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A REVIEW OF CLASSIFICATION TECHNIQUES FOR THE PREDICTION OF HUMAN EMOTION THROUGH HEART RATE AND EYE MOVEMENT

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ABSTRACT

Classification is the technique applied in data mining to form groups under specified class labels. Classification is a supervised type of machine learning. In this paper, five familiar classification techniques, Fuzzy Inference System (FIS), Adaptive-Network-based Fuzzy Inference System (ANFIS), Convolutional Neural Network (CNN), Support Vector Machine (SVM), and ANFIS-PLS are compared for accuracy of classification of images. Therefore, we present a comparative study of different classification techniques applied in predicting human emotion through heart rate and eye movement. This paper aims to describe and review the differences in classification techniques and the suitability of each classification to apply in the prediction of human emotion through heart rate and eye movement. Based on the literature survey from four databases: ACM, IEEE, Scopus, and Science Direct; some articles have been reviewed. The studies found that the Adaptive neuro-fuzzy inference system (ANFIS) is the most adopted model due to the motivation mechanism applied. A fundamental review of the selected technique is presented for introduction purposes. A brief comparison with other classifiers, the main advantages and drawbacks of these classifiers are discussed as well.

1.0 INTRODUCTION

Classification is the problem of identifying to which categories a new observation belongs. It is performed by using supervised learning. Supervised learning is the machine learning framework in which the training data comprises different groups of data labelled as classes, by training, each class has an inferred function which used in mapping new examples to the closer class. The five classifiers chosen are briefly explained in the next section.

On top of that, image classification is a crucial issue in machine learning and computer vision. A variety of techniques and methodologies have been proposed for efficient and faster classification. Neural networks have greater potential in image and text processing [1]. Sometimes high dimensional images are difficult to process due to high memory and high computation time requirements, feature selection can remove noise, and irrelevant features and reduce the size of the image. Individual object recognition in the image is usually done with feature extraction and classification. Feature extraction typically uses a variety of methods to get a representation of the data and then uses the classifier to classify the data. This article presents a survey of the current state-of-the-art on classifier estimation techniques, with a focus on FIS, ANFIS, CNN, SVM, and ANFIS-PLS. This study also provides information on various classifiers chosen to prove the suitability and accuracy to be applied in human emotion prediction through eye movement and heart rate. Table 1 shows the classification techniques discussed in this paper.

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Table 1. Classification techniques

No.	Techniques	Year
1	Fuzzy Inference System (FIS)	2013
2	Adaptive-Network-based Fuzzy Inference System (ANFIS)	2020
3	Convolutional Neural Network (CNN)	2019
4	Support Vector Machine (SVM)	2019
5	ANFIS-PLS	2003

2.0 CLASSIFICATION

In this research, we deploy various classification techniques. Those techniques are described briefly below:

2.1 Fuzzy Inference System (FIS)

Fuzzy Inference Systems (FISs) is a technology developed for granular rule induction and generalization based on fuzzy logic. Note that since a data cluster can be interpreted as a (fuzzy) granule, data clustering may be closely related to fuzzy rule induction. Neural implementations have provided conventional FISs with a capacity for parallel implementation [2]. Fuzzy inference systems are also known as fuzzy-rule-based systems, fuzzy models, fuzzy associative memories (FAM), or fuzzy controllers when used as controllers [3]. Basically, a fuzzy inference system is composed of five functional blocks (see Figure 1):

- a rule base containing several fuzzy if-then rules; a database that defines the membership functions of the fuzzy sets used in the fuzzy rules.
- a decision-making unit that performs the inference operations on the rules.
- a fuzzification interface that transforms the crisp inputs into degrees of a match with linguistic values.
- a defuzzification interface that transforms the fuzzy results of the inference into a crisp output.

