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# Blaze-Wi : Accurate and Light Weighted System for Gait Based Identity Recognition and Intrusion Detection

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**ABSTRACT** Gait based identity recognition and device-free human detection have gained tremendous attention in recent years since they are key enablers of building smart environments. WiFi-based approaches are more desirable with the contactless and non-line-of-sight nature when compared with vision-based and wearable sensor-based solutions. In this paper, Blaze-Wi, an intelligent, light weighted and privacy-friendly user identification and intrusion detection system that offers significantly higher accuracy and deals with joint tasks, is presented. As a result, based on gait biometrics derived from WiFi signals, an intrusion detection and user identification system has been established. The deep learning side for automated features extraction except for hand-crafted feature extraction and traditional algorithms have been focused on. Our network, Blaze-Wi, is based on Google's Blaze-face network and has only 210 thousand parameters, allowing it to make real-time predictions. The hyperparameters have been tuned to achieve the best results. Experimental results demonstrate that Blaze-Wi can achieve 98.4% for the joint task, 97.3% for gait only, and with the WIDAR 3.0 dataset it achieved 99.27% accuracy for a group of 6 persons..

**INDEX TERMS** Blaze-Wi, Channel State Information (CSI), Deep Learning, Gait Recognition, Identity Recognition, Intrusion Detection, WiFi Sensing.

## I. INTRODUCTION

Device-free human detection and gait based identity recognition have attracted much attention in recent years. It can detect and recognise if there are any people in a specific area and recognize their identification without requiring people to use any special electronic devices [1], [2]. The wireless-based human detection techniques that take advantage of off-the-shelf infrastructure makes it more pervasive. Intrusion detection [3], smart homes [4], [5], [6], border protection [7], smart cars, identity recognition [8], healthcare, and elderly healthcare [9], [10], are some of the critical applications of device-free human detection and recognition. There are many existing methods which can achieve intrusion detection, such as camera-based, sensor-based, and Received Signal Strength Indicator (RSSI)-based while gait can be captured with cameras or internal measurement units (IMU) [11]. Camera-based approaches [12], [13] require a camera installed in the monitoring area to record and detect passive activity by recording a video and analyzing its frames. However, it can only be used in illuminated areas, and the line-of-sight (LOS) condition is a must. Furthermore, its main issues include high false alarm rate and potential privacy leakage. The sensor-

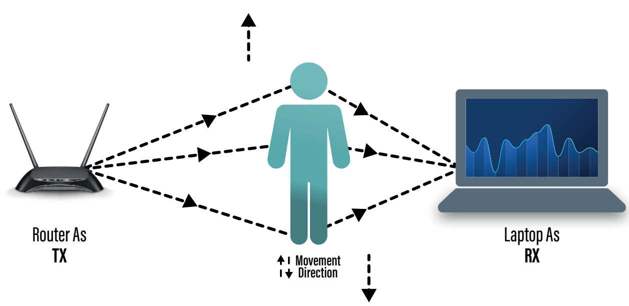



FIGURE 1: The general WiFi sensing system.

based methods [14], [15], [16], [17] utilize body-attached motion sensors such as accelerometers or a gyroscope to collect information on people's activities and behaviors, but these approaches may have a high false alarm rate caused by the environmental noise and disturbance. Attaching a sensor to the body is a limitation to some people since they might feel uncomfortable wearing them, also wearing sensors is infeasible in some scenarios. Moreover, all these approaches share the requirement of infrastructure installation in the area of interest, and also they have high installation cost. Last but not least, intrusion detection using sensors such as fingerprints or cameras are facing many challenges nowadays due to Covid-19 pandemic.

The limitations of the previous methods have prompted the researchers to search for new sensing solutions that are more suitable for indoor environments. With the rapid development of wireless technologies in the past few years, the role of WiFi Radio Frequency (RF) signals has been extended from that of a sole communication medium to a non-intrusive environmental sensing tool. Advantage of the transmission characteristics of opportunistic WiFi signals in wireless channels is taken by the researches of WiFi-based sensings, such as RSSI and Channel State Information (CSI), which are used in many applications such as, indoor localization, activity recognition, gesture recognition, human presence, vital signs, intrusion detection and so on. Since RSSI is only a description of the received power, it faces many challenges such as, dramatic performance degradation due to multipath fading, and vulnerability to environmental noise, especially when the target has little impact on the environment, it is prone to false detection. On the opposite side, the detailed propagation of signals from the transmitter (TX) to receiver (RX) through multiple paths at the granularity of Orthogonal Frequency Division Multiplexing (OFDM) subcarriers is described by the CSI, both amplitude and phase information for each propagation path is contained by the CSI. By analyzing the changed signal paths and channel state on CSI impacted by moving targets, more accurate and robust intrusion detection and gait based identity recognition solutions can be achieved. Intrusion detection is a dynamic process of monitoring that tries to tell the existence of the intruder in the area of interest without any device attached to the intruder, while identity recognition is used to recognize the intruder then making alarms if necessary or providing some features. More and more attention is gained by intrusion detection and gait identity recognition and they have great potential in many applications, such as border protection, smart homes, smart cars, elderly health care, etc...

