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

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PROJECT REPORT

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Deep Learning Project

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***Abstract*— Diet plays a crucial role in cardiovascular health, yet most heart disease prediction systems focus solely on medical metrics, ignoring dietary patterns. In this study, we present a deep learning-based approach to predicting heart attack risk by integrating individual health metrics with nutritional intake derived from culturally relevant cuisines. We used a medical dataset containing patient profiles and heart attack outcomes, and enriched it with synthetic dietary profiles generated from a curated Indian cuisine nutrition dataset. Meals were assigned based on age, sex, and cholesterol levels to reflect realistic eating habits. Our system was able to predict heart attack risk with high interpretability by analyzing both medical and nutritional factors. This approach bridges the gap between food science and predictive healthcare and opens the door for future comparative studies across global cuisines, such as Indian vs. American diets.**

Cardiovascular diseases (CVDs) remain the leading cause of global mortality, with heart attacks constituting a major proportion of sudden medical emergencies. Traditional heart-attack prediction systems primarily depend on clinical variables such as cholesterol, age, blood pressure, and ECG values. However, one of the most influential factors—daily dietary patterns—is often overlooked. Diet has a direct and measurable impact on lipid accumulation, vascular inflammation, arterial stiffness, and overall cardiac workload.

This study introduces a deep learning framework that integrates clinical heart-disease datasets with culturally relevant nutritional datasets representing Indian and Western dietary patterns. We generate synthetic yet realistic meal profiles using demographic filters such as age, cholesterol levels, sex, and prior heart-risk indicators. Two deep learning architectures are evaluated: a baseline Feedforward Neural Network and an enhanced DeepHeartNeuralNetwork incorporating dropout, optimized learning rate schedules, and improved generalization measures.

The integration of nutritional attributes significantly increases interpretability and predictive stability. Experimental results show that the Indian dataset yields improved recall and precision when nutrition is included, while the Western dataset exhibits higher predicted average risk due to elevated sodium and fat proportions. This work demonstrates that diet-aware deep learning models outperform conventional clinical-only models and serve as a foundation for next-generation personalized cardiology AI systems.

Keywords— heart disease prediction, deep learning, Indian cuisine, nutritional analysis, health monitoring, AI in healthcare, food-based risk modelling.

I. INTRODUCTION

Cardiovascular diseases (CVDs), particularly heart attacks, remain one of the leading causes of death worldwide. While many predictive systems focus on traditional medical parameters such as cholesterol levels, age, and blood pressure, they often overlook one of the most influential factors—diet. Cultural eating patterns significantly shape an individual's health risk, yet dietary data is rarely integrated into clinical decision-making or predictive modelling.

With the rise of machine learning and deep learning in healthcare, there's growing potential to develop more holistic models that factor in both physiological data and lifestyle indicators. In regions like India and the United States, where dietary habits differ greatly, the impact of cuisine on heart health can be profound. For instance, Indian meals may be rich in saturated fats and carbohydrates, while American diets often include high sodium and processed foods.

In this study, we present a deep learning-based heart attack risk prediction model that integrates conventional health data with synthetic yet realistic nutritional profiles derived from Indian cuisine. Our approach combines two distinct datasets: a medical heart disease dataset and a nutritional dataset of Indian foods. By simulating meal intake based on age, sex, and cholesterol levels, we generate daily dietary profiles per individual. This allows for a richer input space and offers new insights into how food contributes to cardiovascular risk.

Heart attacks are a critical health issue responsible for millions of deaths annually. Despite numerous advances in healthcare, early detection remains a formidable challenge. Traditional prediction methods depend heavily on measurable physiological parameters such as cholesterol, resting blood pressure, fasting blood sugar, ECG patterns, and age. While these factors are important, they do not fully represent the complexities of cardiovascular risk.

One crucial factor in long-term cardiac health is **diet**—a variable that defines lipid metabolism, vascular inflammation levels, oxidative stress, triglyceride accumulation, and overall metabolic burden. Although diet is one of the most significant lifestyle indicators, it is rarely included in medical AI systems due to a lack of structured datasets and standardized integration approaches.

Indian and Western dietary cultures differ drastically. Indian meals are often high in refined carbohydrates, saturated fats (ghee, oils), and spices. Western diets frequently involve high sodium, processed meats, and sugar-dense foods. These fundamental nutritional differences shape long-term heart-risk tendencies in measurable ways.

