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Enhanced Classifier Accuracy in Liver Disease Diagnosis using a Novel Multi Layer Feed Forward Deep Neural Network

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Abstract: ***Classification techniques are often used for predicting Liver diseases and assist doctors in early detection of liver diseases. As per studies in the past and our experiments, conventional classification algorithms are found to be less accurate in predicting liver diseases. Therefore, there is a need for sophisticated classifiers in this area. For many medical applications, including Liver Diseases, Deep Neural Networks (DNNs) are used but the accuracies are not satisfactory. Deep Neural Network training is a time taking procedure, particularly if the hidden layers and nodes are more. Most of the times it leads to over fitting and the classifier does not perform well on unseen data samples .We, in this paper, tuned a Multi Layer Feed Forward Deep Neural Network (MLFFDNN) by fitting appropriate number of hidden layer and nodes, dropout function after each hidden layer to avoid over fitting, loss functions, bias, learning rate and activation functions for more accurate liver disease predictions. We used a balanced data set containing 882 samples. The data is collected from north coastal districts of Andhra Pradesh hospitals, India. The training process is carried out for 400 epochs and finally It is .observed that our model exhibited 98% accuracy at epoch 363 which is more than the performance of Neural Network models tuned till now by machine learning researchers and also some regularly used classification algorithms like Support Vector Machines (SVM), Naive Bayes (NB), C4.5 Decision Tree, Random Belief Networks and Alternating Decision Trees (ADT) .***

Index Terms: ***Classification, Deep Neural Networks, Feed Forward Neural Network, Liver Disease, Prediction***.

I. INTRODUCTION

As per 2017 World Health Organization reports, deaths caused by Liver Diseases in India touched 259,749 and it is 2.95% of total deaths and stands 63rd rank in the world.. Liver disease is the tenth most usual reason for deaths in India as per the studies of World Health Organization. Liver Cirrhosis is the 14th chief reason for deaths and could be the 12th primary reason for deaths by 2020. It is a difficult task to identify Liver disease at the initial stage because the liver functions in a normal manner, even though it is partly damaged. In this scenario, automatic diagnosis tools will support the doctors a lot for timely detection of the disease and improves the patients' survival rate. Conventional classification methods are used frequently in many automatic medical diagnosis tools which are less accurate. Hence there is a need for sophisticated classifiers for more accurate predictions.

Neural Network training is a type of supervised learning in which the network is trained using a set of labeled samples called training data. A multilayer Feed Forward Neural Network has one input layer, one or more hidden layers and one output layer Deep Neural Network are networks with more than one hidden layer Multilayer Feed Forward Neural Networks can represent a wide variety of nonlinear functions. It uses back propagation technique and learns a set of weights iteratively for prediction of the class label of the unlabelled samples. In these networks, the output of one layer is fed forward into the next layer. The layers are fully connected with no diffident connections. Normally, number of input units and output units are decided as per nature of the problem. However, deciding the correct number of hidden units needs experimentation and time consuming task. If the number of hidden units are too less, the required function can be learnt. At the same time, too many hidden units may lead to over fitting of the training data. Every connection has a weight assigned to it. In addition, there is a special weight known as bias which goes into every node at the hidden layer and threshold value that feeds into every node at the output layer. To start with, small random values close to zero are used as weights. During training of the network, these weights are refined using the back propagation algorithm so that the output by the network matches the expected output. Neural Network training is done iteratively, wherein we repeatedly present the network with an example, compare the output of this example with the desired output and modify the weights in the network with back propagation algorithm to produce better output next time. [23] As the network is trained repeatedly with more and more samples and weights are updated using the back propagation algorithm, the network learns to give the correct prediction. Training the network at least once on every sample of the training data is called as an epoch. In general, the network is trained for many epochs till it converges i.e. we get the right prediction for the input data. The back propagation algorithm uses gradient descent to update the weights so that the squared error between the network output and the expected output reduced.

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The weights are adjusted by computing the partial derivative of the error function with respect to the weights to decide contribution of each weight to the error. This process is repeated for every layer of the network, starting with the last set of weights till input layer.

II. RELATED WORK

Choi, K. J., Jang et.al [1] built up a CT-based DLS for staging of liver fibrosis by utilizing a dataset containing CT images of 7461 liver fibrosis patients of portal venous phase. The working of the DLS was assessed on a test data set containing 891 Patients. The impact of patient qualities and CT strategies on the accuracy of the DLS was assessed by logistic regression. Using a subset of 421 patients, the performance of the DLS was compared with the results of the radiologist, Aminotransferase-To-Platelet Ratio Index (APRI) as well as fibrosis-4 index by using Area under the Receiver Operating Characteristic Curve (AUROC) with Obuchowski index. ***T***he DLS exhibited an accuracy of 79.4% .The AUROC is 0.96, 0.97 and 0.95 for diagnosing major Fibrosis, extremely developed Fibrosis and Cirrhosis correspondingly on the test data sets. At multivariable analysis, merely pathologic fibrosis stage drastically influenced the performance accuracy of the DLS, where as etiology of liver disease and CT technique did not affect.

