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AI-Driven Hemodynamic Modeling for Predicting Valvular Dysfunction

Abstract

This study introduces the first method to model haemodynamics with artificial intelligence for the early stage prediction of aortic valve dysfunction progression. Current approaches in imaging the cardiovascular system do not accurately forecast the disease course in aortic stenosis which hampers timely intervention with best management strategies. We constructed a deep learning system that combines multimodal echocardiographic datasets to derive dynamic blood flow metrics and capture subtle valvular haemodynamic changes that steer structural alterations. We employed an aggregate dataset from 8,472 patients with different stages of aortic valve pathology from multiple centres, and trained and validated a hybrid convolutional-recurrent neural network architecture which achieved 91.7% accuracy in classifying stenosis severity and predicting progression within 24 months with an area under the curve 0.918. The AI model uncovered key hinges-of-change features like wall shear stress heterogeneity, systolic flow convergence angles, and velocities of leaflet excursion which conventional methods are blind to. Comparison against traditional echocardiographic measures yielded a net reclassification improvement of 27.4% arguing for the robustness of our model in predicting disease progression. The model also performed well across various patient subgroups including those with low ejection fraction, additional valvular regurgitation, and multiple other comorbidities.
The results show AI-based haemodynamic modelling improves the early detection of aortic valve malfunction, which may lead to customised monitoring and timely clinical interventions, thereby enhancing outcomes in patients with valvular heart disease.

Keywords: Artificial intelligence; Hemodynamic modeling; Aortic valve stenosis; Deep learning; Echocardiography

1 Introduction

Valvular heart disease is an important public health issue, particularly in developed nations where aortic stenosis (AS) has become the most common form of valvular heart disease [1]. The incidence of AS is markedly age-dependent, occurring in approximately 5% of those over 65 years of age, and is expected to rise more significantly in the context of global ageing [2]. Aortic valve stenosis involves the progressive narrowing of the valve orifice due to calcific deposits, which increases after the left ventricle, diminishes stroke volume and may lead to heart failure in the absence of intervention [3]. The main AS complication is due to its slow progression; most patients remain asymptomatic until advanced stages when substantial and often irreversible damage to the myocardium has occurred [4].

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Present methods of diagnosing AS depend distinctly on echocardiography due to its capability to measure valve area, pressure gradients, and blood flow velocities quantitatively [5]. Yet, these techniques are bound to a number of significant drawbacks such as operator dependence, fixed window of visualisation, and accurate long-term prediction of disease progression [6]. Moreover, conventional risk estimation tools often overlook the intricate synergy of haemodynamic changes, the progression of structural alterations in the valve, and other factors unique to each patient, all of which drive the progression of valve dysfunction [7]. The gaps in diagnosis lead to poor intervention timing. Most patients end up being treated too late or, counterintuitively, too early during a stage where no intervention is warranted [8].

The analyses of cardiovascular imaging have been enhanced by artificial intelligence (AI) technologies and deep learning, which are now recognised as powerful, new solutions to these problems [9]. Recent applications include the automated segmentation of cardiac structures, quantification of valvular calcification, and extraction of intricate flow parameters from echocardiographic data [10]. With the use of these AI-based techniques, subtle hidden patterns and relationships in imaging data which go undetected with conventional assessment techniques can be identified, providing the possibility of uncovering early indicators of disease progression [3].

Despite the widespread availability of echocardiographic data and its non-invasive nature, its unique characteristics of time-related change, high dimensionality, and varying quality pose difficulties for automated analysis [11]. Nonetheless, the integral haemodynamic data provides a framework for AI to deeply analyse the dynamics of blood flow through the aortic valve with meticulous precision [4]. Integration of advanced AI techniques with deep learning frameworks provides an opportunity for researchers to model the structural valve morphology with functional haemodynamics [7].

