Anomaly Handwritten Text Detection for Automatic Descriptive Answer Evaluation

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ABSTRACT

Although there are advanced technologies for character recognition, automatic descriptive answer evaluation is an open challenge for the document image analysis community due to large diversified handwritten text and answers to the question. This paper presents a novel method for detecting anomaly handwritten text in the responses written by the students to the questions. The method is proposed based on the fact that when the students are confident in answering questions, the students usually write answers legibly and neatly while they are not confident, they write sloppy writing which may not be easy for the reader to understand. To detect such anomaly handwritten text, we explore a new combination of Fourier transform and deep learning model for detecting edges. This result preserves the structure of handwritten text. For extracting features for classification of anomaly text and normal text, the proposed method studies the behavior of writing style, especially the variation at ascenders and descenders. Therefore, the proposed work draws principal axis which is invariant to rotation, scaling and some extent to distortion for the edge images. With respect to principal axis, the proposed method draws medial axis using uppermost and lowermost points. The distance between the medial axis and principal axis points are considered as feature vector. Further, the feature vector is passed to Artificial Neural Network for classification of anomaly text. The proposed method is evaluated by testing on our own dataset, standard dataset of gender identification (IAM) and handwritten forgery detection dataset (ACPR 2019). The results on different datasets show that the proposed work outperforms the existing methods.

ICCPR 2022, November 17–19, 2022, Beijing, China

ACM ISBN 978-1-4503-9705-6/22/11…$15.00
https://doi.org/10.1145/3581807.3581855

CCS CONCEPTS

• **Image processing, Pattern recognition, Handwritten text, Machine learning and Deep learning.**;

KEYWORDS

Fourier transform, Convolution, Edge detection, Principal axis. Medial axis and Artificial neural network, Anomaly text detection

ACM Reference Format:
Nilanjana Chatterjee, Nc, Chatterjee, Palaiahnaakote Shivakumara, Ps, Shivakumara, Umapada Pal, Up, Pal, Tong Lu, Tl, Lu, and Yue Lu, Yl, Lu. 2022. Anomaly Handwritten Text Detection for Automatic Descriptive Answer Evaluation. In *2022 11th International Conference on Computing and Pattern Recognition (ICCPR) (ICCPR 2022), November 17–19, 2022, Beijing, China.* ACM, New York, NY, USA, 7 pages. https://doi.org/10.1145/3581807.3581855

1 INTRODUCTION

Automatic descriptive answer evaluation is challenging and is essential for reducing manpower as well as improving the process of assigning the grades. In addition, to expedite the processing of evaluation, it is necessary to develop an automatic evaluation system [1-5]. However, due to free style writing, paper, pen, female, male and different mood, one can expect large variations in the handwritten text. At the same time, when the student is confident in writing answer to the question, he/she write legibly. If the student is not sure about answer and is not confident, usually the students may not write the text legibly so that tutor cannot read and understand it. Sometimes, we can also expect totally irrelevant answer to the question. Therefore, when the answer script includes such sloppy/awkward sentences, the performance of Optical Character Recognizer (OCR) degrades because the text loses actual structure. When OCR fails to recognize the handwritten text accurately then the prediction step generates incorrect meaning. In this way, if the handwritten document contains mix of ugly and good writing, it is not so easy to achieve the best recognition results for answer script evaluation. Furthermore, aging, paper quality, ink quality and other degradations make problem more challenging. Thus, this work considers the sloppy sentences as anomaly text because there

(a) Example of normal handwritten text

(b) Example of anomaly handwritten text

Figure 1: Analyzing the behaviour of normal and anomaly handwritten text of the same answer written by the same student for the same question.

are chances of sudden change in writing style when the student is confident about answer.

One such sloppy sentences written by the student can be seen in Fig. 1, where it is noted that there is a clear difference between normal and anomaly text of the same answer written by the same student as shown in Fig. 1(a) and Fig. 1(b). The difference can be seen in terms of structure, style, loss of shapes and spacing between the characters. These observations motivated us to propose a new method for classification of normal and anomaly text in this work.

In the past, the methods were developed for gender classification [6], writer identification [7, 8] nationality identification [9], writer age classification [10, 11], forged handwritten text classification [12–14]. However, none of the methods consider anomaly text of the same answer written by the same student for classification. The above-mentioned methods may not be effective for anomaly text classification because there are no constraints like gender, age, writer, quality in the case of anomaly text classification. However, when we compared to forgery text detection, the problem looks similar. But it not true because forgery text classification method works based on the fact that the forgery operations introduce distortion while anomaly text classification works based on missing information due loss of shapes, incomplete characters and dense characters. This makes sense because forged text is readable while anomaly text is not readable. Therefore, anomaly text classification is open challenge for automatic answer script evaluation.