Rafiei, S. et.al [2] proposed a competent liver segmentation with 3D to 2D fully convolution network (3D-2D-FCN) for automatic organ segmentation in accidental and emergency situations .The segmented mask was better when the conditional random field on the boundary of the organ was used. They could fragment the target liver with 93.52% Dice score.

Reddy, D. S. et.al [3] proposed a new CAD using CNN and transfer learning for improving the accuracy of classifying Fatty and normal Liver ultrasound images. Fatty Liver Disease (FLD), if not treated in time, can lead to serious persistent diseases like fibrosis, liver cancer and cirrhosis and may lead to eternal liver malfunction. Ultrasound scanning is used by doctors as the main source to quantify the fat accumulation in liver tissues as well as to classify the FLD into regular and irregular. But, the diagnostic precision depends on the talent and ability of the radiologist. With the use of Computer Aided Diagnosis (CAD) techniques, the accuracy in predicting FLD using the ultrasound can be improved a lot. Moreover, the CAD will help the radiologists to treat more patients in less time. Performance studies show that their proposed model gave FLD classification accuracy of 90.6%.

Tai .S. K. et.al [4] used deep learning technique and developed a grading system to assess the segmentation of liver nucleus. The objective here is to grade nucleus segmented images by using cancer biopsy images. However, complicated stoma backdrop will degrade the performance of segmentation. If the unsuccessful segmentation can be eliminated from the grading method, it will drastically improve the grading precision . The investigational results show that the performance of their method is 90.5%.

Fatima M. et.al [5] compared the results of a variety of classification algorithms for diagnosis of diverse diseases like Diabetes, Heart disease, Dengue, Liver and Hepatitis. They observed that SVM exhibited better accuracy of 94.60%. Naïve Bayes precisely diagnosed diabetes diseases and gave highest classification accuracy of 95%. The FT algorithm had shown 97.10% accuracy for predicting liver diseases. 100% classification accuracy is exhibited by RS theory in predicting dengue disease.

Liu, X. et.al [6] proposed a computer-assisted cirrhosis diagnosis system by means of ultrasound images by extracting a liver capsule from an ultrasound picture. They fine-tuned a deep Convolution Neural Network (CNN) which extracted features from the patches found in the region of the liver capsules. Finally, they applied a trained Support Vector Machine (SVM) for classifying the samples into normal or abnormal cases. It was observed that their technique successfully extracted the liver capsules and precisely classified the ultrasound images. In-Yu Jin et al., [7] proposed a Convolution Neural Network (CNN) to predict the liver diseases. The low accuracy problem of traditional Convolution Neural Network is overcome by fusing with Random Forests using Ensemble methods. They have used RF as the base classifier. The ensemble method is opted as the majority voting method. The CT images in 3D-IRCAD dataset are used for the experiment. CNN + Ensemble learning gave 98.6% classifier accuracy. Yidong Liu et.al. [8]) used backward propagation technique and proposed a stochastic computational multi-layer perceptron though it gave less accurate results and execution speed; it is advantageous to implement artificial neural networks with lesser hardware and lower power utilization. In conventional implementations, weights of the layers are pre determined hence they cannot update layer weights in artificial neural networks. Both Training and inference process can also be implemented with their design. The SC-MLP circuit a hybrid network structure consisting of conventional SC and ESL (Extended Stochastic Logic) circuits and more efficient. They had shown that their SC-MLP could classify problems by implementing various activation functions, adjusting the network structure and by altering the layer weights. Their proposed design succeeded in obtaining lower area consumption of energy compared to a binarized neural network. When compared to the similar implementations of fixed and floating point, the SC-MLP is more advantageous.

S. Pushpalatha et.al.[9] proposed a structure for diagnosing the Hepatitis disease. They clubbed Robust BoxCox Transformation (RBCT) and Neural Network (NN) models. They obtained an improved accuracy of 97.07% using RBCT-NN algorithm. They used Indian Liver Patients dataset for their experiment. To uncover the normality of the dataset, their framework scales the dataset in the beginning. Then the linearity of the dataset is estimated using different regression techniques. Their proposed model not only categorizes the disease types but also finds the rigorousness of the disease.

Dong Xu et al.[10]proposed a combination model based on LMBP neural network & Rough Set (RS). They chose Neural Network with Back Propagation for an early diagnosis for liver lesions.

The BP Neural Network has restrictions due to slow convergence speed. So, they used LM (Levenberg-Marquardt) algorithm, to improve the convergence speed and make it stronger.Also, usage of rough set theory reduces the training data of LMBP neural network because it discovers the redundant information. Medical CT liver images collected from hospitals were given as input. RS_LMBPNN had shown an accuracy of 96.67% whereas with conventional LMBPNN, the accuracy is only 90%.

Xin-Yu Jin et al.[11] proposed an advanced Back Propagation Neural Network for finding of liver diseases. The usual Back Propagation Neural Network has a problem of taking more time for getting trained and obtaining a local optimum. The back propagation neural network was improved using self-adaptive learning rate and thus speeding up the training process. Liver CT images obtained from a hospital in China were given as input. Improved BPNN had given a precision of 94.6%.

