WiFi-based In-home Fall-detection Utility: Application of WiFi Channel State Information as a Fall Detection Service

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Abstract— **Falls are a leading cause of injury and death in older generations. An in-home fall monitoring system increases safety while allowing for continued independence. The WiFi-based In-home Fall-detection Utility monitors a user by harnessing WiFi Channel State Information, distinguishes falls from normal daily activities, and, if a fall occurs, automatically notifies the user's selected emergency contacts.**

Keywords— Aging in Place, Channel State Information, Fall Detection, Machine Learning, Smart Home

I. INTRODUCTION

The average life expectancy in the United States has increased from 70 years in 1961 to 78 years in 2018, according to the World Bank Group [1]. Healthcare and technological developments have allowed for there to be a much larger elderly population than there has been historically and this trend is likely to continue into the future. Of this large amount of elderly people, the majority aged 65 and up would prefer to age in their own home [2], due to both a desire to maintain independence and the high financial obligation of assistive living. However, there are some risks associated with this. According to the CDC, falls are the leading cause of injury and death in older generations [3]. When living alone, reporting a fall could be a daunting or even impossible task due to injuries sustained and an inability to get to a phone. These falls could also lead to death if the person can not get help in a short amount of time.

While fall detection systems exist, most are wearable devices such as wristbands or pendants, which must be activated by pressing a button. There are some risks with button-operated services, because a fall could render the resident unconscious. Additionally, wearable devices may be physically invasive to some clients, and products such as smartwatches also require regular battery charging. An alternative approach towards fall-detection is the use of cameras. In the same way baby monitors help ensure a baby's safety, this would provide caretakers with the ability to track the resident's safety. However, this approach greatly eliminates privacy and thus detracts from in-home independence.

With the existing fall detection services in mind, WiFi-based In-home Fall-detection Utility (WIFU) has been developed in an attempt to create a service which non-invasively brings safety to the home. Low-maintenance design was a major focus, helping ensure that the user doesn't have to regularly interact with the product after its initial installation.

This product monitors user status through WiFi Channel State Information, or CSI. Having been trained on an extensive dataset of both nominal daily activities and potential types of falls, it is able to identify when the user has fallen. It then automatically sends a notification to the user's specified emergency contacts, ensuring that aid can be sent to the home even if the resident is injured, unconscious, or otherwise unable to contact family/emergency services for assistance after they fall.

The user interacts with the system through a touchscreen display embedded in a 3D printed chassis. Following the initial setup, which includes connecting WiFi and adding user/emergency contact information, WIFU operates constantly and independently.

In this paper, we will first discuss similar research efforts and relevant existing technologies to provide an understanding of how this technology has been approached historically. We will then further elaborate on our work, beginning with a discussion of relevant technologies. A description of the WIFU system, including hardware components and user interface, is provided. The most significant portion of our efforts, the machine learning model, is discussed at length; its structure, method of training, and a post-test analysis are all provided. We conclude with a discussion of limitations to WiFi-based fall detection as a technology and suggestions for future development upon our work.

II. EXISTING THEORIES AND PREVIOUS WORK

Walabot HOME is a fall detection service currently on the market. Intended for use in bathrooms, it provides constant fall monitoring with limited need for user interaction. Walabot HOME provides its service through "smart motion sensing technology"; unlike WIFU, which relies on CSI, the Walabot product analyzes radio wave signals throughout the room. In the event of a fall, Walabot automatically calls emergency contacts if the user does not cancel the alarm within a two-minute period [4].

Another product which provides fall monitoring through the use of RF is WiTrack[5]. WiTrack provides 3D motion tracking by transmitting an RF signal and capturing the reflection off of a human body. The product's ability to track motion allows it to define a fall based on the speed of a body's change in elevation.

An academic group at Stanford University implemented a fall detection project based around the interpretation of WiFi CSI. This group created a dataset which included eight distinct activities (no motion, walking, running, picking objects up, sitting down, standing up, lying down, and falling) in a home environment. Categorizing these activities as either a fall or a non-fall, they applied a variety of supervised learning algorithms, including Multinomial Logit Regression and Decision Trees, as well as a deep-learning Lo= Short-term Memory method. They found the LSTM to have the highest accuracy in fall detection, at 80% [6].

III. METHODS

A. Presented Study, Research Question, and Hypothesis

Although previous research efforts have been made in generating a wireless-based fall detection device, the accuracy of such devices fall short in creating a viable product to be used in-home. Many devices can detect falls with 90% accuracy [12], while the state-of-the-art reaches a 94% precision (true positive predictions divided by the sum of true positives and false positives) at best [9]. Although this seems to insinuate a successful implementation, this is not the case. Due to the fact that these devices are ultimately intended to be placed in the homes of elderly people, attaining a true positive rate for 90 out of every 100 measurements would result in a large number of false detections when aggregated over the course of a device's lifetime.