Hence this work aims at developing a new method for classification of anomaly and normal handwritten texts based on the notion that the behavior of the anomaly text changes as mindset of the student changes. In addition, it is true that edges or strokes in the handwritten text are prominent features. When there are changes in the handwritten text, the changes reflect in the stroke or edges. This observation motivated us to propose a method for edge detection for the input images. Inspired by the Pixel Difference Convolutional (PDC) operation which explores gradient information for efficient edge detection [15], we explore the PDC in frequency domain for detecting edges in this work. To extract the above-mentioned observations to study the behavior of the strokes, the proposed work extracts novel distance features based on the spatial relationship between principal axis and medial axis of the edge images of the input images. The extracted features are fed to simple Support Vector Machine (SVM) for classification of anomaly and normal handwritten text. The reason to use simple SVM for classification is that since the extracted features are robust and captures distinct properties of variations in the handwritten text, it does not need complex classifier for classification, which requires a large number of samples for accurate classification. Overall, to the best of our knowledge, this is the first work to explore the above novel combination of edge detection and distance feature extraction for classification of normal and anomaly text for assisting automatic descriptive answer evaluation.

The key contributions of the proposed work are as follows. (i) Exploring Pixel Difference Convolution (PDC) in frequency domain for edge detection is new. (ii) Extracting distance features, which are invariant to rotation and scaling by defining spatial relationship between principal and medial axes is new. (iii) Overall, the combination of edge detection by modified PDC, extracting invariant features and conventional simple classifier is the key contribution compared to the state-of-the-art methods.

2 RELATED WORK

The methods for gender, writer, nationality identification, document age classification, writer age identification and forged handwritten text detection are reviewed in this section.

The approaches developed for gender identification work are based on the fact that text written by male involve large variations while text written by female involves fewer variations [6]. However, these methods are not suitable for anomaly text detection or classification. The reason is that anomaly text classification can include text written by male and female. The variations or changes in the handwritten text may overlap with the text of male and female. The approaches developed for writer identification using handwritten text analysis works based on the notion that each writer has a unique writing style [7, 8]. However, since the methods were developed for analyzing variations in handwritten text for writer identification, the methods are not effective for anomaly text classification. This is due to the variations of anomaly text that may overlap with the variations of different writers. Therefore, these methods may not work well for anomaly text detection and classification.

There is a method for nationality identification using handwritten text analysis [9]. The methods consider English text written by different national as input for classification. It is assumed that each national has his/her own way of writing style and the same reflects in writing English text. Putra et al. [10] proposed a method for document classification according to age group. Basavaraj et al. [11] used disconnectedness features for writer age estimation in handwriting. Since the scope of the above-discussed methods is limited to particular language and specific features, therefore, the methods may not be effective for anomaly text classification. In the same way, there are methods for fraud document classification and forged handwritten text detection in the literature [12-14]. However, the distortion created by forgery operation may not exist in the case of anomaly text detection considered in this work because he or she writes text such that reader should not understand the meaning of the text properly. Therefore, the forged text detection method may not work well for anomaly text detection. In summary, although, several methods have been proposed in the literature for analyzing handwritten text to extract variations in writing with different objectives, the methods are not effective for anomaly text detection.

There are approaches for automatic script evaluation [1-5]. It is noted from the methods of descriptive answer evaluation that none of the methods consider the problem of anomaly text as defined in this work. This shows that state-of-the-art method ignore the effect of anomaly for improving performance of descriptive answer evaluation. However, in reality, writing style changes when the students are not sure about the answer, which is common. Therefore, anomaly text classification is vital to develop an accurate and reliable descriptive answer evaluation system. Hence, this work aims at developing a new method for addressing challenges of normal and anomaly text classification.

