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RESEARCH ARTICLE

An Innovative Method to Analyse the Prediction Rate and Accuracy for Handwritten Digit Recognition with Convolutional Neural Network Over Connection Temporal Classification

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ABSTRACT

Aim: Recognizing the Handwritten Digits to find the best accuracy using Machine learning methods such as Connectionist Temporal Classification (CTC) and Convolutional Neural Network (CNN). **Methods and Materials:** Accuracy and loss are performed with the MNIST dataset from the Keras library. The two groups Connectionist Temporal classification (N=20) and Convolutional Neural Network algorithms (N=20). **Results:** A CNN is used for recognizing the innovative handwritten digits. The accuracy is analysed based on correctness of the exact digits of 92.67% where the CTC has the accuracy of 89.07%. The two algorithms CNN and CTC are statistically satisfied with the independent sample T-Test (α=.001) value ($p<0.05$) with confidence level of 95%. **Conclusion:** Recognizing the handwritten digits significantly seems to be better in CNN than CTC.

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Introduction

Handwritten Digit Recognition (HDR) is one of the major problems that every system faces. Nowadays, there is no application-based system yet to recognize handwritten digits. (Ahlawat et al. 2020). It is important to recognize the handwritten digits which are with different handwritings. If all the digits are the same, then it is possible to recognize the digit to a human.(Shamim et al. 2018). But every individual has their own handwriting that may not be possible for a human to recognize. Handwritten digit recognition has various troubles in recognizing the digits due to different types of writing styles. It is very difficult to recognize every style of the handwritten digits.

Digit strings of handwritten documents are not able to read every digit separately by the human (Baldwin, Martin, and Stylianidis 2020). So, the system may be useful to not miss a single digit to produce the data which is there in the document. (Han and Li 2015). This HDR is useful in the sectors of Banking, Data Entry centres, etc(Shamim et al. 2018). The postal address to sort the posts. (Islam et al. 2017).

Handwritten digit recognition is carried out by researchers to promote business. Totally 20 related articles published in IEEE and 6 related articles are published in Google Scholar like ResearchGate, Science direct. (D. Gupta and Bag 2021) implemented Handwritten digit recognition using Convolution Neural Network tells about how to find the handwritten digits with different languages. With this system, the number of different languages is recognized and produced as a required text language. In this system, the accuracy of

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eight languages has got 97.23% in the recognition that focuses on thinking about how to do the multilingual in CNN still exists. (Zada and Ullah 2020) discussed Pashto is the type that is arabic language digits that are isolated to get the digits clearer and make the digits to produce to find the results. All the isolated digits were recognized with an accuracy of 84.19%. (Alani 2017) Handwritten digit recognition has been implemented for Farsi digits. It is a language that has different types of digits like hindi, arabic, roman, etc. The accuracy rate has been produced as 96.38%. There was only a 1.5% increase in recognition error in comparison with the full data. (Shopon, Mohammed, and Abedin 2016) implemented Bangala handwritten digit recognition has used the NumtaDB dataset with the sample images and which is large and unbiased. This trained dataset got the accuracy of 92.72% which is better than the biased data.

Previously our team has a rich experience in working on various research projects across multiple disciplines (Sathish and Karthick 2020; Varghese, Ramesh, and Veeraiyan 2019; S. R. Samuel, Acharya, and Rao 2020; Venu, Raju, and Subramani 2019; M. S. Samuel et al. 2019; Venu, Subramani, and Raju 2019; Mehta et al. 2019; Sharma et al. 2019; Malli Sureshbabu et al. 2019; Krishnaswamy et al. 2020; Muthukrishnan et al. 2020; Gheena and Ezhilarasan 2019; Vignesh et al. 2019; Ke et al. 2019; Vijayakumar Jain et al. 2019; Jose, Ajitha, and Subbaiyan 2020). Now the growing trend in this area motivated us to pursue this project.

Based on the literature survey, the CTC has very less accuracy, correctness of the digit is shown very low percentage while analysing the digits and the manual input is not possible to add to the dataset. The aim of the study is to improve the accuracy of the digits, improving the correctness percentage of the recognized digits and to reduce the loss of data while training and testing the dataset.

