Hierarchical Image Classification on Bayesian Cascade Neural Learning

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Abstract

The performance of image classification on Bayesian cascade neural learning techniques using in coarse and fine layer in LSTM. Recurrent Neural Network (RNN) system experience from Vanishing Gradient (VG) issues. The Gradients needs to proliferate down through numerous layers of the Recurrent Neural Network (RNN).So we integrate the LSTM do not go through from vanishing gradient problem that forward layer. It support different number of layers in Convolutional Neural Network (CNN) is designed for image classification. The Long Short Term Memory (LSTM) processed with Bayesian Cascade Neural Learning (BCNL) with CNN of GoogleNet framework to designed the hierarchical image classification. The elasticity of LSTM model to computed hierarchical label on standard dataset of CIFAR-100.

Index Terms—Deep learning, Recurrent Neural Network, LSTM, Bayesian cascade, Image classification.

I. INTRODUCTION

Artificial Neural Network (ANN) have accomplished the presentation over a wide scope of use are CV (Computer Vision), NLP(Natural Language Processing), SR(Speech Recognition)[5,6,15]. The field of Artificial Intelligence originate from ANN. ANN isn't reasonable for image on the grounds that the system prompts over fitting effectively because of the size of images. The CNN is one of the image order methods [4,5,6] for various leveled highlight extraction. The supervised learning is produced that the accurate output values are called as class labels. The class labels are not form as cluster or tree like structure .In the proposed method, the most successful l hierarchical image classification proven efficient of CNN. To build deep layer community in during training method. The community appear of a problems understand as vanishing gradient problem [4, 14]. In the state –of –the art to deal with the gradient weight using learning algorithm that trains the network from backside to pinnacle layers one after the opposite with Bayesian cascade neural learning set of rules. Bayesian cascade techniques into the design able to learn the coarse and fine layer [21, 22] to be relevant hierarchical category tree shown in Fig .2.

It can be processed by parameter to GoogleNet on hierarchical CNN architecture to use in image classification. LSTM framework to deal with the hierarchical image classification task [21,24].LSTM network is a type of recurrent neural network . It is used to classifying in order data. The recurrent neural network by back propagation through time [24]. The normal networks have only feed forward values are also drawbacks in traditional models. In this paper we focus diminishing the vanishing gradient problem using integration of GoogleNet with LSTM aim to overcome the issues of value of gradient problem by using the gates to selectively retain information that relevant and forget information. LSTM is an assortment of memory cell, input gate, yield gate and overlook entryway notwithstanding concealed state in conventional RNN. The LSTM are blend enhance the grouping of coarse and fine marks to improve the characterization execution by investigating the connection between the progressive names. CNN are improved layer by layer[12,20], GoogleNet is the adaptable profound learning basic structure comprise of the early layer, center layer, last layer .The image are partitioned into patches [5,6]. The data patches are set up by convolutional layers set as portion size and walk estimation of focus layers is molded by rehashing structure called inception layer regards went into maxpool set as channel is link with early layer finally connected dense layer with softmax classifier produce a last a last image classification. GoogleNet engineering contain 22 layers made a methodology called inception module [2,6]. We facilitate the Time Complexity (TC), Memory Utilization (MU) can be utilized on preparing calculation and the proposed design are GoogleNet (Inception module) with LSTML models appeared in Fig .1.

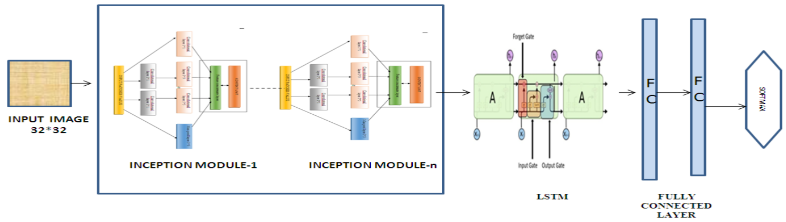

Fig.1 Architecture of Proposed System

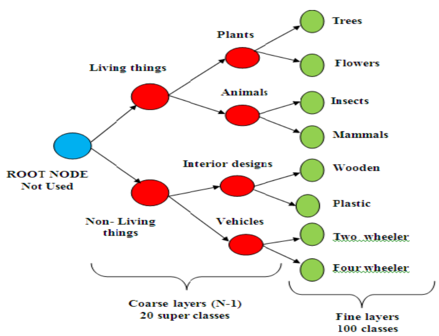

Fig.2 Manually constructed hierarchical level image classification for CIFAR-100 data set

II. RELATED WORK

Table I. Summary of Previous Work on Bayesian cascade neural learning and image classification.

