International Journal of Future Generation Communication and Networking
Vol.14, No. 1, (2021), pp. 4631 - 4637

Identification Defect in Steel Microstructure

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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 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, marten site etc. 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.

II. LITERATURE REVIEW

Table 1 Literature Review

AUTHOR NAME/YEAR	SYSTEM USED	TITLE	CONCLUSION

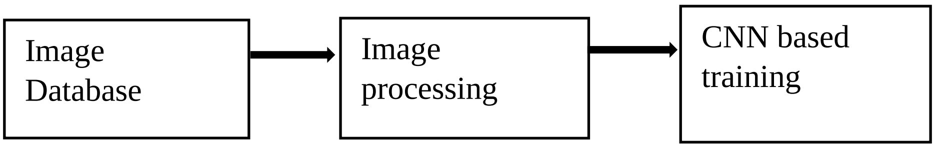
ISSN: 2233-7853 IJFGCN

Tasan, C. C. et al. ,2014	CNN,ARTIFICIAL NEURAL NETWORK	Advances in Microstructure-oriented Processing and Micromechanically Guided Design	This is focusing specifically on microstructure evolution during processing, experimental characterization of micromechanical behavior, the simulation of mechanical behavior.
Luiz A.O.Martins,Paulo Almeida ,2010	Iimageacquisition,Iimage preprocessing, Feature extraction, Feature selection, and Defect classifier.	Automatic Detection Of Surface Defects On Rolled Steel Using Computer Vision and Artificial Neural Networks	This work addresses the problem of automated visual inspection of surface defects on rolled steel, by using Computer Vision and Artificial Neural Networks.
QiwuLuo.XiaoxinFang ,Yichuang Sun , 2011	Convolutional Neural Architecture.	Automated Visual Defect Detection For Flat Steel Surface	This article attempts to present a focused but systematic review of the traditional and emerging automated computer-vision-based defect classification methods
Khedkar, P., Motagi, R., Mahajan, P. & Makwana, G.,2016	Image Processing.	A Review on Advance High Strength Steels.	Advanced High Strength Steel (AHSS),it gives car safety,fuel economy, and increases performance standard these applications only can achieve by its properties like high strength, Light weight, high stiffness

III . METHODOLOGY

Implementation of the system is done using software and hardware specifications-Python,Open CV, Intel core I3, RAM 4GB,HDD 80 GB

A.BLOCK DIAGRAM -



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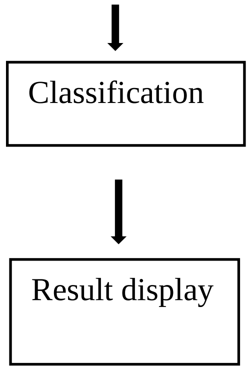

Fig. 1 Block Diagram

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.

B. Implementation –

In order to train and test CNNs and FCNNs, Cafe33 framework and a K40 m NVIDIA GPU was used. Cafe framework is a library in which most of the fundamental layers of neural networks have been implemented efficiently by C++ programming languages. Training object-based CNN. All of the cropped object images were resized to 224×224 px which is the fixed input size of VGG16. We also considered this size of input for training networks from scratch. We used a fixed learning rate of 0.001, a momentum of 0.9 and weight decay of 0.004 in stochastic gradient descent algorithm For training CIFARNet from scratch, the standard deviation of Gaussian noise for initial random weights for the first convolutional layer is 0.0001 and for the rest is 0.01. For fine tuning, a pre-trained VGG16 network was used. We initialized the last fully-connected layer with random Gaussian noise with standard deviation of 0.01. The learning rate of 0.0001 (chosen on validation set) was used to train CIFAR Net and VGG16 respectively. Using pre-trained extracted features (De CAFs). To classify De CAF features using SVMs, we trained a multi-class SVM with RBF kernel with extracted features from pre-trained VGG198 network. In VGG19 architecture, a fully-connected layer before the classification layer (size of 1×1×4096 px) was considered as the feature vector. Therefore, the feature vector is a 1×1×4096 dimension vector. Training MVFCNN. In training MVFCNN, we used learning rate of 10−10, 10−11 and 3 10 12 ∗ − to train FCN32s, FCN-16s, and FCN-8s, respectively. A bigger learning rate causes the training loss to explode. The momentum of 0.9 with weight decay of ∗ − 5 10 4 was considered.

Regarding input images, patches were cropped with 1000×1000 px size with a batch size of 1, due to memory issues. We first trained a FCN-32s model, and then added a skip layer (FCN-16s) and fine-tuned it. Afterwards, another skip layer (FCN-8s) was added to fine-tune the final model. Direct training of FCN-8s gave worse results. A pre-trained FCN-32 model was trained with an ImageNet

ISSN: 2233-7853 IJFGCN

dataset. The network was trained with 7000 iterations for ~4.5 days. The inference time for a 1000×1000 px input image was ~600ms. Class Balancing and Data Augmentation. In order to address the problem of class unbalance in the dataset, in the MVFCNN method cropping was carried out for different classes with different stride (step size) parameters in horizontal and vertical directions which in the end all of classes had the same number of patches i.e. the class with least number of images had smaller stride than the class with the largest number of training images.

