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Effective Tamil Handwritten Character Recognition Using Deep Learning Technique

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Abstract

Computer vision applications for real-world problems include handwriting recognition. Nowadays handwritten character recognition is commonly used for reading postal addresses, bank check amounts, and forms. A few works have also been done for recognizing the Tamil character. The Tamil character syllable is a segment of a Tamil word that has a single vowel sound and is spoken as a single unit. Recently, Tamil character recognition has been implemented through deep learning techniques. The hyperparameters used in the deep learning techniques signify the training algorithms' behavior, which has an impact on model performance in predicting the characters. One of the major challenges in training the model is overfitting the data. This has to be overcome by choosing the values of hyperparameters appropriately. However, the proposed system uses the bayesian optimization algorithm for tuning the values of the hyperparameters. In addition to the hyperparameter values, the proposed system classifies the given Tamil character using a convolutional neural network. The proposed system performance is assessed using tuned hyperparameters and the standard accuracy metric. The proposed system produces an accuracy of 87.3% when compared to the existing Tamil character recognition system.

Keywords: Tamil character recognition, Deep Learning, ConvNets, Tamil handwritten character recognition, Hyperparameters Tuning

Introduction

Hyperparameters are variables whose values have an impact on the learning process. As the prefix ' hyper ' implies, these are 'top-level' parameters that manage the learning process and the model parameters. The hyperparameters are chosen before training begins and the learning algorithm uses them to learn the parameters. As a result, choosing the appropriate hyperparameter values is important because they directly impact the model's performance when employed during model training. Hyperparameter tuning is the process of deciding which hyperparameters are best for the model. In applications such as intelligent scanners, text-to-speech conversions, and automatic linguistic translations, recognition is important[10].

Tamil is the world's oldest language and the oldest language of the Dravidian family. Around 5000 years ago, the Tamil language had the longest uninterrupted history. The Tamil language has 12 vowels (Uyirezhuthu), 18 consonants (Meyyezhuthu), and one special character (Aythaezhuthu) in the Tamil language. The total number of Combinations (uyirmeyyezhuthu) of a consonant plus a vowel alone in the completed script are 247 (12+18+216+1) [1]. There are five Sanskrit consonants that, when joined with vowels, give 60 additional compound letters, bringing the total number of characters to 307 characters [9]. Tamil handwritten characters are difficult to recognize because various people write the same character in several different styles. [20]. The handwriting of the same person might change over time. A tiny difference in the character size and shape image has a large impact on extracted features and minute components distinguish different character classes [11]. Tamil characters have a complex structure that includes a lot of curves and loops making feature extraction difficult.

The goal is to select the optimal model that best matches the datasets. The proposed CNN model was built with two Conv layers followed by two fully linked layers, the best results were obtained. The model begins with two Conv layers with 32 kernels of size (3X3), followed by two Conv layers with 64 kernels of size (3X3) and max pool layers with a kernel dimension of (2X2). The nonlinear activation function RELU is used. Finally, the softmax function is used to make predictions.

The loss function is minimized, and a backward propagation technique is used to update the weight and bias values. A dropout is applied to the outputs of the preceding layer that are fed to the consequent layer in a model between the fully connected layer to avoid overfitting and to improve CNN performance the hyperparameters are fine tuned.

Related work

The Traditional approaches have been employed in most of the work done in Tamil till now. Using classic machine learning approaches, a typical HTCR strategy would include preprocessing, character segmentation, feature extraction, classification, and finally prediction of new characters. The proposed model [14] in which pixel densities are retrieved as characteristics and an SVM classifier is used to classify 106 characters. For 34 characters, they got an accuracy of 82 %. The Tamil character is classified in [1] used symbol- modeling HMM. For training 60 Tamil characters are used.

With this approach, an accuracy of 85% has been obtained. In [8], the wavelet transform was utilized for feature removal and a back propagation neural network was used for classification, resulting in an89 % recognition accuracy. According to studies, in [15] statistical and structural representations had a significant role in recognizing 30 Tamil characters. For character extraction, this approach relies on both structural and statistical methods of symbolization. In [2] introduced a new approach that included feature extraction and a three-prediction approach. The datasets from the "HP- India handwritten Tamil character dataset", with only 100 characters used, and pre-processed them using Otsu's approach, Gaussian noise removal, skeletonized normalizing procedures. The pre-features were then retrieved using the Junction point division to divide the structure. The recognition was done using hierarchical SVM and the divide-and-conquer method.