Mehdi Neshat et al. [12] worked towards diagnosing liver disorders accurately by using Fuzzy Hopfield Neural Network and Hopfield Neural Network. They collected the liver diseases dataset from the UCI machine learning repository. Hopfield Neural Network exhibited 88.2% accuracy and where as Fuzzy Hopfield Neural Network gave an accuracy of 92%.

Sangman Kim et al.[13] designed a constructive technique for recognition of liver cancer based on Neural and fuzzy Neural Networks. They had collected clinical data of 400 Liver cancer patients and used a super computer in the process. They were able to detect liver cancer with an accuracy of 96.19% when they used 132 parameters basing on neural network and with precision of 97.19% when they used 226 parameters which are based on the fuzzy neural networks.

C.Mahesh et al. [14] devised an Expert System based on Generalized Regression Neural Network (GRNN) to aid Hepatitis B virus identification. Their proposed system could classify every patient as whether infected or not infected. It could also tell the rigorousness of the infection, in case, a particular patient was infected. They achieved an accuracy of 94%.

Table I: Literature review on applications of Neural Networks on Liver Diseases

Authors	Contribution	Area Of Application	Year
Choi, K.J., Jang et.al	DLS ,79.4% accuracy	Liver Fibrosis	2018
Reddy, D. S. et.al	CAD using CNN ,90.6% accuracy	Fatty liver diseases	2018
Tai .S. K. et.al	DNN, 90.5%	Segmentation of Liver nucleus	2018
S.Pushpalatha et.al	RBCT-NN,97.7%	Hepatitis disease	2017
Dong Xu et al	RS_LMBPNN,96.67%	Liver lesions	2016
Xin-Yu Jin et al	BPNN,94.6%	Liver diseases	2015
R. G. Alam et.al	BPNN, 91.42%	Liver Diseases	2015
O. D. Fenwa et al	ANN, 71.25% Accuracy	Liver Cirrhosis and Hemachromatosis	2015
Mehdi Neshat et.al	Fuzzy Hopfield Neural Network and Hopfield Neural Network,92%,88.2%	Liver Disorders	2014
Sangman Kim et al	Neural And Fuzzy Neural Networks, 96%,97%	Liver Cancer	2014
C.Mahesh et al.	Generalized Regression Neural Network	Hepatitis B Virus	2014
Sana Ansari et al	FFNN, 91.33%	Hepatitis Virus	2011

Vahid Beiranvand et al. [15] reviewed three AI techniques namely genetic algorithms, Artificial Neural Networks and Particle Swarm Optimization and then they compared their applications in the financial domain. They classified the financial market into three domains namely credit assessment, portfolio management, financial planning and forecasting. The performances of algorithms varied according to the kind of market.

R. G. Alam Nusantara Putra Herlambang et al. [16] joined Iridology and Back-Propagation Neural Network to identify Liver Diseases. According to Iridology, iris structure reflects an organ's condition in the body. To discriminate the condition of iris that contains the regular and irregular liver, they utilized the classification procedure and texture analysis. They used Gray Level Co-occurrence Matrix (GLCM) to extract the features. The images of iris of 60 individuals collected from Indonesia and given as input to GCLM.The resulting images, after feature extraction are used as the dataset for training as well as testing.The test results had shown that BPNN algorithm gave precision of 91.42%.

Sana Ansari et al. [17] presented an ANN based technique for the detection of hepatitis virus. They borrowed the dataset from the UCI Machine Learning repository. They observed that supervised Neural Network performed better compared to unsupervised model. The FFNN algorithm had shown an accuracy of 91.33%. In the Supervised algorithms category, the GRNN algorithm performed with 92% accuracy and was better than FFNN algorithm.

Rahma.ouhibi et al.[18] classified the faults affecting asynchronous machine using an approach based on probabilistic Neural Networks. For model inputs they used the stator RMS values of 3-phase voltages and currents. Out of MLP, PNN and GRNN, the PNN had performed better with an accuracy of 96.25% and took less training and testing times. Though MLP gave 96.63% accuracy, it took more time for training as well as testing compared to PNN. The GRNN algorithm had shown an average performance of 95.21%.

Raghesh Krishnan K and Sudhakar Radhakrishnan [19] presented an iso-contour-segmentation based strategy for automatically classifying ten different types of diffused and crucial liver diseases. The input images were collected from voluson 730 Expert GE Ultrasound System and Philips HD15 Pure Wave Ultrasound System. The isocontour segmentation used Marching Squares graphics algorithm. They got, by and large, classification correctness of 92% using fractal features and ANN. O. D. Fenwa et al.[20] compared the accuracy of Artificial Neural Network(ANN) and Support Vector Machine(SVM) for categorization of two chief liver diseases cirrhosis and hemachromatosis.

A set of images containing both Liver cirrhosis as well as hemachromatosis were input for testing and validation. They observed that Support Vector Machine had shown a better classification capability with an accuracy of 87.5% than Artificial Neural Network, which exhibited only 71.25% of precision. Wu, K., Chen, X et.al [21] proposed a classification technique using deep learning for contrast improved ultra-sound imaging .The model was trained using the extracted TICs from CEUS videos. Wide testing exhibited that the new technique did better compared to the other existing methods with respect to specificity, accuracy and sensitivity.

