Research Article

Deep Neural Network Associate Efficient Elephant Herding Optimization for Diagnosing Angiographic Disease Condition

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Abstract: The significant intention of the research is to diagnosing the normal and abnormal situations of heart diseases through the Artificial Intelligence (AI) technique. The analysis anticipates employing various AI techniques, amid Deep Neural Network (DNN) performs superior over other methods. Investigating the methodology of DNN, it is evident that weights associated with neurons play a vital role, and changes in weights influence the result. The research aims to identify appropriate weights to associate with neurons, which is time-consuming and complicated through the trial-and-error process. The complication urges incorporating optimization techniques to identify appropriate weights to diagnose heart disease situations. The techniques involved in this process are an evolutionary strategy and swarm intelligence strategy. The result shows an Efficient Elephant Herding Optimization (EEHO) performs better in the three-test case database. EEHO configure weights employed in DNN unveils accuracy of 98.9% in Cleveland database, 98.8% in Hungarian database, and 97.1% in Switzerland database. In general, the result from the three-test case database exhibits proficient performance in most test-case measures.

Keyword: Heart diseases diagnosing, Artificial Intelligence (AI), Deep Neural Network (DNN), Efficient Elephant Herding Optimization (EEHO).

1. Introduction

The heart failure fundamentally implies that the heart isn't pumping just as it ought to be. Essentially the greater part of the heart failures emerge in view of coronary issues, hypertension and diabetes that harm the heart[1]. World Health Organization (WHO) records cardiovascular disease as one of the uppermost issue to human deaths in the years[2]. Heart disease[3] is a dangerous disease that influences the functionality of the heart, and offers ascend to problems namely the infection of the coronary artery and diminished blood vessel function[4]. Normally, medicinal experts reach at diagnoses dependent on sonography, electrocardiography, angiography, and blood test results. CHD isn't adequately diagnosed among the early disease stage, but for positive treatment, its initial analysis is important[5]. Though, diagnoses are prepared dependent on medical experts' personal experiences and understanding of the disease, which increase the dangers of mistakes, increase treatment times, interruption suitable treatment, and significantly increase costs[6]. In request to deal of these problems, various assessments have been led on clinical decision emotionally support systems employing various techniques, for instance, data mining and machine learning[7,8,9]. Different classification and regression processes have been utilized to distinguish heart disease[10]. A wide range of smart-systems have been advanced to develop community-health, decrease healthcare expenses and encourage excellence of life, among others. Such systems heavily depend on artificial intelligence[11]. Deep Neural Networks (DNNs)[12,13] might be extremely in effect for the cataloguing over highly sized data sets, particularly in the medical field, where the recognition of a particular connected to a disease is significance[14]. Elephant Herding Optimization (EHO) approach is a latest swarm intelligence method and the motivation for this procedure was the herding of the elephants[15]. The uses of EHO algorithm display its outstanding performance in solving optimization issues[16].

2. Literature review

Ivanoe De Falco et al.[17] 2019, had planned the method to discover appropriate model for a DNN utilized for a classification issue regarding accomplishment of the uppermost classification accurateness. The methodology depends on a distributed version of Differential Evolution (DE), a variability of an evolutionary algorithm. To assess the methodology, in that research they research the problem to Obstructive Sleep Apnea (OSA). Also, the technique outperforms in terms of accurateness all the various classifiers examined, as it is prove additionally by statistical analysis.

Haotian Shi et al.[18] 2019, had anticipated to develop the ECG heartbeat classification, the research offers a programmed ordering model. In convolutional neural network (CNN) and long short-term memory (LSTM) network, a deep structure with several input layers was anticipated. The system was estimated by couple of division systems of the MIT-BIH arrhythmia database. The class focused on system attained a general precision of 99.26% and issue concerned with scheme acquired a precision of 94.20%. The assessment with preceding mechanism demonstrated the outstanding presentation of the system.

Nahian Ibn Hasan and Arnab Bhattacharjee[19] 2019, had suggested to categorize numerous heart diseases utilizing 1D deep-CNN that can altered ECG signal was given as an input signal to the network. The technique is functional on three-publicly accessible ECG records and it is found to be better than different methodologies as far as classification precision. In MIT-BIH, St.-Petersberg, PTB databases the planned technique attains maximum precision.

Gai-Ge Wang et al.[20] 2015, had planned a sort of swarm-based metaheuristic search technique, named EHO, for resolving optimization tasks. In EHO, the elephants in respectively clan are efficient by its present location and matriarch through clan updating operator. To show its viability, EHO is benchmarked by 15-test cases associating with BBO, DE and GA. The outcomes demonstrate that EHO could discover the superior standards on maximum benchmark issues than those 3-metaheuristic techniques.

3. Proposed Methodology

The research includes three-database namely Cleveland, Hungarian and Switzerland (*available in Heart Disease Data Set, UCI Machine Learning Repository*) consists of 720-data's for diagnosing angiographic disease status. Collectively, 70% of database used for training and 30% of database used for testing. The previous research exhibits the performance of DNN over other AI techniques, which is not consider to be optimum performance for diagnosing the normal and abnormal conditions of heart diseases. Configuring DNN with appropriate weights is an alternate choice of action in terms of performance enhancement. The process of identifying appropriate weights for configuring DNN through trial-and-error process is complicated. The proposed approach includes optimization techniques to configure DNN, which reduces computational complexities. The techniques involve in the process of DNN configuration are Evolutionary Algorithm (EA), Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), Artificial Fish Swarm Optimization (AFSO), Social Spider Optimization (SSO), Elephant Herding Optimization (EHO), opposition based Elephant Herding Optimization (OEHO) and Efficient Elephant Herding Optimization (EEHO). The process of incorporating opposition strategy and Cauchy distribution strategy in updating process make the proposed technique an efficient methodology.

3.1 Efficient Elephant Herding Optimization (EEHO)

The working procedure to configure DNN with appropriate weights inspired from elephant's herding behavior. Elephants are social behaving mammals calm of about clans and individually clan headed under matriarch (female elephant) illustrate in figure-1. In optimization problem the matriarch is consider as fittest individual elephant in this clan. Each generation starting, a male elephant leave the clan and live solitarily far away from the key elephant assembly. In addition, the research includes opposition based solution generation to increase the chance of finding optimal weights and Cauchy distribution process along with clan updating operator and separating operator, which drives the solution towards optimal point without getting into trap.

