Human Activity Recognition (HAR) using FMCW Radar

M.Tech. Thesis

by

Krishna Kumar Mishra

Department of Electrical Engineering

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A Thesis

Submitted in partial fulfillment of the requirements for the award of the degrees
of
Master of Technology

by

Krishna Kumar Mishra

Department of Electrical Engineering
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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled **Human Activity Recognition (HAR) using FMCW Radar** in the partial fulfillment of the requirements for the award of the degree of **Master of Technology** and submitted in the **Department of Electrical Engineering**, **Indian Institute of Technology Indore**, is an authentic record of my own work carried out during the time period from **July 2023** to **May 2025** under the supervision of **Prof. Ram Bilas Pachori**.

The matter presented in this thesis has not been submitted by me for the award of any other degree of this or any other institute.

Krishna
20/05/2025

Signature of the student with date

(Krishna Kumar Mishra)

This is to certify that the above statement made by the candidate is correct to the best of my knowledge.

RB Pachori 20.05.2025

Signature of Supervisor of Thesis (with date)

(Prof. Ram Bilas Pachori)

Krishna Kumar Mishra has successfully given his M.Tech. Oral Examination held on 07 May 2025.

RB Pachori 20.05.2025

Signature of Supervisor of M.Tech. thesis

Date:

Saptarshi Ghosh

Convener, DPGC

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Krishna Kumar Mishra

Dedicated

to

My Parents, My Wife, My Daughter, and Teachers

ABSTRACT

Human activity recognition (HAR) is an approach that is used to identify and classify human activities based on sensor data such as frequency modulated continuous wave (FMCW) radar, camera, accelerometers etc. HAR has gained a significant application in healthcare, smart home automation, search and surveillance, and monitoring of suspicious activity. Traditional approaches for HAR are based on the vision-based approach and wearable sensors. Vision-based systems fail due to privacy concerns, light illumination, and a limited field of view angle. The wearable sensor-based approach suffers due to inconvenience to the user and requires continuous use of the HAR sensor. Among the prominent sensing modalities, radar-based approach has gained significant attention due to their ability to operate in non-intrusive, privacy-preserving ways, ability to work in low lighting conditions or darkness, ability to penetrate through walls. The robustness of the radar-based approach against changing environment conditions making them suitable for HAR.

The FMCW radar-based framework has gained a significant interest in HAR due to its ability to capture micro and macro movement of humans. It has several key features such as better range resolutions, and can measure range and velocity simultaneously. The FMCW radar also offers a non-contact, privacy-preserving, and environment-independent alternative. Its ability to capture both micro and macro motion through micro-doppler signatures enables robust and detailed activity analysis without requiring subject cooperation.

In this thesis, we have studied the higher-order synchrosqueezing transform-based time-frequency representations (TFRs) with deep learning techniques for HAR. According to a study by the world health organization, the occurrence of falls is a key focus in HAR, due to its implications in safety-critical applications such as monitoring of the elderly and assisted living. In previous studies, radar-based HAR utilizes discrete Fourier transform (DFT), short-time Fourier transform (STFT), and wavelet transform-based approaches, but fail due to poor resolutions and fixed basis function to distinguish closely spaced frequency components in radar signals. To mitigate these limitations, we present a new method for HAR based on the higher-order synchrosqueezing transform and deep learning classifiers from radar return signals. The FMCW radar return signal captures the micro and macro motion

of human activity. To analyze such signals, the fourth-order synchrosqueezing transform (FSST4) technique plays a vital role due to its impressive time-frequency resolutions in the resultant TFR. Deep learning techniques (such as MobileNetV2, GoogleNet, AlexNet, VGG16, and VGG19) are used to classify TFR based on FSST4 into various activity classes. The method based on FSST4 and AlexNet achieved the highest accuracy of 99.40% among the studied classifiers. A comparative study is also performed to study the effectiveness of FSST4-based TFRs compared to STFT, continuous wavelet transform (CWT), Fourier synchrosqueezing transform (FSST), second-order Fourier synchrosqueezing transform (FSST2), third-order Fourier synchrosqueezing transform (FSST3), and FSST4-based TFRs in the proposed method. The proposed method with TFR based on FSST4 provided superior performance compared to the other proposed method based on TFR. In this work, the comparison of computational complexity analysis of FSST4 with other methods such as STFT, CWT, FSST, FSST2, and FSST3 is also studied. The CWT method is found to be the fastest among the methods studied for TFR computation. The FSST4 method required a similar computation time compared to STFT, FSST, FSST2, and FSST3 to obtain TFRs providing relatively better performance.

In this thesis, we also tried to address issues with the growing complexity of HAR tasks and the increasing demand for computationally efficient models. We proposed a new framework based on quantum convolutional neural networks (QCNNs) have emerged as a promising alternative to classical CNNs. Unlike traditional CNNs, which rely solely on classical computing principles, QCNNs harness quantum properties such as superposition and entanglement to process high-dimensional features in parallel, potentially leading to enhanced pattern recognition with fewer parameters. This is particularly beneficial in radar-based HAR, where subtle motion variations and fine-grained temporal dynamics must be captured. Moreover, QCNNs are well-suited for deployment on emerging quantum hardware, paving the way for scalable and resource-efficient HAR systems in the future. In this work, the Fourier-Bessel series expansion empirical wavelet transform (FBSE-EWT) based TFRs approach is combined with QCNN to accurately classify human activities from radar signals. This framework achieves an impressive classification accuracy of 95.71% and outperforms the existing framework in the literature.

List of Publications

1. **K. K. Mishra**, R.B. Pachori, “FMCW radar-based human activity recognition based on higher-order synchrosqueezing transform”, *IEEE, Sensors Journal, 2025.* (**Under Review**)

2. **K. K. Mishra**, R.B. Pachori,“Human activity recognition from radar signals based on FBSE-EWT and quantum convolution neural network” , *IEEE, Sensors Letters, 2025.* (**To be submitted)**

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List of Abbreviations

FMCW	Frequency modulated continuous waveform
DL	Deep learning
STFT	Short-time Fourier transform
CWT	Continuous wavelet transform
FSST	Fourier synchrosqueezing transform
FSST2	Second-order Fourier synchrosqueezing transform
FSST3	Third-order Fourier synchrosqueezing transform
FSST4	Fourth-order Fourier synchrosqueezing transform
CNN	Convolutional neural network
HAR	Human activity recognition
FBSE-EWT	Fourier-Bessels series expansion based empirical wavelet transform
QCNN	Quantum convolutional nueral network
TFR	Time-frequency representation
TFA	Time-frequency analysis
HHT	Hilbert-Huang transform
EWT	Empirical wavelet transform
NNs	Neural networks
QML	Quantum machine learning
QIP	Quantum information processing
NHT	Normalized Hilbert transform
UWB	Ultra-wide band

Chapter 1

Introduction

Human activity recognition (HAR) is a technique that is utilized to classify different human activities. It has found many applications in healthcare care, smart environments, and elderly monitoring. The main objective of HAR is to identify and recognize human activities such as falling, jumping, jogging, squatting, etc. The frequency modulated continuous waveform (FMCW) radar-based approach has gained promising attraction due to its ability to function in harsh weather conditions such as low visibility, darkness, and fog. The FMCW radar can capture micro and macro motion of human behavior, making it well suited for human activities applications. In this study, six different activities are performed in different locations to the radar and a multiclassification problem is formulated for HAR. FMCW radar has found a promising approach over the continuous-wave and ultra-wide band (UWB) radar due to its ability to measure range and doppler simultaneously, its fast measurement time, and better range resolution for sensing human activities [1].

The common approaches for the classification of human activities in radar-based methods require preprocessing of the radar return signal using different techniques such as discrete Fourier transform (DFT) and classify human activities using different machine learning (ML) classifiers. However, the above approach fails due to poor resolutions and non-adaptive nature. To address these limitations, FMCW radar-based HAR is proposed to obtain the time-frequency representations (TFRs) using short-time Fourier transform (STFT), continuous wavelet transform (CWT), Fourier synchrosqueezing transform (FSST), second-order FSST (FSST2), third-order FSST (FSST3), and fourth-order FSST (FSST4) [2] of six human activities, namely, falling, jogging, jumping, squatting, walking, and stepping and classify them using deep learning classifiers namely, AlexNet [3], MobileNetV2 [4], GoogleNet [3], VGG16 [3], and VGG19 [3]. The combination of FSST4 and AlexNet provides an effective classification accuracy as compared to other methods.

Deep learning (DL) models such as convolutional neural networks (CNNs) have significantly impressive accuracy by enabling automatic feature extraction from FMCW radar signals. However, DL models require a large labeled dataset, computationally intensive models, and scalability is limited by hardware constraint. To address these limitations, quantum CNNs (QCNNs) is proposed to handle a large-dimensional data set, improve scalability, and increase computational time due to the superposition and entanglement property [5]. In this work, the combination of Fourier-Bessel series expansion-based empirical wavelet transform (FBSE-EWT) and QCNNs framework is used for HAR from FMCW radar signal. Furthermore, we also conducted comparative studies of the proposed framework with other existing classical CNNs.

This work introduces a novel architecture for constructing a quantum version of a convolutional CNN aimed at multiclass image classification. The proposed circuit features a highly parameterized design, enabling richer transformations through the convolutional layers, and a pooling configuration that facilitates strong entanglement. To bridge the gap between classical and quantum processing, a preprocessing scheme is used to encode classical data into quantum amplitudes in a way that preserves the behavior of classical convolutions. Once encoded, the data is processed through the quantum circuit, and a measurement assigns class labels. The model parameters are optimized using a classical algorithm by minimizing the cross-entropy loss for multiclass outputs, and the updated parameters are iteratively fed back into the quantum circuit until convergence is achieved [6].

1.1 Wearable sensor-based HAR

The traditional approach generally relies on wearable sensors to capture different types of human motion such as falling, squatting, jumping, etc. The wearable-based HAR can work in indoor and outdoor environments [1]. It does not capture visual or video information. Hence, the wearable-based approach reduces privacy concerns. It can work in low visibility and unaffected by harsh weather conditions. Wearable sensors have gained prominence in healthcare for their affordability, ease of use, and support for continuous remote monitoring, particularly for the elderly.

Despite their advantages, wearable sensors face several challenges, including user comfort, aesthetics, device size, development and maintenance requirements, real-time data acquisition and processing, high energy consumption, and potential privacy concerns [7]. Wearable sensor-based approaches, while effective in controlled environments, are often not feasible for real-world HAR due to the discomfort and inconvenience associated with the use of electronic sensors throughout daily life [8]. It also has a limited operational time due to battery constraints [9].

1.2 Vision-based HAR

The vision-based sensing technique [10] is very popular in short-range and indoor environments. The vision-based approach provides detailed visual information about human motion without the need for the subject to wear any device. This approach can capture the complete body movements of human activities. It can capture the activities of multiple individuals at the same time. However, the vision-based approach fails due to privacy concerns, performance degradation under low light conditions, and inconvenience to users due to continuous monitoring. The performance of the vision-based approach is degraded when parts of the human body are blocked or the camera view angle narrows.

Recently, vision-based sensing techniques have emerged as a key technology to monitor human activities and security purposes due to the evolution of closed-circuit television (CCTV) technology. Vision-based technology provides better quality videos and secure communication. With the rapid advancement of HAR, vision-based HAR has emerged as a practical alternative to sensor-based methods. Unlike sensor-based HAR, which requires strategic sensor placement for each activity, vision-based HAR leverages real-time video data—readily available due to the growing use of CCTVs and cameras. As a key area in computer vision, vision-based HAR enables the identification of activities in images or videos. However, it faces significant challenges such as background clutter, object shape variations, lighting conditions, camera placement, viewpoint diversity, and whether the camera is static or dynamic, all of which vary with the type of activity. The vision-based sensing system outlines the essential components of an automated "smart video" surveillance framework designed to monitor pedestrian activity and identify potentially hazardous situations. The purpose of this system is to detect people who may be in distress and to recognize suspicious motions or behaviors that occur in proximity to critical transportation infrastructure. This intelligent system integrates video analytics with real-time tracking to enhance situational awareness and security in sensitive public spaces [11].

