International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

June 2023 | Issue 55 | Volume 15 | Number 2 | Pages 125-133

HUMAN DISEASE DETECTION USING ARTIFICIAL INTELLIGENCE

V. Jain [1] B. Jha [1] S. Joshi [1] S. Miglani [1] A. Singal [1] S. Babbar [1]
M. Demirci [2] M.C. Taplamacioglu [2]

1. Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, vanita.jain@bharatividyapeeth.edu, Bhawanand.jha@bharatividyapeeth.edu, souravjoshimails@gmail.com, sourabhmiglani57@gmail.com, amansingal6@gmail.com, shubhambabbar17.sb@gmail.com
2. Electrical and Electronics Engineering Department, Gazi University, Ankara, Turkey
mervedemirci@gazi.edu.tr, taplam@gazi.edu.tr

Abstract- In twentieth century machine learning is being used in various fields; one of the most popular fields among them is the Medical. Few years ago, all the diseases were diagnosed by doctors through expensive machines like X-ray machines, MRI machines and others. Over the last decade disease detection through Machine learning has become quite popular. In this research work, the authors have diagnosed four human diseases viz. Pneumonia, Heart Disease, Breast Cancer and Thyroid. Seven Machine Learning and Deep Learning Algorithms have been used. The accuracies of all Machine Learning models have been compared on different splitting ratio of dataset in order to find the maximum accuracy. The maximum accuracy for heart disease and thyroid by Random Forest is 98.05% and 97.9% respectively. The best result for Breast Cancer by Neural Network is 98.2%. A Hybrid model which consists of Convolutional Neural Network and Support Vector Machine is proposed in this work which gives the maximum accuracy of 97.3% for Pneumonia. Precision, F1-score, Recall have been calculated to compare the results of various Machine Learning and Deep Learning models. Dataset splitting statistics have also been used to compare and evaluate the performance of different Machine Learning algorithms.

Keywords: Machine Learning, Deep Learning, Convolution Neural Network, Hybrid Model, Data Splitting.

1. INTRODUCTION

Medicine and healthcare are major elements of the economic growth and human life. Machine learning is used in a wide range of fields, which includes various areas which benefit human life [1-6]. Machine learning is very popular as technology due to numerous advantages viz. higher computational power and freely available open-source datasets etc. In Machine Learning, different ways to capture the data for medical diagnosis like photographs, patient data, and other information are utilized to discover trends and make predictions [7]. In case of a serious disease, the diagnosis may not be always accurate. Medical diagnosis system which uses machine learning (ML) algorithms and deep learning techniques for disease prediction [8-11] aids in a more accurate diagnosis than the traditional way, hence machine learning has become inevitable in the field of healthcare. Machine learning is used in healthcare industry to solve several problems [12]. It has a wide range of applications such as early diagnosis and diagnosis in progression stages of diseases, monitoring of treatment processes, classification and regression in health-care sector [13].

In [14], machine learning paradigms have been used for the detection of pneumonia on segmented lungs. A model has been proposed to predict pneumonia for 185 schizophrenic patients at a Taiwanese district mental hospital [15]. In [16], authors have proposed CT radiomics models to predict the hospital stay for 52 patients infected with COVID-19 pneumonia. Benign and malignant modules for lung cancer using 9 different classifiers have been studied in [17]. Authors in [18] have implemented and compared the accuracy of 4 deep learning schemes to classify the brain MRI slices. Four large datasets are used to analyze the k-fold cross-validation and hold-out validation [19]. K-fold validation shows better results till a certain threshold over other schemes. [20] have used Siamese convolution neural network to classify chest X-ray images into different classes i.e., pneumonia, normal, covid, severe covid. In [21-23], authors are using different machine learning algorithms to detect heart disease. Apple Developers Vision Framework has been used in [24] for text extraction and localization from an image.

In [25-26], Machine learning algorithms are studied to diagnose thyroid disease. Yong Feng Wang [27] diagnosed thyroid using deep learning technique and used VGG16 model with fine-tuning. The highest accuracy on the testing data was 74.69%. The work presented in this paper uses machine learning models to estimate the risk of four human diseases viz. Pneumonia, Breast Cancer, Heart Disease and Thyroid Disease using related datasets. Artificial Neural Network (ANN), Naive Bayes (NB), Decision trees (DT), logistic regression (LR), Support Vector Machines (SVM), Random Forest (RF),

Convolutional Neural Network (CNN) have been used. Accuracies of all machine learning models have been compared on different splitting ratio of dataset to find maximum accuracy. In addition to this a Hybrid Model which is a combination of Convolutional Neural Network and Support Vector Machine is also proposed for Pneumonia which gives promising results.

The paper is organized in five sections. Section 2 describes the datasets used. In Section 3 the proposed methodology has been described. Results and discussions have been shown in Section 4. Finally, Section 5 concludes the paper.

2. DESCRIPTION OF DATASETS

Data from Kaggle open-source platform [28] have been used for datasets of the four diseases; Pneumonia, Breast Cancer, Heart disease, and Thyroid disease. Kaggle is an online community platform for data scientists and machine learning enthusiasts**.** There are two target values Positive and Negative in the dataset for each disease. Positive means the patient suffering from a particular disease and Negative means not suffering.

2.1. Dataset for Pneumonia

Pneumonia dataset [28] is organized into two folders (train and test). It contains subfolders for each image category i.e., Pneumonia or Normal. There are 5,863 X-Ray images in JPEG format. Snapshot for the dataset is shown in Figure 1.