Stride parameters are the parameters determining the steps using which patches are cropped. For example if the horizontal stride is 100 px, it means when a patch is cropped, the next patch will be cropped with a 100 px step. The same goes for the vertical direction. In our experiments, we chose different stride parameters corresponding to the number of images for each class. Stride parameters in horizontal and vertical directions were chosen the same. For an example, an image of 7000 × 8000 px includes 7 8 ∗ = 56 patches with 1000 × 1000 px size stitched together. By using a stride parameter of 100 px, one can produce 61 7 ∗ =1 4331 patches each with the size of 1000×1000 px. Resulting cropped patches were also rotated by 90°, 180° and 270° to augment the dataset. In this case, the number of the training images can increase three times.

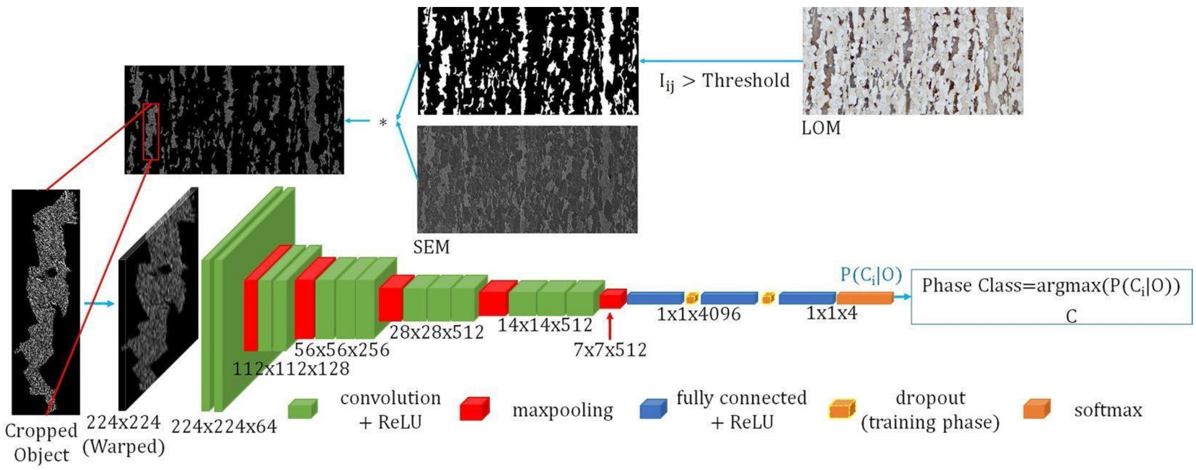

Fig. 2 Cropping and classification of images

E. System Flow Diagram –

ISSN: 2233-7853 IJFGCN

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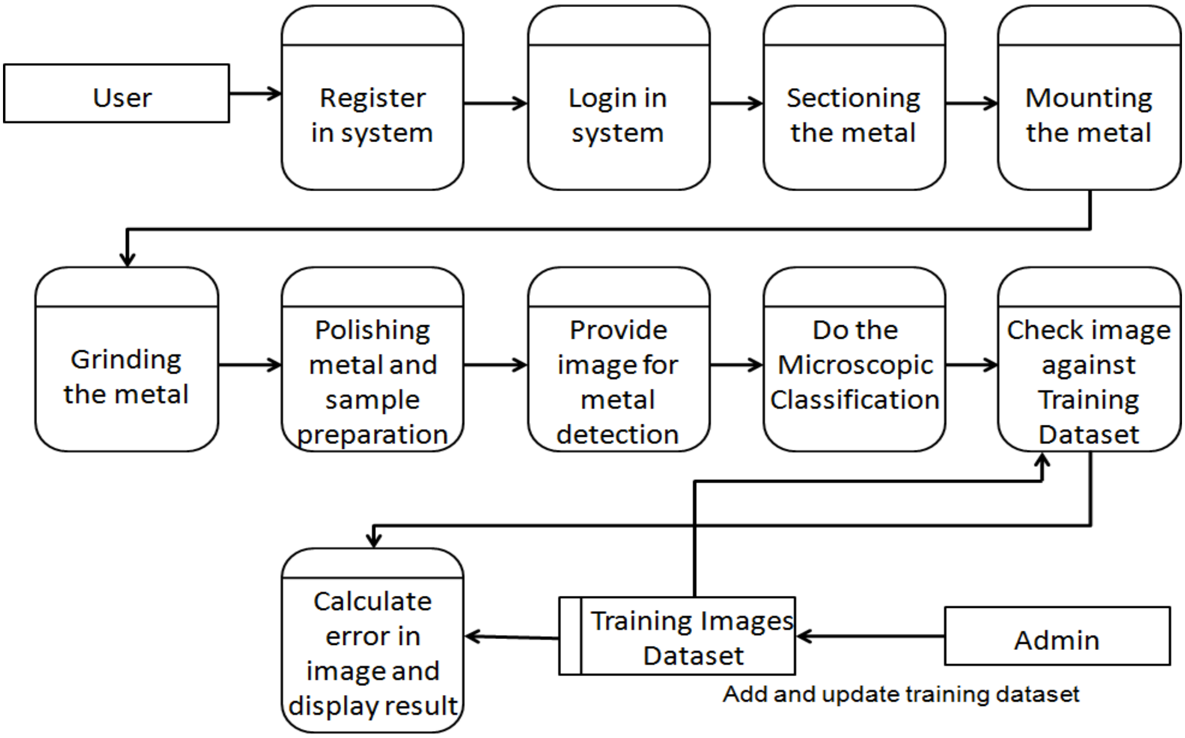

Fig. 3 System Flow Diagram

User provides the images of metals and system will do the microscopic classification of metal. 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 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 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.

