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Novel Heuristic Recurrent Neural Network Framework to Handle Automatic Telugu Text Categorization from Handwritten Text Image

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Abstract - In the near future, the digitization and processing of the current paper documents describe efficient role in the creation of a paperless environment. Deep learning techniques for handwritten recognition have been extensively studied by various researchers. Deep neural networks can be trained quickly thanks to a lot of data and other algorithmic advancements. Various methods for extracting text from handwritten manuscripts have been developed in literature. To extract features from written Telugu Text image having some other neural network approaches like convolution neural network (CNN), recurrent neural networks (RNN), long short-term memory (LSTM). Different deep learning related approaches are widely used to identification of handwritten Telugu Text; various techniques are used in literature for the identification of Telugu Text from documents. For automatic identification of Telugu written script efficiently to eliminate noise and other semantic features present in Telugu Text, in this paper, proposes Novel Heuristic Advanced Neural Network based Telugu Text Categorization Model (NHANNTCM) based on sequence-to-sequence feature extraction procedure. Proposed approach extracts the features using RNN and then represents Telugu Text in sequence-to-sequence format for the identification advanced neural network performs both encoding and decoding to identify and explore visual features from sequence of Telugu Text in input data. The classification accuracy rates for Telugu words, Telugu numerals, Telugu characters, Telugu sentences, and the corresponding Telugu sentences were 99.66%, 93.63%, 91.36%, 99.05%, and 97.73% consequently. Experimental evaluation describe extracted with revealed which are textured i.e. TENG shown considerable operations in applications such as private information protection, security defense, and personal handwriting signature identification.

Keywords: Deep learning, neural networks, handwritten Telugu Text, extraction of features, classification, sparse related features, gradient feature selection**.**

I. INTRODUCTION

Before, the man-made reasoning field has achieved a quantum jump. Presently, studies using man-made brainpower are directed and different fields are applied [1-3]. Particularly, attributable to the improvement is done in figuring power, in the field of PC vision the areas of use continually become more extensive. Besides, past examinations perform the research connected with picture text acknowledgment [4-7]. Likewise, optical person acknowledgement having the studies, which is going to be considered the agent method of today for recognizing the texts using picture information [8-11]. Text and penmanship acknowledgment began with the number acknowledgment in Latin text in the last part of the 1950s and is extending to incorporate different dialects, like Telugu, Japanese, Telugu, and Persian. Right now, the strategies for perceiving new dialects are turning out to be more precise [12,13]. The acknowledgment exactness has expanded through the different models of acknowledgment on account with which the differences in the structure of each and every language and in note-taking techniques. As of late, the interest for penmanship acknowledgment, for example, the robotization of mail arranging and electronic notice cushions, has dramatically expanded in different modern fields. Also, in the picture acknowledgment field, strategies utilizing convolutional neural networks (CNN), which show remarkable execution, applied to penmanship acknowledgment [14, 15].

Penmanship acknowledgment framework may be considered as an option in contrast to the current console-based methodology, if a productive acknowledgment framework can be made. The strategy of PC framework characters of perceives and different images are composed by the hands of human is named as penmanship acknowledgment framework. The two groupings of penmanship acknowledgment comprise of disconnected penmanship

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acknowledgment and web-based penmanship acknowledgment. In disconnected penmanship acknowledgment, a piece of paper is used to compose the text and to examine. The information of examined, at that point, handled for acknowledgment. The information is as bitmap picture. Disconnected written by hand acknowledgment [1] is similarly troublesome, as various individuals have different penmanship styles, and at times, the composing style of a similar individual fluctuates at various examples. On the web penmanship acknowledgment framework is the one in which they perceive the text of transcribed, while composing through the touch cushion utilizing pointer pen. There are numerous utilizations of penmanship acknowledgment, for example, deciphering fathomable penmanship, paper contribution, contact screen gadget, number plate of vehicle following, and board of sign perusing and mark check. Different displaying strategies are utilized for acknowledgment of the examples like secret Markov model, support vector machines [2], flexible coordinating and counterfeit neural organization. Acknowledgment text is essential and the most requesting in the design field acknowledgment which is utilized in a wide scope of significant applications. As of now, tremendous work on written by hand dialects is done in over American dialects, European dialects, Telugu dialects [3] and Indian [4] dialects. Safeguarding the reports of paper is an exceptionally dreary and tedious undertaking. All together to protect such transcribed paper records, whenever changed over to an advanced arrangement it would lessen recovery process and additionally make treatment of such records simpler and dependable. Disconnected OCR (optical person acknowledgment) is thought of two sub classes: first is composed text is composed first and written by hand text is composed second. In the acknowledgement of web-based text, characters and words are perceived at run time as fast as they are composed and subsequently have the transient data. Optical acknowledgment online users are in PDAs, tablet of PCs and advanced cells. OCR generally have significant examination subject in design acknowledgment, machine vision and fake learning. OCR is in any case called disconnected person acknowledgment structure. In some disconnected manually written records, an average issue faced is to have the choice to isolate each person successfully. As the making style out of outstandingly person shifts, to character and remember them is inconvenient on any occasion, for the regular eye.

