Patient Benefactor Linker

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Abstract

This paper discusses a new evolution in the healthcare sector through a device by investigating the principle application of Artificial Neural Networks (ANN) for the selection of an optimal benefactor-donor match in organ transplantation. The device aims to correlate ABO blood type, age and bone density of healthy subjects. Firstly, linker phase integrates a light intensity(lux) meter and an RGB Color Sensor module to perform an experimental observation of agglutination of RBC's which is measured through a halogen illumination source that measures the light intensity which is displayed on a screen through the microprocessor interface. Secondly, we aim to study the possibility of calcium quantification via near-infrared spectroscopy to estimate bone density which involves the use of an emitting source and a photodiode as a detector/ receiver. At last the device involves designing an Artificial Neural Network (ANN) model through the Neural Network Toolbox of MATLAB software to get the optimal network architecture suitable for the analysis. This architecture is achieved by simulating different Artificial Neural Network (ANN) configurations. We used a non-linear ANN which can predict benefactor and patient organ matches, while measuring ABO blood typing and calcium density of the donors in real time and for recognizing mapping functions for which there is no requirement for a particular basis of functions. A database was created through an intensive survey of benefactor profiles. The results generated by ANN are promising for identifying optimal benefactor and patient matches. This approach has potential benefits as an increase in the number of input and parameters will provide better matches and risk associated with human error are reduced. The network can further be modelled to predict survival rates.

Keyword: Artificial Neural Network, RGB color sensor module, infrared spectroscopy, MATLAB Neural Network Toolbox, Optimal benefactor-donor match

1 Introduction

Organ transplantation serves as a life-saving remedy for all the patients that are subject to organ deterioration. [1] The important factors to accomplish this are the availability of organs and the proper matching of donor and recipient organs. Higher life expectancy and improved survival rates have somewhat urged patients to opt for this treatment but lack of organs limits their hope for better lives. Today, the fundamental criteria standard for matching a potential recipient with a suitable donor are ABO blood typing, age, gender and urgency level. [4] The immune system of a human acts up when a foreign invasion takes place, it is obvious that there

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will be immunological incompatibility and this serves as a risk. A perfectly matched organ is considered to lower risks of immunological rejection and infection improving survival rates overall.[5] Since organ transplantation has come into practice it is mandatory for ABO blood typing to be compatible for both benefactor and patient. High risk of hyper acute rejection is the main consequence of ABO mismatch. [6] Organ transplantation and ABO incompatibility are never taken intentionally because of high dying rate of some accidental cases that have been reported [7]. In order to avoid such fatal accidents, it is important to match ABO blood typing in adults, as neonates have delayed development of immunity to antigens [8]. Benefactor age is another important criterion in organ matching. It is said that organs can be donated at any age, donors have given up their organs at the age of ninety years. It is up to doctors to check the viability of these organs. Relative studies and researches show that old age organs can affect the transplantation process. A significantly greater impact occurs when old age donor organs are transplanted, age matters most in liver transplantations. [9] Donor with advance ages has disadvantageous influence on patient continuity for liver patients, this is seen when the donor's age exceed from forty years or over[9].

