

**MULTISCALE ANALYSIS-DRIVEN HIGHER  
ORDER TENSOR-BASED MACHINE  
LEARNING APPROACHES FOR AUTOMATED  
DETECTION OF CARDIAC AILMENTS USING  
12-LEAD ECG SIGNALS**

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**BHARTI SCHOOL OF TELECOMMUNICATION  
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INDIAN INSTITUTE OF TECHNOLOGY – DELHI  
INDIA**

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by

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**BHARTI SCHOOL OF TELECOMMUNICATION  
TECHNOLOGY AND MANAGEMENT**

Submitted

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

to the



**INDIAN INSTITUTE OF TECHNOLOGY – DELHI  
INDIA**

**September 2023**

*Dedicated to*

*My Parents*

*and*

*my brother*

*(Late Dr. Pawan Bharti Chauhan)*

# Certificate

This is to certify that the thesis entitled “**Multiscale Analysis-Driven Higher Order Tensor-Based Machine Learning Approaches for Automated Detection of Cardiac Ailments Using 12-Lead ECG Signals**” being submitted by **Mr. Chhaviraj Chauhan (aka Chhavi Kumar Bharti)** to the Bharti School of Telecommunication Technology and Management, Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** is the record of the bona-fide research work carried out by him under my supervision. In my opinion, the thesis has reached the standards fulfilling the requirements of the regulations relating to the degree.

The results contained in this thesis have not been submitted either in part or in full to any other university or institute for the award of any degree or diploma.

(Prof. Monika Aggarwal)

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# Abstract

Cardiovascular diseases (CVDs) are the leading cause of high mortality rates in India due to unhealthy lifestyles and lack of daily exercise. The continuous recording and monitoring of 12-lead ECG data are highly required for the diagnosis of CVDs. A huge volume of data is produced during the continuous recording of 12-lead ECG data from the subject for arrhythmia monitoring in the intensive care unit (ICU). Therefore, efficient methods for automated analysis of the huge volume of 12-lead ECG data are required for the accurate detection of CVDs. This thesis work documents the development of tensor domain machine learning approaches for automated detection of different CVDs using longer duration 12-ECG recordings.

There are five major contributions. The first contribution is the multi-lead fusion (MLF) algorithm for accurately detecting the QRS complex. The QRS complex is dominant in the cardiac cycle or beat. Hence detection of the QRS complex is the first step in automated ECG signal analysis algorithms. The second contribution proposes a third-order tensor-based cardiac disease detection method. The 12-lead ECG beats are decomposed into modes by multivariate projection-based fixed boundary empirical wavelet transform (MPFBEWT). The 3D tensor formed contains the information of lead, modes and samples. This 3D tensor is fed to a deep Convolutional neural network (CNN) to classify various classes of cardiac diseases. This 3D tensor contains the information of a beat only. For the patient-specific model, where complete patient information can be processed, a higher-order tensor is required. The third contribution proposes a patient-specific fourth-order tensor-based approach for the detection of Myocardial Infarction (MI). A fast and adaptive multivariate empirical mode decomposition (FA-MVEMD) is used to decompose the 12-lead ECG data into the modes. A 4D

tensor containing the information of lead, beat, mode and sample has been formulated. The tensor domain feature extracted after multi-linear singular value decomposition (MLSVD) is further classified by the KNN, SVM and stacked autoencoder-based deep neural network (SAE-DNN). The proposed 4D tensor-based approach shows improved performance over the existing method for MI detection. The fourth contribution of this thesis proposes a fifth-order tensor base bundle branch block detection method using multivariate fast-iterative filtering (MVFIF) decomposition method, continuous wavelet transform (CWT) and Bi-LSTM based classifier. The fifth-order tensor contains the information of the lead, beat, mode, frequency and sample. The fifth and final contribution of this thesis proposes a projection-based multivariate empirical Fourier decomposition (PMVEFD) technique for the decomposition of non-stationary multi-channel signals. The Proposed PMVEFD technique is used to detect atrial fibrillation (AF) in 12-lead ECG signals. The chirplet transform (CT) is used for the time-frequency-phase (TFP) analysis. A sixth-order tensor containing the information of the lead, beat, mode, frequency, phase and sample is formulated. The tensor domain features extracted after MLSVD are classified by the ensemble learning-based classifier into healthy and AF patients.

In summary, the primary objective of this thesis is to propose an accurate framework for cardiac abnormalities detection in 12-lead ECG using higher-order tensor-based machine learning and signal processing techniques. This tensor-based method enables the implementation of a patient-specific framework in which multiple signal-processing techniques can be used to extract the maximal amount of information from a 12-lead ECG recording of a patient. The framework based on higher-order tensors proposed in this thesis may be applied to other non-stationary multichannel data.

