

Arabic Voice Recognition Using Fuzzy Logic and Neural Network

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Abstract

This research adapted and implemented an algorithm for commanding using speech recognition in ARABIC language in addition to English, and the ability to train the system using other languages. The recognition based on discrete coefficient of the wavelet transform. Intelligent recognizer is built for two models, the first is Neural Networks, and the second is Fuzzy Logic Recognizer. The proposed speech recognition system consists of three phases; preprocessing phase (two processes are performed on the sound, DC level removal and resizing of sample for 2000 samples for each sound), feature extraction phase (features that distinguish each sound from another, it is wavelet transform coefficients), and recognition phase (many classifiers could be used for speaker recognition, in this research supervised neural networks, MLP and Fuzzy Logic classifiers are used. This research is also concerned with studying the recognition ability of MLP neural Network and Sugeno type Fuzzy Logic systems, for the recognition of Arabic and English Languages. The neural networks trained with features extracted from discrete wavelet transform. The use of Wavelet Transformation enables to extract an exact features form the speech. The research illustrates the effect of using two different intelligent approaches using MATLAB, and by applying the voice commands directly to an automated wheeled vehicle.

Keywords: MLP neural Network, Arabic Voice Recognition, wavelet transform and Fuzzy Logic.

1. INTRODUCTION

Pattern recognition (PR) deals with the problem of classifying set of patterns or objects obtained from the measurements of physical or mental processes into number of categories or classes [1, 2]. Pattern recognition has a long history of theoretical research in the area of statistics. Recent advances in computer technology have increased the practical applications of pattern recognition, which in turn have led to further theoretical developments. Today, automation in industrial production and the need for efficient information storage are also becoming increasingly important. This trend

has led pattern recognition to be in the high edge of engineering applications and research of the industrial fields. There is no doubt that pattern recognition is an important, useful, and rapidly developing field with cross-disciplinary interest and participation [3].

PR plays an important role in many applications such as document processing, robot vision, recognition of paintings, character recognition and other fields. Automation of pattern recognition helps to speed up processing time as well as to automate processes without human intervention [4]. Generally, PR is the study of concepts, algorithms, and implementations that provide artificial systems with a perceptual capability to put patterns into categories in a simple and reliable way. It has been applied to a wide range of areas including image analysis, computer vision, automatic radar target detection, land cover classification, fingerprint identification, face recognition, handwriting and character identification, speech and voice understanding and computer-aided diagnosis [3].

The use of biometric information has been known widely for both person identification and security applications in addition to special needs applications. It is common knowledge that the human speech can be used as a command input instead of traditional input unit. The main biometric characteristic that can be used in commanding as input unit, with flexibility and wide range of input command is the human speech [5].

A system for speaker independent speech recognition was presented by Rehman et al. in [6], which was experienced on isolated words from three oriental languages, i.e., Pashto, Persian, and Urdu. This system combines feed-forward artificial neural network (FFANN) and discrete wavelet transform (DWT) with the aim of speech recognition.

For feature extraction DWT is utilized and for the classification purpose the FFANN is utilized. The isolated word recognition was achieved firstly by speech signal capturing, then creating a code bank of speech samples, and finally by applying pre-processing techniques. In order to classify a wave sample, resilient back-propagation (Rprop) with the four layered FFANN model was utilized. This system produced high accuracy when using two and five classes. For

db-8 level-5 DWT filter accuracy rate of 98.40%, 95.73%, and 95.20% is achieved with 10, 15, and 20 classes, respectively. Haar level-5 DWT filter shows 97.20%, 94.40%, and 91% accuracy rate for 10, 15, and 20 classes, respectively.

An effective approach for Chinese speech recognition on small vocabulary size is proposed by Huang in [7], the independent speech recognition of Chinese words based on Hidden Markov Model (HMM). The features of speech words are generated by sub-syllable of Chinese characters. To improve the performance, keyword spotting criterion is applied into the system.

The technological revolution influenced everything [8-38], even the methods of marketing, pattern recognition, business and educational applications for the real world business issues [24]. Today, the use of Artificial Intelligence (AI) algorithms is expansive, particularly in providing solution to challenging problems including image segmentation [39-48], analysis of medical image [49-53], nurse rostering problem [54], healthcare monitoring system [55, 56], patterns recognition and retrieval of information [57-72], learning management system [73], as well as prediction of river flow [74-76]. Accordingly, utilizing the AI algorithms, countless scholars have created as well as implemented an algorithm for commanding using speech recognition in ARABIC language [77-79].

2. PROPOSED METHOD

The main characteristic of any speech recognition is the determination of the specific features of speech. Speech recognition system consists of several modules in addition to the classification engine. The proposed system consists of three main modules as shown in figure 1:

The first step is recording sounds and then preprocessing the recorded sounds. The sounds waves that resulted were entered to the feature extraction module for features extraction.

At last, the features that were extracted are passed to the recognition module which is composed of two phases, the training phase and the testing phase. The trained system is used to recognize the speech.

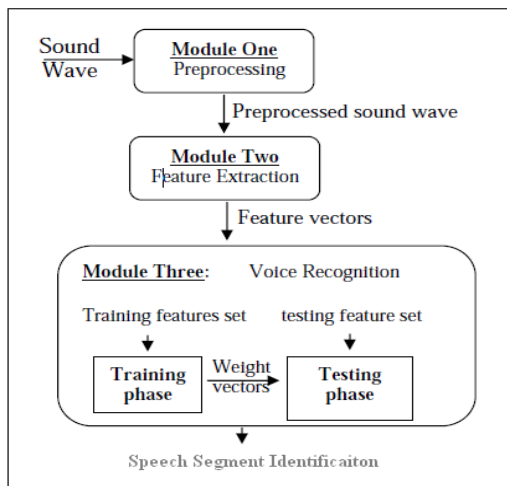


Figure 1: Basic Program Diagram of the Proposed System.

2.1 Preprocessing Module

After recording voices from different languages and persons, the preprocessing phase will start. In order to pick up the voiced signal and convert it into electronic signal a microphone system is used, the signal is then entered to the computer using Microsoft sound recorder. There are three main elements in this process:

- **Sampling rate:** 8 KHz
- **Bit per sample:** 16 bit
- **Channels number:** stereo or mono.

In most application, mono is sufficient, because speech is relatively low bandwidth (mostly between 100Hz 8 kHz), 8000 samples/sec (8 kHz) is sufficient for most basic speaker recognition. But, some people prefer 16000 samples/sec (16 kHz) because it provides more accurate high frequency information. For the preprocessing module, the recorded sounds are the input, which are passed using:

1. DC Level Removal:

DC-blocking filters used for removing the DC bias voltage from the microphone signal. When the average of the wave is greater than zero, then there is noise. By applying the DC level, the average of wave back to the zero. By this step some noise can riddance from. See figure 2.

