Activity Classification using 24 GHz Radar System and Deep Learning

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1 Abstract

The task of automated activity classification has attracted various avenues of research and has inspired different methodologies in solving the problem. In this report we outline an unobtrusive method of detecting and classifying different activities and exercises using a 24 GHz radar transceiver module and a deep neural network. The radar transceiver module is used to record data of a single individual carrying out a specific activities and the subsequently processed radar signals are used to train a convolutional neural network (CNN), which is also be used to classify activity signals. We define the methods used to record the activity data using the radar transceiver and the techniques used to process the raw radar signals. We detail the proposed CNN model, including training parameters and regime used to learn the custom built dataset. Furthermore, we show that the CNN model achieves a test accuracy of 92% on unseen data for classifying between two activities. We summarize the complete system and show that deep learning can be used in conjunction with radar systems to classify activities.

2 Introduction

Significant developments have been made in technologies relating to home assistants and artificial intelligence enabled systems for the home [10]. Home assistants are now trained to carry out complex tasks such as speech-to-text translation [7], searching the internet for useful information [10, 11] and automation of other household devices connected to the network [5]. With the ever growing demand for home assistants collecting data to make complex decisions, there exists a real security concern regarding collection, storage and analysis of data recorded using home assistants. Within the scope of this project, we focus our attention to the task of an automated home gym assistant capable of classifying various exercises and differentiating between different intensities of exercise, such that it can inform the user about their performance to the exercises. We investigate the use of unobtrusive 24 GHz radar system in conjunction with a deep neural network (DNN) for the classification of physical activities and exercises. The DNN model we focus on in our study is the convolutional neural network (CNN).

Global and national guidelines on physical activity constitute as one of the primary components in a comprehensive framework for public health management and action [1]. The World Health Organisation outline general guidelines for physical activity uptake and promote regular physical activity amongst the general population. The lack of regular physical exercise has wide reaching impacts on the greater society, as a mitigating factor of diseases [13]. Oftentimes, it is apparent that guidelines alone are not sufficient in increasing the uptake of regular physical exercise amongst the general population [12] and further communication is required in order to encourage regular physical activity. From the perspective of public health, research suggests that activity tracking devices provide a cost-effective method of increasing physical activity motivation. We aim to utilise and automated technology, in the form of a deep learning agent, to recognise different physical activities and exercises whilst also suggesting recommendations of improving or maintaining the activity intensity and movement.

There exists various technologies providing methods of physical activity and movement tracking, many of which using wearable devices equipped with accelerometers, vibration sensors and visual sensors [17]. One of the major concerns with on-person devices capable of regular activity and exercise monitoring are the privacy vulnerabilities of wearable technologies [3, 17]. The system proposed within the context of this study is capable of circumventing the issue of data security by utilising the unobtrusive 2.4 GHz radar system for data measurement. The main contributions (Innovation points) of this work are as follow:

- We collect a novel dataset consisting of radar measurements recording basic activities such as squatting, star jumps, walking and standing. The collected dataset also includes three different levels of exercise intensity relating to the range of motion for each exercises, from light motion, medium motion and full motion.
- We develop a CNN model, outlined in Section. 5 and apply a segment of the collected dataset to train the CNN model to classify different activities. We reserve the remaining dataset omitted from the training set as the validation set to which we test the CNN model against in order to test the ability of the CNN model to classify activities on unseen data.
- We extend the CNN model to classify three levels of motion intensity for each exercise and present our findings in Section 7.
- We propose an time-sensitive algorithm for the counting of specific exercise repetitions over an evaluated period of time and relate this to the motion intensity prediction to infer exercise intensity.

3 Related Work

The following section presents state-of-the-art work with regards to using deep learning in conjunction with radar systems to classify/predict various properties from the radar measurements. The current commercially available state of the art devices for physical activity monitoring can be broadly classified within the domains of wearable technologies [2, 17] equipped with an array of sensors to measure various motions and visual systems that use video data to classify specific activities. Wearable and visual technologies, however, pose concerns regarding data security, as the data collected may consist of sensitive information about the users and environment [3].

