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Recognition of Offline Hand Written Telugu Script using Deep Learning

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ABSTRACT

Automatic character recognition is one of the significant parameters that allow the data processor to distinguish letters and numbers, using contextual data. Various efforts have been made to resolve this problem using different choices of classifiers and attributes, however problem remains complex. In this work, mainly focuses on the problem of handwriting recognition (HWCR) for a script in Telugu. A crosscutting structure is used for segments an image from text, classifies characters, and selects strings using a language model is provided. Segmentation is based on mathematical morphology. Writing in Telugu is a complex alpha syllable. For this suitable language is required, which complicates the problem. Conventional methods used artisanal characteristics, which required a priori knowledge of the field, which is not always possible. In this case, automatic feature retrieval could potentially attract more interest. In this work, a classical Convolutional Neural Networks (CNN) for the identification of Telugu symbols offline is presented. Qualified analysis demonstrated the effectiveness of the proposed CNN compared to previous methods with an interesting data set. In the test data set, the classification method provided with n accuracy of 98.7%.

Keywords : CNN, HWCR, Telugu, Machine Learning, Neural Networks

I. INTRODUCTION

Handwriting varies by person, as well as by style, speed, age, mood, and surprisingly even by gender. Including all these factors, handwriting is also language dependent. By switching to another language, a person imitates a different style of writing. Specifically, the way you write in English, Telugu, and Hindi may differ depending on your style and the nature of the language [1]. For example, an average person has five different writing styles in one language, and with three different languages there can be fifteen styles. When it comes to recognizing the handwritten characters of different faces, you are not on the chart. On the other hand, handwriting recognition is difficult and vulnerable to large variations compared to printed character recognition, which has a specific font with a limited number of variations. In the language there are different words of different length and distinctive height. The recognition of an autonomous character depends on the underlying style of the factor, as well as the size and length of the word levels. Autonomous manuscript recognition really helps sort mail, process bank checks, reading aid for the blind, read documents and recognize email addresses, process forms, digitize old manuscripts. Much work has been offered for handwriting recognition of languages such as English and Asian such as Japanese, Chinese, etc., very few attempts have been made in Indian languages such as Telugu, Hindi, Tamil, etc., and resulted in an accuracy of no more than 85% [2].

The need for autonomous handwriting recognition is intense but complex, as handwriting varies from person to person and also depends on several other factors related to a person's attitude and mood. However, we can achieve this by converting a handwritten document into digital format. It has been improved with the introduction of devious neural networks and works more efficiently with pre-prepared models that can reduce learning time and increase the accuracy of character recognition. Studies in handwriting recognition for Indian languages are less than compared to other languages like English, Latin, Chinese, etc., mainly because it is a multilingual country [3]. Recognition of Telugu is more difficult, as the literacy of these languages is mainly shorthand and has more diacritics. Therefore, research work in this direction must have a tendency towards the precision of its recognition. Some research has already begun and is succeeding up to eighty percent in autonomous recognition of handwritten characters in Telugu. Character recognition is one of the research areas of pattern recognition. Handwritten character recognition can be done online or offline. In the past, not many important works have been published on the development of hand recognition systems (HWCR) for Telugu text. However, none of them offer 100% accuracy in Telugu recognition. So this is an area of ongoing research [4].

Neural networks are widely used in pattern recognition. Handwriting varies from person to person; therefore, it is a tedious task to recognize the characters. In the field of pattern recognition, handwriting recognition (HR) has become a recent research area that is of interest due to the exponential use of resources such as paper documents, photos, smartphones, iPad, etc. Human resources can be attributed to the internet and offline. The off-grid is recognized at the end of writing [5]. Offline HR mode converts an input image to a binary image where pixel values are only 0 or 1. Most Telugu characters do not contain horizontal, vertical, or diagonal lines. Unlike Latin and Chinese, Indian scripts, such as Telugu, are mainly created by fusing circular shapes (full or partial) of different sizes with small modifiers. These modifiers are composed of bars or a circular shape, which causes a big problem in recognition accuracy [6].

