Boosting Fabric Defect Recognition and Classification using Grey Wolf Optimizer with Deep Learning Model

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Abstract: ***Fabric defect detection has been instrumental in the textile production method, however, still, there are certain problems in accurately and rapidly identifying defects. Fabric defect recognition and categorization were examined for their significance in industrialization and urbanization. Meanwhile, the fabric industries are majority industrialists of textile, so the possibility of defect will added in the small - scale industries. Therefore, classification based on certain configurations can also be performed by the computer vision - based automated scheme. The complicated information attained from the real - world fabric model has a high complication owing to the multi - dimensional data set, higher order variable and high - variety data made from the images. In recent years, the usage of the deep learning (DL) approach in the textile industry for defect recognition has become a growing tendency. This article introduces Fabric Defect Recognition and Classification using Grey Wolf Optimizer with Deep Learning (FDRC - GWODL) model. The FDRC - GWODL technique applies bilateral filtering (BF), an innovative image processing method, to effectively mitigate noise interference and optimize image clarity. Leveraging the Residual Network (ResNet) model as a feature extractor, the technique extracts discriminatory features critical for precise defect demonstration. Hyperparameter tuning is performed by the Grey Wolf Optimizer (GWO), enhancing model parameters to increase recognition accuracy. Consequently, defect classification is performed by the Random Forest (RF) classifier, recognized for its efficiency and robustness in managing complicated classifier tasks. Simulation outcomes illustrate the betterment of the presented FDRC - GWODL technique in fabric defect recognition, illustrating its possibility to enhance quality control measures in textile manufacturing process.***

Keywords: Fabric Defect Detection; Grey Wolf Optimizer; Deep Learning; Image Processing; Defect Classification

1. Introduction

Till now the textile industry is worried because they mainly concentrate on defect - free clothes and designs they yield [1]. The method projected and upheld the texture classification in the attires manufactured and the past of their faults to improve them. The model offers good precision in categorizing the imageries depending upon their designs [2]. The technique employed for identification is logical regression (LR) and multi - scale image decomposition in deep learning (DL) finds the faults. The defects in cloth were formed throughout its manufacturing procedure [3]. Defect recognition is vital in fabric business in order to certify the superiority of the clothes to the clients. The physical procedure of inspection covers the trend for failure in defect recognition [4]. The task is to offer effective outcomes in defect recognition and classification of texture. The textile sector uses a best on superiority and works hard to meet severe goals without sacrificing product criteria [5]. About 85% of textile business flaws are caused by defective cloth, while producers frequently only create 45% to 65% of second - hand or reduced products. In January 2020, India placed 2nd worldwide in textile and attire manufacture and trades as per the data collected by NITI Aayog. Contamination and lower - quality fibre are main problems [6]. India has the world's peak manufacturing capability, but it employs old models. Modern fabric industries cannot endure without utilizing innovative technologies.

The main concerns are the contamination and the poor superiority of the fibre. India utilizes old technology even if it has the biggest installed manufacturing bases [7]. Definitely, by accepting advanced technologies linked to fabric manufacturing, competitive manufacturing can be completed. Presently, fabric defects are being noticed physically by skilled checkers, who have their part problems [8]. Initially, examiners who have been used should be expert and experienced. Likewise, looking at the cloth for long time strains one's eyes, which takes a toll on the precision with which mistakes can be recognized [9]. Hence, to detect, classify and avert these faults from reoccurring there is a mounting demand for an automatic fabric fault recognition method in the business. General fabric defects contain scratches, holes, loose yarn, stretching, cracked points, dirty spots, colour bleeding, misprints, etc [10]. Utilizing computer vision (CV) to find out this issue is a good solution and we use an artificial intelligence (AI) - based method to categorize probable defects like cuts, holes, colour, metal contamination and thread.

