Non-negative matrix factorization for classifying the defects on steel surface using Convolutional Neural Network

MSc Research Project
Data Analytics

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Project Submission Sheet
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Student Name:	Pranay Shyamkuwar
Student ID:	X18135749
Programme:	Data Analytics
Year:	2019
Module:	MSc Research Project
Supervisor:	Noel Cosgrave
Submission Due Date:	12/12/2019
Project Title:	Non-negative matrix factorization for classifying the defects on steel surface using Convolutional Neural Network
Word Count:	7820
Page Count:	23

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Non-negative matrix factorization for classifying the defects on steel surface using Convolutional Neural Network

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Abstract

Classification of defects on steel surface in a steel industry can significantly improve the production which can increase in profit. This has become a concern for all the companies worldwide increasing profit and reducing the production error. For a certain period of time machine-based inspection of the defects on steel surface has widely received attention. Due to the limitation of a human eye for manually recognizing the flaw is a very slow process. This research mainly focuses on classifying six different types of defects usually occurred during production of steel slab with the help of machine learning algorithm. This study focuses on using Deep CNN with Gaussian blur and Non-negative matrix factorization. First, we implemented by applying Gaussian blur on images with kernel size of (3x3 & 5x5) with Non-negative matrix factorization and 44.4% of accuracy is achieved when applying gaussian blur for kernel size of 3x3. However, accuracy is reached to 45.6% for kernel size of 5x5. Whereas for second experiment NMF is applied excluding gaussian blur and accuracy is reached to 93.1%.

Keywords: Gaussian Blur, Deep CNN, Non-negative matrix factorization.

1 Introduction

Steel defects, but what is a defect on a steel? Variation in the end result of a product is called as defect Patel and Jokhakar (2016). It can be a scratch, crack holes, shrinkage etc. All these defects can be seen during the manufacturing process. During the production this kind of flaw affects the grade of steel which leads to wear resistance, fatigue strength and corrosion in steel this can degrade the strength of the steel. And disturb the following batch of the product during manufacturing process. This defect can occur during the production of steel, patches appeared on steel surfaces due to sand embedded casting. The rolled in scale (defect) can be seen on the exterior of steel due to the rolling of mill scale into the metal and many more defects can be seen. Identifying the blemishing in steel during the production is highly important for any steel industrial company. By using the traditional approach of classifying the defect on a steel is a slow process, time consuming and an intense labour work is required and needed an expert for correctly describe fault. But during the making of the steel at high speed and pinpoint the surface defect gets difficult for a human eye for real time identification. There are six types of regular defects which is more important to classify, are scratches (Sc), rolled in scale (RS), pitted surface (PS), inclusion (In), patches (Pa) and crazing (Cr) Fu et al. (2019).

1.1 Motivation

In the World, all the manufacturing companies of the steel want to produce their product a defect free and high-class grade of steel. The steel can be used in transport, home appliance, construction etc. Though producing of steel is a very tangled process. The most important thing in an industry during production of steel is to identify the surface defect in a steel slab. For the increase in business the industries are focusing on the imperfection of the final product Patel and Jokhakar (2016). If the defect on the surface of steel is not correctly recognized which can later degrade the performance of the steel and leads to the safety issues where the defective steel is used in different materials. Despite that identification of a defect during the real time is a challenging task due to high speed production line Li, Geng and Yin (2018). As manually recognition of flaw in steel is a very slow process. So, during the last few years machine-based inspection of defect widely received attention of the people in industry.Aghdam et al. (2012) conducted the research on the rail surface data set for the recognition of the defect. This can be weld, light squat, joint, sever squat, medium squat and normal. Applied a deep CNN for the classification of the defects, both the activation function (ReLU and Tanh) has been applied. For finding which one is better. If all the defects are correctly classified with maximum accuracy, the rail tracks will be removed or repaired. And will be saved from the accident in future. Classification of the defects like patches, scratches, inclusion and many more in a steel strip will benefit the industrial company's business and increase profits. If the flaw is found during the production can be repaired, if not found and same defected piece is sent to the customer will leads to decline in earnings of the company. Moreover, the same faulted piece of steel is used in the household appliances, producing industrial goods, constructions, in renewable energy sources etc. will reduce the shelf life of the product. Manually classifying the defects on steel is tedious process and expert people in this field is limited. The aim of this research is to correctly classifies the defects on surface of steel by using the deep CNN. This study will conduct the research on images downloaded from the NEU surface defect database. Different studies conducted in the field of surface defects as discussed in literature review refer to section 2. This study will include NMF (non-negative matrix factorization) as a dimensionality reduction technique with Deep CNN. Next we brifely discussed, at what certain extent Gaussian blur and Non-negative matrix factorization for classifying the defects on steel surface will significantly improve the performance of Deep CNN. And to find out if the Gaussian blur with various levels along with NMF will effectively classifies the defects on steel surface. Or can NMF is alone efficient for classifying the defects on steel surface.

1.2 Plan of the paper

The plan of the paper is organized as section 2 related work done for this research, section 3 & 4 Methodology and Implementation of this research, section 5 Evaluation of the results and Section 6 Conclusion.

2 Related Work

The basic idea of critically reviewing the literature Review is to acquire knowledge from the previous research, of the related subject matter that will help the current research findings. As this research mainly focuses on the classification which is improvised by reading the past research.

The research conducted by the Fu et al. (2019) developed a model of pre-trained SqueezeNet for the classification of flaws rapidly on the surface of the steel using the CNN (Convolutional Neural Network). For precisely categorising the multiple defects of various scale on the exterior of the steel, i.e. the MRF (multi receptive field) is used to creates 'scale-dependent' higher-level features. Two different methods are proposed by the author to increase the defect identification precision of the CNN model. First method- fine tuning is done for well describing the flaw on the steel surface in the pretrained model on the low-level features. Second method- Scale invariance is enhanced for classifying the defect on the surface of the steel of high-level features. CNN network model is created that consists of the 10 layers. In addition, in order to improve the texture related flaw 'low level feature for fine-tuning and for shallower layers higher learning rates' are set. And then MRF is applied for correctly categorised the steel defects by enhancing the high-level features. For improving the efficiency correctly categorizing the steel defect, the model is pre-trained on the Image dataset of 1,300,000. Guizhong used the NEU surface defect dataset which consist of the 1800 images (grayscale) and contains 6 different categories containing 300 images for each category and checks the model performance is checked against the camera motion blur, sensor noise, non-uniform illumination. MRF is added for measuring the performance of the SqueezeNet model. proposed model performs well against the other models.

On the other case study done by Li, Geng and Yin (2018) multi scale features of the defected region on the steel surface are extracted by creating convolutional network and enhance the efficiency of YOLO (You Only Looked Ones) by removing the pooling layers and making it convolutional network. The surface defect data is been collected from the cold-rolled steel surface during production and identifies the 6 kind of fault on the surface is spotted by the author. The recommended YOLO network, to correctly find the defect in an image and improve the speed of the model. For this the image features are extracted by the convolutional layer and to label the defect of the object classes SoftMax classifier is used, for finding the position of this object bounding box is used.The convolutional layers in the network are used for extracting the defect features and image is divided into S S grids by the YOLO network. The total of 27 convolutional layers are created where the 25 layers are used for feature extraction of the image of blemish surface on the steel and the last two layers will anticipate the faulty region. Collected Image dataset was cut into 300 x 300 then send to the network. The sum-squared error is applied in the loss function and the network make uses of the batch normalization for better performance. The defect feature is extracted from the whole image and on the defected Image sharpness and contrast argumentation is done before training the network and reduces overfitting. At last for final layer linear activation function is used. The proposed model achieves the 99% of detection rate.

