ISSN: 2454-4248
178 – 183

Performance Evaluation of RBF, Cascade, Elman, Feed Forward and Pattern Recognition Network for Marathi Character Recognition with CLAHE Feature Extraction Method

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Abstract- The purpose of this paper is to study, analyze and improve the performance of RBF, Cascade, Elman, Feed Forward and Pattern Recognition Networks using 'Contrast-limited Adaptive Histogram Equalization method' of featureextraction. This work is divided in to two sections. In the earlier work, we have performed the performance analysis of RBF neural network, Cascade Neural network, Elman Neural network and Feed forward neural network for the character recognition of handwritten Marathi curve scripts using 'Edge detection and Dilation method' of feature extraction. In this paper, we have applied the feature extraction methodknown as Contrast-limited Adaptive Histogram Equalization (CLAHE). This feature extraction method enhances the contrast of images by transforming the values in the intensity image. For this experiment, we have considered the six samples each of 48 Marathi characters. For every sampled character, the CLAHE feature extraction method is applied. Then we have studied and analyzed the performance of these five Neural Networks for character recognition. It is found that except Elman Network, the performance of rest of all the networks is increased.

Keywords-*Histogram Equalization; Performance analysis; RBF neural network; Cascade neural network; Elman neural network; feed forward network; Pattern Recognition Networks, CLAHE.*

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I. INTRODUCTION

An artificial neural network (ANN) is a well-established technique for creating the artificial intelligence in the machine. This is an attempt to simulate the human behavior in the machine for the various pattern recognition tasks [1]. One of the human behaviors is ability to write the text. Such writing may vary from person to person. This can have different style, spikes and strokes while writing the characters.

Handwritten text recognition is an important aspect of the pattern recognition task. It plays the major role in many real world problem domains. Its applications include recognition of postal envelopes, bank checks, examination forms, Visa application forms and medical prescriptions etc. The automated processing of handwritten material saves time and shows higher accuracy in terms of more data being processed in less time as compared to human processing [2].

Nowadays, although recognition of printed isolated characters is performed with high accuracy, recognition of cursive handwritten characters still remains an open problem in the research area and to increase the character recognition accuracy, novel features extraction techniques are indispensible [3].

The word "Feature" denotes a quantity that has been found from some measurements [4].Feature extraction step plays one of the most important roles in recognition system. In simplest case, the binary images are fed to a recognizer and a template matching is done. However, in most of the recognition system, in order to avoid extra complexity and to increase the accuracy of algorithms a more compact representation is required. For this purpose, a set of feature is extracted for each class that helps distinguish it from other classes [3]. A feature extraction algorithm must be robust enough such that for a variety of instances of the same symbol, similar feature sets are generated, thereby making the subsequent classification task less difficult [5].

Subhash Pawar and Neeta Jain[3] have proposed a feature extraction methodology for offline cursive character recognition using both statistical and structural features which improved the recognition accuracy due to use of extensive features and improves the efficiency due to novel curve fitting encoding of character features.

Gauri Katiyar and ShabanaMehfuz introduced simple off-line handwritten character recognition system using four approaches of feature extraction namely, box method, diagonal distance method, mean and gradient operation have been used. Five different recognition networks are built. The network is trained and tested on the CEDAR CDROM-1 dataset.The results indicate that the network with thecombined feature extraction method gives the highest recognition rate up to 93.23%.

J.Pradeep, E.Srinivasan and S.Himavathi [7] have proposed a simple recognition system for recognizing handwritten English alphabet characters using a new type of

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feature extraction, namely, diagonal feature extraction is proposed.Experimental results show that the diagonal feature extraction with feed forward propagation neural network yields good recognition accuracy of 96.52% with 54 features and 97.84% with 69 features.

AmalRamzi and AmmarZahary in their research work “Online Arabic Handwritten Character Recognition using Online-Offline Feature Extraction and Back Propagation Neural Network” have used Using Hybrid Feature vector with Chain code features + 9-zones offline features and found 99.5% training recognition rate [8].

