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Microstructure Recognition of Steel using Machine Learning

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Abstract: It is certain that optical and electronic microscopy images of steel-based specimen can 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 classifier could assist in choosing the appropriate pattern recognition method from various steel microstructures, which we have recently reported. This means that, 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 machine learning algorithm.

Keywords: Metallography, Machine Learning, Microscopy, Metallurgy.

I. INTRODUCTION

Steel is proved to be one of the most reasonable and more used types 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, 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. Based on the steel manufacturing process and due to these parameters, the microstructure consists of different constituents such as ferrite, cementite, intermediate phases [4], austenite, pearlite, bainite and martensite [3].
Metal alloys, or even pure metals, present different structure, since they can have specific grain boundaries, phase boundaries, inclusion distribution, and so forth. Thus, during microscope observation, material engineer has to focus on many details to get a better identification. However, observing material structure is hard even for the most trained engineer, since different materials have different characteristics and specific protocol. Learning the whole set of protocols and procedures for all materials, is not just almost impossible, but also useless since, protocols are reviewed frequently. Since Metallography studies relies on imaging observation and decision making by observers, this work presents an approach for metallography of commercially available materials by image classification with machine learning algorithms. Hence we are developing a automated machine learning assisted system which will detect the microscopic structure of steel and classify it. There are a lot of protocols to direct recognize material structure, for instance ASTM E112[1], which provides directions to determine average grain size for metals. However, observing material structure is hard even for the most trained engineer, since different materials have different characteristics and specific protocol.

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.
- To develop a System, which processes the microscopic images of the Steel and classify them into different phases/types as:
  - Martensite
  - Ferrite
  - Ferrite-Pearlite

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- Spheroidized
- Defect, if any.

III. EXISTING SYSTEM

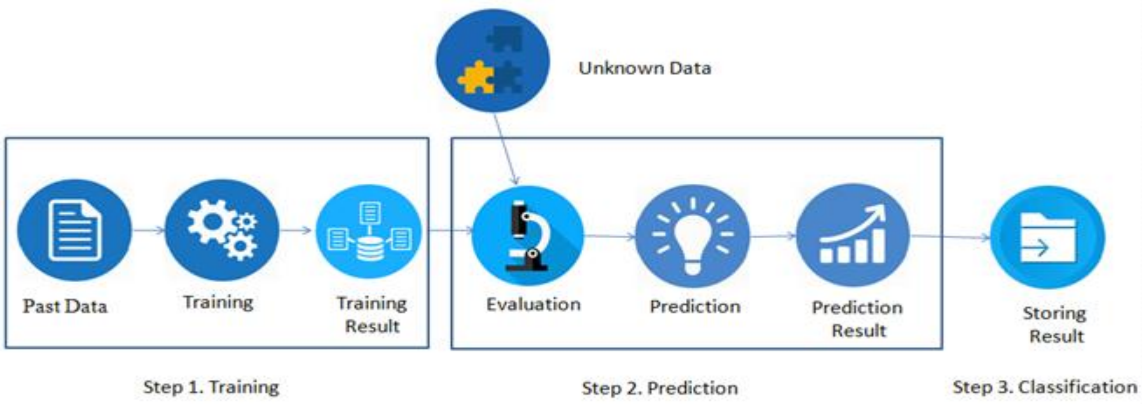

Fig. 1 Existing system

The internal structure of a metal is called microstructure. It stores the genesis of a metal and determines all its mechanical, metallurgical properties. The characterization of metal microstructure is widely used and well known, the microstructure classification is generally done manually by human experts, which gives rise to uncertainties due to subjectivity and expertise of individual. As the microstructure is a combination of different phases, constituents with complex and intermediate substructures, intermediate phases its automatic classification is very challenging and only a few prior studies exist. Prior works are mainly focused on designed and engineered features by experts and classified microstructures separately from the feature extraction step. Lately, Deep Learning methods have shown strong performance in vision applications by learning the features from data together with the classification step. In existing system, it proposes a Deep Learning method for microstructural classification in the examples of certain microstructural constituents of low carbon steel. This method uses pixel-wise segmentation via Fully Convolutional Neural Networks (FCNN) accompanied by a max-voting scheme. Existing system achieves 93.94% classification accuracy, drastically outperforming the state-of-the-art method of 48.89% accuracy. Beyond the strong performing capabilities of the method, this line of research offers a more robust and first of all objective way for the difficult task of steel quality appreciation.

