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"Deep Learning for Fall Risk and Health Detection in Individuals with Multiple Sclerosis: A GoogLeNet-Based Approach with UWB Dataset"

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Abstract - Falls are a prevalent cause of injuries among seniors, particularly within indoor environments such as homes, nursing homes, senior living communities, and care facilities. Recognizing the paramount importance of predicting and understanding the actions of older individuals during falls, this study explores the application of deep learning, specifically the GoogleNet model, in predicting fall risks. The investigation encompasses both seniors and individuals with Multiple Sclerosis (PwMS), utilizing a dataset derived from Ultra-Wideband (UWB) technology.The research addresses the significant risk that falls pose to the well-being of both persons with Multiple Sclerosis and the general aging population. Leveraging UWB technology and the deep learning capabilities of the GoogleNet model, the study seeks to develop an accurate and reliable predictive system for fall risk assessment.The methodology involves preprocessing UWB data, organizing it into labeled folders, and applying the continuous wavelet transform (CWT) to generate a time-frequency representation of the data. The GoogleNet model, pretrained on a diverse dataset, is then adapted for transfer learning to suit the specific task of fall risk prediction. Modifications include introducing a new classification output layer and adjusting the fully connected layer to accommodate the required output classes.Training the model utilizes the UWB dataset, with probabilistic gradient descent and mini-batch updates. Validation on a separate dataset monitors training progress, and the final model is tested on validation data. The predictive system is assessed for both persons with Multiple Sclerosis and healthy individuals, acknowledging the unique challenges faced by each group.

Keywords *Ultra-wideband Radar Fall detection Healthcare Channel Selection Convolutional Neural Network*

I Introduction

In the modern world, people are living longer and more often, which has made the demographic structure uneven. The United Nations and the Department of Social Affairs say that the world's population, which is now 7.7 billion people, will rise to 10 billion by 2050 [1]. 9 percent of the population, or 701 million people, are over 65 years old. This number is expected to rise to 16 percent by 2050. Care for the elderly will be one of the most important problems in the world at that time. Additionally, the World Health Organization and other groups say that falls are the cause of 50.96 percent of unexpected injuries [2] and even deaths in older people. To protect the health of older citizens, it is important to find and treat falls as soon as possible. Different methods [3–5] have been used by researchers to find and spot falls in geriatric care. A first use for wearable sensors like accelerometers, gyroscopes [6, 7], and electrocardiograms (ECG) is to keep an eye on the health and fitness of older citizens so that falls can be identified. Devices that you wear, on the other hand, are easy to lose or forget [8]. Because of this, non-contact methods have been used to record fall movements. One way is to use methods based on computer vision [9, 10]. The problem with this method is that it makes people worry about their privacy. Ambient sensors [11], which are mostly made up of pressure sensors, thermal sensors, and ultrasonic sensors, are another method that is used. Ambient sensors collect a lot of different kinds of data, but based on how big and complicated the environment is, you might need to use more than one device [12]. For this study, we used an ultra-wideband (UWB) radar to get raw data, and an adaptive channel choose method [13] to tell the difference between the useful signal and the background signal. Next, a fused feature set of pictures from both the frequency domain and the time domain are used to teach the model how to recognize falls.

Multiple Sclerosis is characterized by progressive demyelination and axonal damage throughout the central nervous system [1,2]. As a result, persons with multiple sclerosis (PwMS) experience symptoms including debilitating fatigue and impaired coordination, muscle strength, and sensation, leading to difficulty with postural control in dynamic activities which, in turn, leads to falls [3]. Over 50% of falls result in injury and 66% of first-time falls require a visit to the emergency department, reducing quality of life and yielding an estimated annual healthcare cost of $80 billion in the United States alone [4]. Of the 2.3 million PwMS globally, over half will experience a fall in any three-month period [5]. As MS is a chronic condition, injurious falls pose a substantial and long-term burden to patient quality of life and the healthcare system [6]. Given these impacts, effective fall prevention is critical. Fall risk in PwMS is difficult to assess as it is known to vary both within and across days. Fall risk may be elevated in the absence of an assistive device (e.g., walking sticks) [7] or during balance-challenging tasks, such as walking, position transfers, and changes of direction [8]. However, current clinical assessments often only occur once every six months; an observation frequency incapable of capturing the true time-varying nature of symptoms in MS, limiting the ability to prescribe preventative interventions [9]. There is a clear need for novel assessments that are sensitive to this inherent variability and that can capture the relationship between symptom fluctuations and fall risk. One approach is for assessments to incorporate continuous monitoring in freeliving conditions, which provide far more than a twice-per-year snapshot of symptoms, and advanced machine learning techniques that can effectively capture the complex relationship between these movement data and fall risk. With the growing availability of wearable sensor data, it may now be possible to leverage machine learning, and particularly deep learning models, to learn high-level outcomes like fall risk directly from raw sensor data without manual feature engineering [10,11]. Studies employing deep learning for time series classification tasks, such as our prior work classifying fall risk in PwMS from in-lab measurements [12] and work from others to detect falls and classify fall risk in non-MS populations with balance and mobility impairment [13–21], have found superior results when compared to machine learning techniques that rely on manually constructed features. Notably, these results are achieved despite the significant amounts of

data needed for training deep learning models. It is possible that given larger available datasets, performance of these models could improve further, but the accumulation of these large datasets remains a barrier to entry for many into the use of deep learning models for characterizing fall risk. Remote gait monitoring in PwMS may enable continuous fall risk assessment and the deployment of personalized fall prevention interventions. In this approach, data from individual walking bouts could inform fall risk status instantaneously. This vision has motivated the development of fall risk classification models that require only wearable sensor data from a single gait bout as model inputs [12,22,23]. However, deploying these models remotely comes with additional challenges that may impact model performance. For example, it is well established in PwMS [24–26] and other populations [27–29] that gait observed in the clinic differs from gait observed remotely (especially for gait speed-dependent variables). Similarly, studies in older adults [30] and PwMS [24] have also discovered that gait parameters change with walking bout duration. However, it is currently unclear how walking bout duration relates to fall risk in PwMS [7,30], and this has not been evaluated in previous development of fall risk classification models [12,22,23]. The primary objective of this work is to share a new, open-source dataset that can help other research groups develop digital biomarkers of impairment and fall risk in PwMS. In service to this objective, we present a framework for remote gait analysis on this dataset and use it to examine how gait parameters and fall risk classification performance, based on featurebased machine learning and stride acceleration based deep learning methods, change in relation to walking bout duration in PwMS.

