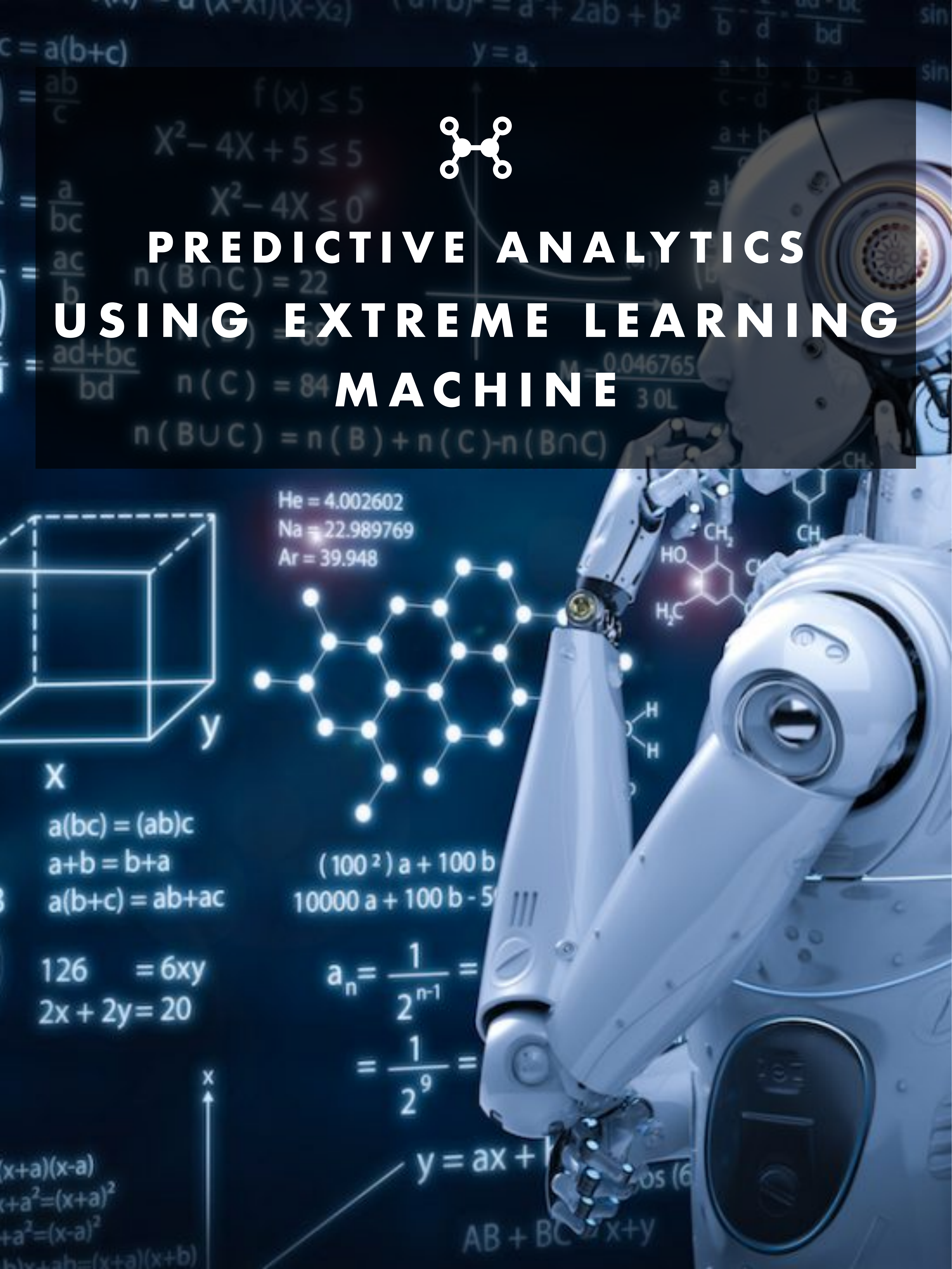
PREDICTIVE ANALYTICS USING EXTREME LEARNING MACHINE



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Predictive Analytics Using Extreme Learning Machine

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Abstract -- In today's technology driven world, large amount of data is being produced every second. The wonder lies in the fact that, with the help of efficient prediction and forecasting algorithms we are able to harness the potential information lying in this huge ocean of data and with this information we can solve many real world problems that involves business problems, health care, banking, finance, crime detection and many other domains. One such algorithm is the Extreme Learning Machine (ELM). It is a feed-forward neural network without back-propagation and hence has faster learning rate, also it does not need any weight or bias tuning and is initialized randomly. It has been applied to several domains and has provided promising solutions with better accuracy as compared to that of other back propagation neural networks. This survey paperhighlights various work done using ELM and the research gapin ELM on different problems across different domains and data.