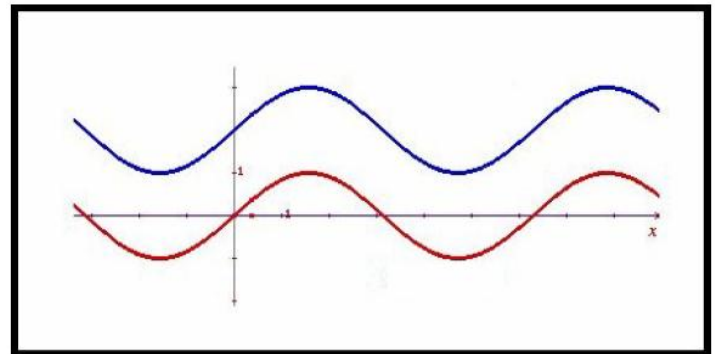


Figure 2: Removing the DC level

2. Resizing of Samples

When the sounds recorded from people, the sounds have different sample numbers, the sample is resized to 2000 samples because the number of samples can't be controlled while recording.

3. Low-Pass Filter for Noise Removal

The original signals go through complementary filters and produces two signal, low pass filter eliminates the frequencies above half of the highest signal frequency, for example if the signal has a maximum of 1000 Hz component, the low pass filter remove all frequency above 500 Hz. In order to remove noise (see figure 3 and 4 bellow), Infinite Impulse Response (IIR) Butterworth low pass filter of a cutoff frequency about

500 HZ is applied to the signal (using MATLAB signal processing toolbox).

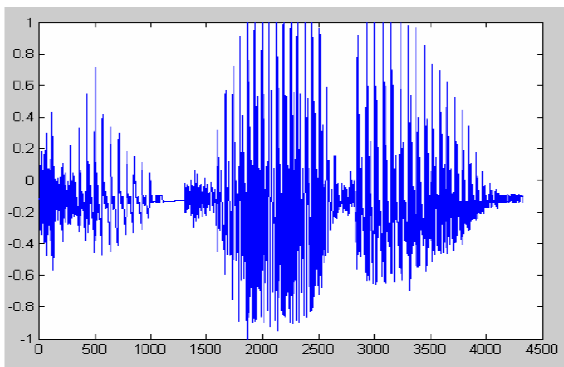


Figure 3: A Voice Signal Sample BEFORE Noise Removal.

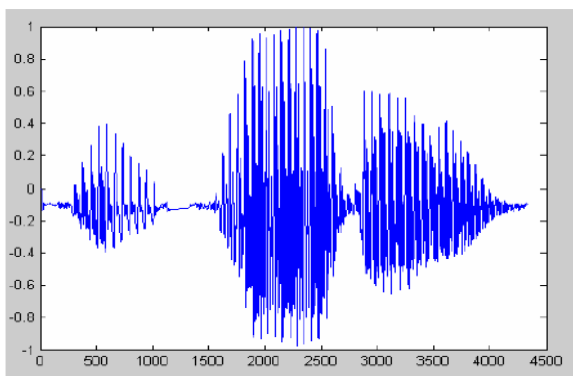


Figure 4: A Voice Signal Sample AFTER Noise Removal.

2.2 Feature Extraction Module

The second step is extracting the features from the sound to categorize and distinguish each sound from the others. Features can be extracted using different methods, in this work features are extracted after applying DWT.

DWT is a wavelet transformation special case which provides a time and frequency compact representation for the signal. In DWT case, the signals pass through two filters low-pass filter to analyze the low frequencies, high-pass filter to analyze the high frequencies, the low-pass filter result is the coefficient and the result of high-pass filter is details. The filtering process is shown in figure 5 where A represents coefficient and D represents details.

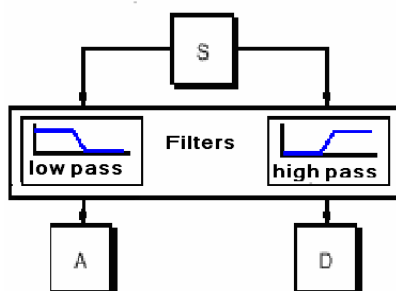


Figure 5: The filtering process.

For many signals the low-frequency content is the most important part, it gives the signal its identity, if enough of low-frequency components removed from the sound the unwanted frequencies, while on other hand if the high-frequency component removed, the sound different but we still understand it. And mostly, the high frequency is considered as noise.

2.2.1 Mutli-Level Decomposition

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components (levels). This is called the wavelet decomposition tree as shown in figure 6.

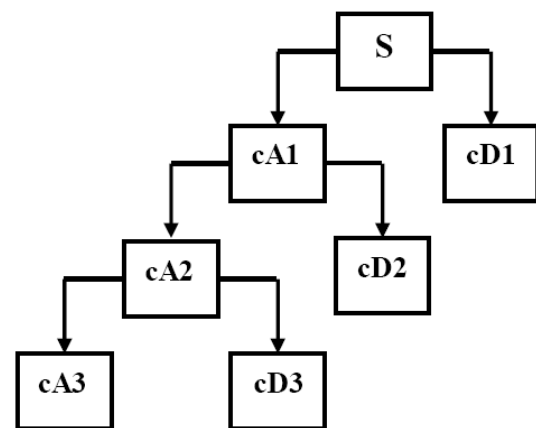


Figure 6: The wavelet decomposition tree

The signal pass through low-pass filter and high pass filter, just the output of low pass filter is processed which are in figure 6 the (cA n) The decomposition can proceed only until the individual details consist of a single sample. In this research, the signal decomposition is being stopped in the third-levels, hence, the third level minimized the size of data and in the same time gives the coefficients that save the most speech data. The generated features then fed to the recognition module.

2.3 Recognition Phase

Following the stage of file sound reading and noise removal, the DWT is employed and the sounds are proceeded to the NN. After features (coefficient) extraction of different wavelet transformation the recognition of speaker stage is employed. And in order to achieve the phase of recognition a BP NN and Fuzzy Logic are utilized. Classification process generally is composed of two phases (training and testing) as illustrated in Figure 7 and Figure 8.

