Intelligent Disease Diagnosis with Vortex Optimization Algorithm Based ANFIS

Tuncay Yigit

Suleyman Demirel University, Dept. of Computer Engineering

Sena Celik*

Mehmet Akif Ersoy University, Dept. of Information Security Technology

Abstract

Artificial intelligence is a very important field since it can provide good solutions for different problems from real world. We can see different solutions of intelligent systems and these solutions generally support people to experience better standars in their life. The field of medical is one of important fields in which artificial intelligence is often used. Objective of this study is to introduce an intelligent diagnosis system using both adaptive neuro fuzzy inferencing system (ANFIS) and vortext optimization algorithm (VOA) to form a diagnosis system for different diseases. In the system, ANFIS is trained by VOA for better training against target disease. The study provides information for the background, developed ANFIS-VOA system and reports some findings for example diseases.
Keywords: , artificial intelligence, ANFIS, VOA, disease diagnosis

1. Introduction

Artificial intelligence is an important field, which is creating our future. Even today, we can see effective use of artificial intelligence in different problems. Because artificial intelligence can provide flexible, fast and learning based solutions, it can be used for all kind of problems from real world as such problems can

*Corresponding author
Email address: scelik@mehmetakif.edu.tr (Sena Celik)

be mathematically and logically modeled Russell & Norvig (2016); Ginsberg (2012). Because of that, intelligent solutions by the field of artificial intelligence are often used for advanced problems that cannot be solved with traditional methods or can take too much time to have solutions at the end. Problems that cannot be solved or taking too much time have been problem for us. So, there has been always a research effort for using artificial intelligence based solutions for problems of all fields Elmas (2007); Michalski et al. (2013). Nowadays, we can see applications of artificial intelligence in both natural and social sciences. Among different kind of applications, artificial intelligence generally uses some known solution ways such as control, optimization, prediction and recognition Russell & Norvig (2016); Alpaydin (2009); Bonabeau et al. (1999); Nabiyev (2005). Thanks to these solution ways, it has been always effective to use intelligent systems for making the life better for humans.

When it comes to human life and as well as all kind of living creatures' life, the field of medical has an importance for providing treatments through history of the world. Because of that, technological developments are always adapted to medical immediately following their appearance. Artificial intelligence is among such technological developments and its solutions are often used for medical problems Nilsson (2014); Jiang et al. (2017). As a problem scope, medical diagnosis often receives support from intelligent systems developed thanks to artificial intelligence. Because of the machine learning mechanism of artificial intelligence, it has been easier to design medical diagnosis systems using some previously known data for accurate diagnosis in the future states of a target disease. Nowadays, applications of artificial intelligence are still attracting researhers to develop new systems and report their results.

Objective of this study is to introduce an intelligent diagnosis system using both adaptive neuro fuzzy inferencing system (ANFIS) and vortext optimization algorithm (VOA) to form a diagnosis system for different diseases. In the system, ANFIS is trained by VOA for better training against target disease. As the ANFIS is a hybrid formation of artificial neural networks and fuzzy logic, it is even trained by an intelligent optimization algorithm to introduce a hybrid system of learning approach, designed for understanding how it can diagnose medical disease. In order to understand that, the developed ANFIS-VOA system was aimed to apply into different diseases and make some discussions over obtained findings.

Remaining sections of this study includes a general review of the research on medical diagnosis with artificial intelligence (section 2) first, and then a wide explanations of the used methods as well as the designed solution for ensuring an ANFIS-VOA system for disease diagnosis (section 3). Next the section 3 includes discussion on results and the study is ended with conclusion.

2. Related Work

In the literature of artificial intelligence, there are many research works that were reported for medical diagnosis problems. Solutions for medical diagnosis are associated with use of machine learning techniques for dealing with diseases. Among all research works, it is remarkable that Artificial Neural Networks and ANFIS are widely used for diagnosis purposes. In the works Amato et al. (2013); Al-Shayea (2011), essentials of using Artificial Neural Networks for diagnosis are explained widely for enabling readers to understand medical diagnosis capabilities of neural network based solution structures. Artificial Neural Networks is too effective that it can be even applied for diagnosing cancer and positive results have been obtained so far Khan et al. (2001); Wu et al. (1993); Abbass (2002); Snow et al. (1994). In this perspective, Artificial Neural Networks become an effective tool for decision support in hospitals Lisboa & Taktak (2006); Chen et al. (2003). It is also remarkable that the Artificial Neural Networks has been effective for not also diagnosis but also predicting survival state by giving ideas to doctors for further treatments over cancer patients. In this way, the cancer survival prediction, which cannot be done accurately by doctors every time has been solved with Artificial Neural Networks Burke et al. (1997).

