SURFACE DEFECT RECOGNITION USING AUTOENCODER BASED CONVOLUTIONAL NEURAL NETWORK

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Abstract

Surface defect detection is the main part of quality control in the production industry. Traditional defect inspection is usually performed manually under the supervision of skilled workers. These manual visual methods have various limitations including low efficiency, lack of accuracy, high labor costs, slow verification speed, largely time-wasting, and poor precision for long-term industrial applications. On the other hand, automated approaches [1, 2, 3, 4] have been proposed for this purpose using Convolutional Neural Networks (CNN). In this work, we propose a novel approach to classify surface defects using Convolutional Autoencoder (AE) and CNN. Our approach requires small amount of data for training compared to only using CNN.

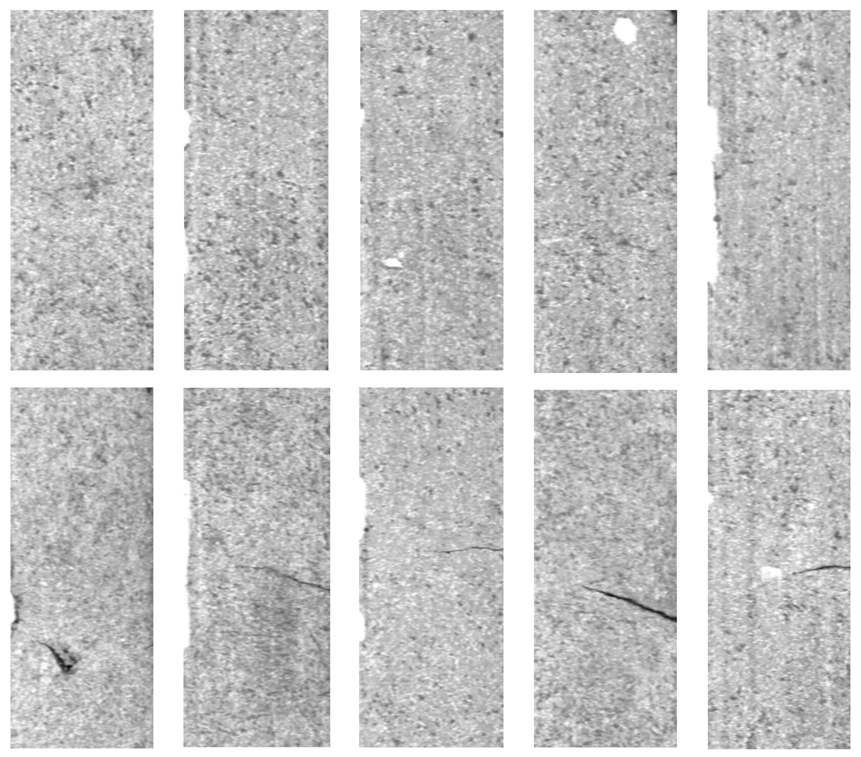
Dataset

Dataset :- KolektorSDD [6]

The dataset consists of 400 images. There are 52 defective images and 348 non-defective images. The raw images were different resolutions from 1240 x 500 pixels to 1270 x 500 pixels.

