Supplementary File-Novel XRayNet framework for lung disease detection and infection region identification

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Confusion Matrix:

The CHMNN model classified the lung diseases into Cardiomegaly, Pleural Effusion, Pulmonary Fibrosis, Pulmonary Consolidation, and No Finding. We used a total of 600 chest X rays from the NIH Chest X-ray dataset and the dataset is split into training and testing in the ratio of 80:20. Out of 600 images, 480 images were used for training, and 120 images were used for testing. For Cardiomegaly, Consolidation, Effusion, and Fibrosis 80 images were trained for each class and a total of 160 images were chosen for the "No Finding" category. For Cardiomegaly, Consolidation, Effusion, and Fibrosis 20 images were tested for each class, and a total of 40 images were chosen for the "No Finding" category. The confusion matrix is plotted in **Figure S1**.

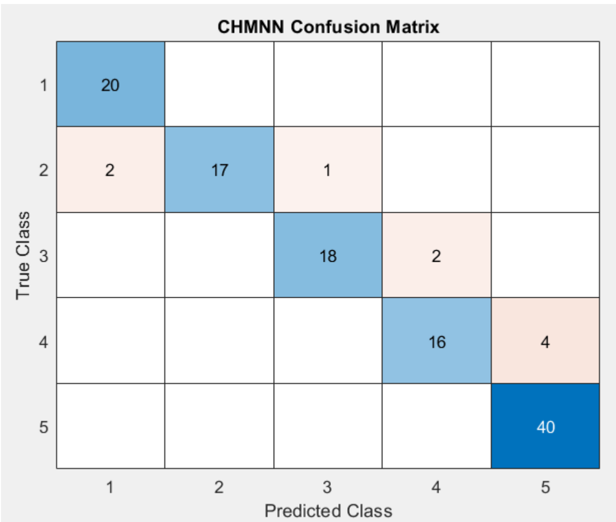

Figure S 1: Confusion Matrix of CHMNN classifier

The summary of related works on lung disease detection is illustrated in **Table S1**.

Table S 1: Summary of related works in Lung disease detection

Reference	Aim	Pre-processing	Dataset	Model	Accuracy
Kieu et al.Ho & Gwak (2019)	Disease detection	SIFT, GIST, LBP, and HOG	ChestX-ray14	pretrained DenseNet-121	Accuracy 84.62%
Lakhani et al. Lakhani & Sundaram (2017)	Disease detection	ImageNet, AlexNet-TA together with GoogLeNet-TA model (Augmentation)	Montgomery Shenzhen, Belarus and Thomas Jefferson University dataset	Deep CNNs (AlexNet, GoogLeNet)	95.83%
Han et al. Liu et al. (2019)	Disease detection	CNN(Feature extraction)	Chest X-ray 14	SDFN	AUC(81.50)%
Chen et al. Chen et al. (2019)	Disease detection	DenseNet and ResNet(feature extraction)	ChestX-ray14	DualCheX Net	AUC(0.823)%
Aswathy et al. Aswathy et al. (2021)	Disease detection	augmentation, transfer learning	COVID-CT dataset	Pre-trained network	98.50%
Johnatan et al. Souza et al. (2019)	Lung segmentation and reconstruction	segmentation	Montgomery	Deep CNN	96.79%
Fatih et al. Demir et al. (2020)	lung sound classification	CNN(feature extraction)	ICBHI 201	SVM	65.5%,63.09%
Wang et al. Wang et al. (2020)	Disease detection	pre-trained on ImageNet	NIH Chest X-ray 14 dataset	KGZNet	87.80%
Bharati et al. Bharati et al. (2020)	Disease detection	augmentation	NIH Chest X-ray 14 dataset	VDSNet (Hybrid deep learning model)	73.00%
Qiao et al. Ke et al. (n.d.)	Disease detection	detect degraded lung X-ray	Montgomery Shenzhen	Neural Network architecture	79.06%

Figure S2 shows the results of the linear regression between the network outputs and the corresponding targets. Here the targets are represented as open circles and the dashed line represents that it is the best linear fit. The solid line illustrates that the output is equal to the target means perfect fitting. The R-value or the correlation coefficient measures the fitness of the model. The perfect correlation between targets and outputs is a clear indication of a good fit model.

