



### Welcome to:

### Machine Learning in Manufacturing and Petroleum Industries



### **Unit objectives**



### After completing this unit, you should be able to:

- Understand applications of machine learning in manufacturing industry
- Learn about deep learning techniques for smart manufacturing
- Understand how machine learning is used for quality control in manufacturing
- Gain knowledge on applications of machine learning for surface defect inspection
- Learn how machine learning can be used for fault assessment

### Introduction

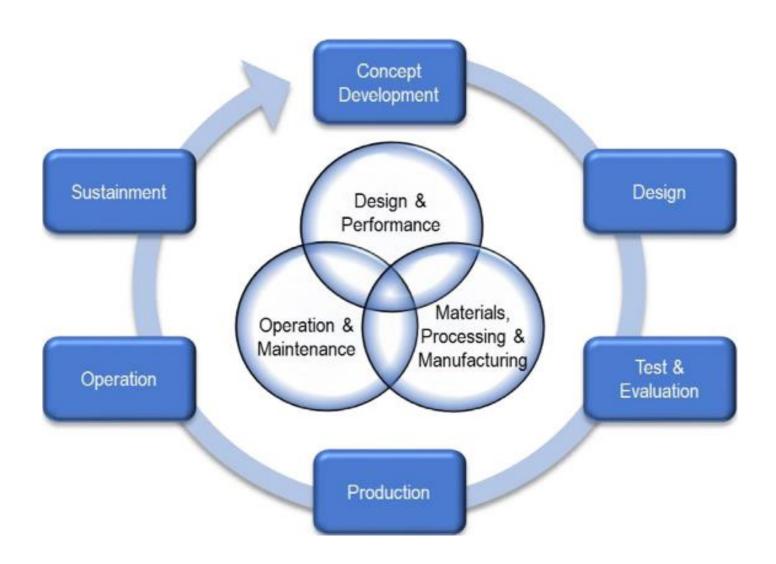


- Today's manufacturing industry is witnessing an enormous rise in data available.
- Big data changes the way decisions are made within the production environment based on various scientific fields such as:
  - Computer science.
  - Mathematics.
  - Advanced statistics.
- The area, which incorporates all these sciences, is Machine Learning (ML).
- ML becomes the most effective tool used to predict and identify the problem-solving issues within production systems.
- Another major issue concerns the data security element.
- Given this problem, ML must use the various techniques and algorithms to maximize the value of the data.

## manufacturing industry



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Applications of machine learning in

Figure: Schematic representation of applications of machine learning in manufacturing industry





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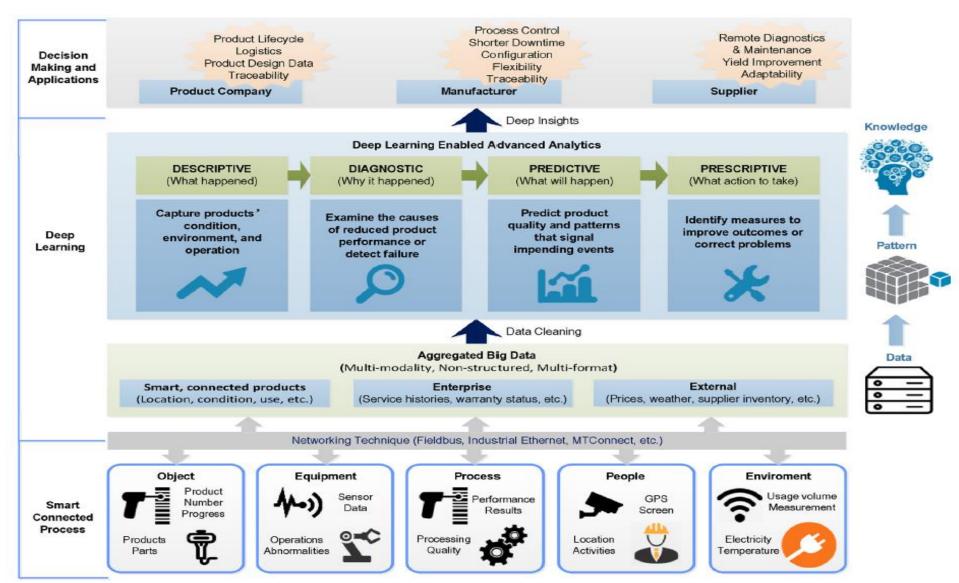


