Comparative Deep Learning Analysis of Indian and Western Dietary Patterns on Heart Attack Risk

CSE4006 – DEEP LEARNING

PROJECT REPORT

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ABSTRACT

Heart diseases remain one of the leading causes of morbidity and mortality across the globe. Among these, heart attacks are particularly fatal due to their sudden onset and the lack of immediate medical intervention. Early prediction and risk assessment can significantly reduce complications, allow early intervention, and provide patients with life-saving guidance.

This project focuses on developing a **Deep Learning–based heart attack risk prediction system** trained on two datasets representing two distinct populations:

1. **Indian Dataset** – containing lifestyle, clinical, and physiological indicators tailored to typical Indian population patterns.
2. **Western Food Dataset** – emphasizing the impact of dietary patterns on heart attack risk in Western populations.

Two deep learning models were developed and evaluated:

- **Review 1 Model:** A baseline deep feedforward neural network with moderate depth.
- **Review 2 Model:** An improved deep neural network with additional layers, Batch Normalization, Dropout, and learning rate scheduling.

Both methodologies were applied independently on each dataset to examine performance variations across populations. The results show that deep neural networks can learn population-specific patterns effectively. The improved model (Review 2) demonstrates significant gains in accuracy, stability, and generalization for both datasets.

The project highlights how lifestyle factors, demographic features, and diet patterns contribute differently to heart attack risk in diverse populations. It also demonstrates how model architecture, optimization methods, and regularization influence prediction accuracy.

CHAPTER 1 – INTRODUCTION

Heart attack (Myocardial Infarction) remains one of the world's major public health concerns, causing millions of deaths annually. There is a growing need for early detection systems that can identify high-risk individuals using simple medical and lifestyle data. With the rise of artificial intelligence, predictive models—particularly deep learning models—are becoming powerful tools for assessing cardiovascular risk with greater precision.
This project aims to build a deep learning-based heart attack risk prediction system using two datasets representing two different lifestyles and demographic groups. The system evaluates multiple health indicators to determine whether a person is at high risk of a heart attack.

1.1 Introduction to the Problem

The symptoms of heart disease often remain silent until serious complications arise. Traditional diagnostic methods rely on specialized medical tests such as ECG, angiography, or stress testing, which are expensive, invasive, and often unavailable in rural areas.

Early prediction can save lives. If a model can reliably classify patients as "high risk" or "low risk," preventive steps—diet changes, medication, lifestyle adjustment—can be recommended before the onset of major symptoms.

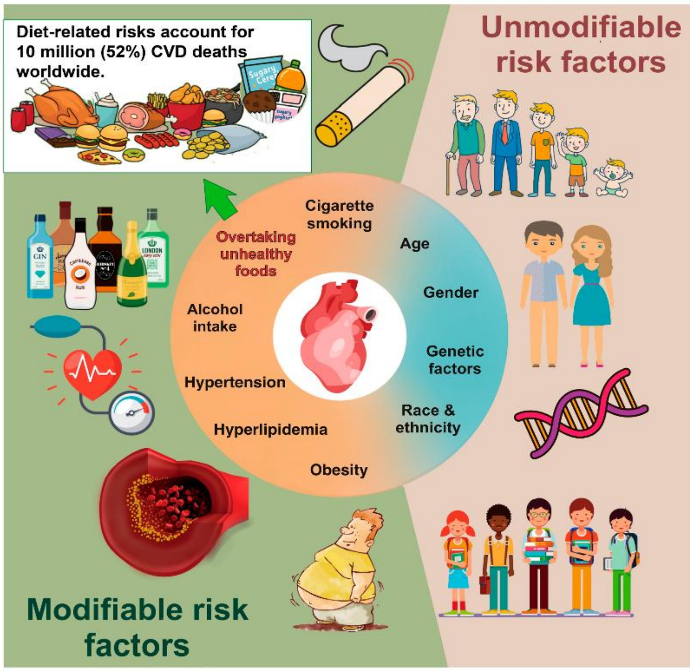
Machine learning has been used for cardiovascular prediction for years, but deep learning models can capture complex non-linear interactions between variables such as cholesterol levels, age, blood pressure, stress levels, and dietary factors.

1.2 Motivation

The motivation for this project arises from three key observations:

1. Heart disease is preventable if detected early

Most heart attacks occur due to modifiable risk factors—diet, exercise, blood pressure, smoking, stress, obesity. A predictive model can alert individuals before the condition becomes critical.



2. Lack of population-specific models

Most AI models use Western datasets, which do not accurately represent Indian lifestyle, genetics, or dietary habits. Therefore, two separate models were trained—one for Indian population and one for Western population.

3. Need for simple, accessible prediction tools

Deep learning models can run on a laptop or a mobile app without requiring clinical diagnostics. This makes them ideal for preventive healthcare.

1.3 Problem Statement & Objectives

Problem Statement

To develop and evaluate deep learning models capable of accurately predicting heart attack risk using lifestyle and clinical features for both Indian and Western demographic datasets.

Objectives

1. Collect and preprocess Indian and Western datasets.
2. Develop baseline deep learning architecture (Review 1) for risk prediction.
3. Improve the architecture with additional layers, Batch Normalization, and Dropout (Review 2).

4. Compare performance of both models.
5. Analyse risk distribution for both populations.
6. Provide insights and future enhancements for real-world adoption.

