A Robust Heart Disease Prediction System Using Hybrid Deep Neural Networks

NAME: Sri Varsha Pasham
Student Id : 700759090

Motivation

- Heart disease or cardiovascular disease is one of the biggest reason for death across the globe. So, if somehow we manage to find the risk of someone having a heart disease beforehand then it would be helpful.
- Challenges in HD Prediction: Complexity of HD makes it difficult for medical practitioners to diagnose promptly and accurately.
- Role of Deep Learning (DL): DL-based systems show good efficiency in disease prediction and diagnosis.

Problem Statement

- Heart Disease (HD): Leading cause of worldwide mortality according to WHO.
- Annual Deaths: Approximately 17.9 million.
- Significance: Early detection and accurate prediction are critical for timely medical interventions and improving patient outcomes.
- This work introduces an enhanced and novel (HDNNs) system, utilizing a larger and a smaller dataset to design the system effectively.
- Additionally, the proposed system was measured through comparison with conventional systems concerning sensitivity, Matthews Correlation Coefficient (MCC), F1-measure, accuracy, precision, AUC, and specificity.The promising accuracy achieved through the proposed system is 98.86%

Contributions

Models Used:

- Artificial Neural Networks (ANN)
- Convolutional Neural Networks (CNN)
- Long Short-Term Memory (LSTM)
- Hybrid CNN-LSTM with additional Dense layers
- Four ML methods (SVM, KNN, DT, and RF)

Datasets Used

- Cleveland Dataset
- (Switzerland + Cleveland + Statlog +Hungarian+ Long Beach VA)

Preprocessing:

- Data preprocessing was done on the collected data.

Feature Selection:

The method of feature selection involves picking features in order to reduce computational latency and complexity while boosting accuracy.

Objectives

- Main Contribution: Design a robust HD prediction system using Hybrid Deep Neural Networks (HDNNs).
- Method: Combining multiple neural network architectures to extract and learn relevant features from input data.
- Train the model using two heart disease datasets:

1. UCI Kaggle Cleveland HD dataset (2 classes, 14 attributes,and 303 occurrences)
2. Comprehensive HD dataset combining (Switzerland, Cleveland, Statlog, Hungarian,Long Beach VA data.)includes 11 features, 1190 instances,and 2 classes.

- The proposed system is implemented using the Anaconda framework(Jupyter Notebook) Python ,fundamental ML/DL libraries, including Scikit-learn NumPy, and TensorFlow ,

Continued

Data Splitting:

- Data splitting is a technique that involves dividing a datasetinto smaller subsets.
- Normalized preprocessed HD data is partitioned into two chunks (train, and test set).

Prediction Models:

- After determining the features, the models were built using the four DL prediction and categorization techniques, including ANN, LSTM, CNN, and Hybrid CNN-LSTM.
- One comparison is carried out with the individual method, where the hybrid CNN-LSTM model is tested against deep ANN, LSTM, and CNN methods.
- The other comparison compares the performance of the proposed system with conventional ML techniques using deep neural networks.

Results

HD dataset types	Number of instances
Hungarian	294
Switzerland	123
Stalog (Heart)	270
Long Beach VA	200
Cleveland	303
Total	1190

Feature	Ranking
ST slope	0.16502219208594232
chest pain type	0.12464289848775935
max heart rate	0.10104757501424239
cholesterol	0.0917755431380437
exercise angina	0.13491029293081083
oldpeak	0.09079997817697384
age	0.07816976039185529
resting bp	0.07691931331560171
sex	0.06263122053450898
resting ECG	0.03856771210569106
fasting blood sugar	0.03551351381857052
ST slope	0.16502219208594232