1 Introduction

Predictive Analytics is an advanced analytics technique to forecast and predict the future happenings and events. It involves many techniques like data mining, statistics, modeling, machine learning and artificial intelligence. It combines these techniques together to find a solution for future problems that may be in modeling business processes, information technology or the real world problems like health care, fraud detection, prediction of natural calamities,say drought or earthquake etc.

The neural networks can provide promising solutions to such problems by predicting the values for parameters used to measure the quantities in the problem domain after applying mathematical models to the input variables. One such neural network is the Extreme Learning Machine (ELM). ELM is a feedforward neural network used for classification regression, clustering, compression, sparse approximation or feature learning having a single layer or multiple layers of hidden neurons where the parameter of the hidden nodes need not be tuned and are initialized randomly. It was invented by Guang - Bin Huang. The major advantage of ELM over other neural networks is that it does not have back-propagation, hence the learning time of ELM is very less as compared to other neural networks.

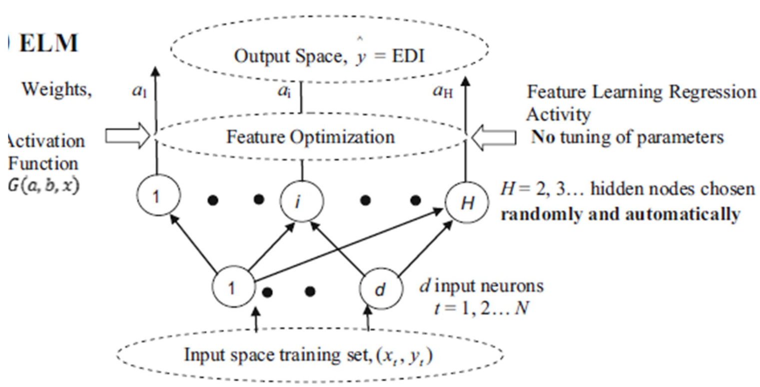

Fig 1. Architecture of ELM

In most applications, ELM is implemented as single hidden layer feed-forward network however if needed the number of hidden layers can be increased.The input layer contains N nodes with each neuron having linear activation function that passes the input to the hidden layers as it is, without any processing , further in the hidden

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layers , the number of hidden nodes is decided by the user which depends on the type of problem. Each of the hidden nodes has a activation function that decides whether a node fires or not according to the threshold value. The choice of activation function depends on the problem to be solved.

In the first stage, ELM randomly initialize the input weights W and bias B of the hidden neurons. Whenw_j=[w_{j1}, w_{j2}, ...,w_{jN}]represent the connectionweights between N input neurons and j^{th}hidden neurons, then the output of the hidden layer H is calculated as follows,

$$H = \sum_{i=1}^{N}\sum_{j=1}^{L} g(w_j x_i + b_j)$$

The output matrix of hidden layer is given by:

$$\mathbf{H} = \begin{pmatrix} h_{11} & h_{12} & . & h_{1L} \\ h_{21} & h_{22} & . & h_{2L} \\ . & . & . & . \\ h_{j1} & h_{j2} & . & h_{jL} \\ . & . & . & . \\ h_{N1} & h_{N2} & . & h_{NL} \end{pmatrix}$$

whereh_{ji}represent the output of the j^{th}hidden neuronsfor the i^{th}input, here i=1,2,..N and j=1,2,..L. Calculatethe output weights β between the hidden layer and the outputlayer using,

$H\beta = T$

$\beta = H\dagger T$

where

$$\beta = \begin{pmatrix} \beta_{11} & \beta_{12} & . & \beta_{1C} \\ \beta_{21} & \beta_{22} & . & \beta_{2c} \\ . & . & . & . \\ \beta_{kj} & \beta_{j2} & . & \beta_{jc} \\ . & . & . & . \\ \beta_{L1} & \beta_{L2} & . & \beta_{Lc} \end{pmatrix}$$

The vector β_j=[β_{j1}, β_{j2},...,β_{jc}], where j=(1,2,..L) represent the connection weight between j^{th} hidden neuron and $c^{th}$the output neuron.

The ELM algorithm is given as:

For the given N training sample (x_i, t_i) with the activation function g(x) and the number of hidden neurons L, the implementation of the original ELM proceeds according to the following steps:

1: Randomly initialize connection weight W between the input layer and the hidden layer and bias B of the hidden neurons.