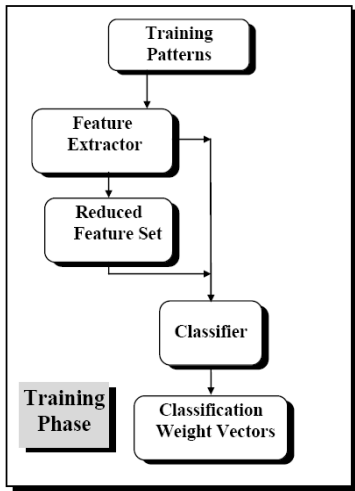


Figure 7: Training Phase Flow Chart

• **Training phase**

Training the classifier is done on patterns set (which denote DW coefficients set extracted from different Wavelet training patterns, and the speech segment ID). The DWT is training feature Extractor, that reduces the feature set that should be trained the classifier.

Classifier training is a process of generating and adapting the Weight Vectors on the classifier, in addition to the internal structure in some cases. The weight vectors are correctly classified the training set within some defined error rate. The speech segment ID is so called Training Set Target.

• **Testing phase**

The trained classifier (classifier which utilizes the weight vectors produced from training phase) assigns the unknown input pattern to one of the class (speech segments ID's) based on the extracted feature vector. Training and testing operations are performed using cross validation technique.

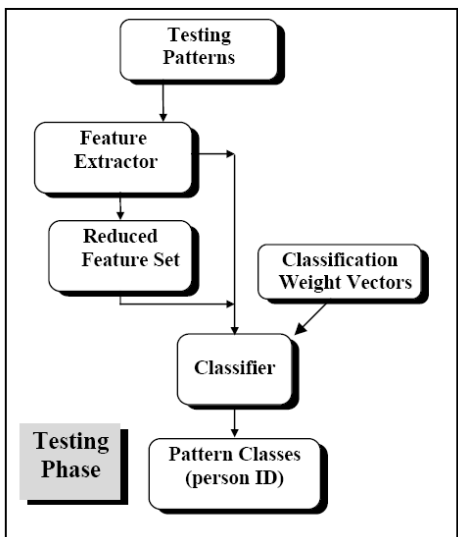


Figure 8: Testing Phase Flow Chart.

2.4 Feed-forward Back propagation (BP) Neural Network

Back propagation Neural network was created by generalizing the Widrow-Hof learning rule to multi-layer networks and nonlinear differentiable transform function, input vectors and corresponding target vectors are used to train network until it can approximate function (associate input vector with specific output vector) or reach high classification accuracy. Networks with biases, a sigmoid layer, and a sigmoid output layer are capable of approximating any function with finite number of discontinuities. Figure 9 shows the architecture of the Back propagation neural network used in this work.

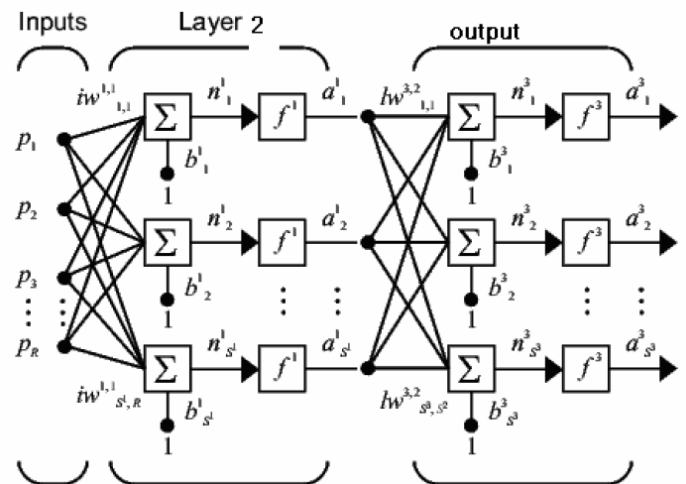


Figure 9: Architecture of Back propagation (MLP) Neural Network

In this work, 25 hidden nodes (5 words each words repeat 5 times) are found as the most proper number of nodes, with three-layer architecture. The NN contains one hidden layer, two activation functions are used:

- Tansig activation function is used between the first layer and the hidden layer.
- Logsig activation function is used between the hidden layer and the output layer
- The Sigmoid function is the most commonly used activation function; it is preferred because it is smooth and bounded, and it has a simple derivative.

The proposed BP neural network used in this work consists of three layers:

- Input layer: this layer consists of n nodes; n represents the number of input features. Since different sets of features are used to train the net, it so varies according to the length of each features vector length of each set.
- Hidden layer: this layer consists of k nodes, 25 nodes.

- Output layer: this layer consists of m of nodes, where m represents the number of persons to identify. In this work, m=50.

2.5 Fuzzy Logic

This work proposed a sugeno-type fuzzy logic system for the purpose of recognizing or classifying the input matrix which is generated from feature extraction phase. This fuzzy system is composed of 250 input variables each one is considered as step membership function. The 250 variables are gotten from third level wavelet transformation coefficients. Neural network based training is adapted to train the fuzzy logic rules

and to build the internal structure of member ship functions. The adapted neural network is auto-trained using MATLAB Adaptive Neuro Fuzzy Inference System (ANFIS). The training is similar to the Neural Network Training that described in the previous section. The inputs of training are; the feature set of coefficients that gotten from wavelet transformation, and the target which are the speech segments ID's.

Figure 10 shows the internal structure of membership functions. Figure 11 shows a sample of the rules that generated from ANFIS training. Whereas, figure 12 illustrates the structure of the total fuzzy inference system (FIS).

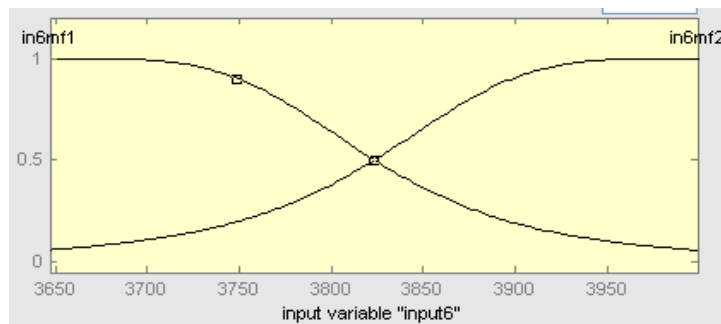


Figure 10: Internal Structure of Member Ship functions

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1. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
2. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
3. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
4. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
5. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
6. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
7. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
8. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
9. If (input1 is in1mf1) and (input2 is in2mf1) and (input3 is in3mf1) and (input4 is in4mf1) and (input5 is in5
    
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Figure 11: Sample of the Generated Rules

