IMPLEMENTING THE MEDICAL RESEARCH PAPER BY USING ARTIFICIAL NEURAL NETWORK

Analysis of Cardiotocogram Data for Fetal Distress Determination

Although the research uses the decision tree technique in implementing the above mentioned we will be using deep learning model in predicting the outcome...

Sample Code For Study:

```
library(keras)
## read the data by using file.choose ##
data <- read.csv(file.choose(),header=T)
str(data) ## to see the structure of the data
## changing the data into matrix ##
data <- as.matrix(data)
dimnames(data) <- NULL # to remove any default names from the data
#
##### NORMALIZATION OF THE DATA SET ######
## this is done in order to make data lie on between '0' and '1'##
data[,1:21] \leftarrow normalize(data[,1:21])
data[,22] \le as.numeric(data[,22])-1
##### DATA PARTITIONING #####
set.seed(1234)
ind <- sample(2,nrow(data), replace=T,prob=c(0.7,0.3)) ## splitting the data into '1' and '2'
with weights into 0.7 and 0.3 or we say 70% and 30% ##
training <- data[ind==1, 1:21]
testing \leftarrow data[ind==2, 1:21]
trainingtarget <- data[ind==1, 22]
testingtarget <- data[ind==2, 22]
###### ONE HOT ENCODING ######
## classification of classes into 0 1 2 3 ..... using 0 and 1 which the class
## lying within that category is given 1 otherwise 0 ##
trainlabel <- to categorical(trainingtarget)</pre>
testlabel <- to categorical(testingtarget)
###### SEQUENTIAL MODELLING ######
```

```
model <- keras model sequential()
model %>% # piped function --- takes information from left side and passes it onto the right
side
layer dense(units=8, activation='relu',input shape = c(21)) %>%
layer dense(units=8, activation='relu')%>%
layer dense(units=8, activation='relu')%>%
layer dense(units=3, activation='softmax')
summary(model)
#
###### COMPILING THE MODEL ######
model %>%
   compile(loss='categorical crossentropy',
       optimizer='adam',
       metrics='accuracy')
###### FITTING THE MODEL FOR LEARNING ######
history <- model%>%
      fit(training,
       trainlabel.
        epoch=10,
        batch size=32,
        validation split=0.2)
##MODEL EVALUATION USING TEST DATA##
test model <- model %>% evaluate(testing,testlabel)
##CONFUSION MATRIX ANALYSIS OF TEST DATA##
prob <- model %>% predict proba(testing)
pred <- model %>% predict classes(testing)
confusion matrix <- table(Predicted = pred, Actual = testingtarget)
cbind(prob , pred , testingtarget)
##
##FINE TUNE THE MODEL##
test model
confusion matrix
```

Required Outputs

1) Structure of the dataset:

Out of these 22 observational variables we have 21 numerical data and the last one (22^{nd}) as the NSP or categorical data which will be crucial for classifying the test data

```
2126 obs. of 22 variables:
$ LB
          : int
                 120 132 133 134 132 134 134 122 122 122 ...
$ AC
                 0 0.00638 0.00332 0.00256 0.00651 ...
          : num
$ FM
                 0 0 0 0 0 0 0 0 0 0 ...
          : num
$ UC
                 0 0.00638 0.00831 0.00768 0.00814 ...
          : num
$ DL
                 0 0.00319 0.00332 0.00256 0 ...
            num
$ DS
                 0 0 0 0 0 0 0 0 0 0 ...
            num
$ DP
                 00000...
          : num
 ASTV
           int
                 73 17 16 16 16 26 29 83 84 86 ...
$ MSTV
          : num
                 0.5 2.1 2.1 2.4 2.4 5.9 6.3 0.5 0.5 0.3 ...
$ ALTV
                 43 0 0 0 0 0 0 6 5 6 ...
          : int
$ MLTV
                 2.4 10.4 13.4 23 19.9 0 0 15.6 13.6 10.6 ...
          : num
$ Width
                 64 130 130 117 117 150 150 68 68 68 ...
          : int
$ Min
                 62 68 68 53 53 50 50 62 62 62 ...
           int
$ Max
                 126 198 198 170 170 200 200 130 130 130 ...
           int
$ Nmax
                 2 6 5 11 9 5 6 0 0 1 ...
           int
$ Nzeros
                 0 1 1 0 0 3 3 0 0 0 ...
           int
                 120 141 141 137 137 76 71 122 122 122 ...
$ Mode
           int
$ Mean
                 137 136 135 134 136 107 107 122 122 122 ...
           int
                 121 140 138 137 138 107 106 123 123 123 ...
$ Median
           int
                 73 12 13 13 11 170 215 3 3 1 ...
$ Variance: int
                 1001100111...
$ Tendency: int
                 2 1 1 1 1 3 3 3 3 3 ...
$ NSP
          : int
```