3 PROPOSED METHOD

As discussed in the previous section, the main aim of the proposed work is to develop a novel method for classification of anomaly and normal handwritten such that the performance of the descriptive answer system improves. However, the key challenge of accurate descriptive answer evaluation system is the presence of anomaly text, which is not actual answers, and the text is written in such a way that the reader should not understand the text meaning properly. Therefore, in order to classify the anomaly text from normal, we propose a method based on the fact that anomaly text has high writing variations, such as the random behavior of strokes, shape of the characters and loss of shapes etc compared to regular or normal text. Based on this observation, we develop a new model for edge detection such that the proposed method work can study the behavior of the text in terms of variations. For edge detection, inspired by the Pixel Difference Convolution (PDC) which helps us to detect efficient edges [15], we explore the same PDC in the frequency domain for edge detection in this work. To extract the features which represent variations, the proposed work draws principal axis for the edge image and then considers the principal axis as reference line to draw medial axis for the edge images. Then the distance between the pixels of medial axis and principal axis is estimated and considered as the feature vector. Further, the feature vector is fed to the Support Vector Machine (SVM) for classification of anomaly text classification from normal text.

3.1 Edge Detection

Inspired by the model introduced in [15], where it is shown that Deep Pixel Difference Convolution (PDC) Neural Network (PDC) is efficient and accurate for edge detection in medical images, we explore the same PDC in frequency domain for edge detection for handwritten text images. The pixel difference operation is similar to the conventional way as defined in Equation (1), where the original pixels in the local feature map patch covered by the convolution kernels are replaced by pixel differences when performing the convolutional operation. where x_i and x_i' are input pixels and v_i is the weight of the convolutional kernel. The pixel pairs are selected accordingly in different directions such as angular, radial and central with respect to the pixel x_i.. x_k, c*c is the dimension of the convolutional kernel. c is 3 for our experiment.

$$y = \sum_{i=0}^{c*c} v_i \cdot \left(x_i - x'_i\right) \tag{1}$$

The PDC operations are performed 3×3 kernel-wise on the entire image. When processing each kernel this input mask is transferred to the Fourier image. As shown in Equation (2) $F(u,v)$ is the values of coordinates (u,v) in frequency domain. f(u,v) is the pixel value of the input mask and m and n signifies the row and column number n and m respectively.

$$F\left(u,v\right) = \sum\nolimits_{m=0}^{c} \sum\nolimits_{n=0}^{c} f\left(u,v\right) e^{-j2\Pi\left(\frac{m}{c}+\frac{n}{c}\right)} \tag{2}$$

The proposed work considers the output of Equation (1) as the mask, and it multiplies with Fourier transform of the input images as defined in Equation (3) and then passes to the next layer. This whole process is presented in Fig. 2 and Fig. 3.

$$Z = y + F\left(u,v\right) * y \tag{3}$$

This architecture has 4 blocks with a total of 16 convolutional layers where layers periodically apply Angular PDC, Radial PDC and Central PDC. However, the key limitation of the model of edge detection is the lack of an efficient backbone. To overcome this problem, we propose PidiNet basic architecture, where whole backbone has 4 stages. Each stage has 4 residual blocks with a number of channels keeping limited to stay to the true form of smaller models for edge detection. Sometimes, this process misses important edge information. This observation motivated us to introduce Fourier Transform for performing multiple kernel operations, which helps us extract minute details of edge. Therefore, as it is suggested in Equation (1) every time the pixel difference kernel is passed to the next layer it is converted to the frequency domain and then multiplied with the input image mask of that layer to carry additional information. After successfully fusing the frequency mask with the input kernel, the image is again transformed to the spatial domain. We train this model with the help of HED-BSDS dataset [15], which provides ground truth for defining edges. Further, the proposed work concatenates edge maps generated by 4 blocks. This results in the final edge map. The complete architecture of the proposed model can be seen in Fig. 2 and Fig. 3, where we can see detailed information of the process of obtaining edge images for the input of handwritten text images. The operation between the two layers can be seen in Fig. 3.

For CNN, we use 3 type of pixel difference convolution namely angular PDC(APDC), Radial PDC(RPDC) and central PDC(CPDC). The proposed model calculates pixel difference by choosing pixel pair in the same direction. For example, APDC with a 3×3 kernel provides 8 pairs of pixels in angular direction. Then the pixel difference obtained is convolved with kernel weights by multiplication. And then the resultant mask is taken to the frequency domain with Fourier transform and it is multiplied with the input mask just before the pixel difference. This result of this mask operation is passed to the next layer. There are 4 main blocks with each of them with 4 sublayers. In the main block, the input pixel pairs are passed, and the pixel difference convolution is performed. The result of this step is fed the next layer. This process repeats for APDC, RPDC and CPDC kernels in the order.

