



IJIRCCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 9, Issue 7, July 2021

ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA

Impact Factor: 7.542



9940 572 462



6381 907 438



ijircce@gmail.com



www.ijircce.com

Recognition of Hand Writing Using Convolutional Neural Networks

Mr. N.Ashok¹, P.Divya², M.Pavithra³, K.Teja Sri⁴, K.Sravani⁵

Assistant Professor, Department of Information Technology, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, Andhra Pradesh, India¹

Students, Department of Information Technology, Vasireddy Venkatadri Institute of Technology, Nambur, Guntur, Andhra Pradesh, India^{2,3,4,5}

ABSTRACT: In recent times, with the increase of Artificial Neural Network, deep learning has brought a dramatic twist in the field of Machine Learning by making it more artificially intelligent. This is a system that provides a full alphanumeric recognition of printed or handwritten characters at electronic speed by simply scanning the form. In deep learning, Convolutional Neural Network(CNN) is at the center of spectacular advances that mixes Artificial Neural Network(ANN) and up-to date deep learning strategies. It has been used broadly in pattern recognition, sentence classification, speech recognition, face recognition, text categorization, document analysis, scene and handwritten alphanumeric recognition. The goal of this project is to observe the variation of accuracies of CNN to classify handwritten alphanumeric characters using various numbers of hidden layers and to make the comparison between accuracies. For this experiment, we train huge amount of datasets and further CNN algorithm is used to which a classifier is added to get the desired output.

KEYWORDS: Convolutional Neural Networks, Deep Learning, Machine Learning

I. INTRODUCTION

Text recognition is a territory of example distinguishing proof that has been the subject of extensive study amid the current decades. Manually written text shows wide complex varieties. Penmanship is a standout amongst the most important means in day by day discussion. Amid the current years, by far most of the conspicuous field of study and applications joined for bank check taking care of, sent wraps address perusing, and composed by hand message recognizable proof in records and recordings. Character Recognition System (CRS) used to distinguish mortal print image. These images might be alphabetic. These images might be either printed or composed by submit an assortment of various size and textual style. All the more exactly character recognition is the way toward distinguishing and perceiving character from information picture and change it into American Standard Code for Information Interchange or other comparing machine editable form. The chore of recognition comprehensively segregates into two kinds: written by hand and machine printed. The printed character reference is uniform and extraordinary.

II. LITERATURE SURVEY

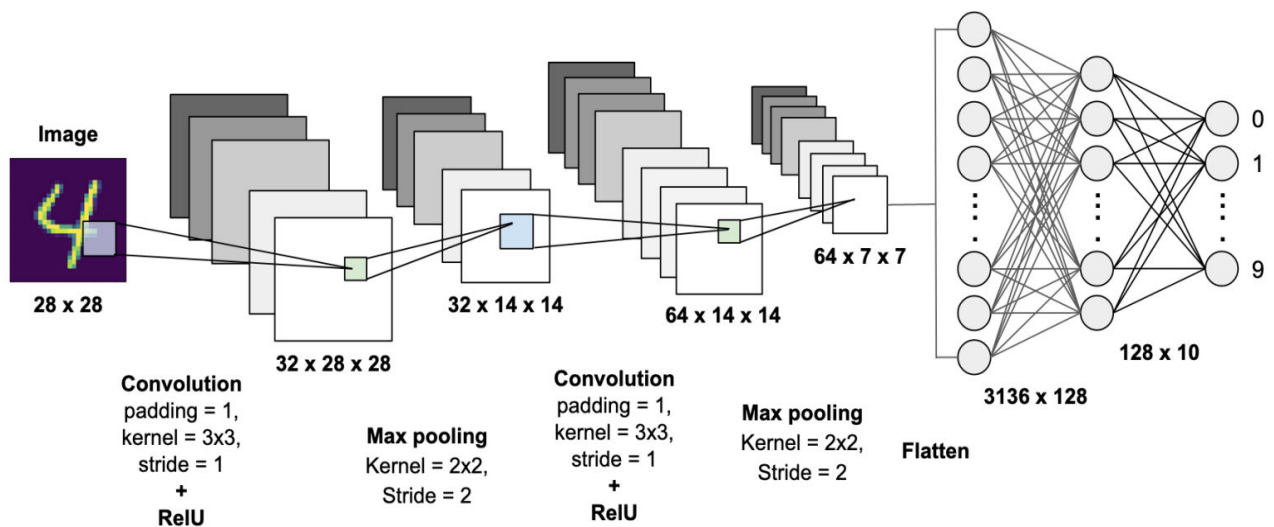
Amit Choudhary et al. proposed an Off-Line Handwritten Character Recognition using Features Extracted from Binarization Technique. This work is to extract features obtained by Binarization technique for recognition of handwritten characters of English language. The recognition of handwritten character images have been done by using multi-layered feed forward artificial neural network as a classifier. This algorithm delivers outstanding classification accuracy of 85.62 %. Baheti M. J et al. proposed a comparison of the offline handwritten character recognition system for the isolated Gujarati numerals. They used affine invariant moments based model for the feature extraction. They used KNN classifier and PCA to reduce dimensions of feature space and used Euclidean similarity measure to classify the numerals. KNN classifier obtained 90 % as recognition rate whereas PCA obtained recognition rate of 84%. After the comparison it is observed that KNN classifier has shown better results as compared to PCA classifier.

