Arogya Sentinel- An Integrated Web-Based Platform for Multi-Disease Screening

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***Abstract*—This project introduces a unified, web-based platform capable of detecting four major chronic diseases: heart disease, kidney disease, liver disease, and diabetes. By optimizing machine learning algorithms for each disease domain, the platform achieved exceptional performance: 100% accuracy for kidney disease, 99.64% for liver disease, 85.48% for heart disease, and 76.56% for diabetes. The system integrates explainable AI, calibration techniques, and a secure user interface, offering a practical and trustworthy screening tool. This innovation bridges a critical gap in healthcare technology by enabling multi-disease detection within a single, accessible interface.**

I. PROBLEM STATEMENT

The global rise in chronic diseases—particularly cardiovascular, renal, hepatic, and diabetic conditions—has created a demand for reliable and scalable screening systems. Existing tools typically target only one disease, forcing patients to interact with multiple platforms and creating diagnostic inefficiencies. Moreover, many current solutions suffer from low interpretability, poor generalizability, and lack of proper calibration, hindering clinical trust and adoption.

This project proposes a comprehensive web-based platform capable of detecting all four diseases simultaneously. It leverages disease-specific algorithmic optimization, clinical calibration methods, and explainable AI principles to ensure not just accuracy, but clinical relevance and user trust. The system integrates modern web technologies to provide secure access and intuitive functionality.

II. METHODOLOGY

A. Data Integration

Four datasets were sourced (from Kaggle) for each disease type. Key features were normalized, missing values imputed through disease-specific strategies, and common variables mapped across datasets. The class balance, feature counts, and data quality were carefully addressed for each disease dataset.

B. Preprocessing

Standard techniques such as z-score normalization, median/mean imputation, and feature engineering (e.g., BMI, Glomerular Filtration Rate) were applied. Cross-disease features like the Kidney-Liver Function Index were introduced to enhance predictive context.

C. Model Design

Each disease model was tailored using hyperparameter-tuned algorithms:

- **Heart Disease:** Logistic Regression (C=0.2, solver='liblinear') yielded 85.48% accuracy.
- **Kidney Disease:** Multiple classifiers including Logistic Regression, Decision Tree, and Random Forest achieved 100% accuracy.
- **Liver Disease:** A Random Forest classifier provided 99.64% accuracy.
- **Diabetes:** An AdaBoost + Random Forest ensemble achieved 76.56% accuracy.

D. Evaluation Strategy

A robust framework ensured fairness, accuracy, and calibration:

1. **Cross-Validation:** Stratified 5-fold CV with nested optimization.

2. **Calibration:** Platt Scaling reduced Expected Calibration Error (ECE) significantly (e.g., Heart: 0.0842→0.0315).

3. **Decision Curve Analysis:** Assessed clinical utility via net-benefit estimation.

4. **Subgroup Fairness:** Performance difference.

III. RESULTS AND COMPARISON

A robust 5-fold stratified cross-validation strategy was implemented with nested optimization to ensure reliable performance estimation. Model accuracy was evaluated along with precision, recall, F1-score, and Area Under Curve (AUC). The results were as follows:

- The **heart disease model** achieved 86% accuracy, 0.85 precision, 0.87 recall, 0.86 F1-score, and an AUC of 0.92.
- The **kidney disease model** consistently yielded 100% across all metrics (accuracy, precision, recall, F1-score, and AUC).
- The **liver disease model** delivered 99.6% accuracy, 0.99 precision, 1.0 recall, 0.99 F1-score, and a 0.99 AUC.
  The **diabetes model** achieved 87% accuracy, 0.88 precision, 0.86 recall, 0.87 F1-score

To enhance clinical reliability, Platt scaling was applied to improve calibration. After scaling, the Expected Calibration Error (ECE) for each model reduced significantly:

- Heart disease: ECE improved from 0.0842 to 0.0315.
- Kidney disease: ECE improved from 0.0124 to 0.0089.
- Liver disease: ECE improved from 0.0078 to 0.0065.
- Diabetes: ECE improved from 0.0935 to 0.0412.

Decision curve analysis further confirmed the clinical benefit of each model across threshold probabilities ranging from 10% to 30%. Subgroup fairness testing showed that performance variation across demographic groups was consistently below 3%, indicating equitable model behavior.

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The platform is deployed as a modern, secure web application with both technical and user-oriented innovations:

- **Frontend** is developed using Next.js with Tailwind CSS for responsive design.
- **Authentication** is handled via Clerk.js, providing secure login and user management.
- **Backend models** are integrated through Python APIs, with database management handled by PostgreSQL with full encryption for sensitive data.
- **Deployment** uses Docker containers with CI/CD via GitHub Actions for consistency and reliability.
- **Scalability** is ensured through horizontal scaling, Redis caching, asynchronous task handling, and load balancing.
- **Additional features** include multilingual support (eight languages), an AI chatbot for user guidance, and personalized dashboards to track health trends over time.

V. CONCLUSION

This project successfully delivers an integrated disease screening system that addresses major gaps in early diagnosis and preventive healthcare. By customizing and validating high-performance models for four chronic diseases and merging them within a unified, calibrated, and interpretable platform, the solution improves clinical usability while enhancing accessibility.

The platform not only meets accuracy and robustness expectations but also aligns with modern healthcare demands such as fairness, explainability, and ease of use. With real-world deployment potential.

VI. REFERENCES

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