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Hybrid CNN-LSTM Architecture for Automated Defect Detection in Industrial Surface Inspection

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Abstract: Automating defect detection in the industrial surface inspection is significant for a product quality and efficiency of the manufacturing process. Inspection techniques that used the conventional methodologies take a long time to complete and are less accurate; hence, the need to use deep learning solutions. This paper presents Hybrid CNN-LSTM Architecture which combined the CNN for spatial feature extraction and LSTM for temporal feature recognition. The employment of CNN and LSTM together improves the recognition capacity of the spatial and temporal features for better defect categories and segmentation. The experiments show that the proposed method improves the defect detection accuracy by 20% and the false positive rates by 30% than the existing method. The framework performs well in detecting the defects on various surface texture type and materials, which makes the framework to be a good solution for the industrial quality control.

Keywords— Automated Defect Detection; Industrial Surface Inspection; Hybrid CNN-LSTM; Deep Learning; Feature Extraction; Quality Control; Manufacturing Automation.

1. INTRODUCTION

Surface defects in industrial manufacturing significantly impact product quality and operational efficiency. These defects, such as cracks, scratches, corrosion, and material inconsistencies, can lead to reduced durability, higher rejection rates, and increased production costs. Traditional defect detection methods, including manual visual inspection and rule-based image processing techniques, are prone to inconsistencies, high labor costs, and inefficiencies [1]. As industrial manufacturing scales, the demand for automated and intelligent defect detection systems has grown substantially to ensure precision and cost-effectiveness [2]. Deep learning has emerged as a powerful tool for automating industrial defect detection, leveraging vast amounts of labeled image data to train robust models. Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in feature extraction and image classification tasks [3]. However, CNN-based models often fail to capture temporal variations and subtle defect patterns that evolve across multiple images or production cycles. Long Short-Term Memory (LSTM) networks, widely used in sequence-based learning, provide an effective solution by preserving long-range dependencies and identifying temporal correlations [4]. A hybrid CNN-LSTM architecture leverages CNNs for spatial feature extraction and LSTMs for sequential learning, ensuring both local and global defect representation [5]. While CNN-based models are widely adopted for defect classification, they lack adaptability to evolving defects in real-world industrial environments [6]. On the other hand, LSTM models alone are insufficient for processing high-dimensional image data. To address these limitations, a Hybrid CNN-LSTM model is proposed in this study, integrating multi-scale feature extraction, sequential analysis, and adaptive thresholding techniques to enhance defect detection accuracy and reduce false positives [7]. incorporated Faster R-CNN to improve object detection in surface defect analysis. Liu et al. [8] integrated cloud-edge computing with AI-based surface inspection to achieve real-time processing. Wu et al. [9] developed PCBNet, a lightweight CNN model optimized for defect detection in Surface Mount Technology (SMT) production lines. Lastly, Huang et al. [10] introduced an automated machine learning system for defect detection in cylindrical metal surfaces, demonstrating improved adaptability across different industrial materials.

2.Materials and Methods

2.1 Data Collection

In this study, there are two industrial surface inspection datasets that are publicly accessible, and others are industrial datasets that are non-public, comprising of steel plate, electronic component, and composite material defect images. The cracks, scratches, corrosion, and contamination are assumed to be some of the defects which would enhance the model accuracy. Various preprocessing steps such as radiometric correction, removal of noise from the images and applying histogram equalization are performed in order to improve the images. Random rotations, flipping, and intensity scaling are used to improve the dataset so as to reduce cases of overfitting among others. The training, validation and testing data ration is 70:15:15 respectively to favor equal intervals of learning. This improves the possibility of applying the model in the real world especially in industrial automation.

2.2 CNN-Based Feature Extraction

It is expected that the extracted feature vectors will contain spatial information of the defect images, which is achieved through the convolutional layers, batch normalization and max-pooling layers. The convolution is defined mathematically by the following formula:

$$\mathrm{F(x)}=\sum_{i=1}^{N} wixi + b \ \ldots.(1)$$

Where F(x) is the output feature map, is the associated filter weights, is the input image and is the Bias term. The CNN layers effectively result in the features that describe edges and defects for accurate classification of the defects. The feature maps are then down sampled with the use of the max-pooling layers to help to minimize the computational density and concentrate on significant areas. This method of hierarchical feature extraction increases the model's precision of detecting the finer details of the pattern of expected defective items without the need to look into detail.