IV. PROPOSED SYSTEM

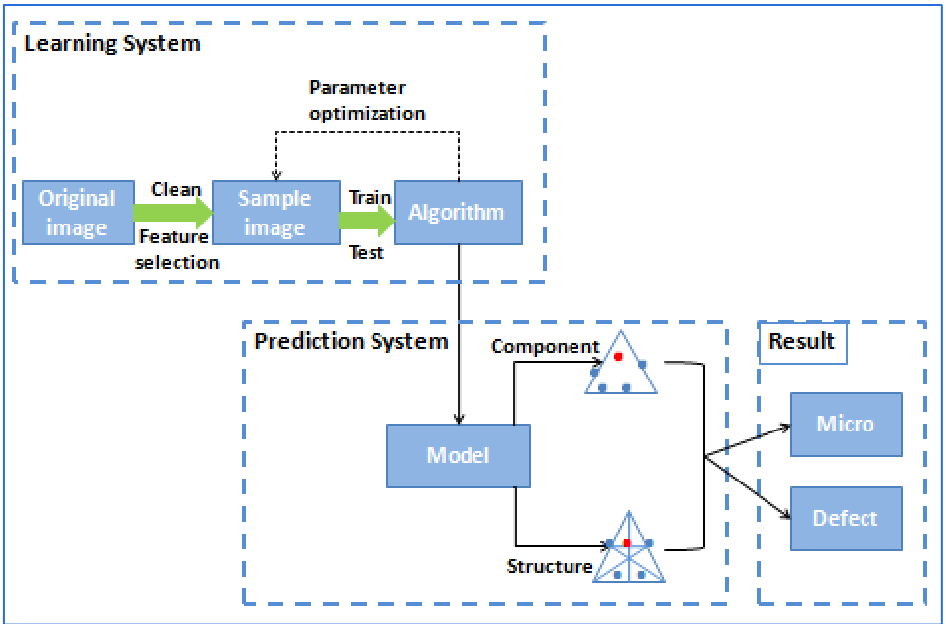

Fig. 2 System architecture

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1. Eigenvalue and Eigenvector:
To understand significance of eigenvalues and eigenvectors everywhere, one should first understand reason behind encounter of matrices and vectors everywhere.
In a various situations, the objects we study and the thing we can do with them link to vectors and linear transformations, which are represented as matrices.
So, in many interesting situations, important relations are expressed as, $y = Mx$
Where y and x are vectors and M is a matrix. This ranges from systems of linear equations you have to solve (which occur virtually everywhere in science and engineering) to more sophisticated engineering problems (finite element simulations). It also is the foundation for (a lot of) quantum mechanics. It is also used to describe the basic geometric transformations we can do with vector graphics and 3D graphics in computer games.
Currently, it is generally not straightforward to look at some matrix M and immediately decide what it is resultant when we multiply it with some vector x. In addition, in the study of iterative algorithms we should know about higher powers of the matrix M, i.e. $Mk=M \cdot M \cdot ... M$ k=M·M·...M, k k times. This is a bit awkward and costly to compute in a naive fashion. This observation is summarized by the theory of eigenvectors. An eigenvector of a matrix M is any vector x→ that only gets scaled (i.e. just multiplied by a number) when multiplied with M. Formally, $Mx = \lambda x$ so, if your matrix M describes a system of some sort, the eigenvectors are those vectors that, when they go through the system, are changed in a very easy way. If M, consider, describes geometric operations, then M could, in principle, stretch and rotate the vectors. But eigenvectors only get stretched, not rotated.
The eigenbasis also plays an important role. By selection of a different basis for vector space, we can alter the aspect of the matrix M in that basis. In other words, the i-th column of M tells you what the i-th basis vector multiplied with M would look like. If all our basis vectors are also eigenvectors, then it is clear that the matrix M is *diagonal*. Diagonal matrices are a welcome sight, because they are *really* easy to deal with: Matrix-vector and Matrix-matrix multiplication becomes very efficient, and computing the k-th power of a diagonal matrix is also trivial.

