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DEVELOPMENT AND REALIZATION OF AN AUDIOMETER WITH AUTOMATIC TESTS AND INTELLIGENT DIAGNOSTICS USING NEURAL NETWORKS

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Keywords: Audiometer; Arduino; Graphical user interface (GUI) MATLAB; Intelligent diagnosis; Neural network model.

An audiometer is a medical device that measures hearing state; most audiometers are for manual and physical use. The audio signal generator generates all the frequencies between 20 Hz and 22 kHz. This project will produce a tone-based audiometer (software and hardware) based on the Arduino board with GUI MATLAB. This work allowed us to do the test automatically with intelligent diagnosis. The smart part is based on the Neural Network Model. Our work comprises an electronic card and three parts or interfaces: Interface 1: subject management, Interface 2: hearing test, and Interface 3: audiogram. The tests and results of the prototype are very satisfactory; this is a positive sign that the prototype is working as expected and is a viable solution.

1. INTRODUCTION

The ear's function is to transform acoustic vibrations into nerve signals that the brain will decode through the different parts of the ear. The hearing is constantly awake because it is solicited permanently by all the sounds emitted in our near environment. The human ear has different parts. When the ear, ear canal, and minor bone defects are responsible for hearing loss, it is called conductive hearing loss; nerve problems are responsible for hearing loss, and sensorineural hearing loss is also called. Suppose the damage caused by both is then called mixed hearing loss [1]. Hearing loss is the third leading contributor to years lived with disability worldwide; according to the World Health Organization, an estimated 1.57 billion people experience some degree of hearing loss [2]. The human ear perceives frequencies between 20 Hz (lowest frequency) and 20000 Hz (highest perceived frequency). Any frequency lower than 20 Hz is qualified as infrasound. Any frequency higher than 20 kHz is called ultrasound [3]. Deafness can exist at birth, settle abruptly after an illness, or appear gradually without apparent cause. To ensure that the hearing system of an individual perceives the audible signal.

Identifying hearing loss is often difficult in many cases. It affects an individual's social, psychological, professional, and educational skills [4,5]; an audiometer can be used. Hearing loss is measured by performing voice and tone audiometry tests using conventional audiometers [1,5–9]. The perception threshold is represented by a value expressed in decibels, from which the participant detects the sound presented. Auditory system diagnosis has entered a new era thanks to advanced technologies from electronics and biomedical engineering [10, 11]. The professional noise and genetic origin can have detrimental effects on hearing ability. The frequency range of 9 to 20 kHz is useful for the early diagnosis of hearing loss [9].

The audiometer tonal allows us to verify the proper functioning of individuals' auditory systems and establish absolute detection thresholds for each frequency tested.

Computerized audiometers are being developed, and they have many benefits, such as storage and audiogram data retrieval [12,13]. However, these audiometers are constrained by their inability to analyze test results or reproduce conventional audiometric procedures in an exact way [5,14].

The optimization of artificial intelligence systems, particularly neural networks, has been a central focus in numerous scientific and technological disciplines [15–20]. Researchers in these fields strive to improve the efficiency and effectiveness of these systems, driving advancements across diverse areas. This project used a neural network model to develop an intelligent diagnostic tool to identify disease signs.

In this paper, we study and develop a prototype of an audiometer with automatic testing and intelligent diagnosis. It is based on an Arduino board with GUI MATLAB programming.

The main interface allows us to generate all the test frequencies at different decibel levels. This interface replaces the linear oscillator with frequencies and variable amplitudes in electronic circuitry.

2. METHODOLOGY

The hearing test generates sound waves with different frequencies applied to the patient's ear for testing. For each frequency, the patient must respond when he hears the sound. If not, the doctor will change the amplitude on that frequency until he hears the sound. To test, an audiogram will be plotted.