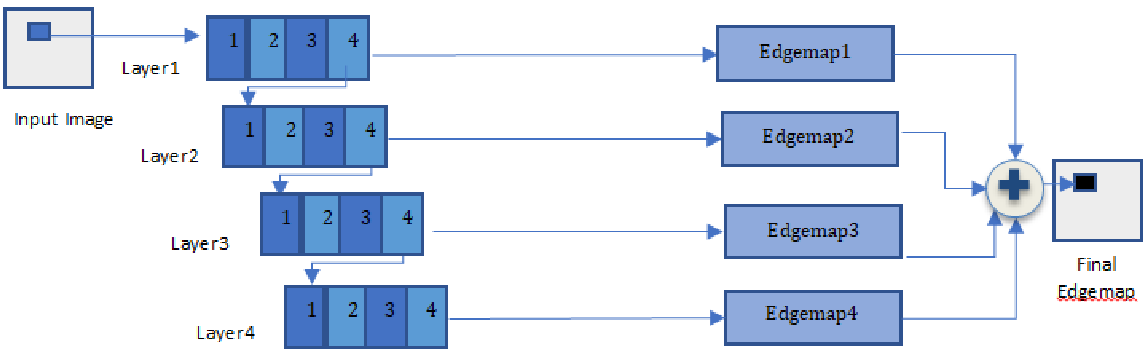


Figure 2: Proposed architecture for edge detection

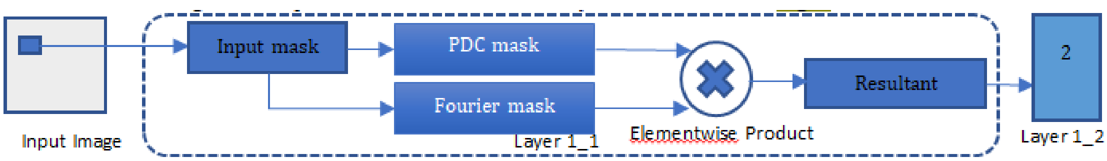
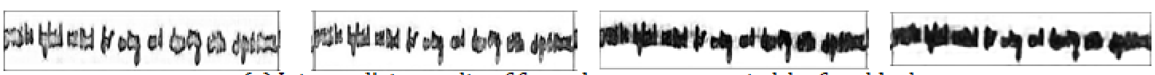
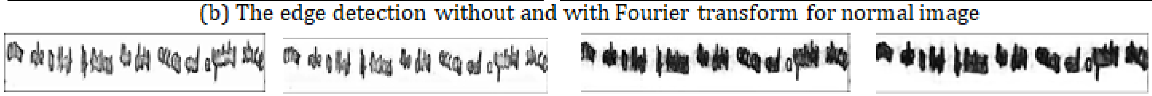


Figure 3: The operations happening in between 2 layers



(a) Intermediate results of four edge maps generated by four blocks.

(b) The edge detection without and with Fourier transform for normal image



(c) Intermediate results of four edge maps generated by four blocks for anomaly image

(d) The edge detection without and with Fourier transform for anomaly image

Figure 4: Illustrating the effect of edge detection using the proposed edge detection

The effect of the proposed architecture compared to alone PDC is shown in Fig. 4. The intermediate results of four edge maps are generated by four blocks for normal and anomaly text are shown in Fig. 4(a) and Fig. 4(c), respectively. Similarly, the edge detection results of proposed method without and with Fourier transform (frequency domain) for normal text and anomaly text are shown Fig. 4(b) and Fig. 4(d), respectively. It is observed from Fig. 4(b) and Fig. 4(d) that the results without Fourier transform look clumsy compared to the results with Fourier transform for both normal and anomaly text. This shows that the proposed method with Fourier is better than the method without Fourier especially for edge detection in normal and anomaly text.

3.2 Invariant Feature Extraction

As discussed in the Proposed Methodology section, in order to extract distinct variations for classifying normal and anomaly texts we draw principal axis by feeding x and y coordinates of pixels of edge image. It is considered as reference line for extracting rotation and scaling invariant features. It is illustrated in Fig. 5(a) where principal axis for normal and anomaly texts is drawn. It is observed from Fig. 5(a) that the principal axis passes through almost middle of normal text while it does not for anomaly text. In this way, edge detection helps us to extract distinct features for classification. This makes sense as Principal axis direction is based on angles of majority pixels in the image. This gives accurate reference despite loss of information, the number of words in the text line.