The proposed work focuses on improving accuracy in less time by recognizing these selected languages and is capable of achieving the expected values. Convolutional Neural Networks (CNN) has solved the above problem with an accuracy of better than 90%. CNN is used to recognize various font patterns such as paper documents, photographs, touch screens, medical image analysis, and various other devices. CNN can be used for both online and offline character recognition [7]. For inline character recognition, the movements of the digital tip are converted as input and converted to a coordinator list, while in stand-alone character recognition, character images are used as input. Previous work on handwriting recognition has used highly developed features in both standalone and online data sets. Few instances of proprietary design features constitute pixel density in image areas, sizes, character curvatures, and number of vertical and horizontal lines [8].

Based on the explanation above, three areas remain for study. One is to study autonomous hand recognition, two is to study autonomous recognition in Indian languages, and the third is to study for more accuracy, that is, more than 80 percent. This article is about the autonomous Telugu character recognition algorithm with high recognition accuracy of more than 90 percent with minimal learning time. Pre-prepared models are used to achieve greater precision compared to previous studies. Telugu is the most widely spoken Dravidian language in South India, Andhra Pradesh, and Telangana [9]. Telugu handwritten symbols, their diacritics, and writings are reflected in the data set. The Telugu language consists of 16 vowels and 35 consonants, which are used sequentially, as shown in Figures 1a, 1b. Unlike English, Telugu in a sense is not italic. For this reason, the pen usually separates the main graphemes at the time of writing. Therefore, the data set constitutes elementary writing graphemes, that is, vowel diacritics, independent vowels, consonants, and consonant modifiers. Some consonant consonants cannot be simply segmented. However, the writers have a stable model, despite the fact that several characters do not have a language version [10].

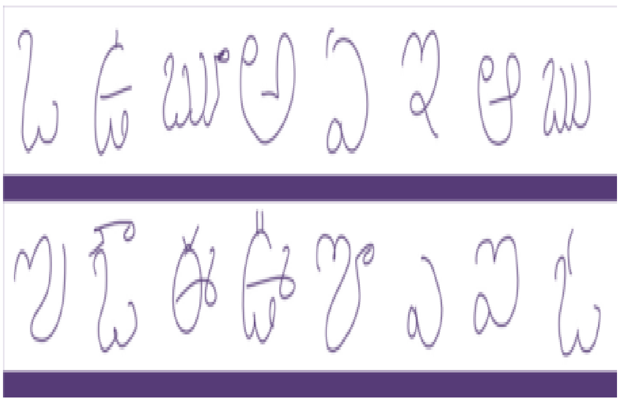

Fig. 1 (a). Telugu Language Vowels

Fig. 1 (b). Telugu Language consonants

Rest of the article is organized as follows. Existing works of HWCR are explained in section II. Section III discusses about data examination and Section IV describes the proposed methodology, which is used to maximize the accuracy of Telugu HWCR. Section V reports the experimental results and observations carried out on handwritten characters. Conclusion and future scope described in Section VI.

II. LITERATURE REVIEW

Many researchers have done considerable work in recognizing Telugu handwritten numbers, such as S.V. Rajashekararadha [11], T. Vakabayasi [12], Schuyler Kumar Srivastov [13]. But research on Telugu HWCR is not essential. The density-based feature method proposed by Vijaya Lakshmi T.R. et al. in [14] use the nearest neighbor classifier algorithm to classify. The images of the characters were binary and enlarged to 50x50 pixels. Each image is divided into 100 equal zones. The feature vector is the sum of all the pixel intensities in the area. Thus, 100 functions are extracted from each image. This method provides 78% accuracy for vowels and consonants. Another method that uses multilayer perceptron networks (MLP) to recognize Telugu HWCR has been proposed by K. Vijay Kumar and R.