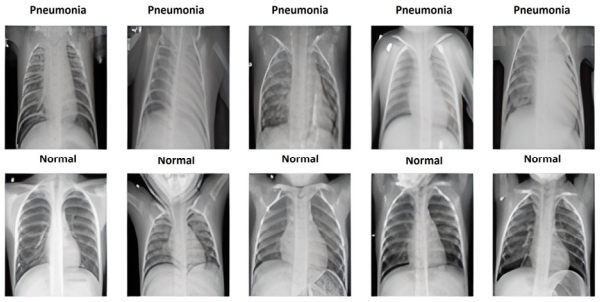


Figure 1. Chest X-ray images (pneumonia/normal) [28]

2.2. Dataset for Thyroid

There is total 29 attributes for thyroid disease which are either Boolean or continuous in nature, and some of the attributes are shown in Table 1.

Table 1. Thyroid Dataset [28]

age	sex	on thyroxine	query on thyroxine	on antithyroid medication	sick	FTI measured	FTI	TBG measured
41	F	f	f	f	f	t	109	f
23	F	f	f	f	f	f	?	f
46	M	f	f	f	f	t	120	f
70	F	f	f	f	f	f	?	f
70	F	f	f	f	f	t	70	F

2.3. Dataset for Heart Disease

There is total 1025 instances in this dataset. Each instance is having 14 attributes, either Boolean or continuous valued. Dataset is shown in Table 2.

Table 2. Heart Disease Dataset [28]

	thalach	exang	oldpeak	slope	ca	thal	target
0	168	0	1.0	2	2	3	0
1	155	1	3.1	0	0	3	0
2	125	1	2.6	0	0	3	0
3	161	0	0.0	2	1	3	0
4	106	0	1.9	1	3	2	0

	age	sex	cp	trestbps	chol	fbs	restecg
0	52	1	0	125	212	0	1
1	53	1	0	140	203	1	0
2	70	1	0	145	174	0	1
3	61	1	0	148	203	0	1
4	62	0	0	138	294	1	1

2.4. Dataset for Breast Cancer

There is total 569 instances for breast cancer. Each instance is having 33 attributes which are having real values. Snapshot of dataset which is having ten attributes is shown in Table 3.

Table 3. Breast Cancer Dataset [28]

worst	Perimeter _worst	Area _worst	Smoothness _worst	Compactness _worst
17.33	184.60	2019.0	0.1622	0.6656
23.41	158.80	1956.0	0.1238	0.1866
25.53	152.50	1709.0	0.1444	0.4245
26.50	98.87	567.7	0.2098	0.8663
16.67	152.20	1575.0	0.1374	0.2050
23.75	103.4	741.6	0.1791	0.5249
27.66	153.20	1606.0	0.1442	0.2576
28.14	110.60	897.0	0.1654	0.3682
30.73	106.20	739.3	0.1703	0.5401
40.68	97.65	711.4	0.1853	1.0580

concavity_ worst	Concave points_worst	symmetry_ worst	fractal_dimension _worst	unnamed : 32
0.7119	0.2654	0.4601	0.11890	NaN
0.2416	0.1860	0.2750	0.08902	NaN
0.4504	0.2430	0.3613	0.08758	NaN
0.62869	0.2575	0.6638	0.17300	NaN
0.4000	0.1625	0.2364	0.07678	NaN
0.5355	0.1741	0.3985	0.12440	NaN
0.3784	0.1932	0.3063	0.08368	NaN
0.2678	0.1556	0.3196	0.11510	NaN
0.5390	0.2060	0.4378	0.10720	NaN
1.1050	0.2210	0.4366	0.20750	NaN

3. PROPOSED METHODOLOGY

Figures 2a and 2b illustrate a schematic diagram of the experimental setup.

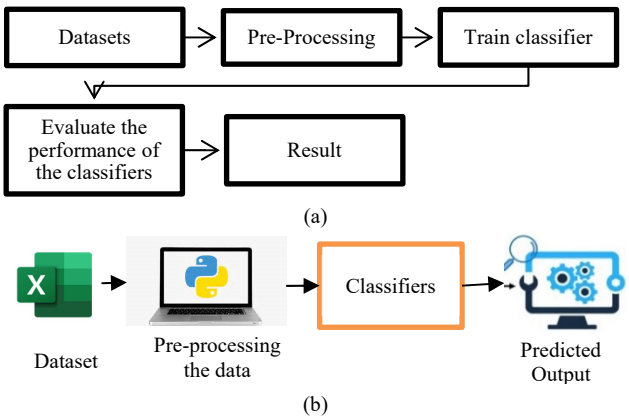


Figure 2. (a) Schematic diagram of the experimental setup, (b) Proposed system flow diagram

In pre-processing the null values have been removed and string objects have been encoded into numerical values for enabling Machine Learning algorithms. Pandas and NumPy library have been used to load data and feature reduction has been performed to remove unwanted features for Thyroid, Heart disease and Breast cancer dataset.

In Pneumonia dataset, Chest X-rays are pre-processed by cv2 library to convert the images into pixel matrix and they are normalised. For image classification, we have used Hybrid Model which consists of a Convolutional Neural Network and Support Vector Machine. In the hybrid model, CNN works as an automatic feature extractor and SVM works as a binary classifier. SVM is also used to substitute CNN's SoftMax layer. The design of proposed hybrid CNN-SVM is shown in Figure 3.

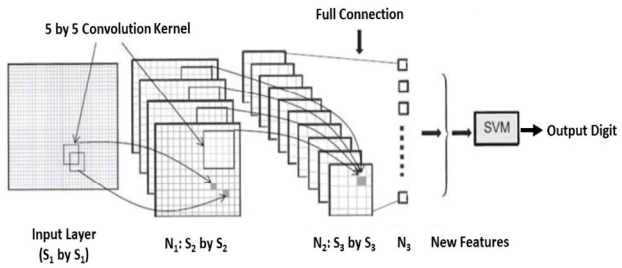


Figure 3. Architecture of proposed Hybrid CNN-SVM Model [29]

The Pneumonia dataset provides 5863 images of chest X-ray for the CNN input layer. The convolutional layers utilize a 55% convolutional filtering and a stride of size 2. The N1 and N2 feature map layers retrieve values that are used to differentiate the input image's features. CNN is trained for numerous epochs until the training process converges. The SVM classifier replaces the final layer of the CNN. The features of input chest X-ray obtained in N3 layer are treated as an input for the SVM classifier. These new automatically created characteristics of training photos are used to train the SVM classifier. Finally, the trained SVM classifier is utilized to recognize the X-ray images.