Our audiometer mainly comprises a PC with MATLAB, which manages the test (generating sound waves, changing frequencies and amplitudes, displaying the patient's response, and controlling the electronic card). The electronic card is a main element in this project; the PC controls it. Its role is to select the air conduction in the helmet, either to the right or left, and to indicate the presence of the sound and the ear to be tested to inform the patient. A push button to answer, a stereo headset, and it restores sound contents.

This section will discuss our project: the electronic editing, the program that makes the hearing test, and its results. Figure 1 illustrates the basic prototype diagram created in this paper.

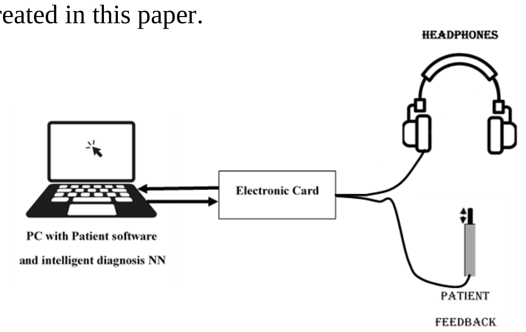

Fig. 1 – Block diagram of the audiometer's functionality.

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We relied on custom-built hardware and software tools for data acquisition and analysis in our experiment. The hardware component comprised an Arduino Uno microcontroller-based electronic interface equipped with a stereo headset for stimulus presentation, a pushbutton switch for subject response recording, bi-directional diodes with integrated resistors for signal conditioning, electromagnetic relays for circuit control, and an LED indicator for visual feedback. The software side utilized a laptop computer equipped with a standard sound card and MATLAB software for data capture and analysis. The intricate connections between these elements are illustrated in Figs. 2 and 3.

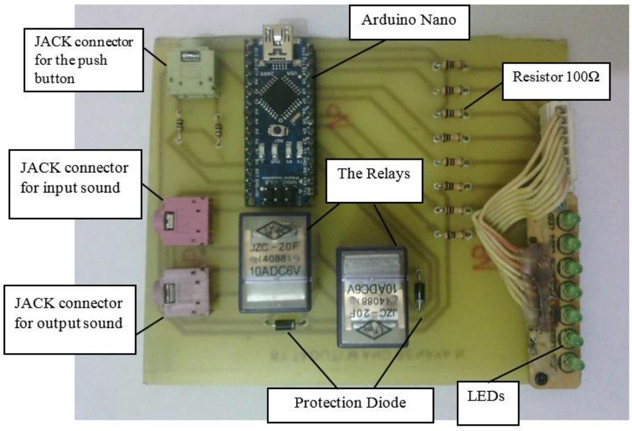

Fig. 2 – Installation of electronic components on the printed circuit board.

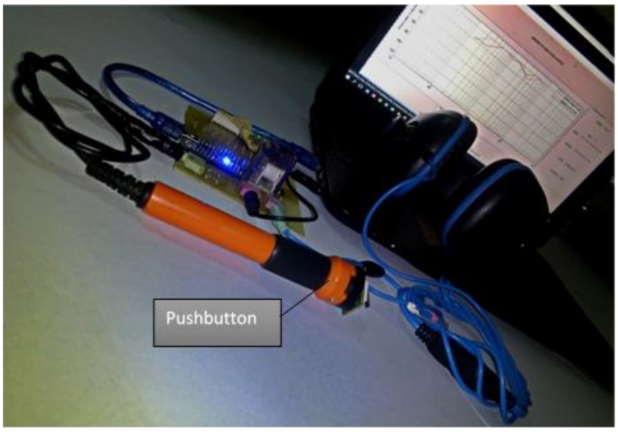

Fig. 3 – The final prototype realized with the software part for communicating with the patient.

Arduino card. Arduino is a brand of low-cost microcontroller-based programmable boards. Several versions of Arduino boards (Nano, Uno, Mega, Due…) have varying dimensions. These boards offer various capabilities, including varying dimensions, memory capacities, and input/output interfaces, making them versatile tools for interfacing sensors and actuators.