Reference [Year]	CNN MODEL	DATASET
[3] (2018)	Visual Geometry Group(VGG)	Minst , CIFAR-10, CIFAR-100
[21] (2017)	Wider Resnet/ LSTM	CIFAR-100,ImageNet 2012, Subnet of ImageNet 2010
[17,18,19] (2018,2019,2019)	Lenet - 5,AlexNet	Minst , CIFAR-10, CIFAR-100
[22] (2017)	Visual Geometry Group	Minst , CIFAR-10, CIFAR-100
[5] (2019)	GoogleNet	CIFAR-100
[6] (2019)	GoogleNet	CIFAR-100

III. Bayesian Cascade Neural Learning

A. Dataset

The proposed method is used unbalanced CIFAR-100 datasets information shown in Table II.

Table II. Summary of CIFAR-100 dataset

Classes	Image size	Image Per Class	Training	Testing
100	32*32 color images	600	500	100

B. Proposed Design

The building block of the proposed GoogleNet with coarse layer and fine layer in convolutional neural network is a parallel neural network [12]. The 3-level hierarchical image classification Input sided as coarse layer and other side (output) as fine layer. GoogleNet represented by several stages of convolutional layer and maxpool layer. GoogleNet is used as the feature extract from flow diagram of shown in Fig.3 it contain 6 inception modules ,LSTM, fully connected layer and softmax classifier. Each input image size are 32*32 that are evaluated into vector values into CNN models to training and testing input image progress it through a convolutional layer of inception modules. Each inception modules contain 1*1,1*1,1*3,1*5 convolutional layers, maxpooling layer , concatenate layer connected with fully connected layer and be appropriate to softmax classifier classifying an labels with probabilistic value between 0 and 1. The convolutional first layer to extract feature from an input image , the layer care for the pixels by learning image vector values of input data. The inception modules evaluate the vector values moves to LSTM models, fully connected layer with softmax classifier to linear independently vector values sending to

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classifier for all fine layer sequentially. The classifier is used to expect coarse class probability of fine layer of fine labels. The input feed is coarse layer and output channel are fine layer. 3- level hierarchical level image classification of coarse and fine layers on GoogleNet implemented by Algorithm 1 and Algorithm 2 to compute the both forward and backward propagation of coarse and fine layer. The Bayesian cascade method is quickly to solve the hierarchical image classification and Fig. 2 represent the manually constructed 3-level hierarchical image classification on CIFAR-100 dataset. The root node is a single node is never used and final node is called child node (final labels). The root node are coarse layer n-1 are fine layer produced different classification of 2-100 labels.

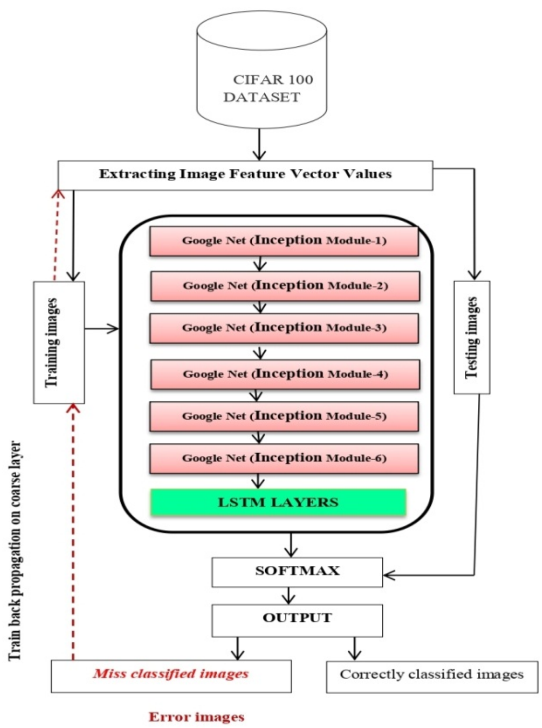

Fig.3 Flow diagram of BCNL technique

C. Bayesian Cascade Neural Learning on coarse and fine labels

Bayesian Neural Network are neural network whose weight or parameter are express as distribution rather than a deterministic value and learned using Bayesian Cascade. The full Bayesian cascade neural learning use Bayesian Rule D={(x,y)} to estimate full posterior distribution of the parameter[19,21].

