
WORKSHOP ON
EMERGING
AI TECHNOLOGIES
FOR DECISION MAKING
IN MARITIME DOMAIN
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# FAULT DETECTION IN ROLLING ELEMENT BEARINGS THROUGH IMPLEMENTATION OF TRANSFER LEARNING


**PRESENTED BY**:

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# SCOPE

1. INTRODUCTION
2. PURSUED METHODOLOGY
3. SPECIFICS OF ANALYSED DATASETS
4. EXPERIMENTAL DETAILS AND COMPARATIVE ANALYSIS
5. CONCLUSION AND FUTURE SCOPE
6. REFERENCES

# INTRODUCTION

- **Bearings**
  - Ball and roller bearings, together called rolling element bearings.
  - Most common machine elements that permit rotary motion of shafts.
  - Most critical components of rotating machines as a large majority of system failures arise from faulty bearings.
  - Defects: Cage, ball, outer race and inner race.
  - Acc to IEEE and EPRI, bearing fault are 41% and 42% respectively. In case of large IMs, bearing faults can account for 44% of the total failures.
  - Contemplated condition monitoring of bearings and early detection of faults necessary.
- **Techniques of Condition Monitoring**
  - Different analyses like chemical analysis, electrical analysis, and mechanical analysis.
  - Vibration analysis is the most commonly employed technique owing to its numerous advantages.
  - Vibration analysis of REBs taken up to be studied as a strategy for fault detection of rotating machines.

# INTRODUCTION

- **Data Acquisition and Processing**
  - Helps in making informed decisions about the health status of any given rotating component.
  - Two primary methods for vibration data collection: manual and automated.


  - Further pre-processing required for data de-noising and filtering through various signal processing techniques.
  - **Even with numerous methodologies for data acquisition and signal processing being researched and established in the world, analysis of complexities of real-world machinery health signals requires domain-expertise assistance to achieve desired accuracies.**

# INTRODUCTION

- **Need of Artificial Intelligence**
  - Manual analysis of the vibration signals is not competent enough as vibration signals often contain background noise or low-amplitude signals measured in a noisy background.
  - Manual inspection impractical for early detection of faults.
  - Application of AI in the form of ML or further, DL becomes obligatory. Direct use of raw vibration signals is challenging, leading to feature engineering and AI-based classifiers.
  - Most publications in this field use data acquired from accelerated degradation test beds instead of real industrial equipment due to various reasons. However, application of test-rig trained models to real-world industrial environments poses the biggest challenge.

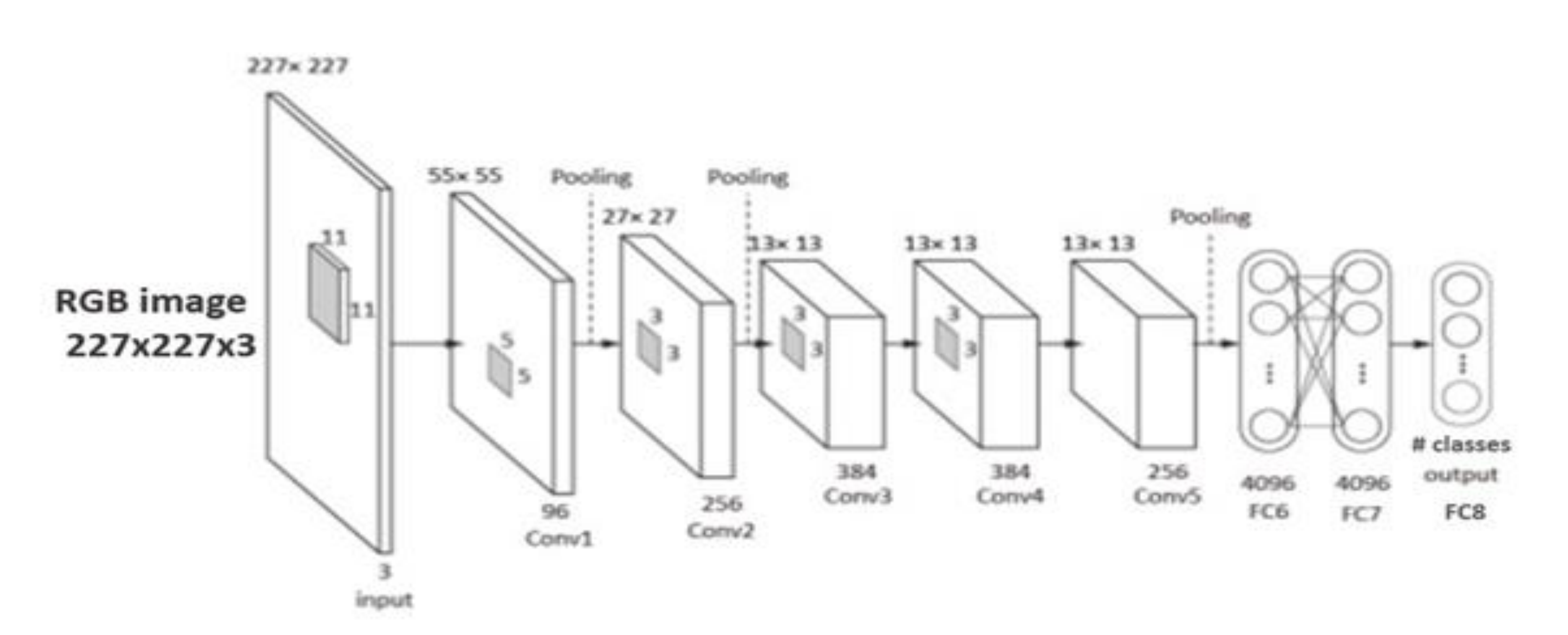
# TRANSFER LEARNING

- Concept in deep learning (and machine learning).
- Technique to transfer the knowledge and experience learned from existing datasets to help identify unforeseen bearing fault conditions at different setups in real-world applications.
- Aids in transferring a test-rig specific developed ML or DL model/ network to industrial applications in real-world scenarios with slight tuning of the existing trained model.
- This project work aims to delve deeper in this concept of Transfer Learning and its practical applications.

# ALEXNET

- Designed by Alex Krizhevsky in collaboration with Ilya Sutskever and Geoffrey Hinton in September, 2012.
- Proposed advancement over existing networks for applications in image classification.
- Pre-trained on the Imagenet dataset which contains almost 14 million images across a thousand classes.
- 08 layers with learnable parameters, first 05 layers convolutional layers with a combination of max pooling layers followed by 03 fully connected layers.
- Convolutional layers - ReLU activation function, output layer - Softmax activation function.

# ALEXNET

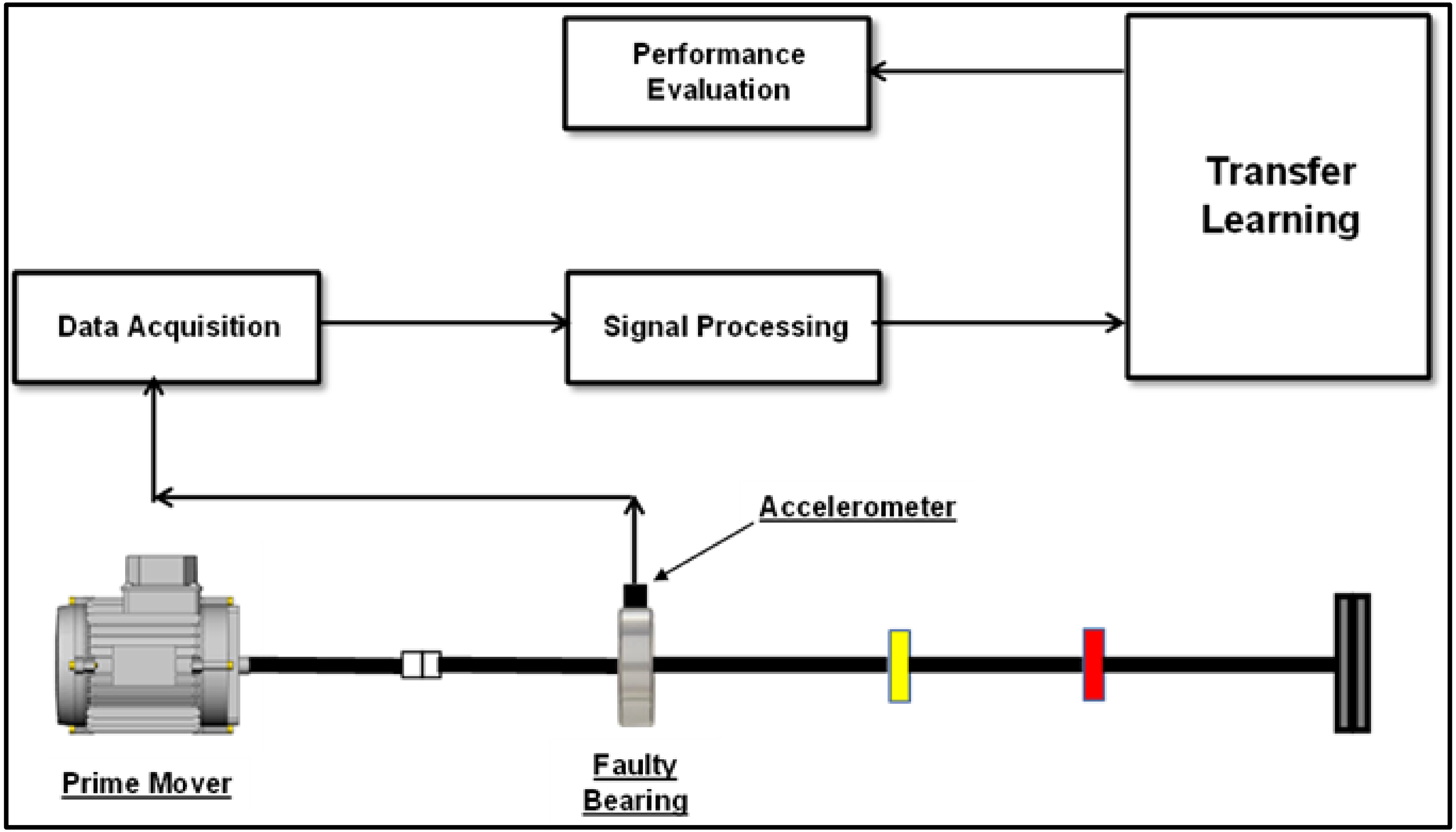



- Number of filters keeps on increasing as we move deeper into the network resulting in extraction of more features in every layer with simultaneous reduction in filter size leading to decreased feature map shape with every step.