Methods and Materials

The study setting of the proposed work is done in our university laboratory. The study setting of the proposed work is done in our university laboratory. Sample size was calculated by using clincalc.com by keeping G power (Kane, Phar, and BCPS n.d.) and minimum power of the analysis is fixed as 0.8 and maximum accepted error is fixed as 0.5 with threshold value as 0.05% and Confidence Interval is 95%. Mean and standard deviation has been calculated based on the previous literature for size calculation. The two groups are used namely Connectionist Temporal Classification (N=20) as an existing model as group 1 and Convolutional Neural Network (N=20) as Proposed model as group 2.

Data Preparation

The Convolutional Neural Network is to find all the digits that are stored in the dataset, to train and test through the MNIST (Modified National Institute of Standards and Technology) dataset. The dataset includes the 70,000 data in the form of images which are taken as a sample from the University of America students with their respective handwritings. There are 60,000 trained images and 10,000 tested images. The sample images of digits present in the MNIST dataset has been shown in Fig. 1.

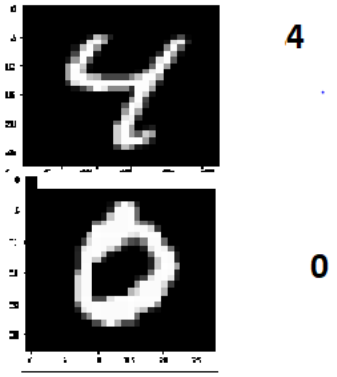

Fig. 1. Handwritten Digits from MNIST dataset

Connectionist Temporal Classification (CTC)

(Ibrayim, Simayi, and Hamdulla 2021) CTC is one of the classification methods of Neural Networks which is the advanced one of the Recurrent Neural Networks (RNN). CTC is done or used for the detection of Face recognition, Image Processing, Handwritten Digit, and Character Recognition, etc. (Fontaine and Shastri, n.d.) CTC can be used for assigning a probability value for any Y-axis given as X. The main lead for calculating this probability in CTC considers alignment between input images and output text. Fig.2 represents the working flow of the Connectionist Temporal Classification (CTC) algorithm. (Abdulrazzaq and Saeed 2019) This is used to compute the loss function of the MNIST dataset and perform inference.

In Fig.2 the process of CTC has been mentioned with input image with preprocessed. Then verified with given digits are handwritten or not, if yes tensorflow has processed those HDR images. The flow diagram steps as follows,

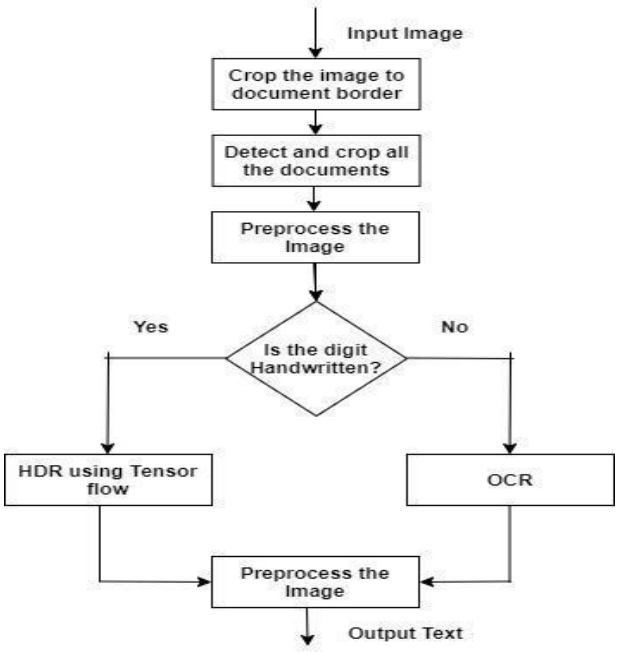

Fig. 2. Connectionist Temporal Classification

- Give the input as an image with pixel 28*28.
- Take input and crop the image to present in the code

- Pre-process the image and find it handwritten or not.
- If yes, then it will go to the tensor flow function and exit.
- Once the image is in the tensor flow function it will pre-process the image.
- After the preprocessing is done with the images are well processed and produce the output image with the text format i.e., which is present in the digit image.

