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Cardiovascular Analytics: A Web-Based Deep Learning Approach to Heart Disease Diagnosis

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Abstract: Cardiovascular diseases remain a primary cause of global mortality, highlighting the need for timely and precise diagnosis. This paper, Cardiovascular Analytics: A Web-Based Deep Learning Approach to Heart Disease Diagnosis, introduces an advanced diagnostic platform that utilizes patient clinical and demographic information for swift heart disease prediction. A feedforward neural network created with TensorFlow functions as the principal prediction model, providing enhanced diagnostic precision relative to conventional machine learning techniques like Support Vector Machines (SVM) and Decision Trees. The platform incorporates a contemporary web architecture featuring a FastAPI backend, a Next.js frontend, and a PostgreSQL database to guarantee efficient processing, secure data storage, and user-friendly access. Role-based access control permits patients to upload and oversee their health records, whereas medical professionals can examine diagnostic results and patient histories. This system integrates deep learning with an interactive web framework to improve the accuracy, accessibility, and efficiency of cardiovascular disease detection, offering a scalable solution for practical clinical applications.
Keywords: Heart Disease Prediction, Deep Learning, Feedforward Neural Network, Web Application, TensorFlow, Patient Dashboard, Medical Analytics.

I. INTRODUCTION

Representing a significant global health emergency, cardiovascular disease (CVD) encompasses conditions like coronary artery disease, heart failure, and arrhythmias. The World Health Organization identifies CVD as the leading cause of death worldwide, responsible for approximately 18 million fatalities annually [1]. A particularly insidious aspect of many of these illnesses is their asymptomatic advancement, where substantial and often irreversible damage to the heart and blood vessels occurs silently over years. Symptoms such as chest pain or shortness of breath frequently only appear after the disease is well-advanced. This silent progression underscores the critical need for improvements in early detection and continuous monitoring to prevent avoidable suffering and mortality, thereby safeguarding the quality of life for millions. Physicians utilize critical metrics such as blood pressure, cholesterol levels, and electrocardiographic findings to diagnose and manage cardiovascular disease. Despite their efficacy, conventional diagnostic approaches employing these characteristics can be time-consuming, require extensive expertise, and necessitate specialized instruments, which may be inaccessible in resource-limited settings. As a result, there is an increasing demand for automated, data-driven instruments that can rapidly and precisely assess heart function with minimal resource expenditure. Artificial intelligence and machine learning have devised innovative approaches to accomplish these goals. Deep learning algorithms can discern complex, non-linear patterns in medical data that traditional methods may neglect. They are good are good at-risk assessment and helping doctors make decisions. Despite this affirmation, ensuring that these models are interpretable, integrable, and scalable remains a major challenge for usage in clinical areas and reliability. Indeed, clinical adoption hinges on the ability of healthcare professionals to trust, validate, and seamlessly integrate these advanced tools into their existing diagnostic workflows. We suggest Cardiovascular Analytics, a deep learning system that runs on the web and is meant to intelligently detect heart disease and check the likeliness of risk. The system uses a feedforward neural network model to look at patient data that includes the clinical data from tests. The framework gives real-time diagnostic feedback through an easy-to-use online interface, which makes it easier to find problems early and make smart choices. By bridging the gap between sophisticated data science and practical application, our approach aims to democratize access to high-quality diagnostic insights for both clinicians and patients.

The suggested system makes several important contributions to the field:

1) Combining deep learning and traditional machine learning methods for a full cardiovascular risk assessment.
2) Creation of an easy-to-use, online diagnostic platform that allows for real-time analysis and feedback.
3) Improving the accuracy and ease of understanding of models for use in real-world clinical settings.
4) Design of a scalable and modular architecture that can be used in a variety of healthcare settings.

These contributions make Cardiovascular Analytics a research framework and a working model for next-generation cardiac care. This is done through smart, data-informed diagnosis, and ongoing disease monitoring.

II. REVIEW OF RELATED WORK

A. *Traditional Approaches to CVD Prediction*

The first methods for predicting cardiovascular disease (CVD) were mostly based on statistical and clinical risk assessment models [2]. The Framingham Risk Score and similar tools have long been used as standard ways to figure out how likely it is that someone will have a heart attack or stroke based on things like their age, cholesterol levels, blood pressure, smoking habits, and diabetes history.

