Development of an Optimized Deep Learning Technique for Fabric Defect Classification Using Osprey Optimization Algorithm

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ORIGINAL RESEARCH

Abstract----- Fabric defect classification system lowers the expenses related to low-quality products by improving productivity and product quality. There is quite a number of existing fabric defects classification techniques but most of them are not suitable for real-time classification in complex environment due to insufficient deep feature extraction. Hence, this research developed an enhanced deep learning technique using Osprey Optimization Algorithm (OOA) for fabric defect classification because of the strong eye sight of the osprey bird the algorithm is model to simulate. Fabric defects datasets were obtained from kaggle.com. Three thousand, seven hundred and ninety three (3793) datasets were obtained: two thousand six hundred and fifty five (70%) and one thousand one hundred and thirty eight (30%) were used for training and testing, respectively. The acquired datasets were pre-processed in MATLAB using k-means clustering for segmentation of region of interest, Gaussians filter for noise removal and Contrast Limited Adaptive Histogram Equalization (CLAHE) for image contrast enhancement. Densenet Cross Stage Partial Network Darknet53 (DCSPDarkNet53) was Optimized with Osprey Optimization Algorithm. The resulting OspreyDCSPDarkNet53 was used to extract features from the pre-processed datasets. The developed OspreyDCSPDarknet53 was implemented with MATLAB (R2022) and its performance was evaluated using False Positive Rate (FPR), Specificity, Sensitivity, and Accuracy. The developed method was compared with DCSPDarknet53 and YOLOv4 methods. The FPR, Specificity, Sensitivity, and Accuracy for OspreyDCSPDarknet53 were 3.30%, 96.70%, 96.09%, and 96.40%, respectively while the FPR, Specificity, Sensitivity, and Accuracy for DCSPDarknet53 were 4.86%, 95.14% 94.48%, and 94.82%, respectively and the FPR, Specificity, Sensitivity, and Accuracy for YOLOv4 were 7.47%, 92.53%, 91.81%, and 92.18%, respectively. The developed OspreyDCSPDarknet53 performed better than other techniques in terms of all the evaluated metrics. Hence, it can find its application in real time classification of fabric defects.

Keywords: Osprey, denseNet YOLOv4, CSPDarknet53, False Positive Rate and OspreyDCSPDarkNet53

1 INTRODUCTION

Fabric defect classification being a quality control process in the fabric industry is a highly challenging task because of the complex shape and a wide variety of fabric defects (Liu *et al.*, 2022). The quality and price of any fabric is also dependent on the efficacy of defect detection system. Human inspection with eyes for fabric defects is the traditional method used in the fabric industry (Wu *et al.*, 2021), and visual inspections can identify and locate the defects. Unfortunately, the human detection rate is limited to just 12 meters per minute. Moreover, it is an extremely repetitive task that wastes human resources and drives up prices, making it unsuitable for scale manufacturing. While human detection is straightforward, workers face challenges in accurately recognizing the location of faults due to the increasing complexity of fabric production lines and cloth outputs. Additionally, cloth defects lead to a reduction in cloth prices, resulting in losses of 45%-65% (Srinivasan *et al.*, 1992) for the cloth manufacturer. Therefore, a new detection method, which has high detection accuracy and detection speed, is needed to replace the manual method currently used (Liu *et al.*, 2022). An automated defect detection and identification system enhances the product quality and results in improved productivity to meet both customer needs and to reduce the costs associated with off-quality (Mahajan *et al.*, 2009). Automatic defect detection has four main approaches: Model based approach, spectral approach, Statistical approach and learning based approach. Statistical approach is the foundation of deep learning, including the methods and instruments for data analysis and interpretation. Essentially, deep learning algorithms are constructed using the theoretical foundation provided by statistics. In learning-based approaches, classifiers that can discriminate between defective and non-defective samples are trained using labelled samples. There are fabric defect detection studies made using classifiers such as the Support Vector Machines (SVM), (Basu *et al.*, 2012) feedback Artificial Neural Network (ANN), (Kumar *et al.*, 2003) and the Bayes classifier (BC) to learn signatures of defected and non-defected classes. However, the majority of those pattern categorization techniques require a wide range of data. Moreover, once the algorithm is trained for one particular data set, the network structure cannot be modified, which is inconvenient for practical applications as it is therefore a binary linear classifier that is non-probabilistic (Adio *et al.*, 2024).

