Comparative Analysis of Deep Learning Architectures for Cardiovascular Disease Detection from ECG Images

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Abstract:

The research addresses worldwide heart disease challenges through the convenient and needle-free ECG tool which enables early heart disorder identification. The authors suggest ECG conversion to twelve-lead images before applying deep learning techniques with SqueezeNet alongside AlexNet and a customized CNN. The present models identify four categories comprising arrhythmias together with risk/history of myocardial infarction.
Keywords: - Cardiovascular diseases, Heart conditions, Mortality, Timely prediction, Electrocardiogram (ECG), Deep learning, Transfer learning, Neural networks, Squeeze Net, Alex Net.

I. INTRODUCTION

Heart diseases combined with other cardiovascular diseases exist as the top homicidal cause worldwide as recognized by the WHO. The detection of heart conditions at an early stage leads to better treatment results alongside improved patient health quality. An ECG stands among multiple diagnostic instruments as a well-known non-invasive tool used to measure heart electrical signals for medical evaluation purposes.Through the mentioned project we see how artificial intelligence based on machine learning and deep learning technology automatic heart disease prediction systems help reduce medical uncertainties while enhancing diagnostic precision as well as operational efficiency.The American Health Monitoring Organization together with CDC [1] reports heart disease as the main source of fatalities among 74% of the population each year. An early diagnosis will help stop cardiovascular complications from forming [2].The coronavirus disease COVID-19 originated in Wuhan during December 2019 before WHO proclaimed it an emergency in January 2020 followed by its name declaration in February and pandemic announcement in March 2020 (Kim 2021, Zhu et al. 2020). The pandemic rapidly invaded Italy and Spain and United States territory according to Ceylan (2021).These days our information age produces overwhelming amounts of unprocessed data through data system operations. Healthcare practitioners need help extracting valuable information from datasets to the extent data science tools including statistical methods and machine learning constitute their primary operations [3].

II. LITERATURE SURVEY

The exploration in this paper addresses machine learning (ML) methods for detecting heart disease (HD) by analyzing ECG signals. Support vector machine and logistic regression together with adaptive boosting received the best results among all models during their evaluation with unbalanced datasets. The ensemble voting from all three classifiers produced superior results through 0.946, 0.949, and 0.951 for accuracy, F1-score, and AUC measurement on the PTB ECG data and 0.921, 0.926, and 0.950 on the MIT-BIH data. The proposed methodology can detect diseases through other physiological signals and it shows first validation evidence for medical detection systems. [1]This study evaluates different ML algorithms for diagnosing HD using ECG data signals. The combining model obtained optimal accuracy ratings of 0.946 and 0.949 and AUC of 0.951 through evaluation on PTB ECG data. [2]The paper explores clinical heart disease prediction by testing selection methods and classification systems using the Cleveland dataset. Decision tree classification running backward feature selection produced a detection accuracy level of 88.52% and returned precision at 91.30% while sensitivity reached 80.76% alongside the f-measure value of 85.71%.[3]The detection of COVID-19 using Xception-based neural networks resulted in a 0.996 accuracy for two-class datasets and 0.989 for three-class and 0.924 for four-class X-ray image analysis.[4]The research by Hussain and Malik presents a method for cardiac disease detection through automated ECG image analysis. Through the utilization of SSD MobileNet v2 Deep Neural Network and 11,148 manually collected and annotated ECG images their system detected major cardiac abnormalities with 98% accuracy. The system has received cardiologist approval for screening cardiac disorders.[5]

III. METHODOLOGY

A) System Architecture

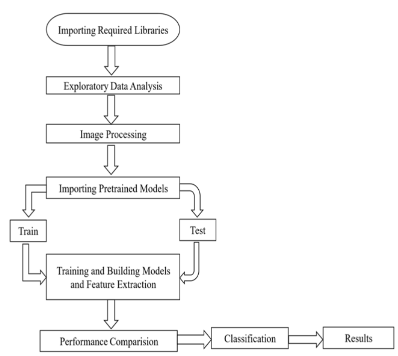

Fig 1: System Architecture

Proposed Work: As shown in Fig 1, at first imported required libraries. Collected dataset from Mendeley website, it consists of 928 images. Other steps include data exploration, image processing and then importing pretrained models like cnn, alexnet, squeezenet and exception net. For these models, imported dataset is given for training and testing after that feature extraction from the images is done by these models. Furthermore, for the comparison of deep learning architectures machine learning algorithms are used based on evaluation metrics.Finally,using the selected deep learning architecture classification is done.

