Research Reports in Clinical Cardiology

Dovepress
open access to scientific and medical research

Open Access Full Text Article

ORIGINAL RESEARCH

Machine Learning-Driven Mortality Prediction in Heart Failure Patients with Atrial Fibrillation: Evidence from the Jordanian Heart Failure Registry

Mahmoud Izraiq[1], Raed Ibrahim Alawaisheh Snr[1], Ismail Hamam[2], Mohammad Hajjiri[3], Ibrahim K Jarrad[2], Qutaiba Albustanji[1], Yaman B Ahmed[4], Omran A Abu-Dhaim[1], Ibrahim Zuraik[5], Ahmad A Toubasi[5], Mohammad Ali Dmour[1], Hadi Abu-Hantash[6]

[1]Cardiology Section, Internal Medicine Department, Specialty Hospital, Amman, Jordan; [2]Department of Cardiology, King Hussein Cancer Center Amman, Amman, Jordan; [3]Department of Cardiology, Abdali Hospital, Amman, Jordan; [4]Cardiology Section, Internal Medicine Department, King Abdullah University Hospital, Irbid, Jordan; [5]Cardiology Section, Internal Medicine Department, Jordan University Hospital, Amman, Jordan; [6]Department of Cardiology, Amman Surgical Hospital, Amman, Jordan

Correspondence: Mahmoud Izraiq, Cardiology Section, Internal Medicine Department, Specialty Hospital, Amman, Jordan, Tel +962795652260, Email izraiq@yahoo.com

Research Reports in Clinical Cardiology downloaded from https://www.dovepress.com/
For personal use only.

Introduction: Heart failure (HF) and atrial fibrillation (AF) are constantly linked together as predictors of a substantial increase in morbidity and mortality. In this study, we investigated the effects of atrial fibrillation in patients with heart failure.

Methods: This study was a prospective observational multicenter national registry encompassing 21 health institutes in Jordan, comprising university hospitals, private hospitals, and private clinics. Patients visiting the cardiology clinic or inpatients admitted due to acute decompensated HF were included. The collected variables included age, sex, BMI, comorbidities, HDL, LDL, triglycerides, BNP, Sodium, potassium, hemoglobin, and creatinine.

Results: Our study of 1571 patients showed significant differences between those with and without atrial fibrillation (AF). AF patients included more females (49.4% vs 34.0%), had a higher prevalence of hypertension (88.0% vs 78.5%), and were older (57.8% aged ≥70 years). Smoking rates were lower in patients with AF (22.3% vs 37.0%), while dyslipidemia was less common (54.5% vs 65.3%). Patients with AF also had more hospital admissions than those without AF (16% vs 11.6%). In addition, triglyceride levels were notably lower, hemoglobin levels were < 10 g/dL, and eGFR was reduced in patients with AF. In predicting death, the Random Forest Classifier had the highest accuracy (93.02%) and AUC (92.51%), whereas Logistic Regression had higher sensitivity (72.09%). Creatinine, Length of Hospital Stay, and other factors influenced the predictions, with creatinine levels being a strong predictor of patient outcomes.

Conclusion: Atrial fibrillation patients were older and had a higher proportion of females compared than non-atrial fibrillation patients. Hypertension, a family history of premature coronary artery disease, and structural heart disease were notably higher in the atrial fibrillation group. Patients with atrial fibrillation had higher rates of hospital admissions than those without atrial fibrillation.

Keywords: atrial fibrillation, heart failure, Jordan, registry, machine learning

Introduction

Atrial fibrillation (AF) is a common cardiac arrhythmia worldwide. The global incidence of AF is estimated to be 33.5 million individuals according to the global burden of disease.[1] Heart failure (HF) and atrial fibrillation (AF) are constantly linked together as predictors of a substantial increase in morbidity and mortality.[2–6] In patients with pre-existing heart failure, atrial fibrillation coexists in 10–50% of patients.[7–9] Since both atrial fibrillation and heart failure synergistically coexist and potentiate each other's effects, this number is increasing. HF is a cardiac condition that occurs because of inadequate pumping of the cardiac output.[10] AF is a serious cardiac condition that occurs when erratic electrical impulses are fired, causing irregular and fast cardiac contractions. This results in palpitations, dizziness, and shortness of breath.[11] Previous studies have explained the relationship between AF and HF through the following mechanisms: increased atrial stretch, activation of the renin-angiotensin-aldosterone

Received: 27 March 2024
Accepted: 28 May 2024
Published: 4 June 2024

© 2024 Izraiq et al. This work is published and licensed by Dove Medical Press Limited. The full terms of this license are available at https://www.dovepress.com/terms.php and incorporate the Creative Commons Attribution – Non Commercial (unported, v3.0) License (http://creativecommons.org/licenses/by-nc/3.0/). By accessing the work you hereby accept the Terms. Non-commercial uses of the work are permitted without any further permission from Dove Medical Press Limited, provided the work is properly attributed. For permission for commercial use of this work, please see paragraphs 4.2 and 5 of our Terms (https://www.dovepress.com/terms.php).

system (RAAS), and electrophysiological structural changes in the atria.[12,13] The incidence of AF increases with other risk factors that simultaneously increase the incidence of HF, including age, hypertension, diabetes, and heart remodelling, owing to hemodynamic and electrophysiological changes.[11] These factors alter the morbidity and mortality of patients with AF and HF.

