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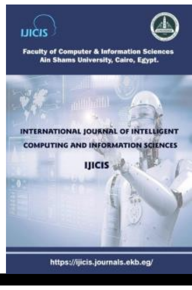

A COMPARATIVE STUDY OF THE DIFFERENT FEATURES ENGINEERING TECHNIQUES BASED ON THE SENSOR USED IN FOOTSTEP IDENTIFICATION AND ANALYSIS USING THE FLOOR-BASED APPROACH

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Abstract: *Humans can be recognized by their distinctive walking patterns, which have been established using a variety of techniques, including the use of sensors. Footstep recognition, which analyzes the distinctive characteristics of a person's footsteps, can be applied in a range of scenarios, including security, criminal investigations, human behavior security applications, and healthcare for monitoring and analyzing gait abnormalities. This paper discusses the most recent work on footstep analysis and identification systems in terms of using the floor-based approach. It explains the various artificial intelligence methods as well as the machine learning and deep learning algorithms applied to the recognition and analysis of footsteps, the various feature engineering techniques applied to each type of sensor, the affection of the engineered features on the footstep identification and analysis systems, and the best suitable features for each type of sensor and application, which provide researchers in this domain with an appropriate grounding in footstep identification and analysis utilizing the floor-based technique.*

Keywords: *Footstep Identification and Analysis, Machine learning, Pattern recognition, Deep Learning, Pressure Sensor.*

1. Introduction

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Footstep identification and analysis is the process of detecting and studying the characteristics of footsteps to gain insights into various aspects such as security, forensics, human behavior, and more [1–4]. This can involve the use of various sensors, technologies, and analytical techniques to extract valuable information from footprints. There are various sensors that can be used to collect footstep data; these include pressure sensors, accelerometers, microphones, and even video cameras. The footstep detection process can involve the use of signal processing algorithms to identify footstep patterns in the data collected from the sensors. Once footstep data is collected, relevant features are extracted. These features can include step length, step duration, foot pressure distribution, and even the sound profile of footsteps [4–5].

Gaining insights into the various aspects is a major benefit of footstep analysis [4–5]. In criminal investigations, footstep analysis can be used to link a suspect to a crime scene; shoeprint analysis, for instance, can involve comparing the tread patterns of shoes found at a crime scene with those of a suspect. Footstep identification can be used for security purposes, such as in access control systems. Biometric data based on gait or Foot pressure can be utilized to allow or prohibit entry into specific locations. Footstep analysis can also be applied in healthcare for monitoring and assessing gait abnormalities. It can be used to track the progress of patients undergoing rehabilitation after injuries or surgeries. Footstep analysis can provide insights into human behavior and biomechanics. It can be used to study the impact of footwear on posture, gait, and overall health. The study of footstep patterns on different surfaces can be used in architecture and urban planning to design more comfortable and safe pedestrian pathways.

Footstep recognition can be approached using various methods, including floor-based approaches and other techniques [4–5]. Each approach has its advantages and limitations, and the choice between them depends on the specific use case and requirements. Floor-based systems, for instance, do not require individuals to wear any special devices or markers, making them non-intrusive and convenient for subjects. Floor-based sensors can provide accurate data, especially in controlled environments with well-maintained equipment. This approach is suitable for various applications, including security, access control, healthcare, and forensics.

Other approaches, like video-based gait analysis, can allow for comprehensive gait analysis, including body movements and posture, it can be used for both indoor and outdoor scenarios, but it may require a clear line of sight to the subject, and privacy concerns may arise when using video surveillance for gait analysis in public areas [4–6]. Real-time data on a person's gait and posture can be gathered by wearable sensors such as gyroscopes and accelerometers, making them suitable for continuous monitoring and healthcare applications, but users must wear the sensors all the time, which can be uncomfortable or inconvenient, and the accuracy may vary depending on sensor placement and calibration [7–8]. The choice between floor-based footstep recognition systems and other approaches depends on factors such as the specific application, accuracy requirements, privacy considerations, and cost constraints. Floor-based systems are well-suited for controlled environments where accuracy is crucial and where privacy concerns can be addressed. However, other approaches like video-based analysis and wearable sensors may be preferred in scenarios where real-time monitoring, comprehensive gait analysis, or portability are essential.

Machine learning, deep learning, and pattern recognition techniques can be trained to identify specific individuals based on their gait patterns or to identify some sort of walking pattern and classify them [4–9]. Feature engineering is essential to the performance and effectiveness of the floor-based footstep identification and analysis systems, where the efficient engineered features can make the system more compatible with machine learning algorithms, which can significantly enhance the accuracy and reliability of the systems [4–9]. Feature engineering allows for the extraction of relevant information from floor-based data, making it easier for the system to discriminate between different individuals' footsteps or to detect specific characteristics, such as gait abnormalities or shoe types. The engineered features can also make the system more robust to environmental variations; for example, by extracting features that are less affected by lighting conditions or floor surface variations, the system can perform consistently in different settings. Reducing the dimensionality of the data while maintaining its ability to discriminate can lead to more efficient and faster processing without sacrificing accuracy.

Features can be designed to filter out noise or irrelevant information from the floor-based data, improving the system's signal-to-noise ratio and overall performance. Different applications may require different engineered features. Feature engineering allows for tailoring the system to specific use cases; for example, security applications might focus on identifying individuals, while healthcare applications might prioritize gait analysis features. Engineered features can also sometimes provide insights into the underlying factors contributing to footstep characteristics, making it easier to interpret and understand the results generated by the system. Well-engineered features are often more compatible with machine learning algorithms, making it easier to build accurate predictive models for footstep recognition. Efficient feature extraction methods can enable real-time processing of floor-based footstep data, which is crucial for certain applications like security and access control.

There are different engineered features for floor-based footstep recognition [4-6]; for example, features related to pressure distribution patterns, features based on the timing of footsteps, characteristics of the footprints, features extracted from frequency domain, analysis of footstep signals, and the statistical measures of the footstep signals. The features relate to pressure distribution patterns such as peak pressure, pressure centroid, and pressure distribution asymmetry, while on the other hand, the features which are based on the timing of footsteps, including stride length, step duration, and cadence. The characteristics of the footprints include footprint area, aspect ratio, width, length, and the features extracted from frequency domain analysis of footstep signals can capture subtle variations in gait. The statistical measures of the footstep signals can be represented by the skewness, kurtosis, mean, and standard deviation of pressure values within a footprint. The dimensionality reduction technique can also be used as part of feature engineering to capture the most discriminative information. Feature engineering is a critical step in the development of floor-based footstep identification and analysis systems. Effective feature engineering can lead to more accurate, robust, and efficient systems that are tailored to specific applications and environmental conditions.

In this paper, we discuss the most recent work on footstep analysis and identification systems in terms of using the floor-based approach, where we discuss the most frequently used machine learning and deep learning algorithms, as well as the different features engineering techniques applied to each sensor and the affection of the engineered features on the footstep identification and analysis systems, the best suitable features for each type of sensor, and the best suitable sensor for each type of application. The remainder of the paper is organized as follows: Section 2 discusses the different sensors applied to the footstep identification and analysis systems. Section 3 addresses the most recent relevant work on footstep analysis and identification systems using the most frequently used sensors and algorithms, as well as the feature engineering strategies that are applied to each type of sensor. Our discussion and comparison are discussed in Section 4. Section 5 contains the conclusions of our work.

2. The Applied Sensors on Footstep Identification and Analysis Systems

Footstep recognition can be achieved by integrating different types of sensors into the floor or floor carpet; these sensors are developed to capture the characteristics of footsteps. The setup of the sensors is quite similar, except for the accelerometer and the gyroscope, which can be implemented in a smartphone or smartwatch to detect changes in velocity, acceleration, and the orientation of a person.

The installation of a sensor that can be integrated into a floor or a floor carpet, like the piezoelectric sensors, can be as follows [10–11]:

- The sensors are strategically placed on the ground or within footwear to capture the pressures or forces exerted during each footstep. These sensors can be embedded in shoes, walkways, mats, or even directly on the ground .
- When a person walks or runs over a sensor, the pressure from their foot's impact causes the piezoelectric material to deform, generating an electrical signal. This signal is proportional to the force applied by the foot.
- The generated electrical signal is then captured by data acquisition systems, which convert the analog signal into a digital format that can be processed and analyzed by computers or microcontrollers.
- The collected data can be processed to extract various parameters, such as step count, stride length, gait cycle duration, foot pressure distribution, and more. Signal processing techniques may involve filtering, noise reduction, and feature extraction to obtain meaningful insights.

The same steps can be applied to any type of sensors to obtain similar data based on the type of sensor, then data analysis can be applied to the collected data to obtain insights. The system can determine gait parameters such as stride length, step duration, and walking speed by analyzing the time intervals between successive footsteps. Another type of data analysis is footstep recognition systems, which can potentially identify individuals based on their unique walking patterns. This could be useful in security applications or access control. Also, changes in footstep patterns can indicate falls or irregularities in gait, which could trigger alerts or notifications in healthcare or elderly care scenarios. The rest of this section discusses some of the most frequently used sensors in footstep identification and analysis.

