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ORIGINAL ARTICLE

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Abstract In the present study, the authors propose DE(A)NN, an integration of data envelopment analysis (DEA) and artificial neural networks (ANN) as a decision making tool. The performance of proposed DE(A)NN is validated on a case study for measuring the relative efficiency of 21 Indian state education boards. As expected, it is observed that DE(A)NN increases the discriminatory power of DEA for ranking of the decision making units.

Keywords Data envelopment analysis · Relative efficiency · Artificial neural network (ANN) · DE(A)NN approach · State boards · Higher secondary education

1 Introduction

Data envelopment analysis (DEA) is a multi criteria decision making (MCDM) technique used for measuring the relative efficiency of decision making units (DMU). Since its introduction in (Charnes et al. 1978), DEA has proved itself to be an effective MCDM technique and a practical tool for performance analysis of different sectors of the society (Banker et al. 1984; Munoz 2016; Mogha et al. 2014; Jauhar et al. 2018; Atici and Podinovski 2015; Kumar and Natarajan 2015); Yang and Li 2017). Some of the reasons of popularity of DEA include its simple structure; it's non parametric nature and its independence for a transforming function. Mathematically, DEA is a linear programming approach that tries to maximize the relative efficiency of a DMU by considering the ratio of weighted sum of inputs to the weighted sum of outputs. Detailed description of the mathematical model of DEA is provided in methodology section.

Thus DEA tries to figure out optimal use of resources to provide the desired output. Efficient use of DEA may help an organization in minimizing or avoiding the wastage of energy, material, time etc. to achieve a quality output. Despite having several advantages, like other MCDM approaches DEA also has some shortcomings making it vulnerable under certain circumstances. For example results obtained through DEA are sensitive to the selection of inputs and outputs; it is difficult to test DEA for the best specification; the number of efficient firms on the frontier tends to increase with the increase in the number of inputs and output variables; DEA can only analyze the relative efficiency of a DMU but cannot predict any future trend about the performance of DMUs. The current trend in DEA research is to increase the efficiency of DEA by hybridizing it with other techniques (Karamouzis and Vrettos 2008; Athanassopoulos and Curram 1996; Wu et al. 2006; Çelebi and Bayraktar 2008; Sreekumar and Mahapatra 2011; Azadeh et al. 2017).

In the present study, an integration of DEA is proposed with Artificial Neural Networks. The resulting algorithm named DE(A)NN is validated by measuring the relative efficiencies of the 21 state boards of higher secondary

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education (HSE) in India. The proposed method is expected to be better than the simple DEA approach because of two reasons: (1) it is likely to improve the discriminatory power of DEA (2) it may help in determining the future estimation of efficiency evaluation.

Figure 1 represent the proposed DE(A)NN model of the approach.

1.1 Case study

The case study considered to validate the performance of DE(A)NN is to measure the efficiency of state boards in India for HSE. Education System in India may be divided into three categories viz. primary, secondary and higher education. Classes I–VIII comes under primary education category and classes IX–XII come under secondary education category. Degree or diploma courses after class XII, comes under the category of higher education. The focus of this study is secondary education which comprises of High School (Xth) and Intermediate (XIIth) examinations. State boards in India play an important role in higher secondary education (HSE).

Here, state education boards of India are represented as DMUs and relevant input and output parameters are considered to formulate an appropriate LPP model. A detailed description of the model along with input/output parameters is given in methodology section later.

The present study is an extension of the work presented in WICT 2017 (Singh and Pant 2018). In which the authors worked on data of 1 year only. In the present paper data of 6 years is considered and given approach DE(A)NN is discussed in detail. This study also provides an extended literature review on DEA, ANN, and the integrated DEA-ANN approaches available in literature.

1.2 Organization of the paper

This paper is segregated into 5 sections including Sect. 1, which is introductory in nature. Section 2 contains a brief literature review on DEA used in education sector; study presented in different application areas of artificial neural network as well as some limited survey available on integrated DEA—ANN approaches. Section 3 of the paper presents methodology used in this paper. Section 4, discusses the case study. The paper is finally concluded in Sect. 5.

2 Literature review

2.1 Data envelopment analysis

DEA was initially proposed by Charnes et al. (1978) and was later extended by Banker et al. (1984). The main objective of DEA is measure efficiency for the cases having multiple output and input criteria where converting these parameters into a single aggregate output or input parameter is neither feasible nor possible.

Some salient features of DEA are as follows:

- DEA is a non-parametric technique modeled as a linear programming problem (LPP).
- It attempts to measure the relative efficiency of DMUs that are carrying out similar operations.
- In DEA, for each individual, optimization is done with the aim of obtaining an efficiency frontier, determined by the set of Pareto-efficient DMUs.
- DEA is applicable when the DMU's are similar or are taken to be as similar in terms of their functionality and in terms of input/output parameters. Further, the problem is modeled such that the DMU's minimize the inputs and maximize the outputs.

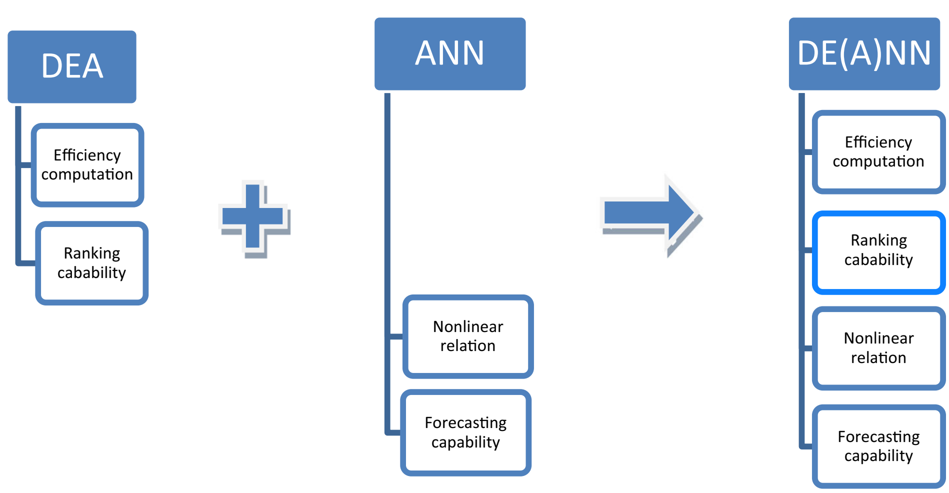


Fig. 1 Proposed DE(A)NN model

Thus, DEA tries to evaluate the maximal performance measure for each DMU relative to the other DMUs in the population. Here, an important point is that each DMU should lie either below or on the frontier. Mathematical model of DEA is given in Sect. 3.1 under methodology.