To our knowledge, clinical characteristics and outcomes of patients with AF and HF have not been described in Jordan. Accordingly, we conducted a heart failure registry in Jordan to study the clinical correlations between heart failure and its associated comorbidities, one of which was atrial fibrillation. In this study, we investigated the ramifications of atrial fibrillation in patients with heart failure. In addition, we aimed to develop machine learning models to predict mortality in patients with AF and heart failure.

Methods

Study Design and Setting

The registry method has been previously described. The JoHF registry and protocol characteristics of this study were registered at ClinicalTrials. gov (NCT04829591). In summary, this was a prospective observational multicenter national registry encompassing 21 health institutes in Jordan, comprising university hospitals, private hospitals, and private clinics. The patient recruitment period started on July 1, 2021, and continued for 12 months of enrolment. Patients meeting the inclusion criteria either visited the cardiology clinic or were admitted to the inpatient department because of acute or chronic HF, whether it was a newly diagnosed or pre-existing condition. Exclusion criteria included individuals under 18 years of age, those unable to provide informed consent, and those unable to adhere to follow-up requirements.

Ethical Consideration

Following the ethical guidelines and standards outlined in the Declaration of Helsinki, we confirmed that our study fully complies with these principles. The Research Committee of the Faculty of Medicine and the Institutional Review Board at the Specialty Hospital approved the study, and the Institutional Review Board provided the ethical approval. The ethics committee approved a waiver of consent from the patients because the study did not include any therapeutic intervention and the planned outcomes were routinely registered in patients with heart failure.

Data Collection

Data collection for this registry included multiple variables, such as demographics, including sex, age (<40, 40–49, 50–59, 60–69, and ≥70 years), and Body Mass Index (BMI), which were categorized as normal (18.5–25), overweight (25–30), and obese (>30). In addition, it included concomitant comorbidities, including hypertension, diabetes, dyslipidemia, arrhythmias (especially atrial fibrillation), and structural heart disease. We also collected data on systolic and diastolic blood pressures at presentation. Moreover, several laboratory investigations were also collected, including cholesterol (Normal<200 and high>200), Low Density Lipoprotein (LDL) (Normal<130 and high>130), High Density Lipoprotein (HDL)(Normal<40 and high<40), triglyceride (Normal and high>150), Barium Natriuretic Peptide (BNP)(Normal<100 and high>100), Sodium (Hyponatremia<136, normal=136-145, and hypernatremia>145), Potassium (Hypokalaemia<3.5, normal=3.5–5.5, and Hyperkalaemia>5), Haemoglobin level (<10 and >10), BUN (Normal<20 and High>20), and Creatinine (Normal<115 micromoles/L, High>115 micromoles/L). Echocardiographic measures, including ejection fraction, left ventricular diameter, and left atrial diameter, were also included. Finally, the patients' medications at baseline were collected. The outcome of interest was the morbidity and mortality of patients with both AF and HF, and their relationship with other comorbidities. Finally, the CHA_2DS_2-VASc score for both groups were calculated and compared.

Statistical Analysis

The data were entered using Microsoft Office Excel 2019 and then imported and analyzed using IBM SPSS v.25 software. Patient demographics, comorbidities, laboratory investigations, and echocardiographic measures were compared according to outcome using the *T*-test and Chi-square test for continuous and categorical variables, respectively. Statistical p-value<0.050 was considered statistically significant. We employed multiple imputations

in R using the "mice" package to address missing data, generating five imputed datasets through Predictive Mean Matching (PMM). After imputation, the same statistical analyses were performed on each dataset, and the results were pooled to provide the final estimates. This approach ensured the robust handling of missing data and enhanced the reliability of our findings, thereby accounting for the uncertainty introduced by the imputation of missing data.

Machine Learning Analysis

This study employed a machine learning-based approach to predict the "Death". Numerical columns were subjected to median imputation for missing values, whereas categorical columns were imputed with the most frequent values. All the numerical data were standardized using StandardScaler to ensure feature comparability. Recursive Feature Elimination with Cross-Validation (RFECV) was applied using a random forest classifier as the estimator. This method provides the most relevant features for predicting the target variables. The data were split into training, validation, and test sets, with 40% allocated to the combined validation and test sets. To address the class imbalance, the training set was resampled using the SMOTEENN technique, a combination of synthetic minority oversampling (SMOTE) and Edited Nearest Neighbors (ENN) algorithms, to enhance the model's performance on minority classes, and a grid search over a predefined range of hyperparameters was conducted using fivefold cross-validation on the resampled training data. The best performing parameters were then used to train the final model. Our study evaluated six machine learning models to identify the most effective approach for predicting target variables. These models included Random Forest Classifier (RFC), Logistic Regression (LR), Support Vector Machine (SVM), AdaBoost Classifier, K-Nearest Neighbors (KNN), and Gradient Boosting Classifier (GBC). Several evaluation metrics were employed to compare the effectiveness of each model, including the accuracy, precision, recall, F1 score, and Area Under the ROC Curve (AUC). To understand the contribution of each feature to our model's predictions, we employed permutation features. All models were analyzed using Python version 3.10.9.