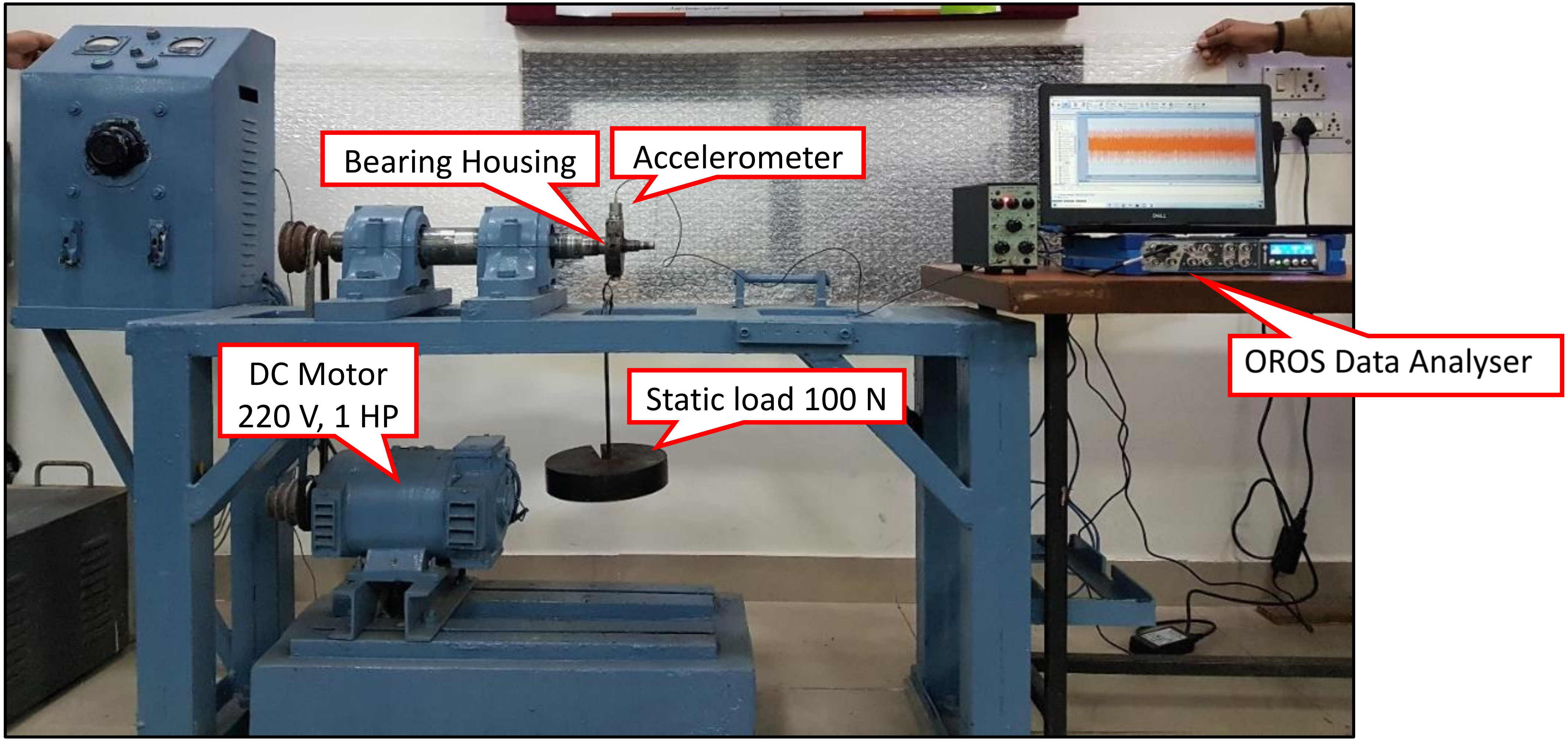
# ALEXNET

| Layer | Filters/ neurons | Filter Size | Stride | Padding | Size of Feature Map | Activation function |
|---|---|---|---|---|---|---|
| Input | - | - | - | - | 227 x 227 x 3 | - |
| Conv 1 | 96 | 11 x 11 | 4 | - | 55 x 55 x 96 | ReLU |
| Max Pool 1 | - | 3 x 3 | 2 | - | 27 x 27 x 96 | - |
| Conv 2 | 256 | 5 x 5 | 1 | 2 | 27 x 27 x 256 | ReLU |
| Max Pool 2 | - | 3 x 3 | 2 | - | 13 x 13 x 256 | - |
| Conv 3 | 384 | 3 x 3 | 1 | 1 | 13 x 13 x 384 | ReLU |
| Conv 4 | 384 | 3 x 3 | 1 | 1 | 13 x 13 x 384 | ReLU |
| Conv 5 | 256 | 3 x 3 | 1 | 1 | 13 x 13 x 256 | ReLU |
| Max Pool 3 | - | 3 x 3 | 2 | - | 6 x 6 x 256 | - |
| Dropout 1 | Rate = 0.5 | - | - | - | 6 x 6 x 256 | - |
| Fully Connected 1 | - | - | - | - | 4096 | ReLU |
| Dropout 2 | Rate = 0.5 | - | - | - | 4096 | - |
| Fully Connected 2 | - | - | - | - | 4096 | ReLU |

# PURSUED METHODOLOGY



# EXPERIMENTAL SETUP
# SOURCE DOMAIN



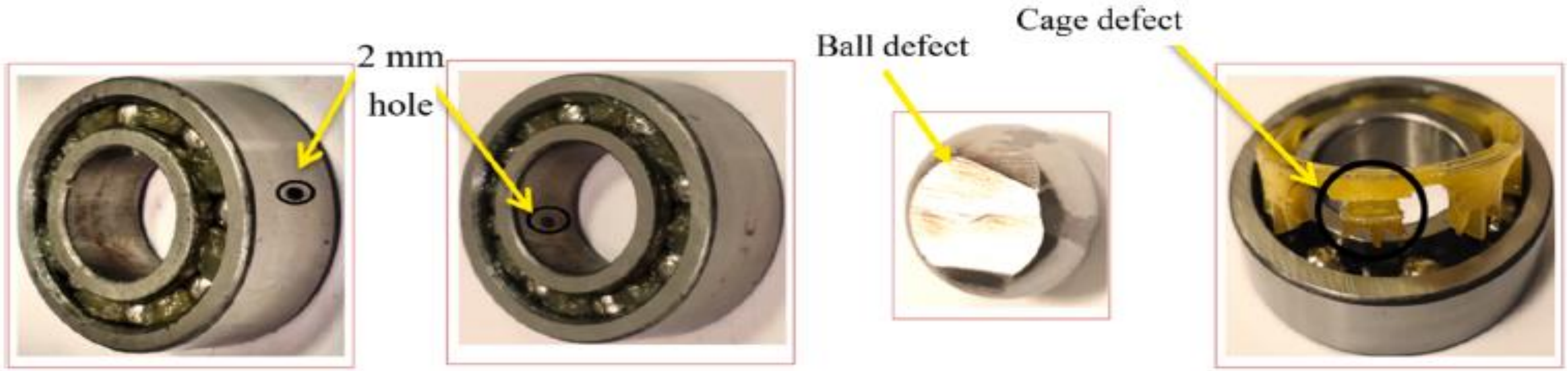

Bearing test rig setup

# EXPERIMENTAL SETUP
# SOURCE DOMAIN

- DC motor of 220 V and 1 HP
- **Bearing used**: Make SKF, model BB1B420205
- Uniaxial ICP TEDS accelerometer (Make: B&K, Type: 4533-B-001, Range: 0.2 Hz – 12.8 kHz) mounted on the bearing housing.
- Variety of defects in bearings i.e., outer race (OR), inner race (IR) defect, ball defect (BD), and cage defect (CD) are Introduced.

Specifications of deep grooved ball bearing

| | |
|---|---|
| **Number of balls (z)** | 8 |
| **Pitch Diameter (D)** | 37.9 mm |
| **Contact Angle (ϕ)** | $0^0$ |
| **Outer Diameter (OD)** | 52 mm |
| **Ball Diameter (d)** | 8.7 mm |
| **Bore Diameter (Bd)** | 25 mm |



# DATA ACQUISITION AND ANALYSIS SOURCE DOMAIN

- Output of the accelerometer fed to a data analyser (Make: OROS, 8 channel, Model: OR35).
- A static load of 100 N applied and system is left to run for an hour to reach a steady-state situation and five-minute data is subsequently captured.
- Data collected for different bearing conditions and three speeds *viz*. 19 Hz, 23 Hz, and 29 Hz with the sampling frequency selected as 6400 Hz.
- A healthy bearing condition used as a reference line to make the distinction with other conditions.

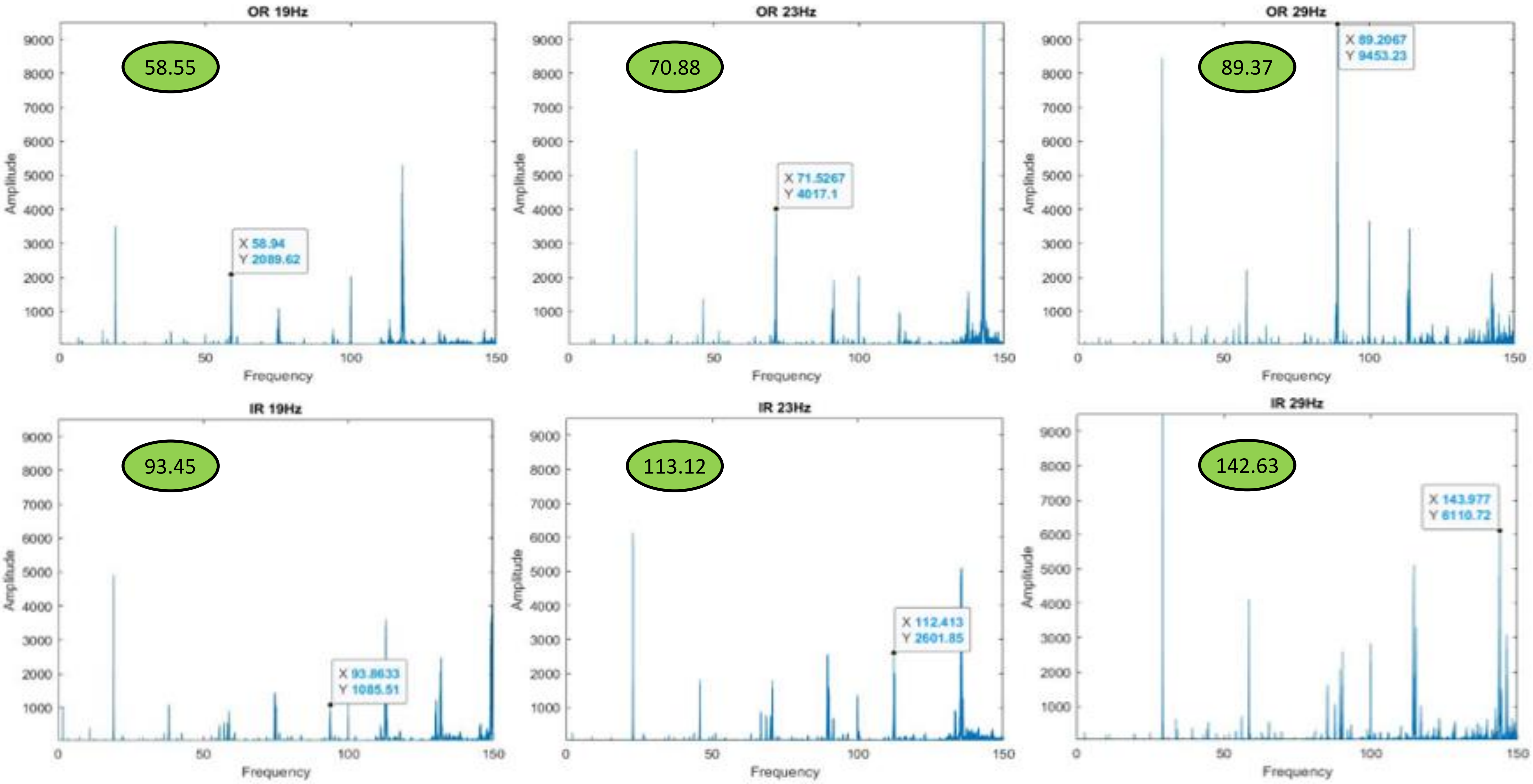
# DATA ACQUISITION AND ANALYSIS SOURCE DOMAIN

- Using the bearing specifications and experimental data, characteristic defect frequencies are calculated:

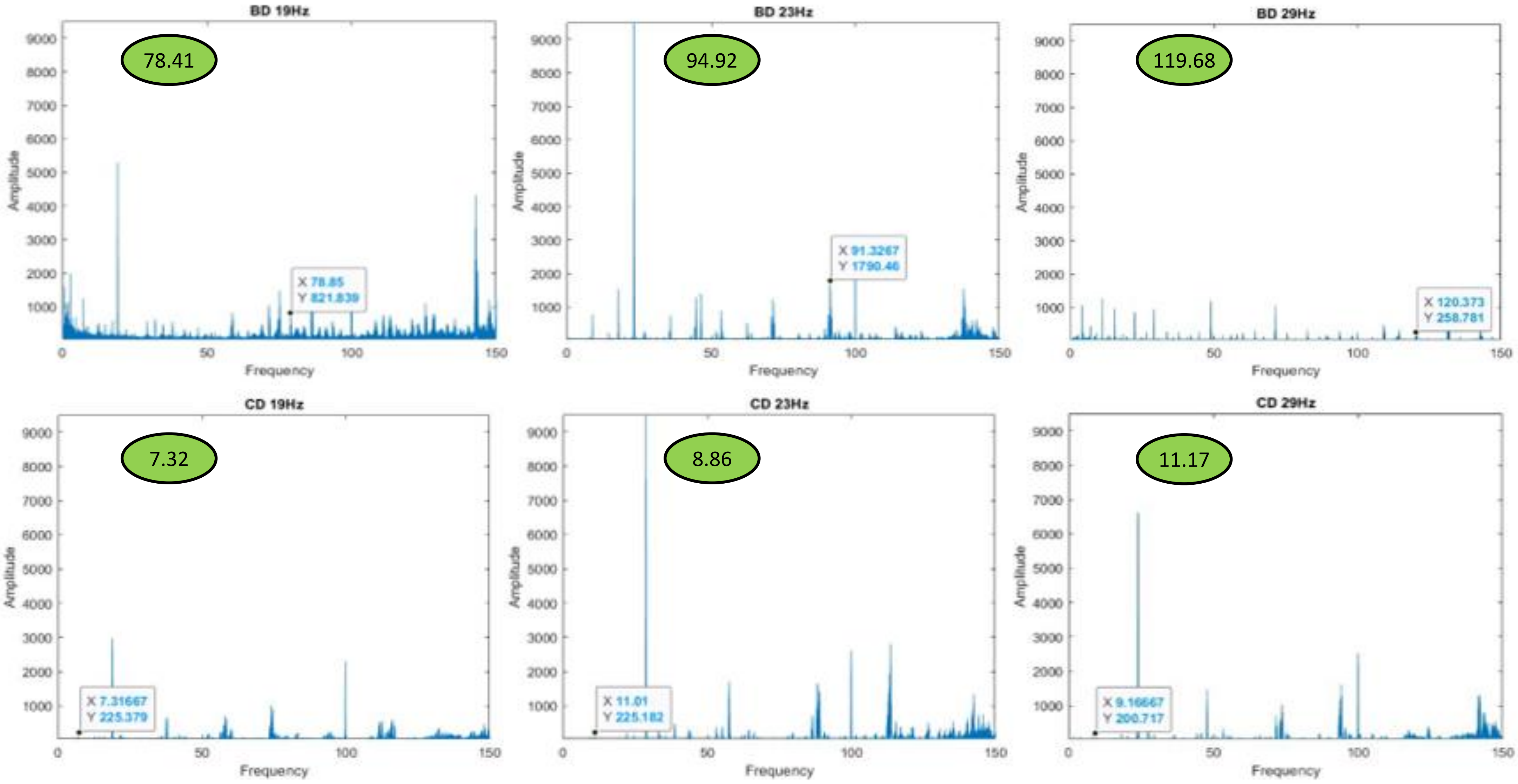
| Defect frequency expressions | Computed defect frequencies | | |
|---|---|---|---|
| | 19 Hz | 23 Hz | 29 Hz |
| $f_{0R} = \frac{f_r}{2} z \left(1 - \frac{d}{D}\cos\phi\right)$ | 58.55 | 70.88 | 89.37 |
| $f_{IR} = \frac{f_r}{2} z \left(1 + \frac{d}{D}\cos\phi\right)$ | 93.45 | 113.12 | 142.63 |
| $f_{BD} = \frac{f_{r*}D}{d} \left(1 - \frac{d^2}{D^2}\cos^2\phi\right)$ | 78.41 | 94.92 | 119.68 |
| $f_{CD} = \frac{f_r}{2} \left(1 - \frac{d}{D}\cos\phi\right)$ | 7.32 | 8.86 | 11.17 |

- Fast Fourier transform (FFT) implemented to detect these characteristic defect frequencies from analytic signal for each bearing fault condition.

# DATA ACQUISITION AND ANALYSIS
# SOURCE DOMAIN

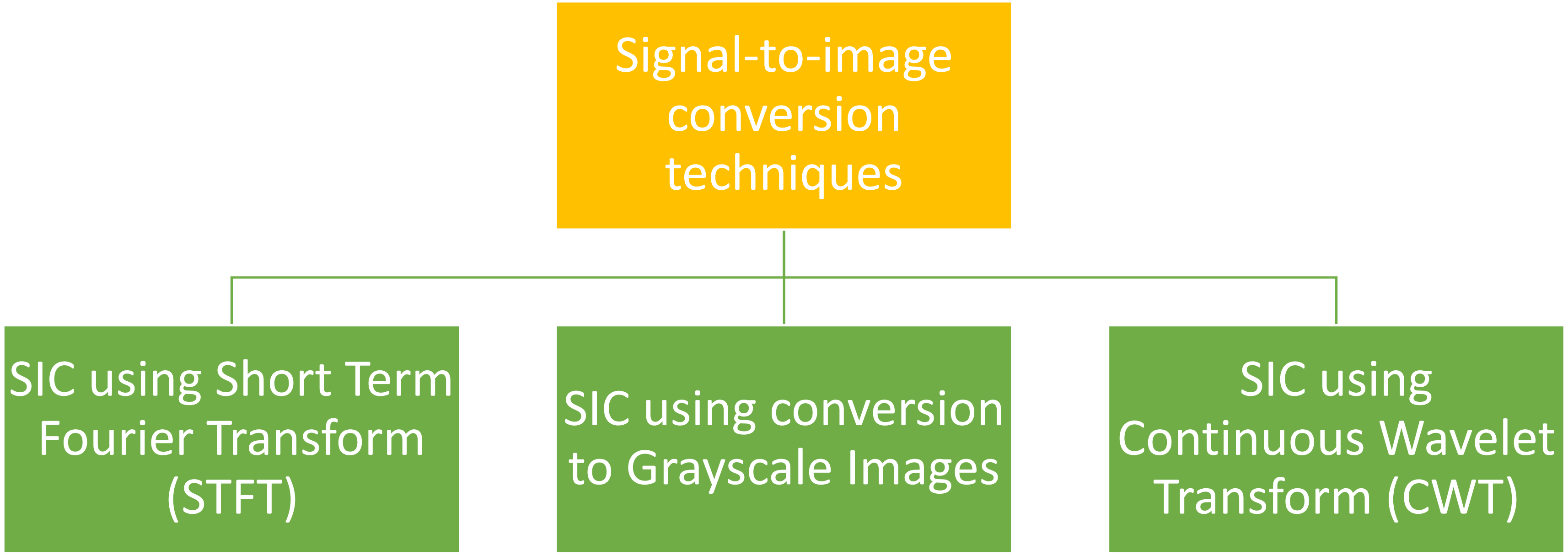


# DATA ACQUISITION AND ANALYSIS SOURCE DOMAIN



# SIGNAL-TO-IMAGE CONVERSION TECHNIQUE SELECTION

- **Signal-to-image conversion (SIC) techniques**
  - Selected on the basis of common application and efficiency.
  - Three techniques selected for comparison.

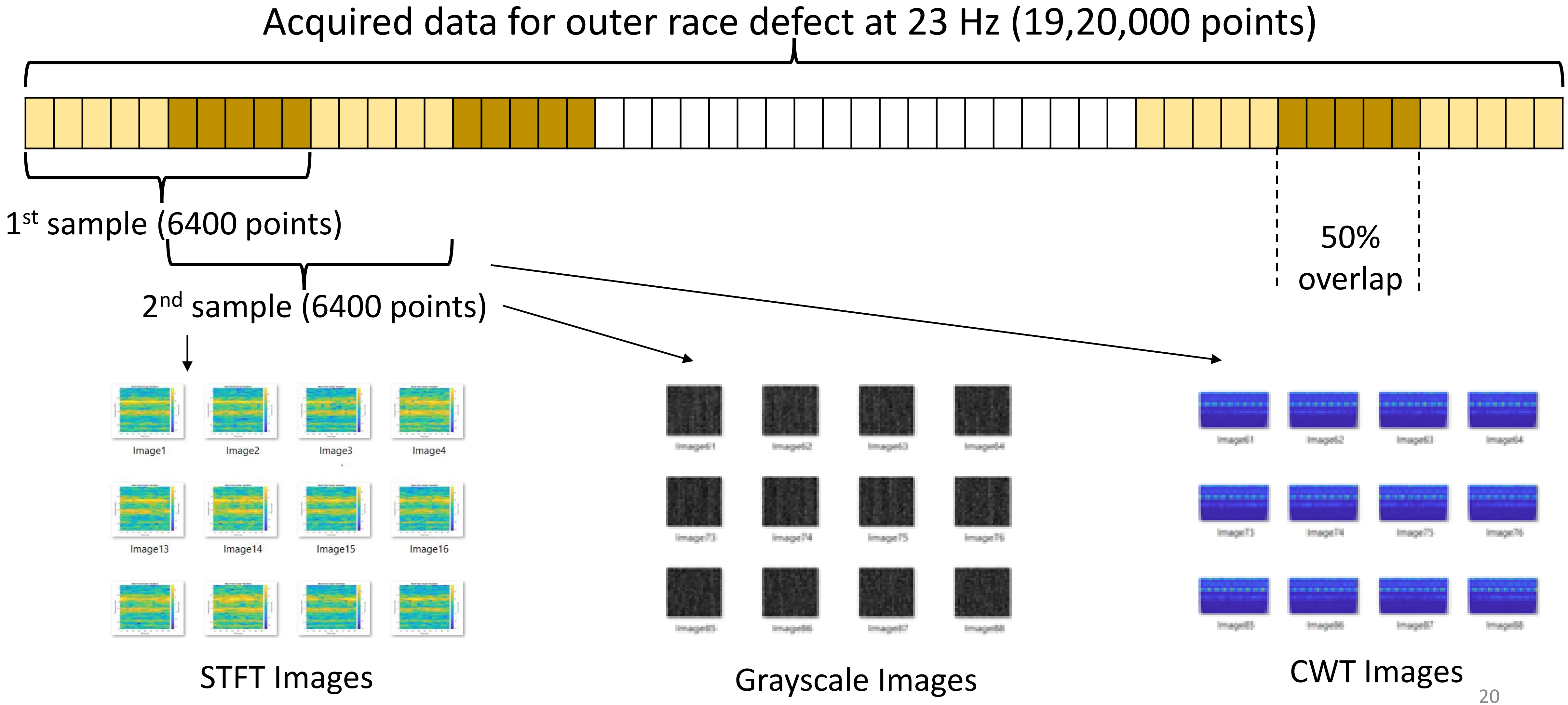


# PROCESSING OF DATA SOURCE DOMAIN

- Splitting of acquired data for each bearing condition and each test speed into smaller equal signal samples undertaken towards generating training data.
- Each signal sample must contain enough sampling points to convey the information of the bearing status.
- Minimum running speed = 19 Hz
- Sampling frequency = 6400 Hz