The Arduino Nano board was selected for this project due to its simplified connectivity and seamless communication with MATLAB. Its compact size makes it an ideal choice for applications where space is a limiting factor. Smaller microcontrollers are also available for scenarios with even more stringent size constraints [21].

The relays. To conduct individual ear testing, the helmet utilizes relays that redirect the audio signal to either the left or right ear. The ARDUINO board must control this switch; in this case, it is possible to use relays or transistors to choose the right or left earpiece.

Excessive current sensitivity hampered our initial attempt to utilize a transistor circuit. Residual noise, attributed to the Grand problem, persisted despite incomplete sound cancellation. The implementation of relays became necessary to address this noise issue and achieve complete elimination.

The LEDs are used to indicate the presence and level of the sound and the ear tested (left or right).

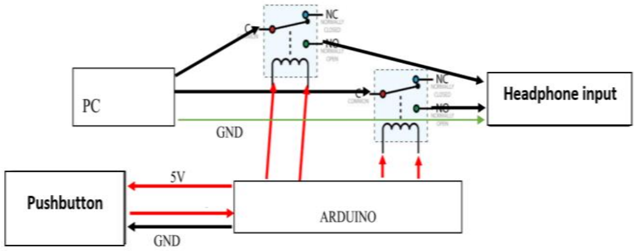

Fig. 4 – Ear selection circuit.

Pushbutton. By pressing this button, the patient confirms hearing the sound, prompting the system to record the corresponding decibel level for the audiogram automatically.

The following figure illustrates the operating flowchart of the audiometer to have an automatic test and audiogram.

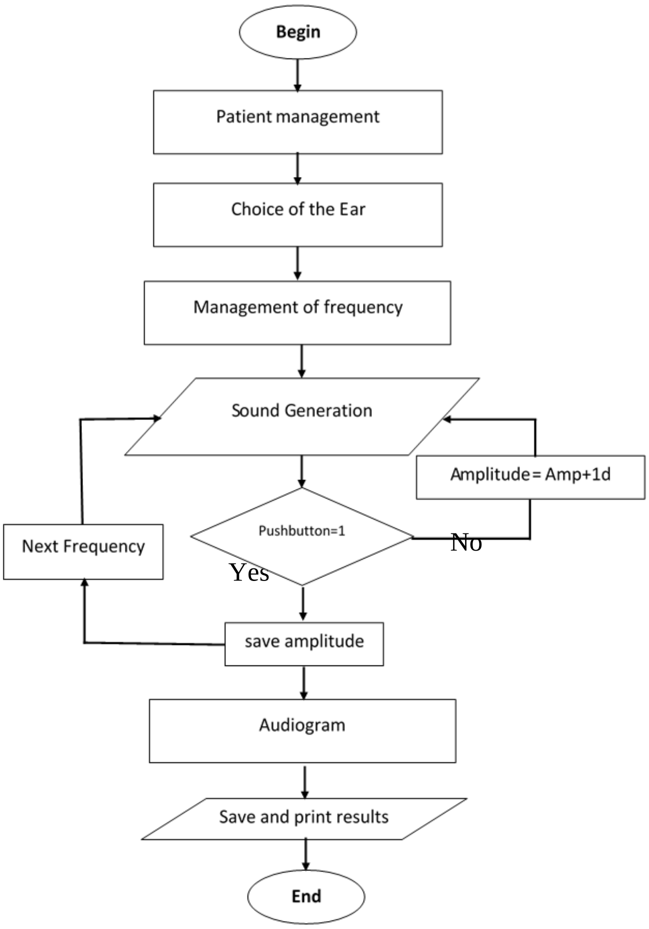

Fig. 5 – Flowchart of the automatic audiometric test.

This work consists of the hardware and software parts. The second part is a set of several graphical interfaces. So, the following part illustrates the details of each interface:

Interface 1. This interface has been developed to gather the necessary information about the patient. Contact information such as name and surname, age, telephone number, and patient category are requested. The current date is automatically saved from our computer (see Fig. 6).