There exists various studies and model proposed on using deep learning for the task of recognising different physical exercises [17]. In their work, Soro et al. [15] present an end-to-end deep learning approach to classifying complex physical exercises using data recorded from wearable technologies. Ravi et al. [14] also proposed a deep learning approach to on-node sensor data analytics for classifying activities using wearable devices. We direct the reader to the works of [9] which details the use of deep learning for human activity classification using radar systems. In their work Gurbuz and Amin [4] detail numerous applications of deep learning for radar-based human-motion recognition. There has also been research conducted into using deep learning enabled radar systems for safety critical activity classification amongst elderly people [16, 6].

The task for exercise recognition using DNNs poses distinct problem specifications, particularly when considering repetitions and exercise intensities. The works of [15] deal with a similar problem statement, the primary dissimilarity between the their work and the work proposed in this research, being the type of data used and the method of collecting data. We aim to utilise the ability of radar systems to recognise minute and often complex motions, similar applications can be found in the works of [6, 16, 4], where they outline a method to recognise and classify different exercises, along with repetitions and intensities.

4 Signal Processing and Experimental Set-Up

In this section we outline the methods used to process the raw noisy radar signals, such that we extract important features from the measurements and prepare the signal to be applied to the CNN model detailed in Section. 5. We also outline the experimental set-up used to acquire the radar measurements detailing the set-up procedures and experimental routine.

4.1 Signal Processing

We begin by considering the raw radar signal recorded for an activity. The raw signal contains within in unwanted features (noise) that we remove first using a 2^{nd}-order low-pass ChebyShev Type II filter with a critical frequency of 1000 Hz and 3 dB ripple to remove any high frequency components. This can be seen in Figure. 5. Due to the nature of the recordings, splitting the signal into 5 individual repetitions from the full signal cannot be done efficiently due to the overlapping nature of each repetition signal and and noise contained within the signal. We proceed by transforming the data into a spectrogram (as shown in Figure. 1) where we can see the frequency spectrum of the signal with respect to time and measure the points in time where the signal shows to contain lower average frequency components, indicating a still motion or relative lack of activity. We separate each repetition from the full signal containing 5 repetitions using the signal spectrogram. When recording the activity measurements, the motion routine is noted and referenced when carrying out the signal segmentation procedure.

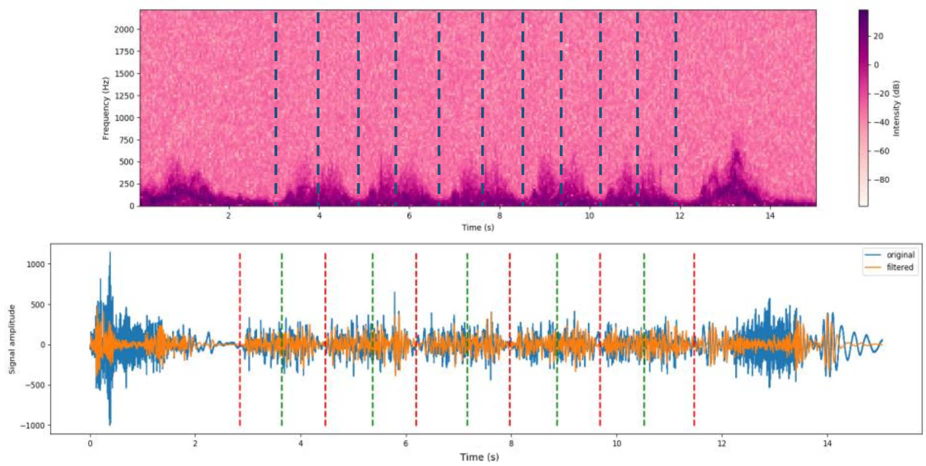

Figure 1: (**Top**) figure shows the radar signal transformed into a spectrogram, such that we can analyse the signal over time at various frequencies and identify each repetition of an exercise. (**Bottom**) figure shows how the noisy, full signal is split into its constituent repetitions using the spectrogram.

4.2 Heart Rate Estimation

For extracting the rate at which an individual's heart is beating at per minute using the radar transceiver, we must process the raw signals differently to the activity data, as the frequency bandwidth we are interested in to extract heart rate ranges from 0.5 Hz to 5 Hz. We use a 3^{rd}-order Butterworth bandpass filter to remove baseline signal variation below 0.5 Hz and above 5 Hz. The original normalised radar signal and resultant signal can be seen in Figure. 2. Here we use a Butterworth filter for its smooth transient characteristics at the critical frequencies.