2. KAZE:
Multiscale image processing is a very important tool in computer vision applications. We can abstract an image by automatically detecting features of interest at different scale levels. For each of the detected features an invariant local description of the image can be obtained. These multiscale feature algorithms are a key component in modern computer vision frameworks, such as scene understanding [1], visual categorization [2] and large scale 3D Structure from Motion (SfM) [3]. The main idea of multiscale methods is quite simple: Create the scale space of an image by filtering the original image with an appropriate function over increasing time or scale. In the case of the Gaussian scale space, this is done by convolving the original image with a Gaussian kernel of increasing standard deviation. For larger kernel values we obtain simpler image representations. With a multiscale image representation, we can detect and describe image features at different scale levels or resolutions. Several authors [4, 5] have shown that under some general assumptions, the Gaussian kernel and its set of partial derivatives are possible smoothing kernels for scale space analysis.
However, it is important to note here that the Gaussian scale space is just one instance of linear diffusion, since other linear scale spaces are also possible [6]. Multiscale image processing is a very important tool in computer vision applications. We can abstract an image by automatically detecting features of interest at different scale levels. For each of the detected features an invariant local description of the image can be obtained. These multiscale feature algorithms are a key component in modern computer vision frameworks, such as scene understanding [1], visual categorization [2] and large scale 3D Structure from Motion (SfM) [3].
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Multiscale image processing is a very important tool in computer vision applications. One can extract an image by automatically detecting features of interest at different levels. Each of the detected features is associated with an invariant local description of the image. These multiscale feature algorithms are a key component in modern computer vision frameworks, such as scene understanding, visual categorization and large scale 3D Structure from Motion (SfM). The main idea of multiscale methods is quite simple: Create the scale space of an image by filtering the original image with an appropriate function over increasing time or scale. In the case of the Gaussian scale space, this is done by convolving the original image with a Gaussian kernel of increasing standard deviation. For larger kernel values we obtain simpler image representations. While representing a multiscale image, we can detect and describe image features at different scale levels or resolutions. Several authors have shown that under some general assumptions, the Gaussian kernel and its set of partial derivatives are possible smoothing kernels for scale space analysis. However, it is important to note here that the Gaussian scale space is just one instance of linear diffusion, since other linear scale spaces are also possible.

3. Algorithm:
Step 1: Read the training data (images).
Step 2: Apply KAZE Algorithm to extract feature of training image
Step 3: Store the feature of all training images in .pck file.
Step 4: Give an input to system, new image
Step 5: Apply KAZE algorithm to new image and extract the feature
Step 6: Now compare the training Image and new input image using EIGENVALUE algorithm
Step 7: Find the microstructure and defect of metal
Step 8: As result get the microstructure and defect of metal.

V. RESULT AND DISCUSSION

The system demonstrates the feasibility of an effective steel microstructural classification using Machine Learning methods without a need of separate segmentation and feature extraction. Following table demonstrates the sample results of microstructure recognition of steel:

Table 1: Field image classification result

Original	Identified	Defect	Defect %
Ferrite	Ferrite	Yes	8
F-Pearlite	Ferrite	Yes	15
Car	Micro not found	None	None
Martensite	Martensite	No	0
Spheroidized	Spheroidized	Yes	3

Above table indicates that system is capable of identification fixed set of microstructures under specific conditions. In case of improper surface preparation[2], system may not be able to identify the microstructure. System is able to distinguish between microstructural classes.

VI. 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[3], currently scattered across laboratories worldwide to enable more powerful knowledge-driven microstructure and process design for this important material class.

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