We believe that distance features capture the spatial relationship between the pixels, which usually changes according to writing

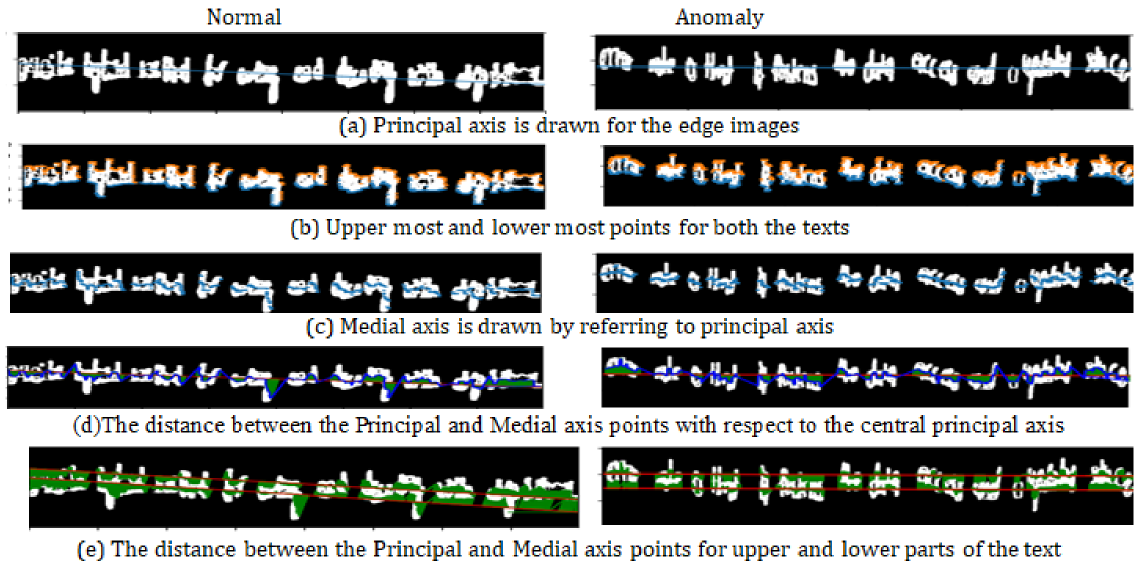


Figure 5: Illustrating the steps of the proposed method for feature extraction

style. With this notion, the proposed method detects medial axis points using upper and lower most points, which are detected by traversing in perpendicular direction to pixels of principal axis as shown in Fig. 5(b). Then the middle points are connected, which is considered as medial axis as shown in Fig. 5(c). The steps to find medial axis by referring to principal axis are as follows. For every pixel in principal axis $u_{i,}$ the uppermost white pixel and l_i, the lowermost white pixel is determined, and their midpoint $M[i]$ is marked as the point of medial axis as defined in Equation (4). The distance between medial axis points and principal axis points is calculated, which results in feature vector as defined in Equation (5). For every $i \in Axis$ distance between the medial axis point and principal axis is calculated, and it is illustrated in Fig. 5(d), where the lines are drawn between medial and principal axis points.

$$M\left[i\right] = \sum_{i \in Axis} \frac{u_i + l_i}{2} \tag{4}$$

$$Dis\tan ce\left[i\right] = \sqrt{\left(M[i]_x - Axis[i]_x\right)^2 + \left(M[i]_y - Axis[i]_y\right)^2} \tag{5}$$

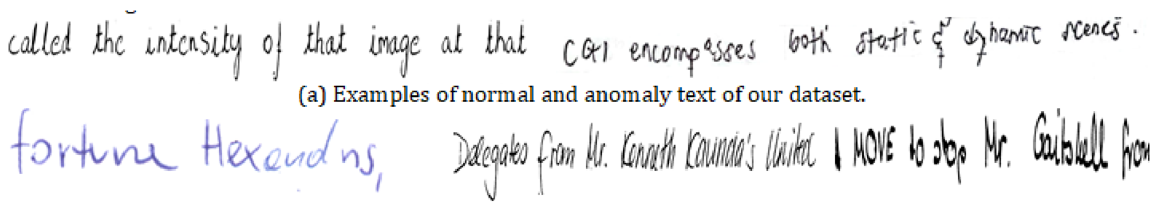
Due to large variations in writing style, length of the text and the number of words, the extracted feature vector is not sufficient to achieve the best classification results. The above feature vectors encode only global variations of writing style while missing local variations. Therefore, to extract local variations, the proposed method considers upper (above principal axis) and lower portion (below principal axis) of handwritten with respect to principal axis and the upper and lower portion are fed to principal axis step. This step divides the upper and the lower portion into two equal sized halves further as shown in Fig. 5(e), where two new principal axes. The same steps are used to extract distance features for the upper and the lower portion separately. This process output two more feature vectors. Furthermore, the proposed method concatenates these three feature vectors as single feature vector for classification. The feature vector is supplied to Support Vector Machine for classification of normal and anomaly text.