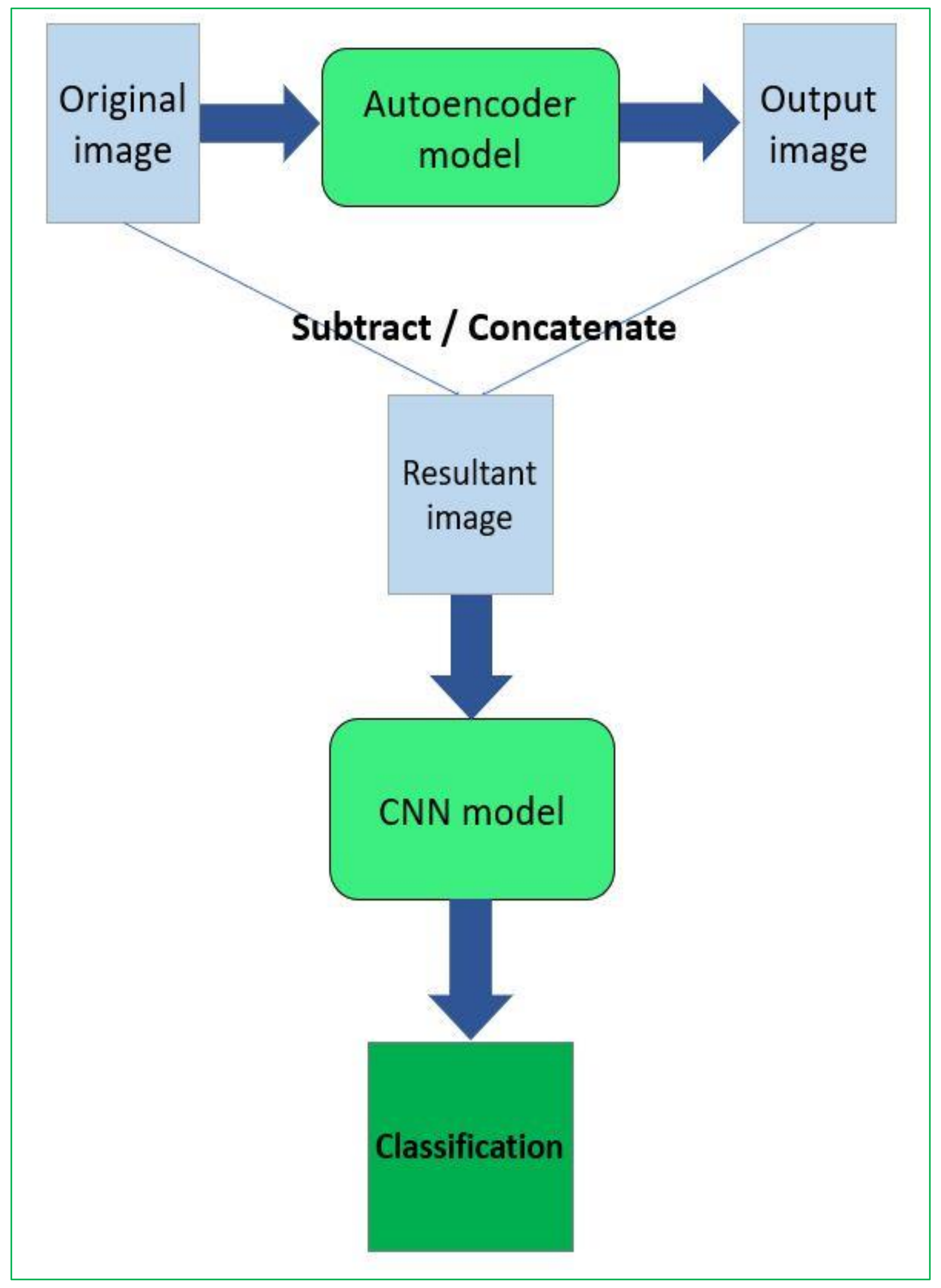
Samples of non-defective images

Samples of defective images



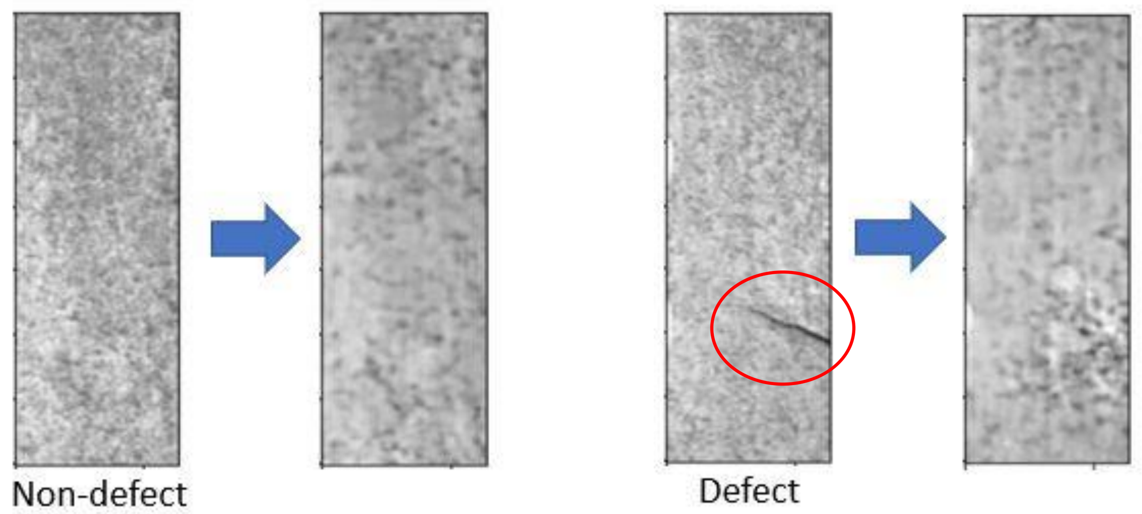
	Number of Images	Number of defect images	Number of non-defect images
Training	321	42	279
Testing	79	10	69
Total	400	52	348

