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**DEVICE-FREE DETECTION OF HUMAN  
MOVEMENT IN OUTDOOR ENVIRONMENTS  
USING WI-FI CHANNEL STATE INFORMATION**

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Sri Lanka

May 2025



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## DECLARATION

I declare that this is my own work and this Thesis does not incorporate without acknowledgement any material previously submitted for a Degree or Diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Date: 29/07/2025

The supervisors should certify the Thesis with the following declaration.

The above candidate has carried out research for the Master of Science (Major Component Research) Thesis under our supervision. We confirm that the declaration made above by the student is true and correct.

Name of Supervisor: Prof. S A D Dias

Signature of the Supervisor:

Date: 29/07/2025

Name of Supervisor: Dr. K T Hemachandra

Signature of the Supervisor:

Date: 30/07/2025



## **DEDICATION**

To my beloved parents.



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## ABSTRACT

Real-time pedestrian sensing at crossings is essential for Intelligent Transportation Systems (ITS). World Health Organization (WHO) reports that vehicular accidents claim nearly 3,500 lives daily and result in 20 to 50 million injuries annually. Traditional vision-based solutions and wearable devices attempts to solve this challenge however face privacy, cost and deployment challenges. While Wi-Fi channel state information (CSI) has shown promise in indoor environments, its potential for dynamic outdoor environments remains largely unexplored. This paper presents a device-free, CSI-based system for detecting human movement and walking direction in crossings and alert oncoming vehicles to enhance pedestrian safety. A two-stage classification framework is adopted with Amplitude and Phase-sensitive features filtered with a adaptive noise suppression and evaluated using classical and deep learning models. Tested across four outdoor locations and seven subjects, the system demonstrates **95.9%** accuracy for movement detection and up to **62.4%** for directional classification. Results demonstrate the feasibility of deploying low-cost commercial off-the-shelf (COTS) hardware such as ESP32 and Raspberry Pi hardware for scalable, privacy-preserving ITS applications.

**Keywords:** Outdoor CSI, Smart Pedestrian Crossing using CSI, Smart Crosswalk application using CSI



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## LIST OF ABBREVIATIONS

<b>Abbreviation</b>	<b>Description</b>
ANN	Artificial Neural Networks
AP	Access Point
BiLSTM	Bi-directional LSTM
CARM	CSI-based human Activity Recognition and Monitoring system
CFO	carrier frequency offset
CFR	Channel Frequency Response
CNN	Convolutional Neural Network
ConvLSTM	Convolutional-LSTM
COTS	commercially off-the-shelf
CSI	Channel State Information
DNN	Deep Neural Networks
DWT	Discrete Wavelet Transform
EMF	electromagnetic force
ENTC	Department of Engineering and Telecommunication
EoL	End of Life
ESP32	Espressif Systems 32
ETSI	European Telecommunications Standards Institute
FFT	Fast Fourier Transform
GPU	graphics processing unit
HAR	Human Activity Recognition
HMM	Hidden Markov Model
I/O	Input and Output
IFFT	Inverse Fast Fourier Transform
ISAC	Integrated Sensing and Communication
ITF	International Transport Forum
ITS	Intelligent Transportation Systems
LOOCV	Leave-One-Out Cross validation
LSTM	Long Short-Term Memory
NIC	Network Interface Card
NLOS	Non-Line-Of-Sight
OFDM	Orthogonal Frequency-Division Multiplexing

<b>Abbreviation</b>	<b>Description</b>
PCA	Principal Component Analysis
PHY	physical layer
PRI	Pedestrian's Risk Index
RF	Random Forest
RFID	Radio Frequency Identification
RNN	Recurrent Neural Networks
RSSI	Received Signal Strength Indicator
RSU	Road-side Unit
SoC	System-on-Chip
STA	Station
STFT	Short-Time Fourier Transform
STO	sampling time offset
SVM	Support Vector Machine
ToC	Time-To-Collision
Tx-Rx	Transmitter-Receiver
UART	Universal Asynchronous Receiver/Transmitter
UNO	United Nations Organization
UoM	University of Moratuwa
USB	Universal Serial Bus
UWB	Ultra-Wideband
V2I	Vehicle-to-Infrastructure
V2P	Vehicle-to-Pedestrian
V2V	Vehicle-to-Vehicle
V2X	Vehicle-to-Everything
VAM	VRU Awareness Message
VRU	Vulnerable Road User
WHO	World Health Organization

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