The developed CNN architecture in [19] to recognize the Tamil character. The technique employs three Conv layers, three max pool layers, and one fully linked layer. The dataset contains 35 classes with 32 samples in each class and the model was trained with an adaptive learning rate, the regularization technique dropout 0.2 was used to avoid overfitting. They discovered that removing one of the conv layers has an impact on the final result. An architecture- based technique was described [12] there are two conv layers, max pool layers, fully linked layers, and an output layer. The dataset contains 124 classes and is trained with the Rectified Linear Unit activation function (RELU), to avoid overfitting dropout regularization can be used with a probability of 0.4. The network has achieved less testing accuracy compared to testing accuracy based on symbols similar symbols. In [13] used a deep learning technique to construct digitizing for digitizing offline Tamil handwritten character recognition (THCR). The pattern was detected using the CNN recognized the recognized characters were converted into printed characters using multimedia tools and applications. On the obtained datasets, the proposed technique achieved the maximum accuracy, according to the experimental results. By combining the ideas of Principle Component Analysis and Convolutional neural networks, [17] have presented a new TCR system. The dataset contains 146 classes and is trained with a learning rate of 0.001, batchsize cross-entropy to calculate the training and validation loss. In a total of 50 epochs, the model was trained and achieved the highest validation accuracy. The proposed model's resultant had a higher convergence rate. Validation accuracy must be improved.

Using a modified artificial neural network [10] predicted that TCR could be recognized efficiently. The authors have used the Elephant Herding Optimization (EHO) to optimize the weight of ANN. When compared to standard categorization methodologies, the evaluation's outcome showed better performance. Although the recognition rate is improved and the recognition time is reduced this method suffers from overfitting. In [6] proposed a CNN model enhancing the architecture by optimally tuning the hyperparameters. The dataset contains 85124 images and the model is trained with a learning rate of 0.01 with mini-batch size. The model has trained 100 epochs with dropout 0.3 and obtained maximum accuracy. In [4] proposed deep conv Neural Networks (CNN). The system was trained using an RMS Prop optimizer with an adaptive learning rate and the regularization technique dropout 0.5.

In [18] proposed a CNN is a type of deep neural network with a batch size of 128 with a learning rate of 0.001 and 155 epochs were used to train the model. The dropout approaches with a suitable drop rate of 0.4 are also used to reduce the overfitting problem.

The majority of the research has concentrated on the recognition of a small class of handwritten characters. When the full Tamil character set is considered, the process of recognition becomes more difficult due to the occurrence of a lot of characters with structural resemblances in their shapes. The hyperparameters like batch size, learning rate, and dropout are used to forecast the model's accuracy. As a result, fine-tuning hyperparameters is required to improve accuracy.

Process of Tuning Hyperparameters

The variables that control the training process are called hyperparameters. Choosing how many hidden layers of nodes to employ between the input and output layers, as well as how many nodes each layer should utilize, is an example of how to set up a deep neural network. whereas hyperparameters are typically stable. The network runs several hyperparameters necessary for the network's proper training.

Each layer has its own set of hyperparameters, such as activation function (AF), optimizer, learning rate (LR), batch size (BS), epochs and drop out (DO) may be adjusted to improve the model. An activation function describes how a node or nodes in a layer convert the weighted sum of the input into an output. A neural network optimizer is a function or algorithm that modifies the weights and learning rate of the network. As a result, it helps decrease all loss while also increasing accuracy. The learning rate is a hyperparameter that controls how abundant the model should modification when the model weights are adjusted in response to the predicted error. The batch size denotes the number of samples that were processed in advance the model was updated. The number of epochs is the total number of times the training dataset has been traversed. A dropout is a regularization approach that prevents complex co-adaptations on training data, which reduces overfitting in neural networks.

