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DEVELOPMENT OF A URINE STRIP ANALYZER USING ARTIFICIAL NEURAL NETWORK USING AN ANDROID PHONE

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ABSTRACT

Point of Care Testing (POCT) improves clinical process outcome. It has the potential to reduce errors and the wastage of resources. There is a significant amount of information obtained through the examination of urine. The routine urinalysis consists of two major components: physiochemical determination and microscopic examination of urine sediment. The physiochemical determination includes the appearance, specific gravity and reagent strip measurements. The physiochemical properties of urine may include the following analytes: pH, protein, glucose, ketone, blood, biliburin, urobilinogen, nitrite, leukocytes and specific gravity. Reagent strips provide a simple, rapid means for performing medically significant chemical analysis for urine. Assessment of the dipstick test result is done manually by visually comparing the reactive color of each reagent with dipstick color chart based on the color similarities. The manual interpretation has its weaknesses or failure. It includes the differences in a perception of color, differences in lighting condition and a failure to read several reagents in a specified time. The study of artificial neural networks is motivated by its similarity to work with biological systems successfully. It can learn from training samples or by means of neural network capable to learn. After successful training, a neural network can find reasonable solutions for similar problems of the same class that were not explicitly trained. This in turn results in a high degree of fault tolerance against noisy input data. The study developed a urine analyzer in android environment. It is able to read a 4 parameter and 10 parameter urine strip in real-time. This study also used digital image processing that includes cropping, image segmentation, thresholding, smoothing and recognition. The training is different for each parameter. This is done through Levenberg Marquardt. It performed evaluation through comparison of the standard urinalysis and the device. The prototype is evaluated and certified by a professional registered medical technologist. The accuracy test performed proved to have an accuracy of 96%.

Keywords: rough urinalysis, urine analyzer, health engineering, android, artificial neural network.

1. INTRODUCTION

Point of Care Testing (POCT) is a test performed where the result enables a decision. This action is taken immediately that leads to an improved health outcome. It is seen as a means of reducing the complexity associated with obtaining a test result. This improves clinical process outcome to reduce errors and wastage of resources while reducing the cost of care and increasing societal gain. The commercial POCT market is reported to make up to nearly 30% of the total in vitro diagnostics (IVD) market. This is worth in excess of USD 13 billion [1].

There is a significant amount of information obtained through the examination of urine. The careful examination enables the detection of disease processed in the urinary system [2]. The systematic processes are detected through the recognition of abnormal quantities of disease-specific metabolites excreted in the urine [3]. The abnormalities can be endocrine and metabolic [4].

Urinalysis is a testing of urine with procedures performed in a quick, reliable, accurate, safe and cost-effective manner [5]. This aids in diagnosis of disease and screening asymptomatic undetected disorders. It also monitors the progress of disease and effectiveness of therapy [6].

Routine urinalysis is an integral part of any medical examination [7]. The presence of any abnormality in the basic urinalysis findings serves as starting point for further laboratory examination [8]. Homeostasis of extracellular fluid environment is regulated by two organs: the lungs and the kidneys [9]. The lungs primarily regulate levels of oxygen and carbon dioxide [10]. The kidneys control the nongaseous chemical environment [11]. This regulation by kidney is in addition to its other main function as removal of metabolic waste products [12].

The routine urinalysis consists of two major components: the physiochemical determination and the microscopic examination of urine sediment [13]. The physiochemical determination includes the appearance, specific gravity and reagent strip measurements [14]. Dipstick urinalysis provides information about multiple physiochemical properties of urine [15]. This is predominantly used in screening and requires less sophisticated training of personnel. The results are obtained in only a few minutes [16]. The physiochemical properties of urine may include the following analytes: pH, protein, glucose, ketone, blood, biliburin, urobilinogen, nitrite, leukocytes and specific gravity [17].

2. CONCEPTUAL FRAMEWORK

The study is divided into three main blocks which are the Input, Process and Output as shown in Figure-1. The project started with data gathering from an institution that performs urinalysis using a machine. The data gathered are images of urine test strip used as data for digital image processing. The images are stored for training in neural network. After the training, testing is done for different sets of urine strip images. Evaluation is done by comparing the output of the machine to the urine

test strip. The efficiency of the device is calculated through the comparison of manual reading and the errors read by the project.