Figure: Deep learning enabled advanced analytics for smart manufacturing

## Machine learning for quality control in manufacturing



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- Modern machine learning has made tremendous strides.
- It has delivered reliable results in many cases, but the representation of features may need to be updated from conception for modern artificial intelligence.
- Deep training has been researched to know standard characteristics at the highest level.
- It has also implemented to a broad scope of graphics and detectable defects.

## **Case study**



- Machine learning: Based imaging system for surface defect inspection.
- This case study indicates an automatic visual inspection program for dirt, scuffs, burrs and wore. on the ground section.
- Imaging analysis of training samples using Convolution Neural Network (CNN) is used to verify that the defect occurs in the target region of an object.

## Construction of CNN (1 of 3)

- CNN is a feedback level for creating data, a production level for generating category sort, and many secret levels.
- The production surface with FC strands has a duty to identify the secret layer's high-level characteristics.

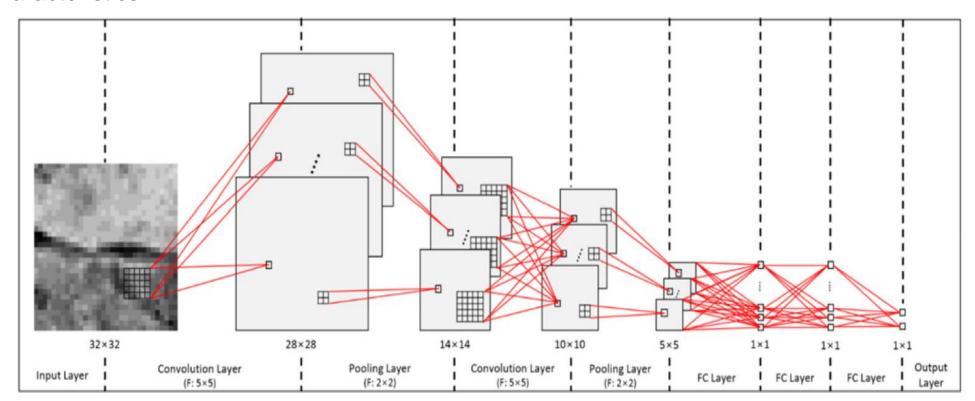


Figure: Sample structure of CNN



Equation 1:

$$X_j^n = f\left(\sum_i w_{ij}^n X_i^{n-1} + \theta_j^n\right)$$

• Equation 2:

$$X_{j}^{n} = f \left( \sum_{i - \frac{m}{2}}^{i + \frac{m}{2}} w_{ij}^{n} X_{i}^{n-1} + \theta_{j}^{n} \right)$$

• Equation 3:

$$X_j^n = \max\left(\left[X_{i-\frac{m}{2}}^{n-1}, X_{i+\frac{m}{2}}^{n-1}\right]\right)$$

## Construction of CNN (3 of 3)



• Equation 4:

$$L = \sum_{k=1}^{m} c_k \log h(x_k) + (1 - c_k) \log(1 - h(x_k))$$

Equation 5:

$$h(x_k^i) = \frac{e_k^i}{\sum_i e_k^i}$$

## **Experimental results**

- CNN can conduct simultaneous abstraction and identification of features, an actual abstraction unit of features is not needed.
- The identification quality could be improved with more concealed strands.