Deep Learning (DL) has become increasingly popular in the field of defect detection due to its rapid development (Saberrionaghi *et al.*, 2023) and effective processing of

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Section B- ELECTRICAL/COMPUTER ENGINEERING & RELATED SCIENCES
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visual media. They can extract and learn complex features compared to shallow methods (Guo *et al*., 2016). DL methods do not require the extraction and representation of handcrafted features (Moustafa, 2015). This makes it possible to gain from growing data and processing capacity without the need for subject experts' assistance. During the training in DL, the extraction and classification of features are combined in an end-to-end process (Xing *et al*., 2017). In the field of deep learning, the Convolutional Neural Network (CNN) is the most famous and commonly employed algorithm (Li *et al*., 2021). The main benefit of CNN compared to its predecessors is that it automatically identifies the relevant features without any human supervision (Gu *et al*., 2018). As a classic deep learning method and end-to-end target detection algorithm, You Only Look Once (YOLO) has evolved rapidly with many versions and has been applied in many industries, showing good Performance (Liu *et al*., 2022). YOLOv4 is the fourth version in the You Only Look Once family of models. YOLOv4 makes real-time detection a priority and conducts training on a single Graphics Processing Unit (GPU). For real-time multi-scale illness identification, an enhanced version of the YOLOv4 algorithm has been created to increase detection accuracy and speed. However, an optimal accuracy can be achieved if this model is enhanced by an optimization algorithm such as Osprey.

Osprey Optimisation Algorithm (OOA) is primarily inspired by the tactics used by ospreys to hunt fish in the ocean. The osprey finds its prey, hunts it, and then carries it to a suitable feeding spot using its hunting strategy. A mathematical model for the two stages of the suggested OOA technique—exploration and exploitation—is developed by simulating osprey behaviour during hunting. The performance of OOA has been evaluated in the optimization of twenty-nine standard benchmark functions from the Congress on Evolutionary Computation (CEC) 2017 test suite (Delghani and Trojosvky, 2023). Additionally, the performance of OOA is compared to twelve well-known metaheuristic algorithms. The simulation results show that OOA has provided superior performance compared to competitor algorithms by maintaining the balance between exploration and exploitation (Dehghani and Trojosvky, 2023). In this research, a denseNet YOLOv4 will be enhanced with Osprey Optimization Algorithm to develop the method of classifying fabric defect with low processing time and high accuracy.

2. REVIEW OF RELATED WORKS

This section discusses about a few of the related works that were reviewed: A number of optimisation strategies have been put forth to improve defect classification in pattern recognition.

Bo *et al.* (2009) proposed the machine vision technique in which defects are detected by the Gabor filter, which is based on image processing, however, it has poor detection results for some types of defects (Bo *et al*., 2009). Wiener filter is used to classify defective images by converting RGB images into binary images to improve the detection effect (Yildiz *et al*., 2017). In addition, there are other methods to detect fabric defects.

Kazim *et al*., (2016) adopts a thermal-based defect classification method with K-nearest neighbor algorithm and dimensionality reduction to classify textile defects respectively (Yildiz, 2017). Image processing (Yildiz and Buldu, 2016) and thermal images (Buldu *et al*., 2015) are also used in defect detection. Nevertheless, image processing and thermal imaging are limited to resolving the categorisation issue. The photos have visible flaws that can only be identified; they cannot be accurately located when using these approaches. Due to the limitations of most classic image processing algorithms, only photos with simple backgrounds and large objects may be handled efficiently. Therefore, several researchers are looking at neural network-based techniques.

