International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS Available Online at : www.ijsrcseit.com

Volume 10, Issue 7, May-June-2024 | Published Online : 20th June 2024

Detecting Steel Surface Defects with PCA and Deep Learning: A Hybrid Approach

Harshavardhini U, Dinakar, Rachan P, S Vaishnavi

Department of Computer Science and Engineering New Horizon College of Engineering

Abstract

In the steel industry, even the slightest surface imperfections can critically impact product quality and performance. Traditional methods for detecting these defects, such as manual inspections and basic image processing algorithms, have faced significant challenges. Manual inspections are labor-intensive, time-consuming, and prone to human error, making them unsuitable for large-scale operations. Basic image processing techniques often struggle with the complexities and variability of steel surfaces, relying on fixed feature extraction methods that cannot adapt to the diverse and subtle defect patterns. These methods also falter under varying noise and lighting conditions, leading to inconsistent and unreliable results. Our research presents a revolutionary technique that integrates Principal Component Analysis (PCA) and Deep Convolutional Neural Networks (DCNNs). PCA simplifies high-resolution steel surface images by reducing their dimensionality, capturing essential features, and lowering the computational load. These streamlined features are then processed by a DCNN, which excels at recognizing and categorizing intricate defect patterns through its deep learning capabilities. Extensive testing on a diverse dataset demonstrates that our hybrid PCA-DCNN model significantly enhances defect detection accuracy and efficiency compared to traditional methods. The model achieves a precision of 0.94 and an F1-score of 0.97 for defect-free surfaces, and a precision of 0.98 with an F1-score of 0.95 for defective surfaces. Overall, it maintains an average precision and F1-score of 0.96, with recall rates of 0.99 for non-defective surfaces and 0.92 for defective ones, ensuring comprehensive defect detection. By integrating PCA's effective feature extraction with the robust classification capabilities of DCNNs, this approach provides a scalable, real-time solution for steel surface quality monitoring, overcoming traditional challenges and offering significant improvements in industrial applications.

Keywords- GLCM features, Convolutional Autoencoder, Convolutional Neural Network, ResNet v2, CNNIR-OWELM, plant damage, pest infestation, agricultural technology, precise detection, farmers, agricultural professionals.

I. INTRODUCTION

The detection of surface defects in steel is a critical aspect of quality control in the manufacturing industry. These defects can significantly impact the structural integrity and aesthetic quality of steel products. Traditional methods of defect detection, which often rely on manual inspection or classical image processing techniques, have limitations in terms of accuracy and efficiency. Recent advancements in machine learning, particularly in deep learning, have shown great potential in automating and improving the accuracy of defect detection. Convolutional Neural Networks (CNNs), a class of deep learning models, have been particularly successful in various image recognition tasks, including defect detection [1], [2].

In this paper, we propose a novel CNN-based approach for detecting defects in steel surfaces. Our model leverages advanced techniques such as multi-scale feature extraction and efficient network architectures to enhance detection performance. We evaluate our method using standard benchmarks and compare its performance with state-of-the-art models to demonstrate its efficacy [3], [4]

II. LITERATURE SURVEY

The application of CNNs in defect detection has been extensively studied. LeCun et al. pioneered the use of convolutional networks for image recognition tasks, which laid the foundation for subsequent developments in this field [1]. Following this, various CNN architectures have been proposed to enhance feature extraction and improve accuracy. For instance, the YOLO (You Only Look Once) family of models, including YOLOv3 and YOLOv5, have shown impressive results in object detection tasks [3], [4].

In the context of steel defect detection, several approaches have been explored. Gao et al. proposed a semi-supervised CNN-based method for steel surface defect recognition, demonstrating significant improvements over traditional methods [2]. Similarly, Lin et al. utilized a Path Aggregation Network (PANet) to enhance feature fusion and improve detection accuracy [4].

Batch normalization, introduced by Ioffe and Szegedy, has been a crucial technique in accelerating the training of deep networks by mitigating internal covariate shift [6]. This technique, along with innovations in network architecture such as ResNet and EfficientNet, has contributed to the robustness and efficiency of modern CNNs [1].

