

Article

Cyber–Physical–Human System for Elderly Exercises Based on Flexible Piezoelectric Sensor Array

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Abstract

Developing flexible, cost-effective, and durable sensors is a key challenge for integrating Cyber–Physical–Human Systems (CPHSs) into smart homes. This paper introduces a flexible pressure sensor array designed for CPHS applications, addressing the need for cost-effective and durable sensors in smart homes. Our approach combines flexible piezoelectric materials with Swept Frequency Capacitive Sensing (SFCS). Unlike previous pressure sensors made of flexible piezoelectric materials, which can only measure dynamic pressure due to charge leakage, by using SFCS, the piezoelectric material is not directly in the circuit, and our sensor can effectively measure static pressure. While traditional arrays require multiple I/O ports or a matrix configuration, our design measures four distinct locations using only a single I/O port. The sensor is also mechanically flexible and exhibits high durability, capable of functioning even after being cut or torn, provided the electrode contact area remains largely intact. To decode the complex, multiplexed signal from this single channel, we developed a two-stage deep learning pipeline. We utilized data from thin-film resistive pressure sensors as ground truth. A classification model determines which of the four sensors are being touched. Then a regression model uses this touch-state information to estimate the corresponding pressure values. This pipeline employs a hybrid architecture that integrates Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. The results show that the system can estimate pressure values at each location. To demonstrate its application, the sensor system was integrated into a power recliner, thereby transforming the chair into an interactive tool for daily exercise designed to improve the well-being of older adults. This successful implementation establishes a viable pathway for the development of intelligent, interactive furniture for in-home exercise and rehabilitation within the CPHS paradigm.

Keywords: piezoelectric sensor; swept frequency capacitive sensing; CNN; LSTM; health promotion; sensor-based



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1. Introduction

The global population is rapidly aging [1]. This demographic shift poses significant challenges to healthcare and social systems. This model requires new technologies that can be easily integrated into the home environment to monitor health and promote well-being [2–4].

CPHS aims to establish an interactive loop between people and smart physical environments [5]. These systems embed sensors and computers into everyday objects, transforming

passive living spaces into active ones that support health management [6]. For example, ordinary furniture can be transformed into interactive tools for daily exercise. This approach offers a practical way to encourage physical activity in older adults.

The main technical obstacle to creating such interactive furniture lies in the sensor technology itself. Traditional pressure sensors [7,8], such as force-sensitive resistors, have several drawbacks for such applications. Their mechanical properties are often unsuitable. They are generally rigid, making them difficult to adhere to soft or uneven surfaces. Measuring multiple points typically requires separate input/output (I/O) ports for each sensor. This leads to complex wiring and increased hardware costs. Furthermore, traditional sensors can degrade in performance or break down and fail under long-term, repeated force.

The piezoelectric effect is a property of certain materials to generate an electric charge in response to applied mechanical stress [9]. This is known as the direct piezoelectric effect. Flexible piezoelectric materials offer excellent mechanical compliance and demonstrate high pressure sensitivity. However, charge leakage is inevitable when connected to a circuit, making them suitable for dynamic pressure measurement [10]. They are less effective for measuring static pressure, such as when a person sits on a chair, requiring additional sample-and-hold circuitry. Traditional piezoelectric materials still require multiple I/O ports (or a matrix configuration) to achieve multi-position sensing.

Swept-frequency capacitive sensing (SFCS) is an emerging technology [11]. It sweeps a signal across a wide frequency range and analyzes the resulting frequency-dependent impedance curve. This method allows for the characterization of complex interactions through a single channel.

The combination of piezoelectric materials and SFCS has been relatively understudied. The objective of this paper is to combine flexible piezoelectric materials with SFCS technology to fabricate a novel flexible pressure sensor array. The sensor is flexible, allowing it to conform to various surfaces. Furthermore, we apply machine learning to decode the complex, frequency-dependent sensor data to simultaneously estimate both contact pressure and location. This system can measure multiple pressure locations using a single I/O port. Finally, the proposed pressure sensor is applied to a CPHS to provide elderly individuals with an enhanced exercise experience in their daily lives.