For distinguish the defect on the steel surface the author Aghdam et al. (2012) uses neural networks, decision tree and SVM (Support Vector Machine) for classification. Decision tree is used because of the feature selection and complexity reduction. Two different feature extraction technique is used based on the texture analysis. First technique is Local Binary Pattern (LBP) is a texture analysis process used for categorization of images which is presented by Ojala et al. (1996) and the LBP is a well-known methodology of grayscale texture classifier. Second, for New LBP operator 7 x 7 method is used furthermore U (uniformity criterion) specified as the number from 1 to 0 and vice versa. PCA (Principal Component Analysis) is used for preventing the hindrance caused due to the use of decision tree which affect the execution speed during classification, because of the large dataset. For reducing the variance related with the decision tree Bootstrap Aggregating is used. For the categorizing of two class problem Decision tree is used and for multi class classification multiclass SVM is applied. 2400 images were used for evaluating the accuracy of the model contains 700 defected images. The ration of 60 and 40 percent is used for training and test set. Features is extracted from the 100 x 100-pixel image with the help of PCA applies on feature vector. Decision tree is significantly faster for two class classification after applying the Bootstrap Aggregating (Bagging) with 97.18%, compared two other algorithm and for multiclass classification SVM is preferred with accuracy of 94.79%.

A new method CAE-SGAN is applied by the Di et al. (2019) which means CAE (Convolution Autoencoder) and SGAN (Semi supervised Generative Adversarial Network). Autoencoder is a part of neural network used for feature encoding of the unsupervised learning. When we compare autoencoder as feature extractor with various deep learning methods performs well. The structure of the auto encoder consists of two parts encoder and decode. In encoder the input data is reformed into lower-dimensional and at the decoder transformed input data is reproduced to its original form. For feature extraction CAE uses the convolutional layers, which takes the input image of size 224 x 224 processed with 8 convolutional layers and 4 max pooling layers. Features will be lost when convolution and max pool layer is increased. To avoid the detailed feature loss from an image, passthrough layer is introduced. Furthermore, the output of the encoder is feed into the decoder and generates the original image by using the 9 convolution and up-sampling layer works opposite of the max pool layer. At the end reconstruction error is calculated. SGAN consist of two network generator and discriminator. Discriminator is a CNN that categorises the image as real or fake fed into the system. New data is generated by the generator. The training operation is split into two parts. Firstly, the data is collected from the production line of steel i.e. unlabelled feed into the CAE for extracting the features of steel defect. Secondly 'to build the discriminator the CAE is reserved as feature extractor and fed into the soft max layer'. Various data augmentation methods are implemented such as mean filtering, gaussian blur and random drop out. Author has performed steel defects classification on hot, cold rolled strips and hot rolled plates and compare the model with different classification models. 21,000 unlabelled images are used to train the CAE and it can be found that the CAE-SGAN outperforms the other models. Classification rate for the hot rolled strips is remarkably enhanced by 16%. A small number of images are used for detection and classification of the defects on the steel surface by Batsuuri et al. (2012). For training the SVM (classifier) model multiple features are generated from few samples of images which are applied to the model. Suvdaa uses the technique of feature detection called SIFT for both detection of defect and feature description. Feature vectors is used for training the SVM and where SIFT can produce many feature vectors from an image. One of the methods used is one-versus-all (binary classifier) whereas, one class is trained as positive label and another class is trained as negative label for all classes. During the testing phase the class labelled is decided by selecting the 'binary classifier' with highest output. Voting strategy is used for making the final decision of sorting the defect into different categories. The 70% of the sampled data is used for training and the remaining 30% of the data is used for testing. During the feature extraction and detection of dark field black line type of scars. For the first input image 31 features are accurately classified out of 42. Moreover, during the second image 28 out of 31 features are classified precisely and so on. The performance of the SVM remarkably increased by using the voting strategy.

A study done by Faghih-Roohi et al. (2016) on detection of defects on rail surface by using DCNN (Deep Convolutional Neural Network). For training of the dataset mini batch gradient descent method is chosen. A total of 22408 images of different groups are collected and labelled manually. Small, medium, Large DCNN is created by combining of multiple parameters such as feature maps, no of layers and fully connected layers. Parameters that has been picked based on the maximum classification accuracy. The sample is divided into 90% for training and 10% for testing of each classes. During building of the model consists of 3 convolutional, max-pooling layer, fully connected layer. Sampled image is of size 100 x 50 pixels of gray scale with 2 colour channels. Normalized image is feed into the first layer of the network and filtered it with the size of 9x5 pixels. Pooled feature maps is applied to the second layer. Two activation function is used namely ReLU and Tanh. Fully connected layer carried out the high-level reasoning in the CNN. The 120 and 30 nodes have been used in the fully connected layers. The CNN is trained over 40 epochs. To classify the defects into three classes the network is trained on both the ReLU and Tanh function. Weld and normal samples come under first class. Second class represent the small defects, squats and third contains the rail joints. By applying the ReLU activation function can increase the performance of the network and providing improved results. Computational time for both the ReLU and Tanh are the same. Three DCNN (small, medium, large) out of this Large DCNN outperforms the other two networks with 92% precision.

On the other case study done by Ren et al. (2018) where to increase the speed of network the author consider us-ing the depth wise separable convolutional layers instead of feature extraction in faster CNN. Miss de-tection is also decreased by using this network. For extracting the feature of the sample images 13 convolutional layers is used. Regional proposal is produced by two layers RPN slide over by the output of the conv feature maps. 3x3 RPN consist of first layer. Two sibling 1x1 conv layer makes second lay-er. Finally, Region of interest (RoI) takes as an input of regional proposal and the last feature maps and feed into the fast R-CNN. Faster R-CNN cannot achieve a real time detection. To overcome this Slight-er Faster R-CNN is used by replacing the feature extraction by depthwise separable convolution. Which is 4 times faster compared to original network. For increasing the speed of network, the batchnorm and ReLU is used behind each layer. The collected data consist of 6 classes of 800 sample images of total 4655. The dataset is augmented by applying various methods like sharpness and contrast aug-mentation. The model is trained using stochastic gradient descent. After training the model with 98.32% accuracy is achieved. Based on the visual mechanism Guo et al. (2017) detect the defects on the surface of steel. Low level features in a bottom up approach are extracted from an image such as intensity, colour, orientations. Later feature maps are created followed by sub-saliency maps. Colour image is pro-cessed by applying linear filtering, gaussian filter, gabor filter afterwards line interpolation method is carried out for creating the gaussian pyramid. Saliency maps, feature maps are obtained by calculating the cross-scale reduction and cross-scale addition. By applying this method, we can get better improvement in the result.

Zhou et al. (2017) uses the CNN model with 7 layers and gray scale image is entered as input to CNN. The dataset consists of the 6 different categories of steel defects with 1800 gray scale images of 200 x 200 pixels. Data augmentation technique is applied like rescaling the image to 40x40 pixels, rotating an image by counter clockwise by 90, 180, 270, flipping to prevent overfitting. From the original data set of images 14400 images were created during data augmentation process and data was normalized. During the training phase the model is trained with different image size, epochs, batch size and different acti-vation function. Mini batch stochastic gradient descent is applied to the training dataset and 99% accuracy is achieved. Ze-song (2017) uses the BP (Back Propagation) neural network for identifying the defects on steel plate but in-stead of using the traditional approach of collecting data by CCD camera. The author uses another method of magnetic flux leakage detection. Further the image is generated from the data with the help of image conversion technology. To represent the magnetic flux leakage data a one-dimensional curve is the best way from which by looking at the ups and downs curve in an image shows the leakage of the data. This leakage data is spotted by several sensors. Three steps of value correction are performed on leakage flux data. In first step median value is taken from all the sensors of magnetic flux leakage data. Step two mean value is gained from step 1. At last processed data is achieved for edge detection and feature extraction, before that image is converted to gray scale and evaluate the image for other in-formation to look for defect. If area is darker and size is large, greater the chance of defects and more severe. For edge detection wavelet multi-scale technique is used. Features of edge are extracted based on short, long axis and circumference. At last back propagation neural network is applied with 5 inputs and 2 hidden layer and 3 neurons at the output layer. Model is evaluated based on the absolute error and relative error and by considering the error rate model can precisely identify the defects of size and depth.