***Minimum Sample Length = 6400 / 19 ≈ 337 sampling points***

# PROCESSING OF DATA SOURCE DOMAIN



# PROCESSING OF DATA SOURCE DOMAIN

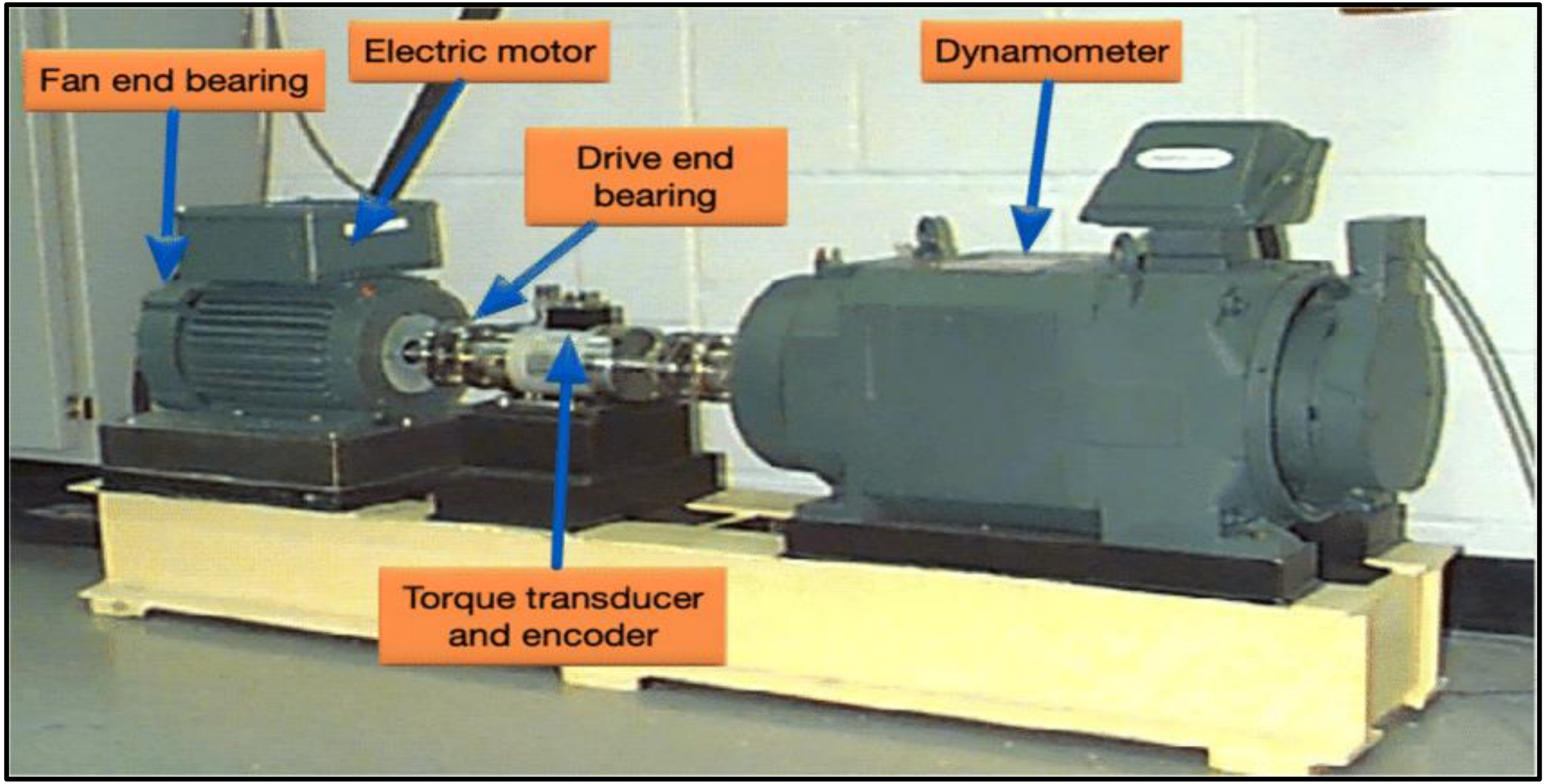
| **Data under consideration** | | |
|---|---|---|
| Split Sample length | : | 6400 points |
| Overlap to minimize data loss | : | 50% |
| Samples obtained for each parent signal | : | 599 |
| Total parent signals (bearing conditions and speeds) | : | 15 |
| Total no of split signals | : | 8985 |

# EXPERIMENTAL SETUP
# TARGET DOMAIN

- Obtained from two different experimental setups so as to validate proposed model under different working conditions and for varied bearing dimensions.

- TARGET DOMAIN DATASETS
  - Case Western Reserve University (CWRU) Bearing Dataset
  - Data acquired from MFS

# EXPERIMENTAL SETUP
# TARGET DOMAIN DATASET 1




CWRU test rig setup

# EXPERIMENTAL SETUP
# TARGET DOMAIN DATASET 1

- DC motor of 220 V and 3 HP
- **Bearing used**: Make SKF, model 6205-2RS JEM
- Data from accelerometers fed to 16 channel DAT
- Variety of defects in bearings i.e., outer race (OR), inner race (IR) defect, and ball defect (BD) are Introduced.
- Sampling frequencies – 12 and 48 kHz at motor loads of 0 to 3 HP.
- Experimental conditions approximating to source domain data experimental setup selected, pertaining to fault size of 0.021” at Drive End (DE) bearing with centered OR for a sampling frequency of 12 kHz.

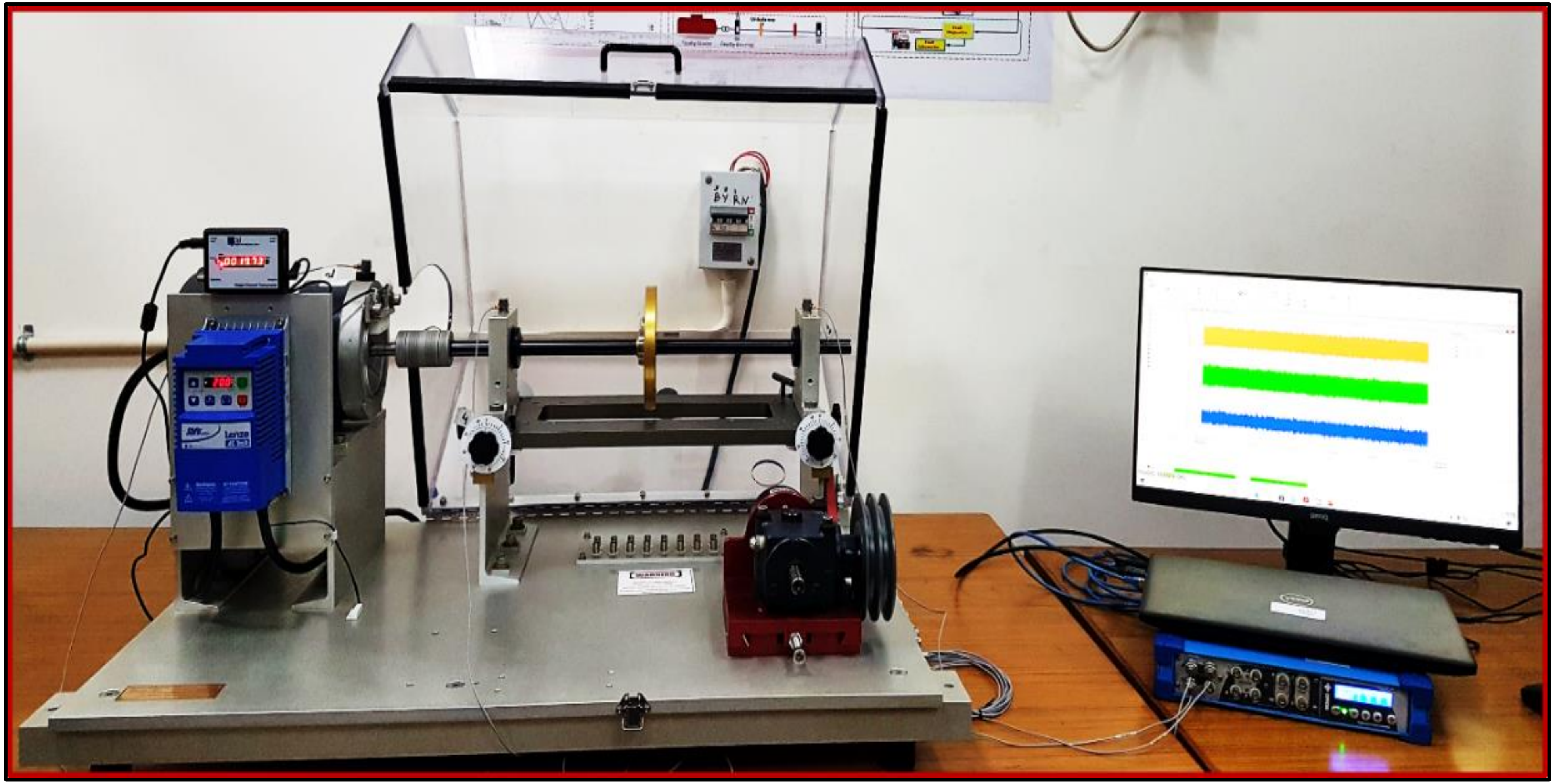
Specifications of deep grooved ball bearing

| | |
|---|---|
| **Pitch Diameter (D)** | 1.537” |
| **Contact Angle (ϕ)** | $0^0$ |
| **Outer Diameter (OD)** | 2.0472” |
| **Ball Diameter (d)** | 0.3126” |
| **Bore Diameter (Bd)** | 0.9843” |

# EXPERIMENTAL SETUP
# TARGET DOMAIN DATASET 1

- Only four defect viz. HB, IR, OR, BD present in downloaded data.
- Data divided into five different datasets on the basis of motor speeds viz. four constant speeds and one combined data of different speeds.
- Every signal trimmed to first 121556 sample points.
- Each signal split into smaller samples same as done with source domain data and subjected to CWT, thereby generating 378 images for each class of the four datasets.
- Fifth dataset created by taking 95 images from each class of the four datasets, thereby creating five datastores.

