Vibrational Analysis on the Shaft of a DC Motor

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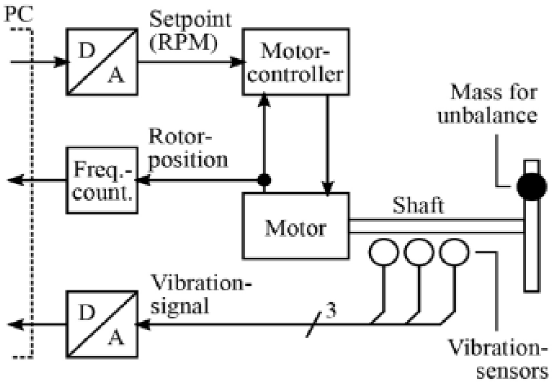
***Abstract*— Fault detection in rotating machinery is critical for preventing production downtimes. This project presents a dataset for unbalance detection in a rotating shaft using vibration sensors. Machine learning algorithms convolutional neural networks and Fast Fourier Network were applied to analyze the dataset. The best results were achieved using a Convolution Neural Network with a prediction accuracy of 97.2% on the evaluation dataset while Fast Fourier Transform gave maximum accuracy of 84 %.**

I. Introduction

Advancements in machine learning have yielded impressive outcomes in recent years, particularly in image recognition [1]–[4], natural language processing [5]–[9], and reinforcement learning [10]–[13]. Beyond the well-covered examples in the media, these algorithms hold significant potential for industrial applications [14]–[18]. An illustrative case involves analyzing vibrations on rotating shafts to identify unbalances or detect damage to roller bearings [19]–[27]. In this discussion, our focus is on the initial use case. Unbalances in rotating shafts can lead to reduced lifetimes of bearings and other machinery components, resulting in additional costs. Early detection of these unbalances proves vital in minimizing maintenance expenses, preventing unnecessary production stops, and extending the service life of machines. The algorithmic detection of unbalances incurs minimal additional effort. This automated approach facilitates real-time analysis of streamed data, enabling the prompt identification and correction of unbalances, even before potential damage to the drive train occurs. This particular use case, which is the primary focus here, underscores the critical role of early detection in mitigating the adverse effects of unbalances. The repercussions, such as reduced lifetimes of bearings and increased machinery-related costs, emphasize the practical significance of this approach. Efforts to minimize maintenance expenses, prevent production disruptions, and extend the operational lifespan of machines are paramount. Algorithmic detection of unbalances emerges as a valuable tool, characterized by its efficiency and minimal additional effort. The automation achieved through this methodology not only streamlines the detection process but also facilitates real-time analysis of streamed data. Consequently, unbalances can be identified and corrected promptly, even before potential damage to the drive train occurs.This intricate interplay between machine learning algorithms and practical industrial challenges showcases the transformative potential of technology in enhancing operational efficiency and minimizing disruptions in critical systems.

II. Experimental Setup

The experimental framework involves a LabVolt Universal DC Motor (8254-00) integrated with an MPU6050 accelerometer strategically placed along all three axes of the motor's shaft. This arrangement, facilitated by an Arduino Uno, captures the intricate vibrational nuances of the motor under various conditions. The initial dataset of 20,000 values is meticulously extended to 100 million using VBA code, ensuring a rich and varied dataset for comprehensive analysis.



Block diagram of the measurement setup

III. Dataset Generation

A cornerstone of this project is the dataset, meticulously curated to encapsulate the diverse vibrational profiles of the Motor. Initial data collection involves 10,000 values captured by the accelerometer, while an additional 100 million values are generated through VBA code. This expansive dataset serves as a robust foundation for the development and assessment of machine learning models for effective fault detection.

In total, datasets for 4 different unbalance strengths were recorded as well as one dataset with the unbalance holder without additional weight (i.e. without unbalance). Each dataset is provided as a csv-file with five columns: V in the input voltage to the motor controller Vin (in V), Vibration 1 the signal from the vibration sensor on x axis, Vibration 2 the signal from the y axis, and Vibration 3 the signal from the z axis. The sampling rate in each column amounts to 4096 values per second in case of CCN and 4096/2 in FFT.