It is likely the case that the fault lies in both the features and the machine learning models used. Features used in previous research were forced to condense the input data into a form that leaves out a lot of information that could be crucial to a higher fall detection rate. Additionally, most of the traditional models, when applied to complex data such as multi-channel wireless signals gathered over time, tend to hit

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a relatively low accuracy peak. Fortunately, a new family of machine learning models have been presented in recent years. Deep neural networks (DNNs) possess many characteristics that would likely assuage the discrepancies left by previous frameworks, both in terms of the features required and the model itself.

Our goal with this project is to develop a device using a DNN to produce a proof of concept for future work, and to see if a DNN implementation is a viable approach for wireless fall detection. In order to accomplish this, a fully operational system prototype containing all the necessary hardware as well as a graphical user interface, is produced and tested.

B. *Applied Research Methods*

Channel State Information, or CSI, characterizes how wireless signals propagate from a transmitter to a receiver. A human moving through the “sea” of WiFi waves interferes with this transmission, scattering and reflecting signals. Different motions and activities will cause different forms of interference. By collecting CSI in short phases, it can be determined when a user is carrying out regular, “daily activities,” or if they have fallen.

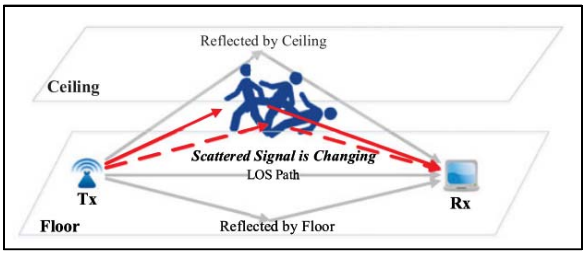

Fig. 1. The “sea” of radio waves transmitted from transmitter to receiver. As the person falls, the waves travelling through their body bend, changing the amplitude and phase of the signal reaching the receiver. Obtained from [11].

The incoming CSI data is received as a three-dimensional matrix of integers. During data collection, each trial consisted of 15 seconds of data, which was later sliced into three-second blocks, taken at one-second increments. Once trained, the data is collected continuously, but only the previous three seconds are used for prediction. Coupled with the fact that the CSI is sampled at a rate of 50Hz, each matrix during data collection becomes 750 elements long. Training and prediction occur on matrices that are 150 elements long. The WIFU device contains two functional antennas and the router contains three. Each device-router antenna pair produces its own set of information, resulting in six total sets. The incoming data is represented in phasor notation, a complex number that describes the amplitude and phase of the incoming radio waves. The real and imaginary parts are then separated, making the total number of sets of data equal to twelve. Finally, the CSI contains information about thirty separate frequency bands. The shape of the resulting training and prediction matrices is 150x12x30.

Once trained, the continuously collected data is fed into the DNN. The model then evaluates whether a fall occurred during the three-second segment. If a fall was detected, the system will display a message and alert any contacts via text message.

C. *Research Model(s) and Instrument(s)*

There are two main subsystems of the WIFU device prototype: the information gathering and processing system, and the user interface. Each component’s structure and functionality is discussed below, in addition to the DNN architecture.

1) *Information Retrieval and Processing*

All user interaction is conducted through a Raspberry Pi Model 3B+ microcomputer connected to a Raspberry Pi touchscreen display [7]. This display runs a simple graphical user interface (GUI), through which the user can perform system tasks such as modifying personal information, adding emergency contacts, and viewing a record of falls previously detected by the system.

The GUI reads the SFTP-transferred text file from the fall detection software every three seconds. If this file indicates that a fall has occurred, the GUI logs current date and time in its fall records table and begins the emergency contact notification process. Additionally, a new GUI screen is displayed at this time, making it apparent to the resident that the system has detected a fall. If they have recovered and are no longer in danger, they may select a button to verify that they are alright, resetting WIFU to its idle monitoring mode.

Contact notification is performed through the use of the javax.mail package. JavaMail [8] models an email system. After establishing a Secure Mail Transfer Protocol (SMTP) connection, it is used to send an automated notification to the emergency contacts’ cellular devices. This notification comes from an email account created specifically for use with the WIFU prototype. If the resident was able to confirm that they are no longer in danger, the contacts will receive an additional message relaying this information.

All code for the GUI is written in the Java programming language. The interface layout was developed in the Java Netbeans IDE. The GUI has been designed with an emphasis on readability and ease of use; we feel these are major factors in ensuring our target demographic can easily interact with WIFU when necessary. One way this is ensured is in all text displays a large, simple font is used To make your equations more compact, you may use the solidus

2) *User Interaction*

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3) Deep Neural Network Architecture

The neural network testing and final implementation was done using Tensorflow's Keras API. Both convolutional neural network and fully-connected neural networks were tested, with the best results obtained via the fully-connected architectures. Due to the limited data size, the neural network architecture achieved optimal performance on more shallow networks.