Lin et al., (2017b) proposed the focal loss method, which can reduce the weight of large sample losses and increases the weight of small samples in total loss. However, focal loss is not effective in practical applications, and evenly reduces mAP (mean average precision) (Redmon and Farhadi, 2018). As a result, compared to a one-stage network, a two-stage network typically has greater precision. Faster R-CNN represents a two-stage network, which is typically lower than the others. YOLO, a common first-order algorithm, has been refined over numerous generations. Algorithms for YOLO have advanced quickly. YOLOv4 has better performance and uses tricks (Bochkosvskiy, 2020) to improve the accuracy. Liu *et al*., (2022) proposed an improved YOLOV4 algorithm with higher accuracy for fabric defect detection, in which a new SPP structure that uses SoftPool instead of MaxPool is adopted. The enhanced YOLO v4 feature map may be processed efficiently by three SoftPools, which has a major benefit in lowering the unfavourable impacts of the SPP structure and raising detection accuracy. Liu et al. enhanced the image quality by using contrast-limited adaptive histogram equalisation beforehand, which leads to strong anti-interference capabilities and an elevated mAP of 86.5%.

Wang and Jing (2020) suggested a detection technique that made use of the benefits of multiscale target identification, increased detection accuracy while lowering the network model parameters and the capacity to identify small targets based on the DeeplabV3+ model. The defect dataset yields positive findings.

Roy et al., (2022) suggested a You Only Look Once (YOLOv4) algorithm improvement. By combining the DenseNet in the backbone to maximise feature transfer and reuse, two additional residual blocks in the neck and backbone to enhance feature extraction and lower computing costs, the Spatial Pyramid Pooling (SPP) to enhance receptive field, and a modified Path Aggregation Network (PANET) to preserve fine-grain localised information and enhance feature fusion, the modified network architecture maximises both detection accuracy and speed. Furthermore, by using the Hard-Swish function as the principal activation, Roy et al. were able to extract better nonlinear features, which increased the accuracy of the model. The accuracy and speed of the suggested model's identification of four distinct illnesses in tomato plants grown in a variety of difficult conditions were shown to have improved. There is a 70.19% detection rate. But most of these reviewed related works

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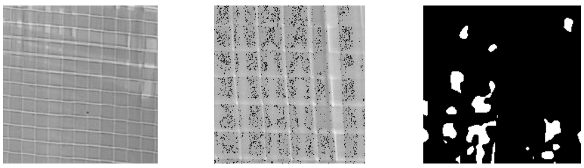
are not suitable for real-time classification in complex environment due to insufficient deep feature extraction.

3. DESIGN APPROACH

The developed system consists of five major stages; the first stage is data acquisition which involves obtaining dataset or images of fabric defects. Pre-processing which is the second stage involves image segmentation of region of interest from the defected image. Image enhancement was done to improve the contrast of the image. The third stage is Feature Extraction by Osprey-denseNetYOLOv4 (OspreyDCSPDarknet53) which is finding a smaller set of new variables each being a combination of the input variables. Classification which is the fourth stage was done by the Osprey-denseNet YOLOv4 algorithm. The fifth stage is the evaluation of the developed system in order to check the performance of the system; this was done using these performance indices: False Positive Rate (FPR), Specificity, Sensitivity and accuracy. The general block diagram of the developed Osprey-denseNet YOLOv4 algorithm is shown in Fig. 2; the steps involved are data acquisition, preprocessing, feature extraction, image classification and performance evaluation.

3.1 Data Acquisition

The datasets used in this research was obtained from www.Kaggle.com. Three thousand, seven hundred and ninety three (3793) datasets were obtained out of which two thousand, six hundred and sixty five (2655) were used for training and one thousand, one hundred and thirty eight (1138) were used for testing and the fig. 1 shows the samples of fabric defect datasets used.



A. Original B. Contrast Enhancement C. Segmentation

Fig 1. The samples of fabric defects

3.2 Pre-processing

Guassian filter was used for noise removal and Contrast-Limited Adaptive Histogram Equalisation (CLAHE) was used. CLAHE is an improved form of Histogram Equalisation (HE), a straightforward and efficient technique for improving photographs. By altering the grey distribution of the image, CLAHE can boost contrast and improve classification accuracy.