The research done by Chen et al. (2018) on edge detection of defects on laminated wood surface with the help of canny edge detection technique. Different type of edge defects such as cracks, joints and slipknot these flaws in a wood outlined by a method called canny operator. Moreover, a feature extraction method named hough transform is applied and for training the network ANN (Artificial Neural Net-work) is implemented and achieved good results to classify the cracks, slipknot and joint. On the basic of the machine vision technology Chen and Deng (2018) locate a defect on the stainless-steel spoon with efficiency. The system consists of the different module for instance image algorithm, image pre-processing etc. AFT_TL7250R model is selected for identification. Before applying the sample to the model image pre-processing need to be done for removing the noise before apply segmentation. The original image is converted to a gray scale so that the defect is visible and later mean filter is applied. Dynamic threshold segmentation technique is applied followed by the mean filter method for tackling the noise in image. During the screening process of defected area on stainless-steel the flaw can be recognized after segmentation. During the categorization imperfection can round or a scratch. For pointing out defect a sample of 50 stainless-steel spoon images were used and with 97% of precision, scratch and point defect were identified making it faster with 0.432s.

Kim et al. (2019) applied few shot learning method with the Siamese neural network using the CNN for training few Images to categories the defects on the steel surface with the help of few images. Two images are inserted into Siamese neural network to find out whether the entered images belong to the similar class or not. Instead of using the binary cross entropy for training the network similarity function is used. For finding if the images are same or not the distance is calculated between the features of the two images called contrastive loss. The efficiency of the model can be improved by adjusting the reference value, when features has similar distribution. Proposed Siamese CNN model, each convolutional layer has a 3x3 filter size, max-pooling layer is inserted after every two conv layers. feature vector of 512 generated at the end of the network for a pair of images. During the training of the neural net 5 images from 8 different classes were picked up randomly and one class is used for the testing purpose. By applying the few shot learning method 86% of accuracy is achieve with Siamese neural network to classify the defects on the steel surface images. Khan et al. (2017) analysis the grayscale and RGB histogram for finding the defect on hot and cold roll coil on color images. The image is converted for grayscale histogram and waveform of the pixel quantity is acquired. For spotting the defect in coil sheet, 151 - 157 considered the ideal range for grayscale images to lie in between. RGB histogram creation is complicated as compared to grayscale histogram. Whereas we can get more information from a color image. In RGB histogram for every 256 scales we count the number of pixels. The comparison of both the histogram has been done and found that grayscale histogram is easier as compare to RGB histogram. Sample of 12 1000 x 1000 pixels is taken for analysis of cold roll sheet and to find out the scratches. For removing the noise from images gaussian filter is applied and low pass frequency is supressed by applying the linear filter. After smoothing an image, the technique called line profile is applied. Whereas in grayscale or RGB images the intensity value along with the line or multiple line is recovered. By using the MATLAB, the intensity value on the scratch is retrieved with the help of multiple line on an image connecting from one end at x axis. For the scratch analysis, range of 181 – 198 considered the normal as the maximum values lies between this range. If it is found that values are exciding this range, then its detecting scratches.

Hsu et al. (2016) comes with a technique of fast vision based for inspection of steel billets defects. For clear understanding and finding of fault in an image the pixels are set to 0 for no defects and 255 for defects. During the pre-processing stage Based on Hough line detection skew correlation is performed after wards ROI (Region of Interest) is carried out. Due to the lighting effect on images the illuminance is adjusted to a predefine value. Following the inspection stage, the defect is the darker region in image. With predefined threshold L2 set to 51 we binarized the image. Any pixel smaller than the L2 considered as defect, morphological operation is executed to remove noise. 560 samples were used to find the fault, 0.08 seconds is taken for recognizing a defect with accuracy of 99.21% and 84% for sponge and corner defects. Another author Liu et al. (2018) uses the GLBP (gradient local binary pattern) for surface defects identification, dimensionality of the LBP data matrix is decreased by using the images sub-block. In

LBP the core pixel of the gray vale is compared with the neighbouring pixel and if its less the value is set to 0 otherwise 1. Whereas, GLBP method joins the 8 neighbouring centre point of gradient value. these values can be used to determine the defects. And it is found that the defected area and normal area differs. For the recognition of the defects like air bubble, scratches many more GLBP can efficiently identify the flaw on the surface with average accuracy of 68%.

Ma et al. (2018) conducted a research on fast detection of defect on the surface by using Gabor filter. Image is inputted into the system and afterwards then it is blurred and normalized before Gabor filter is applied. Energy map is produced in each direction with the help of Gabor filter bank, appropriate values need to be selected when developing a filter bank. Single-scale and Multi-scale Gabor filter can be used depending on the performance. Single scale is acknowledged by the author in terms of speed and accuracy. Segmentation of the energy maps is done by hysteresis thresholding and can precisely detect curvilinear defect curve. Implementation of pruning and region grouping are carried out individually after getting the regions with two thresholds. 70 samples of the scratch dataset are considered and 118 images of the road crack dataset. The detection accuracy of 93.05% on scratch defect and non-defect data set is achieved. The method proposed by Bong et al. (2018) recommends the SVM algorithm for the classification of defects on leather surface. The images were gathered using the image grabbing system. Firstly, image pre-processing is done on collected images from image grabbing system. Where RGB image is transformed to Lab color space. For lowering the effect of bright area on the image caused by the light source is reduced from 1 to 0.87, with the help of gaussian thresholding image is convert grayscale. For differentiating the defects from the leather background segmentation approach is used. Furthermore, for extraction morphological operation is used for smoothing, cleaned and highlighting the defects. For highlighting and extracting edge the Laplacian method is implemented. Median blurring handles the salt and pepper noise whereas closing operation uses 3x3 elliptic filter. Defect is extracted and resized it into 32x32 pixels. Afterwards data is divided into training and testing and attain 98.8% of accuracy.

Renwei and Dong (2016) proposes an image segmentation approach for detection of defects on components surface. Two iteration technique is used as gray level selection of threshold for image segmentation. The partitioning of the defected region is done on components surface. With the help of morphological operation defect is classified and detected, afterwards features are extracted and matched in an image. The algorithm used by author split up into two parts one is defected region segmentation and feature and defect extraction. After entering the image, it is converted it into gray scale and noise is removed from the original image with the help of gauss filtering. Two iteration method is performed based on gray level threshold segmentation selection. And then feature were matched and extraction of defects from an image is done. Pitting type defect is concluded when length of the defected area and width is less than 4 else it is a scratch. For the sample of 1000 images, 96.4% and 98.8% accuracy are found while identifying the pitting and scratch type defect. Selvathi et al. (2019) have suggested thresholding based and canny edge detector method for identifying the defects like crack that takes place during welding and holes on a flat steel surface with the help of various image pre-processing technique. Two datasets were obtained from a video of pulsed and lock-in thermography, comprises of 500 images were taken from pulse thermography which makes dataset 1 and dataset 2 contains 16 images from lock-in thermography. Author applied first method on dataset 1 for identifying holes on the flat surface. color median filter is applied for removing the thermal noise. PCT (principal component thermography) tool is applied after removing the noise for finding the useful information in image. For detecting and extracting the edges canny edge detector is used and are filled. Later in order to locate the defect shape and size quantitative analysis is done. This method does not work well with dataset 2 for cracks defects.A different approach is taken, to spot the edges in image Laplacian filter is implemented. To highlight the edge of a crack original image and Laplacian filter image is subtracted. Thereafter, in order to enhance the clarity of an image histogram equalization is performed. Thresholding is done to segment the crack zone from the image, the value of pixel from 0 to 50 are considered 0 and remaining are consider 255 here improvement can be seen by applying this technique.