This article introduces Fabric Defect Recognition and Classification using Grey Wolf Optimizer with Deep Learning (FDRC - GWODL) model. The FDRC - GWODL technique applies bilateral filtering (BF), an innovative image processing method, to effectively mitigate noise interference and optimize image clarity. Leveraging the Residual Network (ResNet) model as a feature extractor, the technique extracts discriminatory features critical for precise defect demonstration. Hyperparameter tuning is performed by the Grey Wolf Optimizer (GWO), enhancing model parameters to increase recognition accuracy. Consequently, defect classification is performed by the Random Forest (RF) classifier, recognized for its efficiency and robustness in managing complicated classifier tasks. Simulation outcomes illustrate the betterment of the presented FDRC - GWODL technique in fabric defect recognition, illustrating its possibility to enhance quality control measures in textile manufacturing process.

2. Literature Works

Sajitha and Priya [11] presented an Automatic Fabric Defect Detection utilizing a Hybrid Particle Cat Swarm Optimizer with a DL (AFDD - HPCSODL) model. In this method, dual phases of data pre - processing take place such as bilateral filtering (BF) - based noise extraction and contrast enhancement. Also, a combination of feature extraction procedures was implemented utilizing InceptionV3 and EfficientNet - B3. Furthermore, the Attention Convolutional Long Short - Term Memory (ACLSTM) system has been developed for the recognition and identification of FD. Also, the HPCSO system executes the hyperparameter range of ACLSTM method. Revathy and Kalaivani [12] projected a DL - based IM - RCNN system. Initially, the imageries are collected from the dataset of HKBU and these imageries are denoised utilizing a contrast - limited adaptive histogram equalization filter to remove the noise objects. Finally, the developed improved Mask RCNN (IM - RCNN) was employed for categorizing defective cloth into 6 types dependent upon the segmented area of the material. In [13], an enhanced YOLO v5 fabric defect recognition technique, FD - YOLO v5 has been projected. Initially, the coordinate attention component is inserted in the YOLO v5 backbone structure. Next, an activation function of smoother Mish is employed in the novel method; the SIoU loss functions considering the way of the anchor box were employed to recover the speed of convergence and recognition precision of the method. Lastly, uniting the focal and GHM loss functions is the objective confidence for resolving the issue of sample imbalance.

Sabeenian et al. [14] concentrated on planning a DL structure to identify numerous fabric kinds and categorize the defects utilizing AI. The projected work has dual stages; in stage 1, the input imagery is pre - processed with a new Pseudo–CNN (P - CNN) having 0 tunable parameters. In stage 2, an adapted CNN is used to the pre - processed imagery to identify and categorize main cloth defects. The CNN utilizes suitable hidden layers to obtain an undeniable degree of precision for defect identification utilizing imageries. In [15], a non - woven fabric defect recognition model dependent upon hyperspectral image and enhanced YOLO v5 is projected. Mainly, hyperspectral image technology was utilized. Furthermore, the LSK attention component is presented in the YOLO v5 backbone system. Lastly, an enhanced light repetitive group frequency permutation network (Light - RepGFPN) was developed in the structure of neck. It is united with the Light - RepGFPN and LSK components, and an amended YOLO v5 (LL - YOLO v5) defect recognition method has been projected.