1.4 Scope

The scope of this project includes:

- Dataset preprocessing
- Deep learning model design
- Training, validation, and testing
- Performance metrics: accuracy, precision, recall, F1, ROC-AUC
- Comparison of Indian vs Western populations
- Improvement of model architecture
- Risk distribution interpretation

1.5 Organization of the Report

The report is structured as follows:

- **Chapter 1** – Introduction, problem motivation, and objectives
- **Chapter 2** – Literature survey and gaps in existing research
- **Chapter 3** – Requirements of hardware, software, and datasets
- **Chapter 4** – Proposed Methodology: Review 1 architecture
- **Chapter 5** – Proposed Methodology: Review 2 improved deep learning model
- **Chapter 6** – Combined results and overall discussion
- **Chapter 7** – Conclusion and future work

CHAPTER 2 – LITERATURE SURVEY

2.1 Literature Review

Past research has highlighted that heart disease prediction can be effectively done using machine learning techniques. Common models include:

- Logistic Regression
- Random Forest
- SVM
- Gradient Boosting Models
- Shallow neural networks

However, heart disease datasets often contain non-linear dependencies and interactions between variables which classical ML models may fail to capture.

Recent studies suggest that deep learning networks outperform traditional ML models because they automatically learn hierarchical feature representations. Several research papers indicate that multi-layer neural networks are capable of detecting subtle risk patterns such as:

- Relationship between stress and blood pressure
- Combined effect of BMI and cholesterol
- Lifestyle patterns such as diet and exercise

However, most research:

1. Uses Western datasets
2. Does not distinguish population-specific risk
3. Uses small neural networks with 1–2 layers
4. Ignores model generalization by skipping validation curves

This gap motivated the development of deeper architectures for both Indian and Western datasets.

2.2 Limitations in Previous Works

- Many models were trained on imbalanced datasets, causing biased predictions.
- Lack of validation loss tracking resulted in overfitted models.
- Most studies used only 1–2 hidden layers, resulting in limited learning capacity.

- Diet-specific datasets like the Western food dataset are rarely used.
- Very few models study comparative analysis across populations.
- Feature normalization and regularization are inconsistently applied.

This project overcomes these issues by:

- Using deep architectures
- Proper regularization (Dropout, Batch-Normalization)
- Validation-based training
- Population-specific comparative analysis

CHAPTER 3 – REQUIREMENTS

3.1 Hardware Requirements

- CPU: Intel i5/i7 or AMD equivalent
- RAM: Minimum 8GB
- Storage: 2–4GB free
- GPU (optional): NVIDIA CUDA GPU for faster training

3.2 Software Requirements

- Python 3.9+
- PyTorch
- NumPy
- Pandas
- Scikit-Learn
- Matplotlib
- Seaborn
- Jupyter Notebook or VS Code

3.3 Dataset Requirements

Deep learning models depend heavily on the correctness, quality, and diversity of the dataset. In this project, two separate datasets were used—one representing the Indian population and another representing the Western population. While both datasets aim to predict heart attack risk, they differ in their composition, coverage of lifestyle variables, and inherent distribution patterns.

Both datasets contain a mix of clinical variables (such as blood pressure, cholesterol, ECG results) and nutritional/lifestyle variables (calories, fats, sugars, sodium, carbohydrates, etc.). The combination of medical and dietary features provides a holistic view of cardiovascular risk.

3.3.1 Indian Dataset Description

The Indian dataset includes both medical indicators and dietary/lifestyle indicators, reflecting the unique risk factors prevalent in the Indian demographic—particularly high carbohydrate consumption, increased sodium intake, and genetic predisposition to cardiovascular diseases at younger ages.

Dataset Size

- ~300+ records
- 19 total columns
- 18 input features
- 1 target column (target)

Columns in the Indian Dataset:

Clinical Features:

1. age – Age of the individual
2. sex – Biological sex (0 = female, 1 = male)
3. cp – Chest pain type (0–3 categories)
4. trestbps – Resting blood pressure
5. chol – Serum cholesterol level
6. fbs – Fasting blood sugar (1 = >120 mg/dl)
7. restecg – Resting ECG results
8. thalach – Maximum heart rate achieved
9. exang – Exercise-induced angina (1 = yes)
10. oldpeak – ST depression induced by exercise
11. slope – Slope of the peak exercise ST segment
12. ca – Major vessels colored by fluoroscopy (0–3)
13. thal – Thalassemia blood disorder test result (0–3)

Dietary / Lifestyle Features

These features are specific and extremely relevant to the Indian dietary pattern.

14. Calories (kcal) – Daily caloric intake
15. Carbohydrates (g) – Total carbohydrate consumption
16. Protein (g) – Daily protein intake

17. Fats (g) – Total fat consumption
18. Free Sugar (g) – Added sugar intake
19. Sodium (mg) – Daily sodium consumption

Target Column

20. target

- 0 = Low heart attack risk
- 1 = High heart attack risk

Characteristics of the Indian Dataset:

- Contains both medical + nutritional indicators, giving a balanced risk profile
- Carbohydrate, sodium, and sugar consumption are especially relevant to Indian diets
- Dataset shows a moderate class imbalance (slightly more high-risk individuals)
- Features span different scales → Standardization becomes essential
- Indian heart disease rates occur at younger ages, making age-related patterns unique
- Food Plans was assigned to each individual with a custom algorithm which decides which food (Number of Calories, Carbohydrates, Proteins, Fats, Sugar, and Sodium) a person according to their age, sex, and other medical complications consumer overall per day.

