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Microstructure Recognition of Steel Using Machine Learning

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Abstract: It is tried and tested that optical and electronic microscopy images of steel material specimen could be categorized into phases on preset ferrite/pearlite, spheroidized, ferrite, pearlite, and martensite type microstructures with image processing and statistical analysis which include the machine learning techniques. Though several popular classifiers were get the reasonable class-labelling accuracy, the random forest was virtually the best choice in terms of overall performance and usability. The present categorizing classifier could assist in choosing the appropriate pattern recognition method from our library for various steel microstructures, which we have recently reported. That is, the combination of the categorizing and pattern recognizing methods provides a total solution for automatic classification of a wide range of steel microstructures.
In this work we present an innovative approach for metallurgical sample identification and error calculation based on imaging classification with classic machine learning algorithms.

Keywords: Metallography, Machine Learning, Microscopy, Metallurgy

I. INTRODUCTION

Steel is one of the most reasonable and more used classes of materials because of its mechanical properties while keeping costs low and it gives a huge variety of applications. The mechanical properties of steel are primarily determined by its microstructure shown in Fig., so that the performance of the material highly depends on the distribution, shape and size of phases in the microstructure. Thus, correct classification of these microstructures is crucial. The microstructure of steels is consists of various distinct phases such as austenite, bainite, martensite etc. based on a vast number of parameters such as base metal, alloying elements, rolling setup, cooling rate, heat treatment and further post-treatments such as tempering. Depending on how the steel is produced due to these parameters, the microstructure consists of different constituents such as ferrite, cementite, austenite, pearlite, bainite and martensite shown in Fig.

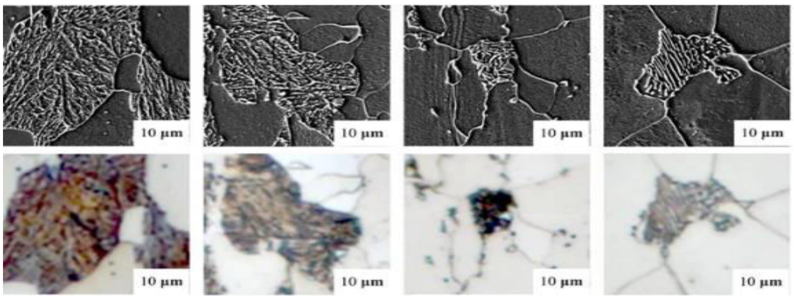

Fig. 1 Some examples of different microstructure classes

In columns from left to right: martensite, tempered martensite, bainite and pearlite phases or rather constituents as “objects” (second-phase) have been illustrated. Ferrite is the base phase in these images, as the background. The upper row images are taken by Scanning Electron Microscopy (SEM) and lower row are taken by Simple Optical Microscope called as Light Optical Microscopy (LOM).
To develop a System, which processes the microscopic image of the Steel & classify them into different phase/types as:

- Martensite
- Ferrite
- Ferrite-Pearlite
- Spheroidized

II. OBJECTIVE

- To develop a machine learning system for classification of different types of steel metal based upon their microscopic images.
- To use a image processing algorithm which provides the maximum accuracy and least cases for erroneous results.
- To detect the defects present in the microscopic structure such as pores, cavities, impurities and display the purity percentage of the given sample.

