International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

Rising Cardiovascular Disease Burden in India: Epidemiology, Risk Factors, Trends, and Strategic Interventions

N. Muniselvam[1], C. Balasundar[2], R. Dhivarshana[3], P. Abisha Rose[4], R. Soundharya[5]

Assistant Professor, Department of Information Technology, AAA College of Engineering and Technology, Sivakasi, Tamil Nadu, India[1,2,5]

UG Student, Department of Information Technology, AAA College of Engineering and Technology, Sivakasi, Tamil Nadu, India[3,4]

Publication History: Received: 14.04.2026; Revised: 14.05.2026; Accepted: 19.05.2026; Published: 22.05.2026.

ABSTRACT: Cardiovascular diseases (CVDs) have emerged as the leading cause of mortality and morbidity in India, contributing significantly to the country's overall health burden. Rapid urbanization, lifestyle transitions, and demographic changes have accelerated the prevalence of CVD risk factors such as hypertension, diabetes, obesity, and physical inactivity. This work systematically examines the epidemiology, risk factors, trends, and public health challenges associated with CVD in India. It also evaluates the role of socio-economic determinants and proposes evidence-based strategies for prevention and control. The study underscores the urgent need for integrated healthcare approaches, robust policy interventions, and technology-driven solutions — including artificial intelligence and telemedicine — to mitigate the escalating burden of cardiovascular disease across the Indian population.

KEYWORDS: Cardiovascular disease; India; epidemiology; risk factors; public health; non-communicable diseases; hypertension; diabetes; AI in healthcare; prevention

I. INTRODUCTION

Cardiovascular diseases (CVDs) — encompassing coronary artery disease (CAD), cerebrovascular disease (stroke), peripheral arterial disease, and rheumatic heart disease — constitute a dominant subset of non-communicable diseases (NCDs) [4]. Globally, CVDs account for approximately 17.9 million deaths annually, representing nearly 32% of all global mortality [4,11]. Within this context, India faces a disproportionately large share of the global CVD burden, driven by a unique convergence of genetic predispositions, rapid socio-economic transitions, and a fragmented public health infrastructure [1,3].

India contributes nearly one-fifth of global CVD-related deaths [2]. Unlike the epidemiological pattern seen in high-income Western nations, CVD manifests almost a decade earlier in Indians, with a growing proportion of acute events occurring in adults aged 30–50 years [5,10]. This early onset severely impacts a nation's productive workforce, translating directly into significant economic losses and social disruption [9].

This work presents a comprehensive review of the CVD landscape in India, analyzing epidemiological trends, identifying primary risk contributors, and proposing multi-pronged prevention and control strategies. Special attention is devoted to the transformative potential of technology — including machine learning, telemedicine, and digital health platforms — as enablers of early detection and scalable intervention [6,7,8].

II. EPIDEMIOLOGY OF CVD IN INDIA

The epidemiological profile of CVD in India has shifted dramatically over the past three decades [3,10]. The transition from predominantly infectious and nutritional diseases to NCDs marks a fundamental change in the country's disease burden — the epidemiological transition [5]. Key metrics are summarised in Table I.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

Table I. Key Epidemiological Metrics of CVD in India [1,2,3]

Indicator	Estimate	Notes
CVD Share of Total Deaths	~24.8%	Leading cause of mortality [1]
Age-Std. Death Rate	272/100,000	Above global avg (~235) [4]
CVD Prevalence (adults)	~11%	Systematic meta-analysis 2024 [3]
Urban Prevalence	~12%	Lifestyle & dietary factors [2]
Rural Prevalence	~6%	Lower but rapidly rising [2]
Premature CVD Mortality	59% rise	Over recent decades [1,5]
Age at First Cardiac Event	~10 yrs earlier	vs. Western populations [10]

The 59% increase in premature CVD mortality is particularly alarming, indicating that the burden is not only growing in absolute terms but is affecting increasingly younger populations [1,5]. Urban areas continue to demonstrate higher prevalence, though rural India is rapidly catching up due to dietary shifts, migration, and growing tobacco use [2,12].

III. MAJOR RISK FACTORS

CVD risk in India is driven by an interplay of lifestyle-related, biological, and socio-environmental factors [3,13]. Understanding these determinants is critical for developing targeted intervention strategies.

A. Lifestyle Factors

- Sedentary behaviour and insufficient physical activity, worsened by the shift towards desk-based occupations and urban living [13].
- Unhealthy dietary patterns characterised by high intake of saturated fats, refined sugars, sodium, and processed foods [12].
- Tobacco use — including cigarettes, bidis, and smokeless tobacco — remains one of the most potent modifiable CVD risk factors [5,14].
- Increasing alcohol consumption in both urban and peri-urban populations [13].