Convolution Neural Network (CNN)

(Ahlawat et al. 2020)Machine Learning method CNN is the deep neural network with different activation functions and which is formed as a three-layer function that will produce the results. (Siddique, Sakib, and Siddique, n.d.) It is a deeper neural network that has three layers that are input layer, hidden layer, and output layer. The hidden layer consists of many forms to recognize the given digit image and produce the recognized digit in the text format. (A. Gupta, Narwaria, and Singh 2021) CNN is loosely inspired by the neurobiology of the visual system. CNN features will feed to a hidden layer followed by an output classification layer using soft-max and ReLU. The functioning of the Convolutional Neural Network has been represented in Fig.3. Soft-max is the function that will produce the values of the categorical value that proposed the value to find the accuracy. The Fig. 3 flow has been mentioned in the below steps.

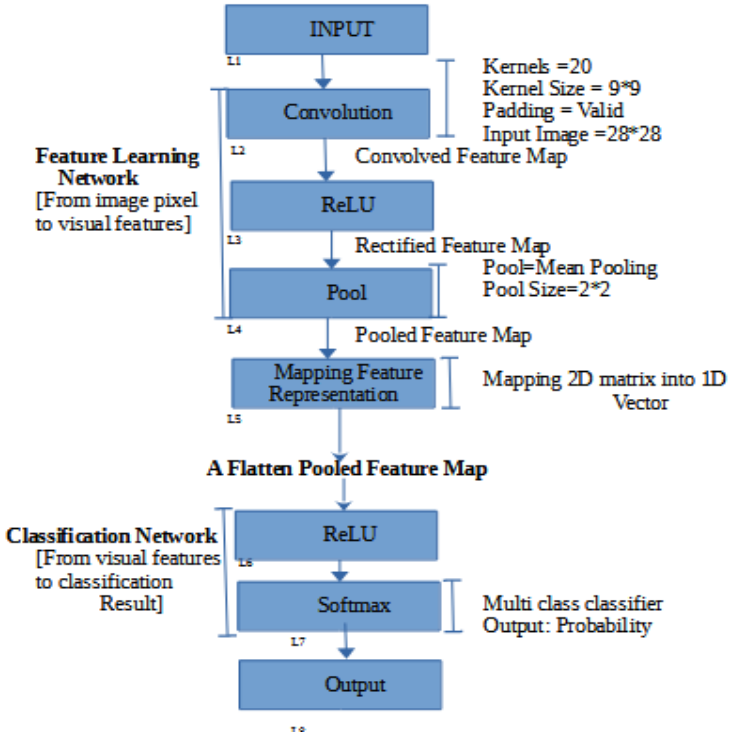

Fig. 3. Conventional Neural Network

- Downloading the dataset to load
- Initialize the variables to train and test the data.
- Define a model. fit () function to describe the components which are to be accessed for running the code to get accuracy.
- Define Categorical () function to categorize the data.
- Print the model. fit () function with the required epochs and find the accuracy.

For comparing both the models, the dataset has been trained with five different sample sizes. the accuracy values are recorded.

The system configuration is used for the algorithm to run in 64 - bit Operating System, 4GB RAM PC and used Windows 10, Google Colab and Microsoft Office for software specification.

To estimate the performance of the training model, the data has been splitted for training and testing to validate the dataset. Then load and reshape the data arrays to categorize the numbers. Normalize the pixel values of gray scale images All the layers will be functioned through ReLU activation function to the categorical cross_entrophy to find the loss function. The model will be evaluated with the fit() function which has the metrics function to validate the accuracy and loss of the data.

Results

CNN algorithm forms the layers with all the images of each number, whenever it runs in different times due to the initialization of sample size (N=20). The layers formed due to the iterations, the accuracy value changes with the duration of running time and produces the accuracy and loss with respect to the time period which are shown in Table 1. CNN has better accuracy and less loss than the CTC due to the activation functions and metrics, the CTC algorithm has not compatible to the advanced activation functions which is only restricted to the adam, adaleta and adagrad which takes more time and the functions are not taking the whole data to analyse the similar digits in the dataset whereas the CNN takes the data and forms layers with each digit individually

and finally gives the result. With the respect of the activation functions the Accuracy and loss have changed and has proven that CNN is better than the CTC.

