

**DEVELOPMENT AND VALIDATION OF  
AUTOMATED MECHANICAL PROSTHETIC  
HEART VALVE DYSFUNCTION DETECTION  
USING CINE FLUOROSCOPY AND  
IOT-ENABLED PHONOCARDIOGRAPHY**

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by

**ANANDITA BHARDWAJ**

Centre for Biomedical Engineering

Submitted

in fulfillment of the requirements of the degree of Doctor of Philosophy

to the



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*Dedicated to my beloved family, Col D N Sharma, Mrs. Anju Sharma, and Ms. Madhulika Bhardwaj, without whom this dissertation wouldn't have been possible.*

# Declaration of Published Chapters

I, Anandita Bhardwaj, hereby declare that the contents of the following chapters in this thesis have been published in the following respective journals. The published content has been included in the thesis according to the chronology given below.

## Published Chapters

### 1. Chapter 2: Introduction

- Contains information derived in parts from the published works referenced in chapters 4, 5, and 6.

### 2. Chapter 3: Literature Review

- Contains information derived in parts from the published works referenced in chapters 4, 5, and 6.

### 3. Chapter 4: Cine Fluoroscopy-based Mechanical Prosthetic Heart Valve Dysfunction Detection

- **Revision: A. Bhardwaj**, S. Singh, D. Joshi, “Physiological Knowledge-based Automated Localization of Mechanical Prosthetic Heart Valve in Cine Fluoroscopy Videos: A pilot study”, **Measurement Journal**.
- **Under review: A. Bhardwaj**, S. Singh, D. Joshi, “A Lightweight and Interpretable Deep Learning Framework for Automated Detection of Mechanical Prosthetic Heart Valve Dysfunction using Cine Fluoroscopy Imaging”, **Biomedical Signal Processing and Control Journal**.

### 4. Chapter 5: Phonocardiography-based Native and Mechanical Prosthetic Heart Valve Dysfunction Detection

- **Published as: A. Bhardwaj**, S. Singh and D. Joshi, ”Explainable Deep Convolutional Neural Network for Valvular Heart Diseases Classification Using PCG Signals,” in **IEEE Transactions on Instrumentation and Measurement**, vol. 72, pp. 1-15, 2023, Art no. 2514215, doi: 10.1109/TIM.2023.3274174.
- **Published as: A. Bhardwaj**, S. Singh and D. Joshi, ”Phonocardiography-Based Automated Detection of Prosthetic Heart Valve Dysfunction Using Persistence Spectrum and Interpretable Deep CNN,” in **IEEE Sensors Journal**, vol. 25, no. 4, pp. 6869-6880, 15 Feb.15, 2025, doi:

10.1109/JSEN.2024.3523393.

5. **Chapter 6: Deployment of Phonocardiography-based Mechanical Prosthetic Heart Valve Dysfunction Detection Model**

- **Under review:** A. Bhardwaj, S. Singh, D. Joshi, “Development and Validation of an IoT-enabled PCG Sensing Framework for the Deployment of Mechanical Prosthetic Heart Valve Dysfunction Detection Model: A Lab-to- Hospital Case Study”, **IEEE Embedded Systems Letters**.

6. **Chapter 7: Summary and Conclusion**

- Contains information derived in parts from the published works referenced in chapters 4, 5, and 6.

7. **Chapter 8: Limitations and Future Scope**

- Contains information derived in parts from the published works referenced in chapters 4, 5, and 6.

I certify that the above declaration is accurate and that I have adhered to applicable institutional and copyright policies in the preparation of this thesis.

Date:

Anandita Bhardwaj

# Certificate

This is to certify that the thesis entitled “**Development and Validation of Automated Mechanical Prosthetic Heart Valve Dysfunction Detection using Cine Fluoroscopy and IoT-Enabled Phonocardiography**”, submitted by **Anandita Bhardwaj** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** in Biomedical Engineering, is a record of the original, bona fide research work carried out by her under my supervision and guidance. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma to the best of my knowledge.

**Prof. Deepak Joshi**

Centre for Biomedical Engineering,  
Indian Institute of Technology Delhi.