III. METHODOLOGY

Fig. 1 below is the structure of our proposed and implemented multi layer Feed Forward Deep Neural Network. The Input layer consists of 10 nodes as our data set contains 10 attributes. There are three hidden layers and each layer has 64 nodes each. Output layer consists of one node as the expected prediction is either “yes” or “no”.

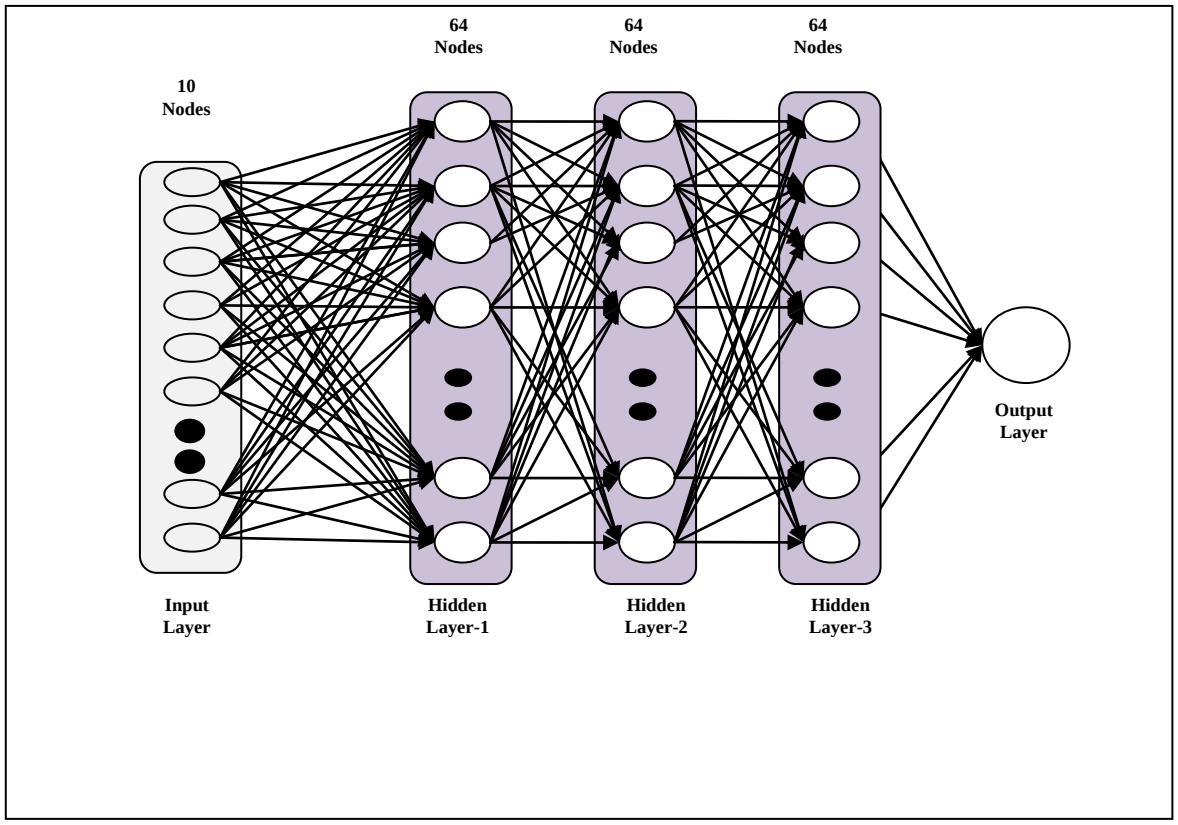

Fig.1. Structure of our MLFFDLNN

The proposed model is implemented using python .The kernel_initializer function generates random numbers between 0 and 0.05 as initial weights from a uniform distribution of the samples. The problem with Deep Neural Networks is ,if the model has many hidden layers , hidden units and large data , then after training the network ,

training performance will be very good but leads to model over fitting and bad generalization. T o avoid this problem, after each hidden layer a dropout function i.e. 0.25(25%) is applied to prevent Neural Networks from over fitting. The drop out value represents the percentage of neurons whose output will not be passed to the next layer. The Fig.2 below shows how the drop out technique works in neural network training. We arrive at the right dropout value by trial and error method only.

The drop out technique is widely used now days in machine learning to build accurate and more generalized models, particularly in Deep Neural Networks.