1.3 Radar-based HAR

Recently, radar-based HAR is an emerging technique to monitor human activities in a smart environment, monitor suspicious activity at the border, monitor patients in hospitals, elderly care and assisted living. Radar-based HAR is gaining attention due to its potential in applications such as fall detection and gesture recognition, particularly for supporting independent living among the elderly. While existing studies have shown promising results, most rely on controlled, lab-based data focused on isolated activities with fixed durations. this work highlights the emerging challenge of continuous activity recognition—detecting and classifying sequential human activities with unknown durations and transitions in real-time. It reviews current advancements in this area and outlines future research directions for enabling real-world deployment of radar-based HAR systems [12]. While radar-based HAR and fall detection have seen substantial research, current methods largely focus on isolated activities performed under controlled conditions. Typically, each activity is recorded separately with fixed durations and clear transitions. However, real-world scenarios involve continuous streams of actions with varying durations and interspersed static postures. To enable practical applications, especially in home healthcare, advancing continuous activity recognition using radar is essential for capturing natural, uninterrupted human behavior. Radar-based HAR is a technique that can be used to identify, detect and classify different human activities without requiring direct contact with humans [1, 10]. It is a non-contact, non-invasive approach, making them suitable for HAR. It can work in low lighting conditions and harsh environmental conditions. It can detect human activities through walls and occlusion scenarios. It is highly sensitive to small movements and can measure range and velocity simultaneously, making it suitable for HAR [13, 14, 15, 16].

1.4 Deep learning (DL)

In this study, the DL technique is used to classify different human activities for HAR. DL techniques refer to a class of artificial neural network (ANN) algorithms that use multiple hidden layers to learn pattern features from data automatically, without the need for human expertise. These techniques can handle large datasets [3], perform feature extraction and selection efficiently, making them superior to traditional ML models [17]. Furthermore, DL is also well established for classifications of large datasets especially image, speech, and signal processing tasks. Its performance is constrained by several factors, including the need for large labeled datasets, limited scalability due to hardware resource constraints, and a computationally intensive training process. Figure 1.1 illustrates a basic architecture of DL models for classification of images.

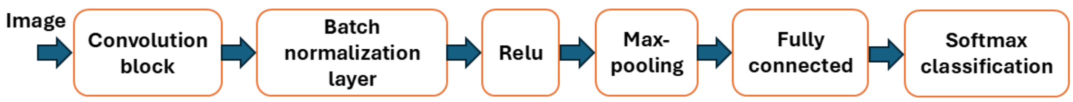


Figure 1.1: Basic architecture of DL models for classification.

They are a type of ANN with multiple layers between the input and output layers [18]. They are designed to automatically learn and represent complex patterns in data through a hierarchy of layers. Each layer processes information and passes it on to the next layer, gradually transforming the input data into more abstract and high-level representations. The input layer receives the input data. DLs contain multiple hidden layers sandwiched between the input and output layers. Each hidden layer performs transformations on the input data. These transformations are learned during the network training phase. Then, each layer typically applies an activation function to the weighted sum of their inputs. Activation functions introduce non-linearities into the network, enabling it to learn complex relationships in the data. Common activation functions include the sigmoid, tanh, and rectified linear unit (ReLU) functions. Furthermore, the max-pooling layer picks up the maximum number out of the previous convolutional block. In the end, the fully connected layer (FC) and the soft-max classification layers are used for the final decision [10].

1.5 Quantum convolutional neural network (QCNNs)

The classical CNN models are used for image classification and pattern recognition. The CNN models has gained a significant application in computer vision. Quantum computers are emerging as a promising solution to computational problems that are not solved by classical CNN models. Unlike traditional architectures, quantum computers operate within a fundamentally different computational paradigm, leveraging principles such as superposition and entanglement to perform complex calculations more efficiently [19, 20]. CNNs typically operate by sequentially stacking convolutional and pooling layers. The convolutional layers extract hidden features by applying linear combinations to local pixel neighborhoods, effectively capturing spatial dependencies. Pooling layers follow to downsample the feature maps, which reduces computational complexity and mitigates the risk of overfitting. This process is repeated until the data is sufficiently abstracted, at which point fully connected layers are employed to perform classification. The model is trained by minimizing the loss between predicted and actual labels using optimization techniques such as gradient descent. The basic architecture of CNN models for image classification is illustrated in Fig. 1.2.

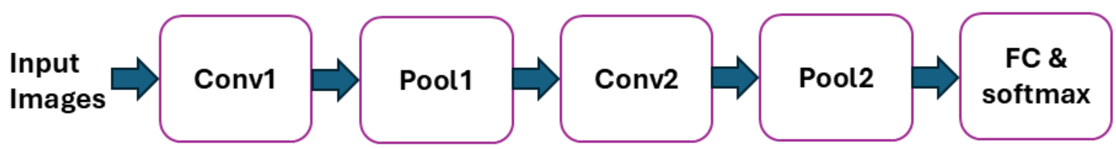


Figure 1.2: Basic architecture of CNN models for image classification.

In Figure 1.2, Conv1, Conv2, pool 1, pool2, FC represent the convolutional layer 1, convolutional layer2, pooling layer 1, pooling layer 2, fully connected layer, respectively. A simple example of a QCNN describes the structure of a classical CNN, comprising convolution and pooling layers. Similar to CNNs, the convolution layer in a QCNN extracts new features (or quantum states) from input data. The pooling layer serves to reduce the dimensionality of the system. However, a key distinction is that, in QCNNs, quantum error correction (QEC) techniques can be incorporated. This is achieved by applying quantum measurements in place of controlled gates within the pooling layers, allowing the model to enhance robustness while maintaining quantum coherence [21].

Figure 1.3: Basic architecture of QCNN models for classification.

Figure 1.3 illustrates the basic architecture of the QCNN models utilized for classification purposes. The classical image data is first preprocessed and then encoded into a quantum circuit using a data encoding scheme. Within the QCNN, feature extraction is performed by a quantum convolutional layer comprising quantum gates [22, 23]. This is followed by a pooling layer that reduces the dimensionality of the quantum feature space. QCNN retains a key advantage of classical CNNs, translation invariance, by applying identical parameters for convolution operations across qubits within the same layer. At the final stage of the QCNN, essential information is condensed into a single qubit, which is measured to produce the model's prediction. The model parameters are optimized through gradients calculated through the parameter shift rule, with updates handled by a classical computer, thus enhancing prediction accuracy through hybrid quantum-classical training. Quantum computers offer unique advantages such as superposition and inherent parallelism, which enable faster learning and evaluation compared to classical computing systems. These properties allow quantum models to process complex computations more efficiently. However, the practical deployment of quantum computing is currently constrained by hardware limitations, restricting operations to relatively small-scale quantum systems [24]. The QCNN is an advanced technique that is used to classify classical data such as images for HAR. It is a combination of ML and quantum computing. It leverages the quantum properties like superposition and entanglement. These properties of QCNN making it effective for classification of human activities and other classification approaches [5].

CNNs are widely used in computer vision due to their ability to effectively capture spatial correlations in data. However, their performance can degrade when dealing with high-dimensional data or large-scale models, making training computationally intensive and less efficient. QCNNs models offer a promising alternative by leveraging the advantages of quantum computing. QCNNs can either provide a novel approach to solving problems traditionally handled by CNNs or enhance the performance of existing models by incorporating quantum principles, enabling more efficient learning in complex, high-dimensional spaces [25].

1.6 Time-frequency representations (TFRs)

Time-frequency analysis (TFA) is particularly valuable when no precise signal model is available, as it enables a more comprehensive characterization of signals that are otherwise inadequately described by representations of the time or frequency domain only. In many practical applications involving nonstationary signals such as radar signals, the time domain lacks spectral insight, while traditional Fourier analysis fails to capture the temporal evolution of frequency components. To address this, TFA integrates the time variable into frequency-based analysis, allowing for a joint TFR that reflects how a signal's spectral content evolves over time [26]. Ideally, TFR offers a direct view of the frequencies present at each moment by combining the local resolution of instantaneous frequency spectra with a global understanding of temporal behavior [27, 28]. TFRs are broadly categorized based on the analysis techniques employed—often involving translations, modulations, and scalings of basis functions that are well-localized in both time and frequency [29]. An exhaustive review of TFRs and their detailed properties lies beyond the scope of this work. For a deeper understanding, readers are encouraged to explore references that provide comprehensive insights into various TFR techniques and their underlying theoretical foundations [30, 31, 32, 33].

The TFRs are techniques that convert a one-dimensional signal into two-dimensional signal. The main goal of TFRs is to analyze the signal characteristics in the time-frequency domain. TFRs play a key role in the analysis of the radar signals [34]. In order to analyze such signals, different techniques are proposed, such as STFT, CWT, FSST, FSST2, FSST3, and FSST4 [2, 35, 36]. The STFT and CWT techniques fail due to poor resolution and fixed basis function to capture the different human motions. FSST, FSST2, and FSST3 also suffer to accurately classify human activity due to poor resolution and energy concentrations compared to FSST4. The higher-order FSST4 has a better resolution and energy concentration making it ideal for HAR.

In this work, we also introduced an automated HAR framework using the FBSE-EWT method to detect and classify human activities from radar signals. We have used the FBSE-EWT method for the TFRs of human activities. The other TFRs-approach, such as STFT, HHT, and CWT failed due to poor resolutions and a fixed basis function. To address these limitations, the FBSE-EWT method is proposed to identify the closely spaced frequency component in the nonstationary radar signals [37]. The FBSE-EWT method is used to decompose time-segmented radar return signals into narrow subband signals [38]. These sub-band signals are used to obtain instantaneous amplitude (IA) and instantaneous frequency (IF) and then time-frequency representations are obtained from these extracted IA and IF components [39].

1.7 Organization of the Thesis

This thesis contains five chapters including an introduction. The remaining part of thesis is organized as follows:

Chapter 2 - describes a review of previous work and problem formulation for HAR using FMCW radar. In this chapter, we also discuss the ML, DL, and QCNN techniques for HAR classification. This chapter presents an enhanced HAR framework that utilizes TFRs derived from radar signals in combination with advanced neural networks, including quantum inspired models, and delivers improved recognition performance in realistic privacy-sensitive environments.

Chapter 3 – In this chapter, we have explored FMCW Radar-based human activity recognition based on the higher-order synchrosqueezing transform. This chapter describes FMCW radar-based dataset, convolutional neural network and synchrosqueezing transform of different orders, and proposed methodology for HAR. Finally, this chapter summarizes the proposed framework.

Chapter 4 – In this chapter, we have introduced a new HAR from radar signals based on FBSE-EWT and the quantum convolution neural network. This chapter describes dataset details, proposed framework, preprocessing, FBSE-EWT and QCNN. Finally, this chapter concludes the proposed framework.

Chapter 5 - Conclusions and scope for future work

Chapter 2

Review of Past Work and Problem Formulation

HAR has become increasingly vital in applications such as eldercare monitoring, smart homes, security, and health diagnostics. Although traditional HAR approaches using wearable sensors or vision-based systems have shown promise, they suffer from limitations that include discomfort, privacy concerns, and dependence on lighting or line of sight. To address these limitations, a radar-based approach, particularly using FMCW radars, has emerged as a privacy-preserving solution for HAR. The FMCW radar can function reliably in low light, through obstacles, and under occlusions, making them highly suitable for ambient intelligence scenarios in a real world context [10]. These advantages establish FMCW radar as a critical modality for the development of scalable, privacy-conscious, and robust HAR [1].