Jarernsri L. Mitrpanont and UrairatLimkonglap [9] in their paper, “Using Contour Analysis to Improve Feature Extraction in Thai Handwritten Character Recognition Systems”, have stated that overall evaluation shows that the THW-CR system has generated reliable results for improving the accuracy rate of the previous work which is 3.62% and 8.33% for the feature extraction rate and the character recognition rate, respectively. In the test, the average character recognition rate reaches 95.35% and the average feature extraction rate meets 97.73%, approximately.

Feedforward neural networks, or multilayer perceptrons(MLPs), are the quintessential deep learning models. The goal of a feedforward network is to approximate some function f*. For example, for a classifier, $y = f^*(x)$ maps an input x to a category y. A feedforward network defines a mapping $y = f(x;\theta)$ and learns the value of the parameters θ that result in the best function approximation.

Elman neural network architectures are proposed by Jeffrey Elman. Elman networks were recurrent and designed to learn sequential or time-varying patterns. In this way, the algorithms could recognize and predict learned series of values or events. Elman's primary interest in this architecture was for language processing algorithms, but he suggested its usefulness for just about anything involving sequences.

Cascade-forward networks consist of Nl layers. These are similar to feed forward networks with a small change. The first layer has weights coming from the input. Each subsequent layer has weights coming from the input and all previous layers. All layers have biases. The last layer is the network output.

The RBF network approach is more intuitive than the MLP. An RBF network performs classification by measuring the input’s similarity to examples from the training set. Each RBF network neuron stores a “prototype”, which is just one of the examples from the training set. When we want to classify a new input, each neuron computes the Euclidean distance between the input and its prototype. Roughly speaking, if the input more closely resembles the class A prototypes than the class B prototypes, it is classified as class A.

Pattern Recognition network is an N-layer feed-forward backpropagation network. The transfer functions can be any differentiable transfer function such as tansig, logsig, or purelin. The training function BTF can be any of the backpropagation training functions such as trainlm, trainbfg, trainrp, traingd, etc.

In this paper, we are improving the performance of RBF, Cascade, Elman, Feed Forward and Pattern Recognition Network for Marathi characters withContrast-limited Adaptive Histogram Equalization (CLAHE) feature extraction method.

II. EARLIER WORK

In the earlier work, we have investigatedthe performance in terms of regression valuesofRBF, Elman backpropagation, Cascade, and Feed forward models for handwritten character recognition of Marathi curve scripts using ‘Edge detection and Dilation method’ of feature extraction.

a]Edge Detection and Dilation Method Feature Extraction.

The data set used in the earlier experiment was consisted of 288 handwritten characters of Marathi language. The said set was created by collecting six samples of 48 characters each from six different people on paper. Out of these 288 characters, 192 characters (4 samples of each character) were used as training samples. There, we applied a series of preprocessing operations on scanned images. Firstly we converted the images of RGB characters into gray scale. Then gray scale images were converted to binary form by thresholding. Morphological dilation operation was performed next to fill the gaps in characters, followed by edge detection operation to get the boundary of the character. The exact portion of image was cropped so as to apply the further operation. In that experiment, we haveformed the P as the training pattern and T as the testing pattern with which we performed the recognition.

b] Methodology was the same as that is used here. i.e. 1. Create the network 2. Train the network 3. Simulate the network and 4. Plot the regression plot.

C] The results mentioned in Table 1 are the results of earlier experiments in terms of regression values of Cascade network, Elman BP network, Feed Forward network and RBF network.

Method	Regression value
Cascade NN	0.46994
Elman BP NN	0.48278
Feed Forward NN	0.47774
RBF NN	1.00000

Table 1: Showing the Regression values in earlier Experiment

III. FEATURE EXTRACTION (CLAHE)

The feature extraction method used in this present work is ‘Contrast-limited Adaptive Histogram Equalization method (CLAHE)’ of feature extraction. The data set used in the present research work comprises of 288 handwritten characters of Marathi language. The said set is created by collecting six samples of 48 characters each from six different people on paper. All the 288characters are used as training samples. Following are the steps used in ‘Contrast-limited Adaptive Histogram Equalization method (CLAHE)’ of feature extraction. In this experiment, with the help of CLAHE, we have created the P as the training pattern which is nothing but all the characters which are converted into a matrix form. T is the testing pattern with which we have to perform the recognition.

