Ç. Şenel, G. Ayhan, Z.E. Uran, and B.U. Töreyin

Abstract— The pages that appear in front of users on digital platforms used for online advertising to attract attention to target product are called landing pages. Landing pages aim to increase advertisement conversion rate using the metrics like clicks, views or subscribes. In this study, a method is presented to automatically classifier the most commonly used components on landing pages which are buttons, texts, and checkboxes. Landing page images given as inputs are segmented by morphological and threshold-based image processing methods, and each segment is classified using a Transfer Learning based method which combines pre-trained Inception v-3 networks and Support Vector Classifier (SVM). Furthermore, different classifiers were applied to compare the results. The proposed method is anticipated to be an essential step in the process of designing landing pages automatically with high advertisement conversion rates. Thanks to the proposed transfer learning based method, this is achieved by using fewer number of training data.

Keywords—Landing Page Segmentation; Transfer Learning; Image Processing; Image Classification.

1. INTRODUCTION

ALANDING page is a page specifically designed for a particular target audience or product, especially for being used in digital marketing activities. The purpose of these pages is to increase digital conversion rate by using metrics like clicks, views or subscriptions. Landing pages have designs that contain an aim and message intended for the target audience and affect the conversion rate. Landing pages that are inadequate in design and do not correspond the expectations of users lead to low conversion rates [1,16].

Designs of landing pages commonly consist of components such as buttons, checkboxes, texts, and pictures. A representative landing page with related components is shown in Figure 1.

To the best of our knowledge, there are a very limited number of studies to segment and classify the landing pages for online advertising [19]. However, there are many studies about image segmentation and classification in computer vision and image processing literature [2-4,6-11].

Çağla Şenel, is Cerebro Yazılım Hizmetleri, İstanbul, Turkey, (e-mail: cagla.senel@cerebro.tech).

Gülşah Ayhan, is Cerebro Yazılım Hizmetleri, İstanbul, Turkey, (e-mail: gulsah.ayhan@cerebro.tech).

Zeynep Eda Uran, is Cerebro Yazılım Hizmetleri, Istanbul, Turkey, (email: zeynepeda.uran@cerebro.tech).

Behçet Uğur Töreyin, is with Department of Informatic Institute, Istanbul Technical University, Istanbul, Turkey, (e-mail: toreyin@itu.edu.tr).

Manuscript received June 7, 2018; accepted Sep 3, 2018. Digital Object Identifier:



Fig.1. A representative landing page in online advertising and the most commonly used components of landing pages; "text," "checkboxes" and "buttons."

Among them, there exist studies on text detection in color images, as well [5-6]. Segmentation methods divide the image into components by using properties, such as, pixel density, color, texture, etc., [9]. The methods used for successful segmentation of the images differ [10]. Multiple image segmentation methods can be combined considering the ambiguity and variety of images [11].

Deep learning algorithms, especially Convolutional Neural Networks (CNN), have been widely used to classify images [23-25]. Even though CNN has acquired remarkable achievement in image classification [12-14], there have been some cases that image classification through CNN was not the proper approach. In particular, there may arise overfitting and convergence related issues when dataset sizes are too small to train a CNN model [26]. Due to increase in the performance of CNNs with massive datasets, network sizes have been increased in many studies with complex architectures [27]. However, the complexity of model may lead overfitting [18]. Consequently, domain adaptation and transfer learning based approaches may be utilized to mitigate overfitting problems [29,30].

Transfer learning, is a machine learning approach, which allows to use a pre-trained model for different tasks or domains [27-30]. In the literature, many studies having tasks with limited training data problem have utilized transfer learning [25]. Since it is allowed to use pre-trained models for the datasets from different domains, transfer learning is preferable for most problems where collection of data/data acquisition is difficult [25]. In this paper, transfer learning is deployed for landing page component segmentation, as the labelled dataset for landing page components is limited.

Due to the design limitation of these components, collecting a vast amount of data was a hard issue. In order to

handle this problem, transfer learning including CNN and Support Vector Classifier (SVM) has been used. There are many studies combining CNN and support vector methods to classify images [21]. After extracting features from the images using CNN, performing classification by SVM yields remarkable results [20,21]. In some cases, it is observed that combining CNN and SVM performs better in image analysis than using either one of the methods [22].

