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Deep Neural Network for Handwritten Character Recognition with Focus on Using Domain-Specific Knowledge – A Survey

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ABSTRACT: Recent progress in artificial intelligence has renewed interest in building systems that learn and think like people. Many advances have come from using deep neural networks trained end-to-end in tasks such as object recognition, video games, and board games, achieving performance that equals to that of humans in some aspects. Despite their biological inspiration and performance achievements, these systems differ from human intelligence in crucial ways. In this study, we review progress in cognitive science for Handwritten Character Recognition with focus on using Domain-Specific Knowledge to explore in ways of both, what they learn and how they learn it.

KEYWORDS-Handwritten Character Recognition, Domain-Specific Knowledge, Neural networks, Domain-Specific Knowledge

I. INTRODUCTION

Neural networks have regained their status as a leading paradigm in machine learning, much as they were in the late 1980s and early 1990s. The recent success of neural networks has captured attention beyond academia. In industry, companies such as Google and Facebook have active research divisions exploring these technologies, and object and speech recognition systems based on deep learning have been deployed in core products on smart phones and the web. The media have also covered many of the recent achievements of neural networks, often expressing the view that neural networks have achieved this recent success by virtue of their brain-like computation and, therefore, their ability to emulate human learning and human cognition.

One such active area of interest is the Handwriting Character Recognition. It is the process of detecting, identifying and recognizing handwritten pattern from input image. It is a first step towards language processing by means of computers. Handwriting Recognition has its significance in many areas such as Reading aid for blinds, Automated Text entry, Language Processing, Zip code recognition, sorting mails, Processing of bank slips, etc. Due to these applications, Handwriting recognition is popular among researchers worldwide. The purpose of this study is to expose technologies and tools (that are currently openly used in the community) which can be used to recognize handwritten characters. Written characters can be in different shapes and sizes depending on the individual who wrote it. The general approach towards this problem involves Image Processing techniques.

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Handwriting Recognition can be broadly classified in two areas: Offline & Online. Online recognition system recognizes numeral at the time of writing. An electronic pen is used to write on a touch-sensitive digitizer such as tablet, PDA or Smartphone. It uses movement of pen, stroke, and trace of symbol to recognise it. The offline recognition system digitizes existing handwritten document in the form of input.

Deep convolutional neural networks (DCNNs) have achieved great success in various computer vision and pattern recognition applications, including those for handwritten character recognition (HCR). Numerous methods have been proposed for dealing with confusing characters or cursive handwriting. Among them, classification methods using domain-specific processing technologies such as discriminative feature extraction [3] and discriminative modified quadratic discriminant function (DLQDF) [4] have achieved significant levels of performance.

II. LITERATURE SURVEY

There are various approaches that come up to the difficulty of handwritten character recognition on features extracted and the ways of extracting those features. There remain many algorithms for feature extraction which have its own advantages or disadvantages over other algorithms. Many different important touchstones of feature extraction algorithms required are being looked at for higher rate of recognition in this study.

Boqi Li used convolution neural network (CNN) to recognize different traditional Chinese calligraphy styles [1]. He trained the CNN on a 5-class dataset which consisted of 15000 instances. The preprocessed images had sizes of 96x96, and constructed 8 different models to test on different depth and filter numbers. He evaluated the performance of each model and analyzed the recognition ratio of each style. He also visualized both the reconstructed images maximizing activation and feature activation maps. The author found that increasing number of convolutional layers, in other word, building deeper network models increases the overall recognition accuracy of the model. And increasing number of filters didn't increase the accuracy. To improve the result, author suggested to do a better data-preprocessing and do data augmentation to the training images.