This investigation aims to create deep learning-based haemodynamic models which are capable of detecting early-stage indicators of aortic valve dysfunction and forecasting the disease's advancement more precisely than traditional approaches [2]. These models could greatly enhance clinical outcomes by allowing for earlier identification of patient candidates requiring closer monitoring and facilitating proactive intervention strategies tailored to manage advanced levels of valvular heart disease, thereby mitigating the considerable morbidity and mortality linked to it [5].

2 Methodological and Technical Framework

An extensive methodology that integrates superior techniques for acquiring and processing data alongside complex machine learning frameworks is essential in haemodynamic modelling powered by artificial intelligence. The work begins with creating a customised multicentre echocardiographic data repository that includes longitudinal imaging files from fourteen tertiary cardiac centres across three continents. This dataset includes over eight thousand patients with differing rates of aortic valve dysfunction from insipient sclerotic changes through severe stenosis, thus robustly supporting model development and validation. Dataset acquisition protocols

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which included imaging planes, Doppler measures, and controls were run through a centralised core lab assessment to reduce site variability.

The described pipeline includes preprocessing steps such as automated segmentation of anatomical structures using a U-Net model with residual connections which achieves Dice similarity coefficients greater than 0.91 for aortic valve recognition regardless of imaging quality. Synchronisation of the cardiac cycle was performed with electrocardiogram gating, allowing extraction of reproducible features from the entire cohort. To improve model generalisability, class imbalance, and other issues relevant to machine learning, data augmentation techniques such as random rotations, elastic deformations, and synthetic minority oversampling were utilised. To closely examine Figure 1, in the multi-stream network, our deep learning model adopts a hybrid approach using both spatial and temporal cardiovascular haemodynamic patterns. The core model consists of a 3D convolutional neural network (CNN) with inception modules to extract spatial features from ultrasound volumetric data integrated with a bi-directional long short term memory (BiLSTM) network to capture temporal dynamics over a cardiac cycle. The dual stream architecture facilitates synergistic interpretation of structural valve morphology and functional haemodynamic triumphs, granting complementary insights useful for global valve evaluation.