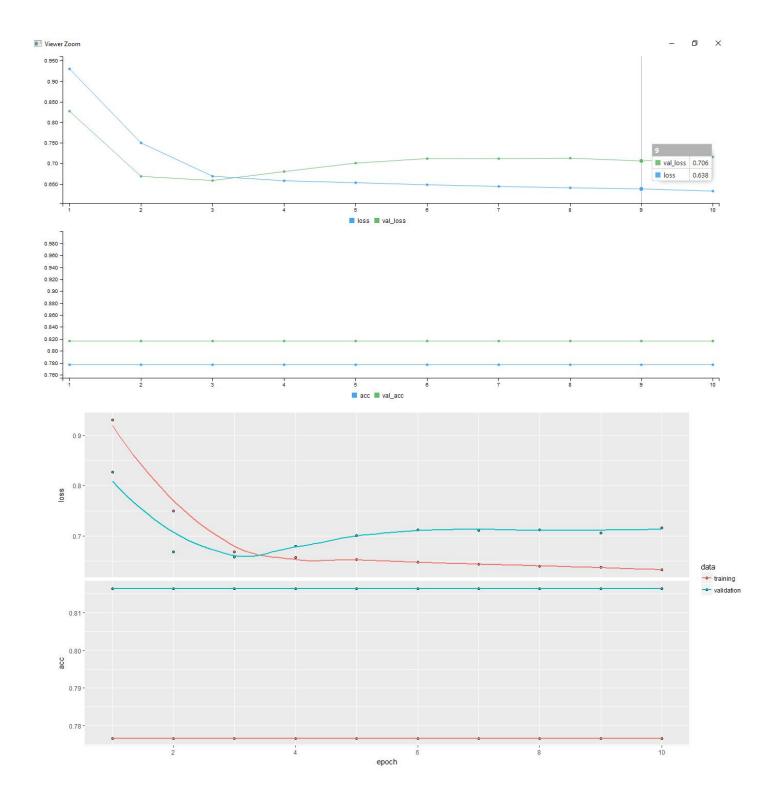
2) Structure of the neural network model

```
Layer (type)
                                                     Output Shape
          Param #
dense_1 (Dense)
                                                     (None, 8)
          176
dense_2 (Dense)
                                                     (None, 8)
          72
dense_3 (Dense)
                                                     (None, 8)
          72
dense_4 (Dense)
                                                     (None, 3)
          27
Total params: 347
Trainable params: 347
Non-trainable params: 0
```

3) Hereon we will be seeing the output of the trained network and its output on various epochs—some considerations are as follows: activation function at the hidden layer is *ReLu*, activation function at the output is *Sigmoid*, optimizer is *ADAM* and we have loss as *categorical cross-entropy*

a) Number Of Epochs = 10

Training Accuracy and Loss:-



pred testingtarget // this is basically the classification of the testing data into ca tegories namely N(normal) , S(suspect) , P(pathological)//