4.3 Experimental Set-Up

The radar system used in this study is the 24 GHz I/Q channel K-LC2 [1] radar transceiver with the ST100 evaluation board [2] board. The radar system, and the accompanying development board used for and data transfer, were powered using a 5V DC power supply. All radar recordings were carried out under laboratory conditions and the raw dataset consisted of two individuals (1 male and 1 female) carrying out the following exercises: squat, star-jumps, walking and standing. Each recording signal consists of 5 repetitions of each exercise and there are 3 recordings per exercise measured. All recordings are made under laboratory conditions and carried out with the individual being recorded carrying out various activities with a distance of 2m away from he radar transceiver.

From Figure. 3 we show two example exercises and the signal segmentation method in which we manually classify the different motions that constitute each exercise. The resultant

[1] https://www.rfbeam.ch/product?id=5
[2] https://www.rfbeam.ch/product?id=34

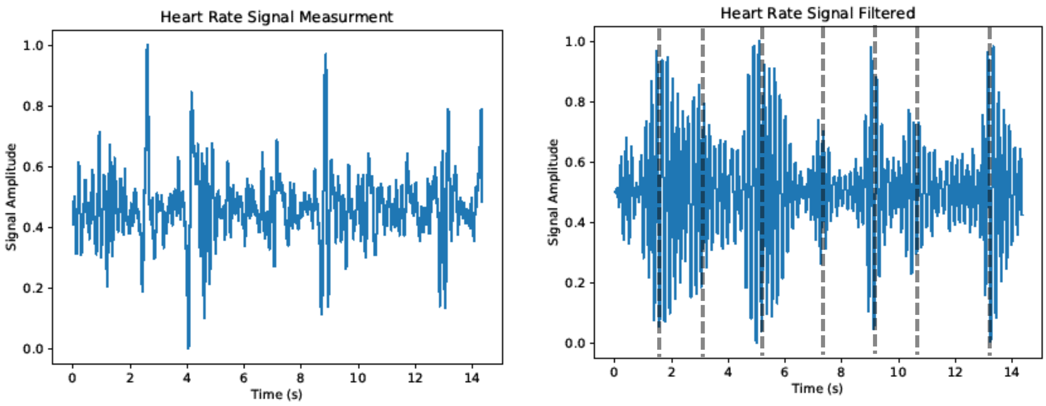

Figure 2: (**Left**) figure shows the radar measurement with the transceiver standing at a distance of 2m from of an individual standing still. (**Right**) figure shows the filtered signal; we use the filtered signal to approximate the locations of heart beat signatures. Showing in the dotted lines are the approximates of the heart beat signatures that are used to train a CNN model to classify, thus measuring the repetition of each instance.

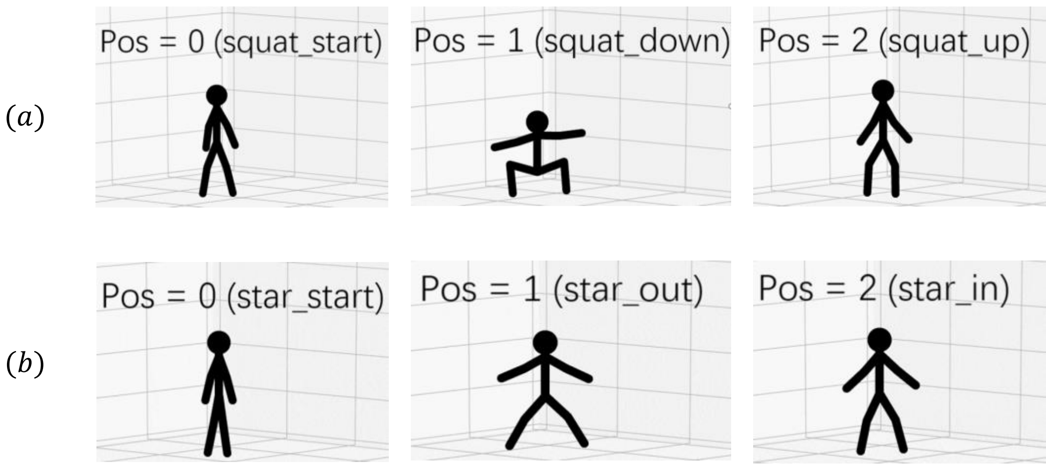

Figure 3: (**a**) shows the expected motions when recording for a squat exercise with accompanying labels for the three motions considered to make up the squat exercise. (**b**) Shows the expected motions when recording for a star jump exercise with accompanying labels for the three motions considered to make up the squat exercise.

signal is segmentation of the original radar signal and represents one instance of a given activtiy.