A brief overview of implementation of DEA in education sector is presented in Table 1 in reverse chronological order. This table provides the specific area (in the field of education) along with input/output parameters. It also provides a short remark on application of DEA.

An examination of the literature is presented in Table 1, it can be seen that there is a plethora of literature of DEA applications in the education sector for many countries like Mexico, Turkey, Italy, Burkina Faso, China, Organization for Economic Co-operation and Development (OECD) countries, England, etc.

Secondly, from the Table 1, it can be noted that most of the studies have been conducted for higher education systems like universities or professional institutes. There is a lack of research for the middle level or secondary education system. This is an important point because a good secondary education system builds up a strong foundation for a well-developed higher education system. These studies are more relevant for a developing country like India where there are number of state boards looking after the development and maintenance of secondary and higher secondary education.

2.2 Artificial neural networks

ANN represents a family of models inspired by structure of neurons in human brain. These models are developed such that they are strongly interconnected and have high capability of computations in parallel with a large number of processors.

Commonly, ANN is made up of three different layers, the output layer, the hidden layer and the input layer. the hidden layer is the middle layer connected to the input as well as to the output layers separately.

The ANN model used in this study is Back Propagation algorithm proposed by Rumelhart et al. (1986), perhaps the most common ANN in practice. This algorithm performs learning based on multilayer feed forward neural network. The three layers ANN model are shown in Fig. 2.

As evident from literature, ANN has been extensively employed to deal with problems occurring in different disciplines. Since this study focuses on education sector, we provide only the references where ANN is applied in education sector. Wang (1992) suggests an ANN model for the pattern oriented comparative study of the national education system of China. Their model estimated the proper national expenditure on education. Stevens et al. (1999) explored the capability of ANN technologies for generating performance models of complex problem-solving tasks without the detailed a priori knowledge of the nature of the task. Authors tested the applicability of their approach by applying this analysis to two diverse domains—high school genetics and clinical patient management. They observed that for both domains ANN generated multiple classification groups defining different levels of competence.

Mahapatra and Khan (2007) proposed EduQUA for evaluating service quality in education sector. They proposed neural network models based on back-propagation algorithm to predict quality in education for different stakeholders.

Santín et al. (2004) provided an introduction to ANNs and review the applications of ANNs in respect of efficiency and concluded that artificial neural networks have a potential to measure technical efficiency and can outperform other techniques when the production process is unknown.

Ogor (2007) presented a methodology by deriving performance prediction indicators to deploy a simple student performance assessment and monitoring system in a teaching–learning environment by focusing on performance monitoring of students' continuous assessment (tests) and examination scores in order to predict their final achievement status on graduation. Karamouzis and Vrettos (2008) and Oladokun et al. (2008) also proposed an ANN model for predicting students' graduation outcomes and academic performance in higher education system, respectively.

Kotsiantis (2012) presented a case study for envisaging students' marks. The research of Kardan et al. (2013) was a study on the difficulties associated with the selection of course in framework of e-learning. They focused on identifying the potential factors affecting student's satisfaction while selecting the online courses. Chhachhiya et al. (2017) applied ANN in an university education system and obtained an optimal neural network architecture with the help of swarm optimization.

3 DE(A)NN approach

To overcome the drawbacks of conventional DEA many researchers integrated it with other econometric methods such as Kuo et al. (2010) proposed a model for green supplier selection by combining ANN and Multi Attribute Decision Analysis (MADA). Authors claimed that the proposed ANN-MADA technique overcomes the drawbacks of conventional DEA. They also showed that their method performs better in comparison to other hybridized variants of DEA by implementing the proposed model on a camera manufacturing unit. Liu et al. (2013) compared

Table 1 Review of data envelopment analysis in education sector

Author(s)	Year	Application area and location of case study	Inputs	Outputs	Remarks
Sagarra et al. (2017)	2017	Higher university education Mexico	Full time equivalent faculty Total enrolment First joining graduates	Scopus papers Graduates	Three way scaling model (INDSCAL) is used Evolution of efficiency in three universities is discussed here
Munoz (2016)	2016	Higher education Chile	No. of under graduate students enrolled No. of graduate students enroll Total no. of professors affiliated to a university No. and percentage of professors with doctoral degrees No. and percentage of full-time professors affiliated to the university Weighted score of the universal Chilean national admission test Universal score that can be used as a proxy of the quality of the students	No. of publications of a university Total amount of monetary resources, expressed in thousands of Chilean pesos that are earned through public grants	Provide the assessment of research efficiency of the Chilean HEIs Different models are proposed to measure the research efficiencies at various levels: the size of the university; proxies of financial and quality factors; research capacity; and complete-hybrid research efficiency
Selim and Bursalıoğlu (2015)	2015	Higher education Turkey	Central government budget appropriations Own Revenue Project allocations (TÜBİTAK) Project allocations (Scientific Research Projects) The total academic	Number of graduate students per academic Number of post graduate students per academic Number of post graduate students per academic Number of publications The number of students graduating who are employed	The two stage DEA is used for performance measurement of universities in Turkey First boot-strapped efficiency of universities is measured using DEA Second factors are measured that affect the efficiency of the universities using random effects Tobit model
Agasisti (2013)	2013	Secondary education Italy	Students: teachers ratio Proportion of computers connected to the web Highest educational level and highest occupational status of parents	Student achievement in math Student achievement in science	Improvement of school results by increasing no. of schools
Miningou and Vierstraete (2013)	2013	Primary education Burkina Faso	Number of reader books/student Number of arithmetic exercise books/student Number of principal teachers/100 pupils Number of certified teachers/100 pupils Number of certified assistant teachers/100 pupils Number of classrooms/100 pupils	Primary school completion rate Gross school attendance rate	Measure the efficiency of primary education in term of transformation of resources to quality and quantity of education and conclude that basic education system is not utilizing the resources optimally Find a relationship between inefficiency and standard of living, and conclude a school is more efficient if it has electricity access, close to a healthcare center or a secondary school