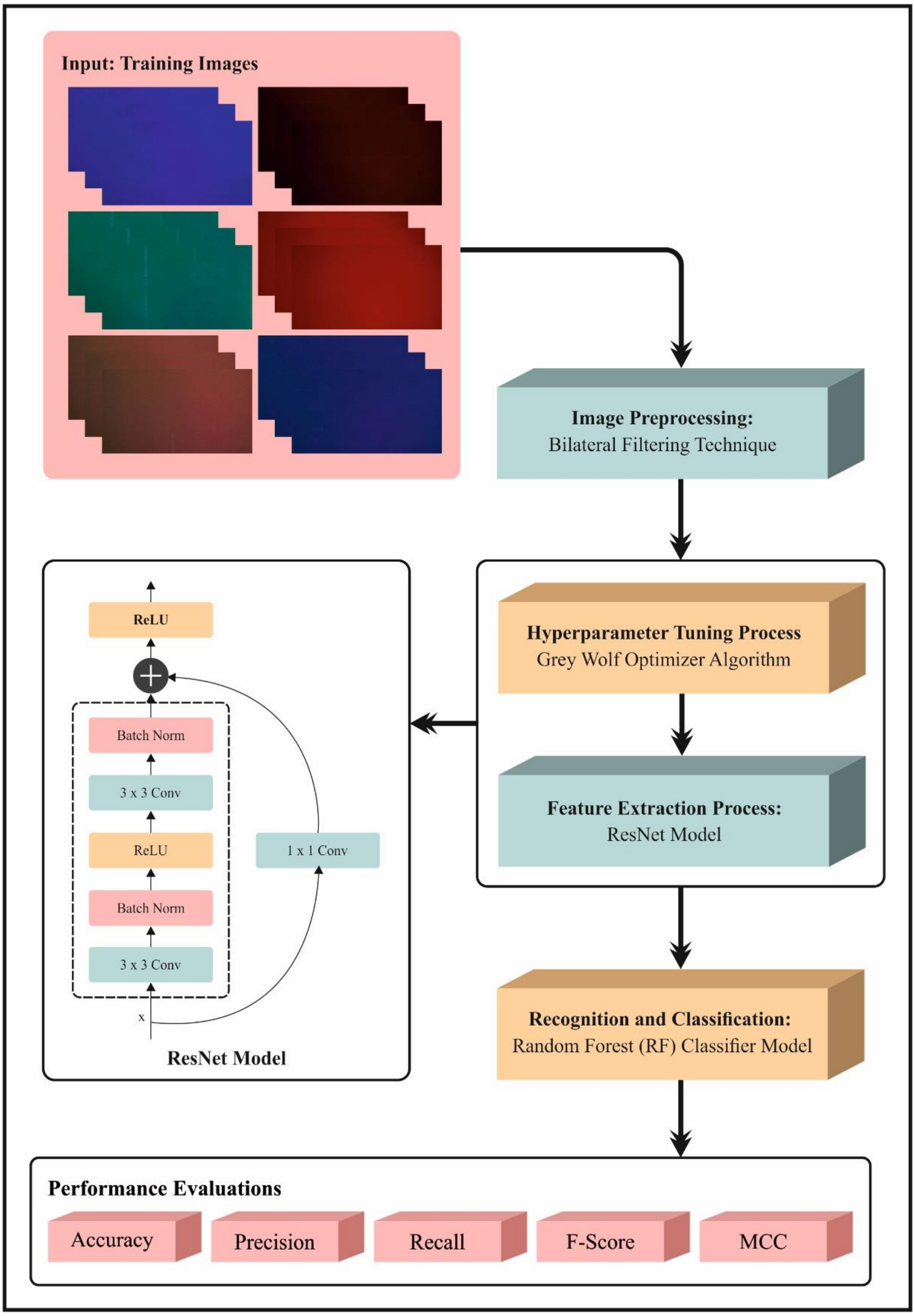

Figure 1: Workflow of FDRC - GWODL model

3. Methodology

In this article, we have introduced an FDRC - GWODL model. To accomplish that, the FDRC - GWODL technique contains different stages involved as BF - based preprocessing, ResNet - based feature extractor, GWO - based parameter tuning, and RF - based defect detection. Fig.1 represents the workflow of FDRC - GWODL model.

3.1 BF based Preprocessing

At primary, the FDRC - GWODL technique applies BF, an innovative image processing method, to effectively mitigate noise interference and optimize image clarity. BF is a complicated edge - preserving smoothing method utilized extensively in image processing workflow [16]. Different from classical linear filters, BF considers the intensity difference and spatial distance between pixels while calculating the weighted average for smoothing. This dual - domain filtering technique enables BF to efficiently eliminate noise while retaining significant image features like textures and edges. As a result, BF is more popular in applications like stereo vision, image denoising, and HDR tone mapping, where preserving visual fidelity is dominant.