Persons with multiple sclerosis (PwMS). Multiple sclerosis (MS) is a chronic neurological condition that affects the central nervous system, including the brain and spinal cord. Individuals with multiple sclerosis are often referred to as people with multiple sclerosis (PwMS). MS is characterized by the immune system attacking the protective covering of nerve fibers, leading to communication problems between the brain and the rest of the body. Here are some key points and considerations regarding persons with multiple sclerosis:

Ultra-Wideband (UWB)

Ultra-Wideband radar, or UWB radar, is a system that supports sending and receiving signals by using a very large frequency range. Unlike traditional narrowband radar systems, which only work within a certain frequency range, wide-band (UWB) radar systems use a large range of frequencies, usually several gigahertz. Ultra-wideband (UWB) transmissions have a bandwidth of more than 500 megahertz (MHz) or a fractional bandwidth of more than 20% of the center frequency, according to the US Federal Communications Commission (FCC). Here is some of the most important facts about UWB radar, including what frequencies it uses:

Frequency Range: UWB radar devices usually work in a pretty wide frequency range, from a few hundred megahertz (MHz) to a few gigahertz (GHz).The frequencies that can be used for ultra-wideband radar uses are between about 3.1 GHz and 10.6 GHz, and sometimes even higher.

Bandwidth: The bandwidth of most broadband ultra-wideband radar devices is more than 500 megahertz. Because the bandwidth is pretty wide, it is possible to do high-resolution images and range.

Pulse Characteristics: Ultra-Wideband radar uses waves that last only a few picoseconds or nanoseconds most of the time. When you use short pulses, you can get exact time-domain resolution, which is needed for range and target separation.

The concept of UWB radar sensor

Radar devices send signals and then pick up signals that are reflected by things in the way. This is the main idea behind radar detectors. IR-UWB sensor sends out short-term bursts. It's also called pulse radar ultra-wideband, which is another name for it. A single pulse usually lasts between a few nanoseconds and a few hundred picoseconds [1]. There are many good things about this kind of signal, such as its high penetration, fine resolution, and resistance to various paths. It is very accurate for infrared-UWB radar sensors to use very little power.

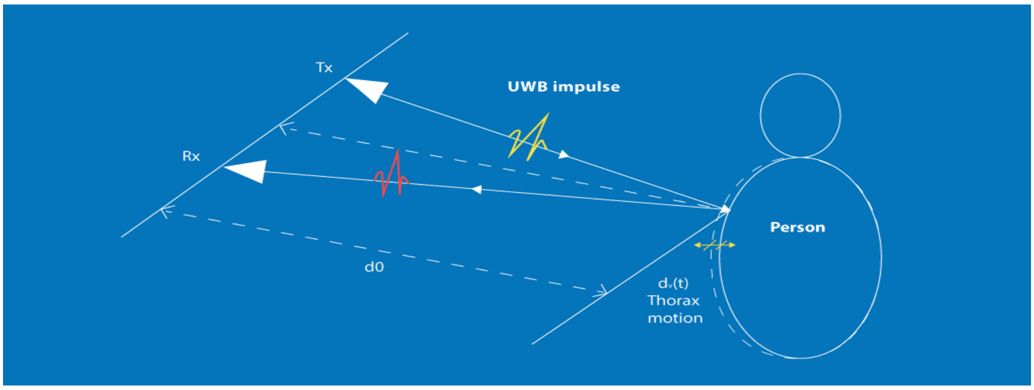

Fig.1 concept of UWB radar sensor

Ultra Wideband Radars, or UWB radars, use Ultra Wideband technology to send and receive short-lived, low-energy, wideband radio frequency signals that are reflected by target objects. A single pulse that lasts between a few nanoseconds and a few hundred picoseconds is what these radars really send out. The length of time a single pulse lasts is in the middle of these two ranges. The UWB signal's pulse width is inversely related to its bandwidth in the time domain. The signal's frequency stays the same. There will be more information in the signal's spread when the pulse width is shortened.

When looking at time, a narrower signal is more distinct than a wider signal. Because of this, ultra-wideband radars can give position data at the centimeter level between a transmitter and sensor that are only ten to fifteen meters apart. Companies like Apple have used UWB-based radar technology in their iPhones and AirTags because the information about range and location is much more accurate than that from Bluetooth beacons (note that this does not include the new Bluetooth direction finding feature) and Wi-Fi access points (APs). Apple's iPhone 11 was the first model in its class to use this technology. This type of radar works great for medical tasks like checking someone's breathing and heart rate to see if they are awake or asleep. Location-based services, indoor range and positioning, radar target tracking (whether fixed or moving), and other related uses also work well with them.

The frequency range that UWB radars can use is from 3.1 GHz to 10.6 GHz. In addition, UWB signals have a spread of at least 20% of the center frequency, which is the same as at least 500 MHz. For example, a UWB signal with a 4 GHz center frequency uses a 1 GHz bandwidth, while a UWB radar device with a 6 GHz center frequency uses a 1.5 GHz bandwidth1. United Wireless Broadband (UWB) radars can send pulsed data to the listener very quickly because they can use a very large spectrum. For example, the shorter pulse width makes it possible to use Pulse Position Modulation (PPM), On/Off Keying (OOK), and Pulse Amplitude Modulation (PAM).

Also, the wide bandwidth lets radars send messages with low power spectral density. This makes it less likely those devices nearby that work in the same band as UWB radars will interfere. The FCC has limited the spectral density of ultra-wideband (UWB) signals to -41 dBm/MHz. This means that UWB radars can now send out signals that are weaker than the unwanted signals that other devices around them send out.

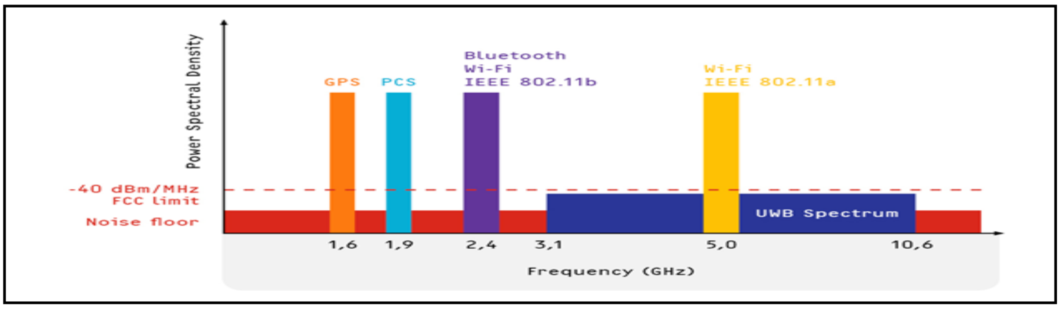

Fig.2 UWB Frequency

In addition to keeping other devices and radars from interfering, UWB radar emissions provide protection because they are very hard to find. This is because the low power spectral density makes it impossible for the listener to tell if the radar is broadcasting or not. This is because the difference between the amplitude of the broadcast pulse and the amplitude of the noise in the background is not very noticeable.