Rajeshwara.Rao in [15]. This method is based on the MLP classifier, which is trained by an error backpropagation algorithm. With this method, the image size of each character changes up to 32x32 pixels. The input layer takes an image intensity of 32x32. The output layer has 54 output units for recognizing vowels and consonants. This method gives an accuracy of 84.9% for consonants and vowels. A recent notable paper submitted by [16] Raju Dara and Urmila Panduga uses a 2D fast Fourier transform to highlight image features and support the vector machine as a classifier. This method gives an accuracy of 71%.

Das et al. [17] proposed a new approach to combining using core component analysis (PCA) or modular PCA (MPCA) and hierarchically derived four-tree-based longer-running functions (QTLR) for Devanagari handwritten OCR digits. In the CMATERdb 3.2.1 data set, the combination of MPCA with QTLR achieved an accuracy of 98.70%. CNN has ushered in a new era in pattern recognition. CNN has proven to be quite effective at recognizing different Indian scenarios. Gandmandle et al. [18] proposed a fuzzy system where normalized distance functions are extracted using different windows and achieve 95% accuracy for Devanagari handwritten numbers. Another approach, based on fuzzy walkie-talkie, scale and invariant translation, was proposed by Patil et al. [19] for handwritten recognition of Devanagari digital numbers. The recognition rate was 99.5%. Acharya et al. [20] proposed a large-scale Devanagari character recognition system based on CNN, that is, a simple five-layer CNN similar to LeNet-5 (Maitra et al. [21]). They presented the Devanagari Character Dataset (DCD) with 92,000 images of 46 classes. In their proposed model, they focused on the screening approach and the dataset approach to reduce over-preparedness. They reported the highest accuracy of 98.47%. Sarkhel et al. [22] proposed a multi-scale, four-tree-depth feature selection method for isolated handwriting recognition, where they took Devanagari, Urdu, and Bengali scripts based on the new multi-column multi-scale convolutional neural network (MMCNN). They reported the highest recognition of Devanagari characters with 95.18%. They used a multi-step approach using different CNNs for function extraction and SVM for recognition in nine control and publicly available data sets of isolated handwritten characters and numbers, such as CMATERdb 3.1.1, CMATERdb 3.1.2, CMATERdb 3.1.3, CMATERdb 3.2 .1 and CMATERdb 3.3.1.

III. DATA INVESTIGATION

The Telugu dataset is available on the HP Labs India website. The data set contains 270 essays of each of the 138 Telugu "characters" written by many Telugu writers to gain variability in writing styles. Telugu writing has 36 consonants and 18 vowels, of which 35 consonants and 13 vowels are common practice and are available in the TIFF files shown in Fig. 2. The Telugu writing style is expressed without urgency, for what the pencil generally separates the main graphic symbols, although not always. Therefore, graphic symbols, that is, vowels, consonants, consonant modifiers and diacritical marks, are included in the character set. Also included are some consonant vowels that can be easily separated. In addition, the character set also includes certain characters that do not have a dialect interpretation, but have a constant schema in the writers and help reduce the total number of characters collected. Therefore, there are 166 characters mapped to Unicode characters [23].

A folder containing the character name in English is created for each character. Each folder contains 1700 images of the corresponding character. Shortcuts (character name in English) are not provided separately. Therefore, when extracting the character name from the folder, the data is pre-processed and stored in a specific array, which is then used to train the model. Each image is a 32 * 32 grayscale image that must be converted to a matrix and then smoothed, which is stored in the image matrix, to train the model. Although the dataset consists of images of each character independently, some characters in these images have been skewed to some extent. This was because the data set participants were asked to write on blank white paper without lines, and some words were written in more italics. This case happens very often in real life, regardless of whether there is a string on the page, so we decided to make our training data more dynamic for this topic by rotating the image clockwise at a very small angle with a random probability and adding this image to our training data set. This method of augmenting data has helped us create a model that is more powerful for some trivia, but such consistent detail that it can appear in a test data set. Character self-recognition continues to be an area of study for pattern recognition ignition. The use of neural networks to highlight important characteristics of characters in images has been very useful in extracting the characteristics of the image and thus simplifying the classification of characters with the help of various classifiers. Additionally, experimenting with cropped and partial images of characters using different neural network architectures helped to understand how the quality of the extracted functions changes, affecting the classification model and its accuracy. In conclusion, it is noted that character recognition, character mapping, neural networks, and image processing are several popular areas of research, and the results of these topics can be obtained in the report.

