Hyperspectral Image Analysis for Writer Identification using Deep Learning

Ammad Ul Islam[1], Muhammad Jaleed Khan[1], Khurram Khurshid[1], Faisal Shafait[2,3]
[1] Artificial Intelligence and Computer Vision (iVision) Lab, Department of Electrical Engineering,
Institute of Space Technology (IST), Islamabad, 44000, Pakistan.
[2] School of Electrical Engineering and Computer Science (SEECS),
National University of Sciences and Technology (NUST), Islamabad, 44000, Pakistan.
[3] Deep Learning Laboratory, National Center of Artificial Intelligence (NCAI), Islamabad, 44000, Pakistan.
Email: khurram.khurshid@ist.edu.pk

***Abstract*— Handwriting is a behavioral characteristic of human beings that is one of the common idiosyncrasies utilized for litigation purposes. Writer identification is commonly used for forensic examination of questioned and specimen documents. Recent advancements in imaging and machine learning technologies have empowered the development of automated, intelligent and robust writer identification methods. Most of the existing methods based on human defined features and color imaging have limited performance in terms of accuracy and robustness. However, rich spectral information content obtained from hyperspectral imaging (HSI) and suitable spatio-spectral features extracted using deep learning can significantly enhance the performance of writer identification in terms of accuracy and robustness. In this paper, we propose a novel writer identification method in which spectral responses of text pixels in a hyperspectral document image are extracted and are fed to a Convolutional Neural Network (CNN) for writer classification. Different CNN architectures, hyperparameters, spatio-spectral formats, train-test ratios and inks are used to evaluate the performance of the proposed system on the UWA Writing Inks Hyperspectral Images (WIHSI) database and to select the most suitable set of parameters for writer identification. The findings of this work have opened a new arena in forensic document analysis for writer identification using HSI and deep learning.**

Keywords- deep learning; hyperspectral image analysis; writer identification; document forensics; convolutional neural network

I. INTRODUCTION

Handwriting style is an important characteristic of an individual. It is very difficult to counterfeit the exact handwriting style of another person due to considerable variations among text letters, pen-pressure on the page, writing angle, word or alphabet spacing and number of strokes [1]. Due to its unique nature, handwriting is treated as a personal biometric in forensics as it plays a vital role in document authentication [2]. Recent advancement in machine learning and document analysis has attracted researchers towards the development of automatic and robust document authentication methods. Most of the existing writer identification methods based on conventional machine learning techniques use human defined features, such as texture and visual features. Adak et al. [3] studied the intra-variability of handwriting in a Bengali documents dataset with 110 writers based on both handcrafted and auto-derived features. Chahi et al. [4] employed the block wise local binary count features for offline text independent writer identification in IAM, CVL and Arabic documents datasets. The performance of traditional methods is limited in terms of accuracy and robustness due to the lack of spectral information. Most of the recent techniques are based on color imaging and are applicable in scenarios with low complexity. However, the spatial information provided by color images is not sufficient for forensic analysis of documents with highly skilled and fabricated forgery. In crime cases, criminals tend to erase or manipulate the evidence [5] due to which it is very hard to detect forgery or identify a writer using color images.

In the last decade, the trend towards hyperspectral imaging (HSI) for such complex problems has gained a boost because it can capture rich information content in a scene in numerous spectral bands of the electromagnetic spectrum [6]. Hyperspectral images exhibit different spectral response for each intrinsic material in a captured scene due to the unique chemical composition of each material. If a document is illegally manipulated and the evidence is spoilt, the writer or forger may not be visually detected but chemical properties of the forged document can aid a HSI based forgery detector to identify the writer. Also, the modern deep learning models such as Convolutional Neural Network (CNN) are being widely used for automatic feature extraction for complex problems in the areas of signal processing, computer vision, natural language processing and data science [7]. A multitask learning based deep adaptive technique is proposed for writer identification of single word handwritten images [8], in which the reusability of features extracted for auxiliary task in writer identification is studied. A new adaptive layer in the CNN was proposed for exploiting deep features which improved its accuracy as compared to non-adaptive and simple adaptive methods. Nguyen et al. [9] employed local features aggregation from global features by using sampled tuples of the images and validated the proposed method on Japanese documents dataset JEITA-HP with 99.97% accuracy for 100 writers. The technique is also tested on IAM and Finemarker data sets achieving 91.80% accuracy using one page per writer and for total of 900 writers. The performance of modern deep neural networks is even better than humans in terms of speed and error rate [10].