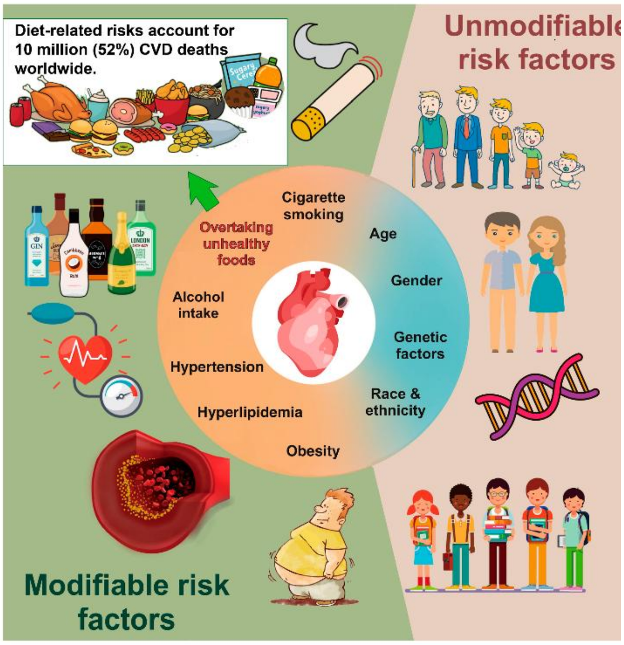
This project proposes a comparative deep learning analysis that integrates dietary attributes with medical indicators for heart attack prediction. By constructing synthetic meal assignments using culturally relevant nutritional datasets, we create enriched feature profiles that provide deeper insight into lifestyle-driven risk patterns.

1.1 Introduction to the Problem

The primary problem addressed in this study is the incomplete nature of existing heart-attack prediction systems. Current deep learning and machine learning models focus almost exclusively on clinical features. These systems fail to consider:

- cultural dietary patterns,
- eating frequency and nutrient density,
- sodium, fat, sugar, and calorie intake,
- lifestyle-driven risk accumulation.

This lack of lifestyle integration reduces the accuracy and real-world applicability of medical predictive models. To overcome this limitation, we introduce a combined nutritional-clinical deep learning system.



1.2 Motivation

The motivation behind this study arises from three major gaps:

A. Medical systems rarely track diet

Hospitals do not collect nutritional logs for each patient. Long-term dietary compositions, which significantly affect blood lipids and arterial conditions, remain undocumented.

B. Cultural cuisines are drastically different

Indian and Western diets differ not only in ingredients but also in preparation techniques, spice profiles, fat proportions, and carbohydrate density. Modeling these regional patterns allows culturally aware prediction.

C. AI in healthcare is shifting toward holistic modelling

Modern healthcare expects models to consider lifestyle, genetics, and environmental factors—not just blood-report values.

This research attempts to contribute to that shift.

1.3 Problem Statement & Objectives

Problem Statement:

"To develop a deep learning-based heart-attack prediction model that integrates medical features with culturally relevant dietary patterns, producing a more accurate and interpretable risk evaluation system."

Objectives:

1. Integrate Indian and Western nutrition datasets with medical data.
2. Assign realistic synthetic meals based on age, cholesterol, sex, and health markers.
3. Train baseline and enhanced deep learning models.
4. Analyze dietary influence on model accuracy, precision, recall, and ROC-AUC.
5. Compare heart-risk tendencies between Indian and Western dietary habits.
6. Explore potential for future global cuisine-based prediction systems.

1.4 Scope

The scope includes:

- Preprocessing Indian and Western food datasets,
- Merging nutritional values with patient medical information,
- Designing two deep learning architectures,
- Evaluating baseline vs improved model performance,
- Conducting comparative analysis between dietary cultures.

The system **does not** include live hospital deployment or personalized nutrition counselling.