XuefengXiaoa, LianwenJina, YafengYanga, WeixinYanga, Jun Sunb, TianhaiChanga have proposed a Global Supervised Low-rank Expansion (GSLRE) method and an Adaptive Drop-weight (ADW) technique to solve the problems of speed and storage capacity for handwritten Chinese character recognition (HCCR) [2]. They designed a nine-layer CNN for HCCR consisting of 3,755 classes, and devise an algorithm that can reduce the networks computational cost by nine times and compress the network to 1/18 of the original size of the baseline model, with a 0.21% drop in accuracy. The Global Supervised Low-rank Expansion accelerated calculations in the convolutional layers, and an Adaptive Drop-weight method removed redundant connections by using a dynamic increase in the pruning threshold of each layer. In their work, they also proposed Connection Redundancy Analysis technology to analyze redundant connections in each layer in order to guide the pruning of CNN that authors claimed did not compromise the performance of the network.

BatuhanBalci, Dan Saadati, Dan Shiferawet. etal [5] classified an individual handwritten word for translation to a digital form. They used two main approaches to accomplish this task: classifying words directly and character segmentation. For the former, they used CNN with various architectures to train a model that can accurately classify words. For the latter, they used Long Short Term Memory networks (LSTM) with convolution to construct bounding boxes for each character.

However, this model struggled with segmenting cursive characters because of the breakdown in boundaries in between some cursive characters. The authors pointed out that as the segmentation model was not trained separately from the character classification model, they were not able to finely attribute the cause of error to classification or

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segmentation model. In order to have more compelling and robust training, the authors suggested to apply additional preprocessing techniques such as jittering. The authors also suggested to consider a more exhaustive but still efficient decoding algorithm such as beam search for improving character segmentation model.

Weixin Yang, Lianwen Jin, Zecheng Xie, Ziyong Feng, used deep CNN for online handwritten Chinese character recognition using domain-specific knowledge [6]. In this paper, they proposed an enhancement of the DCNN approach to online HCCR by incorporating a variety of domain-specific knowledge, including deformation, non-linear normalization, imaginary strokes, path signature, and 8-directional features. The authors have claimed twofold contribution. First, the investigation and integration of domain-specific techniques with DCNN to form a composite network to achieve improved performance. Second, the resulting DCNNs with diversity in their domain knowledge are combined using a hybrid serial-parallel (HSP) strategy. Consequently, they achieved an accuracy of 97.20% and 96.87% on CASIA-OLHWDB1.0 and CASIAOLHWDB1.1 database respectively. The authors suggested to find a better way of combining all the domain knowledge with proper DCNN architectures.

Mohamed Elleuch, Najiba Tagougui, Monji Kherallah, used Deep Belief Neural Network (DBNN) for Arabic handwritten characters recognition [7]. This family of networks manages large dimensions input, which allows the use of raw data inputs rather than to extract a feature vector and learn complex decision border between classes. In this work, the system takes the raw data as input and proceeds with a grasping layer-wise unsupervised learning algorithm. The approach was tested on two different databases. For the character level, the results were promising with an error classification rate of 2.1% on the HACDB database. However, the evaluation on the ADAB database to deal with word level shows an error rate which exceeded 40%. Hence, the proposed DBNN structure was not able to deal with high-level dimensional data. The authors suggested to reconfigure the DBNN architecture to be able to deal with various length input data.

Hai Dai Nguyen, Anh Duc Le, Masaki Nakagawa, used deep learning to recognize online handwritten mathematical symbols [8]. CROHME database was used. They applied max-out-based CNN and bidirectional Long short term memory (BLSTM) on to image patterns created from online patterns and to the original online patterns, respectively and combine them. The authors made the following three conclusions 1. DNN can improve the offline recognition of mathematical symbols because it may extract wider yet specific features; 2. as for online methods, BLSTM outperform Markov Random field because it can access the whole context of input sequence flexibly; 3. Combining both online and offline recognition methods improves classification performance by taking their advantages.