B) Dataset Collection

Dataset is collected from Mendeley website. Each image in the ECG dataset represents heart rhythm as graph in Fig 2 shows dynamic electrical impulses.

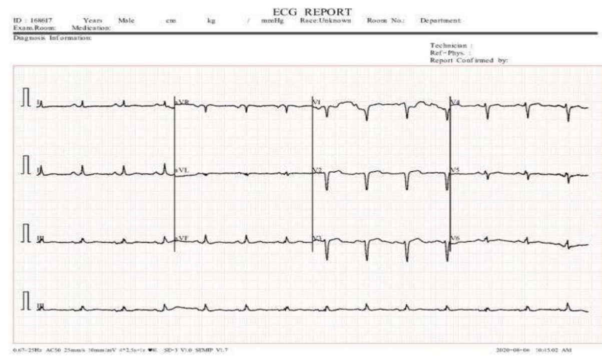

Fig 2: Sample ECG Image

The ECG Image Dataset serves as the foundation for creating machine learning algorithms that seek automated diagnosis systems along with automated clinical practices. Artificial intelligence systems require machine learning models using advanced computer methods to analyze image data and detect minor heart signal irregularities which indicate various types of heart diseases. Driven by different body electrodes the image leads to separation into multiple parts as shown in Fig 3 that shows heart rhythm patterns to detect different heart diseases. Programmer-designed constructs allow the image to produce different leads which correspond to body electrodes.

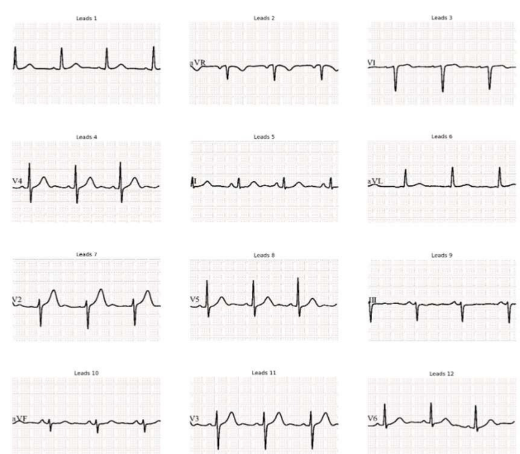

Fig 3: Divided leads

C) Pre-processing

In the pre-processing stage, image undergoes gray scale conversion and image is resized to 224*224*3 those are height, width and RGB channels.

D) Training & Testing

As dataset contain 928 images,80% of images is given to training and 20% of images is given to testing the models i.e., 745 images belong to training data and 183 images belong to testing data.

E)Performance Comparison:

Deep learning models like CNN extract the features and those models can be compared based on the evaluation metrics but it doesn't give accurate result. So, for each dl model ,machine learning algorithms like SVM, KNN,Random Forest, Decision Tree are assigned and trained with dataset .After that all the hybrid model are compared based on evaluation metrics.

F)Classification:

Based on performance evaluation of all hybrid models,best dl model is choosen and used for classification.

IV. EXPERIMENTAL RESULTS

A) Comparison Graphs → Accuracy, Precision, Recall, f1 score

- Accuracy = (TP + TN)/ (TP + TN + FP + FN)

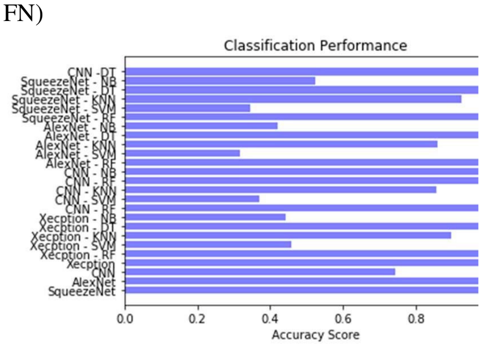

Fig 4: Accuracy Graph

ML Model	Accuracy
SqueezeNet	1
AlexNet	0.995
CNN	0.743
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.459
Xecption - KNN	0.896
Xecption - DT	1
Xecption - NB	0.444
CNN - RF	1
CNN - SVM	0.37
CNN - KNN	0.858
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.317
AlexNet - KNN	0.861
AlexNet - DT	1
AlexNet - NB	0.42
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.346
SqueezeNet - KNN	0.927
SqueezeNet - DT	0.994
SqueezeNet - NB	0.525
CNN -DT	1

Fig 5: accuracy table

Fig 5 shows the accuracy graph and Fig 6 shows the corresponding values of that particular graph. As shown in figures, by using only dl models accuracy values are not so accurate. And when each dl model is combined with ml algorithms, we can see that in every section i.e., xception ,cnn and alexnet the accuracy values are almost 1 which is not correct. Whereas in squeqqzenet model,squeezenet-RF is giving high accuracy i.e., 0.998.Finally,as per the figures ,we can conclude that squeeze net is best when evaluated based on accuracy.

- Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

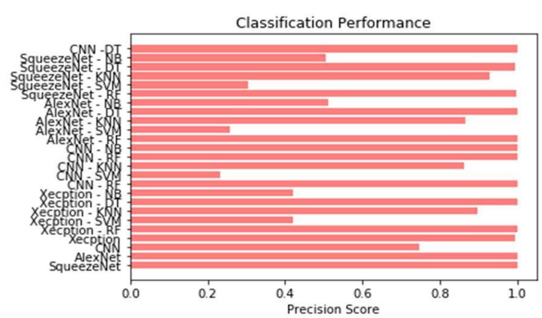

Fig 6: Precision Score Graph

ML Model	Precision
SqueezeNet	1
AlexNet	1
CNN	0.747
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.421
Xecption - KNN	0.899
Xecption - DT	1
Xecption - NB	0.421
CNN - RF	1
CNN - SVM	0.232
CNN - KNN	0.862
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.257
AlexNet - KNN	0.865
AlexNet - DT	1
AlexNet - NB	0.513
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.305
SqueezeNet - KNN	0.928
SqueezeNet - DT	0.994
SqueezeNet - NB	0.504
CNN -DT	1

Fig7:precision table

Fig 7 shows the accuracy graph and Fig 8 shows the corresponding values of that particular graph. As shown in figures, by using only dl models accuracy values are not so accurate. And when each dl model is combined with ml algorithms, we can see that in every section i.e., xception ,cnn and alexnet the accuracy values are almost 1 which is not correct. Whereas in squeqqzenet hybrid model,squeezenet-RF is giving high precision i.e., 0.998.Finally,as per the figures ,we can conclude that squeeze net is best when evaluated based on precision.

- Recall = (TP)/(TP+FN)

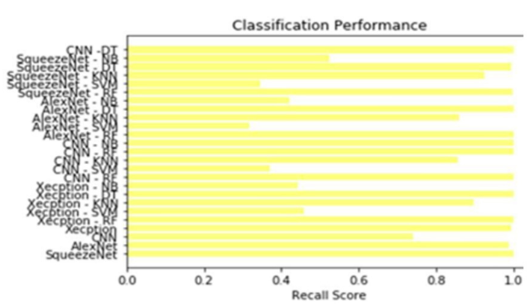

Fig 8: Recall Score Graph

ML Model	Recall
SqueezeNet	1
AlexNet	0.99
CNN	0.742
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.459
Xecption - KNN	0.896
Xecption - DT	1
Xecption - NB	0.444
CNN - RF	1
CNN - SVM	0.37
CNN - KNN	0.858
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.317
AlexNet - KNN	0.861
AlexNet - DT	1
AlexNet - NB	0.42
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.346
SqueezeNet - KNN	0.927
SqueezeNet - DT	0.994
SqueezeNet - NB	0.525
CNN -DT	1

Fig 9: recall table

Fig 9 shows the recall graph and Fig 10 shows the corresponding values of that particular graph. As shown in figures, by using only dl models accuracy values are not so accurate. And when each dl model is combined with ml algorithms, we can see that in every section i.e., xception ,cnn and alexnet the accuracy values are almost 1 which is not correct. Whereas in squeeze net hybrid model,squeezenet-RF is giving high precision i.e., 0.998.Finally,as per the figures ,we can conclude that squeeze net is best when evaluated based on recall.