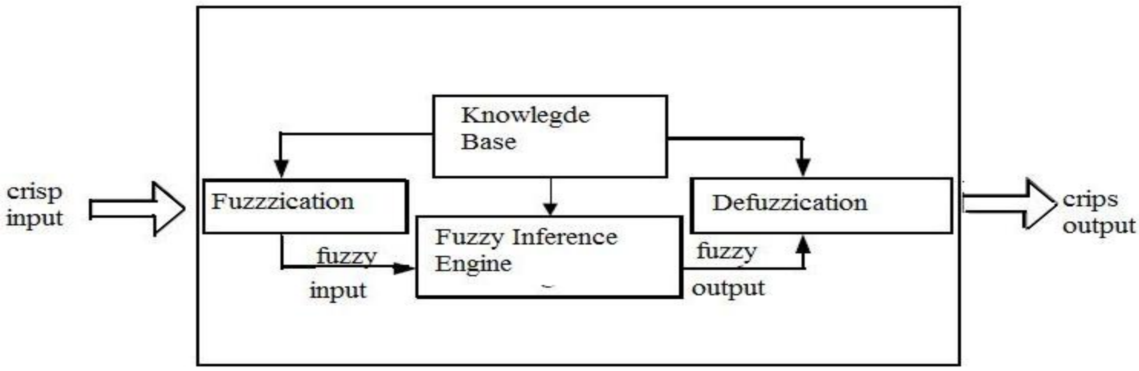

Figure 1. Fuzzy inference system [4]

2.2 Adaptive-Network-Based Fuzzy Inference System (ANFIS)

This work uses ANFIS (Adaptive Neuro-Fuzzy Inference Systems), a fuzzy classifier that is part of the MATLAB Fuzzy Logic Toolbox (FLT, 2011). ANFIS is a fuzzy inference system implemented under the framework of adaptive networks [5]. The next section describes the architecture of ANFIS and sections the learning algorithm of ANFIS [6].

2.3 Architecture of ANFIS

The ANFIS is a fuzzy Sugeno model put in the framework of adaptive systems to facilitate learning and adaptation (Jang, 1992, 1993). Such a framework makes the ANFIS modelling more systematic and less reliant on expert knowledge. To present the ANFIS architecture, two fuzzy if-then rules based on a first-order Sugeno model are considered:

Rule 1: $If\ (x\ is\ A_1)$ and $(y\ is\ B_1)$ then $(f_1 = p_1x + q_1y + r_1)$

Rule 2: $If\ (x\ is\ A_2)$ and $(y\ is\ B_2)$ then $(f_2 = p_2x + q_2y + r_2)$

where x and y are the inputs, A_1 and B_1 are the fuzzy sets, f_1 is the outputs within the fuzzy region specified by the fuzzy rule, p_1, q_1 and r_1 are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Figure 2, in which a circle indicates a fixed node, whereas a square indicates an adaptive node. In the first layer, all the nodes are adaptive nodes. The outputs of layer 1 are the fuzzy membership grade of the inputs, which are given by:

$$O_i^1 = \mu_{Ai}(x), i = 1, 2 \tag{1}$$

$$O_i^1 = \mu_{Bi-2}(y), i = 3, 4 \tag{2}$$

where $\mu_{Ai}(x)$, $\mu_{Bi-2}(y)$ can adopt any fuzzy membership function. For example, if the bell-shaped membership [7].

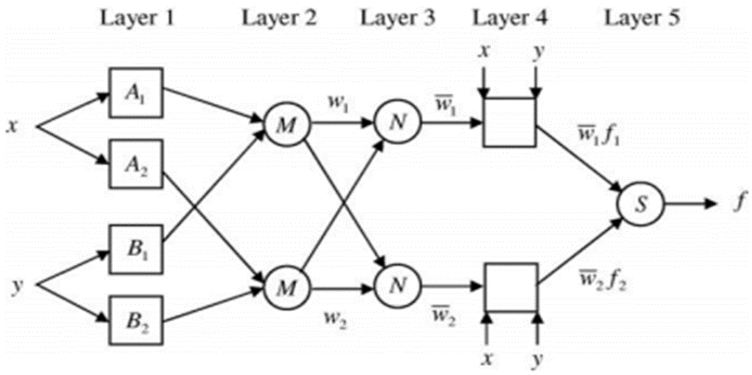

Figure 2. ANFIS architecture [4]

the function is employed, $\mu_{Ai}(x)$ is given by:

$$\mu_{Ai}(x) = \frac{1}{1 + \left\{\left(\frac{x - c_i}{a_i}\right)^2\right\}} \tag{3}$$

where a_i, b_i and c_i are the parameters of the membership function, governing the bell-shaped functions accordingly. In the second layer, the nodes are fixed nodes. They are labelled with M, indicating that they perform as a simple multiplier. The outputs of this layer can be represented as:

$$O_i^2 = \omega_i = \mu_{Ai}(x)\mu_{Bi}(y), \qquad i = 1, 2 \tag{4}$$

which are the so-called firing strengths of the rules. In the third layer, the nodes are also fixed nodes. They are labelled with N, indicating that they play a normalization role in the firing strengths from the previous layer. The outputs of this layer can be represented as:

$$O_i^3 = \bar{\omega}_1 = \frac{\omega_1}{\omega_1 + \omega_2} \tag{5}$$

which are the so-called normalized firing strengths. In the fourth layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first-order polynomial (for a first-order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \bar{\omega}_i f_i = \bar{\omega}_i(p_1x + q_1y + r_1) \quad i = 1, 2 \tag{6}$$

In the fifth layer, there is only one single fixed node labelled with S. This node performs the summation of all incoming signals. Hence, the overall output of the model is given by:

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$$O_i^5 = \sum_{i=1}^{2} \bar{\omega}_1 f_1 = \frac{\sum_{i=1}^{2} \omega_1 f_1}{\omega_1 + \omega_2} \tag{7}$$

It can be observed that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$ which are related to the input membership functions. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first-order polynomial. These parameters are so-called consequent parameters [4].

2.4 Learning Algorithm Of ANFIS

The task of the learning algorithm for this architecture is to tune all the modifiable parameters, namely $\{a_i, b_i, c_i\}$ and $\{r_i, q, r_i\}$, to make the ANFIS output match the training data. When the premise parameters a_i, b_i and c_i of the membership function are fixed, the output of the ANFIS model can be written as:

$$f = \frac{\omega_1}{\omega_1 + \omega_2} f_1 + \frac{\omega_2}{\omega_1 + \omega_2} f_2 \tag{8}$$

Substituting Eqn. (5) into Eqn. (8) yields:

$$f = \bar{\omega}_1 f_1 + \bar{\omega}_2 f_2 \tag{9}$$

Substituting the fuzzy if-then rules into Eqn. (9), it becomes:

$$f = \bar{\omega}_1 (p_1 x + q_1 y + r_1) + \bar{\omega}_2 (p_2 x + q_2 y + r_2) \tag{10}$$

After rearrangement, the output can be expressed as:

$$f = (\bar{\omega}_1 x) p_1 + (\bar{\omega}_1 y) q_1 + (\bar{\omega}_1) r_1 + (\bar{\omega}_2 x) p_2 + (\bar{\omega}_2 y) q_2 + (\bar{\omega}_2) r_2 \tag{11}$$

which is a linear combination of the modifiable consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger, and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard backpropagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS [4-5, 7].

2.5 Convolutional Neural Network (CNN)

In deep learning, CNNs are a class of deep neural networks that are mostly applied to evaluate visual images [8]. They are inspired by the organization of the visual cortex in the brain [8]. The visual cortex is the main region of the brain that receives, and processes visual information transmitted from the eye [9]. As shown in Figure 3 below, CNNs are very similar to regular neural networks made up of different neurons with learnable weights and biases. Each neuron in the network accepts input, performs a dot product operation, and optionally follows the dot operation with a non-linearity operation (such as Rectified Linear Unit (ReLU)). CNN architectures make the explicit assumption that all inputs are images and thus allow users to encode certain properties into the architecture [8]. Typically, a CNN consists of multiple convolutional layers followed by pooling, non-linearity, and finally fully connected layer(s) plus an output layer. The first three layers are responsible for feature extraction, while the fully connected layer is responsible for classification [8-9].