The recent literature shows a high potential of hyperspectral imaging for forensics and document analysis. However, the area of writer identification in this context is not explored yet. The variation of pen pressure exerted within a stroke in handwriting is a unique attribute of a writer, which relates to the reflectance of corresponding pixels in the hyperspectral image of handwritten document. Such discriminatory features provided by HSI have a high potential in the development of robust writer identification methods for document forensics. In this paper, we propose a novel writer identification method which is based on HSI and deep learning. The spectral responses of text pixel and its neighboring pixels in a document image are extracted and passed to CNN for writer classification. Three different spatio-spectral image formats are employed to utilize the spatial as well as spectral information in the handwritten documents. Promising results are achieved after performing comprehensive experiments on the publicly available UWA Writing Inks Hyperspectral Images (WIHSI) database. The results achieved on HSI images are also compared with that of corresponding RGB images, which depicts the significance of HSI over color imaging in writer identification.

The remaining paper is organized as follows. Section II presents the review of various writer identification techniques. In Section III, we present the proposed method. The experimental analysis is discussed in Section IV followed by conclusion and future work in Section V.

II. Related Work

The recent document analysis systems proposed for document authentication in general and writer identification in particular are reviewed in this section. The related works based on conventional texture based writer identification methods include content independent font recognition [11], comparison of questioned document with a document written by the suspect based on global features extracted from both documents, and log-likelihood ratio with Gaussian or gamma estimates [12], local binary patterns and local phase quantization based texture analysis [13], fusion of k-adjacent segments and SURF features and contour gradient descriptors [14]. Artificial Neural Network (ANN) has also been used for classification of 20 writers each in English [15] Farsi [16] documents.

The aforementioned writer identification methods are based on conventional machine learning methods and hand-crafted features, whose performance is limited both in terms of accuracy and robustness. The advent of GPU computing and big data has greatly attracted researchers towards deep learning based automated document analysis systems [17]. CNN has been employed for online writer identification aided by Drop Segment augmentation [18], as well as for text and language independent writer identification [19]. Keglevic et al. [20] proposed a triplet of CNN networks that learns the similarities in image patches, maximizes the intra-class distance and minimizes the inter-class distance, and achieved 86.1% accuracy on the ICDAR-2013 dataset. A comprehensive and detailed review of writer identification methods based on machine learning is provided in [21].

Hyperspectral imaging (HSI) provides the spectral reflectance of each pixel in a captured scene for identifying materials and detecting objects and processes [6]. The applications of HSI in document image analysis and forensics have increased significantly over the past few decades. Khan et al. [22] proposed fuzzy C-means clustering based on selected features for forgery detection in hyperspectral document images and achieved considerable results. R. Qureshi et al. [23] has provided a comprehensive review and comparative analysis of state-of-the-art hyperspectral document image analysis systems, their applications and associated challenges. Khan et al. [24] proposed a nondestructive k-means clustering based forgery detection method for hyperspectral document images and presented the UWA WIHSI database of handwriting notes written with pens from a variety of manufacturers and captured in the visible spectrum under different illumination conditions. The promising results shown in their work encouraged the use of HSI for forensic analysis. Padoan et al. [25] proposed a HSI method for non-destructive analysis of historical documents and showed encouraging results. However, the time complexity of their system was very high. A similar non-destructive method for historical document restoration is proposed in [26]. Silva et al. [27] proposed the use of PCA and MCR-ALS for non- destructive detection of fraudulent documents using near-infrared hyperspectral images.

Khan et al. [28] compared the performance of color imaging and HSI for ink mismatch detection in which HSI outperformed RGB images by a huge margin. Luo et al. [29] used localized hyperspectral analysis and Abbas et al. [30] employed hyperspectral unmixing method based on Minimum-Volume Enclosing Simplex (MVES) and HySime for document forgery detection. Khan et al. [7] proposed a CNN based automated ink mismatch detection method for forgery detection in hyperspectral document images and reported 98.2% accuracy on artificially generated forged documents having mixed ink combinations in unbalanced proportions and varying number of inks. Due to the high correlation between neighboring pixels in a hyperspectral image, the spatio-spectral features result in improved classification of hyperspectral images [31][32]. Shu et al. [33] employed PCA and K-means clustering and Han et al. [34] employed a two-stream convolutional architecture for spatio-spectral hybrid feature extraction and classification of remote sensing hyperspectral images. Khan et al. [35] proposed a document authentication system based on hybrid spatio-spectral features extracted using CNN, which are used for classification of ink pixels in questioned documents.

The recent literature shows a high potential of HSI and spatio-spectral features for document analysis and forensics, however, the area of writer identification in this context is still unexplored. In this paper, an effort has been made to explore the potential of HSI and spatio-spectral features aided by deep learning in the area of writer identification. The discriminatory features of writers provided by HSI, including intra-stroke pen pressure, have a huge potential in the development of accurate and robust writer identification methods.