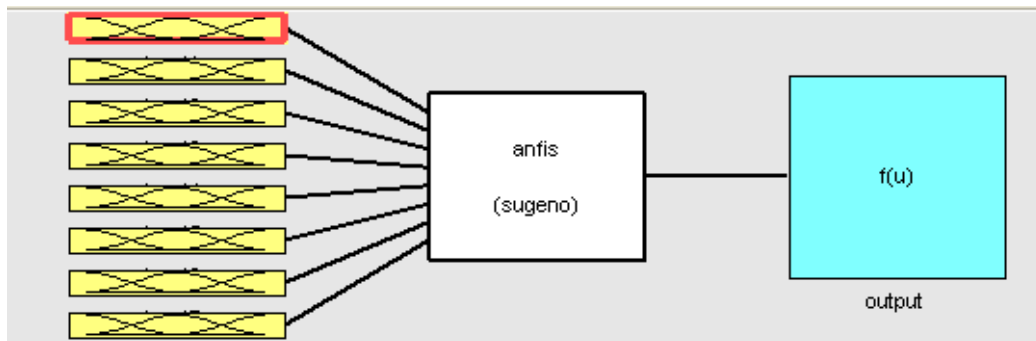


Figure 12: Final Structure of Fuzzy Inference System

After training, the fuzzy inference system (FIS) that was produced will be utilized in the Running Mode. In the running mood, the FIS will use the coefficients that the feature extraction module generated to yield the estimated ID which denotes the ID of the Speech Segments. When the fuzzy logic

is compared with the neural networks it has the following advantages:

- less memory usage due to the minimum Structure.
- Fast estimation and anticipation.

- Easier to modify and build.
- Can help in modeling the uncertainties in the membership rules and functions.

But even though, the neural networks are better than the fuzzy logic in terms of accuracy and precision. Also it is valid over data out of training range. On the other hand, the fuzzy logic is able to anticipate the data that are out of the range after training. Whereas, the neural networks apply all weight vectors and directly estimate the outputs, this makes the output more meaningful and increase the precision. This will be clear in the results that recorded in the validation test process.

2.6 Micro Control and Interfacing

A simple model has been developed to test the commanding system and to demonstrate a sample of usage of the proposed

system in the real life. A steering drive wheeled vehicle was used here.

The system that used here consists of a four-wheeled vehicle with two motors, one for driving and the other for directing the vehicle. The two motors are controlled using a PICmicro MCU microcontroller.

The microcontroller is continuously receiving the command from the PC, and by analyzing those commands, it controls the motors to move the vehicle forward, reverse, write, left, or stop. The command that comes from the PC is being continuously sent by a common serial media protocol which is RS232. Whereas those command are generated from the speech recognition system. When the proposed system recognizes a specific command, it converts it to a digital format of a byte of data and then sends it using the specified RS232 port. Figure 13 bellow is showing the electronic diagram of the used vehicle control and drive system.

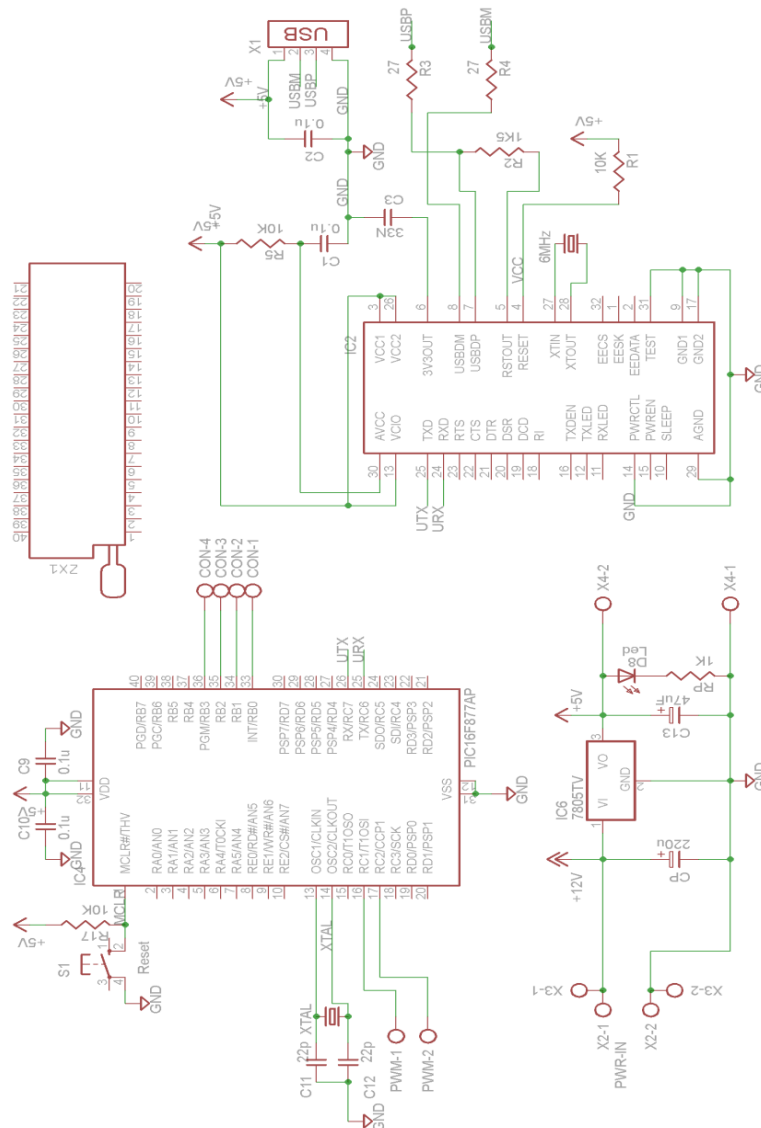


Figure 13: Schematic of the Vehicle Control System

3. EXPERIMENTAL RESULTS AND EVALUATION

The aim of this research is to develop an Arabic Voice Recognition feed-forward Back propagation (BP) and fuzzy logic recognizer. The intelligent recognizers are trained with features extracted from wavelet transform coefficients, then a cross-validation applied to record the results. This research illustrates the effect of using different recognizers with cooperation of wavelet transformation. Then, comparison of their recognition ability is discussed and the best level is determined in addition to the behavior of each recognition system.

The dataset is partitioned into two sets, training set and testing set. For training, three out of five sentences were taken for each person. Three sentences of speech are being used for training and the whole five are used for validation testing. The systems accuracy is tested in two ways: using whole dataset (250 sample), and using K-fold cross validation (i.e. make use of non-trained set samples). The precision of the system result should be calculated as follows [80].

$$\text{Precision} = \frac{\text{Number of Correctly Classified Patterns}}{\text{Total Number of Testing Patterns}}$$

3.1 Performance Evaluation

To design any pattern recognition system, two fundamental problems should be handled:

A. Model Selection (*choose the model that provides the lowest error rate*):

In the employed fuzzy logic and neural networks systems, the key parameters are the training factors (stopping condition, learning rate, ...etc) and the architecture (membership functions and rules with respect to fuzzy logic, and number of hidden layers and number of neurons/hidden layer with respect neural networks) and the parameters selection is accomplished through trial and error, in order to tune the parameters of the classifier.