WiFi gait recognition and intrusion systems are based on the idea of when a person moves through wifi signals this person causes changes to the amplitude and phase of the signals that could be seen in the channel state information of the WiFi signals, as shown in Fig. 1, also everyone has their own custom gait and medical studies have shown that gait is a very complex biological process and is unique to each person [18], [19]. There are studies that also show that when we try to imitate someone else's gait our own gait works against us [20], [21]. These unique characteristics of gait make it ideal for user identification and authentication. Since gait causes custom changes and the WiFi signals are sensitive enough to detect these changes and deep learning helps us to classify them based on these changes. Most systems that are based on solid hand-crafted analysis fail when dealing with a large dataset and huge numbers of users so a system with a deep learning network is going to be built.

In this paper, Blaze-Wi, an intelligent, light weighted and privacy-friendly user identification and intrusion detection system that offers significantly higher accuracy and deals with joint tasks, is presented. Our network is based on depth-wise separable convolutional layers, and a group of volunteers has been classified with a high classification accuracy, we are the first to build gait and intrusion schemes in the same system. In addition to this, a comparison between multiple architectures and learning algorithms has been provided. This process works like any other deep learning-based process.

In summary, the main contributions are as follows:

- A light-weighted and accurate network called Blaze-Wi based on Blaze Blocks inspired by google Blaze-face [56] network and because of its lightweight it allows us to deploy the prediction system on edge devices or any low computational power device which allows it to run the full pipeline end to end on the user which decreases the cost and increase the privacy.
- Combining different schemes which are Intrusion and gait-based human recognition in the same system, this combination is considered as a new technique with gait recognition but it's very useful as it allows building an end-to-end system and allows deployment in real environments.
- The results were achieved using commodity and commercial hardware without additional modification on the hardware which shows the power of the Blaze-Wi network and proves that WiFi sensing systems could be done with traditional hardware and the developers and engineers can just focus on developing software and machine learning models to fit market requirements.
- Blaze-Wi system was tested with multiple datasets for gait recognition and the results were outstanding which shows the network is dependable and shows a promising future for such systems.

The rest of the paper is structured as follows. The related works is introduced in Sec. II, while Sec. III is talking about the used hardware, data collection, and the used topology. The used network is described in Sec. IV, Sec. V is representing result of project experiments and their accuracy, a conclusion of the paper is provided in Sec. VII. Finally, a future vision is discussed in Sec. VI.

## II. RELATED WORKS

### A. INTRUSION DETECTION

Over the years, many passive human detection and intrusion systems have been developed based on various technologies, e.g., camera [24], sound [25], [26], and infrared [27]. Due to the privacy protection requirement, camera-based or sound-based approaches are usually not desirable for indoor intrusion detection [28]. Infrared-based systems [27], [29] can achieve good detection accuracy while preserving the privacy of the user. However, the detection range/angle of infrared is limited, making it difficult to achieve high coverage in practice. Compared with these approaches, WiFi-based human detection achieves a better trade-off between accuracy and privacy protection. Also, WiFi is already widely available, which means that the extra deployment cost can be minimized.

Intrusion detection is a primary and fundamental application in wireless sensing, and recent years have witnessed its rapid development, especially based on CSI provided by off-the-shelf WiFi devices. FIMD [30] utilizes the observation that the temporal correlation of CSI amplitude will fall dramatically when there is a moving human to achieve intrusion detection. PADS [26] is similar to FIMD [30], but it is the first effort to utilize CSI phase information as well to determine human presence. Deman [31] proposes a method to further detect whether a person is in motion or not by fitting CSI sequence to the sinusoidal breathing model to estimate the primary respiratory rate. If the estimated frequency falls within the normal person's respiratory frequency range, then the system assumes that a static person exists. Omni-PHD [32] uses fingerprints and Empirical Mode Decomposition (EMD) algorithm to detect intrusion in all directions. Despite that these works have achieved high accuracy, their performance cannot be guaranteed with a relatively low sampling rate of 15-20Hz and they can hardly be transplanted to embedded devices for commercial use.

RR-Alarm [33], by reusing the existing Wi-Fi signals, is able to detect human intrusion in real-time, at the same time, requiring no additional facilities installation. By utilizing the Doppler effects incurred by human motion on multiple Wi-Fi devices, RR-Alarm is not only able to accurately detect the intrusion without any extra-human efforts but also avoids a large number of false alarms caused by the human motion from outside the house. PetFree [34] on the other hand uses fine-grained CSI of WiFi signals to detect whether there is a human or a pet in the monitoring area. The basic idea of PetFree is to use the Effective Interference Height (EIH) differences between humans and pets. In another literature, TWMD system [35] is a new detection idea that expands the dimension and quantity of features and then it builds Back Propagation (BP) neural network to obtain the mapping relationship between multiple features and detection results. This detection scheme can avoid the system instability caused by improper feature selection and insufficient number of features. At the same time, in order to enhance the reliability of TWMD in low Signal to Noise Ratio (SNR) environments, the output features of BP neural network of each antenna are merged.