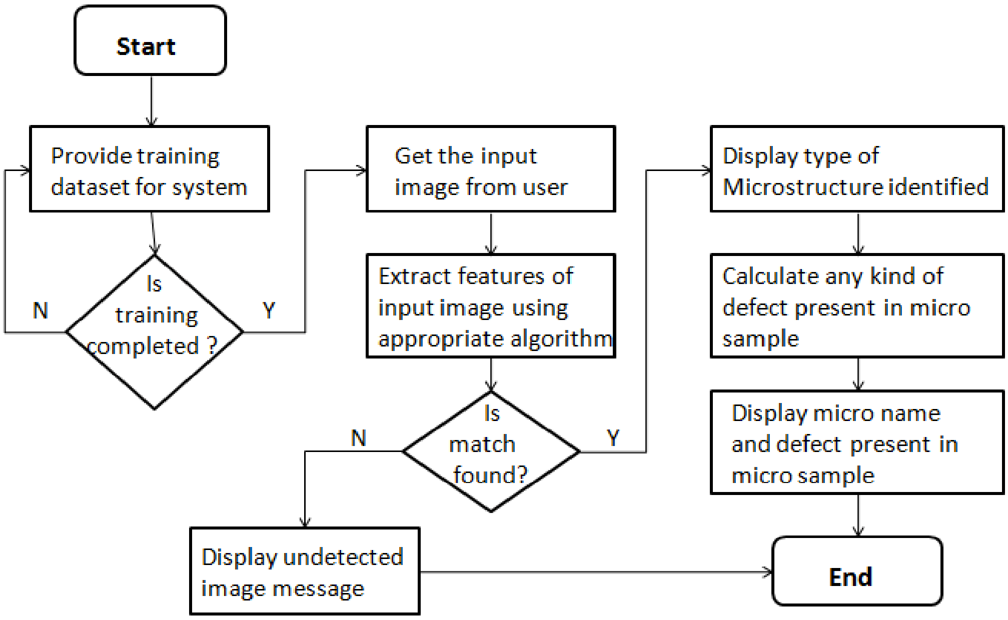

Fig. 2 Architectural Design

The inner structure of a steel material is called microstructure. It stores the genes of a steel material and determines its physical and chemical properties. While microstructural features are widely spread and well known, the microstructural classification is mostly done manually by human experts and manual efforts, which gives rise to erroneous results and uncertainties due to subjectivity. As the microstructure could be a combination of different phases or constituents with complex substructures its automatic classification is very challenging and only a few prior studies exist. Prior research is focused on designed and engineered features by experts and classified microstructures separately from the feature extraction step. Recently, Machine Learning methods have shown strong performance in vision applications by learning the features from data together with the classification step.

Eigen Value Algorithm:
1. Get training set of images.
2. Find mean of images.
3. Find difference between mean image and each of training images.
4. Find covariance matrix of the matrix obtained.
5. Find Eigen values and Eigen vectors of this covariance matrix
6. Find Eigen Images with larger Eigen values
7. Find out weight vector using this Eigen values
8. Give new test image
9. Find out weight vector for test image
10. Find Euclidian distance between weight vectors of test image and training images.
11. If this distance is less than threshold then test image is considered to be in database and hence authenticated. Otherwise not authenticated.

User provides the Images of the metals and system will conduct microscopic classification of the metals. System will do analysis based on the training dataset so the values of the training dataset is cross checked and if any error of defect found is informed to the system.

Here are 2 users, User use the system and admin update the dataset and maintain the dataset. User does the registration and login after that user prepare for the metal microscopic classification. User done this by sectioning the metal, mounting the metal, grinding the metal, polishing the metal. User provide the metal image for detection and system do the microscopic classification and check image against the training dataset for identifying metal and error calculation in metal.

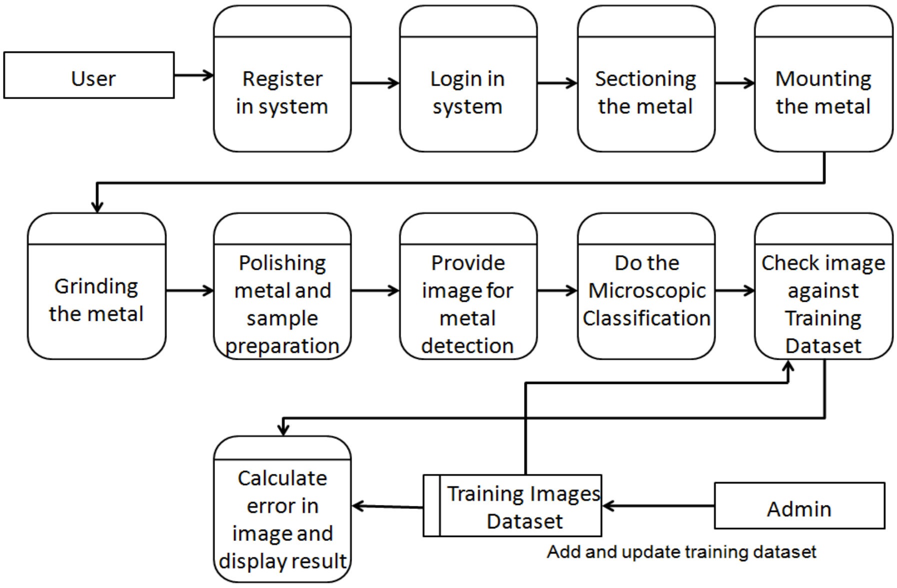

Fig. 3 System Flow Diagram

User does registration and login and then provide image for detection. Metal classification id done and image checked against the training dataset. System return metal name and defect percentage.

III. CONCLUSION

This work demonstrates the feasibility of an effective steel microstructural classification using Machine Learning methods without a need of separate segmentation and feature extraction. The present approach can, in principle, be transferred to similar image-based challenges in other complex microstructures at all scales. In the context of dual phase steels, a meaningful comparison of the manifold of microstructures subsumed under each industrial grade would be an exceedingly fruitful next step that now appears within reach. If successful, it would truly bring together the insights into the materials physics of deformation-induced damage, currently scattered across laboratories worldwide to enable more powerful knowledge-driven microstructure and process design for this important material class.

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