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Deep computer vision for the detection of tantalum and niobium fragments in high entropy alloys

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ABSTRACT

Deep Computer Vision is capable of doing object detection and image classification task. In image classification task, the particular system receives some input image and the system is aware of some predetermined set of categories or labels. There are some fixed set of category labels and the job of computer is to look at the picture and assign it a fixed category labels. Convolutional Neural Network (CNN) has gained wide popularity in the field of pattern recognition and machine learning. In our present work, we have constructed a Convolutional Neural Network (CNN) for the identification of the presence of tantalum and niobium fragments in a High Entropy Alloy (HEA). The results showed 100 % accuracy while testing the given dataset.

Keywords: High Entropy Alloy; Convolutional Neural Network; Machine Learning; Computer Vision

1. INTRODUCTION

Vision is the most important senses that human possess. In day to day life people depend on vision for example identifying objects, picking objects, navigation, recognizing complex human emotions and behaviours. Deep computer vision is able to solve extra ordinary complex tasks which were not able to be solved in the past. Facial detection and recognition and detection are an example of deep computer vision. Figure 1 shows the vision coming into a deep neural network in the form of images or pixels or videos and the output at the bottom is the depiction of a human face [1-4].

The next thing should be a worth answering to the question, how computer process an image or a video and how do they process pixels coming from those? The images are just numbers and also the pixels have some numerical values. So our image can be represented by a two dimensional matrix consisting of numbers. Let's understand this with an example shown in Figure 2 which shows that output variable takes a class label and can produce probability of belonging to a particular class.

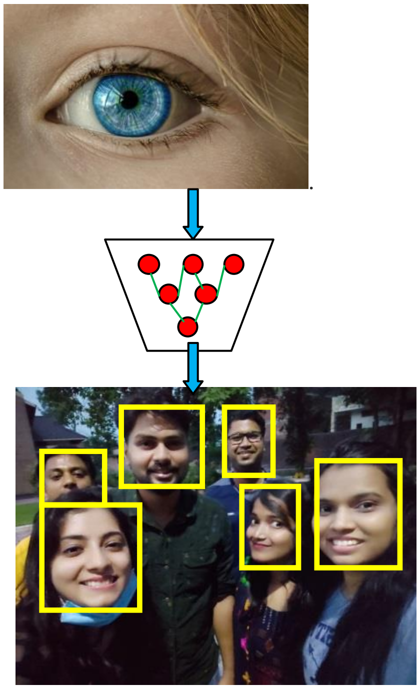

Fig.1. Illustration of the working of Deep Computer Vision

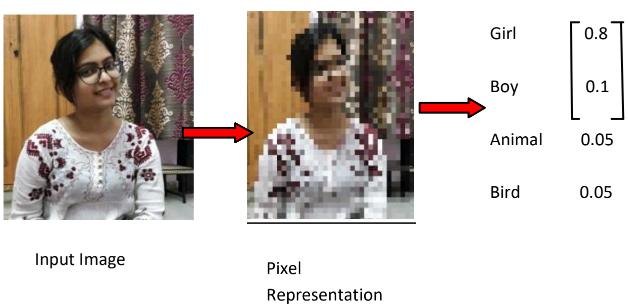

Fig.2. Image Classification

In order to properly classify the image our pipeline must correctly tell about what is the unique about the particular picture. Convolutional Neural Network (CNN) finds application in the manufacturing and material science domain. Lee et al. [5] proposed a CNN model for fault diagnosis and classification in the manufacturing process of semi-conductors. Weimer et al. [6] designed deep convolutional neural network architectures for automated feature extraction in industrial application. Scime et al. [7] used CNN model for the detection of in situ processing defects in laser powder bed fusion additive manufacturing. The results showed that the CNN architecture improved the classification accuracy and overall flexibility of the designed system.

In our present work we have designed the CNN architecture for detecting the trace of tantalum and niobium in the microstructure of high entropy alloy (HEA). In 1995, Yeh et al. [8] firstly discovered the high entropy alloys and in 2004 Cantor et al.[9] coined high entropy alloy as a multi-component system. HEAs are generally advanced alloys and novel alloys which are consist of 5–35 at.% where all the elements behave as principal elements. In comparison to their conventional alloys, they possess superior properties like high wear, corrosion resistance, high thermal stability and high strength. Zhang et al. [10-11] listed down the various parameters for the parameters for fabrication of HEAs which are shown in the below equations:

$$\Delta S_{mix} = -R \sum_{i=1}^{N} C_i lnC_i \qquad (1)$$

$$\Delta H_{mix} = -4 \sum_{i=1, i \neq j}^{n} C_i C_j \Delta H_{mix}^{AB} \qquad (2)$$

$$\Omega = |T\Delta S_{mix}/\Delta H_{mix}| \quad (3)$$

$$r = \sum_{i=1}^{n} C_i R_i \quad (4)$$

$$\delta^2 = \sum_{i=1}^{n} C_i \left[1 - \frac{r_i}{\sum_{i=1}^{n} C_i r_i}\right]^2 \quad (5)$$

HEAs find application in various industries like aerospace, submarines, automobiles, and nuclear power plant industries [12-14]. HEAs are also used as a filler material for micro-joining process [15]. Geanta et al. [16] carried out the testing and characterization of HEAs from AlCrFeCoNi System for Military Applications. It was observed that at the melt state, the microstructure of HEAs have frozen appearance as shown in the Figure 3.