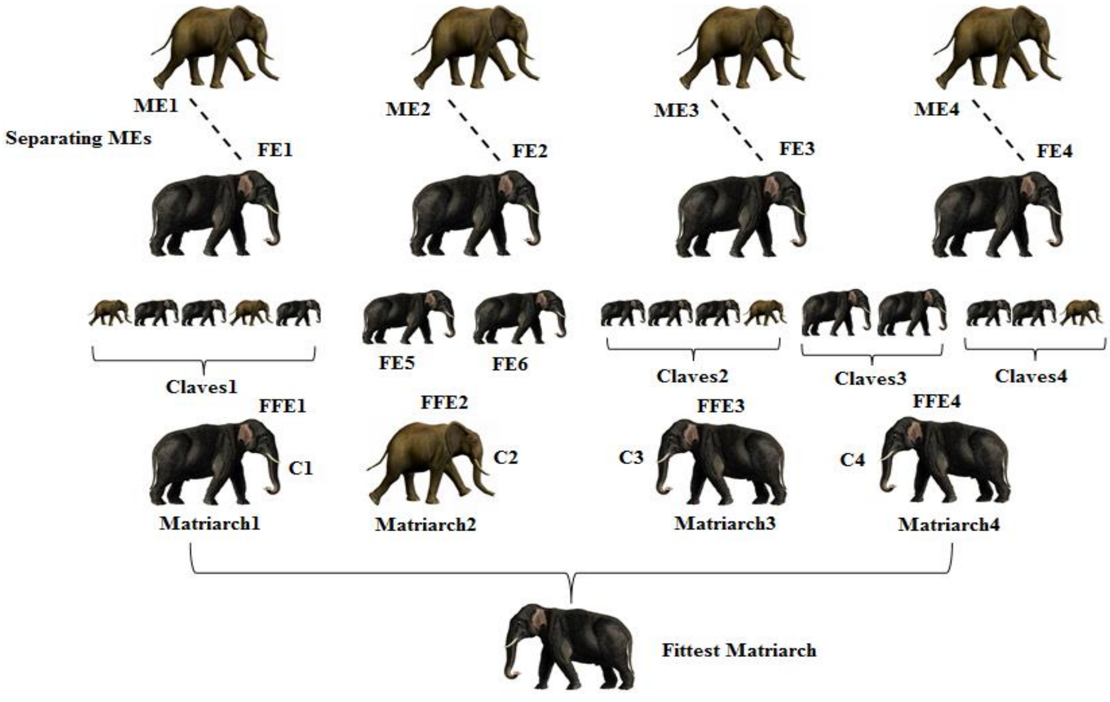

Figure-1, Elephant's-behaviour EHO

Initial solution
The process of generating random solution in the range of -10 to 10 with respect to number of input attributes for finding appropriate weights. The process also includes opposition strategy to increase the chance of finding optimal solution. Iteration holds 10-solutions for computation process and the both mathematical expression detailed below.

$$I_i = I_1, I_2, ... I_n \tag{1}$$

$$Op_i = x + y - Ii \tag{2}$$

Fitness Computation
This process is used to evaluate the fitness of above generated solutions in order to identify the fittest solution appropriate for the research context.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

Clan updating operator
As stated, the elephants live organized beneath the headship of a matriarch in respectively clan. Hence, for individually elephant in clan ci, following place is subjective by matriarch *ci*. For the elephant *j* in clan *ci*, it can be efficient as

$$p_{new,ci,j} = p_{ci,j} + \alpha \times \left(p_{best,ci} - p_{ci,j}\right) \times r \tag{5}$$

Where $p_{new,ci,j}$ and $p_{ci,j}$ are freshly reorganised and old place for elephant *j* in clan *ci*, individually. $\alpha \in [0, 1]$ is a scale factor which regulates the impact of matriarch *ci* on $p_{ci,j}$. $p_{best,ci}$ signifies matriarch *ci*, that is the suitable elephant specific in clan *ci*. $r \in [0, 1]$.
In this regards, the suitable elephant in respectively clan cannot be efficient by equation (5), i.e., $p_{ci,j} = p_{best,ci}$. To avoid the condition, for the fitting elephant, it can be reorganized as

$$p_{new,ci,j} = \beta \times p_{center,ci} \tag{6}$$

where $\beta \in [0, 1]$ is a aspect that controls the stimulus of the $p_{center,ci}$ on $p_{new,ci,j}$. The fresh discrete $p_{new,ci,j}$ in equation (6) is produced by the evidence gained by the elephant individuals in clan ci. $p_{center,ci}$ is the core of clan *ci*, and for the d^{th} dimension it can be considered as

$$p_{center,ci,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} p_{ci,j,d} \tag{7}$$

where $1 \le d \le D$ specifies the d^{th} dimension, and *D* is the overall measurement. n_{ci} is the no.of elephants in clan *ci*. $p_{ci,j,d}$ is the d^{th} of the elephant distinct $p_{ci,j}$. The hub of clan *ci*, $p_{center,ci}$, could be deliberate over *D* designs according to eqn (7)
Separating- operator
In elephant cluster, male elephants will leave their domestic assembly and live single-handedly when they attain puberty. The procedure of separating can be demonstrated into separating operative while resolving optimisation issues. To further advance the exploration capability of the EHO method; consider that the elephant individuals with the wickedest appropriateness will execute the splitting operative at respectively generation as exhibit in equation (8).

$$p_{worst,ci} = p_{\min} + \left(p_{\max} - p_{\min} + 1\right) \times rand \tag{8}$$

where p_{max} and p_{min} are correspondingly higher and lesser bound of the situation of elephant discrete. $p_{worst,ci}$ is the worst elephant distinct in clan *ci*. $rand \in [0, 1]$ is a sort of stochastic distribution and even distribution in the range *[0, 1]* is utilize in the present effort.
Cauchy distribution
The Cauchy Distribution (CD) operator is used to generate solution in an every single iteration; this will upsurge the probability of reaching the best solution. The one-dimensional CD Function (F) focused at the initiation portrayed by:
Where, $k > 0$ is a scale parameter. The CDF is

$$Ft(p) = \frac{1}{2} + \frac{1}{\pi}\arctan\left(\frac{p}{k}\right) \tag{9}$$

The CD operator used as a part of EHO,

$$rand = \left(\sum_{j=1}^{sol\,size} S(Sop)[j][i] \right) \Big/ sol\,size \tag{10}$$

where *SolSize* is the solution size, *S(Sop)[j][i]* is the i^{th} and j^{th} solution in the population and *rand* is a weight within [*-Wmax, Wmax*].

$$Currentbestsolution'(i) = Currentbestsolution(i) + rand * Ca_{df}(p_{\min}, p_{\max}) \tag{11}$$

Where, rand range is (-1 to 1), Ca_{df} is a CD function with the scale-parameter $k = 1$, and $Ca_{df}(X_{min}, X_{max})$ is a arbitrary number within $[X_{min}, X_{max}]$, that is the characterized domain of a test-function. After the new finest solution is visible then matched with preceding finest solution the new solution is exposed after this course till the error minimization updation procedure is recurrent. This CDF is utilized for refining the finest solution and for progression determination then the time consumption is decreased these are the advantages of this function. Figure-2, exhibits the working-flow of proposed DNN model that includes input attributes, hidden layer used for processing and output parameter called Angiographic diseases status.