4 EXPERIMENTAL RESULTS

There is no standard dataset available in the literature for evaluating the proposed method. We create our own dataset from answer scripts written by undergraduate students. The text lines are cropped from the main answer sheet and labeled manually. We choose answers which comprise both normal text and anomaly text. For example, sometimes, for the question, a student writes answers legibly as long as the student is confident about the answer. When the student is not sure, the same student for the same question writes sloppy/ugly answers, which cannot be readable compared to normal text. Based on this observation, we choose text lines from the answer scripts as samples for anomaly class. For the text lines collection, there are no constraints, such as paper, pen, ink, gender and age. Our dataset consists of 200 images (100 images for normal class and another 100 for anomaly class).

If we believe sloppy writing causes type of distortion, degradations and loss of shapes, we can consider forged handwritten text dataset as standard dataset for experimentation. This makes sense because in general, the forgery operations, namely copy-paste, insertion and deletion introduce distortion while altering text, which is named ACPR 2019 dataset [13]. This dataset provides four classes, namely, original, forged, blurred and noisy. Since the scope of the proposed work is to classify normal and anomaly text, which is two class classification problem, we take the images of original class as normal and images from forged class as anomaly.

This dataset consists of 400 images which includes 200 normal and another 200 of anomaly text lines. In the case of gender identification using handwritten text analysis, the methods assume that female writing is clean, legible and neat while male writing is sloppy



(a) Examples of normal and anomaly text of our dataset.

(b) Original and forged images [13]

(c) Female and male of standard dataset of IAM.

Figure 6: Sample images of our and two standard datasets.

and ugly. This observation is same as normal and anomaly text of our dataset. Therefore, we consider one more popular and standard dataset of gender identification, which is IAM dataset. For this dataset, we choose 750 samples randomly from male and female writing. Sample images of normal and anomaly handwritten of our, ACPR 2019 and IAM datasets are shown in Fig. 6(a)-(c), respectively, where we can see all the images appear totally different and at the same time, they are all text. For all the experiments, we consider 80:20 ratio, which is training and testing ratio.

For comparative study, we implement the following state-of-the-art methods. Kundu et al. [13] proposed method for forged handwritten text detection based on Fourier spectral density and variations. Nandanwar et al. [14] used the combination of moments, Fourier transform and CNN for detecting forged handwritten text. To evaluate the proposed and existing methods, we use confusion matrix and average classification rate, which is mean of diagonal elements of confusion matrix.

4.1 Ablation Study

In the proposed method, exploring Pixel Difference Convolution (PDC) in frequency domain for edge detection, distance feature extraction based on principal and medial axis form edge images and use of SVM classifier for classification are the main steps to addresses challenges of normal and anomaly text classification. In order to validate the effectiveness of each key step, we conduct the following experiments on our, ACPR 2019 and IAM datasets. The results of all the experiment are reported in Table 1. (i) Instead of pixel difference convolution and frequency domain, we use Canny edge detector for edge detection for classification. (ii) For this experiment, we calculate Average Classification Rate (ACR) for classification using major axis instead of principal axis. (iii) Middle points are calculated for each column instead of finding medial axis for calculating ACR. (iv) We use ANN as our classifier to calculate avg ACR (v) In this experiment, we supplied the input image directly to ANN (Artificial Neural Network), SVM (experiment (v)) for calculating ACR. The reason to conduct experiments (v),(vi) is to show that the hand-crafted features are effective for classification. (vii) In the same way, to test the contribution of PDC and Fourier transform, the ACR is calculated for the classification with only PDC. (viii) For this experiment, we consider all the steps, which is the proposed method. From all the experiments reported Table 1, it is noted that the results of experiments (i)-(vi) are lower than the proposed method (experiment viii). Therefore, one can infer that integrating the key steps as the proposed method is effective for classification of normal and anomaly texts compared to individual steps.