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Anandita Bhardwaj

# Abstract

**Objective:** Cine fluoroscopy (CF)-based routine checkup is the established method for mechanical prosthetic heart valve (MPHV) assessment to detect a condition called prosthetic valve dysfunction (PVD), which is a serious complication of valve replacement surgery (VRS). The current clinical practices involve extensive manual interventions for MPHV assessment, which are likely to suffer from intra and inter-observer variability. In addition, given the clinical burden, there is a need for automating CF-based PVD detection and making it deployable. MPHV localization in CF is a crucial pre-requisite for its automated assessment. Since CF involves Xray exposure and may not be available to a large population, a wearable modality like phonocardiography (PCG) seems to be a promising alternative. Despite the state-of-the-art performance of PCG-based methods, they are not deployable in clinical settings for early detection, which is crucial for improved survivability and patient management. **Problem statement:** To the best of the knowledge, PVD detection has not been automated yet and it is still carried out manually by the clinicians. The proposed work aims to automate CF and PCG-based PVD detection and then deploy the PCG-based PVD detection scheme in clinical settings. **Methodology:** CF-based PVD detection involves automated MPHV localization followed by PVD detection of CF videos. 38 participants with MPHV implant (20 functional MPHV and 18 PVD) were recruited and their CF was recorded. For automated localization, a novel, knowledge-based, physiologically constrained, method was developed. The key physiological knowledges utilized for the measurement of spatiotemporal prior were: difference in the radio-opacity of MPHV and native tissues in the tho-

racic region enables edge-detection-based spatial saliency determination. Second, MPHV, being implanted inside the heart is subjected to cardiac motion, which is temporally salient with respect to other objects in the thoracic region. For the automated CF-based PVD detection, a novel lightweight 3D convolutional neural network (CNN) framework was explored to perform binary classification (normal vs abnormal) of MPHV functioning and the results were compared with three existing lightweight 3D-CNN frameworks. The first and second frameworks accepted single input volumes, unprocessed CF and CF with localized MPHV respectively. Framework 3 accepted both the inputs, concatenated channel-by-channel. A novel multi-input fusion scheme was proposed (framework 4), which performed weighted-addition of the two inputs without increasing its dimension. The novelty of the framework is that the input weights are tuned during training. The frameworks were trained and tested on a dataset of 1150 CF samples (544 normal, 606 abnormal) and were made interpretable using gradient attribution maps. A customized and extended method was developed to obtain gradient attribution maps for novel framework. For the automated PCG-based classification of valvular heart diseases (VHD, pre-VRS), analytic continuous wavelet transform (CWT) scalograms were utilized as the time–frequency representations (TFRs) of the PCG signals. A 2-D CNN was designed for the multiclass classification (aortic stenosis, mitral regurgitation, mitral stenosis, mitral valve prolapse, and normal) of PCG signal’s TFR. For the automated PCG-based PVD detection, a 2-D CNN was explored towards the automated classification of persistence spectrum images of the PCG. Persistence spectrum, a TFR, displays the duration for which a particular frequency is present. It enables the identification of the hidden components of a signal. This

work explored persistence spectrum for PCG analysis. In all, 4215 PCG samples (2127 normal and 2088 PVD) were used for training and testing the CNN. Two AI interpretation techniques, occlusion maps and deep dream images, were used to introduce interpretability in the DL models' decision-making for both, VHD classification (pre-VRS) and PVD detection (post-VRS). The proposed work also aims to develop an internet of medical things (IoMT)-based automated PVD detection method for deployment in clinical settings. A standalone container was developed for carrying out PVD detection, which was then pushed to a virtual machine (VM). The VM, being a portable and interoperable system, was deployed on a server. An electronic stethoscope, for the collection of PCG, was connected to a smartphone, which was then used to stream the PCG data to the VM. **Results:** The proposed localization task generated an average precision (AP) of 97.87(5.38)%. MPHV was accurately detected in all the frames of all 38 CF videos. Wilcoxon rank sum test ( $\alpha=0.05$ ), performed on AP for PVD and functional-MPHV, generated the p-value, 0.8358, indicating that the proposed localization framework's performance was not affected by MPHV functioning. For the automated CF-based PVD detection, proposed framework 4 outperformed other frameworks with an overall accuracy of mean(SD)=97.34(5.89)% obtained during fivefold cross-validation (CV). Gradient attribution maps provided class-specific spatial features making the frameworks interpretable. The 3D-CNN in framework 4 "looked at" MPHV leaflets for the detection of abnormal class. For the automated PCG-based VHD classification, the highest accuracy achieved during fivefold CV was 99.6%, and the overall accuracy was 98.32(1.02)% for a publicly available PCG database. The overall accuracy of the proposed method for binary classification tested on the PhysioNet