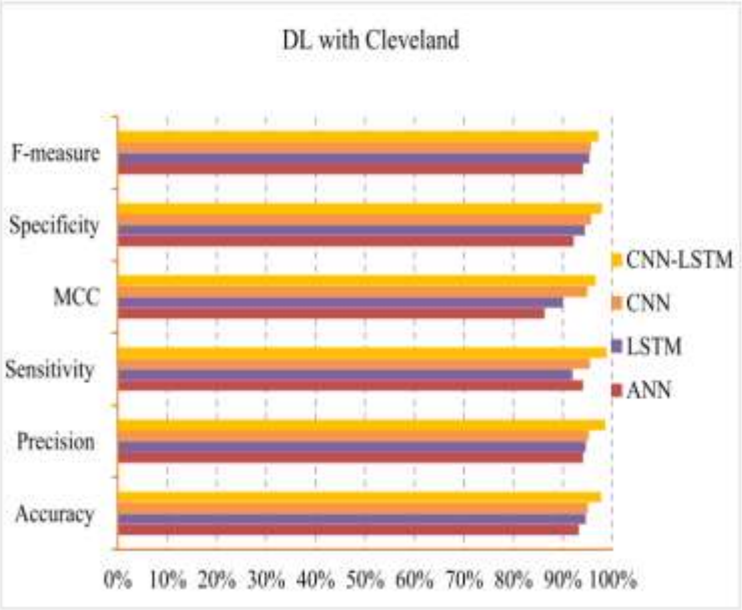
TABLE 3. Evaluation of the proposed DL models using a comprehensive HD dataset (Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA).

Model	Accuracy	Precision	Sensitivity	MCC	Specificity	F-measure	AUC
SVM	89.07%	0.8947	0.9083	0.7790	0.8691	0.9015	0.8791
KNN	89.82%	0.8888	0.91603	0.7789	0.8598	0.9022	0.8885
DT	88.80%	0.8515	0.8787	0.7758	0.8700	0.8969	0.8603
RF	92.17%	0.9381	0.9191	0.8423	0.9250	0.9285	0.9120
ANN	93.21%	0.9408	0.9408	0.8629	0.9220	0.9408	0.9514
LSTM	94.65%	0.9465	0.9191	0.9003	0.9441	0.9533	0.9578
CNN	95.02%	0.9521	0.9546	0.9495	0.9571	0.9563	0.9686
CNN-LSTM	97.75%	0.9857	0.9887	0.9660	0.9787	0.9718	0.9885

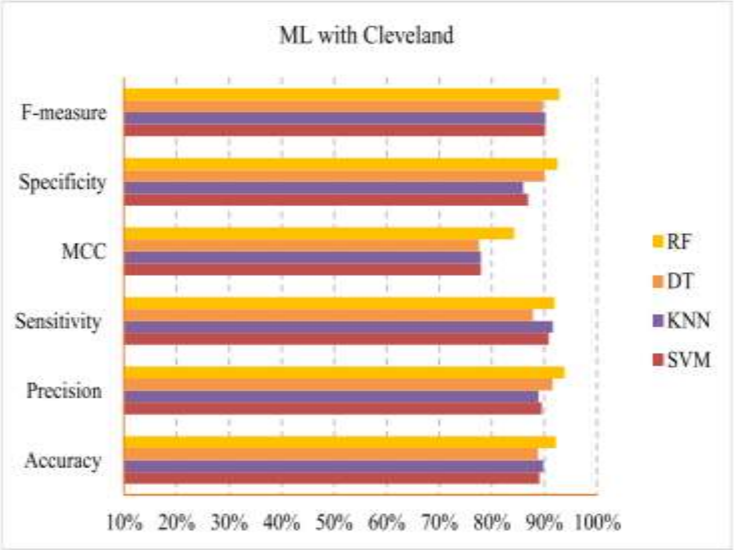
TABLE 4. Evaluation of the proposed DL models using a comprehensive HD dataset (Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA).

