International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
IJISAE
ISSN:2147-6799 www.ijisae.org Original Research Paper

Segmentation Free Approach Using Hybrid Network Model for Optical Character Recognition

Dr. U. Ganesh Naidu [1], Vijaya Krishna Sonthi[2], M. V. B. Murali Krishna M.[3], P. N. V. Syamala Rao M.[4], Syed Muqthadar Ali [5], Chitri Rami Naidu[6]

Submitted: 25/09/2023 **Revised**: 15/11/2023 **Accepted**: 27/11/2023

Abstract: Optical Character Recognition (OCR) have an importance in the research based on image processing and recognizing the pattern. It serves as an automatic technique for identifying the various patterns in diverse applications. The recognition technique effectively explores the characters, images, and even the handwriting of an individual. Much research concerning OCR involves every deep learning, machine learning, and artificial intelligence algorithm. A segmentation-free approach has been introduced in this paper that combines with Hybrid Network Model (HNM) that works on collaborating convolutional neural network and recurrent neural network for minimizing the time in processing and improving the accuracy. In hybrid model we consider CNN in the input layer, the middle layer is LSTM and MLP is the layer generated as an output. The length of sequences in the input and output can vary it need not be specific they are managed by the encoder and decoders present in LSTM.

Keywords: *Optical Character Recognition (OCR), Long Short-term memory (LSTM), Multi-Layer perceptron (MLP), Convolutional Neural Network (CNN).*

1. Introduction

OCR is a conventional methodology that applies an artificial neural network which helps in emulating the thinking of a human and pattern recognition with relevance to artificial intelligence. The existing methodology does not contribute their level best in proving their recognition of visual characters, if they are found to be the same but differ in their size. It also increases the system's time-complexity, and that might be a problem for slower machines. Furthermore, for the identification of few more characters, higher matrices precision is necessary [1]. Another model of machine learning is the genetic algorithm which uses genetic operators for genetic representation. In general pattern recognition extracts the essential features from a pattern. The pattern provided in the input is recognized based on the features of the system. A wrapper-based multi-criterion method is utilized in combination with a multi-layer perceptron neural network to produce intriguing results in classifier complexity reduction [2]. The actual challenge lies in sustaining the suitable features and eliminating irrelevant ones that are the essential step in the system design of pattern recognition.

Two major categories of pattern recognition are handwritten and typewritten patterns where the former attempts for recognizing a text written by a human and later recognize the document which is printed earlier or scanned in before recognition progress. It is applied to digitize books, library papers, and important documents [3]. The OCR stores the text and generates the databases of existing text without the help of the keyboard. The method presented in the paper is a hybrid network model combining the features of CNN, LSTM as two different layers. Regarding the involvement of deep learning for OCR has been initiated through Convolutional neural network (CNN) for postal zip codes developed by Lecun [4].Hybrid HMM or neural methods were adopted in feature extraction at frame level and sequence modeling for HMM. The character-level segmentation is obtained by relying on bootstrapped HMM system. They are also employed to develop neural feature extractors, which was taken into account when developing the HMM model. They were all present in the system where, before to neural model training using frame level cross-entropy, the basic HMM model acquired frame-level segmentation [5]. It was noted that they are frequently employed for the second-pass sequence discriminative training step in conjunction with frame-level cross-entropy algorithms that are similar to Bayes risk. speech synthesis [6]. The stochastic

[1]*Assistant Professor, B V Raju Institute Of Technology, Narsapur, Medak, Telangana, India.*
[2] *Assistant Professor, Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Andhra Pradesh, India.*
[3]*Assistant Professor, Department Of Computer Science And Engineering, Vasavi College Of Engineering, Hyderabad· India*
[4] *Assistant Professor Department of CSE- AIML & IOT, VNRV, JIET, Hyderabad, Telangana*
[5]*Senior Assistant Professor, CSE, CVR College of Engineering, Hyderabad, Telangana*
[6]*Assistant Professor, Department of CSE, Sagi Ramakrishna Raju Engineering College, Bhimavaram, Andhra Pradesh, India.*
* *Corresponding Author Email: ganesh613@gmail.com*

technique was introduced for overcoming the assumption of conditional independence of HMM which makes it complicated for modeling multi-frame structural features [7]. LSTM also overcomes the same because they do not explicitly limit the effect of an existing state. Issues in segmentation are overcome by training cross-entropy through sequence labelling which needs frame-level label allocation. A forward-backward type technique based on segmentation probabilities is intended to be implemented using a connectionist temporal classification (CTC), which initially introduced[7]. Multi-dimensional LSTM (MDLSTM) network handles text images in 2-dimensional data and the method improves digit recognition which was extended for offline Arabic handwriting [8,9]. They are also popular for handwriting recognition systems and are widely used in many applications [10-14]. They are implemented by 1-D LSTM that is relevant to OCR machine print after preprocessing. The difference observed in these methods is, it relies on the separate step for preprocessing even though the model can be processed on unprocessed data. Secondly image pixels in the input are directly fed into the LSTM layer where the extraction layer is before layer LSTM and thirdly it does not utilize language model which is external for the process of decoding.