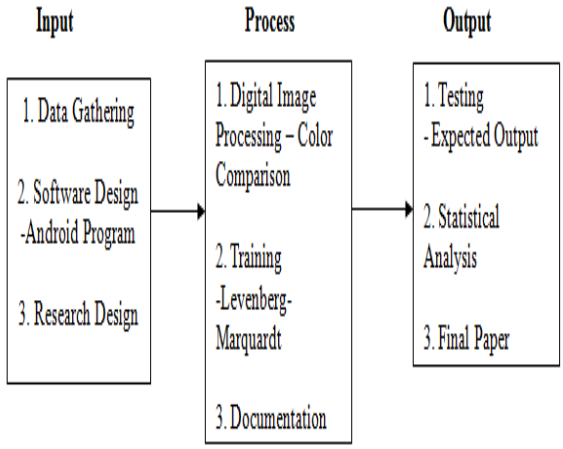

Figure-1. Conceptual framework of the project.

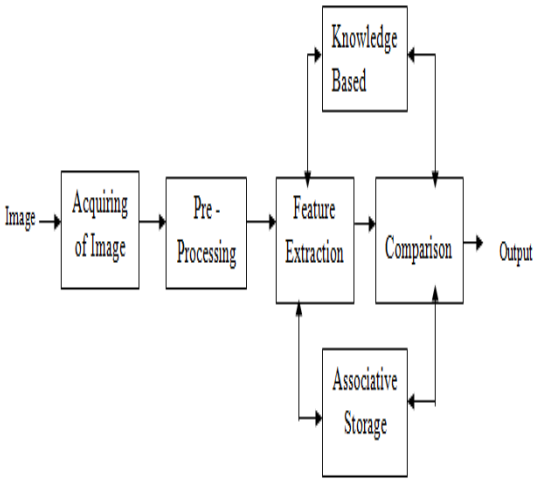

Figure-2. Digital image processing system.

The Digital Image Processing System consists of six stages: image acquisition, pre- processing, feature extraction, associative storage, knowledge base and recognition as shown in Figure-2. The first step in the process is image acquisition or capturing of digital image. A digitized image is an image *f(x,y)* in which both spatial coordinates and brightness is digitized. The elements of a digitized array are called picture elements or pixels. The image acquisition stage is concerned with sensors that capture images. The sensor can be a camera or a scanner. The nature of the sensor and the image it produces are determined by the application.

The pre-processing stage deals with brightness perception as well as image restoration and reconstruction. Image restoration deals with estimating an original image from a degraded one. Restoration techniques compensate for system degradation the image might undergone. Recent neural network models developed image restoration.

The main purpose of feature extraction is to reduce data by measuring certain features that distinguish the input pattern. To extract the features, select a subset of observed input vector. It is also transform the input observation vector. This is obtained by sampling an input image that represents highly correlated data. To reduce the dimensions while retaining most information, the observation vector is mapped into a feature space domain. The data in transformed domain is ranked according to degree of significance of the content and quality of retrieved pattern.

Associative memories are content-addressable memories. It is the ability to get from internal representation to another. This is to infer also a complex representation from a portion form the basis of associative memory. Its basic function is to store associative pairs of pattern on the presentation of corresponding stimulus pattern.

The recognition stage deals with classification. It assigns a label to an object based on information provided by descriptors. Conventional classification techniques are grouped into two t: supervised and unsupervised. In a supervised mode, classifiers learn with the training sets. In an unsupervised mode, classifiers learn without training sets.

Descriptive methods are based on the classification rules that map the input feature vectors to output categories. The classification rule is stored in a knowledge base data. The knowledge based data interacts not only with the feature extraction and recognition stages. It also interacts with the associative storage. The knowledge base is as simple as detailing regions of an image where the information of interest is known to be located.