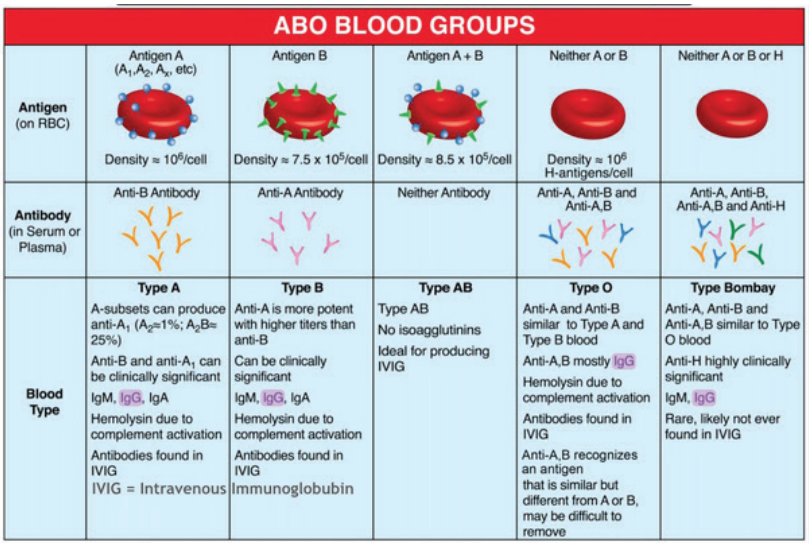

Figure 1: ABO Blood groups and their respective antibodies and antigens (from Ref [27]

This study looks into an unusual but important factor that can serve as a matching criterion for organs. The role of calcium as the fifth most occurring element in a healthy person. Prospective studies show that calcium levels, bone density and bone mass are usually lost after successful transplantations. Fractures and bone loss produces significant morbidity, especially during the period of early post-transplant.[10] It is suggested that both donors and patients have optimum calcium levels so that the transplantation process does not affect them so much as it would affect patients with lower calcium and bone density levels. All candidates of organ transplantation should go through a bone health evaluation before proceeding as it would deem beneficial for them. [11] The aim of this research is to devise an artificial neural network that will predict the match percentage between benefactor and patient keeping in mind the three criteria, ABO blood typing, age and lastly the calcium density. Prior work has been done to predict the perfect match for heart transplantation, using data from a registry and then processing it through the algorithm [2].

Figure 1 illustrates the five known blood types or groups. Branch [27] pointed out in is research that the most prevalent type of blood group is the A-type, similarly, for our research, the subjects which were tested to prove our hypothesis were majority A-blood type participants. The percentage of Type O and Type A is approximately the same, as indicated by Branch, however, among the individuals tested in our study, Type O was the second populous group in the sample. Type "Bombay" did not exist in the study sample. Since Bombay lacks anti-A and anti-B if the sample had at least one individual with this type the results may have significantly varied. On the other hand, "artificial neural networks (ANNs)" are the algorithms which computer-based and modelled at the behaviour and composition of neurons in the brain and can be edified for identification and classification of complex patterns [12].

The parameters of the ANN are adjusted to achieve the pattern recognition through a process known as "error minimization" which corresponds to skill development through experience. Calibration of ANN may be done through input data of any type, such as levels of gene-expression generated by microarrays of cDNA. The output of trained ANN may be grouped into different classes. There are various modern world applications of ANNs such as the application in clinical problems ones such examples is its use to diagnose myocardial infarcts[13] and arrhythmias[14] through the interpretation of radiographs and electrocardiograms.[16] and magnetic resonance images[15].We applied ANNs to obtain a perfect match between benefactor and donor organs depending upon the three criteria. This will be done by collecting patient data and training the network over the three parameters and then the benefactor data will be collected by the linker in the form of ABO blood group and calcium density.

