AN ELECTROCARDIOGRAM CLASSIFICATION METHOD BASED ON NEURAL NETWORK

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Thesis
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Pathrawut Klaynin

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CHAPTER I
INTRODUCTION

ECG. (Electrocardiogram: ECG), an electrocardiogram that represents the behavior of the heartbeat. Useful for the diagnosis of heart diseases types of parameters, both the size and timing of signal as the signal RR interval, PP interval, QT interval, ST interval and the P, Q, R,. S and T will be able to look at the different types of heart disease.

1.1 Background and Statement of Problems

In normally , medical records of patients with ECG recorder (Ambulatory ECG Recording or Holter monitoring) in order to determine abnormal ECG. The physician will make the interpretation of the nature of the ECG waveform. Calculations with different parameters. Both the size and timing of the ECG. This shows the kind of heart disease or not. Recognition and reference points to calculate the parameters of the ECG is a tedious and time-consuming for doctors. In addition, the number of patients it has a lot more heart. Therefore, it needs a system that can automatically classify the ECG to aid in the diagnosis of a type of heart disease in patients.

Methodology of classification of ECG. Many automated method has been developed to indicate the type of heart disease in the individual patient. The various methods that have been developed are still limited in its application to the make continues to innovate and develop new ways to continue to be effective enough to lead. To improve methodology we use Variable selection for classification by neural network. Study data were processed for classification of various cardiac arrhythmias. We propose wavelet transform and selection variable method, then use the Neural Network to classify the ECG Heartbeat[8]. We get ECG Beat data from MIT-BIH arrhythmia database and improve performance of classification.

1.2 Objective of Study

ECG is very important in the diagnosis of various heart diseases in this project to study and develop methods for automated classification of ECG. That are less complex to reduce the processing time. But a good performance. The neuron network theory as a tool to classify different types of ECG. By the study of the electrocardiogram is to select a particular type of data in the MIT-BIH Arrhythmia Database using the six species. By using based on neural networks methodology to diagnostic.

1.3 Scope of Work

This thesis presents a new classification of ECG. Which performs well in the complex to work less. By studying the type of ECG is a popular source for ECG classification system with six types are applied to the system design. The experiments were performed using a computer simulation. The details of the project are as follows: Chapter 2 discusses the theory and related research, Chapter 3 discusses the design and implementation methodology, Chapter 4 discusses the experiments and analysis, Chapter 5 discusses the limitations. conclusions and recommendations.

1.4 Procedure

To begin the study, the ECG of interest. Then study the research that has been done previously. What's important contributions. To begin to design a new system. Will be conducted in accordance with the following procedure.

1) Study the proper way to extract ECG features of each type.
2) Study how to reduce the data size to suit the neuron network is to classify ECG.
3) Analyst the ECG data to cut the beat 300 points.
4) Remove DC noise.
5) Use wavelet transformation to filter the beat.
6) Use variable selection for reduce some variable.

7) Experiment with neural network segment, and then see if the results are satisfactory or not.

8) Compare between neural network results.

9) Conclusion the results.

1.5 Benefits expected

1) Learning style of the electrocardiogram of the heart and blood vessels.
2) A diagnosis of cardiovascular disease with accuracy and efficiency.
3) A diagnosis of cardiovascular medicine down.
4) Has experience and knowledge in the neuron network.
5) Leaning about variable selection feature.
6) Engineering knowledge to practical application.

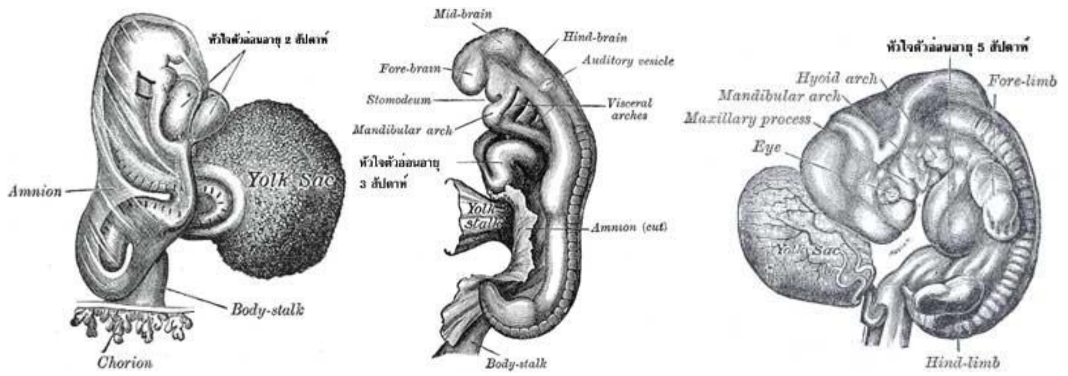
CHAPTER II
LITERATURE REVIEW AND RESEARCH THEORIES

The heart is one of the most important organs of the body. If we lose parts or organs, it is wrong to make lifestyle changes. The thesis of this book may help make it easier to find fault with any kind of heart disease.

2.1 Structure of heart

2.1.1 Anatomy of the heart

2.1.1.1 Origin of the heart The Heart to rise up in the embryonic cells of the blood vessels. The area is called Cardio-genic plate, which saw the light in about 2 weeks after the last blood cells to gather in the second pipe is the pipe on the left and the right. The two pipes together and move together in a single tube called the Heart tube in approximately 3 weeks after Heart tube is gently pushed into the bag itself is called. Pericardium sac. And while there is a segment within the heart chamber and the heart valves and blood vessels and various heart starts beating in Week 4, the larvae are approximately 22 days until Week 8 artery aortic and vascular. All will be red pulse Mona separated completely.



A. B. C.

Figure 2.1 embryonic heart (a) at 2 weeks (B), 3 weeks (c) the age of 5 weeks.

2.1.1.2 Parts of the heart the heart is an internal organ. Shaped like a cone. By the end of the cone pointing down to the bottom left. Located within the chest. Between both lungs. The back of the breastbone. By slightly to the left side of the heart, two in the third to the left of the center, and one in three will be on the right side of the center line.

The size of the heart in adults. Has a length of about 12 cm wide and 8-9 cm in width and has a thickness of about 6 cm.

Weight of the heart. I weigh about 280-340 grams in weight about 230-280 grams for women and heart are enlarged. And more weight as they age. The men are larger than women.

The heart consists of the following. Heart chambers and heart valves. Heart is divided into four rooms, including the right atria, left atria, right ventricular, left ventricles.

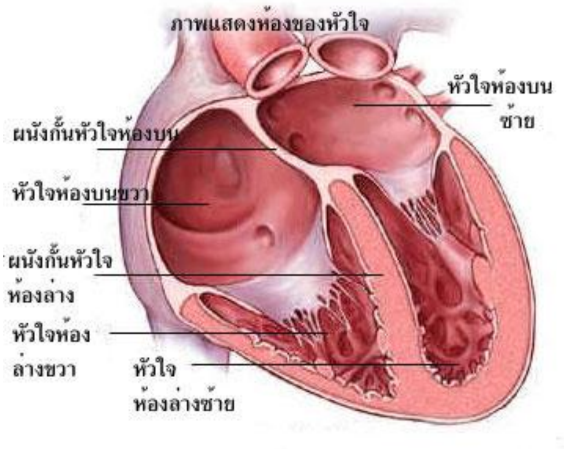


Figure 2.2 shows chambers of the heart.

Right auricle. Larger than the left atrial wall, but there are some more room on the left is about 2 mm and a capacity of about 57 cc.

Left auricle. Smaller than the right auricle. And a wall thickness of approximately 3 mm below the junction of the right auricle. Heart on the wall.

Right ventricles. Triangular. To the right atrium of the heart. The valve block tri Spartacus. The right auricle and the right ventricle. Right ventricular wall is thinner than the left ventricular ratio 1:3, but the left ventricular volume is equal to about 85 cc of right ventricular artery pulse is connected to Mona Pizza. The pulse valve Monique barrier between them.

Left ventricles. Has the shape of a cone. And on the cross-section is shaped like an oval or a circle. And the top part of the heart. The wall thickness is three times the size of the heart right ventricle.

We have all four heart valves control the flow of blood within the heart. From the atria. To ventricular and aortic arterial. And arterial pulse Monari.

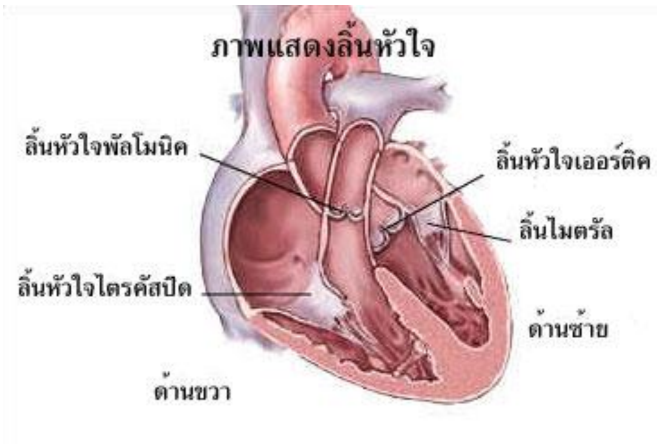


Figure 2.3 the heart valves.

Triple Cut off valve (Tricuspid valve) between the right auricle and right ventricle. The plate. Triangle Heart 3 release planned to open in the heart rhythm, blood flow from the heart to the right atrium to the right ventricle.

The Natural heart valves (Mitral valve) between the left atria and left ventricles. The valve consists of two triangular plans to open in just a heartbeat. The blood flows from the atria to the ventricles left.

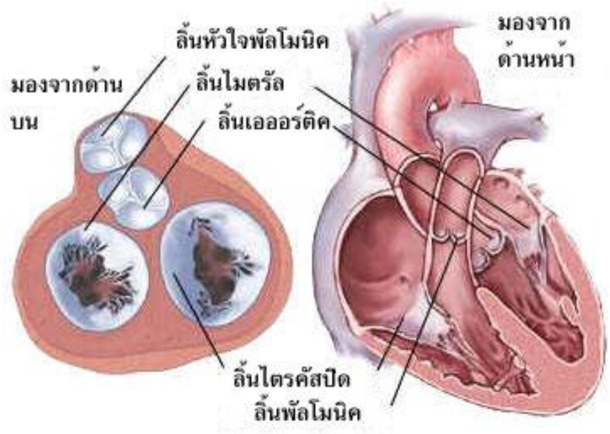


Figure 2.4 A heart valve that separates the upper and lower heart chambers.

Heart pulse Monique (Pulmonic valve) between right ventricular and arterial pulse Mona Pizza. The valve consists of three panels shaped like a crescent moon. The convex side turned to Monash Gallery arterial pulse. Squeeze to open in the heart rhythm. Blood flow from the right ventricular to arterial pulse Mona Pizza.

Valvular aortic Tikrit (Aortic valve) between the left ventricular and aortic arteries. The valve consists of three panels shaped like a crescent moon, with two in front and one behind the opening of the compression stroke, heart. Blood flow from the ventricles to the aortic artery.

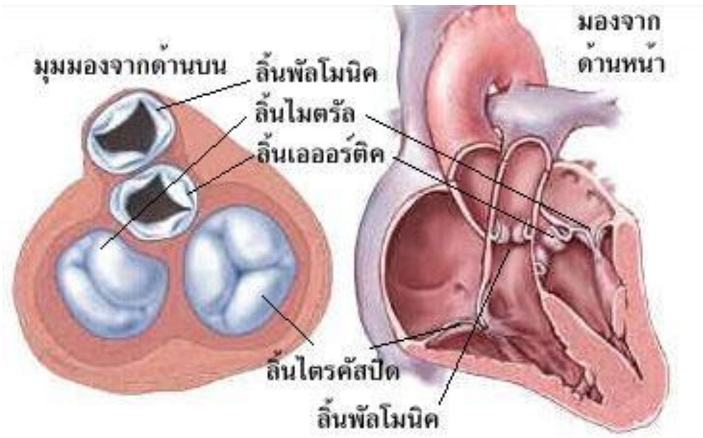


Figure 2.5 shows the valve between the heart chambers and heart valves.

Structure of the heart wall is composed of three layers.

1. Panels cladding the outside cardiac (Epicardium).

2. Cardiac muscle (Myocardium).

3. Walls of the heart. (Endocardium) a thin wall inside the heart. Including a portion of the heart valves.

Pericardium

Bag shaped like a cone. The heart and the arteries of the heart within the pericardium sac. The second disc is a pad on the outside and the inside of the membrane around the heart, between the two sheets of the pericardium. By default, this field is flattening off. However, in the presence of the disease on the Pericardium. May be the accumulation of water in the box. If there is plenty to go directly to the relaxation of the heart.

The electrical conductivity of the heart.

It works by compressing the heart and release it. Caused by electrical stimulation via electrical conduction in the heart. Which has the power in the SA node, located right auricle.

Electrical current travels from the SA node to the atria and the left and right. As a result, both atrial compression. Release in heart rhythm (Diastole), then inverter will come to an area called the AV node, near the junction with the heart ventricles.

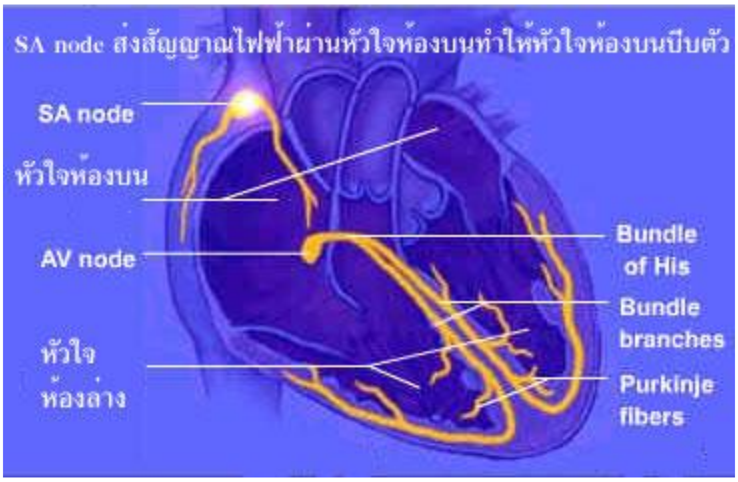


Figure 2.6 shows the cardiac conduction.

The electricity travels down the Bundle of His will then split into two branches that form on the right and on the left side, which is a branch off the front and back.

Finally the electricity to travel from one end to form the conductive fibers are widely distributed by the heart muscle. These fibers are known as Purkinje fibers and ventricular muscle force in the compression stroke, heart (Systole).

Vessels to the heart are called coronary arteries. The opening is at the base of the aortic artery was divided into two lines of the right coronary artery. And the left coronary artery.

The right coronary artery to feed the heart muscle and heart muscle on the right side of the lower left.

The left coronary artery. To feed the heart muscle, left the rest of the field is split into two branches at the front of the Left anterior descending artery and passes behind the sect called Left circumflex artery.

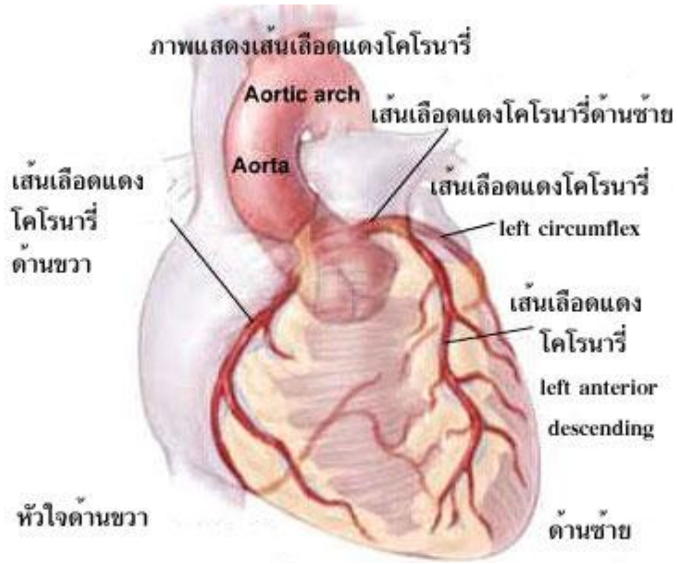


Figure 2.7 shows the coronary artery.

2.1.2 The function of the heart.

The heart is divided into three parts.

2.1.2.1 direct control of the nervous system. Usually, the heart is controlled by the autonomic nervous system (Autonomic nervous system) of the brain stem (Brainstem) with the nerves of the brain, two types of nerve SIM taken à Tikrit (Sympathetic nerve fibers) and spinal CT's (. Vagal motor nerve fibers), which sends nerve signals to the SA node.

The Sims took the nerves to the SA node Milford Post faster. Makes the heart beat faster. While the Vegas nerve to slow the heart SA node slows down.

In addition, parts of the heart and blood vessels are composed of a neural signal that we call Receptors, which are controlled by the nervous system leads SIM à Tikrit. The Post and neurological parameters SIM Tikrit. This will affect the speed and strength of the compression of the heart. Contraction and expansion of blood vessels. The details are quite complex, it is not discussed in detail at this time.

2.1.2.2 The electrical signals in the heart. Normally, I would have an insulation barrier between the atria and the lower chambers are called the Annulus fibrous, but I have the power over what we call the Cardiac conduction system which serves the electrical signals from the atria down. to the lower chamber.

Electrical stimulation on the heart muscle to cause contraction of the heart muscle. Followed by relaxation of the heart muscle. When electrical signals pass. Heart has been squeezed from the atria to the ventricles. Followed by compression of the ventricles send blood to the arterial pulse Mona Pizza and aortic artery. With the right amount of time to squeeze between the atria and ventricles. The blood flows from the atria to the ventricles fully.

Point of electrical conductivity in the heart. From the right auricle in the area we call or Sinus node Sinoatrial node, or SA node of the electrical signals to stimulate the walls of the right and left atria. And into the area which we call the AV node or Atrioventricular node and the position signal is delayed to slow down for a while before sending electrical signals down to the bottom. This is a stroke waiting to squeeze blood from the atria to the ventricles that.

Electrical signal from the AV node to the bundle of nerve fibers that connects the Bundle of His splits into two branches left and right branches stretching along the right side of the right ventricular wall. The left side is bigger heart pierced through the wall to the left and is split into two areas front and rear.

It then passes through the plexus of nerve fibers called Purkinje fibers beneath the inner lining of the heart. (Endocardium) and to stimulate the heart muscle result in compression.

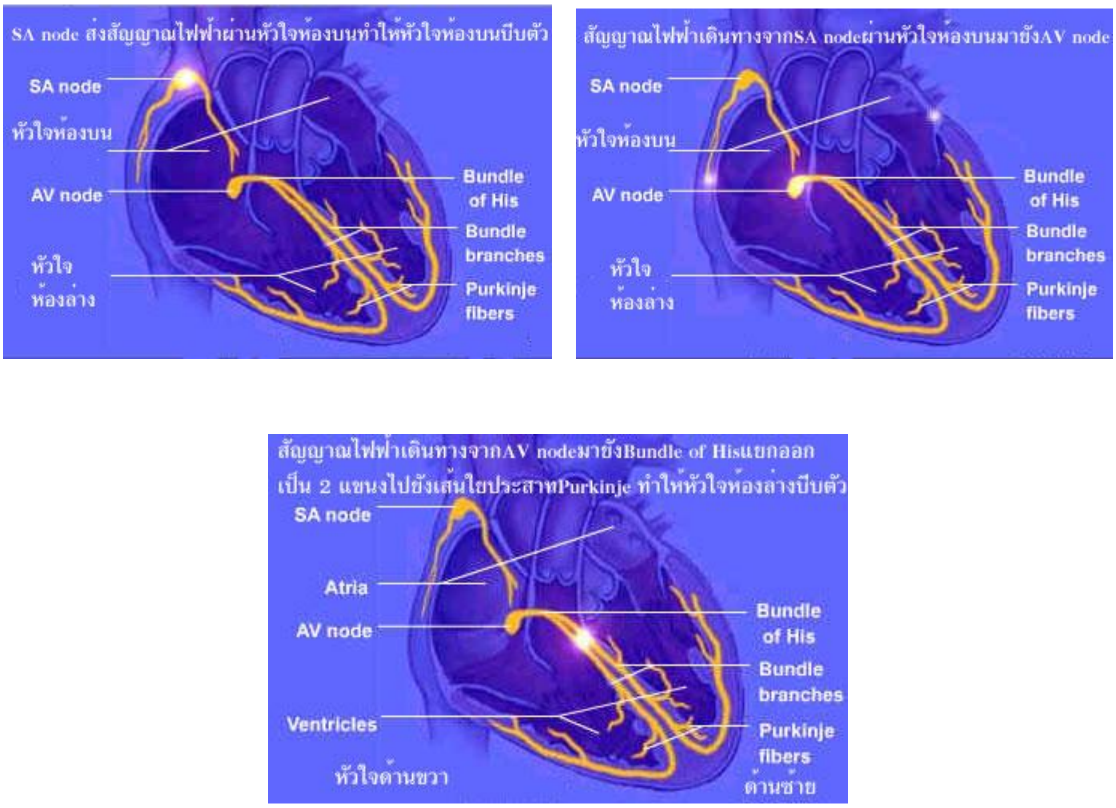


Figure 2.8 shows the electrical signals in the heart.

2.1.2.3 The compression and relaxation of the heart. Heart consists of compression and relaxation of the heart, both top and bottom. Normally, we would break the rhythm of the heart's two ventricles is measured based on the primary.

Compression stroke is called Systole is when the heart valves and heart valve or tri Cut off the Cathedral Close. Right ventricular and left - to force the blood through the heart valves and heart valve pulse Mona Gallery aortic Tikrit, which turned out to Monaghan Gallery artery pulse and aortic artery, respectively.

Rhythm release called Diastole is the heart beat and pulse Mona Gallery aortic valve closure Tikrit. The tri-cut valve closed. And the natural heart valve. It turned out that the blood flow in the atria into the ventricles. This is the exact moment that the right and left ventricles to relax the blood itself. At the end of this term suspension. Both the right and left atria to squeeze out squeeze out the remaining blood from the atria to the ventricles.

It then began a new round of heart Systole is the heart and heart valves do not close the trilogy Kirkus take off again, to the General Meeting ventricles squeeze blood sent. By right ventricular blood to the arterial pulse compression Mona Pizza. (Which actually has black blood) in order to purify the blood of the lung and the left ventricles force blood into the aortic artery. For the blood to tissues throughout the body.

