COMPARISM OF ADAPTIVE NEURO FUZZY INFERENCE SYSTEM AND SUPPORT VECTOR MACHINE FOR THE PREDICTION OF IMMUNOTHERAPY WARTS DISEASE

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ABSTRACT
Warts diseases are caused by virus within the Human Papilloma Virus Family (HPV). HPV are the cause of some types of cancer. Due to social stigma and the fact that warts never develop any symptoms until it full manifestation many patients seek medical treatment; The fast spread of warts disease due to skin-to-skin contact; Treatment are not cheap and simple, low number of treatment sessions and a lot of complications that do arise during the treatment seasons of warts disease; Lack of enough medical personals to treat warts disease cases and expert system to help the medical practitioners. To reduce the aforementioned problems, a machine learning approach of Adaptive Neuro Fuzzy Inference System (ANFIS) And Support Vector Machine (SVM) is proposed to predict Immunotherapy Warts Disease occurrence of before it gets out of hand. Performance comparism of ANFIS and SVM to the response of immunotherapy treatment of warts disease was conducted to get a good model. Selected features like age, type of warts, diameter of the warts, surface area of warts and the number of warts where considered as input variables. The accuracy of ANFIS and SVM models gave 69.697% and 96.29% respectively, the SVM model was considered to perform better than ANFIS in response to immunotherapy treatment of warts disease.

Keywords: immunotherapy, warts, ANFIS, Support Vector Machine, Prediction, Classification.
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1 INTRODUCTION

Warts are the infection of the upper layer of the skin by a virus known as the human papilloma virus HPV. This type of virus attacks the outer layer of the skin that has a cut or has been damaged. When an individual come in contact with warts virus it takes months for the wart diseases to manifest in relation to the type of the skin warts, a popular saying goes by ‘’people gets warts from other people with warts‘’ the very common way people gets warts are direct skin-skin contact, hands shaking, objects like towels, typing on a keyboard, turning doorknobs, from shaving, biting fingernails (Gerend & Magloire, 2008). Human papilloma virus HPV attacks and infect the mucous membrane of the outer skin, study have uncovered that there are over 60 different types of HPV within the HPV family that causes warts each affecting a different and distinct location of the body for instance the type of HPV that cause warts on the inside of the mouth is different from the HPV that cause warts on the genitals or rectal areas of the body (Khozeimeh, et al., 2017).

Treatment is the positive response to patient’s biological, physical and mental status and condition over a session of pharmacological dosage prescription. Response to Treatment can be evaluated as in terms of a scale or with sequence of measurement as a score rating and be classified as responding or non-responding, its largely assume that a patients syndrome or symptoms should be modified after some set of treatment sessions and the rating scale also changed. In the case of non-response to treatment it may not mean that the drug administered is ineffective it can be because of some factors that can cut across the patient’s commitment to treatment, changes in the illness/infection/disease, drug metabolism and drug to food interaction. There are other physical and environmental factors such as nursing and hospital care, clinical standard and charisma, and how severe the disease or disorder appears to be. A patient may experience 'optimistic bias' which is a clinic sincere care to a patients. It's a fact that people tolerate success than failure, as a result of this scientific research have consider blind trial to drugs as a source of treatment (Gelernter & Uhde, 1991).

Immunotherapy is a treatment that stimulates the immune system of a patient to fight against disease and infections. This type of treatment is targeted to boost the body's natural abilities that will protect the body system from disease that are within or outside the body (Parham, 2014). Immunotherapy uses substance like biological response modifiers (BRMS) that is found in the body and also it can be manufactured from the laboratory in large quantities so as to treat disease. Due to the manufactures BRMS produced from the laboratory helps to predict the treatment of immunotherapy. The prediction identifies patients with similar clinical parameters and then applies a suitable treatment which helps to give prior knowledge whether the patient is a treatment respondent or not (Talmadge, Fidler, & Oldham, 2012). The treatment features can be biological or clinical parameters that serves as the baseline for evaluating the degree of patient's response. The history of patient's response to drugs can be a good medical record or information that can be used to predict the response of treatment of a patient across a period of time in consideration to the baseline parameter that is use in evaluating. The rate of response to treatment that be compared and measured using biological features or clinical parameters that could be obtain or gotten from a patient historic medical record before and after the disease infection or disorder. Collection of relevant data is of great significance to comparing and predicting the treatment of any patient in relation to any type of disease (Fayers & Machin, 2013).

