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Writer Identification using Neural Network

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Abstract

Computer Vision has been evolving everyday with advancement in the Deep Learning. Residual Neural Networks is one of such image classification techniques. This paper is an application of ResNet 50 for the purpose of writer identification using handwriting biometric – signature. Different signature verification competitions had used many approaches. Here SigComp2009 dataset is used and experimental results are discussed. ResNet 50 is able to achieved 92% accuracy for 780 signatures used randomly from ICDAR 2009 dataset of genuine signatures.

Keywords: *HandwritingSignature Recognition, Image processing, Neural Network, ICDAR 2009, RES-NET.*

I. INTRODUCTION

Writer identification using handwriting biometrics like signature is commonly used over decades. Even in today's world, most advanced banking system or legal firms also still rely on the offline signatures for transactions. New development in technology helped in the verification of online signatures but still demand for offline writer identification still exist in variety of scenarios like banking transactions, legal documents, commercial and non-commercial application. In all of these cases, writer identification and verification is very important. Compare to online writer identification, offline writer identification is more used and newer aspects of writer identification are still emerging. [1]

Over the periodic development in the computer vision, image processing and pattern recognition has given new approaches for writer identification. Since any writer is unable to replicate exactly same own signature, it's very difficult for any method to classify writer based on their different set of signatures with natural variations. In past, there have been competitions to solve this problem using different approaches. Following is the list of competitions

1. Signature Verification Competition (SigComp2009) – 1953 Signatures[2]
2. Forensic Signature Verification Competition (4NSigComp2010) – 334 Signatures[3]
3. Signature Verification Competition (SigComp2011) - 1932(Dutch) and 1177(Chinese[4]
4. Forensic Signature Verification Competition (4NSigComp2012) – 501[5]
5. Signature Verification and Writer Identification Competitions (SigWiComp2013) - 2340 (Japanese)[6]
6. Signature verification and Writer identification Competition (SigWIcomp2015) – 1268 Signatures [7]

Table 1 Signature Verification Competition

Sr. No.	Competition	signatures	Accuracy (Offline)	Dataset

1	ICDAR 2009 Signature Verification Competition	1953	90.85	Offline& Online
2	SigComp2011	1932(Dutch) 1177(Chinese)	97.67(Dutch) 80.04(Chinese)	Offline & Online
3	4NSigComp2012	501	80.84 (Chinese) 93.17 (Dutch)	Offline & Online
4	SigWiComp2013	2340	99.16 (Japanese)	Offline & Online
5	SigWIcomp2015	1268	99.34 (Italian) 98.02 (Bengali)	Offline & Online

In this paper, we have implemented RESNET 50 for writer identification on ICDAR 2009 dataset and reported the results.

II. DEEP LEARNING MODEL – RES-NET50

Deep learning is used to identify the features of each image to classify them using neural networks. Neural networks create model like feature extraction which is built on extracting distinct features learn from training dataset. In this identified learning is been transferred from upper layer to lower using transfer mechanism.[8] In some cases, higher layer model faced problems like diminishing of the data due to larger Neural network layer transfer making distinct features absolute. To overcome these problems an intuitive model of residual network is proposed in which learning from previous node can be passed to next node in the form of residuals.

RESNET is such deep neural network used for image segmentation. It has been majorly used for the process of analyzing images, classification of images from different sets. The major property of residual network is its connection and specification of node where previous residuals are passed on to next block as it is for deeper layers making it more effective than similar other traditional convocational neural networks[9].

For the process of writer image segmentation and identification RESNET50 has been firstly attempted in the paper. Handwritten signatures identification has been addressing problems like variation in the writers' style, language dependency and multi lingual signatures. In the signature competition mentioned above, researchers have tried to solve such problems using custom made architectures, multi-model approaches and language specific methods. Due to advancement into image processing and considering newer computer vision problem we are focusing on start of art techniques like RESNET50.