2.1. Piezoelectric Sensors

Piezoelectric sensors are gadgets that translate physical changes in force, temperature, acceleration, or pressure into electrical signals by utilizing the piezoelectric effect. The piezoelectric effect occurs when some materials are under pressure or mechanical stress and produce an electric charge. [10-17]. Conversely, when an electric field is applied to these materials, they undergo deformation or strain.

Piezoelectric sensors are commonly used in footsteps data collection for various applications, such as gait analysis, activity monitoring, security systems, and more [10-17]. They provide valuable insights into human movement patterns and can help researchers, engineers, and healthcare professionals understand how people walk, run, or move. Piezoelectric sensors play a crucial role in collecting accurate and detailed footsteps data, offering insights into human movement patterns, and enabling a wide range of applications across industries.

2.2. Plastic Optical Fiber

Plastic optical fibers (POF) and polymer optical fibers are optical fibers made of polymers that are similar to glass optical fibers in that they transmit light (for illumination or data) through the fiber core [18-19]. POF offers unique advantages and characteristics that make them suitable for specific applications, especially those that do not require high data transfer rates and long-distance transmission capabilities of glass optical fibers. Another aspect that is equal is its robustness under bending and stretching. Polymer optical fibers can be used for remote sensing and multiplexing owing to their low cost and high resistance. POF can be used in footstep recognition systems to detect and analyze footstep patterns for various applications [18-19]. Footstep recognition involves identifying and analyzing the unique characteristics of footsteps to determine factors such as gait, stride length, walking speed, and the ability to identify people by their patterns of walking. Although plastic optical fibers have advantages such as flexibility and ease of installation, it is important to note that their relatively low data transmission capabilities might limit their use for certain applications, especially if high data rates or long-distance transmission are required. However, for applications where the unique benefits of POF align with the requirements of footstep recognition, it can be a suitable and cost-effective choice.

2.3. Conductive Polymer Fabric

Polymer fabric sensors are a type of smart textile technology that integrates conductive polymers into fabrics to create sensors capable of detecting various physical or chemical changes [20-21]. These sensors are flexible, lightweight, and can be seamlessly integrated into clothing, wearable devices, and other fabric-based applications. They offer several advantages, including comfort, flexibility, and the ability to gather data from the body or the environment.

Polymer fabric sensors can be used in footstep recognition systems to detect and analyze footsteps, gait patterns, and various aspects of human movements [20-21]. These sensors offer several advantages, such as being lightweight, flexible, and unobtrusive.

2.4. Photo Interrupters

Photo interrupters, also known as photoelectric sensors, are devices that use a light source and a light sensor to determine whether an object is present or absent [22-23]. These sensors are commonly used in various industrial and automation applications for tasks such as object detection, counting, and positioning. Photo interrupters are versatile and reliable sensors commonly found in a wide range of industries due to their ability to provide non-contact and precise object detection capabilities.

Photo interrupters can be used in footstep recognition systems, particularly in applications where precise timing and detection of footfalls are required [22-23]. While other technologies like pressure sensors or accelerometers are more commonly used for footstep recognition, photo interrupters can provide unique advantages in certain situations. Photo interrupters have advantages in terms of precision and speed because they can detect footfalls with high accuracy, and the interruptions are typically brief and well-defined. However, they may have limitations in certain conditions, such as when there is significant ambient light that could interfere with the sensor or if the surface on which people are walking is highly reflective.

2.5. Other Types of Sensors

There are a lot of different sensors that has been used for footstep identification and analysis, but some of them are outdated that have not been used in the recent years, and some of them are still in the development phase that did not reach their full potenal yet. So, we just settled for mentioning some of them without getting into further details of how they have been applied in footstep identification and analysis, and what kind of feature engineering techniques have been applied to the extracted data from them.

2.5.1. Switch Sensors

Switch sensors, also known as switch detectors or simply switches, are devices used to detect the physical state or position of an object, typically to determine whether it is in an open or closed position [24-25]. They are widely used to monitor, control, and automate processes in a variety of applications and industries. Switch sensors come in various types, each designed for specific purposes. Switch sensors play a crucial role in automation, control, and safety systems across various industries. They can be used to trigger alarms, control motors, initiate processes, or provide feedback on the status of equipment. The type of switch sensor selected is determined by the requirements of the specific application, such as the type of object being detected, environmental conditions, and the level of precision required for the task.

Switch sensors can be used in footstep recognition systems, especially when you need a simple and cost-effective solution for detecting footfalls [24-25]. While other technologies like pressure sensors, accelerometers, or photo interrupters are commonly used for footstep recognition, switch sensors can be a viable option in certain scenarios. Switch sensors have the advantage of simplicity and robustness. They are typically durable and can withstand heavy foot traffic. However, they may not provide as much detail as other sensors in terms of the quality of footstep data (e.g., step length, weight distribution) and may not be suitable for very high-precision applications.

2.5.2. Load Cells

Load cells are transducers or sensors that are used to measure force or load in various applications [26-27]. They are designed to convert mechanical force into an electrical signal, typically in the form of voltage, current, or resistance changes. Load cells are widely used in industries such as manufacturing, materials testing, transportation, healthcare, and more. Load cells play a crucial role in ensuring accurate measurements, quality control, and safety in various industries. They come in different capacities and configurations to suit specific measurement needs, from small laboratory applications to heavy industrial environments.

Load cells are not commonly used for footstep recognition in typical applications. While load cells are excellent sensors for measuring force and weight in various contexts, they may not be the most practical or suitable choice for footstep recognition for several reasons, Load cells are highly sensitive to the point of contact or placement of the load. For accurate measurements, the load must be applied directly to the load cell's sensing area [26-27]. In footstep recognition, it can be challenging to ensure that a person consistently steps in the same location on a load cell. Load cells typically require precise installation and calibration. Embedding load cells in a floor or walkway for footstep recognition would be a complex and costly process. Load cells provide information about the magnitude of the force but offer limited spatial information. They cannot easily distinguish between different parts of the foot (heel, arch, toes), which may be important in certain footstep recognition applications. Load cells are sensitive to external vibrations and forces. In a real-world environment with various sources of vibration and movement, it may be challenging to isolate the load cell from interference.

2.5.3. Electro-Mechanical Film

Electro-mechanical films, also known as electroactive polymer films, refer to a class of materials that can change shape or dimensions in response to an applied electrical voltage [28-29]. These materials are often used in various applications for actuation, sensing, and vibration control. One of the most well-known types of electroactive polymers is called "dielectric elastomer." It's important to note that while electroactive polymers have shown promise in various applications, they also have limitations, including the need for high voltage for significant deformation and issues related to long-term stability. Researchers continue to work on improving the performance and durability of these materials for practical use.

Electroactive films have the potential to be used in footstep recognition systems, although they are not the most common choice for this application. Footstep recognition typically relies on sensors that can detect the presence, location, and characteristics of footsteps accurately. While electroactive films can be used for sensing, there are other sensor technologies more commonly employed for this purpose [28-29].

In many footstep recognition applications, pressure-sensitive mats or arrays of pressure sensors, accelerometers, or other specialized footstep sensors are more commonly used due to their proven accuracy and reliability. These sensors can provide more detailed information about footstep characteristics and are well-suited for footstep recognition systems, especially in environments where accuracy is critical.

2.5.4. Force Sensing Resistors

Force Sensing Resistors (FSRs) are a type of passive electronic component that changes its electrical resistance in response to applied force or pressure [30-31]. These sensors are often used for detecting physical interaction with objects, measuring force, and capturing touch or pressure data in various applications. Force Sensing Resistors are versatile sensors with applications across a wide range of industries and technologies. Their ability to provide precise force or pressure measurements in a compact and flexible form factor makes them valuable in both consumer and industrial settings.

FSRs can be used in footstep recognition systems to detect and analyze foot pressure patterns as individuals walk, providing valuable data for various applications [30-31]. FSRs offer advantages such as flexibility, real-time data capture, and the ability to cover large surface areas. However, they also have limitations, including the need for careful calibration and signal processing to accurately interpret the pressure data. Additionally, FSRs may not capture all aspects of the footsteps, such as the precise angle or orientation of the foot during each step. In practice, FSRs are often used in conjunction with other sensors, such as accelerometers or cameras, to provide comprehensive footstep recognition and analysis.

2.5.5. RSscan Footscan

Footscan is a product line developed by RSscan International, a company specializing in foot pressure measurement and gait analysis technology [32-34]. Footscan systems are designed for capturing and analyzing dynamic foot pressure and gait data, making them valuable tools in various fields, including podiatry, orthopedics, sports science, and footwear development. The Footscan platform includes an array of high-resolution pressure sensors embedded in a sensor mat. These sensors capture the pressure distribution across the foot during various activities such as walking, running, or standing. As individuals walk or run across the sensor mat, the Footscan system continuously records and collects pressure data in real time, this data provides insights into the distribution of forces on different areas of the foot. RSscan's Footscan technology is equipped with specialized software for gait analysis. This software allows users to visualize and analyze various parameters related to gait, including pressure distribution, temporal gait parameters, and foot function. Footscan systems can assess dynamic foot function, including factors like stride length, step width, and gait timing. This dynamic analysis can be particularly useful for diagnosing gait abnormalities or assessing the impact of footwear or orthotics. In the field of podiatry and orthopedics, Footscan data can be used to design custom orthotic insoles tailored to an individual's foot shape and gait pattern. Footscan technology is commonly employed to evaluate the performance of footwear. It assesses factors such as pressure points, support, and comfort, aiding in the design and optimization of footwear. Footscan systems are widely used in sports science, sports medicine, and research to study the biomechanics of human movement, foot function, and the impact of sports-related activities on the feet. Physical therapists and rehabilitation specialists utilize Footscan data to assess gait abnormalities in patients and monitor their progress during treatment.