4.2 Experiments on Edge Detection

Qualitative results of the proposed edge detection for sample images in Fig. 6 are shown in Fig. 7(a)-(c) on our, ACPR 2019 and IAM dataset, respectively, where it can be seen that the step preserves the structure of text regardless of different datasets. The results shown in Fig. 7 emphasize that the proposed edge detection is invariant to normal, anomaly text of different datasets.

4.3 Experiments on Anomaly Text Classification

Quantitative results of the proposed and existing methods on our, ACPR 2019 and IAM datasets are reported in Table 2, where it is observed that the proposed method is better than existing methods in terms of ACR for all the datasets. The reason for poor results of the existing methods [13, 14] on all the three datasets is that the success of the existing methods depends on the success of the pre-processing steps. In the case of [13] the threshold used for obtaining Fourier spectrum is sensitive to background and variations in the foreground. Similarly, for [14], the combination of moments and Fourier transform to enhance the fine details in the image is not robust to background and foreground variations. On the other hand, the proposed edge detection step is robust to different type of handwritten texts and generalized approach. Therefore, the proposed method is the best for classification of normal and anomaly text compared to the results of existing methods.

5 CONCLUSION AND FUTURE WORK

We have proposed a novel method for classification of normal and anomaly handwritten text such that the performance of automatic descriptive answer evaluation system improves. This is because the presence of anomaly text in the answers creates confusion for recognizing text accurately. To find solution to this problem, the prosed work introduces the pixel difference convolution in frequency domain for accurate edge detection irrespective of normal and anomaly texts in the images. The features are extracted from edge images by drawing principal axis, medial axis and the estimating the distance between the points of principal and medial axes. The features vector is fed to support vector machine for classification of normal and anomaly texts. Experimental results of the proposed and existing methods on our, two standard datasets of forged text detection and gender identification show that the proposed method outperforms the existing methods in terms of

Table 1: Average classification rate of the key steps for validating the effectiveness of the proposed method

Dataset	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)	(viii)
Our dataset	61.1	61.1	63.8	74	44.4	55.01	75	80.55
ACPR-2019-Forged [13]	53.75	62.82	66.25	70	68.75	46.25	65.82	71.79
IAM-Gender Identification	52.90	54.94	46	57	53.58	49.35	50.51	58.80

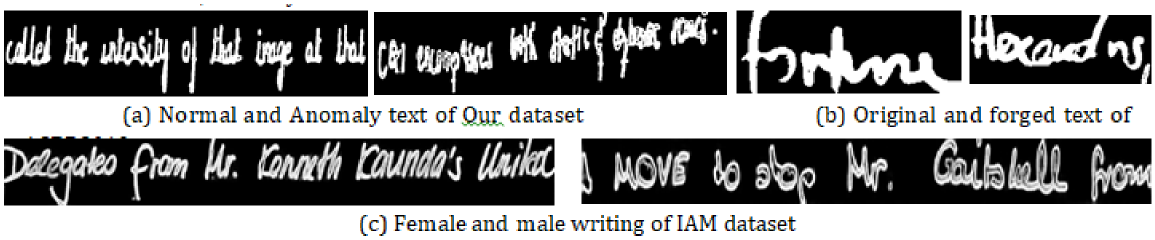


Figure 7: Qualitative results of the proposed method of edge detection on different datasets

Table 2: Performance of the proposed and existing methods for classification on our and two standard datasets (N: Normal class, A: Anomaly class and ACR: Average Classification Rate)

Methods	Proposed method						Kundu et al. [13]						Nandanwar et al. [14]					
Dataset	Our		ACPR		IAM		Our		ACPR		IAM		Our		ACPR		IAM	
Classes	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A	N	A
Normal (N)	88.2	11.8	69.56	30.44	46.37	53.67	70.6	29.4	81.8	18.2	30.6	69.4	57.14	42.86	69.7	30.3	39	61
Anomaly (A)	26.4	73.6	15	75	30.68	69.32	52.6	47.4	27.8	72.2	26.5	73.5	36.84	63.16	40,36	59.64	63.24	64.24
ACR	**80.55**		71.79		58.80		58.33		77.5		51.04		60		64		52.54	

average classification rate. However, sometimes, when the images are affected by severe distortions and the dataset includes text of multiple languages, the performance of the proposed methods degrades. To overcome this problem, we plan to propose end-to-end transformer for robust classification in the near future.

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