Working Principle of UWB Radars

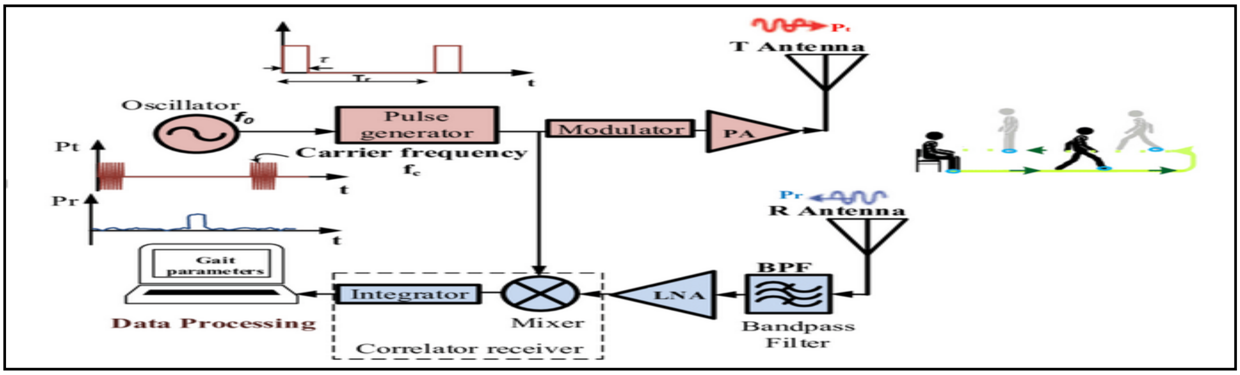

Fig. 3 UWB Radars system

A standard block diagram for a UWB radar transceiver can be seen above with this image. A transmitter and a receiver are both shown in this image. A pulse generator, a power amplifier, a modulator, a mixer, and an antenna are all in the sections that are in charge of sending. Components in the receiving section include a bandpass filter, an integrator, a low noise amplifier, and a correlator (which is made up of an integrator and a mixer).

If you want to send data, the oscillator controls the pulse generator, which creates a pulse in time with a very short pulse width (usually about 2 nanoseconds). Some waveforms, like a Gaussian envelope (which has a very small pulse width and looks like an impulse signal), are sent to the pulse generator by an oscillator. An oscillator also figures out the UWB radar's pulse repeat frequency (PRF). The PRF is a way to measure how fast UWB waves are sent in a certain amount of time. In order to meet the low spectral density rules set by the Federal Communications Commission (FCC), the signal is then boosted to some extent by a power amplifier. The signal is sent to the antenna along a feed line. It is then sent into space in the direction of the specific object.

The signal goes to the receiver and is picked up by the antenna that is in charge of getting it after it has been reflected from the target. You can build filters that block reflections from other items, leaving only the reflection that you want to see. The LNA's signal has less noise than the signal that was being received. It is important to know that the amount of reflection depends on both the size of the reflected surface and the distance between the radar and the target. This means that the time point in the radar frame is directly related to the distance between the radar and the target. Everything in the UWB radar's field of view (FOV) can send out a signal that it can pick up. Ultrawideband radars usually use the Time of Flight (ToF) method to figure out how far away something is. Because UWB pulses are so narrow, it is possible to accurately judge when they have come. Alternative methods, like Time Difference of Arrival (TDoA) and Two Way Ranging (TWR), are used in different ways depending on the situation and the purpose.

Once the distance has been calculated, other tracking methods, such as trilateration, triangulation, and others, can be used to be sure of where the target is exactly. Adding fast DSP processors makes it possible to quickly figure out where something is at any given moment. Users can now always know where the goal is thanks to this feature. Several fall detection methods, including UWB radar, are shown in the table below along with their pros and cons:

Approach	**Advantages**	**Disadvantages**
Wearable Sensors	- Provides real-time monitoring	- Relies on user compliance
	- Portable and non-intrusive	- Limited to the detection range of sensors
	- Can detect various movements beyond falls	- False positives due to daily activities
Computer Vision	- No need for additional devices	- Privacy concerns
	- Can be integrated into existing security cameras	- Limited accuracy in low-light conditions
	- Captures detailed data for analysis	- Limited view angle
Ambient Sensors	- Non-intrusive and does not require user compliance	- Limited to the detection range of sensors
	- Can capture data over a broader area	- Limited specificity in detecting falls
	- Suitable for detecting changes in daily routines	- May miss falls that happen out of sensor range
Machine Learning	- Can adapt and improve accuracy over time	- Requires substantial labeled training data
	- Potential for early detection based on	- May be computationally intensive

	patterns	
	- Can be integrated with various sensor types	- May have challenges with generalization
UWB Radar	- High accuracy in detecting falls	- Limited research and development compared to others
	- Works well in different lighting and environmental conditions	- May be expensive to implement
	- Can provide precise location information	- Limited awareness among users

Ii Related Work

Julien Maitreet.al. 2021 Fall detection is a major challenge for researchers. Indeed, a fall can cause injuries such as femoral neck fracture, brain hemorrhage, or skin burns, leading to significant pain. However, in some cases, trauma caused by an undetected fall can get worse with the time and conducts to painful end of life or even death. One solution is to detect falls efficiently to alert somebody (e.g., nurses) as quickly as possible. To respond to this need, we propose to detect falls in a real apartment of 40 square meters by exploiting three ultra-wideband radars and a deep neural network model. The deep neural network is composed of a convolutional neural network stacked with a long-short term memory network and a fully connected neural network to identify falls. In other words, the problem addressed in this paper is a binary classification attempting to differentiate fall and non-fall events. As it can be noticed in real cases, the falls can have different forms. Hence, the data to train and test the classification model have been generated with falls (four types) simulated by 10 participants in three locations in the apartment. Finally, the train and test stages have been achieved according to three strategies, including the leave-one-subject-out method. This latter method allows for obtaining the performances of the proposed system in a generalization context.

Computer vision-based fall detection

Computer vision-based fall detection systems usually use a camera, which is placed in a certain spot and collects continuous data frames to identify movements. People who wrote [14] suggested using a 3-D convolutional neural network (CNN) to find people who have fallen. With this method, video kinematic data is all that is needed to teach an automatic feature extractor. It might not be necessary to have a large sample size of data. The writers of [15] came up with a way to find falls by looking at how people's shapes change over the course of a video sequence. The tests were done on a real data set with everyday activities and simulated falls, and the results were better than those from tests using other popular image processing algorithms. In an interesting study [16], a lightweight neural network called You Only Look Once third version (YOLOv3) was put forward. Putting together this network was meant to make fall recognition more accurate and quick. Concerns about privacy can't be put off when it comes to the camera-based method, though. With the help of Kinect depth photos, pictures of the patient and their room that look like shadows have been taken to protect the patients' right to privacy in [17]. Studies in the past have led to the creation and installation of a system in hospital rooms that can identify falls. The warnings in this system are set to go off whenever it senses a fall. The nurses would then look at the saved depth footage for any possible injuries and to figure out what might have caused the patient to fall so that similar things wouldn't happen again. Computer vision-based monitors collect data that is simple to understand and useful for analysis, but they can't keep people's privacy safe. The price of these kinds of gadgets is usually pretty high, even though depth cameras don't usually pose a privacy risk.

