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Comparative Study on the Deep Learning Algorithms

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Abstract: Deep Learning methods have paved the way for elevating the future technology that is capable of changing the world. In modern times, size of data is increasing with the level of application. Deep learning enables the huge dataset to process the highly optimized algorithms with high accuracy as well as within low time. The network architecture of deep learning works similar to human brain nerves. The network accepts the input dataset and convert the data into matrix form that passed through multiple layers in which, each layer upgrade the data to deliver the prediction or classification at the end.

Researchers explored the numerous deep learning models that portrayed an inspiration for developers and benefitted in the field of voice recognition, language translation, image categorization, stock market prediction etc. The concern behind the model is to effectively resolve the numerous tasks which need to distributed representation and human intelligence. The highly advanced processors like CPU and GPU has too enhanced the deep learning application through fast matrix calculations and image processing. We will take the sample of wind dataset and used it for comparing the different Deep Neural Network (DNN) artificial algorithm.

Keywords: Analysis, comparison, deep learning, training, prediction.

I. INTRODUCTION

The idea of creating an intelligent machine is as old as modern computing. In 1950, Alan Turing devised the mechanism to qualify the intelligent conversation capability of smart computing machines. It attracted the attention of the leading scientists like Marvin Minsky and John McCarthy and started the most thrilling field of computer science, Artificial Intelligence (AI). In the past year, a prominent enabler of modern artificial intelligence, machine learning has offered many fascinating solutions in a number of real-world applications. The predominant characteristic of machine learning algorithms is its ability to improve the generalization capability in solving problems autonomously by learning from data. It involves learning a hypothesis from examples in such a way that it can be further generalized to unseen data. The parameter turning mechanisms adopted in machine learning algorithms to fit the data often misinterprets this scientific discipline as an extension of parameter optimization problems. This may cause two detracting scenarios such as over-fitting and under-fitting, which should be avoided. Over-fitting is the situation in which the learning models are unnecessarily complex as compared to training dataset and it causes the model to fit irrelevant features of data. Under-fitting is the scenario in which models are too simple and not capable enough to cope up with complexes present in large volumes of data. Balancing these two scenarios is the key challenge in designing machine-learning algorithms. The Machine-learning algorithms are extensively utilized in diverse domains of real-world applications employing pattern identification, object recognition, prediction, classification, dimensionality reduction, etc.

II. LITERATURE REVIEW

In [1] investigated the Neural Network Architecture - a strategy for the categorization of the image. Such structure emulates of two sets natural eyes and variety of succession auto-encoding. The network is trained with numerous complicated pictures, but as the study progressed, the programs gradually improve the MNIST architecture. The MNIST system is the set of training data that act as the open-source database. It can be accessed via street-view house number training dataset in which those outcomes can also be enhanced that natural eyes can't recognize.

As per [2], the literature examines the image categorization method perform on the basis of CNN network architecture. Train data are processed with a proportionate number of face-images and non-face images which are utilized for training by extracting extra face-images of the face-images dataset. Image categorization framework uses the two scaled CNN networks containing 120 trained dataset and auto stage training obtain the 81 percent discovery rate with having just 6 incorrect-positive in Face Detection Dataset and Benchmark (FDDB), while at present it is accomplished with 80-percent detection along with 50 incorrect-positives.

The journal [3], utilized the Decision-Tree (DT) methods for the image categorization. Decision-tree comprised of hierarchical classifiers and each classifier has its own set of data. The process is executed by computing participation of every class in the decision tree. Here, classifier permits the partial denial of some classes in between the phases. Such techniques consist of three sections, where the initial part discovered the terminal-nodes and the next part try to get arranged itself within the class. The final part function is to divide the nodes. Thus, the strategy is very simple and highly effective.

The research work [4], investigate on the Support Vector Machine (SVM) dynamic-learning which was very popular in the last decade. This study further introduced the novel concept of joining the dimensional data through the consecutive spectral trail. It necessitates three methods were initially required euclidean-distance. This computed a few samples of the train data through the major spatial section. The second option was operated with Parzen-window method too and then spatial entropy. The outcome indicated that a couple of pictures reveal high-resolution with reference to regular effectiveness.