### B. GAIT RECOGNITION

#### 1) Gait Recognition in the Old School

Johansson et al. [36] and Cutting et al. [37] conducted research about gait recognition in the 1970s and discovered that by simply viewing video pictures of the walker's prominent joints, viewers could identify the gender of the walker or even recognize the walker they were familiar with. Early human gait recognition systems were mostly relying on video or image sequences, based on these research foundations [38], [39], [40], [41].

However, video-based methods always need subjects to walk perpendicular to the optical axis of cameras in order to obtain more gait information, [38] and they often have a number of other non-negligible drawbacks, such as LoS, light, and personal privacy. For gait recognition, some other advanced sensors were also used. Orr et al. [42] used floor force sensors to record the subjects' footstep force profiles, on which the footstep models were designed, and they were able to achieve a 93% gait recognition accuracy. Sprager et al. [43] and Primo et al. [44] presented a collection of walking dynamics and human gait recognition using the built-in accelerometers of cell phones.

#### 2) Gait Recognition in the Modern School

Many applications [45], [46], [47], [48], including gait recognition [49], [50], have recently been developed using emerging Wi-Fi-based (mainly, CSI-based) sensing techniques. WiStep [51], is a specialized step counting method that uses Discrete Wavelet Transform (DWT) and short-time energy calculation to reveal step patterns in CSI amplitudes, and it can be used to segment the CSI data of each step, i.e., gait cycle detection, for gait recognition. CSI gait features were used to extract time-domain and frequency-domain gait features.

WiWho, WiFi-ID, and WifiU are three gait recognition systems proposed by Zeng et al. [50], Zhang et al. [52], and Wang et al. [49], respectively. WiWho concentrated on the CSI low frequency band 0.32 Hz, which involves a lot of interference caused by small movements and changes in the environment [51]. This prevents WiWho from working when the subject is more than 1 metre away from its transceivers' LoS route. In CSI measurements, WiFi-ID and WifiU focused on the frequency components of 2080 Hz. In WiFi-ID, gait features were extracted in different frequency bands using the Continuous Wavelet Transform (CWT) and RelieF feature selection algorithms, with the Sparse Approximation based Classification (SAC) [53] as the classifier. In WifiU, a synthetic CSI spectrogram was produced using Principal Component Analysis (PCA) and spectrogram enhancement techniques, from which a collection of 170 features was extracted, and the SVM classifier was then used for human identification.

Based on WiWho, Chen et al. [54] added an acoustic sensor (a condenser microphone) as a complementary sensing module to detect gait cycles and developed Rapid, a multimodal human identification device that could provide a more reliable classification result than WiWho. From a group of 2 to 6 subjects, most of these systems could achieve an average human identification accuracy of around 80% to 92%, However, detecting gait cycles from CSI measurements is difficult because the changing patterns caused by walking are often hidden in the noise, [49] hence requiring the use of advanced signal processing techniques to fine-tune the data. Furthermore, hand-crafted gait features derived from gait cycles are constrained in their ability to classify complex walking patterns in various scenarios.

## III. SYSTEM MODEL AND WORKING ENVIRONMENT

### A. HARDWARE

A Dell latitude E5400 laptop operating on Linux 14.04 LTS operating system has been used. It's equipped with Intel 5300 wireless NIC. A Linux 802.11n CSI Tool has been installed on the laptop [55]. A three-antenna access point (AP) operating at 2.4 GHz band has been used.

### B. TOPOLOGY

As shown in Fig. 2, the test environment consisted of an empty corridor It's worth noting that the direction of gaiting is in the y-direction. The laptop and APs are fixed at the opposite sides of the corridor and horizontally facing each other. There are two end-points that are specified on the y-axis in the direction of gaiting.

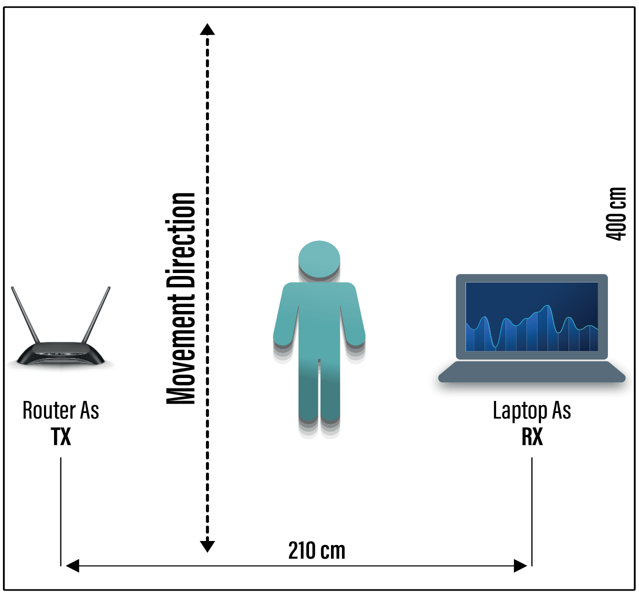



FIGURE 2: Configuration of the topology test

### C. SYSTEM MODEL

CSI shows how signals propagate through the channel. The impairments that the signal faces due to issues such the multipath, shadowing and scattering are embedded in the CSI.

