

A Genetic-Neural System Diagnosing Hepatitis B

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Abstract

Hepatitis B is a life threaten disease and if not diagnose early can lead to death of the infected patient. In this paper a genetic neural system for diagnosing hepatitis B was designed. The system was designed to diagnose HBV using clinical symptoms. The dataset used in training the system was gotten from UCI repository. The system incorporated both genetic algorithm and neural network. The genetic algorithm was used to optimize the dataset used in training the neural network. The neural network was trained for 300 iterations and the system had a prediction accuracy of 99.14

Index terms— genetic algorithm, hepatitis B, neural network.

1 Introduction

he human body is made up of various organs and of these organs the liver is the largest. The liver performs various functions in the human body. It produces bile which aids the breaking down of fat, it breaks down alcohol and toxic waste in the blood stream and passes them out of the body as either stool or urine and it absorbs glucose from the blood and stores them in form of glycogen for subsequent use by the body (WHO, 2014). Some diseases are known to affect the liver are they include Hepatitis A, Hepatitis B, Hepatitis C, Hepatitis D and Hepatitis E to mention but a few (Ghumbre et al, 2009). Hepatitis B is an infectious viral disease caused by the Hepatitis B virus (HBV).

According to WHO about one-third of the entire world population has been infected with HBV at one point in their lives and 750,000 people die each year of the disease (WHO, 2014). In 2013 it was estimated 129 million person where infected with HBV and the number of infected individual is predicted to rise each year by 2.5% (WHO, 2014). Hepatitis B is prevalent in East Asia and Sub Saharan Africa where about 5-10% is chronically affected while in Europe and North America the prevalence rate of HBV is less than 1% (WHO, 2014). HBV is transmitted by exposure to infected blood or body fluid or sexual intercourse with an infected person or by birth from mother to child (Chen et al, 2005). Symptoms of Hepatitis B includes jaundices (yellowish eye and skin), fatigue, dark urine nausea, vomiting, skin rash, polyarteritis and in some cases abdominal pain (Shepard et al, 2006, Chen et al, 2005 and Schroth et al, 2004). These symptoms might last for several weeks. The gold standard for diagnosing HBV is by laboratory test. Although accurate, laboratory test are quite expensive and the infected patient need to wait for at least 30 days before the HBV virus can be detected in the blood. Hence, there is a need for other technique for diagnosing HBV. In recent past, machine learning techniques have been applied in diagnosing hepatitis B virus (Chen et al, 2005, Riudiger, 2001 and Ghumbre et al, 2009). These techniques have provided a non-invasive means for diagnosing Hepatitis B virus and most importantly in a timely manner. Most machine learning techniques utilized by various researchers in diagnosing HBV were neural network, Fuzzy Logic, Neuro-fuzzy system and Support Vector Machine (SVM). The fundamental weakness of these approaches used by these researchers is that no attention was paid to optimal selection and extraction of the dataset used in training their systems. To this, we propose a genetic neural system for diagnosing Hepatitis B virus. The system will comprise of two components genetic algorithm and neural network. Genetic Algorithm (GA) is a strong machine learning tool which is capable of performing feature selection and extraction. On the other hand Neural Network is also a machine learning technique that is capable recognizing patterns based on input fed into it. Combining these two excellent machine learning technique to diagnose HBV will create a system with higher prediction accuracy.