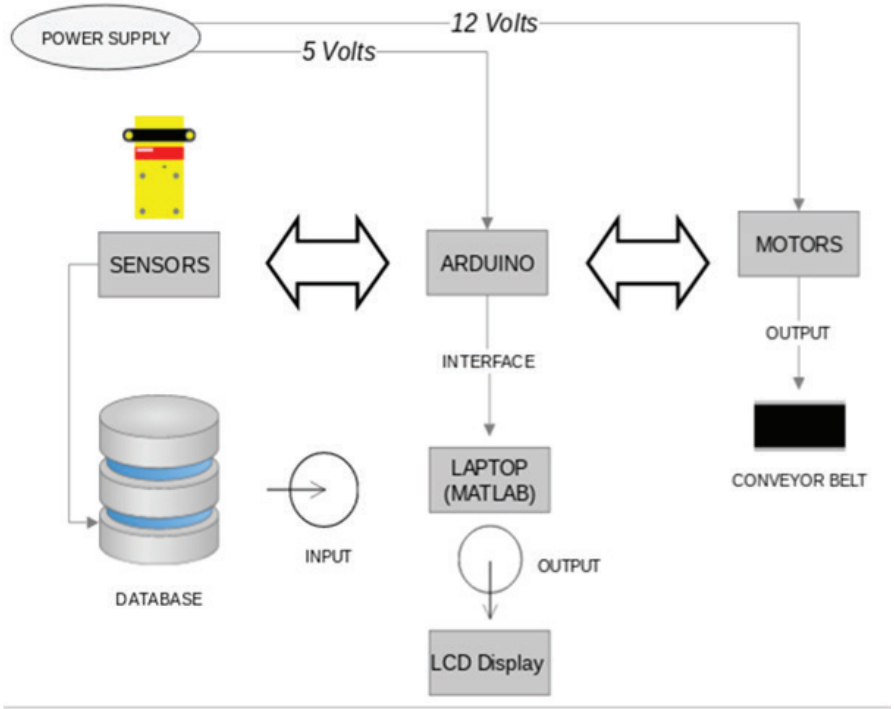

Figure 2: Hardware Flow (Source: self-made)

After the network has been trained, the inputs will be added from the Red blood cell agglutination sensor and the calcium density sensor as shown in Figure 2. The ANN will process the data and as a result, will display the percentage match of organs on the liquid crystal display. Figure 3 displays how the network will flow, the decision box displays the processing of data and working of an algorithm which then results in a digital output of either 1 or 0.

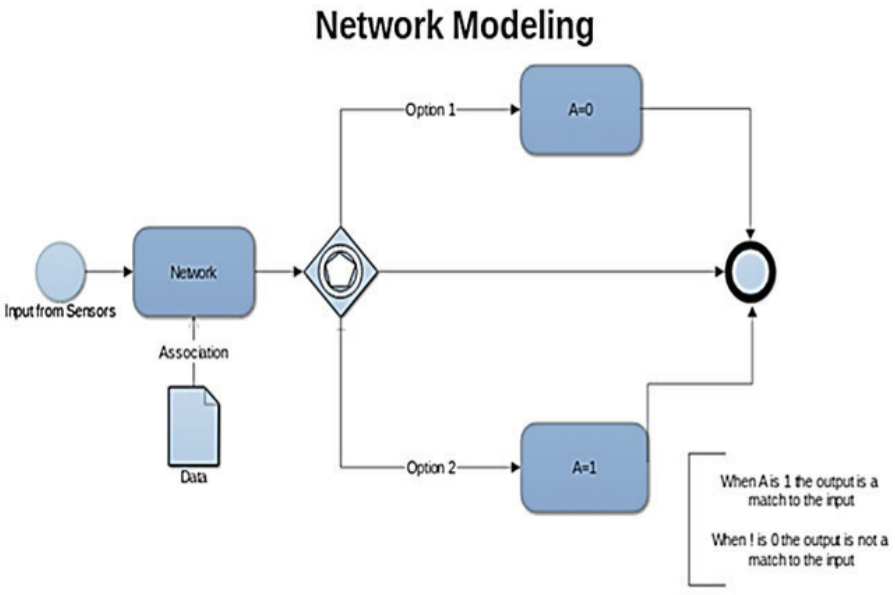

Figure 3: Example of the working of the Network (Source: self-made)

2 Materials And Methods

A ABO Blood Typing Using a Luminosity Sensor

Blood type is typically explored via data recordings of light intensity (lux) calculations that occur within the range from 0.1 - 40000 Lux. However, observation and interpretation of the data exclusively cannot be utilized to establish a cross-match between recipient and Donor blood type. A relationship can be generally identified using a model-based approach. The approach undergoes learning and prediction steps.