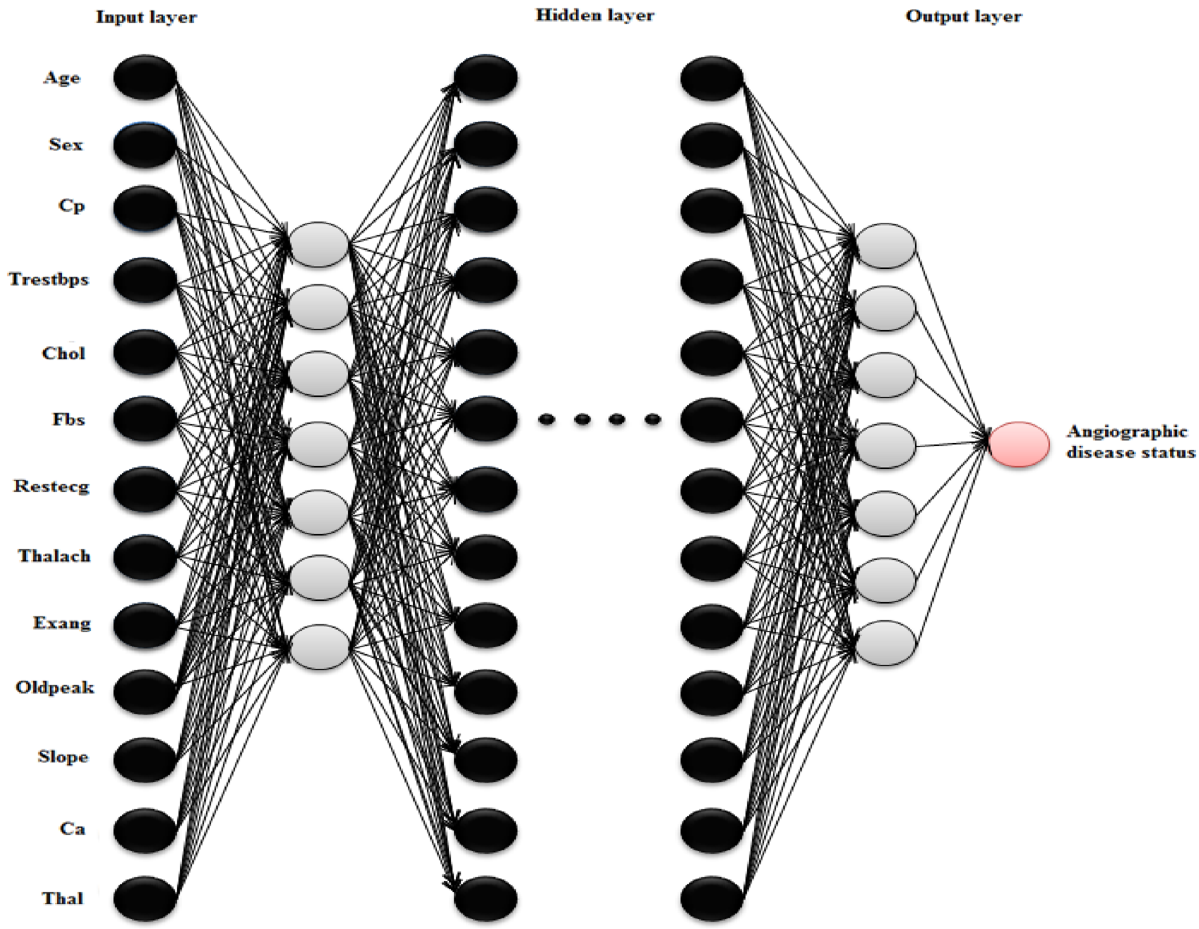

Figure-2, proposed Deep Neural Network model

4. Results and Discussion

To diagnose angiographic disease conditions through the proposed technique employed standard measures to evaluate the performance. The employed measures are accuracy, F1-score, False Discovery Rate (FDR), False Negative Rate (FNR), False Positive Rate (FPR), Matthews's Correlation Coefficient (MCC), Negative Predictive Value (NPV), Positive Predictive Value (PPV), sensitivity, and specificity. The performance of employed optimization techniques also exhibits through a convergence graph. The result unveils that proposed technique having an accuracy of 98.9%, 98.8% and 97.1% from Cleveland, Hungarian and Switzerland database respectively. The obtained results from EEHO configured DNN reveals superior performance over comparative techniques because of the proposed approach (opposition strategy and Cauchy distribution in the updating process). In general, the performance of the proposed method in terms of accuracy is 98.3%, which is 4.86% better than traditional DNN (random-weight distribution). Table-1 exhibits the mathematical formulation for employed measures utilizes to evaluate the performance of involved techniques.

True Positive (TP) - Angiographic disease correctly identified

False Positive (FP) - Angiographic disease incorrectly identified
True Negative (TN) - Angiographic disease correctly rejected
False Negative (FN) - Angiographic disease incorrectly rejected

Table-1 Mathematical expression of performance measures

Accuracy	$\frac{TP+TN}{TP+TN+FP+FN}$
F1 Score	$\frac{2TP}{2TP+FP+FN}$
FDR	$\frac{FP}{FP+TP}$
FNR	$\frac{FN}{FN+TP}$
FPR	$\frac{FP}{FP+TN}$
MCC	$\frac{TP*TN-FP*FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$
NPV	$\frac{TN}{TN+FN}$
PPV	$\frac{TP}{TP+FP}$
Sensitivity	$\frac{TP}{TP+FN}$
Specificity	$\frac{TN}{TN+FP}$

Table 2 shows the performance of EEHO used to configure DNN weights in the three-different database in terms of performance measures. Figure 3 to figure 12 exhibits a performance comparison between employed techniques in terms of measures for the three-different database. The techniques and corresponding index are (1) DNN, (2) DNN-EA, (3) DNN-GA, (4) DNN-PSO, (5) DNN-SSO, (6) DNN-AFSO, (7) DNN-ABC, (8) DNN-EHO, (9) DNN-OEHO and (10) DNN-EEHO. While considering accuracy as a significant measure in terms of diagnosing, the proposed system reveals proficient performance in the research context. In general, DNN-EEHO unveils accuracy as 98.3%; which is 2.05% higher than DNN-OEHO, 2.8% better than DNN-EHO, DNN-ABC, and DNN-SSO, 3.17% higher than DNN-AFSO, DNN-PSO, and DNN-EA, 3.54% superior to DNN-GA and 4.86% proficient than traditional DNN. The result confirms that the incorporation of opposition strategy along with initial solutions and Cauchy distribution strategy along with the conventional EHO updating process enhances the overall performance. Especially, accuracy base performance investigation in Switzerland-database (figure 3) it is apparent that EA, GA, PSO, SSO, AFSO, ABC, EHO, and OEHO get trapped at certain point, whereas Cauchy distribution strategy, along with the traditional EHO updating process, drives the solution towards optimal point.