Based on above conversion, implemented approach explores efficient accuracy by reading of sequential Telugu characteristics with conceivable operations

The tasks expected with organizing game plans of data there presumably won't be a reasonable planning among data and yield portrayals. To build efficient neural network approach on translating different links and compared with other words in each formation of sentence with different considerations. Mainly implemented framework classified into different classifiers like decode and encode for translating data. The one of the apportioned frameworks the encoder is endowed with sorting out some of the way to deliver a single introducing that feasibly consolidates the data, and another apportioned framework decoder is depended on sorting out for some way to make a yield gathering from singular implanting. So, a game plan is to arrangement plan is a blend of two unique designs one to various what's more various to one-all of which is important isolated in other learning tasks.

For automatic identification of Telugu written script efficiently to eliminate noise and other semantic features present in Telugu Text, in this paper, proposes Novel Heuristic Advanced Neural Network based Telugu Text Categorization Model (NHANNTCM) based on sequence-to-sequence feature extraction procedure. Proposed approach extracts the features using RNN and then represents Telugu Text in sequence-to-sequence format for the identification advanced neural network performs both encoding and decoding to identify and explore visual features from sequence of Telugu Text in input data. Experimental evaluation of proposed approach gives better accuracy when compared to different classification related, machine learning related, deep learning related approaches respectively.

Basic implemented contributions are described as follows:

• The Novel Heuristic Advanced Neural Network based Telugu Text Categorization Model (NHANNTCM) model is suggested in this article as a simplified method of reading Telugu characters written by hand. By deleting some encoder layers, this model streamlines the generally complex model structure. Studies reveal that this approach can successfully lower the model's calculation and parameter count, and the recognition accuracy is also acceptable.

• The Novel Heuristic Advanced Neural Network based Telugu Text Categorization Model (NHANNTCM) model increasing the size of window which consists preferable operations and also increasing its size from the original 7 by 7 to 14 by 14. The patch keeps expanding as the network model is developed further. Each patch's perceptual range widens and its information content expands. Additionally, the experimental findings reveal that increasing the window to 1*4 14 somewhat improves the validation accuracy.

II. REVIEW OF RELATED WORK

Here, we discuss how to extract useful information and knowledge from unstructured text using a variety of text classification algorithms that have been applied to several Indian Telugu language.

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Jaydeep Jalindar Patil and Nagaraju Bogiri telugu text is automatically sorted into categories based on the user's profile information, which includes the user's web history. Using the LINGO (Label Induction Grouping) algorithm, the system is able to classify Telugu text texts. The VSM foundation serves as the foundation for LINGO. The software employs a dataset consisting of 200 documents split into 20 different types.

This indicates that the LINGO clustering technique works well with Telugu text content.

Using four supervised learning algorithms—Decision Tree(C4.5), K-Nearest Neighbor(K-NN), Naive Bayes(NB), and Support Vector Machine(SVM)—Ashish Kumar Mandal and Rikta Sen described how information from unstructured online Telugu text documents might be categorized (SVM). KNN and NB outperformed SVM and Decision Tree (C4.5) in the experiments conducted. The training times for four different classifiers were compared, and the results showed that they were significantly different. In contrast to the speedy learning of SVM, the training process for Decision Tree (C4.5) is much longer.

In order to automate the syntactic classification of Telugu verbs, Neha Dixit and Narayan Choudhary suggested a rule-based, knowledge-base-driven application. They also include information on the verb's valency class, syntactic diagnostic tests, and morphological/inflectional type, with the goal of creating the most comprehensive lexical repository for Hindi verbs.

In stated woks the major limitations are the inability to recognize the multi-stroke in Telugu characters. As well as the similar characters are clustered for learning unsupervised methodologies.

An effective approach of extracting C-feature for categorising telugu text documents was proposed by ArunaDevi K. and Saveetha R. C-feature extraction makes document categorization simple because it yields a pair of terms that can be used to place a document into a known group.

The classification system for Telugu texts was proposed by Nidhi and Vishal Gupta, which included Naive Bayes and Centroid-based techniques. Additionally, a novel method involving Naive Bayes and ontology-based categorization is proposed for the Telugu Text Document. The third method is a hybrid strategy, which combines Naive Bayes with ontology-based classification methods. In this method, Naive Bayes is employed as the Feature Extraction technique for text classification, followed by an ontology-based classification algorithm applied to the extracted features. Results from the Centroid-based classifier and the Naive Bayes classifier are rather low, whereas the Hybrid classification method produces superior results.

Using a classification algorithm, Nidhi and Vishal Gupta presented preprocessing approaches, feature selection methods tailored to the Telugu language, and a way for organising Telugu text documents. The authors suggest a domain-based ontology technique to categorise Telugu documents in the sports area.

One of the best performing classifiers applied to English text is the K-Nearest Neighbor (K-NN) technique, which has been implemented by Nadimapalli V Ganapathi Raju et al. The outcomes validate K-potential NN's for use with Telugu texts.

The morphologically rich Dravidian classical language Telugu was the focus of a text categorization presentation by K. Rajan et al. [8], which utilised a Vector Space Model and an Artificial Neural Network. From our experiments, we know that an A.N.N. model can correctly classify 93.33 percent of Tamil documents.

Abbas Raza Ali and Maliha ljaz compared the Nave Bayes and Support Vector Machines statistical methods for text classification in the Telugu language setting. It undergoes a series of linguistic preprocessing procedures in order to produce a lexicon that is both standardised and reduced in terms of the number of features it contains.