$$P\left(\frac{W}{D}\right) = \frac{P\left(\frac{D}{W}\right).P(W)}{P(D)} \quad (1)$$

In Bayesian cascade demonstrating are two sorts utilized they are aleatoric, epistemic vulnerability. Bayesian CNN prepared by variational induction start with low validation [17], precision contrasted with the model prepared by visit derivation. This must diminished from the instatement of the variational back likelihood of conveyance as uniform dispersion while introductory point gauge in engineering train the incessant derivation are arbitrarily draw a standard appropriation. A like hood model can be defined by accessing a standard Gaussian filters prior for classification P(y=c)[22] .The inference in the model is performed by stochastic regularization techniques. We are used this approach to represent model uncertain which classifying CIFAR-100 data set images. To find the posterior distribution over the convolutional network weight of Bayesian cascade given the training data of x and y layer of P(w/x,y).

The advance the dropout probabilities Pi they are fixed for standard worth that limit the cross entropy misfortune work prompts limit uniqueness. The learning of a system with stochastic gradient descent drop prompts learns dispersion network weight. These weight values are descent one of the most powerful optimization algorithm1 to compute both forward and backward propagation for the coarse and fine layers used in image classification. Gradient descent is prone to arriving at such local minima and flaw converge and it comes gradient descent of initial value and learning rate [7].

Algorithm 1: Calculate Gradient Descent for Feed Forward and Backward on GoogleNet model

Step1: Initialize the dataset in neural network from the neuron in l-1 layers.

Step2: Feed Forward

a) Train data as input vector for each neuron in the input layer and label in output layer.

b) Compute the input layer to each hidden layer in the next layers and input layer using an activation function as the output in the next layer.

$$\prod_{t=1}^{T} \mathbf{Pr}\ (c1, c2 \ldots . ct/x_1^T \qquad (2)$$

Step 3: Back Propagation

a) Compute the gradient descent weight from the last input layer to last output layer.

$$\prod_{t=1}^{T} \mathbf{Pr}\ (ct+1, ct+2 \ldots . ct-1/x_1^T \qquad (3)$$

b) Calculate the gradient layer from mathematically equation initial value and learning rate

$$\Theta_{n+1} = \Theta - \alpha \left(\frac{d}{d\Theta_n} J(o_n)\right) \qquad (4)$$

Step 4: Repeat the process until whose weight in the neural network were updated.

D. LSTM based coarse and fine labels.

RNN is a class of Artificial Neural Network where connection between unit form a direct cycle[16]. RNN suffers from gradient problems. The gradient needs to disseminate down through many layers of recurrent network. LSTM provides a solution of gradient problem. The LSTM gates are used to control how much it should read its input. The gates help the input signal to disseminate through recurrent hidden states without affecting the output of the LSTM can deal with gradient and RNN is not capable of learning. LSTM to learn features interrelated with output on each and every layer. The algorithm 1 takes input from the learning rate and computed by the layer by layer to update the weight by descent. The training follows layers by layers approach. The goal of state of the art is generated hierarchical label for images manually constructed tree shown in Fig.2 of CIFAR -100 dataset. The labels are order in a coarse and fine layer. LSTM initiator takes the labels of different level as input where the coarse and fine labels appearance on time steps [21,23,24].

IV. EXPERIMENTAL RESULTS

We evaluate on the bench mark dataset of CIFAR-100 by comparing the performance of coarse and fine GoogleNet with traditional models. LSTM based model for coarse and fine predictions without data augmentation. The images are divided into small patches the values are passed into one at a time through to learning algorithm 1&2 to minimize the error. The concept of transfer learning is used where training is performed on 200 epochs with learning rate of 0.001 and initialized with GoogleNet in hyper parameter to processing on LSTM then values are feed into fully connected layer, gates selectively retain information values with softmax of output classification with equation 5 . To improve the performance of algorithm 1 and 2 with parameter value of 64,128,256,512 convolutional filter of inception modules are processed to LSTM models and final output computed by softmax classifier. All the experiments are run on single Graphical Processing Unit(GPU) can process more than one image in a particular sessions. The GoogleNet reduce the parameter that not affect any convolutional layers [9,10]. The data sets are reduce the over fitting. The training weight gradient descents are update from output layer to input layer [2]. The random weight is used to decrease the vanishing gradient problem and calculated the accuracy and TC of both training and testing with different scale the training image and test images evaluated by both forward and backward propagation of mathematical equation 6.