RSscan's Footscan technology offers a non-invasive and objective approach to assess and analyze the complex interactions between the feet and the ground during various activities. This data-driven approach is valuable for clinicians, researchers, and product designers in understanding foot health, improving athletic performance, and developing customized solutions for individuals with specific foot-related conditions.

It's important to note that while Footscan provides valuable pressure and gait data, footstep recognition systems often combine multiple sensors and technologies to improve accuracy and reliability. These systems may integrate Footscan data with other sensors such as accelerometers, gyroscopes, or cameras for a comprehensive analysis of footstep patterns and characteristics. The use of Footscan technology in footstep recognition is particularly advantageous because it provides highly detailed information about the interaction between the foot and the ground, allowing for precise and comprehensive analysis of footstep data.

2.5.6. Accelerometer

Accelerometers are sensors or transducers used to measure acceleration, which is the rate of change of velocity of an object [7-8]. These devices are commonly used in various applications to detect and measure acceleration, tilt, vibration, and motion. Accelerometers are essential components in many electronic devices, including smartphones, fitness trackers, drones, and automotive systems. Accelerometers are versatile sensors with applications in a wide range of industries and technologies. They provide valuable data for controlling and optimizing systems, enhancing user experiences, and ensuring safety in various contexts.

Accelerometers can play a crucial role in footstep recognition and gait analysis systems by measuring the acceleration and motion patterns associated with each step a person takes [7-8]. While accelerometers are not typically used as the sole sensor for footstep recognition, they can provide valuable data when integrated with other sensors such as gyroscopes and magnetometers. It's important to note that while accelerometers provide valuable information for footstep recognition and gait analysis, they may not be as precise as dedicated pressure sensors or floor-based systems (e.g., pressure-sensitive mats) for certain applications.

2.5.7. Gyroscope

A gyroscope is a device used to measure or maintain orientation and angular velocity [7-8]. It is a fundamental component in many modern technologies, including navigation systems, aerospace applications, robotics, and consumer electronics. Gyroscopes operate on the principle of angular momentum and are designed to provide information about the rotation or angular movement of an object. Gyroscopes are essential for various applications that require accurate measurement and control of angular motion and orientation. They provide critical data for maintaining stability, navigation, and spatial awareness in both consumer and industrial technologies.

While gyroscopes are valuable sensors for measuring angular velocity and orientation, they are not typically used as the primary sensors for footstep recognition [7-8]. Footstep recognition systems primarily focus on detecting and analyzing the pressure distribution and temporal aspects of footsteps, such as step timing and length. However, gyroscopes can still provide useful supplementary information in certain scenarios or applications related to footstep recognition.

3. The Related Work of the Most Frequently Used Sensors

This section discusses the related work of the most commonly used sensors in footstep identification and analysis systems using the floor-based approach, where it discusses the details of the engineered features that have been extracted from the raw sensor data output, the impact of the engineered features on the results of the implemented algorithms, and the variety of algorithms used in each type of footstep identification and analysis system.

3.1. Related Work on Piezoelectric Sensors

Vera-Rodriguez et al. [10-14] proposed using the biggest footstep database (SFootBD) to date to analyze footstep signals as a biometric, including over 120 people and approximately 20,000 signals. The SFootBD signals were acquired using a capture device designed to collect the footstep database, which employs a high piezoelectric sensors density. The sensors were mounted on a large-printed circuit board and positioned beneath a standard mat. The sensor layout geometry guarantees a compact configuration with uniform intersensor spacing. The data is collected using two 45 CM x 35 CM sensor mats; each mat contains eighty-eight piezoelectric sensors to capture two successive footstep signals over 2200 time samples for each footstep signal. To produce more realistic signals, people were asked to walk at a steady pace for a few meters before walking on the sensor mats. The sensors produce a differential voltage output based on the pressure applied to them. The authors proposed three different types of features, some based on the time domain, some based on the spatial domain, and a fused set of features between both two domains.

Vera-Rodriguez et al. [12] focused on signal time information analysis, employing three distinct time domain feature approaches: the ground reaction force (GRF), the spatial average of the sensors (SA), and the upper and lower contour profiles of the time domain signal. The GRF is one of the most important features in footstep identification and analysis, as shown in Eq (1). GRF is a cumulative pressure for each time frame with all the previous time frames for the same footstep signal data file, and then an average is calculated for the eighty-eight piezoelectric sensors to obtain a single value that represents the global ground reaction force at each time *t*.

$$GRF_T\ [t] = \frac{1}{N}\sum_{i=1}^{N}(\sum_{t\,=\,0}^{T}(S_i[t])) \quad (1)$$

Where *T* represents the current time frame, *t* equals the start time frame, *i* represents the sensor, *N* represents the number of sensors which is equivalent to eighty-eight sensors in this case, and the $S_i[t]$ represents the output signal of the *i*th piezoelectric sensor at time *t*.

The SA of the sensors is defined in Eq (2), it is basically calculating the average of the output of the eighty-eight sensors at the time *t*.

$$S_{ave}\ [t] = \frac{1}{N}\sum_{i=1}^{N}(S_i[t]) \quad (2)$$

Eq (3) and (4) represent the upper and lower contours that are obtained from the maximum and minimum pressure voltage output of the piezoelectric sensors at each time *t*, to have a *T* number of maximum and minimum pressures. The output of the two signals is then concatenated into one contour.

$$S_{up}\ [t] = \underset{i=1}{\overset{N}{\mathbf{Max}}}(S_i[t]) \quad (3)$$

$$S_{lo}\ [t] = \underset{i=1}{\overset{N}{\mathbf{Min}}}(S_i[t]) \quad (4)$$

The output of Eq1 and Eq2 are then normalized and merged with the output of Eq3 and Eq4 at the feature level. After concatenating the four features, a vector of 8000 samples per footstep was acquired because the maximum time T was set to 2000 in each of the extracted features. The features vector is a high dimensional vector, so the principal component analysis (PCA) is used to reduce the dimensionality of the data [35]. Finally, the support vector machines (SVM) are employed to perform the matching. The findings obtained in the various settings for the fusion of the three feature techniques in the case of the stride footstep are in the range of 5 to 15% equal error rate (EER) based on the used benchmark.

Their second strategy was to extract biometric information from the pressure distribution of the footstep signals as well as spatial domain and generate a 3D image of the pressure distribution along the spatial domain [13]. It is important to note that, due to the differential nature of the piezoelectric sensors' footstep signals, a simple time integration of the signal would result in a value close to zero. To address this, the integration is performed across each sensor's associated ground reaction force signal (GRF_i) as shown in

Eq (5). This yields the accumulated pressure (AP_i) as shown in Eq (6), which is a measure used for studying the signal's pressure distribution across its spatial domain.

Eq5 is similar to Eq1 which calculates the GRF without calculating the average value of the GRF of all the sensors at the time *t* to obtain the global GRF.

$$GRF_i\ [t] = \sum_{t\,=\,0}^{T} (S_i[t]) \quad (5)$$

After calculating the GRF of all the data signals, we calculated the accumulated pressure which is defined as the formula shown in Eq6.

$$AP_i = \sum_{t\,=\,0}^{T_{max}} (GRF_i[t]) \quad (6)$$

The accumulated pressure is a cumulative summation for each sensor value of the calculated ground reaction force; the T_{max} was set to 2000 time frame because no signal has a larger time frame, which represents that the person has already walked out of the walking mat.

After generating the pressure images from the calculated AP, during the preprocessing stage, the signals were aligned to a single temporal position by applying an energy detector across the 88 sensors of the signals to obtain the starting point of each footstep in order to align the signals to a common time position. The images were then smoothed using a Gaussian filter and the toe and heel regions were rotated and aligned based on the pressure points. The generated image's rows are concatenated to generate a feature vector with a range of 117,600. PCA is also used to minimize data dimensionality, maintaining more than 96% of the original data by using the first 140 principal components. The feature vector for the stride (right and left) footstep is composed of the concatenation of the 140 component feature vectors for the right and left foot, as well as the stride's relative angle and length, for a total of 282 characteristics. In terms of the classifier, SVM with a radial basis function (RBF) as the kernel was used. The results reveal that the suggested methodology achieves high accuracy in identifying individuals based on their footstep signals, with EERs ranging from 6 to 10% in diverse scenarios. The results also suggest that including signals with high heels in the training data considerably improves the system's performance.

Another experiment was conducted to recognize the footsteps through the use of time, space, and a combination of the two [14]. They fused the features obtained in the above two experiments. The two domains perform very similarly, with error rates ranging from 5 to 15% for each domain and 2.5 to 10% for their fusion using the SVM, depending on the number of used signals (40 to 500) and whether the footstep is single or stride footstep.