The CLAHE feature extraction method proposed here has the following steps.
1] Read the image.
2] Convert the image into Gray scale
3] Adjust the image intensity values
4] Create a morphological structuring element P1 (intensity area) by using 22 points in the image
5] Normalization of the input pattern vector
6] Now P is the matrix which is to be trained.

The specialty of this method is that flat disk shaped morphological structuring element is created which considers the different 22 point of the image. This covers the entire morphological structure of the image. The above mentioned steps are applied to each and every image of 288.

IV. METHODOLOGY

In this experiment we have used five different networks so as to train the pattern vector P. T is the target vector with which we are going to train the pattern vector P. These five networks are…

1] RBF neural networks
2] Cascade neural networks
3] Elman neural networks
4] Feed Forward neural networks
5] Pattern Recognition neural networks

For every network, corresponding MATLAB functions are available. Before applying the below mentioned methodology in Figure 2, we have prepared the input pattern vectorP after performing the CLAHE feature extraction technique. Our testing vector T was kept ready. All the steps viz. Extract the features, Create the network, Train the network, Simulate the network and Plot the regression were carried out and the results were stored.

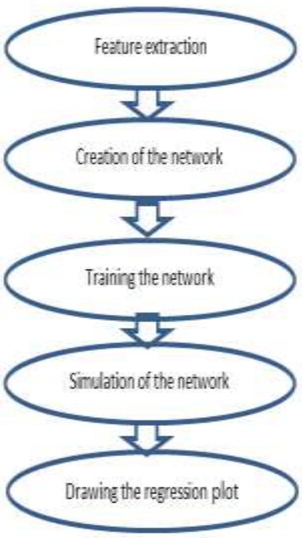

Figure 1. Methodology used for the experiment

After performing all these steps, the regression plots of every network were stored.

V. RBF NEURAL NETWORK

An RBF neural network, is a three layer feed forward network that consists of one input layer, one radial layer and one output layer, each input neuron corresponds to a component of an input vector x. Generally, these classifiers are used for interpolation in multidimensional space [10].

The radial layer consists of K neurons and one bias neuron. Each node in the radial layer uses an RBF denoted with $\phi(r)$, as its non-linear activation function.

The hidden layer performs a non-linear transform of the input and the output layer. This layer is a linear combiner which maps the nonlinearity into a new space. The biases of the output layer neurons can be modeled by an additional neuron in the hiddenlayer, which has a constant activation function $\phi_0(r)=1$.

The RBF network can achieve a global optimal solution to the adjustable weights in the minimum MSE range by using the linear optimization method. Thus, for an input pattern x, the output of the jth node of the output layer can define as;

$$y_j(x)=\sum_{k=1}^{K} w_{kj}\phi_k(\|x_i-\mu_k\|)+w_0 \quad (1)$$

The Radial Basis Function $\phi(.)$ is typically selected as the Gaussian function that can be represented as:

$$\phi_k(x_l)=\exp\left(-\frac{\|x_l-\mu_k\|^2}{2\sigma_k^2}\right) \quad (2)$$

for $k=(1,2,.....,,K)$

and 1 for $k=0$ (bias neuron) Where x is the N- dimensional input vector, μ_k is the vector determining the centre of the basis function ϕ_k and σ_k represents the width of the neuron. The weight vector between the input layer and the kth hidden layer neuron can consider as the centre μ_k for the feed forward RBF neural network.

VI. CASCADE NEURAL NETWORKS

Cascade Forward models are similar to feed-forward networks, but include a weight connection from the input to each layer and from each layer to the successive layers. While two-layer feedforward networks can potentially learn virtually any input-output relationship, feed-forward networks with more layers might learn complex relationships more quickly [11].

$$y_{i,N+h} = f_j\left(\sum_{k=1}^{N} x_{i,k}\theta_k + \sum_{j=N+1}^{N+h-1} y_{i,j}\theta_j\right), \quad (3)$$
$$i = 1,\ldots,M, h \geq 1,$$

Where $f_j()$ is a nonlinear activation function[12] .

$\{\theta_k$, k =1, ・・・,N$\}$ are the weights that connect the input units to thehth hidden unit, and $\{\theta_j$, j = N + 1, ・・・,N + h − 1$\}$ arethe weights that connect pre-existing hidden units to the hthhidden unit.

