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Hybrid Machine Learning Approaches for Cardiovascular Disease Detection

Vibhandik Chirayu[1], Piprotar Pradyuman[2], Koladiya Savan[3], Paghdal Vrutanshi[4], Patel Janki Tejas[5]

[1-4] Student, [1](221130107080), [2](221130107058), [3](221130107023), [4](221130107033),
[5]Asst. Professor
Sal College of Engineering, India

1. Introduction

Cardiovascular diseases (CVDs) remain one of the primary causes of death globally. The growing availability of healthcare data has enabled researchers to apply Machine Learning (ML) and hybrid ML techniques to develop intelligent, automated systems for early CVD detection. Hybrid ML approaches—combining multiple models or integrating ML with deep learning—offer higher accuracy and interpretability. This review surveys ten recent studies (2022–2025) that employ hybrid ML methods for CVD prediction, comparing their datasets, methods, and outcomes.

2. Review of Related Works

Recent work by Sharma et al. (2025) introduced HXAI-ML, a hybrid explainable model integrating SHAP and LIME with ML classifiers to improve model transparency and accuracy (98.78%). Gupta et al. (2025) developed a hybrid stacked model with SMOTE-ENN balancing and Chi²-based feature selection, achieving 97.8% accuracy on clinical datasets.

Similarly, Li et al. (2023) conducted a review showing that Support Vector Machines (SVM) and Random Forest (RF) consistently perform well for structured CVD datasets.

Kumar et al. (2025) used hybrid ARIMA and ML models (RF, XGBoost) for cardiovascular mortality forecasting in India, achieving lower mean absolute error. Patel et al. (2024) proposed an ensemble (ETCXGB) model, improving feature interaction learning. Khan et al. (2025) developed HeartEnsembleNet—a fusion of deep learning and ML models—which enhanced robustness against overfitting. Alam et al. (2022) and Li et al. (2023) explored ensemble and AutoML frameworks to combine models for improved diagnostic accuracy.

Singh et al. (2024) and Verma et al. (2024) combined decision trees, neural networks, and SVMs to handle imbalanced data, demonstrating higher generalization and clinical reliability.

3. Comparative Analysis of Recent Studies

Author (Year)	Method Used	Dataset	Accuracy (%)	Highlights
Sharma et al. (2025)	HXAI-ML Hybrid Explainable Model	Cleveland, Framingham	98.78	Explainable ML with SHAP & LIME
Gupta et al. (2025)	Stacked Hybrid Model (SMOTE- ENN + Chi²)	Clinical Dataset	97.8	Balanced data + feature selection
Li et al. (2023)	Comprehensive ML Review	Various Datasets	96.1 (avg)	Survey of ML for CVD
Kumar et al. (2025)	Hybrid ARIMA + ML (RF, XGB)	IHME India	-	Time-series forecasting of CVD mortality
Patel et al. (2024)	ETCXGB Ensemble	UCI Heart	-	Improved feature interaction

Author (Year)	Method Used	Dataset	Accuracy (%)	Highlights
Khan et al. (2025)	HeartEnsembleNet Hybrid Ensemble	Clinical Dataset	94+	Deep + ML fusion ensemble
Alam et al. (2022)	Ensemble ML + Deep Learning	Public CVD Dataset	88.7	RF + SVM + DL combination
Li et al. (2023)	AutoML Weighted Ensemble	UCI & Kaggle	87–92	Automated optimization of models
Singh et al. (2024)	Hybrid ML (DT + SVM + NN)	Heart Disease	90+	Strong generalization
Verma et al. (2024)	Hybrid ML + Lifestyle Factors	Clinical + Lifestyle	-	Incorporates behavioral data

4. Identified Research Gaps

1. Limited cross-dataset validation and generalization across demographic groups.
2. Insufficient interpretability of complex hybrid and deep hybrid models.
3. Dependence on small or imbalanced datasets.
4. Lack of integration of lifestyle, genomic, and real-time IoT data.
5. Minimal clinical validation or deployment studies.

5. Summary and Connection to Proposed Work

The reviewed studies demonstrate that hybrid and ensemble-based ML methods outperform single models in predicting CVD. However, generalization, interpretability, and integration of real-world data remain challenges. The proposed study aims to develop a scalable, interpretable hybrid ML model that balances data quality, computational efficiency, and clinical relevance, contributing to more trustworthy AI-assisted healthcare solutions.