3.2 Feature Extractor

Leveraging the ResNet model as a feature extractor, the technique extracts discriminatory features critical for precise defect demonstration. The CNN is a robust proficiency for feature extraction that comprises pooling layers and convolution (Conv) layers [17]. A local Conv function in the input data could be executed by utilizing the Conv layers. Next, feature dimensional reduction must be obtained through the pooling layers. The subsequent modification is known as feature maps, might represent the features that will pivotal for the issues. A ResNet has a distinct CNN integrating the residual learning method for solving the degradation complexity of standard deep CNNs (DCNNs). The building block or fundamental component of a ResNet as represented as shown in given mathematical form

$$H(x) = F(x) + x \tag{1}$$

Now $F(x)$ characterizes the residual mapping, $H(x)$ and x describe the output and input vectors, correspondingly; and. As an alternative to structure correlation directly among $H(x)$ and x, a ResNet examines the residual function $F(x)$ that could be attained by employing identity shortcut interconnections. In the condition, the $F(x)$ of the network's deep portion can be denoted as 0 in the training procedure which should be prevented the degradation complexity in a DNN, whereas shallow portion of a ResNet must be appropriately trained for entirely removing the features. Hence, a ResNet has been employed for extracting features from inputs in this system.

3.3 Hyperparameter Tuning Process

Hyperparameter tuning is performed by the GWO, enhancing model parameters to increase recognition accuracy. The GWO algorithm has a meta - heuristic method that repeats the initiative chain of significance as well as follows the technique of dark posers [18]. The optimum configuration could be represented by the sign alpha α in the mathematical approach for the GWO. The delta (δ) and beta (β) have been improved in accordance with the 2nd and 3rd best patterns correspondingly. This must be supposed that the enduring application setups have been called omega (ω). Such 3 applicants have been followed by β, δ and ω applying GWO approaches as well as α like a hunting guide. It directly encloses for the container to follow prey. The next Eqs. (2) - (5) can be utilized for mathematically modelled nearby behavior.

$$\vec{Z}(r+1) = \vec{Z}_p(r) + \vec{B}.\vec{E} \tag{2}$$

$\vec{Z}$ has the grey wolf position, $\vec{Z_p}$ represents the position of prey, $\vec{B}$ and $\vec{D}$ becomes co - efficient vectors, r denotes the counts of repetition number E as presented in Eq. (3).

$$\vec{E} = \left|\vec{D}.\vec{Z_p}(r) - \vec{Z}(r)\right| \tag{3}$$

$$\vec{D} = 2b.t_1 - b \tag{4}$$

$$\vec{D} = 2t_2 \tag{5}$$

Here, b describes linearly lowered at 2 to 0 in the weight time, t_1, t_2 refers random vectors at intervals $[0,1]$. Normally, the α leads the search. Additionally, the β and δ can infrequently be attentive in hunting. To precisely follow the hunting behavior of grey wolves, the α (best candidate solution), β (2nd best rival solution), and δ (3rd best optimistic solution) should be recognized for achieving large data about the possible prey place. The first 3 best application configurations are obtained in this phase, requiring the alternative hunt operators to modify their conditions for relating the best hunt experts. Thus, the replacement of the positions of the GWO can be given by Eq. (6):

$$\vec{Z} = (r+1) = \frac{\vec{Z_1} + \vec{Z_2} + \vec{Z_3}}{3} \tag{6}$$

$$\vec{Z_1} = \left|\vec{Z_\alpha} - \vec{B_1}.\vec{E}a\right| \tag{7}$$

$$\vec{Z_2} = \left|\vec{Z_\beta} - \vec{B_2}.\vec{E_\beta}\right| \tag{8}$$

$$\vec{Z_3} = \left|\vec{Z_\delta} - \vec{B_3}.\vec{E_\delta}\right| \tag{9}$$

Where $\vec{B_1}, \vec{B_2}, \vec{B_3}$ describes as Eq. (6) and $\vec{Z_\alpha}, \vec{Z_\beta}, \vec{Z_\delta}$ refers to the primary 3 best solutions in the expected repetition $r, \vec{B_1}, \vec{B_2}, \vec{B_3}$ can be given in Eqs. (7) − (9) and $\vec{E_\alpha}, \vec{E_\beta}, \vec{E_\delta}$ are specified as Eqs. (10) − (12) correspondingly.