Since the absolute value of the centrifugal force Fc as a function of the rotation speed ω can under a point mass approximation be expressed as

$$Fc = mr\omega 2$$

The product of the mass m and the radius r is a direct measure of the unbalanced strength. The prototype of the dataset is given below, but it should be noted that the vibration values denote the min and maximum values each file contain approximately, there could be a little error which can exist:

CSV File	RPM	Vibration_1	Vibration_2	Vibration_3
0D/0E	0-600	0-0.07	0-0.7	0-0.7
1D/1E	600-900	0-0.1	0-0.1	0-0.1
2D/2E	900-1100	0-0.2	0-0.2	0-0.2
3D/3E	1100-1300	0-0.5	0-0.5	0-0.5
4D/4E	1300-1500	0-0.8	0-0.8	0-0.8

IV. Detection of Unbalanced State and Results

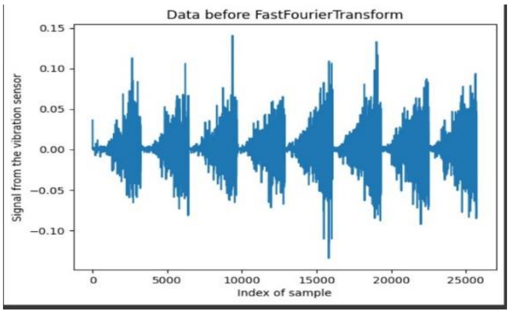
A. Convolutional Neural Network(CNN) on Sensor Data

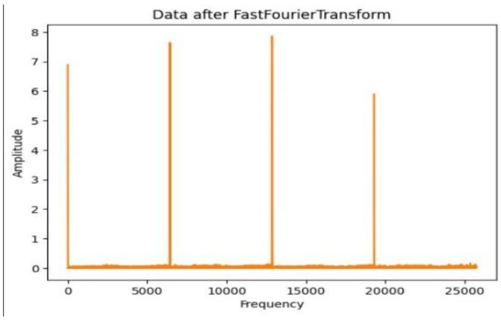
Convolutional Neural Networks (CNNs) are able to recognize patterns in data and to perform classification tasks based on these recognized patterns.

The classification of whether an unbalance is present or not was trained using the data record without unbalance and only one single data record with unbalance each time. Afterwards, all trained models were tested on the corresponding evaluation datasets of the same unbalance factors. The CNN model demonstrated exceptional performance, achieving an impressive accuracy of 97.2%.

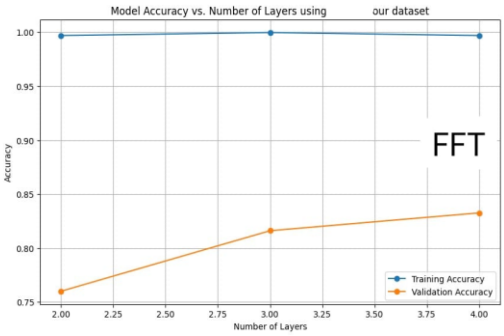
B. Fast Fourier Transform on Data

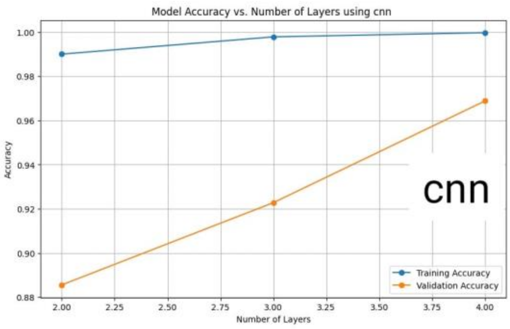
For this approach, the FFT was calculated for each of the windows of one second or 4096 values of the first vibration sensor stream, according to the Shannon Nyquist sampling theorem, this results in 2048 physically meaningful Fourier coefficients for each window, which can be used for classification. The data before and after transform is shown below:



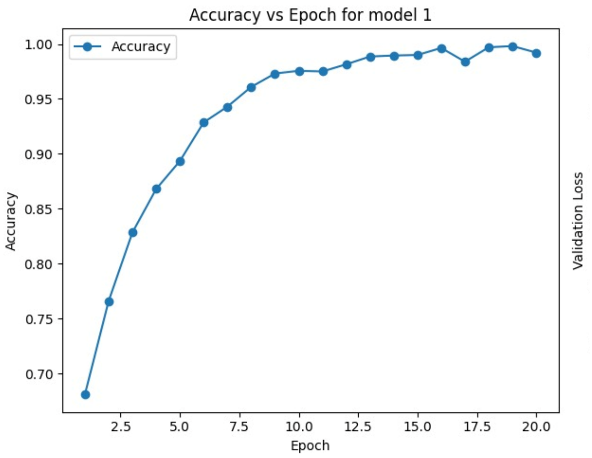


Again, the development dataset transformed in this way was randomly divided into 90 % training data and 10 % test data. Afterwards, the FFT data were scaled as follows: For each Fourier coefficient, the respective median and interquantile spacing of quantiles 5 and 95 was calculated based on the extent of the training dataset (2048 values for the median and the interquantile spacing, respectively). The median values were then subtracted from the FFT values, and the result was divided by the interquantile values. Fully connected (FC) neural networks were then trained on the training data. FFT-based model exhibited a slightly lower accuracy of 84%.