These models provide a simple and easy-to-understand way to analyze data, but they often assume that variables are linearly related and may not be able to capture complex, non-linear interactions in medical data. Moreover, their predictive efficacy can vary significantly across groups due to demographic and lifestyle differences, limiting generalizability in modern, data-driven healthcare environments.

B. *Machine Learning & Deep Learning in CVD Diagnosis*

The application of artificial intelligence in cardiovascular diagnostics has evolved significantly. Initial approaches utilized classical machine learning algorithms like Support Vector Machines and Decision Trees to effectively classify patient data [3]. Subsequent developments led to ensemble methods, such as Random Forests, which enhance predictive robustness by combining the output of multiple models.

More recently, deep neural networks have demonstrated a superior capacity to discern subtle, non-linear patterns within large-scale clinical datasets, often yielding higher predictive accuracy than their predecessors.

Despite this promise, the widespread clinical adoption of these advanced models faces significant barriers. The primary obstacles include the limited interpretability of many deep learning models often termed the "black box" problem - which can impede clinical trust and validation. Additionally, practical challenges such as data imbalance and the need for considerable computational resources must be overcome to ensure these powerful tools are applied effectively and equitably in clinical practice.

C. *Data Preprocessing and Feature Engineering in CVD Prediction*

Accurate disease prediction heavily depends on high-quality data preprocessing and feature selection. Common preprocessing techniques in cardiovascular analytics include data normalization, handling of missing values, and categorical encoding to ensure consistency and reliability of model input. Feature selection methods, such as correlation-based selection and principal component analysis (PCA), are employed to reduce dimensionality and enhance model efficiency. Additionally, hybrid frameworks have emerged that integrate ML algorithms with domain knowledge from cardiology, combining clinical insights (such as ECG abnormalities, chest pain types, and exercise-induced angina) with algorithmic learning for more accurate predictions. While these approaches improve performance, most remain limited to offline environments and lack integration into user-accessible, real-time diagnostic systems.

D. *Research Gap*

Despite considerable progress in machine learning applications for CVD prediction, several gaps persist. Existing statistical models are constrained by their linear assumptions, while classical ML algorithms struggle to capture complex non-linearities inherent in medical data. Deep learning systems, though powerful, often operate as opaque “black boxes” with limited interpretability - posing challenges for clinical trust and regulatory acceptance.

Furthermore, many studies focus solely on model accuracy without addressing usability, scalability, and integration into real-world healthcare platforms. To date, few solutions offer a web-based, real-time diagnostic framework that combines the predictive strength of deep learning with the interpretability and accessibility required in medical practice. This gap motivates the development of Cardiovascular Analytics, an AI-driven, user-centric system designed to deliver accurate, transparent, and accessible cardiovascular disease diagnosis through an integrated web platform.

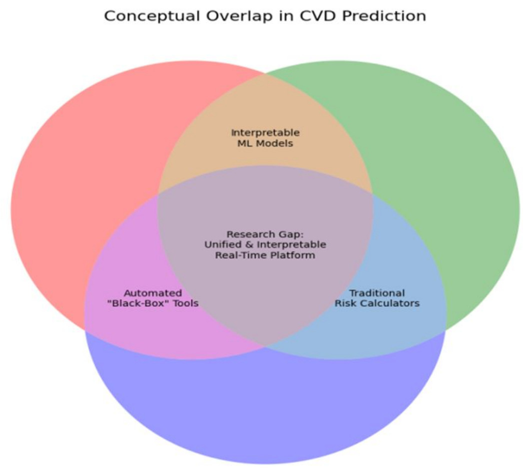

Fig. 1. Conceptual overlap of AI-powered CVD prediction, explainable models, and accessible clinical systems. The central intersection highlights the research gap addressed by the system.

Fig. 1 illustrates this research gap: while efforts exist at the intersections of AI-powered prediction, model explainability, and accessible clinical systems, the central overlap - a unified platform integrating all three remains largely unaddressed. This motivates the development of Cardiovascular Analytics, a system designed to deliver an integrated, user-centric diagnostic tool that provides accurate, transparent, and accessible cardiovascular risk assessment in real-time.