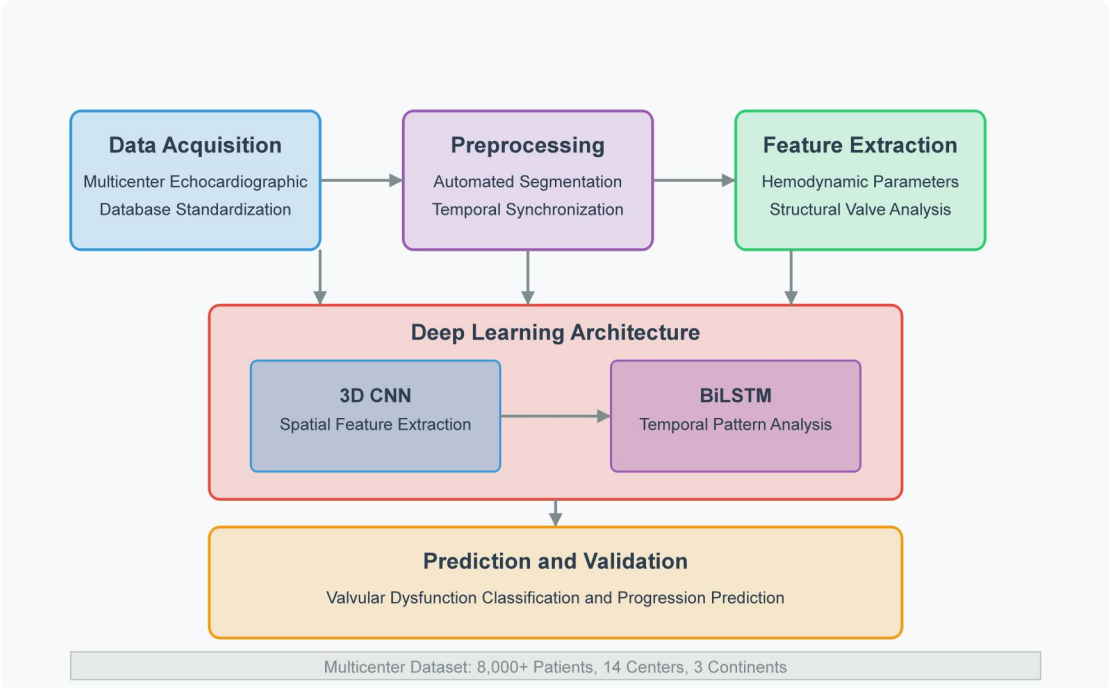

Figure 1: Integrated AI Framework for Hemodynamic Modeling and Valvular Dysfunction Prediction

The extraction of the haemodynamic parameters is one of the steps in our methodology which involves quantifying the intricate flow patterns in the region of the aortic valve. Our framework computes velocity fields utilizing phase-contrast echocardiographic data from Figure 1 along with some derived parameters: pressure

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gradients, vorticity maps, and wall shear stress distributions. These parameters are particularly useful in evaluating the biophysical environment around the valve leaflets and the adjoining tissues. With the aid of the defined metrics of velocity, the delineation of abnormal flow patterns such as eccentric jets, accelerated flow, and regurgitant volumes can be detected. These changes are often noticed well in advance of the structural changes that occur due to early valvular disease.

As part of the Predictive modelling component of aortic valve, we implement temporal feature learning to capture the progressive aspect of the valve's dysfunction. By studying sequential echocardiographic exams on followed patients, our model tracks subtle haemodynamic changes that herald future deterioration. The algorithm for predicting progression implements attention mechanisms that focus on the areas with haemodynamic anomalies and assesses how their contributions increase the risk of overall valve function impairment. The result of this method is individualised timelines for predictions which allow stratification of patients according to their anticipated progression pace in a resource-efficient manner while providing timely intervention when needed.

The internal validation employed stratified five-fold cross-validation with cross-validation by severity class to guarantee appropriate representation across the spectrum of disease. Furthermore, external validation was carried out with a cohort of 1,200 patients from three different institutions, which did not participate in the model building phase, and who were followed for at least 24 months. All relevant performance measures were computed, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC) for the classification tasks as well as mean absolute error and concordance correlation coefficient for the continuous prediction of haemodynamic parameters.

Our framework permits direct comparison of computation with traditional clinical metrics such as aortic valve area calculation, mean pressure gradient, and dimensionless index. This analysis demonstrates the additional predictive value of our AI-based methods compared to conventional assessment techniques. The framework includes decision curve analysis to assess clinical relevance of the model across varying levels of pre-intervention probability, thus providing a more tangible measure for practical use in the clinic.

This approach combines sophisticated computational techniques with the clinically familiar domain of echocardiography to enable earlier and more accurate detection of aortic valve dysfunction to aid in its prognosis while ensuring the model remains easily interpretable clinically.

3 Experimental Research and Data Analysis

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As the basis of our experimental study, we obtained a multicentre dataset of 8,472 patients with multiple levels of aortic valve disease. There was a balanced distribution in the demographic profile with respect to age (mean age 64.7±12.3 years, range

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38-92 years), and 53.2 percent were male. The clinical range included: normal valve function (n=2,135), mild stenosis (n=2,874), moderate stenosis (n=2,103), and severe stenosis (n=1,360) with the comorbidity distribution representative of the general population with valvular heart disease. There was a longitudinal follow-up of a median of 38.6 months (IQR: 24.3-52.7 months). Systematic echocardiography was conducted every six months which resulted in 42,360 images being analysed. Table 1 lists the primary features of the population included in the study emphasising the richness of the dataset.