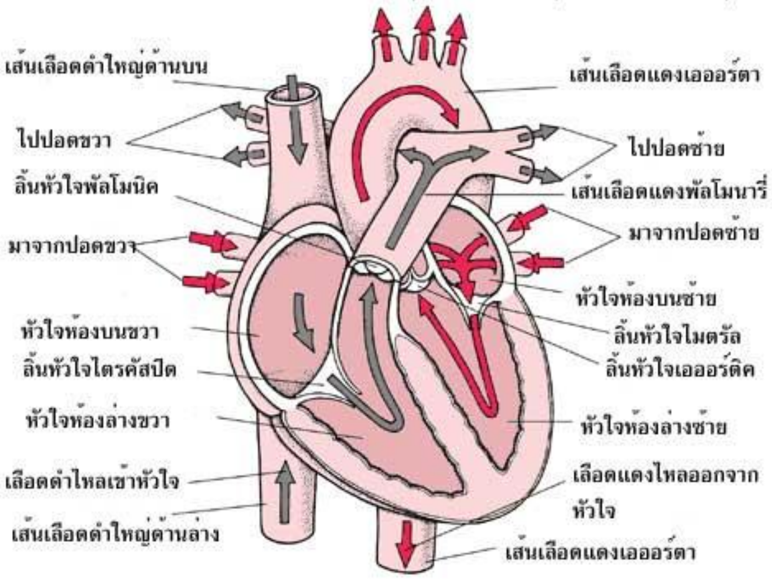
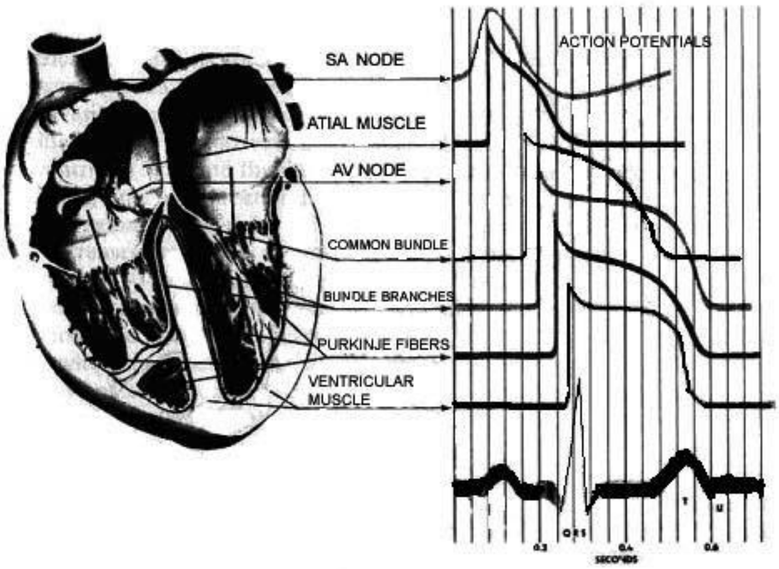


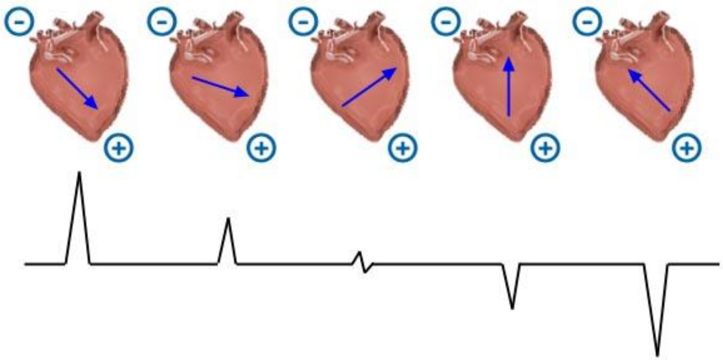
Figure 2.9 shows the flow of blood - the heart.

2.2 Properties and characteristics of ECG.

The muscles caused by electrical pulse stimulation. Cause muscle contraction. The power and prowess to work with. The heart muscle is the same. The movement of ions inside the muscle cells, causing the voltage and make the heart beat. The movement of ions in heart muscle cells to an electric current to flow. And as a result the voltage external skin and tissue of the body. Current flow will occur only when the distribution of the electric potential only. ECG is an electrical signal from the power pole to the chest, arms, legs or Figure 2.11 shows a normal ECG. Consisting of waves P, QRS, T and U, which is important in the analysis of the system of the heart.



(A)



(B)

Figure 2.10 shows the power spectrum at different positions of the heart.

ECG will change the voltage in the range of 0.5-5 mV normal ECG, but by the measure of the patient will be approximately 1 mV electrocardiogram (ECG) can be divided into three main sections.

Spectrum P (P wave) resulting from the atria to a period of approximately 80 to 120 milliseconds.

Wave, QRS (QRS complex) caused by ventricular function and R is the maximum size. The ventricles are squeezing the blood to all parts of the body through the walls of the ventricles are thicker than others, if the electrodes on the right arm and left arm, also known as Leeds l (Lead l). where R is the maximum voltage is the sum of the number of cells with a period of about 80 to 100 milliseconds.

Spectrum T (T wave) caused by the relaxation of the ventricular muscle. And approximately 30 percent of the R wave is a period of approximately 200 milliseconds.

Wave U (U wave) still do not know the exact cause. But assumed to be caused by a return to the level of voltage, static, slowly lower chambers of the heart muscle, known as voltage after (After Potential).

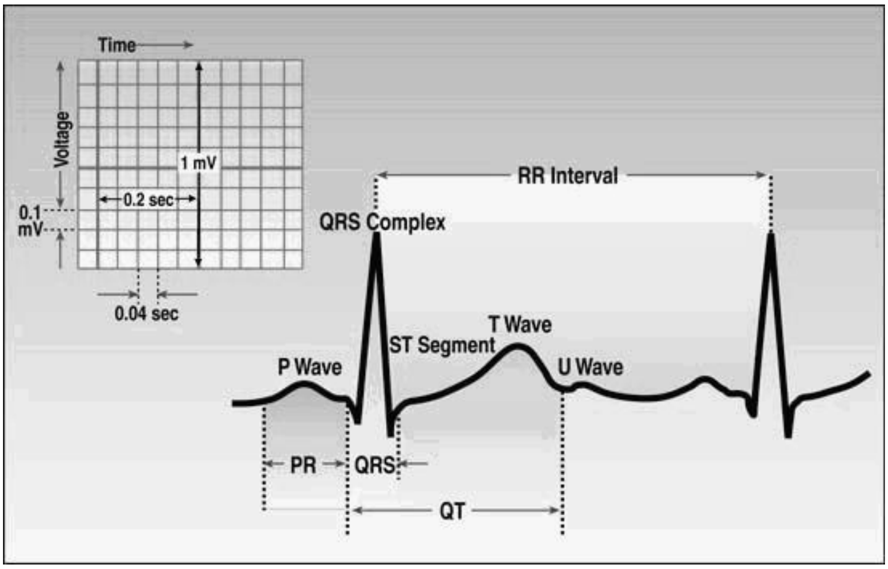


Figure 2.11 Components of a normal ECG.

In one cycle of the cardiovascular system consists of waves P, QRS, T and U are associated with each phase of the wave function of the cardiovascular system. It is important to analyze the system of the heart. The size and duration of the position to be able to tell the condition of the cardiovascular system.

Frequency of the ECG in the range of about 0.05-200 Hz, but in a different application to use a different frequency range below 2.12 were recorded for the patient's bedside ECG frequency standard input device. signal frequency response of the body should be in the range of 0.05-100 Hz for the measurements to the monitor. Should the receiver of the response frequencies in the range 0.5 - 50 Hz, and for measuring the rate of cardiac device used should meet the frequency range up to the secondary frequency band pass with center frequency. At QRS frequency to 17 Hz, which is used to calculate the heart rate?

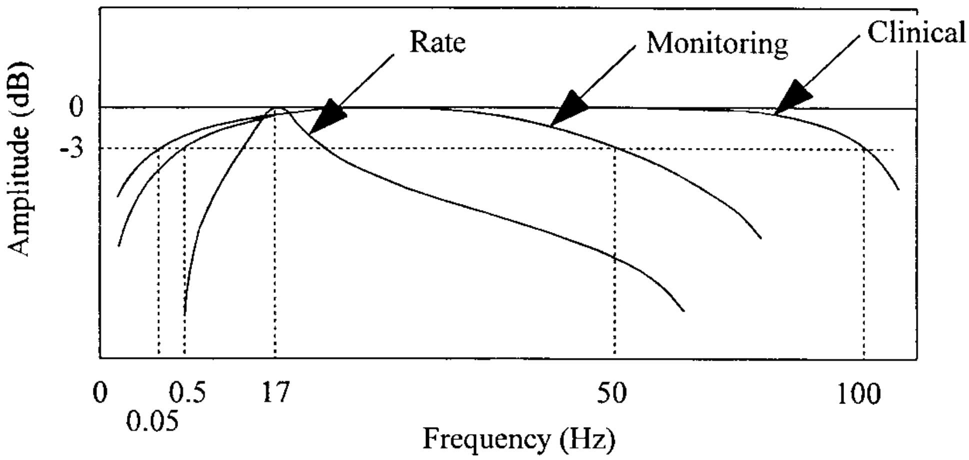


Figure 2.12 shows the frequency range of ECG for various applications.

Methodology of classification of ECG. Many automated method has been developed to indicate the type of heart disease in the individual patient. The various methods that have been developed are still limited in its application to the make continues to innovate and develop new ways to continue to be effective enough to lead. To improve methodology we use Variable selection for classification by neural network. Study data were processed for classification of various cardiac arrhythmias. We propose wavelet transform and selection variable method, then use the Neural Network to classify the ECG Heartbeat[13]. We get ECG Beat data from MIT-BIH arrhythmia database and improve performance of classification.

Guyon and Elisseff [10] use three type method for classify : Filter , Wrapper , Embedded Methods. But almost are not very effective. Filter method use preprocessing step that are not effective . Wrapper methods prediction method as a black box it work but very expensive. Embedded [2], feature selection methods as part of the training process of the prediction method to decide feature removal.

CHAPTER III
MATERIALS AND METHODS

3.1 Materials

Procedures and methods as to how to work the preparation of this thesis from data preparation to complete the work. Section of this chapter describes how the execution of this thesis. The detail are as following:

3.1.1 Software Development

3.1.1.1 Operation system

- Microsoft Windows 7
- Microsoft Office 2013

3.1.1.2 Classification system

- Weka 3.7.5
- Matlab R2012b

3.1.2 Hardware

- Macbook
- HP P4320

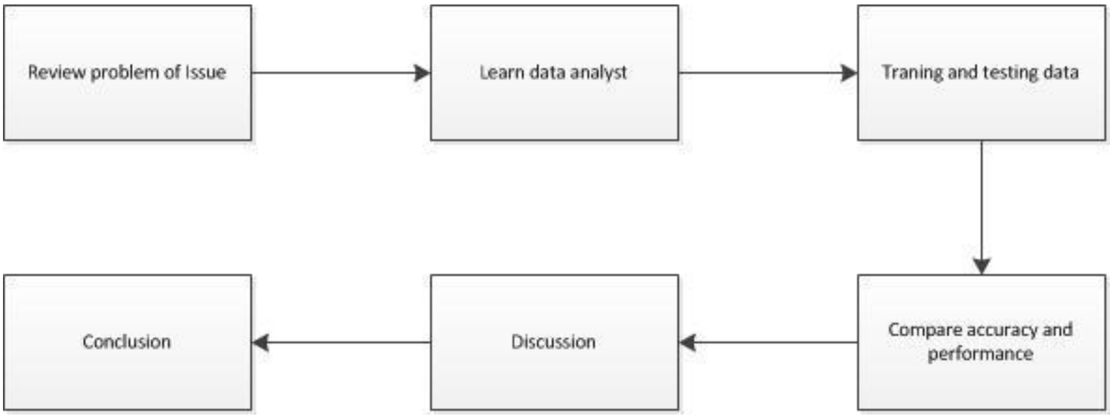
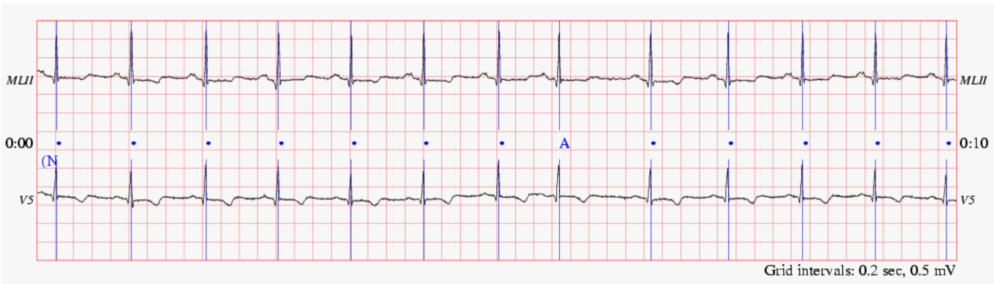


Figure 3.1 Flow chart of research methodology

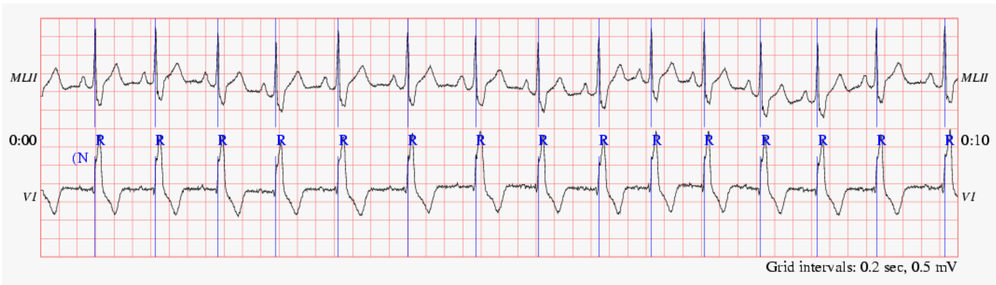
3.2 Methodology

3.2.1 Process Data

The data ECG signals from the MIT-BIH Arrhythmia Database contains the electrical signals to the heart, both normal and abnormal. The frequency of sampling (Sampling Frequency) in this database has a frequency equal to 360 Hz in each of the heart's electrical signals , each person will be provided information that indicates the type of electrical signals in the heart beat. The electrical signal the heart of the individual patient , it is a signal measured from 2 Lead together as shown in Figure 3.1, this project has selected signal in Modified Lead II (MLII) because the amplifiers Jude . Lead is used to measure the maximum and almost all patients. Type of cardiac electrical signals that are used in this project is the most common cardiac electrical signals in the database. Signal by making a selection , there are five types of normal heart electrical signals (NORMAL), left bundle branch block beat (LBBB), right bundle branch block beat (RBBB), premature ventricular contraction (PVC), atrial premature contraction(APC).



(a) Record No. 100



(b) Record No. 212

Figure 3.2 shows the ECG signal from MIT-BIH Arrhythmia Database.

In the process of preparing the information Consecutive cardiac electrical signals to be singled out as the BEAT single ECG signals by the type of each disease. To be used in experiments, the algorithm devised. The system will find the center of the signal is R wave peak and then cut around the right side of the period of the waveform. By the terms of the previous peak R of about 345 ms or 124 data points (fs = 360 Hz) and the signal after peak R of about 486 ms or 175 data points , so the signal in the first BBC (1 waveform.) will contain 300 data points (300.Dimensions) characteristics of ECG signals and 5 are shown in Figure3.2.

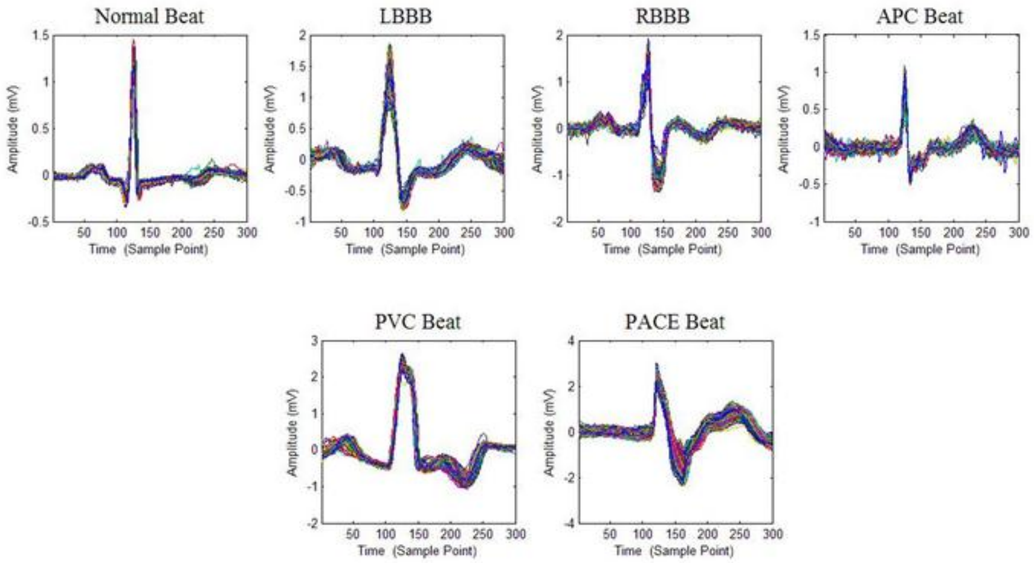


Figure 3.3 shows the characteristics of the six types of ECG signals.

3.2.2 Conversion of ECG in the form of a Bitmap file.

Since the data used to train the neural network model of weightlessness will be in the form of a Bitmap file, so it must be converted and adapted to the size of 200 x 300 pixels (Pixel) Start by finding the value of information minimal vertical (y-min) and the vertical (y-max) and then adjust the size of the ECG in the vertical with equation 3.1.

$$y^*(t) = \frac{y(t) - y\min}{y\max - y\min} \times (y\ size) \quad ; \ (y\min \le y(t) \le y\max) \tag{3.1}$$

by $y^*(t)$ vertical in time. After resizing

$y(t)$ vertical in time. Before resizing *y-size* The standard size of verticals used to adjust the picture on figure 3.4

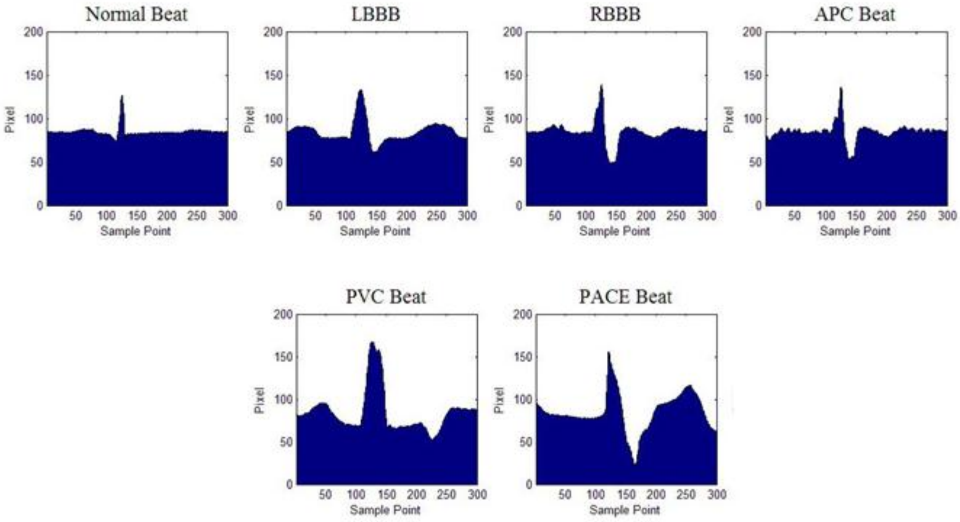


Figure 3.4 ECG data is in the form of a Bitmap file.

3.3 Process and result

3.3.1 The data from the MIT-BIH Database

In this thesis we will use Lead MLII (Lead2) Amplitude of the signal because of the max and a Lead measure in almost all patients.

3.3.2 Open the file in the program MATLAB (rddata_hea_bin.m)

ECG graph to show the number of 10 beats (3000 pt) of a graph can be seen that there is a line graph in two colors red and blue. We use red because it is to see the range of R Peak was more pronounced (suitable for Classify) of Figure 3.5.

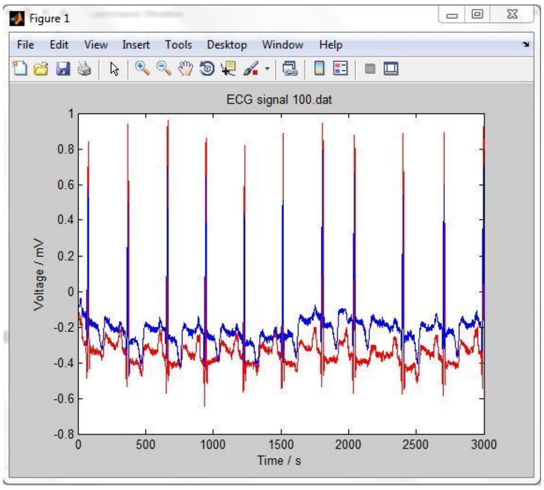


Figure 3.5 ECG from a record 100.

3.3.3 Beat cut out for analysis. By the terms of the previous peak R of about 345 ms or 124 data points (fs = 360 Hz) and the signal after peak R of about 486 ms or 175 data points, so the signal in the first BBC (1 waveform. share), the data points to 300 after cutting out the beat on beat to save each file C: \ MATLAB7 \ work \ ECG beat \ save by Name by disease occur each beat.

Ex. Would be cut by a record 100 is a Normal Beat the filename N_100.mat.

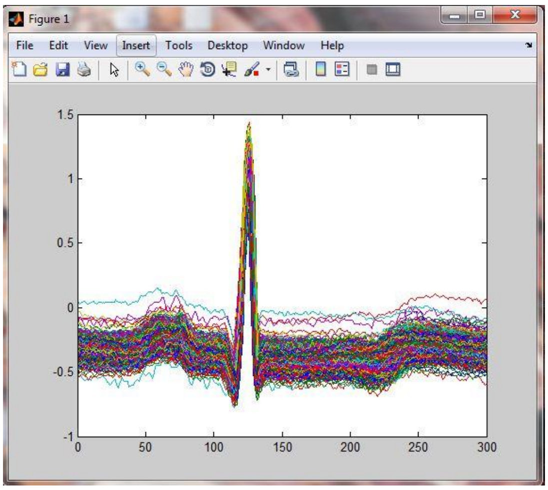


Figure 3.6 Cut out a heart beat.