5 Activity Classification System

Within this section we outline the proposed system with the accompanying CNN models and algorithms for exercise recognition, intensity classification and the repetition counting. We also outline the signal preprocessing techniques used to to prepare the raw radar data for the subsequent classification models, as each model requires different data transformations to be applied to the signal prior to application.

6 Activity Dataset

The measured dataset consists of 3 sets of each exercise; squats, star jumps, walking and standing. Each exercise signal set contains within it, 5 individual repetitions of each exercise (for the walking and standing activities, a continuous signal of the environment with the participant is recorded). Each repetition signal is further processed for the classification model. We have a resultant of 100 signals for each exercise (squats, star jumps, walking and standing) and each person.

We take a signal x and apply a digital 4^{th}-order Chebyshev Type II bandpass filter to remove frequencies below 0.1 Hz, for the purpose of stabilising the signal, and 500 Hz, which from analysis of the signals, found to not contain significant activity features. The enclosed frequency bandwidth is then filtered using a 3^{th}-order Chebyshev Type I notch filter with critical frequencies at $[(15-30),(30-60),(60-120),(120-240),(240-280)]$, resulting in 5 filtered signals from one original repetition signal. the notch filter critical frequencies are found through analysis of sample data. The purpose of the notch filter windowing on the raw signal is to carry out a transformation of the raw signal through removing prominent frequencies, such that we may better understand the nature of motions and their accompanying frequencies.

6.1 Activity Classification Model

The DNN was configured with the following parameters in sequential order: a 32 dense layers, a maximum pooling layer with pooling size of 2, a 64 dense layers, a 32 dense layers and a 16 dense layers, all using ReLu activation functions. A unit dropout rate of 25% was used after the 128 dense layer and 64 dense layer, followed by a 50% rate after the flattened 16 dense layer, this was applied in order to avoid overfitting. An Adam optimizer [8] using back propagation was used for the learning method and the model was trained for 20 epochs.

6.2 Activity Repetition Counter

The task of counting exercise repetition over a given period T, consists of forming a window around the signal in question and classifying the motion activity using the CNN model. As we can control the size of the window used to segment the signal, we can iteratively convolve segments of the continuous signal with the CNN model to result in the activity classification. Furthermore, we can serialise the output of the segmented window prediction and form a time series of repetitions to no repetitions. This process is hinged on the availability of a stat of equilibrium, relative to intensive activity motions. For the activities considered

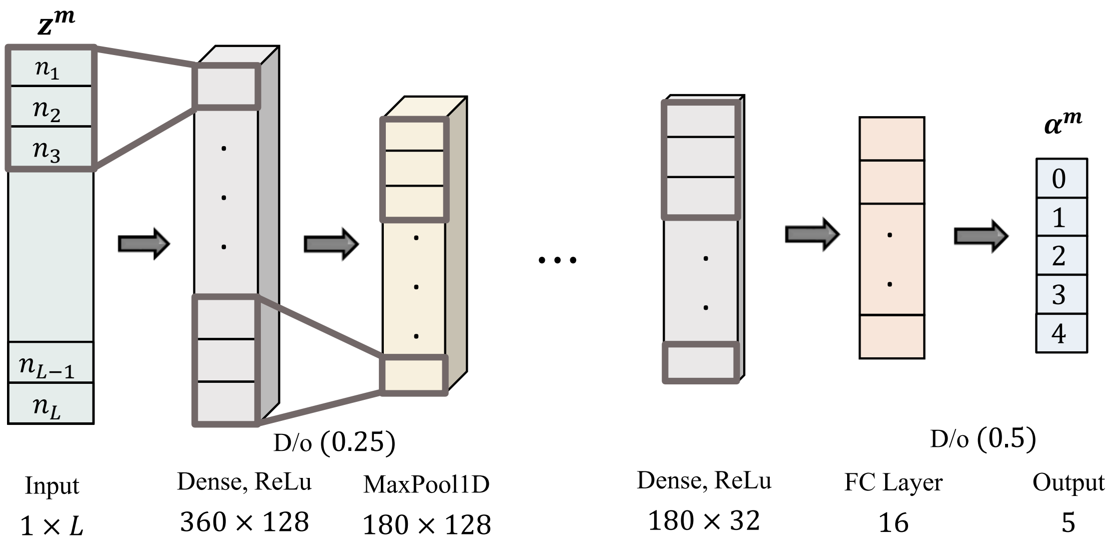

Figure 4: Shown here is a condensed figure for the CNN model developed in this study for the classification of different exercises. The input of the model is controlled by the parameter L and represents the length of the signal. The output of the model is a vector of length 5 representing sit ups, squatting, star jumps, body twisting and standing.

within this study, we take the measurements corresponding to an individual standing still as the point of equilibrium and compare activity to this.