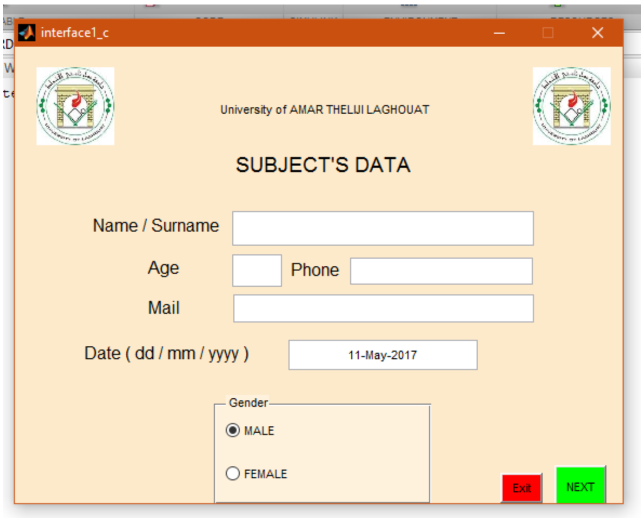

Fig. 6 – Interface of subject's data.

When the user inserts the patient's data, it will be automatically saved in the "C: \ Users \ Public \ Documents" folder on a text file. The information of each new patient will be saved in the same text file (see Fig.7).

```
NAME :  Test 2
AGE :  52
MAIL :  ******************************
PHONE :  ***********************
DATE :  24-May-2017
GENDER :  Female
            RESULTS OF THE TEST
      ______________________________

                 LEFT EAR
      ______________________________

frequences left Ear [Hz] | Amplitudes left Ear [dB]
    11

    11

     125-----------------------------35
     250-----------------------------30
     500-----------------------------15
     750-----------------------------15
    1000-----------------------------10
    1500-----------------------------15
    2000-----------------------------20
    3000-----------------------------25
    4000-----------------------------25
    6000-----------------------------25
    8000-----------------------------45
      ______________________________

                 RIGHT EAR
      ______________________________

frequences right Ear [Hz] | Amplitudes right Ear [dB]
     125-----------------------------35
     250-----------------------------25
     500-----------------------------15
     750-----------------------------10
    1000----------------------------- 5
    1500-----------------------------10
    2000-----------------------------10
    3000-----------------------------25
    4000-----------------------------15
    6000-----------------------------25
    8000-----------------------------35
```

Fig. 7 – The test result file (amplitude and frequency).

Interface 2. This interface allows the user to select the ear to be tested. It will appear and ask the user to choose the ear (Fig. 8). The interface displays an error when the user clicks "Ok" without making a decision.

Fig. 8 – The choice of the ear to be tested

If the manipulator is not selected, the ear will be tested. A message will be displayed to indicate the obligation of choice.

Interface 3. It is the main interface, which allows making the hearing test; this interface provides the different frequencies that the user selects or the doctor in a sound with a preselected amplitude (Fig. 9); the user can see the patient's response to the interface. All the frequencies used will be displayed in a list to better know the only ones with the audacity of each frequency. The number of frequencies tested on the right ear and the left ear must be the same.