Table 1 continued

Author(s)	Year	Application area and location of case study	Inputs	Outputs	Remarks
Kuah and Wong (2011)	2011	Higher education Hypothetical data	For teaching efficiency Number of academic staffs Number of taught course students Average students' qualifications Y (CGPA) University expenditures (Million USD) For research efficiency University expenditures Number of research staff Average research staffs' qualifications Number of research students Research grant	For teaching efficiency Number of graduates from taught courses Average graduates' results (CGPA) Graduation rate (%) Graduates' employment rate (%) For research efficiency Number of graduates from research Number of publications Number of awards Number of intellectual properties	Measuring the efficiencies of 30 higher education institutes based on research and teaching action
Mitra Debnath and Shankar (2009)	2009	Management Institutes India	No of students (Intake) Fee taken by students (Fee) No of faculty	Average salary of faculty Vision of Institute Satisfaction level of students	The business schools must consider their stakeholders rather than focusing only on profit Also, a large number of management schools show lack of using the resources in an optimum way, resulting dissatisfaction among the students
Johnes and Yu (2008)	2008	Higher education China	Full-time staff to student ratio % of the faculty with assoc professor position or higher Proportion of all students who are postgraduates Research expenditure Library books Area of the buildings	An index of prestige of the HEI Total number of research publications Research publications per member of academic staff	Measurement of the research performance and efficiency of higher education Institutions (HEI) of China The significant differences between HEIs is associated with either geographical location, source of funding or type of university produces some interesting results
Garg et al. (2005)	2005	Higher education India	Funding Number of projects	Productivity: research paper published in Indian, Foreign journals, conferences, etc. Human resource development: PhD, ME completed or undergoing Education: BE/ME curricula revised Linkages established: links with industry, R&D and academic institutions	Some findings about AICTE funds to academics of institutions: The institutes give the importance on fabrication of equipment or development of software programmes, while the accentuation on patents was very less affect was better regarding human resource development ability The funding resulted in designing of new courses and revision of existing courses for both ME and BE courses
Mary Martini et al. (2007)	2004	Secondary education OECD countries	Annual expenditure on secondary education per student Hours per year in school Teachers per 100 students	PISA (Programme for International Student Assessment) survey indicator	Computing efficiency measures for producing health and education, with corresponding estimates of efficiency losses An evaluation across the two sectors, health and education, to see they are efficient or inefficient specific to a country
Bradley et al. (2001)	2001	Secondary education England	School size 1993 School size 1998 Pupil Teacher ratio 1993 Pupil Teacher ratio 1998	Unemployment in 1993 Unemployment in 1998 Rivals within 2 km	Here the consequence of competition is studied on the secondary school's efficiency

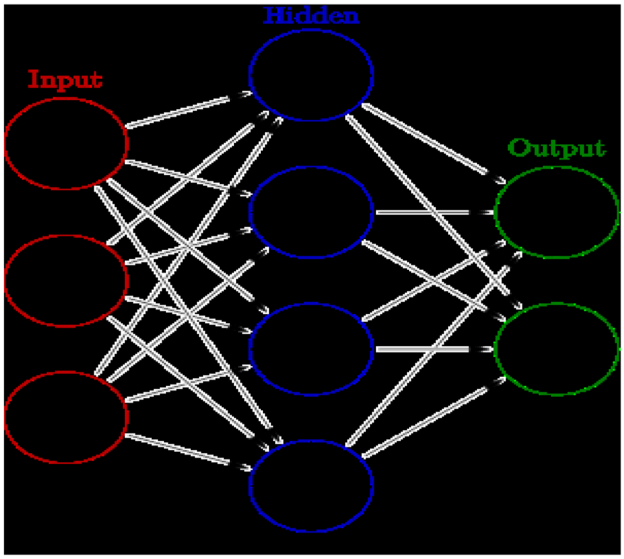


Fig. 2 ANN model

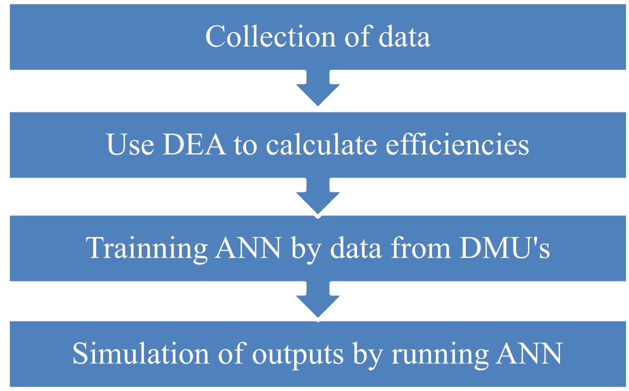


Fig. 3 An integrated DE(A)NN algorithm

conventional DEA, 3-stage DEA, and ANN for efficiency indices estimation. Authors compared these approaches for studying the technical efficiency of twenty-nine semiconductor companies of Taiwan and observed a significant difference in efficiency scores evaluation through different methods. They showed in their study that environmental factors play an important role in technical efficiency evaluation for all three approaches.

Before explaining the proposed methodology in detail, we provide a brief overview of the previous studies where DEA has been integrated with ANN. It is seen from literature that researchers have mostly extended the work of Athanassopoulos and Curram (1996). Here, the authors compared DEA and ANN on theoretical as well as on empirical study basis. They discussed in detail the advantages of DEA over ANNs and ANNs over DEA as efficiency measurement tools for DMUs.

Emrouznejad and Shale (2009) analyzed that when DEA is used for problems having multiple inputs and outputs it taxes the computer resources such as memory and increases the computational complexity due to large data set. Their approach randomly selects a set of DMUs for training neural network (NN) and the obtained NN model is used to calculate the efficiency scores. The authors endorsed their approach on 5 large data sets.

Some other areas where hybridization of DEA and ANN have been applied successfully include the works of Wu et al. (2006) where an integration of DEA and ANN is used to examine the relative branch efficiency of a big Canadian bank. They compared the results with traditional DEA and concluded that the methods are comparable. They also suggested a map to improve the performances of branches and predicted their short term efficiencies with NN.

Çelebi and Bayraktar (2008) proposed an integrated NN-DEA approach for efficient supplier selection. Their method was able to deal with incomplete data. They concluded that the integrated approach performs better than normal DEA. Kwon (2014) demonstrated the benefits of integrating DEA with ANN for measuring the performance of 8 major competitors for mobile phones in the US market.

Though the studies on integration of DEA and ANN are limited, it can be seen from the literature that this approach can help in decision making in real life scenarios in a better manner as compared to the conventional DEA.

3.1 Methodology

The proposed DE(A)NN methodology is expounded in this section. The four steps required for applying the proposed algorithm are shown in Fig. 3 given below.

Step 1: Data collection First step is the collection of data in terms of inputs and outputs parameters relevant for the study taken into consideration. Since such studies are usually done on big organizations/units etc., it is advisable to collect the data from a trusted government organization.

Step 2: Calculation of relative efficiencies through DEA Once the output and input parameters have been decided, the next step is to evaluate the efficiency which can be done either by CCR model or through BCC model of DEA. This is done to measure the relative efficiency of each DMU separately.