For finding the optimum parameters, the step below is done:

1. Dividing the dataset into test set, and training set.
2. Selecting training and architecture parameters.
3. Using the training set to train the model.
4. Model Evaluation using the test set.
5. Using another architectures and training parameters and repeating steps 2 to 4.
6. Selecting the optimum model and training it using the training set.
7. Final model evaluation using the testing set.

B. Performance Estimation (*error rate is the true error rate*):

After the training and model selection, the generalization performance must be assessed using unknown dataset. The mostly used techniques for the generalization performance

evaluation is to divide the entire training set into two parts, while one partition is utilized for actual training, the other partition is utilized for algorithm performance testing and the result is used as an algorithm's performance estimation. Diverse approaches can be utilized [81].

- **Using the whole dataset for testing and using portion of it for training** for classifiers selection and error rate estimation, this technique have one drawback which is the over-fit of training data that leads to being overly optimistic in error rate estimation.(lesser than the actual error rate).
- **Holdout Method** for one test-and-train experiment (divide the training data into separate subsets), if an unsuccessful split occurs the error rate holdout estimate will be misleading. The holdout limitations can be overwhelmed with a group of methods of re-sampling using more random sub-sampling, computations cross-validation, leave-one-out cross-validation, K-Fold cross-validation.

This work used k-fold cross validation which has the advantages of using all data instances (in different times) for training and also for testing which allows data full utilization. Since the procedure is repeated k times, the probability of an unusually lucky or unlucky partitioning is reduced through averaging. To perform the k-fold cross validation, the entire available dataset is split into $k > 2$ partitions, creating k blocks of data. ($k=5$ in this work) blocks, $k-1$ to $k-3$ are used for training and the remaining k^{th} block is used for testing. Repeat the procedure k times, using different blocks for testing in each case. The average of the k test performances is calculated, and is declared as the estimate of the true generalization performance of the algorithm.

3.2 Dataset

This work is based on hands free speech recognition, voice is being continuously recorded using commercial microphone. For testing and validation purposes, specific dataset is being used to record the measurements issues. The testing dataset is composed by using a common microphone to record different sounds from 50 different persons (15 female and 35 males). Every person records five different statements. Totally, the dataset is composed of 250 samples (75 female and 175 male). For picking up the signal of voice and converting it into electronic signal into the computer the microphone system is used. Also to decrease the loss speech signal information the data acquisition parameter should be carefully chosen depending on the speech signal nature to be processed. In this research the signal of speech sampling is done with $F_s=8$ KHz, and quantizing is done with quantization level of 16-bit.

3.3 Experimental Result

As mentioned before, two ways are used for measuring the suggested system performance (K-fold method, and the other method is using the whole dataset for testing and for training using part of the data set). The BP NN is trained and tested

with extracted features from each level individually, to discover the level which has the highest classification ability and the amount of reduction which does not highly impact the ability of discrimination.

The training of MLP NN was done using all of the third wavelet decomposition level features. Table 1 shows the classification accuracy when the MLP NN trained using 50 samples and tested using the whole dataset. The Fuzzy Inference System training and testing were done using features extracted from the third level of wavelet decomposition. The system training was done using 250 samples, and testing was done using the entire dataset. Table 1 illustrates the results for validation for both female and male persons, where the testing is done over 250 speech segment.

Table 1: Results of testing the male and female speech segments.

	Fuzzy Logic	MLP
Number of recognized speech sentences	155	180
Classification Accuracy	72%	90%
Average Running Time	1.68 sec	3.12 sec

Table 2 shows the results for validation of male persons, where the testing is done over 175 male speech segments.

Table 2: Results of testing the male speech segments.

	Fuzzy Logic	MLP
Number of recognized speech sentences	100	120
Classification Accuracy	77.1%	94.5%
Average Running Time	1.7 sec	3.1 sec

Table 3 below shows the results for validation of female persons, where the testing is done over 75 female speech segment.

Table 3: Results of testing the female speech segments.

	Fuzzy Logic	MLP
Number of recognized speech sentences	55	61
Classification Accuracy	77.1%	94.5%
Average Running Time	1.6 sec	3.2 sec

From the results tables, we can see that, the neural network is much better than the fuzzy logic recognizer. But, the processing and recognition time of the neural network is much greater, that implies, the fuzzy logic speeds up the process but it gets less accuracy, and male voice give more accuracy in recognition.

4. CONCLUSION

This research is concerned with building an Arabic Speech Recognition and Commanding System that can be used in special needs and security applications if you want. The behavior of the intelligent classifier in the sound recognition field is being demonstrated and discussed. Feed Forwards Multi-Layer Perceptron Neural Net in Back propagation and Fuzzy Logic Classifiers are used and implemented to recognize speech, the classifiers were trained on extracted features from the DWT third level. The preprocessing phase is the proposed recognizer initial phase, it executes removal of noise; samples resizing and removal of DC level. After that, DWT is employed on the third level signal decomposition for feature extraction. Then the recognition phase in which the NN is trained on extracted features from DWT. Finally, testing the performance of the system utilizing Cross-Validation and using entire dataset (open command limit). The following are the main conclusions drawn from this work.

- Arabic Language recognition is available in good accuracy and precision using intelligent recognition techniques.
- Using Cross-Validation in which testing is done 250 trained sounds commands from male and female; the accuracy is acceptable and relatively better at the Neural Network Recognizer. .
- The use of Wavelet Transformation enables to extract an exact features form the speech.
- Wavelet Transformation also, speeds up the processing by minimizing the amount of data.
- When the whole dataset is fed to the NN, the accuracy will be decreased because of the feature types that negatively affect the rate of recognition.
- Using of speech recognition is best fit for commanding purposes and controlling actions without a touch.
- By studying the NNs and fuzzy logic behavior in speech recognition, NNs are better in accuracy and precision, but it needs high compositionality and longest processing time.
- The female voice is more complex than the male voice.