	Class $C_b^1$	4	Class $C_d^1$
THE RESERVE	Silicon wafer		Silicon wafer
	Background		Defect
	Class $C_b^2$		Class $C_d^2$
	Solid paint	AND DESCRIPTIONS	Solid paint
	Background		Defect
	Class $C_b^3$		Class $C_d^3$
	Pearl paint		Pearl paint
	Background		Defect
	Class $C_b^4$		Class $C_d^4$
	Fabric		Fabric
7600	Background		Defect
	Class $C_b^5$		Class $C_d^5$
	Stone		Stone
	Background		Defect
	Class $C_b^6$	<b>原子和伊里·</b>	Class $C_d^6$
	Wood	原 は	Wood
	Background		Defect

Figure: Experimental results

### Efficiency of CNN for defect detection

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- CNN's relative efficiency varies depending on invisible surface structure, such as grouping and time for learning.
- The width of a test item that is wide sufficient to convey minor faults and materials must be measured for substrate inspection.
- The failure frequency and practice period are the average quantity of 24 combinations of tests and the failure level was determined as obeys.

$$error\ rate = 100 \times \frac{N_{incorrect\ class}}{N_{test\ samples}} (\%)$$

## **Comparative experiments**



- In this chapter, we performed a relative survey on standard techniques of examination utilizing the altered CNN.
- We contrasted PSO-ICA, a recognized silicon wafer examination method, and a Gabor detector displaying performance thickness trends, as well as a machine learning program to relate VOV parameter to RF (spontaneous Forest).
- The first experiment was conducted separately to measure the quality of the six surface types.
- Second experiment was performed simultaneously in order to train and compare more than two different surfaces of the type.

### Machine learning for fault assessment



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- Due to fatigue or unusual working circumstances, production systems are typically susceptible to faults, resulting in unnecessary load, desertion, fracturing, catching fire, oxidation, and tear.
- With distributed data from intelligent auditory and technology tools for software failure detection and recognition, more and more computer vision methods have been thoroughly examined.
- In order to meet application requirements, the intensity range of information on the various methods of motion will also be discussed in substring is achieved by converting data from period sequence into a function and then standardizing it as an picture.
- Usually, a DBM system's performance is the Teager-Kaiser energy operator or wavelet that transforms pre-processed features rather than raw data.
- The main feature is a CNN double layer, i.e. two successive Fourier transform levels without a redistributing layer among them.

## Time frequency methods



- Period rate is simultaneously a signal in period and intensity domains.
- Spectrograms and scalograms are the most common depictions of moment-frequency.
- A spectrogram is a schematic depiction of a wave using STFT in the moment-frequency domain, and a scalogram utilizes the WT.
- The usefulness of the above three description methods was tested by investigators:
  - STFT.
  - WT.
  - HHT.
- Spectrograms: Short-Time Fourier Transform (STFT):
  - Scalograms: wavelet transform.
  - Hilbert-Huang transform.

# **Spectrograms: Short-Time Fourier Transform (STFT)**



 Spectrograms are a graphical depiction of the STFT where, respectively, the x-and y-axis are period and intensity, and the image's colour scale shows the frequency amplitude.

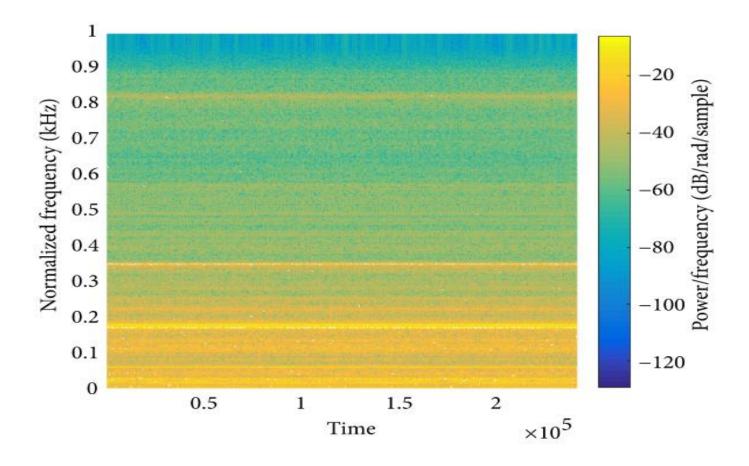


Figure: STFT spectrogram of baseline raw signal

## Scalograms: Wavelet transform

Scalograms are a graphical depiction of a wavelet transform (WT).

$$WT_{x}(b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t) \psi\left(\frac{t-b}{a}\right) dt, \qquad \Psi_{\sigma}(t) = c_{\sigma} \pi^{-(1/4)} e^{-(1/2)t^{2}} \left(e^{i\sigma t} - K_{\sigma}\right),$$

$$\times 10^{4}$$

$$4.5$$

$$4$$

$$3.5$$

$$(2H)$$

$$2$$

$$1.5$$

$$2D$$

$$1$$

$$0.5$$

$$0$$

$$0.02$$

$$0.04$$

$$0.06$$

$$0.08$$

$$0.1$$

$$0.12$$

Figure: Wavelet transform scalogram of baseline raw signal

Time (s)

### Hilbert-Huang transform

 Hilbert-Huang Transform (HHT) as a non-parametric evolutionary method to the method of measurement of moment-frequency.