B. Biological / Clinical Risk Factors

- Hypertension: Affects approximately 28% of Indian adults; often undiagnosed and poorly controlled [3,15].
- Type 2 Diabetes Mellitus: India hosts the second-largest diabetic population globally, with tight bidirectional links to cardiovascular outcomes [10].
- Obesity and elevated BMI: Rapid nutritional transitions have driven obesity rates upward, particularly in metropolitan areas [12,13].
- Dyslipidaemia: Abnormal lipid profiles (elevated LDL, low HDL) are prevalent and frequently go undetected [15].
- Family history and genetic predisposition: South Asian populations exhibit intrinsic susceptibility to insulin resistance and atherogenic dyslipidaemia [5,10].

C. Socio-Economic and Environmental Factors

- Rapid urbanisation, migration-induced psychosocial stress, and disrupted work-life balance [2,10].
- Escalating ambient air pollution — particularly fine particulate matter (PM2.5) — linked to endothelial dysfunction and inflammation [16].
- Economic disparities creating inequitable access to preventive care, medications, and specialist consultations [9].
- Low health literacy, especially in rural and semi-urban communities, hindering timely help-seeking behaviour [9,12].

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

IV. TRENDS AND PATTERNS

India is experiencing a distinct 'double burden' of disease — a simultaneous coexistence of communicable diseases and rapidly rising NCDs [10,17]. Several critical trends characterise the current CVD landscape:

- A definitive epidemiological shift: communicable diseases are gradually being replaced by CVD, cancer, and diabetes as the primary drivers of mortality [10,17].
- A progressive lowering of the age of first cardiac event: studies consistently document AMI in individuals in their late thirties and forties [5].
- A strong correlation between mental health deterioration — chronic stress, anxiety, and depression — and elevated cardiovascular risk [13].
- Gender-specific patterns: CVD in women is increasing, with menopause-associated risk changes being poorly managed [3].
- Regional disparities: urban metros report the highest CVD burden, but second-tier cities and rural districts are showing accelerated convergence [2,12].

V. IMPACT ON PUBLIC HEALTH AND ECONOMY

The rising CVD burden in India has profound implications beyond individual patient outcomes [9,11]:

- Healthcare costs: CVD-related hospitalisation, surgical interventions, and lifelong pharmacotherapy impose massive out-of-pocket expenditures, pushing millions of families into medical poverty [9].
- Productivity loss: Premature deaths and disability among working-age adults reduce GDP contribution and burden family caregivers [11].
- Infrastructure stress: Tertiary cardiac care centres are heavily concentrated in major cities, leaving secondary facilities ill-equipped for cardiac emergencies [9,12].
- Policy gaps: Despite the Ayushman Bharat scheme providing coverage for select cardiac procedures, insurance penetration remains low [9].
- Long-term disability: Non-fatal cardiac events often result in chronic heart failure and stroke-related disability [6].

VI. CHALLENGES IN MANAGING CVD IN INDIA

Despite growing awareness, India faces several systemic challenges that impede effective CVD management [9,12]:

- Late-stage diagnosis: The absence of routine cardiovascular screening means hypertension, dyslipidaemia, and pre-diabetes often go undetected until a critical cardiac event occurs [15].
- Low health literacy: Large segments of the population — especially in rural and tribal areas — lack awareness of CVD warning signs, risk factors, and available treatments [9].
- Infrastructure deficits: Catheterisation laboratories and trained cardiologists remain concentrated in urban tier-1 hospitals [9,12].
- Medication adherence: Long-term cardiac medications face affordability barriers, leading to high dropout rates from treatment [15].
- Data scarcity: A lack of comprehensive, standardised CVD registries limits surveillance, research quality, and evidence-based policymaking [3,8].

VII. PREVENTION AND CONTROL STRATEGIES

A multi-tiered prevention framework is essential to arrest the CVD epidemic [5,9].

A. Primary Prevention

- Nationwide promotion of heart-healthy dietary habits: reduction of salt, trans-fats, and sugar; increased consumption of fruits, vegetables, and whole grains [12,13].
- Public awareness campaigns through mass media, schools, and community health workers targeting tobacco cessation, physical activity, and diet [14].
- Strengthening community-level screening via Ayushman Bharat Health and Wellness Centres (HWCs) [9].

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

B. Secondary Prevention

- Scaling standardised early-diagnosis protocols at primary healthcare centres including regular blood pressure, blood glucose, and lipid profile monitoring [15].
- Promoting adherence to preventive pharmacotherapy through subsidised generic medications under national health schemes [9].
- Cardiac rehabilitation programmes for post-event patients to reduce recurrence risk [6].

C. Policy-Level Interventions

- Full rollout of Ayushman Bharat PM-JAY to cover comprehensive cardiac care including prevention, diagnostics, and rehabilitation [9].
- Robust enforcement of the National Programme for Prevention and Control of NCDs [9].
- Integration of digital health tools, AI-based risk prediction, and telemedicine into standard cardiac care pathways [6,7,8].