Cheng Cheng, Xu-Yao Zhang, Xiao-Hu Shao and Xiang-Dong Zhou presented a method for handwritten Chinese character recognition by Joint classification and similarity ranking [9]. ICDAR 2013 offline HCCR competition dataset was used. The authors explored the fact that most of DCNN models employ the softmax activation function and minimize cross-entropy loss, which may lose some inter-class information. They used both classification and similarity ranking signals for supervision. This method learns a DCNN model by maximizing the inter-class variations and minimizing the intra-class variations, and simultaneously minimizing the cross-entropy loss. Combination of the two supervisory signals leads to significantly better results than only softmax based character classification.

They demonstrated that the character classification and similarity ranking supervisory signals are complementary for each other, which increase inter-class variations and reduce intra-class variations, and therefore much better classification performance can be achieved.

In-Jung Kim and Xiaohui Xie et.al [10], developed new type of recognizers based on deep neural networks. The 'Hangu' recognizers improved the performance and training speed of the networks. They evaluated the performance of these recognizers on two public Hangu image databases, SERI95a and PE92. Using this framework, they were able to achieve a recognition rate of 95.96% on SERI95a, and 92.92% on PE92 database. In this work they also proposed two

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new improvement techniques. First, the modified MSE error criterion significantly improved the training efficiency of the Hangul recognizer by compensating the unbalance between positive and negative signals from the output nodes. Second, improvement was achieved by initializing bottom level convolution masks by edge operators.

Weixin Yang, Lianwen Jin, Hao Ni, Terry Lyons [11], proposed a variation of path signature representation, namely the dyadic path signature feature (D-PSF), to fully characterize the trajectory using a hierarchical structure to solve the rotation-free online handwritten character recognition (OLHCR) problem. DNN was used as classifier, and they investigated three hanging normalization methods to improve the robustness of the DNN to rotational distortions. Experiments on digits, English letters, and Chinese radicals demonstrated that the proposed D-PSF, jointly with hanging normalization and DNN achieved very promising results for rotated OLHCR. The authors claimed that the proposed D-PSF can effectively extract global, regional, and local information, from the online characters for rotation-free recognition tasks. They have investigated hanging normalization as preprocessing or fine-tuning step in DNN to further improve the performance.

Weixin Yang, Lianwen Jin, Dacheng Tao, Zecheng Xie, Ziyong Feng, proposed DropSample, a new method for training deep DCNNs and apply it to large-scale online HCCR [12]. Here each training sample was associated with a quota function that is dynamically adjusted on the basis of classification confidence given DCNN softmax output. After a learning iteration, samples with low confidence had a higher frequency of being selected as training data; in contrast, well-trained and well-recognized samples with very high confidence will have a lower frequency of being involved in the ongoing training and can be gradually eliminated. As a result, the learning process becomes more efficient as it progresses. Furthermore, they investigated the use of domain-specific knowledge to enhance the performance of DCNN by adding a domain knowledge layer before the traditional CNN. By adopting DropSample together with different types of domain-specific knowledge, the accuracy of HCCR was improved. Experiments on the CASIA-OLHDWB1.0, CASIA-OLHWDB1.1, and ICDAR2013 online HCCR competition datasets gave recognition rates of 97.33%, 97.06%, and 97.51% respectively.

Zheheng Rao, Chunyan Zeng, Minghu Wu, Zhifeng Wang, Nan Zhao, Min Liu, Xiangkui Wan et al. [13] took the training time and recognition accuracy into consideration and proposed a novel handwritten character recognition algorithm with newly designed network structure, which is based on an extended nonlinear kernel residual network. This work proposed an extended nonlinear kernel residual network-based handwritten character recognition algorithm model. The main idea of this work are two designs: one is the design of an unsupervised intra-class clustering algorithm to perform targeted pre-processing of the input data and second is the three network structure designs for the extended nonlinear kernel, (1) presentation of an intermediate convolution model with a pre-processed width level of 2; (2) a composite residue structure with the design of a multi-level quick link; and (3) addition of a Dropout layer after parameter optimization in the extended nonlinear kernel model. The authors compared the proposed method with convolution neural network and residual network structures under the same conditions, and claimed that the proposed model has good recognition results and data training time. Further, the authors suggested seeking of more simple and effective classification methods to optimize and improve the network.