Results

The registry included 2151 patients, predominantly male (58%). Only 1571 patients were included in this study. Atrial fibrillation was observed in 494 patients (33.4%). The largest age group was 70 years or older, comprising 45.5% of the cohort. The age distributions were as follows: 60–69 years (26.3%), 50–59 years (16.5%), 40–49 years (7.2%), and < 40 years (4.4%). Smoking was reported in 31.3% of the patients, while alcohol consumption was low (0.6%). Obesity was present in 36.6% of participants, 5.3% had a family history of premature ASCVD, and 23% reported a personal history of premature ASCVD.

Characteristics of Patients with Atrial Fibrillation

The atrial fibrillation group had a significantly higher proportion of females (49.4%) than the non-AF group (34.0%) ($p < 0.001$). This group also had a higher percentage of patients aged ≥ 70 years (57.8%) ($p < 0.001$). Patients in the atrial fibrillation group had higher median ejection fraction compared to the non-AF group ($p=0.003$). Hypertension was more prevalent in the atrial fibrillation group (88.0% vs 78.5%, $p < 0.001$). Smoking rates were lower in the atrial fibrillation group (22.3% vs 37.0%, $p < 0.001$), and dyslipidemia was more common in patients without atrial fibrillation (65.3% vs 54.5%, $p < 0.001$). A history of ASCVD was less frequent in the atrial fibrillation group (59.0% vs 90.5%, $p < 0.001$), whereas a positive family history of premature ASCVD (9.7%, $p = 0.001$) and structural heart disease (7.2%, $p = 0.024$) was higher in the atrial fibrillation group (Table 1).

Impact of Atrial Fibrillation on Patient Outcomes

Atrial fibrillation was associated with a higher number of hospital admissions, with 16% of these patients having more than two admissions in the past six months compared to 11.6% without atrial fibrillation ($p = 0.003$). There were no significant differences between the two groups regarding mechanical ventilation, in-hospital mortality, or mean length of hospital stay ($P = 0.531$, $P = 0.456$, and $P = 0.186$, respectively) (Table 2). Also, the median CHA_2DS_2-VASc score was higher in the atrial fibrillation group compared to the non-AF group (6 (5–7) vs 3 (3–4); $p < 0.001$). Triglyceride levels were significantly

Table 1 Differences in Demographics and Comorbidities According to Atrial Fibrillation Status

Variable, n (%)		Non-Atrial Fibrillation (n=1077**)	Atrial Fibrillation (n=494**)	P-value
Gender	Male	711 (66.0)	250 (50.6)	<0.001*
	Female	366 (34.0)	244 (49.4)	
Age	<40	45 (4.6)	6 (1.3)	<0.001*
	40–49	75 (7.6)	23 (4.9)	
	50–59	187 (19.1)	58 (12.5)	
	60–69	260 (26.5)	109 (23.4)	
	≥70	414 (42.2)	269(57.8)	
Ejection Fraction, median (IQR)		35 (26.8–50)	40 (30–50)	0.003*
Hypertension	Yes	800(78.5)	418(88.0)	<0.001*
	No	219(21.5)	57(12.0)	
BMI	Normal	194 (29.8)	52 (18.8)	<0.001*
	Overweight	250(38.3)	92(33.2)	
	Obese	208(31.9)	133(48.0)	
Diabetes	Yes	702(68.6)	338(71.2)	0.321
	No	321(31.4)	137(28.8)	
Smoking	Yes	377(37.0)	106(22.3)	<0.001*
	No	642(63.0)	369(77.7)	
Alcohol	Yes	6(0.6)	3(0.6)	0.921
	No	1013(99.4)	472(99.4)	
Dyslipidaemia	Yes	665(65.3)	259(54.5)	<0.001*
	No	354(34.7)	216(45.5)	
Obesity	Yes	86(8.4)	43(9.1)	0.694
	No	933(91.6)	432(90.9)	
Family History of ASCVD	Yes	53(5.2)	46(9.7)	0.001*
	No	966(94.8)	429(90.3)	
History of ASCVD	Yes	986(90.5)	295(59.0)	<0.001*
	No	104(9.5)	205(41.0)	
History of ImplantedDevice	Yes	37(3.4)	27(5.4)	0.059
	No	1053(96.6)	473(94.6)	
History of Structural Heart Disease	Yes	78(7.2)	21(4.2)	0.024*
	No	1012(92.8)	479(95.8)	

Notes: *Statistical significance was determined with a p-value ≤ 0.05. ** Totals for some variables may not sum to the total group size due to missing values.

Abbreviations: BMI, Body Mass Index; ASCVD, Atherosclerotic Cardiovascular Disease.

Table 2 The Association Between Atrial Fibrillation and Patients' Outcomes

Variable, n (%)		Non-Atrial Fibrillation (n=1077[b])	Atrial Fibrillation (n=494[b])	P-value
Admissions in past 6 months[a]	0	453(42.3)	192(39.5)	0.003[c]
	1	252(23.5)	87(17.9)	
	2	90(8.4)	36(7.4)	
	>2	277(25.8)	171(35.2)	
Mechanical Ventilation	Yes	33(4.7)	19(5.6)	0.531
	No	673(95.3)	322(94.4)	
Death	Yes	117(10.7)	60(12.0)	0.456
	No	973(89.3)	440(88.0)	
Length of Stay, mean± SD	–	6.00 ±7.53	6.61 ±8.00	0.186
CHA_2DS_2-VASc Score, median (IQR)		3 (3–4)	6 (5–7)	<0.001[c]

Notes: [a]Number of hospital admissions or office visits for heart failure in the past six months. [b]Totals for some variables may not sum to the total group size due to missing values. [c]Statistical significance was determined with a p-value ≤ 0.05.
Abbreviation: SD, Standard Deviation.

associated with atrial fibrillation, with all patients exhibiting levels < 150 mg/dL. Both groups had hemoglobin levels consistently < 10 g/dL, potentially indicating a link to atrial fibrillation. A reduced eGFR was observed in all patients with atrial fibrillation, suggesting a significant association. However, other laboratory parameters, such as cholesterol, LDL, HDL, BUN, HBA1c, BNP, sodium, potassium, and creatinine showed no significant differences between the two groups (Table 3).