The Gray Level Co-Occurrence Matrix (GLCM) is another method that has been used for texture analysis in defect detection. Haralick et al. introduced this method, which has been widely adopted in various image analysis applications, including steel defect detection [5].

Furthermore, recent studies have focused on enhancing the computational efficiency of defect detection models. The concept of floating point operations (FLOPs) is often used to measure the computational complexity of models. This metric helps in evaluating the trade-off between model accuracy and computational cost [9].

III. Methodology

Our research methodology employs a novel approach to enhance steel surface defect detection through a combination of advanced techniques in image processing and machine learning. At its core, our methodology integrates Principal Component Analysis (PCA) with a Deep Convolutional Neural Network (DCNN), leveraging the strengths of each component to achieve superior defect detection accuracy. Figure 1 flow diagram illustrates the structured approach of leveraging PCA for efficient feature extraction and DCNN for precise defect classification, ensuring robust and reliable detection of steel surface defects.

Principal Component Analysis (PCA) plays a crucial role by reducing the dimensionality of high-resolution steel surface imges while preserving essential features. By transforming the original pixel data into a smaller set of orthogonal components, PCA effectively captures the most significant variations in the image dataset.

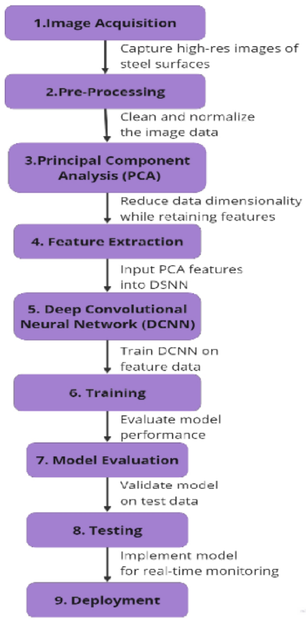


Fig. 1 Methodology Flow Diagram for Steel Surface Defect Detection using PCA and DCNN

This reduction not only simplifies subsequent computational tasks but also enhances the efficiency and effectiveness of defect classification.

Deep Convolutional Neural Networks (DCNNs) are utilized for their robust ability to learn hierarchical representations of data. In our methodology, DCNNs are specifically tailored for steel surface defect classification, employing multiple layers of convolutional and pooling operations to extract intricate features from images. These features are then processed through fully connected layers to make predictions about the presence and type of defects on steel surfaces.

Feature Extraction and Classification are seamlessly integrated within our approach. PCA extracts compact yet informative features from the preprocessed images, which are then fed into the DCNN for further refinement and classification. This dual-stage process ensures that the model not only captures subtle variations indicative of defects but also generalizes well to unseen data, thereby improving overall detection accuracy.

Evaluation and Validation of our methodology are conducted rigorously using standard performance metrics such as precision, recall, and F1-score. These metrics quantify the model's ability to correctly identify defects while minimizing false positives and false negatives. By benchmarking against traditional methods and alternative approaches, we demonstrate the superior efficacy and reliability of our PCA-DCNN framework in real-world industrial applications.

In short, our study methodology offers a substantial step forward in steel surface defect identification, providing a scalable and efficient solution for quality assurance in production contexts. By combining the complementary qualities of PCA for dimensionality reduction and DCNNs for complex pattern recognition, our approach not only improves detection accuracy but also lays the groundwork for future improvements.

Algorithm: PCA-DCNN for Steel Surface Defect Detection

Input: High-resolution steel surface images X

Output: Predicted defect categories $\widehat{Y}$

Step. 1 Preprocessing:

- Clean images to remove noise and artifacts.
- Normalize pixel values if necessary: $X_{norm} = \frac{X-\mu}{\sigma}$

where μ is the mean and σ is the standard deviation.