47 **2 II.**48 **3 Related Work**

49 Several researchers have tried to improve the accuracy of HBV diagnosis and have applied various machine learning
50 techniques in diagnosing HBV. In 2006 Plot and Günes, used a hybrid method comprising of Feature Selection
51 (FS) and Artificial Immune Recognition System (AIRS) with fuzzy resource allocation mechanism in predicting
52 Hepatitis. The system had an average prediction accuracy rate of 92.59% in classifying HBV. In 2011 Chen et al
53 proposed a hybrid method which combined Local Fisher Discriminant Analysis (LFDA) and SVM in diagnosing
54 Hepatitis. The dataset used in the study was gotten from the UCI repository. The Local Fisher Discriminant
55 Analysis was used to perform feature extraction and SVM was using in classifying the data algorithm. The result
56 obtained show that the system had an average prediction accuracy rate of 96.59% in classifying HBV. Also in a
57 similar study conducted by Calisir and Dogantekin, they used Principle Component Analysis (PCA) and Least
58 Square Support Vector Machine SVM (LSSVM) in diagnosing HBV. The dataset used in the study was gotten
59 from the UCI repository. The Principle Component Analysis (PCA) was used to perform feature extraction and
60 while Least Square Support Vector Machine SVM (LSSVM) was used to classify the Hepatitis datasets. The
61 result obtained show that the system had an average prediction accuracy rate of 95% in classifying HBV. In 2011
62 Sartakhti et al, combined Support Vector Machine with Simulated Annealing (SA) to diagnose HBV. The dataset
63 used in the study was gotten from the UCI repository. The result obtained show that the system had an average
64 prediction accuracy rate of 96.25% in classifying HBV. In 2012 Bascil et al used a Probabilistic Neural Network
65 structure to diagnose HBV. The result obtained show that the system had an average prediction accuracy rate
66 of 91.25% in classifying HBV. In 2013 Mahesh et al, used Artificial Neural Network (ANN) to diagnose HBV. In
67 their study 300 cases was used to train the ANN. The HBV dataset was divided into four categories (Normal,
68 light, Severe and Hyper Severe) which indicated the severity of HBV. The ANN used markers in diagnosing each
69 case. The marker were Hepatitis B surface Antigen, anti VHC and anti-VHD. The ANN had a prediction of
70 accuracy of 87% and 89% on acute and chronic HBV respectively. Also in a similar study conducted by Mehdi
71 et al, (2009), they designed a fuzzy expert system and an Adaptive neural Network fuzzy system to diagnose and
72 compare their intensity rate. The dataset used in their study contained 300 diagnosed cases of HBV. The dataset
73 was collected from Imam Reza hospital in Mashad, India. A triangular membership function was used to map
74 the values in the dataset into each membership set for the fuzzy system and the bell membership function for the
75 Adaptive neural Network fuzzy system. Both system had 54 rules. The Adaptive neural Network fuzzy system
76 was trained 100 epoch with an error tolerance of 0. Upon completion of the training the system had an accuracy of
77 94.24% on HBV intensity. In a similar study conducted by Pushpalatha et al, (2016). They designed a framework
78 comprising of neural network, Naïve bayes and Support Vector machine in diagnosing HBV. In their work 155
79 cases of HBV diagnosed patients was used. The dataset has 11 input and an output which indicated the status of
80 HBV. The dataset was used to train the 3 techniques and it had an accuracy of 98.07, 82.58 and 84.52 for neural
81 network, Naïve Bayes and SVM respectively. In 2019 Gulzar et al proposed an automated diagnostic system for
82 predicting Hepatitis B using Multilayer Mamdani Fuzzy inference logic. The system has two layers. In the first
83 layer has two inputs (Alanine Aminotransferase (ALT) and Aspartate Aminotransferase (AST)) the output of
84 this layer is fed into the second layer. The second layer has 8 inputs which are the output from layer 1, HBsAg,
85 Anti-HBsAg, Anti-HBcAg, Anti-HBcAg-IgM, HBeAg, Anti-HBeAg and HBV-DNA. The system had an overall
86 classification accuracy of 92.2% in classifying HBV. In 2018 Rahmon et al, proposed an Adaptive Neuro-Fuzzy
87 Inference System for diagnosing HBV. The dataset used to train their system was obtained from Carnegie-Mellon
88 University database, Yugoslavia. It contained 155 HBV cases. Five symptom attribute were used as inputs in
89 training the system they are; Albumin, Ascites, Alk-Phosphate, Bilirubin, and SGOT. The output of the system
90 graded HBV as either mild or severe. The system had a Mean Square Error (MSE) of 0.11768, Root Mean Square
91 Error (RMSE) of 0.34305, Error Mean of -3.143e-005, Error St.D of 0.34567 and an overall prediction accuracy
92 of 90.2%. In 2013, Mohammed et al, used Support vector Machine in classifying Hepatitis Disease. The dataset
93 used in their study was gotten from UCI machine learning repository. The dataset contained 155 HBV cases.
94 The result obtained from the study showed that 3SVM had a prediction accuracy of 93.2%. In 2017, Ogah et
95 al, proposed a Generalized Regression Neural Network for diagnosing HBV. The dataset used in the study was
96 collected through filed study and observation. The ANN was trained for 50 iterations and it had a prediction
97 accuracy of 87 on classifying HBV%. In 2014, Khosro et al, used Support Vector Machine (SVM) and Fuzzy
98 Cluster Mean (FCM) in diagnosing Hepatitis B. The dataset used in the study was gotten from Vasei Hospital in
99 Sabzevar, Iran. The dataset was normalized and SVM was used to classify the dataset. The classified dataset was
100 fed into the FCM to determine the severity of HBV. The system had an accuracy of 94.09%. In 2016, Ruijing et
101 al, compared and evaluated the prediction of Hepatitis in Guangxi Province, China using three neural networks
102 models; back propagation neural networks based genetic algorithm (BPNN-GA), generalized regression neural
103 networks (GRNN), and wavelet neural networks (WNN). The incidence of hepatitis data used in their study was
104 gotten from Chinese National Surveillance System and the Guangxi Health Information Network. The result
105 obtained from the study showed that back propagation neural networks based genetic algorithm (BPNN-GA)
106 was better and forecasted Hepatitis better than the generalized regression neural networks (GRNN), and wavelet
107 neural networks (WNN). Although from the above reviewed literature these techniques generated excellent results,