In medical diagnosis, Artificial Neural Network has been reported also effective tool for realizing diagnosis and predictions over medical signal data. It is possible to see many examples of using Artificial Neural Networks for performing predictive applications over some known signal based data like ECG or EEG Silipo & Marchesi (1998); Hu et al. (1993); Moavenian & Khorrami (2010); Ozbay & Karlik (2001); Srinivasan et al. (2007); Guo et al. (2009); Vuckovic et al. (2002). All these research works are important for the literature since it can be possible to perform early diagnosis over ECG or EEG for possible heart or brain diseases.

Alternative techniques of machine learning like decision tree or bayesian learning algorithms have been also reported as tools for medical diagnosis. These techniques are widely used for diagnosing different diseases and providing decision making support for medical staff Soni et al. (2011); Kononenko (2001); Azar & El-Metwally (2013). Here, even use of fuzzy logic has been included in research so far Fan et al. (2011).

As another effective artificial intelligence technique, support vector machines is widely used for medical diagnosis processes. Results obtained with especially this recent technique figure out a good potential to develop automated, accurate and sensitive diagnosis systems Polat & Güneş (2007a); Guyon et al. (2002); Polat et al. (2008); Lee & Lee (2003).

As the essential artificial intelligence technique of this work, ANFIS has been widely used for medical diagnosis, too. In the literature, different types of diseases diagnosed by ANFIS and its hybrid systems are introduced often. As a variation of artificial neural networks, ANFIS shows good performances and still used for solving medical diagnosis problems Polat & Güneş (2007b); Özkan et al. (2010); Kalaiselvi & Nasira (2014); Sharaf-El-Deen et al. (2014); Hosseini & Zekri (2012); Walia et al. (2015); Ibrahim et al. (2010); Avci & Turkoglu (2009).

As it is understood from the literature, artificial intelligence and machine learning techniques have great effect on improving medical diagnosis. In each technological development, more advanced intelligent systems can be applied to already solved diagnosis problems in order to improve previously obtained results. Furthermore, even advanced diseases can be diagnosed or at least predicted by use of artificial intelligence and alternative technological components supporting artificial intelligence (i.e. image processing, signal processing Stoitsis et al. (2006); Bonnet (2000); Sahambi et al. (1997); Hemanth et al. (2018); Miller et al. (1992)).

3. Method

ANFIS-VOA system in this study was developed by using two different techniques for achieving a hybrid system for medical diagnosis. Details for these techniques and the solution approach on how the developed system can diagnose medical diseases are explained under the next paragraphs.

3.1. Adaptive Neuro Fuzzy Inferencing System

In the artificial intelligence literature, there are many important techniques. Artificial Neural Networks Patterson (1998) and Fuzzy Logic Yen & Langari (1999) are two of them. These techniques are widely used in many scientific applications and so far, successful results have obtained often by using Artificial Neural Networks or Fuzzy Logic. After a while, research in improving artificial intelligene techniques has led researchers to design and alternative technique which combines both two techniques to ensure better solution for machine learning oriented solutions. Called as Adaptive Neuro Fuzzy Inferencing System in long name format, and introduced firstly by Jang Jang (1993), ANFIS technique is a combination of Artificial Neural Networks and Fuzzy Logic to have fuzzy rule controlled neural network structures. In other words, an ANFIS is a hybrid system consists of human thinking, learning and reasoning learning behaviors to create a network layer based solution technique. ANFIS includes Fuzzy Logic supported Radial Basis Function Neural Network including some nodes with Ellipsoidal or Gaussian functions. Fuzzy Logic includes Takagi-Sugeno model functions to provide an inferencing for the neural network. In other words, fuzzy rules of IF. . . THEN statements are combined with the function based 1st order Takagi-Sugeno to direct the neural network better Jang (1993); Jang et al. (1997). As default, an ANFIS comes with 5 layer model (Figure 1).