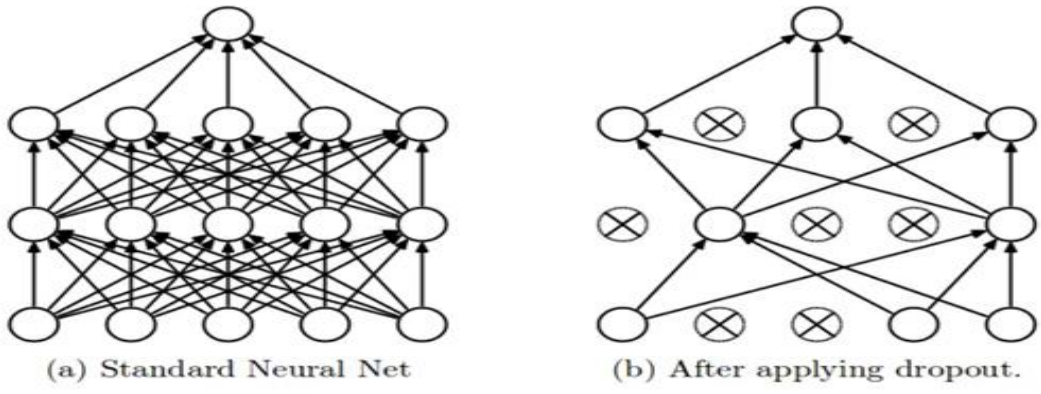

Fig.2: Drop out technique [24]

Think, there are L hidden layers, let $z^{(l)}$) represent the vector of inputs into layer l,$y^{(l)}$ stand for the vector of outputs from layer l,($y^{(0)}$=x is the input).$w^{(l)}$ are the weights and $b^{(l)}$are the biases at layer l. The feed forward process of any standard Neural Network can be illustrated as (for l belong to 0,…, L-1) and any hidden unit i.

$$z_i^{(l+1)} = w^{(l+1)} y^l + b_i^{(l+1)}$$

$$y_i^{(l+1)} = f(z_i^{(l+1)}) \quad (1)$$

Where, f is an activation function. With dropout, the feed forward function is:

$$r_j^{(l)} \sim \text{Bernoulli}(p),$$

$$y^{(l)} = r^{(l)} * y^{(l)}$$

$$Z_i^{(l+1)} = w_i^{(l+1)} y^l + b_i^{(l+1)}, \quad (2)$$

$$y_i^{(l+1)} = f(z_i^{(l+1)})$$

Here * means, an element wise product. For any layer l, $\mathbf{r^{(l)}}$ is vector of independent Bernoulli random variables each one of which has probability p of being 1.This vector is sampled and multiplied element wise with the outputs of that layer ,$y^{(l)}$ to create the thinned outputs $y^{(l)}$ .Then the thinned outputs are sent as inputs to the next layer. At each layer, similar process is repeated for sampling a smaller network from a bigger network. During learning, the loss function derivatives are back propagated all the way through the sub network. At the time of testing, the scaling of weights is done as $W_{test}^{(l)} = pW^{(l)}$ .After that the resultant Neural Network is used without any dropout function. In the hidden layers, we used the 'relu' (Rectified Linear Unit) activation function .It is non linear activation function, widely used in Deep Neural Networks now a days. The ReLU activation function is as follows:

$$(x) = \max(0,x). \quad (3)$$

If x is positive ,it gives x as output, or else it gives 0. It maps the output values between 0 and infinity.So we can pass the highest amount of the error through the network during back propogation. As a result , we can easily back propagate the errors and can activate multiple layers of neurons. ReLu computation takes lesser time compared to tanh and sigmoid computation. At a time , only a few neurons are activated to make the network sparse . We applied Sigmoid function, which is generally used in the output layer for binary classification cases.The 'Sigmoid' activation function is a non linear function which transforms the output values between 0 and 1. For that reason, it is specially used for models where we have to predict the probability as an output.

The equation for Sigmoid function is:

$$A = \frac{1}{(1+e^{-x})} \quad (4)$$

It is used in output layer where the output is either 0 or 1.So, the prediction is 1 if the value is greater than 0.5 and 0 otherwise..

The Neural Network is compiled by using an optimizer called 'adam' which is a method for stochastic optimization .The learning rate is 0.001 by default as the 'adam' optimizer is used. It means, the weights in the network are updated 0.001 * (estimated weight error) each time the weights are updated during back propagation. We applied the Loss function 'binary_crossentropy' as ours is a binary classification problem. The model is updated after every batch of samples is processed. The batch **size** greater than 1 and less than or equal to the number of samples in the training dataset. We have taken batch size as 10.An epoch indicates the number of complete passes through the training dataset. For example, if the data has 2000 samples and the batch size is 400 and then 4 iterations are needed to complete one epoch. The metric we used to judge the performance of the model is accuracy as our data set has very little imbalance or it is almost balanced.

Table II: Structure of a Confusion Matrix

Actual Result	Detected result	
	True Positives(TP) p	False Positives(FP) r
	False Negatives(FN) q	True Negative(TN) s

True Positives are the cases in which we predicted 'yes' and they do have the disease. True negatives are the cases, where we predicted 'no' and they do not have the disease. False Positives are which we predicted 'yes' but actually they do not have disease. False Negatives are the cases which we predict 'no' but actually they have the disease.