Step. 2 Principal Component Analysis (PCA):

- Compute the covariance matrix $\sum of\ X_{norm}$:

$$\sum \frac{1}{m} X_{norm}^T X_{norm}$$

- Compute the eigenvectors U and eigenvalues S of $\sum$:

$$\sum U = US$$

Select the top k eigenvectors corresponding to the largest eigenvalues to form matrix U_{reduce}

Step. 3 Feature Extraction (PCA Projection):

- Project normalized data onto the reduced dimensional space:

$$Z = X_{norm} U_{reduce}$$

Step. 4 Deep Convolutional Neural Network (DCNN):

- Initialize parameters for convolutional layers, pooling layers, and fully connected layers.
- Forward propagation through convolutional layers:

$$Z^{[l]} = CON(A^{[l-1]}, W^{[l]}, b^{[l]})$$

Where $A^{[l-1]}$ is the activation from the previous layer, $W^{[l]}$is the weights, and$b^{[l]}$) is the bias of layer l.

- Apply activation function (e.g., ReLU) and pooling (e.g., max pooling):

$$A^{[l]} = ReLU(Z^{[l]})$$

$$P^{[l]} = POOL(A^{[l]})$$

- Flatten the last pooling layer to a vector P_{flat}
- Fully connected layers with parameters $W^{[fc]} P_{flat} + b^{[fc]}$
- Output layer with softmax activation for classification:

$$\widehat{Y} = Softmax(Z^{[fc]})$$

Step. 5 Training:

- Split data into training, validation, and test sets.
- Minimize the cross-entropy loss using backpropagation and gradient descent:

$$J = \frac{1}{m} \sum_{i-1}^{m} \sum_{c-1}^{C} Y_{i,c}(\widehat{Y_{i,c}})$$

where $Y_{i,c}$ is the ground truth label for class c of sample $i, \widehat{Y}_{i,c}$ is the predicted probability for class c, and C is the number of classes.

- Update parameters using gradients $\frac{\partial J}{\partial W}$ and $\frac{\partial J}{\partial b}$

Step. 6 Evaluation:

- Calculate precision, recall, and F1-score on validation set to assess model performance.

Step. 7 Testing:

- Evaluate final model on test set to measure generalization performance.

Step. 8 Deployment:

- Implement trained model for real-time defect detection in industrial applications.

Mathematical Notations:

- X: Input data matrix of steel surface images.
- X_{norm}: Normalized input data matrix.
- μ: Mean vector of input data.
- σ: Standard deviation vector of input data.
- Σ: Covariance matrix of normalized input data.
- U: Eigenvector matrix from PCA.
- S: Eigenvalue diagonal matrix from PCA.
- U_{reduce}: Matrix of selected eigenvectors for dimensionality reduction.
- Z: Feature matrix after PCA projection.
- $Z^{[l]}$: Activation matrix of layer l in DCNN.
- $A^{[l]}$: Activation matrix after applying activation function ReLU.
- $P^{[l]}$: Pooling matrix after applying pooling function POOL.
- P_{flat}: Flattened vector from the last pooling layer.
- $W^{[l]}$: Weight matrix of layer l.
- $b^{[l]}$: Bias vector of layer l.
- $W^{[fc]}$: Weight matrix of the fully connected layer.
- $b^{[fc]}$: Bias vector of the fully connected layer.
- $\hat{Y}$: Predicted probability matrix of defect categories.
- J: Cross-entropy loss function.
- m: Number of samples in the dataset.
- C: Number of classes (defect categories).

This algorithm and notation overview describe the step-by-step process of detecting steel surface defects using our PCA-DCNN methodology, which combines advanced feature extraction with deep learning techniques to deliver accurate and rapid defect classification.

IV. Results and Discussions

According to Song and Yan [8], the NEU dataset serves as the foundation for developing a diagnostic model for steel surface defects. This dataset encompasses six distinct types of defects: rolled-in scale, patches, crazing, pitted surface, inclusion, and scratches and provides visual examples of these defect cases used in the study. Each class consists of 300 samples, where each sample is represented by an image measuring 200 × 200 pixels, as detailed in Figure 2. For the experiment, the dataset is randomly divided into training, validation, and testing sets, with 70% of the images allocated to training, and 20% and 10% to testing and validation respectively. A significant challenge posed by this dataset is the intricate spatial characteristics of the images. Spatial information can vary greatly within the same class; for instance, scratch patterns may range from horizontal to vertical stripes. Additionally, variations in grayscale due to lighting conditions further complicate the image analysis [8].