3.3.4 Solves the problem of DC offset.

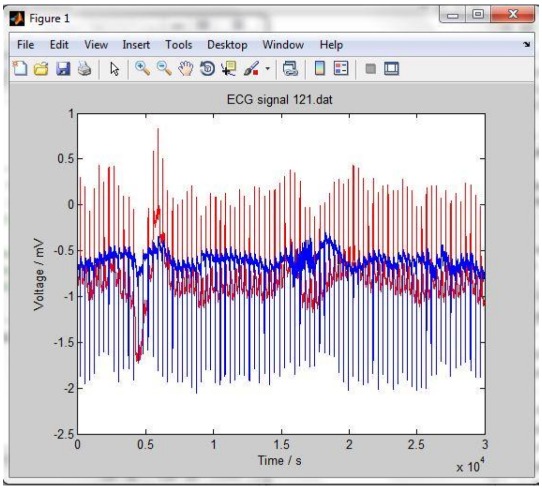


Figure 3.7: Example record 121 from the DC offset.

From Figure 3.7 it can be seen that happen, we must make a DC Offset DC Offset to solve the problem on a graph with the Core Voltage = 0 (DCFilter_FIR.m), which can solve the problem by using Wavelet Decomposition Filters that. Windows is either a High Pass Filter and Low Pass Filter to filter out DC Offset occurring away.

3.3.5 After filtering out DC Offset is it will be the graph in Figure 3.8.

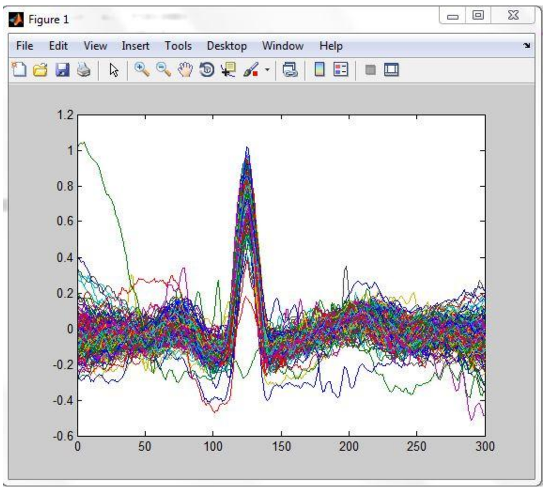


Figure 3.8 solution DC Offset.

3.3.6 The data to be learned and tested in a neural network, which has divided the test into. Two parts: the first part of the experiment, using a neural network feed-forward back propagation. Which the transfer function is called the hyperbolic tangent sigmoid transfer function and the second user. Neural network pattern-recognition models using transfer function which is called Log-sigmoid transfer function.

3.4 How to test / measurement methods.

3.4.1 Neural network testing using a feed - forward back propagation.

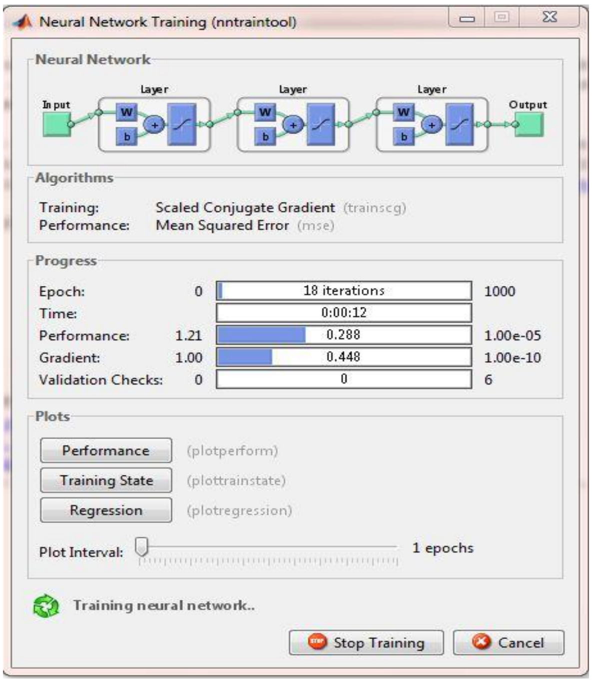


Figure 3.9 The Training and Feed - forward back propagation.

Epoch The total number of cycles used in the Train. Train stops on the data by the Epoch defined.

Time The total time spent in the Train data.

Performance Find the value of the Mean Square Error (mse) where mse is derived from the output target minus the output from the train equation e = ty;

perf = mse (e). Gradient is a difference of mse each round in the Train.

Validation Check Information is divided into sections as follows: 70% took the Train, 15% as validation. Another 15%, the rest is mostly used in the Test, used to stop by the Train of the validation check is the number of times over fit.

3.4.1.1 Neural test the unfiltered DC Offset. We use the information that is used to test the process by which we unfiltered DC Offset at the following chart. Detailed graphs can be found at Chapter 4. The picture below is divided into two parts.

The upper part is a graph in which the x axis represents the Gradient (Epoch) the number of rounds used in the Train and the y axis represents the Gradient in each round of the Train.

The lower part of the graph where the x axis represents the Validation Check (Epoch) the number of rounds used in the Train and the y axis represents the validation fail due to over fit each time.

The experiment will change the value of the variable is 3 Training Epoch, Goal and Gradient Model to find the best.

3.4.1.2 Neural test filter DC Offset Offset is the data used to test the process by which we can filter the DC Offset is the following graph. Detailed graphs can be found at Chapter 4.

The picture below is divided into two parts.The upper part is a graph in which the x axis represents the Gradient (Epoch) the number of rounds used in the Train and the y axis represents the Gradient in each round of the Train. The lower part of the graph where the x axis represents the Validation Check (Epoch) the number of rounds used in the Train and the y axis represents the val fail due to over fit each time. The experiment will change the value of the variable is 3 Training Epoch, Goal and Gradient Model to find the best.

3.4.2 Neural network testing using a Pattern-recognition.

3.4.2.1 Testing the Neural unfiltered DC Offset, we will use the information to test the process by which we unfiltered DC Offset at the following chart. Detailed graphs can be found at Chapter 4.

The picture below is divided into two parts.

The upper part is a graph in which the x axis represents the Gradient (Epoch) the number of rounds used in the Train and the y axis represents the Gradient in each round of the Train.

The lower part of the graph where the x axis represents the Validation Check (Epoch) the number of rounds used in the Train and the y axis represents the val fail due to over fit each time.

The experiment will change the value of the variable is 3 Training Epoch, Goal and Gradient Model to find the best.

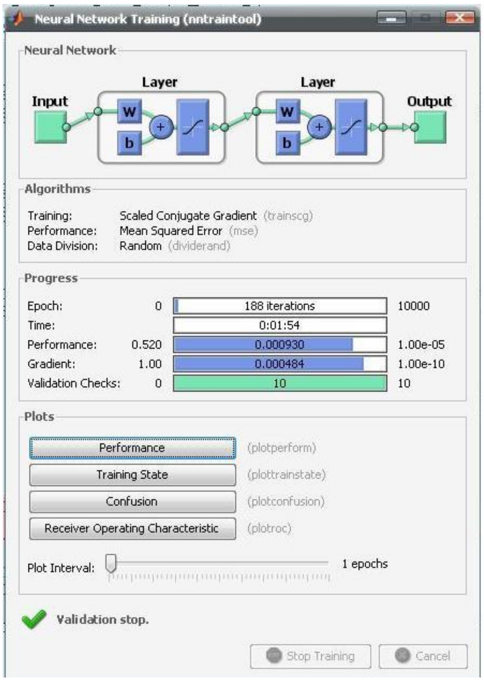


Figure 3.10 The Training Series Pattern - recognition by unfiltered DC Offset.

3.4.2.2 Testing Neural DC Offset filter the information we used to test the process by which we can filter the DC Offset is the following graph. Detailed graphs can be found at Chapter 4.

The picture below is divided into two parts.

The upper part is a graph in which the x axis represents the Gradient (Epoch) the number of rounds used in the Train and the y axis represents the Gradient in each round of the Train.

The lower part of the graph where the x axis represents the Validation Check (Epoch) the number of rounds used in the Train and the y axis represents the val fail due to over fit each time.

The experiment will change the value of the variable is 3 Training Epoch, Goal and Gradient Model to find the best.

CHAPTER IV
RESULTS AND DISCUSSION

The results of this thesis makes the process different of the first method (Neural network and feed-forward back propagation using a transfer function called the Hyperbolic tangent sigmoid transfer function), and the second method (Neural network model. pattern-recognition, which uses a transfer function called Log-sigmoid transfer function) and the third method (Neural network and feed-forward back propagation with selection variable).

4.1The Results

4.1.1 Test results using a Neural Network feed - forward back propagation.An unfiltered DC Offset

Table 4.1 Results Feed - forward propagation unfiltered DC Offset by changing the Epoch.

Epoch	**Goal**	**Gradient**	**Accuracy**	**Performance**	**Gradient**	**Train**	**Time/min**
10	1.00E-05	1.00E-10	17.37%	9.03E-01	5.55E-01	Epoch = 10	0.08
100	1.00E-05	1.00E-10	99.40%	6.55E-03	8.79E-03	Epoch = 100	1.17
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	8.50E-11	Gredient Epoch = 743	9.23
10000	1.00E-05	1.00E-10	99.65%	2.32E-03	8.55E-11	Gredient Epoch = 1405	19.17

Table 4.2 Results Feed - forward propagation unfiltered DC Offset by changing the Goal.

epoch	goal	gradient	Accuracy	Performance	Gradient	Train	Time/min
1000	1.00E-02	1.00E-10	99.35%	1.00E-02	4.59E-02	Performance Epoch = 84	1.03
1000	1.00E-03	1.00E-10	99.89%	9.81E-04	1.38E-03	Performance Epoch = 375	5.28
1000	1.00E-04	1.00E-10	99.98%	2.32E-04	8.59E-11	Gradient Epoch = 808	10.50
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	4.78E-11	Gradient Epoch = 671	8.48

Table 4.3 Results Feed - forward propagation unfiltered DC Offset by changing the Gradient.

epoch	goal	gradient	Accuracy	Performance	Gradient	Train	Time / min
1000	1.00E-05	1.00E-02	99.30%	9.98E-03	8.80E-03	Gradient Epoch = 90	1.13
1000	1.00E-05	1.00E-03	99.49%	3.96E-03	8.81E-04	Gradient Epoch = 176	2.31
1000	1.00E-05	1.00E-04	99.54%	3.13E-03	8.97E-05	Gradient Epoch = 307	4.01
1000	1.00E-05	1.00E-05	99.98%	2.32E-04	8.74E-06	Gradient Epoch = 503	6.36
1000	1.00E-05	1.00E-06	99.98%	2.32E-04	7.36E-07	Gradient Epoch = 530	6.43
1000	1.00E-05	1.00E-07	99.98%	2.32E-04	9.31E-08	Gradient Epoch = 656	8.34
1000	1.00E-05	1.00E-08	99.98%	2.32E-04	9.89E-09	Gradient Epoch = 463	607
1000	1.00E-05	1.00E-09	99.63%	2.55E-03	5.67E-10	GradientEpoch = 562	7.19
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	9.41E-11	Gradient Epoch = 868	11.33

4.1.2 Results using a Neural Network feed - forward back propagation. DC Offset filter

Table 4.4 Results Feed - forward propagation DC Offset Filter by changing the Epoch.

epoch	goal	gradient	Accuracy	Performance	Gradient	Train	Time/ min
10	1.00E-05	1.00E-10	32.37%	5.41E-01	2.38E-01	Epoch = 10	0.06
100	1.00E-05	1.00E-10	99.47%	5.77E-03	8.93E-03	Epoch = 100	1.10
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	9.20E-11	Gradient Epoch = 393	4.21
10000	1.00E-05	1.00E-10	99.98%	2.32E-04	8.20E-11	Gradient Epoch = 461	5.18

Table 4.5 Test Results Feed - forward propagation DC Offset Filter by changing the Goal.

epoch	goal	gradient	Accuracy	Performance	Gradient	Train	Time /min
1000	1.00E-02	1.00E-10	98.81%	9.88E-03	3.09E-03	Performance Epoch = 192	2.31
1000	1.00E-03	1.00E-10	99.93%	9.62E-04	3.95E-03	Performance Epoch = 170	2.22
1000	1.00E-04	1.00E-10	99.98%	1.16E-04	6.45E-11	Gradient Epoch = 798	8.46
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	9.20E-11	Gradient Epoch = 393	4.21

4.1.3 Results Using Neural Network for pattern-recognition.

Table 4.6 Test Results Feed - forward propagation DC Offset Filter by changing the Gradient.

epoch	goal	Gradient	Accuracy	Performance	Gradient	Train	Time /min
1000	1.00E-05	1.00E-02	99.27%	9.59E-03	7.54E-03	Gradient Epoch = 72	0.58
1000	1.00E-05	1.00E-03	82.48%	1.18E-01	7.77E-04	Gradient Epoch = 119	1.21
1000	1.00E-05	1.00E-04	69.46%	2.04E-01	8.77E-05	Gradient Epoch = 160	1.32
1000	1.00E-05	1.00E-05	99.94%	4.65E-04	9.10E-06	Gradient Epoch = 224	2.45
1000	1.00E-05	1.00E-06	99.96%	3.48E-04	7.65E-07	Gradient Epoch = 261	2.58
1000	1.00E-05	1.00E-07	99.96%	3.48E-04	9.68E-08	Gradient Epoch = 275	3.07
1000	1.00E-05	1.00E-08	99.96%	3.48E-04	9.18E-09	Gradient Epoch = 320	3.22
1000	1.00E-05	1.00E-09	99.96%	3.48E-04	8.15E-10	Gradient Epoch = 305	3.11
1000	1.00E-05	1.00E-10	99.98%	2.32E-04	9.20E-11	Gradient Epoch = 393	4.41

An unfiltered DC Offset

Table 4.7 test pattern - recognition unfiltered DC Offset by changing the Epoch.

Epoch	Goal	Gradient	Accuracy	Performance	Gradient	Train	Time /min
10	1.00E-05	1.00E-10	34.80%	1.25E-01	2.77E-02	Epoch=10	0:07
100	1.00E-05	1.00E-10	95.70%	8.47E-03	1.34E-03	Epoch=100	0:50
1000	1.00E-05	1.00E-10	99.40%	9.30E-04	4.84E-04	Val Epoch=188	1:53
10000	1.00E-05	1.00E-10	99.40%	1.11E-03	3.93E-04	Val Epoch=167	2:13

Table 4.8 test pattern - recognition unfiltered DC Offset by changing the Goal.

Epoch	Goal	Gradient	Accuracy	Performance	Gradient	Train	Time /min
1000	1.00E-02	1.00E-10	97.90%	9.53E-03	1.03E-02	Performance Epoch=168	1:32
1000	1.00E-03	1.00E-10	98.60%	2.51E-03	1.41E-03	Val Epoch=181	1:58
1000	1.00E-04	1.00E-10	99.20%	1.99E-03	9.68E-04	Val Epoch=98	1:03
1000	1.00E-05	1.00E-10	99.40%	1.40E-03	2.88E-04	Val Epoch=170	2:18

Table 4.9 test pattern - recognition unfiltered DC Offset by changing the Gradient.

Epoch	**Goal**	**Gradient**	**Accuracy**	**Performance**	**Gradient**	**Train**	**Time /min**
1000	1.00E-05	1.00E-02	98.90%	5.93E-03	9.13E-03	Gradient Epoch=90	0:47
1000	1.00E-05	1.00E-03	98.30%	1.36E-03	9.44E-04	Gradient Epoch=199	2:47
1000	1.00E-05	1.00E-04	99.30%	1.69E-03	1.45E-03	Val Epoch=117	1:22
1000	1.00E-05	1.00E-05	99.20%	1.69E-03	5.84E-04	Val Epoch=117	1:23
1000	1.00E-05	1.00E-06	99.40%	1.21E-03	1.70E-04	Val Epoch=174	2:31
1000	1.00E-05	1.00E-07	95.80%	7.46E-03	8.84E-04	Val Epoch=143	1:49
1000	1.00E-05	1.00E-08	99.40%	9.30E-04	4.84E-04	Val Epoch=188	2:40
1000	1.00E-05	1.00E-09	99.40%	1.11E-03	3.93E-04	Val Epoch=167	2:22
1000	1.00E-05	1.00E-10	99.40%	1.75E-03	6.07E-04	Val Epoch=157	2:14

4.1.4 Test Results Using Neural Network for pattern-recognition. DC Offset filter

Table 4.10 test pattern - recognition by changing the DC Offset Filter Epoch.

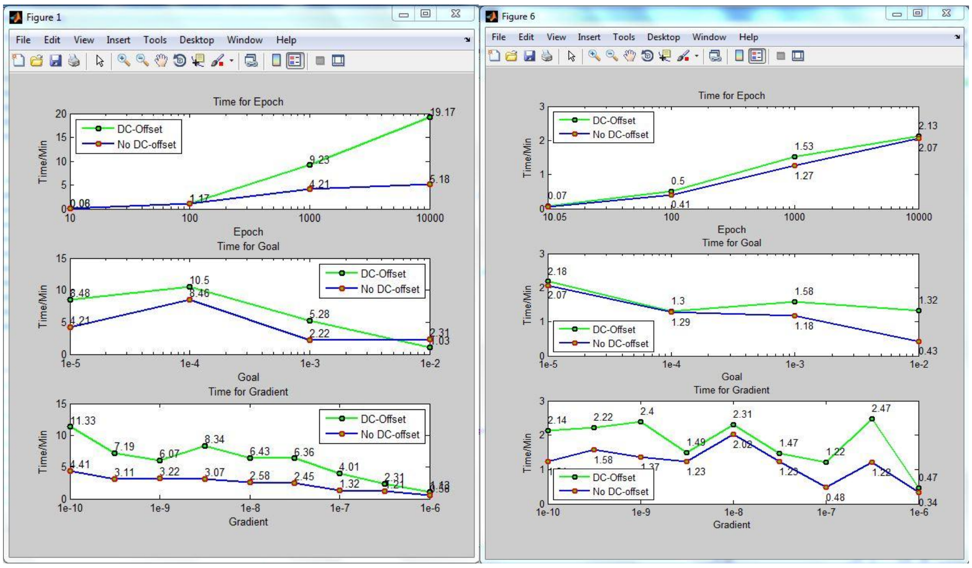
Epoch	Goal	Gra-dient	Accu-racy	Perfor-mance	Gradient	Train	Time/min
10	1.00E-05	1.00E-10	55.40%	9.74E-02	1.99E-01	Epoch = 10	0:05
100	1.00E-05	1.00E-10	84.70%	3.02E-02	3.09E-03	Epoch = 100	0:41
1000	1.00E-05	1.00E-10	99.30%	1.95E-03	2.54E-03	Val = 10 Epoch=180	1:27
10000	1.00E-05	1.00E-10	99.40%	1.75E-03	1.96E-03	Val = 10 Epoch=234	2:07

Table 4.11 Test pattern - recognition by DC Offset Filter Change Goal.

Epoch	Goal	Gra-dient	Accu-racy	Perfor-mance	Gradient	Train	Time-/min
10000	1.00E-02	1.00E-10	98.00%	9.95E-03	2.93E-02	Performance Epoch=104	0:43
10000	1.00E-03	1.00E-10	99.30%	1.81E-03	1.29E-03	Val Epoch=142	1:18
10000	1.00E-04	1.00E-10	99.30%	1.46E-03	1.46E-03	Val Epoch=186	1:29
10000	1.00E-05	1.00E-10	99.40%	1.75E-03	1.96E-03	Val Epoch=234	2:07

Table 4.12 Test pattern - recognition by changing the DC Offset Filter Gradient.

Epoch	Goal	Gra-dient	Accu-racy	Perfor-mance	Gradient	Train	Time/min
10000	1.00E-05	1.00E-02	98.90%	5.22E-03	9.16E-03	Gradient Epoch= 77	0:34
10000	1.00E-05	1.00E-03	99.30%	1.68E-03	7.89E-04	Gradient Epoch= 150	1:22
10000	1.00E-05	1.00E-04	99.30%	1.78E-03	1.46E-03	Val Epoch= 115	0:48
10000	1.00E-05	1.00E-05	99.40%	1.41E-03	3.14E-04	Val Epoch= 194	1:47
10000	1.00E-05	1.00E-06	99.40%	1.35E-03	2.26E-03	Val Epoch= 228	2:02
10000	1.00E-05	1.00E-07	99.30%	1.58E-03	1.00E-03	Val Epoch= 216	2:23
10000	1.00E-05	1.00E-08	99.40%	1.92E-03	1.94E-03	Val Epoch= 164	1:37
10000	1.00E-05	1.00E-09	99.40%	1.12E-03	3.68E-04	Val Epoch= 220	1:58
10000	1.00E-05	1.00E-10	99.40%	1.42E-03	9.62E-04	Val Epoch= 195	1:24



[A] [B]

Figure 4.1A is the Test Feed - forward back propagation.

B is the test Pattern - recognition.

Table 4.13 Variable Selection and classification

Beat type	Accuracy before reduce variables	Accuracy After reduced variables	Time/min Before reduce variables	Time/min After reduced variables
APC	93.84%	98.00%	0:43	0:21
Normal	100%	100%	1:25	0:46
LBBB	94.21%	99.30%	1:29	0:52
RBBB	92.53%	99.47%	2:07	1:02
PVC	87.82%	96.60%	1.46	0.58
Total	93.68%	98.67%	7.5	3.59

Figure shows the solution varies between 3 results of first part (Figure 4.80 [A]) using Neural network is feed-forward back propagation and. the second section (Figure 4.80 [B]) using Neural network for pattern-recognition, which uses a transfer function called Log-sigmoid transfer function, and the third (Table 4.13) shows that Accuracy of the 3 series is no different. But Variable Selection can resolve over fitting and provide accuracy better than the first and two methods.

CHAPTER V
CONCLUSION

This thesis has presented an assortment of electrical signals the heart using the theory of neural networks in an assortment of electrical signals hearts are all important five types of electrical signals normal heart (NORMAL), Left bundle branch block beat (LBBB.), Right bundle branch block beat (RBBB), Premature ventricular contraction (PVC), Atrial premature contraction (APC) , which, in its analysis of the electrical signals of the heart by studying it. Necessary to update the form of electrical signals hearts derived from a database of MIT-BIH because the data are still having issues with the DC-Offset, which in this thesis have presented solutions. DC-Offset by using wavelet decomposition filters and reducing the number of variables that can significantly improve performance in terms of time and accuracy and resolve overfitting. However, because the number of variables that do not decrease, it makes the modeling of neural networks were very good. Proposed to solve the problem by increasing the amount of information needed to lead to even more modeling in the experiments.