III. Proposed Method

A. *Database and Preprocessing*

The UWA WIHSI database [24] consists of 14 hyperspectral data cubes, each having 33 spectral channels in the visible range. One channel is shown as a grayscale image in Figure 1. Each cube contains five lines of handwritten text written with five same-colored pens of different brands. Seven subjects have written one document with five different black pens and one document with five different blue pens. Each cube is normalized and decomposed into five sub-cubes, each containing a single phrase, resulting in 70 sub-cubes. Text pixels are segmented in each sub-cube using Sauvola's local thresholding as shown in Figure 2.

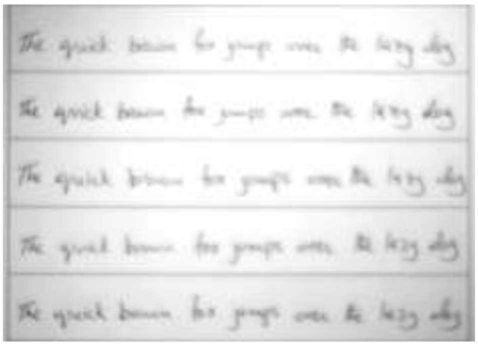

Fig. 1. Single document image written with black pens by one subject

Fig. 2. Segmentation mask obtained by Sauvola's local thresholding

B. *Database Organization*

The spectral responses of text pixels from all documents in the pre-processed database are extracted and organized in three datasets for experimental analysis, with each dataset containing the spectral responses of (i) black text pixels only, (ii) blue text pixels only, and (iii) both black and blue text pixels. In each of the three datasets, the spectral responses of text written with some inks are used for training the CNN and that of the remaining inks are used for unbiased testing of the trained CNN. This division of each dataset is performed in four train-test ratios, i.e. 4:1, 3:2, 2:3 and 1:4 for performance evaluation.

C. *Hyperspectral Mixing of Document Images*

Manipulated documents are artificially generated for performance evaluation by mixing the hyperspectral images of documents written by different subjects in varying ratios as given in Table I. The combinations "I" to "V" represent hyperspectral document images of text written by two authors using the same pen that are merged in varying ratios. The combinations "VI" to "X" represent hyperspectral document images of text written by three to seven authors merged in equal proportions. Only samples of the same color are inter-mixed. Figure 3 shows the hyperspectral mixing maps for three combinations.

D. *Spatio-Spectral Formats for HSI and RGB Images*

In order to make the spectral responses of text pixels compatible for input to 2D-CNN, we format the spectral responses of a center pixel and its neighbors in three spatio-spectral image representations shown in Figure 4(a-c) with only black labelled pixels being used for classification of the center pixel. Figure 4(d-f) show the corresponding image representation for each spatio-spectral format, with alternating light green and dark green labelled pixels showing the spectral responses of the black labelled pixels numerically labelled in Figure 4(a-c), whereas the light gray pixels represent zero values. The input layer size of each CNN architecture is modified for each of these three spatio-spectral formats, without making any changes to the hidden layers. Examples of each spatio-spectral image representation for both black and blue ink pixels are shown in Figure 5.

Fig. 3. Example of mixed hyperspectral document image of combinations (a) I, (b) III and (c) VI.

TABLE I. MIXING RATIOS OF MERGED HYPERSPECTRAL DOCUMENT IMAGES OF TEXT WRITTEN BY DIFFERENT SUBJECTS

S. No.	Combination Name	Number of Subjects	Mixing Ratio
1.	I	2	1:1
2.	II	2	1:4
3.	III	2	1:8
4.	IV	2	1:16
5.	V	2	1:32
6.	VI	3	1:1:1
7.	VII	4	1:1:1:1
8.	VIII	5	1:1:1: 1:1
9.	IX	6	1:1:1: 1:1:1
10.	X	7	1:1:1: 1:1:1:1