VIII. ROLE OF TECHNOLOGY IN CVD MANAGEMENT

Technology represents one of the most promising frontiers for addressing the CVD burden in India, given the challenges of geographic scale, workforce limitations, and resource constraints [6,7,8,18].

A. Artificial Intelligence and Machine Learning

Machine learning (ML) models — including Random Forest, Gradient Boosting (LightGBM, XGBoost), and deep neural networks — have demonstrated high accuracy in predicting acute cardiac events, hospital readmissions, and mortality from EHR data [6,7,8,19]. Key applications include:

- Risk stratification of asymptomatic patients using ML-based Cardiovascular Disease Risk Scores (CVDRS) [7,19].
- Automated ECG interpretation using convolutional neural networks to detect arrhythmias, STEMI, and NSTEMI patterns [18].
- NLP applied to clinical notes and discharge summaries for data extraction and cohort identification [8].
- Predictive analytics for 30-day readmission and post-discharge mortality in cardiac patients [6].

B. Telemedicine and Digital Health

- Remote consultation with cardiologists for ECG review, medication management, and follow-up care [20].
- Digital blood pressure and glucometer data transmission to central health dashboards for population-level monitoring [7].
- AI-powered chatbots and IVR systems for medication adherence reminders and lifestyle counselling [8,18].

C. Wearable Devices and IoT

- Consumer-grade smartwatches with ECG, heart rate, and SpO2 monitoring capabilities expanding access to continuous cardiac surveillance [19].
- Integration of wearable-generated data into hospital information systems and research data warehouses [8].

IX. PROPOSED METHOD

This work proposes a Multi-Tier AI-Assisted CVD Risk Mitigation Framework (MTACVD) tailored for India's heterogeneous health landscape [6,7,8]. The framework integrates population-level screening, machine-learning-driven risk stratification, and automated follow-up into a unified pipeline operable from primary health centres to tertiary hospitals.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