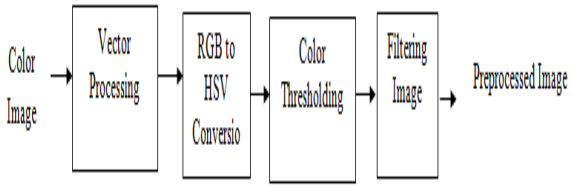

Figure-3. Pre-processing block.

The Pre-Processing Block consists of color vector processing, transformation of RGB color to HSV values, color thresholding and filtering. An image is a vector quantity represented by a matrix with RGB information. The color transformation deals with processing the pixels of each color plane based strictly on the values. This is not on the spatial coordinates. The color vector transformation deals with techniques based on processing the components of a color image simultaneously. Color thresholding is the process of assigning maximum and minimum values of

RGB. It converts image into black and white and performs erosion process. Erosion is placing the center pixel of structuring element on each foreground pixel. This assigns the value of 1. This makes the neighborhood pixels as background pixels and the value of 0. Then the foreground pixel is switched to background. Thresholding is followed by making the image blur to remove the salt and pepper noise of an image. It is eroded afterwards.

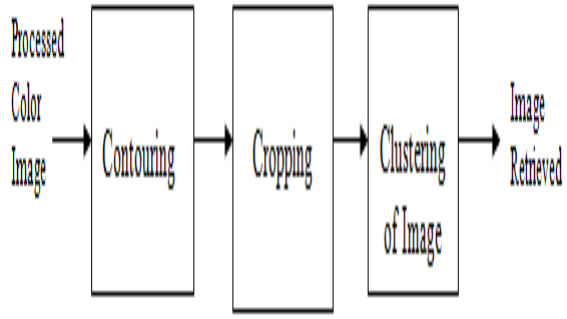

Figure-4. Feature extraction block.

Figure-4 shows the feature extraction block that consists of three blocks: the contouring, the area checking and the cropping. Contouring is the process of getting the color of the centroid of an area. Selection of area is done from left to right order. This is so that it will not scatter the image. It is followed by cropping of image. This crops the image of the four images or the ten images of the strip necessary as data for the next step. Last is clustering of image. It is reducing color to the most dominant color.

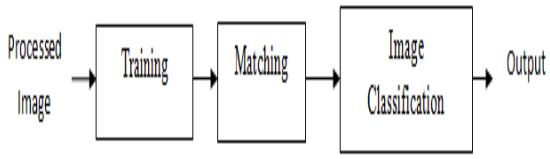

Figure-5. Image matching block.

Figure-5 shows the digital image processing which includes the training, image classification and matching processes. The data gathered after feature extraction is used to compare what is learned from the data. These are used for the training of neural network and image classification.

3. METHODOLOGY

3.1 The prototype design

Figure-6 shows the prototype design of the project. The input of the project is a raw image from urine test strip. This image is converted from BGR (Blue Green Red) value to HSV (Hue Saturation Value) value.

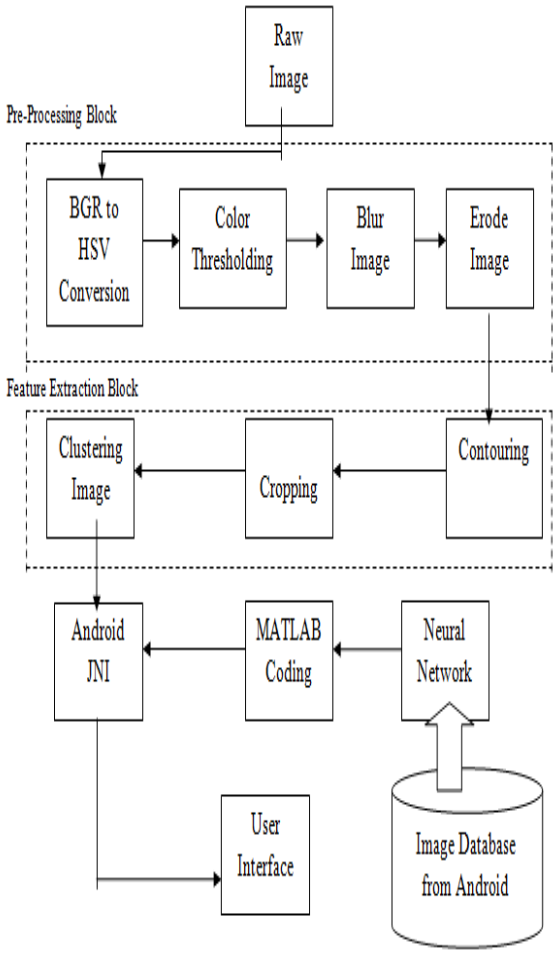

Figure-6. Prototype design of the project.