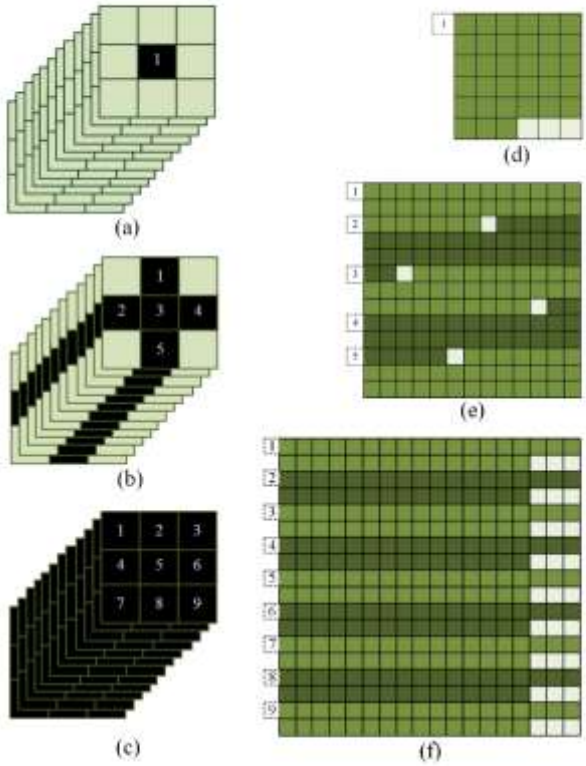

Fig. 4. Three different spatio-spectral formats (a) single pixel, (b) 4-neighbors (c) 8- neighbors, and their three corresponding image representations for organizing the center pixel and neighbor pixels in a single image of size (d) 6x6, (e) 13x13 and (f) 18x18.

In order to validate the significance of HSI over color imaging, the same experiments are conducted on corresponding RGB images for the sake of fair comparison. The hyperspectral document images from UWA WIHSI database are converted into RGB images, and the RGB data is organized in the same format as that of HSI, i.e. in three spatio-spectral formats shown in Figure 4. A text pixel represented by 33 spectral response values in HSI is represented by only 3 intensity values in

RGB, the RGB values are duplicated in order to fill the spatio-spectral image formats.

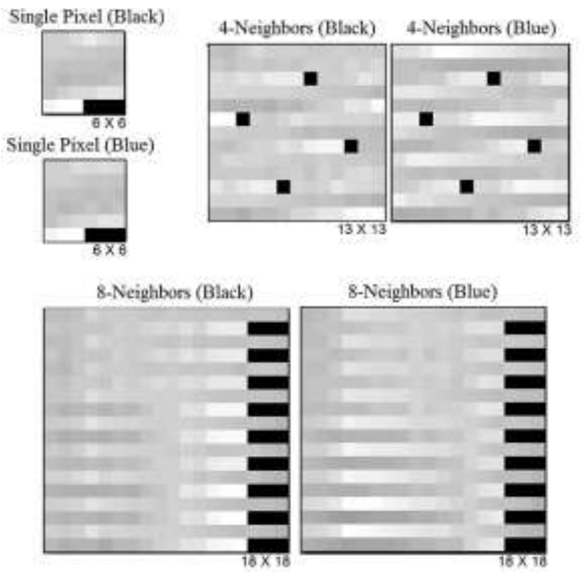

Fig. 5. Examples of spectral response of a text pixel and its neighboring pixels organized in three spatio-spectral image formats

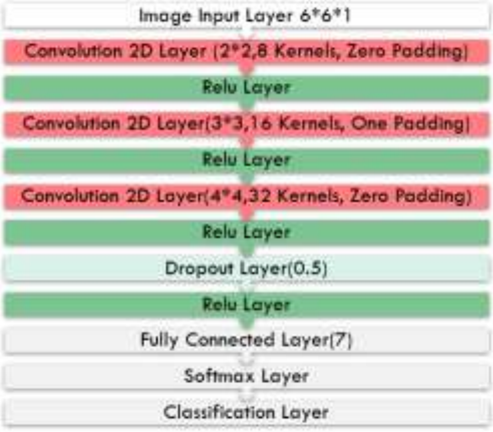

Fig. 6. Block diagram of CNN-4 Architecture

E. CNN Architectures and Hyperparameters

We trained and tested five different CNN architectures with different parameters such as the number of layers and number of filters in each layer, presented in Table II, to select the most suitable architecture and set of hyperparameters for writer identification using UWA WIHSI database. Each CNN is trained with the data organized and formatted as discussed in the previous subsections. The convolutional layers with defined kernels extract representative feature maps. ReLU layers maintain non-linearity in the system. Dropout layer is used in all combinations to avoid overfitting. Batch normalization layer is used to normalize the output for the next layer. Padding in the convolutional layers degraded the results very intensively. The extracted features and activations are merged at the fully connected layer with 7 neurons, representing 7 subjects. The output of fully connected layer is fed to the Softmax layer for calculation of class probabilities for each subject. The class probabilities are used by the classification layer to compute the cross-entropy and assign a class label to the input spectral response of a text pixel. The training parameters include a batch size of 400, 120 maximum epochs, momentum of 0.9, learn rate of 0.02 and SGDM as optimizer.

