# MechDefect Solutions

## Report 3
## Presented by Group 15

| Date | Duration of meet | Purpose of Meet | Presentees |
|---|---|---|---|
| 15/10/2023 | 1 hour | Reviewing existing technical literature | ALL |
| 17/10/2023 | 2 hours | Discussing AL/ML model scheme | ALL |
| 18/10/2023 | 2 hours | Final report making | ALL |


Swapnoneel Kayal - 200100154
Kanika Banjare - 210260027
Shraman Santara - 21D100019
Anand Bhaskar - 200100024
Varad Patil - 22B2270

# Project Title and Objectives

**Advanced AI-Driven Defect Detection Solutions for Manufacturing Excellence**

Objectives:

- Develop AI-powered defect detection and classification solutions for industries that cater to the initial stages of manufacturing
- Leverage transfer learning by training our model on different processes (like casting, mining, etc) gaining knowledge from one and applying it to other processes.

# Technical Background

## Patents in the area

- **Unified neural network for defect detection and classification**
    - Their system includes several computer subsystems which use a neural network to detect and classify defects on a specimen's images.
    - The network analyzes specimen images by extracting features in order to to identify and categorize defects.
- **Training a machine learning model with synthetic images**
    - This patent introduces methods for training ML models using synthetic defect images, employing a system that includes a user-friendly GUI.
    - The system allows users to edit and store modified images in a training set, facilitating ML model training.

## Published literature in the area

- **Detection and Segmentation of Manufacturing Defects with Convolutional Neural Networks and Transfer Learning**
    - Used Mask Region-based CNN architecture for defect detection and segmentation in X-ray images, surpassing state-of-the-art performance.
    - Leveraged transfer learning to enhance prediction accuracy, enabling the model to excel in metal casting and welding quality assessment.
- **Detection and Segmentation of Manufacturing Defects with Convolutional Neural Networks and Transfer Learning**
    - Automated defect management system based on ML and computer vision for porcelain products developed with an industrial producer.
    - Utilizes a CNN to analyze product images, predicting defects, leading to improved production efficiency and reduced costs.
- **Automatic localization of casting defects with convolutional neural networks**
    - Explored various CNN architectures for localization of casting defects in X-ray images.
    - Leveraged transfer learning so as to train state-of-the-art CNN models on a relatively smaller dataset and compare their accuracy and computational performance.

Made by : Swapnoneel Kayal

# Technical Resources

**Open Libraries**

- OpenCV
- Keras / PyTorch
- PIL (pillow)
- Statsmodel
- Scikitlearn (confusion matrices, etc)

**Proprietary Libraries**

None Available

**Github and other resources**

- "Product Fault Detection Using Transfer Learning" on Kaggle
- "Surface Steel Defect Detection" on Kaggle
- "Steel Surface Defect Detection Using UNet" on Github

Made by : Anand Bhaskar

# Data

**For defect detection** : Casting Product Image Data

**Size of the data** : 300*300 pixels grey-scaled 7348 augmented images

**Column details and data type** : We are not dealing with tabular data. However, the dataset already splits the data for training and testing by separating the images into 2 separate folders (train and test). Both these folders contains def_front and ok_front subfolders.

**Authenticity, error, bias and missing data** : The dataset has been collected in stable lighting environment with extra arrangement. The data is authentic and no errors / missing data has been reported yet. The dataset is licensed

**For defect classification** : Metal surface defects dataset

**Size of the data** : This database includes 1800 grayscale images: 300 samples each for the six different kinds of typical surface defects

**Column details and data type** : We are not dealing with tabular data. However, the directory contains three folders i.e. train, valid amd test. The train folder contains six subfolders that have 276 image files in each folder. Accordingly, the test and valid contains six subfolders that have 12 images in each folder

**Authenticity, error, bias and missing data** : The dataset was downloaded from NEU Metal Surface Defects Database. Hence, the data is authentic and no errors / missing data has been reported yet.

Made by : Kanika Banjare

# AI/ML model scheme

## Object Detection + Defect Detection

- To detect the presence of pump impellers in images, we will fine-tune **RetinaNet** (with **ResNet50** backbone). This model is used to detect & segment out the pump impellers so that the defects can be detected in them. This is followed by a model used to detect the presence/absence of defect (any kind) in a submersible pump impeller using Transfer Learning (with VGG16 base model)
- For the Object Detection model, training has been performed with a batch size of 20 using Adam Optimizer. We plan to first train the model for 200 epochs. For the Defect Detection model, training has been performed with a batch size of 50 using Adam Optimizer. We plan to first train the model for 10 epochs. The validation dataset was leveraged to tune the hyper-parameters of our model and the testing dataset was used subsequently to give an unbiased evaluation of our end model.
- Our model is relatively flexible due to the fact that we will be training our model on images that have been pre-processed (rescaled, sheared, rotated etc). This increases the model's ability to handle variations in the input data.

# AI/ML model scheme

## Defect Classification

- The AI/ML model chosen for the task is the VGG16 architecture, selected for its superior performance over ResNet50 for the specific defect classification task
- Training is performed with a batch size of 36 using Adam Optimizer. We plan to first train the model for 10 epochs. We will leverage the validation dataset to tune the hyper-parameters of our model and the testing dataset will help us give an unbiased evaluation of our end model.
- Our model is more on the rigid side as it is focused on a specific task of defect classification in metal surfaces