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Automated Visual Inspection of Oily Components using Machine Learning Techniques

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Abstract: The automated visual inspection may function as an early recommendation system for manufacturing companies as the increase in customer satisfaction in getting a defect free product is increasing day by day in the current market. These removals of the defective products are now done manually, which is time consuming and costlier than the proposed model. The key factor is to maximize the company's profit in the coming years. In this paper a Residual Network (RESNET) Classifier and a RESUNET Segmentation model.

The RESNET is a type of Convolutional Neural network (CNN) that can be used for prediction models. In this paper, there's an investigation to predict the defective products from the non-defective products. The input is passed on the RESNET classifier and RESUNET Segmentation model where the model predicts wheather the product is defective or not and gives us the result that can be viewed by the user.

These methods are being applied on a data set from a steel company. The results are wont to predict the defective products from the non-defective products.

Keywords: Residual Network (RESNET), RESUNET, Classification, Segmentation, Mask, Run Length encoding

I. INTRODUCTION

This application will predict the defective products from the non-defective products in the production line. After prediction they are being removed from the production line to keep up the quality of the product. The prediction is done within the data derived from the company in the market.

This uses a RESNET Classifier and a RESUNET Segmentation model. In this training data is 75% of the total data and 25% of data is being used for testing purpose. The RESNET classification model uses the image data and the csv data of the image and classify wheather the product is defective or not using mask to detect the defect. If the image is defective, then its being passed on to the next phase RESUNET Segmentation where the segmentation is done in each pixel of the image and the specific pixel with the defect is being found and shown to the user. The combination of both the model onto a single model helps us to get an accurate output.

Input data is taken from the steel company's product which consists of both the image of the product and the numerical value of the product which helps to increase the accuracy of the prediction. In this 75% is taken as a training data and the other 25% is taken as a validation data. Our model uses the process od masking and Run Length Encoding (RLE) is being passed onto the CNN where the model is built on a IMAGENET model where its being trained upon the training data and the precited result is being passed on to the next phase of RESUNET Segmentation model where the results from the image segmentation is done on each pixel values and the specific parts of the defective products is being highlighted and shown to the user.

The saved model is then used in the production line to apply it in the real time situation when a fresh image from the production line is captured and passed on to the model.

The model predicts wheather the product is defective or not and the defective products are being removed from the production line and sent for melting and reusing.

The advantage of the application is that it reduces the human intervention and it reduces the cost of production as the system does the work of the fellow humans and the it also reduces the radiation effects the fellow humans working in that a higher temperature which may cause various health issues.

The two models combined together were employed onto the model with the available dataset to train and test the model. The model can predict wheather the product manufactured is defective or not. The defective products are being sent to next stage where the specific defective part is being found and conveyed to the admin.