$$\vec{E_a} = \left|\vec{D_1}.\vec{Z_1} - \vec{Z}\right| \tag{10}$$

$$\vec{E_\beta} = \left|\vec{D_2}.\vec{Z_\beta} - \vec{Z_1}\right| \tag{11}$$

$$\vec{E_\delta} = \left|\vec{D_3}.\vec{Z_\delta} - \vec{Z_1}\right| \tag{12}$$

$\vec{D_1}, \vec{D_2}, \vec{D_3}$ was provided in Eq. (5).

A last statement about the GWO mediator has the updating parameter to normalize the investigation-abuse tradeoff. The parameter can be constantly updated in all cycles to range from 2 to 10 in provided Eq. (13).

$$b = 2 = r\frac{2}{\max Iter} \tag{13}$$

where $MaxIter$ has been a whole number of permissible optimizer rounds and r represents the count of optimized repetitions. The search and hunting positions of grey wolves could need to be updated by binary {1, 0}.

The fitness selection is the key factor which influences the performance of MBES technique. The hyperparameter selection method includes the solution encoding process for evaluating the effectiveness of the solution candidate. Here, the MBES method considers accuracy as the primary condition to develop the FF.

$$Fitness = \max(P) \tag{14}$$

$$P = \frac{TP}{TP + FP} \tag{15}$$

Where TP and FP are the true and the false positive values.

3.4. RF Classifier

Eventually, defect classification is performed by the RF classifier, recognized for its efficiency and robustness in managing complicated classifier tasks. RF is most supervised ML technique and is deployed in uses for both classification and regression [19]. Data can be trained utilizing a range of methods as bagging. RF purposes also to a DT and decides a

Paper ID: SR24516155833 DOI: https://dx.doi.org/10.21275/SR24516155833

classification issue. At this point, a set of DTs can be employed to execute classification and the combination of distinct decision outcomes from the last classification. A tree in the ensemble creates a classification utilizing feature subsets from the entire database. In several instances, the last classification that is generated from the solutions of all such trees correctly represents the trained data forms. Algorithm 5 is shown in pseudocode for RF. Then feature significance values from all the trees can summed and normalized:

$$RandomForestX_x = \frac{\sum_y normX_{xy}}{\sum_{y\epsilon\ all\ features, T\ \epsilon\ all\ trees} norm\ X_y T} \quad (16)$$

$RandomForestX_x$ refers to the feature priority x computed in every tree from the RF algorithm, normX sub (xy) signifies the normalization feature significance for x in tree y. The RF is often deployed for a wide spread of operations as it efficiently makes higher solutions. The progress of many DTs under the trained stage and the combination of their estimations using voting by the common are 2 essential.

Algorithm 1: Pseudocode for RF

To generate A classifiers:
for $i = 1$ to A do
To create D, elect instances at random from Â the trained data D utilizing replacement.
Make a parent node N_i that comprises D_i.
$Call\ BuildTree$ (T_i) $BuildTree$ (T):
end for
if N includes only samples of one class. then
return
else
Choose x% of the probable separating features from T at random.
To divide on, elect the feature F with the one of the information gained.
Generate st child nodes of $T, T_1, \ldots . T_s t$, whereas F take st probable rates $(F_1, \ldots F_s t)$
end if
for $i = 1$ to F do
position the rates of T_i to D_i, whereas D_i implies every T instance that equal F_i.
Call $BulidTree$ (T_i)
end for

4. Result Analysis

The simulation analysis of the FDRC - GWODL method is tested under fabric defect dataset, comprising 56 samples as shown in Table 1.