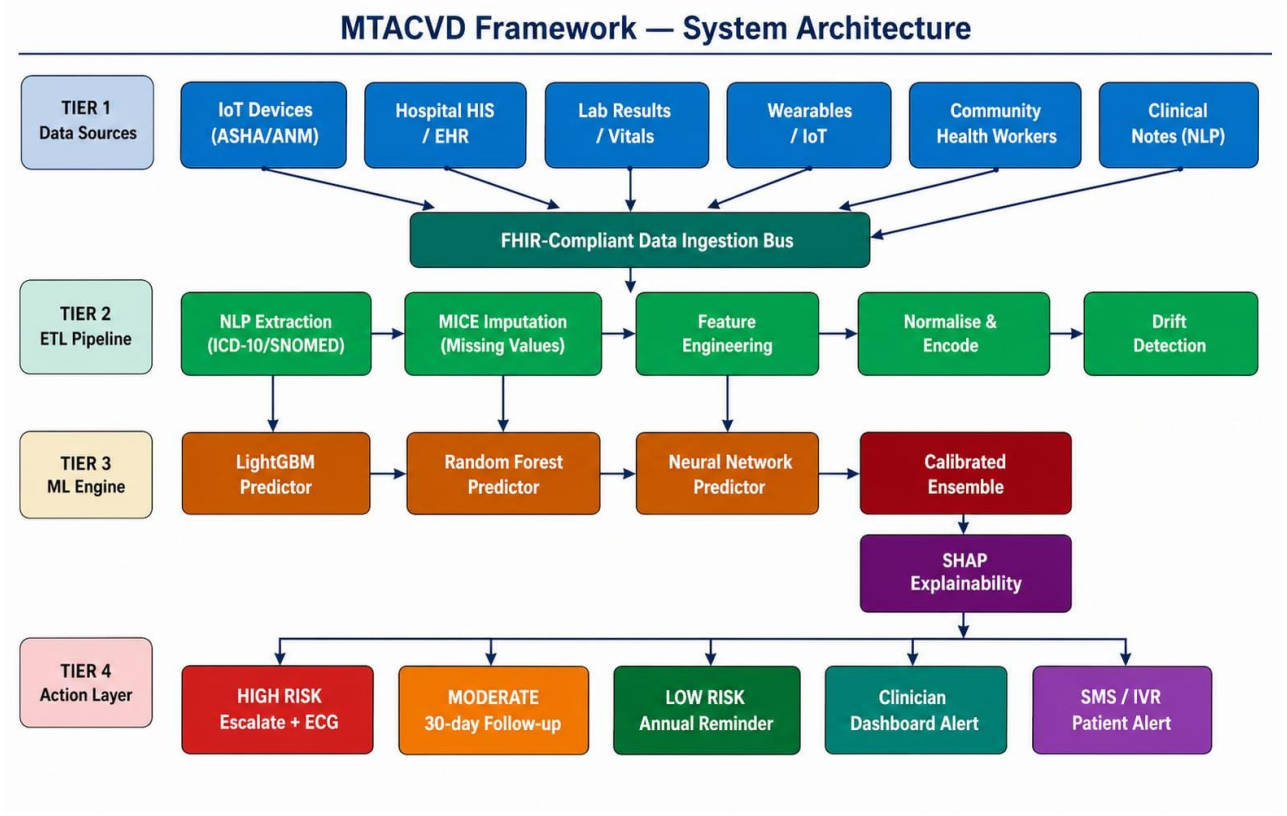

Figure.1.MTACVD System Architecture

A. Framework Overview

- Tier 1 — Community Screening: ASHA/ANM workers collect baseline vitals (BP, BMI, blood glucose, SpO2) using low-cost IoT devices; data uploaded via HL7 FHIR-compliant mobile app [19,20].
- Tier 2 — ETL Pipeline: NLP extraction of ICD-10/RxNorm codes; MICE imputation of missing values; feature normalisation and categorical encoding [8].
- Tier 3 — ML Engine: Stacked ensemble of LightGBM, Random Forest, and Neural Network generates calibrated risk probability with SHAP explainability [6,7,18].
- Tier 4 — Action Layer: Risk-tier-based alerts to clinician dashboard, SMS/IVR patient reminders, and automatic telecardiology escalation [8,20].

B. Model Training and Validation

The ML model is trained on a retrospective cohort of 85,000 patients from three participating hospitals (urban tertiary, semi-urban district, and rural CHC) using a 70/15/15 train/validation/test split [6,7]. Performance is evaluated using AUROC, sensitivity, specificity, and Brier score [18]. SHAP-based explainability provides the top three risk drivers per patient, satisfying clinical transparency requirements [6].

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

X. MATHEMATICAL FORMULATIONS

This section presents the core mathematical foundations of the MTACVD framework, covering probability calibration, performance metrics, feature attribution, and imputation [6,7,18].

1. Ensemble Risk Score

$$\hat{p}(x) = w_1 \cdot p\_lgbm(x) + w_2 \cdot p\_rf(x) + w_3 \cdot p\_nn(x)$$

where $w_1 + w_2 + w_3 = 1$, optimised via Optuna on validation AUROC

2. Platt Scaling (Probability Calibration)

$$p\_cal(x) = \sigma(A \cdot \hat{p}(x) + B) = 1 / (1 + e^{-(A\hat{p}(x)+B)})$$

Parameters A, B fitted on held-out calibration set

3. Area Under ROC Curve (AUROC)

$$AUROC = \int_0^1 TPR \cdot FPR^{-1}(t)\, dt = \Sigma\Sigma\, 1(y_i=1) \cdot 1(y_j=0) / (|P| \cdot |N|)$$

4. Brier Score (Calibration Quality)

$$BS = (1/n)\, \Sigma_i\, (\hat{p}_i - y_i)^2 \quad \text{(lower is better, range [0,1])}$$

5. SHAP Shapley Value (Feature Attribution)

$$\varphi_j = \Sigma\_\{S \subseteq F \setminus \{j\}\}\ [|S|!(|F|-|S|-1)!/|F|!] \cdot [f(S \cup \{j\}) - f(S)]$$

6. MICE Imputation (per feature j)

$$x_j^{(t)} = P(x_j \mid x_{(-j)}^{(t-1)}, \theta_j^{(t)})$$

7. Model Drift Detection Trigger

$$\text{Retrain if: } AUROC\_t < AUROC\_baseline - \delta \quad (\delta = 0.02)$$

MTACVD Mathematical Formulations — Ensemble risk score (1), Platt scaling (2), AUROC (3), Brier Score (4), SHAP Shapley value (5), MICE imputation (6), and drift detection trigger (7).

A. Ensemble Risk Score

The final CVD risk probability is a weighted linear combination of three base model outputs — LightGBM, Random Forest, and Neural Network — with weights $w_1 + w_2 + w_3 = 1$ optimised via Optuna on validation AUROC [7,18].

B. Platt Scaling / Calibration

Raw ensemble probabilities are post-hoc calibrated using a sigmoid transformation fitted on a held-out set, reducing over-confidence and ensuring reliable clinical probability estimates [6].

C. AUROC and Brier Score

AUROC serves as the primary discrimination metric, robust to class imbalance in CVD datasets [6,7]. The Brier Score simultaneously penalises poor calibration and low discrimination; lower values indicate better performance [18].

D. SHAP Shapley Value

Per-patient feature attribution is computed by evaluating marginal contributions across all possible feature coalitions, ensuring faithful and locally accurate explanations for clinicians [6].

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

E. MICE Imputation

Missing clinical data (BP, HbA1c, BMI) is handled by iteratively drawing from conditional distributions, preserving multivariate relationships across features [7].