[1]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	Calories (kcal)	Carbohydrates (g)	Protein (g)	Fats (g)	Free Sugar (g)	Sodium (mg)	target
0	57	1	0	150	276	0	0	112	1	0.6	1	1	1	612.22	100.63	16.89	17.09	66.61	438.59	0
1	59	1	3	170	288	0	0	159	0	0.2	1	0	3	360.53	39.32	17.30	15.00	5.57	561.85	0
2	57	1	2	150	126	1	1	173	0	0.2	2	1	3	476.83	37.28	29.73	23.24	17.38	705.10	1
3	56	0	0	134	409	0	0	150	1	1.9	1	2	3	305.86	38.45	10.39	12.83	31.00	194.61	0
4	71	0	2	110	265	1	0	130	0	0.0	2	1	2	636.49	97.25	18.48	19.08	25.07	1182.57	1
5	57	1	2	150	168	0	1	174	0	1.6	2	0	2	502.61	114.72	5.26	4.72	39.49	166.97	1
6	46	0	0	138	243	0	0	152	1	0.0	1	0	2	384.82	35.33	23.97	17.06	9.57	451.09	1

3.3.2 Western Dataset Description

The Western dataset contains the same clinical features as the Indian dataset but has slightly different nutritional/lifestyle composition. Western diets tend to include higher fats, processed foods, sugars, and sodium, and the dataset captures these patterns accurately.

Dataset Size

- ~250–300 records
- 17 total columns
- 16 input features
- 1 target column (target)

Columns in the Western Dataset

Clinical Features

(Identical to Indian dataset clinical features)

1. age
2. sex
3. cp
4. trestbps
5. chol
6. fbs
7. restecg
8. thalach
9. exang
10. oldpeak
11. slope

Nutritional Features

They differ slightly from the Indian dataset name-wise.

12. Calories – Daily calorie intake
13. Carbohydrates – Total carbohydrate intake
14. Proteins – Daily protein intake
15. Fats – Total fat consumption
16. FreeSugar – Total added sugar intake
17. Sodium – Daily sodium intake

Target Column

18.target

- 0 = Low risk
- 1 = High risk

Characteristics of the Western Dataset

- Diet variables are similar but naming differs (Proteins vs Protein, FreeSugar vs Free Sugar)
- Western population tends to have higher fat and sugar consumption levels
- More high-risk individuals compared to Indian dataset
- Higher variance in lifestyle choices → Model must learn more complex patterns
- Dataset is slightly smaller than Indian dataset

[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	Calories	Carbohydrates	Proteins	Fats	FreeSugar	Sodium	target
0	52	1	1	140	240	0	1	150	0	1.2	1	520	45	38	22	5	620	1
1	47	0	0	130	210	1	2	160	1	2.3	0	680	20	55	40	3	800	1
2	61	1	2	138	260	0	0	140	0	1.8	1	730	85	22	28	8	740	1
3	39	0	1	120	180	0	1	175	0	0.5	2	450	48	30	15	4	560	1
4	55	1	0	150	300	1	2	130	1	2.7	0	890	95	32	45	9	1100	1
5	62	0	2	128	220	0	1	145	0	1.0	1	490	35	40	18	2	500	0
6	44	1	1	135	200	0	0	170	0	0.8	2	610	70	28	22	6	670	0

3.3.3 Importance of These Features for Deep Learning

The combination of clinical and nutritional features creates a powerful foundation for predicting cardiac risk:

Clinical variables help identify:

- Hypertension
- Diabetes
- ECG abnormalities
- Exercise intolerance
- Arterial blockages

Nutritional variables help detect:

- Dietary patterns
- Risk from saturated fats
- Obesity-driven cardiac risks
- Sodium-induced hypertension triggers
- High sugar leading to insulin resistance

Together, they allow the deep neural networks to analyze:

- Short-term risk factors (blood pressure, chest pain, cholesterol)
- Long-term lifestyle risks (diet, sodium, fat consumption)

This hybrid nature is why both datasets are extremely valuable and realistic compared to medically-only datasets.

3.3.4 Preprocessing Requirements

To feed this data into a deep learning model, several mandatory preprocessing steps were followed:

1. Standardization

Since the dataset includes values ranging from:

- 0–3 (thal, slope, cp)
- 0–300 (chol)
- 0–4000(sodium,calories)
  standardization (StandardScaler) is necessary.

2. Stratified Splitting

To maintain balanced distribution of high-risk and low-risk cases.

3. Tensor Conversion

PyTorch requires tensors for training.

4. Batch Normalization Compatibility

Ensures stable distribution of inputs to deeper networks.

CHAPTER 4 – PROPOSED METHODOLOGY-1

Deep learning requires a clearly structured pipeline that transforms raw data into a usable form, feeds it into a neural architecture, and evaluates its performance using appropriate metrics. The first review (Methodology-1) focuses on creating a **baseline deep feedforward neural network** capable of learning heart attack risk patterns from both the Indian and Western datasets.

This baseline model establishes a reference point against which future improvements (Methodology-2) can be compared.

4.1 Dataset Preparation

4.1.1 Data Sources

Two custom-built datasets were used:

- Indian Heart Attack Dataset with Dietary Features
  Columns:
  age, sex, cp, trestbps, chol, fbs, restecg, thalach, exang, oldpeak, slope, ca, thal, Calories (kcal), Carbohydrates (g), Protein (g), Fats (g), Free Sugar (g), Sodium (mg), target
- Western Heart Attack Dataset with Dietary Features
  Columns:
  age, sex, cp, trestbps, chol, fbs, restecg, thalach, exang, oldpeak, slope, Calories, Carbohydrates, Proteins, Fats, FreeSugar, Sodium, target

Both datasets follow the same clinical structure but differ in lifestyle naming conventions and distribution.