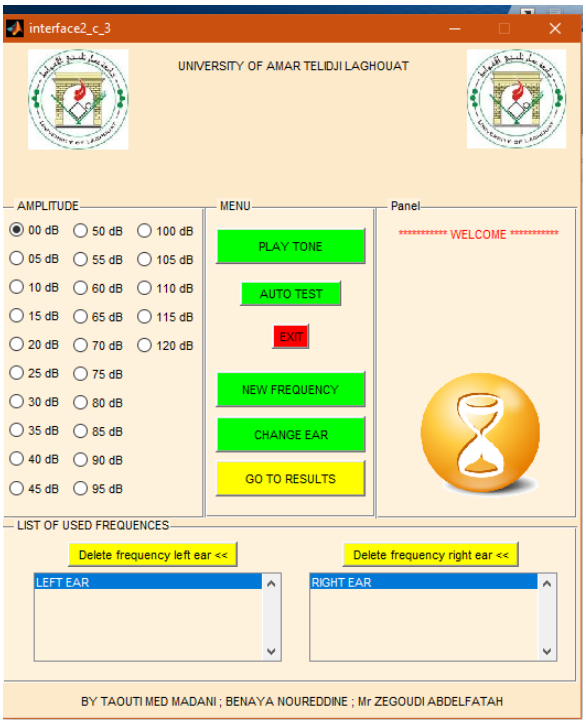

Fig. 9 – Interface for auditory testing.

Fig. 10 – The message displayed when there is an answer or not.

3. AUTOMATIC TEST AND INTELLIGENT DIAGNOSIS

This interface automates audiometry testing, eliminating the need for manual intervention. Figure 11 illustrates the automated frequency and amplitude changes. Additionally, the system allows user-selectable unilateral or bilateral testing (conducted sequentially), streamlining the examination process and minimizing time spent in the clinic setting.

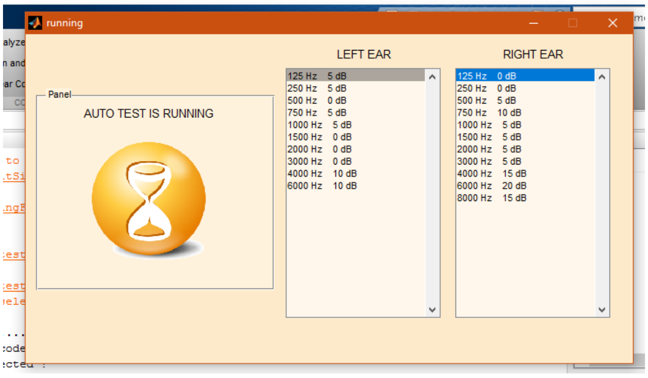

Fig. 11 – The automatic test during execution.

Audiometric neural network-based hearing diagnosis is a promising technology that leverages artificial intelligence to analyze audiograms and detect hearing abnormalities. This technology employs an artificial neural network trained on a vast dataset of audiograms from individuals with varying degrees of hearing loss. The artificial neural network can discern patterns within audiograms indicative of diverse hearing loss types. Once trained, the network can analyze novel audiograms and identify potential hearing abnormalities.

A nonlinear regression model (neural network) to classify auditory abnormalities after the aerial audiogram and bones are formed on data simulated on MATLAB and based on real measurements.

In the diagnostic part, we used artificial intelligence technology to develop a module that plays the role of a doctor and completes this work; in this part, we developed a model of a neuron network. The first model allowed us to diagnose from the aerial audiogram; it is important to classify the four types of audiograms according to the intensity of the deafness seen in Table 1.

Figures 13 and 14 show the steps for creating a neural network model in MATLAB to create an intelligent diagnostic system.

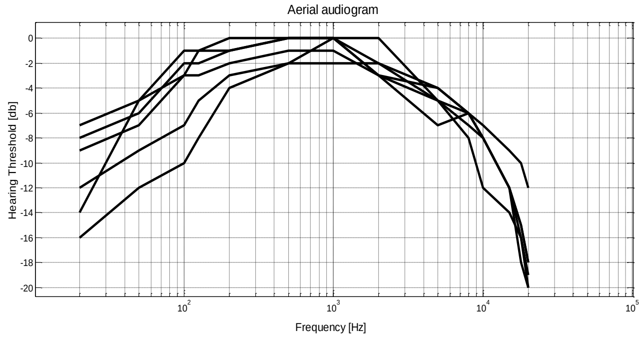

Fig. 12 – Examples of air conduction audiograms.