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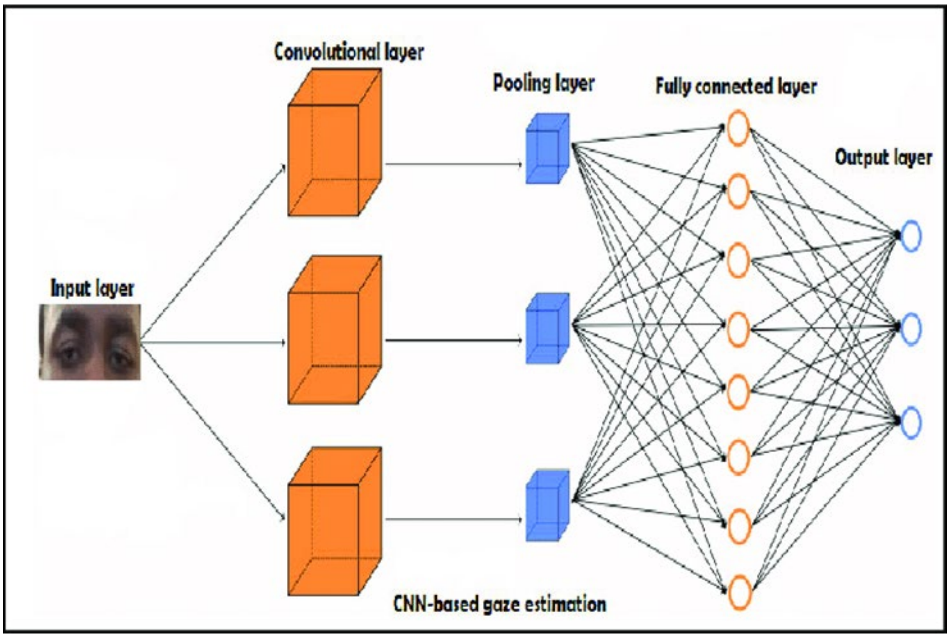

Figure 3. A regular 3-layer neural network and a regular convolutional neural network [7]

2.6 Support Vector Machine (SVM)

The support-vector network is a new learning machine for two-group classification problems. The machine conceptually implements the following idea: input vectors are non-linearly mapped to a very high-dimension feature space. In this feature space, a linear decision surface is constructed. Special properties of the decision surface ensure the high generalization ability of the learning machine. The idea behind the support-vector network was previously implemented for the restricted case where the training data can be separated without errors. We here extend this result to non-separable training data. The high generalization ability of support-vector networks utilizing polynomial input transformations is demonstrated. We also compare the performance of the support-vector network to various classical learning algorithms that all took part in a benchmark study of Optical Character Recognition [10].

SVM is an algorithm for classification or regression that is classified as a supervised algorithm for machine learning and is often used in the classification of data. In SVM, each data item has the value of each function put in n-dimensional space (in this case, N is the number of features). It coordinates explicitly to find a point or area where it can be divided into two (2) classes. SVM is an extended version of a linear regression that can provide high precision and a clear boundary for decision-making. SVM has drawbacks where only 2 groups can be distinguished by it. SVM implementation is commonly used in text classification, spam detection, and identification of device versions [11-12].

2.7 Adaptive Neuro-Fuzzy Inference System-Partial Least-Squares (ANFIS-PLS)

An adaptive neuro-fuzzy inference system-based partial least squares (ANFIS-PLS) method was proposed for monitoring nonlinear processes. The ANFIS was used as a predictor to represent the nonlinear relationship between input and output score variables in each inner loop of PLS, and fuzzy c-means clustering was employed to determine the number of fuzzy rules. Moreover, the hybrid learning algorithm was used to update and optimize the parameters of ANFIS [13].

Referring to research by [5] PLS-SEM, combined with an adaptive neuro-fuzzy inference system (ANFIS) method, was used to develop the study model and determine its main components. Furthermore, the ANFIS results showed that behavioural aspects of safety culture were the most critical predictor of safety at work. Partial least-squares (PLS) and adaptive neuro-fuzzy inference system (ANFIS) models were developed to simultaneously predict water content and salinity in previous research [14]. The PLS model developed for predicting water content performed better than that for salinity. The model predicting salinity showed a nonlinear trend between actual and predicted values. However, the ANFIS model demonstrated a better predicting ability compared to the PLS model [5, 14-15].