Model	Accuracy	Precision	Sensitivity	MCC	Specificity	F-measure	AUC
SVM	89.07%	0.8671	0.8224	0.7811	0.8224	0.9051	0.8844
KNN	88.65%	0.8714	0.9312	0.7712	0.8815	0.9003	0.8815
DT	86.24%	0.8950	0.8579	0.7223	0.8682	0.8761	0.8331
RF	89.93%	0.9112	0.9112	0.7949	0.8837	0.9112	0.8974
ANN	94.53%	0.9402	0.9618	0.8896	0.9252	0.9509	0.9685
LSTM	96.64%	0.9793	0.9595	0.9325	0.975	0.9693	0.9865
CNN	96.86%	0.9722	0.9722	0.9296	0.9574	0.9722	0.9878
CNN-LSTM	98.86%	0.9913	0.9874	0.9705	0.9942	0.9983	0.9978

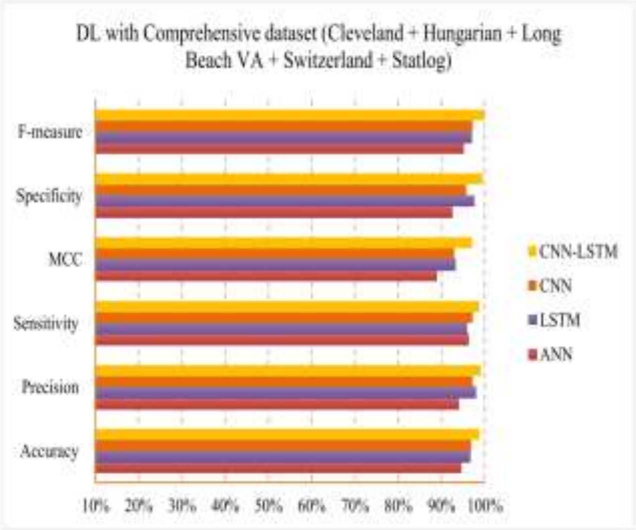
Continued



DL with Cleveland
F-measure
Specificity
MCC
Sensitivity
Precision
Accuracy
CNN-LSTM
CNN
LSTM
ANN
0% 10% 20% 30% 40% 50% 60% 70% 80% 90% 100%



ML with Cleveland
F-measure
Specificity
MCC
Sensitivity
Precision
Accuracy
RF
DT
KNN
SVM
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%



DL with Comprehensive dataset (Cleveland + Hungarian + Long Beach VA + Switzerland + Statlog)
F-measure
Specificity
MCC
Sensitivity
Precision
Accuracy
CNN-LSTM
CNN
LSTM
ANN
10% 20% 30% 40% 50% 60% 70% 80% 90% 100%

Continued

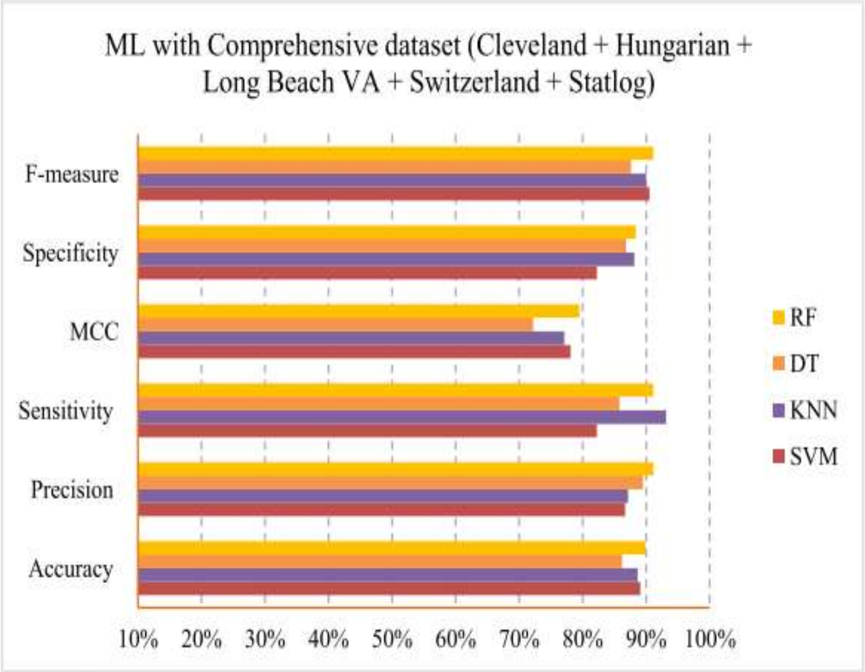


FIGURE 10. Graphical comparison of DL models using a comprehensive dataset. (Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA.)