The accuracies of all machine learning models have been compared on different splitting ratio of the dataset in order to find maximum accuracy. Also, Precision, Recall, F1-Score and Accuracy have been compared. Artificial Neural Network is also used to find out the accuracy of each disease and graphs of Model Loss vs Epoch's and Accuracy vs Epoch's have been plotted to evaluate the performance.

4. RESULTS AND DISCUSSION

Precision, Recall, F1-score, and accuracy have been calculated to compare results for evaluating the performance of different Machine Learning models and the accuracy of Deep Learning model also has been determined. In order to find out the maximum accuracy of all four human diseases dataset splitting statistics have been used. Nvidia GEFORCE GTX 1650ti MAX-Q GPU has been used.

4.1. Thyroid Detection

Values of Precision, Recall, F1-score on different Machine Learning Models is shown in Figure 4a and Figure 4b.

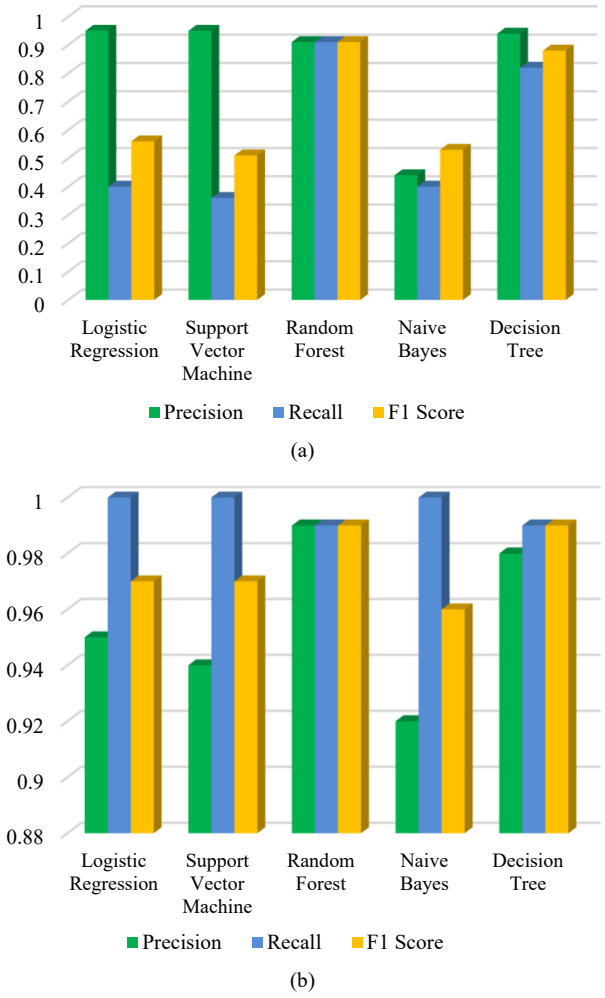


Figure 4. (a) Performance parameters for class 0, (b) Performance parameters for class 1

Accuracy of various Machine Learning models on different splits of Thyroid dataset is shown in Table 4 and Figure 5. It can be observed that for 70:30 data splitting the maximum accuracy of 97.79% has been achieved through Random Forest algorithm.

Naive Bayes assumes that features are independent of each other and there is no correlation between features. Since, expectations do exist, the system is giving a lowest accuracy of 91.99%.

Table 4. Testing Accuracy (%) of different Machine Learning models for Thyroid Detection on Dataset splitting statistics

Splitting	LR	SVM	RF	NB	DT
50:50	95.74	94.97	97.90	92.38	97.51
60:40	95.53	94.38	97.88	92.08	97.14
70:30	95.06	94.16	97.79	91.99	97.00
80:20	94.96	94.09	97.34	92.16	97.20
90:10	94.87	93.06	95.27	92.11	96.50

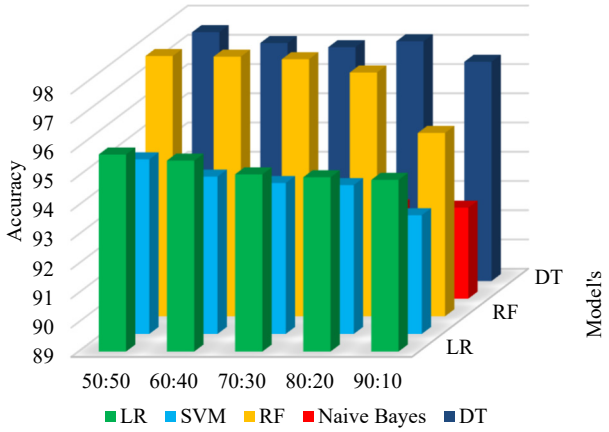


Figure 5. Comparison of various machine learning algorithms on thyroid dataset (Split)

