

Optimizing Gradients Weight of Enhanced Pairwise-Potential Activation Layer in CNN for Fabric Defect Detection

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Abstract

Imperfection classification is the most involved task in the cotton sector for finding Fabric Defects (FDs) and improving fiber productivity. Several approaches have been suggested in ancient times to automatically classify FDs. Presently, an Enhanced Pairwise-Potential Activation Layer in Convolutional Neural Network (EPPAL-CNN) approach depends on improved external memory and Dynamic Conditional Random Fields (DCRFs) to solve the complex pattern correlation of FDs and detect the defective fabrics from the given images. On the contrary, the gradient-based optimization schemes for learning the weights of CNN tend to unusual convergence nature, resulting in inefficient classification. Hence in this paper, an EPPAL-Optimized CNN (EPPAL-OCNN) approach is proposed which introduces an individual weight optimization scheme depending on NWM-Adam for solving the unwanted convergence of CNN. In this approach, a novel first-order gradient descent optimization method is introduced, which applies an adaptive exponential decay percentage for second-moment approximation rather than a preconfigured and constant one. Also, it can simply modify the grade to which how much the previous gradients weigh in the approximation. This novel exponential moving mean deviation is designed based on the fact that assigning additional memory to the previous gradients compared to the current gradients. Thus, it guarantees effective convergence and increases detection accuracy. At last, the testing results reveal that the EPPAL-OCNN achieves 94.64% of accuracy to different state-of-the-art approaches on the TILDA database.

Keywords: Fabric defects classification; EPPAL-CNN; Dynamic conditional random fields; Adam Optimization; Learning rate; Gradients.

1. Introduction

The cotton industry is a frequently developed standard industry. Typically, organic material is used to create cotton filaments. The development phase clearly shows a flaw in the structure of the fabric. A defective steerable device or texture deformation on the sewing system will induce material dissimilarities between the interval of its emergence in fiber, thread, or line imperfections such as strap misdrawing, resources, imprecision, and wool flannel. Production expenses can be minimized by 45-65% of imperfections. Weavers will monitor the cotton substance for vastly technical imperfections in contemporary looms by traversing a pair of devices on a regular basis since a fabric error is being avoided or resolved once observed [1].

As a result, the clothing industry has progressed toward completely automated fabric inspection for relevant textile reliability estimations. Computerization is a benchmarking procedure that detects and reports faults in raw materials, also known as training. Quality assurance on fabrics is typically the only solution to improve reliability, assisting in the quick and efficient recovery of relatively trivial imperfections. However, stiffness causes distortion, and minuscule failings are mostly unobserved. The standard advanced fiber inspection will improve the recognition rate by around 80% compared to the classical observation [2]. So, completely automated observations are a reasonable alternative for increasing textile profitability while decreasing production expenses. Nevertheless, this can be challenging. Many advanced fabric observation models focus on vision-based models, specifically image assessments and feature extraction strategies that often segregate and observe damaged textiles. Recognition approaches for FDs are divided as probabilistic, experiential, structured, composite, training, and design-based. Such approaches seemed to be error-prone, expensive, associated with particular deficiencies, and

incompatible with variations in fabric efficiency and structure. Numerous approaches for observing FDs have emerged in recent years.

Amongst many approaches, the modified version is intended to fulfil good durability in handling inconsistencies in textile structures and deformity classes. However, they have been less efficient in identifying deficiencies than the recurrent module of a textured fabric. Deep learning models, like CNN, have been used in early 20th century to effectively segment fabric motifs. CNN categories [3-5] encompass Fully Convolutional Network (FCN), U-Net, etc., which manage key modules like convolution, pooling, and activation stages, wherein the pooling can avoid overfitting issue and reduce the dimensionality. However, it extracts features along a total contextual correlation and linguistic data that are ineffective for mapping reasonable image characteristics, because classic CNNs are widely scalable and limited variations are eliminated through pooling [6].