Fig. 2. Sample handwritten Telugu characters

IV. PROPOSED METHODOLOGY

In Telugu HWCR there are four main stages. They consist of preprocessing, segmentation, feature selection, classification. Additionally, post-processing is also performed to increase the efficiency of the recognizer. In preliminary processing, basic steps such as binarization, denoising, skeletonization will be performed. The segmentation of strings, words and characters will be done in the segmentation block.

The proposed work uses Convolutional Neural Networks (CNN). CNN is a deep character handwriting recognition design in Telugu that contains an input, a tortuous layer, a corrected linear unit, an aggregation layer, and a fully bound layer that extends the output layer, as shown in Figure 3. The first step required for identification is in the selection of a handwritten character image for classification. The introductory layer will contain the raw pixel values of the selected image height and width 80 X 80 for Telugu. Then pass the input image to the convolution layer. The responsibility of this layer is to enable a random number of filters on the height and width of the image to obtain a feature map. (A filter is a sequence of numbers called a weight or parameter.)

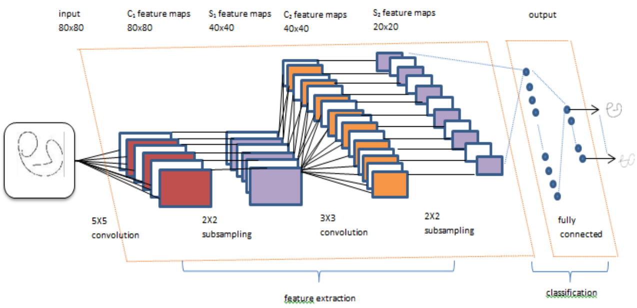

Fig. 3. Visual features in CNN using Telugu characters

The convolution layer and the maximum binding layer are the layer forms in the lower and central diplomas of the system. Even numbered layers work for convolution and odd numbers for maximum association activity. The data centers of the convolution layers and the maximum fusion are collected directly in the 2D plane, which is called the focus screen. Each layer plane is generally solved with a mixture of at least one plane of the previous layers. The center of the plane is connected to the contact zone of each affine plane of the previous layer. Each center of the convolution layer concentrates the selections from the image recordings through the spinning process at the recording centers. The works that change most frequently have a regular interest in information centers. Higher Level Highlights are sourced from characters in Decay grade capes. As the glare diverges towards the most visible layer, the glare ratio decreases depending on the size of the foldable and maximally combined cover. Be that as it may, the number of spots displayed is generally sped up to reflect outstanding adaptation moments of the facts to ensure better order accuracy. The output of CNN's final element maps is applied as a contribution to a fully connected machine, called a feature layer. In terms of placement, you can get the perfect number of highlights using the highlighting preference methods, based on the details of the loading frame of the closing neural device, with selected highlights set in the classifier for the specific photographic information technique. Given the most multiplied truth, the classifier offers a crop for evaluative learning in which photographs of data an area has. The digital niceties of the different layers of CNN are mentioned within the related segment.

a. CNN Layer

In this residue, the element maps of the past layer are convolved with learnable parts, for example, (Gaussian or Gabor). The yields of the piece revel in direct or non-directly enactment capacities, as an instance, (sigmoid, hyperbolic digression, softmax, amended immediately, and character capacities) to frame the yield spotlight maps. As a rule, it very well can be numerically tested as Equation (1).