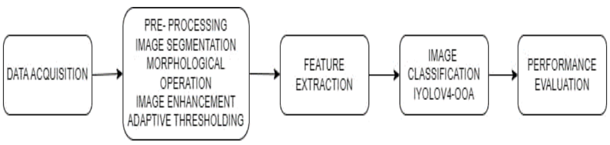


Fig 2. Block diagram of the developed system

3.3 Design of Osprey-denseNet YOLOv4 for Feature Extraction and Classification

This research is to develop an enhanced version of the YOLOV4 algorithm to classify fabric defects. YOLOv4 is a highly accurate single-stage model for object classification, which converts the fabric object classification task into a regression problem by generating bounding box coordinates and assigning probabilities to each class. It represents advancement over the original YOLOv4 algorithm and its variants in terms of both speed and accuracy in classification. The network structure comprises three main components: a backbone for feature extraction, a neck for semantic representation of these features, and a head for classification. Within the existing network architecture, the residual module is incorporated into the ResNet network structure to form Darknet53.

To further enhance the network's performance, Osprey optimization, cross-stage partial network, and DenseNet (DCSPDarkNet53) were merged due to their exceptional learning capabilities, resulting in the creation of OspreyDCSPDarkNet53. This integration involves feeding information from different feature layers into the residual module, which then produces higher-level feature maps as output. This approach significantly reduces the number of network parameters while simultaneously enhancing the quality of residual feature information, thereby improving the network's ability to learn features compared to the ResNet architecture.

Additionally, in the original YOLOv4 backbone, the SPP block has been incorporated into CSPDarknet53, connected to the PANET, thus replacing the Feature Pyramid Networks (FPN) utilized in other YOLO variants. This leads to a notable expansion of the network's receptive field. The SPP employs an efficient approach to detecting objects of varying scales.

Initially, the input feature layer undergoes convolution within the SPP. Subsequently, an optimal maximum pooling operation, determined through osprey optimization, is performed by pooling kernels of four different sizes. The classification network's receptive field is further expanded by concatenating and further convolving the pooled feature information from the SPP. The feature information obtained from both the backbone and the SPP undergo convolution and are subsequently up-sampled in PANET, resulting in a feature layer twice the size of the original input.

The feature layers obtained by the OspreyDCSPDarknet53 are blended post-convolution and then up-sampled and down-sampled in order to capture more semantic data. This process is integrated with the remaining feature layers to enhance the fusion of features. Consequently, the neck component within the backbones plays a pivotal role in extracting intricate semantic features crucial for precise classification. Ultimately, within the YOLOv4 model, tailored for specific input image dimensions, the classification head can identify bounding boxes at three distinct scales. Initially, the input image is divided into N-N evenly spaced grids. Should the target fall within a grid cell, the model will produce predictive bounding boxes alongside corresponding confidence scores. Subsequently, the optimal bounding box classification from each scale is refined using a Non-Maximum Suppression (NMS) algorithm, culminating in the determination of the final bounding box.

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While both the current iterations of YOLOv4 and CSPDarkNet53 have been effective in enhancing the model's classification accuracy, the task of fabric defect classification encounters several distinct challenges within complex environments. These challenges include densely populated fine-grain fabric defects, irregular geometric morphologies of affected areas, the presence of multi-scale infected lesions, similarities in texture between affected areas and their surroundings, varying lighting conditions, as well as instances of overlapping and occlusion. Consequently, the existing YOLOv4 model may yield suboptimal classification accuracy, leading to a significant number of missed classifications and false object identifications. This is primarily due to insufficient extraction of fine-grain features required for addressing the multi-scale fabric defect classification problem. Furthermore, YOLOv4 incurs high computational costs and longer training times, rendering it potentially unsuitable for deployment on mobile devices in field settings.

3.3.1 The developed network architecture

To address the aforementioned challenges encountered in real-time fabric defect classification, this study enhances and optimizes the cutting-edge denseNetYOLOv4 (DCSPDarknet53) algorithm for precise classification of fine-grain, multi-attribute images within complex backgrounds. The comprehensive layout of the refined YOLOv4 network architecture is depicted in Fig. 3, with each modification briefly discussed within this study. The proposed enhancements encompass the incorporation of the Osprey-DenseNet transitional block preceding the standard CSPDarknet53 residual blocks, the introduction of two new residual blocks in both the backbone and neck sections to bolster feature extraction and reduce computational costs, integration of the Osprey-SPP block, and implementation of the Osprey-PANET in the neck segment of the network to preserve finely-detailed localized information. The original YOLOv3 head will be retained for use as it can identify bounding boxes at three distinct scales resulting in prediction at three levels of detection granularity.