Light Source Selection

Previous studies investigated the effects of wavelength (500 to 900 nm) on aspects of RBC aggregation for regular blood suspensions which recorded both reduced and accelerated aggregation statically and dynamically [18].

Results from experiments show that green laser beam (527 nm) performed better for determination of RBC agglutinations in blood typing tests [17]. The routine immuno-haematological tests that are performed by manual techniques that do not use a light source to confirm the results. In the conventional tube technique examination, Anti-A and Anti-B both are

required to deduce if red blood cells acquire or do not have A and or B blood group antigens. "Negative test result" is a lack of agglutination, which illustrates the absence of corresponding investigated antigen. "Positive test result" is the agglutination of red blood cells with given reagent, which indicates the existence of the desired ABO antibody.

B Predicting Match Using a Model-free Approach

Model-Free Approach

The term model-free refers to construction of a machine learning a computer-based tool, rather than a physical model to approximate a numerical function. This numerical function is then used to produce a map between the given inputs. For our research, we used Artificial neural networks (ANNs) for recognizing mapping functions for which there is no requirement for a particular basis of functions. Subject-specific neural models have been established from experimental data that primarily include light intensities and electric potential differences.

In Model-free approach, equations are not used to form relationships thus the process is free from equations modelling it. Therefore, we used the precise approach of a "black-box" where intermediate functional relationships between the observed experimental parameters are done through "macroscopic transfer function" instead of separate modelling. In the context of Cross-matching the mismatch of Donor-Recipient factors such as "gender, allograft, ischemia time, medical conditions prior to transplant, and human leukocyte antigen (HLA)" have all been classified as risk determinants for organ rejection but may not be benefited in the matching of organ. [19, 20, 21, 22]

Age, ABO blood group compatibility and Bone density measurements (in case of Bone graft implants and also to estimate the overall health of Donor) are the parameters chosen to be the constitutive units to the neural network. Conversely, a method to ascertain the conversion of each input variable into output variables via constitutive unit. The term used to describe this relation is called "functional relation".

Due to the inborn complication of "coupled nonlinear biological systems", computational model production is needed for quantitative awareness of their structure and function in medical studies [23]. However, there exists a limitation to this approach a single macroscopic nonlinear transfer function may not prove to be adequate enough to apprehend the complex various "Intermediate nonlinear components" in the observed variables. For data fitting difficulties we desire artificial neural network to sketch between a data set of numeric inputs and of numeric targets. In this context, the interpretation of the regression map is as follows, the more complicated the regression map, the more it will over fit the data resulting in deficit of generalization (i.e. classic overfitting problem).

3 Bone Densitometry Using Near-Infrared Spectroscopy

The traditional method to estimate bone mineral density is by using the "Dual-energy x-ray absorptiometry (DXA)".

Table I: Comparison of radiation doses. Dose limits for occupational exposures are expressed in equivalent doses (from Ref. [24])

Type	Model	Patient Dose(microSv)
i) Body CT scan		5,000-15,000
ii) Head CT scan		2,000-4,000
iii) Lumbar Spine X-ray		600-1,700
iv) Lateral Spine X-ray		820
v) Dental Bitewing		60
vi) Chest X-ray		
vii) DEXA Total body	Lunar Prodigy	0.37
viii) DEXA Total Body	Lunar DPX-L	0.20

Table 1. Shows that the radiation dose for a DEXA scan is very small as compared to other modalities however there is a chance of cancer from excessive exposure to radiation. Radiations may cause cancer due to mutation of cell. The aim is to design a device to measure bone density using the near-infrared emitter and Photo-detector.