Wearable sensor-based fall detection

Apps that you wear are currently the most popular way to find out if someone has fallen. Because monitoring technologies and ubiquitous computing are growing so quickly, this is the case. In fact, this method is mostly about using the motion data that devices like accelerometers and gyroscopes give off. People can wear these sensors because they are built right into products that have microcontrollers, like smart watches and smartphones [18, 19]. A smartwatch machine learning method was used by Ballı et al. to figure out the fall motion [20]. According to Zhao et al., a system that includes a tri-axial gyroscope could be used to recognize falls. [21] While the person is standing, a tri-axial gyroscope is placed around their waist to measure their tri-axial angular motion. De Araujo et al. [22] also talk about an accelerometer that is built on a smartwatch and can detect falls. Wearable devices are often small, light, and easy to set up, but sometimes their wireless connections don't work right. The device is also easy to lose or forget, and it needs to be charged and refilled often.

Ambient sensor-based fall detection

The most common types of ambient devices that are made to detect falls are pressure sensors, thermal sensors, radar systems, and radio-frequency equipment. Reference 23 talks about a brand-new device that is based on two pressure sensors. The result with random forest was the most accurate model for finding falls; it was 100% correct. Using a collection of infrared radiation sensors, Ogawa et al. [24] came up with a way to find people who have fallen. According to Miawarni et al. [25], the main sensor in a fall detection system should be a two-dimensional lidar device. The goal of this method was to be very good at identifying things. When environmental sensors are used to identify falls, infrared sensors, pressure sensors, and other types of sensors are often used. These devices have to work in a certain way in order to work. In some situations, the infrared sensor needs to be placed in a place where there are no items that could block its view, and the pressure sensors need to be spread out over a large area.

UWB radar-based fall detection

Radio frequency is a better way to keep an eye on home care and find accidents like falls than older methods. Using radio waves to gather information doesn't require touching the person and doesn't invade their right to privacy. The researchers by Li et al. [26] used UWB radar and three inertial sensors on the wrist, waist, and ankle to make a bidirectional Long Short-Term Memory (bi-LSTM) network that combined multiple pieces of information very well to find falls. It's harder to understand the program when you use a lot of different kinds of sensors. This is because the steps become more complicated. Using a bagged decision tree and k-Nearest Neighbor (kNN) to find fall traits helped Julien et al. [27] get an accuracy of 91.5% and 88.6%. A weight joint distance time-frequency change was used to get these features. Sadreazami et al. [28] showed a radar-based way to find falls by using narrowed-down parts of radar data. To make the compressed features, deterministic row and column sensing is used. Before the spectrogram is put on a binary picture, the radar time series is put through the time-frequency analysis. Once the binary images are compressed using a 2D deterministic sensing method, the images' aspect ratio stays the same inside the compressed area. This method's effectiveness is tested by using a number of different algorithms. That suggested method using compressive sensing has been shown to be better at detecting fall activities compared to activities that don't involve falling. This study by Khawaja et al. [29] used a lot of UWB radar transceivers to create a fall detection, location, and tracking system for people who need help. No tags or tools are needed for this method, which makes it possible to keep an eye on people with special needs that way. With the goal of making the method more accurate, the writers came up with a new way to find falls that is based on the residual co-variance from an extended Kalman filter. Simulated computer tests showed that the suggested way would work for finding falls. We can understand the pros and cons of the different methods based on the data in Table 1. Because it can monitor without touching, is easy to set up, has great resolution, and doesn't cause privacy problems, UWB radar was picked as a way to find falls among older people. We look at the signal to fully figure out where the fall behavior is happening and what it is doing. To get even better classification, we also use a fusion method that combines it with a deep convolutional neural network. These steps are taken to make fall tracking more accurate and stable.

Iii Material And Method

The study begins with data preprocessing, involving the loading of UWB data from a .mat file and organizing it into labeled folders. Continuous wavelet transform (CWT) is then applied to generate a time-frequency representation (scalogram) of the UWB data, serving as vital features for subsequent neural network training. The preprocessed UWB data is converted into images to create a visual representation capturing essential characteristics for effective fall risk prediction.

Model Design and Transfer Learning:

A GoogleNet model, pre-trained on a relevant dataset, is employed for transfer learning. The layer graph of the GoogleNet model is analyzed to determine its structure. Subsequent modifications include adding a new classification output layer, adjusting the fully connected layer to match the required number of output classes, and incorporating a new dropout layer. This tailored model is then trained using the UWB dataset through probabilistic gradient descent with mini-batch updates.

Validation and Testing:

Validation is conducted using a separate dataset (imgs Validation) to monitor training progress, and the final model is tested on a validation dataset. To enhance real-world applicability, the model's accuracy is assessed by introducing a small amount of randomness during testing, simulating real-world conditions.

Loading UWB data from a .mat file and organizing it into folders based on labels.Creating a time-frequency representation (scalogram) of the input data using continuous wavelet transform (CWT).Converting the UWB data into images and saving them in folders for training. Neural Network Training: Splitting the data into training and validation sets. Using a pre-trained GoogleNet model for transfer learning. Modifying the architecture of the neural network, including adding dropout layers and adjusting the output layer for the number of classes. Training the modified neural network on the UWB data.Using the trained neural network to classify validation data. Displaying confusion matrices and various performance metrics, such as accuracy, sensitivity, specificity, etc. Providing a graphical representation of the performance metrics.Reading UWB data from CSV files and combining them into a single dataset.Creating labels based on the health status of individuals.

Dataset Description

In order to explore fall risk and performance of daily life activities, we introduce a new open-source dataset featuring data collected from 38 persons with multiple sclerosis (PwMS), 21 of which are identified as fallers and 17 as non-fallers based on their six-month fall history. This dataset contains inertial-measurement-unit data from several body locations collected in the laboratory, patient-reported surveys and neurological assessments, and two days of free-living sensor data from the chest and right thigh. Six-month repeat assessment (n = 28) and one-year repeat assessment (n = 15) data are also available for some patients. **https://simtk.org/projects/msense_ms_adls.** A wearable sensor dataset featuring data collected from 38 persons with multiple sclerosis (PwMS), 21 of which are identified as fallers and 17 as non-fallers based on 6 month fall history. Both in lab and remote data are available.