3.1. NEURAL LEARNING

Our database comprises 80 audiograms: half air test and the second half bone. We used 60 % of our base for learning and 40 % for the test.

Selection of neural network:

Framing of neural network development.

a. Number of input variables = 3
b. Number of output = 4
c. Number of input layer neurons = 3
d. Number of Hidden layer neurons = 20.

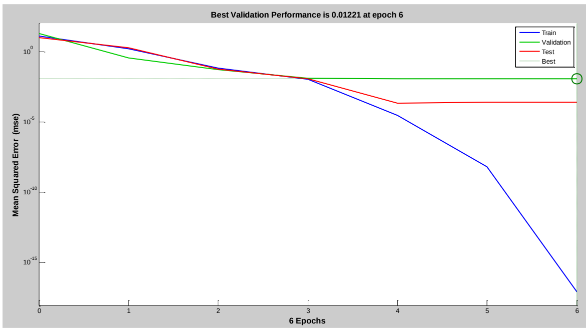

Fig. 13 – Testing data for NN.

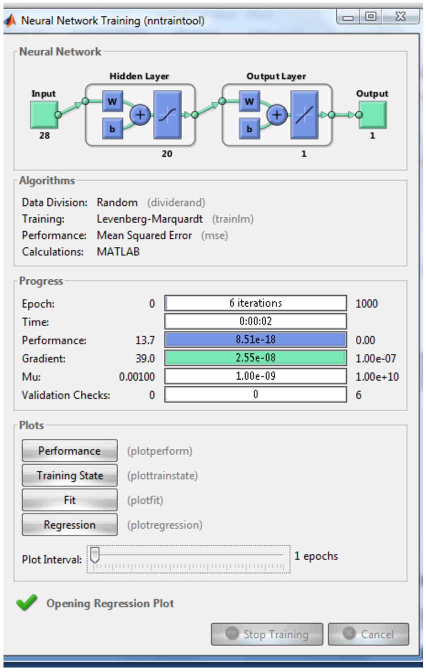

Fig. 14 – Creation of neural network model under MATLAB.

The following table illustrates the results of a detailed neural diagnosis.

Table 1

Neural network prediction results for the four classes

Patients	Neural Network Ranking	Round(NNR)	Abbreviation of the audiogram
Nrm6	0.9462	1	N
Nrm7	0.9848	1	N
Nrm8	0.8618	1	N
Nrm9	0.9898	1	N
Trans6	2.0451	2	T
Trans7	2.0134	2	T
Trans8	1.9297	2	T
Trans9	2.0046	2	T
Perc6	3.0404	3	P
Perc7	3.0534	3	P
Perc8	3.0663	3	P
Perc9	3.0015	3	P
Mixte6	4.0191	4	M
Mixte7	4.1194	4	M
Mixte8	4.0887	4	M
Mixte9	4.0854	4	M

Abbreviation of the audiogram

N: Normal audiogram

T: Transmission deafness

P: Perception of deafness

M: Mixed deafness (Transmission and Perception deafness).

The results presented in Table 1 demonstrate the efficacy of the proposed neural network model for diagnosing and classifying four hearing diseases. Furthermore, the model provides insight into the level of deafness.

4. **RESULTS**

When the test is complete, the user can see the result (audiogram) by clicking on the “GO TO RESULTS” button of interface 3 (Fig. 9). This interface also incorporates a print option.

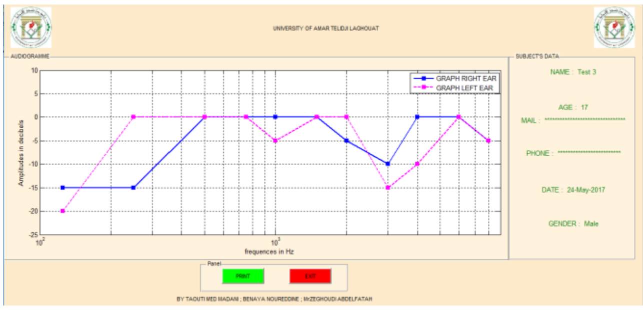

Fig. 17 – Audiogram of first person, 17 years old.