2. Related Works

This chapter reviews existing literature relevant to our research.

2.1. Sensing Technologies for Elderly in Smart Environments

Various technologies monitor human activities and interactions in smart environments [12–14]. Vision-based systems, such as cameras, can capture rich posture and motion information without physical contact [15]. However, they also raise significant privacy concerns [16]. They also require significant computing power and are susceptible to lighting conditions and physical obstructions.

Wearable sensors, including inertial measurement units (IMUs) and electromyography (EMG) sensors, can provide continuous physiological data. Their main drawback is user compliance. Users may find constant wear uncomfortable, and they require regular charging.

Another approach is to integrate sensors directly into the environment. These sensors are unobtrusive and respect user privacy. Embedding sensors in furniture is a promising approach for non-invasive monitoring. This approach has created a demand for effective pressure sensing technology.

2.2. Flexible Pressure Sensor Technologies

Flexible pressure sensors offer advantages over rigid sensors, especially for conforming to soft and irregular surfaces. Several types of flexible sensors are common [17,18].

- Piezoresistive sensors work by the change in electrical resistance when pressure is applied. These sensors have a simple structure. However, they can suffer from durability issues, signal drift over time, and relatively high power consumption.
- Capacitive sensors detect pressure through changes in capacitance. They offer good sensitivity and low power consumption. Their disadvantages include susceptibility to electromagnetic interference and a more complex physical structure [19].
- Piezoelectric sensors generate an electrical charge when subjected to mechanical stress. They respond quickly to dynamic pressure changes and have self-powering characteristics. Traditionally, piezoelectric materials generate an electrical charge in response to applied mechanical stress and are often used for dynamic pressure sensing. This generated charge inevitably leaks away over time. This characteristic makes piezoelectric sensors unsuitable for measuring static or slowly varying pressures [20], as the signal drifts back to zero even under constant load. Consequently, their use requires specialized readout electronics, such as sample-and-hold circuits. This limitation has historically restricted their applications to dynamic events such as vibration or shock sensing, while also increasing the complexity of the required circuitry.

2.3. Swept Frequency Capacitive Sensing (SFCS)

Swept Frequency Capacitive Sensing is an advanced sensing technique. It works by sending a signal across a wide range of frequencies and analyzing the impedance profile of the return signal. This profile contains information about how capacitance and resistance change with frequency. SFCS can capture rich details about an interaction, unlike single-frequency methods that only provide a simple on/off signal.

Instead of using a single frequency, SFCS excites an electrode with a sinusoidal signal that is swept across a wide range of frequencies (e.g., from kHz to MHz) and measures the resulting complex impedance profile. The electrical properties of the object, including its resistance and capacitance, are frequency-dependent. Consequently, the way a touch from human affects the sensing circuit varies significantly across the frequency spectrum. This results in a rich, multi-dimensional signature for each interaction, rather than a single data point.

Seminal work by Sato et al. demonstrated that can accurately recognize human hand movements, body poses, and interactions with liquids and daily objects [11]. It uses SFCS to monitor changes in the electrical signals of touched objects at different frequencies, capturing rich contextual information about complex gestures and user states. This technology makes traditional and non-traditional mediums like screens, bodies, and water touch-sensitive and highly interactive.

SFCS and Electrical Impedance Spectroscopy (EIS), although they share the fundamental principle of measuring electrical response over a frequency sweep. The key differences lie in the measurement methodology and the analytical objective. Traditional EIS aims to characterize a material's physical properties by measuring the complex impedance (both magnitude and phase), which is then often used for physics-based equivalent circuit modeling. In contrast, SFCS, as defined in the seminal work by Sato et al. [11], is a sensing technique that deliberately simplifies the measurement to capture only the amplitude of the response. This amplitude-only profile is then treated as a high-dimensional feature vector for machine learning-based pattern recognition.