Algorithm 2: Extracting features using hierarchical image classification of coarse and fine labels in GoogleNet model
Input : The input images
Output : Accuracy
Step1: Load input image as vector.
Step2: Split the sets of images into training and testing data.
Step3:
a) Load the vector / image values of GoogleNet model.
b) Extract features from the deep layers of GoogleNet model.
Step4: Extract features values are pass incoarse into fine channel layer contain only one element.
Step 5: Pass the coarse value to conditional channel layer into N_{coarse} layer i^{th} layer contain N_i conditional elements.
Step 6: for i=1 to N coarse do
a) S_{coarse} channel layer train RNN on LSTM of S_{fine}
b) S_{fine} and S_{coarse} to retrain the RNN and evaluate on test set.
c) Use the training softmax classifier top coarse channel layer and fine channel layer calculated mathematical equation

$$P\left(\frac{W}{D}\right) = \frac{P\left(\frac{D}{W}\right).P(W)}{\sum_{c=1}^{c} p(D/W P(D)} \quad (5)$$

End for
Step 7: Extract the features from test set and trained classifier to predict the label for test set of output layer with conditional layer.
Step 8: Display the accuracy.

$$o\left(\sum_{l=1}^{d} n_{l-1}\, s_l^2 n_l m_l^2 i\right) \quad (6)$$

Here l is the record of a convolutional layer d the last layer index, n is the measure of channels, s is the spatial size of the channel (input), m is the spatial size of yield. Ni-l is for the most part called the measure of information channel of the lth layer, il address the measure of preparing cycle for the lth layer. In prune course calculations obtains from noteworthy course altering, so we have direct understand a proportionate condition 6. There is no adjustment done in that equation considering the way that in existing framework utilized in GoogleNet[3,5,6,8] and proposed structure execute in

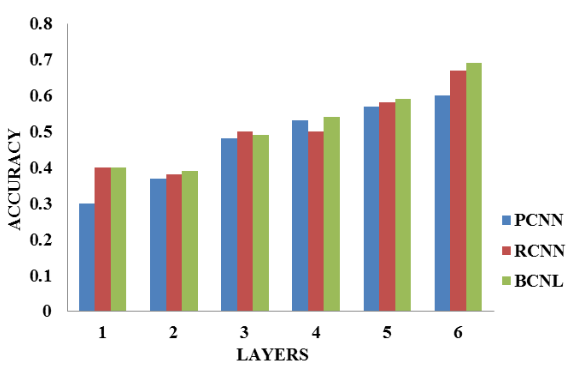

Fig.4 Accuracy of BCNL methods

GoogleNet, consider the time multifaceted plan of both framework in CNN.LSTM mix of coarse and fine names to improve the precision of stood apart from existing work on Table III and Fig. 4 .

Table III. Assessment on precision in BCNL and RCNN, PCNN.

LAYERS (L)	I	II	III	IV	V	VI
PCNN[5]	0.3	0.37	0.48	0.53	0.57	0.6
RCNN[6]	0.4	0.38	0.50	0.50	0.58	0.67
BCNL	0.4	0.39	0.49	0.54	0.59	0.69

V. CONCLUSION

In this paper we conclude the hierarchical image classification using Bayesian cascade neural learning on CIFAR-100 dataset. The class 100 dataset are processed by GoogleNet with LSTM, learning by layer to layer and reduces the patches are processed in inception modules. The proposed work reduce the vanishing gradient of coarse and fine layer has clear forward and backward propagation of learning calculation to limit the blunder and lessen the time complexity and attain the increase accuracy of 0.29% , reduce the time complexity of 1ms compared to existing methods. In future work to explore and improve different deep learning architecture to improve the precision of image classification and reduce the false positive rate, TC, MU.

REFERENCES

[1] A.krizhevsky, I.sutskever and G.E.Minton "Imagenetclssifiction with deep convolutional neural network", in Proc.Adv.NeuralInf.Processing Syst., pp.1097-1105,2012.