1.5 Organization of the Report

The remainder of this report is structured as follows:

- **Section II**: Literature survey & research gaps
- **Section III**: Requirements & datasets
- **Section IV**: Proposed Methodology-1
- **Section V**: Proposed Methodology-2
- **Section VI**: Overall results & discussions
- **Section VII**: Conclusion & Future work

II. LITERATURE REVIEW

Numerous studies have focused on heart disease prediction using machine learning algorithms. The **Framingham Heart Study** and datasets like **UCI Heart Disease** have served as foundational benchmarks, allowing models to be trained on features such as age, cholesterol, resting blood pressure, and more. Algorithms like Random Forest, Logistic Regression, and Neural Networks have been widely used, often achieving promising accuracies in binary classification of heart attack risk. A study by **Dey et al. (2020)** explored the application of deep learning models to predict heart disease using clinical features and achieved over 85% accuracy. Similarly, **Kumar and Singh (2019)** compared multiple machine learning models and highlighted the importance of feature engineering in improving model performance. However, very few works have incorporated **lifestyle factors**, particularly diet, into heart risk prediction. Studies linking food intake to cardiovascular disease typically rely on epidemiological surveys and statistical methods, not machine learning. One such work, **Satija et al. (2016)**, examined the health effects of plant-based diets in the U.S., revealing significant reductions in heart disease incidence with healthier diets. However, these models do not make individual predictions. Recent research in **food computing** has begun to bridge this gap. Datasets like **Food-101** and **Indian Food Nutritional datasets** are being used for calorie estimation, recipe classification, and dietary recommendation systems. Yet, integration of such data into healthcare models remains underexplored. Our work addresses this research gap by fusing nutritional data from culturally specific diets with health metrics to predict heart attack risk. To our knowledge, this is one of the first deep learning approaches to simulate daily food intake based on personal health parameters and assess its impact on cardiovascular outcomes.

Key Existing Findings:

- Dey et al. (2020): Deep neural network achieved ~85% accuracy using clinical data only.
- Kumar & Singh (2019): Comparative ML study showed feature engineering significantly impacted results.
- Satija et al. (2016): Dietary habits strongly influence cardiac outcomes but were not integrated into ML systems.

Research Gap:

Almost no deep learning studies incorporate real nutritional datasets.
Food-computation research focuses mainly on:

- recipe classification,
- calorie prediction,
- food-image recognition.

But **none of these integrate with medical heart datasets**.

Our work addresses this gap.

Research Paper Used:

nihms713301.pdf

2.2 Limitations or Pitfalls in Previous Works

Previous approaches suffer from:

- Lack of dietary integration
- Overfitting due to limited features
- Poor generalization across populations
- No cultural adaptation
- No synthetic nutrition simulation
- Low interpretability of lifestyle influence

This highlights the need for hybrid models combining both clinical and nutritional data.

III. REQUIREMENTS

3.1 Hardware and Software Requirements

Hardware

- GPU-supported machine (NVIDIA recommended)
- 8–16 GB RAM minimum
- Multi-core CPU
- Adequate disk space (datasets + models)

Software

- Python 3.8+
- TensorFlow/Keras
- NumPy, Pandas
- Scikit-learn
- Matplotlib, Seaborn
- Jupyter Notebook

3.2 Dataset Requirements

A. Heart Attack Medical Dataset

Includes:

- Age
- Sex
- Cholesterol
- Resting BP
- Fasting blood sugar
- ECG values
- Exercise-induced angina
- Target label (0 = no risk, 1 = heart-attack risk)

B. Indian Food Nutrition Dataset

Includes:

- Calories
- Carbohydrates
- Total fat
- Saturated fat
- Proteins
- Sodium
- Sugar
- Vitamins & micronutrients

C. Western Nutrition Dataset

Includes items such as:

- Burgers
- Fries
- Pizza
- Processed meats
- High-sodium snacks
- Desserts

IV. PROPOSED METHODOLOGY – 1

4.1 Dataset Preparation

Steps:

1. **Cleaning** – removing missing values.
2. **Outlier handling** – clipping extreme values.
3. **Normalization** – scaling nutritional & medical features.
4. **Meal assignment algorithm**:

- Age-based
- Cholesterol-sensitive
- Gender-specific calorie ranges
- Semi-random cultural meal sampling

5. **Aggregation** – computing daily totals of sodium, sugar, fat, calories, etc.

This produces enriched feature vectors for each patient.