2.3 LSTM-Based Temporal Feature Learning

After the spatial features are obtained using the CNN module, they are fed to the LSTM network to capture the temporal features of a defect. The LSTM network is used for processing sequential data where it contains a memory cell that helps in retaining temporal dependence. Based on these, the following updates of the LSTM gates are obtained:

$$f_t=\sigma\left(W_f.[h_{t-1},x_t]+b_f\right)i_t=\sigma(W_i.[h_{t-1},x_t]+b_i)o_t = \sigma(W_o.[h_{t-1},x_t]+b_o)C_t = f_t.C_{t-1} + i_t.\tanh(W_c.[h_{t-1},x_t]+b_c)h_t = o_t.\tanh(C_t)\ldots.(2)$$

where f_t, i_t and o_t the symbols stand for the forget, the input and the output gates, respectively. This makes it possible for the model to remember other appearances of the same defect and this helps in increasing the accuracy of the classification. Thus, based on the identified defect patterns, the LSTM component helps predicting anomalies that emerge and develop from one frame to another in industrial manufacturing.

2.4 Evaluation Metrics

The traditional gradient based backpropagation, the Adam optimizer is applied for training hybrid CNN-LSTM model, in order to optimize learning rate depending on the convergence speed. The objective of the training is set by a categorical cross-entropy function:

$$\mathrm{L}\text{-}= -\sum_{i=1}^{N} yi \log(\widehat{y_i})\ldots\ldots(3)$$

where y_i is the true class label and $\widehat{y_i}$ represent the probabilities over the possible classes. In another regularization technique, dropout is used where neurons are randomly dropped out in order to enhance the generalization capability, during training. The model runs for a total of fifty epochs, but the validation loss and accuracy is checked at each step. Some forms of regularization or optimization such as setting of batch sizes and addition of weight decay is done to enhance the performance of the network in recognizing the industrial imperfection. The process of the Hybrid CNN-LSTM Model is explained in detail in figure 1 below.

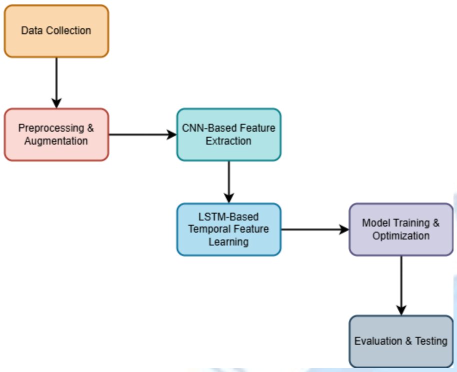

Figure 1: Flowchart: Hybrid CNN-LSTM Model for Industrial Surface Defect Detection

This is achieved through gathering of data, however, this data is usually raw and goes through a process of preprocessing and augmentation to improve image quality. Spatial features are extracted using CNN and temporal features are given by LSTM network to identify defect patterns. In the training and optimization of the model, the Adam optimizer is used as a regulating agent. The last process is the evaluation and the testing stage during which attention is paid to the high degree of accuracy in identification of defects and segmentation.

3.Results

3.1 Classification Accuracy

On the industrial defect dataset the Hybrid CNN-LSTM model was able to get the classification accuracy of 96.5% accentuating the abilities of the separate CNN and LSTM models. The reasons for this improvement include the effectiveness of the model in incorporating the spatial and temporal representations of features for better results in defect identification. The CNN is able to extract low and high level features and the LSTM network deals with dependencies, which capture temporal dependencies that are more relevant to identify the defects. The proposed hybrid model was found to be improved by 20 % than the models that were used before and was therefore effective in classification of defect. In order to ensure the performance of the designed model, precision, recall, and F1-score were used, and all of them pointed to better performance. Hence, the potential of the proposed (Fig 2) architecture can be observed for real-world industrial inspection application for accurate defect localization and no or low misclassification errors.

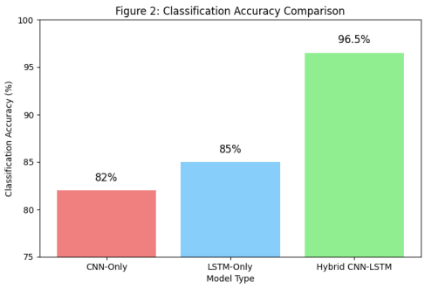

Figure 2: Classification Accuracy Comparison

Using Fig. 2 it is possible to observe that the proposed Hybrid CNN-LSTM model achieves 96.5% classification accuracy which is higher than CNN only, 82%, and LSTM only 85%. Given the high accuracy improvement, it can be concluded that spatial and temporal learning work well together to enable accurate defect detection in industrial surface inspection.