TABLE II. DETAILS OF DIFFERENT CNN ARCHITECTURES

CNN-1	**CNN-2**	**CNN-3**	**CNN-4**	**CNN-5**
Layers				
Input layer (6x6 / 13x13 / 18x18)				
Conv 3-24	Conv 3-24	Conv 2-6	Conv 2-8	Conv 2-16
Relu Layer				
Conv 3-12	Conv 3-12	Conv 3-12	Conv 3-16	Conv 3-32
Relu Layer				
Conv 3-6	Conv 3-6	Conv 3-18	Conv 4-32	Conv 4-64
Relu Layer				
Dropout		B-Norm	Dropout	Conv 2-16
		Relu Layer		Relu Layer
		Dropout		Dropout
Relu Layer				
Fully Connected Layer (7)				
Softmax Layer				
Classification Layer				
Accuracy				
66.04%	62.02%	69.54%	**71.28 %**	14.27%

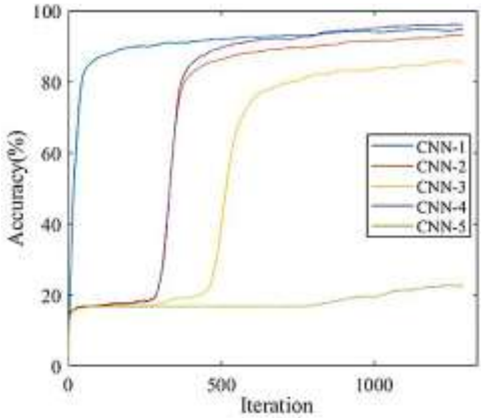

Fig. 7. Training accuracy plots of different CNN architectures trained on the dataset containing spectral responses of blue text pixels

IV. EXPERIMENTAL RESULTS

MATLAB R2018b was used for the experiments on a computer system with 16GB RAM and GTX 1060 GPU with 6GB memory and compute capability of 6.1. The five different CNN architectures shown in Table II were trained using the datasets discussed in subsection III-B and the spatio-spectral image formats shown in Figure 4. The training accuracy plots of each CNN architecture on the dataset of black text pixels with train-test ratio of 4:1 and single pixel image format are shown in Figure 7. CNN-2, comprising three convolutional layers with decreasing number of filters in each convolutional layer, converged most quickly whereas CNN-4, comprising three convolutional layers with increasing number of filters in each convolutional layer, reached the highest training accuracy. The corresponding test accuracies of all CNN architectures are mentioned in Table II. CNN-4 achieved the highest test accuracy of 71.28%. It is noted that smaller number of neurons in the starting layers and increasing the number of neurons towards the output layer improves the network performance. Moreover, smaller filter sizes of 2x2 and 3x3 are more suitable due to the small image sizes in the proposed method. Due to its better performance, CNN-4 is selected for further experimentation.

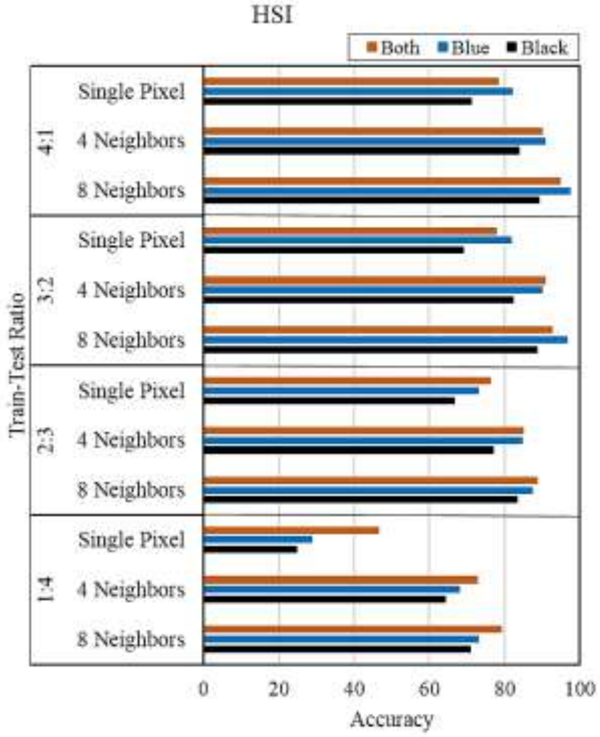

Fig. 8. Performance of CNN-4 with different train-test ratios of each of the three datasets of spectral responses using three spatio-spectral formats