Table 1: Details of dataset

Class	No. of Instances
Horizontal Defect (HD)	33
Vertical Defect (VD)	23
Total Number of Instances	56

Table 2 and Fig.2 show the defect recognition outcomes of the FDRC - GWODL approach. With 80%TRAS, the FDRC - GWODL method obtains average $accu_y, prec_n, reca_l, F_{score}$, and MCC of 96.47%, 97.24%, 96.87%, 96.74%, and 96.21%, correspondingly. Besides, with 20%TESS, the FDRC - GWODL method attains average $accu_y, prec_n, reca_l, F_{score}$, and MCC of 98.56%, 95.59%, 96.50%, 97.95%, and 98.26%, correspondingly.

Table 2: Defect recognition of FDRC - GWODL method with 80%TRAS and 20%TESS

Class	Accuracy	Precision	Recall	F - Score	MCC
Training Phase (80%)					
HD	95.91	97.19	97.76	94.90	96.15
VD	97.03	97.28	95.98	98.58	96.26
Average	**96.47**	**97.24**	**96.87**	**96.74**	**96.21**
Testing Phase (20%)					
HD	100.00	97.29	97.21	97.26	98.95
VD	97.12	93.89	95.79	98.64	97.56
Average	**98.56**	**95.59**	**96.50**	**97.95**	**98.26**

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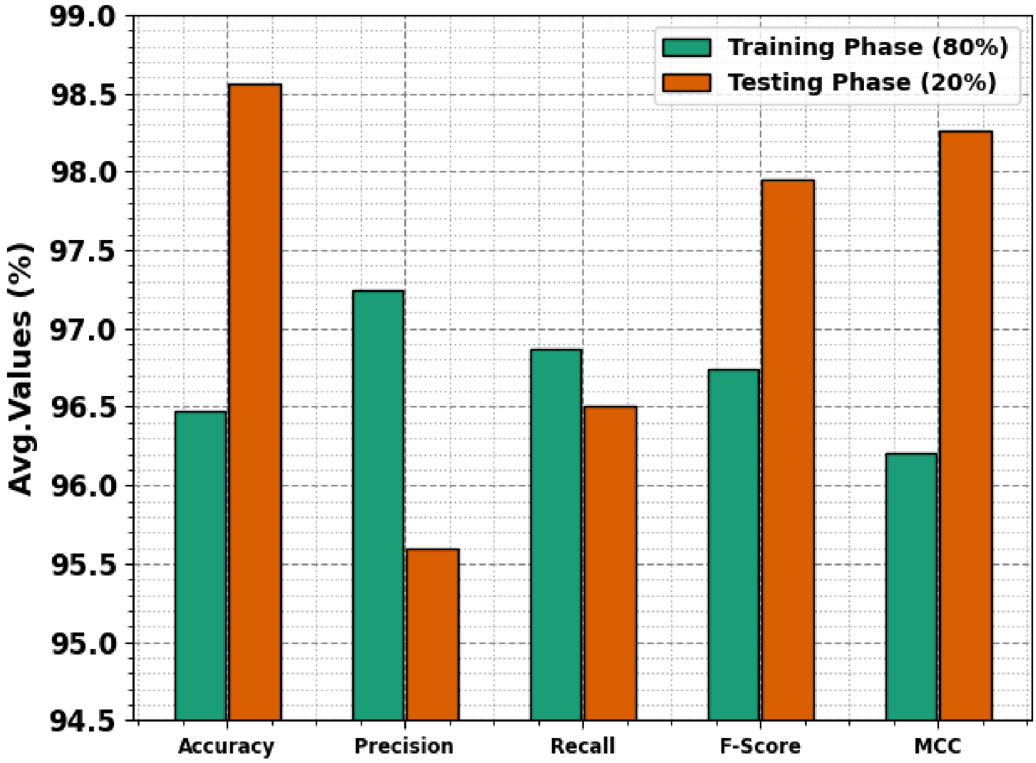