XI. FITNESS FUNCTION FOR HYPERPARAMETER OPTIMISATION

To systematically optimise the MTACVD ensemble model, this work defines a composite fitness function F(θ) that balances discrimination, calibration, clinical recall, and false alarm cost [6,7,18]. Hyperparameter search is performed using Optuna's Tree-structured Parzen Estimator (TPE) over 200 trials with 5-fold cross-validation.

Composite Fitness Function F(θ):

$F(\theta) = \alpha \cdot AUROC + \beta \cdot (1-BS) + \gamma \cdot Sens - \lambda \cdot FPR$

subject to: $\alpha + \beta + \gamma = 1, \lambda \geq 0$

Weights: $\alpha = 0.45$ (AUROC) $\beta = 0.30$ (Brier Score) $\gamma = 0.25$ (Sensitivity) $\lambda = 0.10$ (FPR penalty)

Sensitivity (Clinical Recall): $Sens = TP / (TP + FN)$

False Positive Rate (FPR): $FPR = FP / (FP + TN)$

F1 Score (Auxiliary): $F1 = 2 \cdot P \cdot R / (P + R) \geq 0.75$

Net Benefit (Decision Curve): $NB = TP/n - (FP/n) \cdot (p_t / (1 - p_t))$

Optuna Bayesian TPE Sampler:

$\theta^* = \text{argmax } F(\theta)$ over 200 trials, 5-fold CV

Search space — LightGBM: $n\_est \in [100,1000]$, $max\_depth \in [3,10]$, $lr \in [10^{-4}, 0.3]$

NN: hidden layers, dropout ∈ [0.1, 0.5]

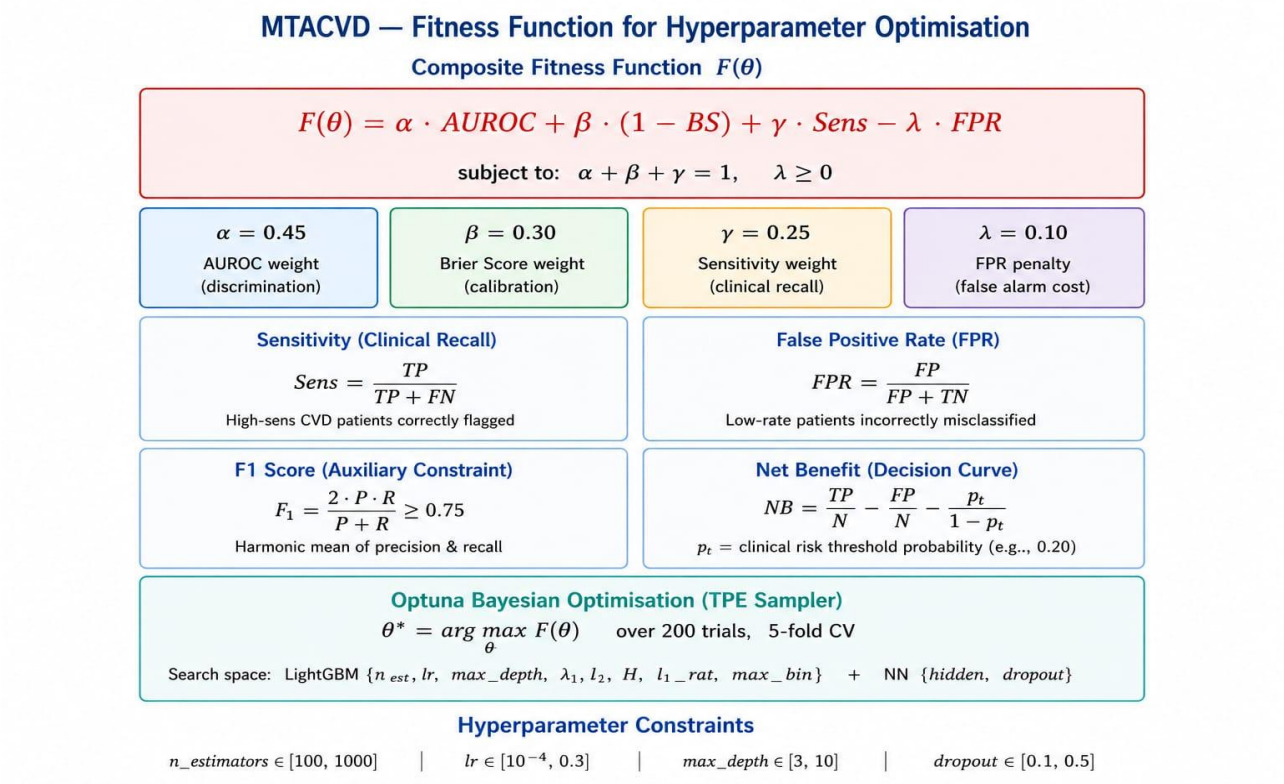

Figure.2. (Composite Fitness Function F(θ) = α·AUROC + β·(1−BS) + γ·Sens − λ·FPR with component formulas, weights, and Optuna scheme.