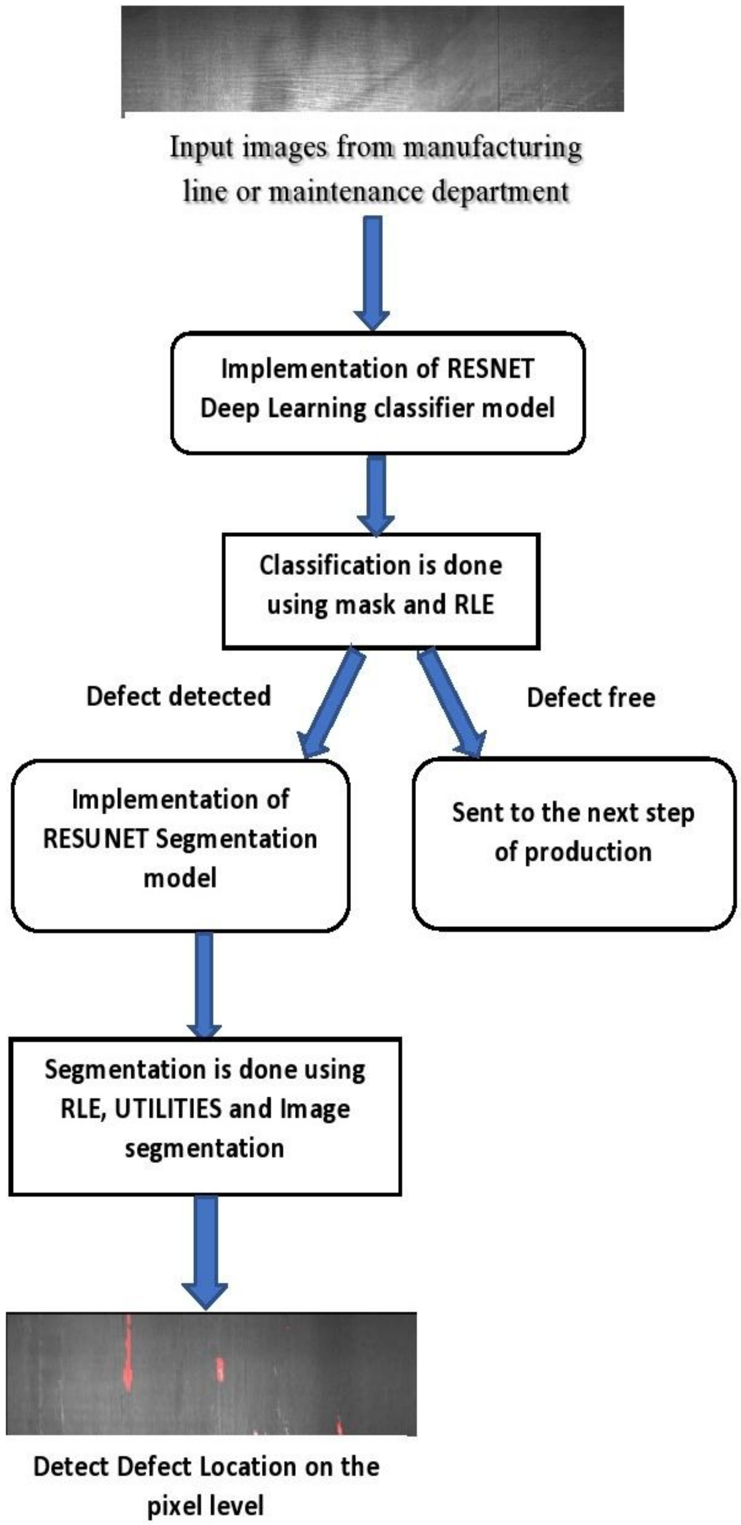

Figure 1: System Architecture of Automated Visual Inspection of Oily Components.

II. METHODOLOGY

A. Collection of Input data

Input data is taken from the steel company using the following steps:

1) *Step 1:* The project considers images and numerical data from the company compiled in a specific manner.
2) *Step 2:* Each image is given a specific id and matched with numerical data.
3) *Step 3:* Each image is rendered into a specific shape.
4) *Step 4:* Further the data is divided into two parts: training data and testing data where 75% of the data is used for training and 25% is used as testing data.

B. Generation of the Output

Following steps is performed to generate the output:

1) *Step 1:* The input images are passed onto the RESNET Classifier model.
2) *Step 2:* It uses mask and RLE to classify the image and pass onto the next step.
3) *Step 3:* The defective images comes to the RESUNET Segmentation model and non-defective ones are passed onto the next step of production and the segmentation model gives pixel level defect detection.
4) *Step 4:* Train the model.
5) *Step 5:* System will predict the output.

C. Work Flow

The entire system would be implemented in Python using open source libraries.

1) *Step 1:* System Architecture diagram roughly summarizes the entire process that takes place in the prediction of the automated defect detection process of the components.
2) *Step 2:* Obtaining data set from the steel company in the form of both image and csv linked together via a image id.
3) *Step 3:* We use a combination of two models RESNET Classifier and RESUNET Segmentation model.
4) *Step 4:* RESNET and RESUNET are types of CNN models where there are trained on a ImageNet pretrained Model where the weights are feezed.
5) *Step 5:* Certain values such as shape and types of defects are visualized and calculated.
6) *Step 6:* The predicted image is generated with pixel level defect detection. . Here we also know that 25% of the data is used for testing purposes and the other 75% is used for training of the data.