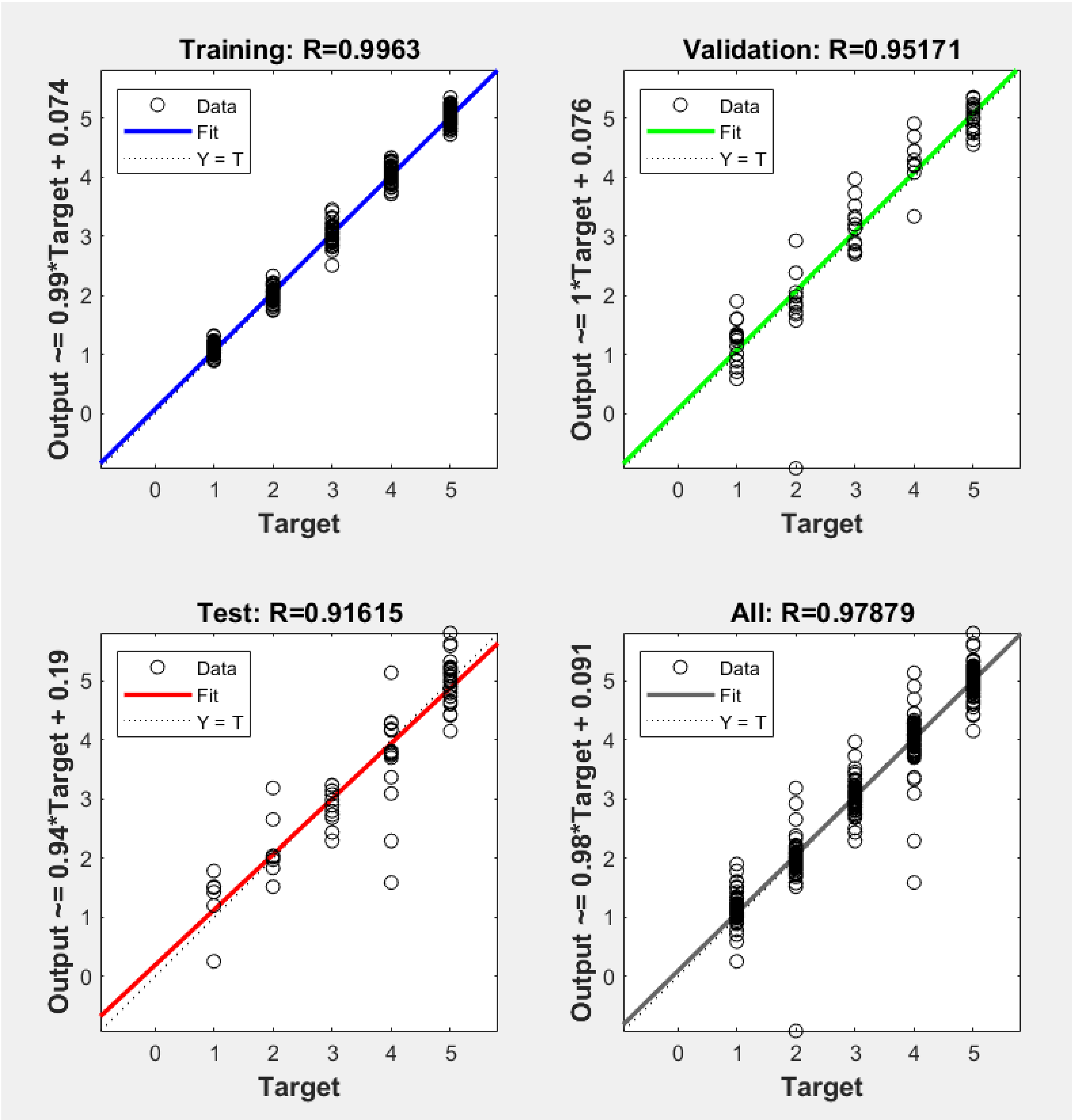

Figure S 2: Plot of linear regression of targets relative to outputs for CHMNN

Figure S3 depicts neural network training with 50 hidden layers and 10 iterations. The figure displays the time, performance, gradient, Mu, and validation checks. Mu is the momentum parameter being used in the weight update expression to manage the local minima problem. Mu is used for the Levenberg-Marquardt optimization process to determine parameter updates, and it has a range of 0 to 1.**Figure S4** illustrates the training state of CHMNN classifier.The plot of mean square error with number of epochs is illustrated in **Figure S5**.