According to Charnes et al. (1978), the performance of DMU is the ratio of the weighted sum of outputs to the weighted sum of inputs.

$$Efficiency = \frac{Weighted\ sum\ of\ the\ outputs}{Weighted\ sum\ of\ the\ inputs} \quad (1)$$

It can also be written in the form given below in order to measure the efficiency.

$$Max\, E_m = \frac{\sum_{p=1}^{O} w_p Output_{p,m}}{\sum_{q=1}^{i} z_q Input_{l,m}} \quad (2)$$

$$0 \leq \frac{\sum_{p=1}^{O} w_p Output_{p,m}}{\sum_{q=1}^{i} z_q Input_{l,m}} \leq 1; \quad \mathrm{n = 1,2,3,\ldots, m,\ldots N} \quad (3)$$

$$\mathrm{w_p,\ z_q \geq 0; \quad for\ all\ p,\ q} \quad (4)$$

where E_m—mth DMU's efficiency, p = 1 to O, q = 1 to I and n = 1 to N, $Output_{p,m}$—pth output of the mth DMU, w_p—weight of output $Output_{p,m}$, $Input_{q,m}$—qth input of mth DMU, Z_q—weight of $Input_{q,m}$, $output_{p,n}$ and $input_{q,n}$ are the pth output and qth input respectively of the nth DMU, where n = 1, 2, 3,…,m,…N.

This fractional model obtained is reduced to a linear model and is solved through linear programming technique. If there are N numbers of DMU's, then the efficiency of each DMU is maximized relatively. The fractional model shown in Eqs. 2, 3, and 4, is reformed as a linear program shown in Eqs. 5, 6, 7, and 8.

The general form of CCR DEA model Charnes et al. (1978) can be written as:

$$Max\, E_m = \sum_{p=1}^{O} w_p Output_{p,m} \quad (5)$$

s.t.

$$\sum_{q=1}^{I} z_p Input_{q,m} = 1 \quad (6)$$

$$\sum_{p=1}^{O} w_p Output_{p,n} - \sum_{q=1}^{I} z_p Input_{q,n} \ll 0; \quad for\ all\ p,\ q \quad (7)$$

$$w_p,\ z_q \geq 0; \quad for\ all\ p,\ q. \quad (8)$$

The general form of BCC DEA model Charnes et al. (1978) can be written as:

$$Max\, E_m = \sum_{p=1}^{O} w_p Output_{p,m} + z_{0q} \quad (9)$$

s.t.

$$\sum_{q=1}^{I} z_p Input_{q,m} = 1 \quad (10)$$

$$\sum_{p=1}^{O} w_p Output_{p,n} - \sum_{q=1}^{I} z_p Input_{q,n} + z_{0q} \ll 0; \quad for\ all\ p,\ q \quad (11)$$

$$w_p, z_q \geq 0; \quad for\ all\ p,\ q \quad (12)$$

Step 3: Training of artificial neural network with data Once the efficiencies are calculated we proceed on to the next step where ANN is activated. The input parameters, and the output parameters of DEA, as in step 2, are used as input layer while the efficiency scores evaluated with conventional DEA are considered to be the output layer for ANN. Efficiency scores are considered as targets for ANN and it is expected that through the training process, we can achieve these targets as closely as possible. Through a trained ANN, one can identify the relations among these parameters.

For finding the suitable network or architecture, we specified the learning algorithm and each layer's transfer function; the hidden layer neurons are arbitrary in number and are determined on trial and error basis. As the targets are already set and the ANN is designed so as to meet these targets, error is calculated in each step through performance function between actual and estimated outputs.

Step 4: Simulation of outputs In the fourth and the final step, simulations are done for future prediction and for ranking. With simulation we predict the efficiency and performance of the forthcoming years on the basis of the input parameters considered.

4 The case study: state education boards of India

The proposed DE(A)NN approach is used to measure the relative efficiency of 21 State Education Boards for HSE in India (i.e. Intermediate level). The steps discussed in the previous section are implemented in the following manner.

Step 1: Data collection Input and output data is taken from Statistical Report of Ministry of Human Resources and Development, India for the years 2009–2014. Since we have considered 21 states boards of India, the total number of decision making units becomes 126.

Table 2 provides the input and output criteria used in this study and Table 3 provides the numeric data for efficiency calculation of DEA. Basis of taking input parameters is that for any education system; numbers of students are the primary concern. Appearance of girls shows the participation of social aspects (gender). Furthermore output parameters concern, every educational entity is judged by the parents as well as society; on how many students

Table 2 Inputs and outputs

Inputs	Outputs
I_1: No. of boys appeared	O_1: No. of boys passed
I_2: No. of girls appeared	O_2: No. of girls passed
I_3: Total no. of students appeared	O_3: Total no. of students passed
	O_4: %age of students passed
	O_5: %age of students secured 60% and above marks

Table 3 Inputs and outputs for efficiency evaluation

Characteristic	Inputs			Outputs				
	I_1	I_2	I_3	O_1	O_2	O_3	O_4	O_5
Max	1,564,481	1310227	2,874,708	1,410,578	1,248,678	2,659,256	93.616	68.670
Min	2330	2548	4972	1721	1766	3487	46.3	1.0452
Avg/mean	216,519.63	173,129.06	389,648.69	163,645.77	144,575.32	308,221.1	76.9757	20.9263

passed? What is the passed percentage? and how much students secured high percentages?

Step 2: Calculation of relative efficiencies through DEA The CCR model, input oriented, of traditional DEA is used for the efficiency measurement of DMUs. The Table 4 provides the 126 DMUs, that is, 21 state boards for 6 years along with their technical efficiency (TE) and pure technical efficiency (PTE) scores. Technical efficiency is a unit that operates under constant returns to scale (CRS) value if an increase in inputs results in corresponding increase in the outputs, and pure technical efficiency measure is obtained by estimating the efficient frontier under the assumption of variable returns to scale (VRS) value and is obtained through BCC model. A comparison between technical efficiency and pure technical efficiency for the different years is shown in the Fig. 4. These efficiency scores are calculated using DEAP software.

Step 3: Training of artificial neural network with data For training the ANN, three input and five output parameters, given in section data collection in Table 2 are considered as input layer and the efficiency scores evaluated with DEA in step 2 as the output/target layer. The hidden layer in ANN and the number of neurons are determined by hit and trial method. The topology of the proposed network is given in Fig. 5. Here, sigmoid function is used for the hidden layer while the output function is linear. The network is trained for data obtained for 4 years 2009–2012.

MATLAB implementation of the ANN model used in this study is depicted in Fig. 6 showing 8 inputs; 1 output; 1 hidden layer and 8 neurons in the hidden layer.

The training parameters of the neural network in the MATLAB are provided in Fig. 7.