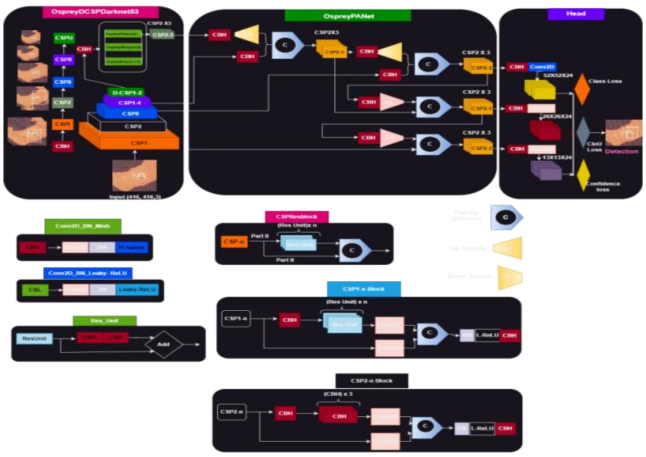

Fig 3. Schematic diagram of the developed OspreyDCSPDarknet53 network for fabric defect classification.

3.3.2 Enhancement of the backbone feature extraction network

The residual model within the OspreyDCSPDarknet53 aids the network in acquiring more nuanced features while concurrently reducing the number of trainable parameters, thereby enhancing its efficiency for real-time classification. The residual unit (Res-unit) in the original YOLOv4 model performs 1 x 1 convolutions, followed by 3 x 3 convolutions, and then combines the two outputs with the feature information that was retrieved. Within the CSPDarknet53 network, feature layers of input images undergo continuous down sampling through convolution operations to extract detailed, semantic information. Given that the last three layers harbor relatively heightened semantic information, they are forwarded to both the Osprey-SPP and the Osprey-PANET. As shown in Figure 3.2, the last layers contain the best feature information and are connected to the Osprey-SPP, and the other two layers are incorporated into the Osprey-PANET. While YOLOv4's residual module lowers computational expenses, it also lessens the amount of memory needed for high-resolution real-time categorisation. A novel residual block, CSP1-n (where n is the number of residual weighting operations), is proposed within the OCSPDarkNet53 network topology to increase classification performance.

3.5 Implementation of the developed denseNet (OspreyDCSPDarknet53)

The system was implemented in MATLAB (R2022) on window 10 ultimate 64bit operating system, intel core i7 CPU with a speed of 4.4GHZ, 8GB RAM and 1 terabyte hard disk drive to detect the fabric defects and evaluate the performance of the system was done using these parameters: False Positive Rate (FPR), Specificity, Sensitivity and accuracy to validate the system.

4. RESULTS AND DISCUSSION

An interactive Graphic User Interface (GUI) was developed in MATLAB using guide toolbox with a real time database consisting of 3793 fabric defects dataset reflecting stain defects in order to determine the system performance to classify stain defects in fabric by optimizing DenseNet YOLOv4 (DCSPDarknet53) using Osprey Optimization Algorithm. The development tool was MATLAB (R2022) on window 10 ultimate 64bit operating system, intel core i7 CPU with a speed of 4.4GHZ, 8GB RAM and 1 terabyte hard disk drive.
The system was experimented with 2655 fabric defects dataset. The datasets contains 1310 defectives (stain) and 1345 non-defectives which were used in training the system. The system was trained with YOLOv4 (CSPDarknet53), denseNetYOLOv4 (DCSPDarkNet53) and Osprey-denseNet YOLOv4 (OspreyDCSPDarknet53). To test the performance of the system, 1138 datasets were used as 562 defectives and 576 non-defectives. The system is tested with YOLOv4, DCSPDarkNet53 and OspreyDCSPDarknet53 one after the other in order to find their False Positive Rates (FPR), specificities, sensitivities and classification accuracies.