IV. RESULTS

ISSN: 2233-7853 IJFGCN

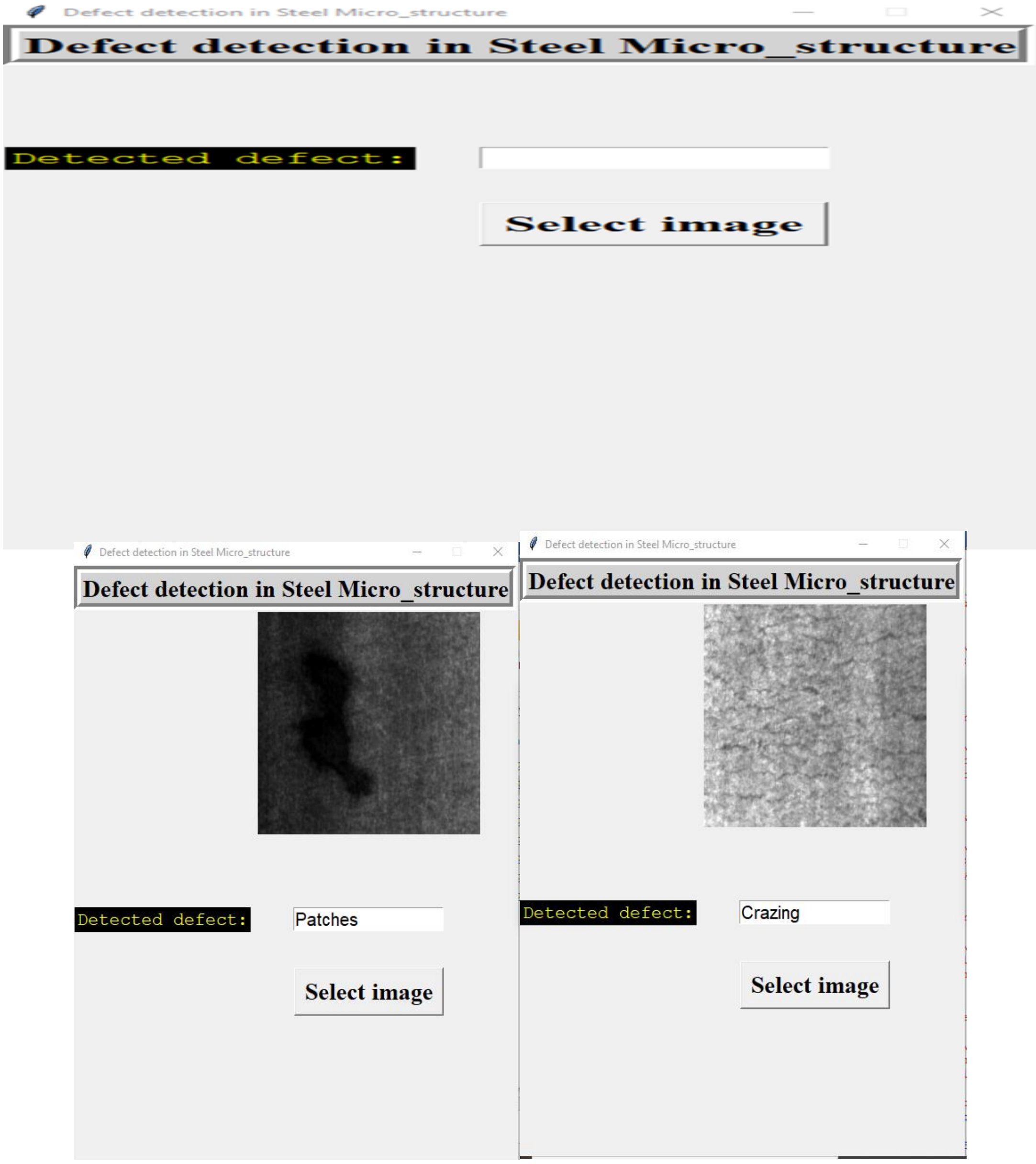

Fig. 4 Defect detection

V. CONCLUSION

This work demonstrates the feasibility of an effective steel microstructural classification using Deep Learning methods without a need of separate segmentation and feature extraction. We performed a pixel-wise micro- structural segmentation using a trained FCNN network followed by a max-voting scheme. The observed strong improvements in classification performance over the prior state of the art confirm our idea of leveraging the raw data input for training Deep Learning-based classification systems. Besides the high accuracy result, wearable to achieve a very fast prediction.

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ISSN: 2233-7853 IJFGCN