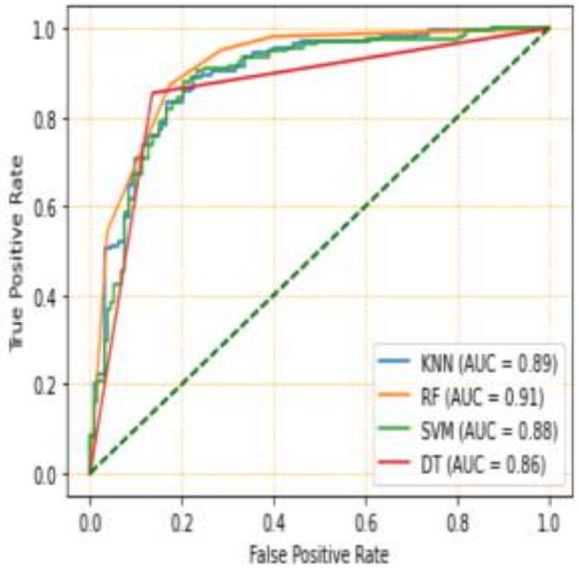


FIGURE 12. ROC/AUC score of ML models using Cleveland.

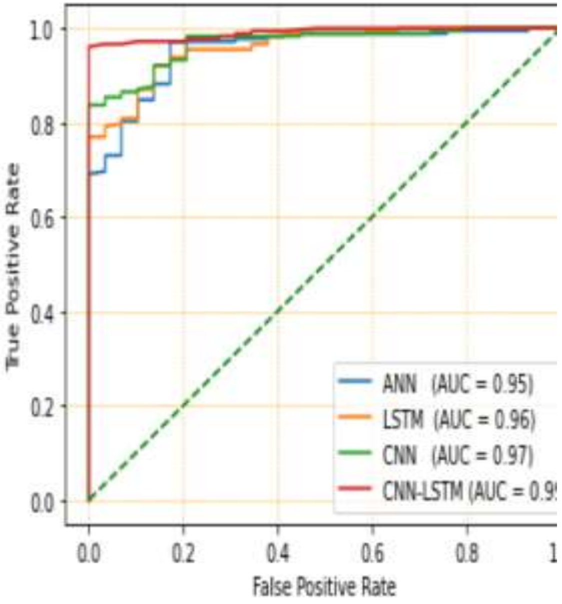


FIGURE 13. ROC/AUC score of DL models using Cleveland.

Continued

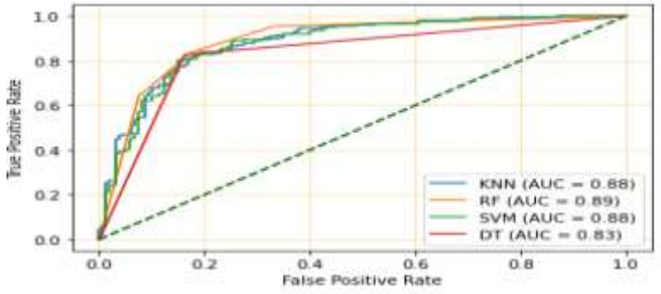


FIGURE 14. ROC/AUC score of ML models using a comprehensive dataset. (Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA)