DL methods [3] like CNNs improve radar-based HAR, helping in tasks such as fall detection and motion tracking. Transfer learning helps overcome data scarcity, while data fusion combines inputs from various sources. Furthermore, numerous studies have explored radar-based HAR using both classical ML techniques, such as k-Means and support vector machines (SVM), and more recent DL approaches [40]. ML methods typically depend on shallow, manually engineered features derived from basic statistical properties, requiring domain expertise, while DL is a specialized branch of ML that eliminates the need for manually crafted features, which typically depend on domain expertise. Instead, DL models automatically extract high-level, though often non-interpretable, features in a generalized and data-driven manner. Their layered architecture also enables enhanced computational efficiency, allowing for optimization techniques such as parallelization during training and inference. In recent years, the advent of deep ANN has significantly advanced radar-based HAR due to their powerful capability for automatic feature extraction from raw radar echoes [10].

Recent research has demonstrated the viability of radar-based HAR using TFRs and DL models. However, existing methods often trade off between accuracy and computational efficiency. This work presents an enhanced HAR framework utilizing TFRs (such as STFT, CWT, FSST, FSST2, FSST3, and FSST4 [2, 35]) derived from radar signals in combination with advanced neural networks, including quantum-inspired models, to address these limitations and deliver improved recognition performance in realistic, privacy-sensitive environments. Despite its potential, the use of FMCW radar in HAR presents challenges, including signal complexity, clutter, and the need for efficient feature extraction and classification. The high model complexity requires a more computational time, complex hardware architecture, and a limited application in real-time deployment. This study explores TFR based on the advanced signal processing technique [34, 37] and QCNN [21] to improve the accuracy, scalability, and generalizability of radar-based HAR systems. The objective of this work is to integrate FBSE-EWT based TFRs with QCNNs based DL model to enhance classification of human activities by leveraging quantum computing for efficient feature extraction while maintaining scalability and handling a large dimensional data.

Chapter 3

FMCW Radar-based Human Activity Recognition based on Higher-Order Synchrosqueezing Transform

3.1 Introduction

HAR is a method used to detect and categorize a range of activities performed by human, such as falling, walking, or running, by evaluating data collected from various sensors such as radar and camera. The aim of HAR is to develop systems or algorithms that can autonomously identify and understand a person's actions in real-time. Injuries resulting from a fall are more likely to occur in older persons and are a key factor in pain, disorders, ailments, and unanticipated death. Approximately 28-35% of people aged of 65 years and over fall each year increasing to 32-42% for individual aged 70 years and above [41]. Recognizing the importance of HAR systems for independent living among older adults, and the literature describes various data acquisition methods, categorized as wearable and non-wearable devices. Wearable devices [42] such as accelerometers, gyroscopes, and magnetometers are widely used. But, it's practical use is limited due to user inconvenience and lack of privacy preserving. Radar-based technology has several features like privacy preserving, ability to work in low visibility, non-contact operation. This technology plays a key role in the detection of falls, enabling prompt responses in smart home and health monitoring, ultimately improving the quality of life and independence of older adults.

In the literature, the radar-based HAR utilizes the DFT to preprocess the radar signals and has a limitation like limited resolution. Furthermore, STFT and CWT are used for TFR of radar signals [34]. But their performance is limited by the proper selection of the window function and mother wavelet. To address these challenges, better time-frequency resolution in TFRs is essential. These enhanced TFRs can be effective in distinguishing different human activities, especially when the movements are similar in both micro scales like analyzing movements of individual limbs or frame-by-frame posture changes and macro scale like identifying broad activity classes like walking and running. The FSST4 based technique provides an enhanced time-frequency resolution which provides a better HAR. Hence, this method can accurately classify human activities. This motivated us to develop FMCW Radar-based HAR using FSST4 for accurately classifying human activity. In [43], authors present a novel deep neural network (DNN) training method for radar micro-Doppler classification to generate diverse and realistic training data by varying body size, speed, and gait. Kanjilal et al. [44] propose a subtransfer learning approach to improve HAR accuracy for outlier users by combining transfer learning and data augmentation. Taghanaki et al. [45] present a self-supervised learning approach for HAR using accelerometer data, with dual pipelines in time and time-frequency domains. Kanjilal et al. [46] show that deep learning, using spectrograms as input, outperforms traditional subject-agnostic features in HAR. Luo et al. [47] models both frequency and temporal features of radar signals and outperforms other methods, offering a versatile solution for activity recognition using various sensor types. Chakraborty et al. [48] applied transfer learning using pre-trained deep convolutional neural network (DCNN) (e.g., MobileNetV2, VGG19, ResNet-50) on their DIAT-RadHAR dataset and achieved 98% accuracy in HAR. In [49], authors explore HAR using radar by extracting histogram of gradients features from synchro-squeezed time-frequency representations, specifically SSFT and SSWT on a different dataset. Ding et al. [50] propose the FMCW lightweight vision transformer (FML-Vit) for HAR. In [51], six pre-trained CNN models were evaluated using DIAT-μRadHAR dataset and achieved an impressive accuracy of 98% using VGG19. The versions of the FSST such as second-order FSST (FSST2), third-order FSST (FSST3), and FSST4 were introduced in [2, 35, 52]. The higher-order transforms provide improved capabilities for handling complex frequency-modulated signals and are better suited for real-world applications that involve such signals. In this work, we have shown the effectiveness of FSST4 method for HAR.

In this study, we have considered FMCW radar-based reflected signals from individual performing different types of activities. The received signal is preprocessed, and FSST4 approach is utilized for obtaining TFRs of activities. Then, deep learning techniques such as AlexNet (through CNNs) are utilized for recognition of distinct human activities.

The major contributions in this study are as follows:

1. An FSST4 technique is utilized for the first time in HAR purpose to the best of our knowledge. This technique leverages high time-frequency resolution to effectively characterize and distinguish between complex human activities.

2. Studied the performance of STFT, CWT, FSST, FSST2, FSST3, and FSST4 based techniques for HAR.

3. Extensive analysis conducted to evaluate the performance of MobileNetV2, GoogleNet, VGG16, VGG19, and AlexNet integrated with STFT, CWT, FSST, FSST2, FSST3, and FSST4 for HAR.

4. Carried out computational complexity analysis (in terms of runtime and memory usage)

of STFT, CWT, FSST, FSST2, FSST3, and FSST4.

5. Carried out comparative studies of our method with other approaches studied on the FMCW radar dataset in terms of accuracy, precision, and recall.

The structure of thesis is in the following order. Section 3.2 illustrates FMCW dataset for HAR, CNNs, and synchrosqueezing transform of different orders. Section 3.3 describes the proposed methodology for HAR. Section 3.4 explores the results and offers a discussion. Section 3.5 outlines conclusion pertaining to the proposed approach.

3.2 FMCW Radar-based dataset, convolutional neural network and synchrosqueezing transform of different orders

3.2.1 FMCW radar dataset

In this study, a dataset named Human Activity Data with a 5.8-GHz FMCW Radar is utilized which is collected at the School of Electronic and Optical Engineering, Nanjing University of Science and Technology and made publicly available at [53] . It contains data from 16 participants (11 male and 5 female, age ranging from 22 to 32 years), each performing 240 repetition of six different human activities, namely, falling, jogging, jumping, squatting, walking, and stepping. The FMCW radar used in data collection has a 5.8 GHz center frequency, 320 MHz bandwidth, 150 m maximum detection range, 192 kHz sampling frequency, 3.3 ms ramp repetition period, 0.47 m range resolution, 3.88 m/s unambiguous velocity, and 8 dBm transmitted power. The recordings were performed at two different locations; location 1 contains 150 samples and location 2 contains 1290 samples. In this study, we have utilized 1290 samples collected at location 2.

3.2.2 CNN

The foundation of our approach is built upon the application of the transfer learning (TL) methodology. TL [54], [55], [56], is a useful technique in DL where a CNN model developed for one activity is utilized as the starting point for other activity.

Use of TL eliminates the need to train a CNN from scratch. Furthermore, TL plays a crucial role in mitigating overfitting and improving the generalization capability of the model. This approach involves leveraging pretrained weights from widely used datasets which is particularly effective in addressing class imbalance issues in the dataset studied.

In this study, we investigate the effectiveness of five prominent CNN architectures: AlexNet [3], VGG-16 [17], VGG-19 [17], GoogLeNet [17], and MobileNetV2 [4]. AlexNet was ground breaking in demonstrating the power of DL, particularly CNNs, in solving real-world computer vision problems. It inspired the development of deeper and more sophisticated networks such as VGGNet, ResNet, and InceptionNet.

3.2.3 Synchrosqueezing transform of different orders

Multi-component signals (MCSs), such as back-scattered radar signals, have garnered significant interest in the signal processing domain. This is due to their capability to accurately represent non-stationary signals. TFR plays a key role in characterizing such time-varying signals. In this study, FSST and its variants such FSST2, FSST3, and FSST4 are used for TFRs of non-stationary signals such as radar signal and suited for effective analysis of such signals. In our study, we have used the FSST4 for the analysis of radar return from human activities.

Suppose a signal $g \in L^1(\mathbb{R})$, Fourier transform of g signal is represented as,

$$\hat{g}(x) = F\{g\}(x) = \int_{\mathbb{R}} g(t)e^{-i2\pi xt}\, dt \tag{3.1}$$

The STFT of a signal is described $h \in L^{\infty}(\mathbb{R})$ by,

$$V_g^h(t,x) = \int_{\mathbb{R}} g(\xi)h(\xi - t)e^{-2i\pi x(\xi - t)}\,d\xi \tag{3.2}$$

If g, $\hat{g}$, h, and $\hat{h}$ are emcompassed by $L^1(\mathbb{R})$, g may be restored from STFT of g signal when $h \neq 0$ at 0 as follows:

$$g(t) = \frac{1}{h^*(0)} \int_{\mathbb{R}} V_g^h(t,x)\,dx \tag{3.3}$$

where h^* indicates the conjugate value of h.

Under this work, we are going to analyze MCSs which are represented as,

$$g(t) = \sum_{m=1}^{K} g_m(t) \quad \text{with} \quad g_m(t) = A_m(t)e^{i2\pi\phi_m(t)} \tag{3.4}$$

given defined value $M \in \mathbb{N}$, where $A_m(t)$ and $\phi'_m(t)$ denote the instantaneous amplitude (IA) and instantaneous frequency (IF) of the *m*th component, respectively.

3.2.3.1 First-order synchrosqueezing transform

The first-order synchrosqueezing begins by describing the local IF $\hat{\omega}_g$, when $V_g^h(t,x)$ is nonzero, by [57],

$$\hat{\omega}_g(t,x) = \frac{\partial \arg V_g^h(t,x)}{\partial t} = \Re\left(\frac{1}{2i\pi}\frac{\partial_t V_g^h(t,x)}{V_g^h(t,x)}\right) \tag{3.5}$$

The first-order frequency synchrosqueezing transform of g based on the threshold η is produced by moving any coefficient $V_g^h(t,x)$ with amplitude greater than η to the point

$(t, \hat{\omega}_g(t, x))$. Then SST is represented as,

$$T_g^{\eta}(t, \omega) = \int_{|V_g^h(t,x)|>\eta} V_g^h(t, x)\delta(\omega - \hat{\omega}_g(t, x))\, dx \tag{3.6}$$

3.2.3.2 Second-order synchrosqueezing transforms

The relevance of FSST is constrained to a kind of MCSs consists of marginally influenced oscillatory modes. In order to overcome these limitations, an expansion of FSST, called the FSST2 is [57], [58], has been presented based on a more precise IF estimate than $\hat{\omega}_g$.