VII. ELMAN NETWORKS

Elman's definition of a context revolved around prior internal states, and thus he added a layer of "context units" to a standard feed forward network. In this way, the states of the hidden units could be fed back into the hidden units during the next stage of input. Elman (1990) best describes it. Both the input units and context units activate the hidden units and then the hidden units feed forward to activate the output units. The hidden units also feedback to activate the context units.This constitutes the forward activation.

Elman networks are two-layer back propagation neural networks, with the addition of a feedback connection from the output of the hidden layer to its input. This feedback path allows Elman networks to learn to recognize and generate temporal patterns, as well as spatial patterns [13].

Output of the hidden layer is given by [13].

$$y_j(t) = f(net_j)$$

$$net_j(t) = \sum_i w_{ji}x_i(t) + \sum_h u_{jh}y_h(t-1)+ \quad (5)$$

The final output is given by [13].

$$y_k(t) = g(net_k) \quad (6)$$

$$net_k(t) = \sum_j v_{kj}y_j(t) + \vartheta_k \quad (7)$$

Where $V_{kj}$is the weight vector from layer k to layer j. $y_j(t)$ is the input vector and$\theta_k$is the bias.

VIII. FEED-FORWARD NETWORKS

A feed forward neural network is an artificial neural network wherein connections between the units do not form a cycle [14].

In this network, the information moves in only one direction, forward, from the input nodes, through the hidden nodes (if any) and to the output nodes. There are no cycles or loops in the network. The best example of feed forward network is a multi-layer perceptron. This type of networks consists of multiple layers of computational units, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function.

Here, the error is given by..

$$\varepsilon_k = \frac{1}{2}\sum_{j=1}^{p}\left(d_j^k - \delta(y_j^k)\right)^2 = \frac{1}{2}E_k^T E_k \quad (8)$$

Where $\varepsilon_k$is summed squared error, $d_j^k$is the desired output and $\delta(y_j^k)$ is the actual output.

$$\varepsilon = \frac{1}{Q}\sum_{k=1}^{Q}\varepsilon_k \quad (9)$$

The hidden to output layer weight update is given by

$$w_{hj}^{k+1} = w_{hj}^k + \Delta w_h^k \quad (10)$$

The input to hidden layer weight update is given by

$$w_{ih}^{k+1} = w_{ih}^k + \Delta w_{ih}^k \quad (11)$$

Where Δw_{hj}^k and Δw_{ih}^k are the weight changes

IX. PATTERN RECOGNITION NETWORK

Pattern Recognition network is an N-layer feed-forward Backpropagation network. The transfer functions can be any differentiable transfer function such as tansig, logsig, or purelin. The training function BTF can be any of the backpropagation training functions such as trainlm, trainbfg, trainrp, traingd, etc.

X. RESULTS AND DISCUSSION

In our experiment, we are comparing the performance of all of the five neural network models for the created pattern vector P and testing vector T. These results are compared with the earlier method's results. Here, we have used the 'Contrast-limited Adaptive Histogram Equalization (CLAHE) method' of feature extraction.We have applied the five neural network methods – Cascade, Elman, Feed forward and RBF and Pattern Recognition. For every method, we have created the network, trained the network, simulated the network and plotted the regression plots. The table 2 shows the comparative table of previous and present Experiment's regression values.

Method	Regression Values	
	Edge detection & Dilation Method of Feature extraction	Contrast-limited Adaptive Histogram Equalization (CLAHE) Method of Feature extraction
Cascade NN	0.46994	0.6038
Elman BP NN	0.48278	0.44163
Feed Forward NN	0.47774	0.54682
RBF NN	1	1
Pattern Recognition NN	0.22561	0.47162

Table 2: A comparative table of Method and Regression Values

Fig. 2a and Fig. 2b shows the regression plot for feed forward network, Fig. 3a and Fig. 3b shows the regression plots for Cascade network, Fig. 4 shows the regression plot for Elman network, Fig. 5a and Fig. 5b shows the regression and performance plots for RBF network, Fig. 6a and Fig. 6b shows regression Plot and Confusion Matrix of Pattern Recognition Network.