- F1 Score = 2*Precision*Recall/Precision+Recall

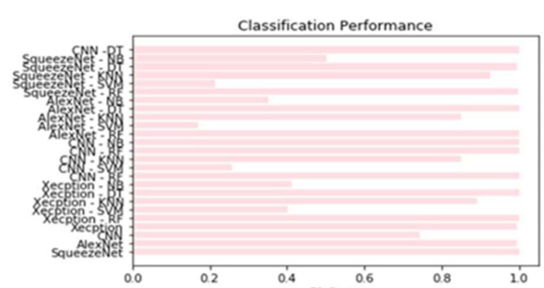

Fig 10: F1 Score graph

ML Model	F1_score
SqueezeNet	1
AlexNet	0.995
CNN	0.745
Xecption	0.995
Xecption - RF	1
Xecption - SVM	0.403
Xecption - KNN	0.892
Xecption - DT	1
Xecption - NB	0.411
CNN - RF	1
CNN - SVM	0.259
CNN - KNN	0.85
CNN - RF	1
CNN - NB	1
AlexNet - RF	1
AlexNet - SVM	0.169
AlexNet - KNN	0.85
AlexNet - DT	1
AlexNet - NB	0.352
SqueezeNet - RF	0.998
SqueezeNet - SVM	0.215
SqueezeNet - KNN	0.925
SqueezeNet - DT	0.994
SqueezeNet - NB	0.503
CNN -DT	1

Fig 11:F1 Score table

Fig 10 shows the F1 Score graph and Fig 11 shows the corresponding values of that particular graph. As shown in figures, by using only dl models accuracy values are not so accurate. And when each dl model is combined with ml algorithms, we can see that in every section i.e., xception ,cnn and alexnet the accuracy values are almost 1 which is not correct. Whereas in squeeze net hybrid model,squeezenet-RF is giving high precision i.e., 0.998.Finally,as per the figures ,we can conclude that squeeze net is best when evaluated based on F1Score.

B)Performance Evaluation table:

ML Model	Accuracy	Precision	Recall	F1_score
SqueezeNet	1	1	1	1
AlexNet	0.995	1	0.99	0.995
CNN	0.743	0.747	0.742	0.745
Xecption	0.995	0.995	0.995	0.995
Xecption - RF	1	1	1	1
Xecption - SVM	0.459	0.421	0.459	0.403
Xecption - KNN	0.896	0.899	0.896	0.892
Xecption - DT	1	1	1	1
Xecption - NB	0.444	0.421	0.444	0.411
CNN - RF	1	1	1	1
CNN - SVM	0.37	0.232	0.37	0.259
CNN - KNN	0.858	0.862	0.858	0.85
CNN - RF	1	1	1	1
CNN - NB	1	1	1	1
AlexNet - RF	1	1	1	1
AlexNet - SVM	0.317	0.257	0.317	0.169
AlexNet - KNN	0.861	0.865	0.861	0.85
AlexNet - DT	1	1	1	1
AlexNet - NB	0.42	0.513	0.42	0.352
SqueezeNet - RF	0.998	0.998	0.998	0.998
SqueezeNet - SVM	0.346	0.305	0.346	0.215
SqueezeNet - KNN	0.927	0.928	0.927	0.925
SqueezeNet - DT	0.994	0.994	0.994	0.994
SqueezeNet - NB	0.525	0.504	0.525	0.503
CNN -DT	1	1	1	1

Fig 12: Performance Evaluation Table

As discussed above and as per the values in the fig 23,squeeze net is having accurate metrics when compared to other models. By this performance evaluation, squeeze net is declared as best model to predict cardiovascular diseases from ECG images.

C)UserTesting with Flask:

Frontend application was built using flask API.

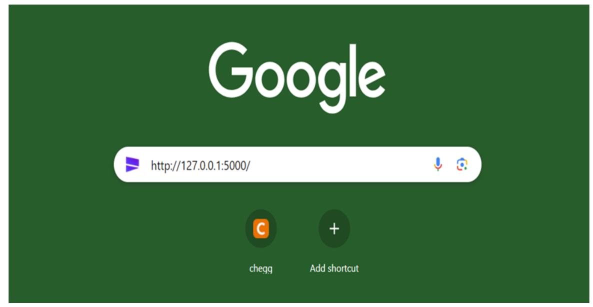

Fig 13: website link

- As shown in fig 13 ,at first we should start the server. Copy paste the local host link which we get on prompt shell.