108 but it is obvious that no attention was paid to feature selection and extraction on the dataset used in training
109 these models.

110 4 III.

111 5 Experiment and Simulation

112 The proposed model for diagnosing HBV seeks to eliminate the challenges faced with the current system. It uses
113 a hybrid system comprising of Genetic Algorithm (GA) and Neural Network (NN). The Genetic algorithm will
114 perform feature selection and extraction on the dataset before it is used to train the neural network. The GA
115 component will optimize the clinical dataset by performing feature extraction and selection. It will utilize the
116 value encoding method where each gene in a chromosomes is value between the lower and upper range of the in
117 each column in the dataset. The GA component will include the fitness function component, selector, crossover,
118 mutation and acceptance component.

119 6 a) Objective function of the Genetic Algorithm

120 The objective function is the function that determines the diagnosis. The Objective function will be a
121 mathematical model used to represent the diagnostic process of HBV. The objective function was arrived at
122 after several consultation with several medical doctor. Objective function = $\sum_{i=1}^n \text{Symptom } i \times \text{Weight } n \ i$

123 Where n = total number of symptoms, $i=1, 2, 3 \dots n$ Fitness Function: The fitness function should be able
124 to measure how fit a given chromosome is. The fitness for the proposed model is given below Where n = total
125 number of symptoms $i=1,2,3 \dots n$ Selection: The idea of selection phase is to select the fittest individuals and let
126 them pass their genes to the next generation. Two pairs of individuals (parents) are selected based on their fitness
127 scores. Individuals with high fitness have more chance to be selected for reproduction. The roulette selector will
128 be employed in selecting chromosome because study has shown that it provides more optimal solution and has
129 better convergence speed than the simple genetic algorithm (Yadav et al, 2017).

130 Crossover: Crossover is the most significant phase in a genetic algorithm. For each pair of parents to be mated,
131 a crossover point is chosen at random from within the genes. Offspring are created by exchanging the genes of
132 parents among themselves until the crossover point is reached. The new offspring are added to the population.
133 The One point mutation operator will be used because study has shown it generates the best results (Jorge,
134 2013).

135 7 Mutation:

136 In certain new offspring formed, some of their genes can be subjected to a mutation with a low random probability.

137 Mutation occurs to maintain diversity within the population and prevent premature convergence. The power
138 mutation operator will be employed because it performs better than other mutation techniques (Siew et al, 2017).

139 The multilayer perceptron neural network was used to train the model. This is a type of the feed forward
140 neural network. The multi-layer perceptron neural network is very powerful because it utilizes nonlinear activation
141 functions. In this model the sigmoid pole activation function was utilized. Equation ??.1 shows the mathematical
142 representation of the sigmoid transfer function. The output of the hidden layer are computed using the equation
143 stated in 3.2 $y_j(p) = \sum_{k=1}^n w_{jk}(p) \cdot f(x_{jk}(p))$ (3.2)

144 Where n is the number of inputs for the neuron j from the hidden layer, and f is the sigmoid activation function.
145 The outcome is then sent to the output layer to generate the final output of the system. The output layer using
146 the equation stated in 3.3 V.

