missed defective cases. In order to correct this, I experimented with different classification thresholds, adjusted the feature selection process using PCA, and experimented with other machine learning techniques like other decision tree ensembles. These improvements significantly improved the model's reliability such that it can identify faults with a satisfactory level of accuracy when running repeatedly. While this version of the model is the best to date, some faulty classifications of normal files as faulty indicate that refinements are still necessary and will be made in the future to continue this project further,.

The existing system is biased toward a conservative system, which is to say it plays it safe by indicating potential errors even if the file can be perfectly fine. This is an improvement over missing a real defect, but in future work, I hope to have the model be 100% accurate by making further improvement on feature extraction, improving dataset quality, and research into more complex machine learning techniques such as deep learning or combination models. In the next phase, I plan to incorporate a larger dataset to reduce variability, use K-Fold Cross-Validation to make it more reliable, and utilize an adaptive classification threshold that adjusts itself based on the type of input data. All these improvements will ensure that the model eliminates false positives without losing its ability to detect true faults efficiently.

Though still room for improvement, the system in its current form is already a firm foundation for fault detection in real-world endodontic instruments, and whatever additional improvements are developed will make it completely accurate.

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