The performance of the classifier is analysed using the Prothom-Alo news corpus, and it was discovered that an n-gram based algorithm was the most effective in classifying Telugu texts. The results reveal that the text categorization performance improves as n increases from 1 to 3, but declines as n increases to 4. Category-wise normalised tf-idf is utilised as feature values, and Kavi Narayana Murthy's suggested supervised classification using the Nave Bayes classifier has been applied to Telugu news items across four key categories.

Naive Bayes, Centroid, K-Nearest Classifier, and Modified K-Nearest Classifier were proposed by Meera Patil and Pravin Game for effectively classifying Telugutext. Naive Bayes was shown to be the most effective of the four classifiers when both classification accuracy and classification time were taken into account.

III. BASIC PRELIMINARIES

The basic preliminaries used in proposed implementation i.e., recurrent neural networks, objective functions, labeled data connection are describes in this section.

3.1 Multi labeled telugu data generative function

Let's look at some alternative Telugu text data sets to evaluate supervised learning procedures for labelled data, as

$$\gamma = \sum_{(a,b)\in K_l} \zeta(a,b) + \sum_{a\in K_u} v(a) + \alpha \mathrm{E}_{(a,b)\in K_l}[-\log p_\phi(b|a)] \quad \text{………..} \quad (1)$$

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Data sets of telugu texts that have been classified in multiple ways (Kt,Ku) and for which α an extra hyper-parameter for classifying the texts has been labelled.

$p_\phi(b|a)$ act as the probability density function for a set of textual annotations, $\zeta(a,b)$ & $v(a)$ from unlabeled data to data with several labels. $\zeta(a,b)$ Is described as follows:

$$\zeta(a,b) = \mathrm{H}_{CL}(p_\phi(z(a,b)\,\|\,q(z)) - \log p_\phi(b) - \mathrm{E}_{p_\phi((z(a,b))}[\log q\theta(a\,|\,b,z) \quad \text{………… (2)}$$

The first term in this context is a Leibler-Kullback divergence between the prior distribution function q(z) and the joint distribution function. $p_\phi(z(a,b)$ Is the conditional expectation of a latent variable, as in the hood function, the posterior function, $v(a)$ should be described as

$$v(a) = \sum_b p_\phi(b\,|\,a)\zeta(a,b) - \mathrm{T}(p_\phi(b\,|\,a)) \quad \text{…………… (3)}$$

T $(p_\phi(b|a))$ be the input data's entropy for the classifier $(p_\phi(b|a))$, Multi labelled distribution functions are computed after noise is removed from Telugu textual inputs. $p_\phi(b|a), p_\phi(z(a,b) \,\&\, q\theta(a|b,z)$ Function generators for creating multi-label datasets.

3.2 Recurrent neural network (RNN)

With its time series generative function and ability to accurately answer a wide range of scientific issues and forecast a wide range of scientific parameters, recurrent neural networks (RNNs) have emerged as the cutting-edge method of choice in deep learning. RNNs can be used for a wide variety of purposes, from the prediction of sentiment on voice recognition to the forecasting of stock prices and time series to the mining of both structured and unstructured data in Telugu. Figure 1 depicts the fundamental RNN architectural architecture..

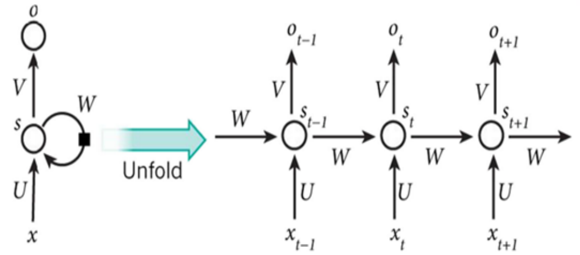

Figure 1.Semantic representation of recurrent neural network

Figure 1 depicts the calculation of the output at each time step and the hidden state prediction that follows it, where x, s, and 0 indicate the output, input, and hidden nodes, respectively. Perform in-place hidden processing on every sequence of timestamps, where W,V,U represent the relative importance of the matrices that are the same in both the input and the output directions. There are three models outlined for use in real-time data processing: a simple model, a long short-term memory (LSTM), and a gated recurrent unit (GRU) model. In our actualized plan, we use the GRU model to classify multi-labeled data in place of the LSTM model to reduce the number of tensor operations (update, reset). The following is a description of the properties and functions of tensor cells:

Update (zt), reset (rt), and state of hidden (ht) are GRU components that collectively reflect more cellular equations.

$$r_t = \sigma(W_r * [a_t, h_{t-1}] + y_r)$$
$$z_t = \sigma(W_z * [a_t, h_{t-1}] + y_z)$$
$$\tilde{h}_t = \tanh(r_t * [a_t, h_{t-1}] + y_h))$$
$$h_t = z_t * \tilde{h}_t + (1 - z_t) * h_{t-1} \quad \text{…………. (4)}$$

As we saw above, input and output are spread out over a wide range of timestamps based on their interdependencies. As an example of our implementation, we will describe the steps we took to take measurements from many labels and produce multiple labelled outputs after applying various labels to the inputs. Structured Telugu Text Data.

IV. PROPOSED IMPLEMENTATION

This section describes in-detail discussion about proposed approach which helps to identify the handwritten text into meaning character identification. Proposed approach extracts the features using RNN and then represents Telugu Text in sequence-to-sequence format for the identification advanced neural network performs both encoding and decoding to identify and explore visual features from sequence of Telugu Text in input data. Basic representation of proposed approach is shown in figure 2.