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APPENDIX

THE RESULT OF AN ELECTROCARDIOGRAM CLASSIFICATION METHOD BASED ON NEURAL NETWORK

How to install Matlab.

Figure A1 Windows Systems - Insert the DVD into the DVD drive connected to your system or double-click the installation file you downloaded from the MathWorks web installer will start automatically.

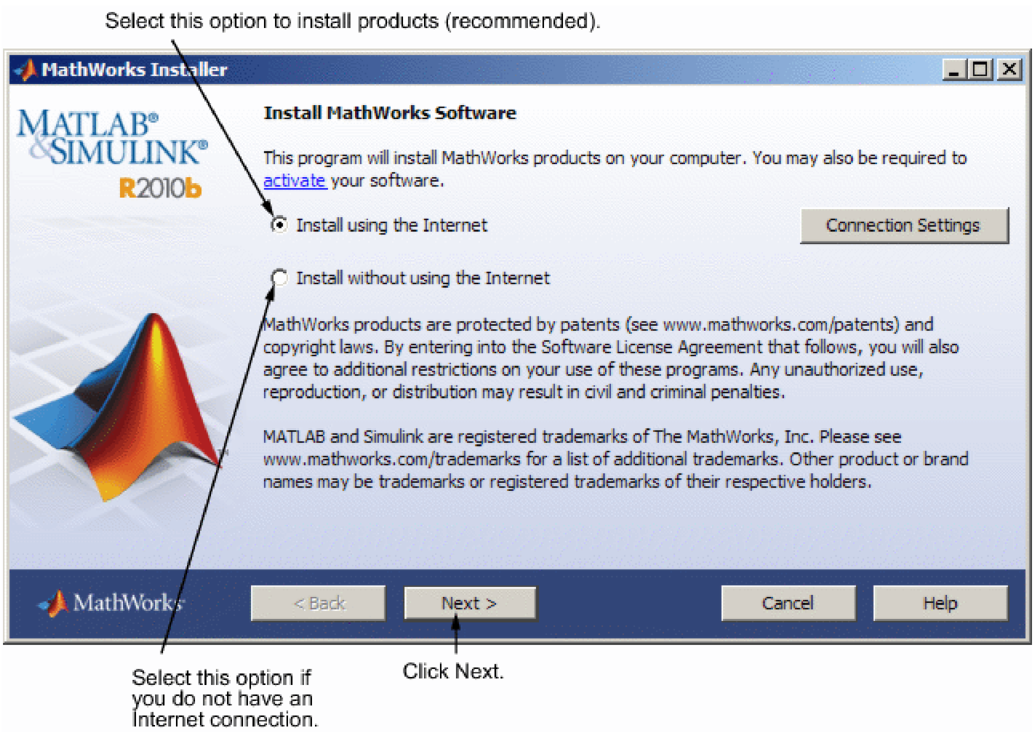

Figure A2 Choose whether to install using the Internet. Choose whether you want to install the Internet connection or no Internet connectivity . If you connect to the Internet out of the installation by using the Internet option (the default) and click Next in the setup gives you access to MathWorks your account select the license you want to install and follow. the prompts in the dialog box to install other this is the easiest way to install .

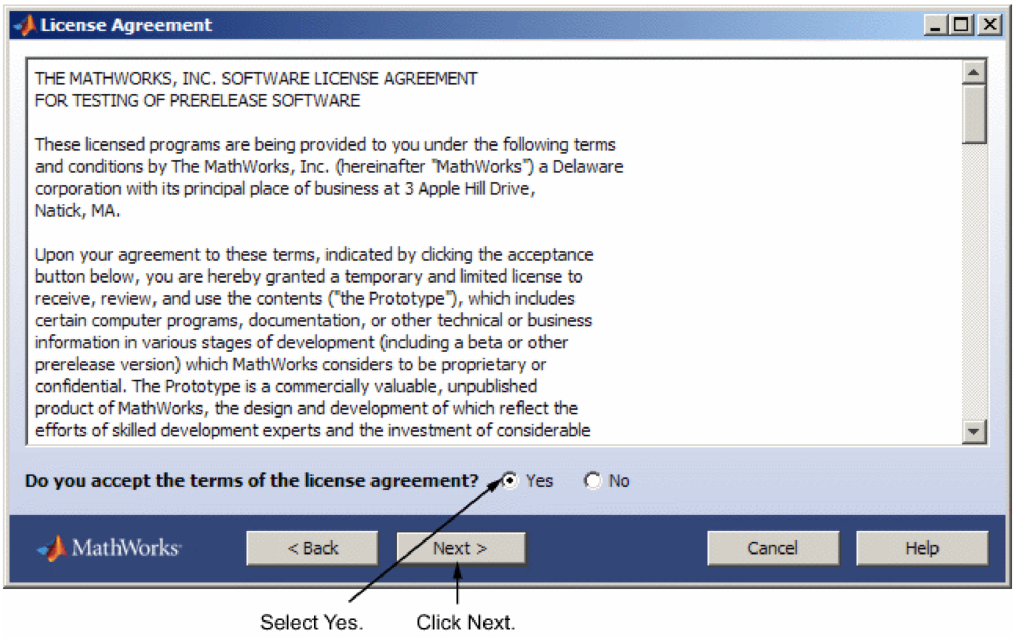

Figure A3 Review the software license agreement and if you agree with the terms, select Yes and click Next. After installation is complete, you can view or print the license agreement, license.txt file in the top level installation folder.

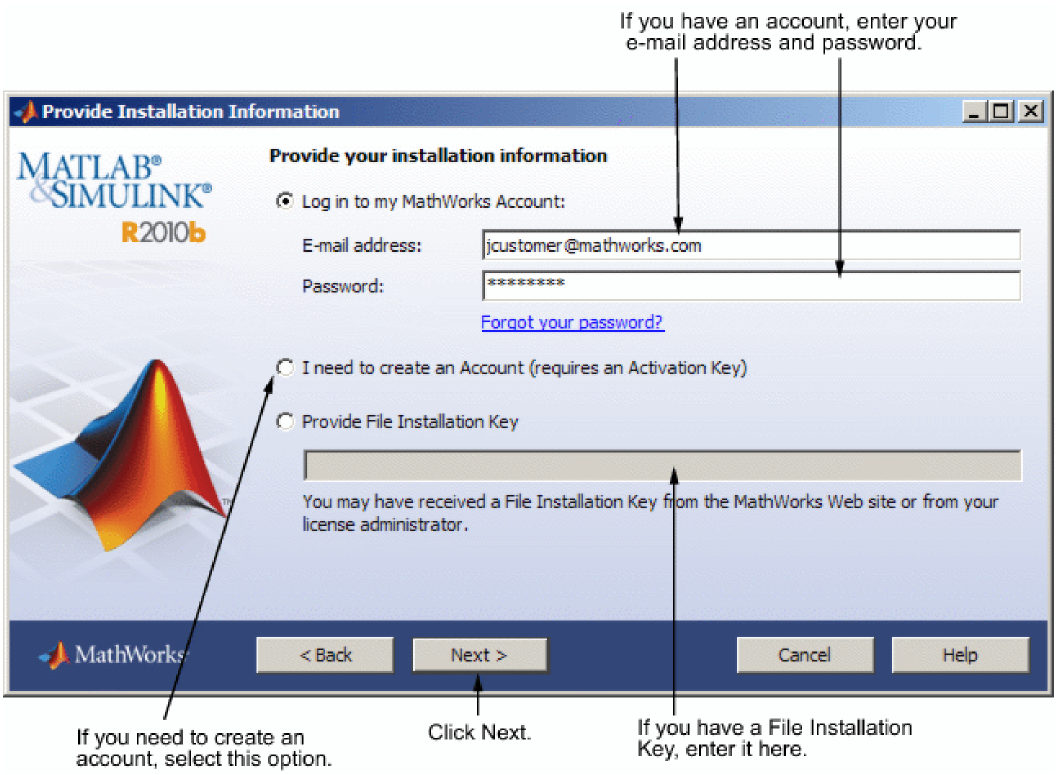

Figure A4 Log in to your MathWorks Account

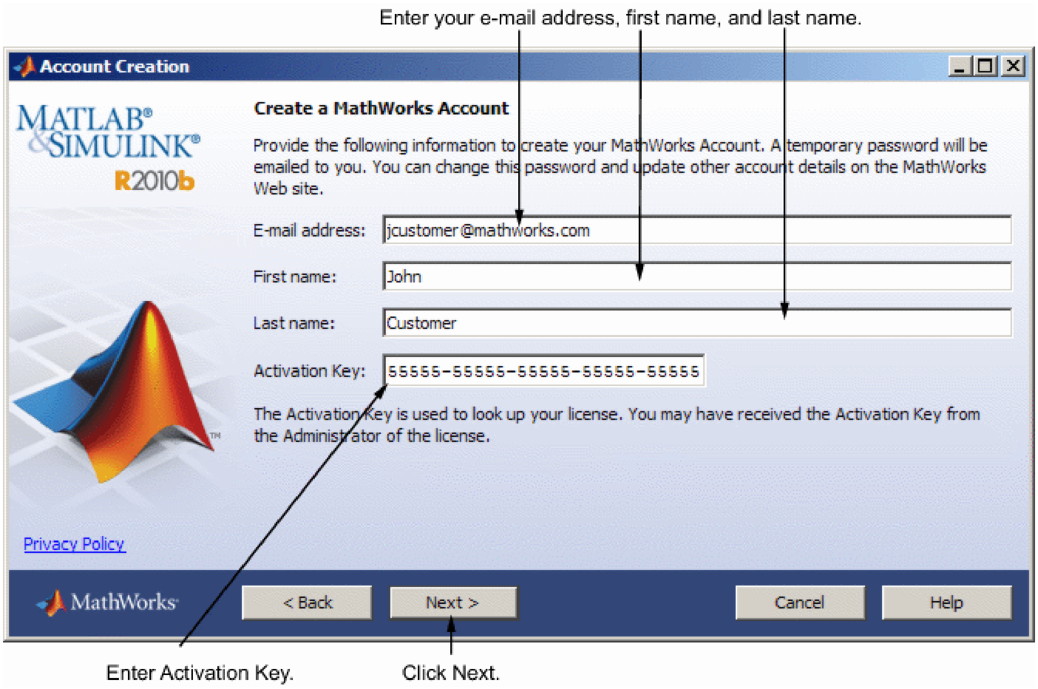

Figure A5 Create Account MathWorks

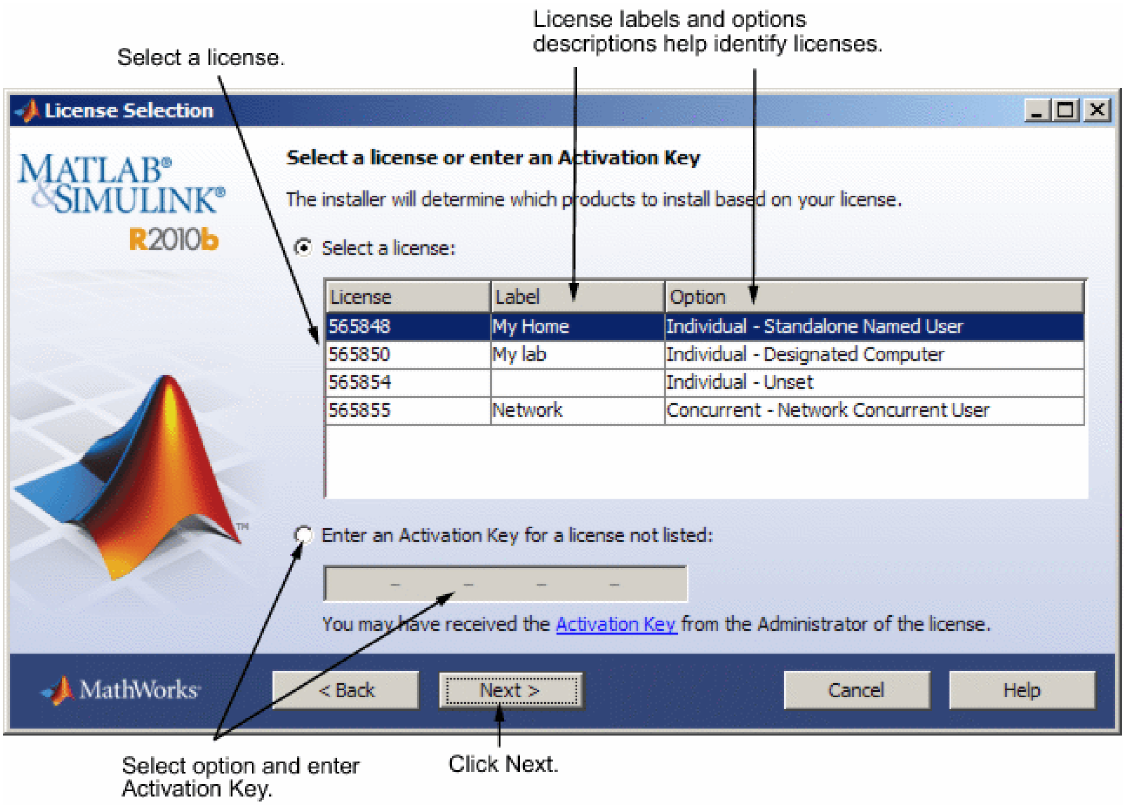

Figure A6 Select the license you want to install.

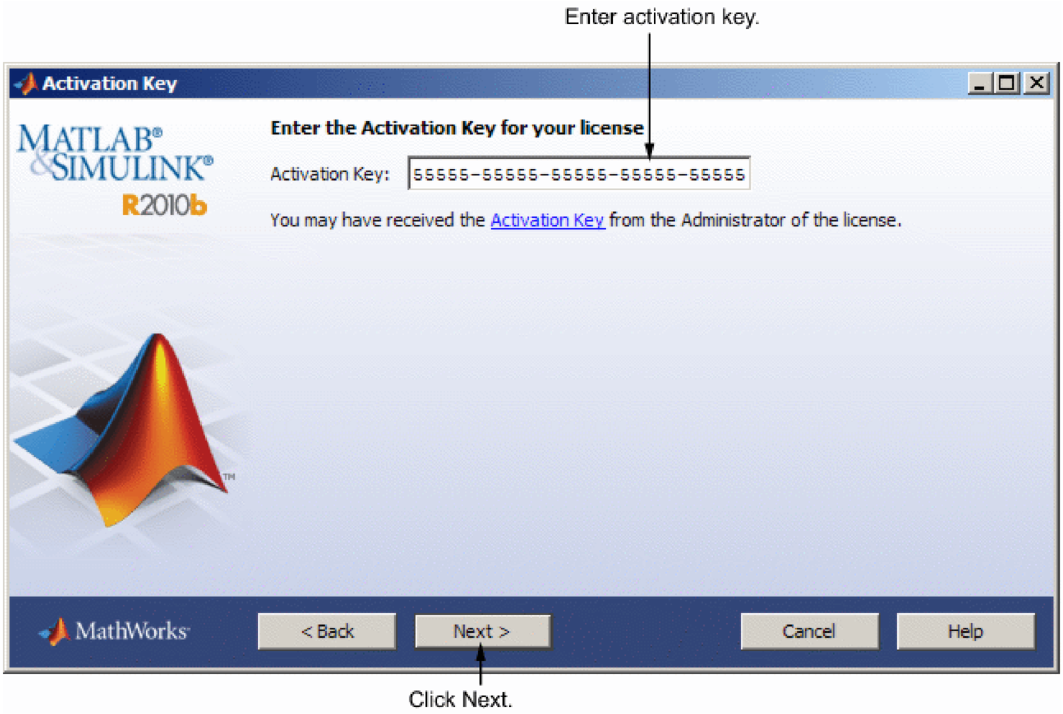

Figure A7 Input your Activation Key

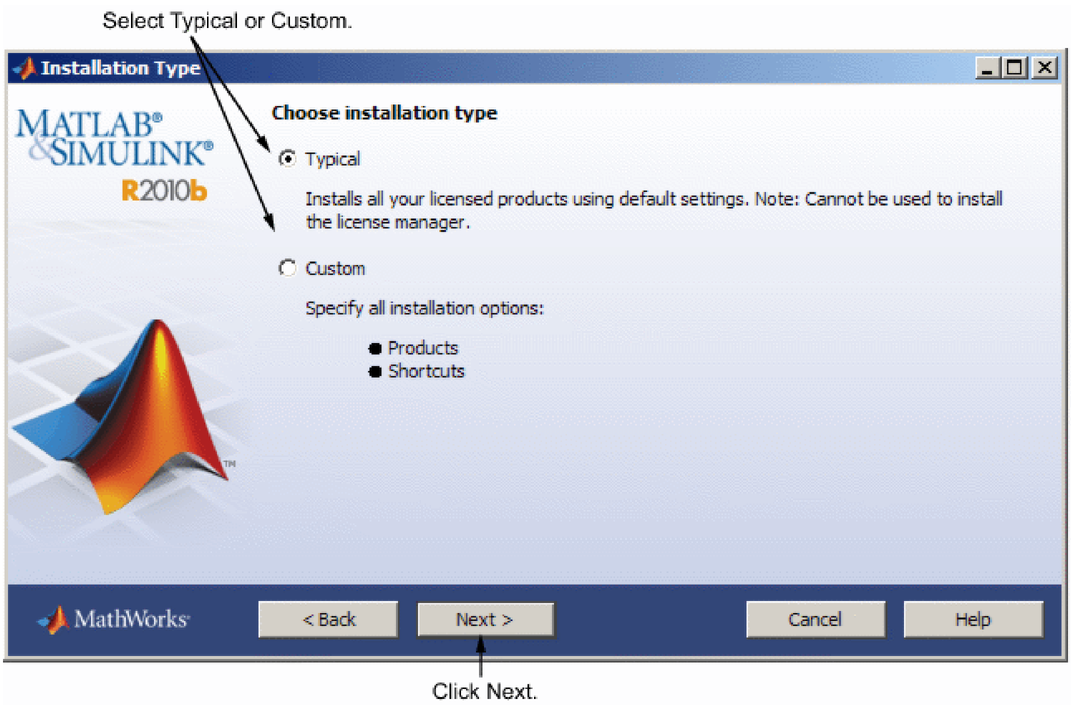

Figure A8 Select Installation Type

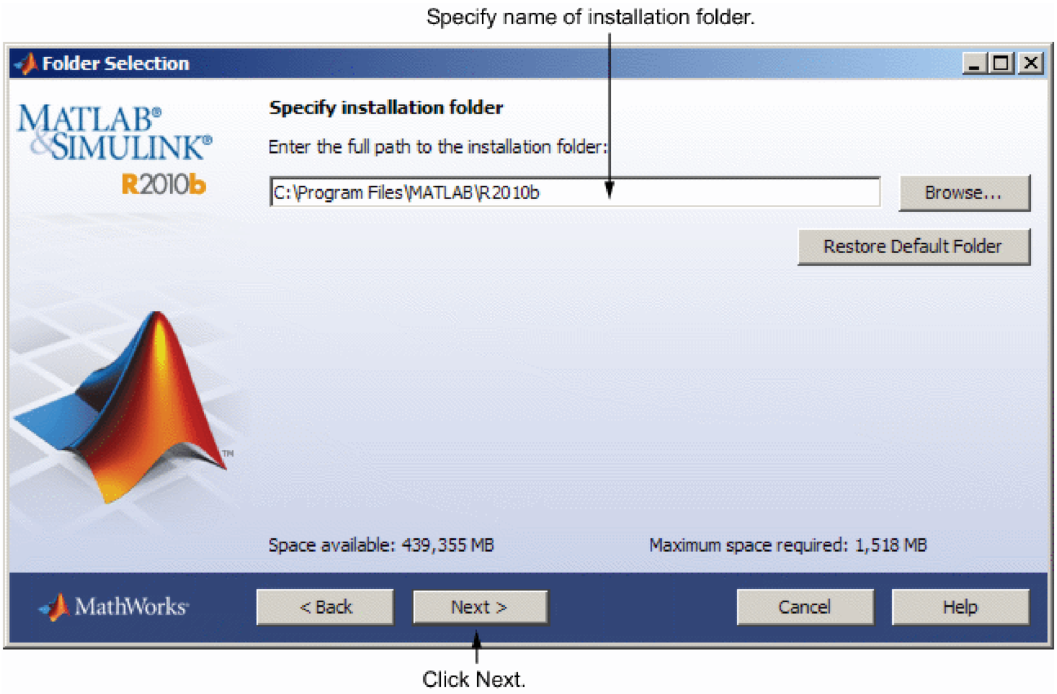

Figure A9 Procedures specified installation folder.