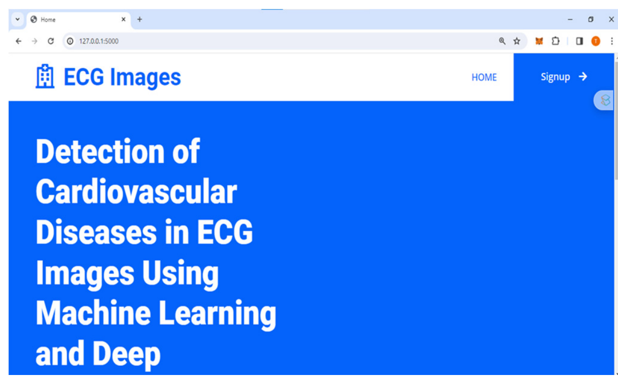

Fig 14: Home page

- Home Page of website looks like as shown in figure, in navbar there are buttons like home and signup.

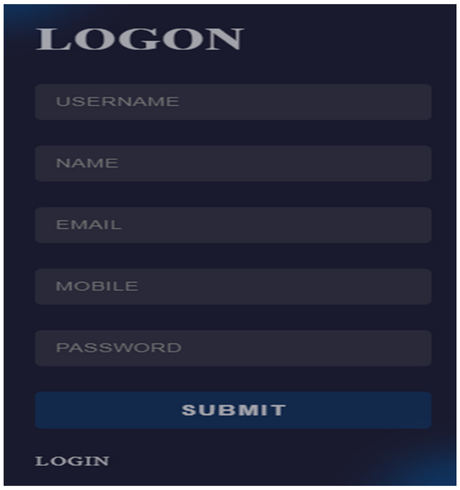

Fig 15:Sign up page

- The signup of page looks like as shown in figure 15.

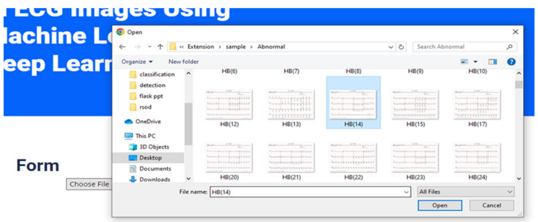

Fig 16: uploading image

- After logging into the page,user need to upload an ecg image as shown in fig 16.

Fig 17:Result page

- When user upload an image, at the backend squeeze net model have been saved. Image undergoes pre processing and squezeenet extact features and does the classification and gives the final result.

V. CONCLUSION

The model demonstrates outstanding capabilities in early detection because it targets the four important cardiac abnormalities. We are most proud that our system effectively retrieves important ECG image features while collaborating with conventional machine learning systems. The solution combines accuracy improvements with an economical noninvasive heart-monitoring system for addressing a leading worldwide health concern. This study reveals how artificial intelligence technology can revolutionize healthcare analysis although it specifically helps save lives by enhancing diagnosis of cardiovascular conditions.

VI. FUTURE SCOPE

The performance of the CNN model can be improved through future development involving optimal parameter tuning of learning rate alongside batch size with dropout. Business applications of Industrial IoT could utilize this model to carry out anomaly detection duties together with quality control tasks. The model can be optimized for extended use across diverse larger datasets which will enable its application from cardiovascular predictions to expanded IIoT classification needs.

REFERENCES

[1] Lopes, Ricardo R., et al. "Improving electrocardiogram-based detection of rare genetic heart disease using transfer learning: An application to phospholamban p. Arg14del mutation carriers." *Computers in Biology and Medicine* 131 (2021): 104262.

[2] Rath, Adyasha, et al. "Heart disease detection using deep learning methods from imbalanced ECG samples." *Biomedical Signal Processing and Control* 68 (2021): 102820.

[3] Dissanayake, Kaushalya, and Md Gapar Md Johar. "Comparative study on heart disease prediction using feature selection techniques on classification algorithms." *Applied Computational Intelligence and Soft Computing* 2021.1 (2021): 5581806.

[4] Ozcan, Tayyip. "A new composite approach for COVID-19 detection in X-ray images using deep features." *Applied Soft Computing* 111 (2021): 107669.

[5] Khan, Ali Haider, Muzammil Hussain, and Muhammad Kamran Malik. "Cardiac disorder classification by electrocardiogram sensing using deep neural network." *Complexity* 2021.1 (2021): 5512243.

[6] El-Habibi, Mohammed F. "Automated Detection of Cardiovascular Diseases using Deep Learning and Electrocardiogram (ECG) Images: A Convolutional Neural Network Approach." *complexity* 7.8 (2023): 10-20.

[7] El-Habibi, Mohammed F. "Automated Detection of Cardiovascular Diseases using Deep Learning and

Electrocardiogram (ECG) Images: A Convolutional Neural Network Approach." *complexity* 7.8 (2023): 10-20.