III. METHODOLOGY

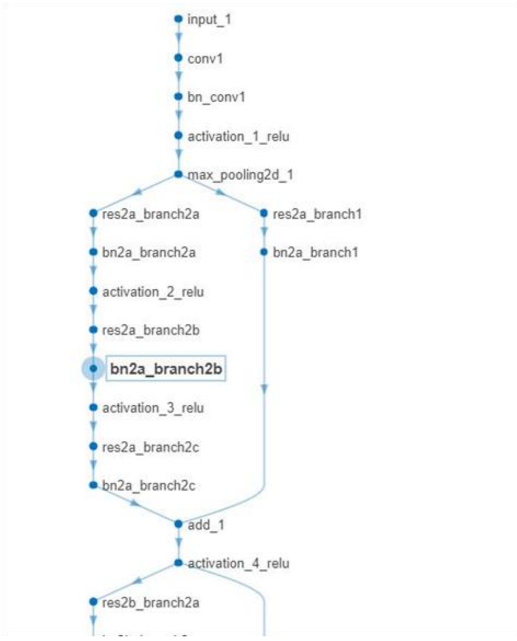

Figure 1. ResNet50 Architecture

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Design of ResNet 50

Fig. 1 Shows ResNet50 architecture. In the methodology, input is passed on to first conventional neural network to create first convolutional layer weights. Network model goes layers wise to deeper network to update weights till max weight polling weight assigned. This process continues till last layer convolutional layers' weights are calculated and store as shown in Fig.2. Once learning model complete this process, testing set of images are being classify using learned weights and results are compared with saved writer values and confusion matrix is calculates.

Initially each writers' 10 signatures are randomly taken out of those 7 set of signatures were used as input to ResNet 50. Weights were calculated based on these images. Remaining 3 signatures were passed to learn model to classify them as per learned weight results were compared. Supervised learning model used to check accuracy of each user and overall accuracy was reported.

add_10 Element-wise addition of 2 inputs	Addition	14×14×1024	-
activation_31_relu ReLU	ReLU	14×14×1024	-
res4d_branch2a 256 1x1x1024 convolutions with stride [1 1] and padding [0 0 0 0]	Convolution	14×14×256	Weigh… 1×1×1024×2… Bias 1×1×256
bn4d_branch2a Batch normalization with 256 channels	Batch Normalization	14×14×256	Offset 1×1×256 Scale 1×1×256
activation_32_relu ReLU	ReLU	14×14×256	-
res4d_branch2b 256 3x3x256 convolutions with stride [1 1] and padding 'same'	Convolution	14×14×256	Weights 3×3×256×256 Bias 1×1×256
bn4d_branch2b Batch normalization with 256 channels	Batch Normalization	14×14×256	Offset 1×1×256 Scale 1×1×256
activation_33_relu ReLU	ReLU	14×14×256	-
res4d_branch2c 1024 1x1x256 convolutions with stride [1 1] and padding [0 0 0 0]	Convolution	14×14×1024	Weigh… 1×1×256×10… Bias 1×1×1024
bn4d_branch2c Batch normalization with 1024 channels	Batch Normalization	14×14×1024	Offset 1×1×1024 Scale 1×1×1024
add_11 Element-wise addition of 2 inputs	Addition	14×14×1024	-
activation_34_relu ReLU	ReLU	14×14×1024	-
res4e_branch2a 256 1x1x1024 convolutions with stride [1 1] and padding [0 0 0 0]	Convolution	14×14×256	Weigh… 1×1×1024×2… Bias 1×1×256
bn4e_branch2a Batch normalization with 256 channels	Batch Normalization	14×14×256	Offset 1×1×256 Scale 1×1×256
activation_35_relu ReLU	ReLU	14×14×256	-
res4e_branch2b 256 3x3x256 convolutions with stride [1 1] and padding 'same'	Convolution	14×14×256	Weights 3×3×256×256 Bias 1×1×256
bn4e_branch2b Batch normalization with 256 channels	Batch Normalization	14×14×256	Offset 1×1×256 Scale 1×1×256
activation_36_relu ReLU	ReLU	14×14×256	-