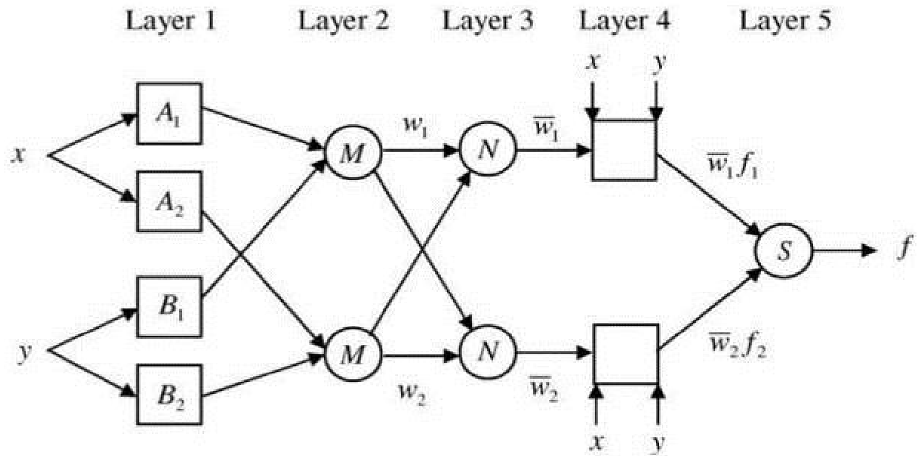

Figure 1: Default organization of the ANFIS system Übeyli (2009).

ANFIS system uses some parameters, which are called as premise, and consequent. For machine learning purpose, these parameters are optimized by using some algorithmic steps for making the system output to match some training data, which is for a target problem (supervised learning)Jang (1993); Jang et al. (1997). In the literature, there are some algorithms for realizing that learning mechanism. Two widely known ones are Gradient-Decent Backpropagation and One Pass of Least Square Estimates. But as intelligent optimization algorithms have the ability to optimize any parameter of mathematically formed problems, it is possible to use such algorithms for optimizing the premise and consequent parameters of the ANFIS. In the literature, there are many examples of that Ghasemi et al. (2016); Mohanty & Parhi (2015); Panapakidis & Dagoumas (2017); Shoorehdeli et al. (2009a); Kose & Arslan (2017a); Karakoc (2018); Shoorehdeli et al. (2009b). In this study, a new algorithm of vortex optimization algorithm (VOA) was used for same purpose. It is explained briefly under the next title.

3.2. Vortex Optimization Algorithm

Vortex Optimization Algorithm (VOA) is a recent intelligent optimization technique, which was introduced by Kose and Arslan Kose & Arslan (2015). It inspires from movements of vortex in the nature (i.e. in thw water or air) and provides an optimization based solution by inspiring from the concept of vortex. VOA groups its particles into vortex and non vortex particles and performs some evolution oriented algorithmic steps to use good particles for finding optimum values of the target problem Kose & Arslan (2015, 2017b).

VOA steps can be expressed as below Kose & Arslan (2015); Köse (2017):

(1) Define N particles, vorticity (v) values for each particle, maximum and minimum value limits for that vorticity parameter and build the whole problem.

(2) Spread the particles randomly into the solution space.

(3) Calculate fitness function values for each particle and update v value of the best (optimum) particle by improving the current value with a random number. That particle is also a vortex.

(4) Until a stopping criteria, repeat the rest:

- Particles with fitness value under the average fitness of all particles are each vortex. The other ones are non vortex particle.
- Update v value for each particle by:

$$particle_{i_{vchange}} = particle_{iv} + (randvalue * (gbest_v / particle_{iv})) \quad (1)$$

$$particle_{iv} = particle_{i_{vchange}} \quad (2)$$

- Improve v value of each vortex particle (except from the best one) with a random number.
- Update position of each particle (except from the best one) by:

$$particle_{i_{position}} += (randvalue * particle_{i_{vchange}} * (gbest_{position} - particle_{i_{position}}))) \quad (3)$$

- Calculate *fitness* and determine the best (optimum) particle.

- If total number for non vortex particles is under the parameter: e, remove all non vortex particles and replace them with new particles randomly. Realize in system optimization for advanced solutions.
- If the stopping criterion is not met, go to the first sub step of *Step 4*.

(5) The best (optimum) values are solution for the target problem.

Flow chart for the VOA is shown in Figure 2.