2. Related Work

Conventional methods mostly involve template matching for recognizing the characters. Here pattern matching is done for comparing two structures with exact features and their match between the characters. Normalization of characters is impossible in these methods but the shape of the pattern and position normalization is essential in all the methods [13]. Schematic perceptron is changed by a sigmoidal function that uses a back propagation algorithm and the differentiable function [14]. It works effectively for simple trained problems but when complexity increases by dimensionality and other factors then the performance of the algorithm fails. It's due to complex space for global minima which is observed to be sparse in local minima. Training the characters present is part of the work in artificial neural networks. If an unknown character is provided as an input ANN identifies it through its generalization feature [15]. Many techniques involved in character recognition are based on four general approaches in pattern recognition those are template matching, statistical techniques, and neural networks as mentioned in [16]. The unknown sequences can be predicted through the Hidden Markov statistical model. The input's unidentified character is likewise recognized. It has been found that the algorithm performs poorly when there is an unknown input and a huge training dataset. The HMM model's flaw is that it fails to account for letter correlations [17]. Adaptive character recognition was proposed by Alexander J.Fabborg which uses a neural network. The system is built using a hidden layer back propagation neural network. An algorithm is trained and tested using both typed and handwritten English alphabets. The experimental results proved that better accuracy is given for handwritten character recognition [18]. Gradient search techniques are trapped at local minima and a scaling problem occurs in BPN [19]. Back Propagation-based neural network proves by identifying various functions by choosing basic parameters that include initial weights, learning rate, and network topology. These parameters determine the success of the training process [20]. Beginning from 1980 attempt on combining GA and NN has encouraged numerous publications like face recognition, animates, and classifying normality of thyroid gland and predicting color recipe. Encoding strategies were also implemented along with the above-mentioned techniques. Therefore, many techniques are involved for character recognition through deep learning and machine learning techniques but this paper involves a segmentation-free approach through a Hybrid Neural Network which proves to provide more accuracy than existing methods and minimizes the segmentation time.

Deep Convolutional De noising Auto encoder for preprocessing OCR was introduced by Christopher Wiraatmaja and their team [21]. It has a process for converting the physical documents to digital text with a help of a scanner tool for obtaining images of the document with good and high quality. Those images are read by OCR for obtaining text results in digital format. The disadvantage of this approach is that for great accuracy, the software requires a high-quality document with little blur noise and no parallax pictures. The developed application increases the image quality of the document by Deep Convolutional Denoising Auto encoder that is later read by OCR. The increase in accuracy of blurred image compared to Tesseract OCR with average testing.

Convolutional Neural network (CNN) belongs to the Artificial neural network (ANN) category. It has weights and biases that are trained with a back propagation algorithm with a different architecture from multi-layered perceptron's. The main advantage is it can opt for feature learning and data classifier [22]. Additionally, they demonstrated how the ConvNet approach outperforms other traditional methods using one or more kernels of a specified size. The necessary kernels are evolved along with the input as the input is given as images. A non-linear function is chosen to receive the output, which is obtained using convolutional processes [23].

3. Proposed Methodology

The process of converting scanned copy of the document, text printed converting to editable text from text written by hand for processing is the initial step. The machine automatically recognizes the text by combining the eyes and brain of a human body. The brain processes and interprets the text that is scanned by human eyes as the eye examines the text that is included in the photographs. The problem that occurs in computerized OCR is mild difference between letters and digits that are machine readable. Secondly it is complicated for extracting the text that is encompassed in a dark background or text printed on graphical image. A segmentation free approach combined with Hybrid neural approach has been proposed for enhancing the accuracy of OCR. The modules involved in the planned technique are as follows

1. Collecting the data.

2. Preprocessing.

3. Extraction of features through Hybrid Neural approach

4. Modelling the sequences involved

5. Classification

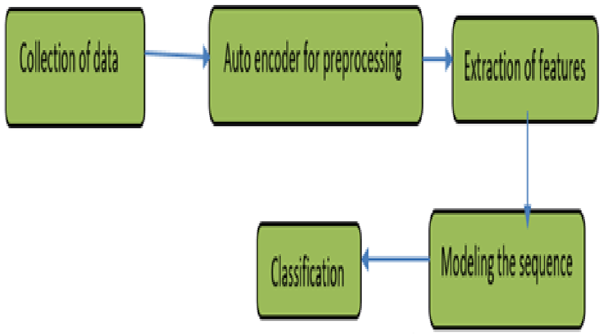


Fig. 2 Stages involved in Segmentation free OCR

Segmentation-free OCR consists of the above-mentioned stages, Initially, it starts with the collection of data and the collected data is in image format of various machine-printed letters. Preconditioning is the subsequent step, during which the data is transformed into binary format. The noise is removed at the preprocessing stage, after which the segmentation-free technique is used, in which a neural network is applied to the width of an image through a sliding window. Imagine that up until this point, all of the images entered have been resized. As a result, they maintain a constant line height. Exploration in the internal phase comprises adjusting the settings that control computing cost while maintaining accuracy.