# EXPERIMENTAL SETUP
# TARGET DOMAIN DATASET 2



Machinery Fault Simulator

# EXPERIMENTAL SETUP TARGET DOMAIN DATASET 2

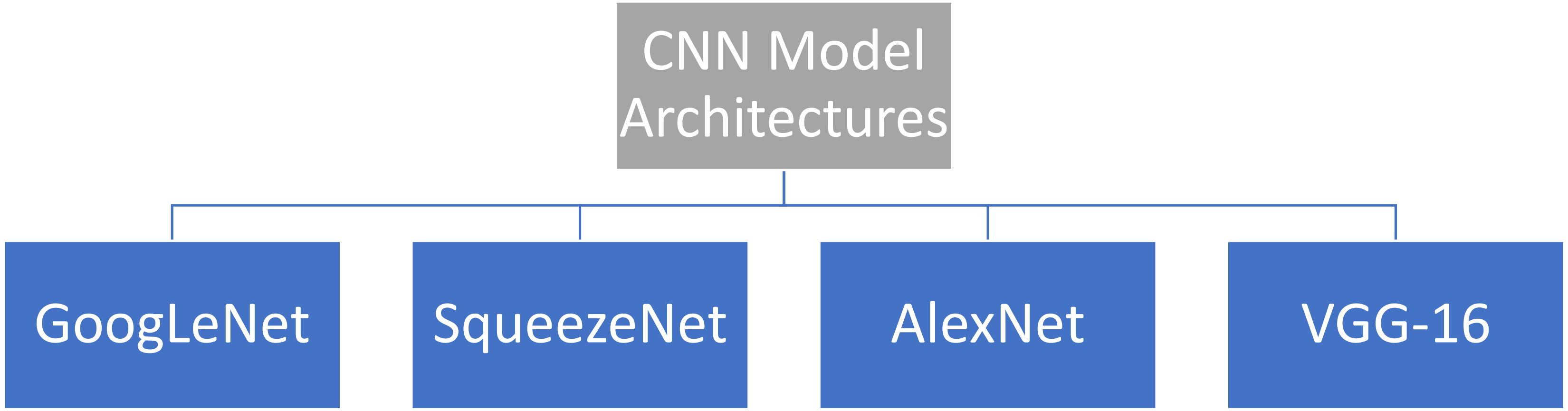
- DC motor of 220 V and 1 HP.
- Variety of defects in bearings i.e., outer race (OR), inner race (IR) defect, and ball defect (BD) are introduced.
- Data acquisition and processing same as source domain, thereby generating 1797 (599 images x 3 rotational speeds) images per class.
- Only four classes available view unavailability of CD in MFS.

Specifications of deep grooved ball bearing

| | |
|---|---|
| **Number of balls (z)** | 8 |
| **Pitch Diameter (D)** | 1.318 in |
| **Contact Angle (ϕ)** | $0^0$ |
| **Ball Diameter (d)** | 0.3125 in |
| **Bore Diameter (Bd)** | 0.75 in |

# CNN MODEL ARCHITECTURE SELECTION

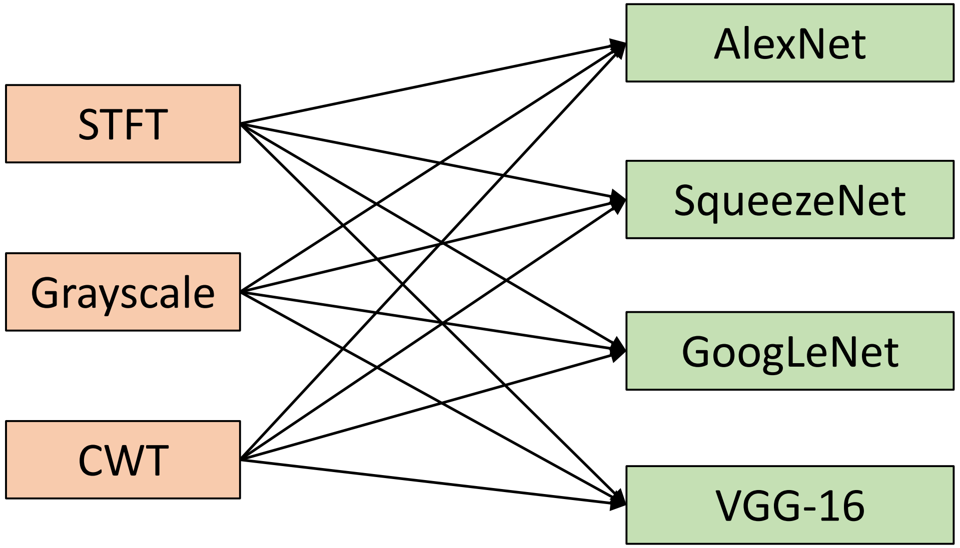
- **CNN model architectures**
  - Selected on the basis of efficiency, speed in image classification, architecture depth and number of parameters.
  - Four architectures selected for comparison.



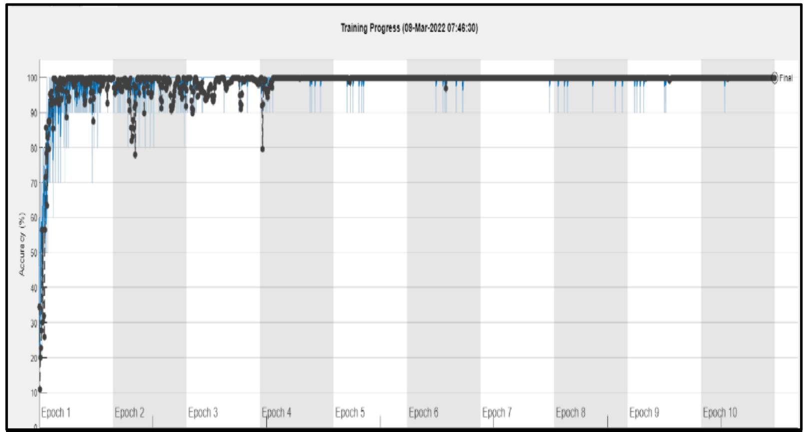

| | AlexNet | GoogLeNet | SqueezeNet | VGG-16 |
|---|---|---|---|---|
| Depth | 8 | 22 | 18 | 16 |
| No. of parameters (in mn) | 61 | 7 | 1.24 | 138 |

# TRANSFER LEARNING

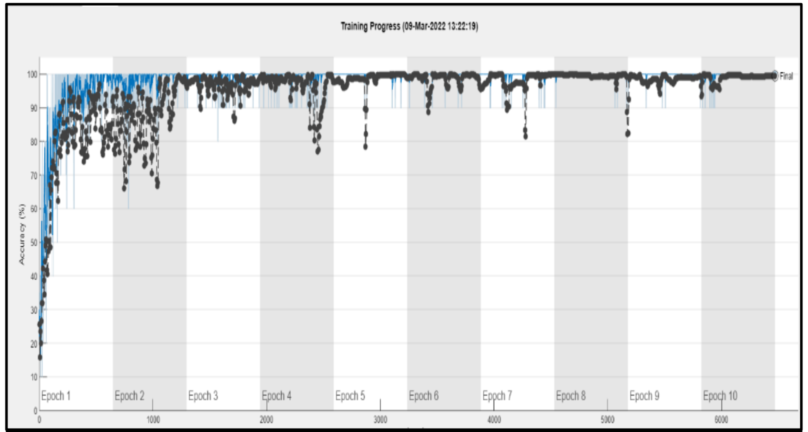
- Transfer learning implemented for comparative analysis using Deep Network Designer tool of MATLAB.
- Total 12 combinations of SIC techniques and CNN models (3 techniques x 4 models).
- Training data divided into training, validation and testing data in the ratio of 70%, 20% and 10% respectively