4.2 Results for YOLOv4

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Table 1 presents overall results of YOLOv4 for stain defects at threshold values 0.25, 0.35, 0.5 and 0.85 and the best accuracy was recorded at threshold 0.85 on 516 True positive (TP), 46 False Negative (FN), 43 False Positive (FP), 533 True Negative (TN) while FPR, Specificity, Sensitivity, and Accuracy for YOLOv4 were 7.47%, 92.53%, 91.81%, and 92.18%, respectively.

Table 1: Results generated with YOLOv4

Threshold	TP	FN	FP	TN	FPR(%)	SPEC(%)	SEN(%)	ACC(%)
0.25	519	43	51	525	8.85	91.15	92.35	91.74
0.35	518	44	48	528	8.33	91.67	92.17	91.92
0.5	517	45	45	531	7.81	92.19	91.99	92.09
0.85	516	46	43	533	7.47	92.53	91.81	92.18

4.3 Results for DCSPDarkNet53

Similar procedure was carried out to test the system with DCSPDarkNet53 for stain defects at threshold values 0.25, 0.35, 0.5 and 0.85 and the best accuracy was recorded at threshold 0.85. Table 2 presents overall results of DCSPDarkNet53 for all the defects based on 531 True positive (TP), 31 False Negative (FN), 28 False Positive (FP), 458 True Negative (TN), 4.86% while FPR, Specificity, Sensitivity, and Accuracy for DCSPDarknet53 were 4.86%, 95.14% 94.48%, and 94.82%, respectively.

Table 2: Results generated with DCSPDarkNet53

Threshold	TP	FN	FP	TN	FPR(%)	SPEC(%)	SEN(%)	ACC(%)
0.25	534	28	36	540	6.25	93.75	95.02	94.38
0.35	533	29	33	543	5.73	94.27	94.84	94.55
0.5	532	30	30	546	5.21	94.79	94.66	94.73
0.85	531	31	28	548	4.86	95.14	94.48	94.82

4.4 Results for OspreyDCSPDarkNet53

Similar procedure was carried out to test the system with OspreyDCSPDarkNet53 for stain defect at threshold values 0.25, 0.35, 0.5 and 0.85 and the best accuracy was recorded at threshold 0.85. Table 3 presents overall results of OspreyCSPDarkNet53 for all the defects based on 540 True positive (TP), 22 False Negative (FN), 19 False Positive (FP), 557 True Negative (TN), while FPR, Specificity, Sensitivity, and Accuracy for OspreyDCSPDarknet53 were 3.30%, 96.70%, 96.09%, and 96.40%, respectively.

Table 3: Results generated with OspreyDCPDarkNet53

Threshold	TP	FN	FP	TN	FPR(%)	SPEC(%)	SEN(%)	ACC(%)
0.25	543	19	27	549	4.69	95.31	96.62	95.96
0.35	542	20	24	552	4.17	95.83	96.44	96.13
0.5	541	21	21	555	3.65	96.35	96.26	96.31
0.85	540	22	19	557	3.30	96.70	96.09	96.40

4.5 Comparison of Results among YOLOv4, DCSPDarkNet53 and OspreyDCSPDarkNet53

Summarily, Table 4 shows the measured parameters and values obtained after implementing Osprey Optimization Algorithm and DCSPDarkNet53 and the results of their combination which is OspreyDCSPDarkNet53 on Fabric Defects datasets. Each of the classified results is interpreted as follows: True Positive, False Negative, False Positive, True Negative, False Positive Rate, Specificity, Sensitivity, and Classification Accuracy. The study discovered that the optimization of DCSPDarkNet53 with Osprey Optimization Algorithm has better performance in classification accuracy than DCSPDarkNet53 and YOLOv4 Algorithm as enumerated in table 4.4. The Classification Accuracy with YOLOv4 generates 7.47% False Positive Rate (FPR), 92.53% Specificity, 91.81% Sensitivity, and 92.18% overall Classification Accuracy. DCSPDarknet53 generates 4.86% False Positive Rate (FPR), 95.14% Specificity, 94.48% Sensitivity, and 94.82% overall Classification Accuracy while OspreyDCSPDarknet53 generates 3.30% False Positive Rate (FPR), 96.70% Specificity, 96.09% Sensitivity, and 96.40% overall Classification Accuracy while fig. 4 and fig. 5 show the Interface of the system after testing with OspreyDCSPDarknet53 and the chart that describes the results comparison among the three techniques respectively.