A research done by the Li, Zhang, Zhuang and Wang (2018) using matlab to analyse the defect on metal surface of spoon. Two modules were recommended by the author is 'image acquisition module and image pre-processing and analysis module'. Spoon is identified and an image is capture by the camera in first module and then image pre-processing is done. As the captures image is in RGB it is converted to grayscale. Followed by the image enhancing technique such as sharpen filtering, histogram equalization and median filtering is applied out of which sharpen filtering is selected because it has given better results. Feature extraction is performed based on edge detection with the help of canny operator and log operator. Because of this operator defect recognition percentage is high. [25] in his studies identify the defect on wood based on LBP (local binary patterns) texture extraction. With the help of LBP from an image local texture feature are described. Segmentation of an image is done before defect region is extracted. Three steps are performed like image is binarized and thresholding is adapted, erosion and dilation of an image. Later for detecting the edge canny operator is used. Variance between the wood defect of similarity relation is obtained by histogram and chi-squared coefficient statistic test used for finding similarity. BP neural network is used for classification, comparison is done between GLCM and LBP in addition to it is found out that LBP classify the defect correctly and recognition rate is higher.

A comparative study conducted by Zhang et al. (2016) for recognizing the defects in apples with the help of Gabor wavelets, Haralick features, local binary patterns and kernel PCA. Sample of 320 images were taken which contains four classes. During the pre-processing stage images were adjusted into the size 200 x 200 pixels for standardization. Furthermore, for detecting the ROI (region of interest) the RGB color image is converted to grayscale. K-means clustering is implemented on image pixels for contrasting various regions of apple. Making use of Gabor wavelets features are extracted from grayscale image. For feature descriptor LBP, Haralick features, PCA is used. For K-NN classifier and accuracy achieved for identification of disease when combining the Gabor and LBP ranging from 85.93% to 95.31% and for detection of disease accuracy ranges from 89.8% to 96.25% which outperforms Gabor and haralicks and Gabor and kernel-PCA. Jolly and Raman (2016) performed different segmentation technique to find out which of the technique is efficient for finding the defect accurately. First the sample of data are gathered and pre-processed. Sample images contain noise which can affect the accuracy in further process so removing of noise is done by applying the median filter. After removal of noise the author has use histogram equalization for enhancement of an image.

color based segmentation for Identification of defect with the help of k-means clustering, modified K-means clustering and Otus method. Following the experiment is performed to check the performance of these methods it is found out that Otus method outperformance the other two.

3 Methodology

The CRISP-DM (Cross Industry Process for data mining) is suitable for majority of the data mining proposals. The main objectives of the CRISP-DM are to minimize cost of large projects and make it dependable, manageable and faster Wirth and Hipp (2000). The concept of CRISP-DM is divided into six different phases such as, Business Understanding, Data Understanding, Data Preparation, Modelling, Evaluation, Deployment. For this study CRISP-DM approach is applied and will eventually help in the classification of the defect on steel surface. The process of the CRISP-DM is shown in figure 1.

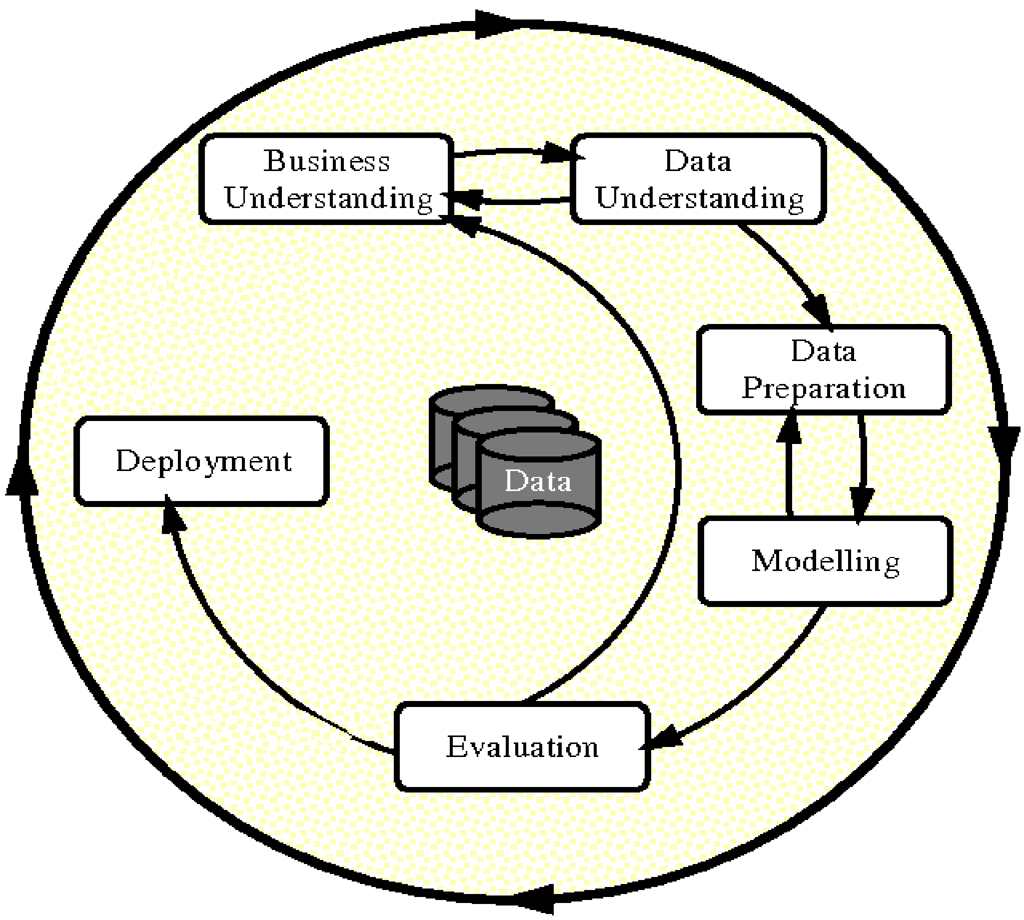

Figure 1: Cross Industry Process for data mining [1]

The CRISP-DM process of this research is explained below.

[1]CRISP-DM: Towards a standard process model for data mining

1. **Business Understanding:**

   This is the first step of CRISP-DM which focuses on understanding the goals of the project and requirements from business point of view. For achieving the project objectives, the knowledge that has been gathered is transformed into a data mining problem definition. To meet the objectives of this research is to efficiently classify the defects on steel surface by using the machine learning algorithm. Which would benefit many steel industries for increasing the profit.

2. **Data Understanding:**

   In this step data is collected and analysed to get familiar with the data. Different data sets have been used by researchers for Classification of defects on surface of the steel. For this research the source of Image dataset is been downloaded from the NEU surface defect database. And it contains 1800 grayscale images in jpg format belonging to six different classes such as rolled-in scale, patches, crazing, pitted surface, inclusion and scratches, each image is of resolution 200x200 pixels.