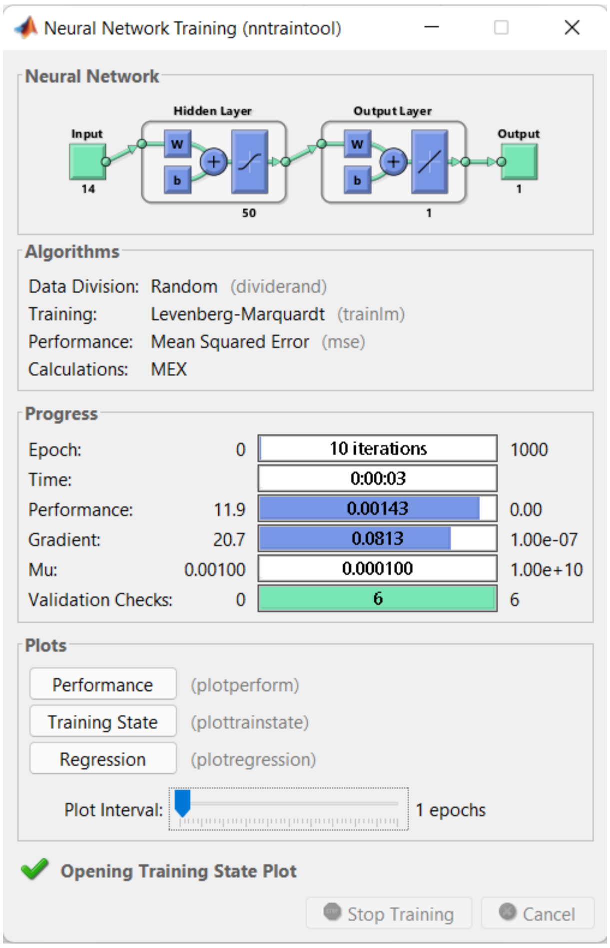

Figure S 3: Neural network training

The accuracy (**Figure S6**) and loss (**Figure S7**) of the proposed CHMNN are given for the number of iterations. Here the number of epochs used is 30 for the total number of iterations. The learning rate is a configurable hyper-parameter used in the training of neural networks that has a small positive value, often in the range between 0.0 and 1.0. Here the learning rate achieved by the proposed method is 0.01. Loss is the prediction error of the network which is estimated with the help of validation data and training data.