Watanabe et al. developed a novel soft sensor called “foamin” which can detect multiple touch and deformation inputs through a single wire connected to a conductive

foam [21]. The sensor utilizes impedance measurement techniques at multiple frequencies, and the authors presented various applications of this method, including creating Deformable Musical Instruments and the Soft Numerical Keypad. The accuracy of the gesture recognition was tested and found to be higher when using a surface shield to reduce interference. The authors also presented various applications of foamin, including deformable musical instruments, a soft numeric keypad, and activity-sensitive cushions. They plan to further explore ways to detect and identify more complex deformation modes and improve the wiring design for each application. Specifically, they selected a conductive polyurethane foam as the main body of the soft sensor. The entire system was modeled as an electrical circuit, where the sensor's internal resistance (R) and the touch capacitance (C) between the user and the sensor are regarded as a series RC circuit. When user input (e.g., touch) deforms the sensor body, the impedance (Z) changes significantly. This change is not only due to variations in contact area caused by the touch, but also due to structural changes arising from the substrate's compression and the distance between the electrode contact and the touch point. By capturing these impedance variations, different input patterns and locations can be identified. For 10 gestures, they achieved classification accuracies of 66%, 84%, and 87% at intervals of 20 mm, 30 mm, and 40 mm, respectively. Essentially, they utilized a highly deformable material, where impedance variations—caused by both material deformation and changes in the human-body contact area—drive the changes in sensor data. Evidently, while this conductive foam approach is suitable for deformation-based gesture classification, it is not well-suited for regression tasks, such as outputting specific pressure values.

In contrast, this paper uses piezoelectric materials. Although they also possess flexibility, they are difficult to deform in the thickness direction. However, they generate an electrical charge in response to pressure, which in turn influences the data acquired via SFCS technology. This will be described in detail in Section 3.

In summary, SFCS captures complex changes in electrical properties through a frequency sweep, providing richer interaction information than traditional single-frequency methods. Changes in the impedance characteristics of the object being measured will alter the SFCS results. In conventional SFCS applications, distance can cause a change in resistance R , while capacitance C typically changes only when a new object connects to the circuit (e.g., human touch) or when the electrode geometry is altered (e.g., deformation of a conductive sponge).

This paper explores a novel application of SFCS by introducing a piezoelectric material as the sensing medium. The current generated by the piezoelectric effect interferes with the impedance measurement performed by the SFCS. The SFCS system interprets this interference as a change in the sensor's overall impedance profile. When this altered impedance is mapped to an equivalent R-C circuit model, it manifests as a change in the apparent capacitance. This pressure-dependent apparent capacitance, combined with the distance-dependent resistance R of the electrodes, creates a unique, frequency-domain signature for each pressure and location combination. This enables the detection of multi-point pressure. Traditional piezoresistive sensors, which operate by changing resistance, are poorly suited for single I/O, multi-point measurements. The results obtained from the SFCS technique will be fed into a machine learning model for decoding to estimate the multi-point pressure values. And the SFCS technique, leverages piezoelectric sensors that are not directly in the circuit loop. This prevents charge loss during measurement, removes the need for sample-and-hold circuits, and ultimately simplifies the design while reducing cost.

Detailed experiments and results will be presented in the following chapters.

3. Hardware Design and Sensing Principles

3.1. Principle of Swept Frequency Capacitive Sensing (SFCS)

Swept Frequency Capacitive Sensing (SFCS) is an advanced sensing technique that extends traditional capacitive sensing by utilizing a wide spectrum of frequencies. Unlike conventional methods that operate at a single, fixed frequency to detect a change in capacitance, SFCS emits a signal that sweeps through a predefined range of frequencies.