2: Calculate the hidden layer output, H as:

$$\sum_{i=1}^{N}\sum_{j=1}^{L} g(w_j x_i + b_j)$$

3: Calculate weight between the hidden layer and the outputlayer $\beta = H\dagger T$

2 Literature Survey

Most of the research applications uses data mining methods for prediction, especially in the field of medical dataset. Poornima et al. (2018) gave a survey on predictive analytics methods for various medical related datasets which concludes that the current data mining algorithms have to focus on handling big data. Many researches rely on weather, finance and inventory applications uses statistical methods to gain prediction accuracy.In past few years, ELM has been applied in so many domains including industrial processes, weather forecasting and have provided with promising solutions.Ravinesh C. Deol et al. (2016) forecasted effective drought index using W-ELM. In this study a wavelet based drought model using the Extreme Learning Machine (W-ELM) algorithm where the input data are first screened through the wavelet pre –processing technique for better accuracy is developed to forecast the monthly effective drought index (EDI).The effective drought index (EDI) is an intensive index that considers water accumulation with a weighting function applied to rainfall data over a period of time in order to predict drought-risk. The authors have stressed on the usefulness of wavelet pre-processing for better accuracy by comparing W-ELM, W-ANN, W-LSSVR with their counterparts without wavelet transformation of the predictor data. The reason for this was stated as because the hydro-climatic properties are highly complex and have a high level of non-linearity and non-stationarity which makes it difficult for standalone ML techniques to map the underlying complexity in the hydrologic data. Wavelet pre-processing makes the task more robust by removing different frequencies at different time intervals, providing clarity in understanding the physical structure of EDI time series. Main drawback was only short term EDI could be forecasted, and other climatic variables like temperature, humidity, etc was not considered in the process.

Salesforecasting is another challenging domain where volatility of demands depends on many factors. Particularly in fashion retailing, a versatile forecasting system is essential. Zhan-Li Sun et al. (2008) applied ELM to a real data set from a fashion retailer in Hong Kong to investigate the relationship between sales amount and some significant factors that affect demand such as design factors. The authors observed that the forecasting accuracy of an approach is often influenced by the inherent nature of product and its sales pattern. In this study the sales amount fluctuations were measured by the coefficient of variation (cvs).When the cv was larger i.e. the fluctuation of product's demand is larger, the training, testing and predicting errors of ELM are generally lower and vice-versa.The reason stated was the neural network tends to be biased with data of relatively small variance (small cv) and the bias will decrease the forecasting accuracy.

Teddy Mantoro et al (2011) attempted to devise a better positioning accuracy based on location fingerprinting taking advantage of two important mobile fingerprints namely, signal strength (SS) and signal quality (SQ) and subsequently building a model based on Extreme Learning Machine (ELM). The study is about location determination technique by attempting to determine the location of mobile users by taking advantage of SS and SQ history data and modeling the location using ELM algorithm. The model outperformed the K-Nearest neighbor model using 80 percent training and 20 percent test datasets with 94.22 % and 93.26 % accuracy respectively. The ELM model mostly focused on overcoming the lower minima convergence problem however 100 percent prediction accuracy could not be achieved.

For the optimal control of a Ladle furnace process, accurate prediction of molten steel temperature is very important for which ELM was chosen due to its good generalization performance and fast learning speed in L V Wu et al. (2012). The complete process was divided into two phases – offline design and online sequential learning phase. The activation function used for offline mode was RBF and the number of hidden nodes needed to be predetermined. Due to online sequential training, the size of offline training dataset need not be larger and just should be slightly larger than the number of hidden nodes. Moreover, the new driving dataset need not be stored and is discarded after updating the output weight,so storage can be minimized. The performance of ELM based model was compared with BPNN and SVM in which ELM based model had better accuracy than BPNN, while it was as accurate as SVM.

Predicting hypoglycemia can play an important role in diabetes control and management. Good specificity makes it effective for patients to take corrective actions. Xue Mo. et al. (2013) combined the readings taken from continuous glucose monitoring (CGM) technology with ELM and regularized ELM to predict hypoglycemia with a better accuracy. These methods were compared in terms of root mean square error (RMSE), sensitivity, specificity under the prediction horizons of 10, 20 and 30 min. Further the area under the receiver operating characteristic (ROC) curve (AUC) as a function of sensitivity and specificity is applied to evaluate the performance for different tests accurately. The bigger prediction horizon (PH) induced the worse performance. It was observed that sensitivity improved at the cost of specificity, as the hypoglycemia threshold was increased. Both ELM and R-ELM had comparable performance in terms of AUC, but the number of input nodes cannot be determined for better prediction and generalized performance. An observed flaw was that the sudden changes in glucose level lead by individual metabolic fluctuations could not be detected instantly to overcome which physiological data describing glucose concentration could be used when applying these methods online.