3. **Data Preparation :**

   In data preparation step where from the raw images final data is generated. This is the pre-requisite step before feeding the final images into the model. Downloaded data contains raw images of steel surface defects and contains noise. Raw images were of size 200x200 pixels, first scaling is done then images were resized to 40x40 pixels. later in order to remove the noise Gaussian blur is applied on all the images. After that NMF (Non matrix factorization) a dimensionality reduction technique is applied where, the factorised matrices V = W x H is of a non-negative. later the data is split into Training set (contains 80% of data) and Test set (contains 20% of data) for first experiment. For Second experiment raw data is split into training set (contains 80% of data), test set (contains 20% of data) after applying NMF.

4. **Modeling:**

   In this step a model is selected for implementation and for this research deep CNN learning algorithm is selected.A deep CNN model consists of 2D convolutional layers that takes input of 2D matrix of Images. For the first two layers the feature detectors are set as 32. Third & fourth layer feature detectors are set as 64, five & six feature detectors are set as 128 of dimension size of (3,3) with the activation function of ReLU. Max pooling layer is applied after every two Convolution layers with pool size of 2x2. To serve as link between the dense layer and convolution 2D layer, flatten layer is added. last layer is the output layer with six different nodes, one node for each possible result.

5. **Evaluation:**

   Build Model will then be evaluated based on confusion matrix, precision and recall.

6. **Deployment:**

   The build model can be deployed for real time classification of defects on steel.

4 Implementation

The most essential part of this research is to implement and evaluate the results based on the above methodology explain in section 3. Two different experiment are performed for classifying the defects on steel surface by applying the techniques Gaussian blur and NMF in first experiment and second experiment without Gaussian blur technique. These experiments were performed on Spyder with python version 3.7 installed on anaconda with keras using TensorFlow at backend.

Data pre-processing

The raw Images Data were downloaded from the NEU surface defect database for classification of defects on the steel surface which is publicly available. Contains 1800 of 200x200 grayscale images.

- For first experiment, Step one – The first step in pre-processing of images is to resize the original images. The actual images contain of 200 x 200 pixels. Which were resized with the help of cv2.resize() from the OpenCV library. Image width and height were changed by preserving the original aspect ratio. Images were resized to 40 x 40.

- Step two – After resizing the images, image scaling is done to bring the data to specific range. It is performed by dividing the images by 255.

- Step three – following the above two steps Gaussian blur is applied. To blur an image the cv2.GaussianBlur() is used from the OpenCV library with various kernel size of 5x5 and 3x3. We applied the Gaussian blur to reduce noise from an image and after applying the gaussian blur all images were saved into a folder with the help of plt.savefig() from the matplotlib library.

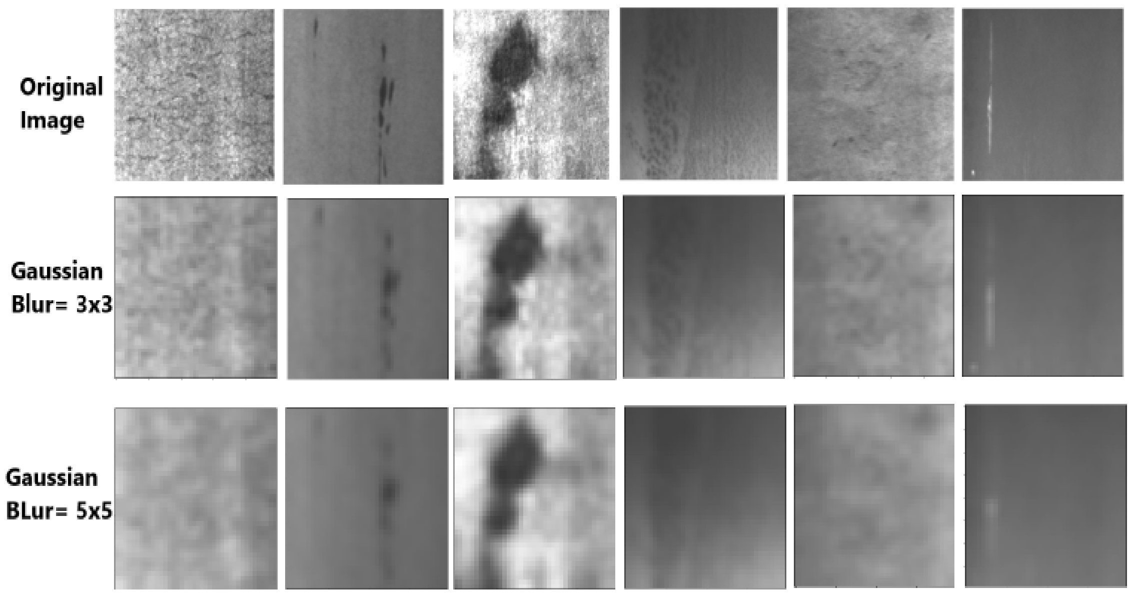

Figure 2: After applying Gaussian blur

From figure 2 we can see the difference in images after applying Gaussian blur at various levels

- Gaussian blur is also known as the Gaussian smoothing which is obtained by blurring an actual image with the help of Gaussian function for removing the noise from an image and later this blurred applied to the algorithm. For smoothing an image with the help of gaussian function, kernel weights are used i.e. a 2D array and gaussian function for two dimensional is shown below. Gaussian distribution is represented by a bell shape graph in figure 3 Dubey and Agrawal (2017).

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}}$$

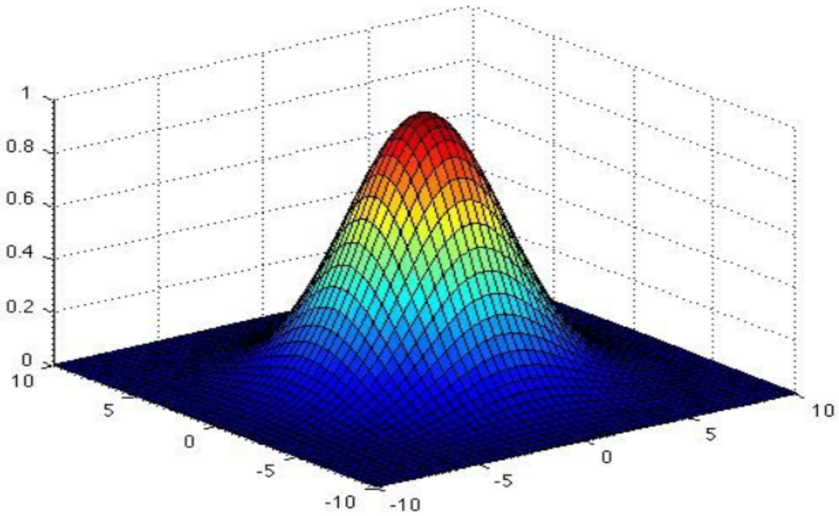

Figure 3: Gaussian bell graph[2]

For getting the output image after applying the gaussian function, input image is multiplied by the gaussian kernel. In kernel center pixel are multiplied with the input image pixel which are overlapping. The results of the multiplication are added up to from the image. As shown in example image 4 shown below, value at the input array (0,0) is multiplied by the value at (c) in kernel array, value at the input array (0,1) is multiplied by the value at (h) in kernel array and so on. At output image the resulting values after addition will get (1,1).