Sonu Varghese K et al. proposed a Novel Tri-Stage Recognition Scheme for Handwritten Malayalam Character Recognition. In the first stage we are grouping characters into different classes based on the number of corners, bifurcations, loops and endings. In the second phase we are identifying exact character in the class based on the

different feature extraction technique specially defined for each class. In the third stage we are checking the probability of occurrence of the current character in the given position based on defined rules for the formation of words. we are implementing a three stage feature extraction technique which uses structural, statistical and moment variant features of the character. Recognition conducted in different stages improves the efficiency, recognition rate and accuracy of the given system.

III. MODELING OF CONVOLUTIONAL NEURAL NETWORK TO CLASSIFY HANDWRITTEN DIGITS

We used convolutional 2D neural network available in keras for training and testing our model. The overall architecture of Conv2D is shown below.



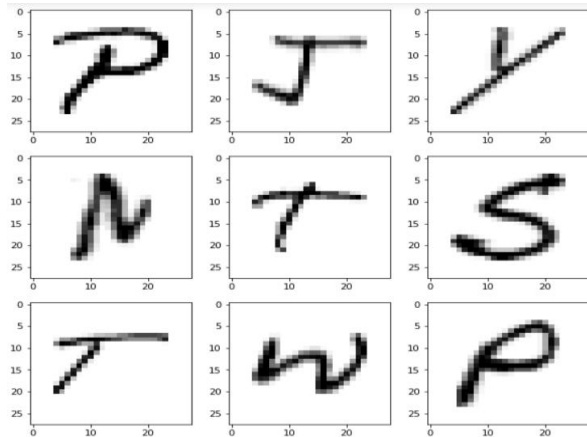
Models in Keras can come in two forms – Sequential and via the Functional API. For most deep learning networks, the Sequential model is likely. It allows to easily stack sequential layers (and even recurrent layers) of the network in order from input to output. The first line declares the model type as Sequential(). Add a 2D convolutional layer to process the 2D input images. The first argument passed to the Conv2D() layer function is the number of output channels – in this case we have 32 output channels. The next input is the kernel_size, which in this case we have chosen to be a 6x6 moving window, followed by the strides in the x and y directions (1, 1). Next, the activation function is a rectified linear unit and finally we have to supply the model with the size of the input to the layer. Declaring Add a 2D max pooling layer. We simply specify the size of the pooling in the x and y directions – (2, 2) in this case, and the strides. Next we add another convolutional + max pooling layer, with 64 output channels. The default strides argument in the Conv2D() function is (1, 1) in Keras, so we can leave it out. The default strides argument in Keras is to make it equal to the pool size. The input tensor for this layer is (batch_size, 26, 26, 32) – the 26 x 26 is the size of the image, and the 32 is the number of output channels from the previous layer. Next is to flatten the output from these to enter our fully connected layers. The next two lines declare our fully connected layers – using the Dense() layer in Keras, we specify the size – in line with our architecture, we specify 512 nodes, each activated by a ReLU function.

The second is our soft-max classification, or output layer, which is the size of the number of our classes. In the training model, we have to specify the loss function, or told the framework what type of optimiser to use (i.e. gradient descent, Adam optimiser etc.). Loss function of standard cross entropy for categorical class classification (keras.losses.categorical_crossentropy). We use the Adam optimizer (keras.optimizers.Adam). Finally, we can specify a metric that will be calculated when we run evaluate() on the model. We first pass in all of our training data – in this case x_train and y_t.

IV. KAGGLE DATA SET

Kaggle allows users to find and publish data sets, explore and build models in a web-based data-science environment, work with other data scientists and machine learning engineers, and enter competitions to solve data science challenges.

Kaggle.com is one of the most popular websites amongst Data Scientists and Machine Learning Engineers. Additionally, all these datasets are totally free to download off of kaggle.com. This platform is trusted by some of the largest data science companies of the world such as Walmart, Facebook and Winton Capital. On Kaggle, data scientists get exposure and a chance to work on problems faced by big companies in real-time.



The dataset contains 26 folders (A-Z) containing handwritten images in size 28x28 pixels, each alphabet in the image is centre fitted to 20x20 pixel box. Each image is stored as Gray-level. All the images are 28x28 pixels, it forms an array which can be flattened into 28*28=784 dimensional vector.

V. RESULTS AND DISCUSSION

In general Neural Network consists of different hidden layer. In most of Conv2D will have two hidden layers with 16 or 32 neurons and more, Hidden layers are multiplied with different random weight of image pixel data which is between 0 to 1. But in Conv2D Neural Network was design with same two hidden layers and each hidden layers consists of large set of neurons i.e. we used 128 dense neurons are taken and this are multiplied with random weights. By using this deep network we got promising results. Here we displaying some labeling of characters in Table 1.