2. LANDING PAGE COMPONENT CLASSIFICATION USING TRANSFER LEARNING

The proposed image analysis method to detect components of landing pages consists of two steps. In the first stage, landing pages obtained as digital images are segmented based on morphological operations and thresholding [19]. In the second stage of the proposed method, each image segment is assigned to one of the 'Button', 'Text', 'Checkbox' classes by SVM, which are the most common components of a landing page. The flow chart of the proposed method is presented in Figure 2 whose details are described below.

2.1. Detecting Landing Page Components with Image Segmentation

In this stage, the single channel gray level image (Y brightness component) is obtained from the three-level Red, Green, Blue (RGB) image belonging to the landing page [15]. Morphological gradient operation is applied to the gray level image by using 3x3 dimensional elliptic structuring element in (1). Afterwards, Otsu thresholding is applied to the obtained gray level output image to binarize it.



Fig.2. Steps of the proposed method to classify and segment the components of landing pages. Digital landing page images obtained as inputs are segmented based on morphological image processing operations followed by thresholding. Each candidate component obtained from segmentation is assigned to one of the 'Button,' 'Text,' 'Checkbox' classes, which are the most commonly used components in landing pages.

The binary image is separated into its candidate segments by using connected components after applying morphological closing operation. The 10x2 rectangular structuring element determined by the common features of the landing page components is used in morphological operation [17]. A sample landing page image is shown in Figure 3, while the candidate components of the same landing page is presented in Figure 4.

$$M = \begin{bmatrix} 0 & 1 & 0 \\ 1 & 1 & 1 \\ 0 & 1 & 0 \end{bmatrix}.$$
 (1)



Fig.3. A sample landing page image



Fig.4. Candidate components of the landing page image in Fig. 3, obtained as a result of the processes in the first part of the proposed method. Respective components are assigned to one of the classes "Button", "Text" and "Checkbox".

2.2. Classification of Segmented Components with Transfer Learning Based Approach

In order to make the system automatically identify which one of 'button', 'text,' 'checkbox' classes do the segmented components belong to, a transfer learning-based approach including CNN and SVM classifier is used. First of all, the features were extracted from the images by using a pre-trained CNN network. Afterwards, different classifiers were trained for classification. From the results obtained, SVM Classifier was selected as the best performing classifier.

2.2.1. Feature Extraction

Inception-v3, one of the pre-trained deep learning models developed by Google, was re-used for our datasets consisting of segmented button, text and checkbox components of landing pages [28-30]. As the last layer (fully connected layer) of the Inception-v3 corresponds to the classification part of CNN model, it is eliminated from the architecture to establish different classification models instead.

Convolutional layers have been used to determine and extract the relevant features of images and classification has been carried out by fully connected layers in image classification using deep learning. In our study, the classification was carried out by transfer learning. Inceptionv3 deep CNN model, which has been trained for ImageNet Large Visual Recognition Challenge using data from 2012, has been re-used for our dataset to extract features of size 2048 [28-30]. Since, the model has already been trained with a huge dataset, using its pre-calculated weights on a different dataset with small size as ours, has been very beneficial to easily extract features with a very small amount of time and cost. Inceptionv3 model was used until it's last fully connected layer.

TABLE I THE NUMBERS OF TRAINING AND VALIDATION DATA SETS BELONG TO EACH CLASS

Components	Number of Training Set	Number of Validation Set
Button	48	12
Checkbox	48	12
Text	56	14

The output obtained by the restricted Inception-v3 model has become the input that is fed to the SVM classifier.

The model was trained with the numbers of training data and validated using five-fold validation, as shown in Table I.

After the features acquired using Inception-V3 model, dimensionality reduction was applied to extracted feature vector by an unsupervised machine learning approach, t distributed stochastic neighbor embedding (t-SNE). Applying dimension reduction to the feature vector reduces dimension from 2048 to 2. Therefore, visualization of features in a lower dimensional space is provided (cf. Fig. 5). According to the figure, buttons (red), checkboxes (blue), and text (green) are well separated from each other.



Fig.5. Demonstration of features in 2-dimension space by t - SNE.

TABLE II ACCURACIES OBTAINED FROM SVM, KNN AND RF CLASSIFIERS ON VALIDATION SET

Classifier Type	Accuracy
SVM	97.6%
KNN	97.5%
RFF	96.6%

2.2.2. Image Classification

After extracting the features, each of SVM, Random Forest Classifier (RF) and K-Nearest Neighbors Classifier (KNN) were trained to classify and results were compared. For the output images obtained after the last pooling layer of Inceptionv3 CNN model have set as inputs of related classifiers. For small-sized component datasets SVM yields better results than the other classifiers. Consequently, in our implementations, we utilize SVM.