The image is limited to a minimum and maximum value and then eroded and dilated. The image is blurred and then eroded. Contouring is performed to select the area at the center of the image. It is then cropped and clustered into 4 images for the 4 parameter strip and another 10 images for the 10 parameter strip. The Java Native Interface connects the Neural Network Coder and the Android User Interface.

3.2 Project development

This study consists of three phases: data gathering, training and recognition.

The data gathering phase consists of identification of institution/s which the proponent can acquire data for the project. It requires a lot of time. The data gathering is not done until all the expected reagent appears in actual urine test strip. The data gathering phase is shown in the block diagram in Figure-7.

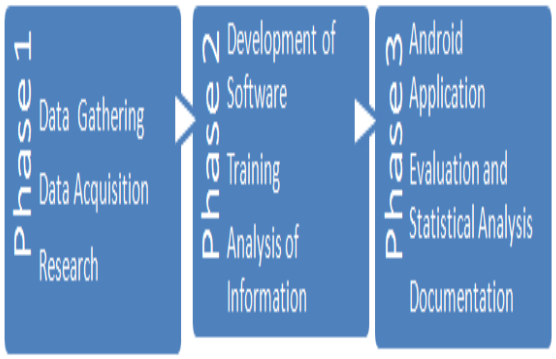

Figure-7. Phases of the study.

3.3 Program flowchart

The project has three (3) main processes for the whole system. This is shown in Figure-8.

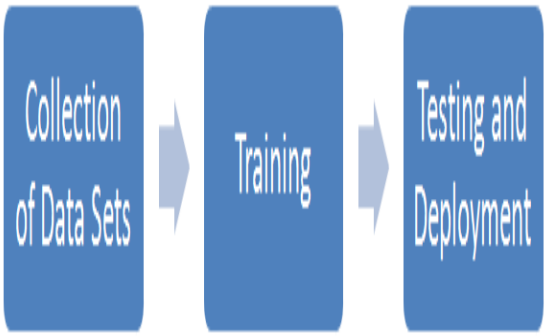

Figure-8. Three main processes for the system.

The whole system consists of 3 main processes namely, collection of data sets, training, testing and deployment. First, the collection of data sets is done in Android. In this process the images gathered in the data gathering is converted to 4 parameters and 10 parameters separately. Second, the training of the data sets. This is done through Artificial Neural Network. Third, the testing and deployment of the Applications, in this process it uses Android and C Language.

3.4 Collection of data sets

The data sets were collected from the image. The image is automatically cropped into bitmap images by the Android for the 4 parameters and 10 parameters. The RGB value is computed by getting the average. The HSV value is also computed that will give more criteria for the image. After grouping the RGBHSV values, it is mapped according to the assigned values. These values have equivalent term value in the Application. For example, 1 is set as negative for Protein and Glucose. The RGBHSV values and the equivalent output consists the Data Set.

3.5 Training

The Training involves processes in Artificial Neural Network. It uses Matlab Coder to convert the function into C code. This C code is used in Java for the interface in Android. The JNI calls the Neural Network to classify the parameters.

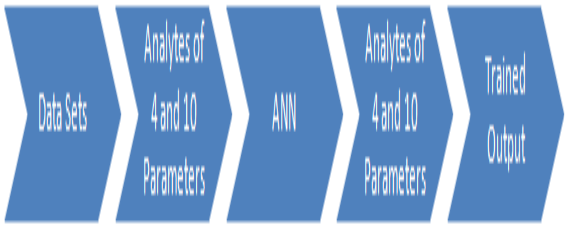

Figure-9. Training process in Artificial Neural Network (ANN).