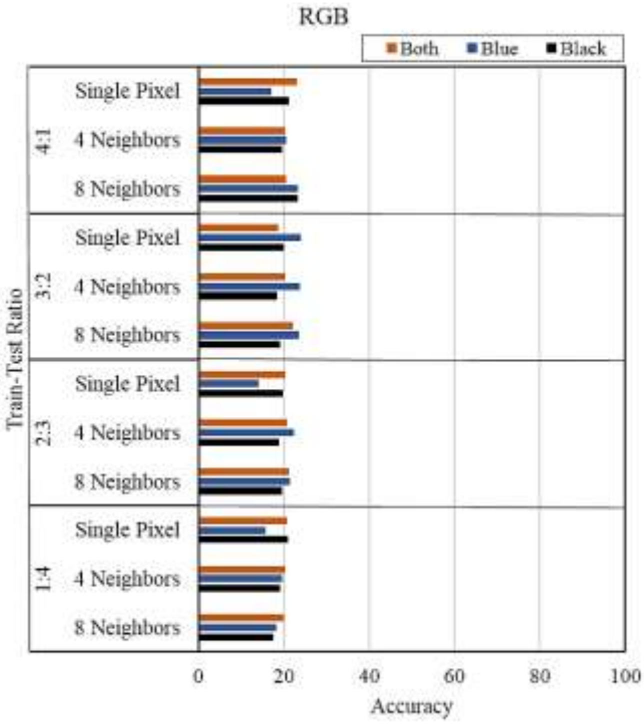

Fig. 9. Performance of CNN-4 with different train-test ratios of each of the three datasets of RGB intensity values using three spatio-spectral formats

Figure 8 shows the performance of CNN-4 with four train-test ratios and three spatio-spectral formats on the three datasets of spectral responses of text pixels. It is observed that decreasing the training data reduces the accuracy. The spectral responses of blue text pixels are confined in a relatively broader reflectance range as compared to those of black text pixels, therefore results on blue text pixels is relatively better than black text pixels overall. Results on the dataset with both blue and black text pixels are better for train-test ratio of 1:4 due to higher number of samples in this dataset. Furthermore, the spatio-spectral hybrid formats incorporating 4-neighbors and 8-neighbors format achieved higher accuracy than single pixel level classification, which depicts the effectiveness of spatio-spectral hybrid features in writer identification. Figure 9 shows the same set of results for corresponding RGB images. It is quite evident that RGB intensity values lack the writer specific features in spatial and spectral domains. Comparing Figure 8 and Figure 9 clearly shows that HSI is a promising technique for writer identification.

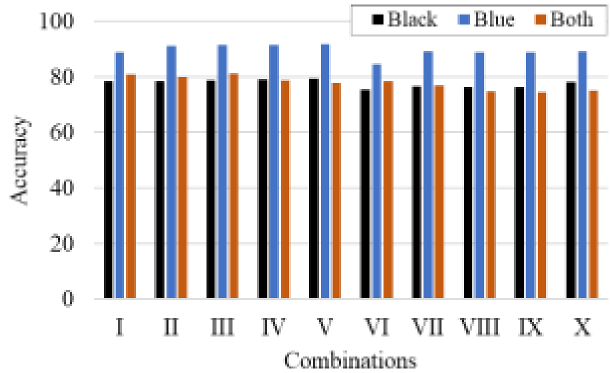

Fig. 10. Accuracy achieved by CNN-4 on all mixed combinations of hyperspectral document images written by seven different authors

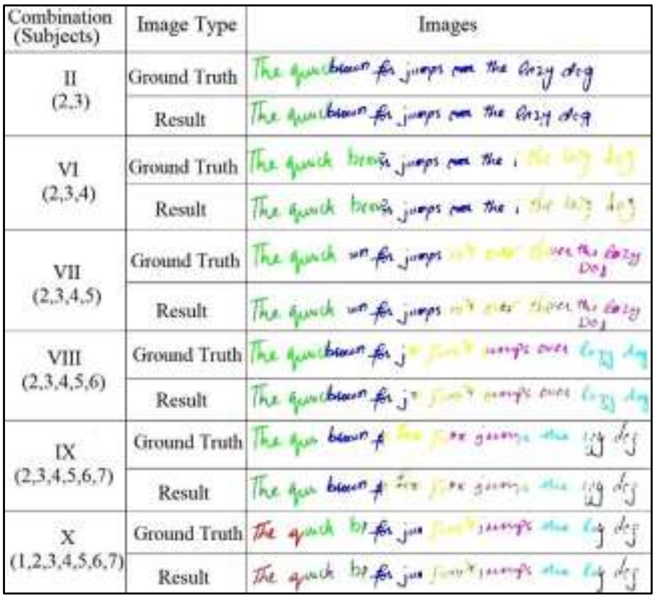

Fig. 11. Document labeling in mixed hyperspectral document images based on CNN classification for writer identification

CNN-4 was used to evaluate the performance of the proposed method on the artificially generated manipulated documents. The accuracy achieved for each combination is shown in Figure 10. An average accuracy of 72% on all mixed combinations with black ink pixels validates the effective use of deep learning and HSI for writer identification in forensic document analysis in highly complex scenarios. The accuracy is almost same for all combinations because the CNN is trained with samples of all subjects and its performance does not depend on the number of subjects or mixing ratio, thus making the proposed system robust to varying conditions. Figure 11 shows these results in visual form. The mixed combinations of hyperspectral documents are labelled based on CNN classification results for visualization. Each color corresponds to a different subject. It can be noticed that most of the writer pixels are correctly classified except some misclassified pixels in cases of high mixing ratio.