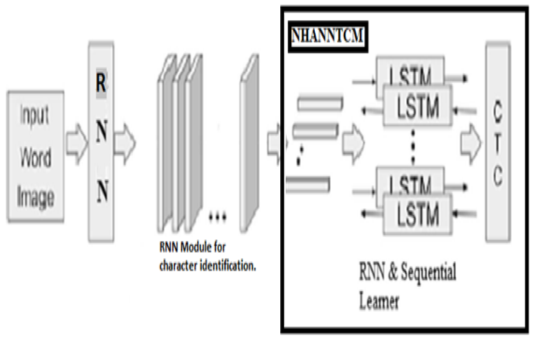

Figure 2.NHANNTCM architecture for identification of handwritten Telugu text.

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The figure shows various sorts of layers. CNN and RNN stages are isolated by these layers. The layers which are present in the CNN stage are as per the following: The input layer is the principal layer, convolutional layer is the second layer, and pooling layers are the middle layers (sub sampling) trailed by completely associated layer lastly the layer of result.

Layer of input: The info layer is the picture layer, which taken care of contribution to the organization. Here Telugu word picture is displayed as info in my present work. Grayscale picture or shading picture (RGB values) can be an information layer. Contingent on the sort of the info picture, w9h9d must be aspect by the information layer. Width is the w9h and stature of the picture and profundity of pictures is the 'd' which is grayscale pictures for 1 and RGB pictures for 3. Consequently, the layer of information has aspect 3293291.

Layer of convolution: Given that a lot of the heavy lifting in terms of computing is done at this level, it serves as the structural square of the entire organization. In this layer, you'll find a collection of limits labeled as "learnable channels." Each channel here must be imagined as a square lattice, where each individual structure is quite small with respect to its width and height., yet it is equipped for broadening itself over the total profundity of the given info volume.

The layer acknowledges the contribution of aspect w9d9h, and utilizing two hyper parameters, for example, size of channel (f) and step (s), produces input for one more layer with aspects w19h1 9d1 where in the Eqs. (1) and (2) w1 and h1 are given, individually. Profundity continues as before, for example, d1=d. Cushioning is addressed as P. It presents a new line and zero section on each and every side of the picture.

w1=(w-f+2P)/s+1 (1) …………. (5)

h1=(h-f+2P)/s+1 ………………... (6)

There are 32 number of channels are picked with the size of 59591 in my proposal work, where p=1 and s=0 for Telugu words translation. Therefore, using Eqs. (1) and (2), we desire the image on the second layer to be 28928932 in all its glory (2). A pooling layer: After the initial convolution layer, a pooling layer is implemented. The primary function of this layer is to gradually reduce the apparent size of spatial features.. Likewise, it attempts to decrease the amount of calculation and boundaries of the organization, consequently controlling the assignment of overfitting. These layer capacities independently over each info profundity cut and spatially do the resize. MAX activity is the most often utilized activity. A layer which is having 2 92 size of channel is applied involving a step of 2 down-examples for each information profundity cut by 2 adjacent to both width and stature, disposing of 75% of the enactments is the most well-known structure. Each MAX activity would choose a greatest worth north of 4 numbers (minimal 292 locale in some profundity cut). The profundity aspect stays unaltered. In first pooling layer having 3 93 of channel size, P=1 and 2nd step is utilized in my proposal work. Along these lines, the result aspects for this layer is 14914932.

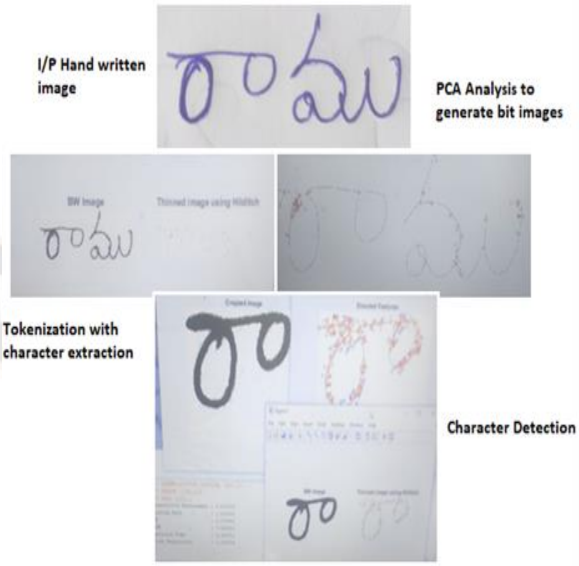

Figure 3. Process of detection handwritten characterization

Neurons in a fully connected layer have connections to all previous layer activations, as they would in typical neural networks. A grid expansion, followed by an inclination offset, allows for the calculation of their beginnings. Depending on the architecture of the programme, there may be multiple independently functioning layers. The latter has as many neurons as there are classes in the problem space.