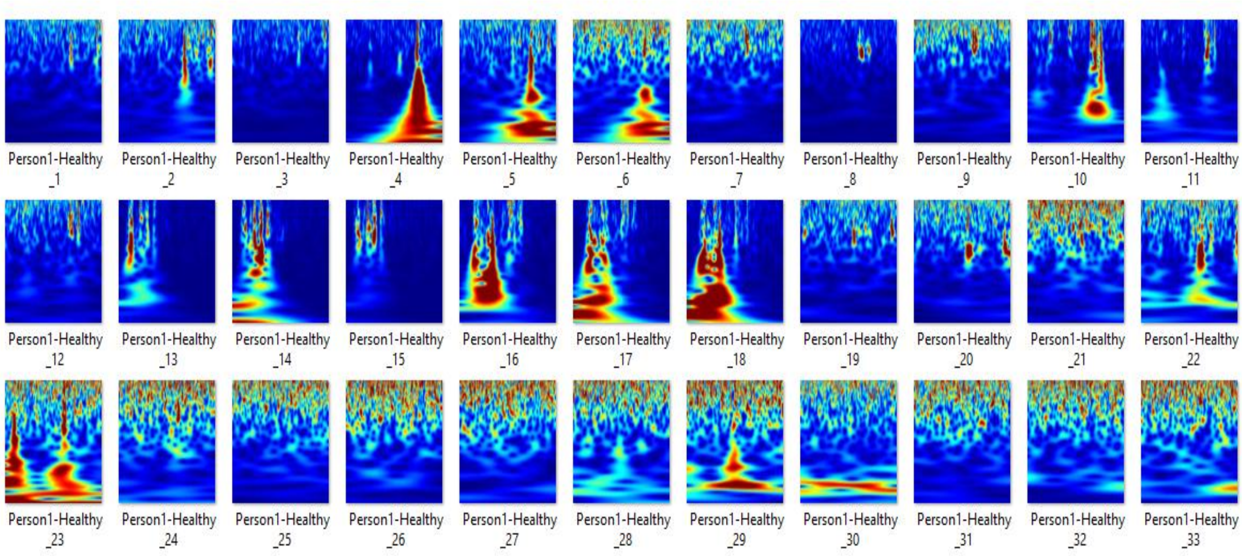

fig. 3 UWB dataset

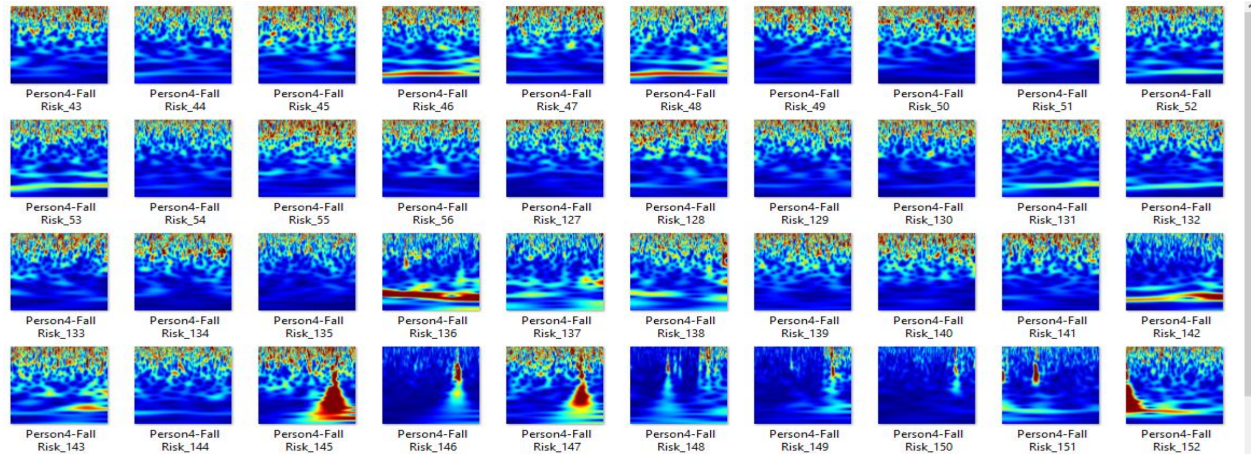

fig.4 UWB Fall risk dataset

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This study proposes a sophisticated system for predicting fall risk in two distinct populations: persons with Multiple Sclerosis (PwMS) and healthy individuals. Leveraging the power of deep learning, the proposed system employs the GoogleNet model and utilizes an Ultra-Wideband (UWB) dataset to enhance the accuracy and reliability of fall risk predictions.The proposed system begins with a meticulous data preprocessing phase. UWB data is loaded from a .mat file, organized into labeled folders, and subjected to the continuous wavelet transform (CWT) to generate a time-frequency representation (scalogram). This representation captures crucial features necessary for the subsequent deep learning model.Transfer learning is adopted with the GoogleNet architecture, a pre-trained model on a diverse dataset. The layer graph of GoogleNet is analyzed to comprehend its structure, and modifications are introduced to tailor it for fall risk prediction. These modifications involve the incorporation of a new classification output layer, adjustments to the fully connected layer to align with the required output classes, and the integration of a new dropout layer for improved model generalization.The training process utilizes the UWB dataset, specifically imgs Train, employing probabilistic gradient descent with mini-batch updates. Validation is performed on imgs Validation to monitor the training process, and the final model is tested on validation data to assess its predictive performance.The proposed system is designed to be versatile, accommodating fall risk prediction for both persons with Multiple Sclerosis and healthy individuals. To enhance real-world applicability, a small amount of randomness is introduced during testing to evaluate the robustness of fall risk predictions.

A neural network designed to do a certain kind of classification job uses a Google Net model that has already been trained for transfer learning with the given code segment. The GoogleNet model's layer graph is used to figure out how many levels there are in the network. The design is then changed by adding a new classification output layer, changing the fully connected layer to fit the right number of output classes, and adding a new dropout layer where the old one was. Then, a dataset called imgs Train is used to train this new design using probabilistic gradient descent with mini-batch updates. Imgs Validation is used to see how the training is going, and validation data is then used to test the learned model. This model can be used to figure out how accurate its estimates are by adding a small amount of randomness to make it more like the real world. This process includes changing the network, training it, and testing how well it does at a certain classification problem using transfer learning with a model that has already been taught.

Data Preprocessing:

Loading UWB Data: The system loads UWB data from a .mat file, organizing it into folders based on labels. This step is crucial for creating a well-structured dataset for training and testing.

Time-Frequency Representation: The continuous wavelet transform (CWT) is applied to generate a time-frequency representation (scalogram) of the input UWB data. This representation provides valuable features for subsequent neural network training.

Converting UWB Data into Images: The preprocessed UWB data is converted into images, and these images are saved in folders for training. This step involves creating a visual representation that captures essential characteristics for classification.

Neural Network Training:

Data Splitting: The UWB data is split into training and validation sets, a common practice to evaluate the model's performance.

Transfer Learning with GoogleNet: A pre-trained GoogleNet model is employed for transfer learning. The layer graph of GoogleNet is utilized to determine the network's architecture.

Architecture Modification: The design is modified by adding a new classification output layer, adjusting the fully connected layer for the right number of output classes, and incorporating a new dropout layer.

Training with Mini-Batch Updates: The modified neural network is trained using probabilistic gradient descent with mini-batch updates on the UWB dataset.