[2]https://medium.com/analytics-vidhya/gaussian-blurring-with-python-and-opencv-ba8429eb879b

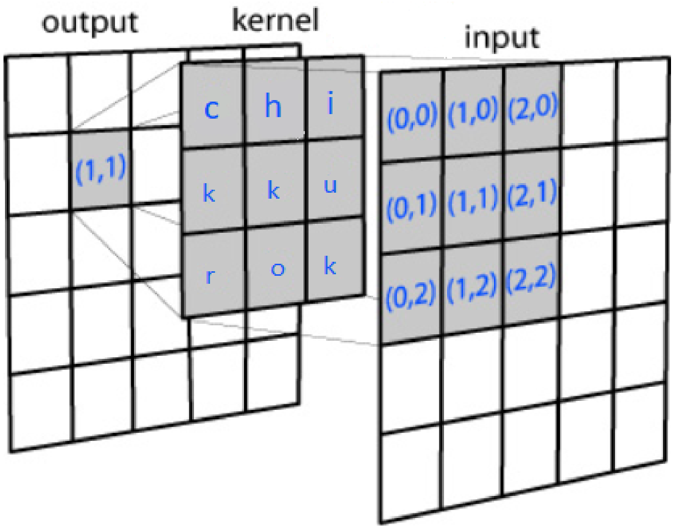

Figure 4: working of Gaussian blur

- Thereafter NMF (non-negative matrix factorization) is applied for both the 5x5 and 3x3 kernel size in gaussian blur. Following normalization is done which is nothing but the method that brings the pixels intensity values to a certain range. Also, Data is divided into training set and test set further this our deep CNN model is trained on 20 epochs and evaluated.
- Non-negative matrix factorization (NMF) is a dimensionality reduction technique, where the V matrix is factorized into two matrix W and H and all the three matrices are non-negative i.e. the values in the matrix are equal to zero or greater than zero but not negative. The equation is V = W x H and becomes clear when we look at the figure below.

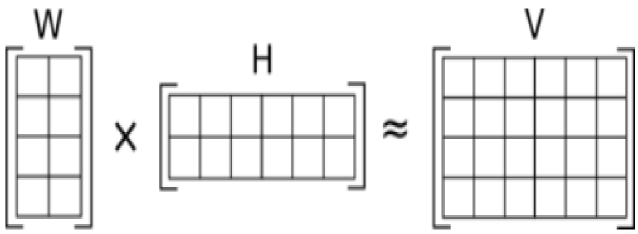

Figure 5: Visualization of the eq V = W x H [3]

Two matrices are produced by NMF such as W and H. whereas, W represents the column contains an image (basic image of faces) and for reconstructing it to an approximation of the original image in order to do so H tells how to sum up the image. In the example shown below of faces dataset.

[3]https://medium.com/logicai/non-negative-matrix-factorization-for-recommendation-systems-985ca8d5c16c

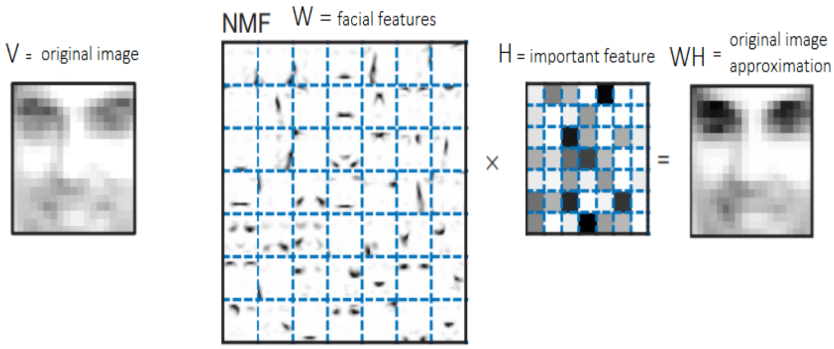

Figure 6: Working of NMF[4]

From the above figure 6 features such as nose, lips and eyes are the basic image and these features are present in which image are stated by the columns of H Lee and Seung (1999).

- For Second experiment – Data were downloaded from the NEU surface defect database for classification of defects on the steel surface which contains 1800 of 200x200 pixels images of six classes of having 300 images per class. These images were converted to grayscale with the help of rgb2gray() function. NMF is applied and normalization is done then data is divided into training set and test set with 80:20 ratio further this our deep CNN model is trained on 20 epochs and evaluated.

Convolutional Neural Network (CNN)

When it comes to machine learning algorithms neural nets has proven to be the best in terms of computational time and accuracy as compared to other algorithms. CNN is considered a fit for image classification, object detection and recognition. An input image is feed to the CNN and it distinguishes one image from another based-on assign weights for example it can tell if an image is of cat or dog etc. Entered image into the CNN model can be RGB or a grayscale image. Which is an array of pixels with width, height and dimension. 4x4x3 where 3 represents an RGB image and 4x4x1 where 1 means a grayscale image. To train and test the ConvNet, each image is pass through the convolutional, pooling, flatten, fully connected layer and softmax function is applied to classifies an object belongs to which categories (Ex. animal's images). We used softmax function because it takes probabilities of class over all the target classes and calculated probabilities will be in ranges from 0 to 1. Features from an image are extracted when the first convolutional layer is created and can get as many feature maps from an image. For reducing the size of the feature maps created in the previous layer pooling is applied either by taking average or the maximum value Dumoulin and Visin (2016). Additional convolutional layers can be added and flatten the output of last layer and feed it to fully connected layer for classification. For this research Deep CNN is used.

[4]Learning the parts of objects by non-negative matrix factorization

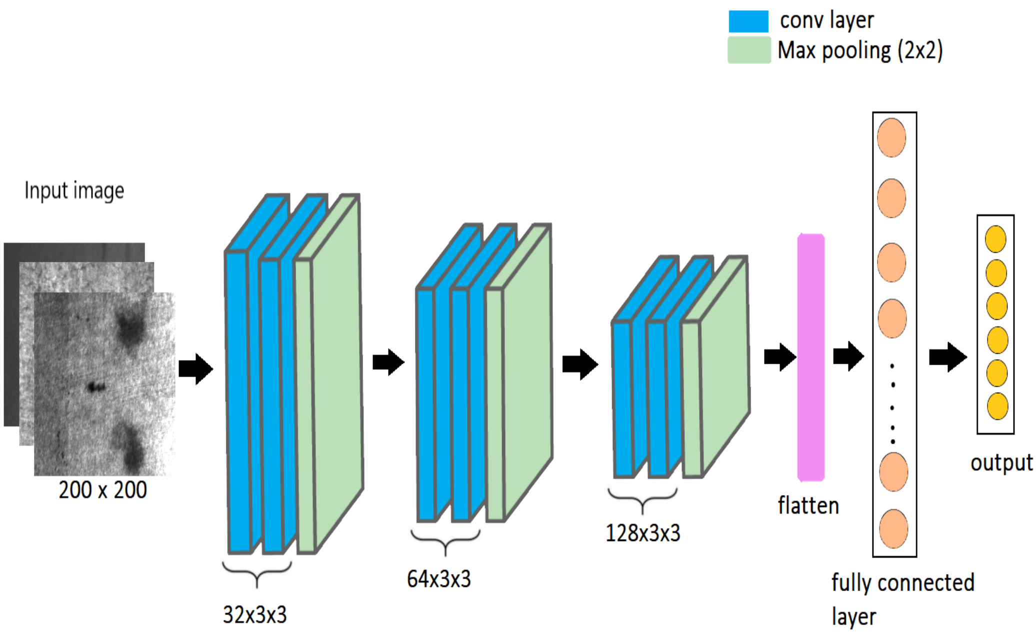

Figure 7: Convolutional Neural Network

As it can be seen from the above figure 7 input image is of size 200 x 200 grayscale image feed into the network and first and second layer of the Deep CNN filters the image with 32 feature detectors of kernel size 3 x 3 for creating the 32 feature maps. Then Max pooling layer of pool size 2 x 2 is applied for reducing the size of the feature maps created in the previous layer, Max pooling is applied by taking maximum value from the feature map [30]. ReLU activation function is used respectively. Third and fourth convolution layer takes reduced feature maps from the previous layer. For this research we used pool size of 2 x 2 for max pooling. Fifth and six convo layer takes the output of 2nd pooling layer. Lastly, we flatten our matrices of last layer and feed it to fully connected layer which has 256 hidden layers. For classification of six different classes we used SoftMax activation function.