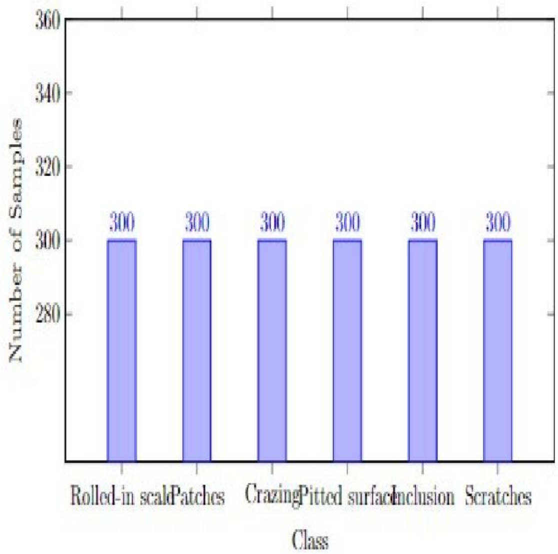
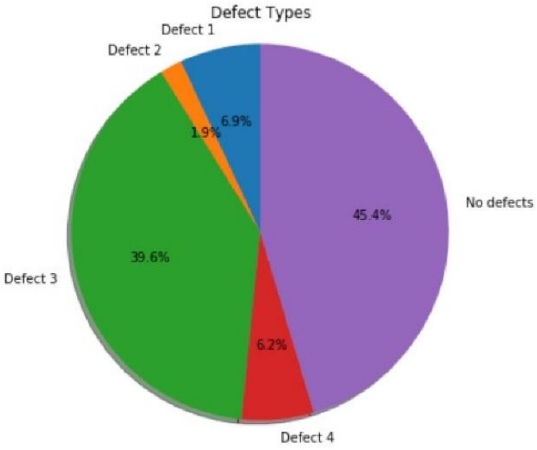
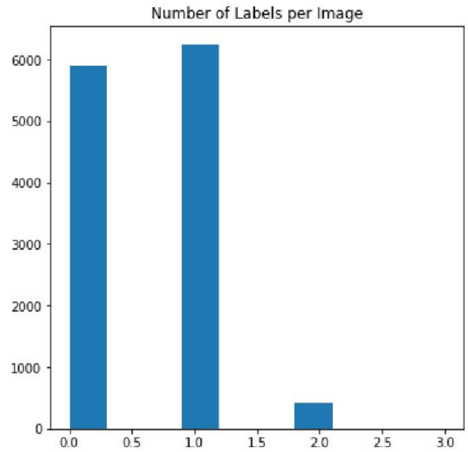