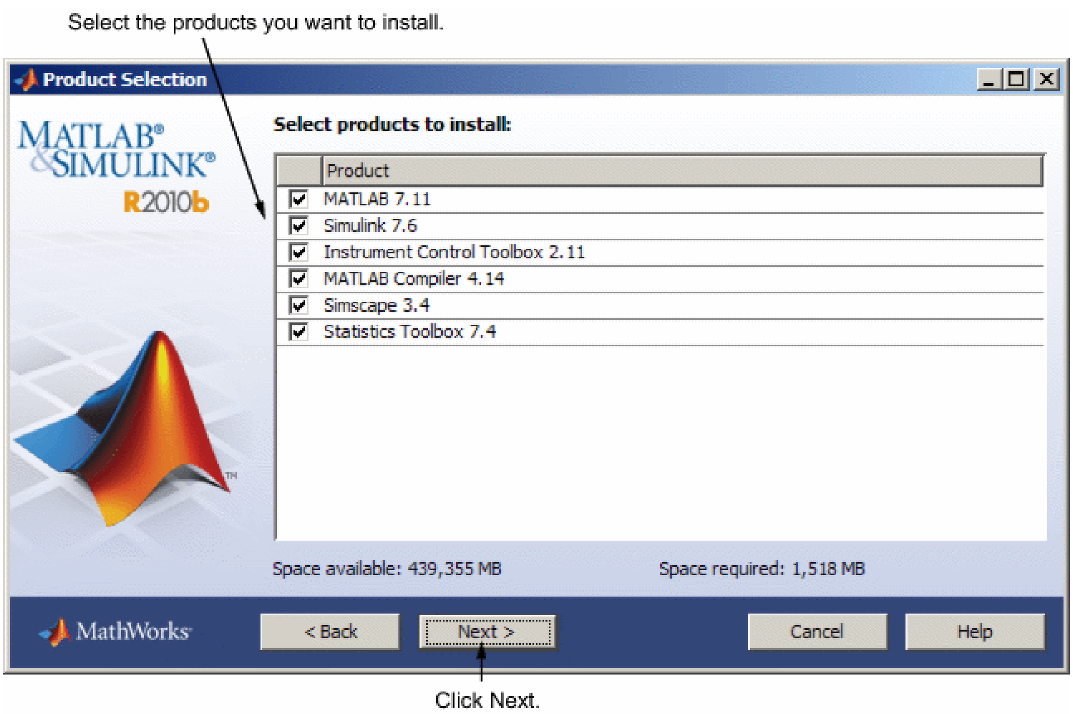

Figure A10 Select a product to install (Custom only)

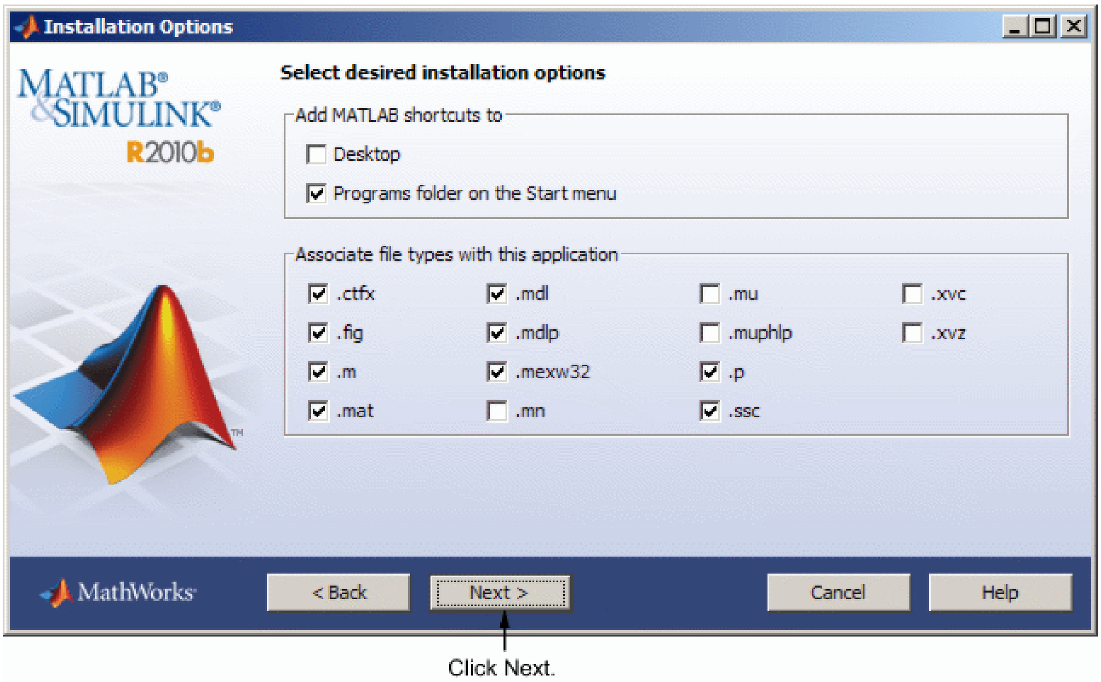

Figure A11 Click the Next button to finish

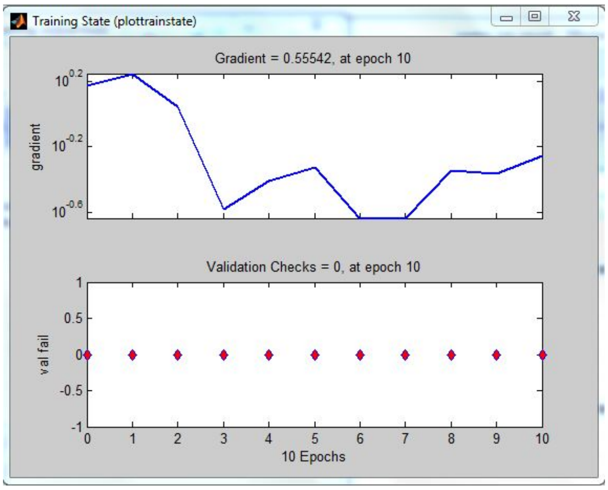

Figure A12 feed - forward propagation unfiltered DC offset configuration Epoch = 10.

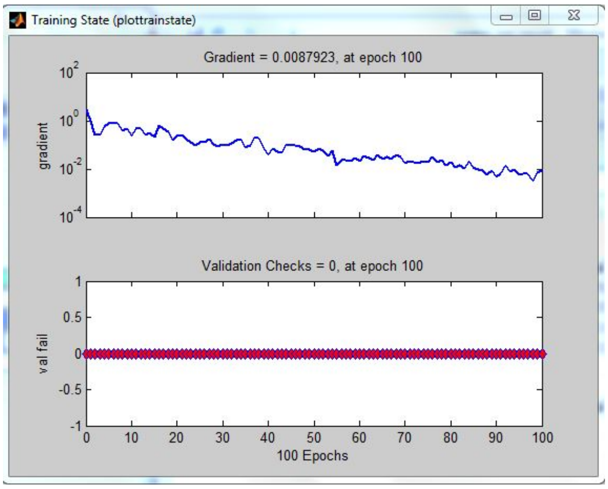

Figure A13 feed - forward propagation unfiltered DC offset configuration Epoch = 100.

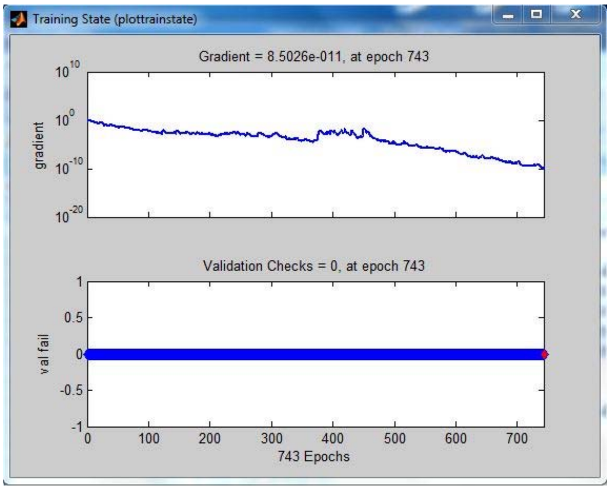

Figure A14 feed - forward propagation unfiltered DC offset configuration Epoch = 1000.

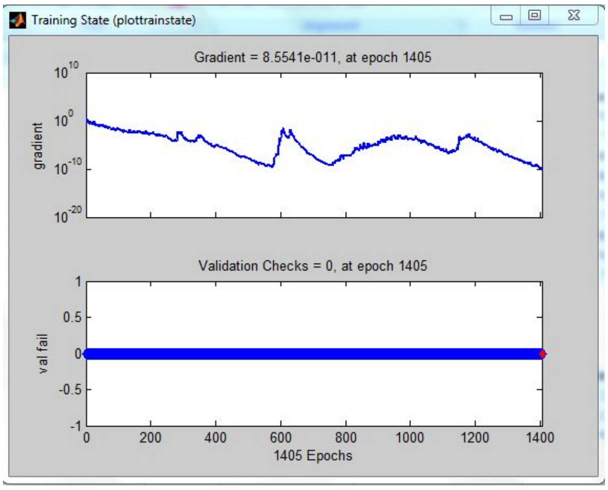

Figure A15 feed - forward propagation unfiltered DC offset configuration Epoch = 10000.

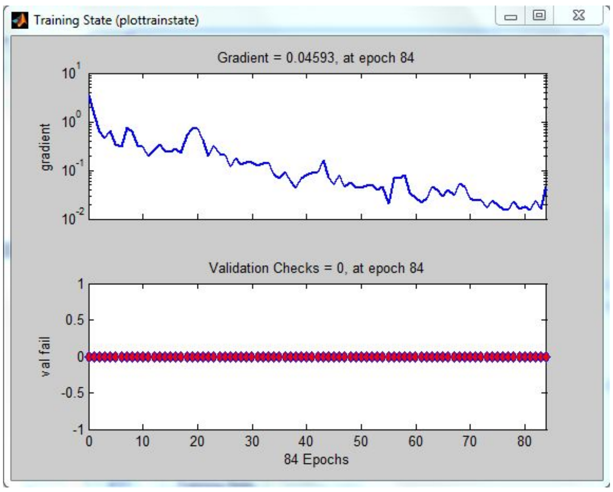

Figure A16 feed - forward propagation unfiltered DC offset configurations Goal = 1.00E-02.

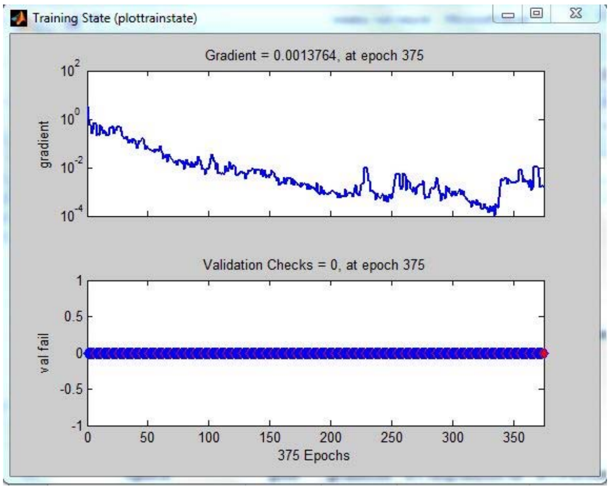

Figure A17 feed - forward propagation unfiltered DC offset configurations Goal = 1.00E-03.

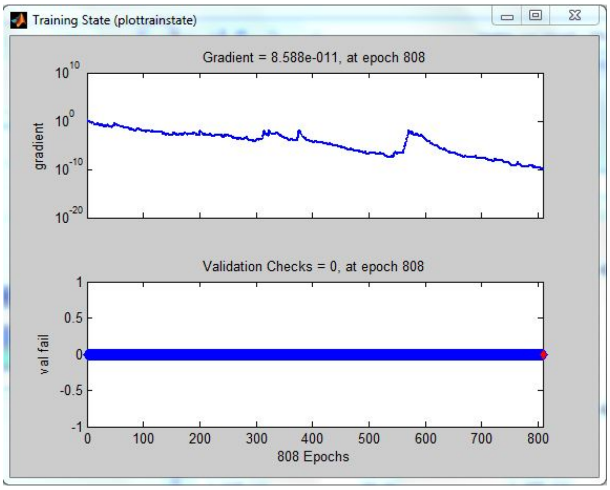

Figure A18 feed - forward propagation unfiltered DC offset configurations Goal = 1.00E-04.

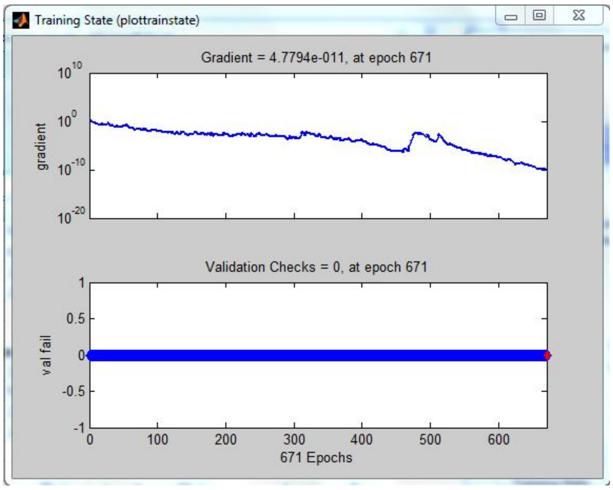

Figure A19 feed - forward propagation unfiltered DC offset configurations Goal = 1.00E-05.

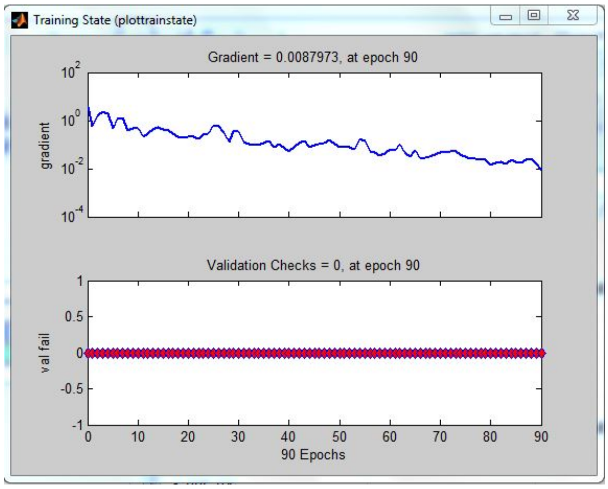

Figure A20 feed - forward propagation unfiltered DC offset configuration Gradient = 1.00E-02.

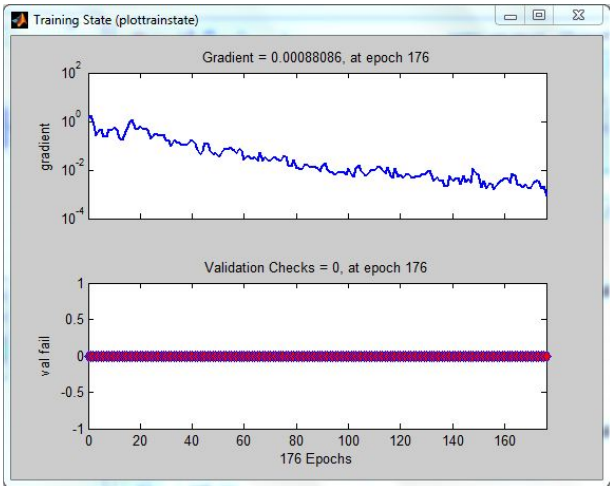

Figure A21 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-03.

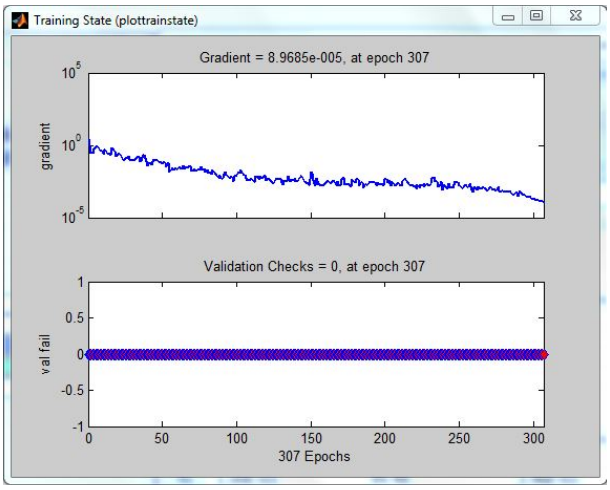

Figure A22 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-04.

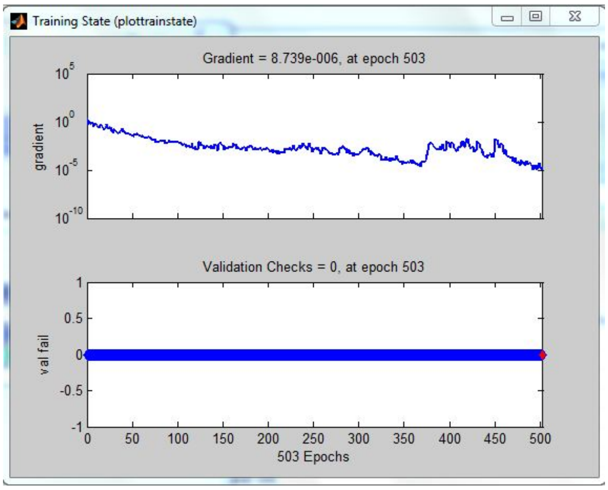

Figure A23 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-05.

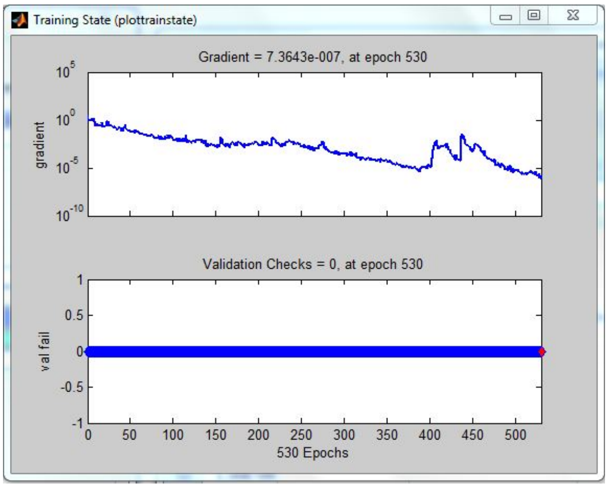

Figure A24 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-06.

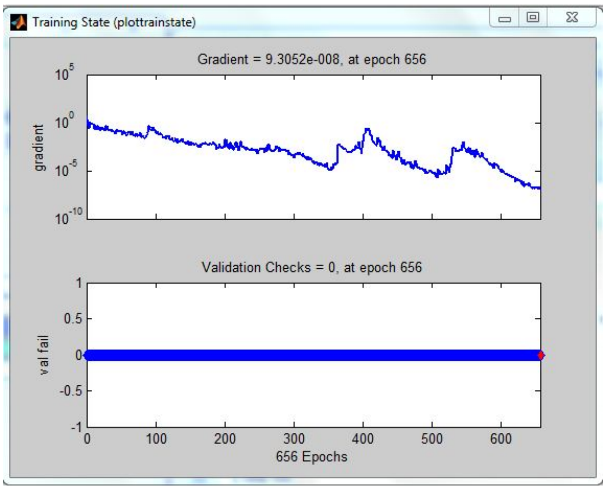

Figure A25 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-07.

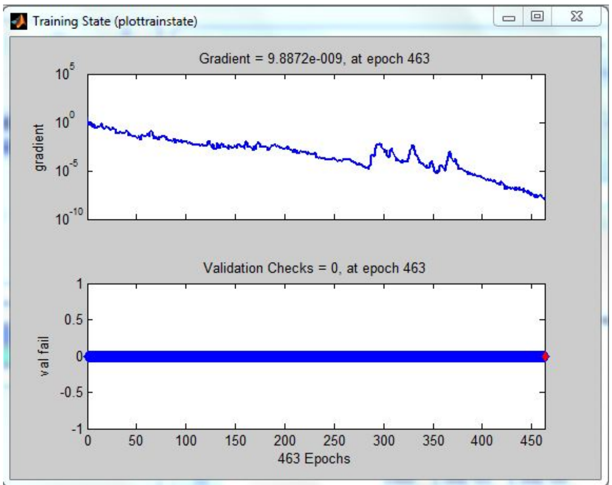

Figure A26 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-08.

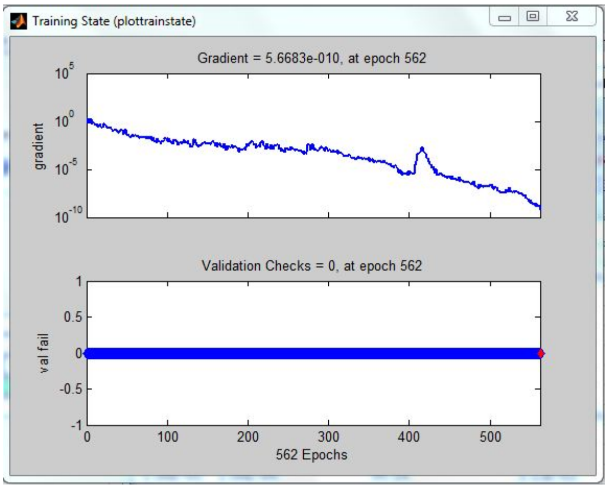

Figure A27 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-09.

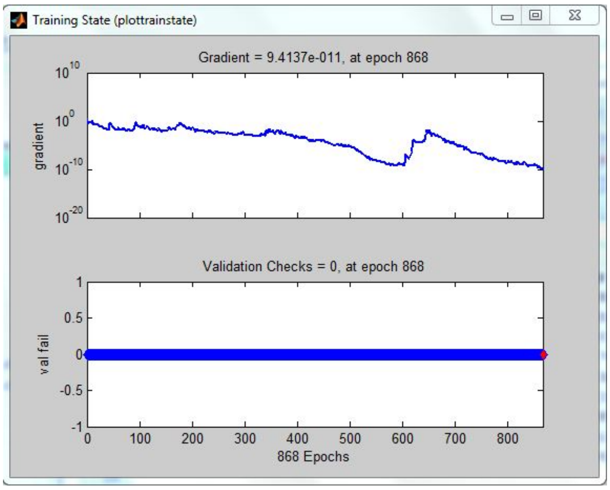

Figure A28 feed – forward propagation Unfiltered DC offset configuration Gradient = 1.00E-10.

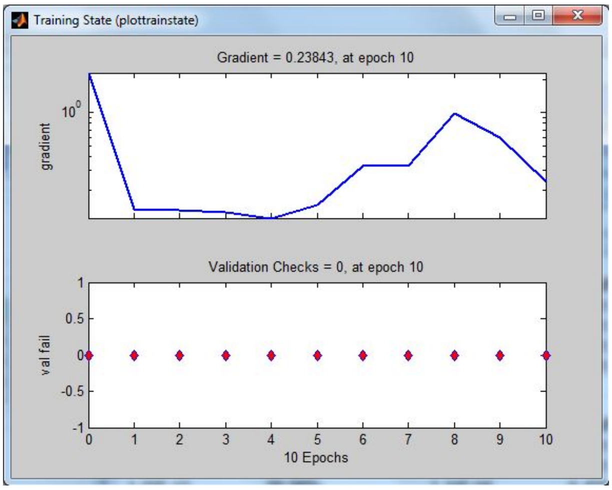

Figure A29 feed - forward propagation DC offset filter configuration Epoch = 10.