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3.0 RELATED WORK

3.1 Classification In Human Eye Movement

Eye movement tracking is becoming a very important tool across many domains, including human-computer interaction, psychology, computer vision, and medical diagnosis. Different methods have been used to tackle eye tracking, however, some of them are inaccurate under real-world conditions, while some require explicit user calibration which can be burdensome [9]. The human eye's state of motion and content of interest can express people's cognitive status and emotional status based on their situation. When observing the surrounding things, the human eyes make different eye movements according to the observed objects, reflecting human attention and interest. Furthermore, eye movement behavior and head motion patterns can be used as a modality of non-verbal information in the computing of human emotional states based on the PAD affective computing model [6].

Besides, according to [6], compute and train the eye-object movement attention model and eye-object feature preference model based on different peoples' eye-gaze behaviors by using ANFIS (adaptive-network-based fuzzy inference system). These models are used to predict humans' object of interest and the interaction intention according to people's heart rates. The recent success and prevalence of deep learning have greatly improved eye-tracking performance. The availability of large-scale datasets has further improved the performance of deep learning-based methods.

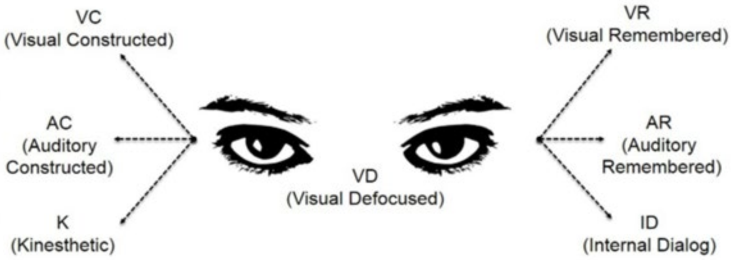

Figure 4. Different EACs in NLP theory [15]

A multiclass classification framework for predicting the EAC classes. Adaptive-Network-based Fuzzy Inference System, or simply ANFIS is used for the classification. The details of the model used are described above. According to [16], the average best accuracy of recognition achieved was around 90 %, and the highest accuracy obtained was for the classification of the amused emotion. They said from the 11 studies that directly used eye-tracking approaches for the task of classifying emotions, the highest accuracy obtained was 90 % using ANN as the classifier with pupil size, pupil position, and motion speed of the eye as the features. Similar to the best outcome of [14], it also appears that a combination of training features is required to achieve good classification outcomes as studies that report high accuracies of at least above 85 % used at least three features in combination [14].

Besides that, researcher in [4] said that ANFIS is a hybrid technique that integrates the learning capability of artificial neural networks and the interpretability of fuzzy inference systems (FIS). While in [4] supported that the customized adaptive neuro-fuzzy inference system (ANFIS) gives 68 % –98 % improvement over the general adaptive neuro-fuzzy inference system. The proposed ANFIS model combined the neural network adaptive capabilities and the fuzzy logic qualitative approach. The total classification accuracy of the ANFIS model was 98.68 %, which concluded that the proposed ANFIS model can be used in classifying the EEG signals by taking into consideration the misclassification rates [4].

3.2 Classification Of Human Heart Rate

Research by Menard M. et al. 2015 decided to process first the collected heart rate and the skin conductivity with a Fourier Transform to get the Fourier coefficients, and then classify these coefficients with the Support Vendor Machine (SVM) [19]. The SVM let us build new models that are more robust and more accurate to fit our emotions set. A new C++ plug-in was created for the platform in order to process the data collected by the previous sensors. It works as a solver where the SVM (integrated with the library LibSVM classifies the data, according to the previously built model, and the output of the emotional state of the subject [20].

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SVM was used as the approach for machine learning by using Python, this is to recognize the emotion classification that is based on the heart rate activity retrieved from the experiment with the subject that is the direct response to the 360O video stimuli shown in the experiment [21] and SVM achieved 46.7%. The results demonstrate the potential of SVM classifiers to classify heart rate as a feature to be used in emotion prediction in four distinct emotion classes in a virtual reality environment. There is currently not much research that classifies heart rate using other classifiers such as FIS, ANFIS, CNN, and ANFIS-PLS.