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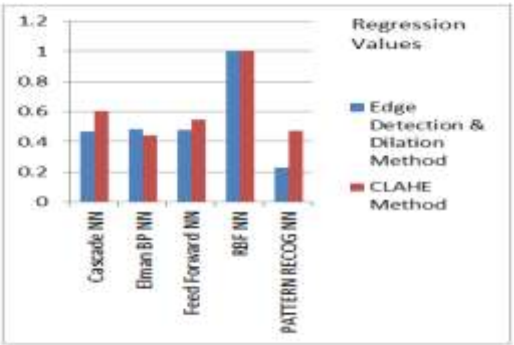
Confusion matrix shows the wrong and right classification of patterns.

XI.COMPARATIVE CHART SHOWING THE REGRESSION VALUES OF FIVE NETWORKS WITH EDGE DETECTION AND DILATION METHOD AND CLAHE METHOD OF FEATURE EXTRACTION



From the above comparative chart, it is clear that the regression value of RBF neural network is 1 in both of the feature extraction methods. All of the networks have performed well except the Elman Network.

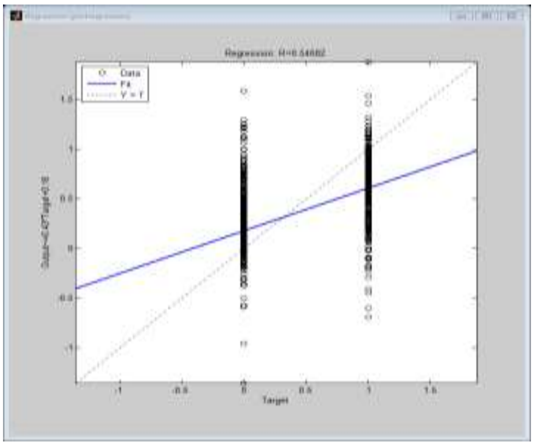


Figure2a. Regression Plots of feed forward network

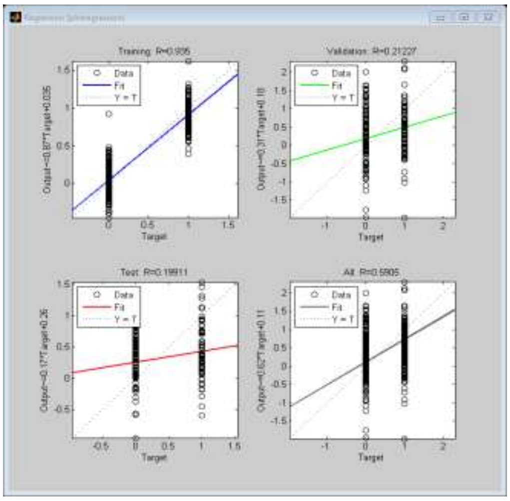


Figure2b. Regression Plots of feed forward network

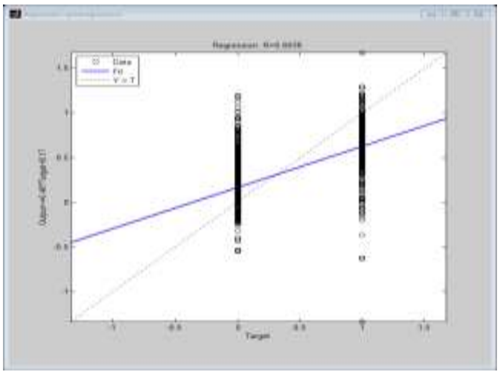


Figure 3a. Regression Plot of Cascade Neural Network

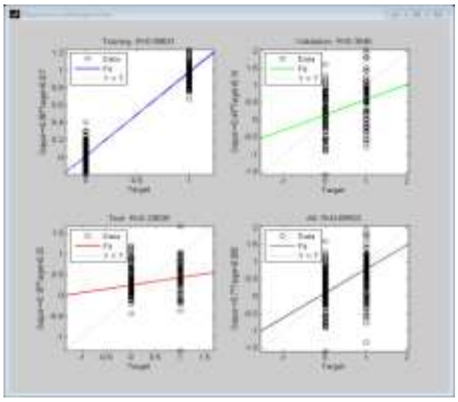


Figure 3b. Regression Plots of Cascade Neural Network

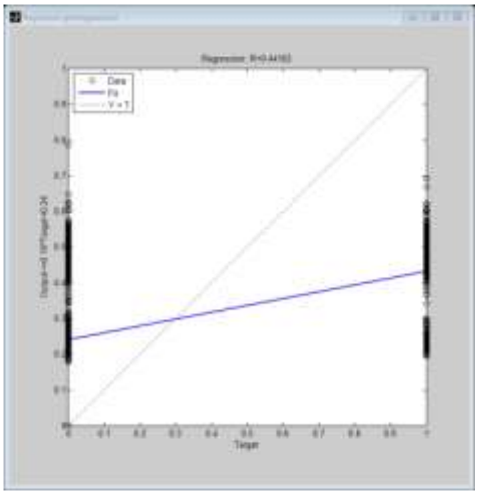


Figure 4. Regression Plot for Elman network

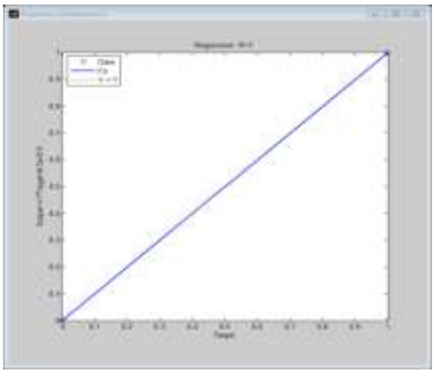


Figure 5a. Regression plot for RBF network

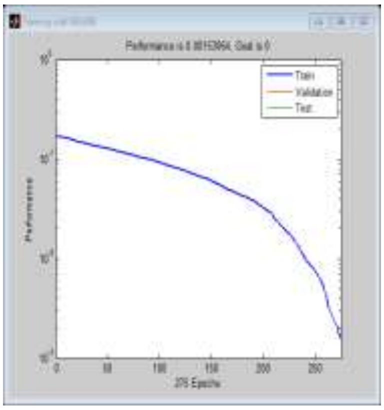


Figure 5b. Performance plot for RBF network

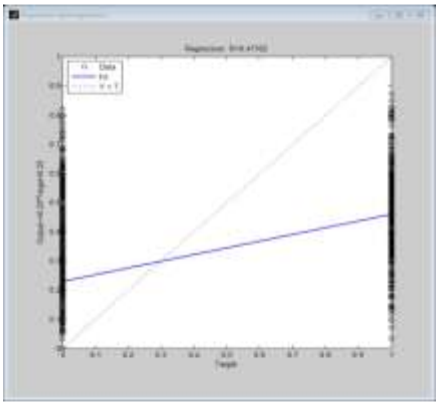


Figure 6a. Regression Plot for Pattern Recognition Network

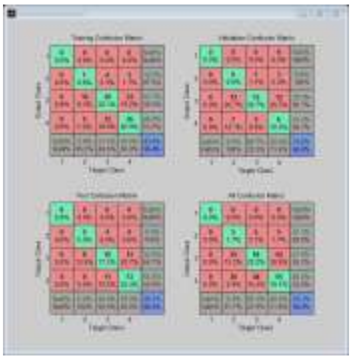


Figure 6b. Confusion Matrix for Pattern Recognition Network

XII. CONCLUSION AND FUTURE SCOPE

The results mentioned in this paper clearly exhibit the earlier and present comparison of performances of Cascade network, Elman BP network, Feed Forward network and RBF network and Pattern recognition network with respect to the two different feature extraction methods. These two methods are 'edge detection and dilation' and CLAHE. The experimental details obtained after applying these four neural network techniques are explored in terms of regression in the form of plots. From the graph, it is clear that the value of RBF classifier is 1 in both of the experiments.In this comparison, regression value of Elman network in the present network is less than the previous experiment by 0.04115. For the remaining networks i.e Feed forward, Cascade and Pattern Recognition, the regression values are increased. This shows the increased performance. In future, we can go for the experiments to enhance the performance of Elman network.

ACKNOWLEDGMENT

The author thanks to Dr. Bharat Shinde, Principal, VidyaPratishthan's Arts, Science and Commerce College, Vidyanagari, Baramati, Dist-Pune (India) for his valuable guidance and encouragement for the research work.

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