Table-1. Classifier assignments of the 10 parameters.

Classifier assignments	Parameters	Data set used
1	Leucocytes	RGBHSV
2	Specific Gravity	RGBHSV
3	pH	RGBHSV
4	Glucose	RGBHS
5	Nitrite	RGBHSV
6	Protein	RGBHSV
7	Ketones	RGBHSV
8	Urobilinogen	RGBHS
9	Biliburin	RGBH
10	Blood	RGBHSV

Table-1 shows the classifier for each analytes, as well as the data sets used for each analytes. Figure-9 shows the processes in training. The Data Sets are separated by 4 and 10 parameters. It is separated further as Analytes in the urine strip. These are Glucose, pH, Specific Gravity, Protein, Leucocytes, Nitrite, Ketones, Urobilinogen, Biliburin and Blood. The Artificial Neural Network uses a neural network tool to train the network. In this project the Levenberg Marquardt is used as neural network tool. After training a new trained values of these data sets are produced. The output is now called the trained output.

4. METHODOLOGY

4.1 Image acquisition

The acquisition of image is done through actual urine testing through an accredited urine testing institution that allows the proponent to take samples of urine.

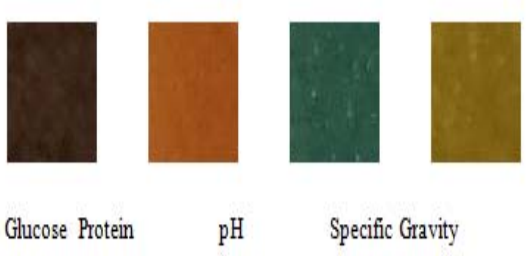

Figure-10. Cropped image of a urine strip.

Figure-10 shows a cropped image of a four parameter strip. The acquired image took the center pixel image through the use of erosion and dilation. This is to minimize the effect of flash or lighting effect to the image. The images were pre-processed and underwent the filtering, smoothing and clustering. The information from the images is used to extract features like RGB and Hue. With the information the system used thresholding to differentiate an output of colors for specific parameters. The thresholding values of RGB are specified for a certain output in the parameters. Therefore, recognizing these values gives specific output in the Android phone.

4.2 Image thresholding

In this section the features noted in the study are the maximum, minimum and average values for each RGB components in each parameter. The maximum, minimum and average values for each of the pixels are also noted to extract important characteristics of the RGB values that may be converted into threshold values. Summary of findings from the study can be visualized in table 2.

Table-2. RGB threshold in image acquired.

	Minimum	Maximum	Average
Red	15	183	99
Green	12	168	90
Blue	28	132	80

4.3 RGB to decimal conversion and the mean values

In Table-3 the data from RGB value is converted to decimal so that it will be recognized by the neural network and the Android. This is because computers can only understand 0 to 1 value only. The computation from RGB to decimal is the division of 255, being 255 the highest value in RGB.

The RGB value ranges from 0 to 255. The RGB value of data samples takes the mean values for the three trials. It is also necessary to convert it to decimal so that it will be useful for the interpretation of color equivalent in digital form, where 0 and 1 values only are understood.

Table-3. RGB to decimal conversion and the mean values.

SAMPLE	RED			MEAN	DEC	BLUE			MEAN	DEC	GREEN			MEAN	DEC
	TRIAL					TRIAL					TRIAL				
	1	2	3			1	2	3			1	2	3		
1	28	28	28	28	0.11	59	59	59	59	0.23	64	66	66	65	0.26
2	46	46	46	46	0.18	66	66	66	66	0.26	56	56	56	56	0.22
3	84	87	84	85	0.33	89	89	89	89	0.35	54	56	54	54	0.21
4	143	143	140	142	0.56	153	153	150	152	0.60	84	84	84	84	0.33
5	99	99	140	113	0.44	89	89	89	89	0.35	36	36	36	36	0.14
6	107	107	107	107	0.42	97	97	97	97	0.38	46	48	46	47	0.18
7	135	135	135	135	0.53	102	102	102	102	0.40	33	33	33	33	0.13

Table-4. The RGB to HSV conversion and the assumed output.