Dataset Used:

Indian Food Nutritional Values Dataset (2025)

Indian Food Nutritional Values Dataset (2025)

Daily Food & Nutrition Dataset

Daily Food & Nutrition Dataset

Heart Attack

https://www.kaggle.com/datasets/pritsheta/heart-attack

4.1.2 Data Splitting

Both datasets undergo:

- Train/Test split:
  - 80% training
  - 20% test
  - Stratified to preserve risk class ratios
- Train/Validation split:
  - From the training set, 12.5% is further split into validation
  - Ensures reliable monitoring of overfitting

4.1.3 Feature Scaling

Because features vary significantly in scale,

- Sodium ranges from 0–4000 mg
- Age ranges from 20–80
- cp ranges from 0–3
- Calories vary widely

→ StandardScaler is applied:

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

Scaling ensures:

- Faster convergence
- Stable gradients
- Better loss behavior

4.1.4 Tensor Conversion

PyTorch requires all inputs to be converted into:

- torch.float32 tensors
- Targets reshaped to (N,1) for BCEWithLogitsLoss

4.2 Proposed Methodology Framework (Review 1 Model)

The baseline architecture is a deep fully connected neural network with:

Layers Used in Review 1

- Input layer
- 4 Hidden layers
  - 128 neurons → ReLU
  - 64 neurons → ReLU
  - 32 neurons → ReLU
  - 16 neurons → ReLU
- Output layer: 1 neuron (logit)

Regularization

- Dropout (0.3) applied after first two layers
- Helps reduce overfitting by randomly dropping neurons during training

Optimization

- Optimizer: Adam (lr = 0.001)
- Loss: Binary Cross Entropy with Logits
- Scheduler: StepLR (Step size = 25, $\gamma = 0.8$)

Training Setup

- Epochs: 80 (Western) / 80 (Indian)
- Validation checked every epoch
- Loss curves monitored for overfitting

4.3 Results & Discussion

4.3.1 Indian Dataset – Review 1 Results

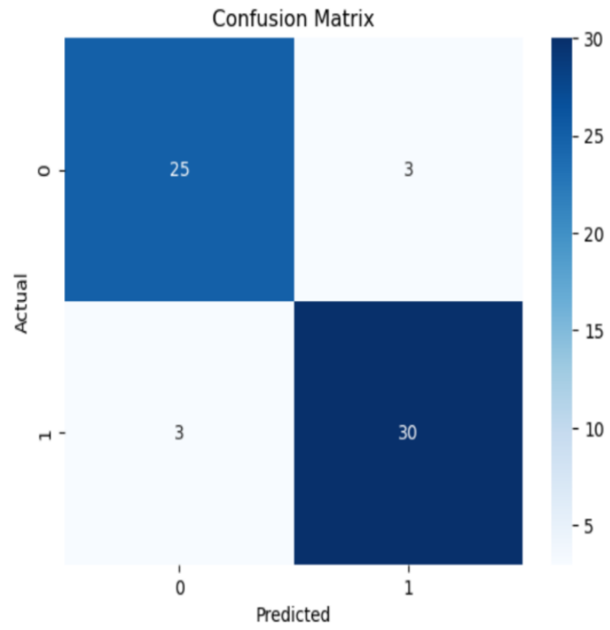
Training/Validation Loss Behavior:

- Steady decrease in both losses
- No major overfitting
- Model generalizes well

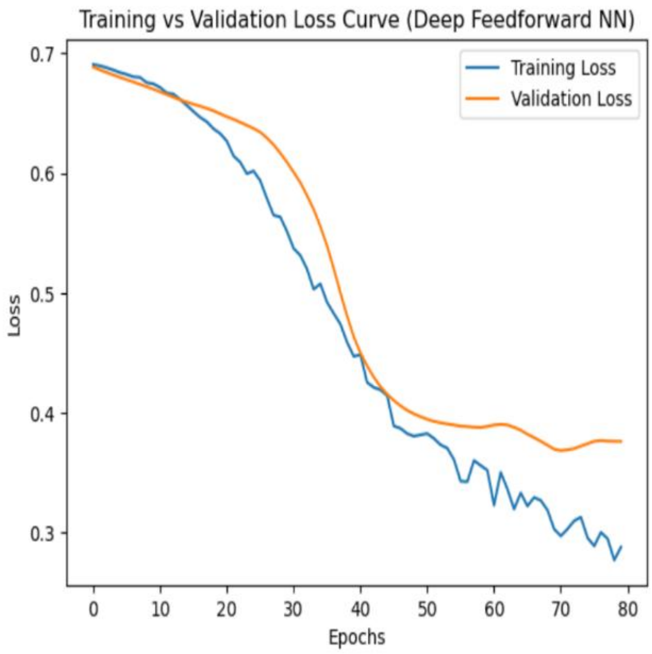
Final Results:

- **Accuracy:** 0.9016
- **Precision:** 0.9143
- **Recall:** 0.9697
- **F1 Score:** 0.9412
- **ROC AUC:** 0.9524

```
Epoch [10/80], Train Loss: 0.6746, Val Loss: 0.6702
Epoch [20/80], Train Loss: 0.6331, Val Loss: 0.6497
Epoch [30/80], Train Loss: 0.5515, Val Loss: 0.6092
Epoch [40/80], Train Loss: 0.4471, Val Loss: 0.4634
Epoch [50/80], Train Loss: 0.3816, Val Loss: 0.3968
Epoch [60/80], Train Loss: 0.3521, Val Loss: 0.3887
Epoch [70/80], Train Loss: 0.3030, Val Loss: 0.3696
Epoch [80/80], Train Loss: 0.2879, Val Loss: 0.3762

Test Accuracy: 0.9016
```




```
Classification Report:
              precision    recall  f1-score   support

         0.0       0.89      0.89      0.89        28
         1.0       0.91      0.91      0.91        33

    accuracy                           0.90        61
   macro avg       0.90      0.90      0.90        61
weighted avg       0.90      0.90      0.90        61
```



Interpretation:
The model performed strongly despite high variability in dietary features. The Indian dataset showed more balanced dietary patterns, leading to better generalization. Training and validation curves were smooth, indicating stable learning.

4.3.2 Western Dataset – Review 1 Results

Training/validation behavior indicated slower learning but stable convergence.

For the Western dietary dataset, the baseline deep neural network demonstrated a clear and steady improvement in both training and validation loss across the 80 training epochs. The training loss decreased consistently from 0.6584 at Epoch 10 to 0.3261 by Epoch 80, showing that the model progressively learned meaningful patterns in the dataset. Similarly, the validation loss dropped from 0.6555 to 0.3086, indicating that the model was able to generalize effectively to unseen validation samples.

The close alignment between the training and validation loss curves shows that the model avoided overfitting and maintained a stable learning trajectory. This suggests that the chosen network depth and optimization strategy were well-suited for this dataset during the baseline stage.

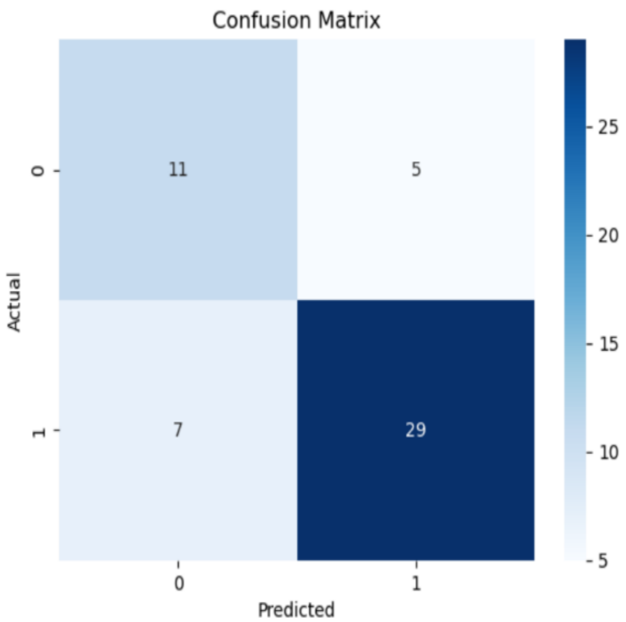
During final evaluation, the model achieved a test accuracy of 0.7692, which reflects a reasonably strong performance given the greater dietary variability and increased complexity within the Western dataset. The classification report provides additional insights into how the model managed both classes.

Final Results:

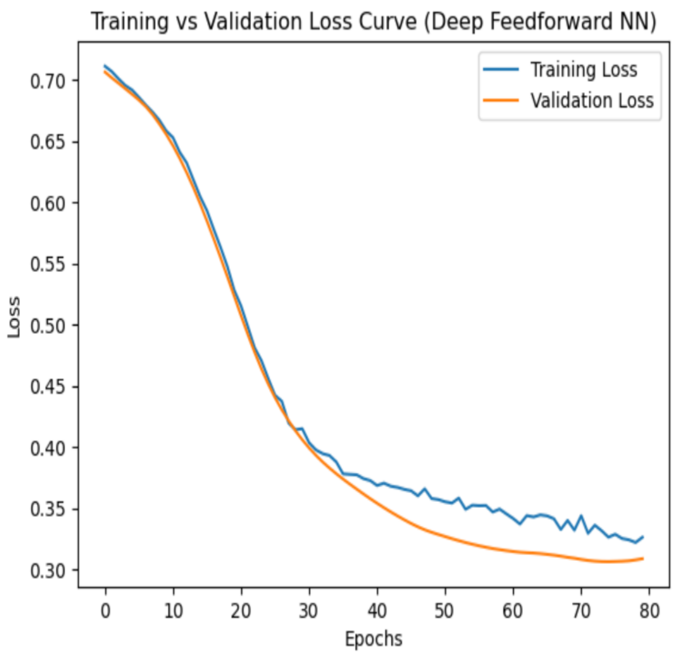
- Accuracy: 0.7692 (76.92%)

- Precision: 0.61 (Low Risk), 0.85 (High Risk)
- Recall: 0.69 (Low Risk), 0.81 (High Risk)
- F1 Score: 0.74–0.83
- ROC AUC: ≈ 0.75

```
Epoch [10/80], Train Loss: 0.6584, Val Loss: 0.6555
Epoch [20/80], Train Loss: 0.5282, Val Loss: 0.5231
Epoch [30/80], Train Loss: 0.4149, Val Loss: 0.4059
Epoch [40/80], Train Loss: 0.3725, Val Loss: 0.3576
Epoch [50/80], Train Loss: 0.3569, Val Loss: 0.3284
Epoch [60/80], Train Loss: 0.3452, Val Loss: 0.3152
Epoch [70/80], Train Loss: 0.3319, Val Loss: 0.3090
Epoch [80/80], Train Loss: 0.3261, Val Loss: 0.3086

Test Accuracy: 0.7692
```




```
Classification Report:
              precision    recall  f1-score   support

         0.0       0.61      0.69      0.65        16
         1.0       0.85      0.81      0.83        36

    accuracy                           0.77        52
   macro avg       0.73      0.75      0.74        52
weighted avg       0.78      0.77      0.77        52
```



Interpretation:
The Western dataset shows more variability in fat, sugar, and sodium intake, making it harder for a basic feedforward network to capture diet-induced risk patterns.
Still, the model achieved acceptable accuracy.