Here, we define complex reassignment operators $\tilde{\omega}_g(t, x) = \frac{\partial_t V_g^h(t,x)}{2i\pi V_g^h(t,x)}$ and $\tilde{t}_f(t, x) = t - \frac{\partial_x V_g^h(t,x)}{2i\pi V_g^h(t,x)}$, describes a frequency modulation in complex domain as [58],

$$\tilde{q}_g(t, x) = \frac{\partial_t \tilde{\omega}_g(t, x)}{\partial_t \tilde{t}_g(t, x)} = \frac{\partial_t \left(\frac{\partial_t V_g^h(t,x)}{V_g^h(t,x)}\right)}{2i\pi - \partial_t \left(\frac{\partial_x V_g^h(t,x)}{V_g^h(t,x)}\right)} \tag{3.7}$$

The 2nd-order localized modulation operator is equivalent to $\Re\{\tilde{q}_g(t, x)\}$, and the 2nd-order estimate of complex IF of g is described by,

$$\tilde{\omega}_g^{[2]}(t, x) = \begin{cases} \tilde{\omega}_g(t, x) + \tilde{q}_g(t, x)(t - \tilde{t}_g(t, x)), \text{if } \partial_t \tilde{t}_g(t, x) \neq 0 \\ \tilde{\omega}_g(t, x), \text{otherwise} \end{cases} \tag{3.8}$$

We substituite $\hat{\omega}_g^{[2]}(t, x) = \Re\left(\tilde{\omega}_g^{[2]}(t, x)\right)$. Clearly, illustrated in [59] as $\hat{\omega}_g^{[2]}(t, x) = \phi'(t)$, where g is a Gaussian linear frequency modulated signal. This turns out to be relevant to mention that $\tilde{q}_g(t, x)$ may be evaluated by five distinct STFTs. In the end, FSST2 is presented through replacement $\hat{\omega}_g(t, x)$ by $\hat{\omega}_g^{[2]}(t, x)$ in (3.5), to be referred as $T_{2,g}^{\eta}$, and restoration of mode is accomplished by substituting T_g^{η} by $T_{2,g}^{\eta}$ in (3.6).

3.2.3.3 Higher-order synchrosqueezing transforms

To address non-stationary signals with considerable $\phi_m^{(m)}(t)$ for $m \geq 3$, specially those with quickly varying phases, we define new synchrosqueezing transform operators based on 3rd- or higher-order estimation of magnitude and phase together [2].

Let $g(\xi) = A(\xi)e^{i2\pi\phi(\xi)}$ with $A(\xi)$ equivalent to its L^{th}-order Taylor series for ξ in the vicinity of t, specifically as,

$$\log(A(\xi)) = \sum_{m=0}^{L} \frac{[\log(A)]^{(m)}(t)}{m!}(\xi - t)^m$$
$$\text{and} \quad \phi(\xi) = \sum_{m=0}^{N} \frac{\phi^{(m)}(t)}{m!}(\xi - t)^m \tag{3.9}$$

Where $Y^{(m)}(t)$ represents the m^{th} derivative of Y evaluated at t with $L \leq N$, it may be described as,

$$g(\xi) = \exp\left(\sum_{m=0}^{N} \frac{1}{m!}\left[\log(A)^{(m)}(t) + i2\pi\phi^{(m)}(t)\right](\xi - t)^m\right) \tag{3.10}$$

Because $[\log(A)]^{(m)}(t) = 0$ for $L+1 \leq m \leq N$. Equivalent STFT can be defined as,

$$V_g^h(t,x) = \int_{\mathbb{R}} \exp\left(\sum_{m=0}^{N} \frac{1}{m!}\left[\log(A)^{(m)}(t) + i2\pi\phi^{(m)}(t)\right]\xi^m\right) \times g(\xi)e^{-i2\pi x\xi}\, d\xi$$

Computing the partial differential of $V_g^h(t,x)$ in relation to t and performing division by $i2\pi V_g^h(t,x)$, the localized operator for the reassignment of complex values $\tilde{\omega}_g(t,x)$ may be defined, when $V_g^h(t,x)$ is non-zero, as,

$$\begin{aligned}\tilde{\omega}_g(t,x) &= \sum_{m=1}^{N} r_m(t)\frac{V_g^{t^{m-1}h}(t,x)}{V_g^h(t,x)} \\ &= \frac{1}{i2\pi}\left[\log(A)\right]'(t) + \phi'(t)) \\ &\quad + \sum_{m=2}^{N} r_m(t)\frac{V_g^{t^{m-1}h}(t,x)}{V_g^h(t,x)}\end{aligned} \tag{3.11}$$

where $r_m(t) = \frac{1}{(m-1)!}\left[\frac{1}{i2\pi}\left(\log(A)^{(m)}(t) + \phi^{(m)}(t)\right)\right]$.

Clearly, in order to obtain an accurate IF estimate for the analyzed signal, requires to subtract $\Re\left(\sum_{m=2}^{N} r_m(t)\frac{V_g^{t^{m-1}h}(t,x)}{V_g^h(t,x)}\right)$ to $\Re\left(\tilde{\omega}_g(t,x)\right)$, which needs the estimation of $r_m(t)$ for $m = 2, \ldots, N$.

To achieve such a goal, we generate a frequency modulation operator $\tilde{q}_g^{[m,N]}(t,x)$, equal to $r_m(t)$ for different modes presented, and the description of the N^{th}-order IF estimate then follows [59]:

$$\tilde{\omega}_g^{[N]}(t,x) = \begin{cases} \tilde{\omega}_g(t,x) + \sum_{m=2}^{N} \tilde{q}_g^{[m,N]}(x,t)(-x_{k,1}(t,x)), \\ \text{if } V_g^h(t,x) \neq 0, \partial_x x_{j,j-1}(t,x) \neq 0, 2 \leq j \leq N \\ \tilde{\omega}_g(t,x), \text{otherwise} \end{cases}$$

with $x_{k,1}(t,x) = \frac{V_g^{t^{k-1}h}(t,x)}{V_g^h(t,x)}$. $\hat{\omega}_g^{[N]}(t,x) = \Re\left\{\tilde{\omega}_g^{[N]}(t,x)\right\}$ is the desired IF estimate.

N^{th}-order FSST is described by substituting $\hat{\omega}_g(t,\xi)$ with $\hat{\omega}_g^{[N]}(t,x)$ in (3.6) to attain $T_{N,g}^{\eta}(t,\omega)$, and MCS may be rebuilt by substituting $T_g^{\eta}(t,\omega)$ by $T_{N,g}^{\eta}(t,\omega)$ in (3.7).

The pseudocode for the Nth-order Fourier synchrosqueezing transform has been illustrated in algorithm 3.1 as follows:

Algorithm 3.1 N-th order Fourier synchrosqueezing transform

Compute STFT:

$$V_g^h(t,x) = \int g(\zeta)h(\zeta - t)e^{-i2\pi x(\zeta - t)}d\zeta$$

for all (t, x) such that $|V_g^h(t,x)| > \eta$ **do**
    for $m = 1$ to $N-1$ **do**
        Compute derivatives: $V_g^{t^m}(t,x)$
    end for
    Compute reassignment operator:

$$\tilde{\omega}_g(t,x) = \frac{1}{2\pi j}\frac{\partial_t V_g^h(t,x)}{V_g^h(t,x)}$$

    for $m = 2$ to N **do**
        $x_{m,1}(t,x) = \frac{V_h^{t^{m-1}}(t,x)}{V_g^h(t,x)}$
        Estimate modulation term: $\tilde{q}_g^{[m,N]}(t,x)$
    end for
    Compute N$^{\text{th}}$-order IF estimate:

$$\tilde{\omega}_g^{[N]}(t,x) = \tilde{\omega}_g(t,x) + \sum_{m=2}^{N} \tilde{q}_g^{[m,N]}(t,x)(-x_{m,1}(t,x))$$

end for
return $\tilde{\omega}_g^{[N]}(t,x)$

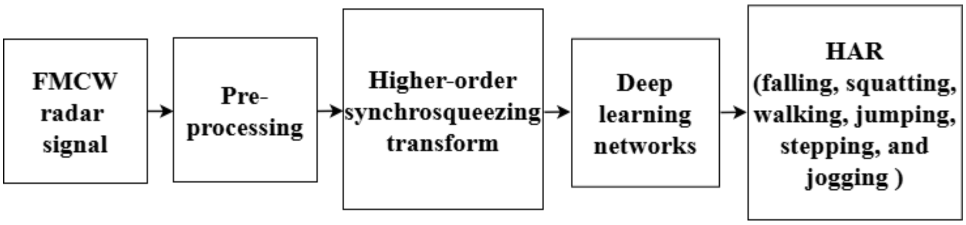
3.3 Proposed Methodology for HAR

FMCW radar operates by transmitting a modulated continuous wave reflected from individuals going about doing different activities. The radar return captures the micro and macro motion of individuals performing different activities. The introduced approach of FSST4 [35], is applied to FMCW dataset [53] to implement a HAR. The radar returns of different human activities are characterized by range, time, and Doppler. The proposed radar-based HAR, as illustrated in Fig. 3.1(a), includes preprocessing of the received FMCW signals followed by applying the introduced approach to FMCW radar signal pertaining to each human activity.

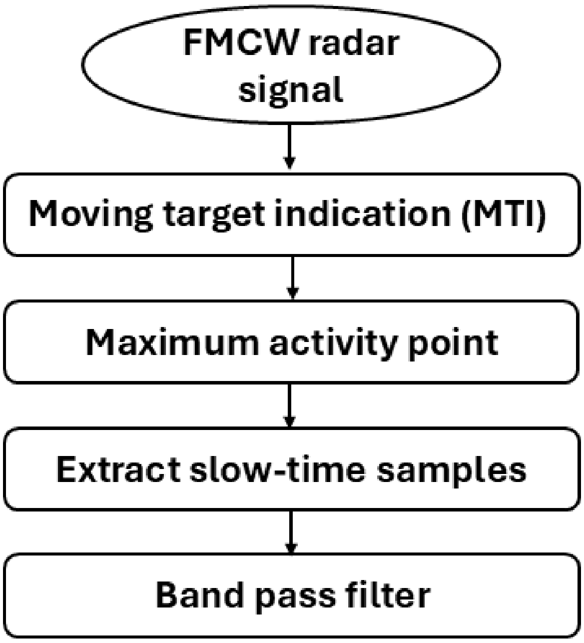
Figure 3.1(b) illustrates the flow chart for complete preprocessing pipeline. In this method, the radar's backscattered signal is organized into a data matrix $S[j, k]$ where row $j = [1, 2, \ldots J]$ and column $k = [1, 2, \ldots K]$ represent Fast-time and Slow-time samples respectively. We have performed moving target indicator (MTI) on the radar return signal. MTI filtering technique is utilized to effectively suppress static background reflections, thereby enhancing the dynamic signatures corresponding to human movements and improving the reliability of activity recognition. The point of highest intensity in the Fast-time Slow-time samples is identified as a peak activity location [1]. Based on this, the corresponding Slow-time profile is extracted as $S[k]$ = $S[\varepsilon, k]$ where ε is the Fast-time index of $\max\{S[j, k]\}$. After finding maximum activity point as shown in Fig. 3.1(c), the resulting signal is filtered using sixth-order butterworth band pass filter in the frequency range from 15 Hz to 136 Hz to isolate the micro-doppler components relevant to human motion. Then, FSST4 based TFR generation is applied to FMCW radar signal to obtain TFR for different human activities. Figure 3.2 demonstrates the time-domain signals and their respective TFRs of each activity carried in this study using FMCW radar dataset for HAR.

3.4 Results and Discussion

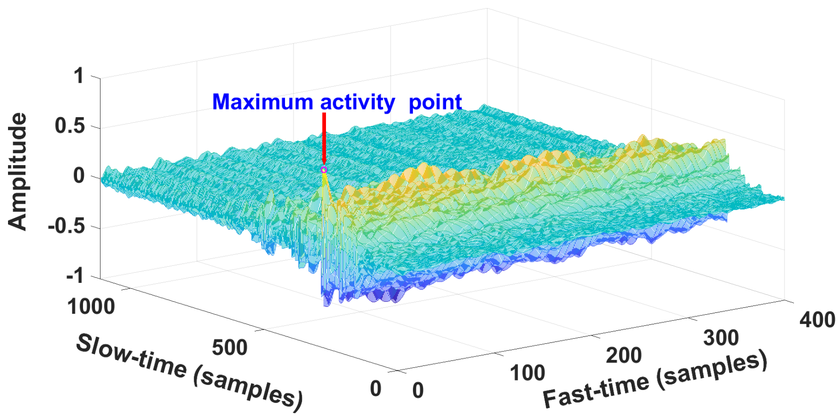
It is crucial to evaluate the performance of FMCW radar data. These results indicate that the models possess strong generalization capabilities, with test accuracies ranging from 95.20% to 99.40% across various activities, reflecting their robustness in diverse condition. The proposed method achieved the highest test accuracy of 99.40%. The personal computer with 32 GB graphics card, 16 GB RAM, Intel (R) core (TM) i7-2600 CPU is used for computational analysis of proposed framework.