Table 3 Differences in Laboratory Variables According to Atrial Fibrillation Status

Variable, n (%)	Not Atrial Fibrillation (n=1077**)	Atrial Fibrillation (n=494**)	P-value
Cholesterol (<200 vs >200)	1077 (100.0%)	494 (100.0%)	0.012
LDL (<130 vs >130)	1077 (100.0%)	494 (100.0%)	0.050
HDL (<40 vs ≥40)	1077 (100.0%)	494 (100.0%)	0.538
Triglycerides (<150 vs >150)	1077 (100.0%)	494 (100.0%)	0.019
Hemoglobin (<10 vs ≥10)	1077 (100.0%)	494 (100.0%)	0.041
eGFR (Reduced (<60) vs Normal (≥60))	1077 (100.0%)	494 (100.0%)	<0.001*
BUN (Normal (<20) vs High (>20))	1077 (100.0%)	494 (100.0%)	0.527
HBA1c (Normal, Prediabetes, Diabetes)	1077 (100.0%)	494 (100.0%)	0.259
BNP (Normal (<100) vs High (>100))	1077 (100.0%)	494 (100.0%)	1.000
Sodium (Hyponatremia, Normal, Hypernatremia)	1077 (100.0%)	494 (100.0%)	1.000
Potassium (Hypokalemia, Normal, Hyperkalemia)	1077 (100.0%)	494 (100.0%)	1.000
Creatinine (Normal vs High)	1077 (100.0%)	494 (100.0%)	1.000

Notes: *Statistical significance was determined with a p-value ≤ 0.05. ** Totals for some variables may not sum to the total group size due to missing values.

Table 4 Performance Metrics of the Used Algorithms for Death Prediction

Model	Accuracy	AUC	Sensitivity	Specificity
Random Forest Classifier	93.02%	92.51%	48.86%	98.39%
Logistic Regression	85.78%	89.15%	72.09%	87.97%
Support Vector Machine	90.74%	90.65%	44.51%	96.54%
eXtreme Gradient Boosting	92.02%	94.21%	55.53%	96.62%

Model Interpretation

In the predictive modeling for death, the Random Forest Classifier demonstrated the highest accuracy (93.02%) and AUC (92.51%), with a sensitivity of 48.86% and specificity of 98.39%. Logistic Regression, while showing lower accuracy (85.78%) and AUC (89.15%), had a higher sensitivity (72.09%) compared to the other models. The Support Vector Machine and eXtreme Gradient Boosting models offered competitive performance, with AUCs of 90.65% and 94.21%, respectively (Table 4, Figure 1). Permutation Feature Importance analysis identified creatinine >115, Length of Hospital Stay, Mechanical Ventilation, Chronic Kidney Disease, Dyslipidemia, Male sex, and Blood Urea Nitrogen >20 as the top factors influencing model predictions (Figure 2). Notably, higher creatinine levels were the most significant predictor of patient outcomes, indicating a strong association between renal function and risk of death.

Discussion

This is the first national multicenter HF registry in Jordan. It includes 21 health institutes in Jordan: university hospitals, private hospitals, and private clinics. The primary focus was to investigate the distinctive characteristics of patients with