Sample	R	G	B	H	S	V	Output
1	0.91	0.59	0.31	0.08	0.66	0.91	1
2	0.61	0.39	0.13	0.09	0.79	0.61	2
3	0.5	0.4	0.11	0.12	0.78	0.5	3
4	0.41	0.39	0.11	0.16	0.73	0.41	4
5	0.39	0.38	0.08	0.16	0.79	0.39	5
6	0.3	0.35	0.15	0.21	0.57	0.35	6
7	0.15	0.29	0.2	0.39	0.48	0.29	7

Table-5. Result RGB values to verify variation through standard deviation.

	RED					GREEN					BLUE				
	TRIAL					TRIAL					TRIAL				
Sample	1	2	3	AVE	STD. DEV.	1	2	3	AVE	STD. DEV.	1	2	3	AVE	STD. DEV.
1	0.91	0.91	0.91	0.91	0.00	0.59	0.59	0.59	0.59	0.00	0.31	0.31	0.31	0.31	0.00
2	0.65	0.65	0.64	0.65	0.01	0.35	0.35	0.35	0.35	0.00	0.13	0.14	0.14	0.14	0.01
3	0.64	0.64	0.64	0.64	0.00	0.34	0.34	0.34	0.34	0.00	0.15	0.15	0.15	0.15	0.00
4	0.64	0.64	0.64	0.64	0.00	0.31	0.31	0.31	0.31	0.00	0.15	0.15	0.15	0.15	0.00
5	0.62	0.62	0.63	0.62	0.01	0.36	0.36	0.36	0.36	0.00	0.12	0.13	0.13	0.13	0.01

The RGB to HSV conversion is performed and shown in Table-4. The output is used in the matching of data. This is used for the decision of the output in the android application.

In Table-5, the standard deviation values are closer or equal to zero. Therefore, the data taken are proved to be reliable.

4.4 Mean values

In this section the relationship of mean value of hue and RGB is shown in Figure-11 below. This is performed by chi test method. The table shows that the relationship has a R^2 is equal to 0.8085 which is a good value to show relativity.

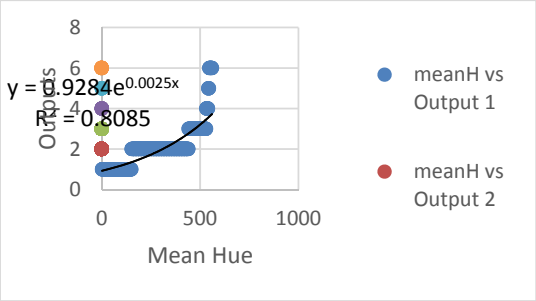

Figure-11. Relationship of hue and RGB through mean values.

4.5 Validation performance

Performance plot shows the mean square error dynamics of all datasets in logarithmic scale. It has three parameters. These are: the training MSE, the validation MSE and the Testing MSE. The training MSE trains the network. It is always decreasing. It is always true with validation and test. Validation MSE authenticates the result. Testing MSE is used to conclude the network is good or not. The ideal value for MSE is zero. In this evaluation, 70% of the samples are for training, 15% of the samples are for validation and 15% for testing. The training stops before it over fit the system.

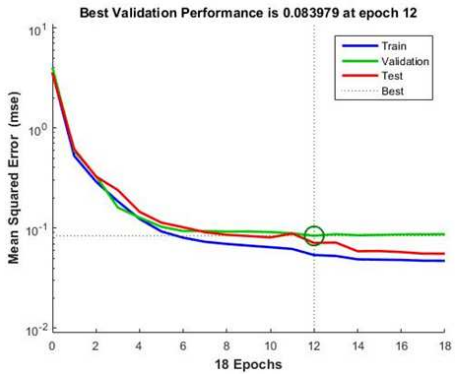

Figure-12. Validation performance of Leucocyte.

Figure-12 shows the performance plot of the leucocyte. The figure shows that the best validation performance is at 0.083979 at epoch 12. This is compared with other urine parameters.