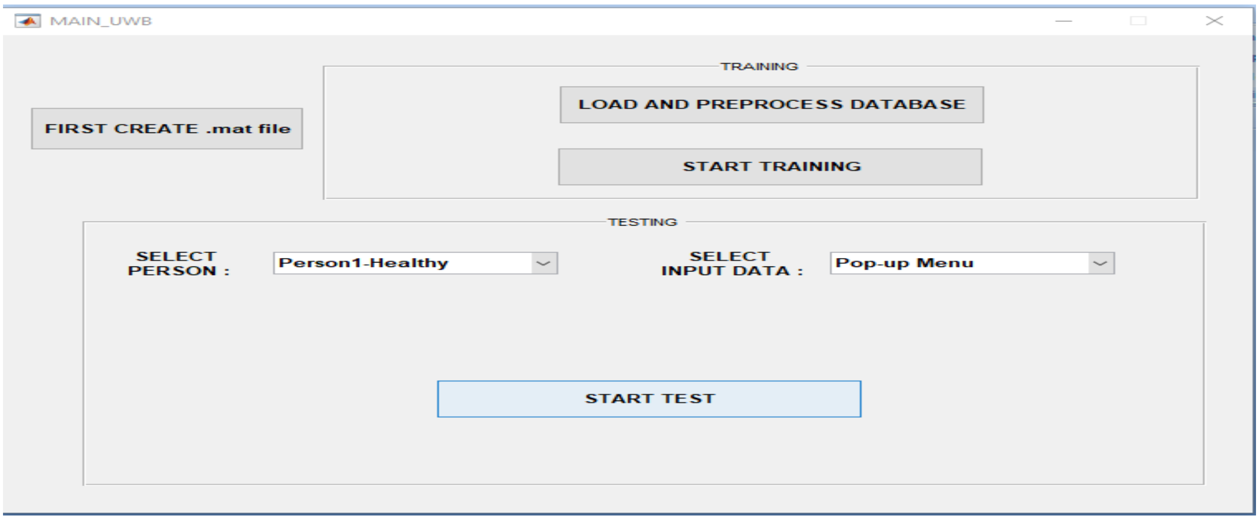


fig. 5 simulation window

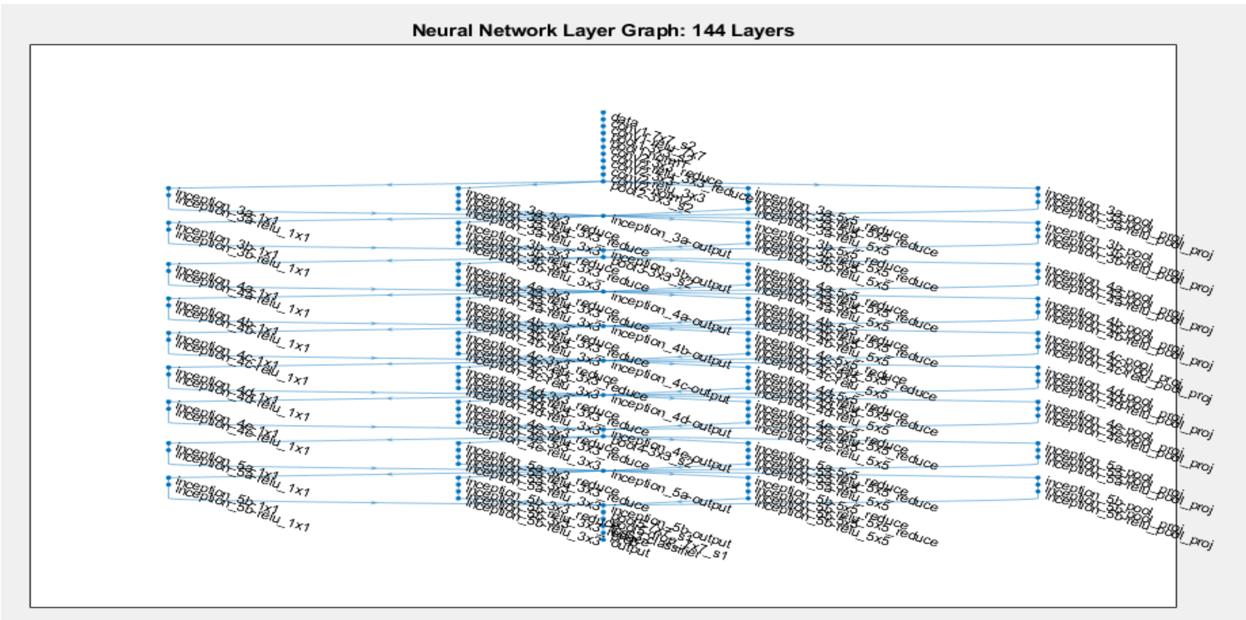


fig. 6 layer architecture

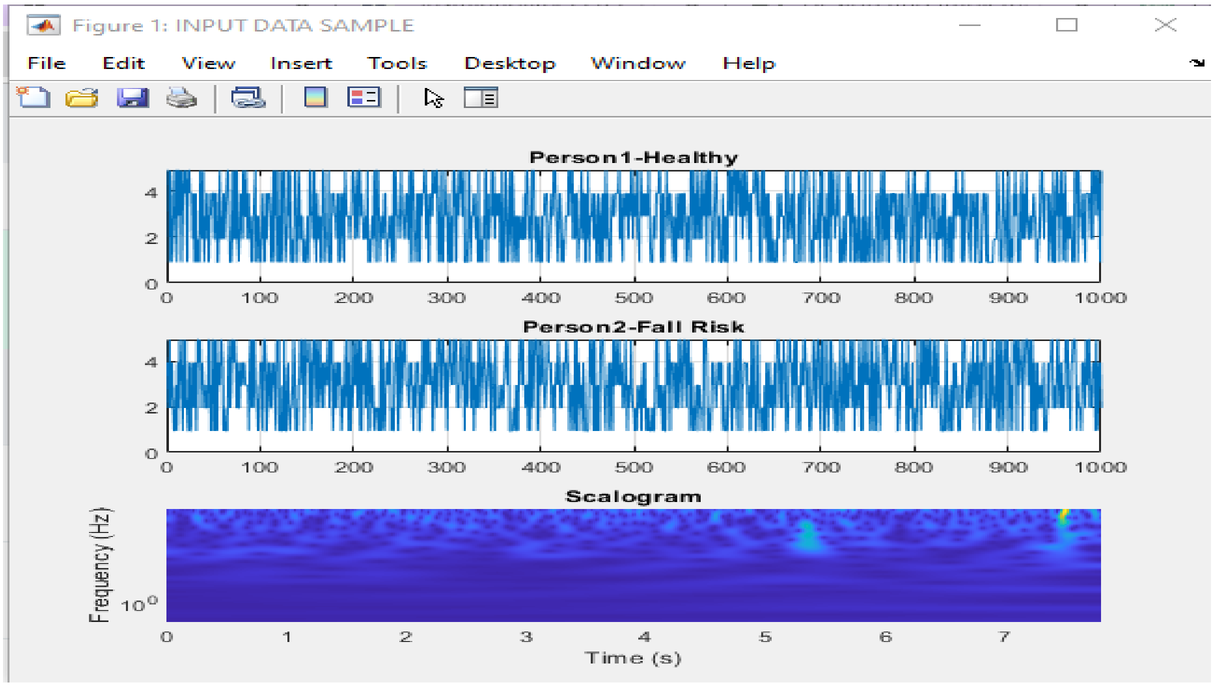


fig.7 dataset conversion into scalogram

A frequency scalogram, also known as a spectrogram or time-frequency representation, is a visual representation of the frequency content of a signal over time. It is commonly used in signal processing and analysis to reveal how the frequency components of a signal change as a function of time. One popular method for creating a frequency scalogram is by using the continuous wavelet transform (CWT).