Figure 2ResNet50 Layered Detail

IV. EXPERIMENTAL RESULTS

In this paper, we are proposing RESNET 50 model for writer identification using signatures. First section of Res-Net50 was displayed as shown in Fig. 3. First convolution layer weights are displayed to view the process of classification as shown in fig.4.Each writers' accuracy being calculated and displayed writer-wise as shown in fig. 5. Our objective is to contribute to the area making effective simple model for everyday use. This method consists of RESENT 50 model used for training and testing of signatures from ICDAR 2009 dataset. All the images used are from ICDAR 2009 signature competition. We have used 78 writers' 12 signature each making dataset of 936 genuine signatures. In the model we have used 546 random signatures for training set and 234 random signatures for testing set.

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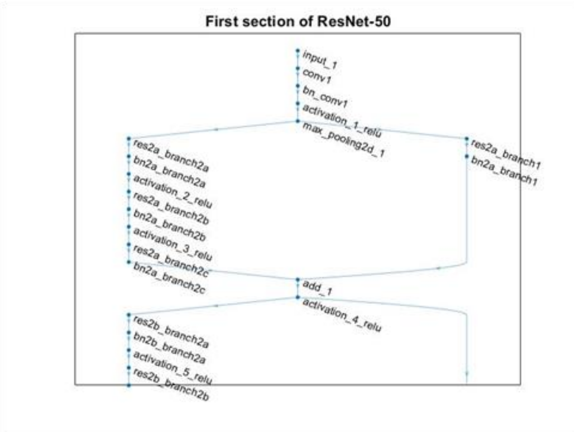

Figure 3 First Section of Res-Net 50

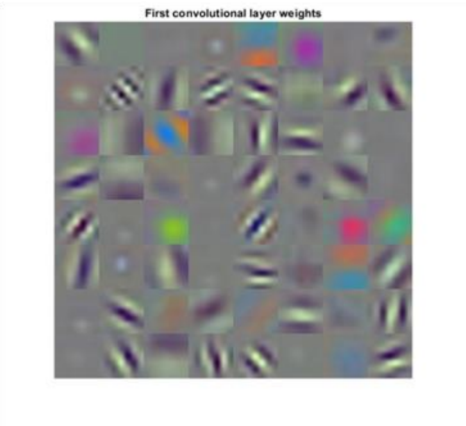

Figure 4 First convolution layer weights

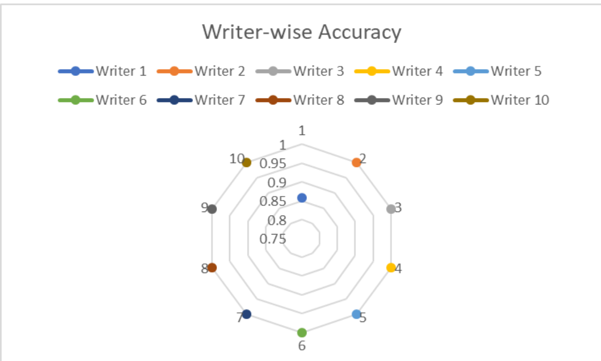

Figure 5 Writer-wise Accuracy

In the preprocessing phase we have randomly selected 78 writers with randomly taken 10 signatures. These signatures are used by ResNet 50 for training and testing further. Each writer-wise and image-wise accuracy was reported. Confusion matrix was stored and overall the model reported accuracy of **92.12%.**

V.CONCLUSION

In this paper we have discussed about different competitions related to writer identification taken place over the years. We have explored the techniques used in for signature classification and provided with alternative approach using deep neural network. In our experimental results we have used ResNet 50 with ICDAR 2009 signature dataset to identify writer. The result of 92.12 accuracy gives us boost to work further. Our future work is to build more robust NN with training transfer engine to use it more effectively.

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