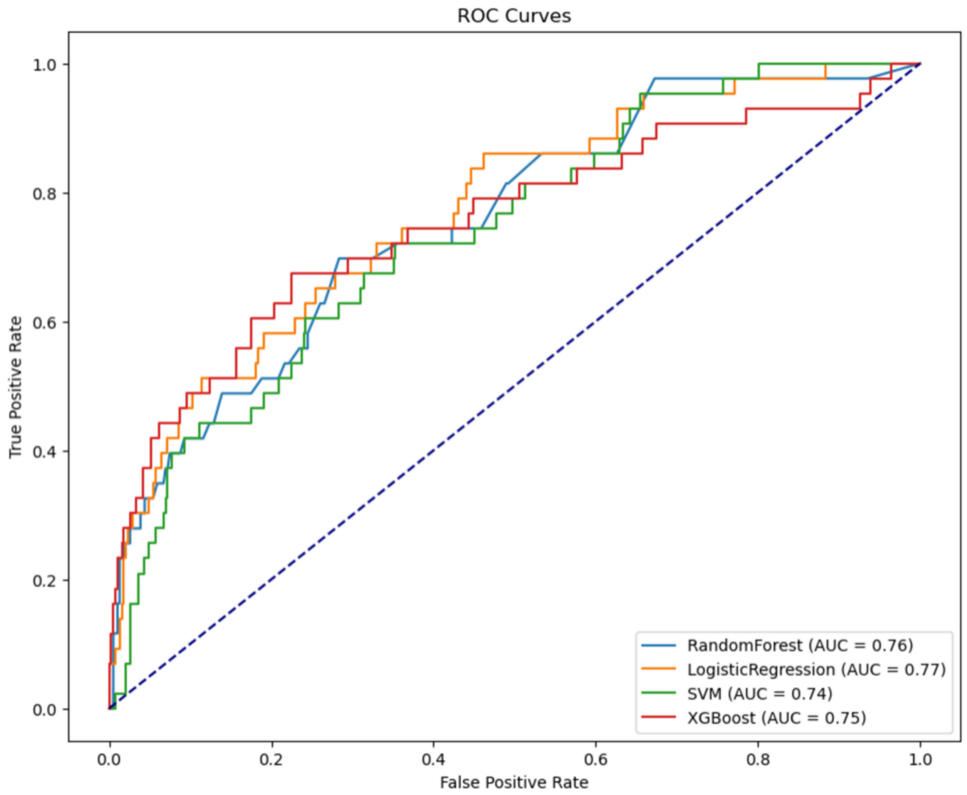

Figure 1 Receiver Operating Characteristic (ROC) Curves for the evaluated models. The dashed line represents the chance level of discrimination. Each model's AUC is noted, with the Random Forest Classifier and Logistic Regression outperforming the SVM and XGBoost models marginally.

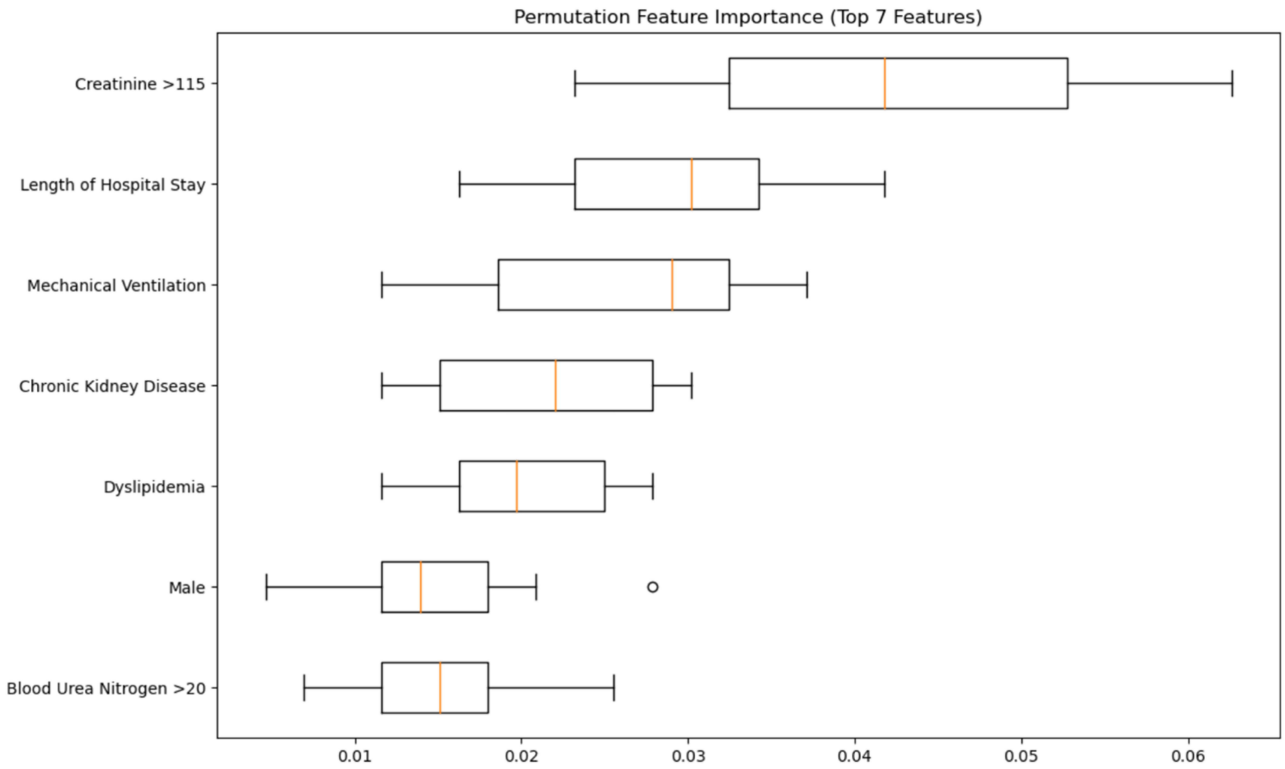

Figure 2 Permutation Feature Importance for the top-performing model, highlighting the mean decrease in model performance when each feature's information is shuffled. The error bars represent the standard deviation of the permutation importance over multiple shuffles.

AF and to assess the impact of atrial fibrillation on heart failure outcomes. The atrial fibrillation group displayed a unique demographic profile compared to those without atrial fibrillation. A significantly higher proportion of females was observed in the atrial fibrillation group than in the non-AF group. In addition, most atrial fibrillation patients were aged 70 years and above. Additionally, hypertension was more prevalent in atrial fibrillation in those without atrial fibrillation.

Furthermore, the incidence of a family history of premature coronary artery disease was higher in the atrial fibrillation group. Additionally, structural heart disease was notably higher in the atrial fibrillation group than in the AF group; conversely, smoking was more prevalent in non-AF patients. Dyslipidaemia was also higher in the non-atrial fibrillation group. Moreover, a history of coronary atherosclerotic disease is more prevalent in patients without atrial fibrillation. In terms of outcomes, patients with atrial fibrillation had higher rates of hospital admissions than those without atrial fibrillation.