The fundamental principle of SFCS is based on the observation that the electrical properties of an object, including its capacitance and resistance, vary with the frequency of the applied signal. When a user touches or interacts with an electrode, their body introduces a complex impedance to the system. This impedance is frequency-dependent due to the dielectric properties of human tissue.

Previous research on detecting human touch with SFCS [11] has shown that the resistive and capacitive properties of the human body oppose the applied AC signal. This opposition, or electrical impedance, changes the phase and amplitude of the AC signal. The amount of this change depends on a variety of factors. It is affected by how a person touches the electrode (e.g., the surface area of skin contact), the body's connection to ground (e.g., wearing shoes or not), and it strongly depends on the signal frequency.

By measuring the impedance profile across the entire frequency sweep, a rich, multi-dimensional dataset is generated for each interaction. This data can be used not only to detect the presence of a touch but also to differentiate between various types of gestures, such as a tap, a grasp, or a multi-finger touch. The unique impedance signature at different frequencies allows for a more nuanced and detailed interpretation of the interaction.

The impedance (Z) of a simple RC circuit can be modeled as a complex quantity that includes both resistance (R) and capacitive reactance (X_C). The total impedance is a function of the angular frequency (ω).

The capacitive reactance of an ideal capacitor is given by:

$$X_C = \frac{1}{\omega C} \quad (1)$$

where:

- X_C is the capacitive reactance.
- ω is the angular frequency in radians per second, where $\omega = 2\pi f$ (f is the frequency in hertz).
- C is the capacitance in farads.

In our SFCS system, the resistance between the I/O port and the piezoelectric material, and the apparent capacitance formed by the charge generated from the piezoelectric material under pressure, can be regarded as a series RC circuit. Based on the transmission path of the AC signal, even if the resistance of the contacting object is high (in this paper, a non-insulating cover is used to cover the entire sensor surface), the AC signal from the SFCS will eventually be grounded. The total impedance $Z(\omega)$ as a function of frequency is therefore [11,21]:

$$Z = \sqrt{R^2 + \left(\frac{1}{\omega C}\right)^2} \quad (2)$$

By sweeping the frequency f , SFCS measures the changes in this impedance to create a detailed profile of the touch interaction.

This work utilizes an Arduino Mega as the hardware platform for both generating the excitation signal frequencies and acquiring the corresponding feedback. The signal is

generated using Fast PWM Mode 14. The frequency f_s of the signal output from the send pin for the SFCS process is determined by the following formula [22]:

$$f_s = \frac{f_{\text{CPU}}}{p \times (I + 1)} \quad (3)$$

where:

- f_{CPU} is the clock frequency of the Arduino Mega, which is 16 MHz.
- The p is prescaler, value is configured via the lower three bits of the TCCR1B register.
- I is ICR1, the top value for the timer, set by the input frequency parameter.

In this study, set TCCR1B = 0b00011001, and the $p = 1$. With the $I(\text{ICR1})$ register value ranging from 3 to 200, the actual signal frequency applied by the hardware spans from approximately 80 kHz to 4 MHz.

3.2. Characteristics of Flexible Piezoelectric Material

The core of our sensor is a flexible piezoelectric material. This section describes its physical and electrical properties. We explain how it converts mechanical pressure into a measurable electrical signal. We also discuss its advantages and inherent limitations, which provide the rationale for using SFCS and machine learning in later stages.

3.2.1. Fundamental Principle of the Piezoelectric Effect

The sensor operates based on the direct piezoelectric effect. This principle states that when a mechanical stress, such as pressure, is applied to the material, an electrical charge accumulates on its surfaces.

The relationship between the applied force and the generated charge can be expressed as:

$$Q = d \cdot F \quad (4)$$

where, Q is the generated charge, F is the applied force, and d is the piezoelectric coefficient. Our sensor design leverages this direct piezoelectric effect to convert user-applied pressure into a raw electrical signal.