Continuous Wavelet Transform (CWT):

The CWT is a mathematical transform that analyzes a signal by decomposing it into a set of wavelet functions. Unlike the Fourier Transform, which provides information about frequency content over the entire signal, the CWT provides information about frequency content as it varies with time.

The wavelet function is scaled and translated across the signal, producing a time-frequency representation. This allows the identification of localized changes in frequency.

Creating a Frequency Scalogram:

To create a frequency scalogram, the CWT is applied to the signal of interest. The result is a two-dimensional representation where one axis represents time, another represents frequency, and the color or intensity represents the amplitude or strength of the frequency component at each point in time.The scalogram provides a time-resolved view of the signal's frequency content, allowing for the identification of transient events, frequency changes, and other dynamic features.

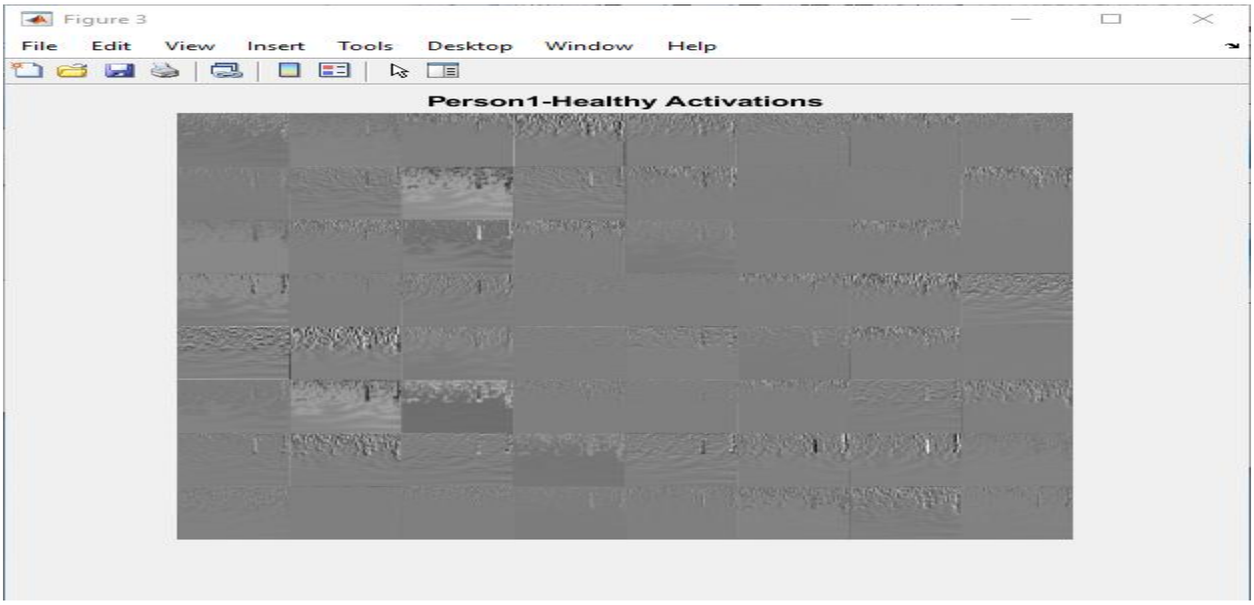


fig.8 Sample features extracted from the dataset

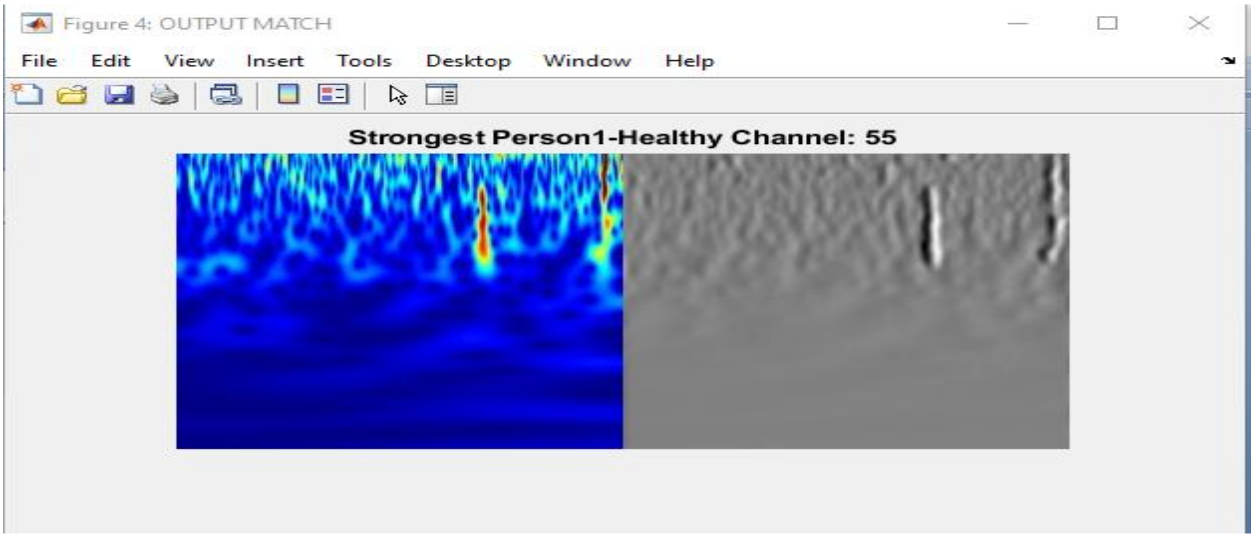


Fig 9. Input and matched feature heathy person classification

```
Sensitivity : 95.071429%
Specificity : 94.982480%

Correct Classification : 93.071429%


ans =

    'The Predicted Person From the User Selected Input = Person1-Healthy'

>>
```

