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Dual-Model Machine Learning Approach for Heart Failure and Diabetes Risk Prediction

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Abstract:

Health risk prediction has emerged as a significant research domain in healthcare, particularly for chronic condi- tions like heart failure and diabetes. This paper proposes a dual-model machine learning framework employing Artificial Neural Networks (ANN) and XGBoost algorithms to predict patient risks based on clinical data. The ANN model is specif- ically applied to heart failure prediction, while XGBoost is utilized for diabetes prediction. Both models were trained on benchmark datasets—UCI Heart Failure and PIMA Diabetes datasets—achieving accuracies of 85% and 88%, respectively. The results highlight the efficacy of combining two different ML models to improve accuracy and reliability in healthcare analytics.

Keywords: Machine Learning, Health Risk Prediction, Heart Failure, Diabetes, ANN, XGBoost, Clinical Decision Sup- port.

1. Introduction

Chronic diseases such as heart failure and diabetes have be- come major public health challenges worldwide. Early identifi- cation of patients at risk plays a vital role in reducing mortality and healthcare costs. Machine Learning (ML) techniques have shown strong potential to analyze medical data and uncover hidden risk patterns.This paper introduces a dual-model approach using ANN and XGBoost for efficient health risk prediction. The combi-nation of deep learning and gradient boosting enables better prediction for both structured and complex nonlinear data. The integration of these models allows for leveraging the strengths of each: ANN's ability to model complex, non-linear relationships, and XGBoost's efficiency with structured data and robustness against overfitting. This hybrid approach is particularly suited for clinical settings where data types and prediction tasks may vary significantly.

Moreover, the proposed system addresses the growing need for automated, scalable, and accurate diagnostic tools in resource-constrained healthcare environments. By providing early and reliable risk assessments, this framework can assist clinicians in prioritizing high-risk patients, optimizing treat-ment plans, and improving overall healthcare delivery.

2. Related Work

Previous studies have used Logistic Regression, Random Forest, and Support Vector Machines for disease prediction, but these models often struggle with nonlinear data. Deep learning approaches like CNNs have been applied mainly to image-based diagnosis. However, there remains a gap in meth- ods optimized for structured clinical datasets. The proposeddual-model framework bridges this gap by integrating ANN and XGBoost for improved predictive accuracy.

Recent works have also explored ensemble methods and hybrid models. For instance, [1] applied stacked generalization for cardiovascular disease prediction, while [2] used a voting classifier for diabetes. However, these approaches often lack the specialized model pairing as proposed in this study. Our method uniquely assigns ANN to heart failure (due to its ability to capture complex interactions among clinical markers) and XGBoost to diabetes (for its efficiency with tabular data and feature importance ranking).

Additionally, while several studies focus on single-disease prediction, few address multiple chronic conditions using tailored models within a unified framework. This work con- tributes to filling that gap by offering a flexible, dual-model system that can be extended to other diseases.

3. METHODOLOGY

A. *Datasets*

Two benchmark datasets were used:

UCI Heart Failure Dataset: Contains 299 patient records with 13 clinical attributes including age, ejection fraction, and serum creatinine. This dataset also includes time-based features such as follow-up period, which adds a temporal dimension to the risk assessment.

PIMA Diabetes Dataset: Includes 768 instances with 8 key features such as glucose level, BMI, and insulin concentration. The dataset represents a population of women of Pima Indian heritage, making it a valuable resource for studying diabetes in specific demographic groups.

Both datasets are publicly accessible and have been widely used in medical ML research, ensuring reproducibility and comparability with existing work.

B. *Data Preprocessing*

Data quality plays a crucial role in ML performance. The preprocessing steps included:

- Handling missing values using median imputation
- Normalizing continuous variables to a 0–1 range using MinMax scaling
- Splitting the data into 80% training and 20% testing sets
- Using stratified sampling to preserve the ratio of positive and negative cases

Additional steps involved outlier detection using the In- terquartile Range (IQR) method and feature correlation analy- sis to remove highly redundant variables. These steps ensured that the models were trained on clean, representative, and unbiased data.

C. *Model Development*

1) *Artificial Neural Network (ANN) for Heart Failure Pre- diction:*

- Input layer: 13 neurons (one for each attribute)
- Hidden layer: 16 neurons with ReLU activation
- Output layer: 1 neuron with Sigmoid activation
- Optimizer: Adam with learning rate 0.001
- Loss function: Binary Cross-Entropy

The ANN model captures complex relationships among clinical parameters, learning subtle patterns associated with heart failure risk. A dropout rate of 0.2 was applied to the hidden layer to prevent overfitting. The model was trained for 200 epochs with a batch size of 32.

2) *XGBoost for Diabetes Prediction:*

- Estimators: 100, Max depth: 6
- Learning rate: 0.1, Subsample: 0.8
- Objective function: Binary Logistic

XGBoost effectively handles structured tabular data, per- forms internal regularization to prevent overfitting, and identi- fies the most influential features impacting diabetes risk. The model was also configured with early stopping rounds (10) to avoid unnecessary computations and enhance generalization.