\begin{array}{l}
fg_{ts} \ =r(A_{fg} z_{ts} \ +\ B_{fg} g_{ts} -1\ +\ bi_{fg})\\ (2)
ip_{ts} \ =r(A_{ip} z_{ts} \ +\ B_{ip} g_{ts} -1\ +\ bi_{ip})\\ (3)
op_{ts} \ =r(A_{op} z_{ts} \ +\ B_{op} g_{ts} -1\ +\ bi_{op})\\ (4)
ZS_{ts} \ =tang(A_{zs} z_{ts} \ +\ B_{zs} g_{ts} -1\ +\ bi_{zs})\\ (5)
ZS_{ts} \ =fg\ *\ ZS_{ts} -1+ip_{ts} \ *\ ZS_{ts}\\ (6)
g_{ts} =op_{ts} \ *\ tang(ZS_{ts}) (7)
\end{array}

Where weight framework is A* and B*. yi* is addressed as inclination vector. ϴ is addressed as Quantitatively, it referred to as the sigmoid layer that generates the output value between the interval [0,1].. Step by step process for the identification of character identification described in algorithm 1.

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```
Input: [a1, a2, : : : , an], Hw, Hh
def Extraction of Feature
LF = [[0, 1, 0][1, -4, 1][0, 1, 0]]
PF = [[1, -1, 1],[-1, 1, -1],[1, -1, 1]]
for i from 0 to n do
for w from 0 toW-Kw do
for h from 0 to H-Kh do
for m from 0 to Kw do
for n from 0 to Kh do
L(w,h) += xi(w + m, h + n) _ LF
P(w,h) += xi(w + m, h + n) _ PF
if L > threshold then L[L > threshold] = 1 else L[L < threshold]
= 0
if P > threshold then P[P > threshold] = 1 else P[P < threshold]
= 0
LSMap(i) = [L, P, xi]
Output: LSMap
```

Algorithm 1. Process of character identification from Telugu text

Process of figure 3 described as

Thresholding: Thresholding is the clearest way to deal with part protests from an establishment. On the remote possibility that establishment is by and large uniform; at that point, we can use an overall cutoff a motivating force to binaries the image by pixel power. In case there is gigantic assortment in the establishment power; in any of the case, flexible thresholding (neighborhood) may convey best results. Adjustable thresholding is used to hide the less obvious concentrations and to enlarge the centres of the edges. In this case, we utilise the cutoff adjustable limit to categorise a picture into two groups, with the latter group consisting of pixels that are adjacent to one another along a shared edge (for instance, close by neighborhoods). Each threshold valuation is an average of the local short equilibrium valuations in the area.

Combined Connection Analysis (CCA): Naming of combined part is used in the PC vision to distinguish the related districts in matched mechanized images, regardless of reality that concealing images and higher dimensionality of data can moreover be dealt with. Right when joined into an image acknowledgment structure or human-PC affiliation interface, related part naming can chip away at a variety of information. The division rank out also to diminish the responsibility of CNN to explicit circumstances where there are revelations of false certain are high and certified positive was nearly nothing, the related part of examination was used. The characters extraction is gotten done with using three features, which are linguistic structures named naming, tokenization, and sentence division.

Grammatical features labeling: Each word is labeled concurring to the grammatical features it has a place with, so the words don't get confused. This interaction makes the extraction of each character easier and productive. Labeling grammatical forms (POS labelling), often called syntactic naming or arrangement of word disambiguation, is the process of defining and expanding the meaning of words in a text according to their context within a sentence or larger text. A superior kind of this is by and large taught to youthful young people, in the distinctive word verification as things, activity words, descriptors, modifiers, and so on

Tokenization: Person plan was given and a portrayed unit of record, Task of tokenization is build to verify tokens of each work from sentence, perhaps at the same time disposing of specific characters, for instance highlight.

Sentence division: Sentence division is the way towards concluding the more broadened getting ready units containing no less than single word. This endeavor incorporates perceiving limit of sentence between words in different sentences. Since most of the created vernaculars have the highlight marks which are occur at the limit of sentence, division of sentence is regularly suggested as limit of sentence area, limit of sentence disambiguation or limit of sentence acknowledgment.

Identification of character: Each and every character was discovered relies upon its component and association with which have a spot. Recognizable proof of character is divided into element area and connection disclosure.

V. EXPERIMENTAL EVALUATION