Methodology

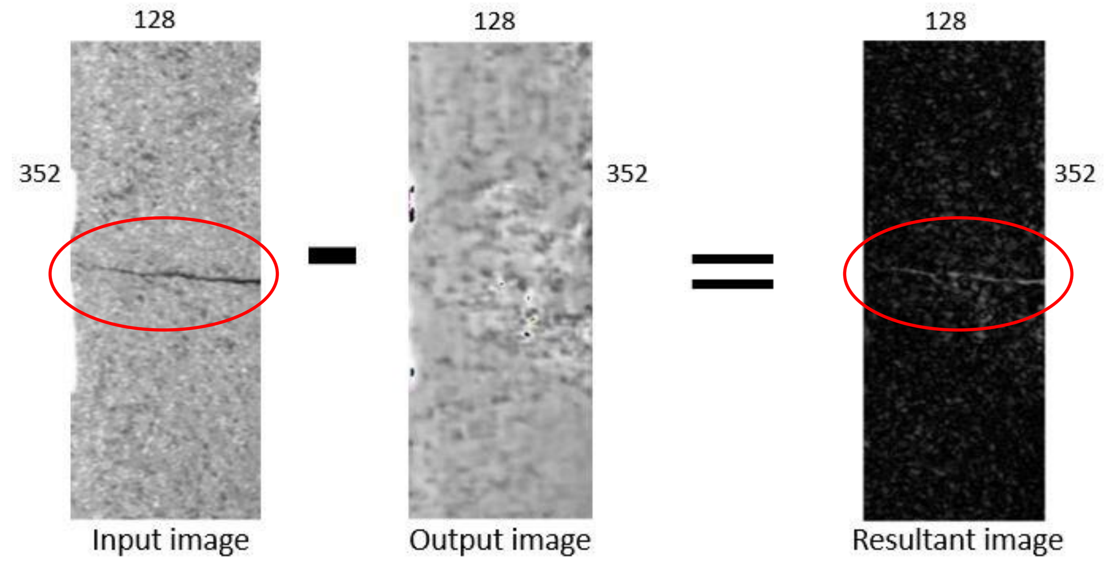


Flowchart of the Proposed Methodology

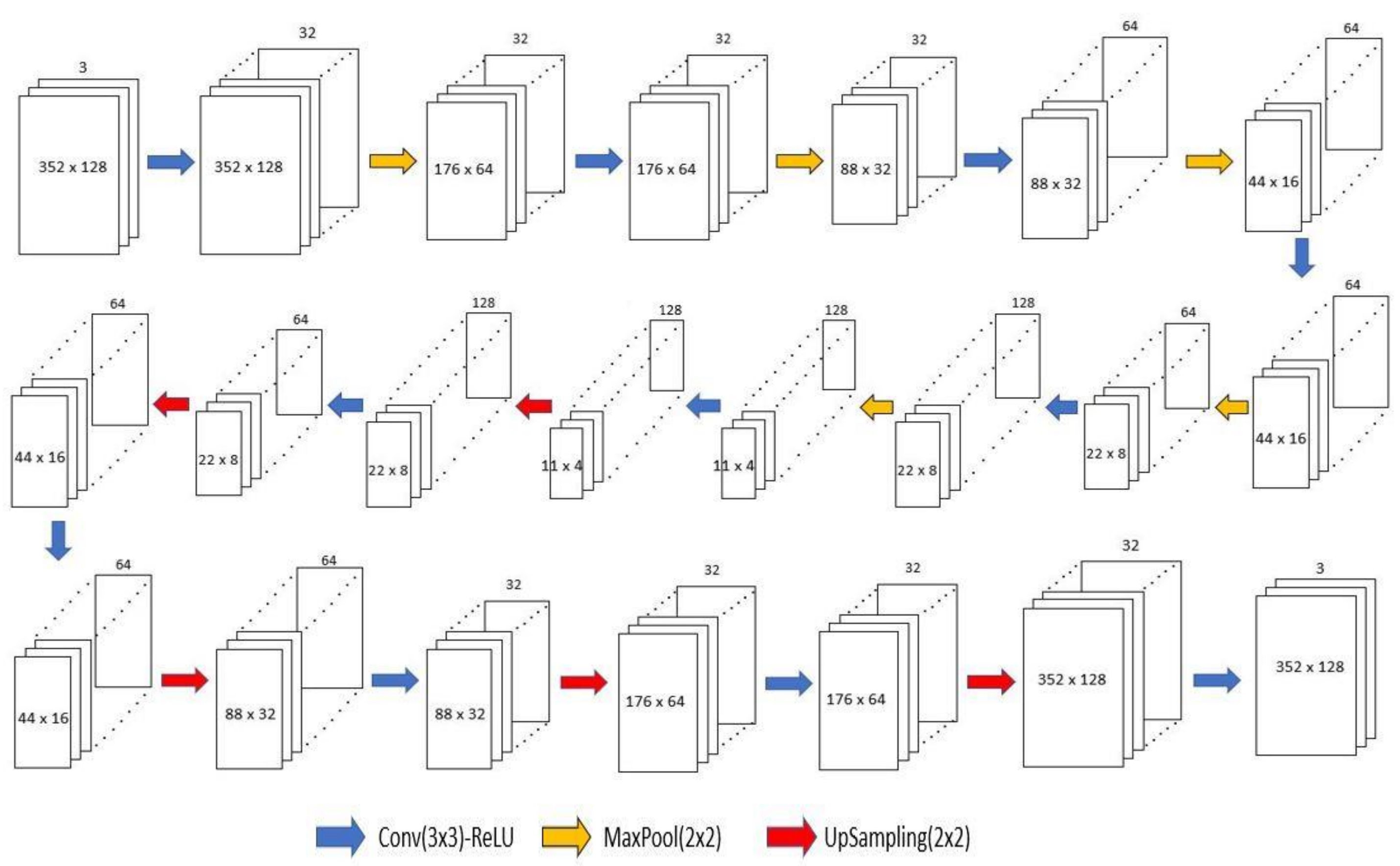
1. Train the Convolutional AE model only using the non-defective images, and therefore, at test time when a defective image is given as the input to this AE, its non-defective version can be produced.