database was 93.07%. For the automated PCG-based PVD detection, the overall accuracy of 95.73(7.62)% was achieved during fivefold CV with the highest accuracy of 100% for three folds. Through AI interpretation, novel findings of native valve and MPHV's PCG characteristics in the spectral domain, corresponding to cardiac events were revealed, making the CNN decision transparent. The IoMT pipeline was successfully deployed and tested in clinical settings, generating correct classifications in a time-efficient manner (processing time=13.80(0.72)seconds, and communication time=6.99(0.80)seconds). **Significance:** The novel localization framework achieves state-of-the-art performance even in the presence of other non-biological objects. Automation is achieved for MPHV localization in CF frames. Clinical translation of the state-of-the-art interpretable and lightweight automated CF-based PVD detection framework has the potential to address the clinical burden imposed by PVD and address the inter and intra observer variability. The novel explainable PCG-based DL model potentially addresses PVD-induced clinical burden in resource-constrained settings with no radiation exposure and can be used for screening. Finally, the proposed IoMT framework for the deployment of PCG-based PVD detection is made scalable, interoperable and portable using commonly available gadgets like smartphones and PC. This ensures prevention of post-deployment failures in clinical settings.

## सार

**उद्देश्य:** सिने फ्लोरोस्कोपी (सीएफ) आधारित नियमित जांच मैकेनिकल प्रोस्थेटिक हार्ट वाल्व (एमपीएचवी) आकलन के लिए स्थापित विधि है, जो प्रोस्थेटिक वाल्व डिसफंक्शन (पीवीडी) नामक स्थिति का पता लगाने के लिए है, जो वाल्व रिप्लेसमेंट सर्जरी (वीआरएस) की एक गंभीर जटिलता है। वर्तमान नैदानिक प्रथाओं में एमपीएचवी आकलन के लिए व्यापक मैनुअल हस्तक्षेप शामिल हैं, जो इंटर और इंटर-ऑब्जर्वर परिवर्तनशीलता से ग्रस्त होने की संभावना है। इसके अलावा, नैदानिक बोझ को देखते हुए, सीएफ-आधारित पीवीडी का पता लगाने को स्वचालित करने और इसे लागू करने की आवश्यकता है। सीएफ में एमपीएचवी स्थानीयकरण इसके स्वचालित मूल्यांकन के लिए एक महत्वपूर्ण शर्त है। चूंकि सीएफ में एक्सरे एक्सपोजर शामिल है और यह बड़ी आबादी के लिए उपलब्ध नहीं हो सकता है, इसलिए फोनोकार्डियोग्राफी (पीसीजी) जैसी पहनने योग्य पद्धति एक आशाजनक विकल्प प्रतीत होती है। **समस्या विवरण:** जहाँ तक हमारी जानकारी है, PVD का पता लगाना अभी तक स्वचालित नहीं हुआ है और यह अभी भी चिकित्सकों द्वारा मैनुअल रूप से किया जाता है। प्रस्तावित कार्य का उद्देश्य CF और PCG-आधारित PVD का पता लगाना और फिर PCG-आधारित PVD का पता लगाने की योजना को नैदानिक स्थितियों में लागू करना है। **कार्यप्रणाली:** CF-आधारित PVD जांच में

CF वीडियो के PVD जांच के बाद MPHV का स्वचालित स्थानीयकरण शामिल है। MPHV प्रत्यारोपण (20 कार्यात्मक MPHV और 18 PVD) वाले 38 प्रतिभागियों को भर्ती किया गया और उनका CF रिकॉर्ड किया गया। स्वचालित स्थानीयकरण के लिए, एक नया, ज्ञान-आधारित, शारीरिक रूप से विवश, तरीका विकसित किया गया था। स्थानिक-कालिक पूर्व के मापन के लिए उपयोग किए जाने वाले प्रमुख शारीरिक ज्ञान थे: वक्षीय क्षेत्र में MPHV और मूल ऊतकों की रेडियो-अपारदर्शिता में अंतर किनारे-पता लगाने के आधार पर स्थानिक प्रमुखता निर्धारण को सक्षम बनाता है। दूसरा, हृदय के अंदर प्रत्यारोपित होने के कारण MPHV हृदय की गति के अधीन होता है, जो वक्षीय क्षेत्र में अन्य वस्तुओं के संबंध में अस्थायी रूप से प्रमुख होता है पहले और दूसरे फ्रेमवर्क ने क्रमशः एकल इनपुट वॉल्यूम, अप्रसंस्कृत CF और स्थानीयकृत MPHV के साथ CF को स्वीकार किया। फ्रेमवर्क 3 ने दोनों इनपुट को स्वीकार किया, चैनल-दर-चैनल संयोजित किया। एक नवीन बहु-इनपुट फ़्यूजन योजना प्रस्तावित की गई (फ्रेमवर्क 4), जिसने इसके आयाम को बढ़ाए बिना दो इनपुट का भारित-जोड़ किया। फ्रेमवर्क की नवीनता यह है कि प्रशिक्षण के दौरान इनपुट भार को ट्यून किया जाता है। फ्रेमवर्क को 1150 CF नमूनों (544 सामान्य, 606 असामान्य) के डेटासेट पर प्रशिक्षित और परीक्षण किया गया और उन्हें ग्रेडिएंट एट्रिब्यूशन मैप्स का उपयोग करके व्याख्या योग्य बनाया गया। नवीन