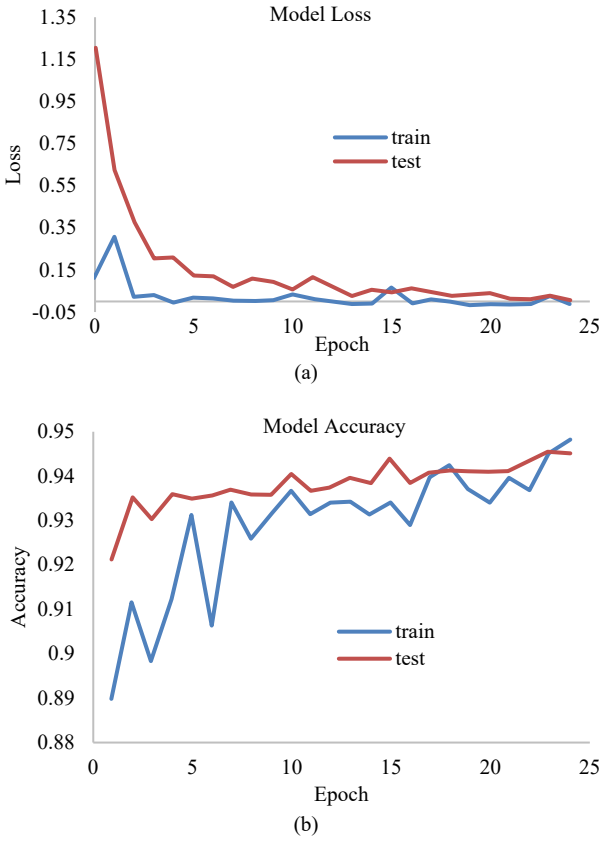


Figure 6. (a) Loss vs Epoch's graph, (b) Accuracy vs Epoch's graph of ANN for Thyroid Disease

Accuracy of 94% for thyroid disease using Artificial Neural Network on Testing Dataset has been predicted. Variation of Model Loss and Model accuracy for various epochs is shown in Figures 6a and 6b.

4.2. Pneumonia Detection

Figures 7a and 7b show values of Precision, Recall, F1-score on different Machine Learning Models. Maximum accuracy of 96.66% is achieved with Support Vector Machine and Naive Bayes gave the minimum accuracy of 71.56%.

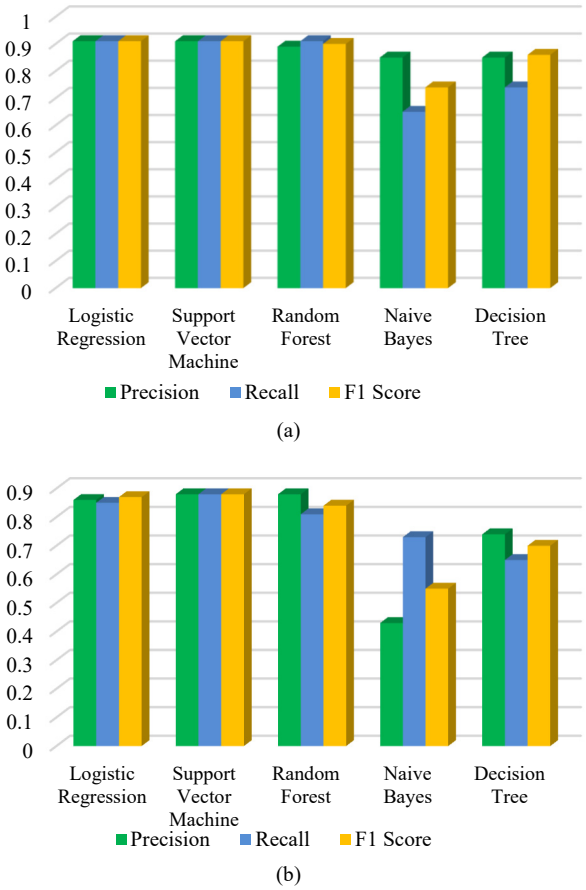


Figure 7. (a) Performance parameters for class 0, (b) Performance parameters for class 1

Accuracy of various Machine Learning models on different splits of Pneumonia dataset is shown in Table 5 and Figure 8. Data splitting of 50:50 results into maximum accuracy for Pneumonia dataset through SVM.

Table 5. Testing Accuracy (%) of different Machine Learning models for Pneumonia Detection on Dataset splitting statistics

Splitting	LR	SVM	RF	NB	DT
50:50	96.05	96.66	95.16	72.20	86.77
60:40	95.94	96.45	94.52	72.86	86.48
70:30	95.56	96.24	94.33	71.71	86.52
80:20	95.44	95.83	94.32	71.98	84.73
90:10	94.97	95.05	93.58	71.56	84.23

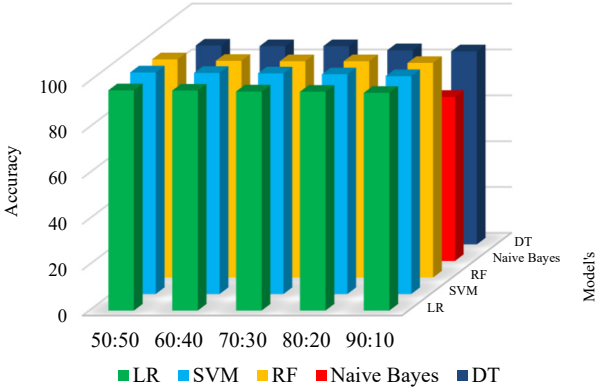


Figure 8. Comparison of various machine learning algorithms on pneumonia dataset (Split)

Figure 9a shows the variation of accuracy with epochs for ANN and gives the training accuracy of 94% and testing accuracy of 89%. Figure 9b shows the variation of accuracy with epochs for Hybrid Model and gives the training accuracy of 100% and testing accuracy of 97.3% which is better than the accuracy resulted from ANN.