A Optical Wavelength

According to the light absorbance properties at near-infrared of skin and bone, it is known that light absorbance of skin and bone largely differs with changing wavelength [25]. In order to select the optimal light source for the hypotheses, two requirements were necessary. To ensure that the collected spectral data is limited to the area of tissue of interest firstly such wavelength of light would be considered which could pass the skin and penetrate into the bone so as to estimate the wavelength of light that was transmitted through the bone. The high value of absorbance of light by the bone can clearly identify the difference of bone density [25]. Secondly, the wavelength of light must pass the skin or absorb light so that experimental results would only provide bone absorption. It was observed that the penetration depth of NIR fluctuated from approximately "1 mm to 2 mm in the 4000-5100 cm-1 range to approximately 3 mm in the 5100-7000 cm-1 range, and to approximately 5 mm in the 7000-9000 cm-1 frequency range" [26]. These findings suggest that the chosen optical wavelength which is 1720 nm at a distance of 25cm could be used for the experiment.

4 Experiment

In order to understand the thickness or bone density, different wavelength were used to illuminate the target area. NIR spectra helped detect the thickness using NIR spectrum. The light source was placed on the thumb or any finger of the subject and the transmitted light was detected by the photodetector. The correlation coefficient R determined confirms the high potential of an optical wavelength at 1720nm. For the blood sample clots, it implies that the blood has reacted with the antibody present in the reagent/Antisera. For instance, if the blood forms agglutination with Antisera A, it has antigen A. The slides may be viewed under a microscope to confirm agglutination. However, we have used a lux sensor in our project to perform the task.

A Training Algorithm

For faster training and processing of input data, a high-performance training algorithm was required. Two main categories of faster algorithm exist. The first category uses a heuristic approach and the other category uses standard numerical optimization techniques. We have used the numerical optimization technique. The best correlation coefficient was observed using Levenberg-Marquardt Training Algorithm. This method is applied whenever the current solution is far from the accurate solution. In case the current solution is close to the accurate solution LM applies the Gauss-Newton method. LM is capable to alternate between a slow decline approach when moving far from the minimum and a swift convergence when being at the minimum vicinity.

1 Network Layers

ANNs are structured by layers of neurons. For the study, two layers which are mandatory are the output and input layer. Hidden layer is in between the input and output layer. A hidden layer can be more than one in number. Hence there exist an arbitrary number of hidden layers each of them being an approximate size. The number of hidden layers for our project is 20. A suitable correlation was obtained using 20 hidden layers and one input and one output layer.

2 Learning Rate

During training in order to measure a more correct output the network figures out the direction in which link value and each bias value can be changed at each step. Learning depends upon the learning rate. The higher the learning rates the faster the learning. Learning rate can be set to a maximum value of 1.0.

3 Epochs

The number of epochs the network uses to perform learning was a total of 1000 epochs.

B Participants

A data sample of 2000 patients included in this study was extracted from a hospital with the consent of the patients and healthy subjects were chosen randomly, their medical profiles were extracted from records for research purposes. Informed consent was obtained by the hospital from patients prior to the start of the study. The full dataset was used to train the network. Dataset consisted of three important parameters which were Age, Blood group and calcium density. The main selection criteria for subjects was their age. Individuals were grouped and a data set ranging from 25 to 60 years of age was constructed.

5 Results

The efficacy of the network is promising. In order to analyze the efficacy of the model, we have utilized a classifier to adjust the imbalanced data. This data is split into training and testing data sets. The training data set is for the purpose of setting and computing hyper-parameters. The test data set is for appraising the classifiers. The performance is adjusted by estimating the means and standard deviations. Efforts have been made to reduce the computation time. The time taken for the

simulation of the network is crucial because we aim to provide instant results but due to a large dataset, a trade-off between computational efficiency and performance is observed.