Table 5 show the input/output parameters, and target data used during the training phase and the evaluation phase.

Step 4: Simulation of outputs For predicting the future efficiency, data for 2 years i.e. 2013 and 2014 is utilized. Figure 8 depicts the error observed in various processes of data sets for the considered ANN. These processes are training, validation, and testing. While Fig. 9 depicts correlations coefficient of these processes among outputs and targets on test data sets. In Table 6, efficiencies of DMUs obtained through ANN along with the corresponding ranking are given. This table also provides the average efficiency values obtained through DEA and ANN. Figure 10 provides a bar chart to compare technical efficiency (TE), pure technical efficiency (PTE) and ANN efficiency for the given years. From these results and figures, it can be easily seen that integration of ANN in DEA helps in improving the discriminatory power of the latter. These results indicate that on the basis of the input and output selected and averaging the 6 years data, Council of Higher Secondary Education, Manipur and Goa Board of Secondary and Higher Secondary are most efficient for HSE while JK State Board of School Education is least efficient. The JK State Board of School Education is least efficient in both assessments. An interesting observation from the results is that highest passed percentage of students came from West Bengal Council of HSE, Kolkata, but still it is not the most efficient board on the basis of the selected input and output parameters.

Table 4 TE, PTE of state boards and their ranking

DMUs	State board	2009				2010				2011			
		TE	Rank	PTE	Rank	TE	Rank	PTE	Rank	TE	Rank	PTE	Rank
1	Board of I E, Andhra Pradesh	0.65	14	1	1	0.709	13	0.773	10	0.722	15	0.73	12
2	Assam HSE Council	0.83	12	0.839	7	0.865	10	0.865	8	0.864	10	0.906	5
3	Bihar I E Council	1.00	1	1	1	1	1	1	1	1	1	1	1
4	Chhattisgarh Board of S E	0.89	10	0.886	5	0.863	11	0.864	9	0.899	7	0.904	6
5	Goa Board of Secondary and Higher S E	1.00	1	1	1	1	1	1	1	1	1	1	1
6	Gujarat Secondary and Higher S E Board	0.99	2	1	1	0.995	2	1	1	0.996	2	1	1
7	Board of SEd Haryana, Bhiwani	1.00	1	1	1	1	1	1	1	0.946	5	0.952	3
8	H.P. Board of SEd	0.95	5	1	1	0.935	5	0.935	3	0.903	6	1	1
9	Jammu and Kashmir State Board of SEd	0.53	16	0.533	10	0.638	15	0.638	12	0.552	17	0.558	14
10	Jharkhand Academic Council, Ranchi	0.86	11	0.858	6	0.631	16	0.633	13	0.68	16	0.682	13
11	Dept of Pre-University Education, Karnataka	0.62	15	0.673	9	0.705	14	0.729	11	0.752	14	0.762	11
12	Kerala Board of HSE	0.93	6	1	1	1	1	1	1	1	1	1	1
13	Maharashtra S B of Secondary and HSE	0.92	8	1	1	0.847	12	1	1	0.8	13	0.934	4
14	Board of S E, Madhya Pradesh	0.97	4	0.971	2	0.916	6	0.916	5	0.89	9	0.89	8
15	Council of HSE, Manipur	1.00	1	1	1	1	1	1	1	1	1	1	1
16	Mizoram Board of SEd	1.00	1	1	1	1	1	1	1	1	1	1	1
17	Nagaland Board of SEd	0.98	3	1	1	0.897	8	0.9	6	0.84	12	0.865	10
18	Tripura Board of S E	0.81	13	0.817	8	0.873	9	0.889	7	0.965	4	0.984	2
19	U P Board of High School and I E	0.92	7	1	1	0.944	3	1	1	0.977	3	1	1
20	Board of SEd Uttarakhand	0.89	9	0.917	4	0.94	4	0.94	2	0.892	8	0.9	7
21	West Bengal Council of HSE, Kolkata	0.89	9	0.936	3	0.915	7	0.932	4	0.855	11	0.866	9
DMUs	State board	2012				2013				2014			
		TE	Rank	PTE	Rank	TE	Rank	PTE	Rank	TE	Rank	PTE	Rank
1	Board of I E, Andhra Pradesh	0.68	14	0.689	13	0.655	17	0.83	11	0.774	16	1	1
2	Assam HSE Council	0.853	10	0.878	9	0.799	15	0.841	9	0.874	11	0.89	9
3	Bihar I E Council	1	1	1	1	1	1	1	1	0.914	8	0.923	6
4	Chhattisgarh Board of S E	0.886	8	0.893	7	0.859	9	0.859	7	0.852	13	0.861	12
5	Goa Board of Secondary and Higher S E	1	1	1	1	1	1	1	1	1	1	1	1
6	Gujarat Secondary and Higher S E Board	0.996	2	1	1	0.949	6	0.949	2	1	1	1	1
7	Board of SEd Haryana, Bhiwani	0.916	6	0.934	3	0.821	13	0.908	6	0.929	7	1	1
8	H.P. Board of SEd	0.921	5	0.929	4	0.888	8	0.927	4	0.871	12	0.898	8
9	Jammu and Kashmir State Board of SEd	0.602	15	0.637	14	0.504	18	0.506	14	0.586	17	0.586	13
10	Jharkhand Academic Council, Ranchi	0.823	11	0.824	10	0.808	14	0.809	13	0.935	6	0.938	5
11	Dept of Pre-University Education, Karnataka	0.809	13	0.81	12	0.792	16	0.826	12	0.832	15	0.863	11
12	Kerala Board of HSE	1	1	1	1	0.961	3	1	1	1	1	1	1
13	Maharashtra S B of Secondary and HSE	0.814	12	0.814	11	0.848	10	0.848	8	0.977	4	0.978	3
14	Board of S E, Madhya Pradesh	0.881	9	0.881	8	0.832	12	0.833	10	0.913	9	0.913	7
15	Council of HSE, Manipur	1	1	1	1	1	1	1	1	0.993	3	1	1
16	Mizoram Board of SEd	1	1	1	1	0.951	5	1	1	1	1	1	1
17	Nagaland Board of SEd	0.93	4	0.948	2	0.834	11	0.922	5	0.9	10	0.944	4
18	Tripura Board of S E	0.961	3	1	1	0.96	4	1	1	0.96	5	0.984	2
19	U P Board of High School and I E	1	1	1	1	1	1	1	1	1	1	1	1
20	Board of SEd Uttarakhand	0.911	7	0.912	5	0.904	7	0.936	3	0.839	14	0.865	10