V. CONCLUSION

The recent literature shows a high potential of HSI and deep learning for document analysis. The area of writer identification however in this context is still unexplored. In this paper, an effort has been made to explore the potential of HSI and deep learning in writer identification. The discriminatory writer-specific features provided by HSI, including intra-stroke pen pressure, have a huge potential in the development of HSI based accurate and robust writer identification methods. A novel writer identification method based on a spatio-spectral convolutional architecture is presented in this paper. The spectral responses of text pixels and their neighboring pixels in a document are extracted and passed to a CNN for writer classification. Encouraging results are reported after performing comprehensive experiments on the UWA WIHSI database, highlighting the advantages in the use of HSI for writer identification.

Development of larger databases of hyperspectral document images is crucial for further exploration of the potential of HSI and deep learning in writer identification. This research gives a new direction to forensic document analysis for writer identification and encourages the development of large databases with hyperspectral document images written by a large number of authors.

REFERENCES

[1] K. M. bin Abdl and S. Z. M. Hashim, “Handwriting identification: a direction review,” in 2009 IEEE International Conference on Signal and Image Processing Applications, 2009, pp. 459–463.

[2] S. N. Srihari, S.-H. Cha, H. Arora, and S. Lee, “Individuality of handwriting,” Journal of forensic science, vol. 47, no. 4, pp. 1–17, 2002.

[3] C. Adak, B. B. Chaudhuri, and M. Blumenstein, “An Empirical Study on Writer Identification and Verification From Intra-Variable Individual Handwriting,” IEEE Access, vol. 7, pp. 24738–24758, 2019.

[4] A. Chahi, Y. Ruichek, and R. Touahni, “Block wise local binary count for off-line text-independent writer identification,” Expert Systems with Applications, vol. 93, pp. 1–14, 2018.

[5] W. Wang, L. Zhang, D. Wei, Y. Zhao, and J. Wang, “The principle and application of hyperspectral imaging technology in detection of handwriting,” in 2017 9th International Conference on Advanced Infocomm Technology (ICAIT), 2017, pp. 345–349.

[6] M. J. Khan, H. S. Khan, A. Yousaf, K. Khurshid, and A. Abbas, “Modern trends in hyperspectral image analysis: a review,” IEEE Access, vol. 6, pp. 14118–14129, 2018.

[7] M. J. Khan, A. Yousaf, A. Abbas, and K. Khurshid, “Deep learning for automated forgery detection in hyperspectral document images,” Journal of Electronic Imaging, vol. 27, no. 5, p. 053001, 2018.

[8] S. He and L. Schomaker, “Deep adaptive learning for writer identification based on single handwritten word images,” Pattern Recognition, vol. 88, pp. 64–74, 2019.

[9] H. T. Nguyen, C. T. Nguyen, T. Ino, B. Indurkhya, and M. Nakagawa, “Text-independent writer identification using convolutional neural network,” Pattern Recognition Letters, vol. 121, pp. 104–112, 2019.

[10] R. Geirhos, D. H. Janssen, H. H. Schütt, J. Rauber, M. Bethge, and F. A. Wichmann, “Comparing deep neural networks against humans: object recognition when the signal gets weaker,” arXiv preprint arXiv:1706.06969, 2017.

[11] Y. Zhu, T. Tan, and Y. Wang, “Font recognition based on global texture analysis,” IEEE Transactions on pattern analysis and machine intelligence, vol. 23, no. 10, pp. 1192–1200, 2001.

[12] S. N. Srihari, M. J. Beal, K. Bandi, V. Shah, and P. Krishnamurthy, “A statistical model for writer verification,” in Eighth International Conference on Document Analysis and Recognition (ICDAR’05), 2005, pp. 1105–1109.

[13] D. Bertolini, L. S. Oliveira, E. Justino, and R. Sabourin, “Texture-based descriptors for writer identification and verification,” Expert Systems with Applications, vol. 40, no. 6, pp. 2069–2080, 2013.

[14] R. Jain and D. Doermann, “Combining local features for offline writer identification,” in 2014 14th International Conference on Frontiers in Handwriting Recognition, 2014, pp. 583–588.