The results from the NNtool application in MATLAB used for the study provided below:

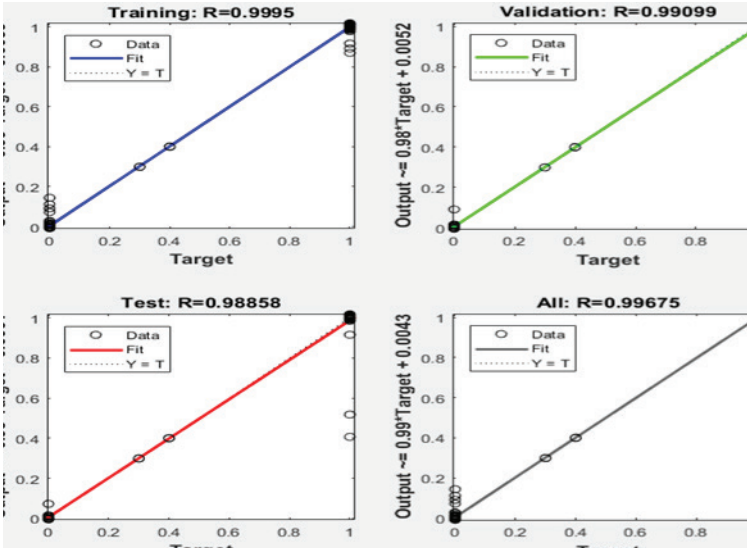

Figure 4: Regression Plot of the neural network. The correlation coefficient R= 0.988 for test input. Hidden layer = 10 and the network is trained using the Levenberg-Marquardt algorithm

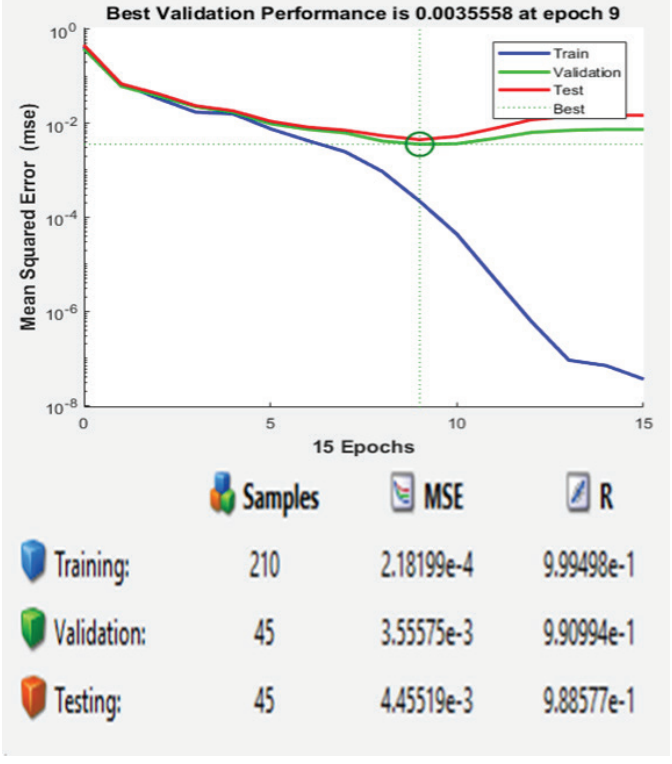

Figure 5: (Top) Plot performances at epoch 9. A total of 15 epochs were used to train the network. (Bottom) Mean square error for 10 hidden layers.