6. Figures and Charts

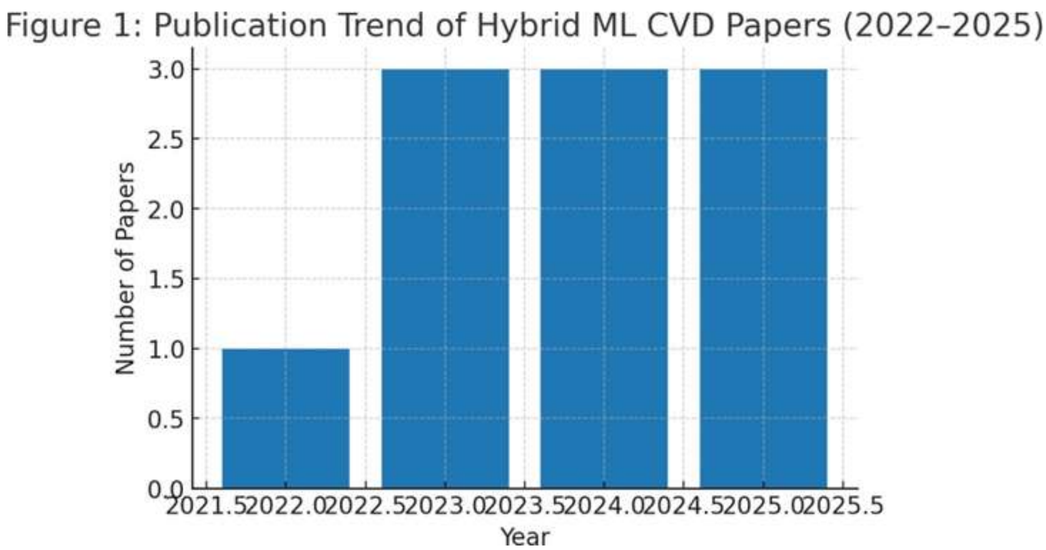

Figure 1: Publication Trend of Hybrid ML CVD Papers (2022–2025)