(a)



(b)



(c)

Figure 3.1: (a) The proposed radar-based HAR based on higher-order synchrosqueezing transform and deep learning networks, (b) flow chart of preprocessing pipeline of the proposed method, (c) maximum activity point of back scattered FMCW for falling signal.

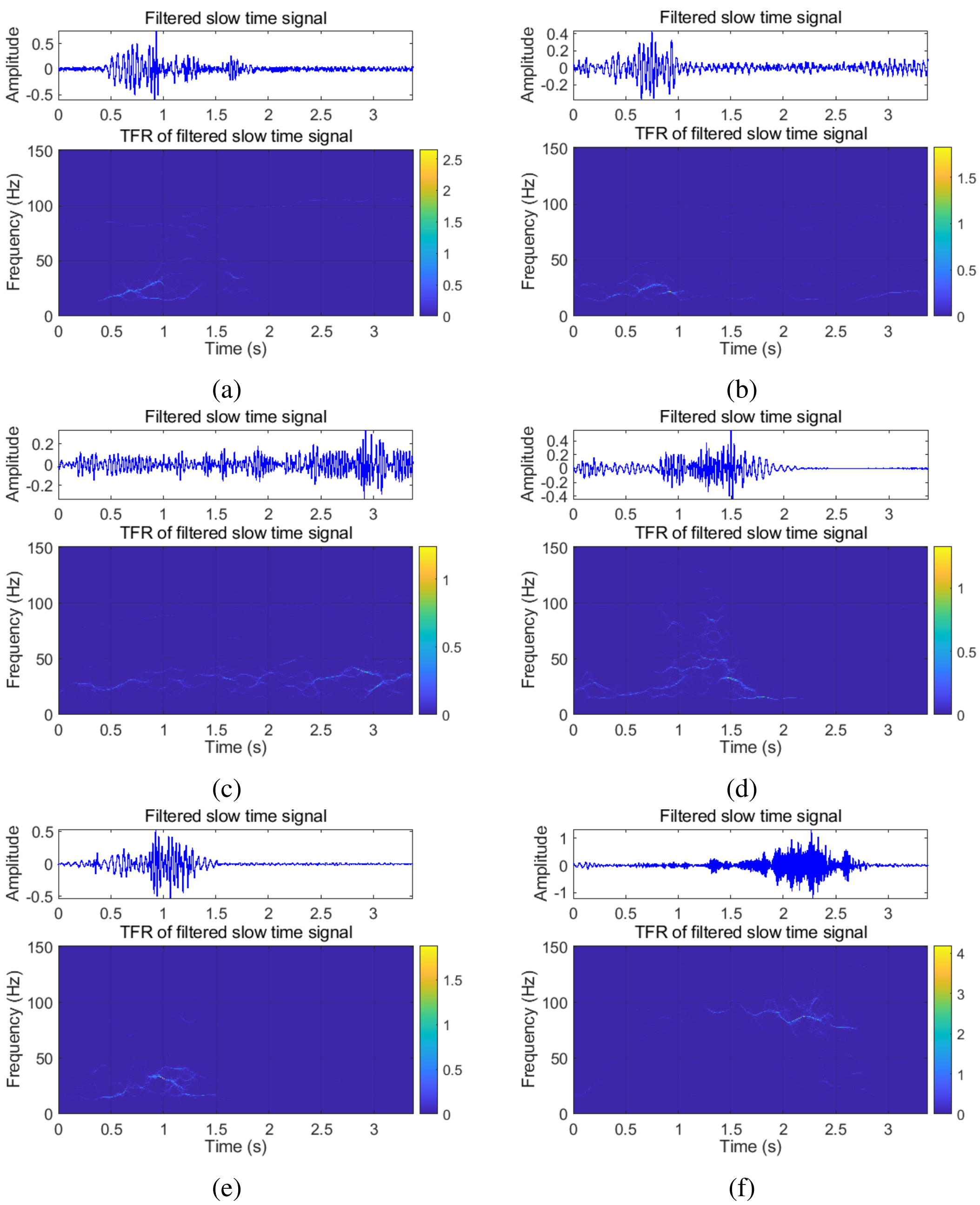


Figure 3.2: Time-domain signals and their respective TFRs of each activity carried in this study in HAR (a) falling, (b) squatting, (c) walking, (d) jumping, (e) stepping, (f) jogging.

From Figure 3.3, it is observed that falling and squatting showed accuracies at 98.50% while walking, stepping, and jumping achieved a perfect recognition accuracy of 100%. Walking and stepping demonstrated superior accuracy due to their periodic body movements, while jumping generates strong reflections. However, squatting produces slower

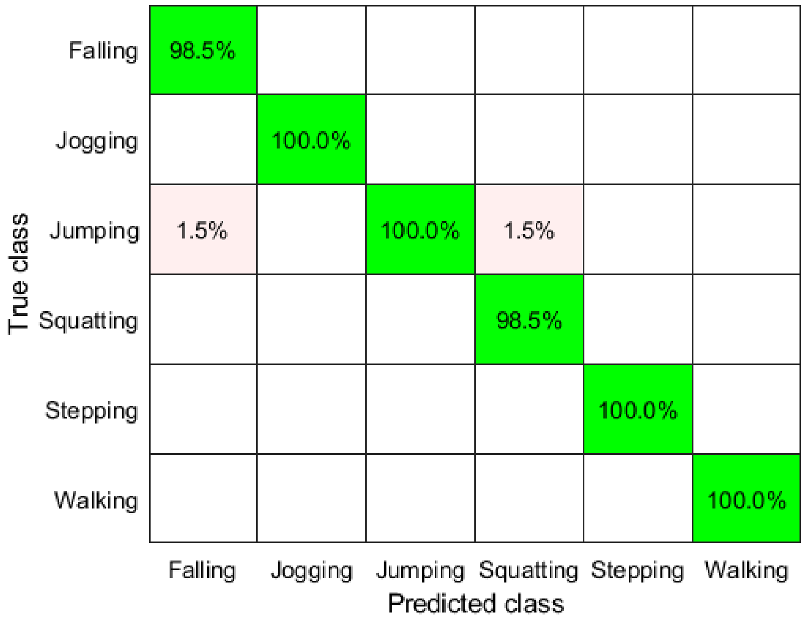


Figure 3.3: confusion matrix for HAR classification of proposed framework.

controlled movements with minimal doppler shifts and falling is characterized by abrupt movements with their transient signals, making them harder to classify reliably. The value of $\eta = 0.001$ is set trial and error basis in this study. The value of window parameter is set to 0.05 in this study. In this work, we have carried out detailed study by comparing performance of five classifiers by using different features TFRs namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4. From our studies, we observed that the TFRs obtained from FMCW radar signals using methods, namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4 with MobileNetv2 achieve accuracy of 84.41%, 93.50%, 86.22%, 93.33%, 94.12%, and 96.41%, respectively. The TFRs obtained from FMCW radar signals using methods, namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4 with GoogleNetV2 achieve accuracy of 81.67%, 86.51%, 84.37%, 86.48%, 88.89%, and 95.23%, respectively. The TFRs obtained from FMCW radar signals using methods, namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4 with VGG16 achieve accuracy of 82.46%, 88.90%, 85.56%, 87.78%, 88.25%, and 95.21%, respectively. The TFRs obtained from FMCW radar signals using methods, namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4 with VGG19 achieve accuracy of 86.67%, 86.67%, 85.66%, 89.78%, 88.25%, and 96.71%, respectively. Comparison of performance metrics in terms of precision, recall, and F1 score is illustrated in Fig. 3.4(a). In this study, we have also carried out the computational complexity analysis of the STFT, CWT, FSST, FSST2, FSST3, and FSST4.

The runtime required for obtaining TFRs from FMCW radar signals using methods, namely, STFT, CWT, FSST, FSST2, FSST3, and FSST4 are 2.447 s,1.489 s, 2.450 s, 2.501 s, 2.517 s, and 2.565 s, respectively. The memory usage of methods STFT, FSST, FSST2, FSST3, and FSST4 are the same, with each requiring approximately 8192 kB, indicating similar storage demands across all approaches. The memory usage required for CWT is 1136 kB. Furthermore, we have also studied the effect of noisy environment for STFT and variants of FSST [2]. The FSST4 is relatively less affected as compared to other methods as shown in Fig. 3.4(b).

Additionally, a comparison of the HAR outcomes from the proposed framework with those according to existing works using the FMCW dataset [53] is illustrated in Table 3.1.

3.4.1 Performance measures for comparing TFRs using Rényi entropy

Measurement of time-frequency sharpness can offer an efficient criterion for analyzing the performance of various forms of TFRs. For noisy conditions, additive white Gaussian noise (AWGN) at Signal-to-noise ratio (SNR) levels, i.e., 0, 5, 10, 15, and 20 dB are considered for falling activity. To measure the effectiveness of developed approach over existing techniques, normalized *Rényi* entropy [60] -[61] is considered which can be mathematically represented by,

$$S_\beta = \frac{1}{1-\beta}\log_2\left(\frac{\sum_{p=1}^{P}\sum_{q=1}^{Q} X^\beta[p,q]}{\sum_{p=1}^{P}\sum_{q=1}^{Q} X[p,q]}\right), \quad \beta \geq 2 \tag{3.12}$$

Where $X[p, q]$ is the TFR, S_β represents the complexity of the TFR, and β is the order of information. In this work, for all simulations, $\beta = 3$ is considered. The normalized *Rényi* entropy for the falling activity using STFT, FSST, FSST2, FSST3, and FSST4 are depicted in Fig. 3.4(c).

The S_β describes the level of complexity in the TFRs, which is identical to the information measure in the field of probability theory that includes two random variables. A smaller value of S_β implies better resolution. Hence, smaller value of S_β is desirable for precise and accurate measure of complexity in TFRs.

A lower value of normalized *Rényi* entropy for FSST4 compared to different TFRs such as STFT, FSST, FSST2, and FSST3 indicate more effective localization and better resolution of the FMCW radar signal's features. FSST4 with a reduced value of normalized *Rényi* entropy represents more accurate TFR making it more suitable for analyzing MCS such as FMCW radar signal.

This, in turn, leads to more accurate results in FMCW radar-based HAR applications. FSST4 with lower normalized *Rényi* entropy provides more concentrated TFR making is more suitable for HAR.