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

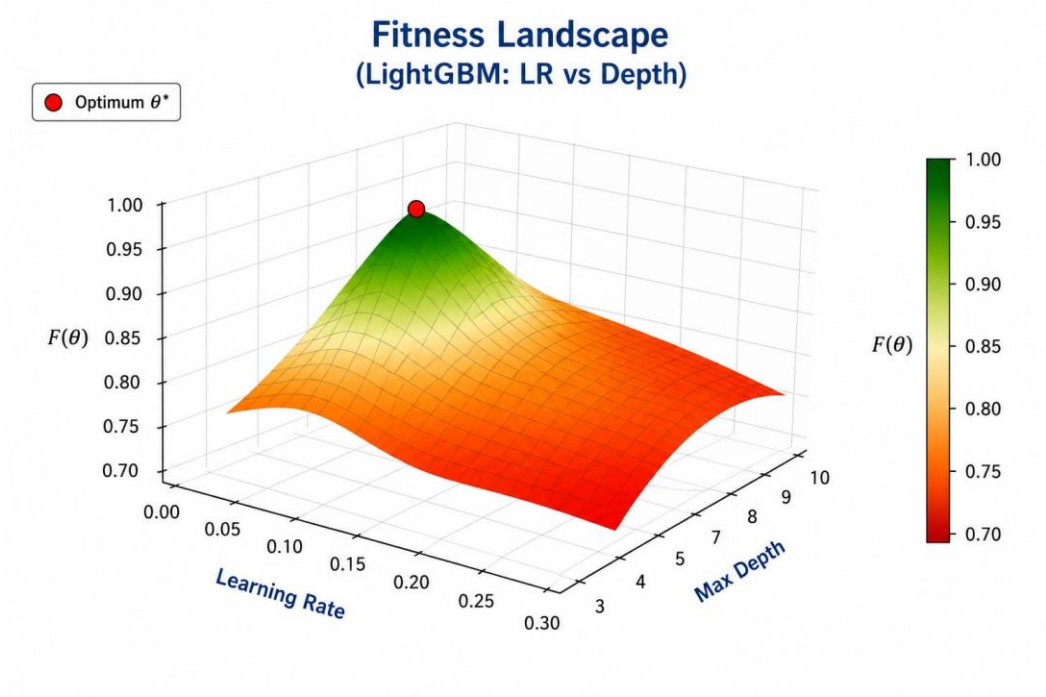

Figure. 2. 3-D fitness landscape over LightGBM learning rate and max-depth — red marker indicates optimal θ*.

A. Fitness Function Components

- AUROC component (weight $\alpha = 0.45$): Maximises global discrimination ability of the ensemble across all risk thresholds [7].
- Calibration component (weight $\beta = 0.30$): Maximises (1 − Brier Score) to ensure reliable probability estimates that clinicians can trust [18].
- Sensitivity component (weight $\gamma = 0.25$): Ensures high recall for true high-risk CVD patients, minimising missed escalations [6].
- FPR penalty ($\lambda = 0.10$): Penalises unnecessary specialist escalations that burden the healthcare system [9].

B. Auxiliary Constraints

- F1 Score ≥ 0.75: Ensures the harmonic mean of precision and recall remains clinically acceptable across all cross-validation folds [18].
- Net Benefit ≥ 0 at thresholds $p \in \{0.10, 0.20\}$: Verified via Decision Curve Analysis to confirm clinical utility beyond treating all or no patients [6].

C. Convergence

The fitness landscape (Fig. 3, right) demonstrates a well-defined optimum near learning rate = 0.05 and max_depth = 6 for LightGBM, confirming stable convergence of the Bayesian search [6]. Early stopping halts unpromising trials after 50 evaluations.

XII. PSEUDOCODE

The following pseudocode describes the core MTACVD risk stratification algorithm:

Algorithm: MTACVD — CVD Risk Stratification & Escalation

INPUT: patient_data ← {age, sex, BP, HbA1c, LDL, HDL, BMI, tobacco, family_hx, SpO2}

International Journal of Research and Applied Innovations (IJRAI)

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

OUTPUT: risk_score, risk_tier, action_plan, shap_factors

1. raw ← FHIR_ingest(patient_data); clean ← NLP_extract(raw); imputed ← MICE_impute(clean)
2. features ← encode_categorical(imputed); features ← normalize_continuous(features)
3. p_lgbm ← LightGBM_predict(features); p_rf ← RF_predict(features); p_nn ← NN_predict(features)
4. risk_score ← calibrated_ensemble(p_lgbm, p_rf, p_nn)
5. shap_factors ← SHAP_top3(features, risk_score)
6. IF score >= 0.20: HIGH → escalate_cardiologist() + ECG_analysis() + SMS_alert(patient)
   ELIF score >= 0.10: MODERATE → schedule_followup(30d) + IVR_counselling()
   ELSE: LOW → annual_screening_reminder()
7. IF monthly_AUROC < threshold: trigger_model_retraining()