Figure 2: Average of FDRC - GWODL technique with 80%TRAS and 20%TESS

The classifier outcomes of the FDRC - GWODL method are graphically shown in Fig.3 for training accuracy (TRAAC) and validation accuracy (VALAC). The outcome displays valuable analysis of the behavior of the FDRC - GWODL model over different epochs, indicating its generalization capabilities and learning process. Notably, the figure indicates a constant development in the TRAAC and VALAC with increasing epoch count. It ensures the adaptable nature of the FDRC - GWODL model in the pattern detection model on both datasets. The increasing tendency in VALAC describes the capability of the FDRC - GWODL model to adapt to the TRA dataset and excel in providing correct classifier of hidden dataset, showing strong generalisability.

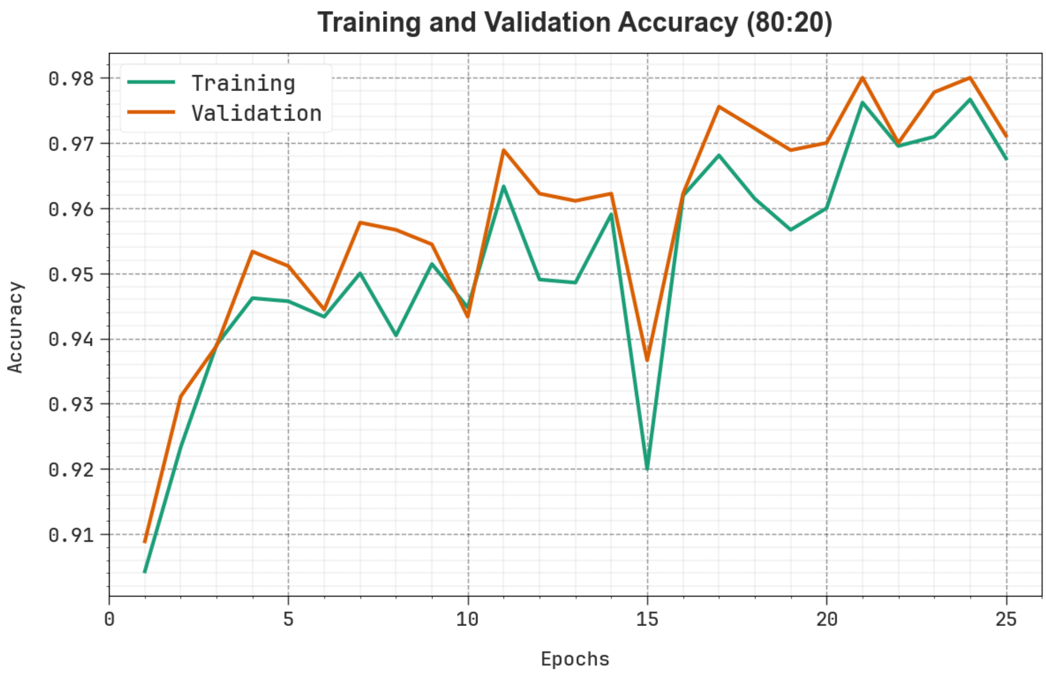

Figure 3: $Accu_y$ curve of FDRC - GWODL technique with 80%TRAS and 20%TESS

Figure 4: Loss curve of FDRC - GWODL technique with 80%TRAS and 20%TESS

Fig.4 exhibits a comprehensive review of the training loss (TRALS) and validation loss (VALLS) outcomes of the FDRC - GWODL technique over dissimilar epoch counts. The progressive decline in TRLA highlights the FDRC - GWODL method enhancing the weights and reducing the classification error on both datasets. The figure demonstrates a clear insight into the FDRC - GWODL model's relationship with the TRA dataset, which highlights its ability to capture patterns within both datasets. Notably, the FDRC - GWODL method recurrently increases its parameters in diminishing the variances amongst the prediction and real TRA classes.