4.0 SYSTEM METHODOLOGY

For the machine learning implementation, Dlib, and scikit-learn libraries are an open-source library that provides support for developing machine learning software in Python, R, MATLAB, and similar environments [22-23]. The block diagram of the system is shown in Figure 5. The process will be used as a classification under a supervised algorithm; that is, images from the database are sorted into classes, and each class contains the image of a certain individual. Practically this is done by collecting the images that include the same person in a sub-folder. In the first phase, the human face within the whole image is bounded into separate frames and thus, the features of each face -which are called landmarks- are extracted. Those landmarks are manipulated to come up with a remarkable identity (function) for each class. This stage is called "training", and a Python function called "train" is used to implement this action. In the next phase, the classifier (FIS/ANFIS/SVM, etc); finds a way to relate the face under the question to its closest class and marks it with the name of that class. If the classifier failed to find a close match with one of the available classes, the face will be marked as "unknown". The Euclidean distances between the query instance and the training samples are calculated to predict the test data classes and sorted according to the smallest difference to determine the nearest neighbour. ANFIS was particularly difficult to implement under python, considering that it was only available under MATLAB.

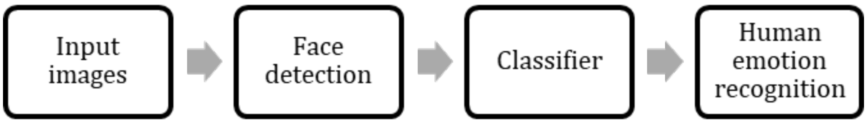

Figure 5. Block diagram of recognition system

5.0 RESULT AND DISCUSSION

In this study, we examine the performance of different classification techniques. According to [4], use accuracy estimates and error estimates of those classifiers. Rule accuracy is 71.51 % and 78.79 % for FIS and ANFIS respectively for different networks and architectures. This is shown in Table 2. Shows the comparison of classification accuracy for the five models chosen.

Table 2. Comparison of classification accuracy for five (5) models

Models	Rules Accuracy (%)
FIS	71.51
ANFIS	98.68
Convolutional Neural Network (CNN)	75.40
Support Vector Machine (SVM)	79.30
ANFIS-PLS	82.28

Besides that, a previous study [17] has proven that the customized adaptive neuro-fuzzy inference system (ANFIS) gives 68 % – 98 % improvement over the general adaptive neuro-fuzzy inference system. While in [5] supports that the total classification accuracy of the ANFIS model was 98.68 %, concluded that the proposed ANFIS model can be used in classifying the EEG signals by taking into consideration the misclassification rates. Finally, the review provides an understanding of why ANFIS will be chosen as the best model of classification.

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6.0 CONCLUSION

Some conclusions concerning the saliency of features in the classification of human eye movement were obtained through analysis of the ANFIS. The classification results and statistical measures were used for evaluating the ANFIS. The total classification accuracy of the ANFIS model was 98.68 %. We, therefore, have concluded that the proposed ANFIS model can be used in classifying human eye movement by taking into consideration the misclassification rates. The study showed that the ANFIS model has a better predicting ability compared to the PLS model, Convolutional Neural Network (CNN), Support Vector Machine (SVM) and ANFIS-PLS. The ANFIS model demonstrated a better predicting ability compared to the PLS model and others. The ANFIS seems more successful than the other four if the lack of data exists or if the size of the database is small. The ANFIS is used to adjust the weights and approximates more and more to produce the desired output, it should be preferred due to its fuzzy logic capability that manages the uncertainty of fuzzy data, ambiguous or incomplete. ANFIS could be a good classifier for medical image classification and assist physicians in earlier diagnosis of different diseases. For future work, more databases are going to be considered in the study, and a clustering technique may need to be applied prior to the classification, so that clearer results and their dependency on the image features and constraints will be concluded.

7.0 ACKNOWLEDGMENT

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