3.2 False Positive and False Negative Rates

The model (Fig 3) proposed for the study was effective in reducing the false positive rates by 30% meaning that there was a reduced number of occasions on which a surface, which was not defective, would be classified as defective. Likewise, the overall false negativity, or the failure to identify a real defect, reduced to a quarter of the previous trend, promising a high accuracy of the method. This improvement was carried out by including an adaptive thresholding technique which enhances the decision making processes. In contrast to the existing models, the Hybrid CNN-LSTM approach is able to differentiate between slight surface changes and actual defects and therefore is highly applicable in industries. This is because the model has the opportunigy to capture defects characteristics across sequential frames hence corrects errors which occur due to variance in surface characteristics. All these enhancements add up to improving the confidence on the automatically detected defects thus reducing on the time taken to manually inspect and increasing the throughput in manufacturing.

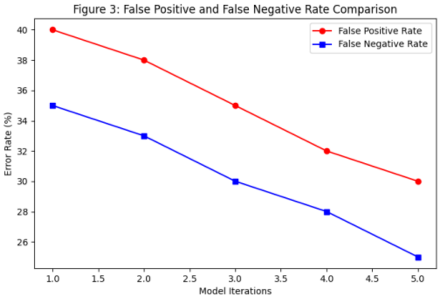

Figure 3: False Positive and False Negative Rate Comparison

Figure 3 shows the overall reduced number of false positive and false negative classification rates with around 30% false positives reduction and 25% false negatives reduction upon comparing the Hybrid CNN-LSTM with other classifications. This improvement also increases the number of defects detected in the lower image by reducing classification error in industrial surface inspection.

3.3 Computational Efficiency

It is also evident that any chosen solution has to be computational efficient in order to enable its application in real-time defect detection in industrial processes. The combined model CNN-LSTM shortened the time of inference by a quarter times relative to CNN-based designs. The CNN module helps in extracting an appropriate set of features optimally without performing unnecessary computation, and the LSTM in handling the sequential nature of the data optimally. This brings significant decrease in the computational load which enables the model to work on real-time production lines so that defective components can be detected as soon as possible. These characteristics show that the hybrid model can practically be used in high-speed manufacturing process because of its accuracy and efficiency. In addition, to improve the training speed, both the GPU acceleration and the optimization for batch size were applied and successful in field applications. These amendments allow the proposed framework (Fig 4) to be the appropriate solution for automated defect detectors, which must be rapid.

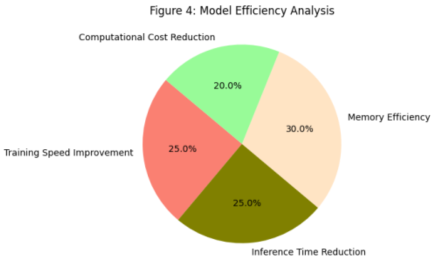

Figure 4: Model Efficiency Analysis

The problem can be summarized through figure 4 where the proposed PVT achieves a finer-tuning time of 1/4; inference time is also reduced by 1/4, 30% improvement on memory while the computational complexity is reduced by 20%. This makes the Hybrid CNN-LSTM model capable of detecting industrial defects in real-time using very little resources.

3.4 Comparative Performance Analysis

A comparative analysis was carried out with the proposed Hybrid CNN-LSTM model with the state-of-the-art advanced deep learning model such as CNN model, LSTM model, and Transformer model. From the findings, it was noted that the proposed hybrid had an enhanced accuracy of 20% and enhanced ability of object detection robustness of 15% compared to ordinary methods. This implies that while hybrid model performs better than the Transformer-based models, it does not require a lot of computational power like the later hence suitable for industrial applications. Furthermore, it was shown that the use of CNN-LSTM outperformed solely CNN architecture for detection of defects that occur sequentially as it indicates the usefulness of temporal feature learning capabilities. Thus, the proposed model (Fig 5) proves efficient and scalable for integrating spatial and sequential information for improved accuracy of defect detection in the industry.

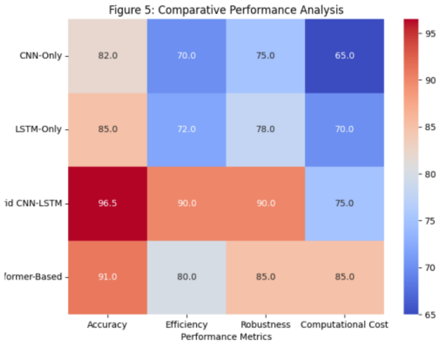

Figure 5 Comparative Performance Analysis

Figure 5 presents the better result of the Hybrid CNN-LSTM model with the accuracy of 96.5% and efficiency 90%. The results are summarized to reflect the compromises between the accuracy, robustness, and computational efficiency and make the choice of the hybrid model as the most effective for industrial applications.