Therefore, several FDs are regarded as limited patterns because they are portrayed by fewer pixel intensities. An imperfection appearance on cotton metaphors, such as overlap, impairment, coarse sets, etc, reflects the significant material structure and often contains only about 35% of pixels, resulting in an extremely unbalanced FD dataset. Alternative practise has been required to reconfigure CNN's performance in order to improve limited pattern localization. Another key concern in deep learning models is that input from practical cases is not always accessed broadly among labels [7]. As a result, when designing the CNN for detecting FDs, 2 important tasks are considered: the restoration of limited structures and the managing an imbalanced dataset. The essential CNN has not contained several convolutional units to solve missing data on fibre images and must preserve image persistence in attribute maps by pooling.

In this regard, PPAL-CNN approach [8] has been designed in which probabilistic fault features to detect FDs. First, the fibre patterns were determined through the auto-correlation of textile images to analyse the redundant fibre patterns. Then, a pattern map was generated through regularizing the cross-correlation. The neuron's distributions could define the fibre patterns consistency for generating the probabilistic principle. This principle was used as PPAL in CNN to link neurons in a pattern neighbourhood to the imperfection choice. Besides, fault probability map was used as a CNN's dynamic activation layer together with the CRF's pairwise-potential function to precisely detect limited patterns and manage the distorted images during CNN learning. On the other hand, the CRF have to be provided a prior distribution rather than being trained. It was challenging for complex correlations among FD labels if many or long-deep correlations were formulated.

To tackle this problem, an EPPAL-CNN approach [9] has been developed which solves the complicated pattern correlation of FDs. At first, the CRF was improved by means of external memory policies encouraged by the memory channels and thus making CRFs to interpret the regional attributes and use the entire image. It comprises a memory and DCRF layer. The memory layer is partitioned as incoming, outgoing and present incoming memory. The incoming and outgoing memories were defined using an attention that assigns the weights based on the importance of incoming and present incoming memory. After, the outcome of memory layer was fed to the DCRF as input. The DCRF's factorial structure comprises the links between cotemporally classes and precisely creating constrained probability correlations between dissimilar classes. So, a higher-order Markov correlation among classes was formed by means of an external memory. Conversely, the gradient-based optimization schemes for training CNN's weights tend to unusual convergence nature, resulting in inefficient classification.

Therefore, in this paper, an EPPAL-OCNN approach is proposed which introduces an individual weight optimization scheme depending on NWM-Adam for solving the unwanted convergence of CNN. In this approach, a novel first-order gradient descent optimization method is introduced, which utilizes the adaptive dynamic exponential decay percentage for second-moment approximation rather than a preconfigured and constant one. Also, it can simply modify the grade to estimate how much the previous gradients weigh in the approximation. It is based on the fact that assigning additional memory to the previous gradients compared to the current gradients. So, it ensures convergence and increases the detection efficiency.

The remaining sections of this article are planned as Section II studies previous research related to FD recognition and classification. Section III explains the methodology of EPPAL-OCNN and Section IV displays its efficiency. Section V concludes the work and suggests further improvement.

2. Literature Review

Zhang et al. [10] developed a model depending on YOLOv2 to automatically detect and categorize the yarn-dyed FDs. Initially, yarn-dyed FD samples were gathered, pre-processed, and labelled. After, different structures of YOLOv2 were applied for creating FDs recognition frameworks. But its efficiency was not effective and so needs to optimize the loss factor.

Xie et al. [11] considered a self-relevance and regional relevance of non-fault regions of periodic texture and pure-color texture for differentiating fault and non-fault regions. Also, an image pyramid was built for every fibre sample and Stacked Denoising Convolutional Auto-Encoder (SDCAE) was applied to restore the images during the learning stage. In the detection stage, the image was split into more blocks and restored by the learned SDCAE network. After, the candidate fault image blocks were approximately localized by structural similarity index, and

also the direction template was used for minimizing the false alarms. But it was performed only at the block level whereas it needs to identify the faults at a pixel level.

Zhao et al. [12] suggested a Visual Long-Short-Term Memory (VLSTM)-based hybrid scheme to categorize the FDs. In VLSTM, different features were extracted: the visual insight data extracted by stacked convolutional auto-encoders, the VSTM data extracted by the shallow CNN, and the VLTM data extracted by the non-regional neural networks. Based on these features, the images were categorized into FDs and non-FDs. But its network structure was complex and it was not suitable to solve the limited image problem.

