



IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: V Month of publication: May 2025

DOI: https://doi.org/10.22214/ijraset.2025.71790

www.ijraset.com

Call: 🕥 08813907089 🔰 E-mail ID: ijraset@gmail.com



Deep Learning for Heart Disease Prediction with Improved Normalization Techniques

Ms. Shubhangi Mahule¹, Gali Lahari Reddy², Seelam Sai Varsha³, Dakuri Sairam Reddy⁴, Vennavelli Pradeep Reddy⁵ ¹Asst. Professor, ACE Engineering College Hyderabad, India

^{2, 3, 4, 5}Student, ACE Engineering College Hyderabad, India

Abstract: Heart disease is a major global health concern, responsible for millions of deaths annually. Early diagnosis plays a crucial role in reducing mortality rates and improving patient outcomes. However, traditional diagnostic approaches, such as ECG analysis, stress tests, and cholesterol measurements, rely heavily on manual interpretation by medical professionals. These methods are not only time-consuming but also subject to human error and variability in expertise. With the rapid advancements in artificial intelligence (AI), deep learning has emerged as a powerful tool in the field of medical diagnostics. These models can process vast amounts of cardiovascular data, identify complex patterns, and provide more accurate predictions compared to conventional methods.

One of the key factors influencing the performance of deep learning models is data preprocessing, particularly normalization. Normalization ensures that different features within a dataset are appropriately scaled, preventing issues such as numerical instability and poor model convergence. In this study, we explore and compare various normalization techniques, including Min-Max Scaling, Standardization, Batch Normalization, and Layer Normalization, to improve the efficiency and accuracy of deep learning models for heart disease prediction.

To evaluate the impact of these normalization methods, we trained deep learning models using a comprehensive cardiovascular dataset. Experimental results demonstrated that advanced normalization techniques significantly enhance model performance. Batch Normalization improves training speed by reducing internal covariate shifts, whereas Layer Normalization ensures consistent performance across different architectures. These improvements contribute to better generalization, leading to more reliable heart disease predictions.

By optimizing preprocessing techniques, this research aims to advance AI-driven healthcare solutions, enabling faster and more accurate diagnoses. Future work could focus on integrating these models into real-time monitoring systems to further enhance early detection and personalized treatment strategies. This study serves as a step towards the broader adoption of AI in clinical decision-making, ultimately improving patient care and reducing the burden of heart disease on healthcare systems.

Keywords: Heart Disease Prediction, Deep Learning, Artificial Intelligence (AI), Data Preprocessing, Normalization Techniques, Min- Max Scaling, Standardization, Batch Normalization, Layer Normalization, Cardiovascular Data, Model Accuracy, Training Speed, Medical Diagnostics, Healthcare AI.

I. INTRODUCTION

Heart disease is one of the biggest health challenges worldwide, causing millions of deaths each year. According to the World Health Organization (WHO), heart attacks are the leading cause of death, especially in developed countries. Factors like unhealthy diets, lack of exercise, stress, and genetic predisposition increase the risk of heart disease. Early detection plays a crucial role in preventing severe complications, but traditional diagnosis methods depend heavily on medical professionals, making the process time-consuming and sometimes less accurate. [1] [2]

With advancements in artificial intelligence (AI), deep learning has emerged as a powerful tool in the medical field. These models can analyze large amounts of cardiovascular data, detect complex patterns, and help predict heart disease more accurately. However, deep learning models need properly processed data to perform well. One important step in data preparation is normalization, which ensures that different features in the dataset are scaled appropriately for better learning. [3]

This project focuses on studying various normalization techniques to improve the accuracy and efficiency of deep learning models for heart disease prediction. Traditional normalization methods, like Min-Max Scaling and Standardization, are commonly used but may not always yield the best results. More advanced techniques, such as Batch Normalization and Layer Normalization, have been introduced to improve training stability and model performance.



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

The research involves testing these normalization techniques on a comprehensive dataset containing cardiovascular health records. The goal is to analyze their impact on model training speed, accuracy, and generalization ability.

Experimental results show that advanced normalization methods significantly enhance deep learning models, making them more reliable for heart disease prediction.

Among them, Batch Normalization is particularly effective in speeding up training, while Layer Normalization performs consistently well across different deep learning architectures.