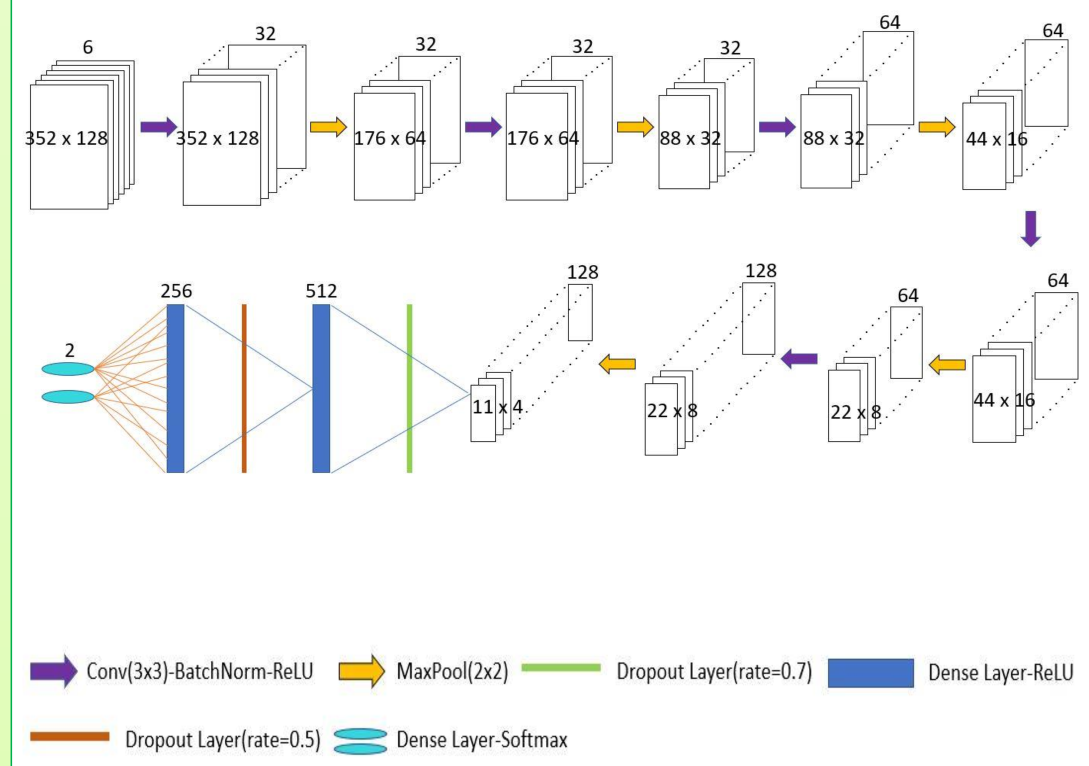
2. Train a CNN with the original and the AE reconstructed images as the input.