3.4.2 Evaluation of time-frequency concentration based on normalized energy

FSST4 improves time-frequency concentration by sharpening the representation of signals, reducing leakage across frequency bins, and focusing energy on the correct time-frequency locations. This improves the accuracy in localizing both time and frequency characteristics of the signal. We utilized the presented approach in [2, 52] to evaluate the performance of various techniques based on normalized energy. From Fig. 3.4(d), it is clear that the normalized energy of FSST4 approaches quickly to 1 as number of coeffi-

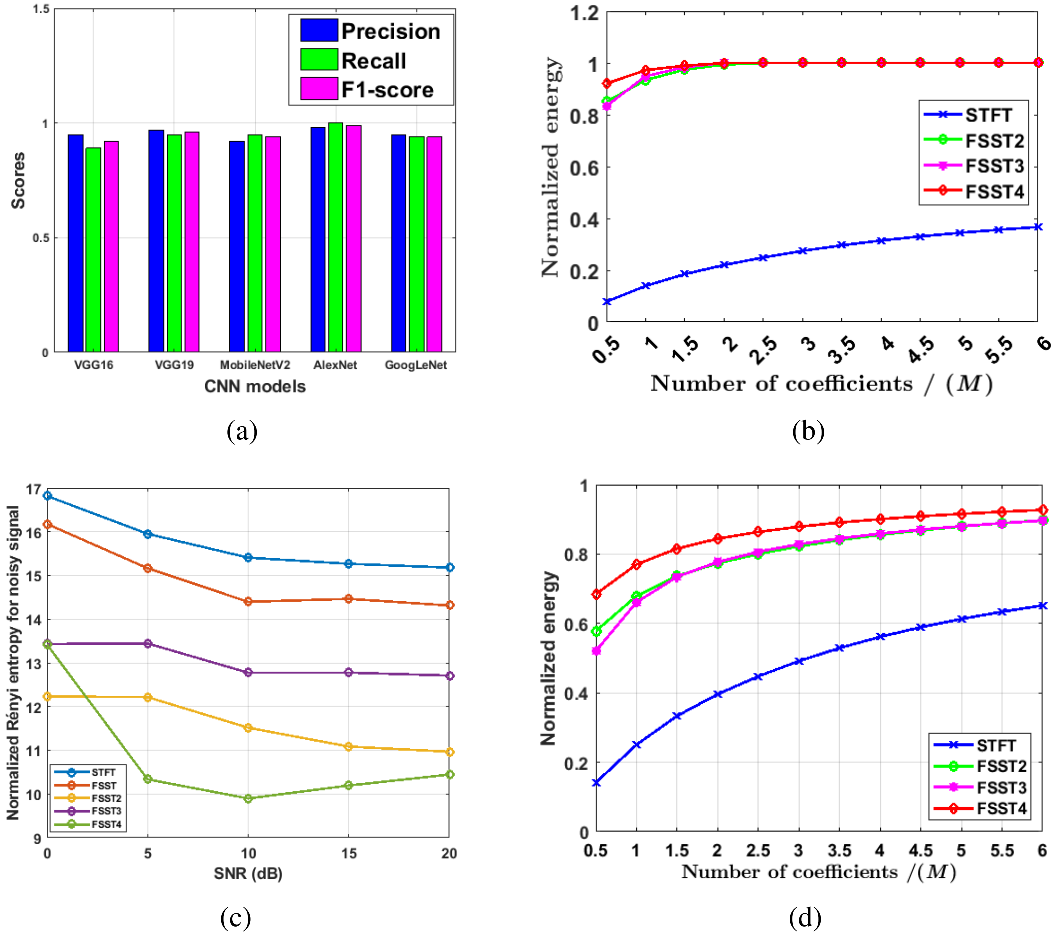


Figure 3.4: (a) comparison of performance metrics for different models, (b) comparison of performance of proposed method with different methods in noisy environment, (c) Time-frequency concentration measure using Rényi entropy, (d) normalized energy concentration for different coefficients values for falling activity with length of signal M=1024 in FMCW radar based dataset.

cients increases. Hence, the FSST4 has a more concentrated TFRs as compared to different techniques like STFT, FSST2, FSST3.

3.4.3 Accuracy comparisons of different models applied on NJUST dataset of HAR

A comprehensive evaluation of the proposed method against existing approaches is shown in Table 3.1. The AlexNet CNN model was trained to achieved 99.40% accuracy.

Table 3.1: Comparative performance assessment of FMCW radar-based HAR based on FSST4 with the approaches studied on the same FMCW dataset.

Methods	**Accuracy (in %)**	**Precision (in %)**	**Recall (in %)**
MobileNetV2 [4]	96.41	92	100
GoogLeNet [40]	95.23	95	94
VGG16 [40]	95.21	95	89
VGG19 [40]	96.71	97	95
Cross-term free WVD+ensemble classifier [1]	99.51	98.74	99.16
DRDT+KNN [62]	95.50	–	–
TDSP+SVM [63]	89.69	–	–
DRDT+ensemble-KNN [64]	94.20	–	–
DRDT+ST-ConvLSTM [65]	96.50	–	–
DRDT+3DCNN [66]	95.60	–	–
CNN+LSTM [67]	94.20	94	94
FSST4+AlexNet	99.40	98	100

DRDT: Dynamic range-doppler trajectory; TDSP: Time-doppler sparse point clouds; SVM: Support vector machine; KNN: K-nearest neighbors; DCNN: Deep convolutional neural network; LSTM: Long short-term memory

The AlexNet model proposed with FSST4 achieved the highest accuracy of 99.40% which makes it better options for HAR. This demonstrates that AlexNet model surpasses the accuracy of other CNNs models trained from scratch.

3.5 Summary

In this work, we introduce a new framework based on FSST4 along with CNN models to detect six human activities, namely, falling, jogging, jumping, squatting, walking, and stepping. In this study, we have performed a detailed study by comparing performance of five pretrained classifiers (namely, AlexNet, VGG16, VGG19, GoogleNet, and MobileNetV2) by obtaining TFRs from FMCW radar signals using STFT, CWT, FSST, FSST2, FSST3, and FSST4. Among these combinations, the pairing of the AlexNet with FSST4 approach achieves an overall highest HAR accuracy of 99.40%. Therefore, the proposed framework has achieved excellent performance in HAR. Furthermore, we have performed a comparative computational time analysis of the STFT, CWT, FSST, FSST2, FSST3, and FSST4, evaluating key parameters such as runtime and memory usage to assess the efficiency and practicality of the approach. In this work, we performed a comparative analysis of the performance metric of the proposed framework with other methods in terms of precision, recall, and F1-score. We have obtained classification accuracy of 98.5% for falling and squatting. In addition to that, we also obtained a perfect classification accuracy of 100% for walking, stepping, and jumping. Therefore, the proposed framework is capable of accurately classifying distinct human activities.

Chapter 4

Human activity recognition from radar signals based on FBSE-EWT and quantum convolution neural network

4.1 Introduction

HAR focuses on recognizing and identifying human movements from sensor data for human-machine interface in smart home monitoring, sports, and health care applications. In this work, HAR plays a critical role in the recognition of human activity based on FMCW signal [68]. The FMCW radar has the ability to measure the range and movement of the activities under consideration simultaneously [10]. The FMCW radar can work in harsh weather conditions and low visibility. It is effective for classification of human micro and macro movements through walls. Consequently, FMCW radar has been adopted for recognizing human activities recently.

Danish et al. [69] propose the QCNN based method for HAR that efficiently handles high-dimensional data leading to enhanced classification accuracy. Salvadi et al. [70] authors present a model that employs the artificial gorilla troop optimizer (AGTO) for parameter tuning via variational quantum methods. In [5], QCLHAR is a quantum contrastive learning framework designed to improve HAR by efficiently extracting features from unlabeled sensor data. Jindal et al. [71] present QBFA-GSA, an optimization technique that combines the quantum-behaved binary firefly algorithm and the gravitational search algorithm for feature selection in HAR.In [72] authors propose the use of quantum support vector machines (QSVM) for HAR. Using quantum computing capabilities to handle the growing data from wearable sensors, the approach outperforms traditional machine learning methods—including LDA, logistic regression, kNN, and classical SVMs—achieving accuracy 98% with a reduced execution time of 19 s. In [69] proposed hybrid architecture leverages quantum computing's strengths to extract complex patterns more effectively, improving classification accuracy while maintaining computational efficiency.

To analyze non-stationary signals, several methods [34] exist, for instance, wavelet transform (WT), and Hilbert-Huang transform (HHT) [73]. Most of the existing methods depend on prefixed basis functions, and hence are considered to be non-adaptive in nature. In [74] empirical wavelet transform (EWT) was utilized for the analysis of multi-component signals like radar and sonar signals. EWT is a dynamic method for radar signals that analyzes spectral features from radar signals. EWT-based approach struggle to resolve the narrowly separated frequency components. To address aforementioned problem, the Fourier-Bessel series expansion-based empirical wavelet transform (FBSE-EWT) [37], method is proposed for analysis of non-stationary radar signals. we have obtained an enhanced TFR as compared to existing methods such as EWT [75] and HHT.

The traditional ML is used for classification of HAR and suffers a challenge like robustness and generalization. In ML, feature extracion is typically manual and heuristic, relying heavily on human expertise and domain knowledge. Unlike traditional ML, DL automatically extracts high-level features through hierarchical architectures, eliminating the need for manual feature engineering.

Recently, quantum ML (QML) [21] has become an emerging field that integrates classical ML with quantum information processing (QIP) to address challenges in traditional ML, such as high computational costs, time consumption, and kernel estimation inefficiencies [76]. Classical ML algorithms encounter challenges in processing big-data under computational constraints. QML leverages quantum concepts like superposition and entanglement, making it well-suited for future ML problems. Advances in computing power and algorithms have enhanced ML's ability to identify patterns efficiently. Quantum computers are expected to surpass classical systems in ML tasks by generating complex patterns that classical computing cannot efficiently replicate.

In this work, a new automated HAR framework based on FBSE-EWT and QCNN from the backscattered FMCW radar signals is proposed. The features are extracted and trained on QCNN models to classify human activities under consideration. As far as our understanding goes, this is the first instance to use QCNN for HAR using FMCW radar.

The major contributions are as follows:

1. To the best of our knowledge, the FBSE-EWT based TFR method has not been used previously for HAR using the FMCW radar signal. In this study, FBSE-EWT method is employed for the first time in the context of HAR with an FMCW dataset.
2. Obtained TFRs of FMCW radar return signals using FBSE-EWT method.
3. The QCNN model and classical CNN models (such as GoogleNet and VGG19) have been explored for classification of HAR using TFRs obtained from radar return signals.
4. Performed comparative performance assessment of accuracy and loss for various sizes of epochs.
5. Conducted a performance comparison of the proposed method with the other existing methods from literature using FMCW dataset.

6. Carried out an accuracy comparison of classical CNN models (such as GoogleNet and VGG19) and QCNN with FBSE-EWT method.

7. Performed a computational time analysis of obtained TFRs using FBSE-EWT method.

The thesis is structured as follows. Section 4.2 describes the proposed methodology, including FMCW dataset specifications, Section 4.3 presents the results and observations, while Section 4.4 concludes this work.

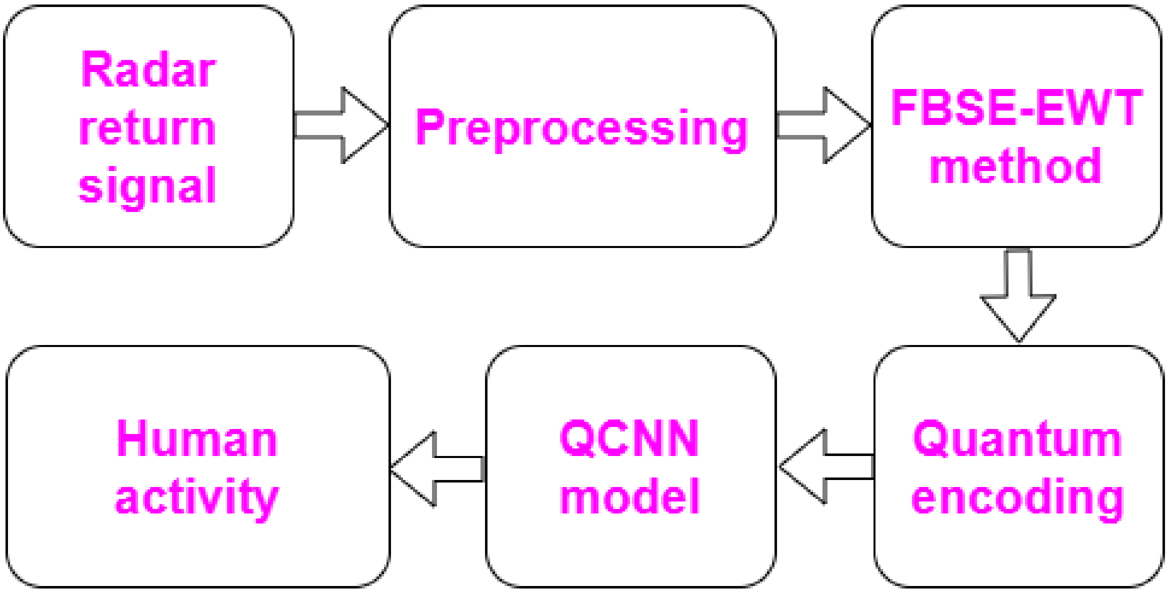


Figure 4.1: Process flow diagram of the proposed method for HAR using FMCW radar signals.