The classifier's accuracy is measured by the proportion of the test samples that are correctly classified by the classifier and is calculated using the equation:

$$Accuracy = \frac{p+s}{p+s+q+r} \quad (5)$$

IV. RESULTS AND DISCUSSIONS

The liver dataset used in this paper is collected from Amrutha Group of Hospitals, Srikakulam, and Andhra Pradesh, India. This liver dataset consists of 11 attributes, out of which 1-10 attributes are considered as input attributes and 11th attribute is considered as target class attribute which is having 0(non-diseased) or 1 class (diseased).The attributes and their descriptions are shown in table III.

Table III: Attribute Description

S. No	Attribute	Description
1	Gender	Gender of the patient
2	Age	Patient's Age
3	TB	Total Bilirubin
4	DB	Direct Bilirubin
5	SGOT	Aspartate Aminotransferase
6	SGPT	Alamine Aminotransferase
7	ALP	Alkaline Phosphotase
8	ALB	Albumin
9	GLB	Globulin
10	A/G Ratio	Albumin and Globulin Ratio
11	Class label	Diseased or not (labeled by experts)

This data set contains totally 882 instances; out of which 403(45.7%) instances are of class 0(non-diseased) and 479 (54.3%) instances are of class 1(diseased). Hence, it is considered that data set is almost balanced Outcome is a class label to split the samples into two classes (liver patient or not). We used 80% of the samples for training and 20% of the samples for testing. Figure 3 below, shows the histogram of the 10 features and exhibits the frequency distribution of the attribute values. From Fig 3 below, it is clear that every feature of the data set seems to be significant.

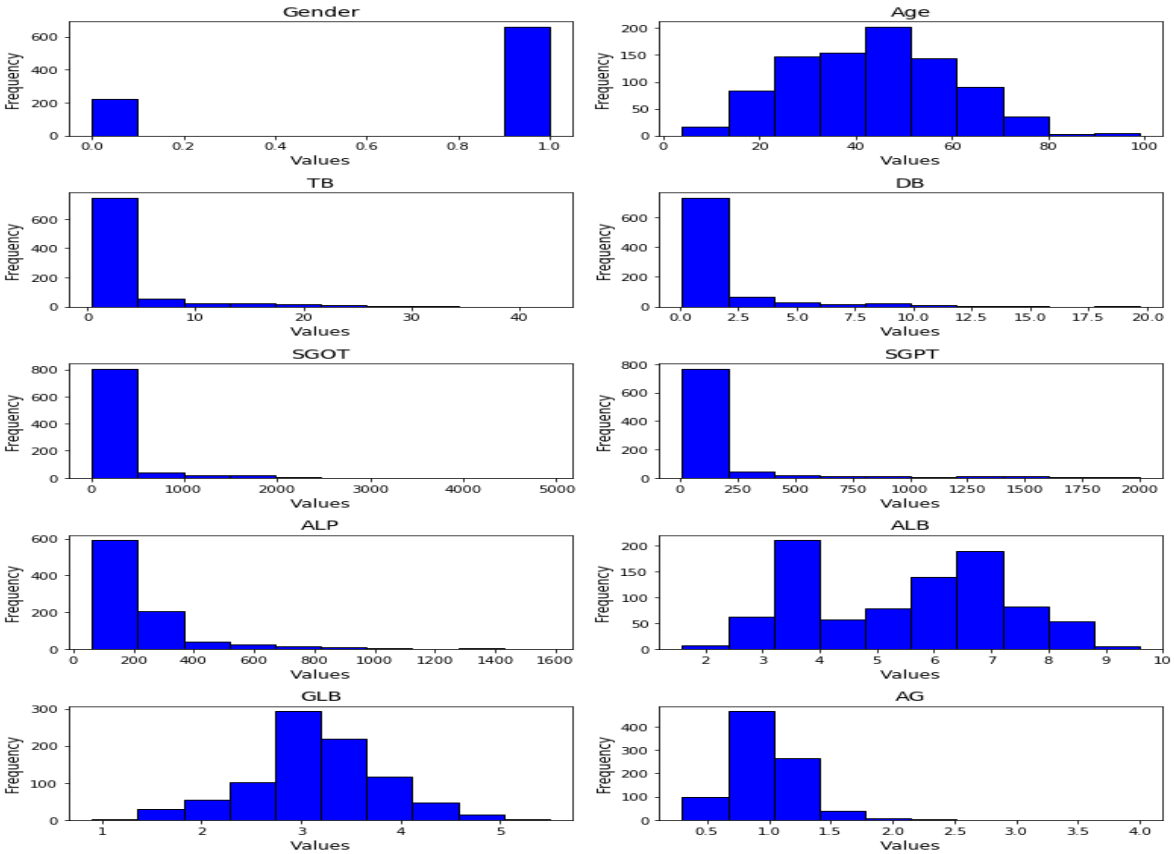

Fig.3: Histogram of 1 to 10 features of Liver dataset

Fig.4 below shows the diagonal correlation matrix of 1 to 10 input Attributes and exhibits the degree of correlation among the attributes.