Xie & Wu [13] designed a robust FD identification model depending on the enhanced RefineDet. First, the RefineDet was utilized as the support framework for identifying the fault images. Then, an enhanced head structure was designed depending on the complete convolutional channel attention block and bottom-up route augmentation transfer link block for increasing the fault identification precision. But few false predicted and missed fault regions were formed because of the highly identical contours of a few fault labels, identical color of the faults and the texture background.

Wu et al. [14] presented FD identification on optical image datasets. Initially, a huge imbalanced FD dataset was gathered and chosen to learn and validate the robust identifier. Then, an effective structure was designed to identify the imperfections using enhanced sub-phases from common structures for object recognition. But, the accuracy of identifier was not highly efficient.

Wei et al. [15] suggested a novel identification framework for increasing the ability of recognizing the small-scale objects. Initially, the attention-associated Visual Gain (VG) method was found that it changes the response amplitude without modifying selectivity and increasing the acuity of visual perception through evaluating the correlation between the attention method and the visual gain method. After, the appropriate methods were integrated into the Faster Region-based CNN (F-RCNN) for creating a novel framework called Faster VG-RCNN. But few false recognized and unrecognized fibre micro-faults were still exist if the tonality of the faults and fabric background were similar and the dimension was very tiny to be differentiated.

Hu et al. [16] designed a new unsupervised technique to automatically recognize faults in fibres depending on the Deep Convolutional Generative Adversarial Network (DCGAN) which has discriminator and generator using a novel encoder unit. In this technique, a residual map was constructed to emphasize possible faulty areas while subtracting the restoration from the actual image. Also, a likelihood map was created for the image under scrutiny where every pixel range denotes the chance of presence of faults at that position. After, the residual and the likelihood maps were synthesized mutually for generating an improved fusion map and final thresholding. However, it does not consider the spatial dependencies among pixels in recognition and may produce noisy segmentations.

Jun et al. [17] presented a training-based model to automatically identify the FDs. Initially, a fixed-size square slider was applied for cropping the actual image to a specific phase and regularity. After, enhanced histogram equalization was applied for improving the cropped images. Also, the Inception-V1 framework was used for predicting the presence of faults in the local region. At last, the LeNet-5 was employed as a voting scheme for recognizing the category of faults in the fibre. But it was highly expensive and time-consuming for detection.

Shi et al. [18] developed a FD identification technique depending on low rank decomposition of gradient data and structured graph algorithm. First, the fibre fault image was split into faultless block with regional attribute and fault damage time according to the features of fibre fault images using structured graph algorithm. Then, an adaptive threshold was assigned based on the number of rounds in the current block in the fusion procedure for supporting intra-lattice fusion and avoiding the fusion of faulty blocks and nearby non-faulty blocks. Moreover, the fault prior data computed from the partition outcomes was utilized for directing matrix decomposition to deteriorate the faultless area and emphasize the fault region under the sparse term. But, it is complex to achieve completely sparse outcomes and so the robustness of the technique was less.

3. Proposed Methodology

In this section, the EPPAL-OCNN approach is described briefly. Acquire a training image: $D = \{x_i, y_i\}_{i=1}^N$ where x_i indicates an input of i^{th} image in D and includes a sequence: $\{x_{i1}, \dots, x_{iT}\}$. Also, y_i includes the corresponding classes $\{y_{i1}, \dots, y_{iT}\}$. In training EPPAL-OCNN for recognizing the faulty fibre patterns, each x_t is the temporal data in any image with the corresponding label y_t . The block diagram of EPPAL-OCNN-based FDs recognition system is portrayed in Fig. 1.