[5] The literature suggests the quick picture categorization by implementing the fuzzy-classifiers and is the basic practice to separate among known and unknown classes. Such techniques merely accelerate the Meta learning knowledge, in which the native features are easily available. The method was initially examined with few data of the big picture and then matched along with the collection of feature-image architecture. The outcome present much accurate classification because of the method take a short time period and can deliver 30% more limited on contrasted with the past one.

[6], shows the utilization of the “complementary-priors” by disposing off the rationalised impacts which makes the deduction troublesome in densely connected networks containing a lot of hidden layers. The method deduce quick - grasping program that can learn more in-depth, can coordinate conviction networks layer in turn, give the best two layers structure to create an indirect acquainted memory. This quick, grasping program is utilized for initiation of a slow learning-process which tweaks the weights using a comparable adaptation of the wake-rest program. Following the modulation, model of manuscript digit images with their category name is obtained through 3 hidden layer network. As a result, model offers the finest classification of the images and training algorithm too.

[7], highlights that irregular training algorithms can be used for training the semi-supervised learning method and kernel may also be applied to each layer or an output layer of the multilayer deep learning network. This network architecture brought a substitute of classical models and shows lower error rates as compared to simple deep learning networks.

[8], highlighted the procedure of the data extraction through the deep network in order to enhance the precision of programs coverings and proficiency. The study also reveals the advantage of trivial metaphysical methods, by utilizing the current lexical database in English (Word-Net) which has the capability to inspect similarities among the data recorded as well as identify the true records. This also possesses elevated accuracy due to the grammatical single section, multi-section and irregular data records and also provides an option to maintain disjunctive data and iterations. Overall, the test deduces that their proposed model can withdraw information webpage with multi-languages and that is free from the domain.

[9], the dissertation provides an outline for the common deep-learning techniques and their need in different types of data handling undertakings and signal processing. Its application zones are picked by keeping three conditions within the brain - (a) The Author's expertise or knowledge. (b) Application zones are effectively modified through useful DNN network innovations like voice identification and computer vision. (c) Application zones which have the capability to affect considerably through DNN network and also encountering research development, normal languages, text processing, information retrieval, text handling, data recovery, and multimodal data preparing enabled by performing various tasks via deep-learning.

III.METHODOLOGY

The goal of the literature work is to analyse the deep learning model and its impact on error rate by altering parameters like learning rate, epochs.

A. Feedforward neural network

Feedforward neural network is the network architecture based on the human brain and mainly used for the classification or prediction of multi series data. The network is composed of numerous interlinked neurons and input data is passed through them. Every neuron is linked to the neuron of the former layer. The three main layers of the simple network are the input layer, hidden layer and output layer. The hidden layer may consist of a number of layers and execution takes place generally between these layers. Initially, data is transferred through the input layer then weights are allocated to each node according to the defined function like logarithm or tanh. In the end, the output is provided on the output layers. During operation, no feedback is required between the network and that’s why the network is called a feedforward network.

B. Cascade neural network

Cascade-forward neural network is the branch of the neural network and process the same as the feedforward network. The network consists of multiple nodes interlinked to each other. The whole process performs between the input and output layer and involves each layer to the former layer. Input nodes are connected to each successive layer.

C. Recurrent Neural Network (RNN)

Recurrent Neural Network is an expansion of a feed-forward neural network with having inbuilt memory. RNN network exhibits the recursive property because of its ability to execute a similar operation for each of the input data when a product of an existing input relies on the former data processing. Subsequently, output yield is reproduced and return again towards the network when it is created. It evaluates the existing input as well as an output that is gained through the past input for providing the result.
Contrary to feed-forward networks, the recurrent network may utilize their inbuilt memory for executing the input series. These allow them to process the function like non-segmented, linked manuscript identification, voice identification. In other networks entire inputs are free from one another while in the recurrent network, every input is linked to one another.