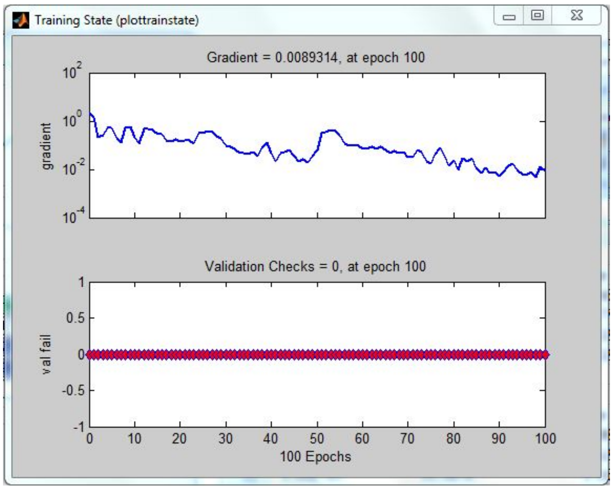

Figure A30 feed - forward propagation DC offset filter configuration Epoch = 100.

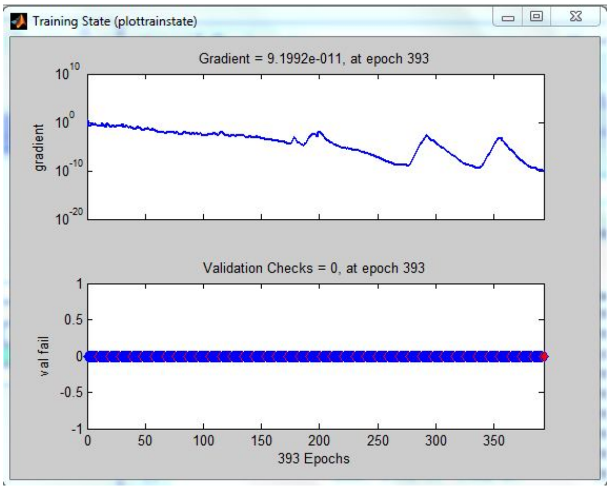

Figure A31 feed - forward propagation DC offset filter configuration Epoch = 1000.

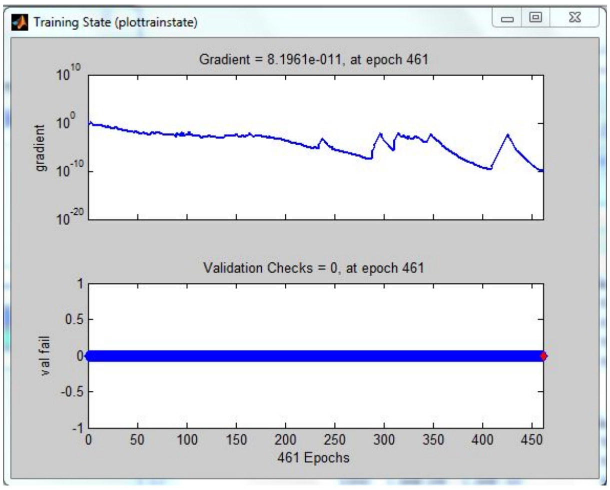

Figure A32 feed - forward propagation DC offset filter configuration Epoch = 10000.

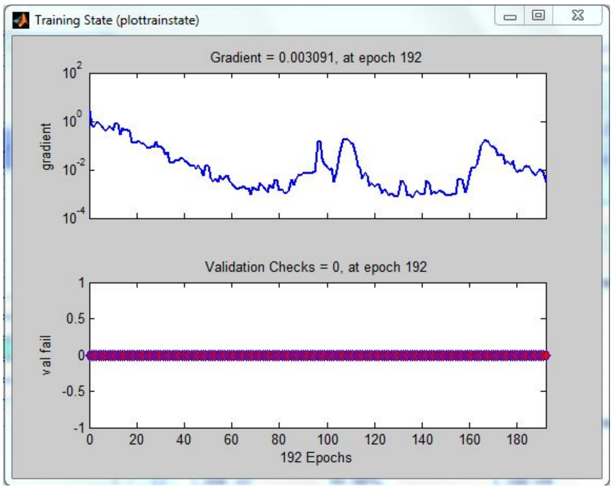

Figure A33 feed - forward propagation DC offset filter configured Goal = 1.00E-02.

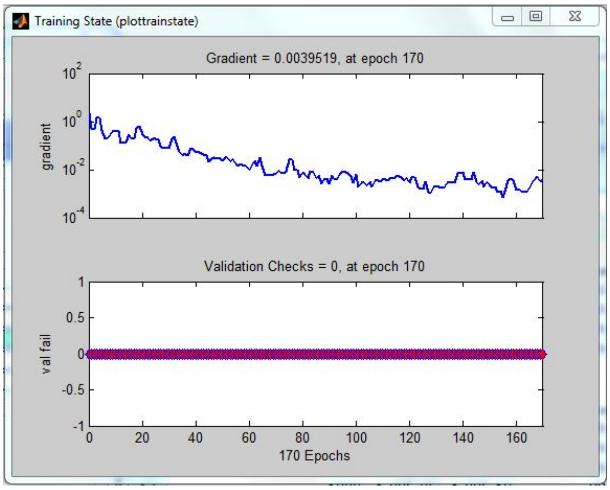

Figure A34 feed - forward propagation DC offset filter configured Goal = 1.00E-03.

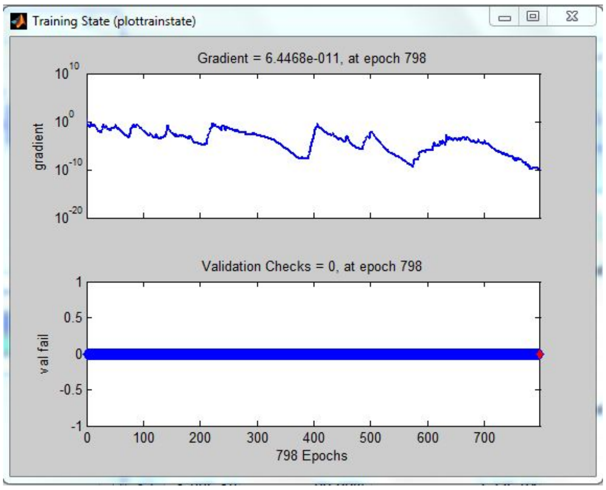

Figure A35 feed - forward propagation DC offset filter configured Goal = 1.00E-04.

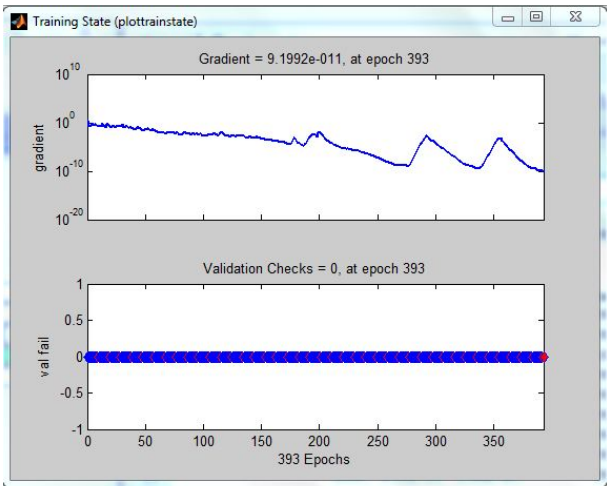

Figure A36 feed - forward propagation DC offset filter configured Goal = 1.00E-05.

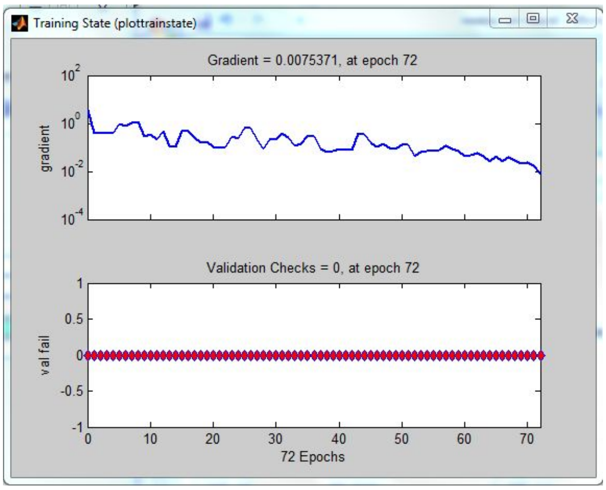

Figure A37 feed - forward propagation DC offset filter configuration Gradient = 1.00E-02.

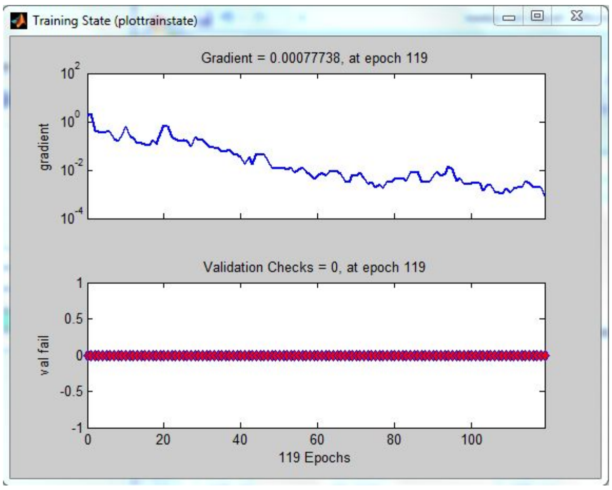

Figure A38 feed - forward propagation DC offset filter configuration Gradient = 1.00E-03.

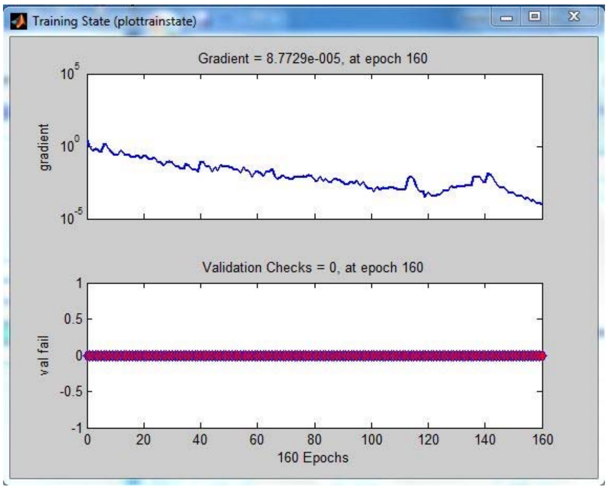

Figure A39 feed - forward propagation DC offset filter configuration Gradient = 1.00E-04.

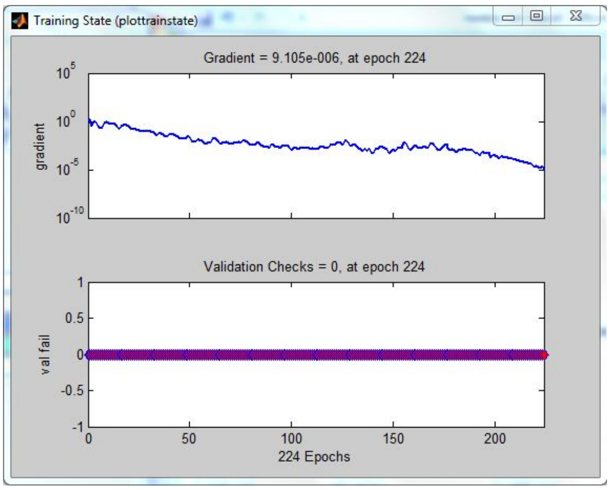

Figure A40 feed - forward propagation DC offset filter configuration Gradient = 1.00E-05.

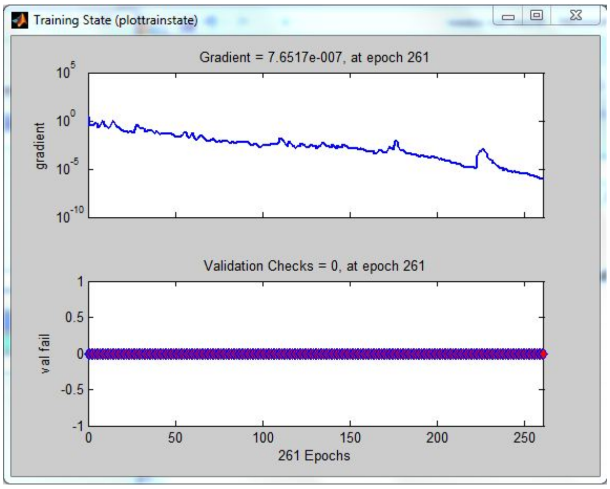

Figure A41 feed - forward propagation DC offset filter configuration Gradient = 1.00E-06.

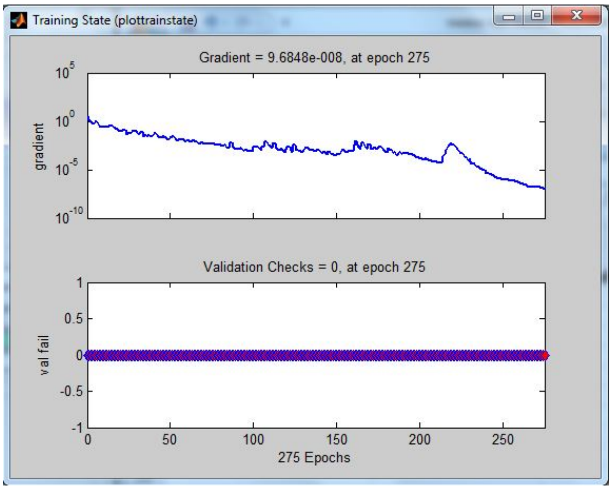

Figure A42 feed - forward propagation DC offset filter configuration Gradient = 1.00E-07.

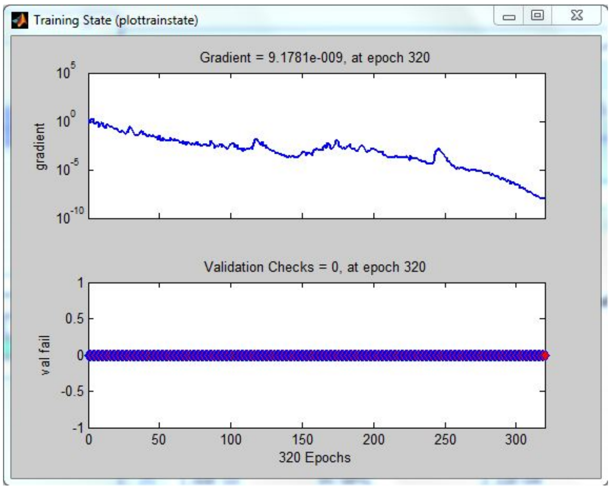

Figure A43 feed - forward propagation DC offset filter configuration Gradient = 1.00E-08.

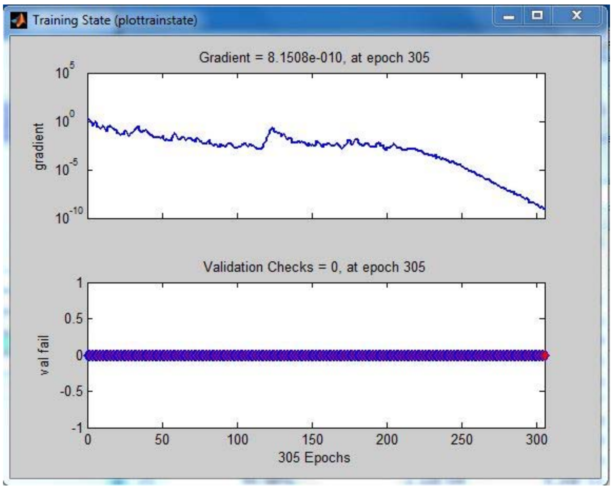

Figure A44 feed - forward propagation DC offset filter configuration Gradient = 1.00E-09.

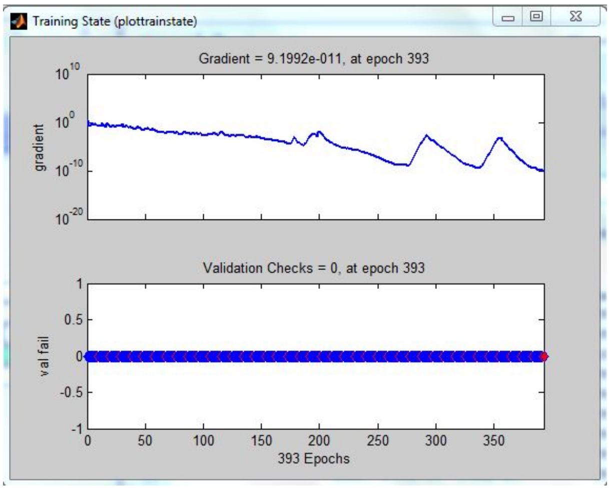

Figure A45 feed - forward propagation DC offset filter configuration Gradient = 1.00E-10.

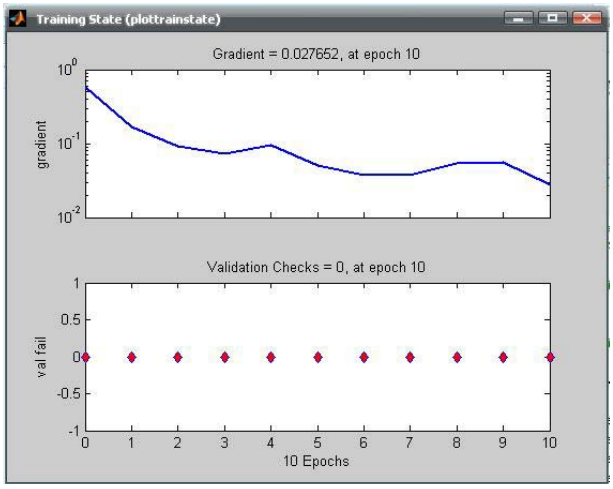

Figure A46 Pattern - recognition unfiltered DC Offset configuration Epoch = 10.

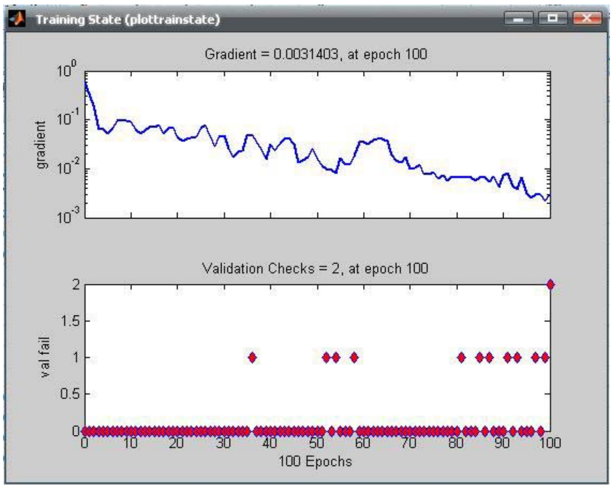

Figure A47 Pattern - recognition unfiltered DC Offset configuration Epoch = 100.

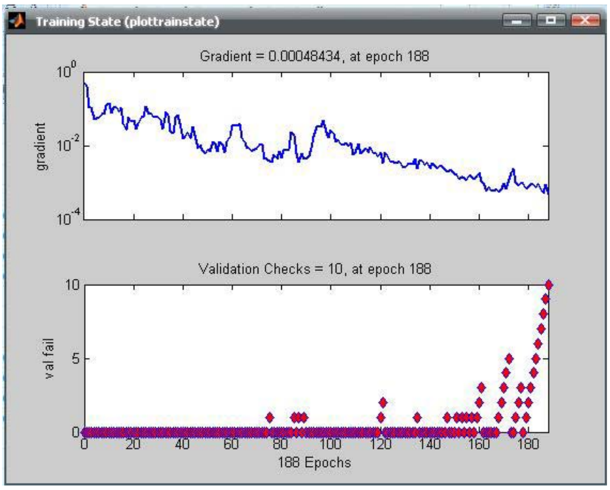

Figure A48 Pattern - recognition unfiltered DC Offset configuration Epoch = 1000.

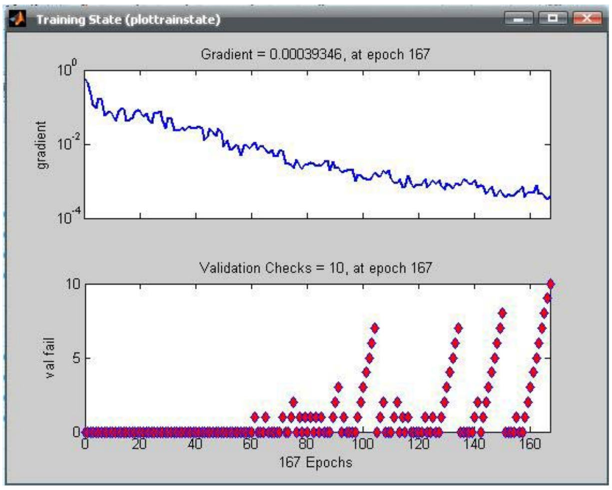

Figure A49 Pattern - recognition unfiltered DC Offset configuration Epoch = 10000.

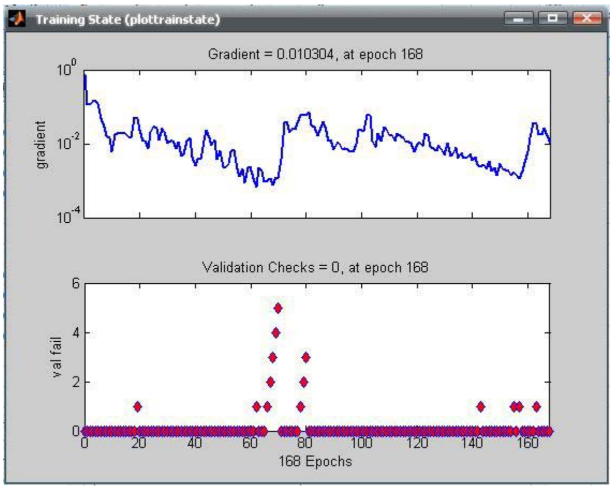

Figure A50 Pattern - recognition unfiltered DC Offset configured Goal = 1.00E-02.