The $accu_y$ outcomes of the FDRC - GWODL method are compared with other techniques in Table 3 and Fig.5. The outcomes appeared that the FDRC - GWODL technique resulted in improved $accu_y$ of 98.56%. At the same time, the IDFODL - FDC, MobileNetV3 - SSDLite, SSD, YOLOv4, YOLOX, CenterNet, and improved MobileNetv2 - SSDLite techniques have shown reduced $accu_y$ values of 98.15%, 96.32%, 92.10%, 92.83%, 96.66%, 96.38%, and 97.64%, correspondingly. Thus, the FDRC - GWODL method can be used for improved detection results.

Table 3: $Accu_y$ outcome of FDRC - GWODL technique with recent models

Methods	Accuracy (%)
FDRC - GWODL	98.56
IDFODL - FDC	98.15
MobileNetV3 - SSDLite	96.32
SSD Method	92.1
YoLoV4	92.83
YoLoX	96.66
CenterNet	96.38
Improved MobileNetV2 - SSDLite	97.64

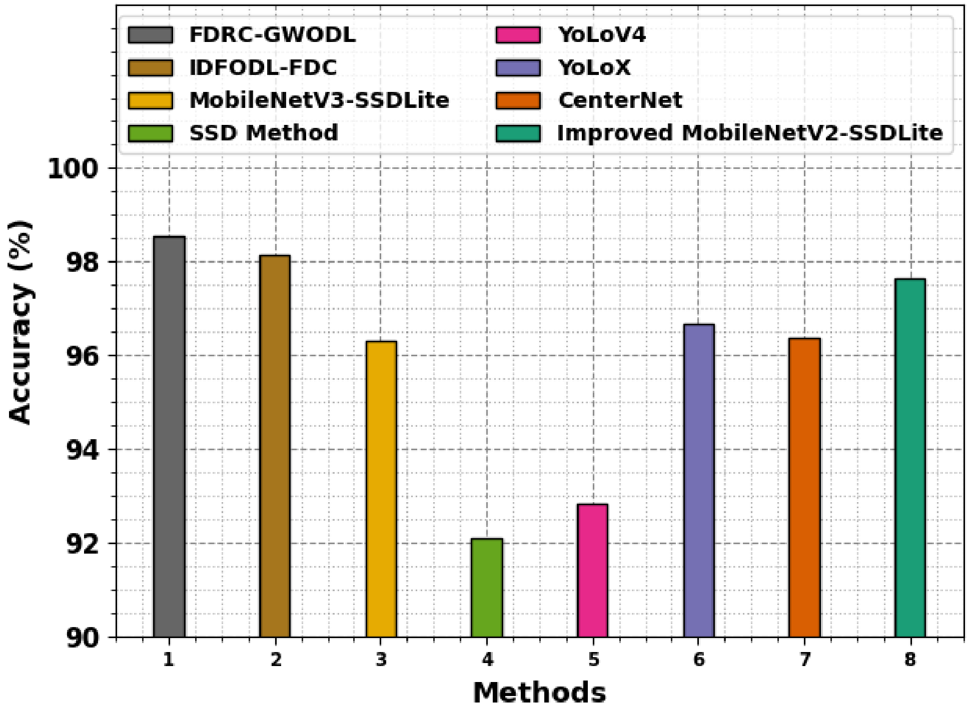

Figure 5: $Accu_y$ outcome of FDRC - GWODL technique with recent models

5. Conclusion

In this article, we have introduced an FDRC - GWODL model. The FDRC - GWODL technique applies BF, an innovative image processing method, to effectively mitigate noise interference and optimize image clarity. Leveraging the ResNet model as a feature extractor, the technique extracts discriminatory features critical for precise defect demonstration. Hyperparameter tuning is performed by the GWO, enhancing model parameters to increase recognition accuracy. Consequently, defect classification is performed by the RF classifier, recognized for its efficiency and robustness in managing complicated classifier tasks. Simulation outcomes illustrate the betterment of the presented FDRC - GWODL technique in fabric defect recognition, illustrating its possibility to enhance quality control measures in textile manufacturing process.

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