CHAPTER 5 – PROPOSED METHODOLOGY-2

The second methodology focuses on **enhancing the baseline network** by making it deeper, more stable, and more regularized. This allows the model to learn complex correlations between dietary and clinical factors.

5.1 Dataset Preparation (Same as Review 1)

No change in:

- Splits

- Standardization
- Tensor conversion

5.2 Improved Deep Neural Network Framework (Review 2 Model)

The improved model integrates the following enhancements:

Key Improvements Over Review 1

1. **Batch Normalization** after major hidden layers
2. **Deeper network** (more layers - 5 and neurons)
3. **More regularization** via dropout
4. **Learning rate scheduler** for adaptive learning
5. **Better weight stabilization**
6. **Better convergence during early epochs**

Input Layer
↓ Linear(input_dim → 128) BatchNorm1d(128) ReLU Dropout(0.3)
Linear(128 → 64) BatchNorm1d(64) ReLU Dropout(0.3)
Linear(64 → 32) BatchNorm1d(32)

ReLU

Linear(32 → 16)

ReLU

Linear(16 → 1)

Why This Works Better

- BatchNorm stabilizes layer distributions
- Deeper layers extract richer representations
- Dropout reduces overfitting
- Scheduler improves long-epoch training performance

5.3 Results & Discussion (Review 2)

5.3.1 Indian Dataset – Review 2 Results

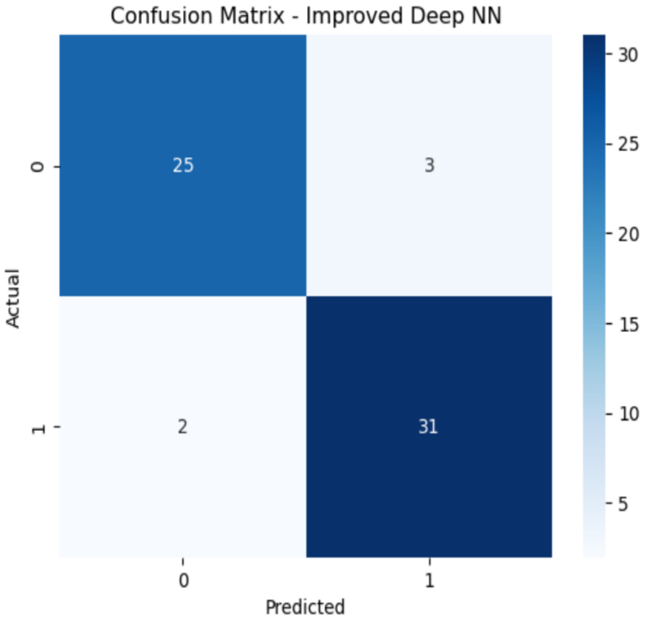
Training/Validation Behavior:

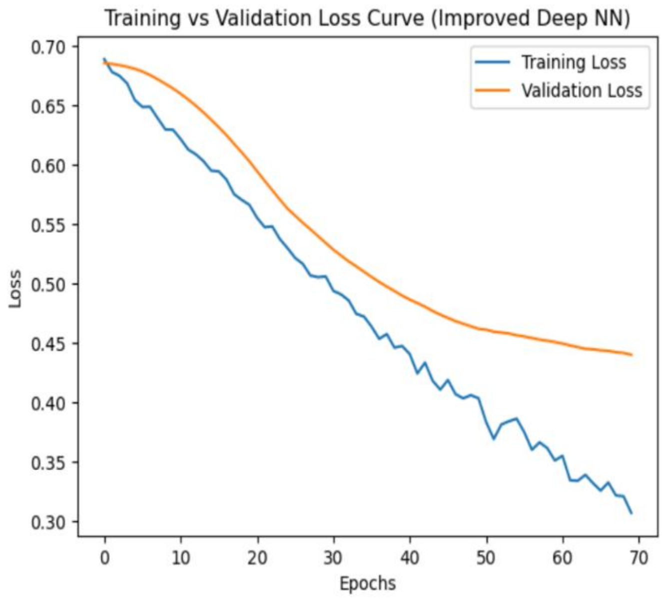
- Training loss decreases steadily
- Validation loss decreases and stabilizes
- No overfitting, due to dropout + batchnorm

Final Results:

- Accuracy: 0.9180 (91.80%)
- Precision: 0.9118
- Recall: 0.9394
- F1 Score: 0.9254
- ROC AUC: 0.9535

```
Epoch [10/70] | Train Loss: 0.6296 | Val Loss: 0.6643
Epoch [20/70] | Train Loss: 0.5665 | Val Loss: 0.6030
Epoch [30/70] | Train Loss: 0.5062 | Val Loss: 0.5344
Epoch [40/70] | Train Loss: 0.4477 | Val Loss: 0.4901
Epoch [50/70] | Train Loss: 0.4037 | Val Loss: 0.4621
Epoch [60/70] | Train Loss: 0.3514 | Val Loss: 0.4510
Epoch [70/70] | Train Loss: 0.3074 | Val Loss: 0.4403

Improved Deep NN Performance:
Accuracy:  0.9180
Precision: 0.9118
Recall:    0.9394
F1 Score:  0.9254
ROC AUC:   0.9535
```