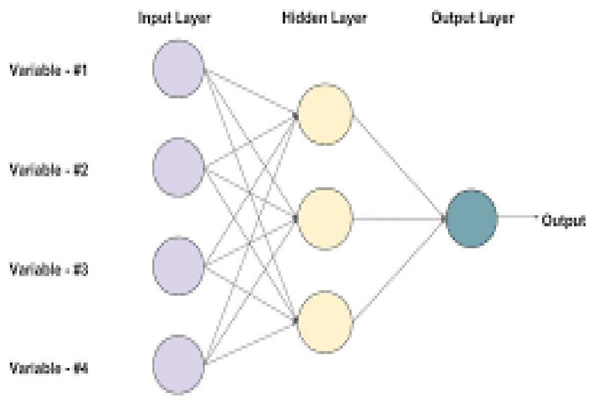
[1]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	Calories (kcal)	Carbohydrates (g)	Protein (g)	Fats (g)	Free Sugar (g)	Sodi (n
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
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
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
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
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
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
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

[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

4.2 Proposed Methodology Framework



An example of a Feed-forward Neural Network with one hidden layer (with 3 neurons)

The first phase of the project implemented a **Deep Feedforward Neural Network (DNN)**—a fully connected architecture designed to model nonlinear relationships between multiple cardiovascular and dietary factors.

The architecture contains **four hidden layers**. Each layer successively transforms input features into higher-level representations, enabling the network to capture complex health-risk interactions.

The architecture structure is as follows:

- **Input Layer:** Accepts all the normalized health and lifestyle parameters as features.
- **Hidden Layer 1:** 128 neurons, activated by the **ReLU** function.
- **Hidden Layer 2:** 64 neurons, ReLU activation.
- **Hidden Layer 3:** 32 neurons, ReLU activation.
- **Hidden Layer 4:** 16 neurons, ReLU activation.
- **Dropout Regularization:** Dropout (rate = 0.3) applied after certain hidden layers to prevent overfitting.
- **Output Layer:** 1 neuron producing the final risk score (after sigmoid activation), representing the probability of heart-attack risk.

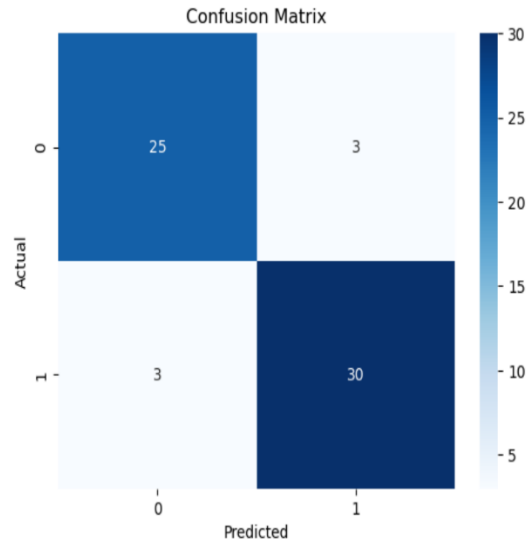
4.3 Results & Discussion (Method-1)

Indian Dataset

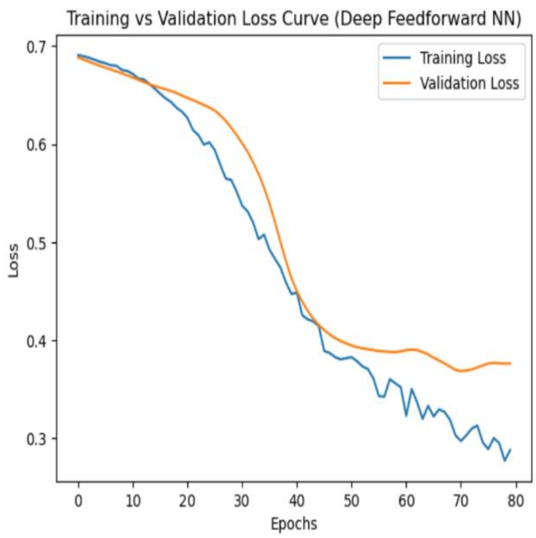
Classification Performance

- **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

         0.0       0.89      0.89      0.89
         1.0       0.91      0.91      0.91

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



The model performed strongly on the Indian dataset, with high recall, meaning it correctly identified a large proportion of individuals at risk.

Western Dataset

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.