Table-2, Performance measures for proposed technique (DNN-EEHO)

Measures	**Database**		
	Cleveland	**Hungarian**	**Switzerland**
Accuracy	0.989011	0.988764	0.971429
F1 Score	0.989899	0.990654	0.971429
FDR	0.02	0.018519	0.055556
FNR	0	0	0
FPR	0.02381	0.027778	0.055556
MCC	0.978093	0.976841	0.944444
NPV	1	1	1
PPV	0.98	0.981481	0.944444
Sensitivity	1	1	1
Specificity	0.97619	0.972222	0.944444

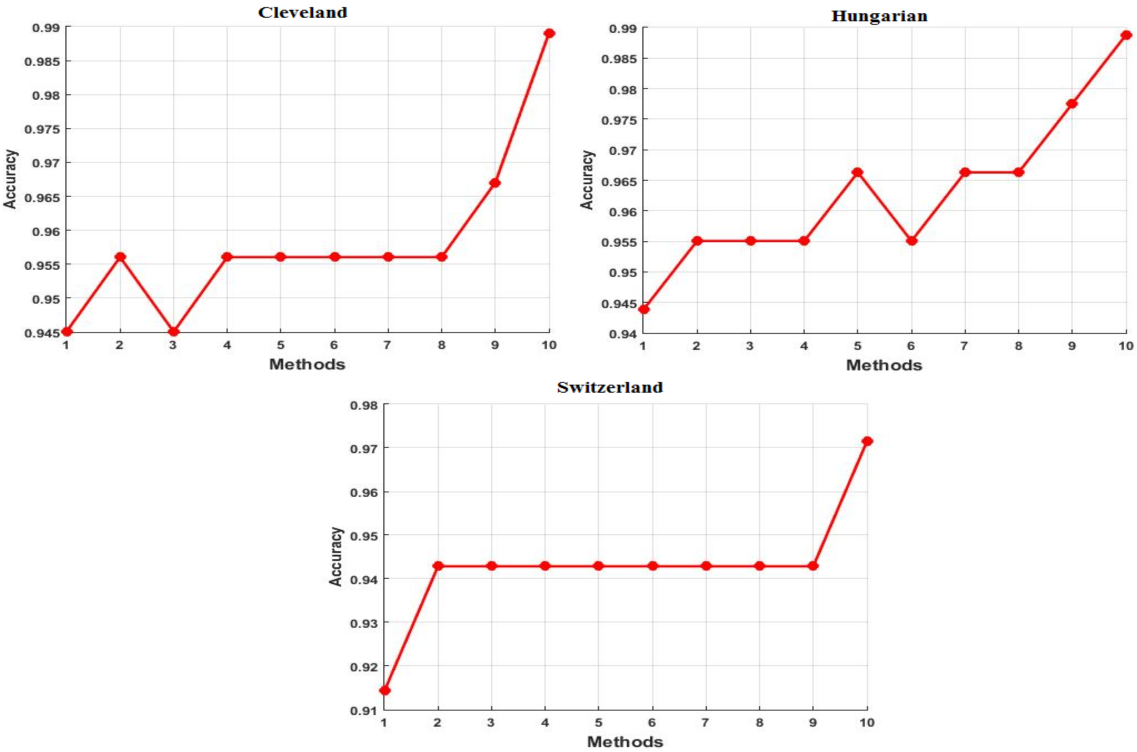

Figure-3, Performance measures with respect to Accuracy

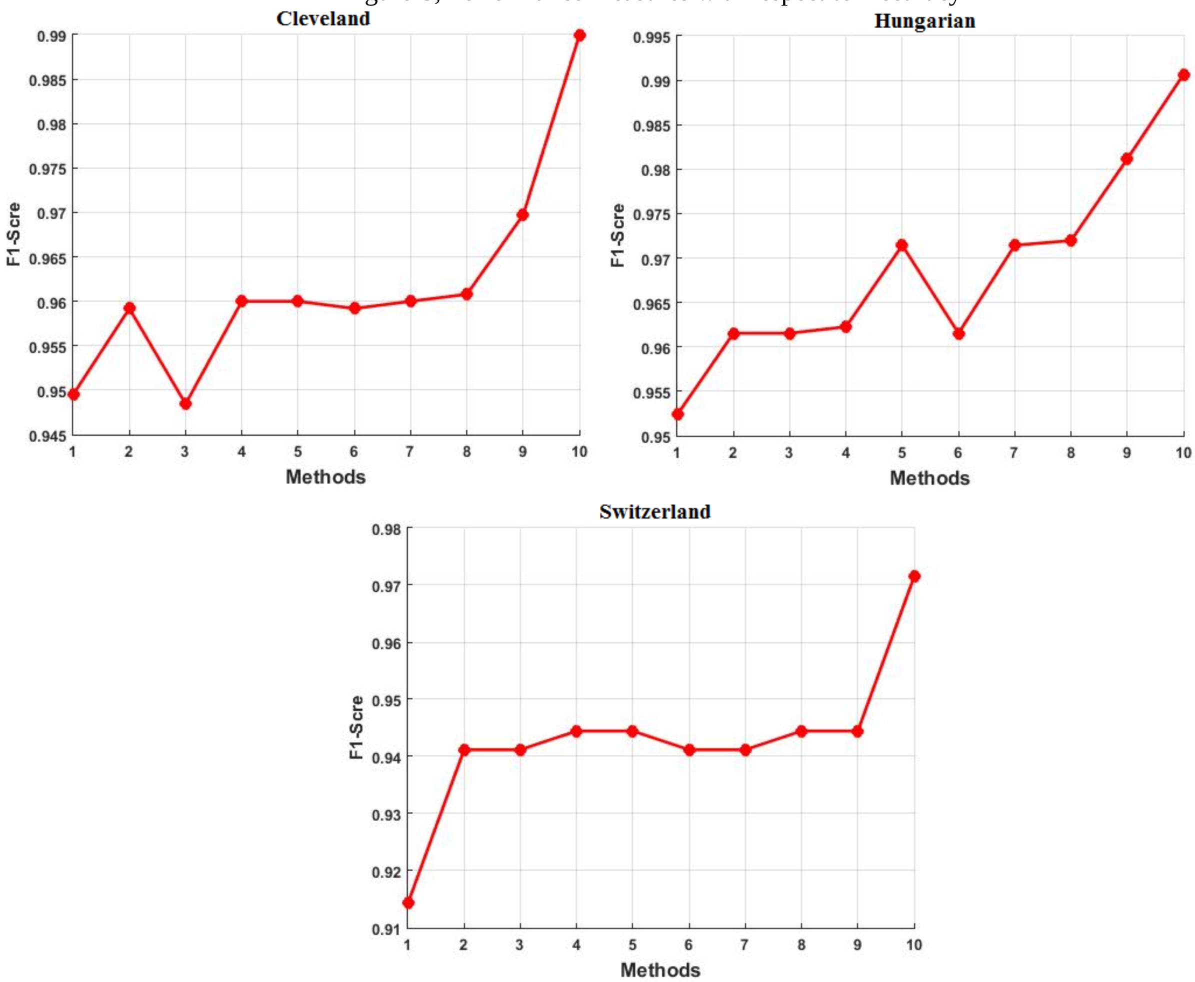

Figure-4, Performance measures with respect to F1-Score

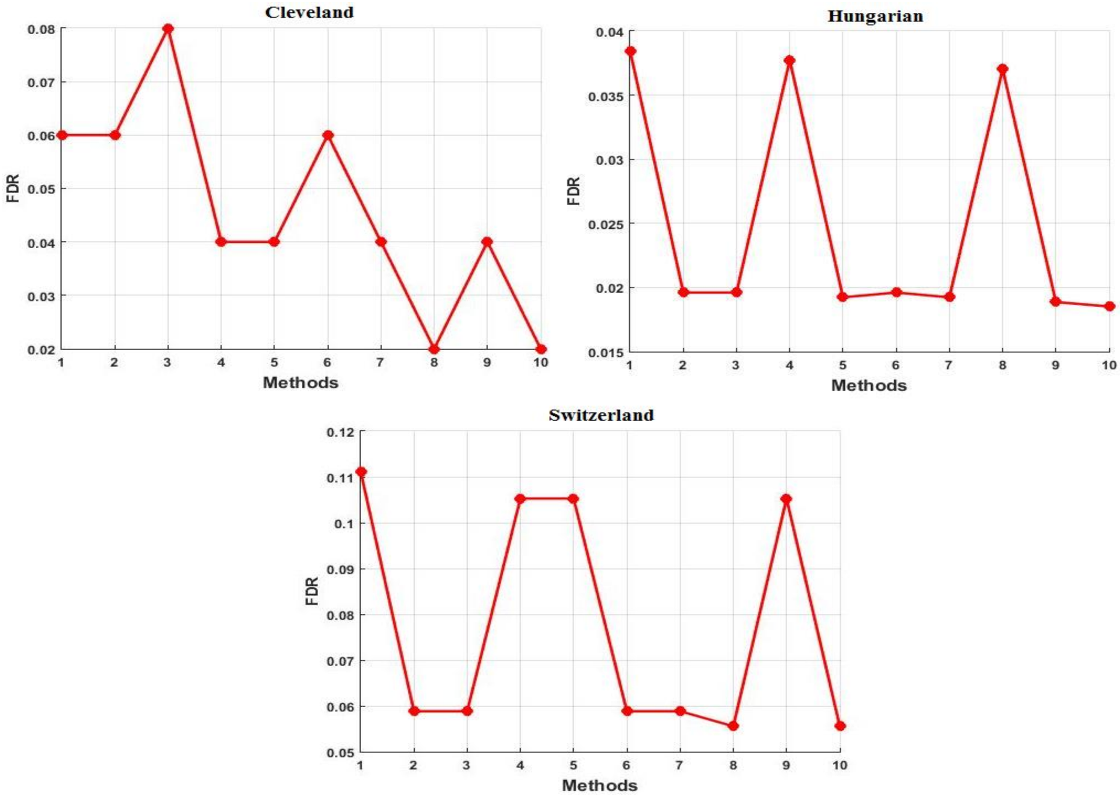

Figure-5, Performance measures with respect to False Discovery Rate (FDR)

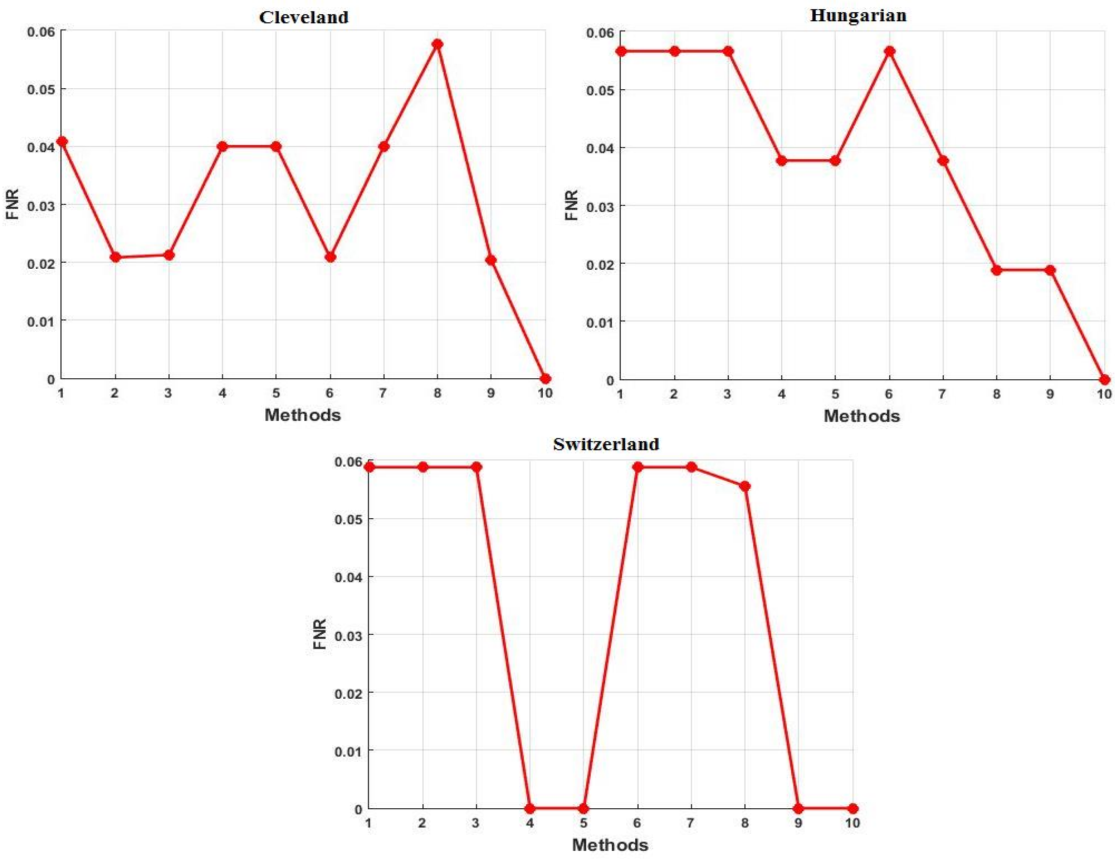

Figure-6, Performance measures with respect to False Negative Rate (FNR)