The number of hidden nodes in ELM varies according to application and the data used for accurate prediction and is decided on a trial and error method based on the prediction results but ideally, the model should not be chosen based on testing accuracy as the testing dataset is unseen at the same time selecting number of hidden nodes based on training accuracy might lead to overfitting. SanyamShukla et al. (2016) developed a variant of ELM that does not require manual tuning of the number of hidden neurons. The proposed model also had a minimum network structure, with slightly less testing performance compared to original ELM. The main idea was to set a higher number of hidden neurons and then remove the highly correlated neuron to minimize the network structure. As hidden neurons are not highly correlated, the problem of overfitting was solved.

Yajnaseni Dash et al. (2017) presented variable monsoon trends over Kerala in winter, pre-monsoon, summer-monsoon, and post-monsoon periods.The main aim was to analyze the intensification of water scarcity in Kerala due to increasing occurrence of the rainfall deficit years and decreasing trends in seasonal and post-monsoon

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rainfall. The period chosen was the summer monsoon as heavy rainfall occurs during this period. ELM's performance was compared with that of SLFN and it was observed that SLFN network prediction model provides 6.3977% of mean absolute error whereas ELM provides 3.8729% of error,thus ELM outperformed SLFN.

The presence of noise in the dataset can lead to poor accuracy of the model especially in case of regression. The constraint optimization based ELM for regression (C-ELM-R) can partially solve the problem for lower noise. However, the real world data may be lead to poor generalization ability due to noise. To overcome this problem Yue-Yue Shi et al. (2018) proposed Constrained optimization ELM for Regression based on Hybrid loss function (HC-ELM-R) that combines the l1 norm loss function and l2 loss norm function for limiting the influence of noise on output. To make sure that hybrid loss function solves the purpose, it was chosen to be smooth and differentiable.The SinC standard testing function was used to evaluate the performance of proposed model where it outperformed C-ELM-R and weighted C-ELM-R with lowest root mean square error.

Heart Disease can often be life threatening if not diagnosed at an early stage. Patients suffering from heart diseases have lot of independent factors such as cholesterol, age, sex, blood sugar etc., which can be used effectively for the diagnosis. Salam Ismaeel et al. (2015) deployed ELM to model these factors. The system can avoid costly medical checkups with a warning system for a probable heart disease. The model has five outputs (0-4) giving better performance as compared to other models based on BPNN with four classes or ELM with a single output. The model gave an accuracy of 80% outperforming the work done earlier based on BPNN whose accuracy was 67%. Because of the faster learning rate of ELM, it can be used for big data such that previous data can be used to analyze a new patient.

Xinquan WANG et al. (2015) applied ELM to get the demand forecasting model of tourism in Liaoning province. For more accurate prediction of annual tourism, the synthetic index method was used to calculate the tourism market boom index. After timing phase, the space reconstruction, the original travel data and the tourism market boom index were merged to get the training dataset which was used to train the ELM model. The performance of proposed model as compared with the SVR model. It was found that when estimating the tourism demand by SVR, the determination coefficient of the model was 0.9967 where as for the ELM model it was 0.9980 showing that ELM model can better fit the data as compared to SVR and accurately forecast the tourism demand.

In order to analyze the advantages and disadvantages of ELM with that of other methods like MLP or BPNN, the below section covers some of the work done so far using other neural networks in the domain of weather data.

Drought is a natural disaster that can cause a huge loss of lives and crops and have hazardous impact on society. Its effects are mostly manifested as hydrological drought. The disastrous effects can be limited by learning about previous drought and predicting such probable events. Norbert A Agana et al. (2017) proposed a Deep Belief Network consisting of two Restricted Boltzmann Machines for long term drought prediction using lagged values of Standardized Streamflow Index (SSI) as inputs. The performance of the proposed model was compared with traditional models like multilayer perceptron (MLP) and support vector regression (SVR) for predicting different time scale drought conditions. It was observed that DBN model had lower errors as compared to MLP model, thus making it more reliable and efficient for long term drought prediction. However, its performance over SVR was less significant.The probable reason stated for this was unavailability of large sample size to fully utilize the capabilities of the deep architecture in the DBN model. Also, one more limitation of the study was stated as use of only standardized streamflow index.