Table 4 continued

DMUs	State board	2012				2013				2014			
		TE	Rank	PTE	Rank	TE	Rank	PTE	Rank	TE	Rank	PTE	Rank
21	West Bengal Council of HSE, Kolkata	0.853	10	0.898	6	0.994	2	1	1	0.999	2	1	1

Abbreviations used in Tables 4 and 6 IE: intermediate education; HSE: higher secondary education; SE: secondary education; SEd: school education

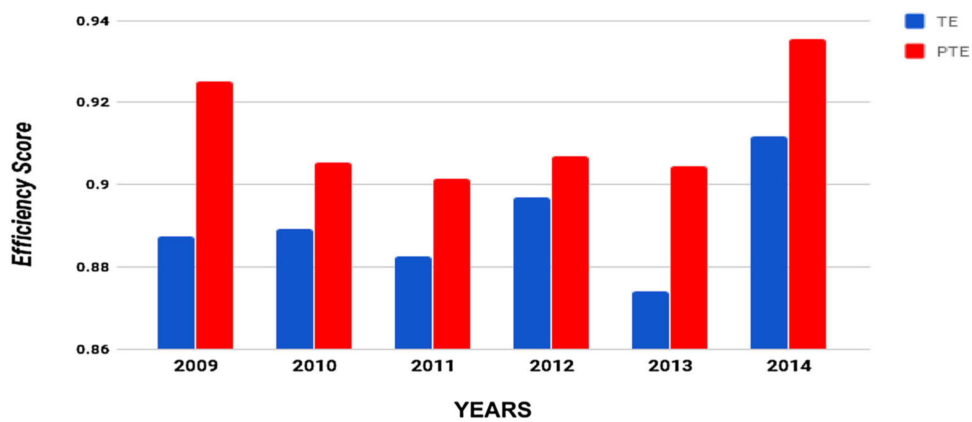


Fig. 4 Comparison of technical and pure technical efficiency scores for various years

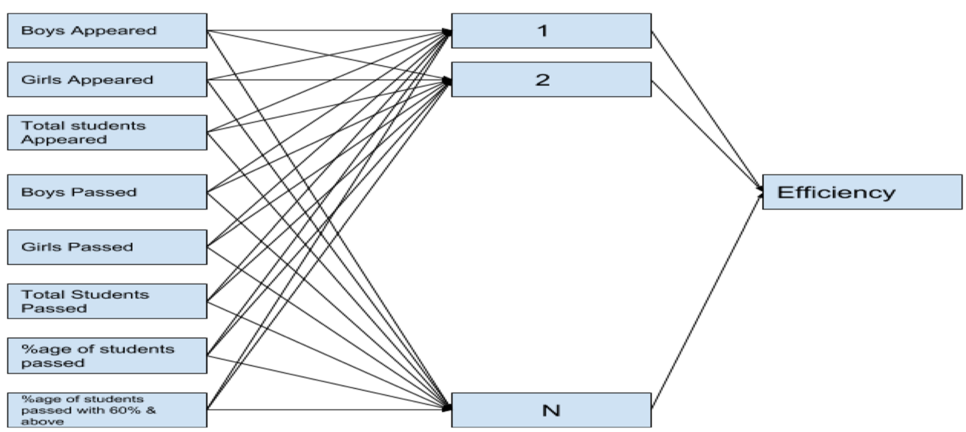


Fig. 5 Proposed network topology

5 Conclusions

One of the drawbacks with DEA is that it does not have a strong discriminatory power due to which sometimes many DMUs get the ranking one (indicating efficiency). This may not be the case in real life scenario. Therefore methods are needed to improve the robustness of DEA. In the present study an effort is made to integrate ANN with DEA to enhance the performance of DEA. The proposed DE(A)NN is more flexible than DEA due to the nonlinearity of NN. Consequently, it is able to address eccentric, corrupted, and noisy data in better manner than the traditional econometric methods.

Further, the inclusion of ANN, can also help in predicting the efficiency of the DMUs for next periods of assessment. This feature could be particularly beneficial for the growth and development of education sector. The present study can be extended in several directions. Social aspects and sensitivity analysis can be included to make the problem more realistic in nature. Board's assessment would be made by including expenditure per board, number of teachers per boards, social aspects of students, etc. as input parameters and number of students going for professional course, number of students stoping their education after secondary education, teachers having higher degree qualifications viz Ph.D., etc. Further some of the