F4 7	0.0100500	0 4045000	0 04604070	•	•
[1,]			0.04624378	0	0
[2,]	0.7961514	0.1490243	0.05482430	0	0
[3,]	0.8167875	0.1361584	0.04705412	0	0
[4,]			0.11354441	0	2
			0.11479316		2
[5,]				0	2
[6,]			0.03989100	0	1
[7,]	0.8278462	0.1293107	0.04284315	0	0
[8,]		0.1363321	0.04707028	0	0
[9,]			0.05087535	Ö	0
				-	
[10,]	0.84//290		0.03568922	0	0
[11,]	0.8510496		0.03388818	0	1
[12,]	0.7630237	0.1695594	0.06741689	0	0
[13,]		0.1360677	0.04646830	0	0
[14,]			0.05575707	Ö	0
			0.06816878	0	0
[16,]			0.04901482	0	0
[17,]	0.8146966	0.1381748	0.04712864	0	0
[18,]		0.1336643	0.04516934	0	0
			0.04313993	Ö	Ö
			0.03799614	0	1
			0.08565662	0	1
[22.]	0.8145925	0.1374473	0.04796017	0	0
			0.04539988	0	0
			0.04947359		Ö
			0.04366616	0	0
[26,]	0.8406563	0.1219606	0.03738302	0	2
[27,]	0.7724525	0.1627864	0.06476122	0	0
Ī28 Ī	0 7875632	0 1553209	0.05711601	0	0
[29,]	0.7573032	0.1333203	0.06873526	Ö	Ö
[30,]			0.06949496	0	0
[31,]			0.04392590	0	0
[32,]	0.7690958	0.1664320	0.06447217	0	0
[33,]			0.04931199	0	0
[34,]		0.1415607		Ö	Ö
[35,]	0.8090619		0.04913053	0	1
[36,]			0.03407443	0	0
[37,]	0.8045968	0.1445093	0.05089384	0	0
[38,]		0.1443592	0.05065272	0	0
[39,]			0.05001321	Ö	Ö
[40,]			0.07018334	0	0
		0.1778071	0.07494207	0	0
[42,]	0.8108293	0.1408888	0.04828193	0	0
		0.1865705	0.08058023	0	0
			0.05899391	Ö	0
[77,] [45]	0.7030073	0.1333210	0.03033331		
[43,]	0.8123661	0.1392788	0.04835503	0	0
			0.03066481	0	0
[47,]	0.7921520	0.1517358	0.05611222	0	0
			0.04939802	0	0
			0.05300760	Ö	1
[1 3,]	0.0003143	0.1404701	0.03300700		
			0.05325122	0	1
[51,]	0.7778296	0.1607458	0.06142469	0	1
Γ52 . 1	0.7796027	0.1594659	0.06093136	0	0
[̃53,́]	0 7808071	0 1590572	0.06013574	0	1
[54,]	0.7030071		0.05560741	Ö	1
[55,]			0.05474891	0	0
[56,]			0.07666215	0	0
[57,]	0.7300381	0.1879021	0.08205976	0	0
[58,]			0.07401697	0	0
			0.06428177	Ö	Ö
[50,]	0.7777463	0.1003713	0.0072017		
[00,]	0./0/0402	0.1001033	0.06596450	0	0
			0.06328920	0	1
[62,]	0.7963328	0.1494886	0.05417855	0	0

