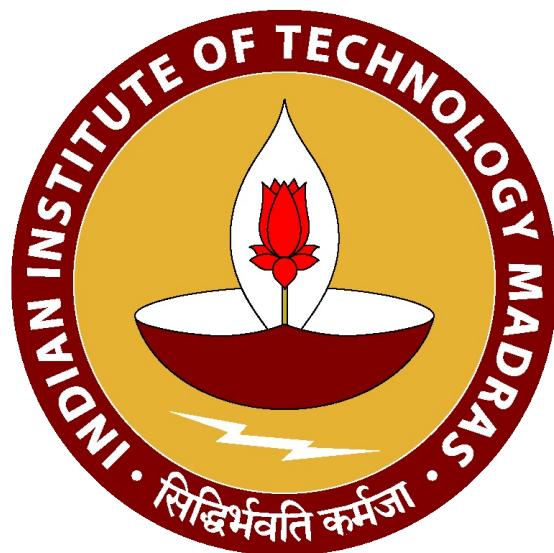


**DATA SCIENCE & AI LAB (BSCSS3001)**

**MILESTONE - 1**

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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.

## 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.

#### Other Approaches:

- Preprocessing techniques: segmentation and patch extraction
- Performance trade-offs through experimentation

#### Customization and Optimization:

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

**Deployment:** Collaboration with steel manufacturing units to implement and test the platform.

## 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).

## 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

Relevant literature and prior research will be surveyed to gain foundational understanding and avoid duplication. Important topics include:

- Microstructure image processing
- Steel phase classification
- Deep learning models in materials science

## 7 Gaps and Opportunities

Most existing datasets and solutions are generic or academic. A major gap exists in the automation of steel microstructures used in daily industrial operations. This work focuses on filling that practical gap, enabling real-world usability.

## 8 Expected Contributions & Impact

### Technical Impact

- Automated microstructure phase classification
- Minimal human intervention in interpretation

### Societal Impact

- Empower non-metallurgists to make informed decisions using AI
- Facilitates adoption of Industry 4.0 in steel sector

## 9 References

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