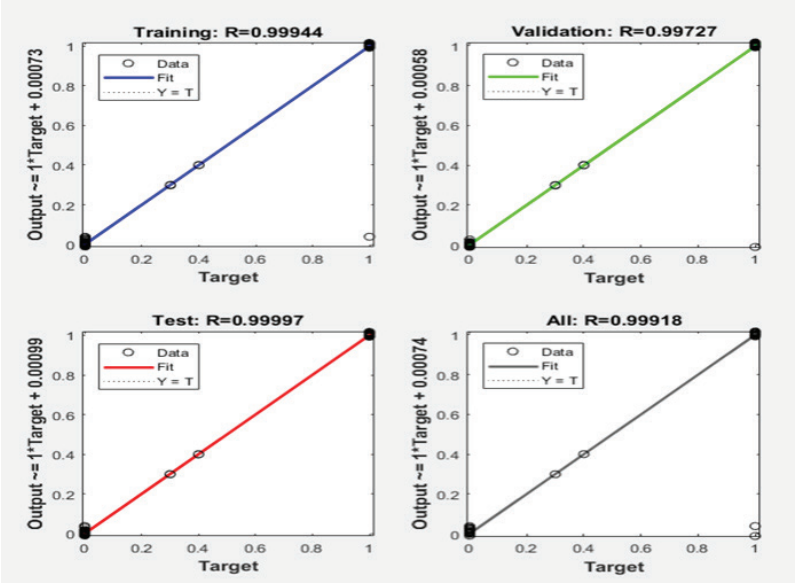

Figure 6: Regression plot for 20 hidden layers. Input= 2000

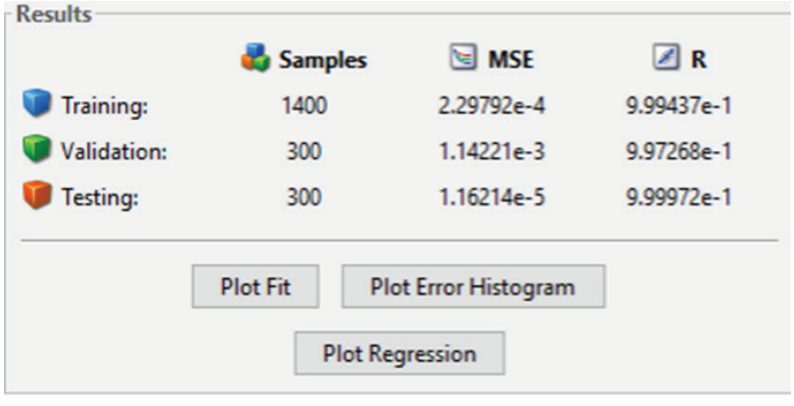

Figure 7: Mean square error for 20 hidden layers. Input=2000

6 Discussion

In this paper, we present a non-linear ANN which can predict benefactor and patient organ matches, while measuring ABO blood typing and calcium density of the donors in real time. This is important as many patients are already waiting for transplants and when they do pass the waiting list there is an immense risk of a mismatch. The network has shown to be somewhat successful in achieving the hypotheses laid out in the beginning. The predicted results have, however, not been achieved yet. Artificial Intelligence is the future and eventually, all problems in medicine will be overcome. The network will hopefully work best in the future with a bit tweaking in the proposed network architecture. At the moment it lacks a bit of accuracy and validity but it proves to be reliable. The RBC agglutination sensor has given us promising results in identifying the donor blood group which was questionable at the beginning. A relatively cheaper method of determining calcium density in the body has been worked out and it has proven to give great results, with a 70-80% match to the original DXA values.

7 Conclusion

This study introduced to explore another technique for the cross-linking of beneficiary benefactor for patients requiring a transplant by utilized artificial neural systems. The device is designed as a significant tool which will not only help the clinicians and doctors to predict the best match but will also reduce patient death due to the rejection of organs. To achieve a profound understanding of the risk factors that cause organ rejection and influence long-term survival rates, the development of the subject-specific data-driven network is a key facet. This approach shows potential to accurately predict the best matches and provides concrete opportunities for easier and more reliable healthcare systems. The proposed device is a useful tool in clinical practice and can also be used to automate other medical procedures. The development of such models in the biomedical field can eradicate human-associated error to a greater degree. The goal of our project was to illustrate 4 to 5 possible matches for a patient and the goal has been achieved with a correlation coefficient of R=0.99. This device exchanges the data obtained from several patients profile to train the network then finally the test data is obtained using the RGB and bone density measuring sensor. The matching is purely done by the ANN and hence no doctor/physician is to be blamed for the outcome.

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