There are three different processes involved in the system, they are defined as follows:

Process of Deskew where the skew effect is removed on the document image. It uses four different coordinates in the document for calculating the homography matrix of the image. The Harris Corner Detection Algorithm is used to obtain the dimensions. If the picture's recognized corner is not four, an error is generated.

Process of Binarize: This progression involves converting threshold image to binary image by an adaptive method based on a threshold. The goal is to prepare the image as input for an autoencoder. The supplementary noise is also eliminated.

Process of denoising: this process removes blur noise present in character image by deep convolutional de noising encoder. Non-blurred image is obtained as an output.

The proposed methodology integrates Back-propagation and learning methods observed in the Genetic algorithm. The system trains the input data by a Hybrid neural network in collaboration with Back-Propagation. The Hybrid neural network consists of the input neurons in CNN layer and result of the pooling layer is forwarded to LSTM layer for character recognition. The overall methodology consists of three steps: The image being processed is first cleaned up, then specific characteristics are retrieved and supplied into the hybrid neural network, which is then utilized in the third step to classify the image using back-propagation. In a hybrid neural network, the input layer is a CNN, the middle layer is an LSTM, and the output layer is an MLP.

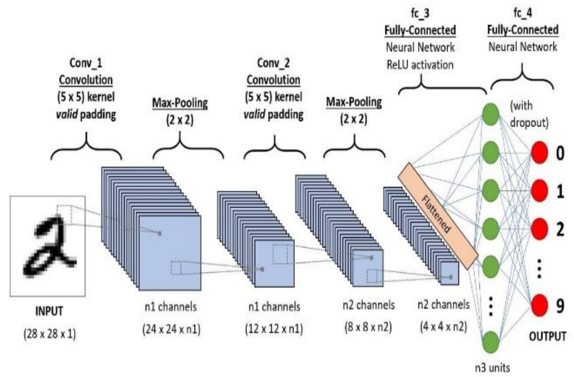


Fig 3. CNN Architecture

Figure 3 shows Architecture of the Convolutional Neural Network. Layer 1 of the CNN Architecture exposed above has padding and striding. Convolutions will not produce output dimensions that match input dimensions be-cause data will be lost over borders, therefore we append a border of zeros and recalculate the convolution to include all of the input values. The term "pooling" refers to a small portion, so in this instance we take a small portion of the input and attempt to take the average value, known as "average pooling," or take a maximum value, known as "max pooling." By performing pooling on an image, we are not removing all the values; instead, we are taking a summarized value over all the values present.

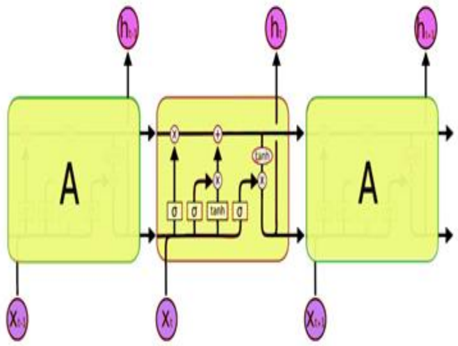


Fig 4. LSTM Architecture

Figure 4 shows basic Architecture of LSTM. The core component of an LSTM model is a memory cell called a "cell configuration" that keeps its state across time. In the diagram below, the top-to-bottom horizontal line that passes through each cell represents the cell state. It can be pictured as a conveyor belt across which data simply and unaltered passes.

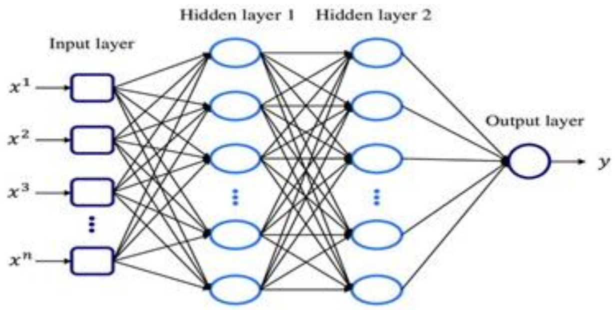


Fig 5. MLP Architecture

A multilayer perceptron (MLP) is a feed-forward artificial neural network that builds a set of outcomes from a number of inputs. An MLP has multiple layers of input nodes coupled as directed graphs between the input nodes and between the input and output layers. Backpropagation is used by MLP to train the network.