D. RESNET Classifier Model

The model would be implemented in the following steps

1) *Step 1:* The input image is being resized into a specific size.
2) *Step 2:* The mask is being applied onto the model to detect the defects.
3) *Step 3:* To reduce to length pf the mask RLE is used and the same process is carried out on the input image which gives lossless compression of the image.
4) *Step 4:* The input image is then passed onto the ImageNet network and the model is being trained.
5) *Step 5:* The trained classifies wheather the input image is defective or not.
6) *Step 6:* The defective images got to next step of defect detection and non-defective ones goes to next step of production.

E. RESUNET Segmentation Model

The model would be implemented in the following steps.

1) *Step 1:* Only the defective images are passed onto the Segmentation model.
2) *Step 2:* Creating a list to pass classid, imageid and RLE onto the image generator.
3) *Step 3:* A user-defined process to pass the classid, imageid and RLE to create image generator.
4) *Step 4:* Loss functions are defined by the user.
5) *Step 5:* Model is trained.
6) *Step 6:* Prediction output is obtained.

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III.RESULTS AND DISCUSSION

A. RESNET Classifier Model Implementation

The implementation of the model is done to classify wheather the input image is defective or not. Each defective image is being masked with defective part and sent to the next model to segment the specific part.

The RESNET model consists of a convolution, polling and flattening process and at last its being passed onto the hidden layers for training the model.

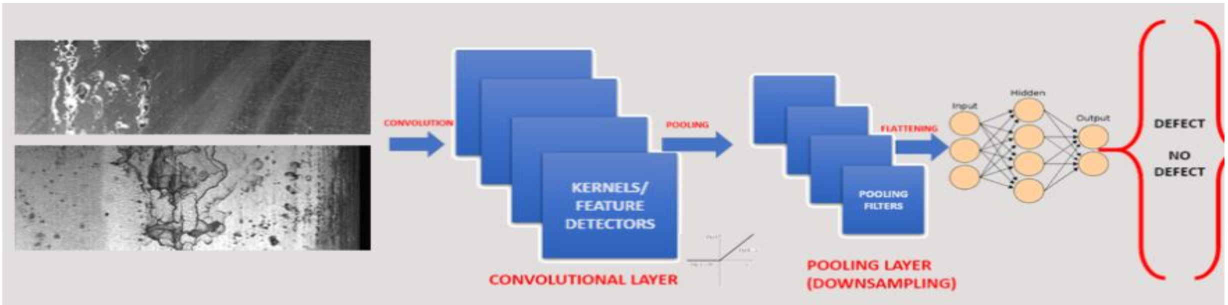

Figure 2: RESNET Classifier model Architecture.

It also gives the Confusion Matrix of 2*2 matrix for 2 classes (Defective and Non-defective). The classes are as follows; True Positive, False Positive, False Negative and True Negative. The outcomes for prediction are shown in figure 3 with values 6.4e+02 for True Positive, 2.4e+02 for False Positive, 1 for false Negative and 1.1e+03 for True Negative.

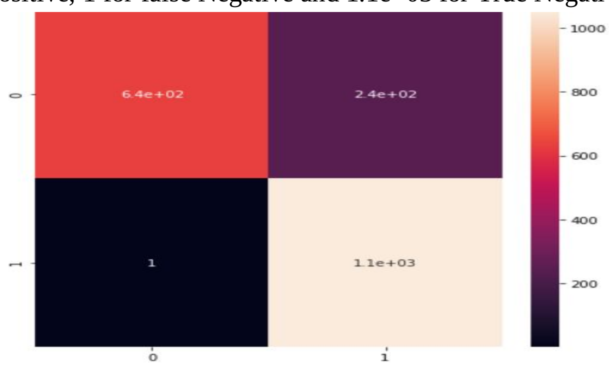

Figure 3: Confusion matrix of the classifier model.

B. RESUNET Segmentation Model Implementation

The implementation of the model is done to locate the specific part of the product that is defective in a pixel level and show it to the user. User defined loss functions is preferred than the normal loss functions for better accuracy. The input image is passed a normal image where the trained model predicts the defective part with help of the available Classid, imageid, RLE and the image which is merged and passed onto the model and the model predicts the defective part in the image.