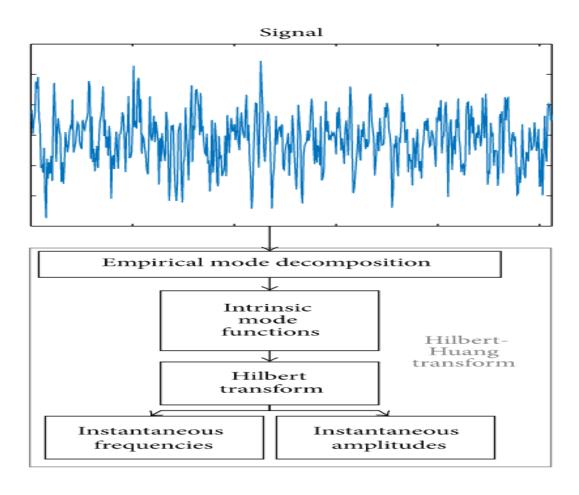


Figure: Overview of HHT adapted from Wang (2010)

# Proposed CNN architecture for fault classification based on vibration signals



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- The main feature of the conceptual model is a double surface CNN, i.e. two successive coevolutionary levels despite a redistributing level among them.
- The lack of a redistributing level decreases the learning criteria and enhances the expressiveness of the apps through an inherent non linearity.

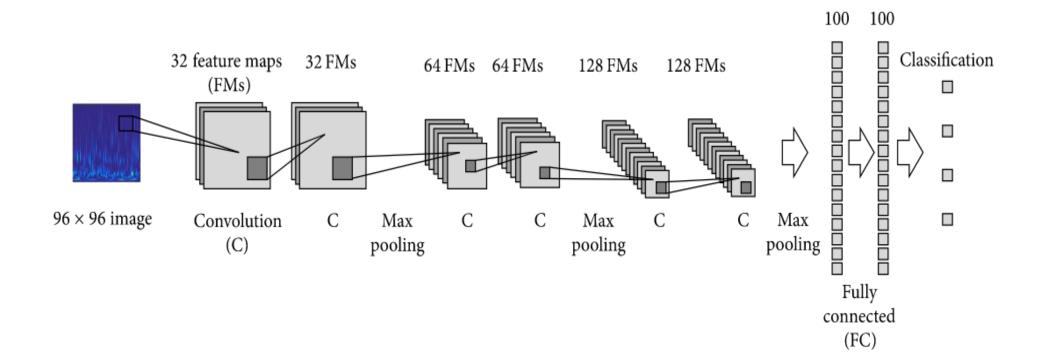


Figure: Proposed CNN architecture

## **Case Study 1**



- Machinery failure prevention technology.
- The Machinery Failure Prevention Technology (MFPT) Society received this information collection.
- At 270 lbs of charge and a recording intensity of 97,656 Hz for six seconds, a research system with a NICE casing collected velocity information for reference purposes.
- The test frequency for the faults was 3 seconds at 48,828 Hz.
- With loads ranging from 0, 50, 100, 150, 200, 250, and 300 lbs, seven internal race faults were analysed.

# Machinery failure prevention technology (1 of 2)

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Table: MFPT baseline images.