3.2.2. Advantages of a Flexible Piezoelectric Material

Traditional piezoelectric materials, like PZT ceramics, are rigid and brittle. This makes them unsuitable for applications on soft or non-flat surfaces. In contrast, our sensor uses a flexible piezoelectric polymer. Flexibility ensures good and consistent physical contact between the sensor and the interaction surface. And its durability. The polymer material can withstand repeated bending and pressure cycles without breaking.

The main challenge with this material is charge leakage. Although piezoelectric materials are good insulators, they are not perfect. When a constant pressure is applied, the generated charge gradually dissipates over time. The charge leaks through the connected measurement circuit.

As a consequence, the sensor is not sensitive to static or very slow-changing pressures. It functions as a dynamic pressure sensor, responding most strongly to the rate of change of pressure (dF/dt). This property makes it difficult to accurately quantify pressure using traditional voltage measurement methods. This challenge is the primary motivation for our use of SFCS and machine learning to decode the sensor's complex signal.

3.2.3. Electrical Model as a Sensor and Key Challenges

From an electrical perspective, the piezoelectric material can be modeled as a parallel-plate capacitor. The capacitance (C) of this structure depends on the material's dielectric

constant, the electrode area, and its thickness. When a force (F) is applied, the generated charge (Q) creates a voltage ($V = Q/C$) across this equivalent capacitor. This relationship is the bridge between the physical piezoelectric effect and the electrical parameters measured by our SFCS circuit. The applied pressure results in a direct change to the sensor's electrical characteristics.

A critical distinction must be made between the material's intrinsic physical capacitance (C_p) and the apparent capacitance (C_{app}) measured by our system. While the physical capacitance C_p of the piezoelectric material is an inherent property and remains constant under pressure, the value measured by our Swept Frequency Capacitive Sensing (SFCS) system changes significantly with applied force. This is the core of our sensing principle.

This phenomenon occurs because the direct piezoelectric effect generates a pressure-dependent surface charge, $Q_p(t)$, on the material. This charge alters the electrical conditions of the sensing circuit. The SFCS system, which operates by measuring changes in an applied AC signal, detects this alteration. Consequently, the system calculates an apparent impedance, $Z_{app}(\omega)$, which is now changed by the pressure-induced charge $Q_p(t)$.

When this pressure-dependent $Z_{app}(\omega)$ is mapped back to an equivalent RC model, it results in a change in the capacitance value. This measured value is the apparent capacitance, C_{app} . The sensor can be modeled as a constant physical capacitor (C_p) in series with a pressure-dependent charge source ($Q_p(t)$) that influences the measured result of SFCS.

Therefore, it is this C_{app} —not the constant physical C_p —that varies predictably with pressure. Our sensor leverages this change in apparent capacitance as a robust proxy for quantifying mechanical force, resolving the challenge of measuring static pressure with piezoelectric materials without complex circuitry.

The material used in this article has properties similar to PVDF and is soft and bendable, shown as Figure 1. To characterize the material's response, a dynamic force of 50 N was applied to a sample with a 5 cm² electrode area and an approximate thickness of 100 μ m, which generated a voltage of approximately 70 mV. The piezoelectric property is inherent throughout the material's volume. This means it can be cut into custom shapes and sizes to fit specific applications without losing its fundamental sensing capability. When integrated with the SFCS circuit, the primary requirement is that the area in contact with the I/O electrodes remains largely intact. Because of the material's low intrinsic conductivity, it is not necessary for the entire sensor patch to be a single, continuous piece. The sensor can tolerate minor physical damage, such as linear tears or even complete breaks where two parts are disconnected, as long as the sections remain in contact with the electrodes.



(a)



(b)

Figure 1. Cont.