3. EXPERIMENTAL RESULTS

In the second part of the proposed method, the Transfer Learning-based approach was performed after components of Landing Pages were segmented in the first part. Obtained components, which were segmented from the pages, are used as datasets in Transfer Learning. At first, the feature extraction was performed by pre-trained Inception v-3 model on this dataset. Secondly, classifiers including SVM, RF, KNN were trained on the extracted features of the dataset. After identifying features and their corresponding ground-truth labels, training was performed with 80 percent of the dataset being allocated as the training set while 20 percent of the is used as validation set.

The number of training and validation images is indicated in Table I and representative images used in training and validation sets are shown in Figure 6.



Fig.6. The representative images of button, checkbox, text classes used in validation and training data sets.

After performing classification using SVM, RF and KNN classifiers, it is observed that the best result was achieved by

SVM classifier with an accuracy of 97.6% Accordingly, SVM classifier has been determined as the final classifier to detect the class of Landing Page components. It is observed that the accuracy scores for the other classifiers are reasonably acceptable for a classification problem. Results of accuracies for each classifier are given in Table II.

4. CONCLUSIONS AND FUTURE WORKS

In this study, image analysis methods based on morphological operations, thresholding and transfer learning method based on CNN and SVM is presented to automatically segment the landing pages used in online advertising applications, to separate them into the three most commonly used components on the page and to recognize what the components are. In the proposed method, collected dataset for training is not an easy task because the components of landing page designs do not differ from page to page. The proposed method has prevented the problems related to small data.

For feature work, re-evaluation of the approach in such a way to classify the properties of the segmented components with respect to color, font, and size will be considered. Thus, the human factor in the designing process of the landing pages can be minimized, and the cost can be significantly reduced.

ACKNOWLEDGEMENT

This work is supported in part by TÜBİTAK-TEYDEB 1507 program with grant number 7180415 ("Görüntü İşleme ve Makine Öğrenmesi Yöntemlerine Dayalı Reklam Sayfası Bileşen Analiz Platformu" - Project).

REFERENCES

- [1] C. Khopkar, et al., "Generating landing page variants." U.S. Patent No. 7,831,658. 9 Nov., 2010.
- [2] S. Eskenazi, G.-K. Petra, and O. Jean-Marc, "A comprehensive survey of mostly textual document segmentation algorithms since 2008", Pattern Recognition, Vol.64, 2017, pp.1-14.
- [3] M. Javed, P. Nagabhushan, and B. B. Chaudhuri, "A Review on Document Image Analysis Techniques Directly in The Compressed Domain", Artificial Intelligence Review, Vol.50, No.4, 2017, pp.1-30.
- [4] P. Arbelaez, et al. "Contour Detection and Hierarchical Image Segmentation", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol.33, No.5, 2011, pp.898-916.
- [5] E. Ortacag, B. Sankur, and K. Sayood, "Locating text in color document images", Signal Processing Conference (EUSIPCO 1998), 9th European. IEEE, 1998.
- [6] N.K. Singh, et al., "Text and Non-Text Segmentation in Colored Images", International Journal of Scientific and Engineering Research, Vol.5, 2014.
- [7] M. A. M., Salem, et al., Recent survey on medical image segmentation." Computer Vision: Concepts, Methodologies, Tools, and Applications: Concepts, Methodologies, Tools, and App., 2018, p.129.
- [8] N. R. Pal, and S. K. Pal, "A Review on Image Segmentation Techniques", Pattern Recognition Vol.26, No.9, 1993, pp.1277-1294.
- [9] D. Kaur and Y. Kaur, "Various Image Segmentation Techniques: A Review", International Journal of Computer Science and Mobile Computing Vol.3, No.5, 2014 pp.809-814.
- [10] G. K. Seerha and R. Kaur, "Review on Recent Image Segmentation Techniques." International Journal on Computer Science and Engineering Vol.5, No.2, 2013, p.109.
- [11] A. K. Jain, Fundamentals of digital image processing, Englewood Cliffs, NJ: Prentice Hall, 1989.
- [12] L. Kang, et al., "Convolutional neural networks for document image classification." Pattern Recognition (ICPR), 2014 22nd International Conference on. IEEE, 2014.