Table 4: Comparison Results among YOLOv4, DCSPDarkNet and OspreyDCSPDarkNet53

SN	YOLOv4	CSPDarkNet53	OCSPDarkNet53
TP	531	531	540
FN	31	31	22
FP	28	28	19
TN	548	548	557
FPR(%)	4.86	4.86	3.30
SPEC(%)	95.14	95.14	96.70
SEN(%)	94.48	94.48	96.09
ACC(%)	94.82	94.82	96.40

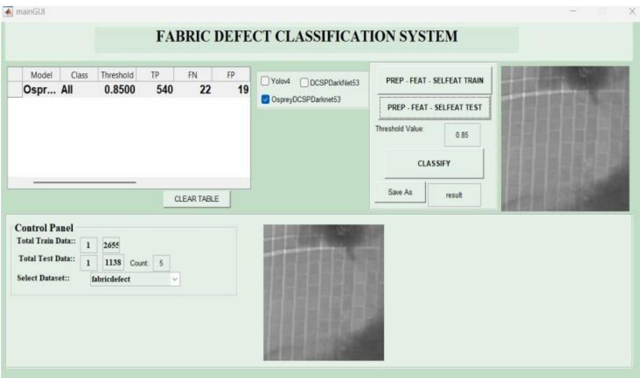

Fig. 4. Interface of the system after testing with OspreyDCSPDarknet53

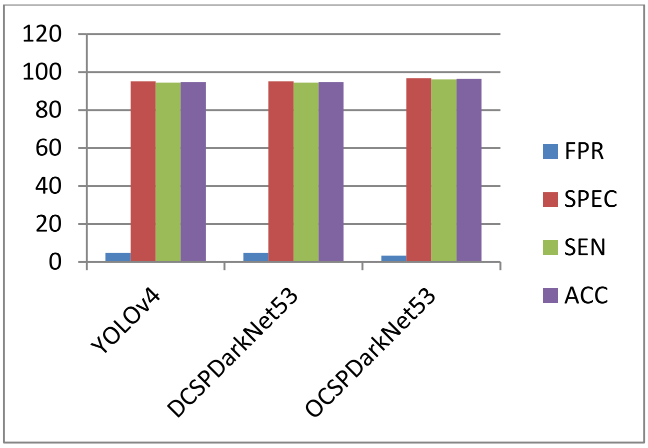

Fig. 5. Chart showing the comparison results among the three techniques

5. CONCLUSION AND RECOMMENDATION

In conclusion, this research has successfully developed and implemented an optimized deep learning technique for fabric defect classification using the Osprey Optimization Algorithm. The utilization of the Osprey Optimization Algorithm to enhance DCSPDarkNet53 has not only contributed to achieving high detection accuracy but has significantly enhanced the system specificity and sensitivity with reduced False Positive Rate (FPR). This work has demonstrated the potential of the Osprey Optimization Algorithm, particularly on the deep learning DCSPDarkNet53, to address critical challenges associated with the existing fabric defect detection system. The focus on detection accuracy, specificity, sensitivity, and FPR aligns with the broader goals of ensuring an accurate and reliable defect detection system. It is recommended that future research can be carried out by hybridizing other object classification algorithms with the considered algorithms in this research to detect different types of fabric defects and predict the type of fabric defect detected. The best-performing algorithm in terms of overall classification accuracy can also be found using the same method.

REFERENCES

Adio, M. O., Ogunwuyi, O. J., Oyediran, M. O., Esan, A. O., & Adedapo, O. A. (2024). Performance Evaluation of Some Selected Classification Algorithms in a Facial Recognition System. *ABUAD Journal of Engineering Research and Development*, *7*(1), 169-177. DOI: https://doi.org/10.53982/ajerd.2024.0701.17-j

Basu, A., Chandra, J. K., Banerjee, P. K., Bhattacharyya, S., and Datta, A. K. (2012). Sub image based eigen fabrics method using multi-class SVM classifier for the detection and classification of defects in woven fabric. In *2012 Third International Conference on Computing, Communication and Networking Technologies (ICCCNT'12)* 1-6. IEEE.