Daniel hong et al. (2015) derived the SPI values for duration of 3 to 9 months using average long term monthly rainfall data for eight stations covering both the dry and wet seasons from Selangor river basin in Malaysia. The drought indicators were used as time series for drought forecasting using multi-layer artificial neural network model. More accurate predictions were achieved using SPI of longer durations (6 months and 9 months) rather than 3 months with RMSE values of 0.56, 0.39 and 0.34 for SPI-3, SPI-6 and SPI-9 respectively.

Xin HUANG et al. (2010) used fuzzy clustering iteration method to cluster data of many years rainfall and then considered sensitiveness coefficient as the foundation of calculating weight, which affects the crop output by valid rainfall in each growth stage. The years of agricultural drought was predicted by using the method of R/S analysis and predicting model to research on time series data mining of rainfall. It was observed that model was convenient and authentically feasible in forecasting the years of occurrence of agricultural drought. One of the advantage of using fuzzy set and R/S analysis was that the result was rainy and drought state, not a concrete number, thus range of prediction expanded to a great extent, improving the accuracy of the prediction result. However, the model could not predict the severity of drought, which needs further improvement.

The use of spectral and temporal information contained in input data is enabled by the application of wavelet transformation making it popular area of interest in hydrological modeling. Kavina S DayaJet al. (2016) predicted a drought index i.e. the Standardized Precipitation Index (SPI) using artificial neural network (ANN) and a hybrid ANN with wavelet analysis (W A-ANN) using the main inputs as :precipitation, potential evapotranspiration Southern Oscillation Index, and Nifio 4 index for Brisbane, Australia. It was observed that WA-ANN outperformed ANN model with an increased accuracy of 49.89% based on (RMSE) root mean square value. This improved performance suggested that the error in the prediction can be reduced significantly when the input dataset is decomposed into separate components based on different frequencies that allowed removal of noisy data and revealing the quasi-periodic and periodic components in the original time-series.

Xiaofan Liu et al. (2009) introduced an early warning system to forecast drought using palmer drought severity index (PDSI) and Markov chain model. Based on Digital Elevation Model (DEM), time series of monthly PDSI of all pixels within theLaohahe Catchment were calculated. It was observed that there is an increasing tendency in the frequency of drought occurring in the area of study, which may be the result of temperature increase 0.024 degree per year. The drought states of 12 months were forecasted using Markov chain model with different steps. The results show that Markov chain model could predict drought states for normal and slight drought but the prediction performance decreases greatly as the severity of drought increases also the prediction performance isn't always satisfactory for drought states transition.

Table1: Comparative study of selective prediction works done so far using ELM and other traditional neural networks.

Author	Methodology Used	Advantages	Disadvantages
Ravinesh C. Deo1 et al. (2016)	Forecasting effective drought index using W-ELM	Wavelet preprocessing makes the prediction robust by removing different frequency components at different time scales	Only short term EDI could be forecasted, other climatic variables not considered eg. temperature, humidity etc
Zhan-Li Sun et al. (2008)	Sales forecasting using ELM in fashion retailing	No weight tuning needed, faster learning rate	Solution depends on input weights and hidden bias initialization.
Xiaofan Liu et al. (2009)	Meteorological drought forecasting using Markov chain model and palmer drought severity index (PDSI)	Markov chain has good prediction capability for normal and slight drought	Predictionperformance decreases greatly as severity of drought increases
Teddy Mantoro et al. (2011)	ELM for user location prediction in mobile environment	The method outperformed K-nearest neighbor approaches	Classification boundaries for learning parameters for hidden layer may not be optimal as they don't change during training.
LV Wu et al.(2012)	ELM based Ladle Furnace (LF) temperature prediction model and its online sequential learning	Predictor outperformed SVM and BPNN based predictors.OS-ELM learns continuously on dynamic arriving data.	The performance depends on predetermined parameters i.e. number of hidden nodes and forgetting factor
Xue Mo et al. (2013)	Hypoglycemia prediction using ELM.	Good specificity, acceptable sensitivity	Sudden changes in glucose level lead by individual metabolic fluctuation can't be detected instantly.
SanyamShukla et al. (2016)	Correlation based Extreme Learning Machine	Does not requires manual tuning on number of hidden neurons, it has minimal network structure	Slightly less testing performance than original ELM
Yajnaseni Dash et al. (2017)	Rainfall Prediction of a Maritime State (Kerala), Indiausing SLFN and ELM Techniques	ELM outperformed SLFN as no tuning required, faster than gradient based learning methods.	SLFN has long computation time, stopping criteria and local minima problem
Yue-Yue Shi et al. (2018)	The Constrained Optimization Extreme LearningMachine Based on the Hybrid Loss	With the help of hybrid loss function , large noise problem is solved , hence making it more robust, use of other noise	Average training time of the algorithm is slightly longer