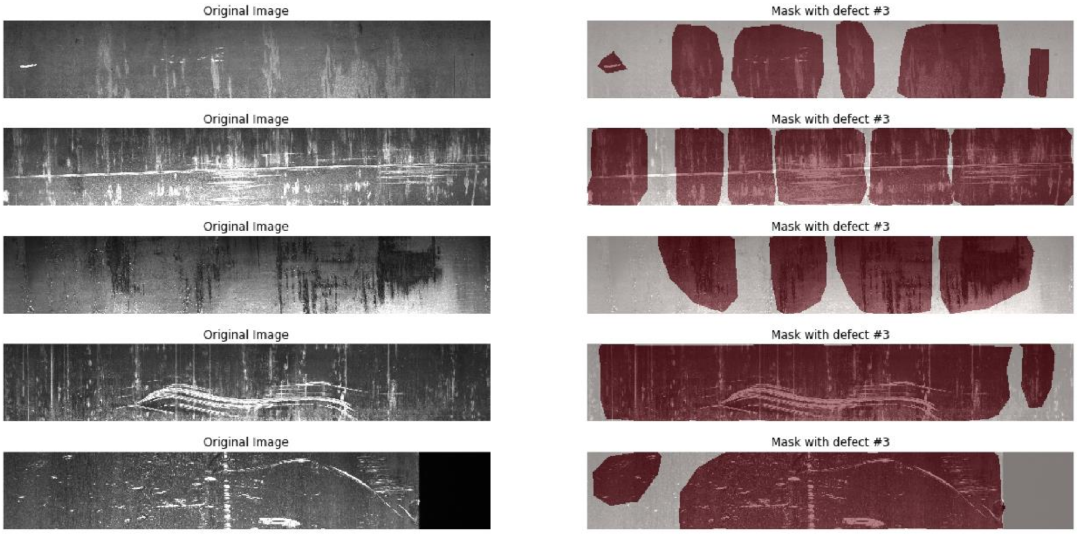
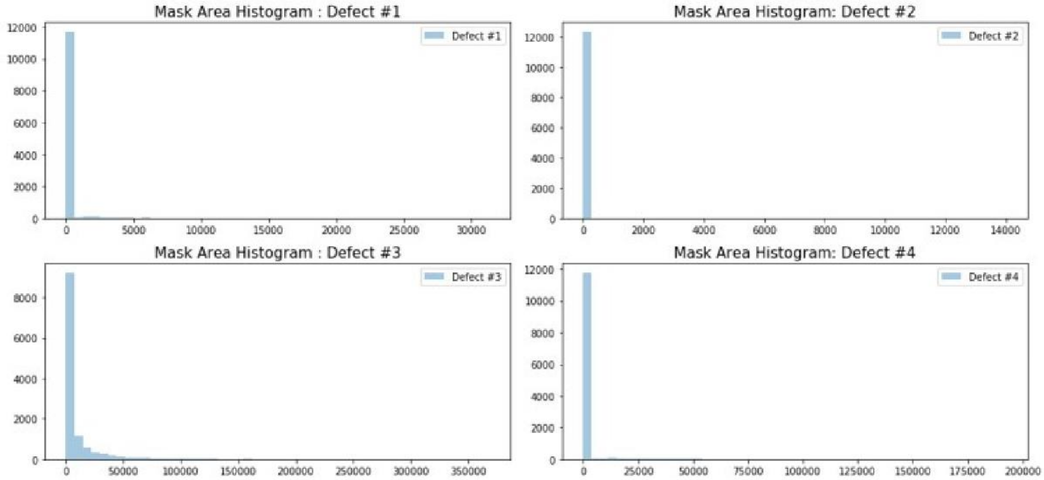