By optimizing these preprocessing techniques, this study aims to contribute to the development of AI-based healthcare solutions that can assist medical professionals in making faster and more accurate diagnoses. This research not only improves prediction accuracy but also highlights the importance of data preprocessing in medical AI applications.

II. RELATED WORK

Heart disease prediction has been extensively studied using a variety of machine learning (ML) and deep learning (DL) techniques to improve early diagnosis and reduce mortality rates. Several recent studies have focused on enhancing model performance, feature selection, and predictive accuracy through innovative approaches.

A 2023 study titled *Hybrid Optimization based Feature Selection with DenseNet Model for Heart Disease Prediction* [4] introduced the Butterfly Optimization Algorithm for effective feature selection. This hybrid approach improved prediction accuracy and reduced model complexity, leading to faster training times. However, the computational intensity and scalability limitations of DenseNet presented challenges when working with large datasets.

In 2019, the study *Deep Learning to Improve Heart Disease Risk Prediction* [5] proposed a deep learning model that utilized 13 risk factors without requiring manual feature engineering. This automated pattern extraction improved predictive capabilities but lacked comparison with standard models like the ACC/AHA model, limiting its validation against established benchmarks.

The 2021 study *Prediction of Heart Disease Using a Combination of Machine Learning and Deep Learning* [6] explored the integration of multiple ML algorithms—K-Nearest Neighbors (KNN), Decision Tree (DT), Naïve Bayes (NB), Support Vector Machine (SVM), and XGBoost—with DL techniques such as Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). While this ensemble approach enhanced prediction quality, improper model tuning posed risks of overfitting and reduced real-world applicability.

A more recent 2024 study titled *Heart Disease Prediction Using Machine Learning* [7] implemented basic ML algorithms including KNN, SVM, and Linear Regression to facilitate early-stage detection. This method supported timely intervention but encountered performance bottlenecks due to the high computational demands of advanced ML algorithms, especially in resource-constrained settings.

Lastly, the 2020 study *Heart Diseases Prediction using Deep Learning Neural Network Model* [8] combined traditional ML methods such as Logistic Regression, KNN, SVM, Naïve Bayes, and Random Forest with deep neural networks (DNNs). This hybrid approach offered improved prediction accuracy and comparative evaluation. Nonetheless, DNNs required significant training time and computing resources, particularly for larger datasets.

Collectively, these studies highlight the growing importance of combining feature selection techniques, traditional ML, and deep learning models in developing efficient heart disease prediction systems. However, challenges such as computational efficiency, model generalizability, and benchmark comparisons still need to be addressed for real-world deployment.

III. PROPOSED SYSTEM

Batch Normalization (BN) is a widely used technique in deep learning that significantly improves the training process of neural networks. Introduced by Ioffe and Szegedy in 2015, BN addresses the problem of internal covariate shift, which refers to changes in the distribution of layer inputs during training. By normalizing the inputs of each layer within a mini-batch, Batch Normalization ensures that the inputs maintain a consistent distribution, which helps stabilize and accelerate the training process. Batch Normalization is typically applied between the linear transformation (such as a dense or convolutional layer) and the non-linear activation function (like ReLU). [9] [10] [11].



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

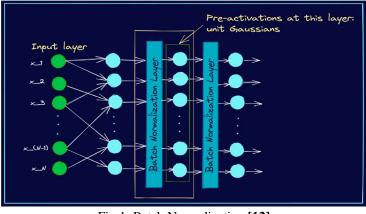


Fig 1: Batch Normalization [12]

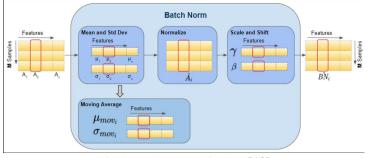


Fig 2: Batch Normalization [13]

Procedure:

- 1. Import necessary libraries (pandas, numpy, sklearn, keras, xgboost).
- 2. Load and preprocess the dataset.
- 3. Encode categorical features.
- 4. Split data into features and target, and split into training and testing sets.
- 5. Apply SMOTE to balance classes in training data.
- 6. Train ANN and XGBoost models on selected features.
- 7. Combine predictions using weighted average.
- 8. Save models and preprocessing tools.
- 9. Deploy it using Flask.