Adaptive neuro fuzzy inference system (ANFIS) is a hybrid learning algorithm with the capabilities of supervised learning, supervised learning is a technique of machine learning which is use to achieve certain precise targeted knowledge from the collection of relevant data. This tool is very useful in modern medicine especially in medical diagnosis, it's also use in profit prediction, crime detection, risk assessment, construction and reengineering of business process. ANFIS uses a hybrid learning algorithms to analyze data in order to uncover the patterns in a very large collection of dataset. This technique is applied by big industries to reduce cost, enhance research outcomes and standards of research, increase product sales and the accuracy of predicting business situations (Taher, 2010).

Support Vector Machine (SVM) is a new and promising method for both linear and nonlinear classification data. SVM is basically the concept of decision planes which specify the boundaries for decision. The decision plane focus on separating a set of objects with different class Memberships, where SVM algorithms share the n dimensional space representation of data into two regions with the help of a hyper plane. The hyper plane usually maximizes the margin in between the two separate regions or classes. This margin is usually defined by the longest distance in between the two class's examples; the margin is computed based on the distance between the instance that is close to both classes to the margin that are referred to as supporting vectors.

2 STRENGTH AND WEAKNESSES OF EXISTING MODELS

A study Conducted on 180 patients, with plantar and common warts, who were divided into two groups, where 90 patients were treated using cryotherapy method with liquid nitrogen and 90 patients with immunotherapy method. A fuzzy logic rule-based system was proposed and implemented to predict the responses to the treatment method. It was observed that the prediction accuracy of immunotherapy and cryotherapy methods was 83.33% and 80.7%, respectively. According to the results obtained, the benefits of this expert system are multifold: assisting physicians in selecting the best treatment method, saving time for patients, reducing the treatment cost, and improving the quality of treatment (Khozeimeh, et al., 2017).

A paper presented a developed hybrid machine learning system using Support Vector Machines (SVM) and Adaptive Neuro-Fuzzy Inference System (ANFIS) alongside domain knowledge to provide a solution to the problem of prediction. The two-stage proposed Domain Knowledge based Fuzzy Information System (DKFIS) worked on improving the accuracy of ANFIS prediction model alone. The framework used a noisy dataset that is incomplete and oil saturation was predicted from four distinct well logs. Stage one of the research used SVM to classify the input vector into two distinct classes (i.e. Class 0 and 1) that was based on zero, near zero or non-zero level of oil saturation. The research further fine-tuned the classified results by applying expert knowledge that depended on the relationship that exist among prediction variables. Stage two used a designed ANFIS that predict a non-zero (Class 1) values of oil saturation. The experimental results reveals the intervention of expert knowledge with qualitative inference at every stage of the work that has made the prediction feasible with realistic ranges. Performance analysis of the model of the prediction reveals that DKFIS based on SVM and ANFIS is a useful model for characterization of oil saturation level in a reservoir (Chaki, Routray, Mohanty, & &Jenamani, 2015).

A study proposed a method using multi-SVM (Support Vector Machine) over 45 digital images that were obtained from MIT BMI unit which consists of warts, benign skin cancer and malignant skin cancer image and also normal skin images. These images were rendered to various pre-processing techniques such as RGB to LAB conversion, resizing and contrast enhancement. Then image segmentation using c-means and watershed algorithms were conducted on the individual images. They performed Feature extraction using Grey Level Co-occurrence Matrix (GLCM) and used Image Quality Assessment (IQA) methods to determine the texture which reveals the statistical parameters of each algorithm individually. These features were combined to obtain a better classification efficiency. The research work used different types of skin diseases that are commonly classified as Benign Skin Cancer, Malignant Skin Cancer and Warts using multi-SVM (Support Vector Machine). Support Vector Machines (SVM) as a machine learning model with associated algorithms was used to analyze images within the database and classify them. In terms of feature selection and extraction the diagnosis system involves two stages of process such as training and testing. Features values of the training data set are compared to the testing data set of each type. C-means algorithm provides better segmentation and feature extraction compared to watershed algorithm (Manerkar, et al., 2016)

A paper proposes a very relevant feature selection for image segmentation of skin lesion, a new unsupervised dictionary learning Theoretic Dictionary Learning (UITDL)method was proposed and it involves two stages in the first stage a feature dictionary was constructed using textual variation of images and are represented non-negative matrix factorization (NMF). The stage two performs feature dictionary selection from adaptive number of dictionary atoms. The result reveals that the model can provide accurate segmentation of skin lesions wich can positively affect the diagnosis provided to patients (Polat & Güneş, 2007).