In our proposed model, we implemented a simple, three-layer DNN approach, with one input layer, a singular hidden layer, and an output layer. Between each layer, batch normalization was performed. After the input layer and before the hidden layer, the data was flattened using a flatten layer. Between the hidden and output layer, a dropout layer was included with a dropout rate of 0.4. The activation function used for the initial input was Rectified Linear Unit, or ReLu, while the output used a sigmoid activation.

Additionally, losses were weighted in proportion to the ratio of both classifications. This means that although there was a much higher percentage of daily activities versus falls, the model valued each individual fall more than each daily activities, assuaging the data imbalance.

D. Experiment (s)

Data collection was conducted without the use of external participants. The six group members conducted data collections in pairs. One group member acted as the facilitator and controlled the data collection program, while the other group member was the actor that performed the predetermined action for data collection. As the computer that collected data needed to be across from the router that produces the WiFi CSI, both the facilitator and the actor stayed in the mock apartment for the duration of the data collection.

The dataset used was comprised of 1,450 trials. Each trial consisted of a daily activity or a type of fall. Daily activities include such behaviors as walking across a room, transitioning from a seated to a standing position, and set.bending over to pick an object up from the floor. Types of falls include tripping forward or backward, falling from a seated position, and fainting. 36 total scenarios were considered, consisting of 20 normal daily activities and 16 types of falls.

To collect daily activity data, the facilitator would enter the label of the trial into the collection program and give the actor a countdown to the start of the 15 second collection time. When the actor switched types of movement, for example, transitioning from a sitting to a standing position, the facilitator recorded the movement change in the collection program. This updated the file's action label in real time.

Falling trials were collected in a similar fashion to the daily activities. During these trials, the actor would perform an activity, such as walking, before falling onto an air mattress setup on the floor to soften the impact. The fall was announced ahead of time to allow the facilitator to record it in real time.

IV. Findings

A. Collected Data

It should first be mentioned that the best metrics for comparison to the previous efforts are used, but that the reported values only paint a fragment of the picture. Due to a low saturation of papers within this subject area, there are no generalizable guidelines to follow in terms of hardware usage, experimental setup, or performance metrics used. This leads to a difficulty in comparison to other methods.

In order to determine the accuracy of our prediction model, cross validation was performed by splitting the training data into five folds. The results of each training-validation split was added together to produce the confusion matrix in fig. 2. The overall performance as determined by cross validation was 81.8%. Additionally, WIFU attains a false positive rate, or false alarm rate, of 15.2%.

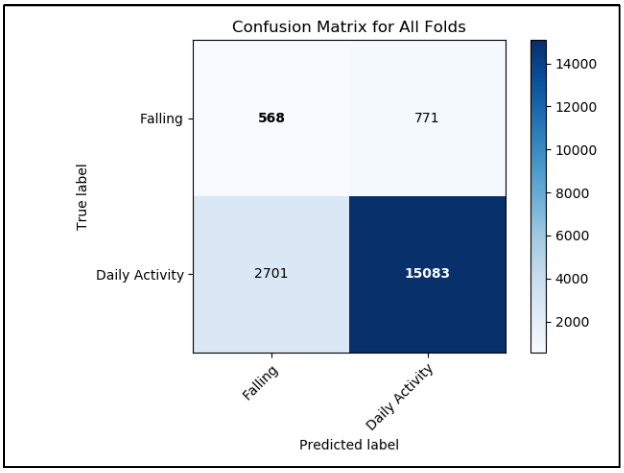

Fig. 2. The confusion matrix produced after summing the results of each validation set.

The accuracy and false alarm rate are used as tools for comparison to previous implementations, when the given metric is discernible from the paper, below.

Table 1. The confusion matrix produced after summing the results of each validation.

Fall Detection Implementation	Accuracy
Dayal et al. (LSTM) [6]	77.5%
Wi-HACS [12]	90.5%
WIFU (ours)	81.8%

Table 2. Miss rate comparison of top papers to our implementation.

Fall Detection Implementation	False Positive Rate
WiFall [9]	10-15%
Cao et al. (SVM) [10]	5%
RT-Fall [11]	7-20%
Wi-HACS [12]	11.2%
DeepFalls [12]	9.1%
WIFU (ours)	15.2%

B. *Analysis of Collected Data*

As mentioned in the previous section, comparing results across works in this field can be more difficult to assess. For instance, our method aggregates the results from each orientation of furniture and test subjects while many of the reports separate them. The results from Tables 1 and 2 represent either a range of results or the best performing subset of results depending on the paper. Thus, the results from our experiments paint a more clear and representative picture at the cost of lower performance values.