Costilla Reyes et al. [15-16] conducted other two experiments on the SFootBD database, For the first experiment there were forty clients in the training set, each with forty stride footstep signals, and eighty-seven impostor subjects [15]. There were 7077 samples in the validation dataset and 550 samples in the evaluation dataset. They proposed using a Convolutional Neural Network (CNN), which is utilized to extract features for the full spatial database by providing the pressure images generated from calculating the GRF and the AP as described in Eq5 and Eq6, the generated images with dimensions of 88 x 44 for left and right footsteps and 88 x 88 for stride footsteps, then the generated images are fed to the CNN to generate the features vector. After the CNN has been trained, the training, validation, and testing datasets are fed into the network, and the CNN features are retrieved at the final layer before softmax activation. This produces a 127-feature vector for each sample in the dataset. The 127-length feature vector created by the CNN model per dataset sample is then employed in a biometric verification scenario with a One-vs.-one linear SVM model. The models were trained in the training set for each user and then tested in the validation and evaluation datasets. The paper's reported EER range is as follows: using the validation dataset, the EER for the left and right footstep models was 14.76% and 14.23%, respectively. The stride footstep model revealed a considerable EER improvement of 9.392% as compared to single footsteps. When the trained model was tested on the evaluation dataset, the EER for the left footstep was 21.30%, the EER for the right footstep was 20.23%, and the EER for the stride footstep was 13.86%.

For the second experiment, they suggested a deep residual ANN based on the ResNet architecture [16]. Using SFootBD, their solution features artificial intelligence that can discriminate between authenticated users and biometric system imposters based on the fine-grained variability of footsteps. The raw spatial and temporal features of the data are represented in a variety of ways. Each footstep frame is molded into a two-dimensional matrix for the spatial component, with sensors generated by the merging of the two mats and pixels derived from the accumulated pressure. The temporal component representation chooses frames that correspond to heel striking, flat foot, and heel-off intervals to optimize data variability versus training time. The authors conducted three distinct studies under three different conditions. The three experimental settings varied the number of users and impostors by varying the amount of Footstep data used to train the machine-learning model. Two ResNet models were trained, one for spatial component features and one for temporal component features. The trained ResNet models were then used as feature extractors to feed linear SVM classifiers. A single class was assigned to the imposter dataset. They applied their work to three benchmarks that were constructed to simulate three different scenarios (airport, workplace, and smart home). For the first benchmark which has the smallest footstep dataset and simulates a scenario involving an airport security checkpoint, included 40 footstep samples from 40 users and 763 imposter footstep samples, and the optimum model yields 7.10% and 10.50% EER for the validation and evaluation sets, respectively. The second benchmark was for the medium-sized training dataset, which included 200 stride footsteps from 15 different users and 2697 impostor footstep signals depicting a working environment scenario. EERs of 2.80% and 4.90% were obtained from the validation and evaluation sets, respectively. As for the third benchmark, which is based on a home-based scenario, it contains 500 footstep samples from 5 individuals as well as 5603 imposter footstep signals. It obtained the best results in comparison to the other two scenarios; the validation and evaluation sets had 0.70% EER and 1.70% EER, respectively.

Leusmann et al. [17] presented a technique for detecting steps based on sensor floor called "The Future Care Floor", which is a sensor floor constructed of 64 wooden bricks (600 × 600 × 40 mm and 300 × 600 × 40 mm) placed on a wooden steel frame sure to free up space for wiring and controlling the devices below. To monitor ground impact data, each corner of the brick has a piezoelectric sensor covered by a Perpex support structure. The piezoelectric output is similarly preprocessed to limit the voltage to the -2.5 to 2.5 V range and shift the voltage to a positive value in the operational amplifier. The quantized piezoelectric output is sampled using the ATmega1280 microcontroller 10-bit A/D converter on 15 Mega board Arduinos. The sampled data is transmitted to the host computer via the serial protocol encapsulated in USB packets. To interpret the intuitive sensor data presented in this article, it is critical to comprehend the unique signal response offered by piezoelectric sensors. Piezoelectric sensors respond to applied force not the weight, which means that the sensors will only distinguish between moving objects. This behavior eliminates the need to eliminate static elements like furniture from the produced room model. The sensors are hidden under the floor of a living laboratory room designed and built by RWTH Aachen University.

The “Future Care Layer” software is divided into 2 parts, the software running on the Arduino microcontroller board that is responsible for sampling the sensor data and transmitting it to the host computer, and java programming language is used on the host computer to implement the software for processing and analyzing the raw sensor data. Several steps of processing raw sensor data must be performed to accomplish the goal of detecting human movement on the ground.

Three consecutives first in first out (FIFO) queues are used for data reading and initial processing. An automatic processing thread is set up for each stage to transfer the processed data to the next queue. The first step is to connect to the serial port and transfer the data to and from the Arduino board. The second step is to decode the raw packet into individual value objects and filter the individual values using three related filters calibration, low pass, and relevance checking. Calibration corrects the change in value in the neutral state using a static lookup table. The low-pass filter removes high-frequency components from the sensor data using the hanning window function. Check the relevance of filter values below a certain threshold to remove noise. The third step is forwarding the filtered values to the listener. The authors calculated an aggregate value for all sensors on the tile, which played a critical role in the system by clarifying the spatial distribution of samples. It mapped individual sensor patterns to their location on the ground and incorporates them into the structure of the floor tiles to analyze impact patterns in order to develop stable rescue protocols in the case of an emergency fall or other emergency occurrence.

The mechanical interference of directly triggered floor tiles with matching surrounding sensors, caused by vibrations of the steel frame or ghosts' vicinity of steel bricks, is the key challenge in evaluating sensor signals from walking individuals. The results of the trials revealed significant variations in the value patterns of directly and indirectly activated cell sensors, with all directly activated cell sensors displaying the observed value pattern. identical orientation, however only one or two sensors of the impacted cells exhibited values over the filtered threshold by chance. To compute the aggregate, two distinct functions, mean and median, were examined.

The mean function sums all the sensor values in a cell at a specific time and location and divides it by the number of sensors in the cell.

$$S_{Avg}[t] = \frac{1}{n}\sum_{i=1}^{n}(SF_i[t,r,c]) \quad (7)$$

where *n* denotes the number of tile sensors and $SF_i[t,r,c]$ denotes the *i*th sensor value of the tile sensors at position [r, c] and time t.

The median function sorts the tile's sensor values at a particular time and position and calculates the median value, which is the middle value in the sorted set of values. If the number of sensors is even, the median is the average of the two middle values.

$$S_{Median}[t] = \begin{cases} SF_{\frac{N}{2}+1}[\mathrm{t,r,c}] & If\ N\ is\ even \\ \dfrac{SF_{\frac{N}{2}}[t,r,c] + SF_{\frac{N}{2}+1}[t,r,c]}{2} & If\ N\ is\ odd \end{cases} \quad (8)$$

where *n* denotes the number of tile sensors and $SF_i[t,r,c]$ denotes the *i*th sensor value of the tile sensors at position [*r*, *c*] and time *t*.

The analysis showed nearly no difference in signal characteristics between the two functions. However, the median function exhibits less noise than the average, this means that the median function is a better choice for reducing signal noise. Noise reduction is important because it can improve the accuracy of data collected by soil sensors. The sensor floor is designed to track the location of residents and analyze impact patterns in the event of an emergency; therefore, in the event of a fall or other emergency circumstance, reliable data is critical for carrying out stable rescue procedures. Using the median can improve the overall performance of the sensor floor and increase resident safety.

The tile vector is calculated to show the total of sensor values within a specific range of the tile's smallest sensor value, the range was defined as Δ. The equation for computing the tile vector is shown in Eq9.

$$\vec{S}(t,r,c) = \sum \begin{cases} \overrightarrow{S_i}(t,r,c) & if\ S_i(t,r,c) \le \hat{S}_i(t,r,c) + \Delta \\ 0 & else \end{cases} \quad (9)$$

Here, $\vec{S}(t,r,c)$ is the tile vector for the impact at time *t* on the tile at row *r* and column *c*. $\overrightarrow{S_i}(t,r,c)$ is the sensor value at time *t* on the *i*th sensor on the tile at row *r* and column *c*. $S_i(t,r,c)$ is the magnitude of $\overrightarrow{S_i}(t,r,c)$. $\hat{S}_i(t,r,c)$ is the smallest value of all sensors on the tile at time *t*, row *r*, and column *c*. The condition $S_i(t,r,c) \le \hat{S}_i(t,r,c) + \Delta$ ensures that only sensor values within the range Δ of the smallest value are included in the tile vector. The technique of using Δ to limit the range of sensor values included in the tile vector improves the resolution of impact location detection from tile level to a higher resolution of four quarters of a tile.

The authors recorded some of the experiments on video while asking the subjects to walk around naturally, the videos were then visually examined in slow motion by counting the number of steps observed on the screen. In addition, each time a step is recognized, an audio signal is played., and the signal is counted. The overall passing rate for all subjects is 72% with successfully detecting 395 out of 545 footsteps. The results showed that the step detection rate of different people depends on each person's gait and body characteristics such as weight. Although the experiments were performed using the same variable attributes, the weight of the object appeared to have a considerable impact on the detection quality.