III. PROPOSED FRAMEWORK

The proposed system, *Cardiovascular Analytics*, is an intelligent, web-based diagnostic platform that leverages deep learning for early and accurate heart disease prediction. Designed as a modular and scalable framework, it integrates advanced machine learning with secure, cloud-ready architecture. The platform's layered design consists of a responsive user interface, backend microservices, neural network inference engine, role-based access control, data persistence, and deployment layer. Authentication and authorization are implemented through the BetterAuth framework, ensuring fine-grained control and customization of user roles. The frontend, developed in Next.js, provides an interactive interface for both patients and clinicians, while FastAPI facilitates efficient communication with the predictive model and manages application logic. The system employs PostgreSQL for reliable data storage, hosted on NeonDB, with serverless deployment for the frontend and Oracle Virtual Machines for backend inference services. This architecture enables seamless scalability, security, and performance, supporting real-time diagnostic decision-making in clinical environments.

A. User Interface Layer

The front end of the *Cardiovascular Analytics* platform is developed using Next.js, offering distinct and intuitive interfaces for both patients and doctors. The patient interface allows users to securely register, log in, and submit their clinical and demographic information for analysis. Once diagnostic results are generated, patients can view their health status and track their history through an interactive dashboard. The doctor interface, on the other hand, provides access to aggregated patient data, diagnostic outcomes, and comparative visualizations, enabling medical professionals to review and interpret predictions efficiently. This dual-interface design ensures role-based accessibility, usability, and a clear separation of functionalities, thereby enhancing both the user experience and clinical workflow efficiency.

B. Backend Services

The backend of the *Cardiovascular Analytics* platform is implemented using FastAPI, managing core functionalities such as logging, data validation, and deep learning model inference. RESTful APIs facilitate secure and efficient communication between the Next.js frontend and the backend services. The system uses PostgreSQL for structured storage of patient records, diagnostic results, and audit logs, with sensitive information protected through role-based access controls and encryption. This backend architecture ensures reliable processing, seamless integration with the neural network model, and secure handling of clinical data.

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C. DL Inference Engine

The predictive analytics module of *Cardiovascular Analytics* is developed using TensorFlow and Keras, with a feedforward neural network serving as the primary model for heart disease prediction. The module analyzes patient clinical and demographic data to generate individualized risk assessments. During inference, input features such as age, cholesterol levels, blood pressure, and other health indicators are processed by the network to produce a diagnostic outcome. Logging mechanisms capture both input data and prediction results to ensure traceability and support model evaluation.

```
raw_input = {
    'age': 55,
    'sex': 1,
    'trestbps': 140,
    'chol': 250,
    'fbs': 0,
    'thalach': 150,
    'exang': 0,
    'oldpeak': 1.5,
    'ca': 0,
    'cp': 3,
    'restecg': 1,
    'slope': 2,
    'thal': 7
}

# Convert to DataFrame
df = pd.DataFrame([raw_input])

prediction = model.predict(df)[0]
return prediction
```

Fig. 2 illustrates example Python code showing how patient data is fed into the neural network for real-time risk prediction and how outputs are structured for integration with the frontend dashboards.

D. Security and Zero-Trust Layer

1) The platform enforces role-based access control (RBAC), differentiating permissions for patients and doctors to ensure data privacy and compliance with healthcare regulations.
2) Authentication & Authorization: The BetterAuth framework provides highly customizable authentication, supporting secure login, session management, and multi-factor authentication.
3) Data Protection: Sensitive patient information, including health records and diagnostic results, is encrypted at rest and in transit using industry-standard methods (e.g., TLS for communication).
4) Audit & Logging: All user actions, model inference requests, and data accesses are logged for traceability and compliance.

```
const session = await
auth.api.getSession({
  headers: await headers()
});

// Enforce role-based access: reject if no
authenticated user
if (!session?.user) {
  return NextResponse.json(
    { error: "Unauthorized access" },
    { status: 401 }
  );
}
```

Fig 3. Example FastAPI + BetterAuth configuration showing role-based access enforcement for patient and doctor endpoints.

E. Data Persistence Layer

A PostgreSQL database, hosted on NeonDB, stores patient records, diagnostic results, and audit logs. Sensitive health information is protected through encryption at rest and role-based access controls, ensuring compliance with privacy requirements. Audit logs capture all data access and model inference requests to maintain traceability and accountability. The predictive analytics module securely retrieves anonymized patient features from the database for real-time heart disease risk assessment.