First, all of the models in the experiment have their hyper parameters set to constant values to ensure a fair and effective comparison experiment. The figures show the precise conditions used in the experiments. For both training and testing, all input images are scaled to a resolution of 224 x 224. There are 150 iterations utilised in training, and the batch size is 8. The window size can be 7, and the learning rate can be 0.0001. Additionally, a dropout regularisation parameter of 0.1 is utilised during training. Training problems like overfitting can be avoided and the model's generalisation abilities can be increased by employing dropout. In this article, we'll see how to use PyTorch to create a network algorithm's workflow.

We implement our proposed method by cropping the original data into subdivided patch Telugu text graphics that comprise semantic dimensions with notations of 256*256 pixels utilising MapLab's programming based on restricted CPU storage. We use random left-to-right and top-bottom flipping in selecting characteristics important to the transformation gradient factors, and we verify that our proposed approach has generalised learning capacities.

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5.1 Quantitative Analysis

Using true positive (TP), false positive (FP), and false negative (FN) results from feature extraction from telugu text images, we employ Intersection over Union (IoU), precision, recall, accuracy of pixel and categorization accuracy, and f-measure in image classification.. Performance metrics of proposed approach are described as

$$P = TP\%(TP + FP)$$

$$R = TP\%(TP + FN)$$

$$IoU = TP\%(TP + FN + FP)$$

$$AP = (TP + TN)\%(TP + FN + FP + TN)$$

$$f - Measure = 2*(P*R)\%(P + R)$$

Based on these metrics, experiments are described in performance results section

Input text Data: Experiments using synthetic, real-time Telugu text images are used to gauge the efficacy of the suggested technique.. All the Telugu text images are captured from local text data. Data relates to Telugu text image repository consists different training and testing Telugu text images, each Telugu image pixel region is 4950*4950.

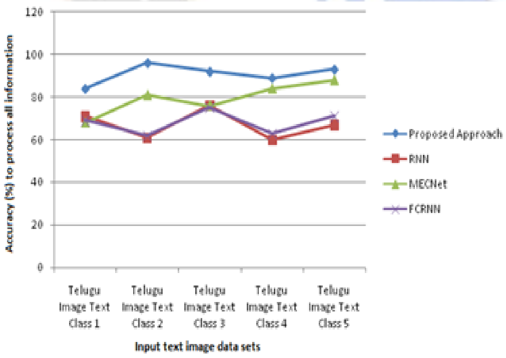

Figure 4.Performance evaluation of Accuracy processing of all text data.

When compared to NHANNTCM, standard RNN, and FCRNN, the proposed approach achieves an accuracy of about 99%, while MECNET virtually achieves higher performance with the proposed approach.

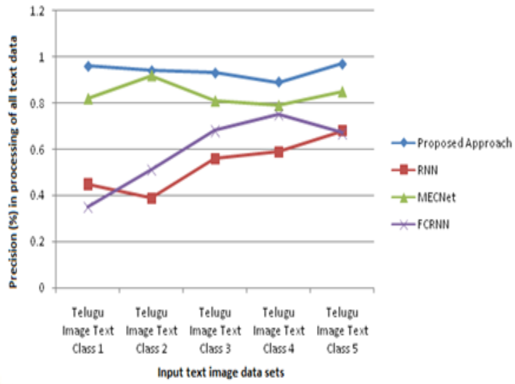

Figure 5.Performance evaluation of Precision in terms of categorization of text data.

Figure 5 displays the results of our tests on several different Telugu input text pictures, comparing the accuracy of our suggested methodology to that of more conventional methods. Other methods perform worse when it comes to matching identifying text categorisation in input text images, however the suggested method achieves almost 92–95% accuracy as the number of text image classes increases.

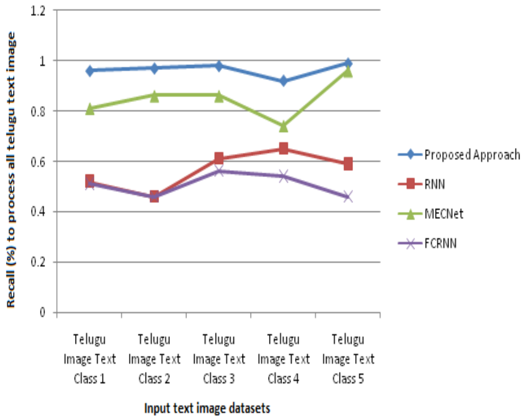

Figure 6.Performance evaluation of Recall with identification text image data.

Figure 6 compares the recall rates of the proposed method to those of more conventional methods applied to several distinct collections of Telugu text images. The proposed method yields an average improvement of 98% in text classification accuracy from the input text images when used to enhance text classes in text data sets..

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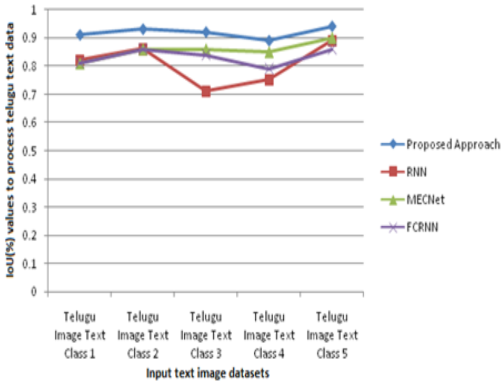

Figure 7.Performance of IoU in classification of text from text images

Precision, recall, efficient true positive and true negative feature selection, and word categorization from input image text data sets are the primary determinants of IoU. The proposed method outperforms RNNs, FCRNNs, and MECNNETs..

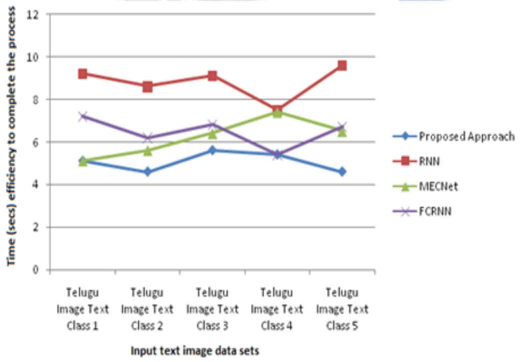

Figure 8.Performance of Time efficiency values to categorize input telugu text data.

Figure 8 compares the suggested method's overall time length to that of more conventional methods. The proposed method takes a fraction of the time that RNNs and FCRNNs do. MECNet provides extremely equal time duration to process all the text characters which are read from input text images, however the aforementioned methods consume considerable time due to iterations performed to evaluate categorization of water body from telugu text images. All of our trial results are depicted above for your perusal in eye-pleasing visual form. When training a two-channel parallel NHANNTCM model, we use a six-layer per-channel encoding structure. After training is complete, there are 85.62 million parameters and a verification accuracy of 98.6%. Currently, you can access 8.52 G FLOPs. The verification accuracy is 97.3 percent when using a four-channel parallel ViT model dataset with three layers of encoders per channel. There are 85.62 million parameters and 4.36 G FLOPs. The number of encoders per channel in the seven-channel parallel NHANNTCM model is set to three layers during training. With this proof, you can feel confident in a success record of 99.1 percent. That's 4.43 billion floating point operations per second. In any case, the parameter value is 148.38 million.