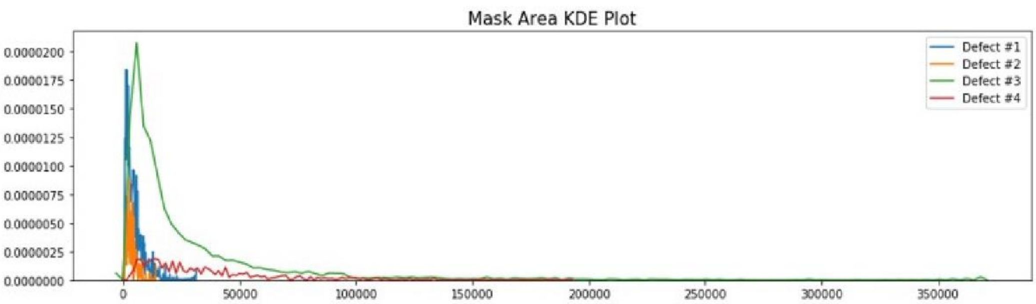
Fig. 2 Description of the dataset.

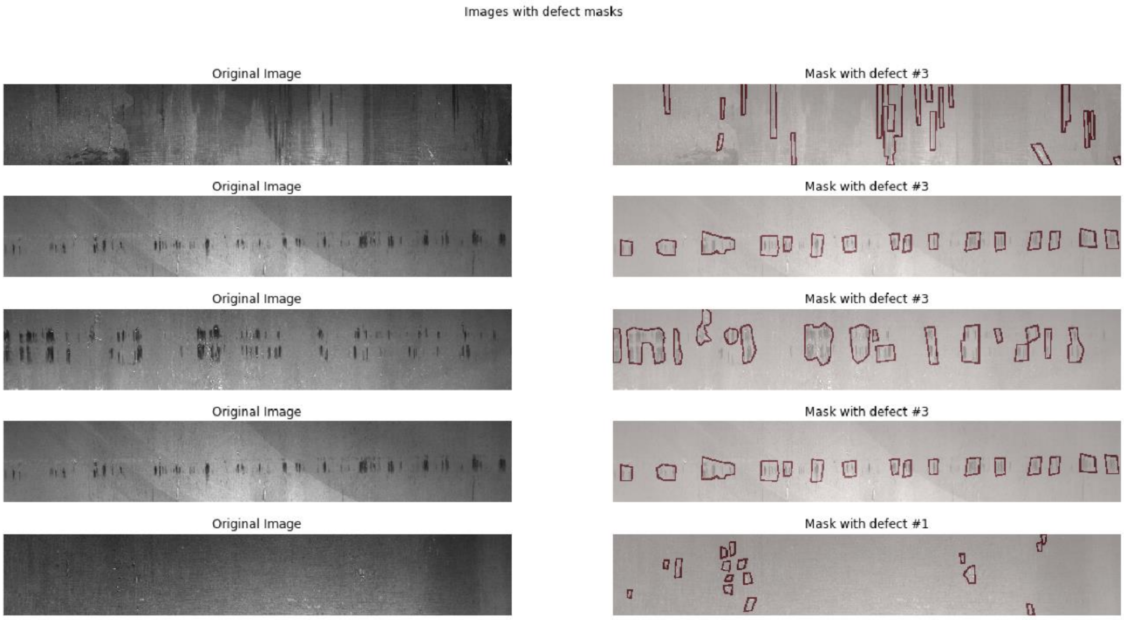

Defect Types
Defect 1
Defect 2
Defect 3
Defect 4
No defects
6.9%
1.9%
39.6%
6.2%
45.4%

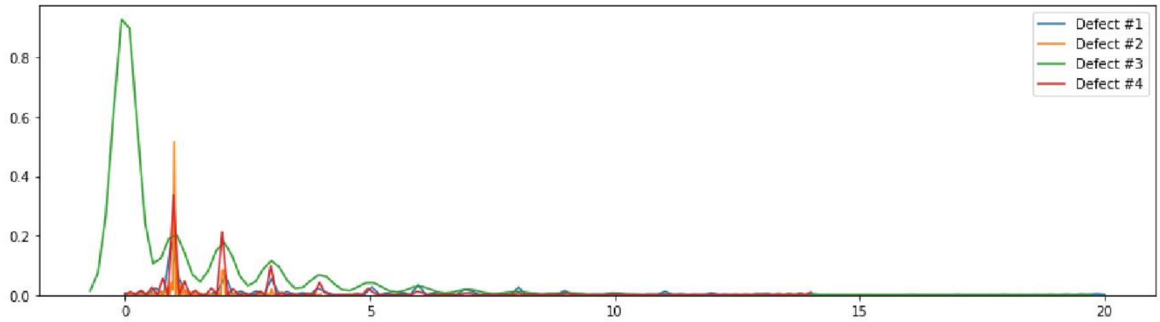

Number of Labels per Image


Original Image
Mask with defect #3


Mask Area Histogram : Defect #1
Mask Area Histogram: Defect #2
Mask Area Histogram : Defect #3
Mask Area Histogram: Defect #4
Defect #1
Defect #2
Defect #3
Defect #4