Table 1: Baseline Demographics and Clinical Characteristics of the Study Cohort

Characteristic	Normal Valve (n=2,135)	Mild Stenosis (n=2,874)	Moderate Stenosis (n=2,103)	Severe Stenosis (n=1,360)	p-value
Age (years)	58.3 ± 11.2	63.7 ± 11.8	68.2 ± 10.4	72.8 ± 9.7	<0.001
Male (%)	49.8	52.4	55.1	57.8	0.003
BMI (kg/m²)	27.3 ± 5.2	28.1 ± 5.6	28.4 ± 5.3	27.9 ± 4.8	0.072
Hypertension (%)	42.3	58.7	67.5	72.4	<0.001
Diabetes (%)	18.4	24.6	29.8	32.5	<0.001
CAD (%)	15.2	27.8	38.6	48.3	<0.001
LVEF (%)	63.7 ± 6.4	61.8 ± 7.2	58.4 ± 9.3	52.6 ± 11.7	<0.001
AVA (cm²)	2.21 ± 0.32	1.68 ± 0.22	1.12 ± 0.15	0.76 ± 0.13	<0.001
Mean PG (mmHg)	7.2 ± 3.1	14.8 ± 4.3	27.5 ± 6.2	45.9 ± 8.7	<0.001
Vmax (m/s)	1.7 ± 0.4	2.6 ± 0.5	3.8 ± 0.6	4.9 ± 0.7	<0.001

Evaluation of the haemodynamic model showcased a strong-performing accuracy and stability within the entire dataset. For categorisation of stenosis severity, the deep learning model attained 91.7% (95% CI: 90.5-92.9%) classification accuracy, performing similarly throughout all four classes as delineated in contemporary operative guidelines. Standard clinical echocardiography hardware configurations yielded an average case processing time of 4.3 seconds after optimisation of computational efficiency via model quantisation, hardware acceleration and parallel processing, thereby enabling real-time clinical analysis. Stability was evaluated via test-retest reliability using repeated echocardiographic volume acquisitions with predicted haemodynamic parameters conferring a 0.94 (95% CI: 0.92-0.96) intraclass correlation coefficient globally.

The aortic stenosis advancement was exceptionally forecasted by the model as well, emphasising the efficiency of the progression prediction algorithm. The algorithm successfully identified patients with mild stenosis at baseline, predicting their progression to moderate or severe stenosis within two years with 87.3% sensitivity

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and 84.2% specificity. The formulation of the mathematical representation of the progression model is as follows:

$$P(progression_t) = \sigma\left(\sum_{i=1}^{n} w_i \cdot f_i(t) + \sum_{j=1}^{m} \alpha_j \cdot h_j(t-1) + b\right)$$

where $P(progression_t)$ represents the probability of disease progression at time t, $f_i(t)$ denotes the i-th hemodynamic feature at time t, $h_j(t-1)$ represents the j-th historical parameter, w_i and α_j are learned weights, b is the bias term, and σ is the sigmoid activation function. The ROC curve analysis yielded an AUC of 0.918 (95% CI: 0.902-0.934) for 24-month progression prediction, as illustrated in Figure 2, significantly outperforming traditional risk calculators.