For weights, the initialization was utilized. The batch size 128withh the size of 40x40 input images was sent to the network. The optimizer Adam and the activation function ReLu with a learning rate of 0.001 were used. The convergence normally happens in 20 to 30 epochs and in all of the trials up to 30 epochs. The 50 epochs are used to get the best outcome model.

A. Bayesian optimization

The Bayesian optimization (BO) is an efficient method for finding the extrema of functions that take a long time to compute [5]. The BO can be used to solve a function that lacks a locked-form expression. BO working for functions

that are time-consuming to calculate, and have difficult derivatives to analyse, or non-convex. The purpose is to find the maximum value for an unidentified function f at the sampling point.

$$X^{+} = \arg \max_{x \in A} f(x) \quad 1$$

where A denotes x's search space. The likelihood P(E|M) of overserving E given model M multiplied by the prior probability P(M) determines the subsequent probability P(M|E) of a model M: The Bayesian theorem [5] is the

$$P(M|E) \propto P(E|M)P(M) \quad 2$$

The formula above encapsulates the idea of BO. The goal of BO is to associate the prior distribution of the function f(x) with the sample information to discover wherever the function f(x) is maximized giving to a criterion using posterior information. The criterion is represented by a utility function u, also known as the acquisition function. The function u is used to regulate the next sample point in order to maximize utility. It's critical to think about both exploration and exploitation while looking for a sampling location [7]. This will help to decrease the number of samples collected. Furthermore, performance will improve even if the function contains several local maxima.

Implementation

The offline Tamil handwritten character Recognition set up a benchmark for the dataset containing 9360 images in tiff format the dataset is retrieved from the online version. The images in different sizes with a background in white and foreground in black were normalized 40 X 40 and scaled to the 0,1 range. The proposed architecture contains the two-Conv layer followed by a max pool layer and two fully linked layers followed by an output layer. Each convolutional layer includes an activation function. The input layer contains images of 40 X 40 sizes and the output layer is a softmax classifier that calculates the output possibility for all the 156 classes.

Dataset

The proposed work uses the International Workshop on Frontier in Handwriting Recognition (IWFHR) database developed by Hewlett-Packard (HP) Labs India [21]. This dataset contains 156 symbols addressing 307 characters. The dataset has 60 samples for each class total of 9360 samples freely available.

Training and Testing process

The 156 classes are used in this experiment, with each class receiving approximately 60 samples. The dataset contained 9360 images, which were divided into three categories 69% training, 20% validation, and 11% testing. The neural network has tested Keras using Tensorflow as the backend for train and test neural networks. The train and test were completed on a Windows 64-bit desktop PC with 8 GB RAM and an Intel Core I5 processor.

After setting an optimizer and batch size, the model is compiled. Because the dataset includes images of various sizes, they were scaled to 40X 40 before being fed into the network. Dropout regularization was employed with a 0.4 dropout probability to avoid the network from overfitting the train data.

result and discussion

The CNN model is implemented and evaluated in (1) Keras's deep learning environment using TensorFlow backend in this work. The following metrics can be used to assess the performance of the model:

The statistic accuracy (A) measures how many correct predictions the model made throughout the whole test dataset. [3]: foundation of Bayesian optimization.

$$Accuracy = \frac{TP + TN}{TP + FP + TN + FN} X\,100 \qquad 3$$

True-Positive (TP) shows the total number of images that can be correctly classified into the class, False-Positive (FP) shows the total number of images that have been incorrectly classified into a class, False-Negative (FN) shows the total number of images that have been incorrectly classified as not to a class, True-Negative (TN) shows the total number of images that have been incorrectly classified.

A. Tuning of CNN Hyperparameters

At first, the proposed model gave 96.8% train accuracy and 77.1% test accuracy representing the overfitting with a dropout t of 0.4. The dropout regularization technique was introduced in each layer to reduce overfitting to a train accuracy by 96.9% and 87.3% test accuracy with a dropout of 0.3.

As shown in Table I, previous work and outcomes are compared. In [19] employed Convolutional Neural Network to classify 35 classes and attained a train accuracy of 99 % and a test accuracy of 94.4 % also the existing system limits to 35 classes. According to existing work [12], the network has achieved a train accuracy of 88.2 % and a test accuracy of 71.1% for 124 classes. When compared to earlier work, the proposed system used all 156 classes and had a train accuracy of 96.9% and a test accuracy of 87.3 %.