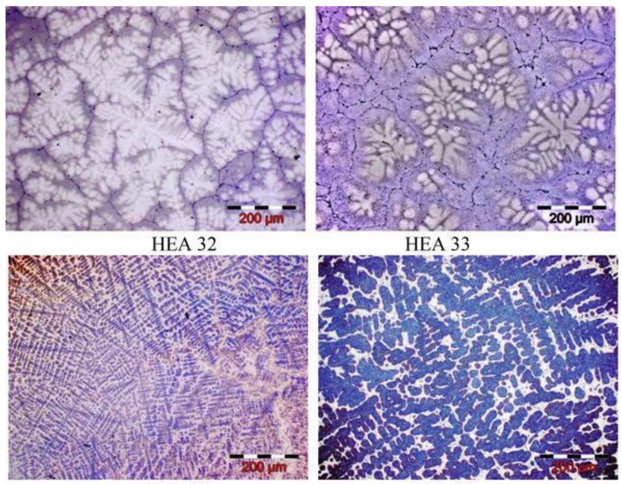

Fig.3. Appearance of frozen microstructure

2. MATERIALS AND METHODS

Geanta et al. [17] fabricated bio compatible FeTaNbTiZrMo HEAs. In our study we have used microstructure data from their research. The obtained microstructure is shown in the Figure 4 and 5.

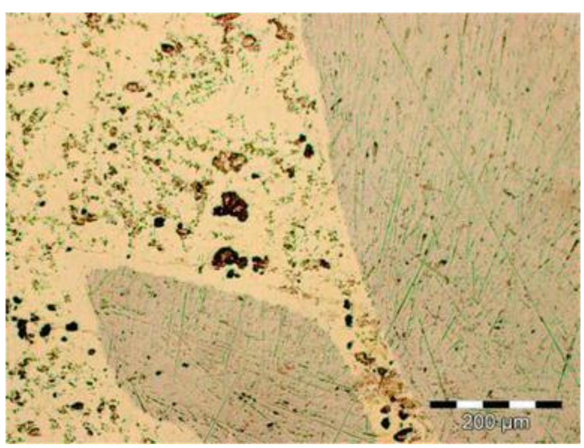

Fig.4. Undissolved Ta and Nb fragments in the FeTaNbTiZrMo alloy [17].

Data collection is the process of gathering and measuring information from countless different sources. In order to use the data we collect to develop practical artificial intelligence (AI) and machine learning solutions, it must be collected and stored in a way that makes sense for the business problem at hand. Since, we had shortage of images, so we first did Image Augmentation.

Image data augmentation is used to expand the training dataset in order to improve the performance and ability of the model to generalize. Image data augmentation is supported in the Keras deep learning library via the Image Data Generator class. So, input data consists of two images. As we know that we can't train our deep neural network with only two images because that would result in over-fitting of model. Over-fitting a model basically means that our model will give best score on training data but not on testing or validation data or the data that it has not seen before. So such an over-fitted model will be of no use to train our model effectively, we will make more images with the help of these input images. We will achieve this by Image Augmentation.

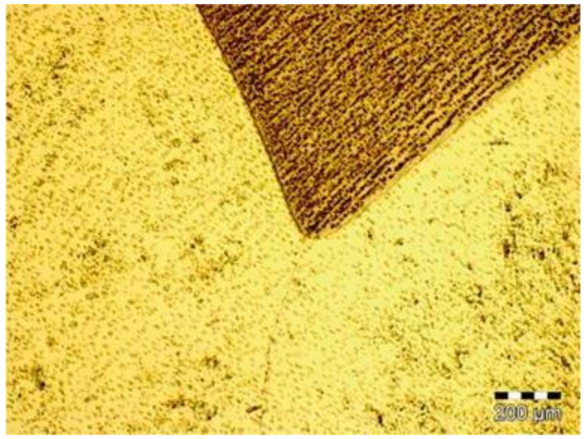

Fig.5.Undissolved tantalum fragment in the FeTaNbTiZrMo alloy.

We can use Image Data Generator class to achieve this. First we will make object of this class. After that we will provide some parameters that are basically the fluctuations or feature that we want to provide the image like luminous intensity, width shift range, height shift range etc. and we can iterate over the directory where the images are kept in , by providing the path in the function. In this way, we can generate numerous data. In this project, we have generated approximately 3000 images for each image. We created two datasets for the training and testing purpose. Python programming was used for development of the code required for constructing the Convolutional Neural Network architecture. A Convolutional Neural Network (ConvNet/CNN) is a Deep Learning algorithm which can take in an input image, assign importance (learnable weights and biases) to various aspects/objects in the image and be able to differentiate one from the other. The pre-processing required in a ConvNet is much lower as compared to other classification algorithms. While in primitive methods filters are hand-engineered, with enough training, ConvNets have the ability to learn these filters/characteristics.