फ्रेमवर्क के लिए ग्रेडिएंट एट्रिब्यूशन मैप्स प्राप्त करने हेतु एक अनुकूलित और विस्तारित विधि विकसित की गई। पीसीजी सिग्नल के टीएफआर के मल्टीक्लास वर्गीकरण (महाधमनी स्टेनोसिस, मिट्रल रेगुर्गिटेशन, मिट्रल स्टेनोसिस, मिट्रल वाल्व प्रोलैप्स और सामान्य) के लिए 2-डी सीएनएन डिजाइन किया गया था। स्वचालित पीसीजी-आधारित पीवीडी का पता लगाने के लिए, पीसीजी की दृढ़ता स्पेक्ट्रम छवियों के स्वचालित वर्गीकरण की दिशा में 2-डी सीएनएन की खोज की गई थी। दृढ़ता स्पेक्ट्रम, एक टीएफआर, उस अवधि को प्रदर्शित करता है जिसके लिए एक विशेष आवृत्ति मौजूद है। यह एक सिग्नल के छिपे हुए घटकों की पहचान करने में सक्षम बनाता है। इस काम ने पीसीजी विश्लेषण के लिए दृढ़ता स्पेक्ट्रम की खोज की। कुल मिलाकर, 4215 पीसीजी नमूने (2127 सामान्य और 2088 पीवीडी) का उपयोग सीएनएन के प्रशिक्षण और परीक्षण के लिए किया गया था प्रस्तावित कार्य का उद्देश्य नैदानिक स्थितियों में उपयोग के लिए इंटरनेट ऑफ मेडिकल थिंग्स (IoMT)-आधारित स्वचालित PVD पहचान विधि विकसित करना भी है। PVD पहचान के लिए एक स्टैंडअलोन कंटेनर विकसित किया गया, जिसे फिर एक वर्चुअल मशीन (VM) में डाला गया। VM, एक पोर्टेबल और इंटरऑपरेबल सिस्टम होने के कारण, एक सर्वर पर तैनात किया गया था। PCG संग्रह के लिए एक इलेक्ट्रॉनिक स्टेथोस्कोप को एक स्मार्टफोन से जोड़ा गया था, जिसका उपयोग PCG डेटा को VM में स्ट्रीम करने के

लिए किया गया था। **परिणाम:** प्रस्तावित स्थानीयकरण कार्य ने  $97.87 \pm 5.38\%$  की औसत परिशुद्धता (AP) उत्पन्न की। सभी 38 CF वीडियो के सभी फ्रेमों में MPHV का सटीक रूप से पता लगाया गया। इसके अलावा, MPHV स्थिति (PVD या कार्यात्मक) का प्रदर्शन पर कोई प्रभाव नहीं पड़ा। PVD और कार्यात्मक-MPHV के लिए AP पर किए गए विल्कोक्सन रैंक योग परीक्षण (अल्फा=0.05) ने p-मान, 0.8358 उत्पन्न किया। स्वचालित CF-आधारित PVD पहचान के लिए, प्रस्तावित ढाँचे 4 ने पाँच गुना क्रॉस-वैलिडेशन (CV) के दौरान प्राप्त औसत (SD)= $97.34(5.89)\%$  की समग्र परिशुद्धता के साथ अन्य ढाँचों से बेहतर प्रदर्शन किया। ग्रेडिएंट एट्रिब्यूशन मानचित्रों ने वर्ग-विशिष्ट स्थानिक विशेषताएँ प्रदान कीं जिससे ढाँचे व्याख्या योग्य हो गए। ढाँचे 4 में 3D-CNN ने असामान्य वर्ग का पता लगाने के लिए MPHV पत्रकों को "देखा"। स्वचालित पीसीजी-आधारित वीएचडी वर्गीकरण के लिए, पाँच गुना सीवी के दौरान हासिल की गई उच्चतम सटीकता 99.6% थी, और सार्वजनिक रूप से उपलब्ध पीसीजी डेटाबेस के लिए समग्र सटीकता 98.32% थी। फिजियोनेट डेटाबेस पर परीक्षण किए गए बाइनरी वर्गीकरण के लिए प्रस्तावित विधि की सटीकता 93.07% थी। स्वचालित पीसीजी-आधारित पीवीडी डिटेक्शन के लिए, तीन गुना के लिए 100% की उच्चतम सटीकता के साथ पाँच गुना सीवी के दौरान 95.73 (एसडी = 7.62)% की समग्र सटीकता