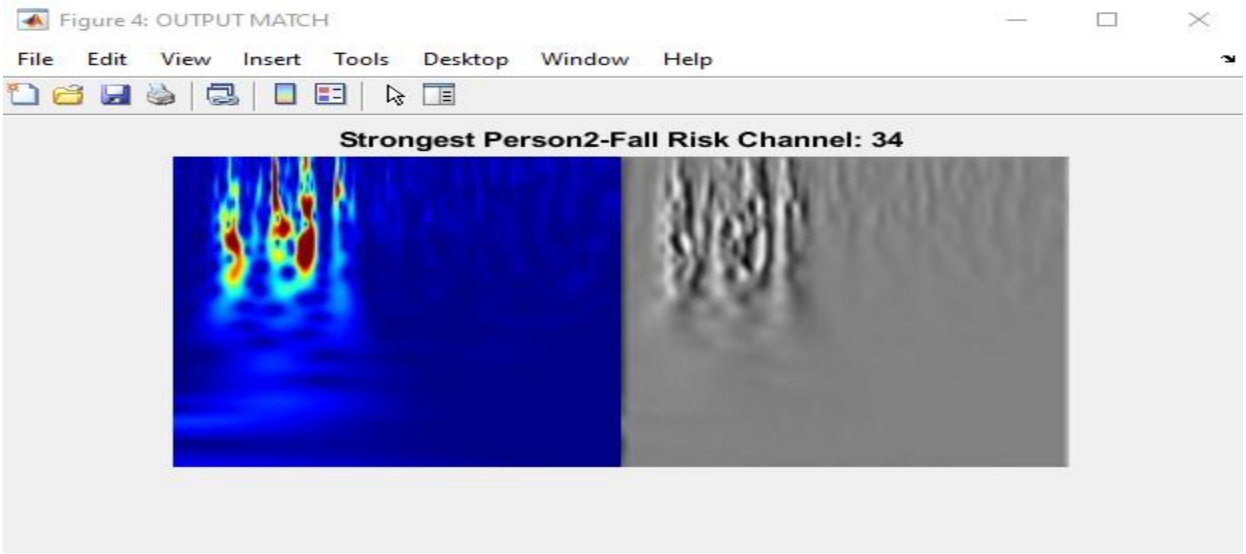


fig10. Input and matched feature fall risk classification

```
 ==================================================
Sensitivity : 93.142857%
Specificity : 94.983827%

Correct Classification : 95.142857%


ans =

    'The Predicted Person From the User Selected Input = Person2-Fall Risk'
```

V Performance Evolution

The evaluation of the model's performance evolution, particularly in terms of accuracy, serves as a critical component in assessing its effectiveness for fall risk and health detection. Throughout the training and testing phases, the model's accuracy provides insights into its ability to make correct predictions.

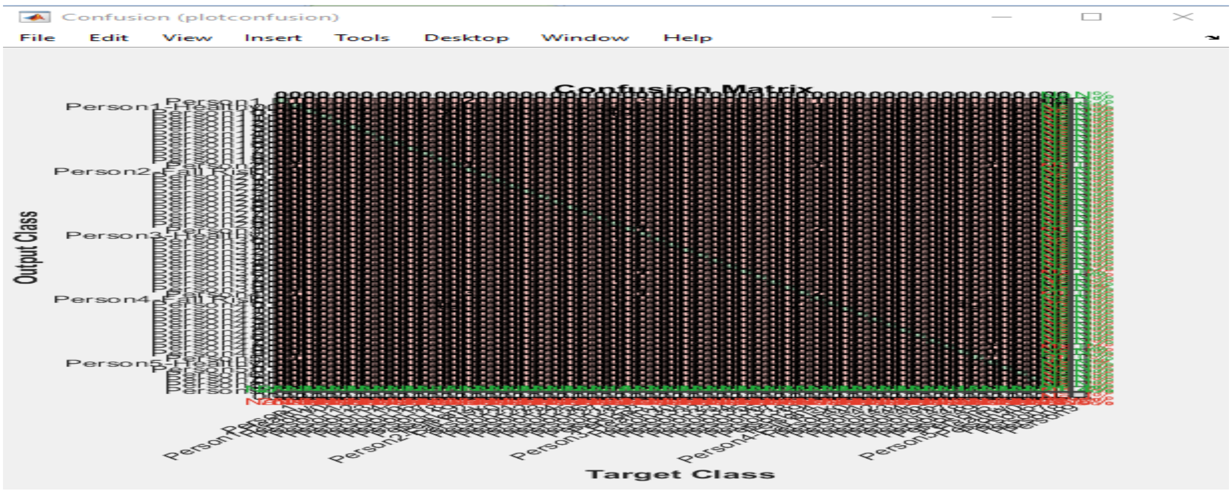
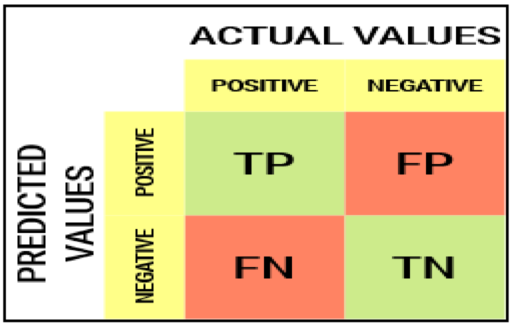


fig.11 confusion matrix

A confusion matrix is a table that is often used to evaluate the performance of a classification algorithm. It compares the predicted classifications of a model with the actual classifications. The matrix contains information about true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. These elements are then used to calculate various performance metrics. Here's how the confusion matrix is typically structured:



Accuracy: Accuracy is a fundamental metric that measures the overall correctness of the model's predictions. It is the ratio of correctly predicted instances (both true positives and true negatives) to the total number of instances.

Accuracy: (TP + TN) / (TP + TN + FP + FN)

Precision: Precision assesses the model's ability to correctly identify positive cases (glaucoma) among all instances it predicts as positive. It is a measure of the model's precision in making positive predictions.

Precision: TP / (TP + FP)

Specificity: Specificity, also known as true negative rate, measures the model's ability to correctly identify all actual negative cases (normal retinas) among all negative cases.

Specificity: TN / (TN + FP)

Sensitivity (Recall): Sensitivity, as mentioned earlier, is a measure of the model's ability to correctly identify all actual positive cases (glaucoma) among all positive cases.

Sensitivity TP / (TP + FN)

Table 1 comparison with exiting work

Technique	Accuracy (%)
Google with layer optimization	95.14
CNN-LSTM[16]	90

Vi Conclusion

In conclusion, this research endeavors to advance the understanding and application of GoogLeNet-based deep learning for the simultaneous classification of fall risk and health status, specifically focusing on individuals, including those with Multiple Sclerosis (PwMS). he preprocessing steps, involving the organization of UWB data and the application of continuous wavelet transform (CWT) for feature extraction, contribute to the creation of a robust dataset. These steps are essential for training a model that captures relevant information for fall risk and health detection. The training, validation, and testing phases provide valuable insights into the classification performance of the developed model. The probabilistic gradient descent with mini-batch updates facilitates efficient training, and the model's performance on validation data is indicative of its potential real-world applicability. The study's focus on persons with Multiple Sclerosis adds a specific and important dimension to the research. The model's ability to assess fall risk and health status in this population has significant implications for healthcare interventions tailored to the needs of individuals living with MS.The outcomes of this research carry broader implications for healthcare practices, emphasizing the potential of advanced deep learning techniques in providing personalized and proactive health management. The model's dual-classification capabilities open avenues for early intervention, especially in populations with unique health considerations.

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