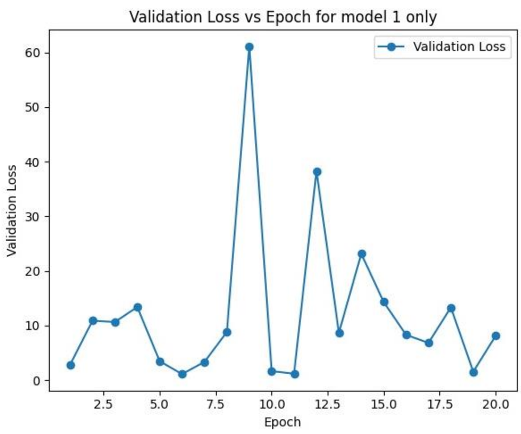




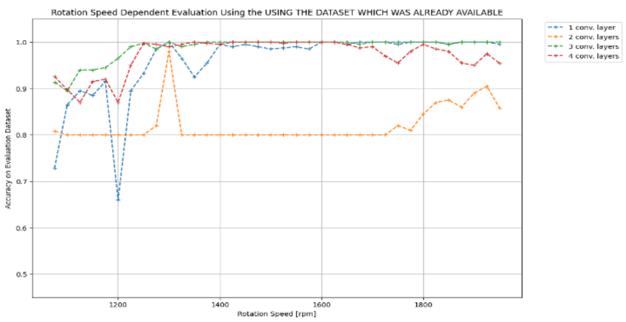
The graphs for particular epochs and its accuracy is also plotted for only model 1 out of 5, the result is as follows:



Furthermore, the validation loss is a metric assessing a model's performance on a separate dataset, the validation set, during the training process. It quantifies the disparity between the model's predictions and the actual values in the validation set. This measurement aids in evaluating the model's ability to generalize to new, unseen data. Its plot against accuracy is also obtained for model 1.



Finally, there are various unbalanced factors which can introduce vibrations, one of which is vibrations behavior against rpm. Firstly, the virtual environment was created to check how it effects the model and then the following plot was generated for different model layers as shown below:



V. FFT CAN WORK BETTER THAN CNN

In the context of vibration sensor readings, particularly in the assessment of rotating machinery, the manifestation of unbalance introduces centrifugal forces due to the deviation from a balanced state. The equation governing these forces is:

$$F_c = m * range * angular\ velocity^2$$

It underscores the impact of unbalancing weights rotating with the shaft. In the two-dimensional representation captured by vibration sensors, akin to a shadow of a clock-hand, the equation transforms into

$$\blacktriangleright F_{sensor} = F_c * \sin(a) \text{ (for vertical positioning)}$$

$$F_{sensor} = F_c * \cos(a) \text{ (for horizontal positioning),}$$

where alpha denotes the position of the shaft. Applying Fourier transformation to F_{sensor} yields amplitude, reflective of the centrifugal force, and implies frequency, corresponding to angular speed. Traditional deep learning models, however, face challenges in handling trigonometric functions such as sine and cosine waves. Despite this, the proposed theory posits that a neural network with four fully connected (Dense) layers adeptly deciphers these intricate relationships, offering accurate insights into the nuanced dynamics of unbalanced rotational systems. Should any refinements be necessary, I am open to further clarification and adjustments to enhance the clarity and precision of these observations. If we cater these observations, it would be an advantage and precision will be achieved.

VI. WHY OVER FFT DID NOT PERFORM BETTER THAN CNN

The expansion of the dataset from an initial size of 10,000 to approximately 104 million through the utilization of a VBA code for Excel represents a commendable effort to enhance the dataset's volume. However, it is crucial to acknowledge potential challenges that may arise from such an augmentation process. The generated dataset, though significantly increased, may exhibit non-uniformity and potential deviations from realism. This could introduce biases and artifacts that may impact the generalizability of the model trained on this extended dataset. Additionally, the scalability from 10,000 to 104 million may introduce imbalances in the distribution of classes, potentially leading to over-representation or under-representation of certain patterns. Consequently, these factors may influence the model's performance, and careful consideration is warranted in the interpretation and application of the findings derived from this augmented dataset. Vigilance in addressing these challenges is imperative to ensure the robustness and reliability of the subsequent analyses and model outcomes. This imbalance can hinder the model's ability to accurately discern minority classes, compromising its overall predictive capabilities.