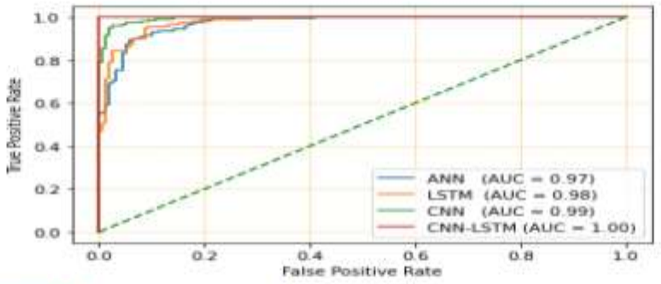


FIGURE 15. ROC/AUC score of DL models using a comprehensive dataset. (Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA)

Work	Heart Disease Dataset	Model	Accuracy
[25]	Cleveland (14, 303)	LR, KNN, SVM, RF, DT, DL	83.3%, 84.8%, 83.2%, 80.3%, 82.3%, 94.2%
[26]	Heart Disease UCI dataset	Hard voting ensemble	90.00%
[27]	Cleveland (14, 303)	NB	84.51%
[30]	Cleveland (14, 303)	KNN	85.00%
[31]	Cleveland (14, 303)	RF+DT	88.70%
[33]	Hungarian (294, 12)	ANN	81.02%
[33]	Cleveland (14, 303)	ANN	82.49%
[33]	Switzerland (13, 123)	ANN	60.06%
[33]	Long Beach VA (13, 200)	ANN	60.00%
[34]	Heart Disease UCI dataset	RF with a linear model	88.70%
[37]	Heart Disease UCI dataset	LOFS-ANN	90.5%
[53]	Hungarian + Cleveland + Long Beach VA + Switzerland + Statlog (11, 1190)	Stacked ensemble classifier with Extra Trees Classifier, RF, XGB	92.34%
[54]	Heart Disease UCI dataset	RF	83%
Proposed	Cleveland (14, 303)	Deep ANN, LSTM, CNN, CNN+LSTM	93.21%, 94.65%, 95.02%, 97.75%
Proposed	Combined [(Switzerland + Cleveland + Statlog + Hungarian + Long Beach VA) (11, 1190)]	Deep ANN, LSTM, CNN, CNN+LSTM	94.03%, 96.24%, 96.86%, 98.86%

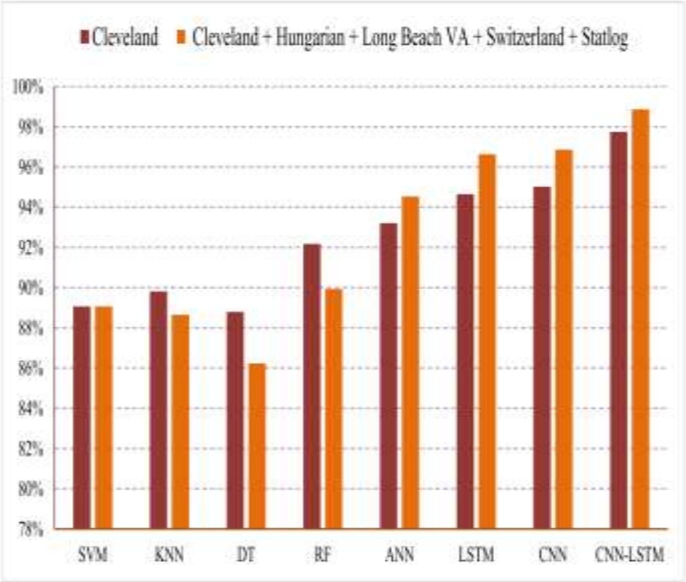


FIGURE 16. Comparison of the proposed ML and DL models for both datasets.