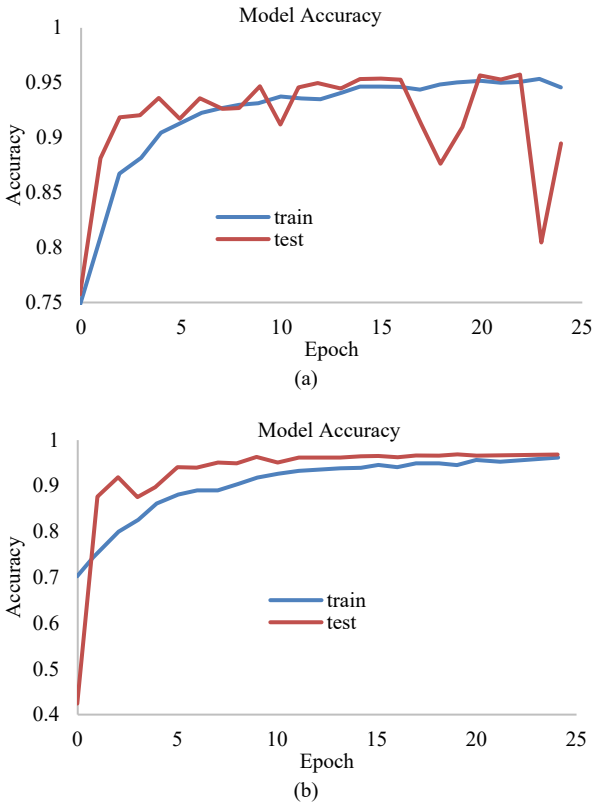
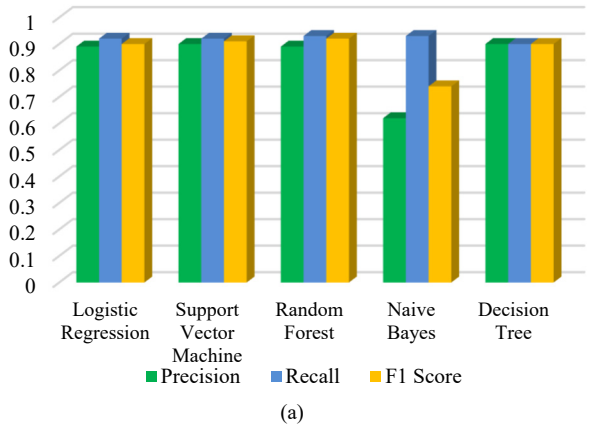


Figure 9. (a) Accuracy vs Epoch's for ANN, (b) Accuracy vs Epoch's for Hybrid Model

4.3. Breast Cancer Detection

Precision, Recall, F1-score for different Machine Learning Models have been calculated for breast cancer disease and are shown in Figures 10a and 10b.



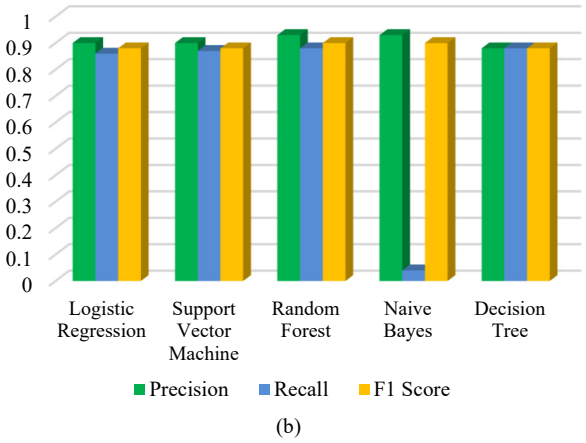


Figure 10. (a) Performance parameters for class 0, (b) Performance parameters for class 1

Maximum accuracy of 97.19% is achieved with Support Vector Machine and the minimum accuracy of 62.37% is achieved with Naive Bayes as shown in Table 6.

Table 6. Testing Accuracy (%) of different Machine Learning models for Breast Cancer Detection on Dataset splitting statistics

Splitting	LR	SVM	RF	NB	DT
50:50	96.84	97.19	96.49	63.50	93.33
60:40	96.78	97.07	96.19	63.45	94.44
70:30	96.24	96.49	95.48	62.90	91.22
80:20	95.39	96.93	93.86	62.72	90.57
90:10	92.98	93.76	93.76	62.37	88.69

Accuracy of various Machine Learning models on different splits of Breast Cancer dataset is shown in Figure 11. Breast Cancer through Artificial Neural Network has been predicted with an accuracy of 99% on Training and 98.2% on Testing Dataset. Variation of Model Loss and Model accuracy with epochs is shown in Figures 12a and 12b, respectively.

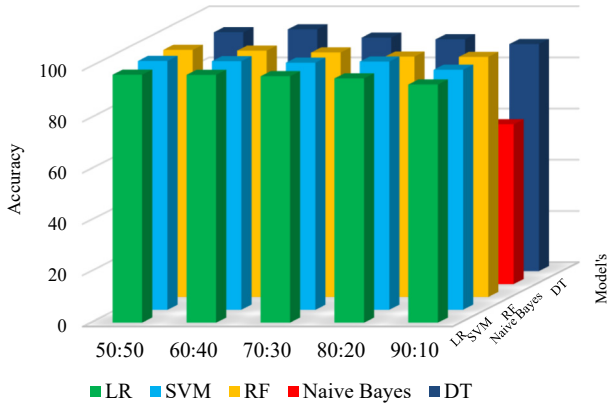


Figure 11. Comparison of various machine learning algorithms on Breast cancer dataset (Split)

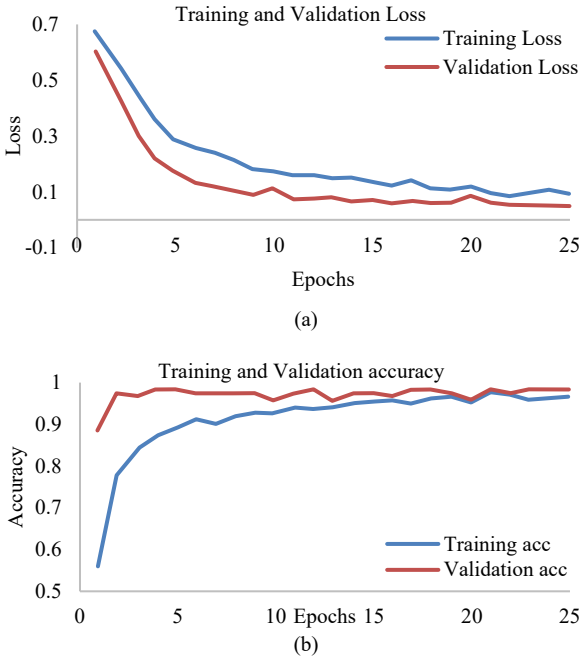


Figure 12. (a) Loss vs Epoch's for ANN, (b) Accuracy vs Epoch'sfor ANN

4.4. Heart Disease Detection

Figures 13a and 13b depicts Precision, Recall, F1-score on different Machine Learning Models for detection of heart disease.