In the 802.11 protocol which is the used protocol in the WiFi technology, two important techniques are used: the first technique is orthogonal frequency division multiplexing (OFDM) and the second is multiple-input multiple-output (MIMO); those techniques allow WiFi signals to provide high accurate channel measurements. Using OFDM allows to measure the CSI at the subcarrier level as the signal is transmitted across multiple subcarriers at different frequencies. On the other hand, in MIMO technique, the multiple TX and RX provide spatial diversity to increase diversity gain, array gain and multiplexing gain.

Therefore, the signal received at the receiver can be written as

$$\mathbf{y}_k = H_k \mathbf{x}_k + \mathbf{n}_k \tag{1}$$

where $k$ is the subcarrier index, $y(k) = [y_1(k)y_2(k).......y_{N_{RX}}(k)] \in R^{N_{RX}}$ and $x(k) = [x_1(k)x_2(k).......x_{N_{TX}}(k)] \in R^{N_{TX}}$ are the received and transmitted signals, respectively, $N_{RX}$ is the number of receiver antennas, $N_{TX}$ is the number of transmitter antennas, $\mathbf{n}_k$ is the noise vector, and $H_k \in C^{N_{RX}N_{TX}}$ denotes the CSI matrix of the subcarrier $k$.

$$H_k = \begin{pmatrix} h_k^{11} & h_k^{12} & h_k^{13} & \cdots & h_k^{1N_{RX}} \\ h_k^{21} & h_k^{22} & h_k^{23} & \cdots & h_k^{2N_{RX}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ h_k^{N_{TX}1} & h_k^{N_{TX}2} & h_k^{N_{TX}3} & \cdots & h_k^{N_{TX}N_{RX}} \end{pmatrix} \tag{2}$$

where $h_k^{pq}$ contains the CSI data between the $p^{th}$ transmitter antenna and $q^{th}$ receiver antenna of the subcarrier with index $k^{th}$.

The $h_k^{pq}$ is a complex value, which have an amplitude of $|h_k^{pq}|$ and phase $\angle h_k^{pq}$ so the $h_k^{pq}$ can be represented as

$$h_k^{pq} = |h_k^{pq}|\, e^{j\angle h_k^{pq}} \tag{3}$$

As shown in Fig. 3, CSI data of subcarrier 18 for device-free presence detection, in which the X-axis represents the packets over time, the Y-axis represents the amplitude of the CSI. Different colors represent the different connections between each antenna in the transmitter and the receiver. The figure also shows that there is a clear difference between movement and no movement data. Therefore, CSI contains meaningful features about the surrounding area which need mining to extract them.

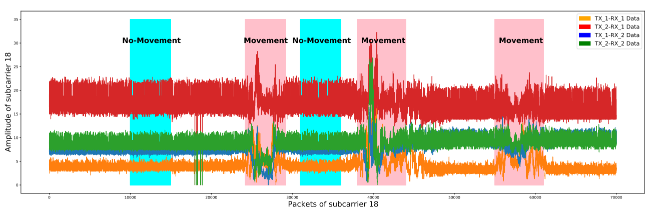



FIGURE 3: Movement and no movement CSI data of subcarrier 18

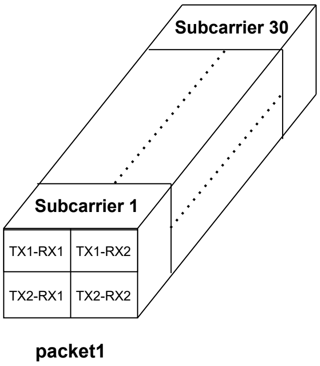



FIGURE 4: Packet explanation

### D. DATA COLLECTION

In this work, 8 participants (7 males and 1 female, aged between 20 to 26 years old) participated in the joint task dataset collection. Each participant is asked to walk within the horizontal distance between the two end-points in a straight line as shown in Fig. 2. As soon as the participant arrives at an end-point, they turn around and walk back to the other endpoint in a periodic motion. At the same time the laptop receives the packets from the access-point then extracts the CSI measurements and saves it in a file named after the participant name.

Six of the participants walked for 20 minutes while the other two walked only for 10 minutes with a total duration of 140 minutes (an alarm is being used to determine the end of the participant's walking duration). The sampling rate is 500Hz, the network input shape is [2500, 120] which means each sample is a 5 second in duration. Each second the collected data shape is [500, 30, 2, 2] where 500 is the number of packets, 30 is the number of subcarriers, 2 is the number of TX antennas, and the last 2 is the number of RX antennas. Fig. 4 illustrates packet structure.

## IV. NETWORK

### A. BUILDING BLOCKS

Blaze-Wi is inspired from Blaze-face network introduced by google and the building blocks are Blaze-1D block and double-1D Blaze block which are based on separable depth-wise conv1D with kernel size of 5 as shown in Fig. 5. Blaze-Wi network considered as a function as follow.

$$\mathbf{z} = Blaze - Wi(\bar{\mathbf{H}}_{5seconds}) \tag{4}$$

Where $H_{5seconds}$ is normalized 5 seconds of CSI collected data, Blaze-Wi is the network and $z$ is the result which then fed into the $softmax$ function (5).

$$\mathcal{P} = softmax(\mathbf{z}) \tag{5}$$

Where $\mathcal{P}$ is the probability distribution, $softmax$ is the softmax function in (6) and $\mathbf{z}$ is the output of the last layer in Blaze-Wi.