With an accuracy of approximately 81%, the current model performs lower than some state-of-the-art methods. This is to be expected for multiple reasons. Most importantly, neural network architectures are incredibly demanding in terms of training data size. Due to the high volume of hyperparameters to be tuned, more data is required than other machine learning methods. Additionally, having a lower amount of data constrained the size of the neural network that would be viable, thus decreasing the computational complexity and potential accuracy of the model.

However, WIFU is competitive with the state of the art in relation to the false positive rate. [9] reports an average false positive rate of 15%, comparative to the 15.2% observed in our system. Although the overall average accuracy is still lower than desired, the system still succeeds in one area and importantly shows promise in all others.

C. *Discussion*

The important contribution of this work is to provide a proof of concept that deep neural network implementations are a viable alternative to other methods utilized to date. It is expected that using more data will substantially increase the performance. Additionally, as neural networks tend to have a higher peak in accuracy in comparison to other models, including enough data would likely allow for the model to outperform other models and more importantly reach a level of accuracy acceptable for the standards demanded for use in real-life scenarios.

The current prototype includes all the necessary components as well as many features that would be desirable for a final implementation. Both the hardware and software have been produced in a manner that makes improvement and the inclusion of many proposed features easy to implement. Due to this, the device has been successful in providing an example for a novel implementation of WiFi-based fall detection.

V. CONCLUSIONS

A. *Limitations*

A major limitation of WiFi-based fall detection is that it requires a constant connection to both electric power and the Internet. If either of these connections is lost in a power or network outage, the power cannot be provided.

Additionally, the current prototype's machine learning model was trained on a dataset featuring one test subject moving about a mock apartment in a lab. As a result, the prototype presently can not detect falls in multiple-resident homes, large homes, or multi-story homes. Providing more data from these scenarios would improve the model's generalization capability while also decreasing the data deficiency.

B. *Concluding Remarks*

WiFi-based fall detection is a novel way of ensuring in-home safety and eliminates some of the limitations of more traditional fall detection technologies, such as the need for a wearable, button-activated device or the intrusiveness of a camera system. To our knowledge, this is the first implementation of a neural network model for such a task. It should serve as a proof of concept, highlighting the advantages of this approach as well as the challenges to overcome in order to create a more robust model.

We feel that we have created a prototype which successfully demonstrates how CSI and machine learning can be applied toward in-home safety. Our Wireless In-home Fall-detection Utility provides this service by utilizing WiFi Channel State Information to monitor the home resident's status. By implementing a machine learning model, we have trained our product to distinguish between nominal daily activities and potentially dangerous falls. We then continue our product's functionality by having it automatically notify emergency contacts of the user's choosing, ensuring that post-fall assistance will arrive.

In order for a diverse dataset to be generated, many individual data collection trials must be run. Our team found data collection to be a major time commitment; we would advise any groups continuing this project in the future to ensure ample time is reserved for data collection purposes.

C. *Future Work*

Future work can be done to increase both the functionality and the features of WIFU. We believe that the suggestions below would improve this product's viability as a commercially available smart home system.

Our first objective is to improve the accuracy to a level that exceeds the current state of the art for non-deep learning methods. The manner by which this will likely be accomplished is twofold. The first step is collecting and including more data. In particular, the number of falls is approximately 7% of the dataset. Having a larger representation in this category would lend to getting the model to learn a more generalized depiction of a fall. The second way to improve accuracy would be to do further optimization of the machine learning model. Given more time, a better neural network architecture could be obtained. The addition of more training data would also allow for the viability of deeper neural networks, allowing for more rich and complex features to be learned, ultimately improving the model accuracy.

Another primary aim is to expand the area by which the system can cover. At the moment, using one WIFU device and a singular router implies that the area covered can only be in a straight line. In reality, however, most houses or apartments contain more complex layouts. This would require the capability of multiple routers or WiFi extenders being connected and monitored by the WIFU system at once. Doing so would make the device more flexible than most products currently on the market.

The current prototype is able to track a single user and alert them if they have fallen; adding the capacity to monitor multiple residents at once would improve in-home safety for elderly couples.

Research could be done into adding the capability to directly contact emergency services when a fall is detected. At present, the user may enter their emergency contacts, who may be relatives or other caretakers. The ability to immediately contact emergency services would improve the safety of homeowners who do not have emergency contacts who live nearby. It also would improve the response time of emergency services, if assistance must be sent to the home. While this would potentially be a valuable aspect of WIFU, it would require significant research and testing to ensure that a call can reach emergency services, that false alerts are not being sent, etc.

Feedback from the WIFU target demographic would be valuable in determining what adjustments must be made to the GUI to make the overall product more viable. This could be done by having subjects from the demographic run through a series of GUI tasks, such as adding their own information and modifying emergency contacts.

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