हासिल की गई थी। एआई व्याख्या के माध्यम से, हृदय संबंधी घटनाओं के अनुरूप स्पेक्ट्रल डोमेन में मूल वाल्व और एमपीएचवी की पीसीजी विशेषताओं के उपन्यास निष्कर्ष सामने आए, जिससे सीएनएन निर्णय पारदर्शी हो गया। IoMT पाइपलाइन को नैदानिक सेटिंग्स में सफलतापूर्वक तैनात और परीक्षण किया गया। **महत्व:** नवीन स्थानीयकरण ढाँचा अन्य गैर-जैविक वस्तुओं की उपस्थिति में भी अत्याधुनिक प्रदर्शन प्राप्त करता है। सीएफ फ्रेम में एमपीएचवी स्थानीयकरण के लिए स्वचालन प्राप्त किया जाता है। अत्याधुनिक व्याख्या योग्य और हल्के स्वचालित सीएफ-आधारित पीवीडी पहचान ढाँचे के नैदानिक अनुवाद में पीवीडी द्वारा लगाए गए नैदानिक भार को कम करने और अंतर-पर्यवेक्षक परिवर्तनशीलता को संबोधित करने की क्षमता है। नवीन व्याख्या योग्य पीसीजी-आधारित डीएल मॉडल बिना किसी विकिरण जोखिम के संसाधन-विवश सेटिंग्स में पीवीडी-प्रेरित नैदानिक भार को संभावित रूप से संबोधित करता है और इसका उपयोग स्क्रीनिंग के लिए किया जा सकता है। अंत में, पीसीजी-आधारित पीवीडी पहचान की तैनाती के लिए प्रस्तावित आईओएमटी ढाँचे को स्मार्टफोन और पीसी जैसे सामान्य रूप से उपलब्ध गैजेट्स का उपयोग करके स्केलेबल, इंटरऑपरेबल और पोर्टेबल बनाया गया है। यह नैदानिक सेटिंग्स में तैनाती के बाद की विफलताओं की रोकथाम सुनिश्चित करता है।

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# List of Abbreviations

ALARA	As low as reasonably achievable
AP	Average precision
A-PV	Aortic prosthetic valve
AS	Aortic stenosis
AV	Aortic valve
Bi-LSTM	Bidirectional long short-term memory
CF	Cine fluoroscopy
CNN	Convolutional neural network
CT	Computed tomography
CV	Cross validation
CWT	Continuous wavelet transform
DFT	Discrete Fourier Transform
DICOM	Digital imaging and communication in medicine
DL	Deep learning
DWT	Discrete wavelet transform
FFT	Fast Fourier Transform
FN	False negative
FOD	First order derivative
FP	False positive
FPS	Frames per second
IoMT	Internet of medical things

IoT	Internet of things
IoU	Intersection over union
LOSOVC	Leave one subject out cross validation
MFCC	Mel-frequency cepstral coefficients
MPHV	Mechanical prosthetic heart valve
M-PV	Mitral prosthetic valve
MR	Mitral regurgitation
MRI	Magnetic resonance imaging
MS	Mitral stenosis
MV	Mitral valve
MVP	Mitral valve prolapse
NIFTI	Neuroimaging Informatics Technology Initiative
NYHA	New York Heart Association
OPD	Out-patient department
OS	Operating system
PCG	Phonocardiography
PCK	Percentage of correct key points
PNG	Portable network graphics
PV	Prosthetic valve
PVD	Prosthetic valve dysfunction
PVT	Prosthetic valve thrombosis
ReLu	Rectified linear unit

RGB	Red green blue
RNN	Recurrent neural network
ROI	Region of interest
SD	Standard deviation
SHAP	Shapley additive explanations
SNR	Signal to noise ratio
TEE	Trans-esophageal echocardiography
TF	Time-frequency
TFR	Time-frequency representation
TN	True negative
TP	True positive
TTE	Transthoracic echocardiography
VHD	Valvular heart diseases
VM	Virtual machine
VRS	Valve replacement surgery