A study proposed Computerized image analysis model for dermoscopy that are of great benefit and interest, as significant information about lesion are provided. A required image processing algorithms that describes mathematical the suspected regions used on diagnostic Computer-based system, the Computer-based technique was used in each of the following steps dermoscopic image pre-processing, segmentation, extraction and selection of peculiar features, and relegation of skin lesions. The paper also presents reasonable judgment to every methodology utilized and in addition to every corresponding results obtained (Pathan, Prabhu, & Siddalingaswamy, 2018).

R. S. Gound et al, January 2018 proposed a system that capture skin image through smart-phone camera. Preprocess them and segment each image. Feature extraction was performed on every skin lesion, in predicting application model Feature Extraction is important. The process of capturing, processing, indexing and retrieval of visual content of images is known as Feature extraction. After feature extraction, then feature classification which compares the image that have been captured to the stored training dataset with image processing techniques that judges using decision tree whether a skin is infected with a disease or not. The system gives medical advice when there is a disease through an android application.

3.0 Machine Learning Models

Machine learning, deals with the development of algorithms and software based on the machine's past experiences. A program capable of machine learning is able to perform a certain task or improve how it performs a task through previous runs and without any additional changes in the software. It involves the extraction of knowledge from data. Machine learning is split into three primary categories: supervised learning, unsupervised learning, and reinforcement learning. The machine learning models attempt to adopt principles based on how humans naturally learn and involve building systems that can 'think' and adapt themselves. One of the primary applications to healthcare for machine learning involves patient diagnosis and treatment. It is important not only in emergency medical situations, but also in general primary care and in specialized physicians as well. (Gupta, 2017)

3.1 Adaptive Neuro-Fuzzy Inference System

ANFIS combines the principle of fuzzy logic and neural networks, The advantage of fuzzy logic is smoothness and the advantage of neural network is adaptability which is built on the processing of partial truth ANFIS allows the translation of the final intelligent system into a set of expert if-then rules, the fuzzy logic model can be viewed as neural network structure as the name implies is a network that consist of nodes and directional links, the input-output structural behavior is determined by collected values of parameters that can be modified through the inter connected nodes. The adaptive network system uses hybrid learning algorithm for parameter identification of Sugeno fuzzy inference systems. It combines the least-square method with back-propagation method for training fuzzy membership function to evaluate a given dataset. There are two learning phase of ANFIS, the forward phase identifies the least square estimate and the backward phase deals with error signals, The learning and training phase of the adaptive network determines the parameters of sufficiently fitted valued for training data. The main advantage of this hybrid model is that it converges faster because it reduces the space in search dimension of back propagation method in neural network, ANFIS are the fuzzy inference model put in framework of the adaptive system which serves in model building and validation of developed model to facilitate training and adaptation (Walia, Singh, & Sharma, 2015).

Fig 3: Basic architecture of ANFIS

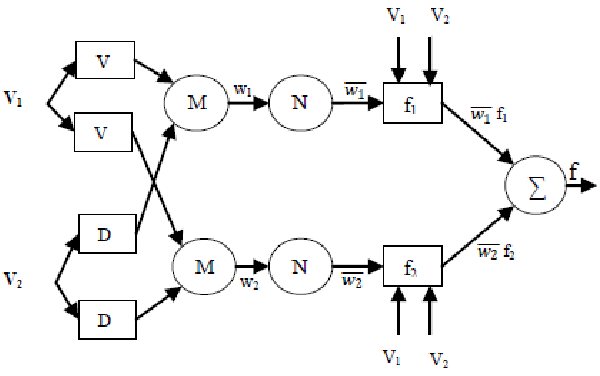

Fig 3: Basic architecture of ANFIS

3.2.3 Learning Algorithm of ANFIS

Neuro-adaptive learning techniques endow with a method for the fuzzy modeling procedure to learn information about a data set. It computes the membership function parameters that best allow the associated fuzzy inference system to track the given input/output data. In order to more efficiently cope with real world problems, the task of the learning algorithm for this architecture is to tune all the modifiable parameters, to formulate the ANFIS output match the training data. To improve the rate of convergence, the hybrid network can be trained by a hybrid learning algorithm combining least square method and gradient descent method can be used. The least squares method can be used to identify the optimal values of the consequent parameter on the layer 4 with premise parameter fixed. The hybrid algorithm is composed of a forward pass (LSM) and a backward pass (GDM). Once the optimal consequent parameters are found, backward pass starts. In the backward pass, errors are propagated backward and the premise parameters corresponding to the fuzzy sets in the input domain updated by gradient descent method (Polat & Güneş, 2007). ANFIS uses a combination of least squares estimation and back-propagation for membership function parameter estimation. Two passes in the hybrid learning algorithm for ANFIS shown in table 1