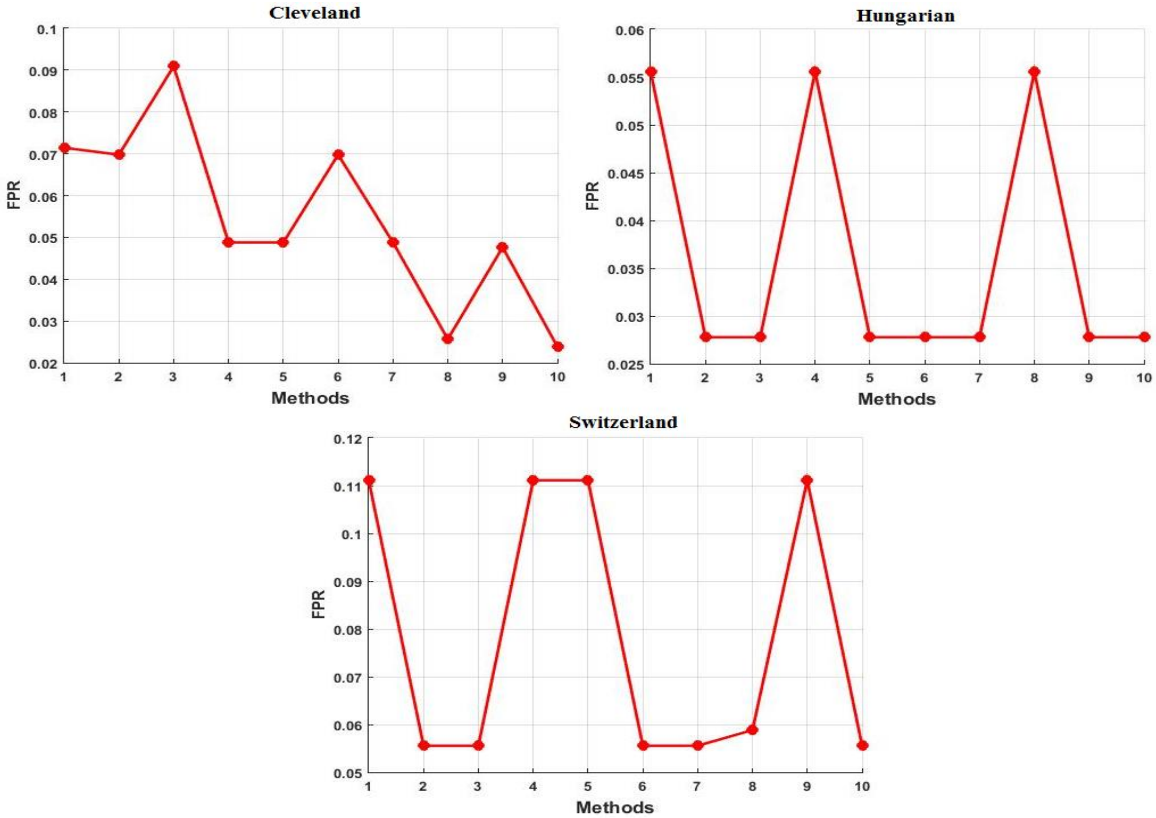

Figure-7, Performance measures with respect to False Positive Rate (FPR)

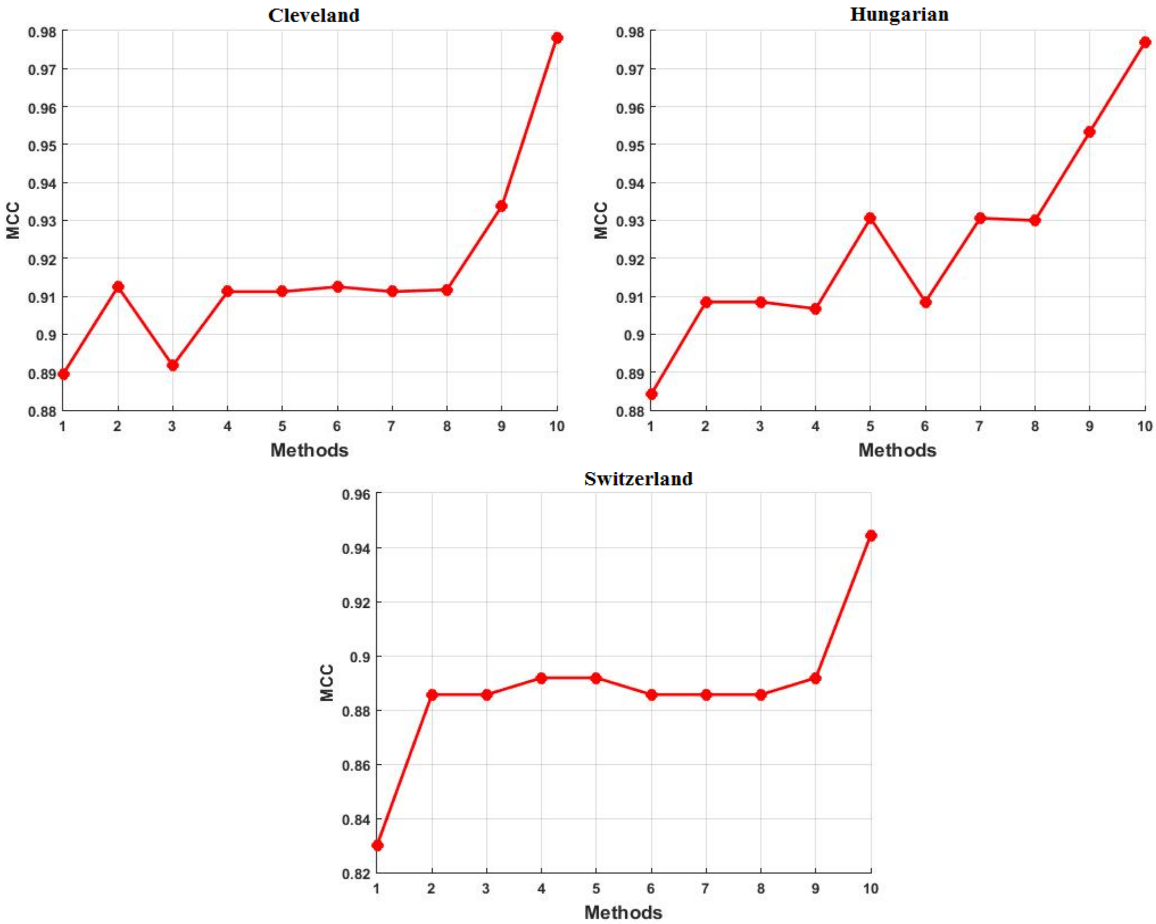

Figure-8, Performance measures with respect to Matthews's Correlation Coefficient (MCC)