Table 1. *Comparison of existing work with the hyperparameter values*

Author	class	Method	Hyperparameters				Accuracy	
			BS	LR	AF	DO	Train (%)	Test (%)
[19]	35	CNN	32	Adaptive	Tanh	0.2	99	94.4
[12]	124	CNN	256	0.001	ReLu	0.4	88.2	71.1
Proposed Work								
Initial	156	CNN	128	0.001	ReLu	0.4	96.8	77.1
Fine-tuned	156	CNN	128	0.001	ReLu	0.3	96.9	87.3

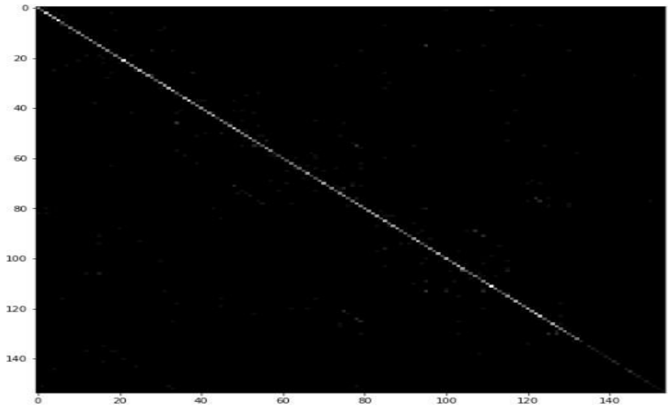

Fig.1 *The Confusion matrix for 156 classes of Tamil characters*

The confusion matrix is represented graphically in figure 1. Shows the white pixels in the confusion matrix's diagonal elements indicate that the majority of the classes were accurately identified with a high degree of accuracy, whereas dark pixels show that a few classes were misclassified. Misclassifications are caused by the high similarity of a few classes, according to an analysis.

Table 2. *Comparison Of 156 Classes Identified*

Classification	No.of class
Misclassified	13
Partially Classified	57
Correctly Classified	86

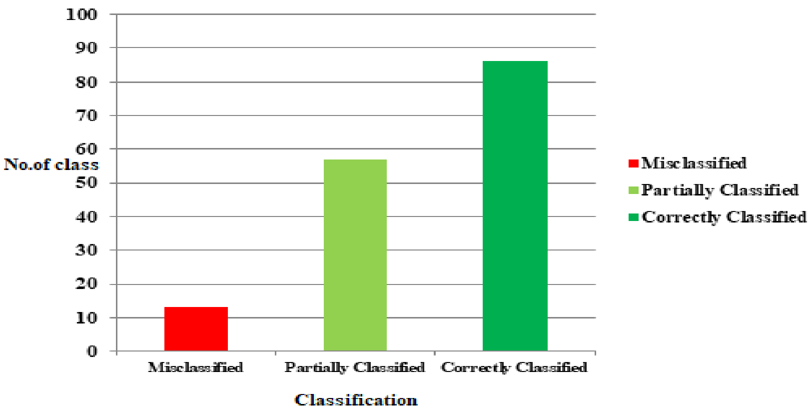

Fig. 3 *Classification of 156 classes*

The confusion matrix is shown in figure 1. and has been illustrated in Table II. Depicts the number of classes that have been identified, partially identified, and misclassified.Fig.3

depicts the Total number of 156 classes classified as misclassified, partially classified, and correctly classified. The misclassified characters are enclosed in the given Table III.

Table 3. *Misclassified Characters*

Actual character	Predicted character
த	ந
ன	ள
ற	ந
ஞி	இ
ழு	டு
டி	ம
கு	ரு
மு	டு
சு	ச

Conclusion

The deep learning techniques have the effect of tuning the hyperparameters to acquire the model performance. The proposed system predicts the Tamil character using a convolutional neural network by enhancing the hyperparameter values. The proposed system is evaluated using accuracy to determine the system performance. When compared to the existing system, an accuracy of 87.3% has been achieved by the proposed system. In the future, this work can be prolonged to recognize highly similar charactersto improve accuracy.

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