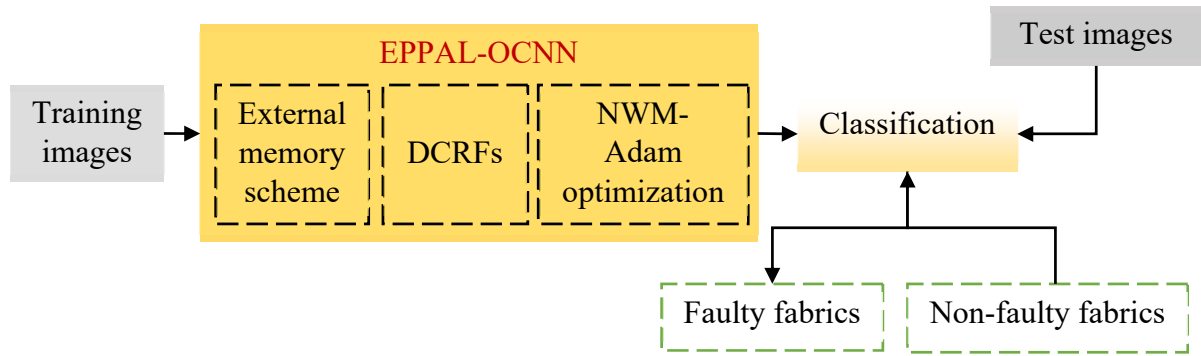


Fig. 1. Block diagram of proposed FDs recognition system.

First, the training images of faulty and non-faulty fabric types are collected and then EPPAL-OCNN classifier is trained to classify the faulty and non-faulty fabric images accurately. In EPPAL-OCNN, external memory scheme and DCRFs are employed to preserve the image resolution in the attribute maps during learning. Also, this EPPAL-OCNN is learned by the novel individual weight optimization algorithm based on the NWM-Adam scheme.

The NWM-Adam procedure utilizes the adaptive exponential decay percentage for second-moment approximation rather of a pre-constructed and constant. Initially, a global update principle is provided which encloses several gradient descent optimizers.

$$\theta_t = \theta_{t-1} - \frac{\eta_{t-1}}{\sqrt{v_{t-1}}} m_{t-1} \quad (1)$$

$$m_{t-1} = \phi_{t-1}(\nabla J_1(\theta_1), \dots, \nabla J_{t-1}(\theta_{t-1})) \quad (2)$$

$$v_{t-1} = \psi_{t-1}(\nabla J_1(\theta_1), \dots, \nabla J_{t-1}(\theta_{t-1})) \quad (3)$$

In Eqns. (1)-(3), η_{t-1} denotes the step size, $\frac{\eta_{t-1}}{\sqrt{v_{t-1}}}$ denotes the learning rate, ϕ_{t-1} and ψ_{t-1} represent the averaging functions. It is shown that the Adam procedure does not converge to the best outcome in the basic 1D convex configuration. Naturally, this basic error occurs in few broadly utilized exponential moving average techniques. The major issue is associated with the below quantity.

$$\Gamma_t = \frac{\sqrt{v_t}}{\eta_t} - \frac{\sqrt{v_{t-1}}}{\eta_{t-1}} \quad (4)$$

This quantity refers to the modification of the inverse of the training ratio regarding every iteration. The update principles of Stochastic Gradient Descent (SGD) and Adagrad normally consequence in non-improving training ratio. Based on the update principles of SGD and Adagrad, it is notice that $\Gamma_t \geq 0$ relating to each $t \in [T]$. But, the desirable semi-definiteness of Γ_t is not ensured regarding the procedures that use exponential moving mean for computing the square of gradient i.e., Adam, Adadelata and RMSprop. It may lead to non-convergence.

So, a new concept i.e., long-term memory of previous gradients is applied to the actual Adam procedure. As a result, the novel exponential moving mean deviation called NWM-Adam is designed which assigns additional memory of the previous gradients compared to the current gradients. It will create Γ_t desirable semi-definite and ensure convergence.

Also, it increases the efficiency of Adam algorithm. The major elements of this algorithm are Eqns. (1)-(3). If m_t denotes the first-moment approximation of gradient and v_t denotes the second-moment approximation of gradient. Such 2 approximations are determined as:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t \quad (5)$$

$$v_t = \beta_{2,t} v_{t-1} + (1 - \beta_{2,t}) g_t^2 \quad (6)$$

In Eqns. (6)-(7), g_t is the gradient of the fitness value J wherein the cross-entropy is applied as the fitness value. Here, $\beta_{2,t}$ modifies over interval t as:

$$\beta_{2,t} = \frac{(t^{\lambda-1})}{t^\lambda} \quad (7)$$

So, it modifies the grade to estimate how much the previous gradients weigh in the assessment. The major dissimilarity of NWM-Adam from Adam is that it uses a modifying $\beta_{2,t}$ to control the exponential decay percentage of moving mean of the squared gradient rather than fixed β_2 in Adam. So, this novel algorithm can

achieve that Γ_t is desirable semi-definite that solves the convergence problem of Adam. After, the weighting mechanism of the gradients in NWM-Adam is defined. Consider Eq. (1) and rewritten as:

$$\theta_t = \theta_{t-1} - \frac{\eta_{t-1}}{\sqrt{E[g^2]}} E[g] \quad (8)$$

Regarding the approximation of $E[g^2]$, techniques using exponential moving average can formulate this approximation unbalanced while the gradient magnitude differs from batch-to-batch. The weighing mechanism in NWM-Adam will give highly robust approximation compared to the AMSGrad and Adam. Also, it will stabilize the approximation while the new gradients oscillate.

Algorithm 3.1.

Input: Training dataset $D = \{x_i, y_i\}_{i=1}^N$

Output: Faulty fabric images and non-faulty fabrics images

Begin

Initialize N number of training images;

Train the EPPAL-OCNN with memory enhanced DCRFs;

Incorporate the temporal data with memory;

Initialize η, β_1 and $\beta_{2,t}$;

$m_0 \leftarrow 0$: //Initialize first-moment vector

$v_0 \leftarrow 0$: //Initialize second-moment vector

while(the stopping criterion is reached)

for($t \in [1, \dots, T]$)

Obtain gradients concerning fitness value at t as $g_t = \nabla_{\theta} J_t(\theta_t)$;

Obtain the hyper-parameter $\beta_{2,t}$ as given in Eq. (7);

Modify the first-moment approximate using Eq. (5);

Modify the actual second-moment approximate using Eq. (6);

Modify parameters as $\theta_{t+1} \leftarrow \theta_t - \frac{\eta m_t}{\sqrt{v_t + \epsilon}}$;

end for

end while

Recognize the faulty and non-faulty fabrics images;

End

4. Experimental Results

In this section, the EPPAL-OCNN is implemented in MATLAB 2017b using The Irish Longitudinal Study on Ageing (TILDA) dataset [19] for evaluating its efficiency compared with the existing approaches: EPPAL-CNN [9], VG-RCNN [15], RefineDet [13], and PPAL-CNN [8]. In TILDA dataset, each image includes a text reporting defective area in it. Also, it comprises 7 labels of fabrics with faults and a label of fabrics without faults. As a result, a whole dataset consists of 3200 TIF images with an overall capacity of 1.2GB. In this experiment, 2100 images are taken for learning and the remaining 1100 images are taken for testing. The comparison is conducted in terms of precision, recall, f-measure and accuracy. The confusion matrix for each label is acquired independently and a mean of recognized results for EPPAL-OCNN is presented in Table 1.

Actual Class	Recognized Class		
		Positive	Negative
	Positive (550 for each class)	True Positive 521	False Negative 29
	Negative (550 for other class)	False Positive 30	True Negative 520

Table 1. Confusion Matrix for 1100 Test Images.

4.1. Accuracy

The fraction of faulty and non-faulty fabrics exactly identified is called accuracy.

$$Acc = \frac{True\ Positive\ (TP) + True\ Negative\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative\ (FN)} \times 100\%$$

TP is the number of faulty fabrics correctly identified as faults whereas TN is the number of non-faulty fabrics correctly identified as non-faults. Similarly, FP is the number of faulty fabrics incorrectly identified as non-faults and FN is the number of non-faulty fabrics incorrectly identified as faults.