			0.06079886 0.06398965	0	0
[65,]	0.7616735	0.1699901	0.06833642	0	0
[66,] [67,]			0.07457235 0.10291921	0 0	0 1
[68,]			0.07662555	0	1
[69,]			0.05587953	0	0
[70,] [71,]			0.05154057 0.06861195	0 0	0 1
[72,]	0.8147402	0.1374263	0.04783344	0	0
[73,] [74,]			0.05840516 0.05999999	0 0	0
[75,]			0.06613730	0	0
[76,]			0.06244026	0	0
[77,] [78,]			0.07129454 0.05542744	0 0	0
[79,]	0.7836518	0.1565428	0.05980542	0	0
[80,]			0.05742206 0.08518227	0 0	0 1
[82,]			0.04792388	0	0
[83,]	0.7641763		0.06502738	0	1
[84,] [85,]			0.08992732 0.08133484	0 0	1 1
[86,]			0.08293275	Ö	1
[87,]			0.09648787	0	2
[88,] [89.]			0.07144007 0.09678880	0 0	1 2
[90,]	0.7403982	0.1836342	0.07596764	0	1
[91,] [92,]			0.08262859 0.08825041	0 0	1 1
[93,]			0.08800627	0	1
[94,]			0.07442641	0	1
[95,] [96,]			0.06831843 0.11278021	0 0	1 2
[97,]	0.7364257	0.1862894	0.07728484	0	1
[98,] [99,]			0.09213055 0.10276470	0 0	1 2
[100,]			0.10276476	0	1
[101,]	0.7450772		0.07465584	0	1
[102,] [103,]			0.04918009 0.05542844	0	1 0
[104,]	0.7820986	0.1580074	0.05989399	0	0
[105,] [106,]			0.10611378 0.07275268	0 0	2 1
[107,]			0.07126606	0	1
[108,]			0.07050546	0	1
[109,] [110,]			0.07298037 0.06769655	0 0	1 1
[111,]	0.7994208	0.1481813	0.05239793	0	1
[112,] [113,]			0.05285915 0.02859097	0 0	0
[114,]			0.06803633	0	0
[115,]	0.7231676	0.1933017	0.08353066	0	1
[116,] [117,]			0.07071458 0.07978050	0 0	1 1
[118,]	0.7302606	0.1893500	0.08038949	0	2
[119,] [120,]			0.07999299 0.06192193	0 0	1 1
[120,]			0.07019388	0	1
[122,]	0.7652016	0.1681137	0.06668465	0	1
[123,] [124,]			0.05056927 0.06613935	0 0	0 1
[125,]	0.7726092	0.1639347	0.06345610	0	1
[126,] [127,]			0.06164753 0.05848721	0 0	1 0
[127,]			0.06298313	0	0
[129,]	0.8321033		0.04027634	0	1
[130,]	U.84368/2	0.1105/94	0.03573348	0	1

F434 7	0 0070006	0 1424706	0.04053606	•	•
			0.04952686	0	0
[132,]			0.04965812 0.05236570	0 0	0 1
_ /_			0.05911729	0	1
			0.07996649	0	1
			0.05631088	0	0
_ , _			0.04631469	Ö	ŏ
			0.07248289	Ö	Ö
			0.07315527	Ö	0
- /-			0.08803201	0	1
	0.7738408	0.1640424	0.06211675	0	2
	0.7386786	0.1847438	0.07657763	0	2
			0.06021107	0	1
- /-			0.04791367	0	0
			0.04792029	0	0
			0.05094925	0	0
			0.03645806	0	0
			0.03887392	0	0
			0.04246755 0.04426674	0	0
			0.04665997	0 0	0
			0.04702384	0	0
			0.04701989	0	0
			0.04677626	Ö	ő
- /-			0.04648969	Ö	Ö
			0.05304229	Ö	0
			0.05586819	Ō	0
			0.06095053	0	0
	0.8300359	0.1281536	0.04181049	0	0
			0.04323001	0	0
			0.05967627	0	1
			0.05445107	0	0
[163,]			0.06154398	0	1
[164,]			0.05013143	0	0
[165,]			0.07169068	0	1
			0.06805811	0	1 1
			0.06781531 0.06795300	0 0	0
[169,]			0.00793300	0	1
[170,]			0.03375737	0	0
			0.04241800	Ö	Ö
			0.03440237	0	0
			0.04062070	0	0
			0.04319243	0	0
	0.8361557	0.1243105	0.03953382	0	0
			0.04824233	0	0
			0.04411837	0	0
_ / _			0.03582739	0	0
			0.07252484	0	0
			0.07108195 0.04968310	0	0
_ , _			0.04966310	0 0	0
			0.04454417	0	0
			0.04548859	0	0
			0.04764506	Ö	ő
			0.04474430	Ö	Ö
[187,]			0.04269938	0	0
[188,]			0.05620039	0	0
	0.8259712	0.1310938	0.04293486	0	0
			0.04819880	0	0
			0.04867946	0	0
			0.05119938	0	0
- /-			0.04729089	0	0
- /-			0.04337973	0	0
- /-			0.05236342	0	0
			0.04727621 0.04188794	0 0	0
			0.04188794	0	1
[+ 2 0 ,]	3.000077	3.2130003	0.03370377	J	1