REFERENCES

- [1] R. J. Schalkoff, "Pattern Recognition: Statistical, Structural and Neural Approaches," 1992.
- [2] H. K. David and B. S. Frances, "Pattern Recognition and Prediction with Applications to Signal Characterization," *AIP press*, 1996.
- [3] Yuan Shao, "Higher Order Spectra Invariants For Shape Pattern Recognition," College of Engineering and Technology, Ohio University, 2000.
- [4] A. M. A. Al-Shatnawi, "A Non-Iterative Thinning Method Based On Exploited Vertices Of Voronoi Diagrams," Phd, Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia, Bangi, 2010.
- [5] A. K. Jain, A. Ross, and S. Prabhakar, "An introduction to biometric recognition," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 14, pp. 4-20, 2004.
- [6] B. Rehman, Z. Halim, G. Abbas, and T. Muhammad, "Artificial neural network-based speech recognition using dwt analysis applied on isolated words from oriental languages," *Malaysian Journal of Computer Science*, vol. 28, pp. 242-262, 2015.
- [7] F.-L. Huang, "An Effective Approach for Chinese Speech Recognition on Small size of Vocabulary," *Neural Networks*, vol. 7, pp. 9-10, 2011.
- [8] I. A. Almrashdah, N. Sahari, N. A. H. M. Zin, and M. Alsmadi, "Instructors acceptance of distance learning management system," in *Information Technology (ITSim), 2010 International Symposium in*, 2010, pp. 1-6.
- [9] F. Haddad, J. Alfaro, and M. K. Alsmadi, "Hotelling's T² Charts Using Winsorized Modified One Step M-Estimator For Individual Non Normal Data," *Journal of Theoretical & Applied Information Technology*, vol. 72, pp. 215-226, 2015.
- [10] I. Almarashdeh and M. K. Alsmadi, "How to make them use it? Citizens acceptance of M-government," *Applied Computing and Informatics*.
- [11] I. Almarashdeh and M. Alsmadi, "Investigating the acceptance of technology in distance learning program," in *2016 International Conference on Information Science and Communications Technologies (ICISCT)*, 2016, pp. 1-5.
- [12] I. A. Almrashdeh, N. Sahari, N. A. M. Zin, and M. Alsmadi, "Instructor's success measures of Learning Management System," in *Electrical Engineering and Informatics (ICEEI), 2011 International Conference on*, 2011, pp. 1-7.
- [13] F. Haddad and M. K. Alsmadi, "Improvement of The Hotelling's T² Charts Using Robust Location Winsorized One Step M-Estimator (WMOM)," *Journal of Mathematics (ISSN 1016-2526)*, vol. 50, pp. 97-112, 2018.
- [14] I. Almarashdeh and M. Alsmadi, "Heuristic evaluation of mobile government portal services: An experts' review," in *Internet Technology and Secured Transactions (ICITST), 2016 11th International Conference for*, 2016, pp. 427-431.
- [15] M. K. Alsmadi, U. A. Badawi, and H. M. Moharram, "Server Failures Enabled Javaspace Service," *Journal of Computer Science*, vol. 10, pp. 671-679, 2014.
- [16] I. A. Almarashdeh, N. Sahari, N. A. M. Zin, and M. Alsmadi, "Acceptance of learning management system: A comparison between distance learners and instructors," *Advances in Information Sciences and Service Sciences*, vol. 3, pp. 1-9, 2011.
- [17] I. A. Almarashdeh, N. Sahari, N. A. M. Zin, and M. Alsmadi, "The Success Of Learning Management System Among Distance Learners In Malaysian Universities," *Journal of Theoretical & Applied Information Technology*, vol. 21, 2010.
- [18] M. K. Alsmadi, "Apparatus and method for lesions segmentation," ed: US Patent App. 15/614,893, 2018.
- [19] M. K. Alsmadi, "Facial expression recognition," ed: Google Patents, 2018.
- [20] I. Al-Marashdeh, G. M. Jaradat, M. Ayob, A. Abu-Al-Aish, and M. Alsmadi, "An Elite Pool-Based Big Bang-Big Crunch Metaheuristic for Data Clustering," *Journal of Computer Science*, 2018.
- [21] M. Alsmadi, U. A. Badawi, and H. E. Reffat, "A High Performance Protocol for Fault Tolerant Distributed Shared Memory (FaTP)," *Journal of Applied Sciences*, vol. 13, pp. 790-799, 2013.
- [22] I. A. Almrashdeh, N. Sahari, N. A. M. Zin, and M. Alsmadi, "Requirement analysis for distance learning management system students in Malaysian universities," *Journal of Theoretical and Applied Information Technology*, vol. 24, pp. 17-27, 2011.
- [23] I. A. Almrashdah, N. Sahari, N. A. H. M. Zin, and M. Alsmadi, "Distance learners acceptance of learning management system," in *Advanced Information Management and Service (IMS), 2010 6th International Conference on*, 2010, pp. 304-309.
- [24] I. Almarashdeh, "Sharing instructors experience of learning management system: A technology perspective of user satisfaction in distance learning course," *Computers in Human Behavior*, vol. 63, pp. 249-255, 2016.
- [25] I. Almarashdeh, "An Overview Of Technology Evolution: Investigating The Factors Influencing Non-Bitcoins Users To Adopt Bitcoins As Online Payment Transaction Method," *Journal of Theoretical and Applied Information Technology*, vol. 96, pp. 3984-3993, 2018.