D. Long Short Term Memory (LSTM)

Long-Short-Term-Memory (LSTM) network is a revised edition of recurrent network and can recollect past data present within a memory. Unlike RNN, lstm has overcome the problem of gradient vanishing. LSTM networks are appropriated for processes like data categorization and prediction of time series data with unknown time intervals. Back-propagation helps to learn the network architecture. Within the LSTM network, the following three types of gates are present;

1) *Input gate*: alter the memory according to the input value. Sigmoid and tanh function control the flow of the data as per their level of importance.
2) *Forget gate*: identify the information dismissed by the sigmoid function within the block. The gate search for the former cell-state and input gives the output value between 0 and 1. Here, 0 means neglect and 1 means store the data in the cell state.
3) *Output gate*: Output data is determined through input data and network inbuilt memory. The two main functions utilized is sigmoid and tanh. Sigmoid function allowed only those entities that are comparable to 0 and 1**.** Tanh function grants the weightage to each entity and then multiplies to the product obtain via sigmoid function.

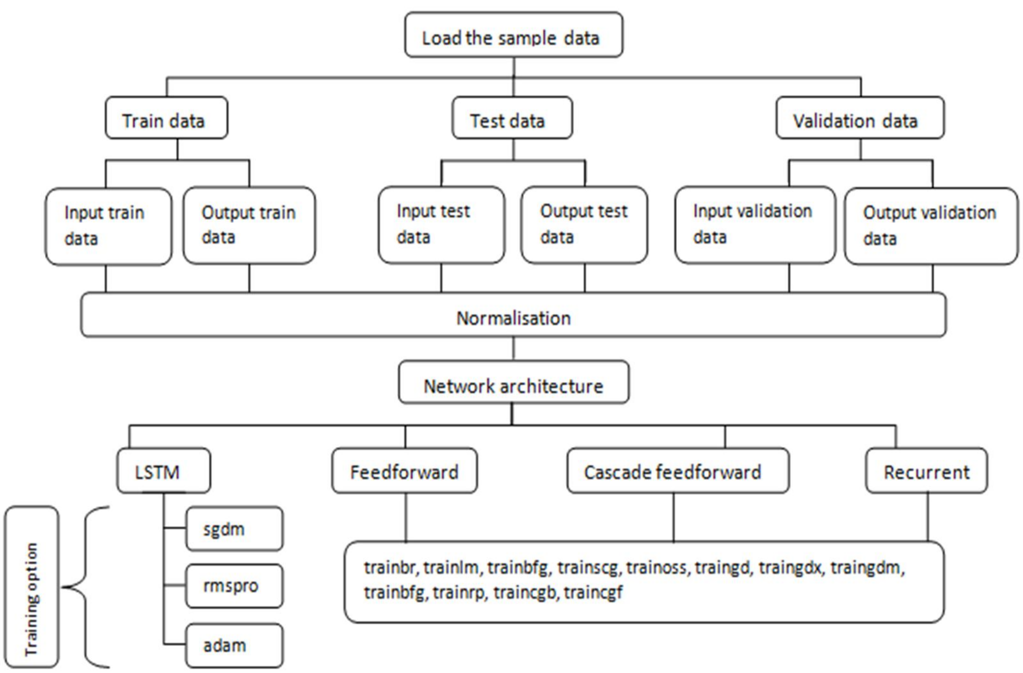

Fig. 1 Method flowchart.

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E. Steps taken for designing the deep learning model

1) Data collection and designing models

a) Sample wind data was collected from the RGPV University, Bhopal and these records were used for the comparison of deep learning and artificial neural network models. Records are comprised of 4 input columns and 6 output columns with 45 rows of numerical values.

b) Sample data was initially divided into train data, test data and validation data. Seventy percent of sample data comprise train data, thirty percent is test data and the rest is the validation data. The following steps are used for designing the model.

2) Normalization: Normalization is the process of transforming the data values in the range between 0 and 1. It enhances the network proficiency and ensures equal distribution of weights to each dataset value.

$$\text{Input\_train\_n} = \frac{((\text{Input\_train} - \text{mean}(\text{Input\_train}))}{standard\ deviation\ (\text{Input\_train})}$$

Same normalization formula was utilized for the train, test and validation data.

3) Network Architecture define: The networks are prepared by using four different methods –feedforward, cascade, rnn and lstm. The lstm models are trained by taking three training option options- sgdm, adam and rmsprop. Then the parameters like learning rate, epochs of the algorithm are changed till the optimum error rates are not found. Similarly artificial neural networks are made in order to compare with lstm model.