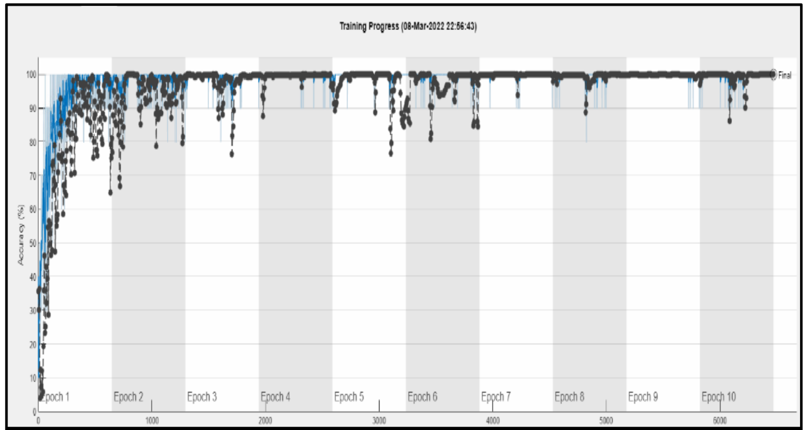

# TRAINING PROCESS WITH STFT



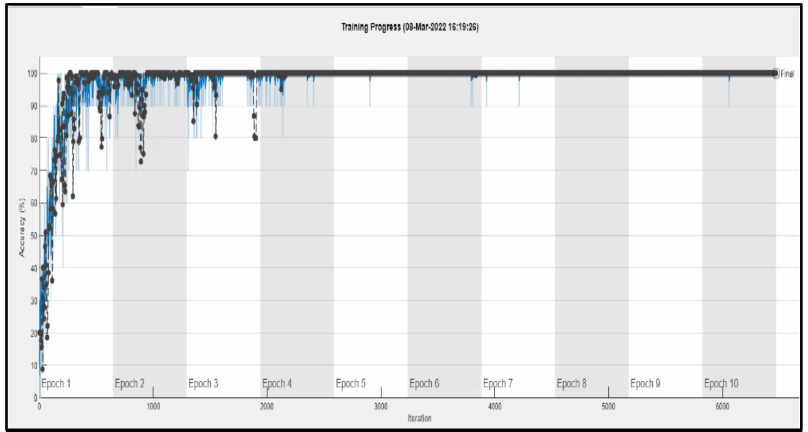

**AlexNet**




**GoogLeNet**

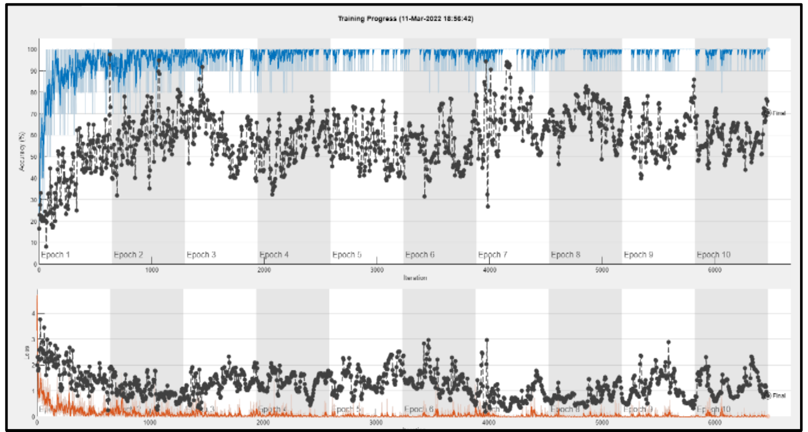



**SqueezeNet**

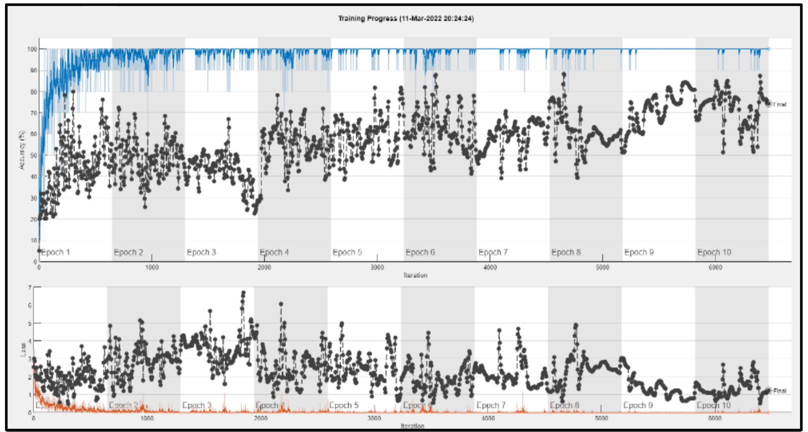



**VGG-16**

# TRAINING PROCESS WITH GRAYSCALE

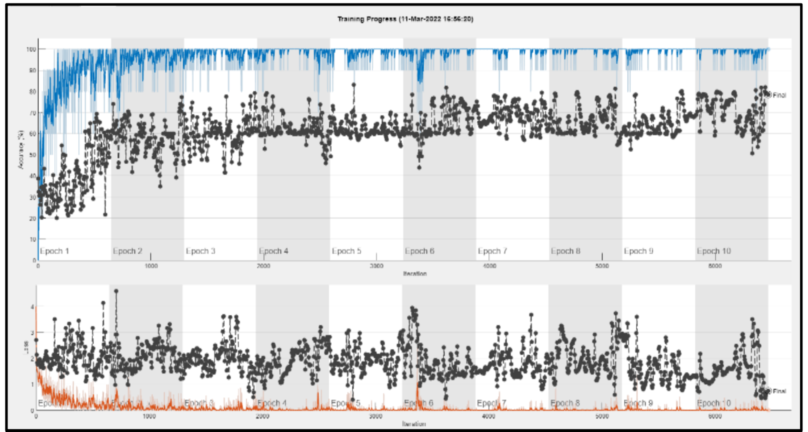


**AlexNet**

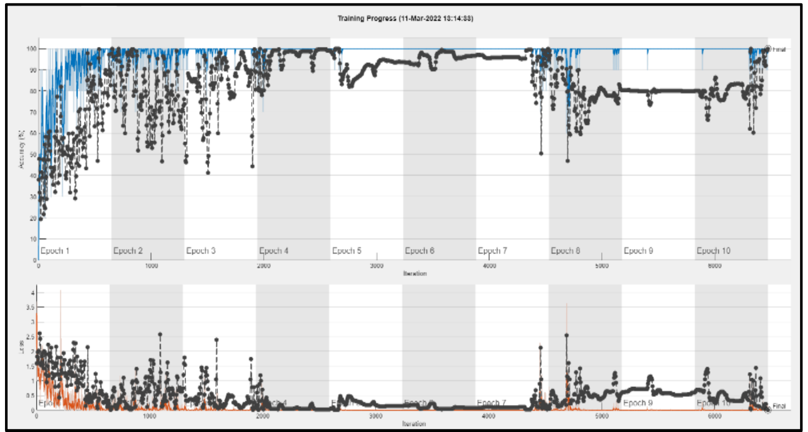


**GoogLeNet**

Overfitting Evident

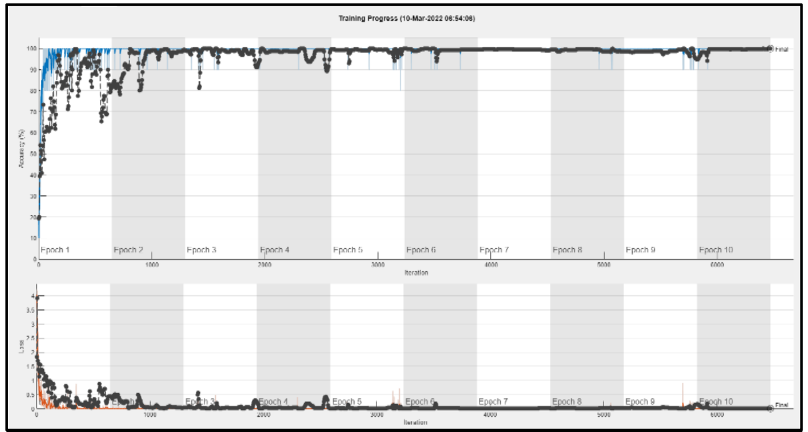


**SqueezeNet**

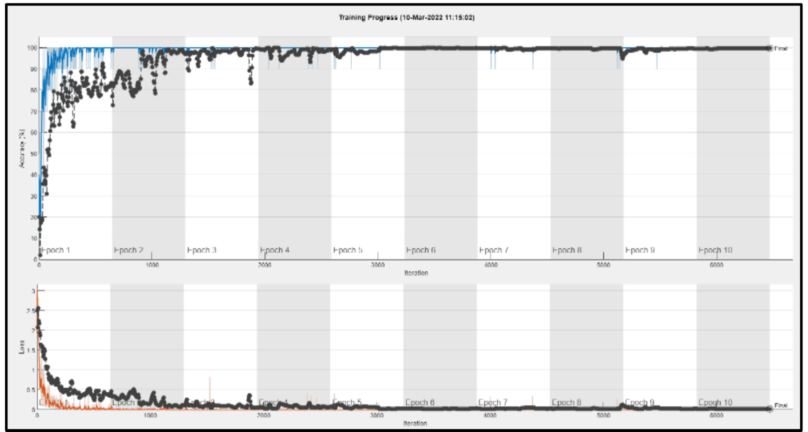


**VGG-16**

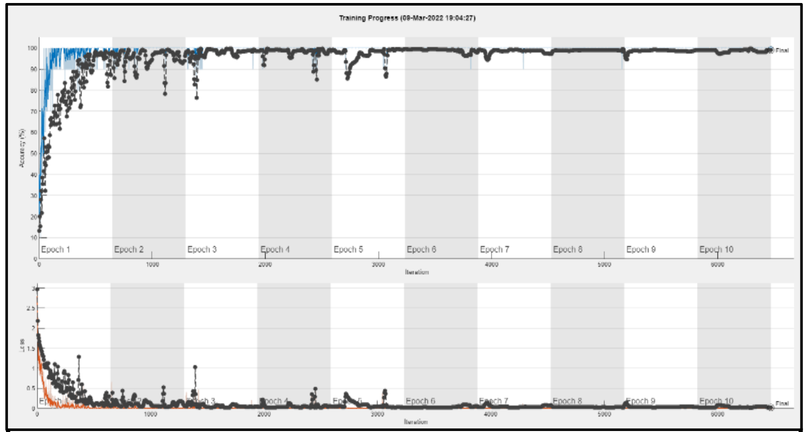
# TRAINING PROCESS WITH CWT



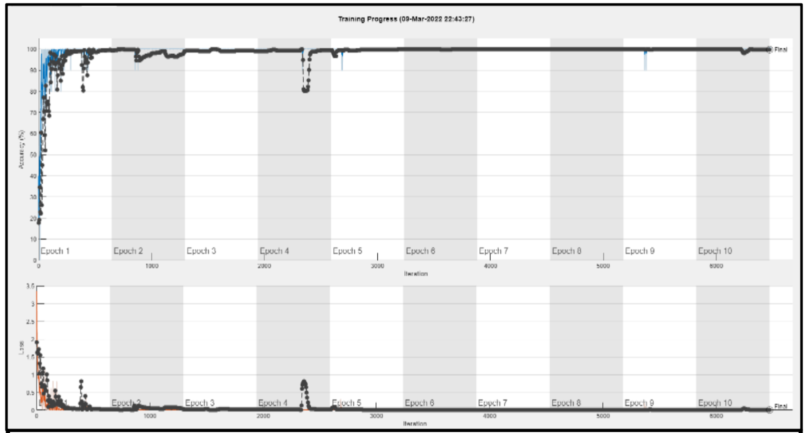

AlexNet




GoogLeNet




SqueezeNet



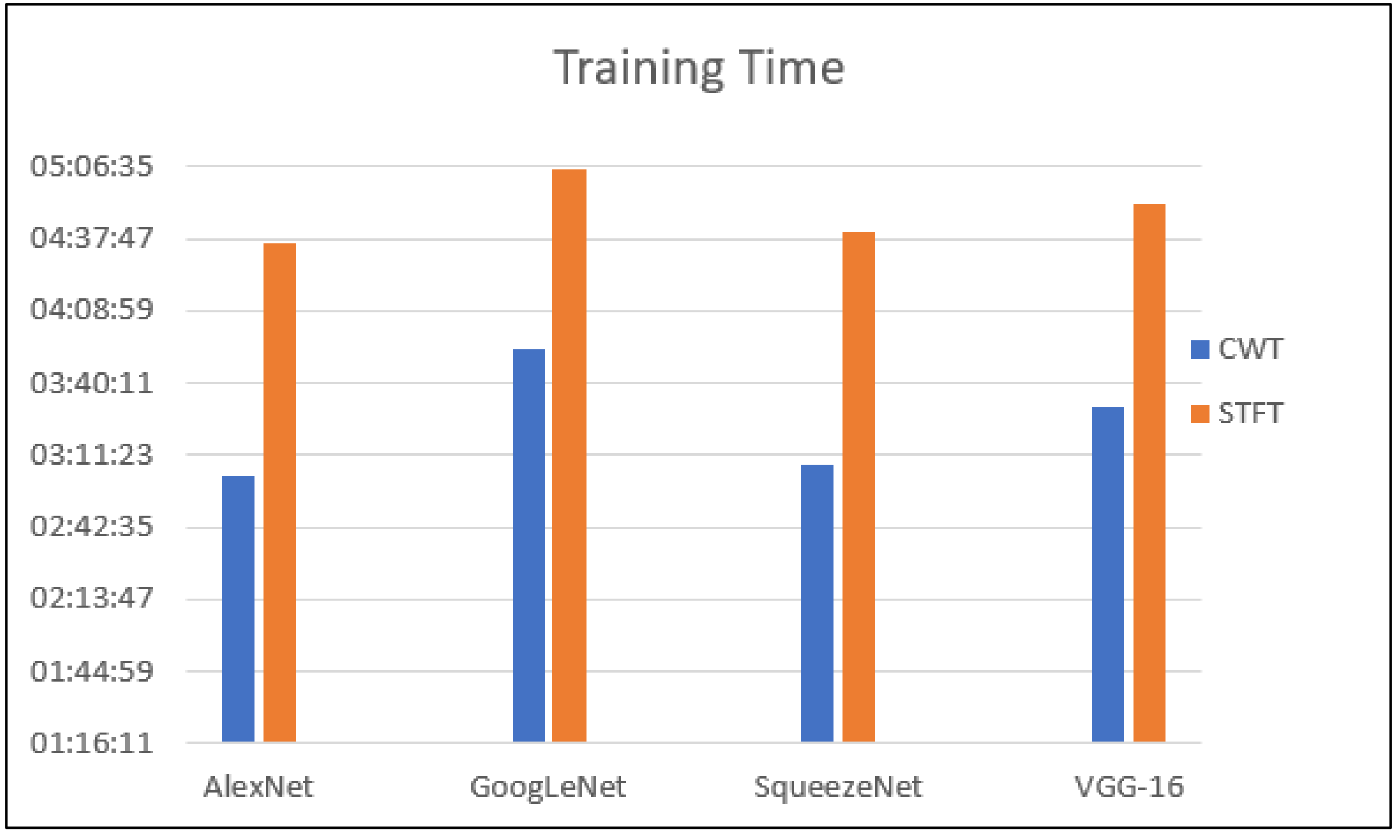

VGG-16

# COMPARATIVE ANALYSIS

- Training of networks done through Deep Network Designer of MATLAB.
- Transfer learning implemented through replacing the relevant network layers and optimally specifying the training parameters, selecting the apt batch size, validation frequency and number of epochs.
- Data augmentation undertaken for rendering the data suitable for passing as input to the respective CNN model.
- Overfitting evident in case of training with grayscale images, thereby entailing comparison between STFT and CWT techniques only.
- Training combinations evaluated on the basis of training time taken, validation accuracy achieved, prediction time as well as relevant confusion matrices.