Critical Analysis

- Combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks.Utilizes Dense layers for a comprehensive learning process.
- Achieves 98.86% accuracy on two publicly available datasets.
- Compared to the traditional ML and existing state-of-the-art, the proposed CNN-LSTM achieved the best accuracy, precision, sensitivity, MCC, specificity, f-measure,and AUC of 97.75%, 0.9857, 0.9887, 0.9660, 0.9787, 0.9718,and 0.9885, respectively.
- Employs diverse datasets (Cleveland HD dataset and a combined public HD dataset).Ensure generalizability and robustness of the model.
- Assists healthcare professionals in early diagnosis and improving patient outcomes.

Improvements

- Limited discussion on handling missing values, normalization, and feature selection.
- Needs more extensive comparison with recent state-of-the-art models.
- Potential risks of overfitting and dataset bias not thoroughly addressed.

References

[1] N. C. Long, P. Meesad, and H. Unger, ‘‘A highly accurate firefly based algorithm for heart disease prediction,’’ Expert Syst. Appl., vol. 42, no. 21,pp. 8221–8231, Nov. 2015, doi: 10.1016/j.eswa.2015.06.024.
[2] UDMI. Accessed: Jul. 24, 2023. [Online]. Available: https://www.udmi.net/cardiovascular-disease-risk/
[3] P. K. Mehta, S. Gaignard, A. Schwartz, and J. E. Manson, ‘‘Tradi tional and emerging sex-specific risk factors for cardiovascular dis ease in women,’’ Rev. Cardiovascular Med., vol. 23, no. 8, p. 288,2022.
[4] J. M. Alves-silva, M. Zuzarte, and H. Gir, ‘‘The role of essential oils and their main compounds in the management of cardiovascular disease risk factors,’’ Molecules, vol. 26, no. 3506, pp. 1–26,2021.
[5] C. Zhou, A. Hou, P. Dai, A. Li, Z. Zhang, Y. Mu, and L. Liu, ‘‘Risk factor refinement and ensemble deep learning methods on prediction of heart failure using real healthcare records,’’ Inf. Sci., vol. 637, Aug. 2023,Art. no. 118932, doi: 10.1016/j.ins.2023.04.011.
[6] F. Ali, S. El-Sappagh, S. M. R. Islam, D. Kwak, A. Ali, M. Imran, and K.-S. Kwak, ‘‘A smart healthcare monitoring system for heart disease pre diction based on ensemble deep learning and feature fusion,’’ Inf. Fusion,vol. 63, pp. 208–222, Nov. 2020, doi: 10.1016/j.inffus.2020.06.008.

Continued

[7] S. P. Barfungpa, H. K. D. Sarma, and L. Samantaray, “An intelligent heart disease prediction system using hybrid deep dense Aquila network,”Biomed. Signal Process. Control, vol. 84, Jul. 2023, Art. no. 104742, doi:10.1016/j.bspc.2023.104742.

[8] S. Amin, B. Alouffi, M. I. Uddin, and W. Alosaimi, “Optimizing convo lutional neural networks with transfer learning for making classification report in COVID-19 chest X-rays scans,” Sci. Program., vol. 2022,pp. 1–13, May 2022, doi: 10.1155/2022/5145614.

[9] S.-C. Huang, A. Pareek, S. Seyyedi, I. Banerjee, and M. P. Lungren,“Fusion of medical imaging and electronic health records using deeplearning: A systematic review and implementation guidelines,” NPJ Digit.Med., vol. 3, no. 1, p. 136, Oct. 2020.

[10] B. He, L. Bergenstråhle, L. Stenbeck, A. Abid, A. Andersson, Å. Borg,J. Maaskola, J. Lundeberg, and J. Zou, “Integrating spatial gene expression and breast tumour morphology via deep learning,” Nature Biomed. Eng.,vol. 4, no. 8, pp. 827–834, Jun. 2020.

[11] S. Amin, A. Alharbi, M. I. Uddin, and H. Alyami, “Adapting recurrent neural networks for classifying public discourse on COVID-19 symptoms in Twitter content,” Soft Comput., vol. 26, no. 20, pp. 11077–11089,Oct. 2022, doi: 10.1007/s00500-022-07405-0.