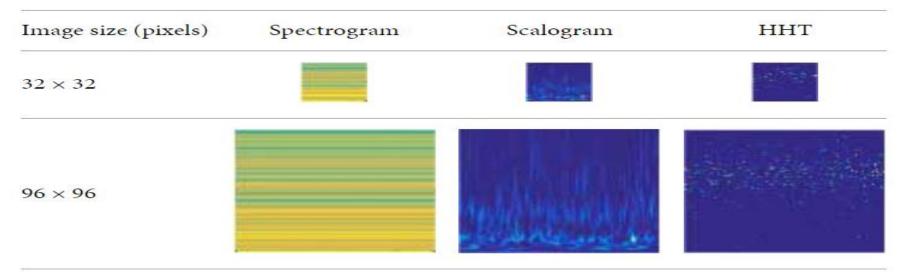


Table: MFPT inner race images.

Image size (pixels)	Spectrogram	Scalogram	ННТ	
32 × 32			\$	
96 × 96				

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# Machinery failure prevention technology (2 of 2)



Table: MFPT paired two-tailed t-test pvalues.

Image type	Architecture 1	Architecture 1	Architecture 2	Architecture 2
	$32 \times 32$	96 × 96	$32 \times 32$	96 x 96
Scalogram	0.080	0.344	0.049	0.108
Spectrogram	0.011	0.037	0.058	0.001
ННТ	0.031	0.410	0.000	0.000

### Conclusion



- The rotating part carrying malfunction diagnosis is a big issue in the sector.
- It is of great strategic significance to locate faults early in planning repair.
- Three period intensity study approach (STFT, WT and HHT) were compared to test the ability
  of the current CNN system to reliably diagnose a malfunction.
- Their efficacy as raw signal representations was evaluated.
- The proposed design of the CNN has shown balanced test noise. It also showed featureless training and efficient automated data description learning.
- The proposed design, by minimizing the number of teachable variables, provides the same precision for scalogram pictures with reduced computing prices.
- Job to fix recognition in a area of enormous industrial investments that are rapidly evolving in the automotive, electronics, aerospace and construction sectors.

### Checkpoint (1 of 2)



### Multiple choice questions:

- In deep learning which neural network is a class of deep neural networks, most applied to analysing visual imagery.
  - a) Convolution neural network
  - b) Recurrent neural network
  - c) Regression neural network
  - d) Boltzmann neural network
- 2. What happens when a <u>machine learning model</u> has become too attuned to the data on which it was trained and therefore loses its applicability to any other dataset.
  - a) Under fitting
  - b) Over fitting
  - c) Side fitting
  - d) All the above
- 3. Which of the following is the counterpart of <u>overfitting</u>, happens when a machine learning <u>model</u> is not complex enough to accurately capture relationships between a dataset's <u>features</u> and a <u>target variable</u>.
  - a) Under fitting
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### **Checkpoint solutions (1 of 2)**



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### Checkpoint (2 of 2)



#### Fill in the blanks:

- 1. ----- refers to using advanced data analytics to complement physical science for improving system performance and decision making.
- 2. In manufacturing----- is a process that ensures customers receive products free from defects and meet their needs.
- 3. ----- is a methodology that improves systems availability and contributes to cost reduction and increase of useful life of production assets.
- 4. ----- is a performance measurement for machine learning classification problem where output can be two or more classes.

### **Checkpoint solutions (2 of 2)**

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#### Fill in the blanks:

- 1. <u>Smart manufacturing</u> refers to using advanced data analytics to complement physical science for improving system performance and decision making.
- 2. In manufacturing <u>quality control</u> is a process that ensures customers receive products free from defects and meet their needs.
- 3. <u>Predictive maintenance</u> is a methodology that improves systems availability and contributes to cost reduction and increase of useful life of production assets.
- 4. <u>Confusion matrix</u> is a performance measurement for machine learning classification problem where output can be two or more classes.

### **Question bank**



### Two mark questions:

- 1. What is smart manufacturing?
- 2. Define surface detection.
- 3. What is fault assessment?
- Define quality control in manufacturing.

### Four mark questions:

- 1. Explain the deep learning methods used in smart manufacturing.
- How machine learning can be used for quality control in manufacturing.
- 3. How machine learning can be used for fault assessment.
- Explain convolution neural network.

### **Eight mark questions:**

- 1. Briefly explain the applications of machine learning in manufacturing industry.
- 2. Explain with an example application of machine learning in surface defect inspection.

### **Unit summary**



### Having completed this unit, you should be able to:

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