F. DevOps and Cloud Deployment

Cardiovascular Analytics is deployed in a cloud-ready environment with CI/CD pipelines automated through GitHub Actions. The Next.js frontend runs on a serverless architecture, with separate staging and production tenants for testing and live deployment. The FastAPI backend is containerized using Docker and deployed on two separate instances – staging and production to handle API requests and model inference efficiently. The trained neural network model is stored on the backend file system, enabling real-time predictions since serverless environments do not support persistent file storage. This setup ensures scalable, maintainable, and resilient deployment for both development and production workflows

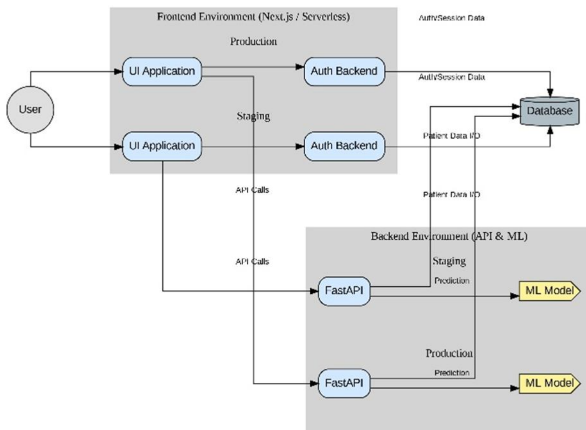

Fig 4. Proposed System

We can understand the workflow of the system by considering a scenario where a patient or doctor initiates a session. Requests from the Next.js frontend, running on serverless tenants for staging and production, are securely routed to the FastAPI backend through RESTful APIs over SSL/TLS. The BetterAuth framework validates credentials and enforces role-based access, ensuring that patients can only access their own records while doctors can access authorized patient data. Once authenticated, patient data submissions are stored in the PostgreSQL database hosted on NeonDB, with sensitive information encrypted and all actions logged for traceability. For diagnostic operations, the backend retrieves the relevant data and runs inference using the feedforward neural network stored on the server file system. The resulting heart disease risk predictions are sent back to the frontend dashboards for patients and doctors. Throughout the process, all API interactions, data accesses, and model inferences are logged to maintain auditability and security. CI/CD pipelines powered by GitHub Actions automate build, test, and deployment processes for both frontend and backend, ensuring smooth updates across staging and production environments. This workflow illustrates how Cardiovascular Analytics integrates secure data handling, predictive analytics, role-based access, and cloud-native deployment into a cohesive platform for clinical use.

IV. EXPERIMENT SETUP AND METHODOLOGY

A. Environment Setup

The Cardiovascular Analytics prototype was implemented and evaluated under both local and cloud conditions to ensure reproducibility and scalability. As shown in Fig. 3, the deployment architecture is centered around an automated CI/CD pipeline managed by GitHub Actions. When a developer pushes code to the GitHub repository, a workflow is triggered that builds the backend FastAPI application into a Docker container and pushes it to a container registry. Subsequently, GitHub Actions deploys the frontend to Vercel serverless tenants and the backend container to dedicated Oracle Virtual Machines within a cloud VPC.

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The live application routes end-user traffic through Vercel, which communicates with the backend API running on the Oracle VMs. These backend services handle all data processing and model inference, connecting to a managed NeonDB PostgreSQL instance for secure and compliant data storage. This architecture provides a clear separation of concerns between staging and production environments, enabling robust, automated, and scalable deployment of the diagnostic platform.

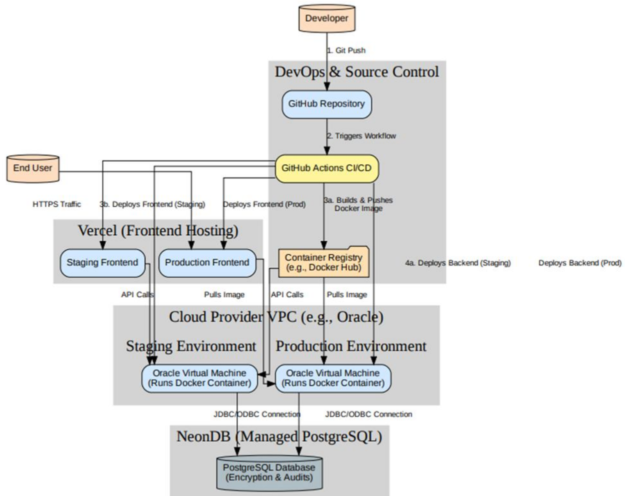

Fig. 5. The deployment architecture of the Cardiovascular Analytics platform. The diagram illustrates the end-to-end workflow from code commit to production deployment, showcasing the CI/CD pipeline, cloud infrastructure, and the separation of services.