147 8 Conclusion

148 The accuracy of medical diagnosis has lately been attributed to the advancement in technology and with the
149 advent of machine learning tools such as Artificial Neural Networks, Genetic Algorithm and Support Vector
150 Machines medical diagnosis became easier. Hepatitis B is a life threaten disease and if not diagnose early can
151 lead to death of the infected patient. In this project work a genetic neural system was designed to diagnoses
152 Hepatitis B virus. The system had a prediction accuracy of 99.14% on predicting Hepatitis B. ¹

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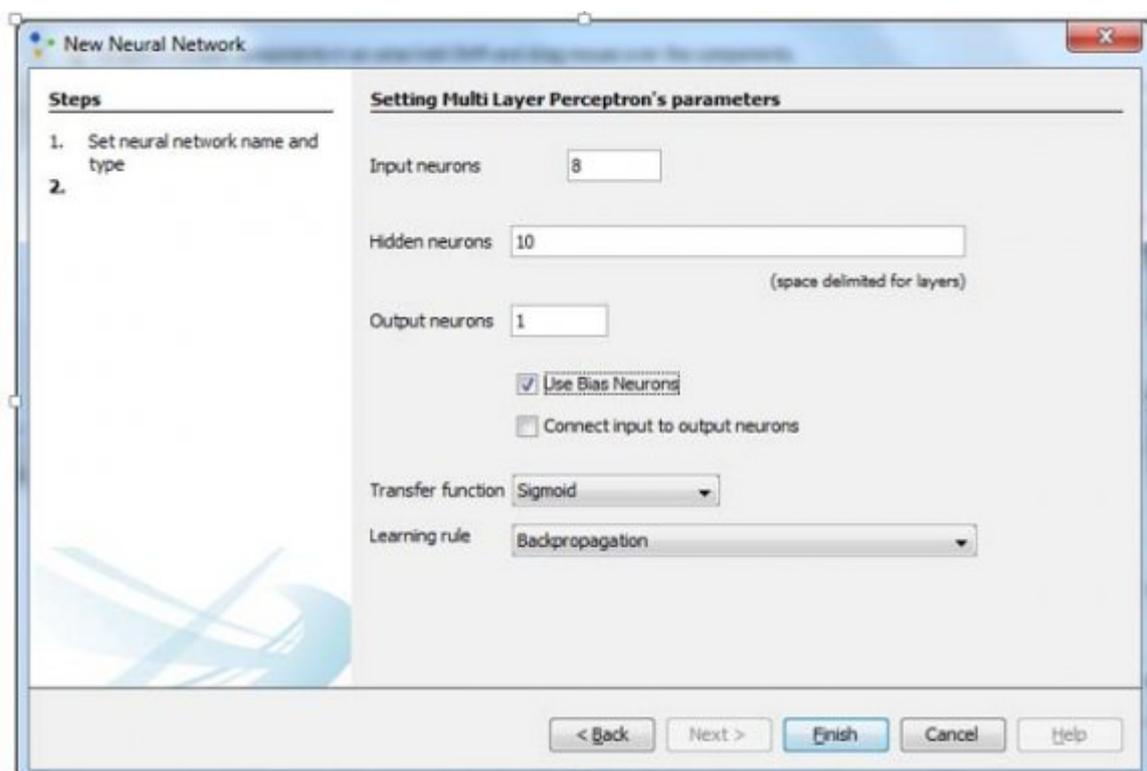
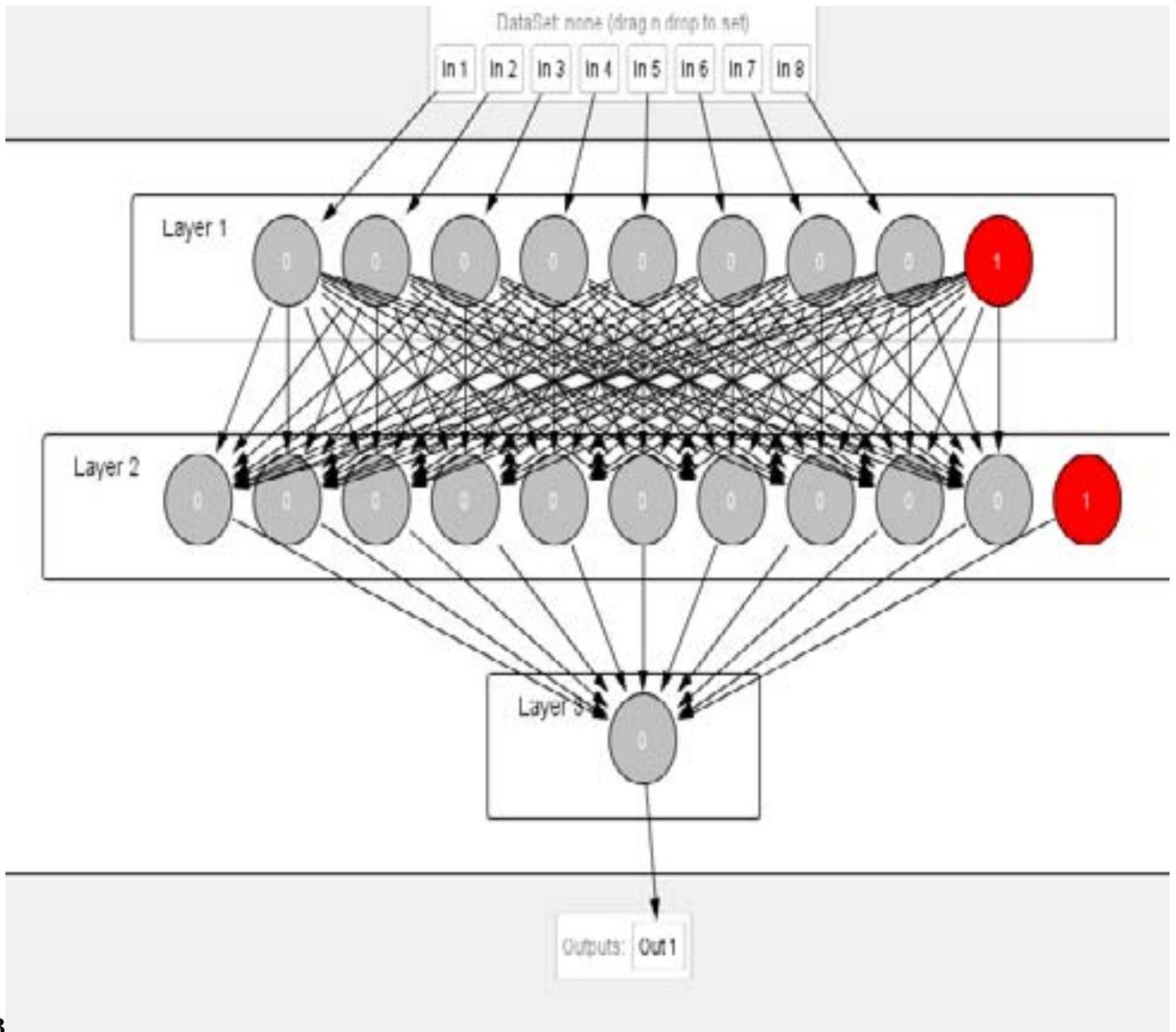