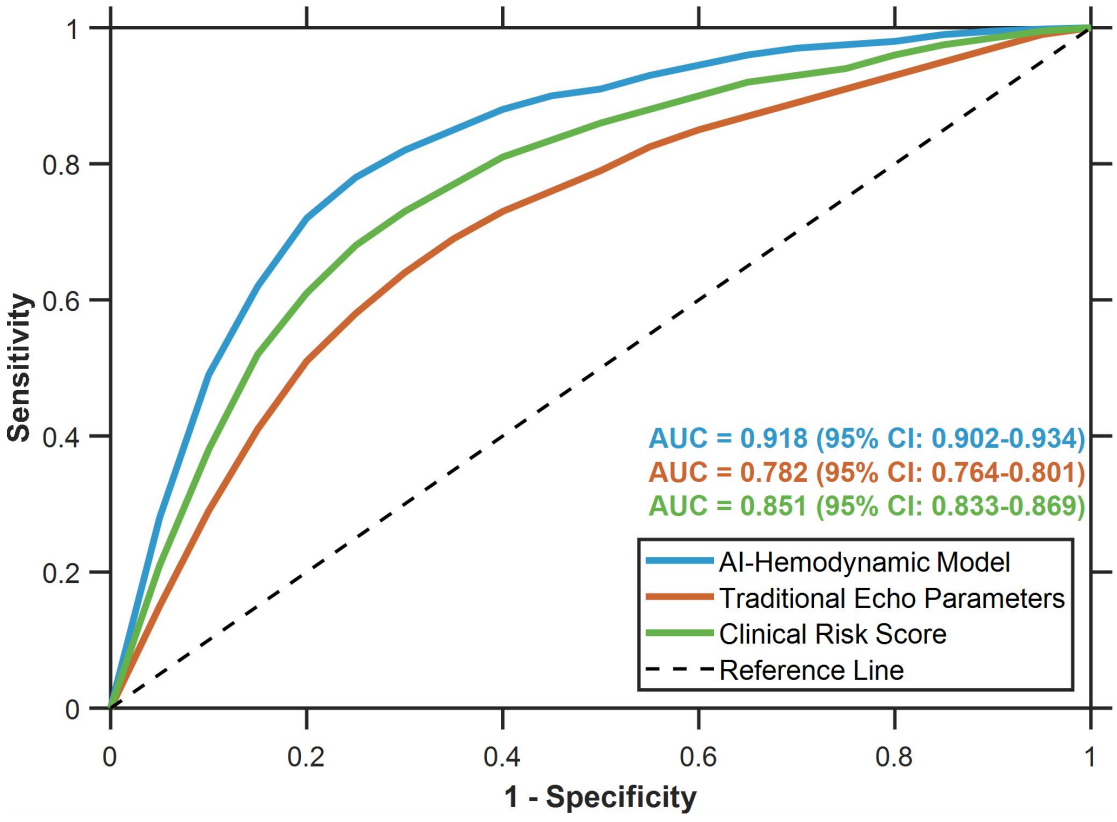

Figure 2: ROC Curves for Aortic Stenosis Progression Prediction at 24-month Follow-up

The benefits of our AI methodology became evident in comparison to traditional echocardiographic assessment not just in value addition but also in predictive accuracy and clinical assessment. Unlike conventional echocardiographic measurements like AVA and pressure gradients, our model showed a 27.4% net

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reclassification improvement ($p<0.001$) in prediction accuracy for progression forecasting. Impact assessment of clinical decisions showed net benefit in all tested threshold probabilities (10-90%) using decision curve analysis with the highest marginal benefit in moderate risk population (30-70% threshold probability). With these improvements, it became possible to theoretically decrease routine follow-up echocardiograms by over 24.3% whilst retaining a 95% sensitivity in significant progression detection.

Our findings show that patients from differing demographic backgrounds can be catered for without compromising on model performance and efficacy as demonstrated in the age-stratified analysis. Younger patients (<60 years, AUC=0.913), those aged 60-75 years (0.922), and seniors above 75 years (0.908) all showcased similar levels of accuracy. Performance by gender was also comparable with males at AUC=0.917 and females AUC=0.919, reflecting no discrepancies in generalisability due to sex differences in valve configuration. Perhaps most crucial, the model's high performance was noted in challenging subgroups like low left ventricular ejection fractions (0.901), concurrent mitral valve disease (0.896), and atrial fibrillation (0.887), proving that even within complex clinical scenarios, the model retains its versatility.