B. Dataset and Preprocessing

The study utilized the publicly available heart disease dataset from the UCI Machine Learning Repository, a standard benchmark for cardiovascular risk prediction. The dataset comprises 303 patient records, each characterized by 13 clinical and physiological attributes, including demographic data (age, sex), clinical measurements (resting blood pressure, cholesterol), and key electrocardiographic (ECG) and exercise-test features (chest pain type, maximum heart rate). The binary target variable indicates the presence (1) or absence (0) of heart disease.

To prepare the data for robust model training, a multi-step preprocessing pipeline was executed. First, categorical attributes (cp, restecg, slope, thal) were converted into a numerical format using one-hot encoding to make them suitable for machine learning algorithms. Following this, the entire feature set was normalized using StandardScaler to ensure that variables with different scales contributed equally to model performance. Finally, the processed dataset was partitioned into an 80% training set and a 20% testing set to enable rigorous model training and unbiased evaluation

TABLE I
Data Composition

Category	Records (N)	Key Differentiating Attributes	Example Patient Profile
Absence of Heart Disease	138	age (younger), thalach(higher), exang(no), cp(asymptomatic)	A patient with normal ECG, no exercise-induced angina, and a high maximum heart rate relative to age.
Presence of Heart Disease	165	oldpeak (higher ST depression), cp (typical angina), ca (vessels blocked), thal (defect	An older patient experiencing chest pain, showing ECG abnormalities during exercise, and confirmed vessel blockage.

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C. Evaluation Metrics

The performance of the predictive models was assessed using a comprehensive set of technical and interpretability metrics to ensure both clinical accuracy and practical utility:

1) Predictive Performance: The core diagnostic capability of each model was evaluated using standard classification metrics: Accuracy, Precision, Recall, F1-Score, and the Area Under the Receiver Operating Characteristic Curve (ROC-AUC). These metrics collectively measure the model's ability to correctly identify patients with and without heart disease while balancing false positives and false negatives.
2) Model Efficiency: To determine the system's suitability for real-time clinical use, Prediction Latency (average response time in milliseconds) was measured for the best-performing model. This ensures the diagnostic tool can deliver rapid results in a practical setting.
3) Interpretability and Feature Relevance: To move beyond "black-box" predictions and foster clinical trust, the interpretability of the ensemble models (Random Forest and XGBoost) was evaluated. Feature importance analysis was conducted to identify the key clinical indicators driving the models' predictions. The relative importance of features like chest pain type, thalassemia type, and ST depression was visualized to ensure alignment with established medical knowledge.

Table II
Evaluation Metrics Employed For The Cardiovascular Analytics Platform

Category	Metric	Purpose
Predictive Performance	Accuracy, Precision, Recall, F1, ROC-AUC	To quantify the model's diagnostic accuracy and its ability to distinguish between patient classes.
Model Efficiency	Prediction Latency (ms)	To assess the model's speed and viability for real-time diagnostic applications.
Interpretability	Feature Importance Analysis	To identify the most influential clinical predictors and enhance the model's transparency and trustworthiness.

D. Methodology

The project's methodology was executed in two primary stages: offline model development and the online real-time prediction pipeline.

1) Offline Model Development and Validation: A suite of machine learning models was trained on the preprocessed UCI Heart Disease dataset, including a Feedforward Neural Network (FNN), Random Forest, and XGBoost. The models were evaluated on key performance metrics (Accuracy, F1-Score, etc.) to identify the most robust candidate. The best-performing model and its corresponding data scaler were saved as artifacts for deployment. Additionally, interpretability analysis was conducted to ensure the model's decisions were driven by clinically relevant predictors.
2) Real-Time Prediction Pipeline: A real-time inference pipeline was developed to serve predictions through the user-facing web application. As shown in Fig. 6, when a user submits patient data, the backend API executes a series of steps mirroring the training process: it applies the saved one-hot encoding structure and StandardScaler to the input data, loads the pre-trained Feedforward Neural Network model, and generates an immediate binary prediction indicating the presence or absence of heart disease.