5 Evaluation of the model

For visually identifying the performance of the machine learning algorithm confusion matrix comes into picture. It is used to evaluate the efficiency of classification algorithm for two or more classes. In confusion matrix there are four important points True positive: algorithm predicted positive and it's true, True negative: algorithm predicted negative and it's true, False positive: algorithm predicted positive and it's false, False negative: algorithm predicted negative and it's false. Overall accuracy of the classification model is calculated as

$$Accuracy = \frac{TruePositive + FalseNegative}{TotalNumberOfSample} \tag{1}$$

Calculating the accuracy of the model is not enough and based on accuracy a model performance cannot be selected therefore, precision and recall are considered. For this research precision evaluate the percentage of defects on steel that are correctly classified. And recall calculate the percentage of relevant defects that were correctly classified Powers (2011).Recall is consider when safety is the main concern, where it evaluates false negatives against true positives. Recall value need to be greater than 0.8 and closer to 1, when minimizing the false negative is the only concern. The equation of precision and recall is mentioned below.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{2}$$

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \tag{3}$$

The evaluation of the result for this research is done with the help of confusion matrix, precision and recall using python. We have executed different experiments with Gaussian blur for various levels of blurring the image with kernel size of 3x3 and 5x5 with Non-negative matrix factorization and implemented NMF without applying Gaussian blur. After implementation we got 3 confusion matrixes with different precision and recall values for each separate experiment.

5.1 Applying Gaussian blur with kernel size of 3x3

After resizing the raw images to 40 x 40 Gaussian blur is applied with ksize of 3x3 for smoothing the image, NMF is applied after smoothing the image and confusion matrix is formed. It can be seen in figure 8, for 3x3 blurring effect 44.4% of accuracy is achieved. By looking at the values of precision & recall of all six classes from figure 9 we can say that our model performance is low when implementing with Gaussian blur kernel size of 3x3.

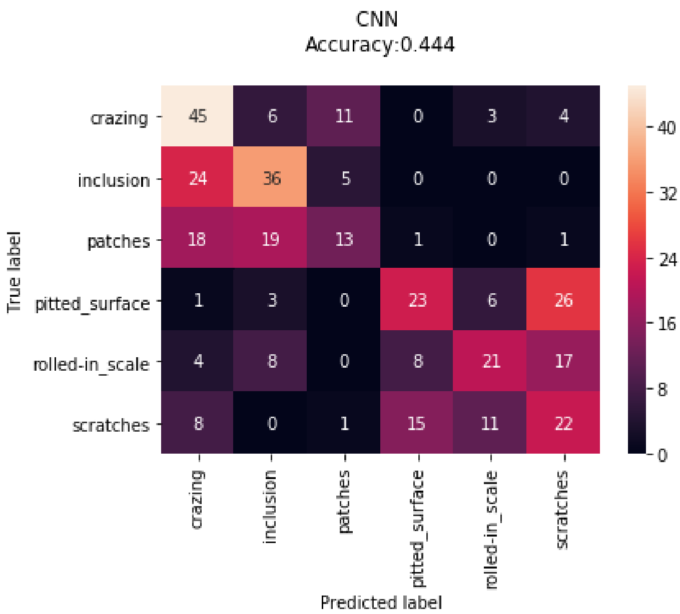

Figure 8: Confusion matrix

Classes	Precision	Recall
Crazing	0.450	0.652
inclusion	0.500	0.554
patches	0.433	0.250
Pitted_Surface	0.489	0.390
Rolled-in_Scale	0.512	0.362
scratches	0.314	0.386

Figure 9: precision and recall

5.2 Applying Gaussian blur with kernel size of 5x5

After resizing the raw images to 40 x 40 Gaussian blur is applied with ksize of 5x5 for smoothing the image, NMF is applied after smoothing the image and confusion matrix is formed. It can be seen in figure 10, for 5x5 blurring effect we can see that accuracy is slightly increased to 45.6%. By analyzing precision and recall from figure 11 we can say that this model did not performed well even with Gaussian blur kernel size of 5x5.

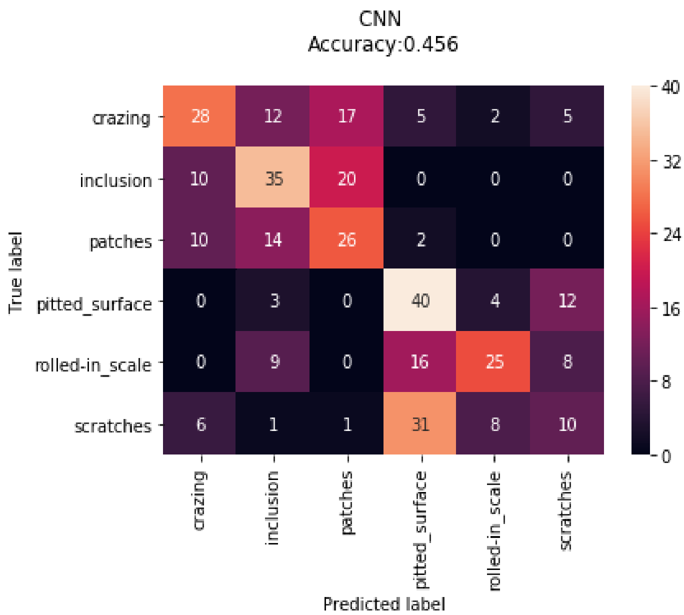

Figure 10: Confusion matrix

Classes	Precision	Recall
Crazing	0.519	0.406
inclusion	0.473	0.538
patches	0.406	0.500
Pitted_Surface	0.426	0.678
Rolled-in_Scale	0.641	0.431
scratches	0.286	0.175

Figure 11: precision and recall

5.3 Applying NMF without Gaussian blur

Non-negative matrix factorization is applied on image data set of 200 x 200 pixels without applying the Gaussian blur and form the confusion matrix shown in figure 12 . By looking at figure 13 precision & recall values are greater than 0.8 for all the six different classes of defects and Our model performed very well without blurring the images. And 93.1% of accuracy is achieved.