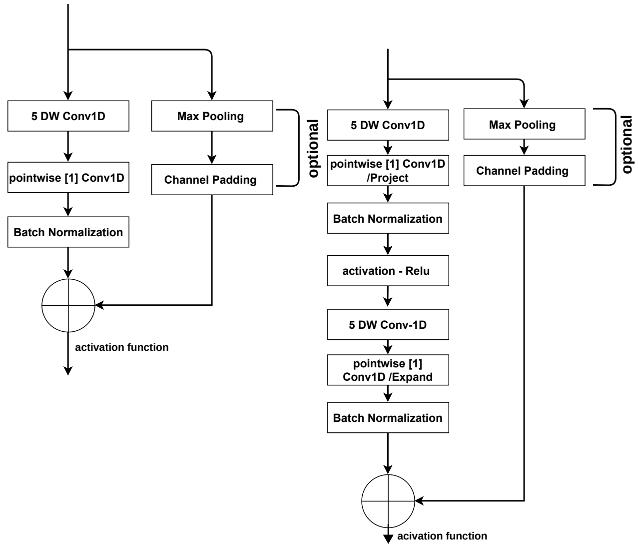



FIGURE 5: Blaze-1D block (left) and Double Blaze-1D (right)

$$\sigma(\overrightarrow{z})_i = \frac{e^{z_i}}{\sum_{j=1}^{num_{cls}} e^{z_i}} \tag{6}$$

where $num_{cls}$ is the number of classes in the multi-class classifier , sigma ($\sigma$) is the softmax function ,out is the function's input vector, $e^{z_i}$ is a standard exponential function for input vector ,and $e^{z_j}$ is a standard exponential function for output vector.

### B. SEPARABLE DEPTH-WISE CONVOLUTION

Separable depthwise convolution (Fig. 6, Fig. 7) has become a very popular technique and is being used in many effective networks [Blaze-face, MobileNetV2, Xception] [56], [57], [58] and these techniques are used in our network as well. Separable depthwise convolution layer consists of two stages, the first one is the depthwise convolution layer which deals with each channel separately thus leading to reducing the operations required. Secondly, the point wise convolution 1 × 1 convolution which is used to create the network features.

Convolution layer with a kernel size of $A * A$ and an input tensor $T_{w_{input}} * T_{h_{input}} * T_{ch_{input}}$ where $T_{winput}$ is tensor input width ,$T_{hinput}$ is tensor input height ,and $T_c h_{input}$ is the tensor channels are being used to produce an output of size $T_{w_o} * T_{h_o} * T_{ch_o}$ where$T_{woutput}$ is tensor output width , $T_{houtput}$ is tensor output height ,and $T_c h_{output}$ is the tensor channels so the computational power is $T_{w_i}$ $T_{h_i}$ $T_{ch_i}$ $T_{ch_o}$ $A.A$ While in the separable depthwise convolution the computation power is $T_{w_i}$ $T_{h_i}$ $T_{ch_i}$ $(T_{ch_o} + A * A)$.

So Thanks to separable depthwise convolution, a light-weighted and deep network have been managed to achieve. Skip connections allows us to avoid the vanishing gradient problem [59]. Also a batch normalization layer has been used with each building block which has a significant effect on the accuracy and number of epochs.

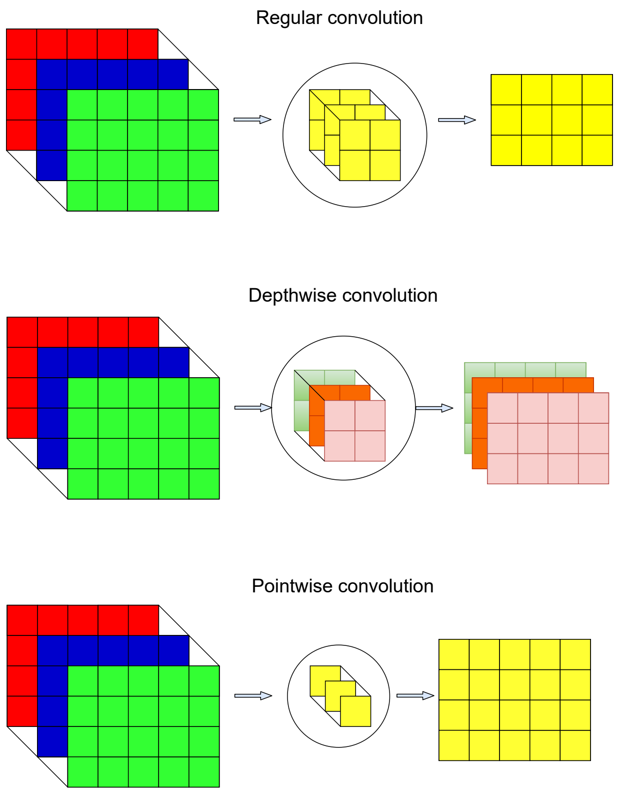



FIGURE 6: Types of convolution

Blaze-Wi full network can be presented as in Table (1) which includes the sequence of the building blocks and shows the input and the output of the network.