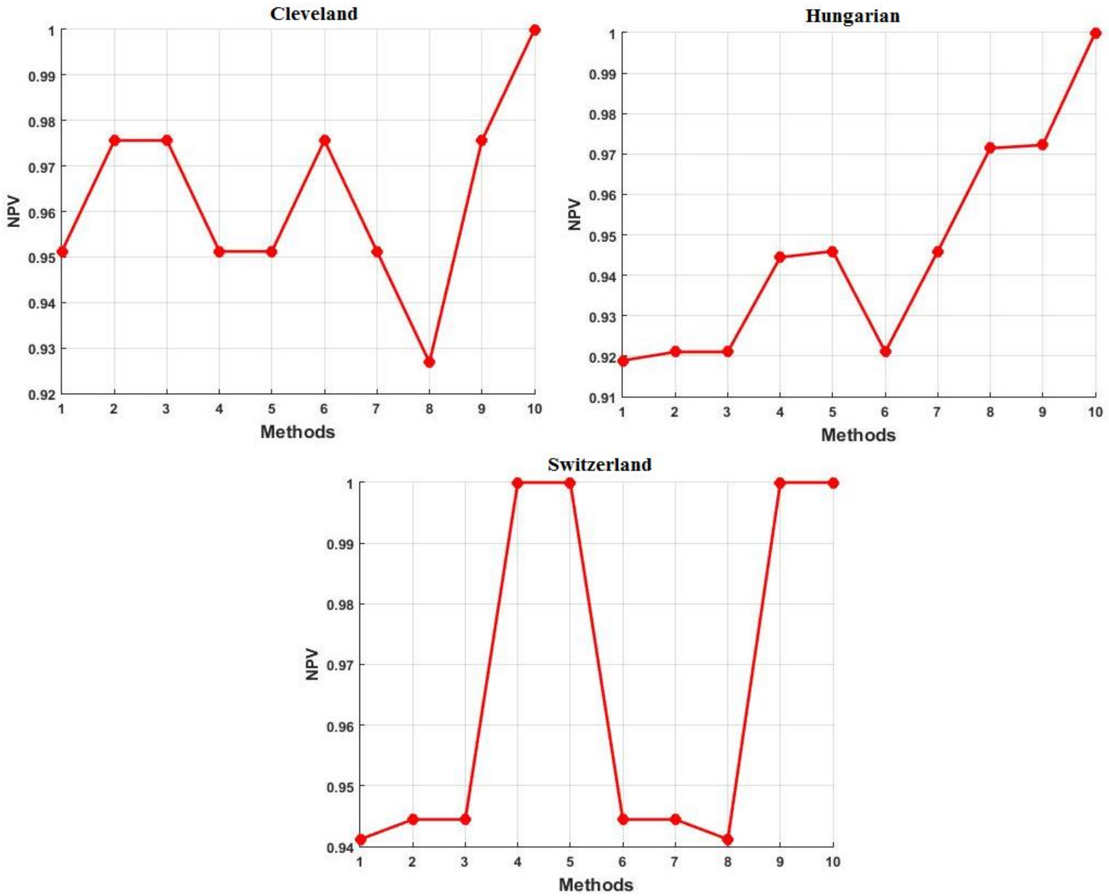

Figure-9, Performance measures with respect to Negative Prediction Rate (NPV)

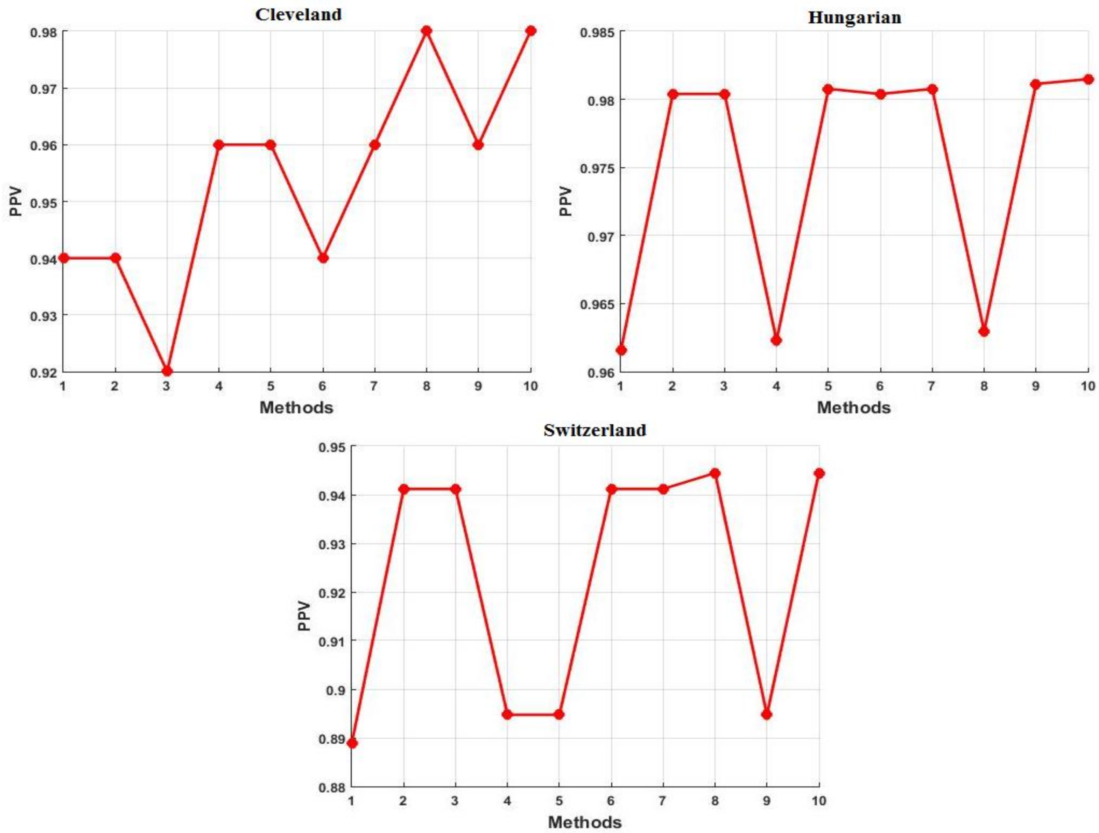

Figure-10, Performance measures with respect to Positive Prediction Rate (PPV)