The proposed method for identifying Telugu text in far-off handwritten text photos outperforms the state-of-the-art algorithms based on the aforementioned performance parameters.

VI. CONCLUSION

This study suggests with the use of a novel heuristic advanced neural network based Telugu text categorization model (NHANNTCM), the original image may be divided into blocks of uniform size for offline HCCR. The CNN classification header then provides the category label after the picture blocks have been linearly processed to produce a vector sequence. Using a dataset of handwritten Telugu characters, experiments were run to compare the efficacy of two-way parallel, four-way parallel, and seven-way parallel ViT model architectures. The experimental results validate the plausibility and accuracy of the model by demonstrating that the network may enhance HCCR precision. This method not only has the advantages of identifying images more faster because to the parallelization of the encoder, but it also captures the interdependence between picture sequence blocks through NHANNTCM, which is a huge advantage.

Additional limitations of the model should be noted. In order to maximise the model's generalisation abilities and guarantee high recognition accuracy in the end, it must be trained on large datasets. However, the model's convergence speed will suffer if there are too many data sets to process. This dataset was generated by randomly picking a small sample of individuals. A data expansion strategy is used to rapidly increase the available datasets at the outset of the study. Second, the higher the pixel value of the image in the dataset, the better the recognition accuracy. The model can be improved in future research to achieve sufficient accuracy on low-pixel image datasets. Possible directions for future progress include using knowledge distillation or model compression to reduce the number of parameters in models and combining them with more complex models...

References

[1] "Transformer: simplified Swin Transformer model for offline handwritten Telugu character recognition" by Dan Y, Zhu Z, Jin W, Li Z. 2022. S-Swin PeerJ Computer Science 8:e1093 https://doi.org/10.7717/peerj-cs.1093.

[2] "Cursive Handwritten Text Recognition using Bi-Directional LSTMs: A case study on Urdu Handwriting" by Shahbaz Hassan Ayesha Irfan Ali Mirza Imran Siddiqi, All content

following this page was uploaded by Stelar Jonglr on 09 June 2021.

[3] "Classification of handwritten names of cities and Handwritten text recognition using various deep learning models" by Daniyar Nurseitov1;2, Kairat Bostanbekov1;2, Maksat Kanatov1;2, Anel Alimova 1;2, Abdelrahman Abdallah*2;3, Galymzhan Abdimanap, arXiv:2102.04816v1 [cs.CV] 9 Feb 2021.

[4] Weiqiang Zhang a,b,c,1, Linfeng Deng d,1, Lei Yang c,1, Ping Yang a, Dongfeng Diao a,*, Pengfei Wang a,**, Zhong Lin Wang, Nano Energy 77 (2020) 105174.

[5] "Effective offline handwritten text recognition model based on a sequence-to-sequence approach with CNN–RNN networks" by R. Geetha1 · T. Thilagam1 · T. Padmavathy1, Neural Computing and Applications https://doi.org/10.1007/s00521-020-05556, 2021.

[6] "Line-segment Feature Analysis Algorithm Using Input Dimensionality Reduction for Handwritten Text Recognition" by Chang-Min Kim 1 , Ellen J. Hong 2 , Kyungyong Chung 3 and Roy C. Park, Appl. Sci. 2020, 10, 6904; doi:10.3390/app10196904

[7] "A Frequency Pattern Mining Model Based on Deep Neural Network for Real-Time Classification of Heart Conditions" by Yoo, H.; Han, S.; Chung, K. Healthcare 2020, 8, 234. [CrossRef] [PubMed]

[8] "PF-ViT: Parallel and Fast Vision Transformer for Offline Handwritten Telugu Character Recognition" by Yongping Dan,Zongnan Zhu,Weishou Jin,and Zhuo Li, Research Article | Open Access Volume 2022 | Article ID 8255763 | https://doi.org/10.1155/2022/8255763

[9] "Context Deep Neural Network Model for Predicting Depression Risk Using Multiple Regression".by Baek, J.W.; Chung, K. IEEE Access 2020, 8, 18171–18181. [CrossRef]

[10] "Detection of Emotion Using Multi-Block Deep Learning a Self-Management" by Shin, D.H.; Chung, K.; Park, R.C. Interview App. Appl. Sci. 2019, 9, 4830. [CrossRef]