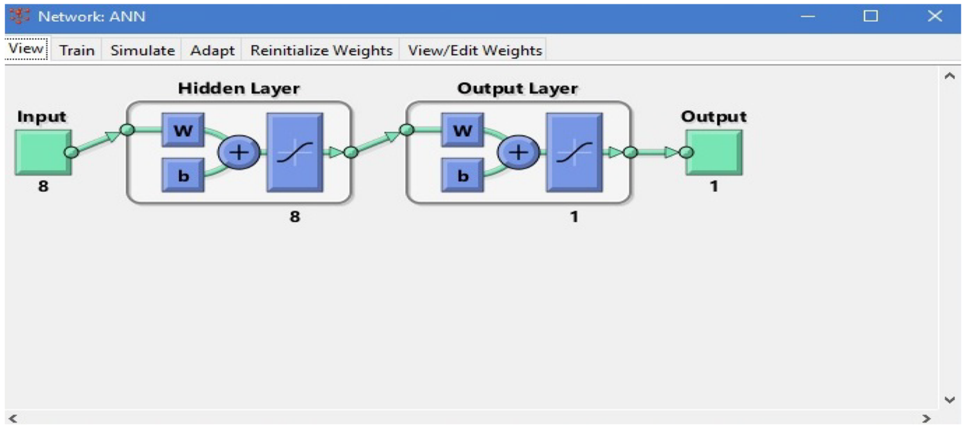


Fig. 6 Proposed artificial neural network

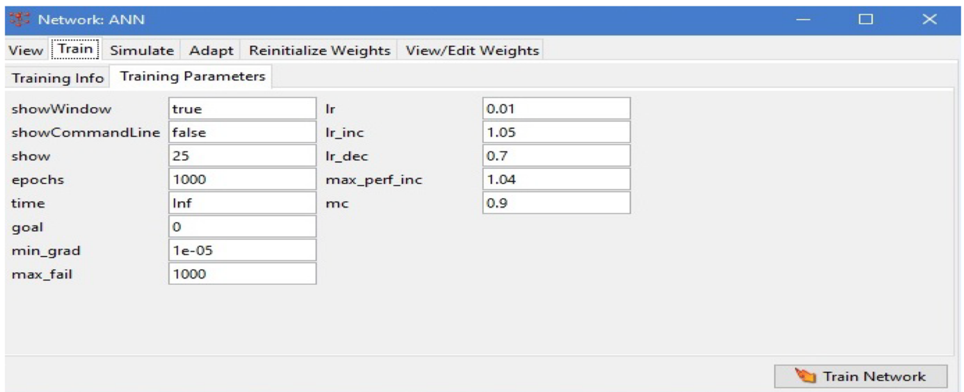


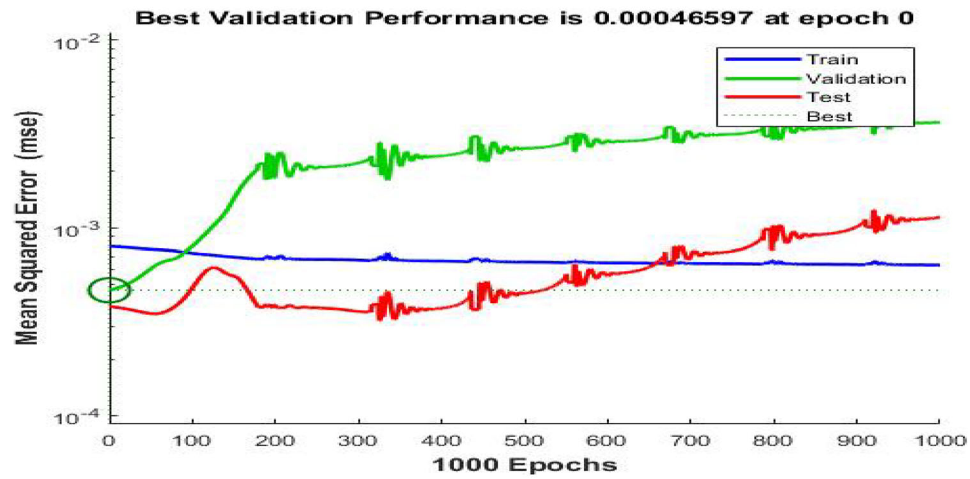
Fig. 7 Training parameters of the network

Table 5 Efficiency evaluation phases of higher secondary education state boards

Training phase	Prediction phase
Here, the data of 4 years i.e. 2009, 2010, 2011 and 2012 is used to train the neural network	Here, the data of 2 years i.e. 2013 and 2014 is used for future prediction of the efficiency
Data provided in training	Data provided in prediction
a. Input: all the input and output parameters of higher secondary state boards	a. Input data: all the input and output parameters of higher secondary state boards
b. Target data: DEA efficiency (TE and PTE)	b. Here no target is provided
	c. Rather we simulate the previously trained network
Data obtained after training	Data obtained after prediction
a. ANN efficiency of 4 years i.e. 2009, 2010, 2011 and 2012	a. ANN efficiency of 2 years i.e. 2013 and 2014
b. Developed the neural network model for further prediction	

input and output parameters taken in this study may involve some amount of uncertainty. Such type of uncertainty may be modelled through fuzzy concepts. So, integration of present approach with fuzzy approach/parameters may be considered as a further research direction. The DE(A)NN approach proposed in this study can be applied in other engineering as well as management problems also, for example banking sector, economic planning, healthcare systems.

Fig. 8 Error in training, validation and the test process



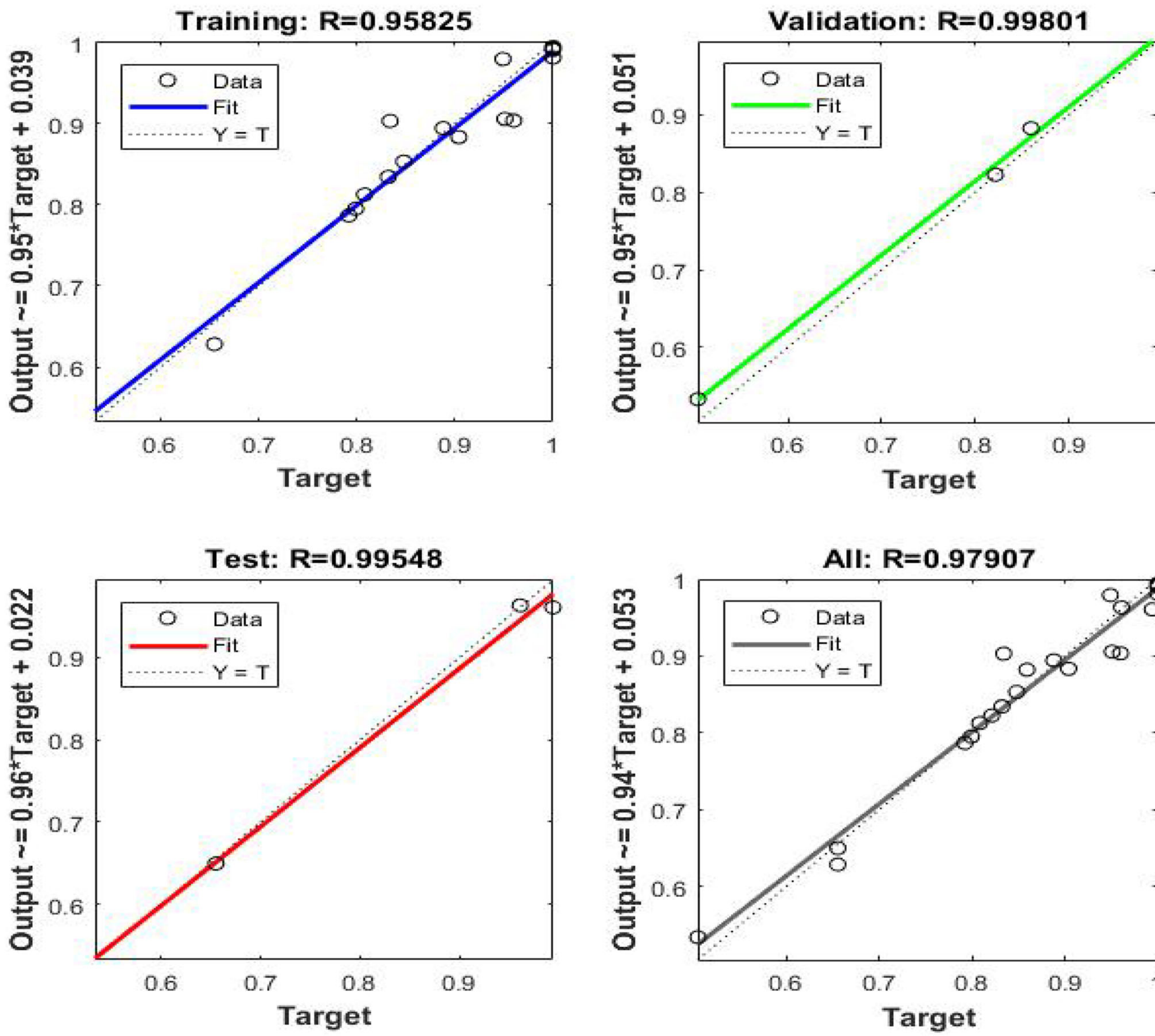


Fig. 9 Regression analysis

Table 6 Efficiency and rank of different DMUs evaluated through ANN and comparison of average rank of DEA and ANN