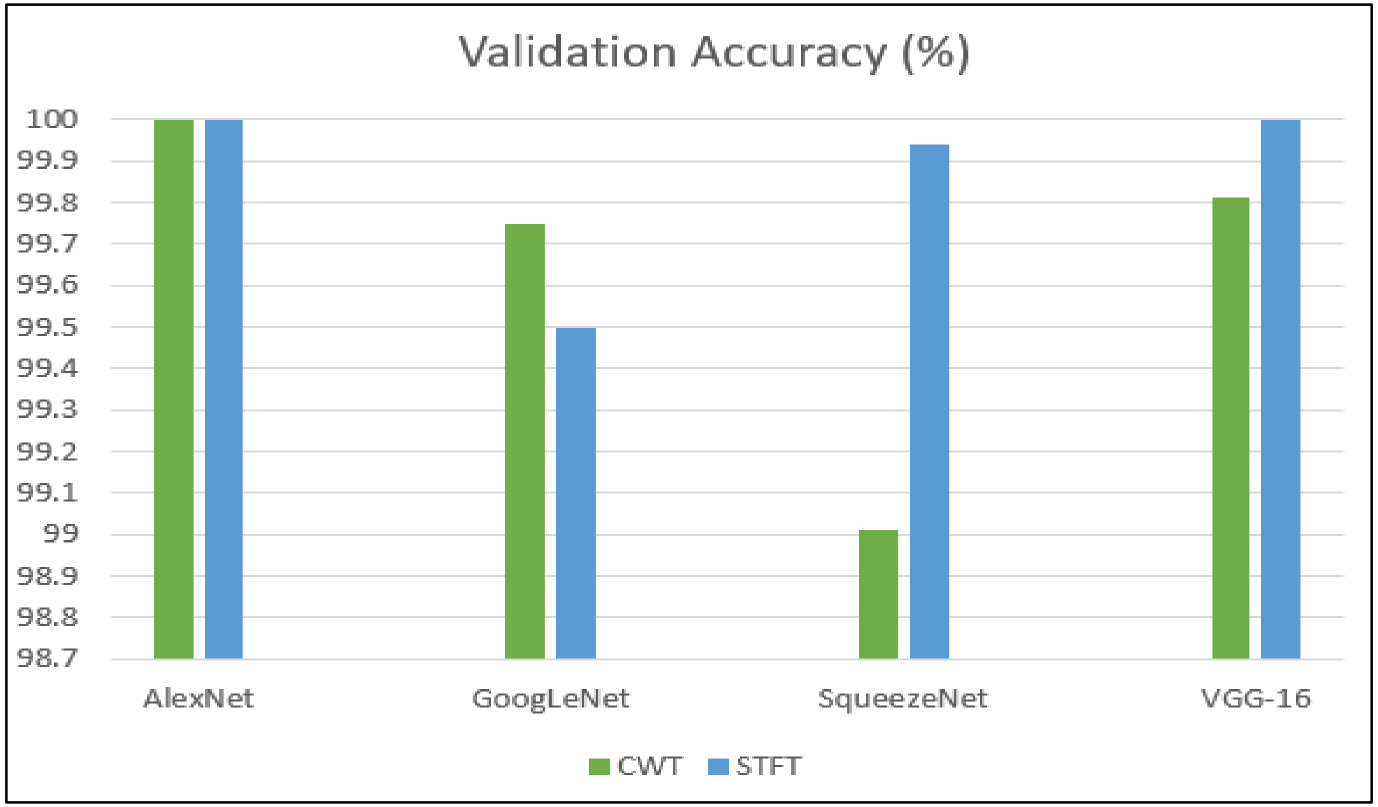
# COMPARATIVE ANALYSIS

- **Training Time**. CWT technique consumes lesser time in training with each network, with the least in AlexNet at **03h 03m 09s**.



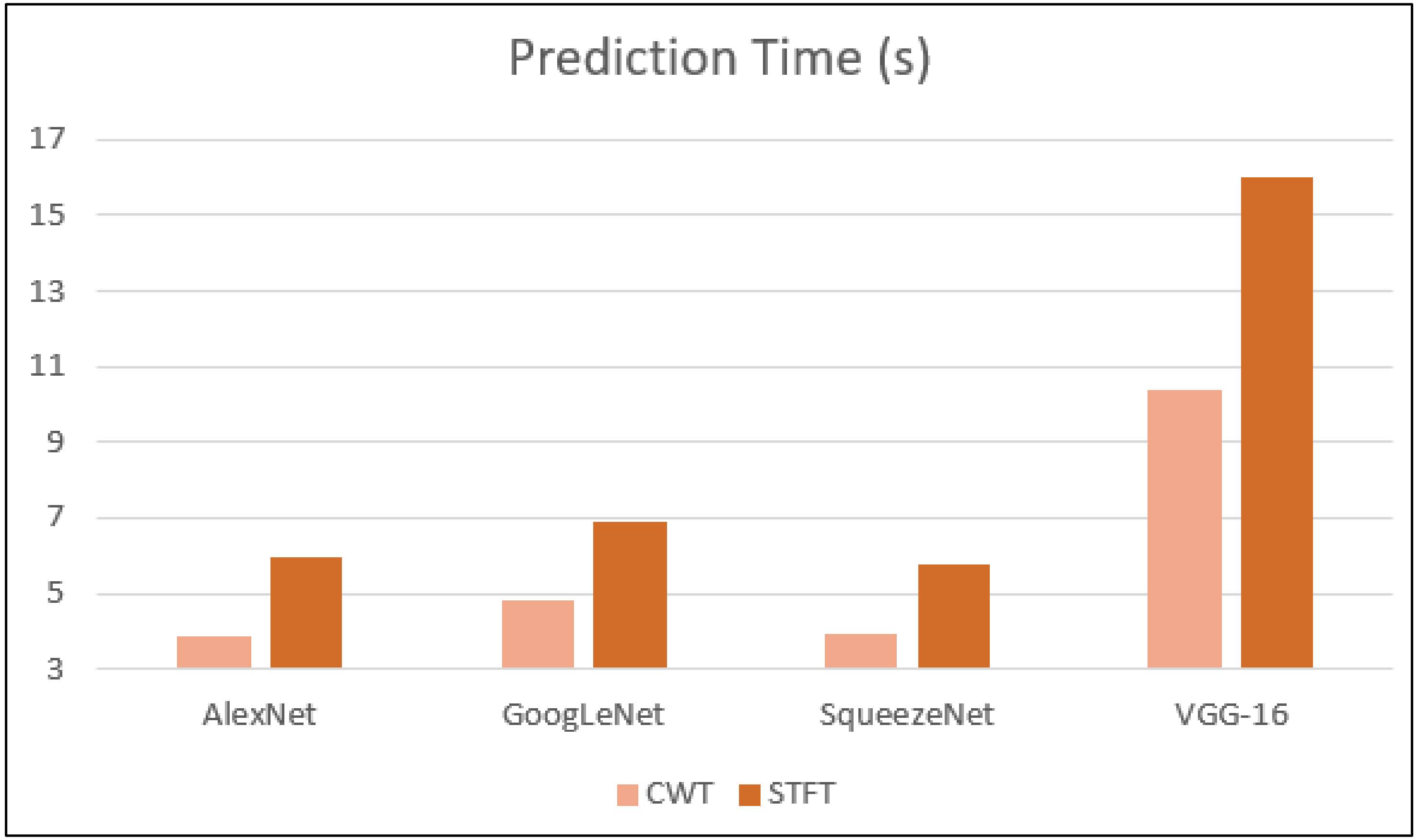
# COMPARATIVE ANALYSIS

- **Validation Accuracy**. Highest for CWT technique with **AlexNet at 100%** followed by 99.81% for VGG-16, 99.75% for GoogLeNet and 99.01% for SqueezeNet.



# COMPARATIVE ANALYSIS

- **Prediction Time**. Prediction time recorded for 900 test images and found to be least for CWT-AlexNet pair at 3.85s.



# COMPARATIVE ANALYSIS

- **Confusion Matrices**. Prediction accuracies found to be 100% for all eight combinations.

**AlexNet**

STFT

| | BD | CD | HB | IR | OR |
|---|---|---|---|---|---|
| BD | 180 | 0 | 0 | 0 | 0 |
| CD | 0 | 180 | 0 | 0 | 0 |
| HB | 0 | 0 | 180 | 0 | 0 |
| IR | 0 | 0 | 0 | 180 | 0 |
| OR | 0 | 0 | 0 | 0 | 180 |

CWT

| BD | CD | HB | IR | OR |
|---|---|---|---|---|
| 180 | 0 | 0 | 0 | 0 |
| 0 | 180 | 0 | 0 | 0 |
| 0 | 0 | 180 | 0 | 0 |
| 0 | 0 | 0 | 180 | 0 |
| 0 | 0 | 0 | 0 | 180 |

**GoogLeNet**

STFT

| | BD | CD | HB | IR | OR |
|---|---|---|---|---|---|
| BD | 180 | 0 | 0 | 0 | 0 |
| CD | 0 | 180 | 0 | 0 | 0 |
| HB | 0 | 0 | 180 | 0 | 0 |
| IR | 0 | 0 | 0 | 180 | 0 |
| OR | 0 | 0 | 0 | 0 | 180 |

CWT

| BD | CD | HB | IR | OR |
|---|---|---|---|---|
| 180 | 0 | 0 | 0 | 0 |
| 0 | 180 | 0 | 0 | 0 |
| 0 | 0 | 180 | 0 | 0 |
| 0 | 0 | 0 | 180 | 0 |
| 0 | 0 | 0 | 0 | 180 |

**SqueezeNet**

STFT

| | BD | CD | HB | IR | OR |
|---|---|---|---|---|---|
| BD | 180 | 0 | 0 | 0 | 0 |
| CD | 0 | 180 | 0 | 0 | 0 |
| HB | 0 | 0 | 180 | 0 | 0 |
| IR | 0 | 0 | 0 | 180 | 0 |
| OR | 0 | 0 | 0 | 0 | 180 |

CWT

| BD | CD | HB | IR | OR |
|---|---|---|---|---|
| 180 | 0 | 0 | 0 | 0 |
| 0 | 180 | 0 | 0 | 0 |
| 0 | 0 | 180 | 0 | 0 |
| 0 | 0 | 0 | 180 | 0 |
| 0 | 0 | 0 | 0 | 180 |

**VGG-16**

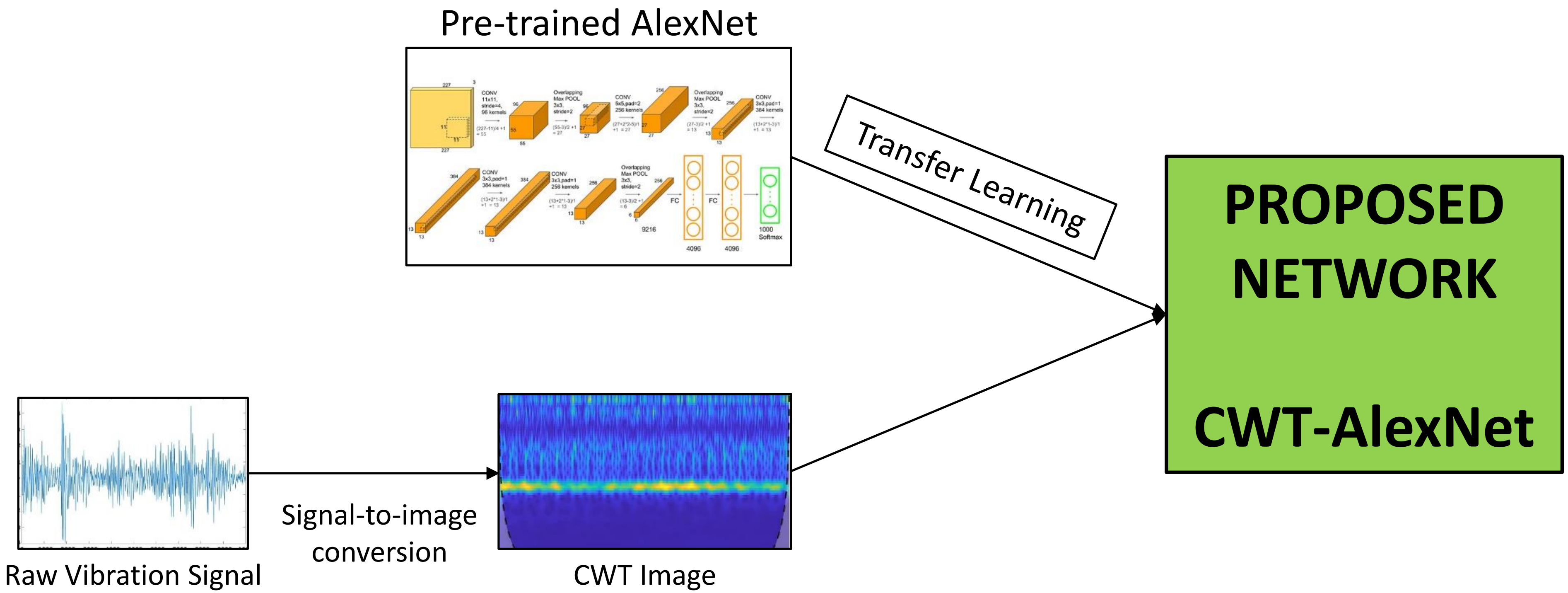
STFT

| | BD | CD | HB | IR | OR |
|---|---|---|---|---|---|
| BD | 180 | 0 | 0 | 0 | 0 |
| CD | 0 | 180 | 0 | 0 | 0 |
| HB | 0 | 0 | 180 | 0 | 0 |
| IR | 0 | 0 | 0 | 180 | 0 |
| OR | 0 | 0 | 0 | 0 | 180 |