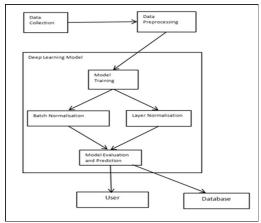


Fig 3: Architecture Diagram



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

IV. RESULT

| Confusion Matrix [[32 4] [2 37]] | : | | | |
|--|----------------------|--------------|--------------|----------------|
| Classification I | Report: precision | recall | f1-score | support |
| 0 1 | 0.94 0.90 | 0.89 0.95 | 0.91 0.93 | 36 39 |
| accuracy macro avg | 0.92 | 0.92 | 0.92 0.92 | 75 75 75 |
| weighted avg Accuracy: 92.00 ROC AUC: 0.9651 | 0.92 6 | 0.92 | 0.92 | 75 |

Fig 4: Classification Report

| Heart Disease I | Prediction |
|-------------------------|------------|
| Age: 67 | |
| Sex: 1 | |
| Chest pain type: 4 | |
| BP: 140 | |
| Cholesterol: 234 | |
| FbS over: 1 | |
| Ekg: 2 | |
| Max hr: 120 | |
| Exercise angina: 1 | |
| St depression: 1.8 | |
| Slope of st: 3 | |
| Number of vessels fluro | : 0 |
| Thallium: 7 | |
| Predict | |
| Prediction: Yes | |

Fig 5: Heart Disease Prediction: YES

| Title | Algorithm | Accuracy (in %) | |
|-----------------------------------|--------------------------------|-----------------|--|
| Cardiovascular disease prediction | SVM | 81.97 | |
| using deep learning techniques | KNN | 67.2 | |
| (Existing System) | Decision Tree | 81.97 | |
| | ANN (binary model) | 85.24 | |
| Deep Learning for Heart Disease | ANN (With Batch Normalization) | 92.00 | |
| Prediction with Improved | | | |
| Normalization (Proposed System) | | | |

Table 1: Comparison with Existing System [13]

This study highlights the critical role of advanced normalization techniques in enhancing the performance of deep learning models for heart disease prediction. By systematically evaluating methods such as Batch Normalization [14], the research demonstrates their superiority over traditional approaches in terms of model convergence, generalization, and predictive accuracy. The findings underscore the potential of improved normalization to address key challenges in medical data analysis, paving the way for more reliable and efficient automated systems to assist healthcare professionals in the early detection and prevention of heart disease.



ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538 Volume 13 Issue V May 2025- Available at www.ijraset.com

V. CONCLUSION

We developed and evaluated a machine learning model for predicting the presence of heart disease using clinical and diagnostic features. We applied data preprocessing techniques, including feature selection, normalization, and class balancing using SMOTE, to improve model performance. Several models were explored, including Artificial Neural Networks (ANN), XGBoost [15], and ensemble approaches.

REFERENCES

- [1] <u>https://www.who.int/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)</u>
- [2] https://world-heart-federation.org/what-is-cvd/
- [3] https://pmc.ncbi.nlm.nih.gov/articles/PMC7485162/
- [4] https://www.researchgate.net/publication/378803559_Hybrid_Optimization_based_Feature_Selection_with_DenseNet_Model_for_Heart_Disease_Prediction
- [5] https://www.researchgate.net/publication/336462310_Deep_Learning_to_Improve_Heart_Disease_Risk_Prediction
- [6] https://www.researchgate.net/publication/357566449_Heart_disease_prediction_model_with_k-nearest_neighbor_algorithm
- [7] https://www.researchgate.net/publication/379561252_Heart_Disease_Prediction_Using_Machine_Learning
- [8] https://www.researchgate.net/publication/341831889_Heart_Diseases_Prediction_using_Deep_Learning_Neural_Network_Model
- [9] https://www.analyticsvidhya.com/blog/2021/03/introduction-to-batch-normalization/
- [10]]https://medium.com/@piyushkashyap045/understanding-batch-normalization-in-deep-learning-a-beginners-guide-40917c5bebc8
- [11] https://static.googleusercontent.com/media/research.google.com/en//pubs/archive/43442.pdf
- [12] https://www.pinecone.io/learn/batch-layer-normalization/
- [13] <u>https://iopscience.iop.org/article/10.1088/1757-899X/981/2/022006</u>
- [14] <u>https://www.baeldung.com/cs/batch-normalization-cnn</u>
- [15] <u>https://www.ibm.com/think/topics/xgboost</u>











45.98



IMPACT FACTOR: 7.129







INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Call : 08813907089 🕓 (24*7 Support on Whatsapp)