Comparison of Enhancement Techniques on Microstructure Images for Crack Detection

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Abstract*—*Due to high demand of accurate crack detection in microstructures it is necessary to enhance sample images for increased accuracy. Doing that manually would be very time consuming and also not always accurate,therefore, we have worked with different methods of histogram equalization for image enhancement and compared their average mean square errors and entropy values. Images with and without cracks were then processed using HE, AHE, CLAHE, BBHE, WTHE and RMSHE and trained using CNN. The resulting metrics were compared for analysis. The analysis showed that CLAHE gives the best accuracy after being trained for crack detection. The code is attached with the following link. Link to code

***Index Terms*—CNN, CLAHE, AHE, BBHE, WTHE, RMSHE, image enhancement, mean square error, crack detection**

I. Introduction

Microstructures are structures of different materials viewed at a micro level. It is important to study how a material has been made and its quality. Study of microstructure can help with obtaining information like defects, impurities, grains etc. As industries run on thousands of different kinds of materials, it is important to detect the flaws in them. One prime example would be cracks which make any material brittle and unfit for industrial use. Early crack detection allows planning for preventive measures and foresee possible damages. The idea is to determine whether the surface has detect or not. Difficulties may arise due to added noise or irregularities in surfaces. Hence, a proper image enhancement technique is also crucial for prominent visuals.

II. CNN Architecture Description

The Convolutional Neural Network (CNN) is a popular subtype of the Neural Networks which is effective for applications in image processing tasks. CNN typically consists of four types of layers that includes convolutional, pooling, fully connected and classification layers.

In our project, we have used self built CNN model that consistes of 3 Conv2D layers, 3 MaxPool2D layers, 2 Dense layers, 1 Dropout and 1 BatchNormalization.The model used was a Sequential Model with total params: 7,487,170, trainable params: 7,486,658, non-trainable params: 512.

This CNN model was used on images after the application of image enhancement technique that include CLAHE (Contrast Limited Adaptive Histogram Equalization), AHE (Adaptive Histogram Equalization), BBHE (Brightness Bi-Histogram Equalization), RMSHE (Recursively Mean-Separate Histogram Equalization) and WTHE (Weighted Threshold Histogram Equalization).

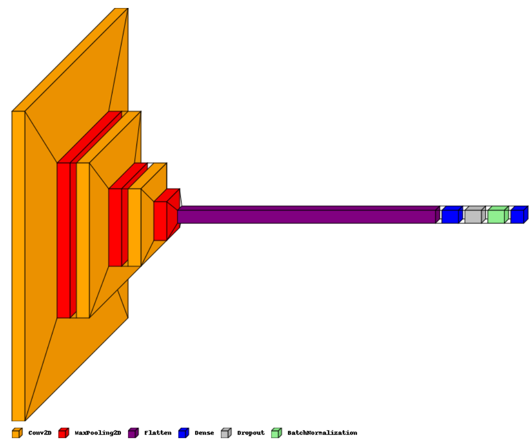

Fig. 1. CNN block diagram

III. Dataset Description

The dataset contains concrete images of 1000 negative images without cracks and 1000 positive images with cracks.Each image is 227 x 227 pixels with RGB channels.The frequency of images from seven classes are shown in fig.2 and sample images from each class is shown in fig.3.

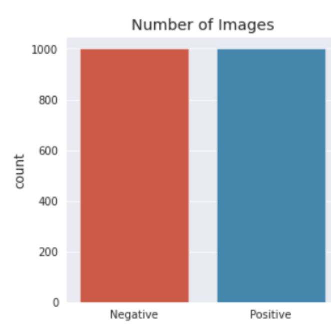

Fig. 2. Distribution of Dataset

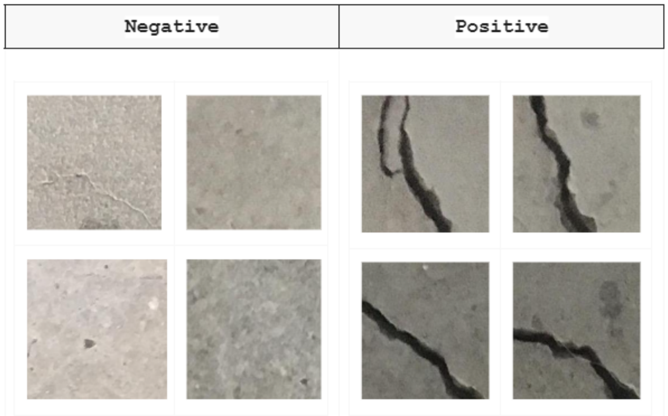

Fig. 3. Sample images from Dataset

IV. Experimental Results and Discussion

After the implementation of CNN, it is evident that CLAHE has the highest accuracy with 95% and performs the best compared to other histogram equalization techniques.The worst performance after the implementation of image enhancement technique is shown RMSHE with an accuracy of 89% . The experimental results for the best and worst are given in fig:4,5 respectively. The following evaluation metrics are used:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

```
Confusion Matrix:
 [[965  35]
 [ 59 941]]
                precision    recall  f1-score   support

Clahe_Negative       0.94      0.96      0.95      1000
Clahe_Positive       0.96      0.94      0.95      1000

      accuracy                           0.95      2000
     macro avg       0.95      0.95      0.95      2000
  weighted avg       0.95      0.95      0.95      2000
```

Fig. 4. CLAHE Result

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Confusion Matrix:
 [[996   4]
 [213 787]]
                precision    recall  f1-score   support

RMSHE_Negative       0.82      1.00      0.90      1000
RMSHE_Positive       0.99      0.79      0.88      1000

      accuracy                           0.89      2000
     macro avg       0.91      0.89      0.89      2000
  weighted avg       0.91      0.89      0.89      2000
```

Fig. 5. RMSHE Result

Fig.6 shows the images after applying different enhancement techniques:

Fig. 6. Overall Result

V. Conclusion and Future Work

In our present work, we can conclude that CLAHE is the best image enhancement technique for detection of crack in concrete microstructure. There is a positive correlation between mean square error and entropy.

Our vision is to work with super resolution and more advanced and extended enhancement techniques.We also intend to work with other CNN models to achieve a higher accuracy for better prediction.

VI. References

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