3. RESULTS AND DISCUSSIONS

The augmented image of the microstructure is shown in the Figure 6.

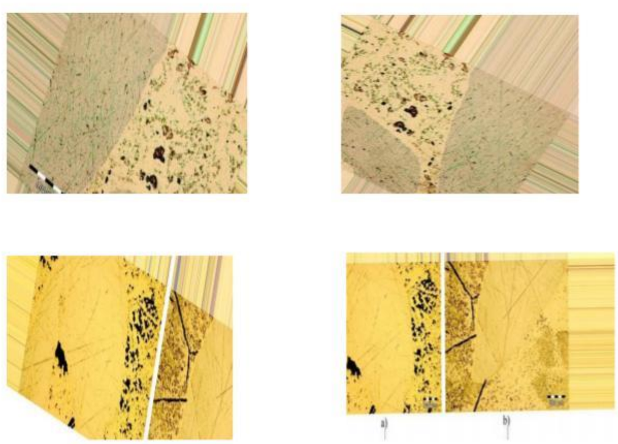

Fig.6. Augmented images of the microstructure

Model is compiled with loss-Binary cross entropy and metrics-accuracy and optimizer is adam. To prevent model from Over-fitting, early stopping and model checkpoints are used so as to prevent model from over training. Early Stopping is basically a process in which model is stopped training when it doesn't undergo any improvement. This parameter is provided in early stopping while making its object. This parameter is known as Patience. Metrics and mode are also provided as parameter to test model on the basis of that. Suppose metrics is value accuracy and mode is maximum, so when the model will not show any improvement (increment in value accuracy), it will wait till the patience parameter and after that it will stop. The results were quite satisfactory when we trained our model against unlabelled images.

As we can see in this Figure 7, during prediction, almost every actual value is matched with predicted value so our model has been trained effectively.

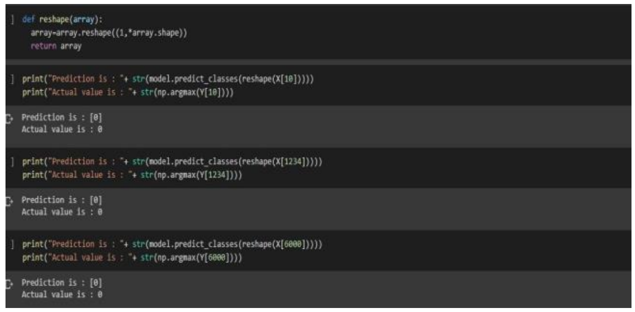

Fig.7. Predicted value matches Actual Value

The graphs in Figure 8 show the changes in metrics while training. As we can see, model loss is getting lower as the epoch increases and accuracy is increasing as the epoch increases.

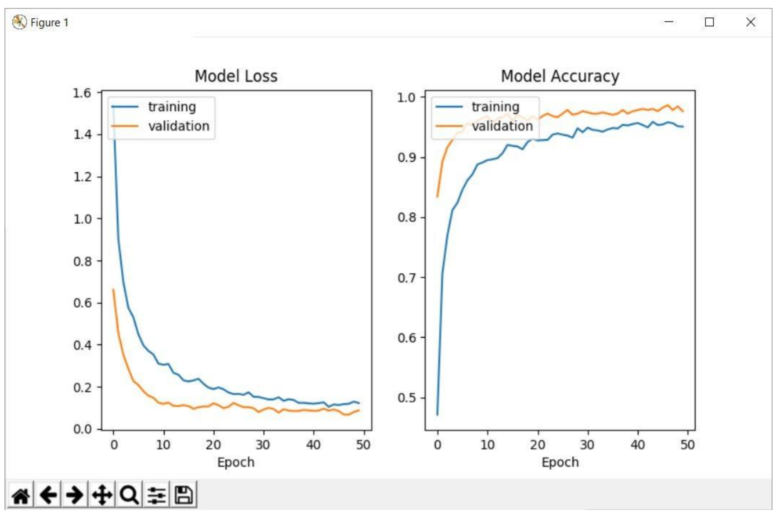

Fig.8. Graph showing model loss and model accuracy

4. CONCLUSION

It can be concluded that the current research is basically about image processing and classification, in which we first collected data due to shortage of data, we did data augmentation to train our deep learning model, after that we implemented our model architecture and compilation is done. After training, the results are shown. It is observed that the predicted value matches with the actual value resulting 100% accuracy for the image classification of the fragments present in HEAs.

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Conflict of Interest:

The authors declare that there are no conflicts of interests.

Data and materials availability

All data associated with this study are present in the paper.

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