3.2. Related Work on Plastic Optical Fiber Sensors

Costilla Reyes et al. [18] evaluated the ability of an unobtrusive footprint image sensor system called “Intelligent Carpet”, to analyze gait effectively in the temporal domain using pattern recognition techniques. The experiment included analysis of 10 ways of walking (normal walking, slow walking, barefoot walking, carrying a 10kg bag while walking, walking with hands behind back, walking backwards, walking with the right foot leading, walking with the left foot leading, and side walking).

The data used in this study were obtained from the "Intelligent Carpet" prototype using the LabVIEW environment. The acquisition rate was set at 256 frames per second, with each plastic optical fiber (POF) sensing element interrogated at 256 Hz. The overall time window for data collection in each test was set at 5.46 seconds, providing enough time to fully capture all walks. These were carried out by a single healthy individual walking in a longitudinal orientation along the prototype, allowing for the capture of at least two walking cycles (4 to 5 consecutive steps). In total, 855 gait samples were captured, yielding roughly 111 million distinct POF sensor readings.

In this study, for time domain analysis, five distinct types of features were devised and evaluated of the Intelligent Carpet system. These five characteristics are spatial average (SA), standard deviation (SD), adjacent mean (AM), cumulative sum (CS), and cumulative product (CP). The time variable t ranges from 0 to 1400, representing a time interval of 5.46 seconds at sampling rate of 256 Hz. The number of POF sensors is denoted as N and SF_i represents the signal of the *i*th POF sensor.

SA is the average of all the POF sensors signals at each time step is calculated using the formula shown in Eq2.

SD is the spread of the distribution of the POFs at each frame step is calculated using the formula shown in Eq10.

$$SD\ [t] = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(SF_i[t] - SA[t])^2} \quad (10)$$

AM is the mean of two signals from adjacent POFs is calculated using the formula shown in Eq11.

$$AM[t] = \frac{SF_{\frac{N}{2}}[t] + SF_{\frac{N}{2}+1}[t]_2}{2} \quad (11)$$

Here, $SF_{\frac{N}{2}}[t]$ is the median of all the signals in each time frame, and $SF_{\frac{N}{2}+1}[t]_2$ is the signal with the next higher index.

CS is a mathematical operation that involves adding up all the values in a sequence up to a certain point. In this case, the POF signals are summed up and averaged at each frame step to generate a single value per time frame. The formula for calculating the cumulative sum is shown in Eq12.
:

$$CS\ [t] = \frac{1}{N}\sum_{j=1}^{N}\sum_{i=1}^{j}(SF_i[t]) \quad (12)$$

where $CS\ [t]$ represents the cumulative sum at time *t*, *N* is the total number of frames, j is the current frame number, *i* is the index of the POF signal, and $SF_i[t]$ is the POF signal at time t for the *i*th sensor.

CP is another mathematical operation that involves multiplying all the values in a sequence up to a certain point. In this case, the product of the POF signals is calculated at each time step, followed by averaging the value of the POFs to provide a single value at each frame step. The formula for calculating the cumulative product is shown in Eq13.

$$CP\,[t] = \frac{1}{N}\sum_{j=1}^{N}\prod_{i=1}^{j}(SF_i[t]) \quad (13)$$

where $CP\,[t]$ represents the cumulative product at time t, N is the total number of frames, j is the current frame number, i is the index of the POF signal, and $SF_i[t]$ is the POF signal at time t for the ith sensor.

Data analysis included the creation of five transitory features, which were subsequently examined using 14 different machine learning models. These models included linear, non-linear, ensemble, and deep learning models. SVM, Perceptron, Logistic Regression, Passive Aggressive Classifier, and Stochastic Gradient Descent (SGD) were the linear models employed in the study. Decision Trees, Extra Trees, K-Nearest Neighbors, AdaBoost, Gradient Boosted Regression Trees (GBRT), and Random Forest were among the non-linear models used. A deep feed-forward Artificial Neural Network (ANN) and a Recurrent ANN were employed as deep learning models. The Random Forest Tree model with the Adjacent Mean function produced the best classification performance, with a mean validation score of 90.09 ± 5.24%. According to the findings of the study, the floor sensing system is capable of detecting variations in gait, making it suitable for gait analysis applications in the health and safety domains.

Costilla Reyes et al. [19] presented a CNN method to accurately classify gait data from raw POF sensor data without the need for image reconstruction. This approach eliminates the computationally expensive and time-consuming step of image reconstruction, making the classification process more efficient and faster. A CNN architecture was used to learn the spatial-temporal features from raw POF sensor data. The spatial-temporal raw sensing technique is used, where raw floor sensor data is treated as the sensor matrix at each frame step to generate a spatial-temporal block, which is then used as input to the CNN model. Feature selection is performed using a linear SVM classifier to select sensor features for the spatial-temporal raw sensing method. The sensor signals are represented as a matrix of spatial dimensions, each sensor signal is represented in each image as a color map with pixel values based on the signal level received. Dimensionality reduction is applied by down sampling the sensor signals in the time domain using an 8th order Chebyshev type I filter, which improves classification accuracy and reduces computation time.

The proposed CNN model was trained and tested on a data set that uses a POF sensors of 892 samples, including testing 10 ways of walking (normal walking, slow walking, barefoot walking, carrying a 10kg bag while walking, walking with hands behind back, walking backwards, walking right foot leading, walking left foot leading and side walking) and 3 cognitive tasks (pronouncing animal names while walking, Performing serial subtraction of 7 from a 3-digit random numbers while walking, and reading books while walking). The dataset includes experiments on 10 walking patterns and three cognitive tasks, resulting in a total of 13 gait patterns. Each sample in the dataset contains 116 sensor signals acquired over a period of 5.4 seconds, for a total of 1400 frames at a sampling rate of 256 Hz. The dataset is unbalanced where each class has an odd number of samples. The dataset presented in this study expands on the previous dataset by including three additional dual task experiments where, while walking normally, the person can be reading, naming animals, and counting backward.

Each signal has a variable amplitude response, which is dictated by the physical characteristics of each POF sensor, and the type of gait pattern applied. Sensors with a constant signal amplitude over time are inactive for this model. The spatial mean was determined using Eq2, which allowed us to observe gait patterns in the temporal domain. The variance in amplitude response of experiments of the same kind is related to users entering different sensing zones in the floor sensor system, and the delay between signals is due to different running times of procedures in experiments.

This study presented the accurate classification of spatial-temporal gait data from raw POF sensor data, attaining an appropriate gait pattern classification F-score performance of 97.88 ± 1.70 % when using the proposed CNN architecture. The automatic recommendation method extracts categorical features from the raw data resulting in significantly better performance than those obtained from reconstructed images, thereby eliminating the need for image reconstruction.

3.3. Related Work on Conductive Polymer Fabric Sensors

Zohu et al. [20] presented a method for human recognition using morphing steps measured from a fabric-based pressure mapping sensor system. The hardware used in this study is a modified version of the detection system used in previous research called “Smart-Mat”. The fabric sensor mat used in this study consists of three layers: The top and bottom metal fiber layers are woven into a non-conductive polyester substrate and the middle layer is CarboTex, a carbon-containing polymer fabric. All three layers are 0.5 mm thick. The top and bottom layers of the mat create 120 x 54 pressure sensitive points, spaced 1.5 cm apart. The rug has an area of 1.8M x 0.8M and is placed under a regular rug. The sensor mat can be installed and removed from any floor without requiring permanent installation, such as drilling or replacing floors. A specially built data acquisition system was used to implement the proposed pressure mapping architecture. The data acquisition system controls the upper layer by scanning stimulus and measures the individual pressure of the lower layer. The data collected by the system is sent to the computer via a USB cable.

The systematic evaluation involved recording the walking habits of a group of 13 people, 11 men and 2 women, aged between 24 and 30 years. Each participant walked on a pressure-sensitive mat with normal shoes usually for at least 12 rounds. Participants wore the same shoes in all repetitions and varied in height, weight, and shoe size to a large extent to account for differences in the recorded data. Participants were free to rest or do anything between repetitions during the experiment, and each repetition was stored into a separate data set and labeled with the specific person. The basic information of each iteration, including the start and end times of each step, was manually marked, and a total of 529 steps were recorded. The assessment is designed to identify a person based on the evolutionary imprint of several phases. The steps are recorded using standard blob detection, and the transformation footprint's spatial-temporal domain is processed using spatial computation, resulting in a sequence of attributes for each state of the footprint.