Figure 1:



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Figure 2: ? (3 . 3)

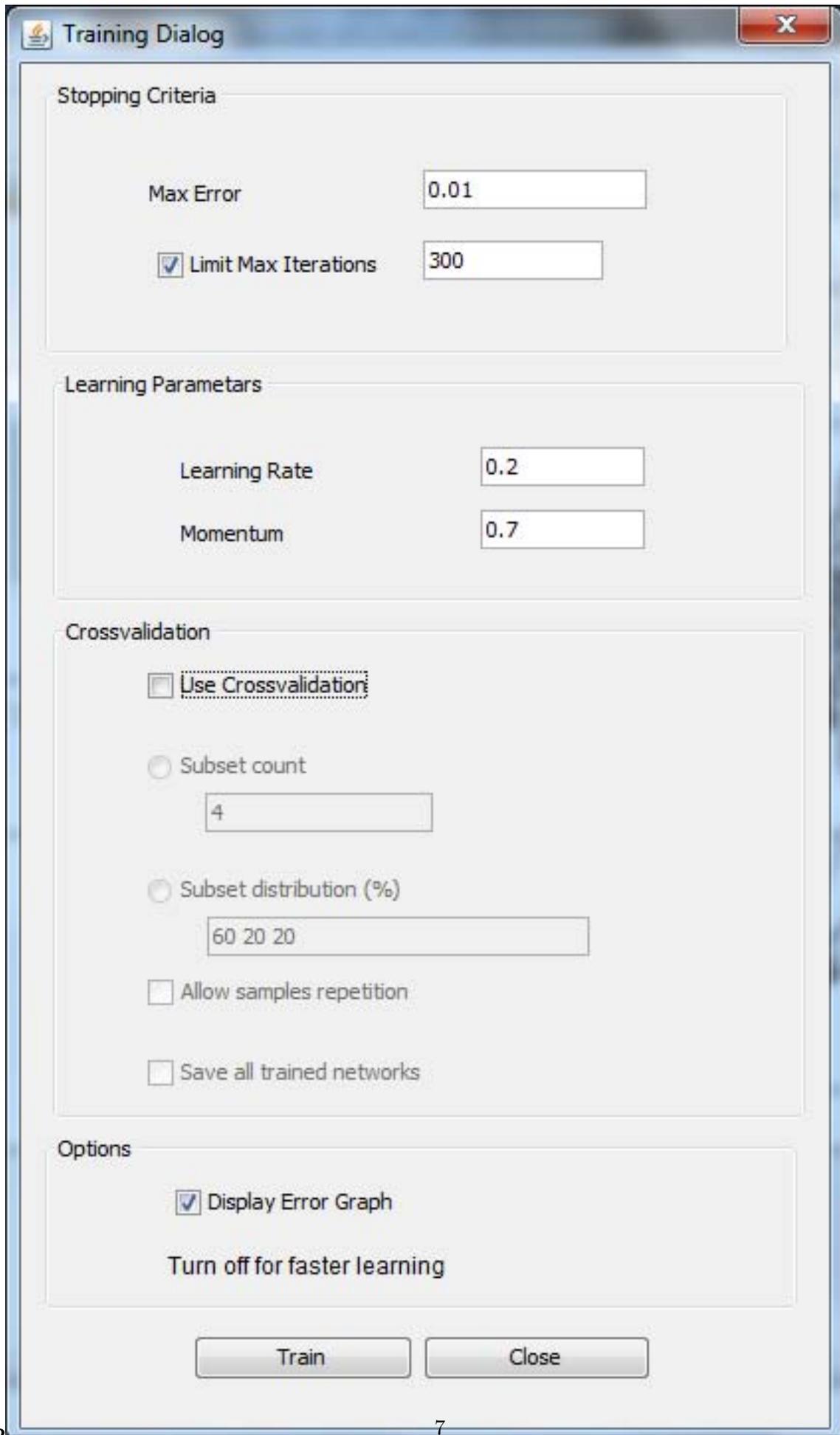
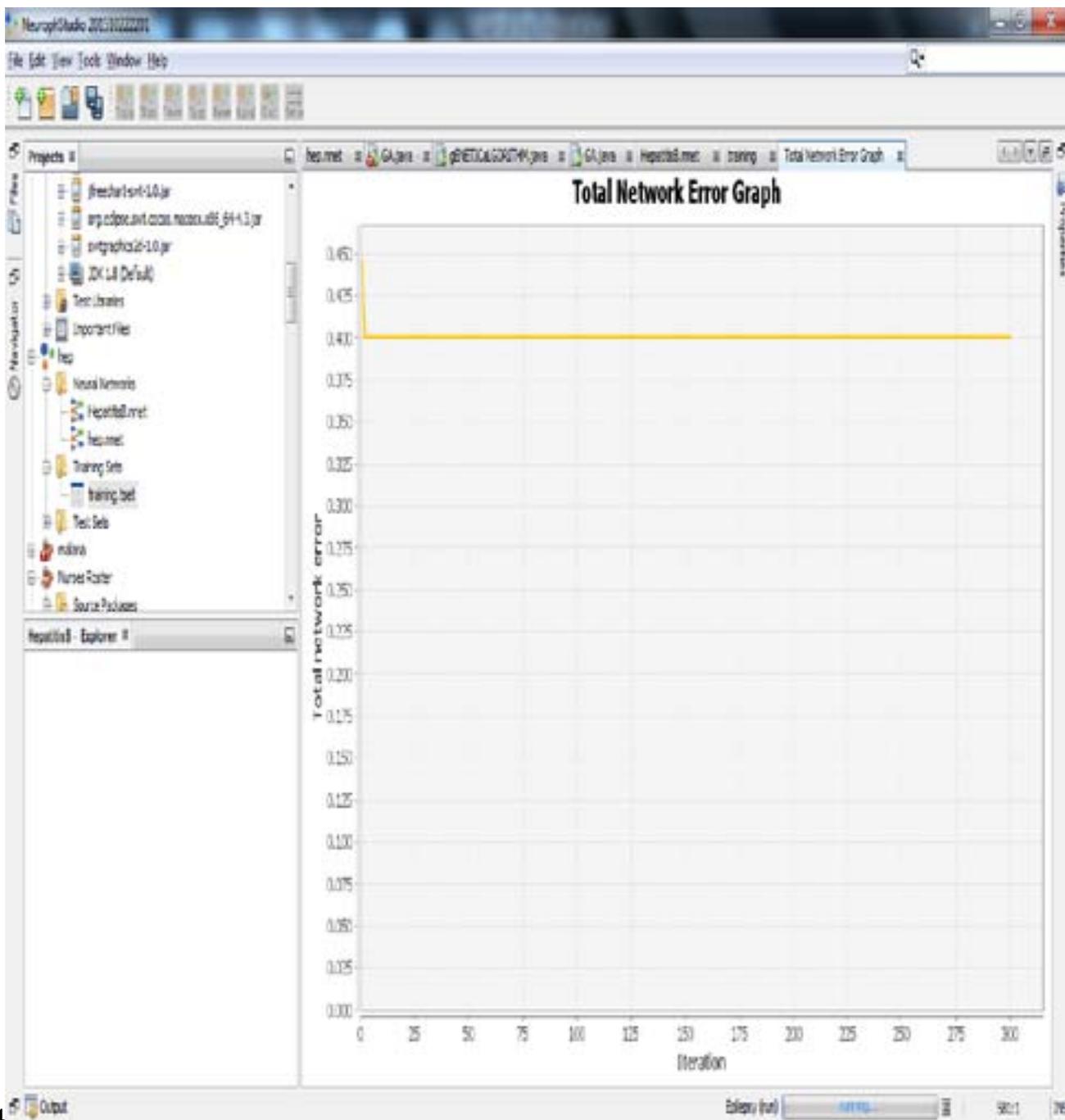