3.1 Auto encoder

An auto encoder's sole purpose is to transform an input into a compressed representation, which is then reconverted back into the original input [24]. With the help of this method, auto encoders can learn practical representations of the input data without the requirement for labeling up front. Depending on the intended representation scheme, an auto encoder can be built using a variety of neural network types, such as ANN, CNN, etc. The auto encoder is initially trained in a semi-supervised way when used as a pre-training approach. This enables the encoding portion of the auto encoder to change its weights to provide appropriate low dimensional representations of the data. Such weights are then added to further layers and trained under supervision. Unsupervised learning is done with auto encoders, which have an input layer, a collection of hidden layers, and an output layer. Extracting features from photos was done using denoise auto encoders. In [25], deep auto encoders were used to do content-based picture search. A thorough explanation of the effectiveness of unsupervised pre-training for supervised learning was provided by Erhan and Bengio [26].

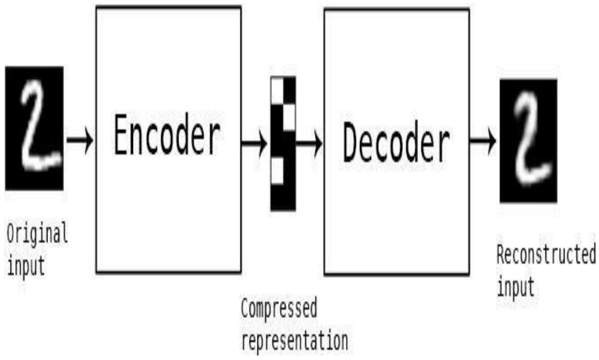


Fig 6. Auto Encoder for Preprocessing

Figure 6 shows how auto encoder can be used for preprocessing. The recognition module is based on a hybrid neural approach combining LSTM and CNN. LSTM approach with a single dimension is used for recognizing printed OCR. The output proved outstanding results on printed object recognition [27-30]. The adapted LSTM is easy to implement and provides the best results of OCR in different scripts. Here in this architecture, we consider a window that has a width equal to a pixel, and the height is based on the input image, is traversed the entire text line. The frame is defined as the column size of an image. The frame's height defines the depth of the sequence. They all provided as input to the LSTM network. The protocol is to equalize the sequencing depth to text line images at the input. This process of equalization is termed normalization. Text line images can be rescaled for normalization. The fundamental and x-height values cannot be properly maintained across every character. This framework employs various methods of normalization which are based on Gaussian filtering and transformation in affine.

3.2 Extraction of Features Through Hybrid Neural Network

In this stage, a hybrid neural network is used to create a sliding window that gives the width of an image by adjusting the step size. After pre-processing, input pictures are expected to be scaled with consistent line heights and observed to be compatible with the neural network's input dimensions. Various variables of the sliding window are adjusted for modifying the computational cost of the model to maintain accuracy throughout the internal exploration phase. It has been found that frames with a higher height endure more overlapping in order to improve the outcomes. The depth of feature extraction of Neural networks in various configurations varies with regard to their activation at hidden layers. We conclude from our experiments that the sliding window cannot be directly connected to the LSTM since it gives ambiguous results. As a result, prior to LSTM layers, a separate feature extraction process is required.

Every character is shown as a feature vector in the hybrid method, which maintains an identity and differentiates each character individually. Characters are categorised based on their characteristics. When there is a lot of variety within a single class of characters, it becomes difficult to recognise them. Font style, document noise, photometric effect, skew in the document, and poor image quality also reflect variations. The process of identifying which attributes are essential for building the model is challenging. Hence Shape-based and boundary-based characteristics are taken into account. Character images are used to extract moment-based traits including Eccentricity, Orientation, Kurtosis Skew-ness, and Mean. The ratio of the ellipse's foci's distance to its main axis' length is known as eccentricity. A particular ellipse's orientation is the angle between its major axis and x-axis. Skewness is the measurement of the asymmetry of the data around the mean.