The raw data for this study is the time series of a 120 × 54 spatial two-dimensional pressure maps. Steps should be segmented not only by spatial region but also by the temporal duration. To segment the steps, the researchers used a step-by-step segmentation algorithm that involves separating the footprints from the background noise by converting the frame into a binary matrix with dynamic thresholds, the threshold is determined by arranging the pixel values of the frame into a 10-panel histogram and selecting the center value of the next highest count bin as the threshold. Bounding boxes are then placed on the binary image through blob detection, and each frame is filled with the mean pixel value in its region. For one-step segmentation, the boxes are verified frame by frame until the mean of the pixels in the box exceeds the second dynamic threshold. This threshold is based on the same histogram selection approach for all average pixel values of bins from all frames in a walk event's recorded data. The commencement of the step (spawn point) is defined as the first active box that crosses the threshold. This step will then be monitored in succeeding frames by locating the box with the closest center to the preceding box and a distance of no more than 30 pixels. When there is no such box to end this step, the algorithm continuously searches for new spawn points while following existing stages, which may take place before the previous one is complete. In testing, the stepwise segmentation algorithm for start and end times yielded 97% accuracy and 91% recall when considering an error margin of ±2 frames.

Calculated attributes for each footprint include mean pixel value, center coordinate, maximum pressure point value and coordinates, and pressed area, the change in these properties reflects a change in the shape of the footprint, which is analyzed using a 25 Hz scan frequency. To perform better time analysis, the attribute sequence was interpolated into the time domain over 150 samples, eliminating variation caused by walking speed. The mean, standard deviation, variance, and range of the interpolated attributes were calculated for each of the seven attributes as a subset of the first features. A fast wavelet transform is applied to the interpolated properties using the LTFAT toolbox with 10 filter bank iterations and “db8” as the original wavelet. The obtained wavelet coefficients are used to calculate the mean, the variance, the standard deviation, the skewness, and the kurtosis of each iteration for lower frequencies. A total of 301 features are obtained from the wavelet transform as a second features subset. Morphological footprints in the time domain were averaged to generate a static footprint of the step, and the set of seven attributes was computed for this single image as a third features subset. A total of 336 features were calculated, with less regard to foot shape detail than high-resolution barefoot studies or footprint shape comparisons.

The authors used the SVM classifier with a quadratic kernel to classify the person’s identity based on features extracted from the footsteps. To evaluate the performance of the classifier, the authors performed 10-fold cross-validation and repeated the procedure with 10 iterations. Some participants had higher precision and recall rates, while others had relatively lower precision, mainly confused with other participants. The authors also analyzed variations in participant demographics, such as height, weight, BMI, shoe size, and gender, to understand how these factors affected analysis performance. When tested with 13 people walking normally on the carpet, the system had an average recognition accuracy of 76.9%. Furthermore, this technology can be used for activity recognition with similar physical carpet sensors.

Singh et al. [21] developed a technique for leveraging pre-trained deep CNNs on 2-dimensional sensor data by converting the sensor modality to the visual domain. The dataset used in this work consists of step samples from 13 persons walking on a pressure-sensitive matrix. In each walking sequence, each person recorded 2-3 steps, with a minimum of 12 samples recorded for each person. The dataset included a total of 529 steps, and each walking sequence is labeled with a specific person ID, which defined the class label for the CNN [36]. Participants in the data set had different heights, weights, and shoe sizes, reflecting large differences in the data recorded. The participant demographics ranged in height from 155 to 195 cm, weight from 64 to 100 kg, and shoe size from 37 to 45.

Firstly, the steps were segmented as mentioned earlier in [20], then the data was converted into visual images. There are numerous methods for converting data from source mode to visual image mode, depending on characteristics such as dimensionality, range, heterogeneity or homogeneity, volume, and noisiness. Ideally, the ideal technique to modify source mode data was to convert it to a form as close to the target mode that the CNN was trained on as possible. Three different strategies to convert sensor data into images for deep learning have been proposed. The first strategy is to select the maximum frame from a sequence of frames for each sample, this maximum image was the image with the highest total pixel value, the selected image was then converted to an image and tagged with a layer ID, this strategy yielded one image per step, and in the dataset used in the study, there were 529 such images. The second strategy is to average all the images in the sequence of a single sample and generate an image with an average pixel value, this averaging frame carried temporal information of all step times and was more efficient than maximum classifier frames. A third strategy is to take all the frames that make up a time series of one step in each sample and turn them into frames. This strategy provided a higher level of granularity than previous feature set calculation methods.

In this study, the authors proposed a transfer learning technique to use pre-trained models from image classification tasks, such as ImageNet or Coco-DB, to extract features from sensor data [37]. The pre-trained CNN employed in the experiments is the Inception-v3 model, which is well-known for its computational efficiency and high performance on the ILSVRC-2012 classification benchmark. The authors removed the classification layer from the pre-trained model and added a new classification layer to adapt it to the new step detection task. The pre-trained CNN is used as a fixed feature extractor, which means the network weights are not updated during training. The proposed Inception-v3 architecture had 17 layers, including three convolutional layers, ten Inception blocks, and a fully connected final layer. The input image is scaled to 229 × 229 pixels, as needed by Inception-v3, and the activations from the fully connected layer extract a 2048-dimensional output for each input. Each output can be interpreted as a descriptor for each image in the sequence, which can be used for classification. The transformed input image is fed to the CNN, and activation for the entire network is computed by forwarding the input signal through the network.

For the maximum frame test, the whole process was performed with 10-fold cross-validation and repeated for 10 iterations, and the results obtained after each iteration were averaged. This strategy yields a final recognition rate of 71.99%. For the average frame test, the evaluation was performed in the same way as for the maximum frame, with 10-fold cross validation. The average recognition rate of the average image is 78.41%. The results showed that the average image outperforms the peak image in terms of classification accuracy; however, the averaging procedure used to obtain average images results in the loss of some information. To solve this problem, the image sequence experiment used a Gated Recurrent Unit (GRU) class to classify the temporal sequence of each step. The images involved in each step are processed through the Inception-v3 model to extract a unique descriptor for each image. These descriptors are then fed into the GRU layer one after another, which generates the classification at the end of the sequence. The same evaluation approach as in the prior trials was applied, and the classification accuracy attained was 87.66%.

3.4. Related Work on Photo Interrupters

Yun et al. [22] provided a floor-based user recognition system called UbiFloorII, which recognized people based on their walking patterns. The system used photo interrupter sensors to measure walking patterns and used a neural network trained on the user's walking patterns for recognition purposes. It can be used to automatically and transparently identify users in a home-like setting.

The dataset used in the test included footprints recorded while walking on the UbiFloorII. Step feature extraction software is used to search and extract footprints from the dataset, the extracted walking patterns and step features will be used as input to the neural network for user recognition. The tests presented in this study included checking the recognition accuracy of the system using different feature sets and different parameters, such as the number of hidden nodes in the network. UbiFloorII is a floor-based user identification system using a 12 x 2 wooden tile set. Each wooden panel had an area of 30 cm^2 and contained 64 equally distributed photo interrupter sensors. Photo interrupter sensors were used to collect data about the user's gait, such as stride length, dynamic range, foot angle, as well as stance and swing time. The microcontroller was responsible for collecting data from the corresponding cell and transmitting the obtained information to the host PC via a CAN (Control Area Network) cable. The host PC then extracted the user's walking characteristics from the received data and identifies the user through a well-trained neural network. The authors developed software modules to extract gait patterns from datasets. Software modules were divided into two categories step feature extraction and walking feature extraction.

The authors assumed three hypotheses while gathering walking samples for their proposed system. The first hypothesis was that subjects would maintain a regular walking pattern as much as possible; this means they will try to walk consistently without any significant change in their gait. Another hypothesis was that the proposed system would be aimed at smaller family homes where occupancy is less than 10 people, this suggested that this system may not be suitable for larger households or public places. The third hypothesis was that the subjects would listen to soft music while walking, which would help reduce the variation in their walking speed because music has a calming effect on the mind and body, which can lead to a more coherent gait. The researchers collected gait samples from 10 subjects between the ages of 27 and 35 and of varying heights. Each subject provided 50 gait patterns using the UbiFloorII system, for a total of 500 gait samples. The researchers only looked at the first five steps of each walking pattern because it took most users five or six steps to pass UbiFloorII. These hypotheses and the data collected from walking patterns were used to develop a software module capable of extracting a user's walking features and identifying them using a neural network.

Step feature extraction software is used to look for all footprints in the dataset acquired during the walk on UbiFloorII. The researchers constructed an 8x4 footprint model to encompass all conceivable footprints and picked the following phases: The X-index of the footprint's outermost sensor, the Y-index of the footprint's outermost sensor, and the footstep's footprint pattern. The authors extracted seven walking features physical X coordinate of the backmost sensor in a footprint area (FX), physical Y coordinate of the backmost sensor in a footprint area (FY), compensated X coordinate based on footprint model (com_FX), compensated Y coordinate based on footprint model (com_FY), the number of sensors pressed into a coverage area (nSensor), heel-strike time of a footstep (f_Start), and toe-off time of a footstep (f_End). X and FY provide the X and Y physical coordinates of the seed sensor in a footprint with the lower left corner of UbiFloorII as the origin. The com_FX and com_FY coordinates reflect the center of the footprint based on the footprint model, including the user's stride length, dynamic range, and foot angle. F_Start and f_End represent the user's swinging position and time while walking.