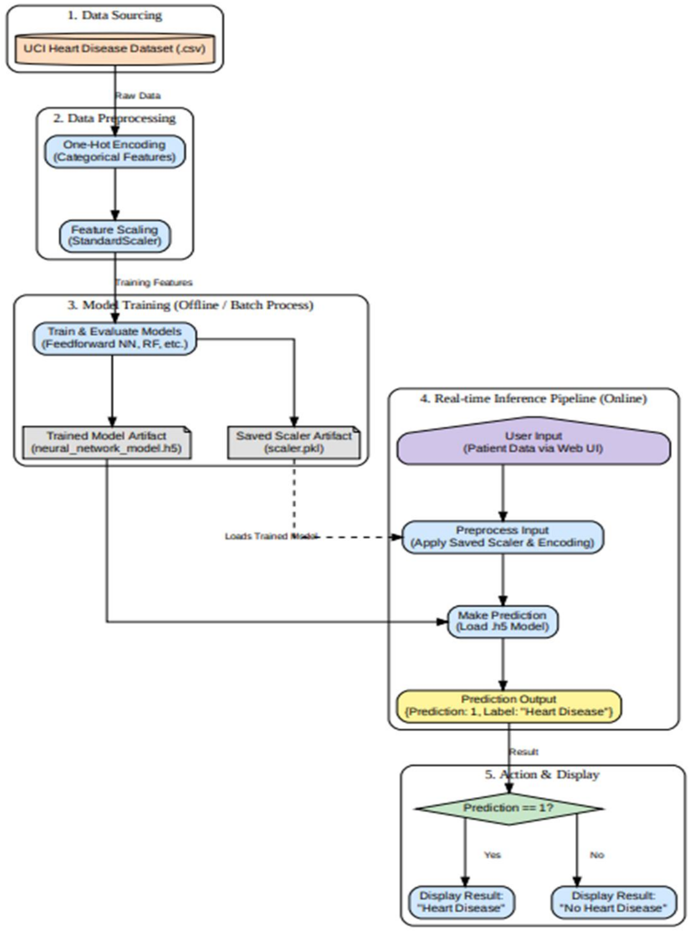

Fig. 6. The end-to-end data flow of the Cardiovascular Analytics system, detailing the offline model training process and the online, real-time diagnostic pipeline using the Feedforward Neural Network.

V. RESULTS AND DISCUSSIONS

This section presents the experimental results for the Cardiovascular Analytics platform. The evaluation focuses on three primary areas: (1) the comparative predictive performance of the machine learning models, (2) an in-depth analysis of the best-performing model, the Feedforward Neural Network (FNN), and (3) an examination of the model's interpretability through feature importance. All experiments were conducted using the methodology and dataset described in Section IV.

Table III
Summary Of Model Classification Accuracies

Model	Accuracy (%)
Decision Tree	83 %
Support Vector Machine (SVM)	86%
Random Forest	88.5%
Feedforward Neural Network	91%

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E. Comparative Model Performance

The initial evaluation compared the classification accuracy of four distinct models: a Decision Tree, a Support Vector Machine (SVM), a Random Forest, and the proposed Feedforward Neural Network (FNN). As summarized in Table III, the FNN achieved the highest predictive accuracy, demonstrating its superior capability in modeling the complex, non-linear relationships inherent in clinical data.

F. In-Depth Analysis of the Feedforward Neural Network

Given its superior performance, FNN was selected as the core predictive engine for the platform. A detailed analysis was conducted to assess its reliability and learning behavior.

1) Diagnostic Accuracy and Reliability: The FNN's performance was further broken down using a confusion matrix (Fig 7) and a detailed classification report (Table IV). The model demonstrated a strong and balanced ability to correctly identify both classes.