Table 1: Passes of Hybrid learning algorithm

Table 1: Passes of Hybrid learning algorithm

	Forward pass	Backward pass
Premise parameters	Fixed	Gradient descent
Consequent parameters	Least square	Fixed
Signals	Node outputs	Error signals

The output error is used to adapt the premise parameters by means of a standard back-propagation algorithm to minimize the mean square error function defined by Eq. (12). It has been proven that this hybrid algorithm highly efficient in training the ANFIS (Gerend & Magloire, 2008)

$\mathbf{E}(\boldsymbol{\theta})= (\boldsymbol{zi-aiT\theta})\mathbf{2}=\boldsymbol{eTe}=\boldsymbol{mi}=\mathbf{1}(\boldsymbol{z-A\theta})\boldsymbol{Tz-A\theta}$ ……..(1)

Where e = $z-A\theta$ is the error vector produced by a specific choice of θ. In Eq. (12) the squared error is minimized and is called the least squares estimator (LSE) (Taher, 2010). Therefore, the hybrid learning algorithm can be applied directly. More specifically, the error signals proliferate backward and the premise parameters are updated by Gradient Descent (GD) and node outputs go forward until layer 3 and the consequent parameters are identified by the Least Squares (LS) method. This hybrid learning is structured as by defining, linear and nonlinear parameters are illustrious each iteration (epoch) of GD update the nonlinear parameters, LS follows to identify the linear parameters.

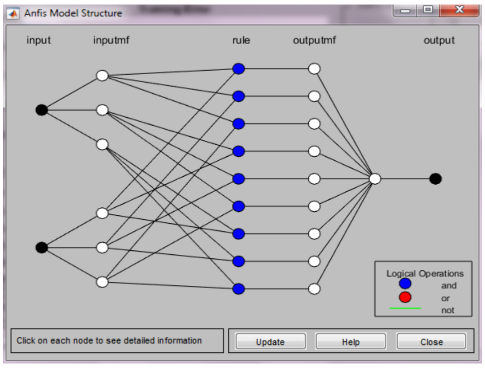

Fig. 3.4 ANFIS Structure

The structure of the model created for immunotherapy dataset was show in Fig. 3.4 where MinMaz normalized data was used consisting of two inputs, three (3)inputs membership function at ever input making a total of six (6) input membership function, nine (9) generated fuzzy rules and nine corresponding output membership function.

3.3 SUPPORT VECTOR MACHINE (SVM)

Support vector machine is a machine learning algorithm that generates support vectors. It is mainly use in activity that cut across pattern recognition, predicting, classification and regression analysis. Severally, SVM has been proved and its application show superior performance compared to prior developed methodologies such as neural networks and other conventional statistical applications (Polat & Güneş, 2007)

SVM application span through variety of fields such as computing, hydrology, medicine and environmental researches (Walia, Singh, & Sharma, 2015).

3.4 SVM CLASSIFICATION

Support vector machine classifies binary class problems without loss of generality but also classifies multiclass problems by adapting a unique algorithm, its primary goal is to separate the two classes by a function induced from an available examples by a classifier called optimal separation hyper plane. This optimal classifier separates the data by finding the maximum margin among the two classes of data.

An SVM training algorithm builds a model that predicts whether a new data mapped and fitted in a category or the other learned from historical examples. SVM models takes a set of input data and predict for each instance the possible output which makes them non probabilistic binary linear class . The operation of SVM algorithm is based on finding the hyper-plane that gives the highest minimum distance to the training examples. Therefore the optimal separating hyper-plane maximizes the margin of the dataset.

3.5 Data Collection

The records of patients with warts disease were collected from the dermatology clinic of Ghaem Hospital from 2013 January to 2015 February in Mashhad. The datasets collected are for patients, with plantar and common warts, that where referred to the Mashhad dermatology clinic. For the purpose of this research the records where obtain from UCI dataset repository.