## संक्षेप

कार्डियोवैस्कुलर रोग (सीवीडी) भारत में अस्वस्थ जीवनशैली और दिन-प्रतिदिन की व्यायाम की कमी के कारण उच्च मृत्यु दरों का प्रमुख कारण हैं। 12-लीड ईसीजी डेटा के नियंत्रण और मॉनिटरिंग का निरंतर रिकॉर्डिंग करना सीवीडी के निदान के लिए अत्यंत आवश्यक है। गहरे देखभाल इकाई (आईसीयू) में अरिथ्मिया मॉनिटरिंग के लिए प्रक्षिप्त होने वाले 12-लीड ईसीजी डेटा के नियंत्रण के दौरान बड़ी मात्रा में डेटा उत्पन्न होता है। इसलिए, सीवीडी के सटीक पता लगाने के लिए 12-लीड ईसीजी डेटा की विस्तृत विश्लेषण के लिए कुशल विधियाँ आवश्यक हैं। इस थीसिस काम में लॉग ड्यूरेशन 12-ईसीजी रिकॉर्डिंग का स्वचालित सीवीडी डिटेक्शन के लिए टेंसर डोमेन मशीन लर्निंग दृष्टिकोण के विकास को दर्ज किया गया है।

पांच प्रमुख योगदान हैं. क्यूआरएस कॉम्प्लेक्स का सटीक पता लगाने के लिए पहला योगदान मल्टी-लीड फ़्यूजन (एमएलएफ) एल्गोरिदम है। क्यूआरएस कॉम्प्लेक्स हृदय चक्र या धड़कन में प्रमुख है। इसलिए क्यूआरएस कॉम्प्लेक्स का पता लगाना स्वचालित ईसीजी सिग्नल विश्लेषण एल्गोरिदम में पहला कदम है। दूसरा योगदान तीसरे क्रम के टेंसर-आधारित हृदय रोग का पता लगाने की विधि का प्रस्ताव करता है। 12-लीड ईसीजी बीट्स को बहुभिन्नरूपी प्रक्षेपण-आधारित निश्चित सीमा अनुभवजन्य तरंगिका परिवर्तन (एमपीएफबीईडब्ल्यूटी) द्वारा मोड में विघटित किया जाता है। गठित 3डी टेंसर में लीड, मोड और नमूनों की जानकारी शामिल है। हृदय रोगों के विभिन्न वर्गों को वर्गीकृत करने के लिए इस 3डी टेंसर को एक गहरे कन्वोल्यूशनल न्यूरल नेटवर्क (सीएनएन) में फीड किया जाता है। इस 3डी टेंसर में केवल एक बीट की जानकारी होती है। रोगी-विशिष्ट मॉडल के लिए, जहां संपूर्ण रोगी जानकारी संसाधित की जा सकती है, एक उच्च-क्रम वाले टेंसर की आवश्यकता होती है। तीसरा योगदान मायोकार्डियल इन्फ्रक्शन (एमआई) का पता लगाने के लिए रोगी-विशिष्ट चौथे-क्रम टेंसर-आधारित दृष्टिकोण का प्रस्ताव करता है। 12-लीड ईसीजी डेटा को मोड में विघटित करने के लिए एक तेज़ और अनुकूली बहुभिन्नरूपी अनुभवजन्य मोड अपघटन (एफए-एमवीईएमडी) का उपयोग किया जाता है। लीड, बीट, मोड और सैंपल की जानकारी वाला एक 4डी टेंसर तैयार किया गया है। मल्टी-लीनियर सिंगुलर वैल्यू डिकंपोजिशन (एमएलएसवीडी) के बाद निकाले गए टेंसर डोमेन फीचर को केएनएन, एसवीएम और स्टैकड ऑटोएनकोडर-आधारित डीप न्यूरल नेटवर्क (एसएई-डीएनएन) द्वारा वर्गीकृत किया गया है। प्रस्तावित 4डी टेंसर-आधारित दृष्टिकोण एमआई का पता लगाने के लिए मौजूदा पद्धति की तुलना में बेहतर प्रदर्शन दिखाता है। इस थीसिस का चौथा योगदान मल्टीवेरिएट फास्ट-इंटरैक्टिव फिल्टरिंग (एमवीएफआईएफ) अपघटन विधि, निरंतर वेवलेट ट्रांसफॉर्म (सीडब्ल्यूटी) और बीआई-एलएसटीएम आधारित क्लासिफायरियर का उपयोग करके पांचवें क्रम के टेंसर बेस बंडल शाखा ब्लॉक डिटेक्शन विधि का प्रस्ताव करता है। पांचवें क्रम के टेंसर में लीड, बीट, मोड, फ्रीक्वेंसी और सैंपल की जानकारी होती है। इस थीसिस का पांचवां और अंतिम योगदान गैर-स्थिर मल्टी-चैनल संकेतों के अपघटन के लिए एक प्रक्षेपण-आधारित बहुभिन्नरूपी अनुभवजन्य फूरियर अपघटन (पीएमवीईएफडी) तकनीक का प्रस्ताव करता है। प्रस्तावित पीएमवीईएफडी तकनीक का उपयोग 12-लीड ईसीजी सिग्नलों में एट्रियल फाइब्रिलेशन (एएफ) का पता लगाने के लिए किया जाता है। चिरप्लेट ट्रांसफॉर्म (सीटी) का उपयोग समय-आवृत्ति-चरण (टीएफपी) विश्लेषण के लिए किया जाता है। लीड, बीट, मोड, फ्रीक्वेंसी, चरण और नमूने की जानकारी वाला एक छठा क्रम वाला टेंसर तैयार किया जाता है। एमएलएसवीडी के बाद निकाले गए टेंसर डोमेन फीचर्स को एन्सेम्बल लर्निंग-आधारित क्लासिफायर द्वारा स्वस्थ और एएफ रोगियों में वर्गीकृत किया गया है।