In contrast, rates of mechanical ventilation and in-hospital admissions following exacerbation of heart failure did not show significant disparities between the two groups. Moreover, the mean length of hospital stay did not differ between cohorts. First, females with atrial fibrillation exhibit a higher incidence of concurrent heart failure than females without atrial fibrillation, which is consistent with other studies.[14] In addition, most patients with atrial fibrillation were of an advanced age (70). As explained in the literature, aging causes significant remodelling of the electrical and structural composition of the atrial myocardium. These alterations can contribute to the initiation and persistence of atrial tachyarrhythmias.[15] Hypertension has a high prevalence among patients with atrial fibrillation. This association may be attributed to the fact that persistent hypertension throughout adulthood induces anatomical and electrical changes in the heart, which can predispose individuals to develop atrial fibrillation.[16] In contrast to the study conducted by Weijs et al, our findings indicate a higher prevalence of premature coronary artery disease among patients with atrial fibrillation; this discrepancy may be attributed to the larger sample size in our study.[17] Similar to the existing literature, our findings showed a higher prevalence of structural heart disease in the atrial fibrillation group.[18]

However, smoking was found to be less prevalent among the atrial fibrillation group, a difference from the findings reported in the literature.[19] Furthermore, dyslipidemia was more prevalent in the non-AF group, consistent with the existing literature.[20] This finding may be attributed to the higher prevalence of atrial fibrillation in the elderly, who tend

to have a lower lipid profile. Additionally, hyperthyroidism, an independent risk factor for atrial fibrillation, can lead to lower LDL-C levels. Finally, chronic inflammation and oxidative stress have been recognized as significant risk factors for atrial fibrillation. Lipoproteins, including HDL-C and LDL-C, exhibit anti-inflammatory properties, particularly against bacterial endotoxins in systemic circulation.[20] In contrast to the study by Yan et al, our findings showed that the non-AF group had a higher prevalence of coronary atherosclerotic disease.[21] Second, the atrial fibrillation group had a higher hospital admission rate than the non-AF group, similar to the existing literature.[22,23] A few suggested mechanisms contributing to the exacerbation of heart failure in the presence of atrial fibrillation include loss of atrioventricular synchrony, impaired diastolic filling, atrial systolic dysfunction, and rapid ventricular response.

Conversely, our findings did not show any differences between the two groups in the rates of mechanical ventilation and in-hospital admissions following heart failure exacerbations. In addition, the mean length of hospital stay did not differ between groups. Atrial fibrillation is the most common cardiac arrhythmia, and its prevalence is steadily increasing owing to population growth and aging.[24]

In this study, we evaluated machine learning algorithms for predicting death in patients with atrial fibrillation (AF). The results, presented in Table 4, show the performance metrics of these algorithms. The Random Forest Classifier achieved the highest accuracy (93.02%) and specificity (98.39%) but had lower sensitivity (48.86%), indicating its strength in identifying patients without death but limited ability to detect those with adverse outcomes. Logistic regression, while slightly less accurate (85.78%) and with a lower AUC (89.15%), exhibited the highest sensitivity (72.09%), making it effective in identifying patients at risk of death. The Support Vector Machine and eXtreme Gradient Boosting models also performed well, with balanced sensitivity and specificity, making them valuable for predicting death among AF patients.

Additionally, our analysis revealed that higher creatinine levels were the most significant predictor of patient outcomes, emphasizing the importance of renal function in assessing the risk of death in patients with AF. In summary, machine learning models, especially the Random Forest Classifier and Logistic Regression, show promise for predicting death in patients with AF. These models can assist healthcare providers in identifying high-risk individuals and in tailoring interventions to improve patient management. Atrial fibrillation can arise due to cardiac remodelling, especially in the atria. This remodelling involves structural changes in myocytes and the extracellular matrix as well as the deposition of fibrous tissue.

Additionally, electrical remodelling occurs because of an increased heart rate and shortened refractory periods.[25] Atrial fibrillation and heart failure often co-occur, as the prevalence of atrial fibrillation in heart failure has been reported in the literature to be 24% and 27%, respectively,[26,27] potentially due to shared risk factors such as hypertension, diabetes mellitus, ischemic heart disease, and valvular heart disease.[28] Furthermore, atrial fibrillation can exacerbate heart failure or lead to tachycardia-induced cardiomyopathy. Tachycardia is linked to reduced collagen content and impaired collagen distribution in the heart, leading to ventricular wall dilation, thinning, and diminished contractility. Additionally, depletion of myocardial energy stores contributes to ventricular dysfunction in tachycardia-induced cardiomyopathy.[29] CHA_2DS_2-VASc score provides a useful prognostic risk stratification for patients with atrial fibrillation.[30] It calculates the risk of thromboembolic events including stroke in patient with atrial fibrillation. Stroke is a major complication of atrial fibrillation and nonvalvular atrial fibrillation increases the risk of stroke by 5 folds.[31] Consistent with this evidence we found that patients with atrial fibrillation had higher risk of thromboembolic events compared to non-Afib group. In regions such as Ethiopia, the healthcare resources may be more limited, which could alter the clinical landscape for heart failure and atrial fibrillation. Niriayo et al,[32] found that 52.7% of the patients with cardiovascular diseases had drug-related problems (DTPs) in Ethiopia. These DTPs included unnecessary drug therapy, the need for additional therapy, noncompliance, and ineffective dose. This observation can be attributed to the socio-economic factors like limited healthcare resources, affordability issues, noncompliance, and ineffective communication between healthcare providers and the patients. Due to that, training healthcare providers on the latest guidelines and treatment therapies will play a critical role in evaluating patient care standards, thereby mimicking improvements seen in more resourced settings like Jordan.