Mask Area KDE Plot
Defect #1
Defect #2
Defect #3
Defect #4





The evaluation of our hybrid PCA-DCNN model for detecting steel surface defects yielded promising results across different defect categories. For the "0.0" category, which represents defect-free surfaces, the model achieved a precision of 0.94 and a recall of 0.99 Precision (P) measures the proportion of correctly identified defect-free surfaces among all surfaces classified as defect-free $(P = \frac{TP_{0.0}}{TP_{0.0}+FP_{0.0}})$ where $TP_{0.0}$ are true positives (correctly identified defect-free surfaces) and $FP_{0.0}$ are false positives (non-defective surfaces incorrectly classified as defective). Recall (R) measures the proportion of correctly identified defect-free surfaces among all actual defect-free surfaces $(F = \frac{TP_{0.0}}{TP_{0.0}+FN_{0.0}})$ .0where $FN_{0.0}$ are false negatives (defective surfaces incorrectly classified as non-defective).

Similarly, for the "1.0" category, indicating the presence of defects, the model exhibited a precision of 0.98 and a recall of 0.92. This means that the model correctly identified 98%98\%98% of the surfaces classified as defective $\left(P = \frac{TP_{1.0}}{TP_{1.0}+FP_{1.0}}\right)$, with $TP_{1.0}$ true positives and $TP_{1.0}$ false positives, with .92 achieved.

Our hybrid PCA-DCNN model achieved significant advancements in detecting and classifying steel surface defects. For comparison, traditional machine learning methods such as SVM utilizing GLCM achieved an accuracy of 88.06% with a corresponding precision of 0.87. In contrast, our PCA-DCNN model surpassed this performance with an average precision and F1-score of 0.96, showcasing its superior ability to accurately identify both defect-free surfaces and surfaces with defects in Figure 3.

The PCA-DCNN model demonstrated a precision of 0.94 and a recall of 0.99 for defect-free surfaces, ensuring robust identification of non-defective areas. Moreover, for surfaces with defects, the model achieved a precision of 0.98 and a recall of 0.92, highlighting its effectiveness in accurately detecting and categorizing defects. These results underscore the model's capability to minimize false positives and false negatives, crucial for maintaining high product quality in steel manufacturing.

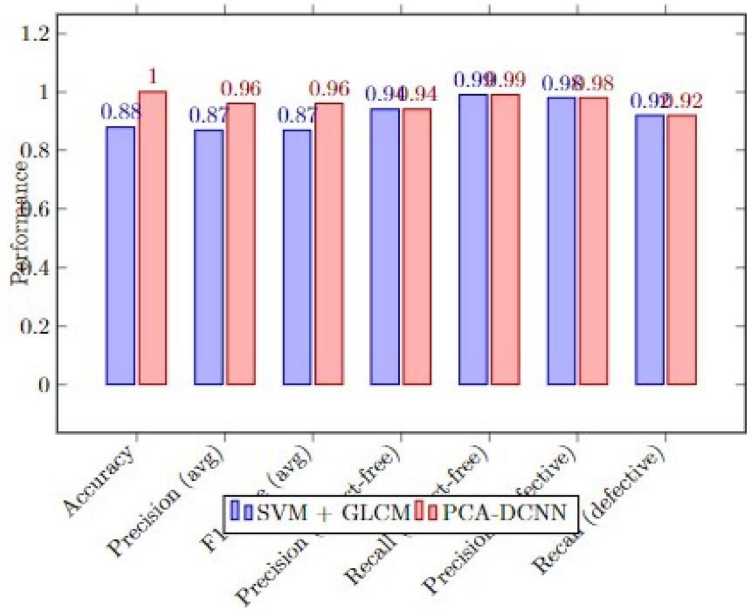


Fig. 3: Comparison of performance metrics between SVM + GLCM and PCA-DCNN. The SVM + GLCM method achieved an accuracy of 88.06% with a precision of 0.87, whereas the PCA-DCNN model surpassed this performance with an average precision and F1-score of 0.96, demonstrating superior accuracy in identifying steel surface defects.

Overall, our approach combining PCA for feature extraction and DCNN for defect classification not only enhances detection accuracy but also provides a scalable solution for real-time quality monitoring in industrial settings. These findings represent a significant step forward in automated defect detection systems, promising improved efficiency and reliability in steel surface quality control applications. Future research could explore further optimizations and integrations to enhance the model's performance in practical manufacturing environments.