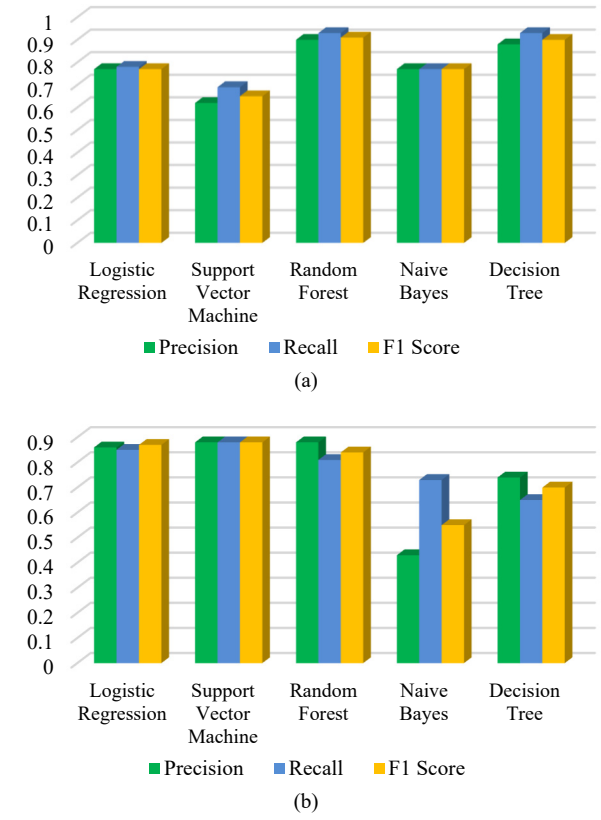


Figure 13. (a) Performance parameters for class 0, (b) Performance parameters for class 1

While, Maximum accuracy of 98.05% is achieved with Random Forest, Support Vector Machine algorithm gives minimum accuracy of 68.10%. Accuracy of various Machine Learning models on different splits of heart disease dataset is shown in Table 7 and Figure 14.

Table 7. Testing Accuracy (%) of different Machine Learning models for Heart Disease Detection on Dataset splitting statistics

Splitting	LR	SVM	RF	NB	DT
50:50	84.04	68.10	98.05	80.50	95.90
60:40	82.60	72.19	94.30	83.41	93.08
70:30	83.98	69.49	91.50	83.08	89.41
80:20	83.53	66.46	87.07	81.21	83.90
90:10	83.64	62.29	85.48	80.93	81.90

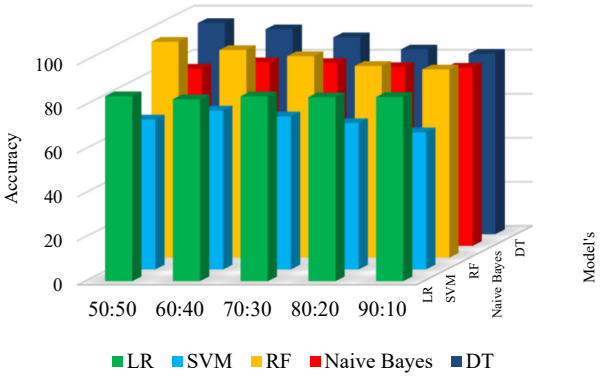


Figure 14. Comparison of various machine learning algorithms on heart disease dataset (Split)

Variation of Model Loss and Model accuracy with epochs is shown in Figures 15a and 15b, respectively which clearly indicates 78% accuracy on Training and 67.2% on Testing dataset for ANN.

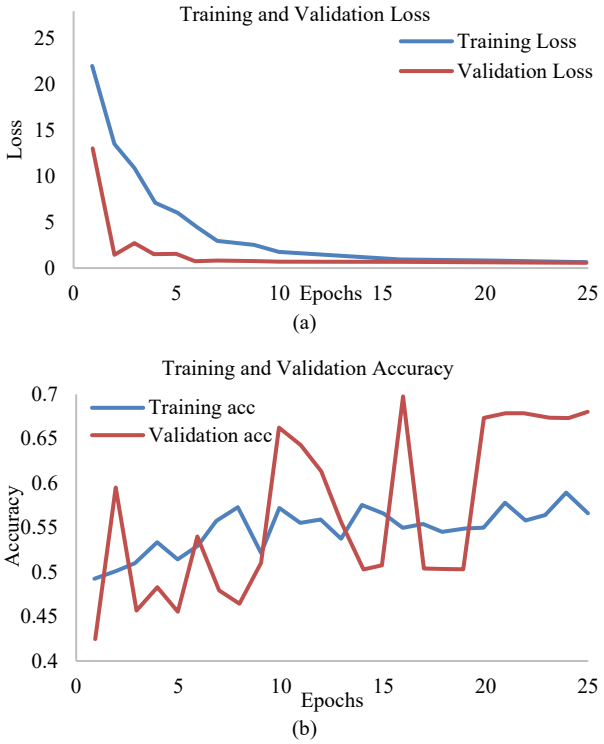


Figure 15 (a). Loss vs Epoch's (b) Accuracy vs Epochs ANN

5. CONCLUSION

Maximum accuracy of 98.05% for heart disease and 97.9% for Thyroid Disease has been achieved through Random Forest Algorithm. Best result with an accuracy of 98.2% was achieved for Breast Cancer through Neural Network. The proposed hybrid model consisting of Convolutional Neural Network and Support Vector machine resulted into a maximum accuracy of 97.3% for Pneumonia Disease. Data splitting used in the presented work efficiently improves the usage of time and assists in achieving the best results. Precision, Recall, F1-score, and accuracy are also calculated to compare results of various machine learning algorithms.