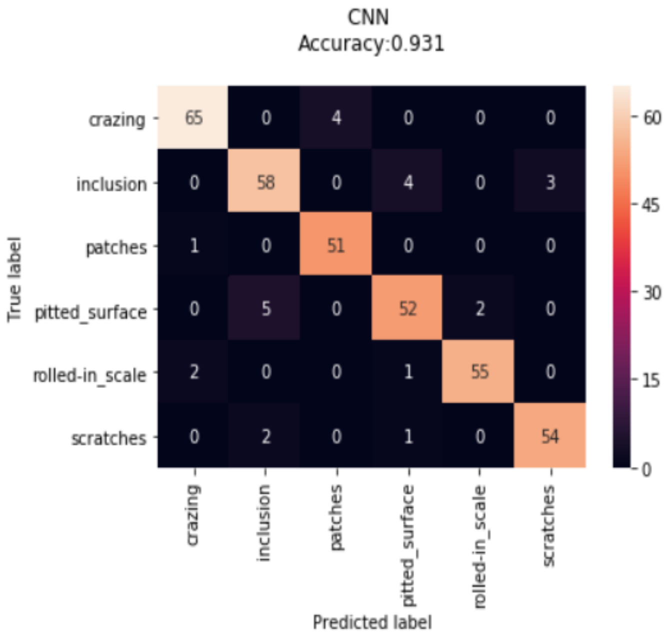

Figure 12: Confusion matrix

Classes	Precision	Recall
Crazing	0.956	0.942
inclusion	0.892	0.892
patches	0.927	0.981
Pitted_Surface	0.897	0.881
Rolled-in_Scale	0.965	0.948
scratches	0.947	0.947

Figure 13: precision and recall

6 Conclusion and Future Work

For this research on classification of defects on steel surface the dataset of images is downloaded from the publicly available data on NEU. The image dataset contains 1800 images of 6 different classes i.e. 300 images for each class. Two Different experiments were performed on the dataset, for first experiment images were resized from 200 x 200 pixels to 40 x 40 pixels. After resizing Gaussian blur is applied on images with separate Kernel size of 3x3 and 5x5. Following NMF (Non-negative matrix factorization) is applied and feed to the Deep CNN. In the second experiment NMF is applied to the images of 200 x 200 pixels without resizing and excluding the Gaussian blur. The results we got after implementation for first experiment when kernel size is set to 3x3 for Gaussian blur, 44.4% of accuracy is achieved but accuracy is slightly increased to 45.6% when kernel size is set to 5x5 for Gaussian blur. Whereas For second experiment accuracy is reached to 93.1%. For future work we would like to work with YOLO object detection with NMF for detecting the defects on steel surface.

References

Aghdam, S. R., Amid, E. and Imani, M. F. (2012). A fast method of steel surface defect detection using decision trees applied to lbp based features, *2012 7th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1447–1452.

Batsuuri, S., Ahn, J. and Ko, J. (2012). Steel surface defects detection and classification using sift and voting strategy, **6**: 161–166.

Bong, H., Truong, Q., Nguyen, H. and Nguyen, M. (2018). Vision-based inspection system for leather surface defect detection and classification, *2018 5th NAFOSTED Conference on Information and Computer Science (NICS)*, pp. 300–304.

Chen, L. and Deng, J. (2018). Research on surface defects detection of stainless steel spoon based on machine vision, pp. 1096–1101.

Chen, N., Men, X., Hua, C., Wang, X., Han, X. and Chen, H. (2018). Research on edge defects image recognition technology based on artificial neural network, *2018 13th IEEE Conference on Industrial Electronics and Applications (ICIEA)*, pp. 1929–1933.

Di, H., Ke, X., Peng, Z. and Dongdong, Z. (2019). Surface defect classification of steels with a new semi-supervised learning method, *Optics and Lasers in Engineering* **117**: 40 – 48.
URL: *http://www.sciencedirect.com/science/article/pii/S0143816618313393*

Dubey, M. and Agrawal, S. (2017). An analysis of energy efficient gaussian filter architectures.

Dumoulin, V. and Visin, F. (2016). A guide to convolution arithmetic for deep learning, *ArXiv* **abs/1603.07285**.

Faghih-Roohi, S., Hajizadeh, S., Núñez, A., Babuska, R. and De Schutter, B. (2016). Deep convolutional neural networks for detection of rail surface defects, *2016 International Joint Conference on Neural Networks (IJCNN)*, pp. 2584–2589.

Fu, G., Sun, P., Zhu, W., Yang, J., Cao, Y., Yang, M. and Cao, Y. (2019). A deep-learning-based approach for fast and robust steel surface defects classification, *Optics and Lasers in Engineering* **121**: 397–405.

Guo, F., Zhao, J. and Jiang, P. (2017). Surface defects detection of steel plate based on visual attention mechanism, *2017 Chinese Automation Congress (CAC)*, pp. 3174–3177.

Hsu, C., Ho, B., Kang, L., Weng, M. and Lin, C. (2016). Fast vision-based surface inspection of defects for steel billets, *2016 IEEE International Conference on Consumer Electronics-Asia (ICCE-Asia)*, pp. 1–2.

Jolly, P. and Raman, S. (2016). Analyzing surface defects in apples using gabor features, *2016 12th International Conference on Signal-Image Technology Internet-Based Systems (SITIS)*, pp. 178–185.

Khan, M. U., Alam, A. and Parveen, Z. (2017). Analysis of defects on hot and cold roll coil using image processing methods, *2017 13th International Conference on Emerging Technologies (ICET)*, pp. 1–6.

Kim, M. S., Park, T. and Park, P. (2019). Classification of steel surface defect using convolutional neural network with few images, *2019 12th Asian Control Conference (ASCC)*, pp. 1398–1401.

Lee, D. and Seung, H. (1999). Learning the parts of objects by non-negative matrix factorization, *Nature* **401**: 788–91.

Li, J., Geng, J. and Yin, Y. (2018). Real-time detection of steel strip surface defects based on improved yolo detection network, *IFAC-PapersOnLine* **51**: 76–81.

Li, Z., Zhang, J., Zhuang, T. and Wang, Q. (2018). Metal surface defect detection based on matlab, *2018 IEEE 3rd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, pp. 2365–2371.

Liu, X., Xue, F. and Teng, L. (2018). Surface defect detection based on gradient lbp, *2018 IEEE 3rd International Conference on Image, Vision and Computing (ICIVC)*, pp. 133–137.

Ma, J., Wang, Y., Shi, C. and Lu, C. (2018). Fast surface defect detection using improved gabor filters, *2018 25th IEEE International Conference on Image Processing (ICIP)*, pp. 1508–1512.

Ojala, T., Pietikäinen, M. and Harwood, D. (1996). A comparative study of texture measures with classification based on featured distributions, *Pattern Recognition* **29**(1): 51 – 59.
URL: *http://www.sciencedirect.com/science/article/pii/0031320395000674*

Patel, S. V. and Jokhakar, V. N. (2016). A random forest based machine learning approach for mild steel defect diagnosis, *2016 IEEE International Conference on Computational Intelligence and Computing Research (ICCIC)*, pp. 1–8.

Powers, D. M. W. (2011). Evaluation: from precision, recall and f-measure to roc, informedness, markedness and correlation.

Ren, Q., Geng, J. and Li, J. (2018). Slighter faster r-cnn for real-time detection of steel strip surface defects, pp. 2173–2178.

Renwei, L. and Dong, Y. (2016). Component surface defect detection based on image segmentation method, *2016 Chinese Control and Decision Conference (CCDC)*, pp. 5093–5096.

Selvathi, D., Nithilla, I. H. and Akshaya, N. (2019). Image processing techniques for defect detection in metals using thermal images, *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)*, pp. 939–944.

Wirth, R. and Hipp, J. (2000). Crisp-dm: Towards a standard process model for data mining, *Proceedings of the 4th International Conference on the Practical Applications of Knowledge Discovery and Data Mining* .

Ze-song, W. (2017). Research on image detection and recognition for defects on the surface of the steel plate based on magnetic flux leakage signals, *2017 29th Chinese Control And Decision Conference (CCDC)*, pp. 6139–6144.

Zhang, Y., Zhao, Y., Liu, Y., Jiang, L. and Chen, Z. (2016). Identification of wood defects based on lbp features, pp. 4202–4205.

Zhou, S., Chen, Y., Zhang, D., Xie, J. and Zhou, Y. (2017). Classification of surface defects on steel sheet using convolutional neural networks, *Materiali in tehnologije* **51**: 123–131.