Plotting a correlation matrix is a good initiative to have a fast exploration of data and firm insights of the variables that correlate. From Fig.4, it is observed that the attribute TB correlates well with ALP, SGPT, SGOT and DB. The attribute DB correlates with the attributes ALP, SGPT and SGOT. The attribute SGOT correlates with ALP, SGPT. The attribute SGPT correlates with ALP. The attribute ALP correlates with ALB. The attribute ALB correlates with GLB. The GLB attribute correlates with AG. This information can be used for more advanced analysis of data

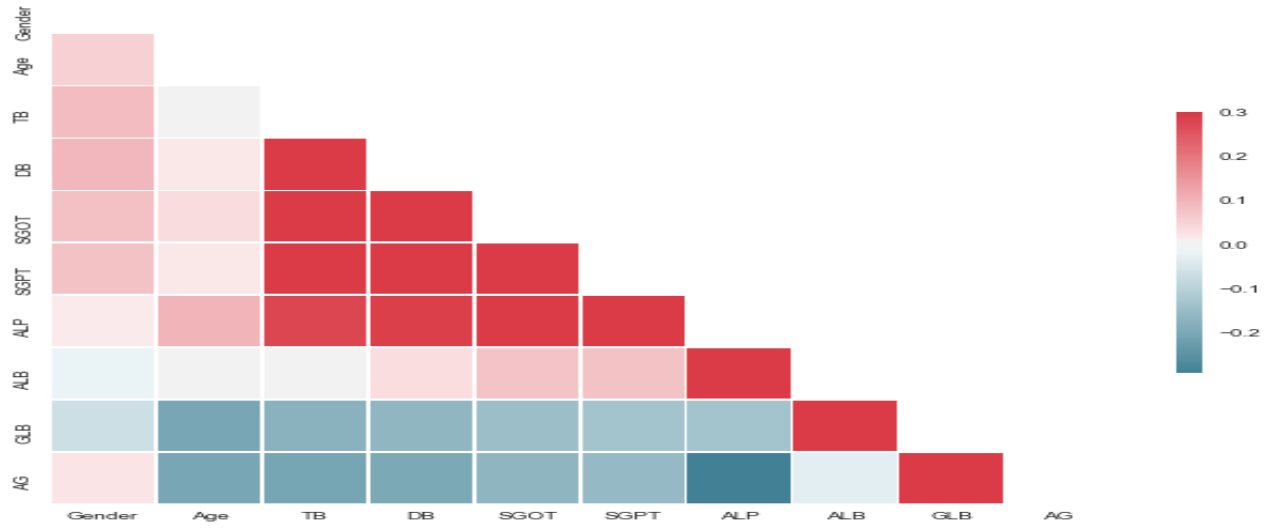

Fig.4. Diagonal Correlation Matrix of 1 to 10 attributes

Fig. 5 below shows decreasing loss values in successive epochs leading to increased accuracy rates.

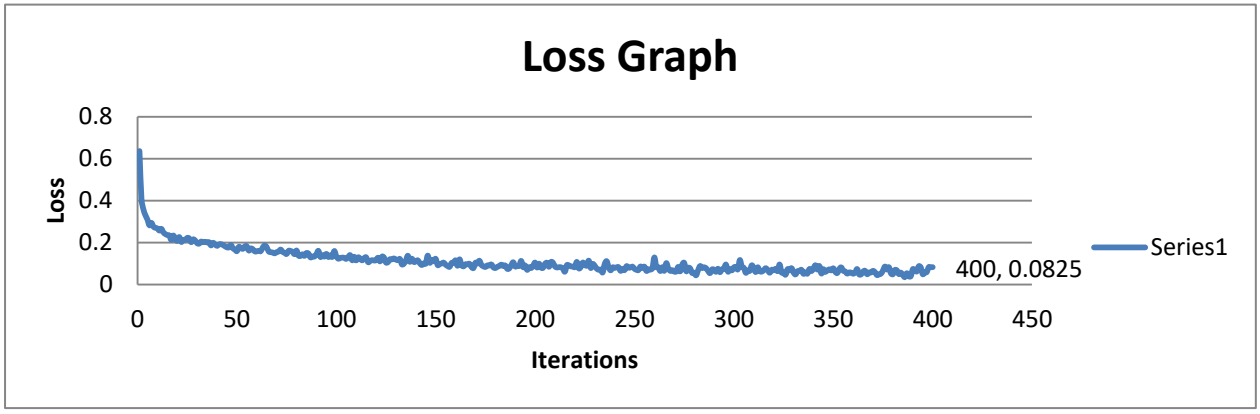

Fig.5. Loss exhibited by the Multi Layer Feed Forward Deep Neural Network Model at various epochs