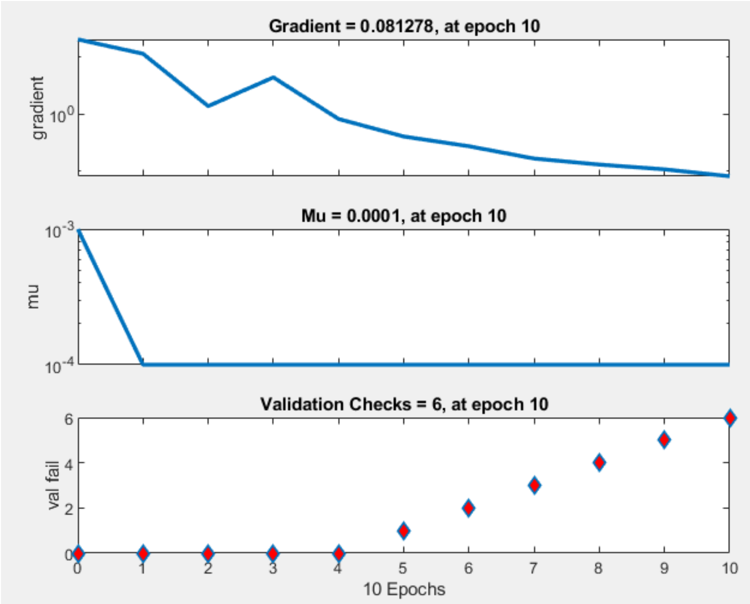

Figure S 4: Neural network training

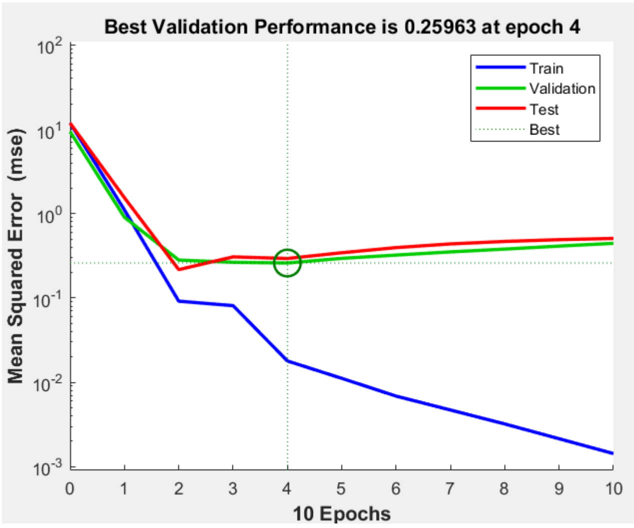

Figure S 5: Validation performance of CHMNN classifier

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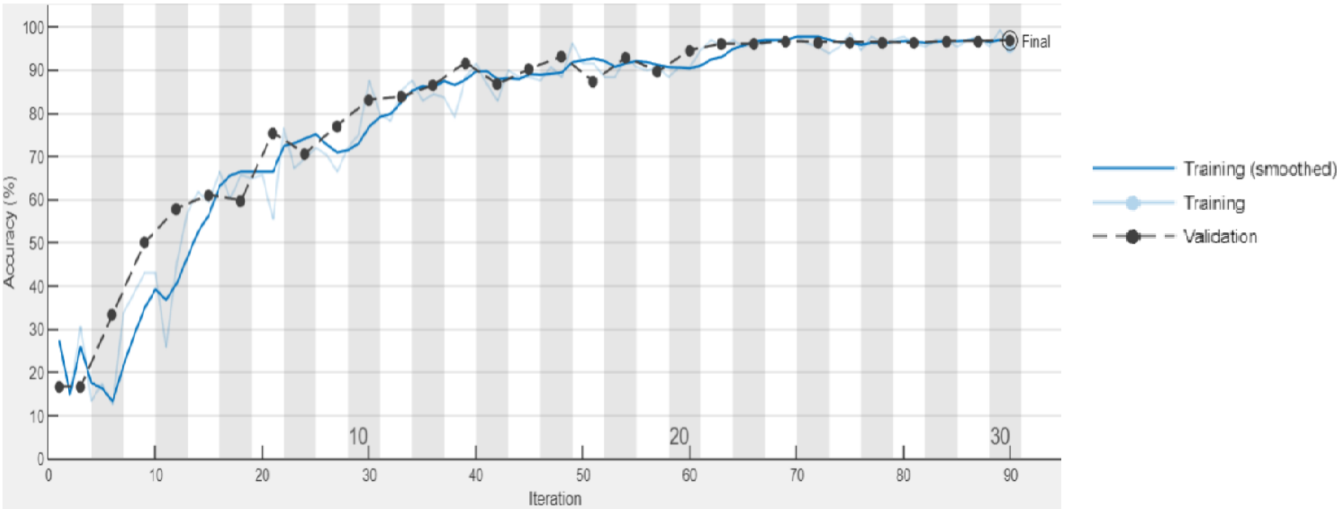

Figure S 6: Accuracy of CHMNN classifier

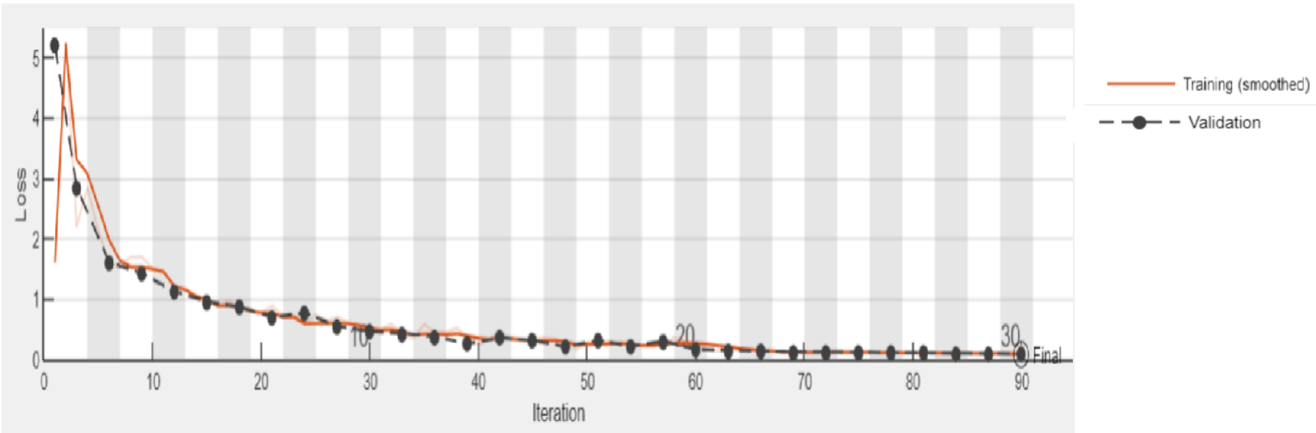

Figure S 7: Loss of CHMNN classifier

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