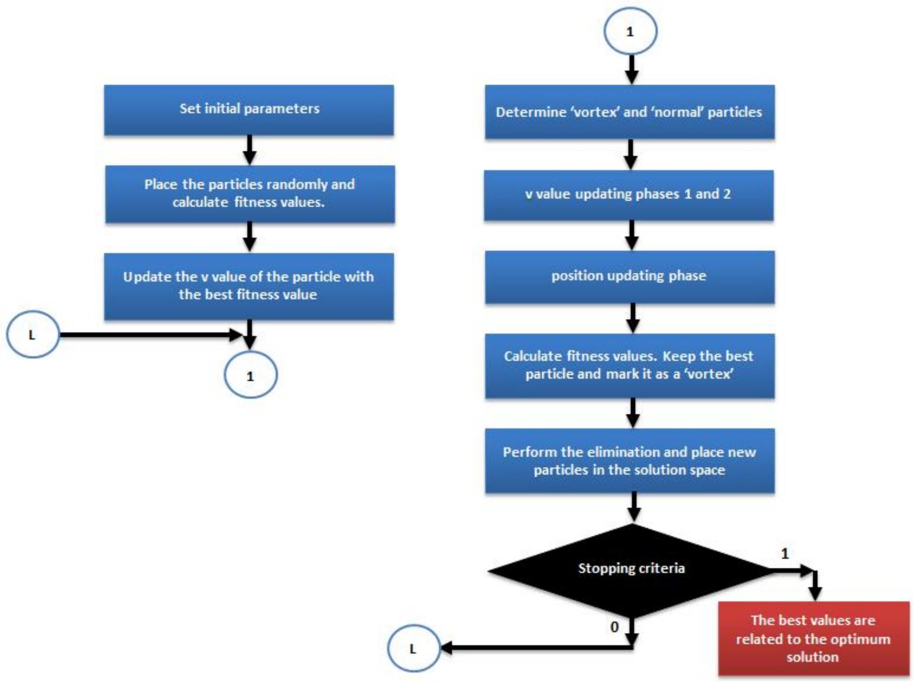

Figure 2: Flow chart for the VOA Demir & Köse (2017).

3.3. Intelligent Disease Diagnosis with ANFIS-VOA

After explaining ANFIS and VOA for training purpose, intelligent diagnosis method by ANFIS-VOA can be expressed easily. In the system VOA is responsible for optimizing ANFIS parameters according to training data set and finally achieving an ANFIS system for disease diagnosis by including as small as error value. Details of the system and solution method can be explained as:

- ANFIS uses different number of inputs according to the considered disease problem. For each additional input, the system is supported with additional 5 fuzzy rules.

- The output of the ANFIS is general 1 neuron as it indicated the result if positive or negative for the target disease. But the output depends on also target disease since some disease may require more than two states to understand better about the disease. In this study, the diseases were in two states: positive or negative presence of the disease.

- VOA is used for spreading the particles for finding optimum ANFIS parameters while going through training data set rows for a target disease.

- In detail, VOA particles are employed according to the algorithm steps by considering a target iteration number and optimum ANFIS parameters resulting in lower error and better diagnosis over training data are used accordingly for ANFIS-VOA diagnosis system.

Figure 3 shows the system of ANFIS-VOA for medical disease diagnosis.

4. Discussion and Results

For having idefa about how ANFIS-VOA system can diagnose diseases, it was applied in three different diseases by using medical data from well known UCI Repository Blake & Merz (2015). As the first disease data set, the Thyroid data set includes 2800 training, 972 test data and considers 21 attributes for input. As the second disease data set, Hepatitis data set employs 100 training, 55 test data and uses 19 attributes for input. As the final disease data set, Chronic Kidney Disease data set provides 295 training, 105 test data, over 25 attributes for input.

In the disease diagnosis applications, VOA employed with a total of 100 particles. Although there are different parameters reported in the literature, an optimum number of 100 particles was tried in the context of this study. Additionally, the iteration number for determining optimum parameters was

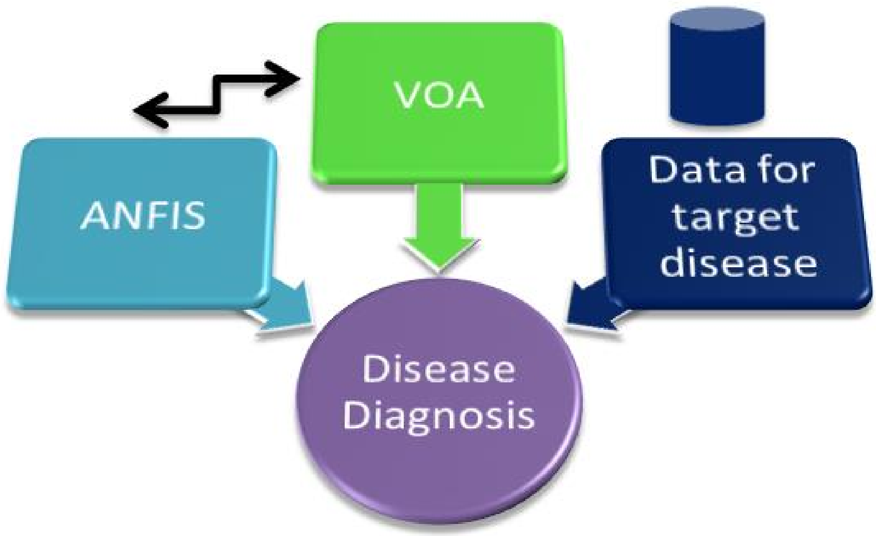

Figure 3: ANFIS-VOA for medical disease diagnosis.

set to 10.000 for all three disease data sets. The ANFIS-VOA system was run 10 times by using the VOA parameters as vorticity (v) starting value: 0.50, *maximum vorticity*: 7.0, *minimum vorticity*: -7.0 and elimination rate (e) as 50 by considering the default values in the work Demir & Köse (2017). At the end, average true diagnosis rates for each diagnose data set were considered for evaluation.