TABLE 1: Full network

| Layer/Block | Input Size | Kernel Size/Dense Num |
|---|---|---|
| normalization | 2500*6 | – |
| SeparableConv1D | | 5×24×1 (stride 2)<br>1×24×24 |
| Single Blaze-1D block | | 5×24×1<br>1×24×24 |
| Single Blaze-1D block | | 5×48×1 (stride 2)<br>1×48×48 |
| Single Blaze-1D block | | 5×48×1<br>1×48×48 |
| Single Blaze-1D block | | 5×48×1<br>1×48×48 |
| Single Blaze-1D block | | 5×48×1<br>1×48×48 |
| SeparableConv1D | | 2×48×1<br>1×48×48 |
| double_Blaze_block | | 5×48×1 (stride 2)<br>1×48×24<br>5×24×1<br>1×24×96 |
| double_Blaze_block | | 5×48×1<br>1×48×24<br>5×24×1<br>1×24×96 |
| double_Blaze_block | | 5×48×1<br>1×48×24<br>5×24×1<br>1×24×96 |
| double_Blaze_block | | 5×48×1 (stride 2)<br>1×48×24<br>5×24×1<br>1×24×96 |
| double_Blaze_block | | 5×48×1<br>1×48×24<br>5×24×1<br>1×24×96 |
| double_Blaze_block | | 5×48×1<br>1×48×24<br>5×24×1<br>1×24×96 |
| SeparableConv1D | | 2×96×1<br>1×96×96 |
| SeparableConv1D | | 2×96×1<br>1×96×96 |
| SeparableConv1D | | 2×96×1<br>1×96×96 |
| SeparableConv1D | | 2×96×1<br>1×96×96 |
| flatten | | 1344 |
| dense | | 64 |
| classification | | 6 or 7 based on the task |

## V. RESULTS AND ANALYSIS

All the datasets have been split into a training set and a testing set with the ratio of 80% and 20% respectively. The test set was not provided to the model during training it's clearly new to the model to check the model generalization. No preprocessing has been done on the dataset except the normalization and let all the work to Blaze-Wi network.

Adam [60] optimizer has been used to optimize the network parameters with initial an initial learning rate of 0.001 .after each 150 epochs the best weights were picked and the learning rate decays by a factor of 5 .the total epochs were 600 epochs and the batch size was 64 .

### A. EVALUATION MATRICES

The network has been evaluated with a lot of matrices and techniques like accuracy, confusion matrix, and classification report.

#### 1) Test set accuracy:

The accuracy is the ratio between the correctly predicted samples and the total tested samples. It's a good indicator during training to check the generalization of the network as the network has never seen the test set during training. it is defined as

$$\text{Test set accuracy} = \frac{\text{total corrected predicted samples}}{\text{total test set samples}} \tag{7}$$

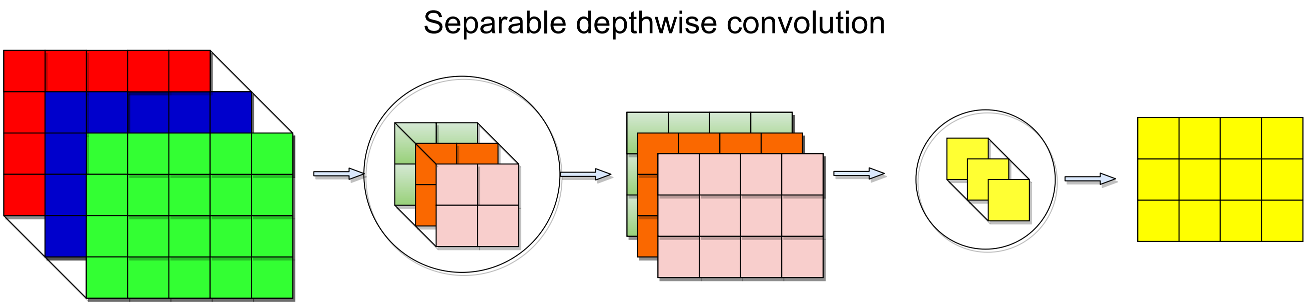



FIGURE 7: The separable depthwise convolution

2) Confusion Matrix:

The confusion matrix is used to provide a clear vision of the classification model results. on $X-axis$ there are the real classes and $Y-axis$ there are the predicted classes. important matrices included in the confusion matrix: true positive samples (TP), true negative samples (TN), false-negative samples (FN), and false-positive samples (FP). These matrices are good indicators of the system's stability and tell how far the system's results are trusted.

3) Classification report:

The classification report provides important relations between the matrices of the confusion matrix. The classification report includes three important matrices:

- Precision: It tells how many positive identifications were actually correct. Where it is defined as

$$Precision = \frac{TP}{TP + FP} \tag{8}$$

- Recall: It tells how many actual positives were identified correctly. Where it is defined as

$$Recall = \frac{TP}{TP + FN} \tag{9}$$

- $f1-score$: Since precision and recall are in tension as changing the decision threshold will increase one of them and the other will decrease, we need another indicator that could be reliable to describe the classification performance $f1-score$ is a weighted harmonic mean of precision and recall Where it is defined as

$$f1-score = \frac{2*(Recall * Precision)}{Recall + Precision} \tag{10}$$

Blaze-Wi achieved high results on these matrices on our collected dataset and WIDAR 3.0 [61] and that will be explained in the upcoming subsections.