4) Denormalization: After getting the predicted data, it was denormalized and converted into actual data, Following formula was used- Output_Predict =(Output_Predict_n).*(std(Output_test))+ mean(Output_test)

IV. RESULTS AND DISCUSSION

Deep learning models were proposed by using LSTM network and the impact of the parameters on the error rates were analyzed. The LSTM models were built by taking three different training options- sgdm, rmsprop and adam. In order to compare these models with each other, four common parameters (learning rate drop period, learn rate drop factor, mini batch size and maximum epoch) were taken into account. Sgdm training model highlighted the lower error rates and uniform trend throughout the training with every parameter. Rmsprop training model showed the downtrend with learning rate drop factor and maximum epoch. The lower error rates are only demonstrated by implementing mini batch size parameters and the error range lie in the range of 0.108-0.145. Further analysis with adam based model does not indicate the relevant result with changing parameters.

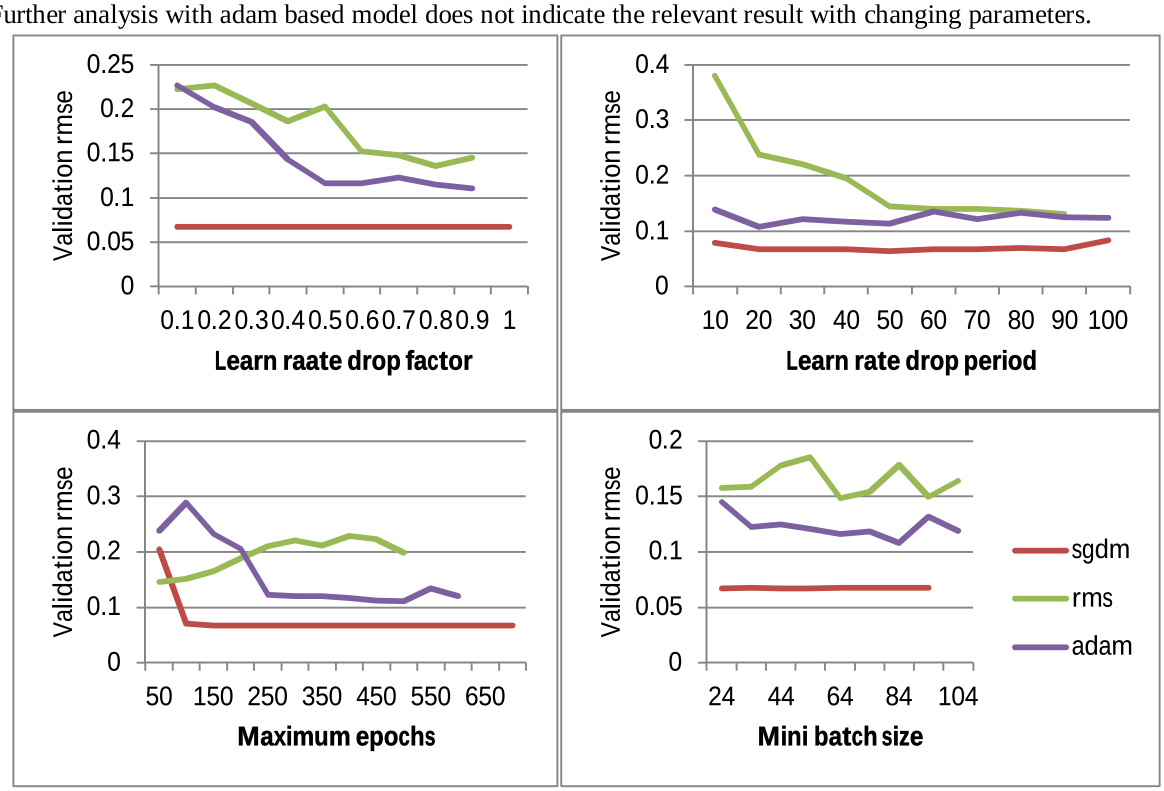

Fig. 2 Comparison of deep learning LSTM parameters with different training option.