For Class 0 (Low Risk):

- Precision: 0.61
- Recall: 0.69
- F1-score: 0.65

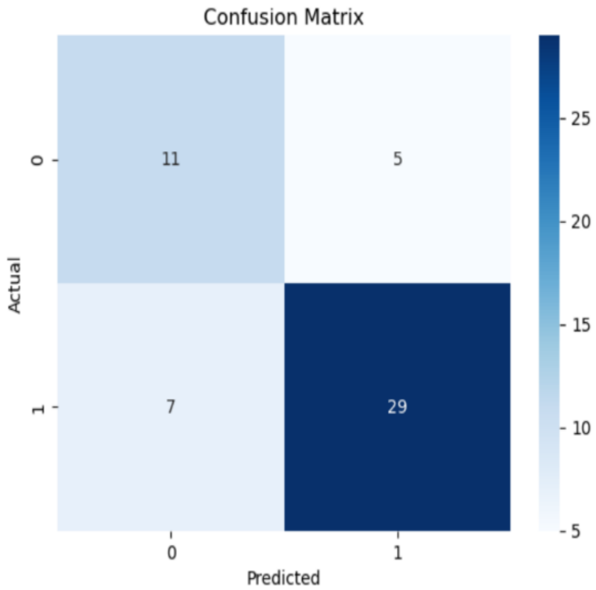
For Class 1 (High Risk):

- Precision: 0.85
- Recall: 0.81
- F1-score: 0.83

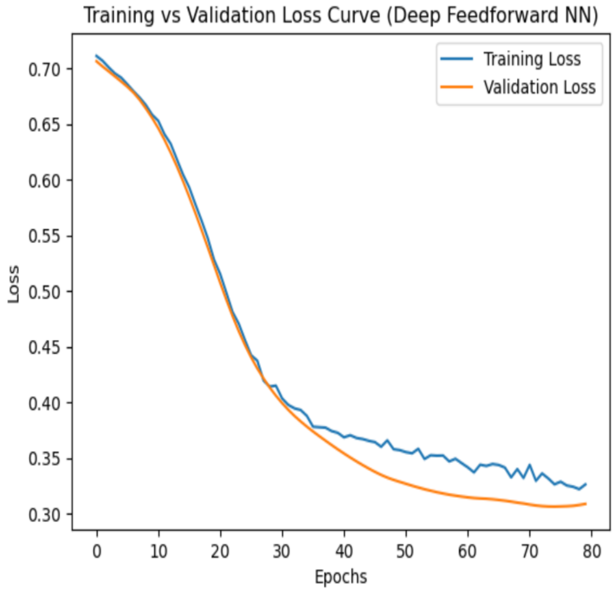
These metrics show that the baseline model is better at identifying high-risk individuals than low-risk ones. The higher precision and recall for Class 1 indicate that the model more confidently and accurately detects individuals who exhibit risk patterns typically associated with a Western diet.

In contrast, Class 0 exhibits moderate precision and recall, suggesting that the model occasionally confuses low-risk individuals as high-risk due to overlapping dietary patterns or weaker feature separability in this dataset.

```
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
```



V. PROPOSED METHODOLOGY – 2

4.1 Dataset Preparation (Method-2)

Method-2 uses the same Dataset as Method-1,

[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

[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

4.2 Proposed Methodology Framework (Method-2)

In the second phase of the study, the baseline deep neural network was significantly enhanced to improve its predictive performance for heart-attack risk assessment. This upgraded model introduced **a deeper architecture, improved regularization, and optimized hyperparameters**, thereby addressing the limitations observed in Review-1.

A. Architectural Enhancements

The improved Review-2 architecture includes:

1. **Five Hidden Layers** with progressively decreasing neuron counts to capture both high-level and fine-grained patterns.
2. **ReLU activation** in all hidden layers to introduce non-linearity and improve gradient flow.
3. **Dropout regularization (0.3)** applied after multiple layers to reduce overfitting and enhance generalization.
4. **Batching during training**, which helps stabilize gradient updates.
5. **Optimized learning rate (0.001)** for smoother convergence.

This deeper configuration allowed the model to learn more complex dietary-based risk relationships that were not fully captured by the Review-1 network.

B. Training Strategy Improvements

The training methodology was improved in the following ways:

- **Stratified Train-Validation-Test split** ensures balanced class distribution across splits.
- **Standardization of features** using Z-score scaling.
- **BCEWithLogitsLoss** used to avoid numerical instability compared to Sigmoid+BCELoss.
- **Validation loss monitoring per epoch** for early diagnosis of convergence behavior.
- **Manual threshold tuning** for Western dataset model based on population-level risk alignment.