- [26] I. Almarashdeh, "The Important Of Service Quality And The Trust In Technology On Users Perspectives To Continues Use Of Mobile Services," *Journal of Theoretical & Applied Information Technology*, vol. 96, 2018.
- [27] I. Almarashdeh, A. Althunibat, N. Fazidah Elias, A. Adewumi, A. Al Thunibat, N. Zin, N. Ashaari, and N. Sahari, "E-Government for mobile societies-stocktaking of current trends and initiatives," *Journal of Applied Sciences*, vol. 14, pp. 104-111, 2013.
- [28] I. A. Almarashdeh, N. Sahari, and N. A. M. Zin, "Heuristic evaluation of distance learning management system interface," in *Electrical Engineering and Informatics (ICEEI), 2011 International Conference on*, 2011, pp. 1-6.
- [29] I. A. Almrashdeh, N. Sahari, N. A. M. Zin, and M. Alsmadi, "Distance Learning Management System Requiements From Student's Perspective," *Journal of Theoretical & Applied Information Technology*, vol. 24, 2011.
- [30] I. A. Almarashdeh, N. Sahari, N. a. M. Zin, and M. Alsmad, "The Success of Learning Management System Among Distance Learners in Malaysian Universitie," *Journal of Theoretical and Applied Information Technology*, vol. 21 pp. 80-91, 2010.
- [31] I. A. E. Al-Marashdeh, "Study of the Usability of Learning Management System Tool (Learning Care) of Postgraduate Students in University Utara Malaysia (UUM)," Graduate School, Universiti Utara Malaysia, 2007.
- [32] G. Jaradat, M. Ayob, and I. Almarashdeh, "The effect of elite pool in hybrid population-based meta-heuristics for solving combinatorial optimization problems," *Applied Soft Computing*, vol. 44, pp. 45-56, 2016.
- [33] R. A. Sheikh, R. Al-Assami, M. Albahr, M. A. Suhaibani, M. k. Alsmadi, M. Alshabanah, D. Alrajhi, I. Al-Marashdeh, H. Abouelmagd, and S. Alsmadi, "Developing and Implementing a Barcode Based Student Attendance System," *International Research Journal of Engineering and Technology*, vol. 6, pp. 497-506, 2019.
- [34] S. Aldossary, A. Althawadi, M. Almotairy, M. k. Alsmadi, D. Alrajhi, M. Alshabanah, I. AlMarashdeh, M. Tayfour, and R. Aljamaeen, "Analyzing, Designing And Implementing A Web-Based Command Center System," *International Research Journal of Engineering and Technology*, vol. 6, pp. 1008-1019, 2019.
- [35] D. A. Daniyah Alkhaldi, Hajer Aldossary, Mutasem k. Alsmadi, Ibrahim Al-Marashdeh, Usama A Badawi, Muneerah Alshabanah, Daniah Alrajhi, "Developing and Implementing Web-based Online University Facilities Reservation System," *International Journal of Applied Engineering Research*, vol. 13, pp. 6700-6708, 2018.
- [36] N. Alsubaie, N. Althaqafi, E. Alradwan, F. Al-Hazza, M. Alsmadi, I. Al-Marashdeh, U. A. Badawi, M. Alshabanah, D. Alrajhi, S. Alsmadi, and M. Tayfour, "Analyzing and Implementing an Online Metro Reservation System," *International Journal of Applied Engineering Research*, vol. 13, pp. 9198-9206, 2018.
- [37] H. Almaimoni, N. Altuwaijri, F. Asiry, S. Aldossary, M. Alsmadi, I. Al-Marashdeh, U. A. Badawi, M. Alshabanah, and D. Alrajhi, "Developing and Implementing WEB-based Online Destination Information Management System for Tourism," *International Journal of Applied Engineering Research*, vol. 13, pp. 7541-7550, 2018.
- [38] R. Aldaej, L. Alfowzan, R. Alhashem, M. K. Alsmadi, I. Al-Marashdeh, U. A. Badawi, M. Alshabanah, D. Alrajhi, and M. Tayfour, "Analyzing, Designing and Implementing a Web-Based Auction online System," *International Journal of Applied Engineering Research*, vol. 13, pp. 8005-8013, 2018.
- [39] T. H. Farag, W. A. Hassan, H. A. Ayad, A. S. AlBahussain, U. A. Badawi, and M. K. Alsmadi, "Extended Absolute Fuzzy Connectedness Segmentation Algorithm Utilizing Region and Boundary-Based Information," *Arabian Journal for Science and Engineering*, pp. 1-11, 2017.
- [40] Z. Thalji and M. Alsmadi, "Iris Recognition using robust algorithm for eyelid, eyelash and shadow avoiding," *World Applied Sciences Journal*, vol. 25, pp. 858-865, 2013.
- [41] M. K. Alsmadi, "A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation," *Ain Shams Engineering Journal*.
- [42] U. A. Badawi and M. K. S. Alsmadi, "A Hybrid Memetic Algorithm (Genetic Algorithm and Great Deluge Local Search) With Back-Propagation Classifier for Fish Recognition " *International Journal of Computer Science Issues*, vol. 10, pp. 348-356, 2013.
- [43] A. M, O. K, and N. S, "Back Propagation Algorithm : The Best Algorithm Among the Multi-layer Perceptron Algorithm," *International Journal of Computer Science and Network Security*, vol. 9, pp. 378-383, 2009.
- [44] M. k. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdah, "Performance Comparison of Multi-layer Perceptron (Back Propagation, Delta Rule and Perceptron) algorithms in Neural Networks," in *2009 IEEE International Advance Computing Conference*, 2009, pp. 296-299.
- [45] M. k. Alsmadi, K. B. Omar, and S. A. Noah, "Proposed method to decide the appropriate feature set for fish classification tasks using Artificial Neural