3.5.2 Data Description

The dataset consist of eight features for immunotherapy method. Table 3.1 presents these features. The attribute *Response to Treatment* is the target feature.

Table 3.1 Immunotherapy dataset description

Attribute	Description	Range
Sex	Male=1 Female=2	41 Man 49 Woman
Age	How old the patients	year 15–56
Time	The month taking for the administration of treatment	month 0–12
Number of warts disease	The number of warts an individual have on his/her body	1–19
Types of warts	Which type of warts is the individual suffering from	1– Common (47), 2– Plantar (22), 3– Both (21)
Surface area of warts	The length and width of warts on the skin	Discrete (mm2)6 –900
Induration diameter of warts	How deep the Immunotherapy treatment administered	Discrete (mm) 5–70
Response to treatment (target)	Response to immunotherapy treatment of warts disease	0 for not treated 1 for treated

3.5 Data Normalization

Data normalization can provide a better modeling and avoid numerical problems. Several normalization algorithms have been developed that can be used to normalize datasets. These algorithms scale a given data in the same range of values for each input feature in order to minimize bias within the network for one feature to another. Data normalization also help to speed up training time by starting the training process for each feature within the same scale. There are many types of data normalization that can be used during modelling of systems.

3.5.1 Min-max Normalization

Min-max normalization algorithm is a linear scaling algorithm. It transforms the original input range into a new data range (typically 0-1). It is given as

$$Yold = \frac{Yold - min1}{max1 - min1}\ (max2 - min2) + min2 \_\underline{equ.\ 4}$$

Where y_{old} is the old value, y_{new} is the new value, minl and maxl are the minimum and maximum of the original data range, and min2 and max2 are the minimum and maximum of the new data range.

Since the min-max normalization is a linear transformation, it can preserve all relationships of the data values exactly.

3.5.2 Zscore Normalization

Zscore normalization algorithm converts an input variable data into zero mean and unit variance. The mean and standard deviation of the input data are calculated first. The algorithm is shown below

$$Ynew = \frac{Yold - mean}{std} \_\_\_\_\_\_\underline{equation\ 5}$$

Where y_{old} is the original value, y_{new} is the new value, and mean and std are the mean and standard deviation of the original data range, respectively.

3.6 NETWORK TRAINING

The preprocessed data where divided into two 70 percent for training which consist of 63 instances of data. The data served as input for training ANFIS and SVM models.

3.7 NETWORK TESTING

The data instances used for testing was 30 of the dataset respectively. 27 instance of immunotherapy dataset where used for testing the developed ANFIS and SVM models. The models where tested to ascertain the instances that where accurately predicted when compared to the target response to treatment.

Table 3.2: sample of data used

1	sex	age	Time	Number_of	Type	Area	induration_	Result_of_Tı
2	1	22	2.25	14	3	51	50	1
3	1	15	3	2	3	900	70	1
4	1	16	10.5	2	1	100	25	1
5	1	27	4.5	9	3	80	30	1
6	1	20	8	6	1	45	8	1
7	1	15	5	3	3	84	7	1
8	1	35	9.75	2	2	8	6	1
9	2	28	7.5	4	1	9	2	1
10	2	19	6	2	1	225	8	1
11	2	32	12	6	3	35	5	0
12	2	33	6.25	2	1	30	3	1
13	2	17	5.75	12	3	25	7	1
14	2	15	1.75	1	2	49	7	0
15	2	15	5.5	12	1	48	7	1
16	2	16	10	7	1	143	6	1
17	2	33	9.25	2	2	150	8	1
18	2	26	7.75	6	2	6	5	1
19	2	23	7.5	10	2	43	3	1
20	2	15	6.5	19	1	56	7	1

4.0 RESULTS

ANFIS model was developed for three different data processes namely; raw data, Minmax and Zscore normalized data. The following results where obtain

Table 4.1: ANFIS Confusion matrix for the raw data

TP = 11	FN = 2	P = 13
FP = 8	TN = 6	N = 14
		P + N = 27

The confusion metric in Table 4.1reveals that eleven (11) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while two (2) instances where the negative instances that were correctly predicted .

Table 4.2: ANFIS Confusion matrix for MinMax

TP = 19	FN = 0	P = 19
FP = 4	TN = 4	N = 8
		P + N = 27

The confusion metric in Table 4.2 reveals that nineteen (19) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while no instances where predicted as negative instances.