To generate input vectors into the neural network, researchers needed to generate sequences of each function walking in steps like [com_FX1, com_FX2, com_FX3,……]. This study's neural network had three layers: an input layer, a hidden layer, and an output layer. The input layer represented the walking features space of each person. The hidden layer was responsible for processing input data and extracting relevant features. The output layer generated user identifiers based on the output values of its nodes. The ID was generated by taking the index number of the output node with the highest output value. The hidden layer's activation function is tangent-sigmoid, however the output layer's activation function is entirely linear, which means that the output values are proportionate to the input values. Using neural networks to recognize users based on walking habits is a promising method that can be used in home environments to identify users automatically and transparently.

The authors used five different feature sets as input to the neural network to evaluate their effectiveness in identifying users based on their walking patterns.

- Set 1 is used as a benchmark to evaluate results with other feature sets. In this set, the FX and FY coordinates were the network inputs.
- Set 2 includes compensated (com) for FX and FY as input to the network, in addition to the standard coordinates.
- Set 3 includes com coordinates as well as the number of sensors used in the system as input to the network.
- Set 4 includes the com coordinates as well as the start and end times of the walk pattern as input to the network.
- Set 5 includes all the features of the previous case, as well as the number of sensors used in the system, as input to the network.

By testing these different feature sets, the authors were able to determine which was most effective at identifying users based on their walking patterns and achieved recognition accuracy. Compensating com_FX and com_FY improved recognition accuracy by about 10%. The information from nSensor affected the compensation process for com_FX and com_FY, and so case 3 was worse than case 2 where case 3 achieved 86.85% and case 2 achieved 89.50%. Using the com_FX, com_FY, f_Start and f_End features yielded a recognition accuracy of 96.20%. Therefore, the position and time of swinging were the dominant features for user identification.

This study achieved recognition accuracy of about 96% when using the UbiFloorII floor user identification system, based on the analysis of users' walking habits. The experiments described in the study involved determining the optimal number of hidden nodes in a neural network. It was found that about 40 hidden nodes are enough to achieve a recognition rate of about 95%. The results showed that the walking pattern, including stride length, dynamic range, foot angle, stance, and swing time, is a prominent feature for user identification.

Yun et al. [23] presented another system for identifying individuals based on their gait patterns, focusing specifically on gait and step patterns. The system uses a biometric sensor called UbiFloorII to collect walking samples and extract gait patterns using a software module. There are two types of software modules designed to extract user gait patterns from datasets: left footprint extraction and walking feature extraction. The footprint extraction software on the left searches for all footprints in the data set received while traveling on UbiFloorII. The generated 8x4 footprint template included all possible footprints and three selected features the X index of the outermost sensor in the footprint, the Y index of the outermost sensor in the footprint, and the footprint model of the footstep. The sensor at the back of the footprint provides the starting point from which other features can be retrieved.

Spatial-temporal walking features are extracted as mentioned in the previous experiment by applying FX and FY (X and Y physical coordinates of the outermost sensor in a footprint), com_FX and com_FY (compensated footprint), f_Start (heel-strike time) and f_End (toe-off start time). To create input vectors in a neural network, sequences of each step characteristic must be generated in steps, such as [com_FX1, com_FX2, com_FX3, ...].

By examining the time variance of each footstep, the walking pattern of each footprint was identified. The variety of transitional footprints from heel-strike to toe-off in each footstep was analyzed using software for extracting transitional footprints. Based on the left footprint retrieved via the gait walking extraction process, a set of transitional footprints was created. The array of transitional footprints (sensors state change) is obtained in terms of event occurrence times. The array of sampled transitional footprints was extracted at uniform sampling time from the original array of transitional footprints network in order to construct a standard progression model. The left footprint and the array of sampled transitional footprints, which were transformed into vectors and fed into a neural network as inputs, were the two progressive features used for user identification. To create input vectors, the left 8x4 footprint of a column, or four sensors, was examined simultaneously. The process is the same for sampling transitional footprints as it is for left footprints, with the exception that the number of rows was 8 times the number of elements in the array. They used the same neural network to recognize the user according to their walking patterns and for their stepping pattern. The input layer, hidden layer, and output layer were the three layers that made up this neural network. The number of neurons in the input layer of a neural network used to identify a person's walking pattern was equal to the product of the number of walking features and the number of walking steps. In the same way, the input for the stepping patterns would be the product of the number of footsteps and the number of components in the step features. The number of neurons in the output layer was equal to the number of users, and the number of neurons in the hidden layer was selected by experimentation. A training set of examples of suitable network activity was provided to the learning rule in order to train the neural network using supervised learning. In this experiment, sigmoid activation functions were employed.

The neural network is divided into two parts, one for walking pattern-based recognition and the other for stepping pattern-based recognition. Pre-processing was required for the walking pattern-based recognition neural network, which includes normalizing input values to the network, this is done to ensure that the input values were within a certain range and to make the training process more efficient. However, the stepping pattern-based recognition neural network did not require preprocessing because all the elements of the input vector already had numeric values. Thus, input vectors could be transmitted directly to neurons in the input layer of the network. Experiments involved increasing the number of hidden nodes while keeping other parameters constant and observing the obtained recognition accuracy, the test results showed that about 30 hidden nodes are enough to achieve a recognition rate of about 95%. Further experiments were performed to determine the epoch and target, and the results showed that after 800 epochs, the original mean square error was less than 10^{-3}, so this value was set proportionally. As mentioned in the previous experiment the com_FX, com_FY, f_Start and f_End features yielded a recognition accuracy of 96.20%.

An experiment employing arrays of collected transitional footprints with a sampling time of 0.04 seconds was carried out to find out how the number of hidden nodes affected the neural network's ability in identifying persons based on their gait. A recognition rate of about 90% could be achieved with about 30 hidden nodes. It is important to note that increasing the number of hidden nodes also increased the computation time required for the neural network. The experiment also involved determining the epoch and target, which were important parameters in training the neural network. After 115 epochs, the mean square error (MSE) became smaller than 10^{-5} is set as the target. The network was trained using two algorithms, Powell-Beale and scaled conjugate gradient, in all experiments. The results of this experiment provided valuable insights into optimizing the performance of neural networks used to recognize users based on gait patterns.

The experimental results were acquired by averaging 10 simulation results while the seed value was changed. The left footprint, which reflected the static shape of the user's sole of the foot in UbiFloorII, was not distinctive enough to identify the individual. Test results with transitional footprints arrays showed that the recognition rate is over 80%. The system achieved a recognition accuracy of about 92% with the transitional footprints array sampled in Case 4, where the sampling time was 0.04 s. The results showed that two steps were not enough to achieve recognition accuracy above 90%, regardless of step order and sampling time. Reduced sampling time to extract the sampled transitional footprints array from the original transitional footprints array may increase recognition performance. However, the small sampling time would require many inputs to the network, resulting in a heavy computational burden. Therefore, it was necessary to consider the sampling time limit to extract the sampled transitional footprints array.

The authors selected five classification methods (k-nearest neighbors, decision trees, Bayesian networks, decision tables, and support vector machine) in addition to the multilayer perceptron, for the walking pattern features. Discriminant machine learning algorithms like multilayer perceptron often gave better performance than the generalized models in step recognition. The SVM was chosen as one of the modern discriminant methods with good performance in many applications. The authors chose a simple k-nearest neighbor algorithm among the instance-based learning algorithms, decision trees and decision tables among the rule-based learning algorithms. The bayesian network was chosen as one of the general models to demonstrate its effectiveness in gait recognition experiments. The experiments were conducted using 10-fold cross-validation, meaning 10 different experiments were performed with the same learning method and dataset, and the results were averaged over 100 results experiment. The multilayer perceptron algorithm showed the highest recognition accuracy with an accuracy of 96.64 $\pm$ 0.38. The SVM showed the second highest accuracy with an accuracy of 95.88 $\pm$ 0.33, and the k-nearest neighbor method also showed good performance with an accuracy of 94.08 $\pm$ 0, 47. However, rule-based learning algorithms, especially decision tables, showed lower accuracy than other algorithms.

The authors applied the same algorithms to stepping pattern features extracted from the gait samples. The SVM showed the highest recognition accuracy among all the classifiers used in this study with an accuracy of 95.61 $\pm$ 0.26. This result was not surprising since previous experiment had also showed that support vector machine classifiers perform well in recognizing different representations of stepping features. The multilayer perceptron algorithm was the second most accurate classifier with an accuracy of 92.44 $\pm$ 0.28, and its accuracy was consistent with the experimental results of the previous experiment. Rule-based learning algorithms showed lower performance than other algorithms. The Bayesian network algorithm showed poor performance compared to the discriminant model.

Different biometric identifiers can be merged using three basic techniques Feature extraction level matching, score matching, and decision level matching. The authors suggested that the feature vector size of the step model is significantly larger than that of the walk model, therefore it was not reasonable to concatenate two feature vectors into a single vector to merge them at the feature level, instead, fit score level matching was applied, where the neural network output values for walking and stepping patterns are combined. The walking samples were fed into the walking pattern extraction module and the stepping pattern extraction module, which then generated output values for each user. The output values of the two neural networks were combined using the max function to obtain the final output value for each user. This approach achieved 99% recognition accuracy. Normalization of the output values was necessary because each neural network produced maximum score values of ±1. The results showed that the walking pattern and stepping extracted from the user's gait on UbiFloorII had enough discriminative power for user identification, and the combination of the two classifiers improved the accuracy of identification.