$$a_j^l = f\left(\sum_{i \in M_J} a_i^{l-1} k_{ij}^l + c_j^l\right) \quad \text{Equation (1)}$$

Where a_j^l is the yields of the present layer, $a^{l-1}{}_i$ is past layer yields, k_{ij}^l is a portion for the present layer, and $c_j^l$is the predisposition for the present layer. M_j speaks to a choice of info maps. For each steo, map is given an added substance inclination b. In any case, the info maps will be convolved with unmistakable pieces to create the relating yield maps. For a moment, the suitable maps of j and k both are summation over the information I which is specifically applied to the j^{th} bit over the info I and takes the summation of its and a similar activity are being considered for k^{th} piece also.

b. Sub-sampling Layer

The sub-sampling layer plays a down sampling interest in the information maps. In this layer, the data and yield maps don't change. For instance, at the off hazard that there are N information maps, at that point, there may be really N yield maps. Because of the down sampling pastime, the dimensions of the yield maps can be diminished relying upon the dimensions of the down sampling veil. In this research, 2 × 2 down sampling cover is utilized. This activity can be figured as in Equation (2).

$$a_j^l = f(\beta_j^l down(a_j^{l-1}) + c_j^l \quad \text{Equation (2)}$$

Where down() signifies a max-pool function through local averaging, multiplicative coefficient and bias respectively. The above function adds up all n X n blocks of the feature maps from preceding layers and selects either highest or average values. The final feature map from the last convention layer is changed into a single dimensional feature vector matrix is taken as 3200 (=128 X 5 X 5) and 100 (=5 X 5 X 4) random nodes which are functionally connected to 138 and 36 output class labels for Telugu and Hindi characters. Errors are minimized through CNN using the following Equation (3).

$$E=\frac{1}{2}\frac{1}{PO}\sum_{p=1}^{p}\sum_{o=1}^{o}(d_0(p)-y_0(p))^2 \quad \text{Equation (3)}$$

It is noted that, in order to retain the image size from the previous layer, the proposed work used zero-padding as hyper parameter. Each convolutional layer uses this hyper parameter around the border of an image to control the spatial size. In the proposed work, two activations like RELU [32] and Softmax [33] have been employed for the convolution and pooling layers during organization of the output layers. The Softmax activation is used for multiple class logistic regression where as RELU functions as output zero if the input is less than 0, and 1 otherwise. The mathematical notations for both functions are mentioned in the following Equation (4) and (5).

$$\alpha(z)_j = \frac{e^{z_j}}{\sum_{k=1}^{k} e^{z_k}} \quad \text{Equation(4)}$$

$$f(x)= \max(x,0) \quad \text{Equation (5)}$$

The previously prepared model is used for Telugu to increase the efficiency or accuracy of existing models or to test new models. We use previously prepared weights from ready-made models to predict new classes. The advantage of using pre-prepared models is that they can be used with a small series of workouts and with less computing power. When training a deep neural network, our goal is to find optimal values in each of these filter matrices so that when the image spreads through the network, the output triggers can be used to precisely find the class to which the image. . The process used to find these values from the filter matrix is a gradient descent. When CNN trains on the Imagenet dataset, filters in the first layers of the convolutional network learn to recognize low-level features followed by high-level details. The following layers gradually learn to recognize trivial shapes using the colors and lines learned in the previous layers. Now the reason transfer training works is that it uses a pre-prepared network that is imposed on the imagenet dataset, and this network has already learned to recognize trivial shapes and small parts of different objects in its previous layers. Using a pre-prepared grid for learning transfer, already learned functions are used and only a few dense layers are added to the end of the pre-prepared grid to help recognize objects in our new dataset. Therefore, only the added dense layers are trained. All of this helps speed up the learning process and requires much less training data compared to learning CNN from scratch.