REFERENCES

[1] A.M.J. Sidey Gibbons, C.J. Sidey Gibbons, "Machine learning in Medicine: A Practical Introduction", BMC Medical Research Methodology, Vol. 19, March 2019.

[2] F. Jiang, Y. Jiang, H. Zhi, et al., "Artificial Intelligence in Healthcare: Past, Present and Future", Stroke and Vascular Neurology, Vol. 2, No. 4, pp. 230-243, June 2017.

[3] T. Davenport, R. Kalakota, "The Potential for Artificial Intelligence in Healthcare", Future Healthcare Journal, Vol. 6, No. 2, pp. 94-98, June 2019.

[4] J. Keto, H. Ventola, J. Jokelainen, et al., "Cardiovascular Disease Risk Factors in Relation to Smoking Behavior and History: A Population-Based Cohort Study", Open Heart, Vol. 3, No. 2, July 2016.

[5] S. Gc, R. Kasaudhan, T.K. Heo, H.D. Choi, "Variability Measurement for Breast Cancer Classification of Masses", Conference on Research in Adaptive and Convergent Systems (RACS), pp. 177-182, Prague, Czech Republic, 2015.

[6] S.G. Durai, S.H. Ganesh, A.J. Christy, "Novel Linear Regressive Classifier for the Diagnosis of Breast Cancer", In Computing and Communication Technologies (WCCCT), 2017 World Congress, pp. 136-139, Tiruchirappalli, India, February 2017.

[7] S. Hafizah, S. Ahmad, R. Sallehuddin, N. Azizah, "Cancer Detection Using Artificial Neural Network and Support Vector Machine: A Comparative Study", J. Teknol, Vol. 65, pp. 73-81, 2018.

[8] L. Vig, "Comparative Analysis of Different Classifiers for the Wisconsin Breast Cancer Dataset", Open Access Library Journal, Vol. 1, 2018.

[9] G.L. Tsirogiannis, D. Frossyniotis, J. Stoitsis, S. Golemati, A. Stafylopatis, K.S. Nikita, "Classification of Medical Data with a Robust Multi-Level Combination Scheme", IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541), Vol. 3, pp. 2483-2487, Budapest, Hungary, July 2004.

[10] W.D. Zhang, Y.H. Huang, "Breast Cancer Prediction Using Machine Learning", International Journal of Creative Research Thoughts (IJCRT), Vol. 66, No. 7, 2018.

[11] B. Akbugday, "Classification of Breast Cancer Data Using Machine Learning Algorithms", Medical Technologies Congress (TIPTEKNO 2019), pp. 1-4, Izmir, Turkey, 2019.

[12] S. Albahli, H. Rauf, A. Algosaibi, V. Balas, "AI-Driven Deep CNN Approach for Multi-Label Pathology Classification Using Chest X-Rays", PeerJ Computer Science, Vol. 7, pp. e495, pmid:33977135, 2021.

[13] S.G. Aydin, H.S. Bilge, F. Hardalac, "Supervised Rigid Image Registration with CNN for MR Brain Images", Innovations in Intelligent Systems and Applications Conference (ASYU), pp. 1-5, 2022.

[14] T. Chandra, K. Verma, "Pneumonia Detection on Chest X-Ray Using Machine Learning Paradigm", The 3rd International Conference on Computer Vision and Image Processing, pp. 21-33, November 2019.

[15] K. Kuo, P. Talley, C. Huang, L. Cheng L, "Predicting Hospital-Acquired Pneumonia Among Schizophrenic Patients: A Machine Learning Approach", BMC Medical Informatics and Decision Making, Vol. 19, pp. 1-8, 2019.

[16] H. Yue, Q. Yu, C. Liu, Y. Huang, Z. Jiang, C. Shao, et al., "Machine Learning-Based CT Radiomics Method for Predicting Hospital Stay in Patients with Pneumonia Associated with SARS-CoV-2 Infection: A Multicenter Study", Annals of Translational Medicine, Vol. 8, No. 14, 2020.

[17] T. Meraj, A. Hassan, S. Zahoor, H. Rauf, M. Lali, L. Ali, et al., "Lungs Nodule Detection Using Semantic Segmentation and Classification with Optimal Features", Preprints, 2019.

[18] S. Kadry, Y. Nam, H. Rauf, V. Rajinikanth, L. Lawal, "Automated Detection of Brain Abnormality using Deep-Learning-Scheme: A Study", 2021 Seventh International Conference on Bio Signals, Images, And Instrumentation (ICBSII), pp. 1-5, Chennai, India, March 2021.

[19] S. Yadav, S. Shukla, "Analysis of K-Fold Cross-Validation over Hold-Out Validation on Colossal Datasets for Quality Classification", The 6th International Conference on Advanced Computing, pp. 78-83, Bhimavaram, India, February 2016.

[20] V. Jain, A. Jain, V. Garg, A. Jain, M. Demirci, M.C. Taplamacioglu, "Siamese Neural Networks for Pandemic Detection using Chest Radiographs", International Journal on Technical and Physical Problems of Engineering, Issue 51, Vol. 14, No. 2, pp. 104-110, June 2022.

[21] E. Taylor, P.S. Ezekiel, F.B. Deedam Okuchaba, "A Model to Detect Heart Disease using Machine Learning Algorithm", International Journal of Computer Sciences and Engineering, Vol. 7, No. 11, November 2019.

[22] A. Hazra, S. Kumar Mandal, A. Gupta, A. Mukherjee, "Heart Disease Diagnosis and Prediction Using Machine Learning and Data Mining Techniques", Advances in Computational Sciences and Technology, Vol. 10, No. 7, pp. 2137-2159, 2017.