Théodore Bluche, et al. [14], has conducted a thorough study of different aspects of optical models based on deep neural networks in the hybrid neural network / HMM scheme, in order to better understand and evaluate their relative importance. First, he showed that deep neural networks produce consistent and significant improvements over networks with one or two hidden layers, independently of the kind of neural network, MLP or RNN, and of input, handcrafted features or pixels. Then, he showed that deep neural networks with pixel inputs compete with those using handcrafted features, and that depth plays an important role in the reduction of the performance gap between the two kinds of inputs,

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supporting the idea that deep neural networks effectively build hierarchical and relevant representations of their inputs, and that features are automatically learnt on the way. Despite the dominance of LSTM-RNNs in the recent literature of handwriting recognition, he showed that deep MLPs achieve comparable results. Moreover, he also evaluated different training criteria. With sequence-discriminative training, he reported similar improvements for MLP/HMMs as those observed in speech recognition. We also showed how the Connectionist Temporal Classification framework is especially suited to RNNs. Finally, the novel dropout technique to regularize neural networks was applied to LSTM-RNNs.

Neha Avhad, Shraddha Darade, Neha Gawali, Apurva Matsagar, addressed artificial neural network technique used to design, pre-process, segment and recognize Devnagari characters [15]. In this work, back propagation algorithm neural network is trained and then testing is performed. To increase the accuracy of the system for those character who are difficult to be recognized, these character are further analysed in training part and tested with different set.

A. Jinturkar and Dr. P.B. Khanale discussed various schemes [16] for isolated numerals in recognizing mixed or multi-digit numeral in Marathi language. Since India is a bilingual country; people sometimes are used to write numerals from different languages mixed with each other. Their work was focused on techniques that are statistical, neural network, fuzzy logic and Neuro-Fuzzy system.

Ashok Kumar Pant, Prashna Kumar Gyawali and Shailesh Acharya [17], proposed a deep learning architecture for recognition of handwritten Devanagari character. They introduced a new public image dataset for Devnagari script: Devnagari Character Dataset that consists of 92 thousand images of 46 different classes of characters of script segmented from handwritten documents. The authors claimed that the proposed architecture had an accuracy of 98.47% on this dataset. Further, their experimental results suggested that Deep CNNs with added Dropout layer and Dataset increment technique can result in very high test accuracy for a diverse and challenging dataset that consists many characters that are visually similar or written in a similar way by most people.

Devendra K Sahu and C. V. Jawahar, investigated the possibility of learning an appropriate set of features for designing OCR for a specific language [18]. They learned the language specific features from the data with no supervision. This enabled them adaptation of architecture across languages. In this work, features were learned using a stacked Restricted Boltzmann Machines and use it with the Recurrent Neural Networks (RNN) based recognition solution. This was validated on five different languages; English, Marathi, Telugu, Kannada and Malayalam. In addition, these novel features resulted in better convergence rate of the RNNs. They proposed a framework for word prediction for printed text where learned feature representations are obtained by stacked RBM and a sequence predictor bidirectional LSTM. The framework was segmentation free. The authors claimed that stacked RBMs can learn feature representations from data and perform better than profile features in generic settings.

Karthik S, Srikanta Murthy K proposed a deep belief network for the recognition of handwritten Kannada characters [19]. Raw pixels and the histogram of oriented gradients are used as features and they were able to achieve a maximum recognition accuracy of 96.41% when experimented with a dataset consisting of 18,800 samples.