Autoencoder Architecture



CNN Architecture



Experiments & Results

- The hyperparameters were fine-tuned of the CNN model which consists of 3 convolutional layers (32, 32, 64) and 3 fully connected layers (512, 256, 2).

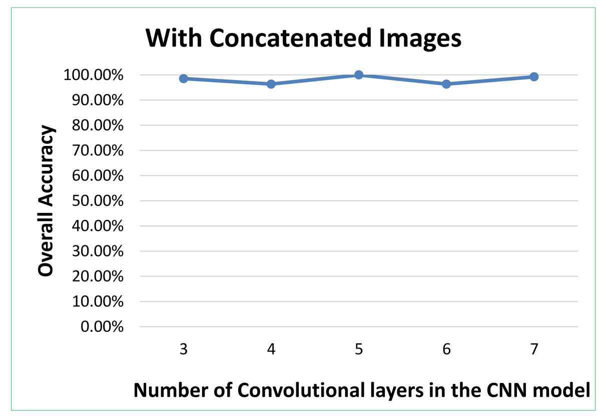
Dropout layers	Batch size	Accuracy (Concatenated images)	Accuracy (Subtracted images)	Accuracy (Original images)
0.7, 0.5	8	**94.28%**	93.55%	50.00%
0.7, 0.5	32	**93.55%**	93.55%	84.28%
-	16	**95.00%**	93.55%	74.28%
0.7	16	**94.28%**	94.28%	89.28%
0.5	16	**92.83%**	89.28%	88.55%
0.7, 0.5	16	**98.55%**	94.28%	89.28%

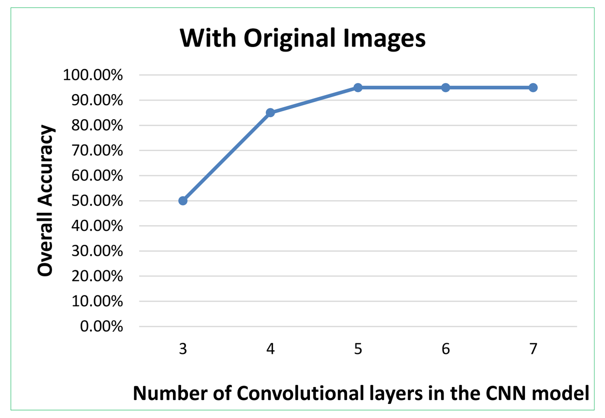
- Effect of data augmentation with concatenated images to train the CNN model.

With Data Augmentation	Without Data Augmentation
98.55%	97.83%

- Effect of the number of convolutional layers in the CNN model.

Number of convolutional layers	Accuracy (With concatenated images)	Accuracy (With original images)
3	**98.55%**	50.00%
4	**96.38%**	85.00%
5	**100.00%**	95.00%
6	**96.38%**	95.00%
7	**99.28%**	95.00%





Confusion matrix for the best classification result

		Predicted Classes	
		Non-defective	Defective
Actual Classes	Non-defective	69	0
	Defective	0	10

- Different evaluation measures

Number of convolutional layers in the CNN model	Accuracy	Precision	Recall	F1_Score
3	98.55%	0.8333	1	0.9091
4	96.38%	0.6667	1	0.8000
5	**100.00%**	1.0000	1	**1.0000**
6	96.38%	0.6667	1	0.8000
7	99.28%	0.9091	1	0.9524

- Comparison with similar approaches on the KolektorSDD dataset.

Approach	Accuracy (%)	F1_score (%)
Zhang et al., (2020) [3]	99.33	98.04
Li et al., (2020) [4]	98.74	98.97
Li et al., (2021) [5]	99.16	96.77
Ours	100.00	100.00

Conclusion

- In this study, we proposed a novel methodology to detect defects using Convolutional AE and CNN. Our approach can be trained with small number of labeled training data.
- We have applied Autoencoder to enhance the images and the CNN model for the classification process. Based on the experimental results, subtracted images & concatenated images (with the Autoencoder model) are performed better than original images (without using the Autoencoder model) with the proposed CNN architecture. The model performance was improved using data augmentation techniques.
- Better results were given by enhanced images using Autoencoder than original images. Enhanced images lead to achieving good results from a small CNN model with a small dataset. Therefore, the proposed approach saved the computational cost and time.
- We were able to gain 100% accuracy from this methodology.

References

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5) Li, Y. and Li, J., "An End-to-End Defect Detection Method for Mobile Phone Light Guide Plate via Multitask Learning." In IEEE Transactions on Instrumentation and Measurement, 70, pp.1-13. 2021.
6) https://www.vicos.si/resources/kolektorsdd/