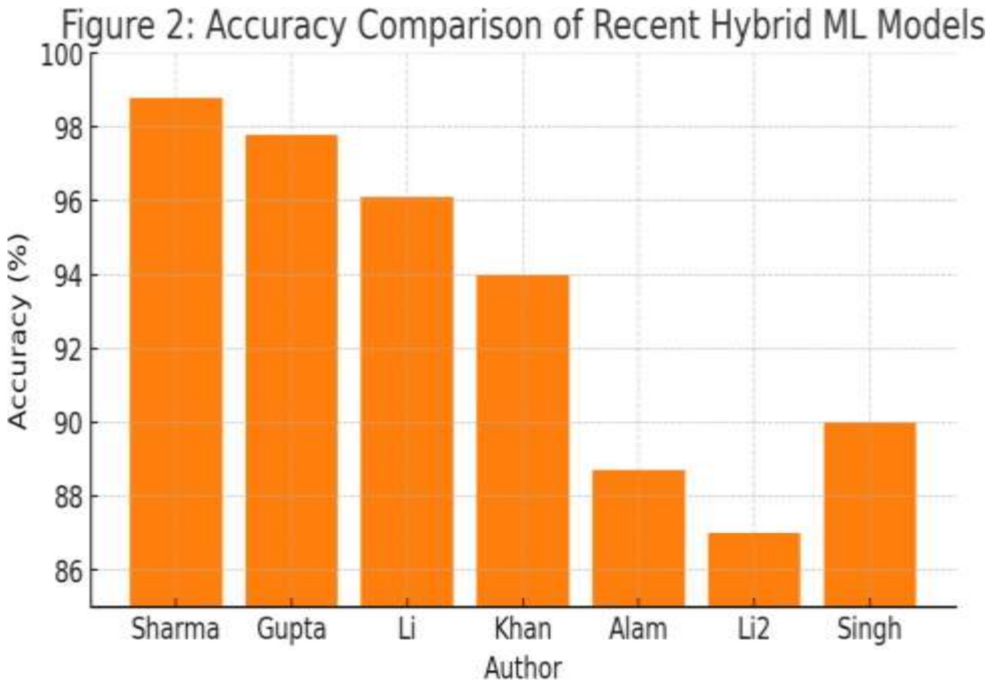

Figure 2: Accuracy Comparison of Recent Hybrid ML Models

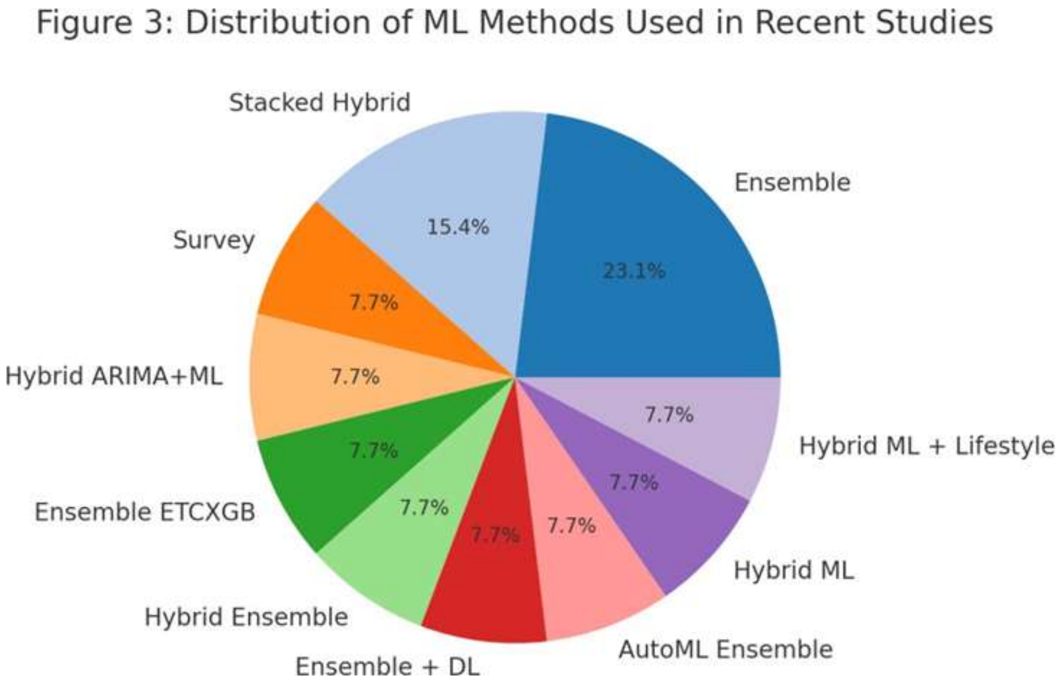

Figure 3: Distribution of ML Methods Used in Recent Studies

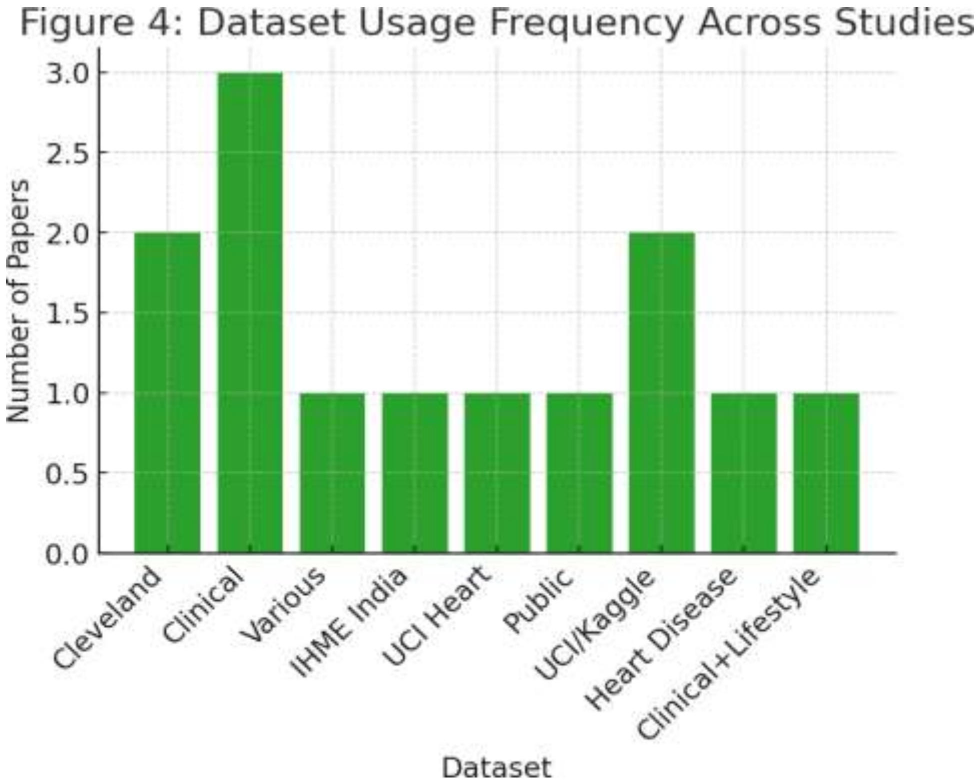

Figure 4: Dataset Usage Frequency Across Studies

7. References

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