3.3 Training the hybrid neural network

The hybrid neural network is proficient by the Back Propagation Algorithm. It requires a strong calculative foundation. It adopts the gradient descent method where the error is obtained through the weights for a given set of input. It is accomplished by the propagation of error backward, i.e., from MLP layer (output layer) to LSTM layer (middle layer) and finally CNN (input layer). The formula for calculating error is shown below:

$$\text{Error rate} = \frac{1}{2}\sum(T_o - O_n) \qquad (1)$$

Here T_o is the output obtained in the target and O_n is the calculated output present in the network. The hybrid neural approach adjusts the weight based on the obtained error function. The best solution is obtained by combining the weights as a result of which the error function is minimized. The function has to be both differentiable and continuous. The sigmoid function initiates the threshold function. Back propagation has the drawback that as the problem's complexity rises, its ability to perform declines. At local minima, the gradient search technique is trapped. Genetic algorithm contributes its best as a global search technique. The random searching method provides various alternatives among which the best one is selected with respect to needed criteria. As a result, a set of strings are taken as the initial population of chromosomes for generating the offspring. It fights for survival for creating the next set of population. It evolves through various operators that are fixed generally in GA (Selection, crossover, and mutation) [31]. The proposed work integrates a hybrid neural network and genetic algorithm through a feed-forward network that has multiple layers. It is found as an efficient algorithm for the recognition of characters. The framework involves various normalization methodologies based on Gaussian filtering and affine transformation. The equation is based on training the forward path in LSTM.

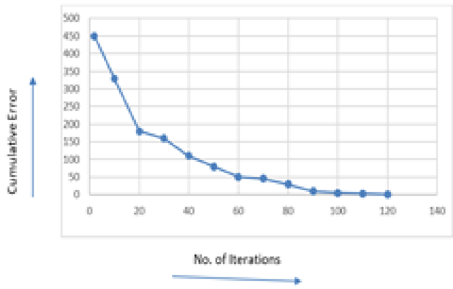


Fig 7. Graph depicting the cumulative errors based on the error function in eqn. 1.

No. of iterations taken on x axis and corresponding cumulative errors shown on y axis in Figure 7.

3.4 Modelling the sequences

Modelling the sequences involves stacking up LSTM layers (middle layer) that are stacked where the input is from CNN to LSTM, and the obtained output is extraction of features at the output. When LSTM layer is entirely connected with linear layer the conversion of dimension at output layer that varies at every step based on the size of the alphabet. Later it's fed as an input to hidden layer for generating probability vector present in the characters. At training phase probability vector is subject to loss in objective function and while decoding they are fed as an input to LSTM layer along with its hidden units.

3.4.1 Obtaining mean and median

Here mean represents both maximum and minimum grey level values and the median involves the full numeral of pixels present in the pictures of a character with respect to above and below mean. The features that are extracted are fed as an input to a hybrid neural approach for recognizing the system.

The algorithm involves following steps:

1) **Coding:** The values present in the initial stage undergo respective coding and the configuration of the network is assumed to be k-l-m. Therefore,

   *Number of weights = ((k+m)*l)* (2)

2) **Extraction of weight:** Fitness value has to be assigned for every chromosome based on which weight is extracted.

3) **Reproduction:** Merging is done at this point by removing the chromosomes with the lowest fitness value. They're swapped out with a duplicate version having low fitness value. Selection, crossover, and mutation are the operators used in the Genetic neural method.

4) **Convergence:** In general, a population has to undergo convergence with 95% of individuals with a population that has the same fitness value. The final weight obtained is adjusted based on the output obtained on the neural network through a hybrid approach.

4 Experimental Results

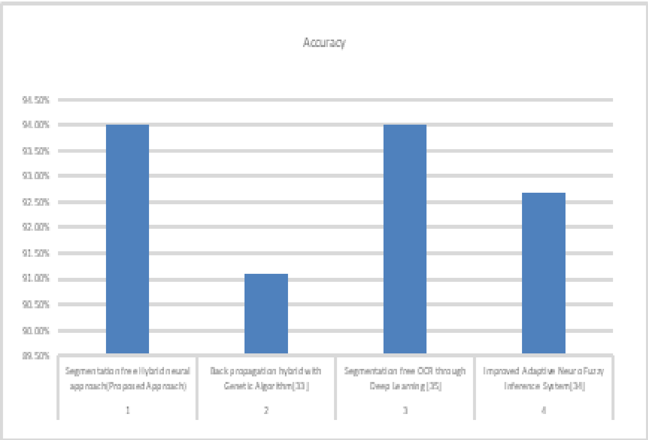


Fig 12. Accuracy comparisn among different character recognition approaches

The suggested segmentation-free hybrid neural approach is contrasted with three other approaches in the above figure and shows more accuracy than all of them.