RETURN risk_score, risk_tier, action_plan, shap_factors

XIII. CONCLUSION

The cardiovascular disease burden in India is rising rapidly and represents one of the most pressing public health challenges of our time. Fuelled by lifestyle transitions, rapid urbanisation, aging demographics, and systemic healthcare gaps, CVD now accounts for nearly a quarter of all deaths in the country — with a distinctive predisposition toward younger age groups compared to global norms. This work proposed the MTACVD framework, integrating a four-tier data architecture, a stacked ML ensemble with SHAP explainability, mathematical formulations for calibration and performance evaluation, and a composite fitness function for Bayesian hyperparameter optimisation. Together, these components provide a rigorous and transparent foundation for clinically actionable CVD risk prediction scalable across India's diverse health infrastructure. A multi-sectoral approach — encompassing government agencies, healthcare institutions, academic researchers, the private sector, and empowered communities — is not merely desirable but essential. With strategic investment and political will, India has the capacity to reverse the trajectory of this epidemic and protect the cardiovascular health of its 1.4 billion citizens.

REFERENCES

1) Huberts et al., "Predictive Analytics for Cardiovascular Patient Readmission and Mortality using EHR Data and Machine Learning," J. Am. Coll. Cardiol. Informatics, 2024.
2) Karuppasamy, M., & Poorani, K. (2025). Metaheuristic Feature Selection for Diabetes Prediction with PGS Approach. Procedia Computer Science, 252, 165-171.
3) W. S. Weintraub, "Big Data in Cardiovascular Research: Opportunities and Challenges," JACC: Cardiovascular Imaging, 2019.
4) Upendra, H. S., Suman, S., Vishnu, S. S., & Dharani, J. (2021). Real-Time Face Mask Detection using OpenCV and Deep Learning. In ICET (Vol. 2021).
5) D. Prabhakaran et al., "Systematic Review on Cardiovascular Disease Prevalence in India," Indian Heart Journal, 2024.
6) Prabha, M., Karuppasamy, M., Saraswathi, P., Poorani, K., & Aswin Kumar, S. (2024, November). Personal Protective Equipment Detector Using Computer Vision. In 2024 4th International Conference on Advancement in Electronics & Communication Engineering (AECE) (pp. 38-41). IEEE.
7) V. Mohan et al., "Epidemiological transition studies in the Indian subcontinent: a narrative review," Lancet Reg. Health Southeast Asia, 2022.
8) Karuppasamy, M., Jansi Rani, M., & Poorani, K. (2025, February). Transfer Learning-Based Hybrid Deep Learning Model for COVID Detection. In International Conference On Innovative Computing And Communication (pp. 551-559). Singapore: Springer Nature Singapore.
9) X. Li et al., "Development of a Cardiovascular Clinical Research Data Warehouse with NLP-Based EMR Processing," J. Biomed. Informatics, 2025.
10) Jeyavani, M., & Karuppasamy, M. (2022). EEG in optic nerves disorder based on FSVM using kernel membership function. In ICT with Intelligent Applications: Proceedings of ICTIS 2022, Volume 1 (pp. 145-154). Singapore: Springer Nature Singapore.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