संक्षेप में, इस थीसिस का प्राथमिक उद्देश्य उच्च-क्रम टेंसर-आधारित मशीन लर्निंग और सिग्नल प्रोसेसिंग तकनीकों का उपयोग करके 12-लीड ईसीजी में हृदय संबंधी असामान्यताओं का पता लगाने के लिए एक सटीक रूपरेखा का प्रस्ताव करना है। यह टेंसर-आधारित विधि एक रोगी-विशिष्ट ढांचे के कार्यान्वयन को सक्षम बनाती है जिसमें एक रोगी की 12-लीड ईसीजी रिकॉर्डिंग से अधिकतम मात्रा में जानकारी निकालने के लिए कई सिग्नल-प्रोसेसिंग तकनीकों का उपयोग किया जा सकता है। इस थीसिस में प्रस्तावित उच्च-क्रम टेंसर पर आधारित रूपरेखा को अन्य गैर-स्थिर मल्टीचैनल डेटा पर लागू किया जा सकता है।

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# Abbreviations

Acc	Accuracy (or Classification Accuracy)
AF	Atrial Fibrillation
BBB	Bundle Branch Block
BN	Batch Normalization
CNN	Convolutional Neural Network
CSE	Common Standards for Electrocardiography
CT	Chirplet Transform
CV	Cross Validation
CVDS	Cardiovascular diseases
CWT	Continuous Wavelet Transform
DWT	Discreate Wavelet Transform
ECG	Electrocardiogram
EMD	Empirical Mode Decompostion
EWT	Empirical Wavelet Transform
FDM	Fourier Decomposition Methods
FIBFs	Fourier Intrinsic Band Functions
FIF	Fast Iterative Filtering
FFT	Fast Fourier Transform
GRU	Gated Recurrent Unit
HC	Healthy Control
HMD	Heart Muscle Disease
HPF	High Pass Filter
HT	Hilbert Transform

HTL	High-to-low
IMF	Intrinsic Mode Function
KNN	K-Nearest Neighbour
LBBB	Left Bundle Branch Block
LPF	Low Pass Filter
LOO	Leave One Out
LSTM	Long Short-term Memory
LTH	Low-to-high
MI	Myocardial Infarction
MLF	Multi-lead Fusion
MLP	Multi-layer Perception
MLSVD	Multi-linear Singular Value Decomposition
MPFBEWT	Multivariate Projection based Fixed Boundary Empirical Wavelet Transform
MVFIF	Multivariate Fast Iterative Filtering
ODC	Optimum Direction Cosine
OSF	Order Static Filter
PMVEFD	Projection-based Multivariate Empirical Fourier Decomposition
RBBB	Right Bundle Branch Block
ReLU	Rectified Linear Unit
ResNet	Residual Neural Network
RNN	Recurrent Neural Network
Se	Sensitivity
Sp	Specificity
SA	Sinoatrial
SAE	Stacked Autoencoder
SAE-DNN	Stacked Autoencoder based Deep Neural Network
SGDM	Stochastic Gradient Descent with Momentum
SVD	Singular Value Decomposition
SVM	Support Vector Machine
TF	Time-Frequency

TFP	Time-Frequency-Phase
VMD	Variational mode decomposition
WHO	World Health Organization
WVD	Wigner-Ville distribution
ZPFB	Zero Phase Filter Bank