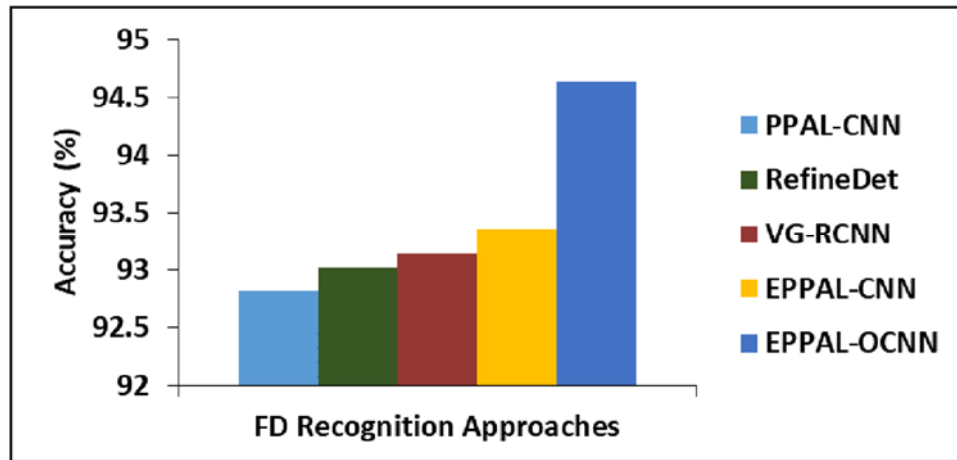


Fig. 2. Comparison of Accuracy.

Fig. 2. displays the accuracy of EPPAL-OCNN, EPPAL-CNN, VG-RCNN, RefineDet and PPAL-CNN approaches. Through this examination, it is observed that the accuracy of EPPAL-OCNN is 1.67% greater compared to all other approaches due to the precise utilization of the previous gradients in the optimization during learning process.

4.2. Precision

The fraction of identified fabrics patterns that are typically faulty fabrics is called a precision.

$$Pre = \frac{\text{No. of correctly recognized faulty fabrics}}{\text{No. of correctly recognized faulty fabrics} + \text{No. of incorrectly recognized faulty fabrics}}$$

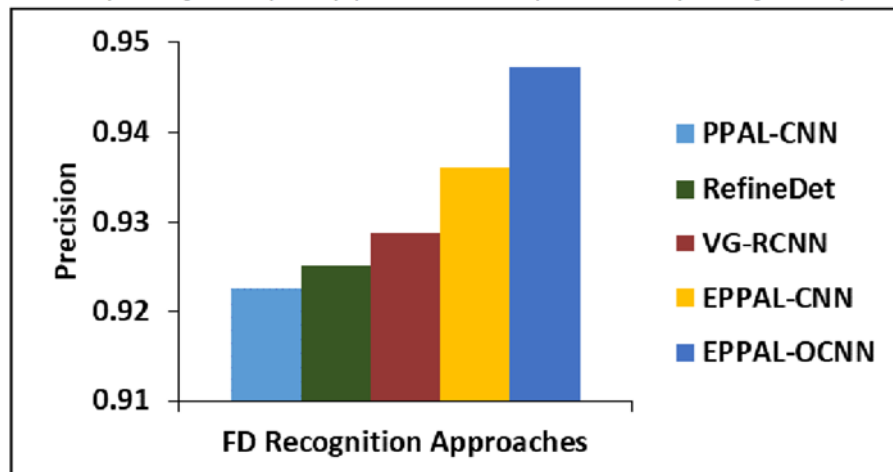


Fig. 3. Comparison of precision.

Fig. 3. illustrates the precision of EPPAL-OCNN, EPPAL-CNN, VG-RCNN, RefineDet and PPAL-CNN approaches. From this scrutiny, it is addressed that the precision of EPPAL-OCNN is 2.07% higher than the all-other FD recognition approaches because of using a proper gradient in optimization for learning.

4.3. Recall

The fraction of faulty fabrics exactly identified that are typically faults is called a recall.

$$Rc = \frac{\text{No. of correctly recognized faulty fabrics}}{\text{No. of correctly recognized faulty fabrics} + \text{No. of incorrectly recognized non - faulty fabrics}}$$

Fig. 4. displays the recall of EPPAL-OCNN, EPPAL-CNN, VG-RCNN, RefineDet and PPAL-CNN approaches. This analysis indicates that the recall of EPPAL-OCNN is 1.21% larger than the all-other approaches

for recognizing the faulty fabrics. Since it uses appropriate gradient values during learning and controls the complicated pattern correlation of FDs using external memory effectively.