Table 1. Data collection from the N=10 samples of dataset for CTC with the size of 28*28 pixel to gain accuracy (%) and reduce Loss (%) and CNN to gain accuracy (%) and reduce loss (%)

Samples (N)	Connectionist Temporal Classification		Convolution Neural Network	
	Accuracy (%)	Loss (%)	Accuracy (%)	Loss (%)
1	51.79	21.76	92.07	2.73
2	62.4	20.75	92.14	2.7
3	69.41	19.28	92.17	2.67
4	73.7	17.2	92.3	2.64
5	77.11	14.63	92.34	2.61
6	78.30	12.09	92.42	2.59
7	80.73	9.85	92.45	2.56
8	88.01	8.28	92.55	2.53
9	85.80	7.17	92.64	2.51
10	89.07	4.68	92.67	2.48

Table1 represents the data collection from the N=20 samples of dataset for CTC with the size of 28*28 pixels to gain accuracy (%) and reduce Loss (%) and CNN to gain accuracy (%) and reduce loss(%).

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Where, TP = True Positive
TN - True Negative
FP - False Positive
FN - False Negative

Loss: A scalar worth that we endeavor to limit during our preparation of the model. The lower the misfortune, the nearer our expectations are to the genuine names.

The IBM SPSS version 21 statistical software is used for our study. The independent variables are shape and size and the dependent variable is accuracy (%). for our study handwritten recognition digits.

In SPSS, the datasets are prepared using N=20 as sample size for Connectionist Temporal Classification and Convolution Neural Network. GroupID is given as a grouping variable and accuracy is given as the testing variable. GroupID is given as 1 for CTC and group 2 for CNN. Group Statistics is applied for the dataset in Statistical Package for the Social Sciences (SPSS) and shown in Table 2. By performing the statistical analysis group statistics represents the comparison of the accuracy and Loss of Handwritten Digit Recognition (HDR) of CTC and CNN. The CNN algorithm had the highest accuracy (92.67) and the lowest loss (2.48). CTC had the lowest accuracy (89.07) and highest loss (3.6) in table 2.

Table 2. Comparison of the accuracy and Loss of Handwritten Digit Recognition (HDR) of CTC and CNN.CNN algorithm had the highest accuracy (92.67) and the lowest loss (2.48). CTC had the lowest accuracy (89.07) and highest loss (3.6).

Groups		N	Mean	Std. Deviation	Std. Error Mean
Accuracy	CTC	10	88.4120	1.01723	.32168
	CNN	10	92.3750	.20887	.06605
Loss	CTC	10	4.3560	.55155	.17441
	CNN	10	2.6020	.08337	.02636

Table 3 represents the Independent Sample T- Test is applied for the sample collections by fixing the level of significance as 0.005 with confidence interval as 95 %. After applying the SPSS calculation it was found that CNN has accepted statistically significant value(P<0.05).

Table 3. Independent Sample T- Test is applied for the sample collections by fixing the level of significance as 0.05 with confidence interval as 95 %. After applying the SPSS calculation it was found that CNN has accepted statistically significant value(P<0.05).

		Levene's test for equality of variances		T-test for equality means						
		f	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std.Error difference	95% confidence interval	
									Lower	Upper
Accuracy	Equal variances assumed	16.099	.001	-12.068	18	.000	-3.96300	.32839	-4.65292	-3.27308
	Equal Variances not assumed			-12.068	9.758	.000	-3.96300	.32839	-4.69761	-3.22884
Loss	Equal variances assumed	16.584	.001	9.944	18	.000	1.75400	.17640	1.38341	2.12459
	Equal variances not assumed			9.944	9.411	.000	1.75400	.17640	1.35761	2.15039

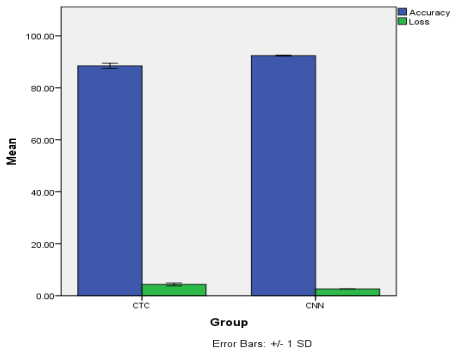

Fig. 4. Simple Bar Mean of Accuracy CTC error range (0.82 - 0.91) and Loss error range (2-4) and CNN error range (0.91 - 0.92) and for loss error range (0.2-0.3) with Mean accuracy of detection ± 1 SD.X Axis: CTC vs CNN Y Axis: Mean accuracy of detection ± 1 SD.

From Figure 4 it was represented by a simple bar Mean of Accuracy CTC error range (0.82 - 0.91) and Loss error range (2-4) and CNN error range (0.91 - 0.92) and for loss error range (0.2-0.3).