4. Discussion

There are a lot of sensors that can be applied to footstep identification and analysis, and each sensor can provide a benefit in terms of the proposed analysis method or application [4-6]. The most effective footstep systems combine multiple sensor types to provide a comprehensive understanding of a person's walking or running patterns. Pressure sensors, for example, are crucial for detecting contact points and pressure distribution during each step, while accelerometers contribute to measuring linear acceleration and movement patterns. Gyroscopes can complement these sensors by providing information about rotational aspects of motion and posture.

Several applications have been introduced in this paper, which indicates the novelty of each sensor in some sort of application. For example, the piezoelectric sensors can be used for footsteps recognition and step detection, the plastic optical fiber can be used for gait analysis, the conductive polymer fibers and the photo interrupters can also be used for identification and various other applications. Each of the discussed applications showed a different feature engineering technique based on the sensor and the application.

We compared different proposed methods for footstep identification using a floor-based approach and summarized the methods in terms of the dataset and the number of persons, the used sensor, the extracted features, the classifier, and the accuracy in Table 1. In Table 2, we summarized three different applications of footsteps using the floor-based approach to detect the number of steps, the walking style, and some cognitive tasks done while walking using the same terms used in Table 1.

Different sensors have been used in the floor-based approach to footstep analysis and identification. The sensors used can be classified as pressure sensors (piezoelectric sensors, electromechanical film, accelerometers, load cells, and force-sensing resistors) and switch sensors (switch sensors and photo interrupters).

In early works, ground reaction force has been the main feature and the most important one in footstep identification and analysis using the floor-based approach because of its ability to track the pressures exerted on the ground by foot during the gait cycle, which made it one of the most significant extracted features in early works [12-16], [26]. Also, calculating the mean of each time frame across the sensors is one of the most unique and repeated features; it is used in gait analysis as well as identification and is also used to reduce noise while detecting footsteps [12-14], [17-18], [21]. A lot of other engineered temporal domain features had proven its uniqueness in terms of footstep applications and identification, like the minimum and maximum pressure contours in each time frame, the pressure centroid coordinates, the number of sensors pressed at certain time frame, the mean, the adjacent mean, and the standard deviation [12-16], [18-22].

Table 1: Comparison between different footsteps identification features using the floor-based approach.

Reference	**Dataset**	**Sensor**	**Features**	**Model**	**Result**
Vera-Rodriguez et al [12]	SFootBD 127-Persons 9990-Sample	Piezoelectric sensors	Time information Analysis represented in the GRF, the SA, and the upper and lower contours of the time domain signal	PCA + SVM	5% – 15% EER based on the number of samples and clients
Vera-Rodriguez et al [13]	SFootBD 127-Persons 9990-Sample	Piezoelectric sensors	Spatial domain information represented in images of the pressure distribution along the spatial domain using the accumulated pressure	PCA + SVM	6% – 10% EER based on the number of samples and clients
Vera-Rodriguez et al [14]	SFootBD 127-Persons 9990-Sample	Piezoelectric sensors	Fusion of the spatial and temporal domains information	PCA + SVM	2.5% – 10% EER based on the number of samples and clients
Costilla Reyes et al [15]	SFootBD 127-Persons 9990-Sample	Piezoelectric sensors	Spatial domain features extracted from CNN of the generated images of the pressure distribution using the accumulated pressure	CNN + SVM	9.392% EER For stride footstep validation set. 13.86% EER For stride footstep evaluation set.
Costilla Reyes et al [16]	SFootBD 127-Persons 9990-Sample	Piezoelectric sensors	Spatial and temporal features extracted from two ResNet models, one for pressure distribution using the accumulated pressure, and the other for the temporal frames represented in heel striking, flat foot, and heel-off	ResNet + SVM	10.50% EER (40 stride –40 clients) 4.90% EER (200 stride –15 clients) 1.70% EER (500 stride – 5 clients)
Zohu et al [20]	13-Persons 529-Sample	Conductive polymer fiber	Spatial domain features using step segmentation applied on spatial two-dimensional pressure maps, and calculated attributes of mean pixel value, center coordinate, maximum pressure point value and coordinates, and pressed area. The mean, standard deviation, variance, and range of the interpolated attributes for each of the attributes as a subset of the first features	SVM	76.9% Accuracy
Singh et al [21]	13-Persons 529-Sample	Conductive polymer fiber	Spatial domain features by calculating the maximum frame, the average frame, and the complete set of sequence.	CNN + RNN	87.66% Accuracy
Yun et al [22]	10-Persons 500-Samples	Photo interrupters	walking features represented in Foot centers, stride length, dynamic range, and heel-to-toe time.	MLP	96% Accuracy
Yun et al [23]	10-Persons 500-Samples	Photo interrupters	walking features represented in Foot centers, and heel-to-toe time. left footprint features represented in array of sampled transitional footprints over 5 consecutive footsteps.	MLP	99% Accuracy

Table 2: Comparison between different footsteps analysis features using the floor-based approach.

Reference	Dataset	Sensor	Task	Features	Model	Result
Leusmann et al [17]	4-Persons 545-Sample	Piezoelectric sensors	Step Detection	Mean and Median function are applied for noise reduction purposes, and the tile vector is calculated to show the sum of the sensor values within a certain range	Same variable properties	72% Accuracy
Costilla Reyes et al [18]	13-Persons 855 - Sample	Plastic optical fiber	Detecting Different 10 Ways of Walking	Five Spatial-Temporal features consisted of SA, SD, AM, CS, and CP.	Random Forest Tree	90.84% Accuracy
Costilla Reyes et al [19]	13 -Persons 892 - Sample	Plastic optical fiber	Detecting Different 10 Ways of Walking and 3 Cognitive Tasks While Walking	Selected some Spatial-Temporal features using SVM linear classifier from the extracted raw POF data without the need for image reconstruction.	3D-Convolutional neural network (3D-CNN)	97.88% Accuracy

By introducing the spatial domain features and deep learning algorithms, it opened the door for a whole new type of feature engineering techniques by constructing footstep images using the sensor data after applying some preprocessing methods, providing the constructed heatmap images to a neural network model to extract a unique feature vector to be used as a template for the classification of the subject, or using the image itself to be the classification feature after training the neural network model, for example, the max frame of the highest values of the footsteps sensors' output, the average frame by averaging all the frames of the footstep sequence, and using all the footstep sequence frames [13-16], [20-23], [28-29]. Also, a highlighted engineered feature is the accumulated pressure images, which are calculated by averaging all the ground reaction forces of all the time frames per sample to obtain a single image per sample. This image can generate a vector template per client to be used in the biometric identification system. The template can be created in many ways, as mentioned in [13-16], [21]. Also, the accumulated pressure images can be used to obtain a full sequence of the footstep sample, instead of creating only one image per sample, it can also create the most important and highlighted frames per footstep sample, for example, the frames that represent the dynamics of the flat foot, as well as the end of the heel strike and the start of the heel off. Combination between the spatial and temporal features can provide more features insights to represent the trajectory of a footprint from the heel-strike to the toe-off, and other features can be obtained from the spatial-temporal features domain, like the stride length, the center pressure of a footprint, the dynamic range, and the heel-to-toe time. The accuracy of the floor-based approach to footstep identification and analysis depends mainly on the engineered features of the raw extracted data from the sensors, and the engineered features are related to the type of sensor used because every sensor provides different types of data, but the results are more dependent on how the sensors are used and the classifier rather than the type of sensor itself.

A lot of different classifiers have been used for footstep identification and analysis, as we mentioned earlier in [38]. The discriminative machine learning algorithms, such as SVM and random forest tree, outperformed the generative algorithms, such as the hidden Makrov model in footstep identification and analysis. The deep learning models can also be used as classifiers, or as feature extractors that can extract features from a given image to create a template per sample and feed this template to another machine learning model. Adding the deep learning as a feature extractor in the recent works really improved the results of footstep identification and analysis.

5. Conclusion

We provided a comprehensive, detailed, and in-depth overview of the various machine learning and deep learning algorithms, various feature engineering techniques, and different applications used in footstep identification and analysis using the floor-based approach. We covered the usage of footstep features in various contexts, such as security, detecting changes in the walking style, and healthcare for monitoring and analyzing gait abnormalities. We compared and discussed the different algorithms and feature engineering techniques applied to each sensor, the effect of the feature engineering on the algorithms, and the most suitable features for the discussed footstep system. In addition to discussion about the different feature engineering techniques based on the temporal domain, the spatial domain, a fusion between the temporal and spatial domains, and the statistically measured features, we also described the most frequently used characteristics and artificial intelligence approaches used in footstep identification and analysis systems using the floor-based approach. We included a discussion of the current state of footstep identification and analysis using a floor-based approach, emphasizing the most important features and the most effective algorithms for the identification and analysis of footsteps and the promising future research direction in this domain. We anticipate that this work will provide researchers in this domain with an appropriate grounding in footstep identification and analysis utilizing the floor-based technique, as well as give some insights into the technological landscape of footstep identification and analysis.

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