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	Function forRegression	insensitive loss functions avoid computational complexity and slow convergence	
Salam Ismaeel et al. (2015)	Using the Extreme Learning Machine (ELM) Technique for Heart Disease Diagnosis	ELM outperformed other BPNN methods, solves learning time problem hence can be used for Big Data	The performance depends on the constant value and number of hidden neurons in proposed model, more computational efforts needed when dimensions of data are large.
Xinquan WANG et al. (2015)	Demand Forecasting Models of Tourism Based on ELM	ELM outperformed SVR algorithm, higher generalization ability and forecasting precision	The accuracy may vary depending on choice of number of hidden nodes and the activation function used.
Norbert A Agana et al. (2017)	Deep Belief Network for long term drought prediction	DBN model had the highest coefficient of determination and recorded the lowest RMSE and MAE errors as compared to MLP and SVR, better prediction accuracy	Poor accuracy for short term predictions, performance of DBN was less significant over SVR.
Daniel hong et al. (2015)	Drought Forecasting Using MLP Neural Networks	Long duration SPI values can be predicted more accurately using the neural network model	Trial and error method applied to find number of hidden and input nodes for better prediction.
Xin HUANG et al. (2010)	Predicting Agricultural Drought Based on Fuzzy Set and R/S Analysis Model	The result of this prediction model is the rainy anddrought state of rainfall, not the concrete number, sothe range of prediction is expanding, to a greatextent, and improves the accuracy of predictionresult.	Severity of drought could not be predicted by the proposed model
Kavina S DayaJ et al. (2016)	Application of hybrid artificial neural network algorithm for the prediction of standardized precipitation index	Wavelet Analysis results in robust model ,handling the noise,WA- ANN outperformed ANN	More number of parameters were used for SPI prediction, apart from precipitation value.

3 Comments On Results

Extreme learning Machine outperforms well in case of computaional complexity due to the absence of backpropagation. The learning rate is faster compared to other nueral networks and it can also handle dynamic data generation which are basic mandatory features to handle big data. Also neural networks can able to handle non linear data and long duration data better than the data mining and statistical methods. There are some issues in ELM to be resolved yet as listed below.

1. Input weights are assigned randomly in ELM, so the results may be better for certain applications but not for all, so tehniques may be developed to assign weights based on the input parameters and the range of values used for those parameters which may results in rduction of error rate.
2. Choosing the number of hidden layers for ELM plays a major role in prediction accuracy, which may vary depending on the dataset also. Only way to determine the number of Hidden noed at present is trial and error so research may be carried out to find out a standard way to decide upon the number of hidden layers to be used.
3. Many nueral network architectures like ELM are available for classification based prediction, but nueral network that predict forecasting values may also be given impotance.
4. Predictions are carried out in nueral networks based on the previos history of data. Due to this reason, abrupt changes in real time cannot be predicted. A solution is needed to handle sudden change of data in real time.

5. Most of the real time data are more succeptible to noise, hence data feeded to ELM must be preprocessed for noise removal.

4 Conclusion

Extreme Learning Machine (ELM) has been applied to many applications and has provided promising solutions be it hydrological data or sales data. The major advantage of using ELM over other neural networks like MLP, Deep Belief Network (DBN), etc.,is that it does not require weight tuning and does not have back propagation mechanism leading to faster learning rate and generalized performance. However for better prediction ELM has been combined with other preprocessing methodologies like wavelet analysis to deal with large noise in the dataset that could lead to poor results. The hybrid models like OS-ELM, R-ELM, W-ELM, etc tend to add to the accuracy of ELM by additional processing and results in more desirable outputs. But the parameters like number of hidden neurons, activation function etc depends on the type of applications and no fixed method lies to decide on these factors due to which accuracy of the model may get affected.The future work may focus on these parameters that affects the accuracy of the ELM model. Since the weights and biases are initialized randomly, finding out a possible way to control or keep track of these initializations is needed so that good results may be obtained and to determine to what extent these initializations affect the prediction outcomes can be an interesting area of research.

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