The signal segmentation process is detailed in Figure. 6 section E (no.3, no.4), where we see how windows can segment the full, continuous signal to classify activities and in doing so, monitor repetitions. It should be noted that in carrying out the signal segmentation and classification introduces latency to the prediction. To circumvent this issue, we propose, where possible, to asynchronously run two window and classification iterations to minimise the affects of latency, as shown in Figure. 6 section E (no.3).

7 Results and Analysis

In this section we begin by describing the resultant methodology from analysis of the 24 GHz radar signals for the purpose of human activity classification. The complete methodology for processing the radar signals can be found in Figure 5, containing initial signal preprocessing (**A**), the signal transformation through windowed filtering resulting in different signals from the original signal (**B**) and the notch filter windowing carried out to remove specific frequencies (**C**). In Figure. 6 we see the outline of the CNN architecture, along with the training parameters and initialisation (**A**) and the repetition counting implementation (**B**).

7.1 Classification Results

The model detailed in section. 5 and Figure. 6 results in a classification accuracy of 92% when tested against 3 classes (squats, star jumps and standing still). This model accuracy for the four classes reduces to 74%, whereas the model accuracy for classifying 2 classes is 97% on average over all exercise pairs.

For motion intensity classification we consider a signal activity and measure three different levels of intensity; high intensity, mid intensity and low intensity. The custom recorded dataset consists of 300 segmented signals (100 signals of each intensity range) which are the result of the moving notch filter transformation, as described in section. 6. The dataset is split into a test set (30% of total signal) and train set (70% of total signal), furthermore the base signals for standing still are also added into the dataset, resulting in 135 test signals and 255 training examples. The intensity classification task using the CNN model detailed in section. 6.1) results in a classification accuracy of 58% over a test set of 135 signals.

7.2 Figure. 5

In part **A** we have (1.) two exercises a (squat) and b (star jump) which are both filtered using a (2.) low pass filter with a critical frequency of 1000 Hz, as detailed in section. 4.1. The resultant signals (3.) of a and b are filtered for high frequency components. Following this, part **B** shows the two signals a and b transformed using $T^(f, t)$ into the signal frequency f and time t, resulting in a spectrogram. We use the spectrogram (1.) to segment the signal in time to extract 5 repetitions from the original signal. An example of a segmented signal (2.) is shown with frequency components. This results in (3.) two signals which have the same motion label as the original, but contain different information. We utilise this behaviour to form **C**, where we take an input signal x (1.) and systematically remove specific frequency bands (2.,3.) and form the final dataset (4.,5.), with only specific frequency components remaining (6.).

7.3 Figure. 6

This figure outlines the CNN model and exercise repetition methodology. In **A** we begin by (1.) splitting the full dataset $\mathbf{X}$ into X_{tr} (training set) and X_{te} (testing set) with a split of 70:30 respectively. We have at the input of the model (2.) a set of filtered signals with a signal motion label, which is input to (3.) the classification model $f(x, \mathbf{W})$ which accepts and input x_i and weight parameter $\mathbf{W}$. The resultant is (4.) a vector $\hat{y}_i$ for each input x_i for a given $\mathbf{x}$ and we proceed by taking the average classification that relates to the the outputs $\hat{\mathbf{y}}$ being the motion labels. For this experiment we have $\hat{y}_a$ and $\hat{y}_b$ representing a squat and star jump classification respectively.

8 Conclusions

In this work we investigate the use of 24 GHz radar system for the measurement and classification of home exercises using signal processing and deep learning. We record a custom dataset for this study consisting of 500 total signals, 25 repetitions of each exercise considered and collected from 2 individuals for activity classification and intensity classification. The four exercises considered in this study are: squats, star jumps, walking and standing upright. We also conduct a study to show how motion intensity (high intensity, medium intensity and low intensity) can be classified using the proposed CNN model.