In this experiment, Neural Network was configured to extract the features from the images. The output of the second last layer (dense layer) from the Neural Networks consisting of the features was extracted after passing the inputs to the model. This output was then divided as train data and test data to evaluate classifier performance. The classifiers were trained using these extracted features and their corresponding labels from the train data. Test data created above was used to assess the performance of the classifiers. When the classifiers are fed with features from this neural network, then their classification accuracy is in the range of 72% to 81%.

V. RESULTS AND DISCUSSIONS

Telugu Character model is experimented using Amazon EC2 server instance with t2.x large instance type on Bitfusion Ubuntu 14 Tensor Flow setup. The python libraries Numpy, Panda, Matplotlib, Seaborn, Sckit-Learn, Keras [ ] are used for high performance and scientific computation. The proposed work considered 166 different character classes, where each consists of 270 samples for Telugu character recognition. After resizing the images, the dataset was splitted into 80% images to be used for training and 20% images for test and validation. The learnable filters of CNN are analyzed such as input image shapes, pooling strategies and optimizer functions on the model.

Table 1 recapitulates the results for all likely groupings of those distinctions on the test set. From this table, the recognition accuracy have detected that has reached to maximum when the model contains four convolutional layers, with zero-padding and max-pooling by two fully connected layers. In addition, the impact of filters size by (7 X 7, 5 X 5 and 3 X 3) also observed. If filter size becomes higher, the model fails to observe tiny details of structurally related character patterns. However, if the size of the filter is too small it may produce duplicate information which, in turn, would decrease the model accuracy. Hence, filter size of 5 X 5 is chosen for the first convolutional layer and 3 X 3 for the remaining convolutional layers is confirmed to be optimal filter size.

Table 1. Achieved classification accuracy by CNN for Telugu characters

S No	Model	Structure	Image Size	Number of Epochs	Loss	Optimizer	Accuracy
1	CNN	4 Conv layers, with zero-padding and max-pooling by 2 fully connected layers	80 X 80	20	Categorical cross entropy	SGD	96.4
2		Pre-trained model of image net	80 X 80	10	Categorical cross entropy	Adam	98.7

Even though a high performance in model accuracy reached with the pre-trained model, additionally the model also tried with the generalization techniques like Dropout and Data augmentation functions. Data augmentation consists of applying transformations to the training set in order to increase the dataset size and variation. By increasing the size of the dataset, data augmentation helps prevent over fitting. However, it is not fool-proof, since the augmented images will be highly-correlated. Finally, for parameter updates, the model optimizer is settled to SGD with learning rate 0.1.

a. Model Evaluation and Validation

We got test accuracy of 98.7% and training accuracy of 96.4% on Telugu character dataset with 20 epochs, if we increase number of epochs, then the accuracy will increase further. The loss reduced from 4.03 to 0.4 as the training progressed. For the first few epochs, the training accuracy is less than the validation accuracy and then after some epochs, train accuracy increased. Some of the characters, Guntitham and Vothulu are shown in Figure 4. The accuracy obtained by the model is greater than the benchmark reported earlier. It's likely that adding more epochs could increase the accuracy further.

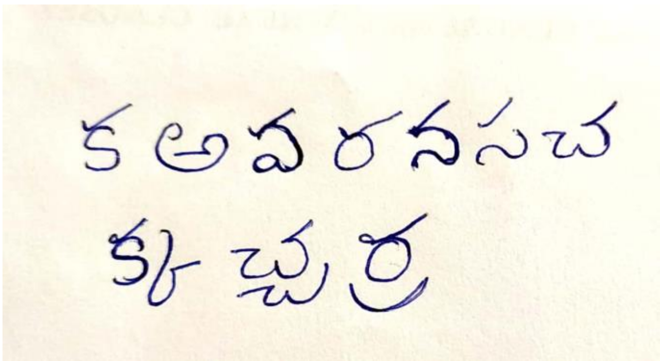

Fig. 4. Some of the characters, Gunitham and Vothulu used in this research

This CNN model is applied on gunithalu and votthulu to get good accuracy compared to existed work. Fig.5 shows that accuracy related to test data and trained data, in this model compared test model trained model got more accuracy. Fig.6 explains that loss parameter in this model loss of test data is more compared to trained model.