\$loss

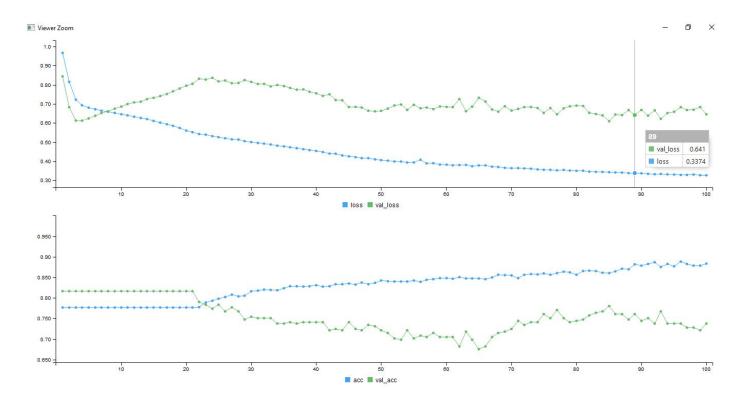
[1] 0.6810004

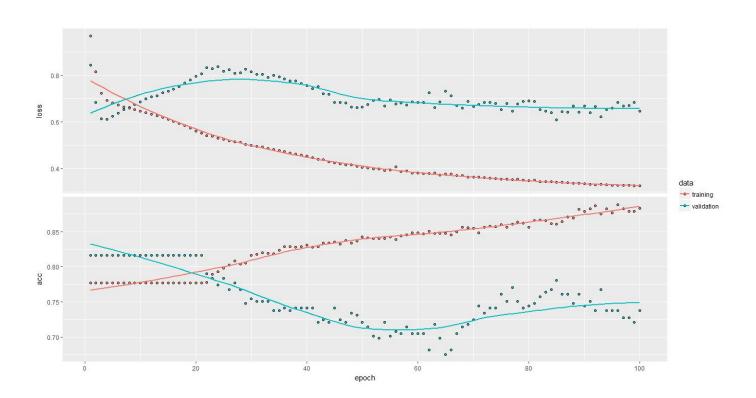
\$acc

[1] 0.7628524

b) Number Of Epochs = 100

Training Accuracy and Loss





\$loss

[1] 0.3940792

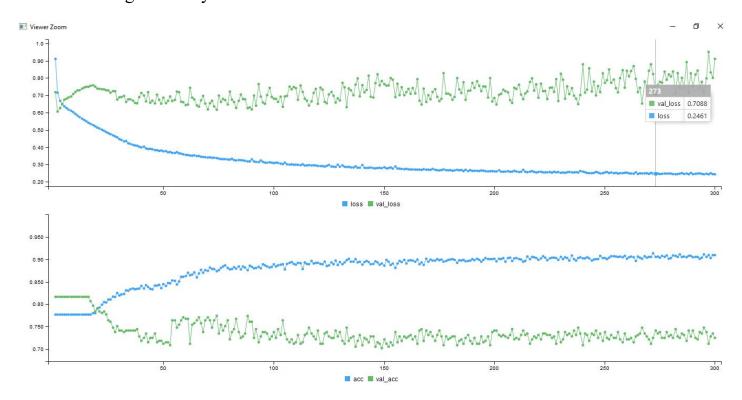
\$acc

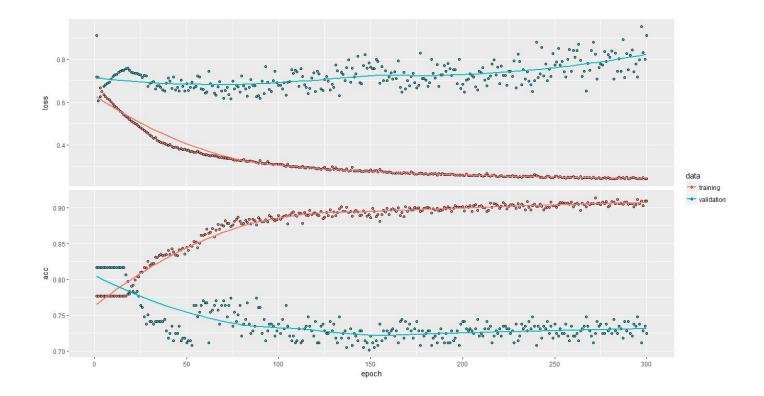
[1] 0.8557214

confusion_matrix

c) Number Of Epochs = 300

Training Accuracy and Loss





\$loss[1] 0.3794846

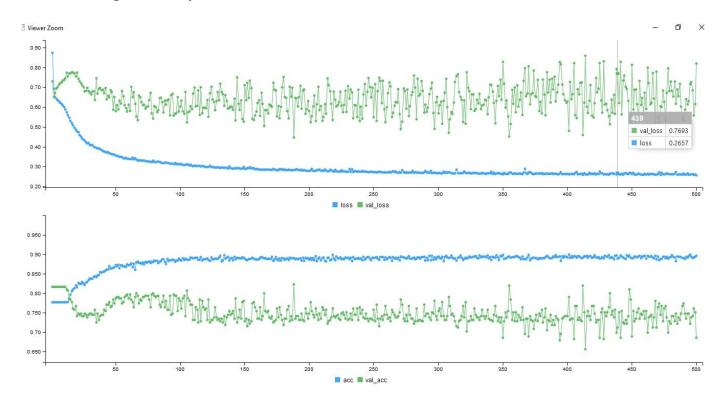
\$acc

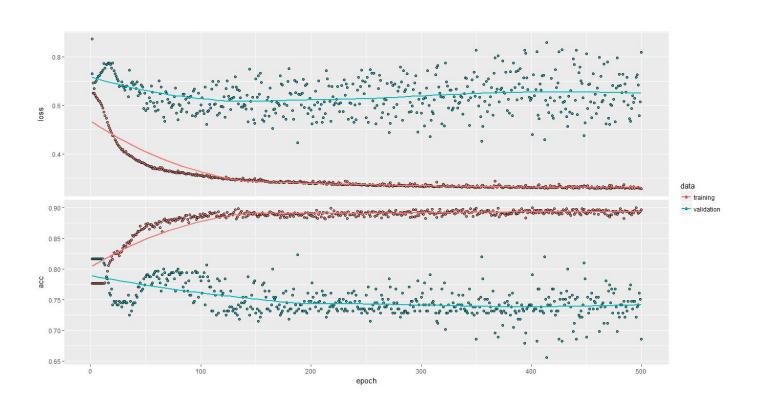
[1] 0.8756219

confusion_matrix Actual Predicted 0 0 420 17 1 2 34 67 10 6

d) Number Of Epochs = 500

Training Accuracy and Loss





CONCLUSION:

The above observation gives us an insight into a very important feature that the accuracy and loss improves with the increment of epochs because it trains well with increase in the number of iteration.

On reaching 500 epochs the accuracy and loss has somewhat become constant and thus it is u nable to achieve further improvement.