This study had several limitations. First, the study's observational design limits inferences to associations rather than causation. Second, associations may be confounded by several variables. Third, another limitation is the short follow-up period for patient outcomes rendered our ability to evaluate long-term patient outcomes.

Conclusion

In conclusion, this is the first national multicenter HF registry in Jordan. We investigated the characteristics of patients with atrial fibrillation and the impact of atrial fibrillation on the outcomes of patients with heart failure. Atrial fibrillation patients had a higher proportion of females compared than non-atrial fibrillation patients; most patients with atrial fibrillation were 70 and above. Hypertension, a family history of premature coronary artery disease, and structural heart disease were notably higher in the atrial fibrillation group. Patients with atrial fibrillation had higher rates of hospital admissions than those without atrial fibrillation. On the contrary, the rates of mechanical ventilation in-hospital admissions following heart failure exacerbations and the mean length of hospital stay did not show significant differences between the two groups. Risk of thromboembolic events as evidenced from the CHA_2DS_2-VASc were higher in the atrial fibrillation group. This study should guide clinicians in identifying and managing patients with HF who are at a high risk of having atrial fibrillation to improve patient outcomes and quality of life. By analysing the intersection of these conditions within the Jordanian population, our research provides insights into the clinical characteristics and healthcare outcomes in Jordan. These findings aim to enhance the understanding of HF and AF in a Middle Eastern context and set a benchmark for future epidemiological studies and healthcare strategies. Future prospective studies should aim to assess the long-term outcomes, survival rates, and novel therapeutic agents for patients with HF and AF.

Disclosure

The authors report no conflicts of interest in this work.

References

1. Morin DP, Bernard ML, Madias C, et al. The State of the Art: atrial Fibrillation Epidemiology, Prevention, and Treatment. *Mayo Clin Proc*. 2016;91(12):1778–1810. doi:10.1016/j.mayocp.2016.08.022
2. Braunwald E. Shattuck lecture--cardiovascular medicine at the turn of the millennium: triumphs, concerns, and opportunities. *N Engl J Med*. 1997;337(19):1360–1369. doi:10.1056/NEJM199711063371906
3. Htm, A.H.A.J.h.w.A.o.s.s. *Heart and Stroke Statistical Update*; 2008.
4. Maisel WH, Stevenson LW. Atrial fibrillation in heart failure: epidemiology, pathophysiology, and rationale for therapy. *Am J Cardiol*. 2003;91(6a):2d–8d. doi:10.1016/S0002-9149(02)03373-8
5. Moser DK, Mann DL. Improving outcomes in heart failure: it's not unusual beyond usual care. *Circulation*. 2002;105(24):2810–2812. doi:10.1161/01.CIR.0000021745.45349.BB
6. Nohria A, Lewis E, Stevenson LW. Medical management of advanced heart failure. *JAMA*. 2002;287(5):628–640. doi:10.1001/jama.287.5.628
7. Bourassa MG, et al. Natural history and patterns of current practice in heart failure. The Studies of Left Ventricular Dysfunction (SOLVD) Investigators. *J Am Coll Cardiol*. 1993;22(4 Suppl A):14a–19a. doi:10.1016/0735-1097(93)90456-B
8. Carson PE, Johnson GR, Dunkman WB, et al. The influence of atrial fibrillation on prognosis in mild to moderate heart failure. The V-HeFT Studies. The V-HeFT VA Cooperative Studies Group. *Circulation*. 1993;87(6 Suppl):Vi102–10.
9. Dries DL, Exner D, Gersh B, et al. Atrial fibrillation is associated with an increased risk for mortality and heart failure progression in patients with asymptomatic and symptomatic left ventricular systolic dysfunction: a retrospective analysis of the SOLVD trials. *Studies of Left Ventricular Dysfunction J Am Coll Cardiol*. 1998;32(3):695–703. doi:10.1016/S0735-1097(98)00297-6
10. Mosterd A, Hoes AW. Clinical epidemiology of heart failure. *Heart*. 2007;93(9):1137–1146. doi:10.1136/hrt.2003.025270
11. Brundel B, et al. Atrial fibrillation. *Nat Rev Dis Primers*. 2016;2:16017.
12. Ariyaratnam JP, Lau DH, Sanders P, et al. Atrial Fibrillation and Heart Failure: epidemiology, Pathophysiology, Prognosis, and Management. *Card Electrophysiol Clin*. 2021;13(1):47–62. doi:10.1016/j.ccep.2020.11.004
13. Carlisle MA, Fudim M, DeVore AD, et al. Heart Failure and Atrial Fibrillation, Like Fire and Fury. *JACC Heart Fail*. 2019;7(6):447–456. doi:10.1016/j.jchf.2019.03.005
14. Schnabel RB, Rienstra M, Sullivan LM, et al. Risk assessment for incident heart failure in individuals with atrial fibrillation. *Eur J Heart Fail*. 2013;15(8):843–849. doi:10.1093/eurjhf/hft041
15. Pandit SV, Jalife J. Aging and atrial fibrillation research: where we are and where we should go. *Heart Rhythm*. 2007;4(2):186–187. doi:10.1016/j.hrthm.2006.11.011
16. Ogunsua AA, Shaikh AY, Ahmed M, et al. Atrial Fibrillation and Hypertension: mechanistic, Epidemiologic, and Treatment Parallels. *Methodist DeBakey Cardiovasc J*. 2015;11(4):228–234. doi:10.14797/mdcj-11-4-228
17. Weijs B, Pisters R, Haest RJ, et al. Patients originally diagnosed with idiopathic atrial fibrillation more often suffer from insidious coronary artery disease compared to healthy sinus rhythm controls. *Heart Rhythm*. 2012;9(12):1923–1929. doi:10.1016/j.hrthm.2012.08.013
18. Brasca FMA, Menè R, Perego GB. Catheter Ablation for Atrial Fibrillation in Structural Heart Disease: a Review. *J Clin Med*. 2023;12(4):1431. doi:10.3390/jcm12041431
19. Chamberlain AM, Agarwal SK, Folsom AR, et al. Smoking and incidence of atrial fibrillation: results from the Atherosclerosis Risk in Communities (ARIC) study. *Heart Rhythm*. 2011;8(8):1160–1166. doi:10.1016/j.hrthm.2011.03.038
20. Li -Z-Z, Du X, Guo X-Y, et al. Association Between Blood Lipid Profiles and Atrial Fibrillation: a Case-Control Study. *Med Sci Monit*. 2018;24:3903–3908. doi:10.12659/MSM.907580