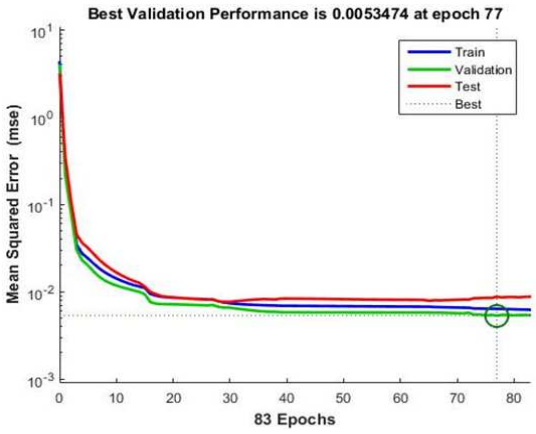

Figure-13. Validation performance of Ketones.

Figure-13 shows the performance plot of ketones. The figure shows that the best validation performance is at 0.0053474 at epoch 77.

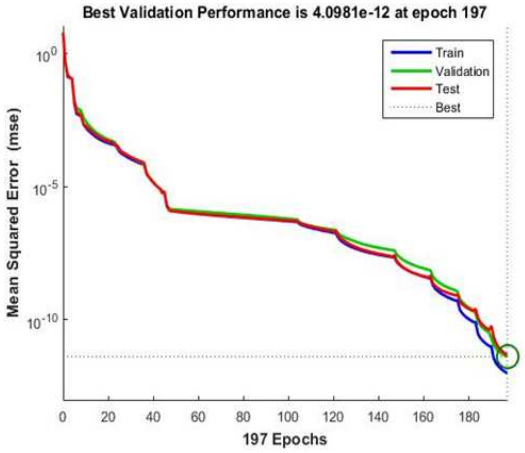

Figure-14. Validation performance of blood.

Figure-14 shows the performance plot of blood. The figure shows that the best validation performance is at almost zero value at epoch 197.

In this evaluation, it is shown that the leucocyte has the lowest validation performance compared to ketones and blood.

4.6 Accuracy test

The accuracy test is computed by comparing the output of the device to the standard urinalysis. There are 35 samples. The accuracy test is shown in the appendices. The accuracy test is done per parameter as shown in Table-6.

Table-6. Accuracy test for the ten parameters of 46 samples.

Parameter	No. Of Similar Output	Accuracy
Blood	45	97.82%
Biliburin	42	91.30%
Urobilinogen	46	100%
Ketones	46	100%
Protein	46	100%
Nitrite	46	100%
Glucose	46	100%
pH	45	97.82%
Specific Gravity	42	91.30%
Leucocytes	40	86.95%

The over-all accuracy is done by getting the mean of the accuracy of each parameter. This gives an over-all accuracy of 96.519%.

5. CONCLUSIONS AND RECOMMENDATIONS

The software model of the urine strip analyzer was successfully implemented in Android. The software can recognize the urine strip image. It is able to compare and classify an output from a urine test strip. It can differentiate color blocks for specific parameter. This is true with the 4 parameter and 10 parameter strip. The standard deviation test proved that the repeatability test in the study is very reliable. It has an output of almost zero to 0.01 of standard deviation.

The study used validation performance test in Levenberg Marquardt. It shows three parameters such as, training, validation and testing mean square error. This test shows that the validation performance test of leucocyte has the lowest validity performance. This is compared with the urine parameters, ketones and blood. The blood parameter has highest validity.

The results shown in the accuracy test gives 96.519% accuracy. These tests were done from more than 45 plus samples. In the chi-test done shows 0.808 value for testing in mean hue against the mean of the RGB which is closer to 1 and therefore, reliable. The software works well with any android phone model with the requirement of Android 4.0 and up.

The current software model is affected with light but this is over came by using the torch mode of android. The project recommends a box that will give a constant lighting for the android phone. The camera specification affects the output of the project. The higher the resolution of the camera the better the output, but this will require another data gathering to extract features of the images. The study would also like to recommend that training used will be fuzzy logic or genetic algorithm. This is to overcome the values of data in between the colors in the color chart.

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