- Network and Decision Tree," *IJCSNS* vol. 9, pp. 297-301, 2009.
- [46] M. Sharma, G. Purohit, and S. Mukherjee, "Information Retrieves from Brain MRI Images for Tumor Detection Using Hybrid Technique K-means and Artificial Neural Network (KMANN)," in *Networking Communication and Data Knowledge Engineering*, ed: Springer, 2018, pp. 145-157.
- [47] Y. Gao, X. Li, M. Dong, and H.-p. Li, "An enhanced artificial bee colony optimizer and its application to multi-level threshold image segmentation," *Journal of Central South University*, vol. 25, pp. 107-120, 2018.
- [48] M. K. Alsmadi, K. B. Omar, and S. A. Noah, "Fish classification based on robust features extraction from color signature using back-propagation classifier," *Journal of Computer Science*, vol. 7, p. 52, 2011.
- [49] M. K. Alsmadi, "A hybrid firefly algorithm with fuzzy-C mean algorithm for MRI brain segmentation," *American Journal of Applied Sciences*, vol. 11, pp. 1676-1691, 2014.
- [50] M. K. Alsmadi, "MRI brain segmentation using a hybrid artificial bee colony algorithm with fuzzy-c mean algorithm," *Journal of Applied Sciences*, vol. 15, p. 100, 2015.
- [51] M. K. Alsmadi, "A hybrid Fuzzy C-Means and Neutrosophic for jaw lesions segmentation," *Ain Shams Engineering Journal*, 2017.
- [52] S. H. Park and K. Han, "Methodologic Guide for Evaluating Clinical Performance and Effect of Artificial Intelligence Technology for Medical Diagnosis and Prediction," *Radiology*, p. 171920, 2018.
- [53] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu, and F. Yan, "Identifying Medical Diagnoses and Treatable Diseases by Image-Based Deep Learning," *Cell*, vol. 172, pp. 1122-1131. e9, 2018.
- [54] G. M. Jaradat, A. Al-Badareen, M. Ayob, M. Al-Smadi, I. Al-Marashdeh, M. Ash-Shuqran, and E. Al-Odat, "Hybrid Elitist-Ant System for Nurse-Rostering Problem," *Journal of King Saud University-Computer and Information Sciences*, 2018.
- [55] i. Almarashdeh, M. K. Alsmadi, T. Farag, A. S. Albahussain, U. A. Badawi, N. Altuwaijri, H. Almaimoni, F. Asiry, S. Alowaid, M. Alshabanah, D. Alrajhi, A. A. Fraihet, and G. Jaradat, "Real-Time Elderly Healthcare Monitoring Expert System Using Wireless Sensor Network " *International Journal of Applied Engineering Research*, vol. 13, pp. 3517-3523, 2018.
- [56] M. Rasmi, M. B. Alazzam, M. K. Alsmadi, I. A. Almarashdeh, R. A. Alkhasawneh, and S. Alsmadi, "Healthcare professionals' acceptance Electronic Health Records system: Critical literature review (Jordan case study)," *International Journal of Healthcare Management*, pp. 1-13, 2018.
- [57] A. M. Al Smadi, M. K. Alsmadi, H. Al Bazar, S. Alrashed, and B. S. Al Smadi, "Accessing Social Network Sites Using Work Smartphone for Face Recognition and Authentication," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 11, pp. 56-62, 2015.
- [58] M. Alsmadi, "Facial recognition under expression variations," *Int. Arab J. Inf. Technol.*, vol. 13, pp. 133-141, 2016.
- [59] M. Alsmadi, K. Omar, and I. Almarashdeh, *Fish Classification: Fish Classification Using Memetic Algorithms with Back Propagation Classifier*: LAP LAMBERT Academic Publishing, 2012.
- [60] M. Alsmadi, K. Omar, S. Noah, and I. Almarashdeh, "A hybrid memetic algorithm with back-propagation classifier for fish classification based on robust features extraction from PLGF and shape measurements," *Information Technology Journal*, vol. 10, pp. 944-954, 2011.
- [61] M. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdeh, "Fish Recognition Based on Robust Features Extraction from Size and Shape Measurements Using Neural Network " *Journal of Computer Science*, vol. 6, pp. 1088-1094, 2010.
- [62] M. K. Alsmadi, "An efficient similarity measure for content based image retrieval using memetic algorithm," *Egyptian Journal of Basic and Applied Sciences*.
- [63] M. K. Alsmadi, "Query-sensitive similarity measure for content-based image retrieval using meta-heuristic algorithm," *Journal of King Saud University - Computer and Information Sciences*.
- [64] M. K. Alsmadi, A. Y. Hamed, U. A. Badawi, I. Almarashdeh, A. Salah, T. H. Farag, W. Hassan, G. Jaradat, Y. M. Alomari, and H. M. Alsmadi, "Face Image Recognition Based On Partial Face Matching Using Genetic Algorithm," *SUST Journal of Engineering and Computer Sciences (JECS)*, vol. 18, pp. 51-61, 2017.
- [65] M. K. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdeh, "Fish recognition based on robust features extraction from color texture measurements using back-propagation classifier," *Journal of Theoretical and Applied Information Technology*, vol. 18, 2010.
- [66] U. A. Badawi and M. K. Alsmadi, "A General Fish Classification Methodology Using Meta-Heuristic Algorithm With Back Propagation Classifier,"

Journal of Theoretical & Applied Information Technology, vol. 66, pp. 803-812, 2014.

- [67] M. Yousuf, Z. Mehmood, H. A. Habib, T. Mahmood, T. Saba, A. Rehman, and M. Rashid, "A Novel Technique Based on Visual Words Fusion Analysis of Sparse Features for Effective Content-Based Image Retrieval," *Mathematical Problems in Engineering*, vol. 2018, 2018.
- [68] R. R. Saritha, V. Paul, and P. G. Kumar, "Content based image retrieval using deep learning process," *Cluster Computing*, pp. 1-14, 2018.
- [69] M. K. Alsmadi, K. B. Omar, and S. A. Noah, "Fish recognition based on robust features extraction from size and shape measurements using back-propagation classifier," *International Review on Computers and Software*, vol. 5, pp. 489-494, 2010.
- [70] M. K. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdeh, "Fish recognition based on robust features extraction from size and shape measurements using neural network," *Journal of Computer Science*, vol. 6, p. 1088, 2010.
- [71] M. K. S. Alsmadi, K. B. Omar, S. A. Noah, and I. Almarashdah, "Fish recognition based on the combination between robust feature selection, image segmentation and geometrical parameter techniques using Artificial Neural Network and Decision Tree," *arXiv preprint arXiv:0912.0986*, 2009.
- [72] M. K. S. Alsmadi, K. B. Omar, and S. A. Noah, "Back propagation algorithm: the best algorithm among the multi-layer perceptron algorithm," *International Journal of Computer Science and Network Security*, vol. 9, pp. 378-383, 2009.
- [73] I. Almarashdeh, M. K. Alsmadi, G. Jaradat, A. Althunibat, S. A. Albahussain, Y. Qawqzeh, U. A. Badawi, T. Farag, and K. E. Eldaw, "Looking Inside and Outside the System: Examining the Factors Influencing Distance Learners Satisfaction in Learning Management System " *Journal of Computer Science*, 2018.
- [74] M. K. Alsmadi, "Forecasting River Flow in the USA Using a Hybrid Metaheuristic Algorithm with Back-Propagation Algorithm," *Scientific Journal of King Faisal University (Basic and Applied Sciences)*, vol. 18, pp. 13-24, 2017.
- [75] J. Adeyemo, O. Oyeboode, and D. Stretch, "River Flow Forecasting Using an Improved Artificial Neural Network," in *EVOLVE-A Bridge between Probability, Set Oriented Numerics, and Evolutionary Computation VI*, ed: Springer, 2018, pp. 179-193.
- [76] A. Ahani, M. Shourian, and P. R. Rad, "Performance Assessment of the Linear, Nonlinear and Nonparametric Data Driven Models in River Flow Forecasting," *Water Resources Management*, pp. 1-17, 2018.
- [77] O. Jemai, R. Ejbali, M. Zaied, and C. B. Amar, "A speech recognition system based on hybrid wavelet network including a fuzzy decision support system," in *Seventh International Conference on Machine Vision (ICMV 2014)*, 2015, p. 944503.
- [78] K. Daqrouq and T. A. Tutunji, "Speaker identification using vowels features through a combined method of formants, wavelets, and neural network classifiers," *Applied Soft Computing*, vol. 27, pp. 231-239, 2015.
- [79] L. Boussaid and M. Hassine, "Arabic isolated word recognition system using hybrid feature extraction techniques and neural network," *International Journal of Speech Technology*, vol. 21, pp. 29-37, 2018.
- [80] P. Maji and S. K. Pal, *Rough-fuzzy pattern recognition: applications in bioinformatics and medical imaging* vol. 3: John Wiley & Sons, 2011.
- [81] Y. Bengio and Y. Grandvalet, "No unbiased estimator of the variance of k-fold cross-validation," *Journal of machine learning research*, vol. 5, pp. 1089-1105, 2004.