[23] P.K. Reddy, T.S. Kumar Reddy, S. Balakrishnan, S. M. Basha, R.K. Poluru, "Heart Disease Prediction Using Machine Learning Algorithm", International Journal of Innovative Technology and Exploring Engineering (IJITEE), Vol. 8, Issue 10, August 2019.

[24] V. Jain, Y. Jain, H. Dhingra, A. Jain, M. Demirci, M.C. Taplamacioglu, "Dynamic Visualization of an Image for Interactive Actions", International Journal on Technical and Physical Problems of Engineering, Issue 53, Vol. 14, No. 4, pp. 363-369, December 2022.

[25] A. Tyagi, R. Mehra, "Interactive Thyroid Disease Prediction System using Machine Learning Techniques", The Fifth International Conference on Parallel, Distributed and Grid Computing, pp. 689-693, Solan, India, 20-22 December 2018.
[26] S. Godara, S. Kumar, "Prediction of Thyroid Disease Using Machine Learning Techniques", International Journal of Electronics Engineering, Vol. 10, No. 2, pp. 787-793, 2018.
[27] Y.F. Wang, W.W. Yue, X.L. Li, S.Y. Liu, L.H. Guo, H.X. Xu, H.Y. Zhang, G. Yang, "Comparison Study of Radiomics and Deep-Learning Based Methods for Thyroid Nodules Classification Using Ultrasound Images", IEEE Access, Vol. 8, pp. 52010-52017, 2020.
[28] https://www.kaggle.com/ Date: 09-03-2022, Time: 03:00 P.M.
[29] S. Ahlawat, A. Choudhary, "Hybrid CNN_SVM Classifier for Handwritten Digital Recognition", International Conference on Computational Intelligence and Data Science, Procedia Computer Science, Vol. 167, pp. 2554-2560, 2020.

BIOGRAPHIES

Name: **Vanita**
Surname: **Jain**
Birthday: 07.11.1966
Birth Place: New Delhi, India
Bachelor: Electrical Engineering, Punjab Engineering College, Chandigarh, India, 1988
Master: Control Systems, National Institute of Technology, Kurukshetra, India, 1990
Doctorate: Design of Controller for Real Time Systems, V.J.T.I., Mumbai, India, 2008
The Last Scientific Position: Prof., Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, Since 2010
Research Interests: Control Systems, Optimization Technique, Soft Computing

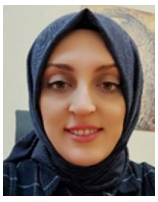
Name: **Bhawanand**
Surname: **Jha**
Birthday: 15.06.1983
Birth Place: Darbhanga, India
Bachelor: Electronics and Communication Engineering, RGPV, Bhopal, India, 2009
Master: Nano Science and Technology, GGSIPU Dwarka, India, 2013
The Last Scientific Position: Assist. Prof., Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, Since 2014
Research Interests: Machine Learning, VLSI Design

Name: **Sourav**
Surname: **Joshi**
Birthday: 23.10.1999
Birth Place: New Delhi, India
Bachelor: Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, 2022
The Last Scientific Position: Programmer Analyst Trainee, Cognizant, India
Research Interests: Generative Adversarial Networks, Speech De-noising using Deep Convolution Neural Network

Name: **Sourabh**
Surname: **Miglani**
Birthday: 11.05.1999
Birth Place: Haryana, India
Bachelor: Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, 2022
The Last Scientific Position: Specialist Programmer, Infosys, India
Research Interests: Neural Networks, Transfer Learning

Name: **Aman**
Surname: **Singal**
Birthday: 22.05.2000
Birth Place: Hisar, India
Bachelor: Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, 2022
Research Interests: Artificial Intelligence, Cloud Computing, Web Development and System Engineering

Name: **Shubham**
Surname: **Babbar**
Birthday: 17.06.2000
Birth Place: New Delhi, India
Bachelor: Electronics and Communication Engineering Department, Bharati Vidyapeeth's College of Engineering, New Delhi, India, 2022
Master: Student, Department of Commerce, Delhi School of Economics, Delhi University, India, Since 2022
Research Interests: Optical Communication, Machine Learning and Data Science



Name: **Merve**
Surname: **Demirci**
Birthday: 08.06.1992
Birth Place: Trabzon, Turkey
Bachelor: Electrical and Electronics Engineering, Department of Electrical and Electronics Engineering, Engineering Faculty, Ataturk University, Erzurum, Turkey, 2014

Master: Electrical and Electronics Engineering, Dept. of Electrical and Electronics Engineering, Institute of Science, Gazi University, Ankara, Turkey, 2018
The Last Scientific Position: Research Assistant, Department of Electrical and Electronics Engineering, Engineering Faculty, Gazi University, Ankara, Turkey, Since 2016
Research Interests: Power systems analysis, artificial intelligence, Machine Learning
Scientific Publications: 4 Papers, 2 Projects

Name: **Muslum**
Middle Name: **Cengiz**
Surname: **Taplamacioglu**
Birthday: 04.10.1962
Birth Place: Ankara, Turkey
Bachelor: Electrical and Electronics Engineering, Department of Electrical and Electronics Engineering, Engineering Faculty, Gazi University, Ankara, Turkey, 1983
Master: Electrical and Electronics Engineering, Dept. of Electrical and Electronics Engineering, Institute of Science, Middle East University, Ankara, Turkey, 1986
Doctorate: University of Wales, Cardiff, United Kingdom, 1993
The Last Scientific Position: Prof., Department of Electrical and Electronics Engineering, Engineering Faculty, Gazi University, Ankara, Turkey, Since 2000
Research Interests: Smart Grid Applications, High Voltage Engineering, Power Systems Analysis
Scientific Publications: 43 Papers, 8 Projects, 53 Theses