[15] U.-V. Marti, R. Messerli, and H. Bunke, “Writer identification using text line based features,” in Proceedings of Sixth International Conference on Document Analysis and Recognition, 2001, pp. 101–105.

[16] A. Rafiee and H. Motavalli, “Off-line writer recognition for farsi text,” in 2007 Sixth Mexican International Conference on Artificial Intelligence, Special Session (MICAI), 2007, pp. 193–197.

[17] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.

[18] W. Yang, L. Jin, and M. Liu, “Deepwriterid: An end-to-end online text-independent writer identification system,” IEEE Intelligent Systems, vol. 31, no. 2, pp. 45–53, 2016.

[19] L. Xing and Y. Qiao, “Deepwriter: A multi-stream deep CNN for text-independent writer identification,” in 2016 15th International Conference on Frontiers in Handwriting Recognition (ICFHR), 2016, pp. 584–589.

[20] M. Keglevic, S. Fiel, and R. Sablatnig, “Learning Features for Writer Retrieval and Identification using Triplet CNNs,” in 2018 16th International Conference on Frontiers in Handwriting Recognition (ICFHR), 2018, pp. 211–216.

[21] A. Rehman, S. Naz, and M. I. Razzak, “Writer identification using machine learning approaches: a comprehensive review,” Multimedia Tools and Applications, pp. 1–43, 2018.

[22] M. J. Khan, A. Yousaf, K. Khurshid, A. Abbas, and F. Shafait, “Automated forgery detection in multispectral document images using fuzzy clustering,” in 2018 13th IAPR International Workshop on Document Analysis Systems (DAS), 2018, pp. 393–398.

[23] R. Qureshi, M. Uzair, K. Khurshid, and H. Yan, “Hyperspectral document image processing: Applications, challenges and future prospects,” Pattern Recognition, 2019.

[24] Z. Khan, F. Shafait, and A. Mian, “Hyperspectral imaging for ink mismatch detection,” in 2013 12th International Conference on Document Analysis and Recognition, 2013, pp. 877–881.

[25] R. Padoan, T. A. Steemers, M. Klein, B. Aalderink, and G. De Bruin, “Quantitative hyperspectral imaging of historical documents: technique and applications,” Art Proceedings, pp. 25–30, 2008.

[26] R. Hedjam, M. Cheriet, and M. Kalacska, “Constrained energy maximization and self-referencing method for invisible ink detection from multispectral historical document images,” in 2014 22nd International Conference on Pattern Recognition, 2014, pp. 3026–3031.

[27] C. S. Silva, M. F. Pimentel, R. S. Honorato, C. Pasquini, J. M. Prats-Montalbán, and A. Ferrer, “Near infrared hyperspectral imaging for forensic analysis of document forgery,” Analyst, vol. 139, no. 20, pp. 5176–5184, 2014.

[28] Z. Khan, F. Shafait, and A. S. Mian, “Towards Automated Hyperspectral Document Image Analysis.,” in AFHA, 2013, pp. 41–45.

[29] Z. Luo, F. Shafait, and A. Mian, “Localized forgery detection in hyperspectral document images,” in 2015 13th International Conference on Document Analysis and Recognition (ICDAR), 2015, pp. 496–500.

[30] A. Abbas, K. Khurshid, and F. Shafait, “Towards automated ink mismatch detection in hyperspectral document images,” in 2017 14th IAPR International Conference on Document Analysis and Recognition (ICDAR), 2017, vol. 1, pp. 1229–1236.

[31] N. Akhtar, F. Shafait, and A. Mian, “Sparse spatio-spectral representation for hyperspectral image super-resolution,” in European Conference on Computer Vision, 2014, pp. 63–78.

[32] J. Leng, T. Li, G. Bai, Q. Dong, and H. Dong, “Cube-CNN-SVM: a novel hyperspectral image classification method,” in 2016 IEEE 28th International Conference on Tools with Artificial Intelligence (ICTAI), 2016, pp. 1027–1034.

[33] L. Shu, K. McIsaac, and G. R. Osinski, “Learning Spatial–Spectral Features for Hyperspectral Image Classification,” IEEE Transactions on Geoscience and Remote Sensing, vol. 56, no. 9, pp. 5138–5147, 2018.

[34] M. Han, R. Cong, X. Li, H. Fu, and J. Lei, “Joint spatial-spectral hyperspectral image classification based on convolutional neural network,” Pattern Recognition Letters, 2018.

[35] M. J. Khan, K. Khurshid, and F. Shafait, “A Spatio-Spectral Hybrid Convolutional Architecture for Hyperspectral Document Authentication,” in 2019 15th IAPR International Conference on Document Analysis and Recognition (ICDAR), 2019.