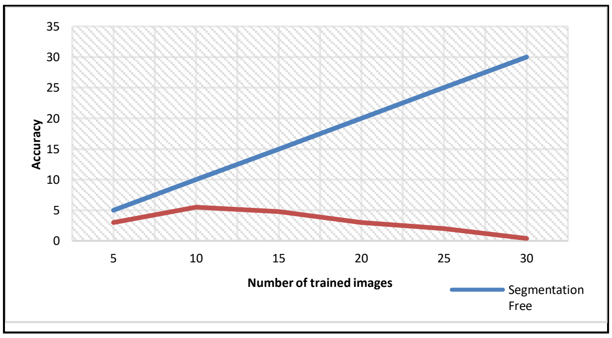
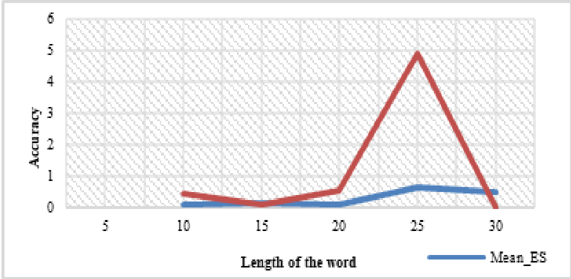


Fig 13. Comparison between the accuracy obtained through OCR with segmentation and segmentation free with trained images

Accuracy measures corresponding to OCR with segmentation and OCR without segmentation are shown in figure 13. Number of trained images are taken on x axis corresponding accuracies shown on y axis.



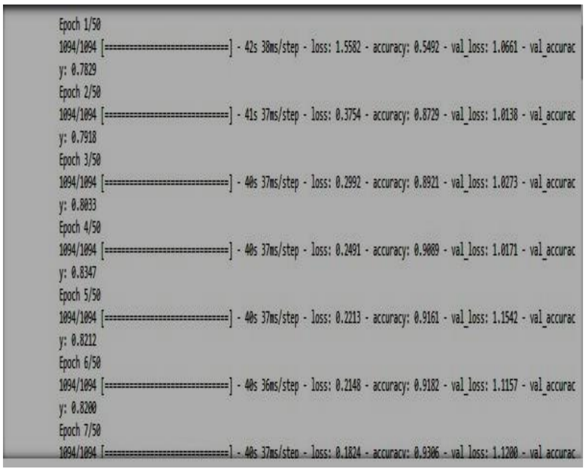


Fig 14. Accuracy Comparison Based On Length Of The Word In OCR

Length of the word and corresponding accuracy are shown in figure 14. Accuracy corresponding to length of the word is the main objective metric that is used to assess how trustworthy Ocr is below:

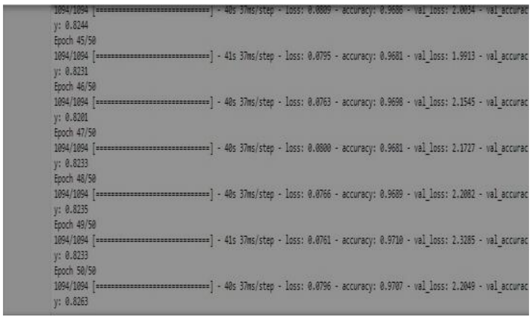


Fig 15. Accuracy and loss results

The accuracy and loss results are shown in the figure 15.

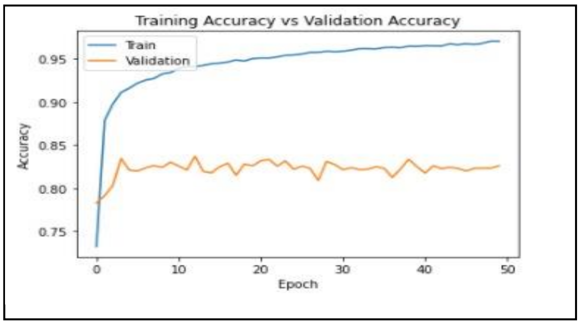


Fig 16: Accuracy comparison based on epoch

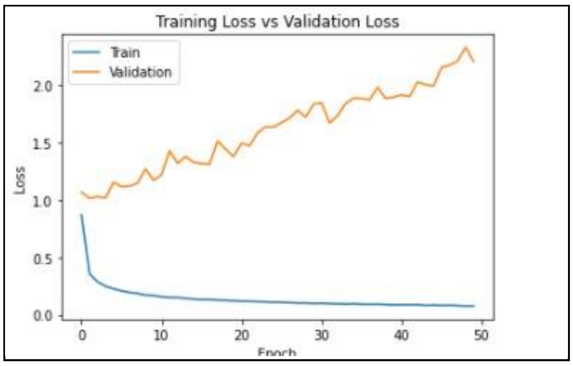


Fig 17: Loss Comparison Based On Epoch

The accuracy and loss comparison based on the epoch are shown in figure 16 and 17 respectively.

5 Conclusion

Improved version of segmentation free approach through hybrid neural net-work is used for identifying various characters and numbers involved in character recognition. At this stage, the image's noise is now almost totally eliminated in preparation for further enhancement. The extracted features are fed into a segmentation-free neural method that reduces processing time and increases character recognition accuracy. The suggested system's findings give a clear depiction of the system's efficiency. In final conclusion, the proposed approach gives accuracy of 94.03% which is better than three existing approaches. The technology will be expanded to include other languages as a potential improvement in the future.