DMUs	State boards	2009		2010		2011		2012	
		ANN	Rank	ANN	Rank	ANN	Rank	ANN	Rank
1	Board of I E, Andhra Pradesh	0.651	19	0.722	18	0.753	18	0.715	20
2	Assam HSE Council	0.89	16	0.876	16	0.895	14	0.905	14
3	Bihar I E Council	0.979	4	0.992	2	0.982	3	0.974	6
4	Chhattisgarh Board of S E	0.895	15	0.943	8	0.919	10	0.915	13
5	Goa Board of Secondary and Higher S E	0.969	5	0.953	7	0.983	2	0.984	3
6	Gujarat Secondary and Higher S E Board	0.984	2	0.988	3	0.988	1	0.988	1
7	Board of SEd Haryana, Bhiwani	0.995	1	0.996	1	0.945	8	0.937	9
8	H.P. Board of SEd	0.98	3	0.963	6	0.958	7	0.96	7
9	Jammu and Kashmir State Board of SEd	0.568	21	0.668	20	0.581	21	0.627	21
10	Jharkhand Academic Council, Ranchi	0.863	17	0.632	21	0.665	20	0.863	15
11	Dept. of Pre-University Education, Karnataka	0.613	20	0.68	19	0.746	19	0.782	19
12	Kerala Board of HSE	0.898	13	0.97	5	0.973	5	0.979	5
13	Maharashtra S B of Secondary and HSE	0.925	10	0.852	17	0.785	17	0.815	18
14	Board of S E, Madhya Pradesh	0.94	7	0.911	14	0.878	15	0.841	17
15	Council of HSE, Manipur	0.966	6	0.987	4	0.981	4	0.986	2
16	Mizoram Board of SEd	0.897	14	0.935	9	0.936	9	0.944	8
17	Nagaland Board of SEd	0.933	9	0.92	12	0.899	13	0.926	11
18	Tripura Board of S E	0.852	18	0.895	15	0.905	12	0.918	12
19	U P Board of High School and I E	0.937	8	0.927	10	0.97	6	0.983	4
20	Board of SEd Uttarakhand	0.915	11	0.912	13	0.915	11	0.929	10
21	West Bengal Council of HSE, Kolkata	0.902	12	0.922	11	0.842	16	0.85	16

DMUs	State boards	2013		2014		Average values for all years			
		ANN	Rank	ANN	Rank	DEA	Rank	ANN	Rank
1	Board of I E, Andhra Pradesh	0.657	20	0.818	19	0.767417	19	0.719333	20
2	Assam HSE Council	0.85	13	0.91	13	0.859	17	0.887667	15
3	Bihar I E Council	0.969	4	0.805	20	0.986417	7	0.950167	6
4	Chhattisgarh Board of S E	0.899	10	0.885	15	0.875917	16	0.909333	11
5	Goa Board of Secondary and Higher S E	0.973	3	0.989	1	1	1	0.975167	2
6	Gujarat Secondary and Higher S E Board	0.911	8	0.905	14	0.98925	5	0.960667	4
7	Board of SEd Haryana, Bhiwani	0.837	15	0.943	9	0.9505	8	0.942167	8
8	H.P. Board of SEd	0.928	6	0.935	10	0.929667	10	0.954	5
9	Jammu and Kashmir State Board of SEd	0.565	21	0.607	21	0.572417	21	0.602667	21
10	Jharkhand Academic Council, Ranchi	0.819	16	0.934	11	0.78975	18	0.796	18
11	Dept of Pre-University Education, Karnataka	0.77	17	0.821	17	0.76475	20	0.735333	19
12	Kerala Board of HSE	0.908	9	0.965	5	0.991083	4	0.948833	7
13	Maharashtra S B of Secondary and HSE	0.847	14	0.947	8	0.898167	15	0.861833	16
14	Board of S E, Madhya Pradesh	0.74	19	0.82	18	0.9005	14	0.855	17
15	Council of HSE, Manipur	0.99	1	0.988	2	0.999417	2	0.983	1
16	Mizoram Board of SEd	0.746	18	0.961	6	0.995917	3	0.903167	13
17	Nagaland Board of SEd	0.866	12	0.95	7	0.913333	12	0.915667	9
18	Tripura Board of S E	0.887	11	0.925	12	0.933833	9	0.897	14
19	U P Board of High School and I E	0.984	2	0.987	3	0.987083	6	0.964667	3
20	Board of SEd Uttarakhand	0.92	7	0.883	16	0.904167	13	0.912333	10
21	West Bengal Council of HSE, Kolkata	0.966	5	0.973	4	0.9285	11	0.909167	12

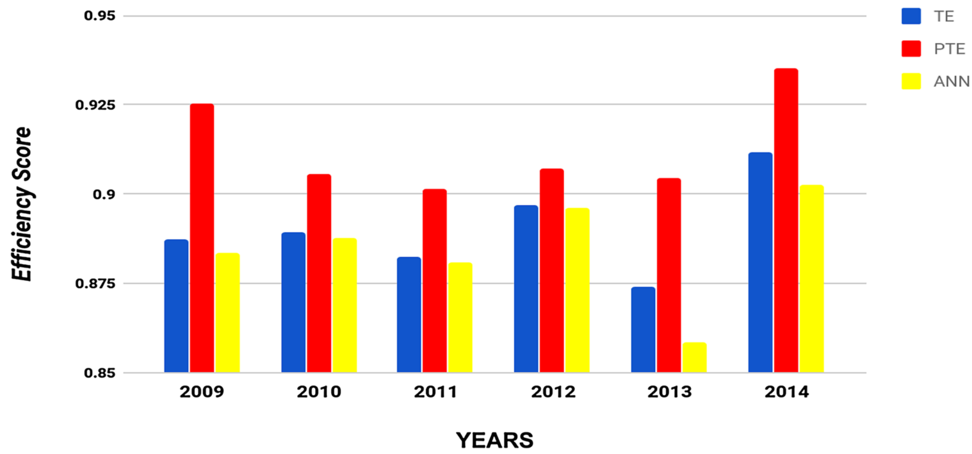


Fig. 10 Comparison of efficiency scores (technical, pure technical, and ANN) of state boards for various years

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