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The training of the sample data was also conducted through ANN model. Feed forward network with Bayesian training showed the result similar to the lstm model with sgdm training options.

TABLE I

FEEDFORWARD NETWORK RESULT

Training _option	Epochs	Time (sec)	Performance (goal)	Gradient	Mu	SSE (error)	Validation checks	Step size	Repeatation of training
Trainlm	6	0	0.208	0.808	0.01	0.2747	3	-	15
Trainbr	11	7	0.34	0.638	0.01	0.0228		-	1
Trainbfg	13	5	0.403	0.254	-	0.0378	1	-	8
Trainrp	14	0	0.377	4.07	-	0.045	2	-	21
Trainscg	250	0	0.22	0.183	-	0.0908	6		25
traincgb	14	0	0.339	1.84	-	0.0663	0	0.205	13
traincgf	14	0	0.562	3.41	-	0.102	6	0.0315	16
trainoss	12	0	0.431	2.65	-	0.0373	0	-	14
traingdx	92	0	0.307	0.332	-	0.0804	0	-	27
traingdm	32	0	7.29	190	-	0.981	6	-	17
traingd	70	0	0.814	2.92	-	0.1115	0	-	14

TABLE III

RECURRENT NETWORK RESULT

Training _option	Epochs	Time (sec)	Performance (goal)	Gradient	Mu	SSE (error)	Validation checks	Step size	Repetition of training
trainlm	9	2	0.221	0.29	0.001	0.0848	0	-	
trainbr	5	2	0.238	1.78	0.5	0.0299	1	-	5
trainbfg	15	18	0.28	2.19	-	0.0333	2	0	5
trainrp	2	0	0.336	9.28	-	0.0593	6	-	
trainscg	65	0	0.283	1.73	-	0.0357	1	-	6
traincgb	28	0	0.296	0.433	-	0.0335	6	0.0626	2
traincgf	40	0	0.296	1.96	-	0.0442	0	0.0374	3
trainoss	17	0	0.343	5.55	-	0.0383	0	-	13
traingdx	72	0	0.449	1.04	-	0.073	0	-	12
traingdm	1	0	16.1	126	-	2.1078	0	-	3
traingd	88	0	0.614	2.53.	-	0.5281	0	-	5

TABLE IIIII

CASCADE NETWORK RESULT

Training _option	Epochs	Time (sec)	Performance (goal)	Gradient	Mu	SSE (error)	Validation checks	Step size	Repetition of training
trainbr	60	202	0.259	0.701	0.005	0.0437	-	-	10
trainlm	5	1	0.165	6.04	-	10.7767	-	-	15
trainbfg	19	17	2.35	54.9	-	3.1597	3	-	5
trainrp	16	17	1.42	9.49	-	7.9151	6	-	1
trainscg	20	0	2.62	20.8	-	2.7422	6	-	2
traincgb	18	0	1.55	29.7	0	0.5885	-	0.0838	22
traincgf	19	0	1.93	16.8	-	3.8334	1	0.0363	18
trainoss	21	0	2.08	27.6	-	4.1413	6	-	30
traingdx	47	0	2.94	14.4	-	6.5575	0	-	32
traingdm	12	0	432	1.93+e03	-	41.033	0	-	8
traingd	38	.	3.07	11.4	-	5.9834	1	-	23

V. CONCLUSIONS

Deep learning is the branch of machine learning and is also known as deep structured or hierarchical learning. Algorithms are the foundation of deep learning which allows the user to build the network or hierarchical model. These models are comprised of an array of layers that filter the data at every stage and enhance the weightage of the unit of the data. Input data are split into a number of units at the beginning then processed through multiple hidden layers and give the result as prediction or classification.

The purpose of the dissertation work is to figure out the deep learning models that can predict efficiently and within less time. Based on the analysis conducted, we concluded that the deep learning LSTM model with “sgdm” training option performs effectively and has shown lower error rates than other models. Also, the result obtained from the lstm-sgdm model is similar to feed forward network with Bayesian training option. One of the advantages of the lstm model over the artificial network is that no repetitions are needed once the models are proposed. Further exploration in the area of machine learning could provide better deep learning models.

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