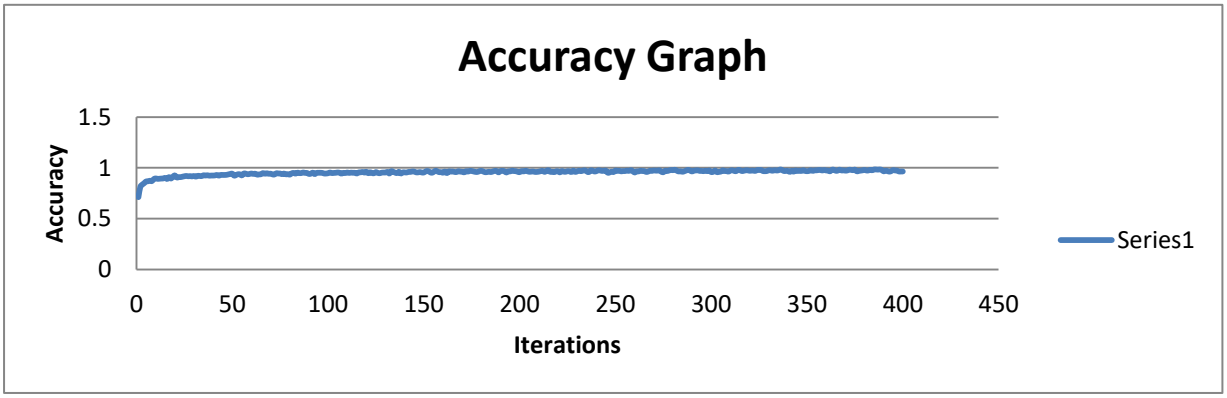

Fig.6. Accuracy exhibited by the MLFFDNN at various epochs

Fig.6 above shows how the accuracy percentage is increasing in successive iterations due to dropout function and updating of weights in the process of back propagation.

Table IV. Accuracy Comparison of Various classification Algorithms

Algorithm	Naïve Bayes	C4.5	AD Tree	SVM	RBF	MLFFDNN
Accuracy	71%	97%	92%	75%	83%	**98%**

Table IV above shows the accuracy exhibited by different classification methods and Multi Layer Feed Forward Deep Neural Network (MLFFDNN) Model. It is observed that Naïve Bayes algorithm gave only 71% of accuracy ,C4.5 gave 97% accuracy, ADTree gave 92% accuracy, Support Vector Machines gave only 75% accuracy ,Random Belief Networks gave 83% accuracy where as our proposed model gave 98% accuracy. From Fig.6, shows the performances of the various algorithms graphically. it is observed that our **MLFFDNN** model exhibits highest classification accuracy compared to other classification methods as observed in our earlier work [23]. In this paper, primarily, we considered accuracy score as the metric because our dataset is having almost balanced target classes. And for balanced data sets accuracy is a good performance measure. The accuracy graph in Fig.7 shows how the accuracy increased gradually after every iteration during the training of the neural network

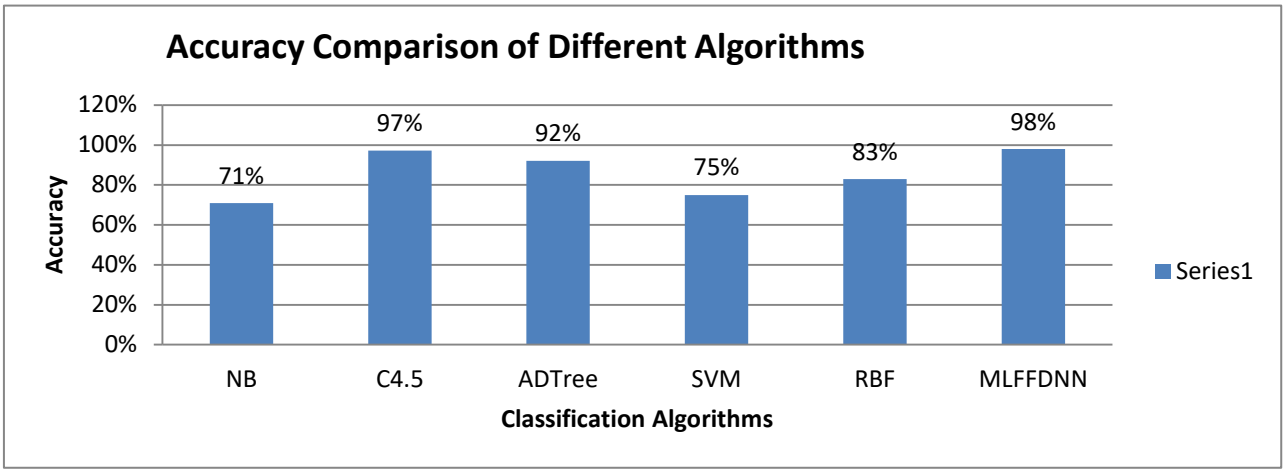

Fig.7. Accuracy comparisons of diverse Classification Techniques

V. CONCLUSION AND FUTURE WORK

We, In this paper, trained a Multi Layer Feed Forward Deep Neural Network (MLFFDNN) with back propagation with suitable number of hidden layers and nodes, dropout value, loss functions, learning rate, bias and activation functions using . We achieved classification accuracy of 98% which is better than some widely used classification techniques as shown in table III .It is also more when compared to the Neural Network models tuned by machine learning researchers till now for Liver Disease predictions. The results are evaluated based on accuracy as our data set is almost balanced and little imbalance in the data set does not cause any considerable performance degradation. We observed that 98% classification accuracy is obtained at epoch 363 by our proposed model.. In future, we will attempt to further improve the accuracy by using boosting techniques and deal with imbalanced data sets also.

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