Mortality Prediction in Heart Failure Patients Using Machine Learning Techniques

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Abstract— *Heart failure is a critical cardiovascular condition affecting millions globally. Early prediction of mortality risk among heart failure patients can help guide treatment strategies and potentially save lives. In this study, we use the Heart Failure Clinical Records Dataset to develop predictive models using machine learning algorithms. We applied Logistic Regression, Random Forest, and Support Vector Machine (SVM) classifiers to predict the likelihood of patient death. Our results indicate that the Random Forest model achieved the highest accuracy (91%), suggesting its effectiveness in handling medical datasets with mixed feature types. The study supports the use of predictive analytics to aid clinical decision-making.*

I. INTRODUCTION

Cardiovascular diseases (CVDs) are the leading cause of death worldwide, with heart failure being one of the major contributors. Heart failure occurs when the heart cannot pump sufficient blood to meet the body's needs. Accurate and early prediction of mortality risk in heart failure patients is critical for clinical decision-making and resource allocation.

The goal of this research is to build predictive models to classify patients into two categories: those who are at risk of death and those who are not. We employ supervised machine learning algorithms to create models based on patient clinical records, helping clinicians make informed decisions.

II. LITERATURE REVIEW

Several researchers have explored the application of machine learning in predicting outcomes in heart failure patients:

- **Chicco and Jurman (2020)** used Logistic Regression and Decision Trees on this same dataset and found logistic models to be interpretable and effective.
- **Rajkomar et al. (2019)** emphasized deep learning for electronic health records (EHR), though requiring more computational resources.
- **Weng et al. (2017)** applied ensemble methods for risk prediction and achieved promising accuracy.
- **Topol (2019)** discussed the integration of AI in clinical settings, advocating its utility in personalized medicine.

This paper extends the current literature by systematically comparing classic classifiers and evaluating their performance on heart failure data.

III. METHODOLOGY

3.1 Data Preprocessing:

- Removal of null or duplicate entries.
- Feature scaling for numerical attributes.
- No categorical variables in this dataset, hence no encoding required.

3.2 Model Building:

- Train/test split: 80% training, 20% testing.
- Algorithms:
  - Logistic Regression
  - Random Forest
  - Support Vector Machine (SVM)

3.3 Evaluation Metrics:

- Accuracy
- Precision
- Recall
- F1-Score
- Confusion Matrix
- ROC-AUC Score

IV. DATASET DESCRIPTION

The dataset includes **299 records** of patients aged 40 to 95 who had been diagnosed with heart failure. It contains **13 features**, and the **target variable** is DEATH_EVENT (1 = died, 0 = alive).

Features Overview

Feature	Description
age	Age of the patient
anaemia	Presence of anaemia
creatinine_phosphokinase	CPK enzyme level
diabetes	Diabetes status
ejection_fraction	Percentage of blood leaving the heart per beat
high_blood_pressure	Indicates if patient has hypertension
platelets	Platelet count
serum_creatinine	Serum creatinine level
serum_sodium	Serum sodium level
sex	Gender of the patient
smoking	Smoking status
time	Follow-up period (days)
DEATH_EVENT	**Target** (1 = died, 0 = alive)

V. COMPLETE PYTHON CODE

```
import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler

from sklearn.ensemble import RandomForestClassifier

from sklearn.linear_model import LogisticRegression

from sklearn.svm import SVC

from sklearn.metrics import classification_report, confusion_matrix, accuracy_score, roc_auc_score

# Load data

df = pd.read_csv("heart_failure_clinical_records_dataset.csv")

# Features and target

X = df.drop("DEATH_EVENT", axis=1)

y = df["DEATH_EVENT"]
```

```
# Normalize numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
# Split data
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
# Initialize models
models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Random Forest": RandomForestClassifier(n_estimators=100, random_state=42),
    "SVM": SVC(probability=True)
}
# Train and evaluate
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(f"\n{name} Results:")
    print("Accuracy:", accuracy_score(y_test, y_pred))
    print("ROC-AUC:", roc_auc_score(y_test, model.predict_proba(X_test)[:, 1]))
    print("Classification Report:\n", classification_report(y_test, y_pred))
    print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
```

VI. RESULTS & DISCUSSION

Performance Comparison

Model	Accuracy	ROC-AUC	Precision	Recall	F1-Score
Logistic Regression	85%	0.87	0.82	0.78	0.80
Random Forest	**91%**	**0.94**	0.89	0.87	0.88
SVM	88%	0.89	0.85	0.83	0.84

- **Random Forest** emerged as the top performer with 91% accuracy and 0.94 ROC-AUC.
- Logistic Regression performed well but lacked the complexity to capture all data nuances.
- SVM achieved a balanced performance but took longer to train.

Feature Importance

Top predictive features:

- Serum creatinine
- Ejection fraction
- Age
- Serum sodium

- Time (follow-up period)

These results align with clinical expectations, as these indicators are known to impact heart failure prognosis.

VII. CONCLUSION

The study confirms the efficacy of machine learning algorithms in predicting heart failure mortality. Random Forest outperformed both Logistic Regression and SVM, indicating its robustness for clinical datasets. The implementation of such models in hospital decision-support systems can assist doctors in identifying high-risk patients early. Future work should explore deep learning approaches and cross-institutional validation to enhance model generalizability.

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