### B. GAIT TASK

The network has been tested with multiple datasets:

1) Blzae-Wi dataset:

An accuracy of 97.3% has been achieved using the collected dataset as shown in the confusion matrix and the classification report in Fig. 8.

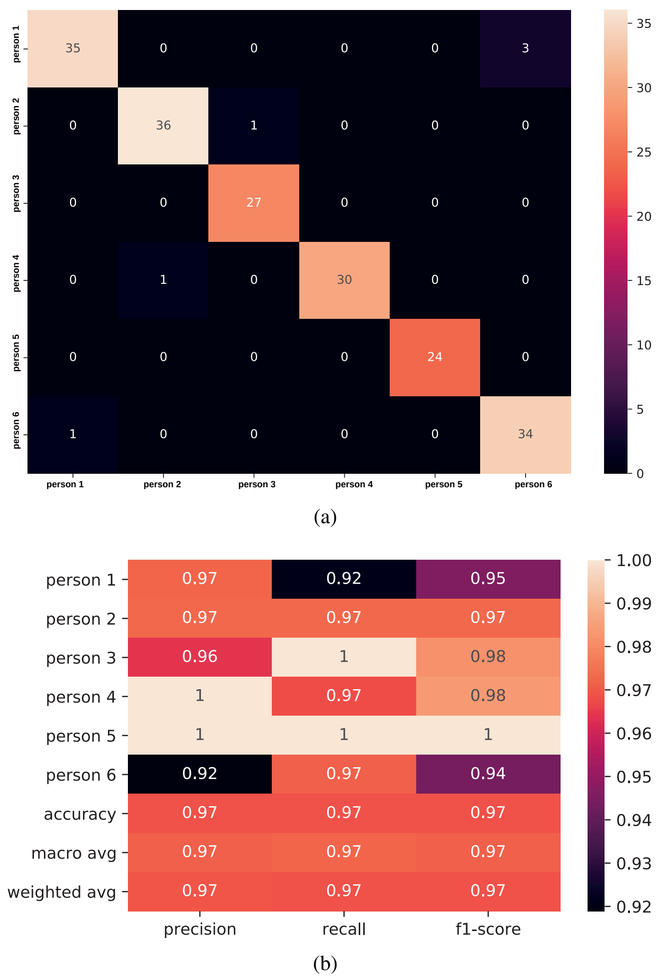
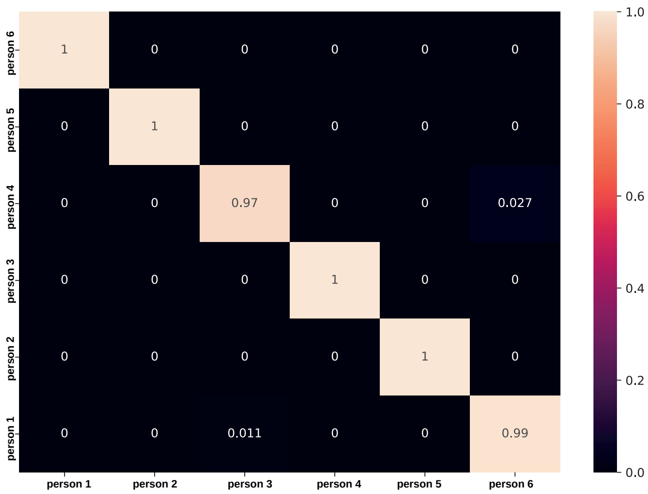



FIGURE 8: The gait-based identification system using our collected dataset for six volunteers (a) the confusion matrix, and (b) the classification report.

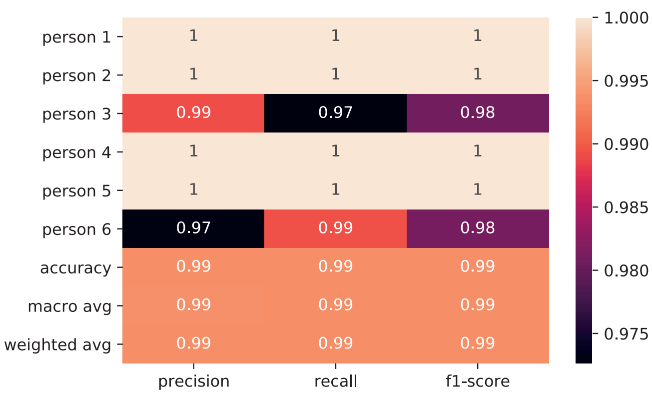
### 2) WIDAR 3.0

WIDAR 3.0 [61] has been used as it's a large dataset and 6 users have been chosen to train the network. Each user's data is about 2340 samples, our network has been trained with this dataset and managed to achieve a 99.27% accuracy with the test set Fig. 9.