4.2 Methodology

The proposed framework utilizes FBSE-EWT approach and QCNN model for HAR from the reflected FMCW radar signals. In this method, FMCW radar is an active system which transmits the radio wave and receives the reflected signal from the human performing different kinds of activities. The reflected signal is received and analyzed and obtained TFRs using FBSE-EWT approach. Then, QCNN is utilized for classification of human activities. A visual representation of the proposed framework is provided in Fig. 4.1.

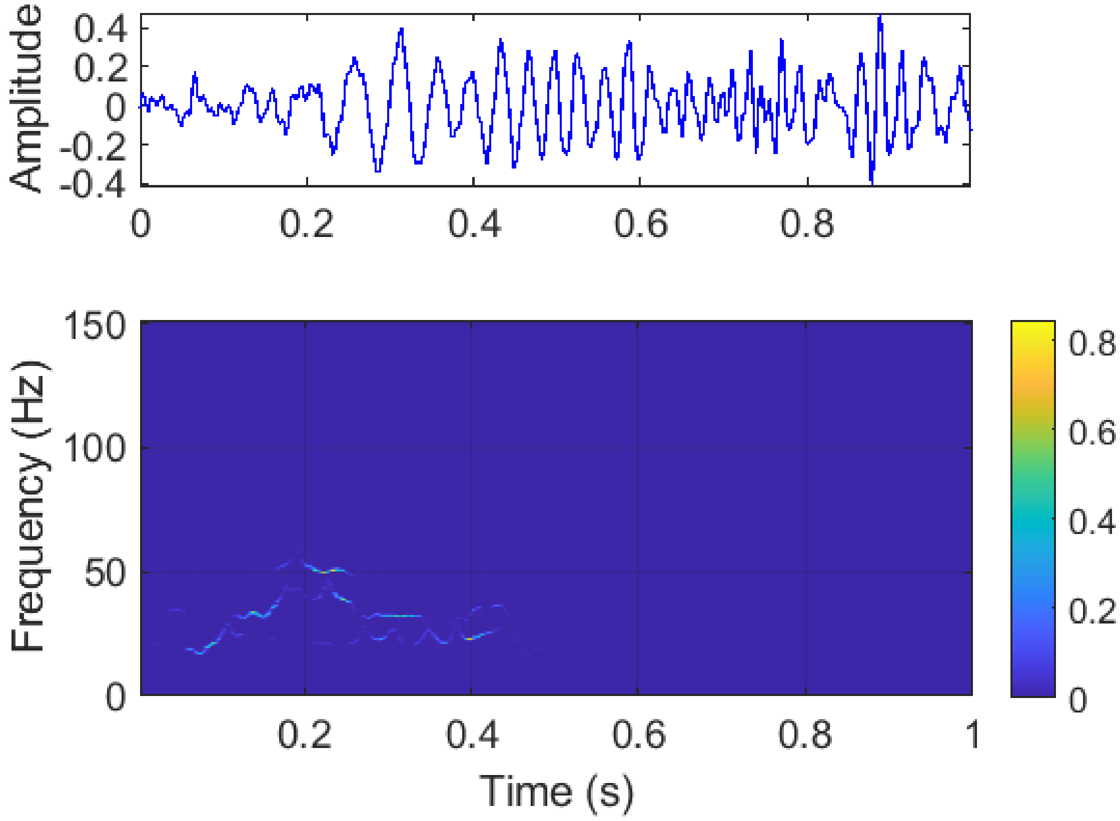


Figure 4.2: Real radar signal from FMCW dataset and its TFR using FBSE-EWT method.

4.2.1 Dataset description

In this study, a data set named Human Activity Data with a 5.8-GHz FMCW Radar is utilized for HAR and is made publicly available at [53]. It contains data from 16 participants (11 male and 5 female, aged 22 to 32 years), each performing 240 repetitions of six different human activities, namely, falling, jogging, jumping, squatting, walking, and stepping. The FMCW radar used in data collection has a 5.8 GHz center frequency, 320 MHz bandwidth, 150 m maximum detection range, 192 kHz sampling frequency, 3.3 ms ramp repetition period, 0.47 m range resolution, 3.88 m/s unambiguous velocity, and 8 dBm transmitted power.

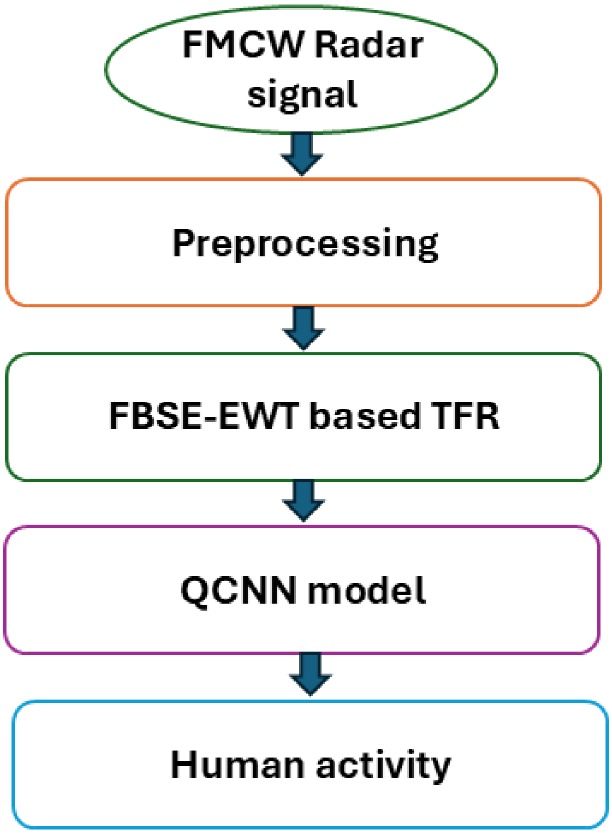


Figure 4.3: Proposed methodology for HAR

4.2.2 Proposed framework

The proposed framework for HAR using FMCW radar signals is presented in the following section.

4.2.2.1 Preprocessing

The MTI filtering step eliminates static background reflections, thereby emphasizing dynamic components associated with human movement. After that, we obtain a maximum activity point as introduced in [1]. Then, the sixth-order butterworth bandpass filter in the frequency range 15 Hz to 136 Hz is used to filter out irrelevant frequency components and retains only the signal portions associated with human motion, ensuring more accurate recognition.

4.2.2.2 FBSE-EWT

This study presents a new framework for HAR from radar return signals using a FBSE-EWT. Unlike previous approaches, which suffer from limitations such as mode-mixing, noise sensitivity, and high computational complexity, the proposed FBSE-EWT method effectively handles nonstationary radar return signals and reduces complexity by utilizing only the first sub-band to extract micro and macro motion of humans [37].

The FBSE utilizes Bessel functions as bases, making it well suited for evaluation of non-stationary signals. The FBSE of signal *x(m)* utilizing zero-order Bessel functions is represented by [77] - [78],

$$x(m) = \sum_{n=1}^{N} D_n J_0\left(\alpha_n m/N\right), \quad m = 0, 1, \ldots, N-1 \tag{4.1}$$

where, D_n are referred to as the FB series coefficients of $x(m)$, represented as follows [77] - [78],

$$D_n = \frac{2}{N^2\left(J_1(\alpha_n)\right)^2} \sum_{m=0}^{N-1} m x(m) J_0\left(\frac{\alpha_n m}{N}\right) \tag{4.2}$$

where $J_0(.)$ and $J_1(.)$ denote the zero and first-order Bessel functions, respectively. The positive roots of $J_0(\alpha) = 0$ are referred to as α_n with $m = 1, 2, \ldots, N$.

The proposed method utilizes FBSE to compute the spectral representation of the signal, replacing FT-based spectrum for boundary detection and segmentation in EWT [73]. The method based on scale-space is then applied for segmentation of the FBSE spectrum. An EWT-based filter bank is generated to extract meaningful modes [37]. Normalized Hilbert transform (NHT) is applied to the synthesized sub-band signals to compute instantaneous amplitude (IA), instantaneous frequency (IF), and obtain the TFR. The FBSE-EWT based TFR of the FMCW radar return signal is shown in Fig. 4.2. The proposed framework for classification of HAR from FMCW radar signal is illustrated in Fig. 4.3.

4.2.2.3 QCNN

QML has gained significant research interest in recent year. In this work, we proposed and examined an innovative novel QML model [21] inspired by CNN [79] for classification of HAR using FMCW radar return signal. In this framework, we utilized QCNN model, as illustrated in Fig. 4.4, for the classification of obtained features from FMCW reflected radar signals. In this work, 16-qubit QCNN model is studied for classification of HAR.

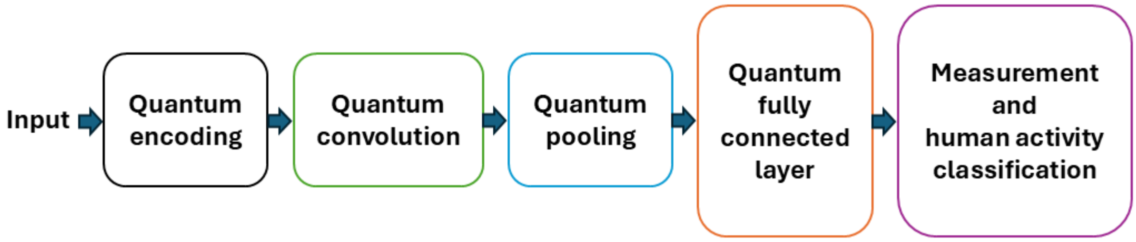


Figure 4.4: Basic fundamental block diagram of QCNN.

In this work, the classical data is mapped to 16-qubits using quantum feature encoding (i.e. amplitude encoding). The quantum convolutional gates are applied to extract quantum features. Next, quantum pooling layer is used to reduce computational cost while keeping relevant features. In quantum fully connected layer, quantum circuits combine extracted features. Finally, quantum states are measured and converted to classical probabilities and a classical softmax function is used for classification.

4.3 Results and Discussion

Here we considered 80% of FMCW dataset for training the developed QCNN model and 20% of test dataset for testing of the trained QCNN. The training and testing performances of the proposed FBSE-EWT based QCNN of FMCW radar signals across various training data sizes are studied and listed in Table 4.1. Figure 4.5 demonstrates the accuracy versus epoch curves of the proposed framework for various epoch sizes, indicating that increasing the training set size increases the accuracy of the proposed methods. From Figs. 4.6 and 4.7, it has been observed that the loss of the QCNN model decreases and accuracy increases with increasing number of epochs, respectively. Furthermore, the training and testing curves across various epochs demonstrate a reduced disparity between training and testing accuracies, indicating improved model generalization. Figure 4.8 demonstrates the accuracy comparisons of the proposed framework with other existing methods. We also studied computational time required to obtain TFRs using FBSE-EWT based method.

Table 4.1: Performance metrics (accuracy and loss) of the proposed framework for various sizes of epochs

Number of epochs	Loss		Accuracy (in %)	
	Training	Testing	Training	Testing
10	0.3229	0.5454	89.30	85.50
50	0.2757	0.4833	90.70	87.00
100	0.2663	0.3679	92.00	89.00
200	0.2307	0.3215	93.40	90.00
500	0.1850	0.2450	93.90	93.00
1000	0.1092	0.2103	96.70	95.71

Table 4.2 compares the performance of the proposed framework with the existing HAR framework from the literature using FMCW radar signals from the dataset in [53]. While achieved a highest accuracy of 95.71% among the methods from the literature. This substantial improvement is noteworthy.