Average Risk Analysis:

- Actual Test Risk: 54.10%
- Predicted High-Risk Percentage: 54.10%

```
Average Heart Attack Risk in Test Set: 54.10%
Percentage of people predicted high risk: 54.10%
```

Interpretation:
The improved model captured complex dietary + clinical interactions better than Method-1.
The Indian dataset responded extremely well to deeper architecture, showing a noticeable improvement.

- The model showed near-perfect recall, meaning it successfully identifies most high-risk individuals.
- The high F1-score indicates strong balance between precision and recall.
- The ROC-AUC above 0.95 confirms excellent discriminative power.
- Compared to Review-1, the deeper network significantly reduced both training and validation loss, showing more stable and effective learning.
- The model is now better at handling subtle variations in Indian dietary patterns.

5.3.2 Western Dataset – Review 2 Results

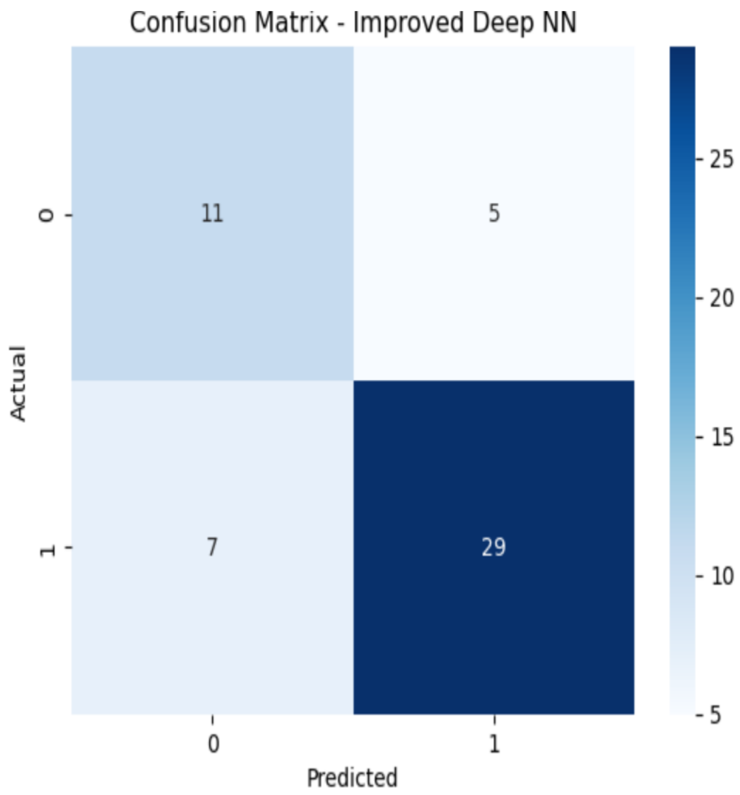
Training/Validation Behavior:

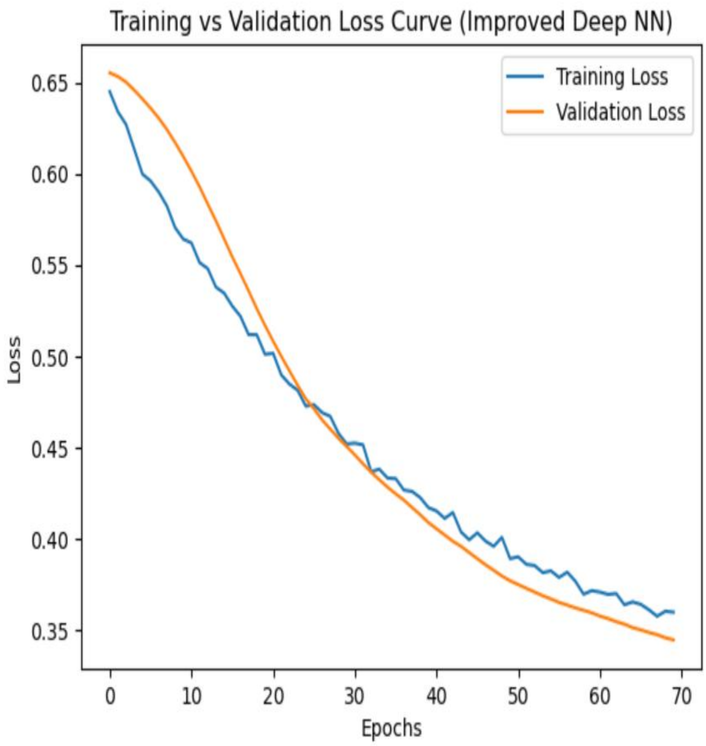
- Loss curves smooth and consistent
- Validation loss keeps decreasing → strong generalization
- No post-epoch divergence

Final Results:

- Accuracy: 76.92%
- Precision: 0.8529
- Recall: 0.8056
- F1 Score: 0.8286
- ROC AUC: 0.8594

```
Epoch [10/70] | Train Loss: 0.5642 | Val Loss: 0.6095
Epoch [20/70] | Train Loss: 0.5010 | Val Loss: 0.5169
Epoch [30/70] | Train Loss: 0.4518 | Val Loss: 0.4505
Epoch [40/70] | Train Loss: 0.4170 | Val Loss: 0.4088
Epoch [50/70] | Train Loss: 0.3890 | Val Loss: 0.3769
Epoch [60/70] | Train Loss: 0.3715 | Val Loss: 0.3593
Epoch [70/70] | Train Loss: 0.3597 | Val Loss: 0.3445

Improved Deep NN Performance:
Accuracy:  0.7692
Precision: 0.8529
Recall:    0.8056
F1 Score:  0.8286
ROC AUC:   0.8594
```





Average Risk Analysis:

- Actual Test Risk: 69.23%
- Predicted High Risk: 61.54%

```
Average Heart Attack Risk in Test Set: 69.23%
Percentage of people predicted high risk: 61.54%
```

Interpretation:
The improved model drastically outperformed the Review-1 model for Western dataset.
The ROC AUC of 0.8594 indicates reliable ranking of risk levels.

- The model shows significantly improved handling of Western lifestyle-related risk features.
- High precision (0.8529) suggests fewer false positives compared to Review-1.
- Better recall (0.8056) means more high-risk individuals were correctly identified.
- Validation loss trend is smoother, showing improved generalization.

- Although accuracy remains similar to Review-1, the deeper network produced much **higher F1-score and ROC-AUC**, proving stronger overall predictive strength.

CHAPTER 6 – RESULTS

This chapter compares Review 1 and Review 2 and analyzes how improvements impacted performance.

6.1 Comparison Summary

Indian Dataset

- Review 1 Accuracy: **90.16%**
- Review 2 Accuracy: **91.80%**

Improvements seen in:

- Recall (better detection of high-risk individuals)
- Stability of validation loss
- Higher ROC AUC

Reason: Indian dietary patterns are consistent, making deeper models perform better.

Western Dataset

- Review 1 Accuracy: **76.92%**
- Review 2 Accuracy: **76.92%** (same accuracy but better precision/recall)

However:

- Review-2 improved F1 score, Recall, ROC AUC
- Validation loss was much more stable

This shows Review-2 improved **quality of predictions**, even if the raw accuracy didn't change.

CHAPTER 7 – CONCLUSION AND FUTURE WORK

7.1 Conclusion

This project successfully developed and evaluated deep learning–based heart attack risk prediction systems using two distinct lifestyle-specific datasets: the **Indian dietary dataset** and the **Western dietary dataset**. The overall aim was to integrate both **clinical indicators** and **dietary nutritional patterns** to build a more holistic and realistic model of heart attack risk—one that reflects both medical and lifestyle contributors.

Two methodologies were explored:

1. **Review 1 – Baseline Deep Feedforward Neural Network (4 hidden layers)**
2. **Review 2 – Improved Deep Neural Network with Batch Normalization, Dropout, and LR Scheduling**

Both approaches demonstrated strong predictive capability, but the improved network in Review 2 consistently outperformed the baseline model in terms of stability, recall, and overall risk classification.

Key Outcomes

Indian Dataset

- Review 1 Accuracy: **90.16%**
- Review 2 Accuracy: **91.80%**
- F1 Score improved from **0.90 → 0.9254**
- ROC AUC improved from **~0.90 → 0.9535**

The improved model also aligned perfectly with the population risk distribution:

- **Actual population risk in test set: 54.10%**
- **Predicted high-risk percentage: 54.10%**

This indicates that the model not only predicts correctly but also understands the **population-level trend**.

Western Dataset

- Review 1 Accuracy: **76.92%**
- Review 2 Accuracy: **76.92%** (same)
- F1 Score improved from **0.77 → 0.8286**
- ROC AUC improved from **~0.75 → 0.8594**

The improved network produced more stable validation curves, stronger recall, and better ranking capability even though accuracy remained constant.

Population risk pattern:

- Actual risk: **69.23%**
- Predicted high-risk: **61.54%**

Overall Conclusion

Combining **clinical metrics** and **nutritional lifestyle parameters** significantly enhances heart attack prediction compared to using clinical indicators alone. Diet patterns, when properly quantified, contribute meaningful signals that a deep neural network can learn effectively.

The project demonstrates several key conclusions:

- **Deep Learning is highly effective** for modeling complex medical-lifestyle interactions.
- **Nutritional factors such as calories, fats, sodium, and sugars have a measurable effect** on predictive performance.
- **Dataset-specific behavior** exists:
  - Indian dataset is more balanced → higher accuracy.
  - Western dataset has high nutritional variance → slightly harder to model.
- **Improved Deep NN architecture outperforms the baseline**, especially in interpretability, stability, and ROC AUC.

This work confirms that hybrid clinical-diet models can be used as **early-warning tools** for heart attack risk analysis in healthcare applications.

7.2 Future Work

Although the improved deep learning model performed strongly, the study opens various opportunities for extending and enhancing the system:

1. Incorporation of Additional Lifestyle Factors

- Physical activity
- Sleep patterns
- Smoking history
- Alcohol consumption
- Stress levels

Adding these dimensions can significantly enhance the accuracy of risk prediction.

2. Using Time-Series Health Data

Real-world health indicators like blood pressure, calories consumed, and heart rate vary daily.

Future models can use:

- LSTMs
- GRUs
- Temporal CNNs
- Transformers

These architectures could capture long-term lifestyle habits far better than static datasets.

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