References

[1] Araokar Shashank," Visual Character Recognition using Artificial Neural Networks" published his paper in 2005.

[2] Oliveira, L. S., Benahmed, N., Sabourin, R., Bortolozzi, F., Suen, C.Y.,"Feature Subset Selection Using Genetic algorithms forHandwritten Digit Recognition" Proc. XIV Brazilian Symposium on Computer Graphics and Image Processing (SIBGRAPI'01), P.362,2001.

[3] Haidar Almohri, John S. Gray and Hisham Alnajjar, PhD," A Realtime DSP-Based Optical Character Recognition System for Isolated Arabic characters", in the Proceedings of The 2008 IAJC-IJME International Conference.

[4] Y. LeCun, B. Boser, J. S. Denker, D. Henderson, R. E. Howard, W. Hubbard, and L. D. Jackel, "Backpropagation applied to handwritten zip code recognition," Neural Comput., vol. 1, no. 4, pp. 541–551, Dec.1989. [Online]. Available: http://dx.doi.org/10.1162/neco.1989.1.4.541[Online]. Available: http://dl.acm.org/citation.cfm?id=1792262.1792276

[5] T. Bluche, J. Louradour, M. Knibbe, B. Moysset, F. Benzeghiba, and C. Kermorvant, "The arabic handwritten text recognition system at the openhart2013 evaluation," in International Workshop on DocumentAnalysis Systems (DAS), 2014.

[6] A. Ghoshal and D. Povey, "Sequencediscriminative training of deepneural networks," in in Proc. INTERSPEECH, 2013.

[7] P. Natarajan, K. Subramanian, A. Bhardwaj, and R. Prasad,"Stochastic segment modeling for offline handwriting recognition," in Proceedings of the 2009 10th International Conference on Document Analysis and Recognition, ser. ICDAR '09. Washington, DC, USA:IEEE Computer Society, 2009, pp. 971–975. [Online]. Available:http://dx.doi.org/10.1109/ICDAR.2009.278

[8] A. Graves, S. Fern´andez, F. Gomez, and J. Schmidhuber,"Connectionist temporal classification: Labelling unsegmented sequence data with recurrent neural networks," in Proceedings of the 23rd International Conference on Machine Learning, ser. ICML '06. NewYork, NY, USA: ACM, 2006, pp. 369–376. [Online]. Available:http://doi.acm.org/10.1145/1143844.1143891

[9] A. Graves, S. Fern´andez, and J. Schmidhuber, "Multi-dimensional recurrent neural networks," CoRR, vol. abs/0705.2011, 2007. [Online].Available: http://arxiv.org/abs/0705.2011

[10] A. Graves and J. Schmidhuber, "Offline handwriting recognition with multidimensional recurrent neural networks," in Advances in Neural Information Processing Systems 21, D. Koller, D. Schuurmans, Y. Bengio, and L. Bottou, Eds. Curran Associates, Inc., 2009, pp. 545–552. [Online].Available: http://papers.nips.cc/paper/3449-offline-handwritingrecognition-with-ultidimensional-recurrent-neural-networks.pdf

[11] T. Bluche, J. Louradour, M. Knibbe, B. Moysset, F. Benzeghiba, and C. Kermorvant, "The a2ia arabic handwritten text recognition system at the openhart2013 evaluation," in International Workshop on DocumentAnalysis Systems (DAS), 2014.

[12] B. Moysset, T. Bluche, M. Knibbe, M. F. Benzeghiba, R. Messina,J. Louradour, and C. Kermorvant, "The a2ia multi-lingual text recognition system at the maurdor evaluation," in International Conference onFrontiers in Handwriting Recognition (ICFHR), 2014.

[13] H. El Abed, V. M¨argner, M. Kherallah, and A. M. Alimi, "Icdar 2009 online arabic handwriting recognition competition," in 2009 10th International Conference on Document Analysis and Recognition. IEEE,2009, pp. 1388–1392.

[14] V. Pham, T. Bluche, C. Kermorvant, and J. Louradour, “Dropout improves recurrent neural networks for handwriting recognition,” in International Conference on Frontiers in Handwriting Recognition (ICFHR),2014.

[15] T. M. Breuel, A. Ul-Hasan, M. A. Al-Azawi, and F. Shafait, “High-performance ocr for printed english and fraktur using lstm networks,” in Proceedings of the 2013 12th International Conference on Document Analysis and Recognition, ser. ICDAR ’13. Washington,DC, USA: IEEE Computer Society, 2013, pp. 683–687. [Online].Available: http://dx.doi.org/10.1109/ICDAR.2013.140

[16] Som, Tanmoy and Saha, Sumit,”Handwritten character recognition by using Neural Network and Euclidean distance metric”, Social ScienceResearch Network, 2008.