Table 4.2: Performance comparison of the proposed method with other existing methods from literature using same dataset

Methodology	Accuracy (in %)
DRDT+KNN [62]	95.50
DRDT+ensemble-KNN [80]	94.20
TDSP+SVM [63]	89.69
DRDF+3DCNN [66]	95.60
TDSP+3D-PointNet [68]	95.00
FBSE-EWT+VGG19	89.10
FBSE-EWT+GoogleNet	92.15
FBSE-EWT+QCNN	**95.71**

DRDT: Dynamic range-doppler trajectory; TDSP: Time-doppler sparse point clouds; SVM: Support vector machine; KNN: K-nearest neighbors; DCNN: Deep convolutional neural network

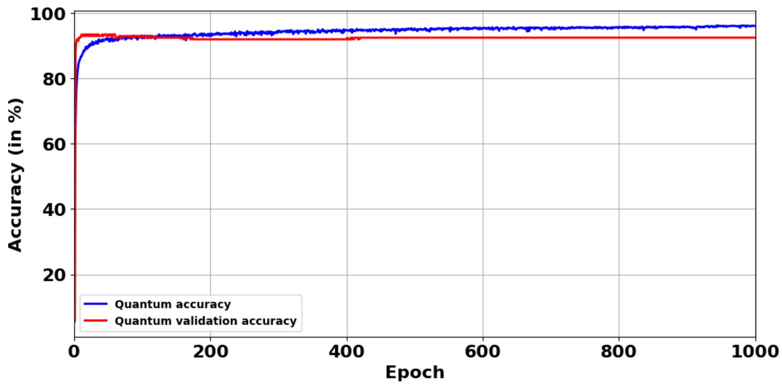


Figure 4.5: QCNN model accuracy versus epoch.

4.4 Summary

In this work, a new approach based on FBSE-EWT and QCNN framework is introduced to detect and classify human activities using the FMCW radar return signals. The FBSE-EWT method is used for obtaining TFRs from the FMCW radar return signals. A more distinct TFRs of FMCW radar return signals are obtained using FBSE-EWT method. The obtained TFRs are utilized for the classification of human activities using QCNN and classical CNN models, namely, GoogleNet and VGG19. We also carried out performance assessment of the proposed framework based on training and testing accuracies. The QCNN

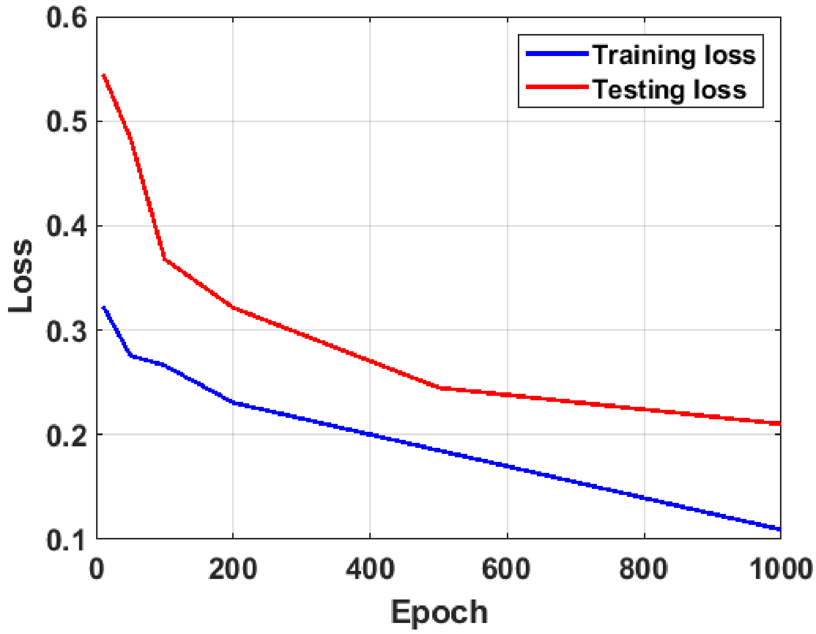


Figure 4.6: QCNN model loss versus epoch.

model is trained for different epochs and the proposed framework achieves the highest testing accuracy of 95.71%.

In this work, we have performed the comparative performance analysis of the classical CNN models such as GoogleNet, VGG19, and other existing methods. we have also conducted comparative analysis of training and testing accuracies over epochs. The computational time required to obtain TFRs using FBSE-EWT from the FMCW radar return signals is 10.0 s. That is relatively more than the existing methods in the literature namely, HHT. Future research will need to address a number of tasks including multiple-subject classification, multi-activity classification as well as more elaborate radar setups for a higher spatial resolution. By considering factors such as sample space, computational requirements, and execution capabilities like distribution and parallelization, new criteria can be established to guide the selection of the most suitable deep learning methods for specific applications. Future research can focus on improving accuracy and performance metrics.

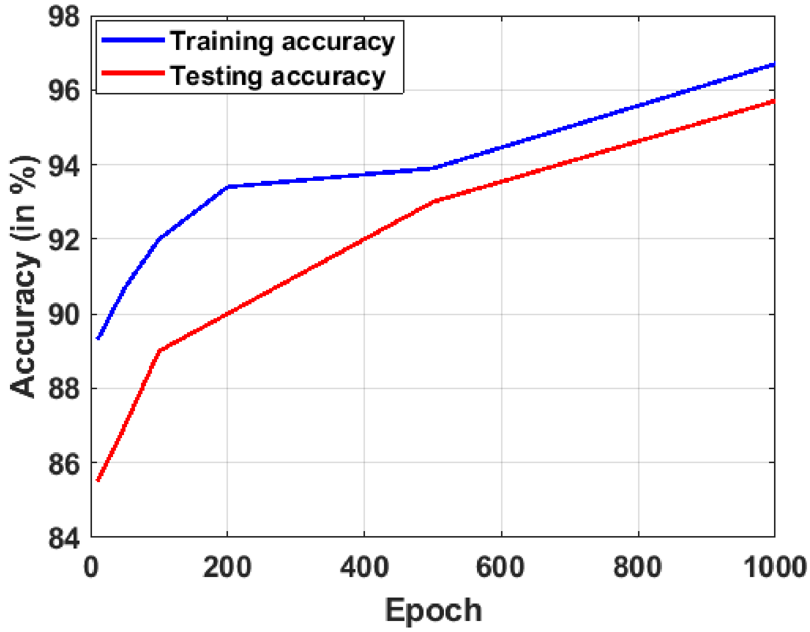


Figure 4.7: QCNN model training and testing accuracy comparison over epoch.

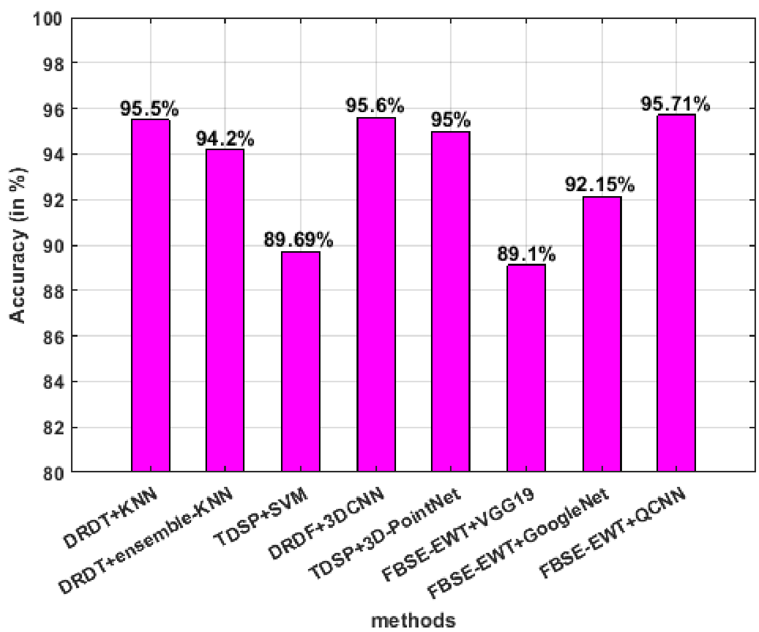


Figure 4.8: Accuracy comparison of classical CNN and QCNN for HAR.

Chapter 5

Conclusions and Scope for Future Work

5.1 Conclusions

In this thesis, we have proposed a novel framework for the classification of six human activities, namely falling, jogging, jumping, squatting, stepping, and walking. In the first approach, the different TFR techniques such as STFT, CWT, FSST, FSST2, FSST3, and FSST4 are studied to capture micro and macro motion of human activities. Then, we used five different deep learning classifiers such as MobileNetV2, GoogleNet, AlexNet, VGG16, and VGG19 to accurately classify different human activities. In this study, we applied the FSST4-based TFR technique combined with AlexNet for HAR. We have achieved an impressive accuracy of 99.40% using the proposed framework in HAR. We also obtained 98.50% accuracy for the classifications of falling and squatting. Furthermore, we obtained perfect classification accuracy for jogging, jumping, jumping, and squatting. we have performed a comparative computational complexity analysis of FSST4 with other methods such as STFT, CWT, FSST, FSST2, and FSST3. It was observed that the computational time required for the proposed framework is more than other approaches, whereas CWT is relatively faster than other methods. In this work, we have performed a comparative analysis of the performance metric of the proposed framework with other methods in terms of precision, recall, and F1 score.

In the second framework, we have proposed a new approach for the classification of human activities based on FBSE-EWT and QCNN framework from radar signals. The classical CNN fails to handle high-dimensional data. To address these issues the above framework is proposed. In this work, we have explored the FBSE-EWT based method to obtain TFRs for different human activities. We have utilized GoogleNet and VGG19 for the classification of human activities. The proposed framework is also compared to existing classical CNN methods in the literature. The proposed framework achieved the highest accuracy of 95.71% among the other methods.

5.2 Scope for Future Work

The proposed framework for HAR utilizes FSST-based TFRs to extract micro-Doppler features from FMCW radar return signals. The proposed approach has attracted significant interest in healthcare, smart home automation, sports, and assisted living. The proposed framework has addressed several issues such as the high computational complexity in terms of runtime and memory usage, the extraction of micro and macro features based on TFRs, and the classification of human activities using FMCW radar signals. However, the work presented in the thesis can be improved and extended further. The developed framework can be implemented on stand-alone dedicated hardware for real-time application, we manually chose the different parameters for deep learning classifiers throughout the work. An optimization technique can be chosen to automate this step and choose the best set of parameters. The developed framework can be validated using different publicly available databases using radar signals. In the future, the performance of the proposed frameworks can be tested on a large set of available data. The proposed framework can be used to develop other applications to analyze a different set of non-stationary signals. The computation time of the proposed framework can be further reduced by properly optimizing the algorithmic steps. In the future, a detailed theoretical assessment and analysis of the robustness of the proposed framework should be carried out. We can also study FMCW radar-based HAR using a lightweight transformer-based technique for the classification of human activities.

Future research should focus on refining algorithms and practical implementations of the HAR, supporting safety and well-being in diverse environments. The development of HAR systems using radar signals requires further research and improvement, but offers the potential to enhance monitoring and understanding of human behaviors in real-world scenarios. Future research in HAR should prioritize several critical areas. Firstly, there is a need to develop advanced methodologies for processing radar data, particularly those that can robustly manage noise and environmental interference. Secondly, integrating multimodal data sources—such as cameras, radar etc. Thirdly, designing novel neural network architectures that are both computationally efficient and suitable for deployment on edge devices with constrained resources is crucial. Lastly, ethical and social considerations surrounding the deployment of HAR technologies must be rigorously addressed to ensure that advancements contribute positively to user safety, privacy, and overall well-being.

Future research must tackle several key challenges, including the classification of multiple subjects, recognition of simultaneous or overlapping activities, and the development of advanced radar configurations to achieve higher spatial resolution. These improvements are essential for enhancing the accuracy and practicality of radar-based HAR systems in real-world environments. Furthermore, HAR based on FMCW radar using transformers will be considered in future studies. The multi-bin range selection strategy for the HAR can be studied as the future part of the carried-out research work. we can also explore to design a robust HAR trained in different real-world environments that can sense and recognize multiple activities. Future work will focus on expanding the variety of data sets, enhancing radar signal processing algorithms, and optimizing deep learning architectures to improve the performance of radar-based HAR in complex and continuous activity scenarios.

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