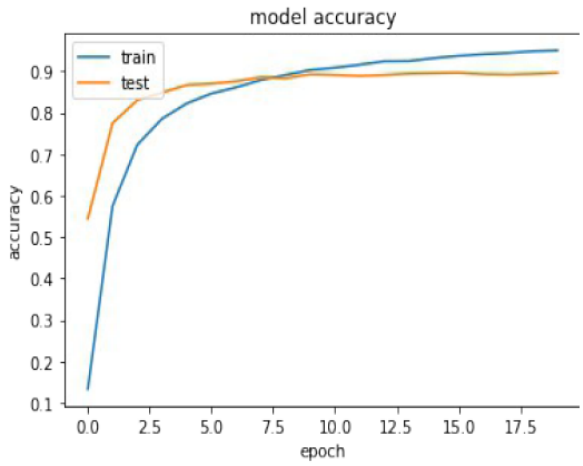

Fig. 5 . ROC curve to display Model accuracy for train and test data.

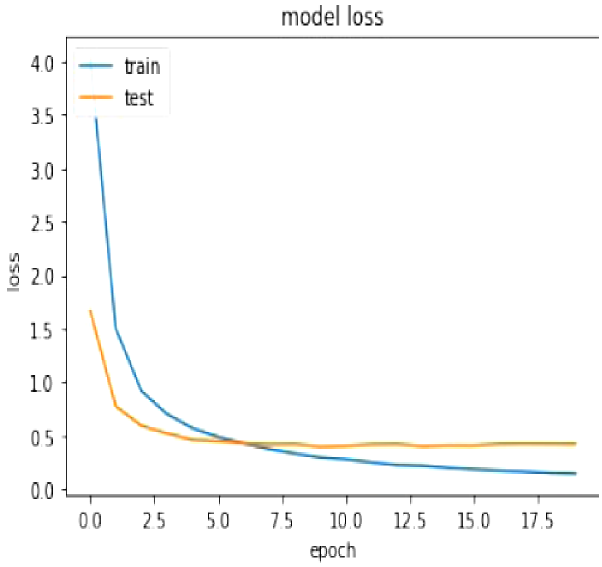

Fig. 6. Error rate curve for train and test data.

Table : 2. explains that CNN model achieves 98.7% accuracy this is good compared to all methods The accompanying table demonstrates the genuine marks and the predicted names of the preliminary 50 snapshots which demonstrates the model is foreseeing practically right names apart from 2 or three out of fifty pictures.

Table 2. Comparative Analysis

Name of the Model	Accuracy
ZF	78%
ADZM	88.8%
2D-FT_SVM	71%
MLP	85%
Bayesian	87.5%
CNN (Proposed Model)	98.7%

VI. CONCLUSION

In this proposed work, the classifier is introduced into a deep convolutional neural network for character recognition. An alternative architecture has been proposed that captures low-level textual features of handwritten characters. The network consists of several conventional layers, central filters and ReLU activation functions, followed by two dense layers with Softmax activation function. The accuracy of learning was observed using various optimizers and classifiers such as SGD, Adam, Random Forest, Multilayer and KNN using the Loss function, called categorical cross entropy. The result of the proposed method is very impressive with the imagenet model prepared previously and compared with modern algorithms. So it in difficult to set up the algorithm, hence different optimizers with different learning speeds are tested the model by changing the number of layers and filters and the filter size. It is observed that, a model that gives 98.7% accuracy. Further there is a scope with this application, which covers Android, iOS, RIM, provides easy access, ML neural network algorithms using segmented data, a set of Telugu gunintham and vothulu together provide better accuracy. The implemented system is also useful for other languages such as Tamil, Kannada, Malayalam, etc., OCR systems for all Indian languages.

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