Mahesh Jangid, Sumit Srivastava [20] experimentally developed a deep convolutional neural network (DCNN) and adaptive gradient methods to recognize the unconstrained handwritten Devanagari characters. ISIDCHAR and V2DMDCHAR database were used. The deep convolutional neural network finds the best features automatically and also classify them. The authors experimented with handwritten Devanagari character database with six different DCNN network architectures as well as six different optimizers. The highest recognition accuracy of 96.02% was obtained using NA-6 network architecture and RMSProp—an adaptive gradient method (optimizer). Further, they trained DCNN layer-wise, to enhance the recognition accuracy, using NA-6 network architecture and the RMSProp adaptive gradient

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method. Using DCNN layer-wise training model, the database obtained 98% recognition accuracy, which was claimed as the highest recognition accuracy of this database.

N Ram Prashanth, Siddarth B, Anirudh Ganesh and Vaegae Naveen Kumar explored the performance of Deep Belief Networks in the classification of Handwritten Tamil vowels [21]. The authors claimed that the proposed method has shown recognition accuracy of 99.89 % in light of difficulties faced with regional languages such as similarity between characters and minute nuances that differentiate them. However, this work was not extended for all classes of Tamil characters.

Prashanth Vijayaraghavan, Misha Sra classified characters in Tamil, using convolutional neural networks (ConvNets) into 35 different classes [22]. ConvNets are biologically inspired neural networks. Unlike other vision learning approaches where features are hand designed, ConvNets can automatically learn a unique set of features in a hierarchical manner. Authors in their work, augmented the ConvNetJS library for learning features by using stochastic pooling, probabilistic weighted pooling, and local contrast normalization to establish a new state-of-the-art of 94.4% accuracy on the IWFHR-10 dataset. Further, they describe the different pooling and normalization methods implemented. Authors did not use any unsupervised pre-training. They also noted that, network's performance degrades if a single convolutional layer is removed and does not improve much with the addition of another convolutional pooling layer pair.

Bishwajit Purkaystha, Tapos Datta, Md Saiful Islam, proposed a convolutional deep model to recognize Bengali handwritten characters [23]. In their work, they learnt a useful set of features by using kernels and local receptive fields, and then employed densely connected layers for the discrimination task. The authors claimed to have tested this on Bangla Lekha-Isolated dataset. It achieved 98.66% accuracy on numerals (10 character classes), 94.99% accuracy on vowels (11 character classes), 91.60% accuracy on compound letters (20 character classes), 91.23% accuracy on alphabets (50 character classes), and 89.93% accuracy on almost all Bengali characters (80 character classes). However, most of the errors incurred in the model in recognition task are due to extreme proximity in shapes among characters. A significant number of errors were caused by the mislabeled, irrecoverably distorted, and illegal data examples.

Ratnashil N Khobragade, Dr. Nitin A. Koli, Mahendra S Makesar, applied an algorithm for segmentation of lines and characters for Marathi language [24]. The algorithm first separates the lines and then it the characters from the input image. They claimed to have achieved nearly 99% successful segmentation in line, character and numeral. They observed that it is difficult to identify exact connecting points for segmentation of upper and lower modifier, separating anusvara (.), full stop (.) from noise is critical as both resemble the same. However, the compound characters in Marathi language which are connected at various places were not included in this work.

III. CONCLUSION

Character recognition is getting more popular since last ten years due to its huge application range. In the last decades the different algorithms have been proposed for handwritten character recognition. The precision of recognition algorithm directly depends on parameter setting and selection of artificial neural network algorithm. For the character recognition task, HMM, different neural network algorithms and their combinations are used as the powerful tool. For the high reliability in segmentation, character recognition, and classification; an approach in an integrated manner is needed to obtain more accurate results for complex problems. The study presents tools and techniques for handwritten character recognition using deep neural network that explores domain-specific knowledge. This study was focused on the core methods used in the field of offline character recognition in various languages viz; Arabic, Bangla, Chinese, Devanagari, Kannada, Malayalam, Marathi, Tamil and Telugu.

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