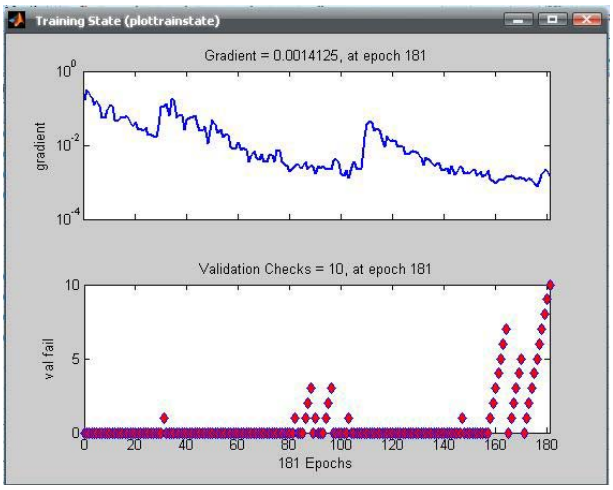

Figure A51 Pattern - recognition unfiltered DC Offset configured Goal = 1.00E-03.

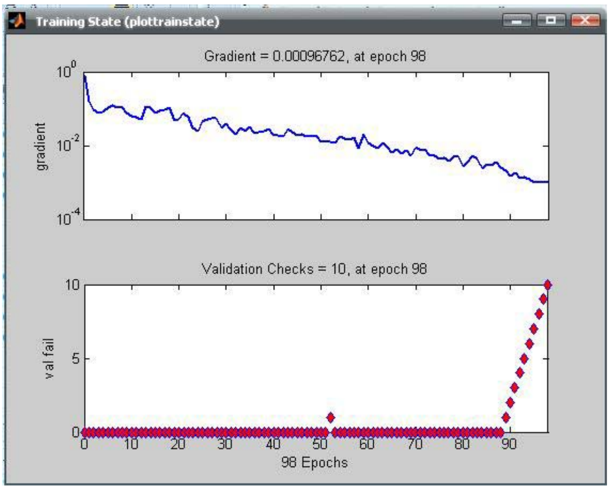

Figure A52 Pattern - recognition unfiltered DC Offset configured Goal = 1.00E-04.

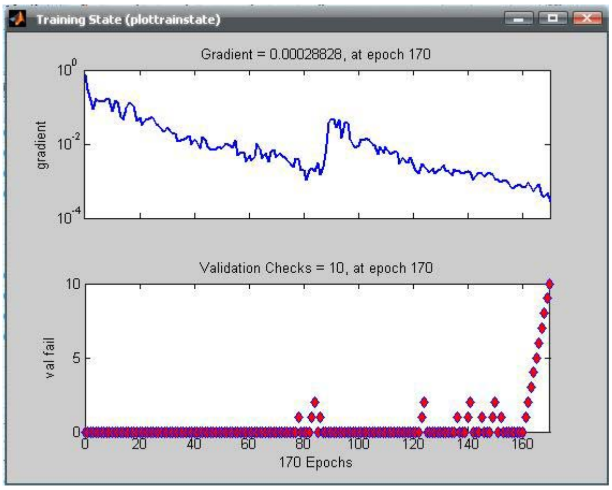

Figure A53 Pattern - recognition unfiltered DC Offset configured Goal = 1.00E-05.

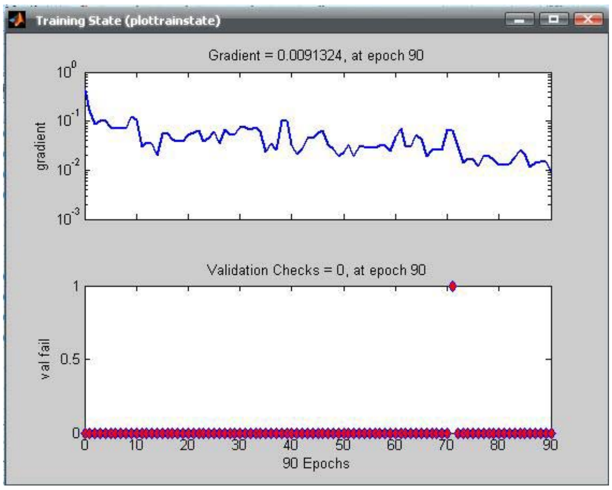

Figure A55 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-02.

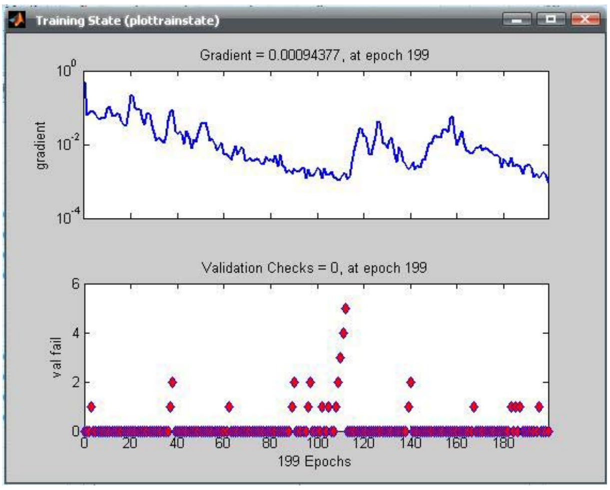

Figure A56 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-03.

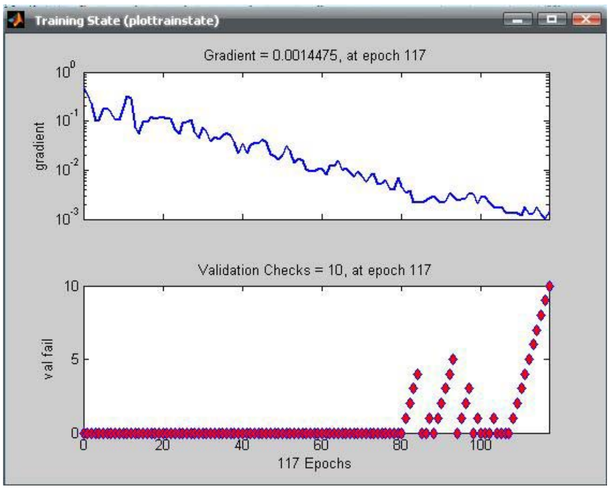

Figure A57 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-04.

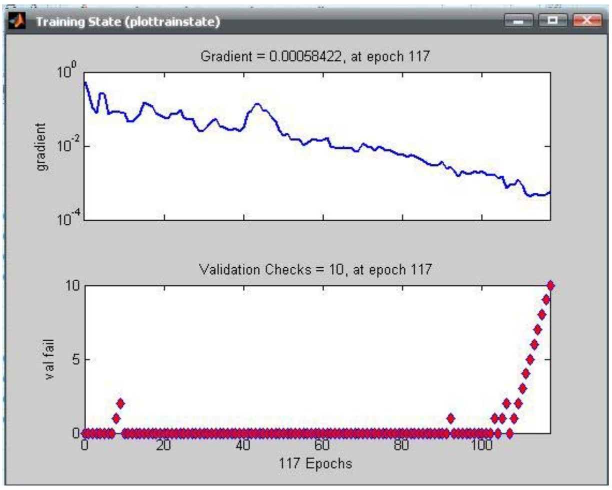

Figure A58 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-05.

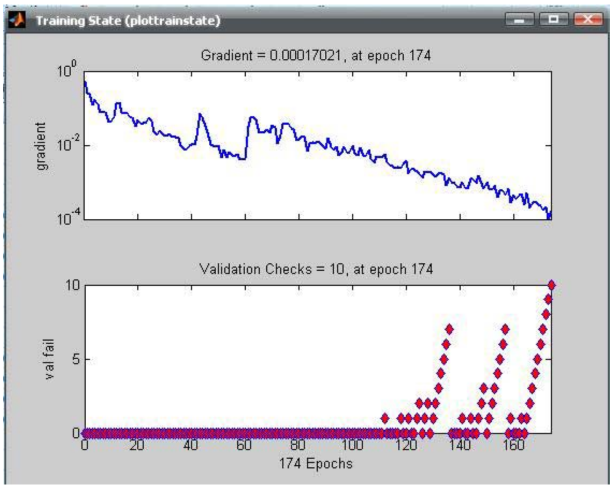

Figure A59 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-06.

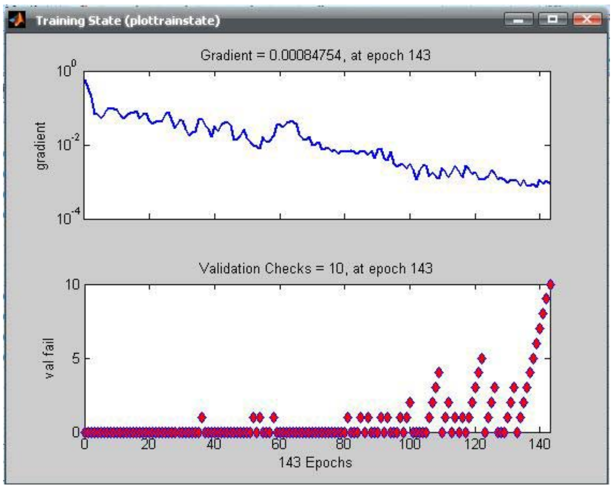

Figure A60 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-07.

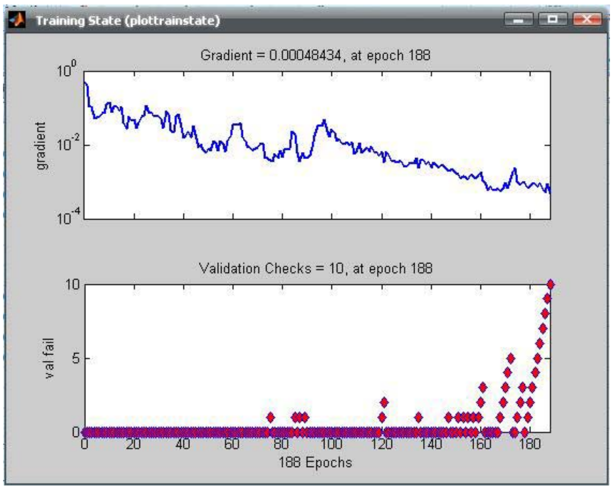

Figure A61 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-08.

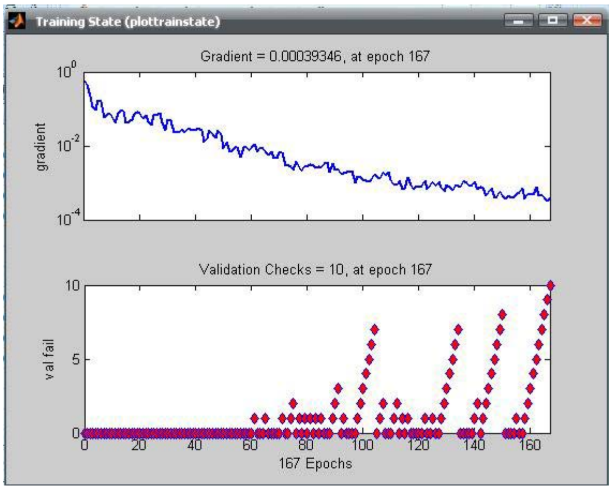

Figure A62 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-09.

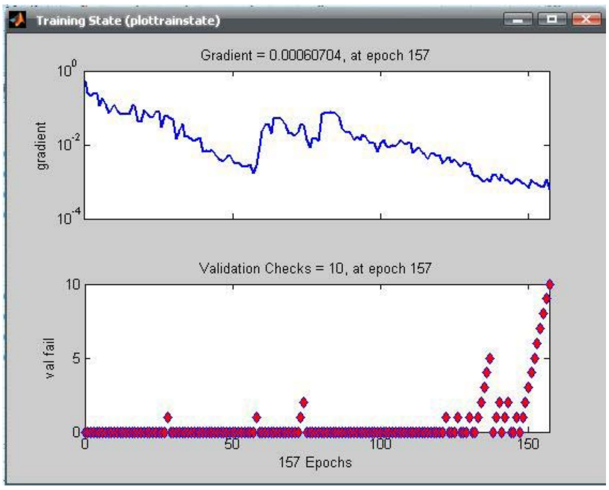

Figure A63 Pattern - recognition unfiltered DC Offset configuration Gradient = 1.00E-10.

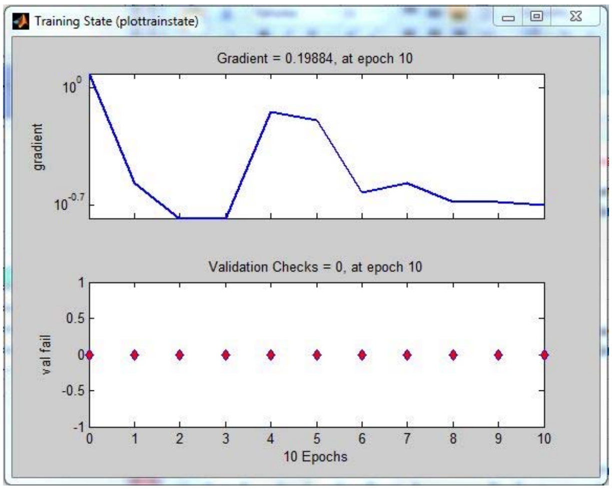

Figure A64 Pattern - recognition Filter DC Offset configuration Epoch = 10.

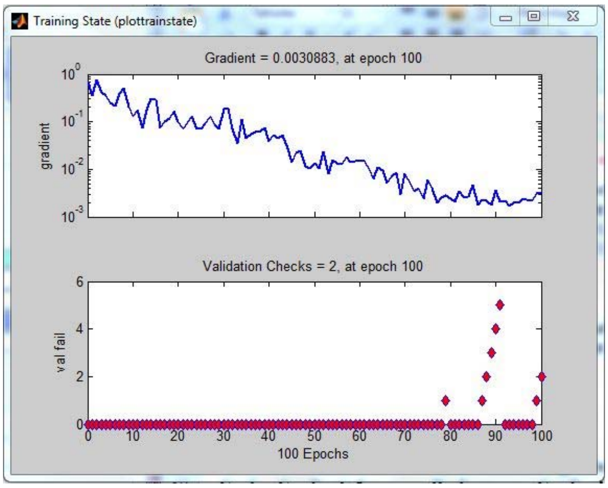

Figure A65 Pattern - recognition Filter DC Offset configuration Epoch = 100.

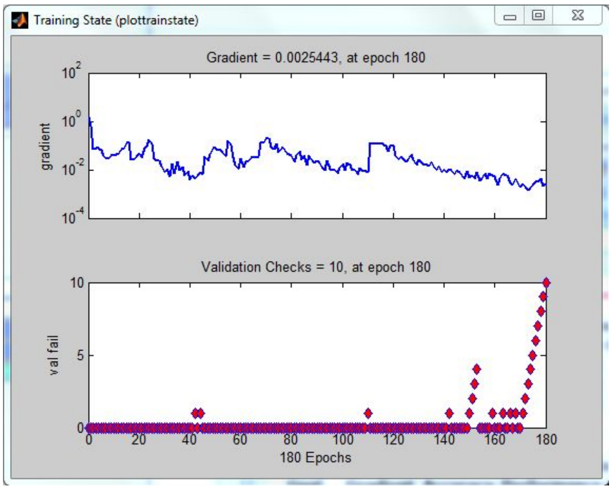

Figure A66 Pattern - recognition Filter DC Offset configuration Epoch = 1000.

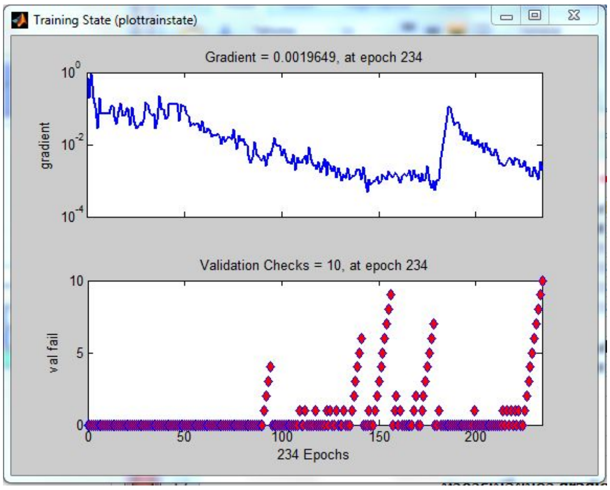

Figure A67 Pattern - recognition Filter DC Offset configuration Epoch = 10000.

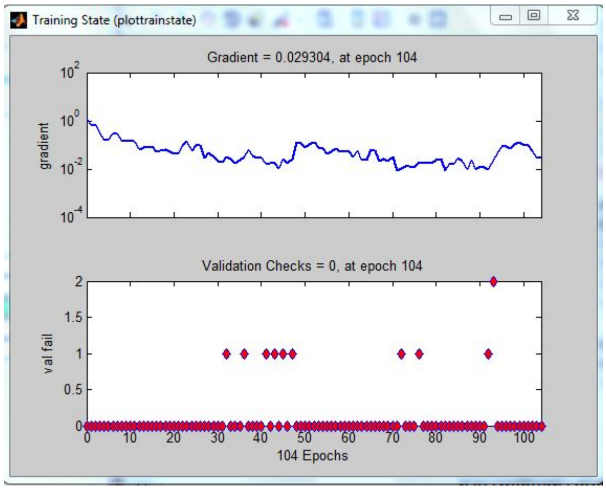

Figure A68 Pattern - recognition Filter DC Offset configured Goal = 1.00E-02.

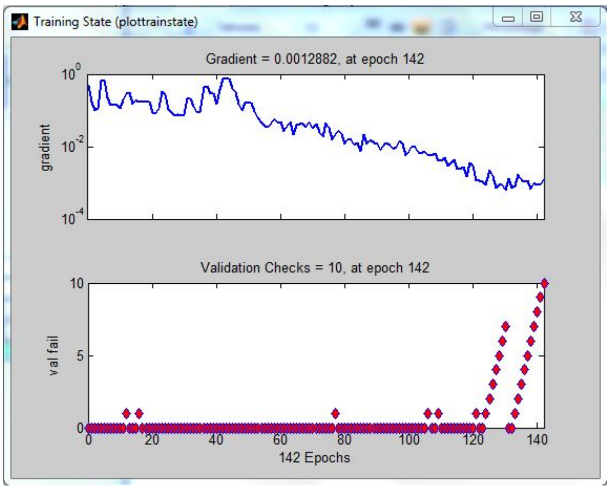

Figure A69 Pattern - recognition Filter DC Offset configured Goal = 1.00E-03.

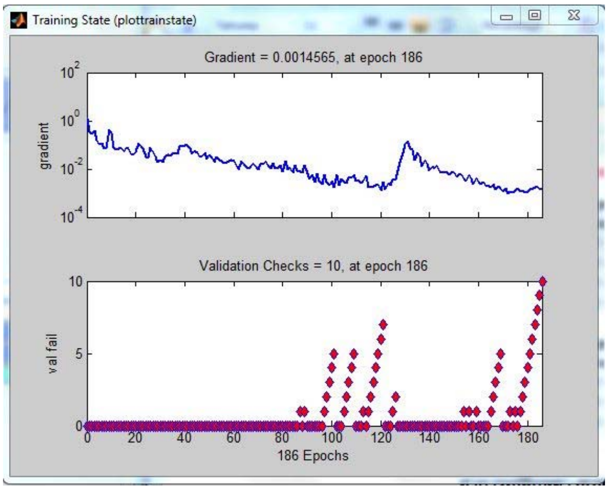

Figure A70 Pattern - recognition Filter DC Offset configured Goal = 1.00E-04.

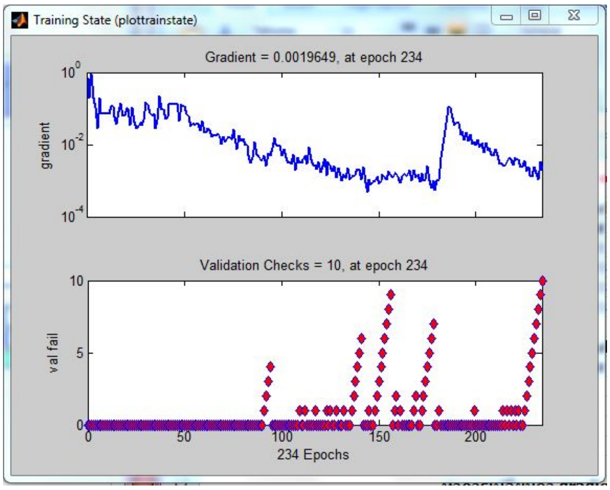

Figure A71 Pattern - recognition Filter DC Offset configured Goal = 1.00E-05.

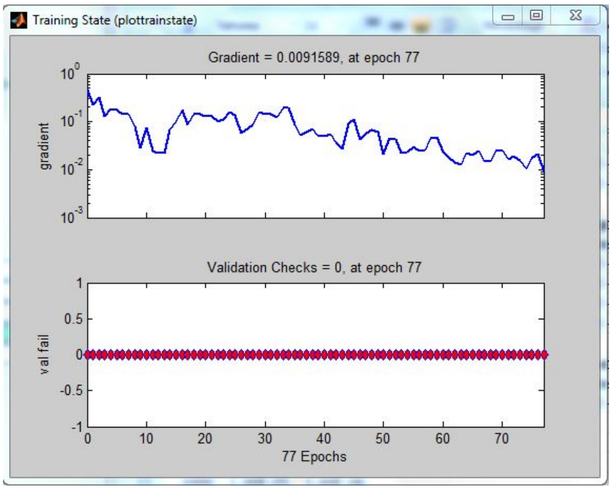

Figure A72 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-02.

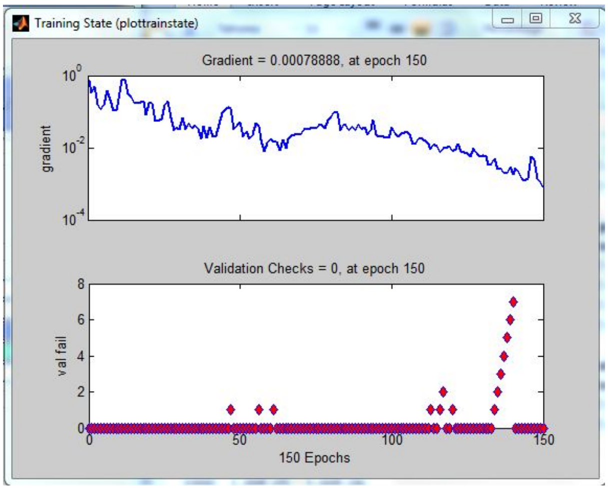

Figure A73 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-03.