[11] Kim, C.M.; Hong, E.J.; Chung, K.; Park, R.C. Driver Facial Expression Analysis Using LFA-CRNN-Based Feature Extraction for Health-Risk Decisions. Appl. Sci. 2020, 10, 2956. [CrossRef]

[12] "OCR-Nets: Variants of Pre-trained CNN for Urdu Handwritten Character Recognition via Transfer Learning" by Mohammed Aarif, K.O.; Roruran, S.. Procedia Comput. Sci. 2020, 171, 2294–2301.

[13] "Decomposition-based handwritten compound character recognition for Bangla OCR" by Pramanik, R.; Bag, S. Shape. J. Vis. Commun. Image Represent. 2018, 50, 123–134. [CrossRef]

[14] "In-air handwritten Telugu text recognition with temporal convolutional recurrent network" by Gan, J.; Wang, W.; Lu, K.. Pattern Recognit. 2020, 97, 107025. [CrossRef]

[15] "Deep Matching Network for Handwritten Telugu Character Recognition" Li, Z.; Wu, Q.; Xiao, Y.; Jin, M.; Lu, H.. Pattern Recognit. 2020, 107, 107471. [CrossRef]

[16] "An efficient recognition method for handwritten telugu numerals using cnn with data augmentation and dropout" by Ashiquzzaman, A.; Tushar, A.K.; Rahman, A.; Mohsin, F. In Data Management, Analytics and Innovation; Springer: Singapore, 2019; pp. 299–309.

[17] "Handwritten optical character recognition by hybrid neural network training algorithm" by Sampath, A.K.; Gomathi, N. Imaging Sci. J. 2019, 67, 359–373. [CrossRef]

[18] "Transient signal analysis based on Levenberg–Marquardt method for fault feature extraction of rotating machines".by Wang, S.; Cai, G.; Zhu, Z.; Huang,W.; Zhang, X. Mech. Syst. Signal Process. 2015, 54, 16–40.[CrossRef]

[19] "CNN-RNN based method for license plate recognition". By Shivakumara, P.; Tang, D.; Asadzadehkaljahi, M.; Lu, T.; Pal, U.; Anisi, M.H. CAAI Trans. Intell. Technol. 2018, 3, 169–175. [CrossRef]

[20] "Multipath-DenseNet: A Supervised ensemble architecture of densely connected convolutional networks". By Lodhi, B.; Kang, J. Inf. Sci. 2019, 482, 63–72. [CrossRef]

[21] "MMCNet: Deep learning–based multimodal classification model using dynamic knowledge" by Park, S.S.; Chung, K.. Pers. Ubiquitous Comput. 2019. [CrossRef]

[22] "Feature selection with multi-view data: A survey " by Zhang, R.; Nie, F.; Li, X.; Wei, X.. Inf. Fusion 2019, 50, 158–167. [CrossRef]

[23] "Computer vision detection of foreign objects in walnuts using deep learning " by Rong, D.; Xie, L.; Ying, Y. Comput. Electron. Agric. 2019, 162, 1001–1010. [CrossRef]

[24] "Optimization of Associative Knowledge Graph Using TF-IDF Based Ranking Score " by Kim, H.J.; Baek, J.W.; Chung, K. Appl. Sci. 2020, 10, 4590. [CrossRef]

[25] "Knowledge expansion of metadata using scriptmining analysis in multimedia recommendation " by Kim, J.C.; Chung, K.. Multimed. Tools Appl. 2020. [CrossRef]

[26] "Current and future applications of statistical machine learning algorithms for agricultural machine vision systems" by Rehman, U.; Mahmud, S.; Chang, Y.K.; Jin, L.; Shin, J. Comput. Electron. Agric. 2019, 156, 585–605.[CrossRef]

[27] "Application of deep learning based multi-fidelity surrogate model to robust aerodynamic design optimization", Tao, J.; Sun, G.. Aerosp. Sci. Technol. 2019, 92, 722–737. [CrossRef]

[28] "Handwriting recognition by attribute embedding and recurrent neural networks" by Toledo JI, Dey S, Forne´s A, Llado´s J (2017). In: ICDAR

[29] "Handwriting recognition on form document using convolutional neural network and support vector machines (CNN-SVM)" by Darmatasia FMI (2017). In: 5th international conference on information and communication technology (ICoIC7). https://doi.org/10.1109/ICoICT.2017.8074699

[30] "Drawing and recognizing Telugu characters with recurrent neural network" by Xu-Yao Z, Fei Y, Yan-Ming Z, Cheng-Lin L, Yoshua B (2018). IEEE Trans Pattern Anal Mach Intell 40(4):849–862

[31] "Evaluation of handwritten Urdu text by integration of MNIST dataset learning experience". By Ahmed SB, Hameed IA, Naz S, Razzak MI, Yusof R (2019) In: IEEE

access, vol 7, pp 153566– 153578. Digital Object Identifier. https://doi.org/10.1109/ACCESS.2019.2946313

[32] "An end-to-end trainable neural network for image-based sequence recognition and its application to scene text recognition" by Shi B, Bai X, Yao C (2016). PAMI

[33] "A review on the effectiveness of machine learning and deep learning algorithms for cyber security" by Geetha R, Thilagam T (2020). Arch Comput Methods Eng. https://doi.org/10.1007/s11831-020-09478-2

[34] "An empirical exploration of recurrent network architectures" by Rafal J, Wojciech Z, Ilya S (2015). J Mach Learn Res 37:2342–2350

[35] "Investigating long short-term memory networks for various pattern recognition problems" by Sebastian O, Marcus L, Dirk K (2014). Proc Mach Learn Data Min Pattern Recogn 484–497.