- [13] S. Sladojevic, et al., "Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification." Computational Intelligence and Neuroscience Vol.2016, 2016, p.11.
- [14] A. Krizhevsky, I. Sutskever and G. E. Hinton. "Imagenet classification with deep convolutional neural networks", Advances in Neural Information Processing Systems, 2012.
- [15] D. A. Forsyth and J. Ponce, "Computer vision: a modern approach", Prentice Hall Professional Technical Reference, 2002.
- [16] W. T. Chu, and H. Y. Chang, "Advertisement Detection, Segmentation, and Classification for Newspaper Images and Website Snapshots", Computer Symposium (ICS), 2016 Int.'l. IEEE, 2016.
- [17] F. Heijden. Image Based Measurement Systems: Object Recognition and Parameter Estimation. Wiley, 1996.
- [18] N. Srivastava, et al. "Dropout: A Simple Way to Prevent Neural Networks from Overfitting", The Journal of Machine Learning Research, Vol.15, No.1, 2014 pp.1929-1958.
- [19] G. Ayhan, et al. "Landing page component classification with convolutional neural networks for online advertising." 2018 26th Signal Processing and Communications Applications Conf.(SIU). IEEE, 2018.
- [20] M. Elleuch, R. Maalej, and M. Kherallah. "A New Design Based-SVM of the CNN Classifier Architecture with Dropout for Offline Arabic Handwritten Recognition", Proc. Computer Sci., Vol.80, 2016, pp.1712-1723.
- [21] Z. Sun, F. Li, and H. Huang, "Large Scale Image Classification Based on CNN and Parallel SVM", International Conference on Neural Information Processing. Springer, Cham, 2017.
- [22] D. X., Xue, et al. "CNN-SVM for Microvascular Morphological Type Recognition with Data Augmentation", Journal of Medical and Biological Engineering, Vol.36, No.6, 2016, pp.755-764.
- [23] D. C. Ciresan, et al. "Flexible, high performance convolutional neural networks for image classification." IJCAI Proceedings-International Joint Conference on Artificial Intelligence. Vol.22, No.1, 2011.
- [24] E. Maggiori, et al. "Convolutional Neural Networks for Large-Scale Remote-Sensing Image Classification." IEEE Transactions on Geoscience and Remote Sensing Vol.55, No.2, 2017, pp.645-657.
- [25] N. Tajbakhsh, et al. "Convolutional Neural Networks for Medical Image Analysis: Full Training or Fine Tuning?", IEEE Transactions on Medical Imaging, Vol.35, No.5, 2016, pp.1299-1312.
- [26] X. Li, et al. "Convolutional neural networks based transfer learning for diabetic retinopathy fundus image classification", Image and Signal Processing, BioMedical Engineering and Informatics (CISP-BMEI), 2017 10th International Congress on. IEEE, 2017.
- [27] C. Szegedy,, et al. "Going deeper with convolutions", CVPR, 2015.
- [28] C. Szegedy, et al. "Rethinking the inception architecture for computer vision", Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.
- [29] Y. Ganin, and V. Lempitsky. "Unsupervised Domain Adaptation By Backpropagation." arXiv preprint arXiv:1409.7495 (2014).
- [30] M. Long, et al. "Deep transfer learning with joint adaptation networks", Proceedings of the 34th International Conference on Machine Learning-Volume 70. JMLR. org, 2017.

$B \, {\tt IO}\, {\tt G}\, {\tt R}\, {\tt A}\, {\tt P}\, {\tt H}\, {\tt IE}\, {\tt S}$

Çağla Şenel obtained her BSc degree in conputer engineering from Istanbul University in 2017. She is currently working as a Data Scientist at Cerebro Tech Inc. Also, she carries out Image Processing and Classification projects.

Gülşah Ayhan obtained her BSc degree in Mathematics from Dokuz Eylul Universiy in 2014. She received MSc. diploma in Economics: Empirical Applications and Policies from University of Basque Country, Spain in 2016. She is currently working as a Data Scientist at OTI HOLDING. Also, she carries out Image Processing and Classification projects.

Zeynep Eda Uran obtained her BSc degree in Computer Science from Bilgi University in 2012. She is currently working as a Project Manager at Obase.

Behçet Uğur Töreyin received the B.S. degree from the Middle East Technical University, Ankara, Turkey in 2001 and the M.S. and Ph.D. degrees from Bilkent University, Ankara, in 2003 and 2009, respectively, all in electrical and electronics engineering. He is now an Associate Professor with the Informatics Institute at Istanbul Technical University and the research group leader of the Signal Processing for Computational Intelligence Group (SPACING: http://spacing.itu.edu.tr).