Our network shows significant results compared to GaitID [62] which got less than 92.5% with 6 users. Table (2) shows Blaze-Wi outstanding most of available systems with 6 users, taking into account differences among datasets




(a)



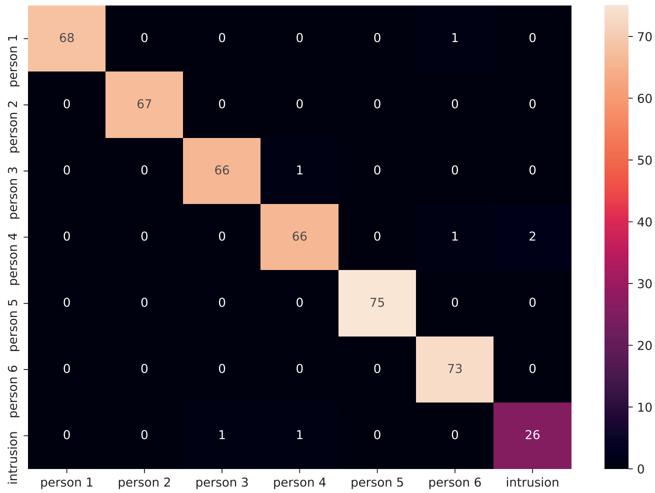

(b)

FIGURE 9: The gait-based identification on WIDAR 3.0 dataset for six volunteers (a) the confusion matrix, and (b) the classification report

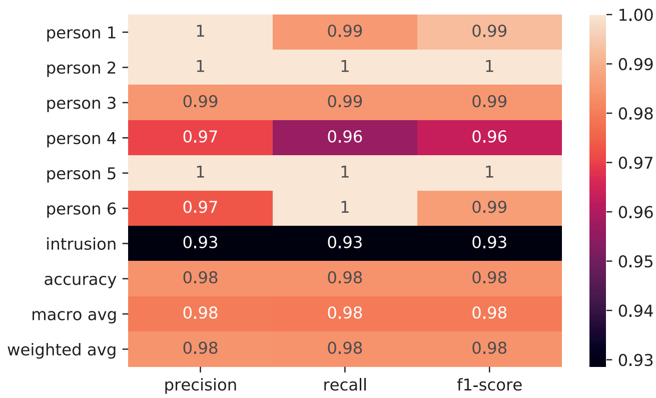
## C. JOINT TASK

In joint task, an accuracy of 98.44% has been managed to achieve on the test set Fig. 10. These results show that identity recognition using gait and CSI is a powerful and promising technique. That should encourage us to build a suitable dataset similar to ImageNet in computer vision for example.

The results in Table (3) show that Blaze-Wi is a robust and accurate system that fits well with joint task and gait recognition.




(a)




(b)

FIGURE 10: The joint task gait-based identification and intrusion task on our dataset for six volunteers (a) the confusion matrix, and (b) the classification report

## VI. FUTURE VISION

- In regards to ***dataset***:
  More data samples will be collected using more volunteers as it has shown better results with WIDAR 3.0 dataset due to the huge amount of data that is required by the deep learning model to achieve generalization.
- In regards to ***algorithms***:
  In the future Siamese network and a variational autoencoder will be used, then latent space will be used as an output with a classifier and more advanced algorithms will be utilized like, transformers.
- In regards to ***system functions***:
  A localization function will be added to the system until a multitasking, stable and reliable system is achieved .

## VII. CONCLUSION

In this paper, an intrusion detection and user identification system based on the gait biometrics extracted from WiFi signals, have been developed. The deep learning side has been focused on to extract the necessary features for the model except for the hand-crafted feature extraction and traditional

TABLE 2: Comparison with other systems with 6 users

| System | Proposed Blaze-Wi | GaitID [63] | Proposed Blaze-Wi | Wihi [64] | Wii [65] | WiWho [66] | WiDIGR [67] |
|---|---|---|---|---|---|---|---|
| Classification accuracy | 99.36 | ∼90 | 97.3 | 96 | 91.5 | 80 | 78.28 |
| Dataset | WIDAR 3.0 Data | WIDAR 3.0 Data | Blaze-Wi datasets | – | – | – | – |

TABLE 3: Comparison of Blaze-Wi with different datasets

| Technique | Blaze-Wi - WIDAR 3.0 dataset | Blaze-Wi - Gait dataset | Blaze-Wi - Joint task dataset |
|---|---|---|---|
| Accuracy | 99.36 | 97.3 | 98.44 |
| Precision | 99 | 97 | 99 |
| Recall | 99 | 97 | 99 |
| F1-score | 99 | 97 | 99 |

algorithms. Our network, Blaze-Wi, which is inspired by Google's network Blaze-face has only 210 thousand parameters which allows it to perform real-time predictions. The hyperparameters have been tuned to achieve ideal results. As a result, for a group of 6 persons, the network managed to achieve a 98.44% accuracy for the joint task, 97.3% for gait only, and with the WIDAR 3.0 dataset it achieved 99.27% accuracy for a group of 6 persons.

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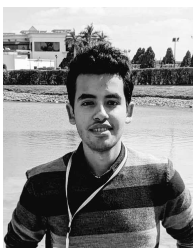

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