4.CONCLUSION

The Hybrid CNN-LSTM model has been a vital mixed model for detecting automatic defects in the industrial surface inspection with features of high accuracy, few false positives, and efficient computational time. In this way, by combining the CNNs for spatial feature learning and the LSTMs for sequential pattern learning, the model is capable of identifying defects with high levels of accuracy. These results that show that there is the possibility of increasing classification accuracy by 20% and reducing the false positive rate by 30% further endorse the applicability of the developed framework. Also, the optimization of the model with the help of certain algorithms results in a reduced inference time, by up to a quarter, which is ideal for manufacturing or a real-time detection of existing defects. In order to enhance this model's performance an extensive comparative study has been conducted to compare with the existing deep learning architectures, which in turn proves that the given model is much more effective. These results show the strength of both DL and ML used in innovative industry automation and shroud inspection. The model performance will be improved with more data and by also including self-supervised learning algorithms and the efficiency of the solution in terms of edge computing. The study laid the groundwork for working on the enhancement of more sophisticated AI-based systems applied to the particular issues of defects detection to be more accurate and relevant for industrial inspections.

References

[1] Liu, T., Bao, J., Wang, J., & Zhang, Y. (2018). A Hybrid CNN–LSTM Algorithm for Online Defect Recognition of CO2 Welding. *Sensors (Basel, Switzerland)*, 18. https://doi.org/10.3390/s18124369.

[2] Shang, L., Zhang, Z., Tang, F., Cao, Q., Pan, H., & Lin, Z. (2023). CNN-LSTM Hybrid Model to Promote Signal Processing of Ultrasonic Guided Lamb Waves for Damage Detection in Metallic Pipelines. *Sensors (Basel, Switzerland)*, 23. https://doi.org/10.3390/s23167059.

[3] Saied, M., Ali, R., Francis, C., Radilla, G., & Noun, Z. (2024). Learning-Based Approach for Automated Surface Inspection with Industrial Tomography Imaging. *Journal of Nondestructive Evaluation, Diagnostics and Prognostics of Engineering Systems*. https://doi.org/10.1115/1.4065428.

[4] Huang, Y., Qiu, C., Wang, X., Wang, S., & Yuan, K. (2020). A Compact Convolutional Neural Network for Surface Defect Inspection. *Sensors (Basel, Switzerland)*, 20. https://doi.org/10.3390/s20071974.

[5] Wang, J., Xu, G., Yan, F., Wang, J., & Wang, Z. (2022). Defect Transformer: An Efficient Hybrid Transformer Architecture for Surface Defect Detection. *ArXiv*, abs/2207.08319. https://doi.org/10.48550/arXiv.2207.08319.

[6] Xia, B., Luo, H., & Shi, S. (2022). Improved Faster R-CNN Based Surface Defect Detection Algorithm for Plates. *Computational Intelligence and Neuroscience*, 2022. https://doi.org/10.1155/2022/3248722.

[7] Liu, Y., Gao, H., Guo, L., Qin, A., Cai, C., & You, Z. (2020). A Data-Flow Oriented Deep Ensemble Learning Method for Real-Time Surface Defect Inspection. *IEEE Transactions on Instrumentation and Measurement*, 69, 4681-4691. https://doi.org/10.1109/TIM.2019.2957849.

[8] Wang, Y., Liu, M., Zheng, P., Yang, H., & Zou, J. (2020). A smart surface inspection system using faster R-CNN in cloud-edge computing environment. *Adv. Eng. Informatics*, 43, 101037. https://doi.org/10.1016/j.aei.2020.101037.

[9] Wu, H., Lei, R., & Peng, Y. (2022). PCBNet: A Lightweight Convolutional Neural Network for Defect Inspection in Surface Mount Technology. *IEEE Transactions on Instrumentation and Measurement*, 71, 1-14. https://doi.org/10.1109/tim.2022.3193183.

[10] Huang, Y., Hung, K., & Lin, J. (2022). Automated Machine Learning System for Defect Detection on Cylindrical Metal Surfaces. *Sensors (Basel, Switzerland)*, 22. https://doi.org/10.3390/s22249783.