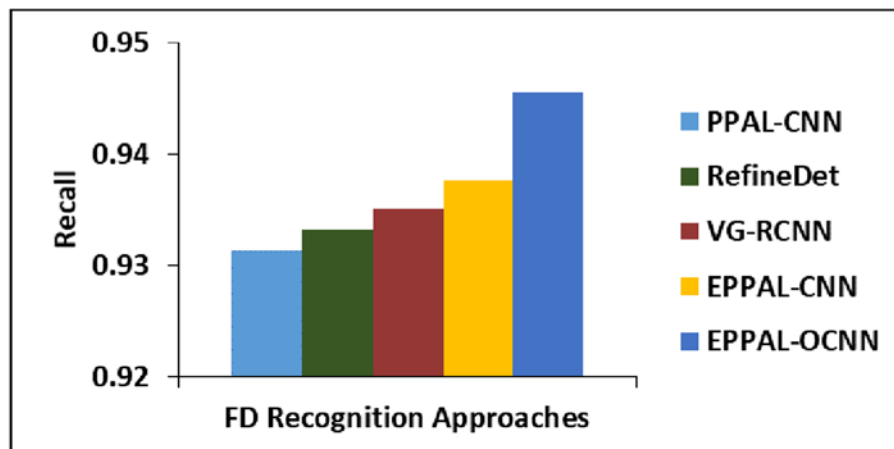


Fig. 4. Comparison of Recall.

4.4. F-measure

The harmonic mean of precision and recall is called f-measure.

$$F - measure = 2 \times \frac{Precision \cdot Recall}{Precision + Recall}$$

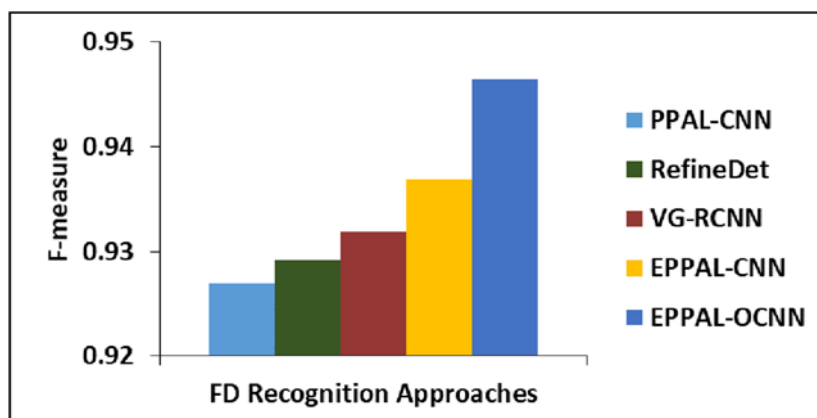


Fig.5. Comparison of F-measure.

Fig. 5. presents the f-measure of EPPAL-OCNN, EPPAL-CNN, VG-RCNN, RefineDet and PPAL-CNN approaches. From this investigation, it is concluded that the f-measure of EPPAL-CNN is 1.64% maximized than all the other existing approaches for recognizing the faulty fabrics and non-faulty fabrics.

5. Conclusion

1. This study introduced an EPPAL-OCNN approach using an individual weight optimization mechanism to resolve the unnecessary convergence of CNN. In EPPAL-OCNN, a novel first-order gradient descent optimization is developed to utilize the adaptive exponential decay percentage for second-moment approximation and update the grade to determine how much the previous gradients weigh in the approximation. This novel exponential moving mean variant was developed by considering the statement that allocating extra memory of the previous gradients compared to the current gradients. Therefore, effective convergence was guaranteed and the accurateness of recognizing the fibres imperfections was increased. To conclude, the findings proved that the EPPAL-OCNN has attained 94.64% of accuracy which was 1.67% greater than the all-other existing approaches on TILDA database. Though it guarantees the desirable convergence, the learning time to construct the recognition model for every type of faults in fibres was high. So, the future extension of this study will focus on reducing the learning time of deep learner using advanced schemes.

Conflicts of interest

The authors have no conflicts of interest to declare.

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3. Authors Profile



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