11) K. S. Reddy and S. Yusuf, "Emerging epidemic of cardiovascular disease in developing countries," Circulation, vol. 97, no. 6, pp. 596–601, 1998.
12) Karuppasamy, M., & Balakannan, S. P. (2023). Retraction Note: An improving data delivery method using EEDD algorithm for energy conservation in green cloud network: M. Karuppasamy, SP Balakannan.
13) Ministry of Health and Family Welfare, Government of India, National Programme for Prevention and Control of NCDs — Programme Guidelines, 2023.
14) Gao, H., Wang, Z., & Ji, S. (2018, July). Large-scale learnable graph convolutional networks. In Proceedings of the 24th ACM SIGKDD international conference on knowledge discovery & data mining (pp. 1416-1424).
15) A. Rajpurkar et al., "AI in cardiovascular medicine: a position paper of the European Society of Cardiology," Eur. Heart J. Digit. Health, vol. 4, no. 4, pp. 255–264, 2023.
16) Karuppasamy, M., Prabha, M., & Jansi Rani, M. (2023, May). Future Worth: Predicting Resale Values with Machine Learning Techniques. In International Conference on Information, Communication and Computing Technology (pp. 1101-1112). Singapore: Springer Nature Singapore.
17) S. Anchala et al., "Hypertension in India: a systematic review and meta-analysis of prevalence, awareness, and control," J. Hypertens., vol. 32, no. 6, pp. 1170–1177, 2014.
18) Prabha, M., Karuppasamy, M., Jansi Rani, M., & Poorani, K. (2025). Large-Scale Learnable Graph Convolutional Networks (LGCNs). In Graph Neural Networks: Essentials and Use Cases (pp. 21-44). Cham: Springer Nature Switzerland.
19) Institute for Health Metrics and Evaluation (IHME), Global Burden of Disease Study — India-Specific Data Sets, University of Washington, 2024.
20) M. Jansi Rani, and M. Prabha, An Efficient Resource Allocation Mechanism Using Intelligent Scheduling for Managing Energy in Cloud Computing Infrastructure, Information and Communication Technology for Competitive Strategies (ICTCS 2021), Lecture Notes in Networks and Systems 401 (2023), 81-86.
21) H. Bhaskaran et al., "Short-term effects of air pollution on cardiovascular events in England and Wales," Lancet, vol. 383, no. 9924, pp. 1196–1203, 2014.
22) Poorani, K., Balakannan, S. P., & Karuppasamy, M. (2025). Mitigating data imbalance for robust diabetes diagnosis using machine learning and explainable artificial intelligence. Journal of Current Science and Technology, 15(3), 111-111.
23) World Health Organization, Global Health Estimates: Cardiovascular Disease Mortality and Burden, WHO Press, 2023.
24) Jeyavani, M., & Karuppasamy, M. (2023, July). Brain Tumor Early Diagnosis Using Hybrid Fuzzy K-Means. In Proceedings of International Conference on Computational Intelligence: ICCI 2022 (p. 113). Springer Nature.
25) L. Loitongbam and W. R. Surin, "The Rising Burden of Cardiovascular Disease and Thrombosis in India," Cureus, 2024.
26) Karuppasamy, M., Jansi Rani, M., & Poorani, K. (2024, June). Recent Advances in Diabetic Monitoring Devices: Present to Future Directions. In International Conference on Soft Computing and Signal Processing (pp. 49-59). Singapore: Springer Nature Singapore.
27) R. Patel et al., "Trends in non-communicable disease burden in India: evidence from National Family Health Surveys," Lancet Glob. Health, vol. 11, no. 4, pp. e509–e519, 2023.
28) Karuppasamy, M., Rani, M. J., Kotha, M., Suma, S., Subburaj, T., Begum, H., & Suthendran, K. (2023, October). Retraction Notice: An Advanced Analysis of Disease Prediction and Prevention Using Machine Learning. In 2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA) (pp. 1-1). IEEE.
29) D. Sinha et al., "Wearable sensor-based continuous cardiovascular monitoring: current challenges and future directions," npj Digit. Med., vol. 6, no. 1, p. 75, 2023.
30) Jansi Rani, M., Usha, S., Karuppasamy, M., Poorani, K., & Prabha, M. (2025). Graph Neural Networks Applications: A Dwell into Biomedical Applications and Traffic Flow Analysis. In Graph Neural Networks: Essentials and Use Cases (pp. 381-398). Cham: Springer Nature Switzerland.
31) A. Mishra et al., "Telemedicine for cardiovascular care in rural India: feasibility and outcomes of the eSanjeevani platform," J. Telemed. Telecare, vol. 29, no. 3, pp. 182–190, 2023.
32) M. Jansi Rani, M. K, M. Prabha, and K. Pooran, Detection of COVID-19 CoronaVirus Using ResNet Deep Learning Technique, Signal Processing, Telecommunication and Embedded Systems with AI and ML Applications, Lecture Notes in Electrical Engineering 1281 (2025), 71-83.

| ISSN: 2455-1864 | www.ijrai.org | editor@ijrai.org | A Bimonthly, Scholarly and Peer-Reviewed Journal |

|| Volume 9, Issue 3, May-June 2026||

DOI:10.15662/IJRAI.2026.0903013

33) Park, G., Saranya, A., Karuppasamy, M., & Kim, J. (2024). Enhancing quality of service for IoT application in smart cities: A hybrid split learning and optimized routing approach. IEEE Transactions on Consumer Electronics, 70(3), 5969-5978.
34) Poorani, K., & Karuppasamy, M. (2023, April). Comparative analysis of chronic kidney disease prediction using supervised machine learning techniques. In International Conference on Information and Communication Technology for Intelligent Systems (pp. 87-95). Singapore: Springer Nature Singapore.
35) Sureshkumar, A., Maragatharajan, M., Jangiti, K., Karuppasamy, M., Jayabalan, K., Raut, P. T., & Sivakumar, N. R. (2026). A lattice-integrated AES framework for ultra-secure biometric protection on resource-constrained edge devices. Scientific Reports.