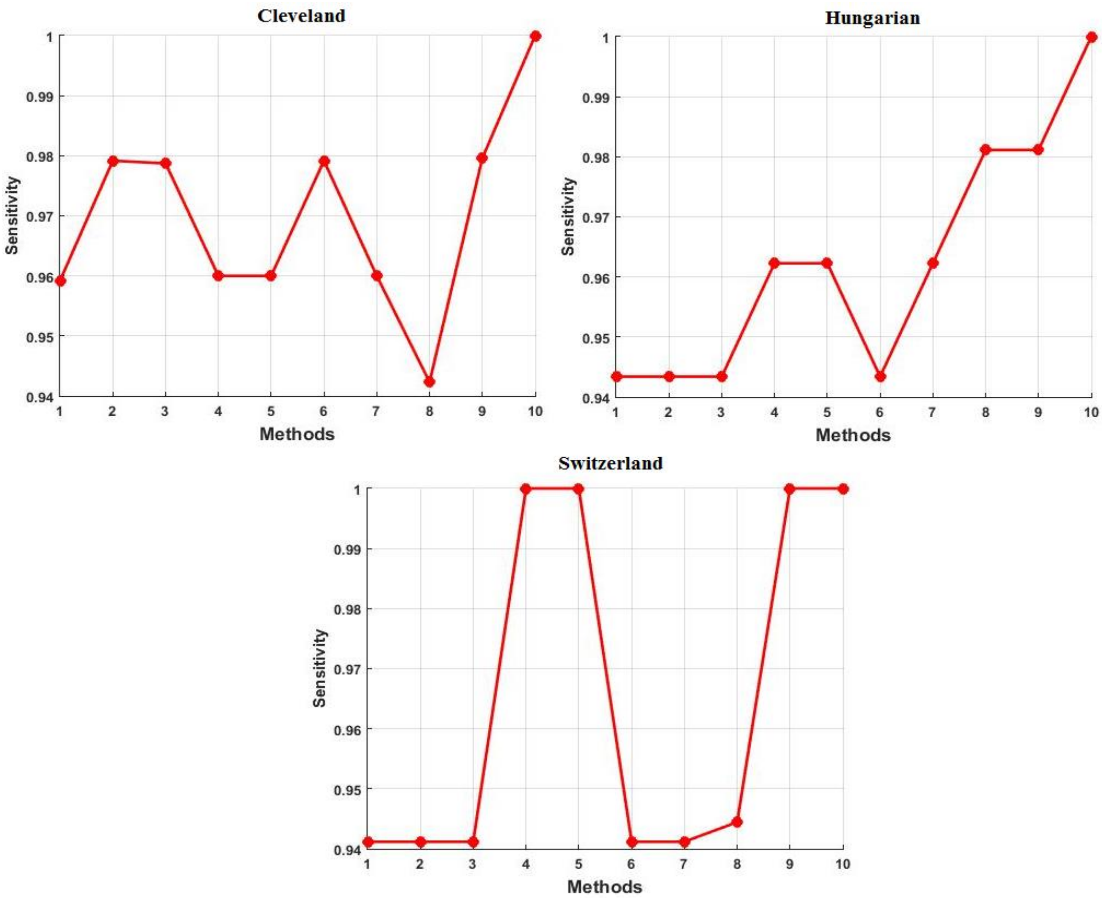

Figure-11, Performance measures with respect to sensitivity

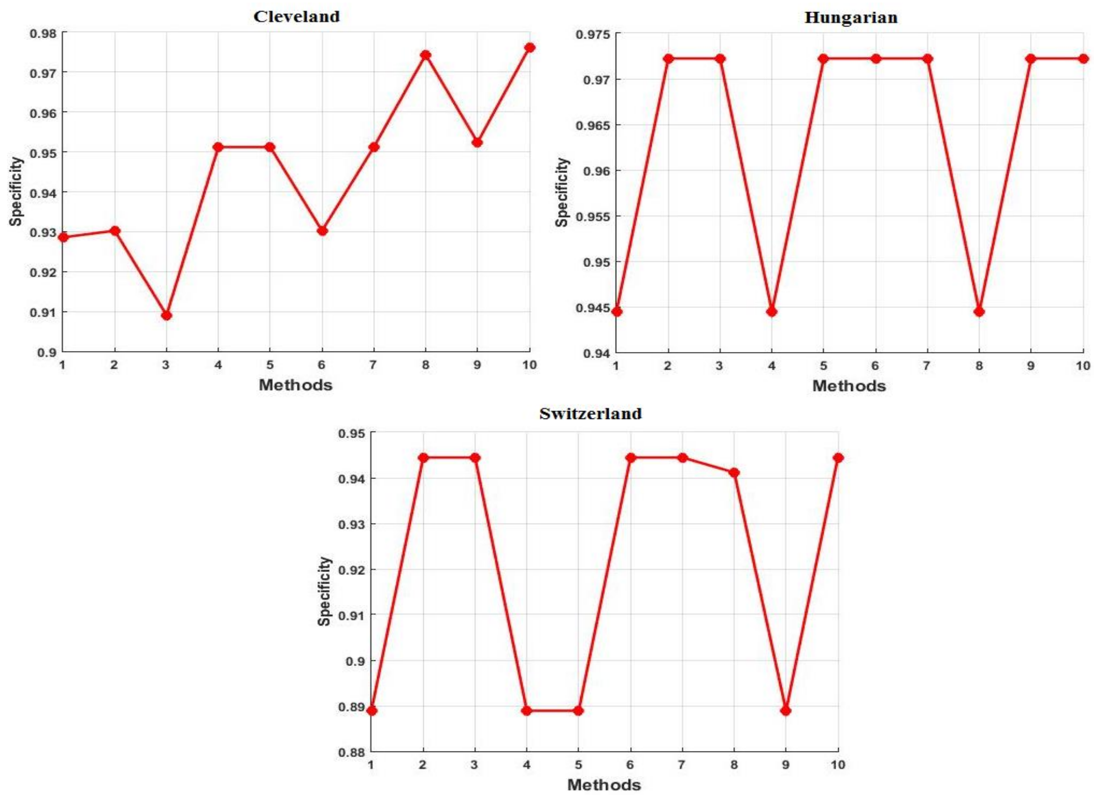

Figure-12, Performance measures with respect to Specificity

4.1 Convergence Performance

Figure 13, illustrate the training-performance of engaged techniques while considering accuracy as a fitness measure. The result shows that DNN-EEHO exhibits top performance over other comparative techniques. The proposed technique get converged in 500th iteration, whereas other techniques get converged in 600th and 700th iteration respectively. Beginning itself proposed technique shows uppermost performance over other technique, which is possible because of incorporating opposition strategy and Cauchy distribution function.

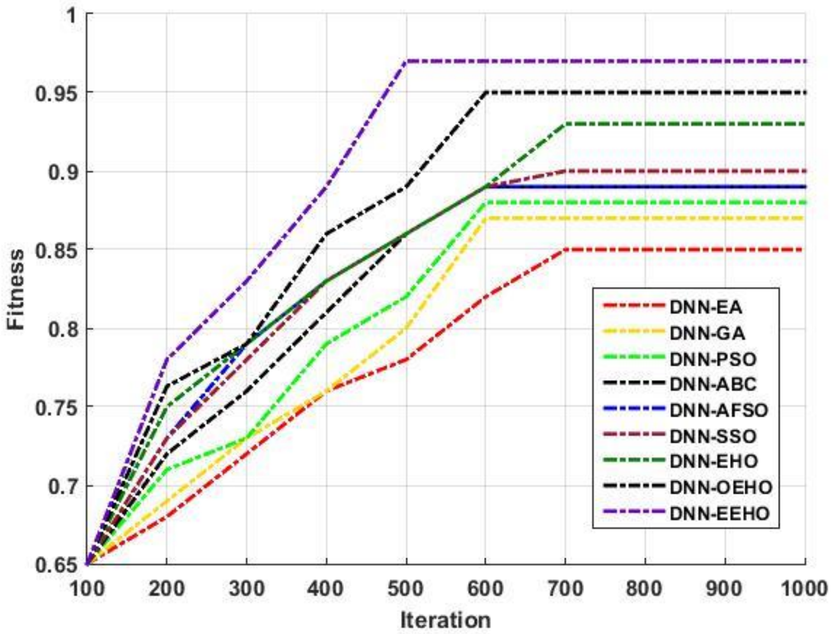

Figure-13, Convergence Graph

5. Conclusion

The intention of incorporating optimization techniques to configure DNN with appropriate weights performed successfully. Whereas, integrating opposition strategy along with initial-random solution and Cauchy distribution strategy for updating elevates the performance of EEHO over other traditional technique and OEHO. The opposition strategy increase the chance of finding appropriate weights for DNN configuration and Cauchy distribution approach drives the updating process without any halt. The results evident that over evolutionary approach swarm intelligence approach having better performance in three-test case databases. EEHO configure DNN diagnosing heart diseases with the accuracy of 98.9%, 98.8% and 97.1% in Cleveland, Hungarian and Switzerland database respectively. In future, the research aim to formulate a technique, which configures DNN weights that can be utilize for diagnosing other biomedical research context.

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