21. Yan T, Zhu S, Xie C, et al. Coronary Artery Disease and Atrial Fibrillation: a Bidirectional Mendelian Randomization Study. *J Cardiovasc Dev Dis*. 2022;9(3). doi:10.3390/jcdd9030069
22. Ahmed A, Ullah W, Hussain I, et al. Atrial fibrillation: a leading cause of heart failure-related hospitalizations; a dual epidemic. *Am J Cardiovasc Dis*. 2019;9(5):109–115.
23. Fung JW, Sanderson JE, Yip GWK, et al. Impact of atrial fibrillation in heart failure with normal ejection fraction: a clinical and echocardiographic study. *J Card Fail*. 2007;13(8):649–655. doi:10.1016/j.cardfail.2007.04.014
24. Miyasaka Y, Barnes ME, Gersh BJ, et al. Secular trends in incidence of atrial fibrillation in Olmsted County, Minnesota, 1980 to 2000, and implications on the projections for future prevalence. *Circulation*. 2006;114(2):119–125. doi:10.1161/CIRCULATIONAHA.105.595140
25. Nesheiwat Z, Goyal A, Jagtap M. *Atrial Fibrillation*. Treasure Island (FL): StatPearls PublishingCopyright © 2023, StatPearls Publishing LLC; 2023.
26. Mahoney P, Kimmel S, DeNofrio D, et al. Prognostic significance of atrial fibrillation in patients at a tertiary medical center referred for heart transplantation because of severe heart failure. *Am J Cardiol*. 1999;83(11):1544–1547. doi:10.1016/S0002-9149(99)00144-7
27. Senni M, Tribouilloy CM, Rodeheffer RJ, et al. Congestive heart failure in the community: a study of all incident cases in Olmsted County, Minnesota, in 1991. *Circulation*. 1998;98(21):2282–2289. doi:10.1161/01.CIR.98.21.2282
28. Lubitz SA, Benjamin EJ, Ellinor PT. Atrial fibrillation in congestive heart failure. *Heart Fail Clin*. 2010;6(2):187–200. doi:10.1016/j.hfc.2009.11.001
29. Wongcharoen W, Chen SJ. The pathophysiology of atrial fibrillation in heart failure. *J Innov Card Rhythm Manag*. 2012;3:865–869.
30. Melgaard L, Gorst-Rasmussen A, Lane DA, Rasmussen LH, Larsen TB, Lip GY. Assessment of the CHA2DS2-VASc Score in Predicting Ischemic Stroke, Thromboembolism, and Death in Patients With Heart Failure With and Without Atrial Fibrillation. *JAMA*. 2015;314(10):1030–1038. doi:10.1001/jama.2015.10725
31. Elsheikh S, Hill A, Irving G, Lip GYH, Abdul-Rahim AH. Atrial fibrillation and stroke: state-of-the-art and future directions. *Curr Probl Cardiol*. 2024;49(1 Pt C):102181. doi:10.1016/j.cpcardiol.2023.102181
32. Niriayo YL, Kifle R, Asgedom SW, Gidey K. Drug therapy problems among hospitalized patients with cardiovascular disease. *BMC Cardiovasc Disord*. 2024;24(1):50. doi:10.1186/s12872-024-03710-8

Research Reports in Clinical Cardiology Dovepress

Publish your work in this journal

Research Reports in Clinical Cardiology is an international, peer-reviewed, open access journal publishing original research, reports, editorials, reviews and commentaries on all areas of cardiology in the clinic and laboratory. The manuscript management system is completely online and includes a very quick and fair peer-review system. Visit http://www.dovepress.com/testimonials.php to read real quotes from published authors.

Submit your manuscript here: http://www.dovepress.com/research-reports-in-clinical-cardiology-journal