Table 1 provides findings for the ANFIS-VOA diagnosis applications over three disase data sets.

Table 1: Findings by ANFIS-VOA for three disease data sets.

Disease Data Set	**Test Data Row**	**True / False Diagnosis**	**ACCURACY**
Thyroid	972	943 / 29	97.02%
Hepatitis	55	51 / 4	92.73%
Chronic Kidney	105	93 / 12	88.57%

For a comparative evaluation, the same ANFIS model was trained with also three alternative intelligent optimization algorithms: Particle Swarm Optimization (PSO) Kennedy (2011), Genetic Algorithm (GA) Holland (1992), and Differential Evolution (DE) Storn & Price (1997) for comparing their diagnosis findings with the ANFIS-VOA. Table 2 shows the findings by all alternative solutions. For each alternative system, T / F / Accuracy columns correspond to true diagnosis, false diagnosis and the accuracy rate respectively.

Table 2: Findings by alternative systems for three disease data sets.

Disease Data Set	**ANFIS-PSO**	**ANFIS-GA**	**ANFIS-DE**
	T / F / Accuracy	**T / F / Accuracy**	**T / F / Accuracy**
Thyroid	921 / 56 / 94.75%	936 / 36 / 96.30%	938 / 34 / 96.50%
Hepatitis	48 / 7 / 87.27%	50 / 5 / 90.91%	52 / 3 / 94.55%
Chronic Kidney	89 / 16 / 84.76%	90 / 15 / 85.71%	92 / 13 / 87.62%

Considering the findings, we can express the followings:

- The ANFIS-VOA system is effective in terms of diagnosing the diseases included in this study.
- Because of the success shown by ANFIS-VOA system, it can be expressed that ANFIS system can be trained well by the recent intelligent optimization technique: VOA and the ANFIS has a good model for the disease diagnosis purpose.
- A total of 100 particles and the training of 10.000 iterations give good results for diagnosis. In this way, a trained disease diagnosing system can be ensured easily.
- ANFIS-VOA system showed better results generally for the target diseases, when it is compared with other systems of ANFIS-PSO, ANFIS-GA, and ANFIS-DE (Table 1 and Table 2).

- For understanding capacity of the system, more additional experiments may be done.
- Diagnosis performance of the system may be improved with additional tasks done for better parameters in the system.
- It is important to use ANFIS-VOA system for alternative diseases in order to see if it provides good results always.
- The ANFIS-VOA system is effective on diagnosis problems, which can be solved with input and output relations over previously known data. For alternative advanced problems, additional research may be required since some diseases should be observed with imaging based analyzses (i.e. Magnetic Resonance, ultrason).
- Artificial intelligence is too important for the field of medical. In this study, an alternative system was introduced for diagnosis purposes. The positive results explain us the importance of intelligent systems for solving advanced problems and how they can be effective to do this.

5. Conclusion

This study provided a research on developing an intelligent medical disease diagnosis system by using ANFIS system and training it with a newly introduced intelligent algorithm: Vortex Optimization Algorithm (VOA). The hybrid system of ANFIS-VOA employs VOA particles, which can search optimum ANFIS parameters for better learned ANFIS model for the target disease diagnosis problem. By using previously gathered diagnosis training data, ANFIS can be trained to achieve an intelligent diagnosis system for diagnosing diseases medical staff want the system to learn. During the learning, VOA particles search for optimum parameters according to learning direction of the ANFIS system along iterations. At the end, the system of ANFIS with low errors on training data can make good diagnosis for new inputs which were not seen before. A well trained ANFIS-VOA system can be used by medical staff in hospitals or similar environments for automating the process of diagnosis.

In this study, the developed system of ANFIS-VOA was tested over some example diseases and the findings showed that the system can successfully make diagnosis over target diseases. ANFIS system was also trained with three alternative intelligent optimization algorithms for diagnosing same diseases and generally ANFIS-VOA showed better results according to other alternatives. More research on the system can be done by realizing additional tests for different disease and comparing the findings with alternative solutions by artificial intelligence.

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