[2] C.Liu,Y.Cao,Y.Luo,G.Chen,V.Vokkarane,Y.ma, "Deep food: Deep learning-based food image recognition for computer aided dietary assesment ",,Dig Healt 3:37-48,2016.[Google Scholar].

[3] E.S Marquez,J.S.Hare, M.Niranjan, "Deep Cascade Learning", IEEE trans on Neural network and learning system,pp.5475-5485,2018.

[4] G.D.Praveenkumar, M.Dharmalingam, " Analysis of vanishing gradient problem in deep learning on CIFAR dataset", Con .Proc., NCAC 2019, ISBN-9789387862463,pp.1-3.

[5] G.D.Praveenkumar, M.Dharmalingam, "Pruned Cascade Neural Network ImageClassification",IJRTE, Volume No 8 ,Issue No 3, pp.6454-6457, 2019.

[6] G.D.Praveenkumar, M.Dharmalingam, "Recurrent Cascade Neural Network for Image Classification",IJSTR, Volume No 8 ,Issue No 10, 2019.

[7] G.E.Hinton,S.Osindero,Y.W.Teh, "A fast learning algorithm for deep belief nets", Neural computing, vol.18 ,no.7,pp.1527-1554,2006.

[8] K.He and J.Sun,"convoluational neural network at constrained time cost",inProc,IEEE conf.CVPR,pp.5353-5360,2015.

[9] K.Simonyan ,A.Zisserman, "Very deep convolutional network for large scale image recognition", arvix:1409,1556,2014.

[10] L.Zumdzinski, "Deep learning guinea pig image classification on using Nvidia DIGITS and GoogleNet", CEUR-ws.org/vol-2240\paper16.pdf.

[11] M.s.Junayed,A.A.Jeny,N.Neebal, "Incept-N: A convolutional neural network based classification approach for predicting nationality from facial features", 3rd IEEE , ICIVC-2018.

[12] N.Sharma,V.Jain,A.Mirsha, "An analysis of CNN for image classification", ICCIDS-2018, pp.377-384

[13] P.Ballester,R.M.Araujo, "On the performance of GoogleNet and Alexnet applied to slatchs",Con.Proc.,AAAI-16.,pp.1224-1128.

[14] S.Squartini, S.Paolinelli, F.Piazza, " comparing different recurrent neural architecture on a specific task from vanishing gradient effect perspective", IEEE, ICNSC, pp.380-385,2006.

[15] R.Amalraj, M.Dharmalingam, "A Work Point System Coupled with Back-Propagation for Solving Double Dummy Bridge Problem", Neurocomputing (Elsevier) Vol. No 168, pp 160-178, June 2015.

[16] G.D.Praveenkumar, M.Dharmalingam, "Detection of skin cancer using artificial neural network Classifier",IJRASET,Vol.No-6,Issues-III,pp-1884-1889,March-201).

[17] K.Shridhar, F.laumann,M.Liwicki, "Bayesian convolutional neural network with variational inference",arxiv:1806.05978v5[cs.lg],14 Nov 2018.

[18] K.Shridhar, F.laumann,M.Liwicki, "Uncertainity estimations by softplus normalization Bayesian convolutional neural network with variational inference",arxiv:1806.05978v6[cs.lg], May 2019.

[19] K.Shridhar, F.laumann,M.Liwicki, "A comprehensive guide to Bayesian convolutional neural network with variational inference",arxiv:1901.02731v1[cs.lg],(Jan 2019).

[20] ChenWang, Yang Xi, "convolutional neural network for image classification",[Google Scholar].

[21] Y.Guo,Y.Liu,E.M.Bakker,Y.Guo,M.S.Lew, "CNN-RNN: a large-scale hierarchical image classification framework", Multimedia tools App, doi:org/10.1007/s11042-017-54443-x, pp-10251- 10263,2017.

[22] R.Fu,B.Li,Y.Gao,P.Wang, "CNN with coarse-to-fine layer for hierarchical classification", doi:10.1049/iet-cvi.2017.0636, pp-1-8,2017.

[23] Srivastava.N,Salakhutdinov, R.R, "Discriminate transfer learning with tree based priors" , Advances in Neural Information Processing System, Lake Tahoe, NV,USA,PP-2094-2102,2012.

[24] Xiaoyu Liu, " Deep convolutional and LSTM neural network for acoustic modeling in automatic speech recognition", pp. 1-9