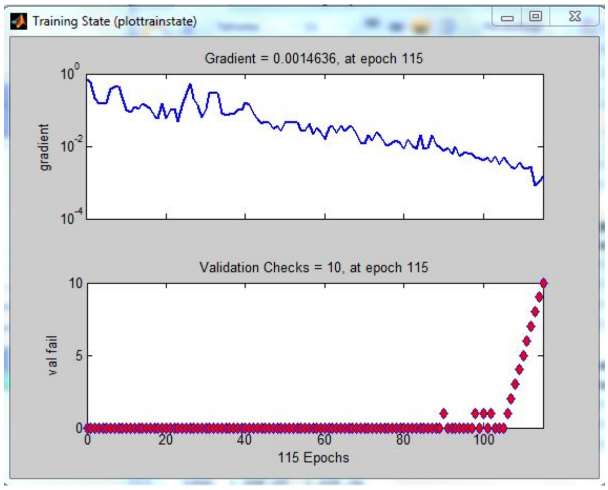

Figure A74 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-04.

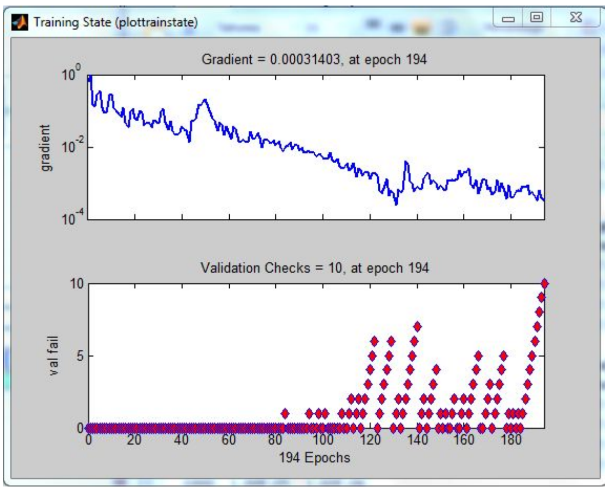

Figure A75 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-05.

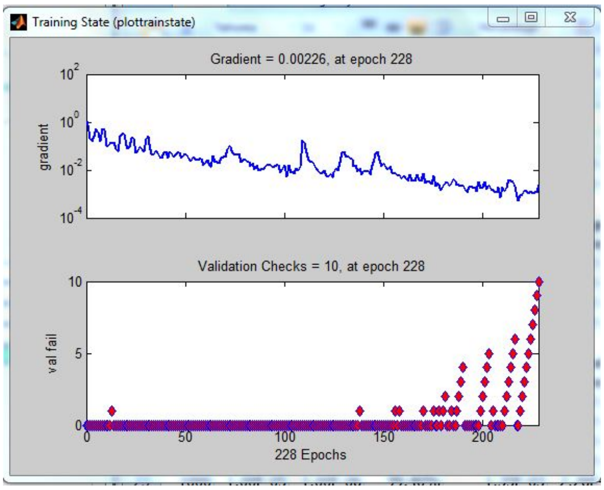

Figure A76 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-06.

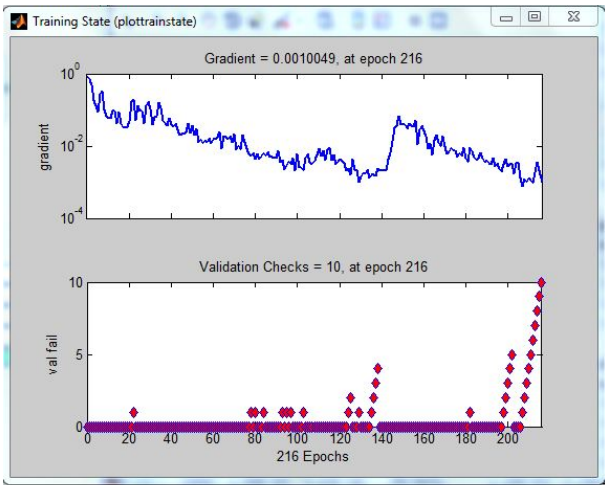

Figure A77 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-07.

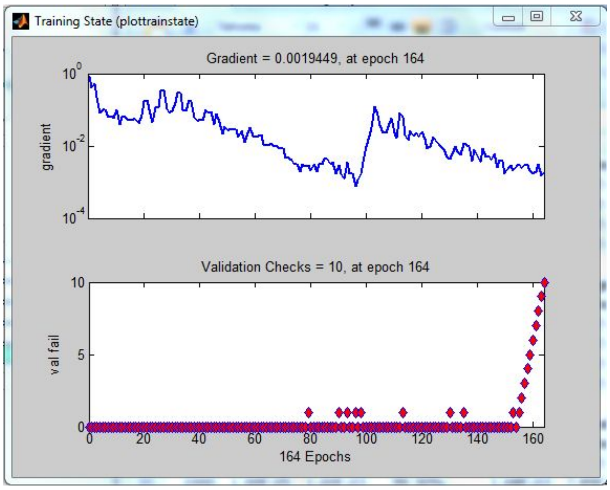

Figure A78 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-08.

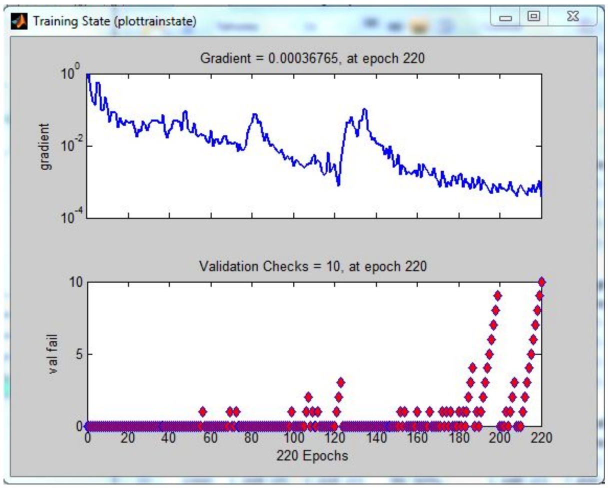

Figure A79 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-09.

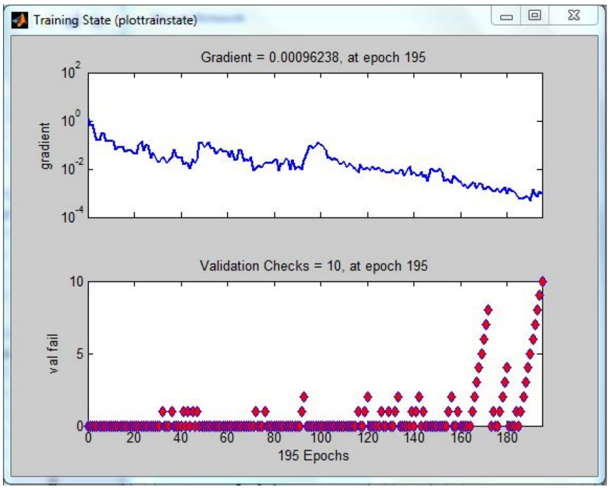

Figure A80 Pattern - recognition Filter DC Offset configuration Gradient = 1.00E-10.

An electrocardiogram classification method based on neural network

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Abstract

This paper illustrates the classification of electrocardiogram (ECG beats) are comparison of feedforwardbackpropergation method and logistic regression variable selection method. The objective of variable selection is reduce a variable of ECG beat ,it will be improving classification , providing faster and avoid over fitting situation. We tested both methods so variable selection method.

Keyword –Variable Selection , Electrocardiogram , Neural Network , classify the ECG , wavelet transformation , feature selection

I. Introduction

In present , medical records of patients with ECG ECG recorder (Ambulatory ECG Recording or Holter monitoring) in order to determine abnormal ECG. The physician will make the interpretation of the nature of the ECG waveform. Calculations with different parameters.Both the size and timing of the ECG. This shows the kind of heart disease or not. Recognition and reference points to calculate the parameters of the ECG is a tedious and time-consuming for doctors. In addition, the number of patients it has a lot more heart. Therefore, it needs a system that can automatically classify the ECG to aid in the diagnosis of a type of heart disease in patients.

Methodology of classification of ECG. Many automated method has been developed to indicate the type of heart disease in the individual patient. The various methods that have been developed are still limited in its application to the make continues to innovate and develop new ways to continue to be effective enough to lead. To improve methodology we use Variable selection for classification by neural network. Various studies have been done for classification of various cardiac arrhythmias (1),(2),(3). We propose wavelet transform and selection variable method, then use the Neural Network to classify the ECG Heartbeat[8]. We get ECG Beat data from MIT-BIH arrhythmia database and improve performance of classification.

Guyon and Elisseff [6] use three type method for classify : Filter , Wrapper , Embedded Methods. But almost are not very effective. Filter method use preprocessing step that are not effective . Wrapper methods prediction method as a black box it work but very expensive. Embedded [2], feature selection methods as part of the training process of the prediction method to decide feature removal.

II. Process and data

All data from MIT-BIH arrhythmia database that contains records of many patients with heart troubles or abnormalities.[7]We will use Lead MLII (Lead2) Amplitude of the signal for a maximum and a Lead measure in almost all patients. Cut the Beat out for analysis. By the terms of the previous wave R about 345 ms or 124 data points (fs = 360 Hz) and the signal after peak R approximate 486 ms or 175 data points, so the signal in one beat (one waveform.), it has 300 data points.

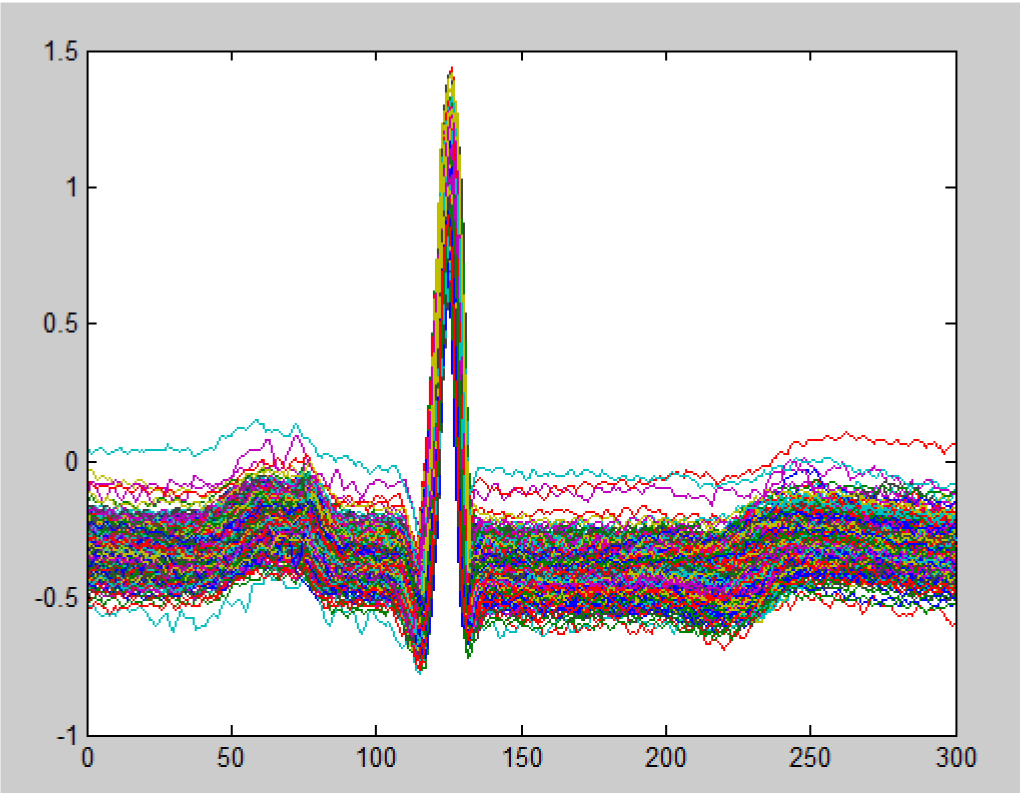

Fig.1 ECG Beat

After perform using lowpass filter and high pass filter to filter electrical noise to make it easier to analyze and reduce the selection variable is to resolve the overfitting and compared with between Data used for the selection variable and did not pass the test Selection variable to bring into training data and testing data compared. Fig.1 showed ECG beat a normal type.

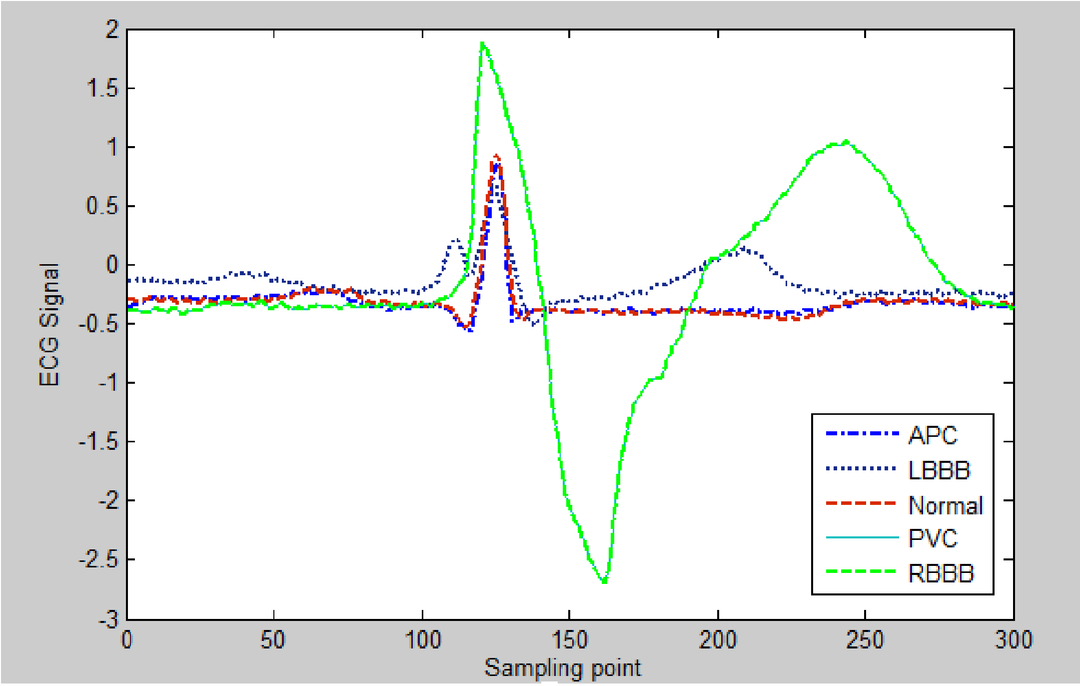

Fig.2 ECG Beat five types

III. Wavelet Transform

A Signal $f(x)$ defined as

$$(W_s f(x) = f(x) * \Psi_s(x) = \frac{1}{s}\int_{-\infty}^{+\infty} f(t)\Psi\left(\frac{x-t}{s}\right) dt \qquad (1)$$

S is scale factor.$\Psi_s(x) = \frac{1}{s}\Psi(\frac{x}{s})$is the dilation of a basic wavelet $\Psi(x)$ by the scale factor s. Let s = $2^j (j \in Z, Z$ is the integral set),then the Wavelet Transform is called dyadic Wavelet Transform[7]. The dyadic Wavelet Transform of a digital signal $f(n)$ can be calculated with Mallat algorithm as follows:

$$S_{2^j} f(n) = \sum_{k\in Z} h_k S_{2^j} - 1 f(n - 2^{j-1}k) \qquad (2)$$

$$W_{2^j} f(n) = \sum_{k\in Z} g_k S_{2^j} - 1 f(n - 2^{j-1}k) \qquad (3)$$

Where S_{2^j} is a smoothing operator and $S_{2^j} f(n) = d_j . d_j$ is the digital signal to be analyzed which is the ECG signal used in this paper. $W_{2^j} f(n)$is Wavelet Transform of digital signal $f(n).\{h_k | k \in Z\}$ and $\{g_k | k \in Z\}$ are coefficients of a lowpass filter $H(\omega)$and a highpass filter $G(\omega)$, respectively that means

$$H(\omega) = \sum_{k\in Z} h_{k^{e^{-ikw}}} , G(\omega) = \sum_{k\in Z} g_{k^{e^{-ikw}}}$$

The wavelet transform is better suited to analyze the signal nonstationary and the signal at a certain lowpass filter and highpass filter.

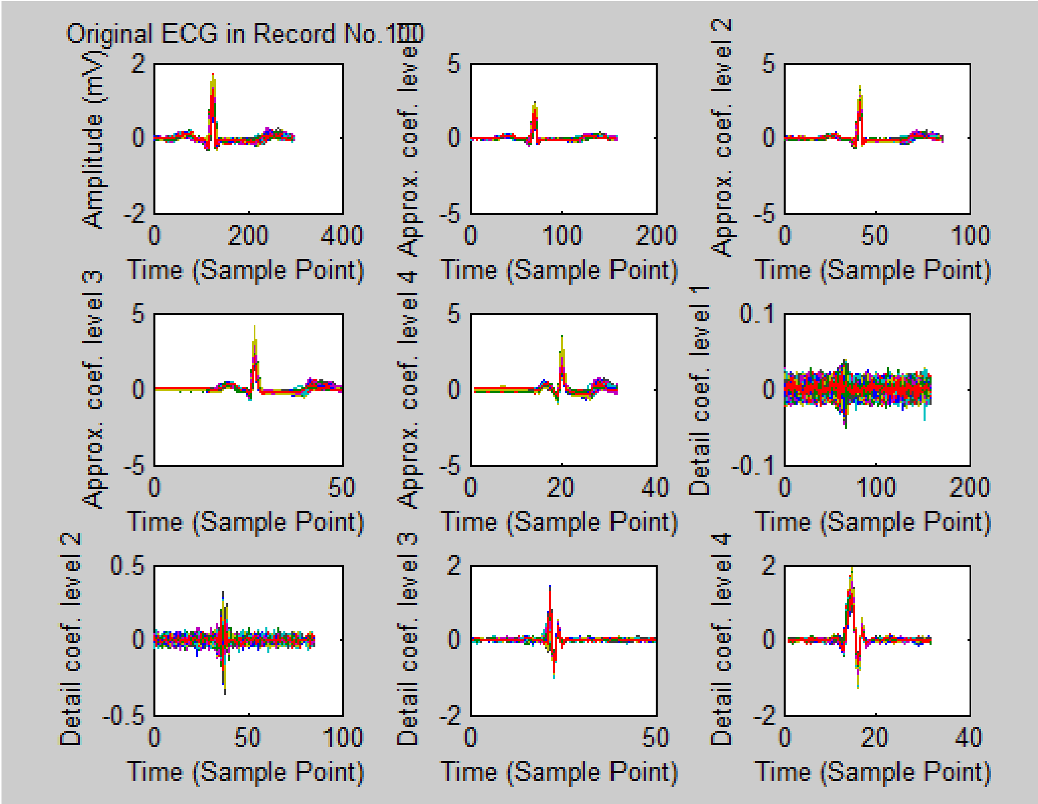

Fig.3 Normal heartbeats Wavelet coefficients

However decomposition level selection is very important in signal analysis. It is depends on the frequency of the dominant chosen such that the signal correlated well with required for classification of the signal will remain in the wavelet coefficients. The ECG signals are usually the test is performed on the type of light gives maximum efficiency for a particular application. The feature selection is important component, it has two meanings: Which set of inputs best represent a given pattern. Fig.3 shows the wavelet coefficients feature of normal beats. So the wavelet is another way to use for some tests.

IV. Neural Networks

A multilayer a feed forward neural network with one layer of hidden unit. The output unit have weights $w_{jk}$and the hidden units have weightsv_{ij}. During the training phase, each output neuron compares its computed activation$y_k$with its target value $d_k$to determine the associated error E for the pattern with that neuron.

$$E = \sum_{k=1}^{m} (d_k - y_k)^2$$

The ANN weights and biases are adjusted to minimize the least-square error. The minimization problem is solved by gradient technique, the partial derivatives of E with respect to weights and biases and have been calculated using the generalized delta rule or the widrow-Hoff rule. This is achieved by back-propagation (BP) of the error. When using momentum, the net is proceeding not in the direction of the gradient, but in the direction of a combination of the current gradient and the previous direction of weight correction. Convergence is sometimes faster if a momentum term is added to the weight update formula. In the back-propagation with momentum the weights for training step t+1 are based on the weights at training steps t and t-1.The weight update formulas for back-propagation with momentum are

$$w_{jk}(t+1) = w_{jk}(t) + \propto \delta_k z_j + \mu[w_{jk}(t) - w_{jk}(t-1)]$$

$$v_{jk}(t+1) = v_{ij}(t) + \propto \delta_j x_i + \mu[v_{ij}(t) - v_{ij}(t-1)]$$

Where the learning factor α and momentum parameter μ is constrained to be in the range [0,1], exclusive of the end points. The weights and biases are initialized to some initial random values , and updated in each iteration (called an epoch) until the net has settled down to a minimum.

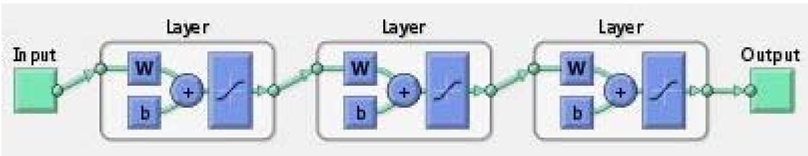

Fig. 4 Neural Network NNtool Box Matlab

RESULTS & DISCUSSION

The ECG data from the MIT-BIH Arrhythmia Database corresponding to normal heartbeat and 4 types of arrhythmias. Then each types heartbeat has a big data set we reduce variables for train and test by neural network compared between before reduce variables and after reduce variables for measure accuracy and times.

Beat type	Training Data	Accuracy before reduce variables	Accuracy After reduced variables	Time/min Before reduce variables	Time/min After reduced variables
APC	300	93.84%	98.00%	0:43	0:21
Normal	300	100%	100%	1:25	0:46
LBBB	300	94.21%	99.30%	1:29	0:52
RBBB	300	92.53%	99.47%	2:07	1:02
PVC	300	87.82%	96.60%	1.46	0.58
Total	1500	93.68%	98.67%	7.5	3.59

Table I -- RESULT OF ECG

CONCLUSION

The results of recognition of 5 types of arrhythmias were carried out on MIT-BIH Arrhythmias Database. The data are reduced variable by selection variable and wavelet transform for reduced noise signal of ECG signal. The Neural Network(NN) used for classification of the ECG beat was trained the results showed that our approach gives the excellent performances of successful recognition, provide improve accuracy 5.33% and reduced time 50.85% . Further work can use to increase to performance ECG Classification.

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