# DATA SCIENCE & AI LAB (BSCSS3001)

# MILESTONE - 1

## GROUP NO. 11

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# Automatic Classification of Steel Microstructures Using Deep Learning

## 1 Problem Definition

### 1.1 The Challenge

Microstructure analysis is a critical aspect of materials science, especially in the steel industry. It is regularly employed in design, development, manufacturing, and quality control. Traditionally, interpreting microstructure images is a human knowledge-intensive and time-consuming task. This presents a significant bottleneck in Industry 4.0-focused digital transformation initiatives in materials manufacturing.

The steel processing industry—particularly sectors like rolling, forging, and extrusion—faces continuous challenges in efficient microstructure evaluation, which is essential for process control and quality assurance.

### 1.2 Proposed Solution

This project proposes a deep learning-based digital platform for automatic recognition and classification of steel microstructures.

**Core Pipeline:**

- Input: Microstructure image (SEM or Optical)
- Processing: Automated deep learning-based interpretation
- Output: Classification + Feedback loop for quality control

**Deployment:** Industry-specific IoT platform for seamless integration and automation.

### 1.3 Scope of Analysis

The project encompasses the complete analysis pipeline—**Segmentation → Detection → Classification**—to ensure comprehensive feature extraction and interpretation:

- **Segmentation:** Isolating and delineating microstructural features from steel samples.
- **Detection:** Identifying and locating specific metallurgical phases within segmented regions.
- **Classification:** Categorizing the identified phases into respective metallurgical classes.

This enables an end-to-end pipeline from raw microstructure images to fully classified metallurgical phases.

## 2 Project Objectives

- Compile a steel microstructure image database using SEM and optical microscopy.
- Develop a deep learning-based platform for automatic phase classification in steel.
- Test and validate the platform under industrial conditions.

## 3 Implementation Feasibility (Model & Approach)

**Model Choices:**

- ResNet-50
- EfficientNet-B7

These models are preferred due to their robustness against vanishing gradients and ability to capture complex image features.

**Segmentation Approach:**

- Initial method: Chan-Vese segmentation algorithm for boundary detection.
- Future exploration: Additional segmentation techniques to be evaluated based on performance.

**Model Training Methodology:**

1. **Manual Annotation:** Dr. Subhas Ganguly will annotate sample images to identify metallurgical phases such as ferrite, pearlite, martensite, and other relevant structures.
2. **Model Training:** Both ResNet and EfficientNet-B7 will be trained using annotated datasets for comparative performance analysis.

**Performance Evaluation:** Evaluation standards will include both classification and segmentation metrics:

- **Classification:**
  - Confusion Matrix for class-wise performance visualization.
  - F1 Score as the primary metric for balancing precision and recall.
- **Segmentation:**
  - Intersection over Union (IoU) for boundary accuracy and overlap measurement.

**Customization and Optimization:**

- Transfer learning using pretrained weights.
- Data augmentation: rotation, zoom, flipping, and patch extraction.

**Deployment:** Collaboration with steel manufacturing units will ensure industrial validation.

## 4 Data Sourcing and Governance

- **Base Dataset:** Curated from reported literature and open databases.
- **Custom Dataset:** Generated through in-house lab experiments.
- **Extended Dataset:** Industry-sourced microstructure images (on demand).

**Dataset Accessibility and Licensing:**

- Images will be sourced from publicly available research publications and peer-reviewed papers.
- Supplemented with data from Dr. Subhas's previous research and experimental work.
- All sources are accessible via standard academic databases ensuring legal and ethical compliance.

## 5 User Experience Design

A feedback loop will be integrated into the system where misclassified or new microstructures from industry are used to iteratively refine the model for increased accuracy and relevance.

## 6 Literature Review

Current industry standard tools such as **ImageJ** are highly effective at microstructure segmentation but lack automated classification capabilities. Manual phase identification still dominates, making analysis time-consuming and reliant on operator expertise.

**Benchmarking Focus:**

- Comparison of segmentation accuracy between traditional and deep learning methods.
- Classification performance benchmarking from recent deep learning studies.

**Research References:** A review of recent literature will include:

- Deep learning applications in materials science.
- Traditional image processing methods in metallography.
- Segmentation techniques for microstructure analysis.

**Novelty and Contribution:** Our system automates both segmentation and classification within a single workflow, addressing the current gap in industry tools like ImageJ. Additionally, this project uniquely targets **Quench and Partition (Q&P) steel**, a high-strength material category with minimal prior computational analysis.

## 7 Gaps and Opportunities

Existing industry tools and academic methods primarily handle segmentation, with no end-to-end automation.

**Identified Gaps:**

- Lack of automated classification in current systems.
- Minimal deep learning applied to Q&P steel microstructures.
- Fragmented workflows with no integrated segmentation–detection–classification pipeline.

**Novel Contributions:**

- **Material Focus:** Introducing automated analysis for Q&P steel, a largely unexplored category.
- **Technical Integration:** Unified deep learning pipeline from segmentation to classification.
- **Impact:** Enables consistent, reproducible, and scalable analysis for industrial use.

## 8 Deployment Strategy

**Architecture:** A cloud-hosted API-based inference service (FastAPI/Flask) will allow:

- Uploading of microstructure images.
- Automated inference with trained models.
- Visualization of segmentation and classification results.

**Advantages:**

- Seamless integration with laboratory workflows.
- Scalable and accessible remotely.
- Continuous improvement and version control for models.

Deployment strategies will be finalized in collaboration with steel manufacturing partners to ensure industrial readiness.

## 9 Expected Contributions & Impact

### Technical Impact

- Automated microstructure phase classification.
- Integrated segmentation–detection–classification pipeline.

### Societal Impact

- Empower non-metallurgists to make informed decisions using AI.
- Facilitate adoption of Industry 4.0 practices in the steel sector.

## 10 References


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## 11 Data Sourcing and Governance

A steel microstructure database was created through an extensive review of published literature. A total of 89 micrographs were compiled from publicly available, peer-reviewed sources. All images were obtained for academic research and benchmarking purposes, ensuring full compliance with open-access and fair-use guidelines.

### Primary Dataset Sources

The following published works were used for dataset compilation:


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**Total Images:** 89 micrographs from 27 publications were used as the foundation for the initial dataset.