Figure 4: Figure 2 :



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Figure 5: Figure 3 :Figure 4 :

- 153 [American Journal of Computing and Engineering] , *American Journal of Computing and Engineering* 1 (1) p.
154 .
- 155 [Schroth and Hitchon] , Robert J; Schroth , Carol A Hitchon . Uhanova, Julia.
- 156 [Chen et al. ()] ‘A new hybrid method based on local fisher discriminant analysis and support vector machines
157 for hepatitis disease diagnosis’. H-L Chen , D-Y Liu , B Yang , Wang G Liuj . *Expert Systems with Applications*
158 2011. 38 (9) p. .
- 159 [Calisir and Dogantekin ()] ‘A new intelligent hepatitis diagnosis system: Pca-lssvm’. D Calisir , E Dogantekin .
160 *Expert Systems with Applications* 2011. 38 (8) p. .
- 161 [Khosro et al. ()] ‘A Novel Algorithm for Accurate Diagnosis of Hepatitis B and Its Severity’. R Khosro , H Javad
162 , R G Mohammad . *Crossover Operators for Genetic Algorithms to Solve the Job Shop Scheduling Problem*,
163 2014. 4 p. . (WSEAS transactions on computers)
- 164 [Bascil and Oztekin ()] ‘A study on hepatitis disease diagnosis using probabilistic neural network’. M S Bascil ,
165 H Oztekin . *MEDICAL SYSTEMS* 2012. 36 (3) p. .
- 166 [Mohammad et al. ()] ‘An Approach to Derive the Use Case Diagram from an Event Table’. I Mohammad , R
167 Muhairat , E Al-Qutasih . *Proceeding of the 8th WSEAS INT. Conference on Software Engineering*, (eeding of
168 the 8th WSEAS INT. Conference on Software Engineering) 2007. p. 185. (Parrallel and Distributed Systems
169 pp 179)
- 170 [Gulzar et al. ()] ‘Automated Diagnosis of Hepatitis B Using Multilayer Mamdani Fuzzy Inference System’. A
171 Gulzar , A K Muhammad , A Sagheer , A Atifa , S K Bilal , S A Muhammad . *Journal of Healthcare*
172 *Engineering* 2019.
- 173 [Yadav and Sohal ()] ‘Comparative Study of Different Selection Techniques in Genetic Algorithm’. L S Yadav ,
174 A Sohal . *International Journal of Engineering, Science and Mathematics* 2017. 6 (3) p. .
- 175 [Ruijing et al. ()] ‘Comparisons of forecasting for hepatitis in Guangxi Province, China by using three neural
176 networks models’. G Ruijing , C Ni , H Daizheng . 10.7717/peerj.2684. *PeerJ* 2016.
- 177 [Computer methods and programs in biomedicine ()] *Computer methods and programs in biomedicine*, 2011. p.
178 .
- 179 [Siew et al. ()] ‘Crossover and Mutation Operators of Genetic Algorithms’. M L Siew , B Abu , N Suliaman , M
180 Aida , K Y Leong . *International Journal of Machine Learning and Computing* 2017. 7 (1) p. .
- 181 [Mehdi and Mehdi ()] ‘Designing a Fuzzy Expert System of Diagnosing the Hepatitis B Intensity Rate and
182 Comparing it with Adaptive Neural Network Fuzzy System’. M Mehdi , Y Mehdi . *Proceedings of the World*
183 *Congress on Engineering and Computer Science* 2009. 2009.
- 184 [Mashesh et al. ()] *Diagnosing Hepatitis B Using Artificial Neural Network Based Expert System*, C Mashesh ,
185 V G Suresh , M Babu . 2013. IJEIT p. 144.