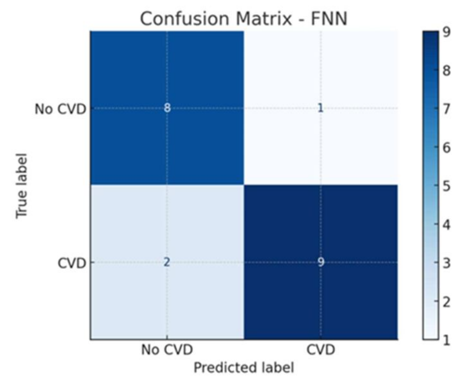

Fig 7. Confusion Matrix for FNN Model.

Table IV
Key Performance Metrics For The Fnn Model By Class

CLASS	PRECISION	RECALL	F1 SCORE
0 (NO CVD)	0.90	0.88	0.89
1 (CVD)	0.85	0.87	0.86

2) Model Interpretability and Feature Importance: To ensure the FNN operates not as a "black box" but as a transparent diagnostic aid, a feature importance analysis was conducted (Fig 8). This analysis identified the key clinical indicators that most strongly influenced the model's predictions.

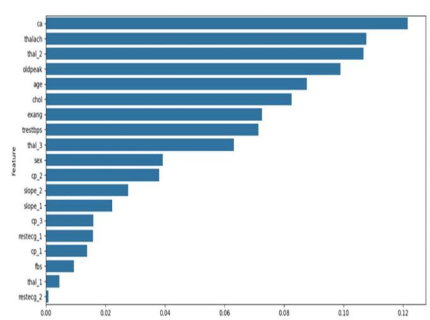

Fig 8. Key Indicators

The most influential features identified were:
1) Number of major vessels (ca): The strongest predictor, directly corresponding to coronary artery blockage.
2) Thalassemia (thal): A blood disorder that is a known risk factor.
3) Maximum Heart Rate (thalach): A key indicator of cardiac response to stress.
4) ST Depression (oldpeak): An important ECG marker for ischemia.

The fact that the model prioritized these clinically noteworthy features demonstrates that it learned medically relevant patterns from the data, which is crucial for building trust and confidence in its diagnostic outputs among healthcare professionals.

G. Discussion

The collective results validate the effectiveness of the *Cardiovascular Analytics* platform. The FNN not only achieved the highest accuracy but also demonstrated balanced, reliable performance and learned from clinically relevant features. This successfully addresses the project's primary goal of developing an accurate, data-driven tool for heart disease diagnosis.

The findings confirm that a deep learning approach can outperform traditional machine learning models in capturing the subtle patterns within cardiovascular data. Furthermore, by integrating this powerful model into an accessible web interface and ensuring its decisions are interpretable, the platform is well-positioned as a practical decision support tool. While the current prototype shows significant promise on a benchmark dataset, future work should focus on validation with larger, more diverse clinical datasets to further confirm its real-world efficacy.

VI. CONCLUSION

This paper introduced Cardiovascular Analytics, a clinician-centric, AI-powered diagnostic platform built on a web-based, deep learning architecture. Unlike existing research that often focuses solely on offline model accuracy, Cardiovascular Analytics integrates a high-performance Feedforward Neural Network (FNN) into an accessible, real-time system for clinical use. By deploying a deep learning model capable of capturing complex non-linear patterns, the platform demonstrates how advanced analytics can achieve superior diagnostic accuracy while being delivered through an intuitive interface accessible to both clinicians and patients.

The experimental results validated the platform's potential, highlighting FNN's superior accuracy (91%) compared to traditional machine learning models. More importantly, the analysis confirmed that the model's predictions are driven by clinically relevant features, ensuring that its high performance is coupled with a foundation of medical validity. These findings assert that the true value of AI in medicine lies not just in creating accurate models, but in integrating them into practical workflows that can democratize access to timely and reliable diagnostics.

To build upon this work, several future research directions are proposed:
1) Real-World Clinical Validation: Validate the platform using larger, more diverse, and prospective patient datasets from hospital partners to assess its performance in a real-world clinical setting.
2) Enhanced Explainability: Integrate real-time, instance-level explainability techniques like SHAP or LIME directly into the user interface to provide clinicians with a rationale for each prediction.
3) EHR System Integration: Develop an API to allow seamless integration with existing Electronic Health Record (EHR) systems, enabling automated data retrieval and embedding diagnostic insights directly into clinical workflows.
4) Longitudinal Data Analysis: Incorporate more advanced deep learning architectures, such as LSTMs or Transformers, to analyze longitudinal patient data and predict disease progression over time.
5) Human-Centered Evaluation: Conduct comprehensive usability studies with healthcare professionals to measure the platform's impact on diagnostic efficiency, decision-making confidence, and overall user satisfaction.