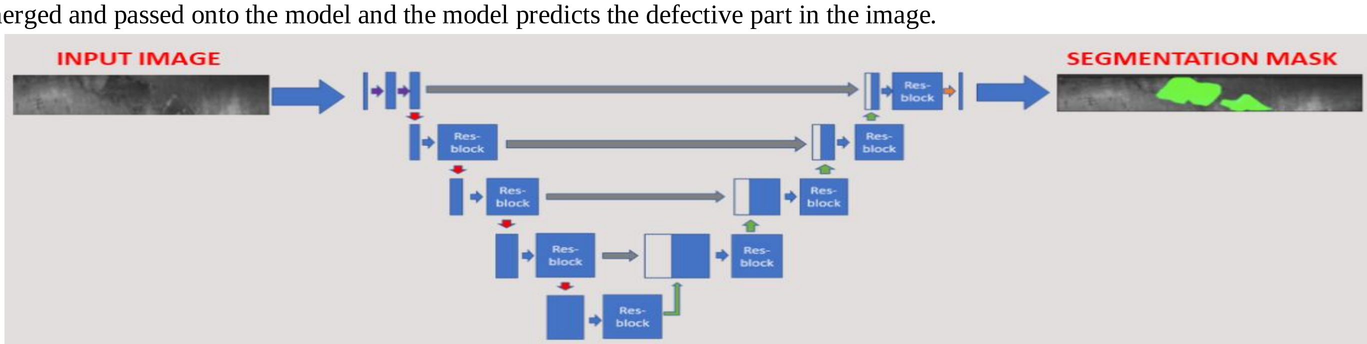

Figure 4: RESUNET Segmentation model Architecture.

On combining both the RESNET Classifier model and RESUNET Segmentation model the Automated visual Inspection model would be able to predict the defective products from the production line or the maintenance department.

IV. CONCLUSION

In this paper, we have studied the utilization of RESNET, RESUNET, Image Segmentation to predict the defective products from the production line or in the maintenance department. ON usage of the RESNET Classifier model we will be able to classify wheather the product is defective or not, whereas on combining both the RESNET Classifier model and RESUNET Segmentation model the defective products can be classified and the defective part of the product is found out in pixel level and marked by the model. Which helps to easily find out which part is defective in the product. So, the combination of both the models is best suited for the Automated Visual Inspection of oily Components.

Two models RESNET Classifier and RESUNET Segmentation model were employed in this model and a data set from some steel company was applied to coach and test the models. The system can predict wheather the product is defective or not from the production line or from maintenance department in a long run. Thus, we can conclude that the combination of both models plays an improved role in achieving an efficient and accurate outcome of the system model.

The model proposed above can also be used for any type of products like bearing, motors and other metallic products where the surface defects are to be found. The only pre-requisite is the data set and changing the code to the respective data set and training the model.

V. ACKNOWLEDGMENT

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REFERENCES

[1] Zhiqun liu, Ruyi Feng, lizhe Wang, YanFei Zhong, Liqin Cao (2019), "Resunet: Resunet and Dilated Convolution for high resolution Satellite Road Extraction", INSPEC Accession number: 19137413, Yokohama, Japan.