VII. OTHER MODELS WHICH CAN BE USED

A. Hidden Markov Model

An exploration of hidden Markov models (HMMs) is detailed in reference [11], highlighting their historical application in speech recognition, such as the Sphinx system [12], [13]. Beyond speech, HMMs have found utility in diverse domains, including biology for tasks like protein structure and genome research [13], sports activities recognition [14], and condition monitoring, where they have been employed for detecting defective roller bearings [41]. The application of HMMs in the design of the unbalance detector discussed in this section is notable. The proposed methodology for determining the unbalance state using an HMM involves segmenting the input signal, consisting of 4096 consecutive values from 'Vibration 1,' into fixed-length, possibly overlapping snippets. For each snippet, mel-frequency cepstral components (MFCCs) are computed as features, feeding into an HMM trained to recognize data without unbalance. Logistic regression interprets the HMM output, discerning whether a given signal originates from a measurement with or without unbalance. The integration of scalers simplifies the training process. Given the sensitivity of MFCC features to rotation speed variations, multiple models are trained for different speeds. Training data selection entails one-second samples from the 'Vibration 1' signal in '0D' and '3D' datasets, ensuring the speed ('Measured RPM') falls within a specified interval. Randomly split training data into three sets for scaler and HMM training, logistic regression, and hyperparameter determination, further refines the approach. It is noteworthy that during the HMM approach development, observations revealed relatively stationary MFCC features in one-second samples without unbalance. The resulting preference for using a single HMM state and the focus on instationary processes underscore the nuanced challenges associated with the problem at hand.

B. Random Forest on Automatically Extracted Timeseries Features

To assess the generalization capabilities of the employed algorithms against a common baseline and explore the impact of increased computational effort on potential improvements in prediction accuracy, a classification task was conducted using a minimal set of features. This feature set comprised the mean of 'Measured RPM' values, along with the standard deviation and kurtosis of vibration values calculated for each partitioned window in the datasets. Two feature calculation variants were implemented: the first variant calculated standard deviation and kurtosis solely for 'Vibration 1,' resulting in three features (including the mean of 'Measured RPM' values). In the second variant, all three vibration sensors were utilized (totaling seven features), referred to as 'minimal features.' A Random Forest model was trained on these minimal features. Similar to previous classification approaches, training was performed with dataset pairs for each unbalance strength and the unbalance-free case, as well as with all existing unbalance strengths. The classification results revealed that even with just three features, the highest unbalance could be almost perfectly detected in both experiments. Utilizing seven features and training on the entire dataset achieved close to 100% accuracy for dataset '3E.' However, for smaller unbalances, a significant drop in prediction accuracy was observed, reaching 82.2% (3 features) or 94.6% (7 features) in the second experiment. Rotation-speed-dependent evaluation showed high accuracy below 1200 RPM, where the minimum set of features outperformed approach 1. In addition to the minimal features, the Python package tsfresh allowed for computing a broader range of time series features. Extracting 748 features for 'Vibration 1' using tsfresh, these were employed as input for a random forest algorithm. The prediction results demonstrated a notable improvement in detection rates for smaller unbalances compared to minimal features, achieving a total prediction accuracy of 93.2% when trained on all unbalance strengths and a mean prediction accuracy of 79.9% when trained with dataset pairs. This level of performance was comparable to that of the CNNs in approach 1 (Section IV-A).

VIII. SUMMARY AND OUTLOOK

For this project, we generated a dataset containing vibration data for the purpose of classifying unbalance on a rotating shaft with varying speed and unbalance strength. We explored various approaches to address the associated classification task. All algorithms successfully identified the largest unbalance with nearly perfect prediction accuracy, even when utilizing only 3 characteristic values per sample for classification. However, for smaller unbalances, we observed broader variations among the different approaches. The most effective method for classifying the dataset involved employing a fully connected (FC) network with two hidden layers, which received the scaled Fast Fourier Transform (FFT)-transformed vibration data as input. Across the entire evaluation dataset, this model achieved an impressive 98.6% correct classification rate. Furthermore, the examined models exhibited diverse behaviors concerning their dependence on speed.

Future studies could leverage this speed-dependent behavior by creating ensembles of different models to enhance prediction accuracy. This approach aims to offset the strengths and weaknesses of individual models across various speed ranges. Additionally, to further refine the models and comprehend the classifications, especially in practical settings such as a productive company, efforts must be directed towards enabling traceability and explain ability of the utilized models.

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