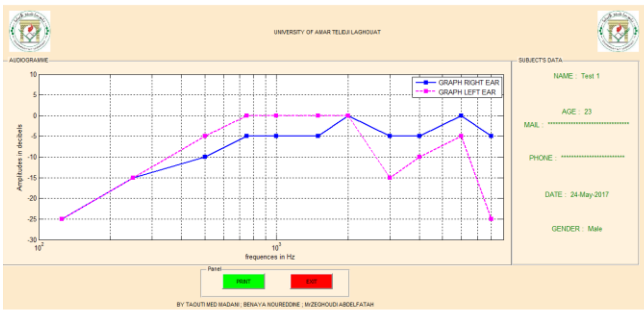

Fig. 18 – Audiogram of the second person, 23 years old.

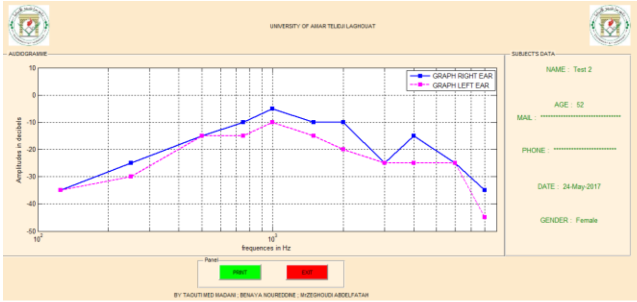

Fig. 19 – Audiogram of the third person, 52 years old.

Three participants (17, 23, and 52 years old) were recruited to evaluate auditory threshold levels as part of the testing phase. Individual audiogram results are presented in Figs. 17–19.

4.1. INTERPRETATION AND DISCUSSION

According to Figs. 17–19, the 17-year-old is sensitive to different frequencies. Compared to the other subjects (23 years and 52 years), specifically in high and low frequencies, the 17-year-old has a better response (audibility) than the others. This suggests that age plays a significant role in auditory acuity, with younger individuals potentially demonstrating greater sensitivity to diverse frequencies.

Following the hearing test and generation of audiograms, the workflow seamlessly integrates the neural network model for automated diagnosis and classification of hearing abnormalities. Reaching this step, it can be considered that the work has become integrated.

Compared to the audiogram results presented in [10,22,23], the audiogram curves exhibit a bell-shaped pattern, with hearing thresholds ranging between –10 and 25 dB across all tested frequencies (250 Hz to 8 000 Hz), characteristic of normal hearing.

Hearing thresholds for high frequencies (1 kHz to 2 kHz) demonstrate a marginal elevation compared to those for low frequencies (250 Hz to 500 Hz); the audiogram curves exhibit asymmetry between the right and left ears.

A significant contribution of this work is the development of a software component that analyzes audiograms, identifies hearing abnormalities, and classifies different types of deafness using a neural network.

5. **CONCLUSION**

This paper presents the development of an audiometer-based Arduino board equipped with graphical interfaces designed in the MATLAB environment. The system facilitates frequency selection, decibel-based amplitude control, patient data management, and audiogram tracing, enabling subsequent diagnosis by a neural network model.

The system employed three interfaces: an initial module for patient management, a second for generating sound waves with adjustable frequencies, and a final “Audiogram” interface for recording and plotting test data. The communication between the Arduino Uno and MATLAB through the USB port for serial communication and the use of relays and LEDs for audio channel control and user feedback proved highly successful, contributing significantly to the project's positive outcomes.

This work demonstrates the feasibility of an automated audiometer combining air conduction testing for comparative audiogram analysis, artificial intelligence-powered neural networks for robust auditory pathology classification, and intelligent diagnosis generation. Moreover, the project delved into fundamental aspects of analog and digital electronics applicable to medical diagnostic instrumentation.

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