In this work, we offer a method of processing the raw radar signals, such that important exercise features are identified and extracted efficiently using a sliding notch filter over an identified frequency range. We propose a 1D CNN model to classify the four different exercises and suggest a method using signal enveloping to measure the number of repetitions over a continuous full exercise signal. The developed CNN model achieves a classification accuracy of 92% for the four different exercises, furthermore we can classify different activity intensities with an accuracy of 58%, which is a 4 class classification problem including the base motion of standing still.

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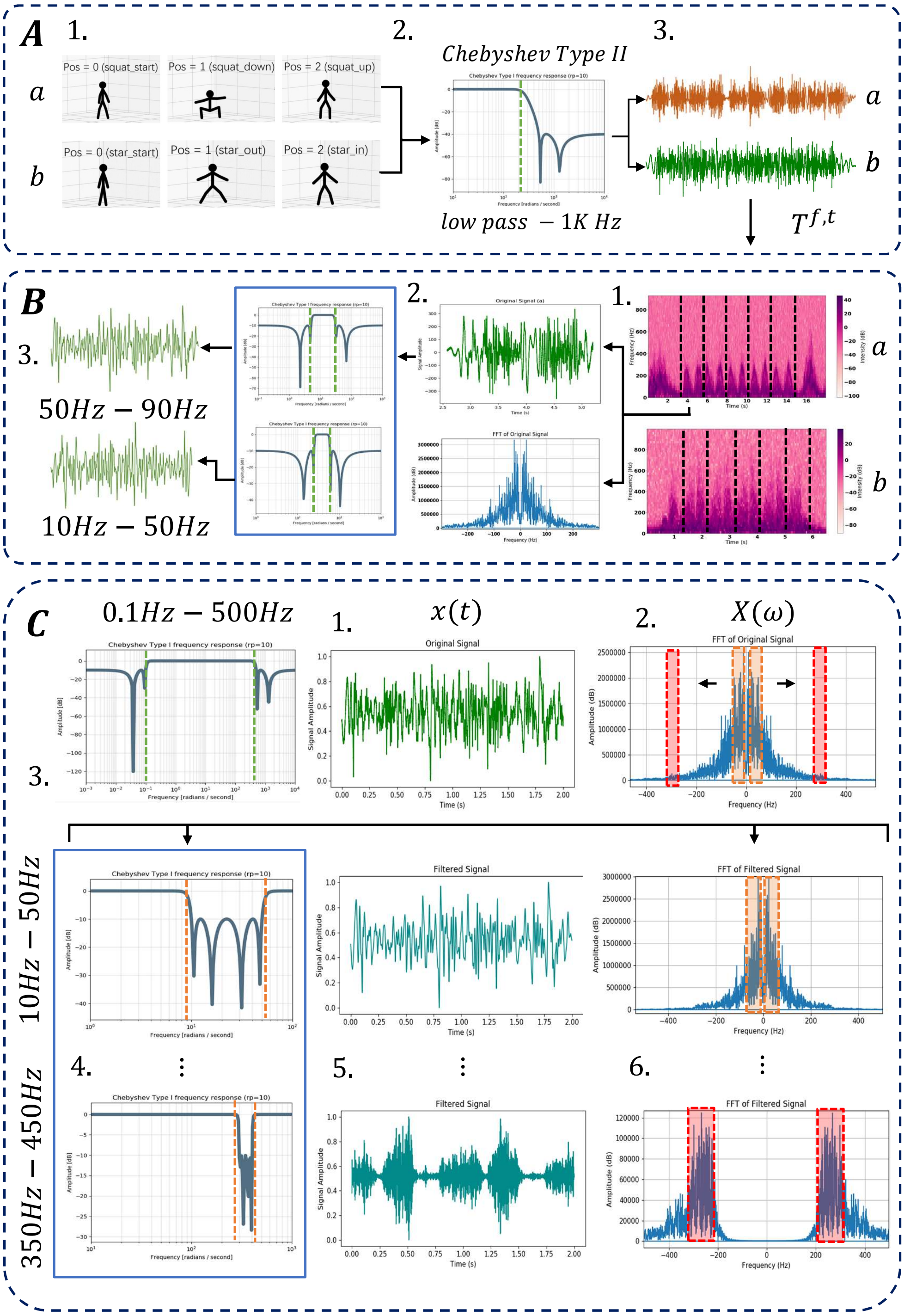

Figure 5: Diagram showing data prepossessing **A**, the result of isolating specific frequencies **B** and the moving notch filter **C** used to extract different features form the orignal signal. Further details on the diagram can be found in section. 7.2.