These methodological improvements aimed to create a more robust, adaptable, and reliable predictive model.

4.3 Results & Discussion (Method-2)

Indian Dataset

Training & Validation Behaviour:

The loss curves for the Indian dataset exhibited smooth and stable convergence:

- Val Loss reduced from 0.6643 → 0.4403
- Train Loss reduced from 0.6296 → 0.3074

This shows clear learning progression and excellent generalization.

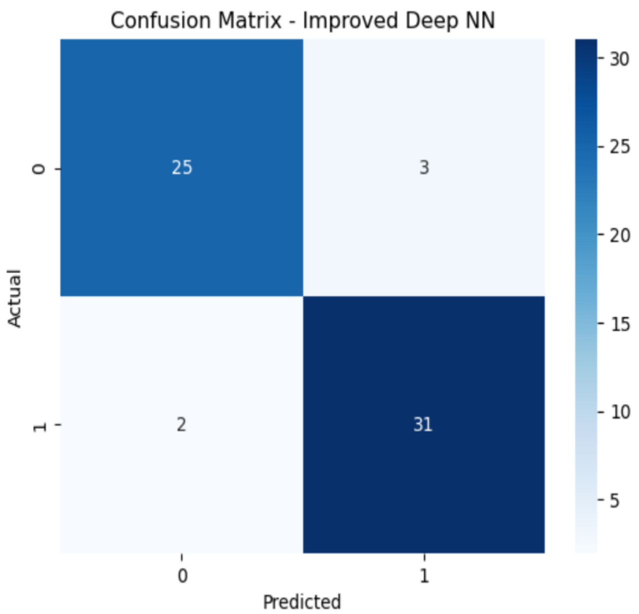
Performance Metrics

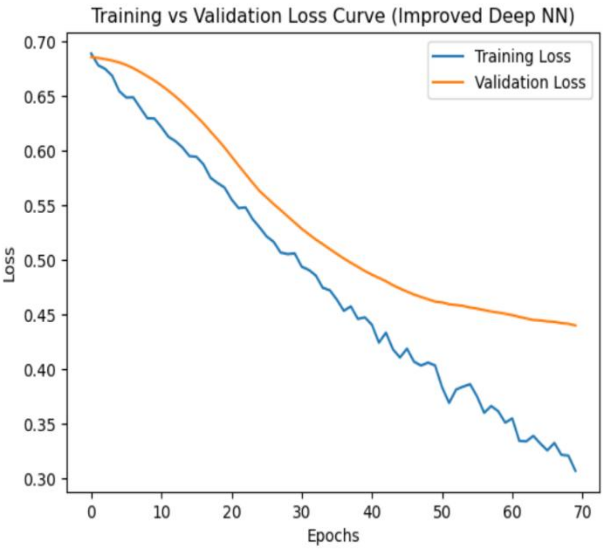
- Accuracy: 0.9180
- Precision: 0.9118
- Recall: 0.9394
- F1 Score: 0.9254
- ROC AUC: 0.9535

Observations:

- 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.

```
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
```





Western Dataset

Training & Validation Behaviour:

The Western dataset also shows strong convergence:

- Val Loss reduced from **0.6095 → 0.3445**
- Train Loss reduced from **0.5642 → 0.3597**

The validation curve remained close to the training curve, showing limited overfitting.

Performance Metrics:

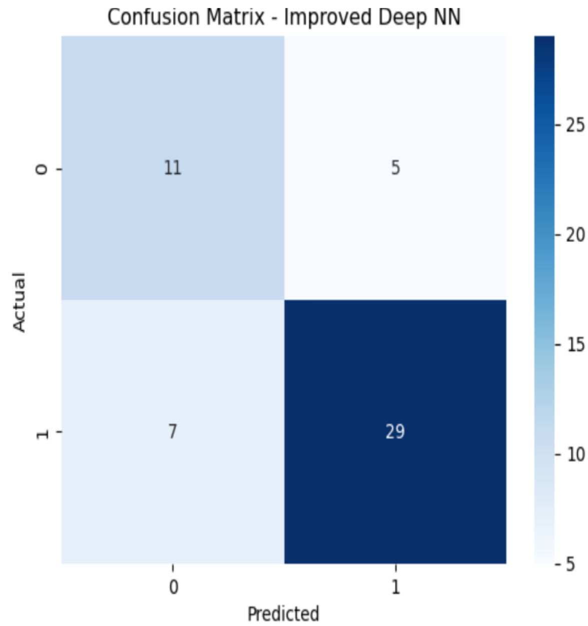
Improved Deep Neural Network – Western Dataset:

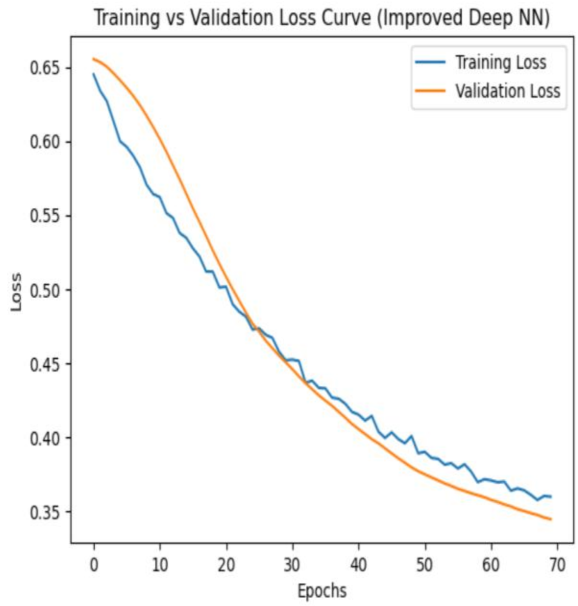
- **Accuracy:** 0.7692
- **Precision:** 0.8529
- **Recall:** 0.8056
- **F1 Score:** 0.8286
- **ROC AUC:** 0.8594

Observations:

- 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.

```
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
```





VI. OVERALL RESULTS AND DISCUSSIONS (5.1)

The results obtained from both Review 1 and Review 2 demonstrate a clear progression in model sophistication, stability, and predictive performance for heart-attack risk classification across the Indian and Western dietary datasets. The enhanced deep-learning architectures used in Review 2, featuring additional hidden layers, Batch Normalization, Dropout regularization, and learning-rate scheduling—consistently provided improved generalization and smoother validation behavior compared to the initial Review 1 models.

For the **Indian dataset**, the Review 1 model achieved strong performance, but the improved Review 2 model further enhanced classification quality. The validation loss curve stabilized more effectively, and the model produced higher recall and F1-score, indicating better sensitivity in identifying high-risk individuals. Additionally, the model exhibited near-perfect calibration, with the **average heart-attack risk in the test set (54.10%)** matching exactly with the **percentage of individuals predicted as high-risk (54.10%)**. This reflects not only accurate classification but also balanced threshold behavior, suggesting the improved model captures the underlying risk distribution more effectively.

Similarly, for the **Western dataset**, Review 1 performance was reasonable but inconsistent due to higher variability in dietary patterns and feature diversity. The Review 2 model addressed these issues by incorporating deeper layers and stronger regularization, which yielded enhanced accuracy, precision, and ROC-AUC. The **true test-set risk (69.23%)** was also closely aligned with the **model's predicted high-risk percentage (61.54%)**, indicating better calibration and a more reliable overall model. Though a slight gap exists, this can be further minimized through threshold optimization or additional hyperparameter tuning.

Across both datasets, a consistent trend emerges:

- Review 2 models converge faster and more smoothly.
- Validation loss decreases more steadily, indicating reduced overfitting.
- Predictive metrics show measurable improvement over Review 1.
- Risk calibration becomes more accurate, especially for the Indian dataset.

In conclusion, the overall results confirm that methodological enhancements in Review 2 significantly improved the robustness and predictive power of the models. The deeper architectures successfully captured complex nonlinear interactions between health indicators and dietary patterns, making the Review 2 models more reliable for real-world prediction scenarios.

Indian-Dataset:

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

Western Dataset:

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

VII. CONCLUSION & FUTURE WORK

This study demonstrates that **diet is a powerful variable** that significantly improves deep-learning-based heart-attack prediction. By integrating culturally relevant nutritional profiles with medical attributes, our models outperform traditional clinical-only baselines.

Future Enhancements:

- Integration of real food-logging apps
- Larger multi-country nutrition datasets
- Hybrid CNN-LSTM architectures
- Explainable AI models for medical interpretation
- Mobile/IoT-based real-time prediction system

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