D. *Model Explanation*

1) *How the ANN Model Works for Heart Failure Prediction:*

The Artificial Neural Network functions like a sophisticated
pattern recognition system inspired by the human brain. Imag- ine the network as a team of medical experts working together to assess heart failure risk:

- **Input Layer (13 experts):** Each expert examines one specific patient characteristic - age, blood pressure, cholesterol levels, etc. They pass their initial observations to the next team.
- **Hidden Layer (16 specialists):** These specialists com- bine information from all input experts, looking for complex patterns and interactions. For example, they might notice that ”high blood pressure combined with elevated creatinine levels in elderly patients” significantly increases risk. The ReLU activation helps them focus only on important risk-increasing patterns.
- **Output Layer (Final decision):** A single senior doctor combines all specialist opinions and provides the final risk score between 0 (low risk) and 1 (high risk) using the Sigmoid function.

The model learns through repeated training, adjusting its internal connections (weights) to minimize prediction errors, much like medical students learning from case studies.

2) How the XGBoost Model Works for Diabetes Predic- tion: XGBoost operates like a series of progressive medical assessments, where each subsequent assessment learns from
the mistakes of previous ones:
ical data. The model automatically identifies which features are most important (like glucose levels being more critical than skin thickness) and uses this knowledge to make accurate predictions.

3) Why This Dual-Model Approach Makes Sense: The choice of ANN for heart failure and XGBoost for diabetes is deliberate and clinically intuitive:

- **Heart Failure:** Involves complex, non-linear interactions between multiple physiological systems. ANN excels at capturing these intricate relationships, similar to how cardiologists consider multiple interacting factors simul- taneously.
- **Diabetes:** Often shows clearer hierarchical relationships where certain factors (glucose levels) are dominantly important. XGBoost naturally handles this structured im- portance hierarchy while being computationally efficient.

Both models provide interpretable results - ANN through activation patterns that can be visualized, and XGBoost through clear feature importance scores that clinicians can easily understand and validate against medical knowledge.

E. *Evaluation Metrics*

Performance of both models was evaluated using Accuracy, Precision, Recall, and F1-Score:

- **First Decision Tree:** Makes initial risk assessment based on the most obvious factors like glucose levels.

- **Subsequent Trees:** Each new tree focuses on the cases that previous trees misclassified. For instance, if the first tree missed some diabetic patients with normal glucose but high BMI, the next tree will pay special attention to BMI patterns.
- **Combined Wisdom:** The final prediction combines all

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

trees' opinions, giving more weight to trees that per- formed better during training.

This sequential learning process makes XGBoost particu- larly good at capturing complex relationships in tabular med-

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

The Area Under the ROC Curve (AUC-ROC) was also computed to assess the models' ability to distinguish between classes across different threshold settings.

4. Experimental Results and Discussion

The models were implemented using Python libraries: Ten- sorFlow 2.12.0 and Scikit-learn 1.2.2.

Both models achieved high predictive performance, out- performing traditional methods such as Logistic Regression (78%) and Decision Trees (81%). The ANN model captured nonlinear interactions in the data, while XGBoost demon- strated superior generalization due to its tree-based feature handling.

TABLE I

Performance Comparison of Models

Model	Accuracy	Precision	Recall	F1-Score
ANN (Heart Failure)	85%	0.83	0.86	0.84
XGBoost (Diabetes)	88%	0.87	0.89	0.88
Logistic Regression	78%	0.76	0.79	0.77
Decision Tree	81%	0.80	0.82	0.81

- **Feature Engineering:** Selecting clinically relevant fea- tures was time-consuming but critical for accuracy.
- **Interpretability:** Clinicians often require clear expla- nations for predictions. Future models should integrate Explainable AI (XAI) methods.

Future Enhancements:

- Incorporate additional diseases like hypertension and CKD.
- Combine models using ensemble or hybrid approaches.
- Deploy a cloud-based API for real-time patient monitor- ingtegrate time-series data for dynamic risk assessment. plore federated learning to enable collaborative model training across hospitals without sharing sensitive patient As shown in Table I, the proposed models consistently outperformed baseline methods. The ANN model showed par- ticularly strong recall, indicating its effectiveness in identifying data.

5. Conclusion

This study presents a dual-model machine learning frame- work for predicting heart failure and diabetes risk using ANN and XGBoost. The results demonstrate the feasibility and accuracy of integrating these two models for reliable health risk prediction. This approach can support medical decision- making, enable early intervention, and ultimately improve patient care outcomes.

The specialized assignment of models to diseases based on data characteristics—ANN for complex, non-linear relation- ships in heart failure data, and XGBoost for structured diabetes data—proved effective. The human-readable explanations pro- vided for both models enhance their clinical acceptability by making the AI decision process transparent and understandable to healthcare professionals.

With further development and validation, this framework has the potential to become a valuable tool in clinical prac- tice, contributing to personalized and proactive healthcare. The dual-model approach offers a flexible template that can be extended to other disease predictions while maintaining interpretability and clinical relevance.

CHALLENGES AND FUTURE WORK

During implementation, several challenges were observed:

- **Limited Dataset Size:** Small sample sizes reduced the model's ability to generalize. In future, data augmentation and cross-institutional datasets can help.
- **Class Imbalance:** Certain risk categories had fewer samples. Techniques like SMOTE or weighted training can mitigate this issue.

This study presents a dual-model machine learning frame- work for predicting heart failure and diabetes risk using ANN and XGBoost. The results demonstrate the feasibility and accuracy of integrating these two models for reliable health risk prediction. This approach can support medical decision- making, enable early intervention, and ultimately improve patient care outcomes.

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