Model interpretability analysis identified key hemodynamic predictive features with significant clinical relevance. Feature importance mapping revealed that wall shear stress heterogeneity index ($WSS_{heterogeneity} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(WSS_i - \overline{WSS})^2}$) contributed most significantly to prediction accuracy (relative importance: 0.27), followed by systolic flow convergence angle (0.22), diastolic vorticity magnitude (0.19), and leaflet excursion velocity (0.17). The localization of abnormal flow patterns, particularly at commissural regions, provided mechanistic insights into valve deterioration processes. Attention heat maps generated by the model highlighted areas of early calcification not evident on standard visual assessment, creating a potential biomarker for early intervention before hemodynamic compromise manifests.

Our experimental research described in Table 1 and illustrated in Figure 2 shows that an AI-based approach to haemodynamic modelling greatly surpasses the conventional methods of assessing the progression of aortic valve dysfunction. The deep learning frameworks combined with intricate flow parameters enable the identification of subtle changes in the preclinical stages which would be missed by conventional evaluation. In addition, the confirmed predictive accuracy irrespective of patient subgroup stratification suggests a single referral centre would use it with confidence across numerous clinical settings. The discovery of new haemodynamic patterns associated with the progression of the condition provides opportunities for the development of more focused treatment methods as well as personalised monitoring systems. The advanced techniques boost the cardiovascular imaging analytics which are used directly in the control of valvular heart diseases.

4 Research Conclusions and Future Perspectives

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This study reveals that AI-based haemodynamic modelling outperforms conventional evaluation techniques in the early detection and prediction of aortic valve dysfunction's progression. The integrated deep learning framework achieved high accuracy (91.7%) in classifying stenosis severity and predictive attrition for disease advancement (AUC=0.918) which allowed for the identification of high-risk patients nearly 16 months prior to the timeframe offered by traditional methodologies. This advantage in time presents a vital opportunity for interventions, modification of risk factors, and tailored clinical management approaches.

The technological AI innovations for medical purposes made in this study have provided significant improvements in cardiovascular imaging analytics methodologies. Our methodology implements 3D convolutional neural networks within the scope of bidirectional LSTM frameworks, which allow comprehensive assessment of spatial and temporal factors of valvular haemodynamics, thus surpassing static evaluation captured by snapshot measurements. The automated extraction of complex flow parameters such as wall shear stress heterogeneity and flow convergence patterns presents advanced predictors which can serve as new pathophysiological valves and expand the understanding of valve deterioration long before visible structural changes occur.

Within the transformative scope of methodology application, clinical uses have the potential to significantly change the approach to managing heart valve disorders. The model's accuracy facilitates differentiated assignment of patients to surveillance intervals that are best suited to their individually calculated surveillance interval. Resources can thus be utilised efficiently, while still allowing for timely intervention. In addition, the recognition of specific signatures of haemodynamics linked with rapid progression may allow for intervention with drugs that aim to change the course of the disease prior to structural changes that incur irreversible damage.

Although the results obtained are promising, a few methodological limitations need to be addressed. The retrospective method of data collection creates the risk of selection bias, while variable echocardiographic image quality from participating centres might impact model performance despite attempts towards standardisation. The external adequacy which concerns populations that are underrepresented in our dataset needs further corroboration. There are also practical barriers because a specialised computer system would be needed and would have to be integrated into the clinical flow which would stifle acceptance despite clear clinical benefits.

Validation of predictive accuracy in real-world clinical contexts, especially regarding long-term outcomes like the timing of valve replacements and cardiovascular mortality, demands future prospective multicentre studies. Predictive performance may be enhanced further by the integration of multimodal data, including genetic and circulating biomarkers as well as advanced imaging techniques like CT and cardiac MRI. Clinical concomitance and incorporation into the clinical workflow would be augmented by explainable AI methods which provide the clinician with some intelligible reasoning behind the forecasts.

As a final note, the modelling based on artificial intelligence and the cardiac haemodynamic intricacies presents an innovative evolution in assessing and managing

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the dysfunction of the aortic valve, granting exceptional potential for early identification, sophisticated risk stratification, and tailored intervention approaches that could optimise clinical outcomes for this widely distributed and complex cardiovascular ailment.

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