[17] Raghuraj Singh, C. S. Yadav, PrabhatVerma and VibhashYadav,”Optical Character Recognition (OCR) for Printed Devnagari Script Using Artificial Neural Network”, International Journal of Computer Science &CommunicationVol. 1, No. 1, January-June 2010, pp. 91-95.

[18] ElieKrevat and Elliot Cuzzillo, Department of Computer Science Carnegie-mellon University” Improving Off-line HandwrittenCharacter Recognition with Hidden Markov Models”, 2005.

[19] Alexander J. Faaborg Cornell University, Ithaca NY,” Using Neural Networks to Create an Adaptive Character Recognition System” inMay 14, 2002.

[20] David J. Montana and Lawrence Davis, “Training Feedforward Neural Networks Using Genetic Algorithms”, BBN Systems and TechnologiesCorp. 10 Mouiton St. Cambridge, MA 02138.

[21] Philipp Koehn,” Combining Genetic Algorithms and Neural Networks: The Encoding Problem” submitted his thesis at The University ofTennessee, Knoxville, in October 1994.

[22] Christopher Wiraatmaja, KartikaGunadi, IwanNjotoSandjaja,The Application of Deep Convolutional DenoisingAutoencoder for Optical Character RecognitionPreprocessing, 2017 International Conference on Soft Computing, Intelligent System and Information Technology (ICSIIT)

[23] U. Bhattacharya and B. Chaudhuri, “Handwritten Numeral Databases of Indian Scripts and Multistage Recognition of Mixed Numerals,”IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 31,no. 3, pp. 444–457, Mar. 2009, doi: 10.1109/TPAMI.2008.88.

[24] U. Bhattacharya and B. Chaudhuri, “Handwritten Numeral Databases of Indian Scripts and Multistage Recognition of Mixed Numerals,” IEEE Trans. on Pattern Analysis and Machine Intelligence, vol. 31, no. 3, pp. 444–457, Mar. 2009, doi: 10.1109/TPAMI.2008.88.

[25] A. Krizhevsky and G. Hinton, “Using Very Deep Autoencoders for Content-Based Image Retrieval,” Proc. 19th European Symp. on Artificial Neural Networks (ESANN), Bruges (Belgium), Apr. 2011.

[26] D. Erhan, Y. Bengio, A. Courville, P.A. Manzagol, P. Vincent, and S. Bengio, “Why does Unsupervised Pre-Training Help Deep Learning?,” J. Machine Learning Research, vol. 11, pp. 625–660, Feb. 2010.

[27] Y. LeCun, “LeNet-5, Convolutional Neural Networks.” [Online].Available: http://yann.lecun.com/exdb/lenet.

[28] F.Simistira,A.Ul-Hasan,V.Papavassiliou,B.Gatos,V.Katosaouros and M.Liwicki”Recognition of Historical Greek Polytpnic Scripts using LSTM Networks”, in ICDAR,Tunisia,2015.

[29] T.M.Breuel,A.Ul-Hasan,M.AlAzami,F.Shafait,”High performance Ocr for printed English and Fraktur using networks”, in ICDAR,Washington D.C.USA, Aug 2013.

[30] A.Ul-Hasan, S.B.Ahmed,S.F.Rashid,F.Shafair and T.M.Breuel,” Offline Printed Urdu Nastaleeq Script Recognition with Bidirectional LSTM Networks” in ICDAR’13,USA.

[31] T.Karayil,A.Ul-HAsan, and T.M Breuel, A segmentation Free approach for printed Devanagiri Script Recognition”, in ICDAR,Tunisia,2015.

[32] Coello C. A.. C., An Updated Survey of Evolutionary Multiobjective Optimization Techniques : State of the Art and Future Trends , In 1999Congress on Evolutionary Computation, Washington, D.C., 1999.

[33] Ranpreet Kaur,Baljit Singh. “A Hybrid Neural Approach ForCharacter Recognition System”, Ranpreet Kaur et al, / (IJCSIT) International Journal of Computer Science and Information Technologies, Vol. 2 (2) , 2011, 721-723.

[34] U.Ganesh Naidu “ Improved Adaptive Neuro Fuzzy Inference System for Handwritten Optical Character Recognition” in IJRET Volume 11,Issue 11 November 2020, pp.778-792. ISSN Print:0976-6480 and ISSN Online:0976-6499.

[35] T.Karayil, A.Ul-HAsan, and T.M Breuel, A segmentation Free approach for printed Devanagiri Script Recognition”, in ICDAR,Tunisia,2015.