CWT

| BD | CD | HB | IR | OR |
|---|---|---|---|---|
| 180 | 0 | 0 | 0 | 0 |
| 0 | 180 | 0 | 0 | 0 |
| 0 | 0 | 180 | 0 | 0 |
| 0 | 0 | 0 | 180 | 0 |
| 0 | 0 | 0 | 0 | 180 |

# COMPARATIVE ANALYSIS: RESULTS

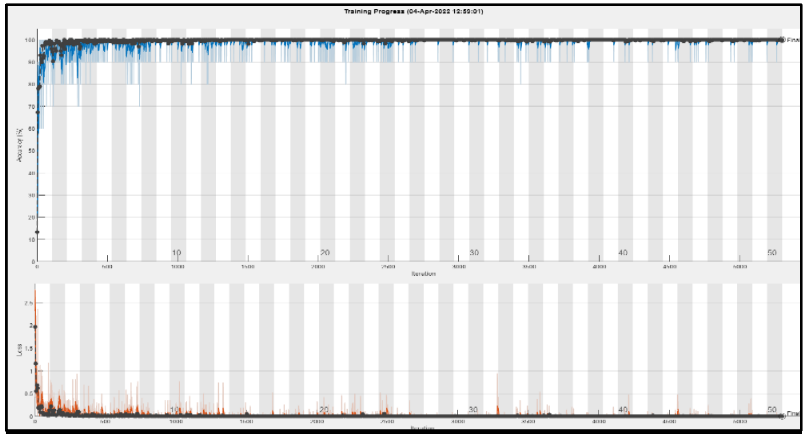



- Raw vibration signal converted to image through application of CWT.
- Pretrained AlexNet trained through transfer learning with generated data.
- Out of the 12 combinations, fastest and most efficient.

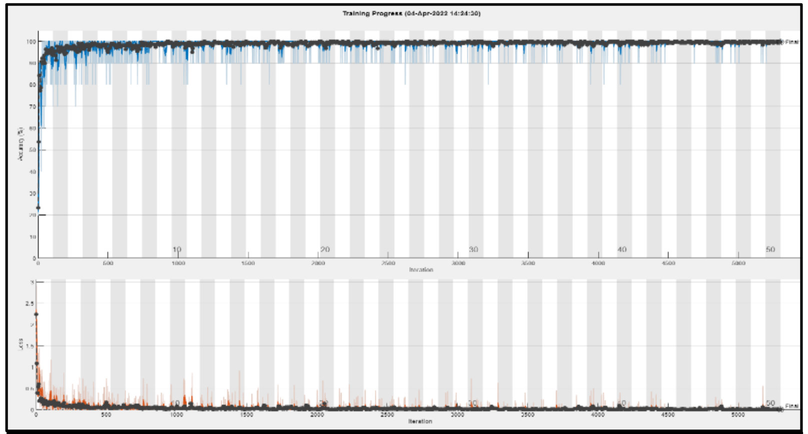
# VALIDATION OF PROPOSED NETWORK : TARGET DATASET 1

- Validation of proposed network undertaken through two target domain datasets.
- With target domain dataset 1 viz. CWRU data, training and prediction with the proposed network undertaken for all five datastores wherein generated data split into training, validation and test data in the ratio 70%, 20% and 10% respectively. (same as source domain data)
- Training process along with training and prediction parameters recorded for all datastores.
- Proposed model achieves 100% prediction accuracy with individual as well as combined speed datasets with minimal training and low prediction time.

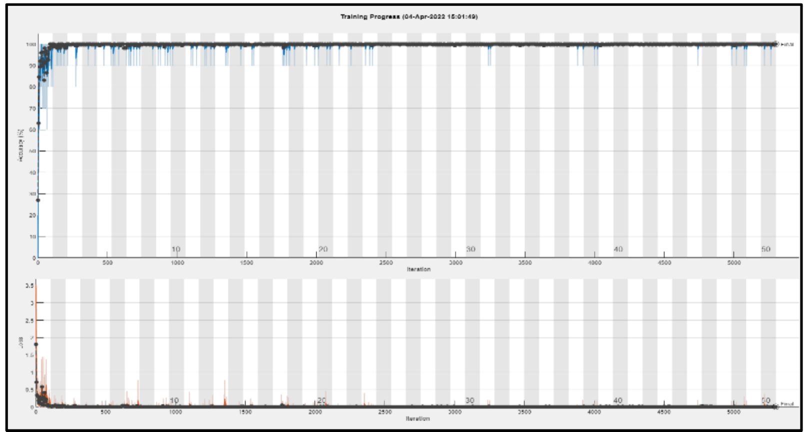
# TRAINING PROCESS OF CWRU DATASETS



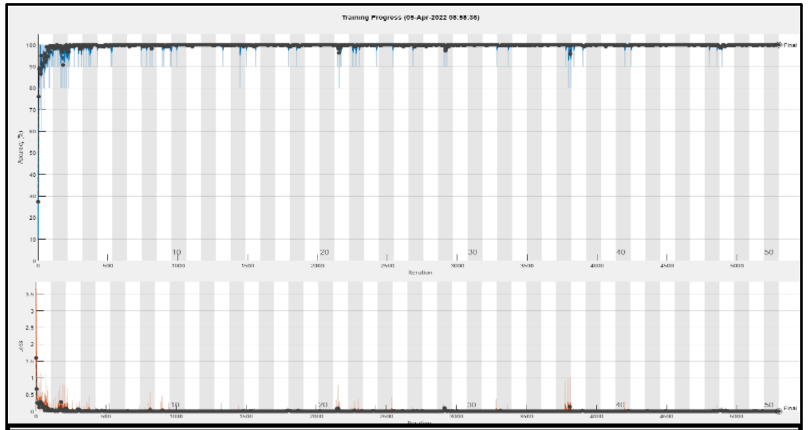
Dataset 1: 0 HP or 1797 RPM



Dataset 2: 1 HP or 1772 RPM

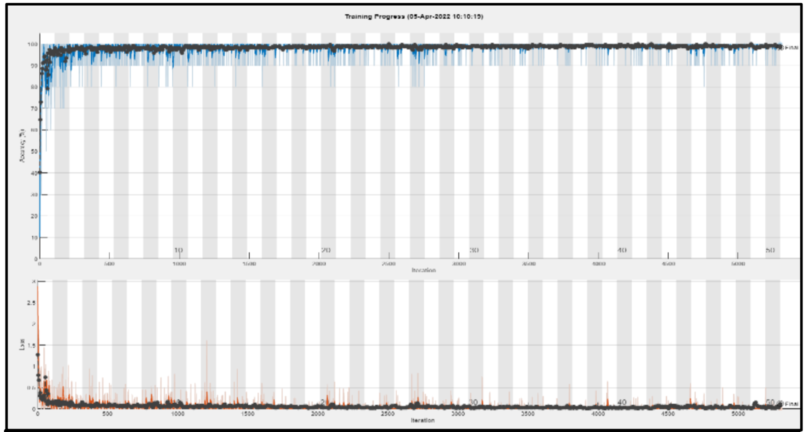


Dataset 3: 2 HP or 1750 RPM



Dataset 4: 3 HP or 1730 RPM

# TRAINING PROCESS OF CWRU DATASETS



**Dataset 5: Combined speeds**

| Datastore | Training Time | Validation Accuracy | Prediction Time (for 152 images) | Prediction Accuracy |
|---|---|---|---|---|
| Dataset 1 | 30m 40s | 100% | 1.03s | 100% |
| Dataset 2 | 31m 4s | 99.67% | 1.29s | 100% |
| Dataset 3 | 30m 49s | 100% | 1.22s | 100% |
| Dataset 4 | 30m 57s | 100% | 1.39s | 100% |
| Combined | 31m 52s | 98.36% | 1.31s | 100% |

**Recorded Parameters for Target Datastores**

# VALIDATION OF PROPOSED NETWORK : TARGET DATASET 2

- With target domain dataset 2 viz. MFS data, training and prediction with the proposed network undertaken for the created datastore wherein generated data split into training, validation and test data in the ratio 70%, 20% and 10% respectively. (same as source domain data)
- Validation accuracy achieved 100% with a training time of 10h 2m 46s.
- Classification of 720 test images completed in 4.7s with prediction accuracy of 99.44% wherein 1 out of 180 images of OR wrongly classified as IR.

| | BD | HB | IR | OR |
|---|---|---|---|---|
| BD | 180 | 0 | 0 | 0 |
| HB | 0 | 180 | 0 | 0 |
| IR | 0 | 0 | 180 | 1 |
| OR | 0 | 0 | 0 | 179 |

# CONCLUSION

- Comparative study of SIC techniques and CNN architectures undertaken through a relatively less explored concept of transfer learning.
- Proposed network performs well for both the target domain datasets and hence, can be put forth as a fast and efficient method of bearing fault classification even at different rotating speeds.
- No pre-processing of acquired vibration data required and the proposed network performs well for raw data while providing highly accurate results.
- Computational costs in terms of time consumed clearly brought out in the analysis for different SIC methodologies as well as for light and dense networks. Therefore, proper selection of SIC technique-CNN pair holds importance.
- Implementation of transfer learning eliminates the need of “large datasets” and the proposed network works fine with limited amount of data as well.

# FUTURE SCOPE

- Selection of SIC methodologies as well as pre-trained networks requires domain expertise in the field of engineering as well as artificial intelligence or data science. Efforts can be put towards development of algorithms for automated suggestion of applicable techniques.
- Further, suitable signal pre-processing techniques and de-noising of the raw vibration signals can be considered to further improve the results obtained in the present study.

# REFERENCES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[2] Georgoulas, G., Loutas, T., Stylios, C.D. and Kostopoulos, V., 2013. “Bearing fault detection based on hybrid ensemble detector and empirical mode decomposition.” *Mechanical Systems and Signal Processing*, *41*(1-2), pp.510-525.

# DISCUSSIONS