Discussion

Our overall results show that there are some variations observed in the accuracy and loss values due to the advancements of the activation functions which proved that the Convolutional Neural Network with accuracy 92.67% is better than the Connectionist Temporal Classification with accuracy 89.07% in recognizing the Handwritten Digits. There is a statistically significant difference in innovative Handwritten Digit Recognition (HDR) accuracy of two

algorithms having the significant accuracy value of 0.001 ($p<0.005$ Independent Sample t Test).

(Ahlawat et al. 2020) The accuracy for the recognized MNIST handwritten digit Recognition with different optimizers like stochastic gradient descent with momentum, Adam, Adaleta and Adagrad are used as activation functions to optimize the performance with the accuracy of 89.99%. But in our study we have used advanced activation functions like ReLU, Soft-max and improved accuracy and an innovative optimized performance to 92.67%. The activation functions perform similar tasks but are not the same. (Alani 2017) A significant achievement to the proposed model is using Restricted Boltzmann Machine deep learning for feature extraction to the arabic digits with the highest accuracy of 97.4%. The CNN classification algorithm is used to extract the features, and can easily get the accurate class with the accuracy of 98.59%. But in our proposed model, CNN algorithm is used for extracting the feature as similar and additionally added to find the structure with all the data in the dataset of each digit. The terms feature extraction and deriving the structure are similar. (Wang et al. 2018) performs the handwritten digit recognition to reduce the number of neurons and also to implement the artificial neurons for the morphic dataset. In our study, CNN algorithm is used to train the MNIST dataset which will form many neurons to train the layers. Deriving the neurons in the Artificial Neural networks is difficult due to higher time complexity than the CNN, but in significant ways both are similar.

(Yang et al. 2015) discussed about the handwritten chinese characters proposed with deep Convolutional Neural Network is much faster than the average ensemble strategies with the accuracy of 84% has been recognized with the test samples of MNIST dataset. In the CNN model the data has taken the more time to train and tested the dataset and also accuracy has been improved to 92.67%. Here, the time complexity is the term that is not similar but the same. (Li, Song, and Zhang 2020) performs the Recognition of chinese characters is trained and tested with the Deep Convolutional Generative Adversarial Network and improved GoogLeNet (DCGANG) has extracted the feature and also blocks the missing layers whereas in CNN model the feature extraction is only done to the images which are present and the missing will not be taken as consideration. The concept of deriving the layers in each dataset while training and testing the data is not similar and not the same due to the training of the dataset. The image processing is involved in the detection of images on a handwritten recognition to use detect relevant details based on the detection by different classification process ((“Recognition and Classification of Diabetic Retinopathy Utilizing Digital Fundus Image with Hybrid Algorithms” 2019; Malathi and Nedunchelian 2018). In the study, the existing model has been derived for the characters whereas our complete study is based on digits. From the overall literature, many authors have cited the proposed algorithm as having better accuracy and less loss compared to existing methods.

Our institution is passionate about high quality evidence based research and has excelled in various fields ((Vijayashree Priyadharsini 2019; Ezhilarasan, Apoorva, and Ashok Vardhan 2019; Ramesh et al. 2018; Mathew et al. 2020; Sridharan et al. 2019; Pc, Marimuthu, and Devadoss 2018; Ramadurai et al. 2019). We hope this study adds to this rich legacy.

(Han and Li 2015) As every research has some limitations like in this review the algorithm is restricted only to the English numerals but not to any other type of digits or digit strings.(D. Gupta and Bag 2021) cription cannot be done. Deeper networks usually require more time to train data, making it practically infeasible in real world applications.

(Han and Li 2015) In the future, we can improve this classification for further development in Deep Convolutional Neural Network Architecture and the applications of some big complex noisy data. we can improve this system to recognize characters in different languages. Systems are to be developed yet to analyse over the real time handwritten digits.

Conclusion

In this research, the innovative HDR (Handwritten Digit Recognition) system performed using MNIST dataset seems to be better accuracy (92.67%) using Convolution Neural Network than Connectionist Temporal Classification (89.07%). The clarity of handwritten digits are found with good accuracy and less loss is achieved.

Declarations

Conflict of Interests

No conflicts of interest in this manuscript.

Authors Contributions

Author PSPM was involved in conceptualization, data collection, data analysis, manuscript writing. Author KM was involved in conceptualization, guidance, and critical review of the manuscript.

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