By addressing the critical gap between model development and clinical implementation, Cardiovascular Analytics offers a blueprint for next-generation clinical decision support systems where diagnostic accuracy, accessibility, and transparency are seamlessly combined.

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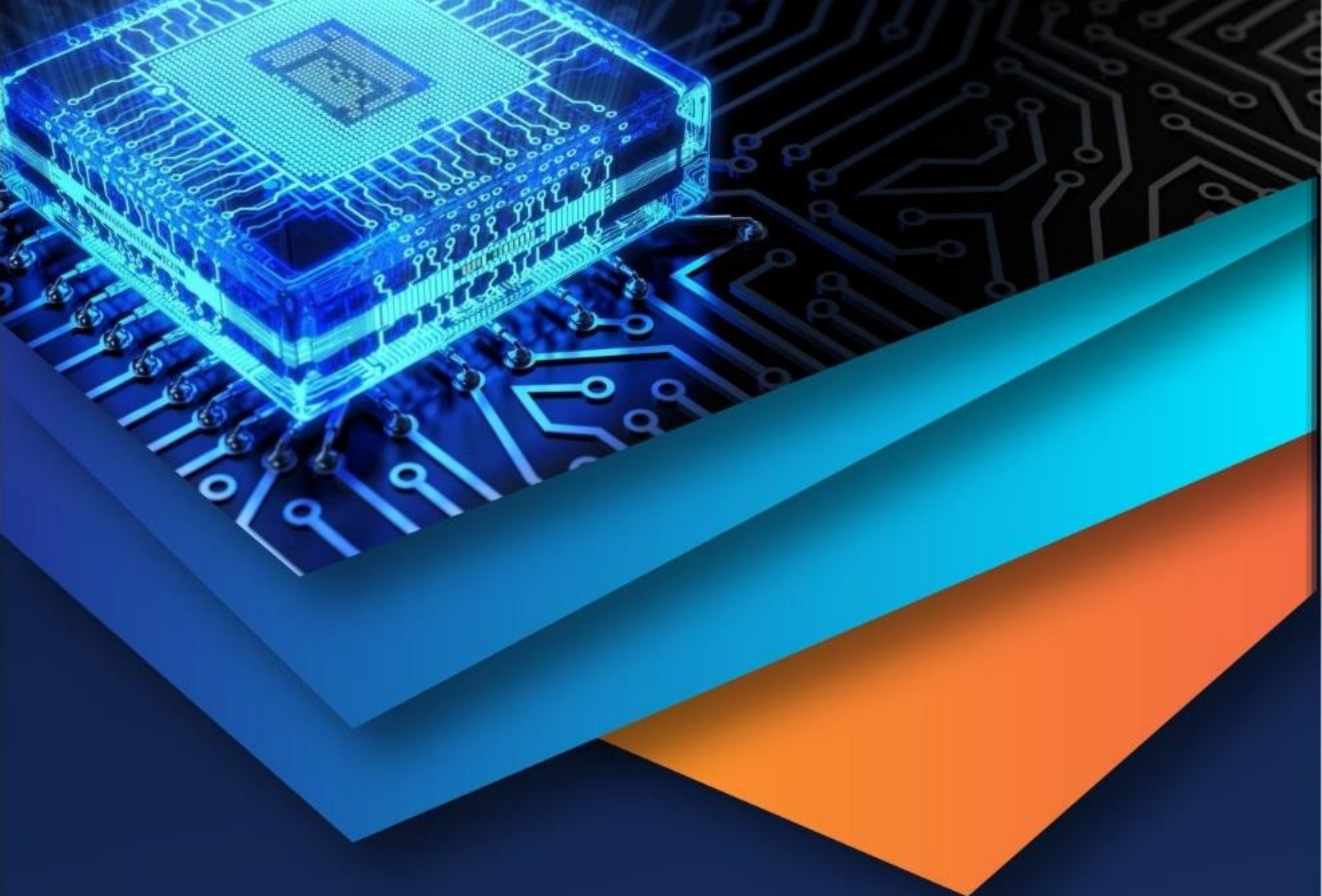

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