Table 4.3: ANFIS Confusion matrix for Zscore

TP = 10	FN = 0	P = 10
FP = 12	TN = 5	N = 17
		P + N = 27

The confusion metric in Table 4.3reveals that ten (10) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while no instances where predicted as negative instances.

Table 4.4: ANFIS result

Data normalization method	Error	Accuracy	Specificity	Sensitivity
Raw data *(without preprocessing)*	0.50622	0.49378	0.40741	0.22222
Minmax normalization	0.30303	0.69697	0.14801	0.70370
Zscore normalization	0.6339	0.3661	0.0.18518	0.33333

In the above results it was observed that Minmax data performed better than the normal data and Zscore data with minimal error of 0.30303, accuracy of 0.69697.

4.3 SVM Result

SVM model was developed for three different data processes namely; raw data, Minmax and Zscore normalized data. The following results where obtain

Table 4.5: SVM Confusion matrix for MinMax

TP = 15	FN = 4	P = 19
FP = 3	TN = 5	N = 8
		P + N = 27

An SVM code was used with polynomial “Pol” as activation function, Fig. 4.1 shows the matlab worksheet environment for MinMAx data it capture the performance measure in the workspace at the left corner of the fig. The confusion metric in Table 4.5 reveals that fifteen (15) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while four (4) instances where predicted as negative instances that are actually negative.

Table 4.6: SVM Confusion matrix for Zscore

TP = 20	FN = 4	P = 24
FP = 3	TN = 0	N = 3
		P + N = 27

An SVM code was used with linear “linear” as activation function, Fig. 4.2 shows the matlab worksheet environment for Zscore data it capture the performance measure in the workspace at the left corner of the fig. The confusion metric in Table 4.6 reveals that twenty (20) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while four (4) instances where predicted as negative instances that are actually negative.

Table 4.7: SVM Confusion matrix for raw data

TP = 23	FN = 0	P = 23
FP = 1	TN = 2	N = 4
		P + N = 27

An SVM code was used with Radio Biases function “Rbf” as activation function. The confusion matrix in Table 4.7 reveals that twenty three (23) instances out of 27 instances used for testing were predicted to be the positive instances that were correctly predicted while no instances where predicted as negative instances.

Table 4.8: SVM result

Normalization method	Activation function	Error	Accuracy	Specificity	Sensitivity
Raw data	Rbf	0.0385	0.9787	0.6667	1
Minmax	Pol	0.0371	0.9629	0.4286	0.7500
Zscore	Linear	0.1835	0.8165	0	1

From the result above it was observed that Minmax data with ‘pol’ activation function produces the best result with an error rate of 0.0371, accuracy of 0.9629, specificity of 0.4286 and Sensitivity of 0.7500

4.4 Discussion of Result

The Comparison of the proposed models ANFIS and SVM values for error, accuracy, sensitivity and specificity are discussed thus.

Table 4.9: ANFIS and SVM result compared

	Error	Accuracy	Specificity	Sensitivity
ANFIS	0.30303	0.69697	0.29629	0.70370
SVM	0.0371	0.9629	0.4286	0.7500

This study, analyze ANFIS and SVM model that where design to predict the response to immunotherapy treatment of warts disease. The accuracy of ANFIS and SVM values of the model are ANFIS 0.69697and SVM 0.9629, respectively, based on their results SVM model performed best in response to immunotherapy treatment of warts disease.

5.0 CONCLUSION

This study has described the architecture and structure of adaptive neuro-fuzzy inference systems alongside it reasoning mechanisms. ANFIS model can improve the generation of relevant if-then fuzzy rules for the prediction of warts disease base on knowledge obtain from human experts which will describe the relevant input and output behavior of warts disease. The set of if-then fuzzy rules can give a desired approximate output. Support vector machine model has the potential of combining human heuristic into computer assisted decision. SVM training algorithm described a model that predicts if an input data of warts disease can fit into response or non-response category base on historic patterns. SVM algorithm operated base on finding the hyper-plane within the warts disease dataset that gives the highest distance to the training pattern, the optimal separation hyper-plane maximizes the margin of the dataset. In this research work, used machine learning techniques to classify and predict immunotherapy treatment of warts disease. ANFIS and SVM models were used to analyze immunotherapy treatment of warts disease dataset, the performance and accuracy of the models compare. This intelligent system will provide a simple way to arrive at a definite conclusion from ambiguous medical data. This will help individuals, medical professionals, world health organizations and government agencies to take appropriate actions. Contributions and suggestions are welcome at this stage of the research.

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