- 186 [Rahmon et al. ()] ‘Diagnosis of Hepatitis using Adaptive Neuro-Fuzzy Inference System (ANFIS)’. I B Rahmon
187 , O Olawale , F Kasail . *International Journal of Computer Applications* 2018. 180 (83) p. .
- 188 [Pushpalatha and Jadesh ()] *Framework for Diagnosing Hepatitis Disease using Classification Algorithms*, S
189 Pushpalatha , P Jadesh . 2016. 2189 p. 2195. (IJAR, 4)
- 190 [Who (2014)] *Hepatitis B Fact sheet*, Who . 2014. 4 March 2019.
- 191 [Noreddin et al. (2004)] ‘Hepatitis B vaccination for patients with chronic renal failure’. Ayman M; Noreddin ,
192 Taback , P; Shayne , Moffatt , ; Michael , James M Zacharias . 10.1002/14651858.CD003775.pub2. 15266500.
193 *Cochrane Database of Systematic Reviews* 19 July 2004. (3) p. D003775.
- 194 [Shepard et al. ()] ‘Hepatitis B virus infection: Epidemiology and vaccination’. C W Shepard , E P Simard , L
195 Finelli , A E Fiore , B P Bell . 10.1093/epirev/mxj009. 16754644. *Epidemiologic Reviews* 2006. 28 p. .
- 196 [Polat and Gunes ()] ‘Hepatitis disease diagnosis using a new hybrid system based on feature selection (fs) and
197 artificial immune recognition system with fuzzy resource allocation’. K Polat , Gunes . *Digital Signal Processing*
198 2006. 16 (6) p. .
- 199 [Sartakhti et al. ()] *Hepatitis disease diagnosis using a novel hybrid method based on support vector machine and*
200 *simulated annealing*, J S Sartakhti , M H Zangooei , K Mozafari . 2011. SVM-SA.
- 201 [Inference and Generalized Regression Neural Networks IEEE International Advance Computing Conference ()]
202 ‘Inference and Generalized Regression Neural Networks’. *IEEE International Advance Computing Conference*,
203 2009. (IACC 2009)
- 204 [Jorge ()] M M Jorge . *A Comparative Study of*, 2013.
- 205 [Ogah et al. ()] *Knowledge Based System Design For Diagnosis of Hepatitis B Virus (Hbv) Using Generalized*
206 *Regression Neural Network (GRNN)*, U S Ogah , P B Zirra , O Sarjiyus . 2017.

8 CONCLUSION

- 207 [Riudiger and Brause ()] ‘Medical Analysis and Diagnosis by Neural Networks’. W Riudiger , Brause . *Proceedings*
208 *of Medical Data Analysis*, (Medical Data Analysis Paulo Novais, Luis Nelas, Moreira Maia and Victor Ribeiro)
209 2001. Victor Alves. 20 p. .
- 210 [Amadin and Bello ()] ‘Prediction of Yellow Fever using Multilayer Perceptron Neural Network Classifier’. F
211 Amadin , M E Bello . *Journal of Emerging Trends in Engineering and Applied Sciences* 2018. 5 (3) p. .
- 212 [Mohammed et al. ()] ‘SS-SVM (3SVM): A New Classification Method for Hepatitis Disease Diagnosis’. H A
213 Mohammed , H Abdel-Rahman , H A Taysir , B M Yousef . *International Journal of Advanced Computer*
214 *Science and Applications* 2013. 4 (2) p. .
- 215 [Chen and Gluud (2005)] ‘Vaccines for preventing hepatitis B in health-care workers’. W; Chen , C Gluud .
216 10.1002/14651858.CD000100.pub3. 16235273. *The Cochrane Database of Systematic Reviews* 19 October 2005.
217 (4) p. D000100.