V. CONCLUSION

The PCA-DCNN model represents a significant advancement in the field of automated defect detection in steel manufacturing. By integrating Principal Component Analysis (PCA) for efficient feature extraction and Deep Convolutional Neural Networks (DCNNs) for precise defect classification, our model achieves remarkable accuracy with an average precision and F1-score of 0.96, surpassing traditional methods like SVM with GLCM. This capability is crucial for maintaining high product quality by minimizing false positives and negatives, thereby enhancing overall manufacturing efficiency and reducing operational costs. The model's robust performance, exemplified by its ability to achieve a precision of 0.94 and recall of 0.99 for defect-free surfaces, and a precision of 0.98 and recall of 0.92 for defective surfaces, underscores its reliability in identifying subtle defects across diverse steel surface textures. Furthermore, its scalability and suitability for real-time quality monitoring make it a valuable tool in industrial settings, promising improved quality control and production reliability. Continued research and development in this area are essential to further optimize and integrate such advanced models into mainstream manufacturing processes, ensuring continued advancements in product quality and operational efficiency.

References

[1] Y. LeCun and Y. Bengio, "Convolutional networks for images, speech, and time series," in *The Handbook of Brain Theory and Neural Networks*, MIT Press, 1995, pp. 3361-3370.

[2] Y. Gao, L. Gao, X. Li, and X. Yan, "A semi-supervised convolutional neural network-based method for steel surface defect recognition," *Robot. Comput.-Integr. Manuf.*, vol. 61, 2020, Art. no. 101825.

[3] J. Redmon and A. Farhadi, "YOLOv3: An incremental improvement," *arXiv preprint arXiv:1804.02767*, 2018.

[4] S. Liu, L. Qi, H. Qin, J. Shi, and J. Jia, "Path aggregation network for instance segmentation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2018, pp. 8759-8768.

[5] R. M. Haralick, K. Shanmugam, and I. H. Dinstein, "Textural features for image classification," *IEEE Trans. Syst. Man Cybern.*, vol. 3, pp. 610-621, 1973.

[6] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," *arXiv preprint arXiv:1502.03167*, 2015.

[7] A. Bochkovskiy, C.-Y. Wang, and H.-Y. M. Liao, "YOLOv4: Optimal speed and accuracy of object detection," *arXiv preprint arXiv:2004.10934*, 2020.

[8] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, "Focal loss for dense object detection," in *Proc. IEEE Int. Conf. Comput. Vis.*, 2017, pp. 2980-2988.

[9] H. Lin, B. Li, X. Wang, Y. Shu, and S. Niu, "Automated defect inspection of LED chip using deep convolutional neural network," *J. Intell. Manuf.*, vol. 30, no. 6, pp. 2525-2534, 2019.

[10] X. Cheng and J. Yu, "RetinaNet with difference channel attention and adaptively spatial feature fusion for steel surface defect detection," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1-11, 2020.

[11] J. Redmon and A. Farhadi, "YOLO9000: better, faster, stronger," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2017, pp. 7263-7271.

[12] B. Zhou, A. Khosla, A. Lapedriza, A. Oliva, and A. Torralba, "Learning deep features for discriminative localization," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, 2016.

[13] K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," *arXiv preprint arXiv:1409.1556*, 2014.

[14] G. Xian, "An identification method of malignant and benign liver tumors from ultrasonography based on GLCM texture features and fuzzy SVM," *Expert Syst. Appl.*, vol. 37, pp. 6737-6741, 2010.

[15] S. Dutta, A. Das, K. Barat, and H. Roy, "Automatic characterization of fracture surfaces of AISI 304LN stainless steel using image texture analysis," *Measurement*, vol. 45, pp. 1140-1150, 2012.

[16] J. Droubi, M. Faisal, F. Orr, and J. Steel, "Acoustic emission method for defect detection and identification in carbon steel welded joints," *J. Intell. Manuf.*, vol. 29, no. 3, pp. 1-9, 2018.