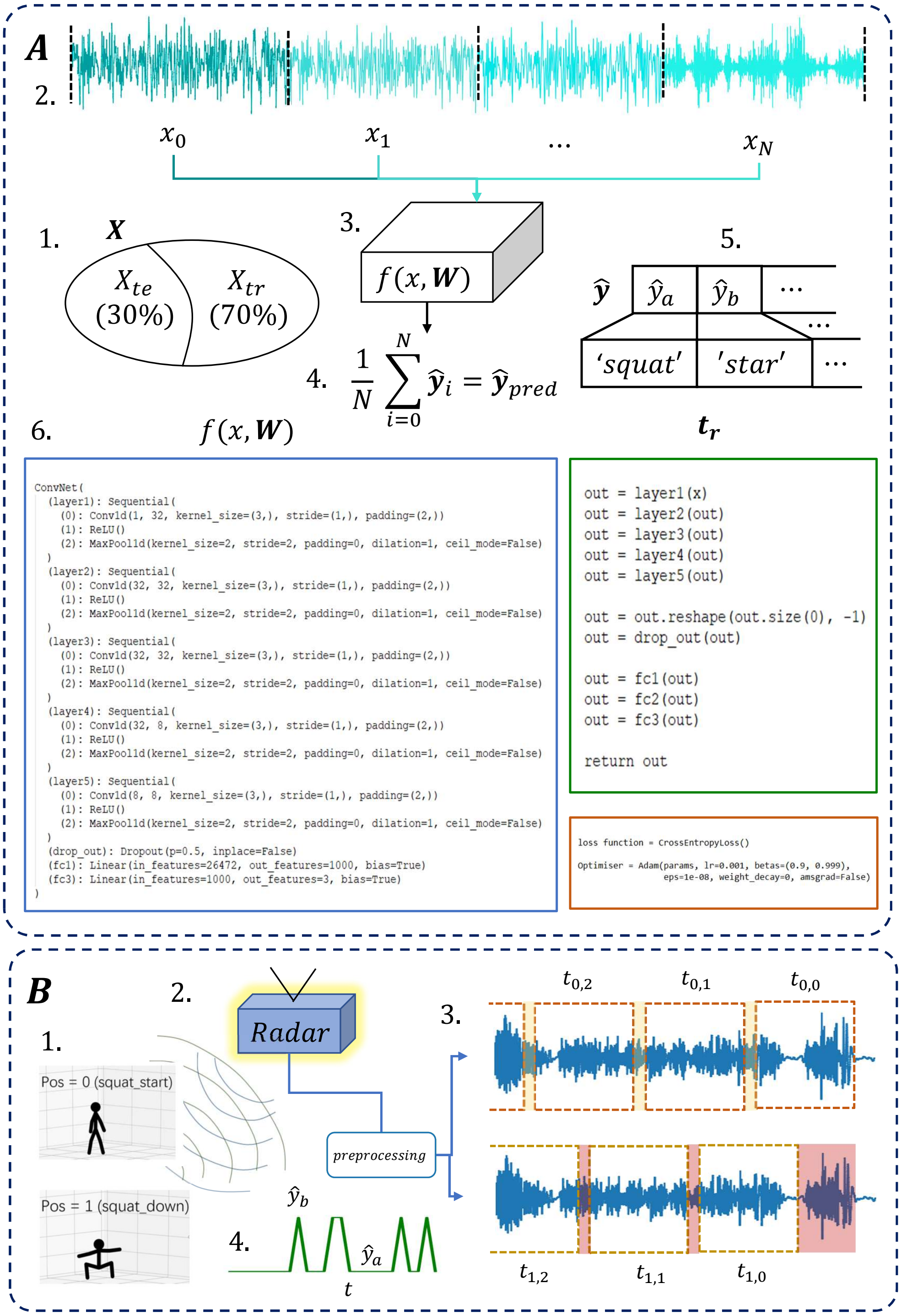

Figure 6: Diagram shows the CNN classification model architecture **A** with the data preparation and model learning parameters. In **B** we see the overview of the proposed system including the online classification method and repetition counting technique. Further details on the diagram and its constituent processes can be found in section. 7.3.