Bo, Q. U., Zhaoyang, L. U., Jing, L. I., Cui, L., and Zhou, F. (2009). An improved multichannel Gabor filter algorithm for fabric defect detection. *J. Textile Res.*, *30*, 37-40.

Bochkovskiy, A., Wang, C. Y., and Liao, H. Y. M. (2020). Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934*..

Buldu, A. (2016). A thermal-based defect classification method in textile fabrics with K- nearest neighbor algorithm.

Dehghani, M., and Trojovský, P. (2023). Osprey optimization algorithm: A new bio-inspired metaheuristic algorithm for solving engineering optimization problems. *Frontiers in Mechanical Engineering*, *8*, 1126450.

Gu, J., Wang, Z., Kuen, J., Ma, L., Shahroudy, A., Shuai, B., ... and Chen, T. (2018). Recent advances in convolutional neural networks. *Pattern recognition*, *77*, 354-377.

Guo, Y., Liu, Y., Oerlemans, A., Lao, S., Wu, S., and Lew, M. S. (2016). Deep learning for visual understanding: A review. *Neurocomputing*, *187*, 27-48.

Kumar, A. (2003). Neural network based detection of local textile defects. *Pattern Recognition*, *36*(7), 1645-1659.

Li, G., Zhang, M., Li, J., Lv, F., and Tong, G. (2021). Efficient densely connected convolutional neural networks. *Pattern Recognition*, *109*, 107610.

Lin, T. Y., Goyal, P., Girshick, R., He, K., and Dollár, P. (2017b). Focal loss for dense object detection. In *Proceedings of the IEEE international conference on computer vision* (2980- 2988).

Liu, Q., Wang, C., Li, Y., Gao, M., and Li, J. (2022). A fabric defect detection method based on deep learning. *IEEE access*, *10*, 4284-4296.

Liu, Q., Wang, C., Li, Y., Gao, M., and Li, J. (2022). A fabric defect detection method based on deep learning. *IEEE access*, *10*, 4284-4296.

Mahajan, P. M., Kolhe, S. R., and Patil, P. M. (2009). A review of automatic fabric defect detection techniques. *Advances in Computational Research*, *1*(2), 18-29.

Moustafa, M. (2015). Applying deep learning to classify pornographic images and videos. *arXiv preprint arXiv:1511.08899*.

Redmon, J., and Farhadi, A. (2018). Yolov3: An incremental improvement. *arXiv preprint arXiv:1804.02767*.

Roy, A. M., Bose, R., and Bhaduri, J. (2022). A fast accurate fine-grain object detection model based on YOLOv4 deep neural network. *Neural Computing and Applications*, 1-27.

Saberironaghi, A., Ren, J., and El-Gindy, M. (2023). Defect detection methods for industrial products using deep learning techniques: A review. *Algorithms*, *16*(2), 95.

Srinivasan, K., Dastoor, P. H., Radhakrishnaiah, P., and Jayaraman, S. (1992). FDAS: A knowledge- based framework for analysis of defects in woven textile structures. *Journal of the textile institute*, *83*(3), 431-448.

Wang, Z., & Jing, J. (2020). Pixel-wise fabric defect detection by CNNs without labeled training data. *IEEE Access*, *8*, 161317-161325.

Wu, J., Le, J., Xiao, Z., Zhang, F., Geng, L., Liu, Y., and Wang, W. (2021). Automatic fabric defect detection using a wide-and-light network. *Applied Intelligence*, *51*(7), 4945-4961.

Xing, J., Li, K., Hu, W., Yuan, C., and Ling, H. (2017). Diagnosing deep learning models for high accuracy age estimation from a single image. *Pattern Recognition*, *66*, 106-116.

Yildiz, K. (2017). Dimensionality reduction-based feature extraction and classification on fleece fabric images. *Signal, Image and Video Processing*, *11*, 317-323.

Yıldız, K., and Buldu, A. (2016). Wavelet transform and principal component analysis in fabric defect detection and classification.

Yıldız, K., Demir, Ö., and Ülkü, E. E. (2017). Journal on Fault detection of fabrics using image processing methods.

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