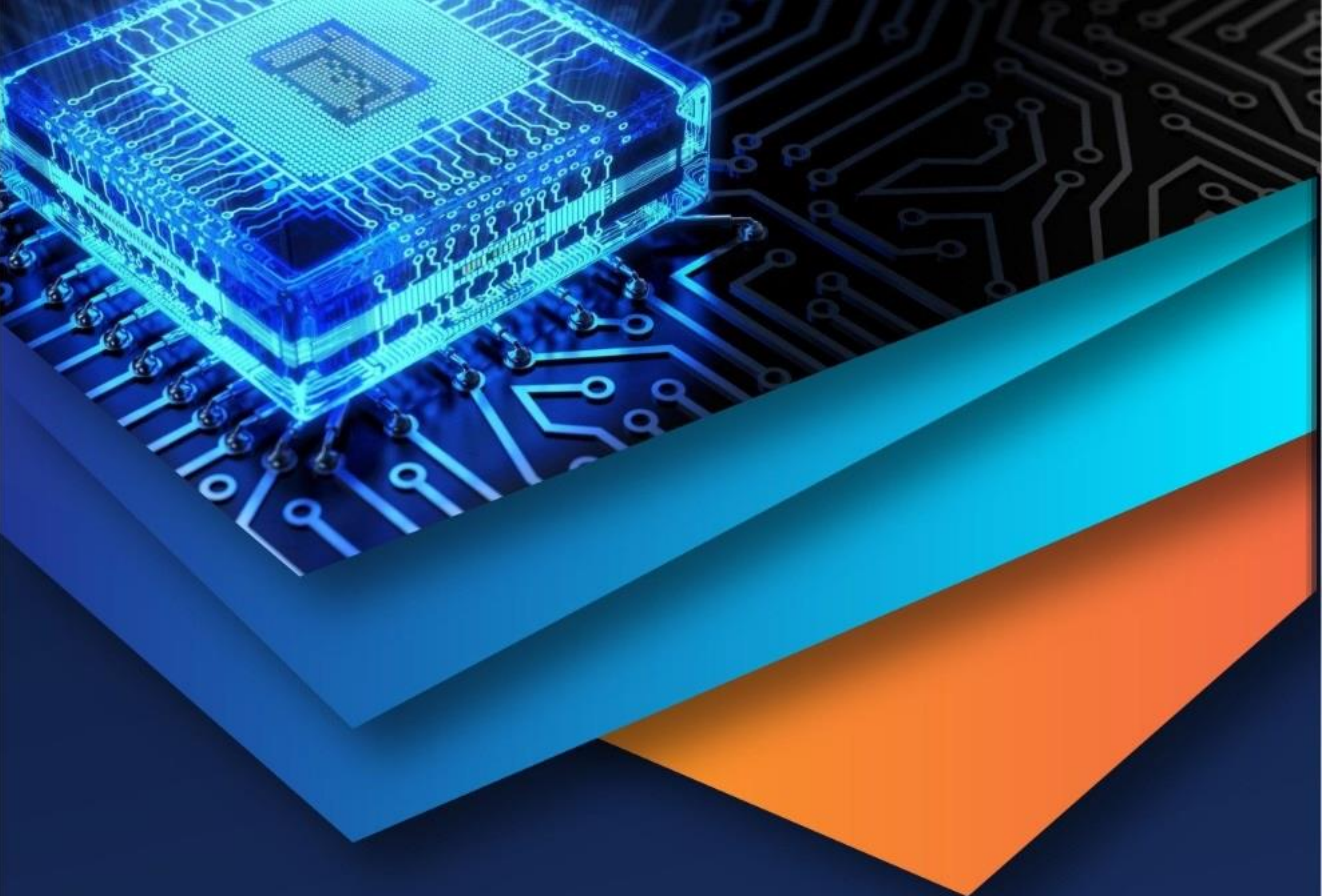
[2] Arief Budhiman, Suyanto Suyanto, Anditya Arifianto (2019), "Melanoma Cancer Classification Using ResNet with Data Augmentation", INSPEC Accession number: 19455567, Yogyakarta, Indonesia.

[3] Fahad Mira, Wei Huang, Antony Brown (2017), "Improving Malware Detection time by Using RLE and N-gram", INSPEC Accession number:17289698, Hudderfiled, UK.

[4] Subramanian M.Sundra, R. Aarthi (2019), "Segmentation and Evaluation of White Blood Cells using Segmentation Algorithms"(2019) , INSPEC Accession number: 19127325,Tirunelveli, India.

[5] Bingqian Lin, Junwei Xie, Cuhua Li, Yanyun Qu (2018), "DeepTongue: Tongue Segmentation Via Resnet", INSPEC Accession number:18096730, Calgary, AB, Canada.

[6] "Data classification with deep learning using TensorFlow. This has been used in data recognition standards",(2017). INSPEC Accession number: 17334937.



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