Table 1- Sample data representation of labeling

Layer Type	Layer operation	No of feature map	Feature map size	Total parameters
C1	Conv2D	32	26 X 26	320

In this testing phase we used two layered Convolutional Neural Networks (CNN) model with Softmax Optimization. On them one layers for convolutional, one layers for max pooling or sub sampling, one Flatten layer which converts this testing phase we used five layered Convolutional Neural Networks (CNN) model . The model gives highest accuracy as 97.66% as training accuracy and 95.47% as validation accuracy.

```
The validation accuracy is : [0.9766680002212524]
The training accuracy is : [0.9547959566116333]
The validation loss is : [0.08453203737735748]
The training loss is : [0.16911868751049042]
```

Evaluation metrics of CNN algorithm for Handwritten character recognition

VI. CONCLUSION

In this paper we proposed different neural network approach for Recognition of Handwritten characters and digits from images. We evaluated the performance using Convolutional Neural Network (CNNs) with optimization techniques and Deep Feed Forward Neural Network. These techniques are train and test on a standard user define dataset which is collect from different users. From experimental results, it is observed that CCN- softmax yield the best accuracy for Handwritten characters compared to the alternative techniques. We achieved promising results from proposed method with high accuracy rate.

REFERENCES

- [1] Siyang Qin and Roberto Manduchi , “A Fast and Robust Text Spotter”, IEEE Winter Conference on Applications of Computer Vision (WACV),pp.1-8,2016.
- [2] Jay H. Bosamiya, PalashAgrawal, ParthaPratim Roy and R. Balasubramanian , “Script Independent Scene Text Segmentation using Fast StrokeWidth Transform and GrabCut”, 3rd IAPR Asian Conference on Pattern Recognition (ACPR), pp.151-155, 2015.
- [3] Femin P D and Dr. Vince Paul, “A Comparative Study of Techniques Used inHandwritten Character Recognition”, International Journal of Innovative Research in Science,Engineering and TechnologyVol. 5, Issue 11, pp.20040-20045,November 2016
- [4] AnshulGupta,ManishaSrivastava and ChitralekhaMahanta, “Offline Handwritten Character Recognition Using Neural Network”AI 2011 International Conference on computer applications and industrial electronics, pp.102-107, April 2011.
- [5] Plamondone ,S.Chaturved, N.R.Sondhiya,R.N.TitreandIzhikevich, “Model Based Pattern Classifier for Hand Written Character Recognition “– A Review Analysis, International Conference on Electronic Systems, Signal Processing and Computing Technologies (ICESC), pp.346-349, 9-11 Jan. 2014.
- [6] Neeta Nain andSubhashPanwar, “Handwritten Text Recognition System Based onNeural Network”, Journal of computer and information technology ,vol2,no-2, pp.95-103, June 2012.
- [7] Arica, N., and Yarman-Vural. F.T., “An Overview of Character Recognition Focused on Off line Handwriting”, IEEE Trans. On Systems, Man, and Cybernetics, Vol. 31. No. 2, pp. 216-233, 2001.
- [8] M. Elzobi, A. Al-Hamadi, Z. Al Aghbari, and L. Dings, “IESK-ArDB: a database for handwritten Arabic and an optimized topological segmentation approach,” International Journal on Document Analysis and Recognition, vol. 16, no. 3, pp. 295–308, 2013.
- [9] S. Al-Ma’adeed, D. Elliman and C. Higgins, “A Data Base for Arabic Handwritten Text Recognition Research,” Proceedings of the 8th International Workshop on Frontiers in Handwriting Recognition (IWFHR 2002), pp. 485-489, August 2002.
- [10] S. Mozaffari, H. E. Abed, V. Maergner, K. Faez and A. Amirshahi, “IfN/Farsi-Database: a Database of Farsi Handwritten City Names,” Proceedings of the 11th International Conference on Frontiers in Handwriting Recognition (ICFHR 2008), pp. 397-402, August 2008.
- [11] S. A. Mahmoud, I. Ahmad, M. Alshayeb, W. G. Al-Khatib, M. T. Parvez, G. A. Fink, V. Margner and H. E. Abed, “KHATT: Arabic Offline Handwritten Text Database,” Proceedings of the 2012 International Conference on Frontiers in Handwriting Recognition (ICFHR 2012), pp. 449-454, September 2012.
- [12] Lorigo, L.M. and Govindaraju, V. (2006). Off-line Arabic Handwriting Recognition: A Survey. IEEE TRANSACTIONSON PATTERN ANALYSIS AND MACHINE INTELLIGENCE. , 712- 724.



INNO  **SPACE**
SJIF Scientific Journal Impact Factor
Impact Factor: 7.542



ISSN INTERNATIONAL
STANDARD
SERIAL
NUMBER
INDIA



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

 **9940 572 462**  **6381 907 438**  **ijircce@gmail.com**



www.ijircce.com

Scan to save the contact details