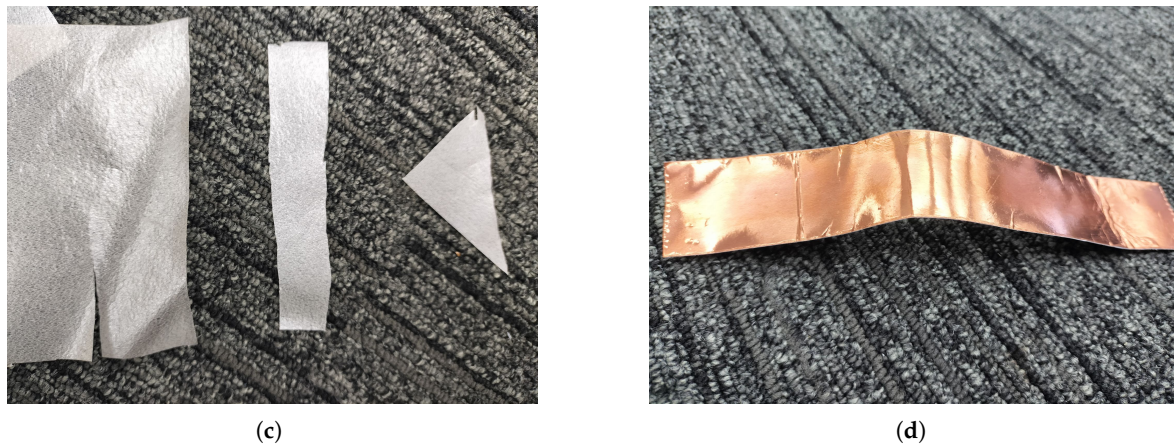


Figure 1. The Characteristics of the flexible piezoelectric material used in this study, demonstrating its flexibility. (a) Total view, a roll of flexible piezoelectric material whose width can exceed 1 m. (b) Crooked view, the material is highly flexible and can be bent freely without affecting its use or performance. (c) The material has high intrinsic impedance and homogeneous properties, allowing it to be arbitrarily cut or segmented. The sensor's performance is primarily dependent on the contact area between this material and the electrode. Minor cuts or damage that do not significantly disrupt this contact area will not impede its functionality. (d) The electrodes can be made from 0.05mm copper foil, which also offers high flexibility.

3.3. Hardware and Preliminary Testing

The hardware and circuit design of SFCS technology refer to Colin Honigman et al. [23]. The controller for their system is also an Arduino Mega. They mention while the Arduino can also produce a signal at these frequencies, its resolution is lower and it can only produce a square wave so there are a lot of unwanted harmonics that are produced as well. Möbius figured out that using a simple LC circuit, also known as a resonant circuit, could help transform the square wave into a sinusoidal wave. We adopted the same design in terms of circuitry.

The preliminary testing of the piezoelectric material sensor is shown in Figure 2. The piezoelectric material is placed directly on electrodes that are connected to I/O ports. An insulating layer is then applied over the piezoelectric material.

To validate the spatial-sensing capability of the SFCS method, the electrodes were fabricated not from a standard conductor, but from a graphite-containing material, exhibiting a resistance per unit length of approximately 10 k Ω /cm. This intentional high resistance is critical to our experiment, as it creates a significant, distance-dependent impedance gradient along the electrode. This gradient allows the SFCS logic to differentiate the location of a pressure event based on its distance from the single I/O port. The electrode structure is segmented into 8 distinct locations, with an approximate resistance of 20 k Ω between adjacent locations. This structure is referred to in this paper as the simplified linear sensor array. It is used for preliminary experiments. The linear sensor array and setup of preliminary testing of the piezoelectric material sensor is shown in Figure 2.

The curves of data obtained when testing touch at various points are shown in Figure 3. It can be observed that each point exhibits distinct characteristics. The result shows a clear trend: the most significant variation between positions occurs in the second prominent peak. We observed that as the touch position moves closer to the I/O port, the frequency of this second peak shifts to be higher. This frequency shift, along with the corresponding differences in signal amplitude across the spectrum, provides the unique signature for each position that our classification model utilizes.

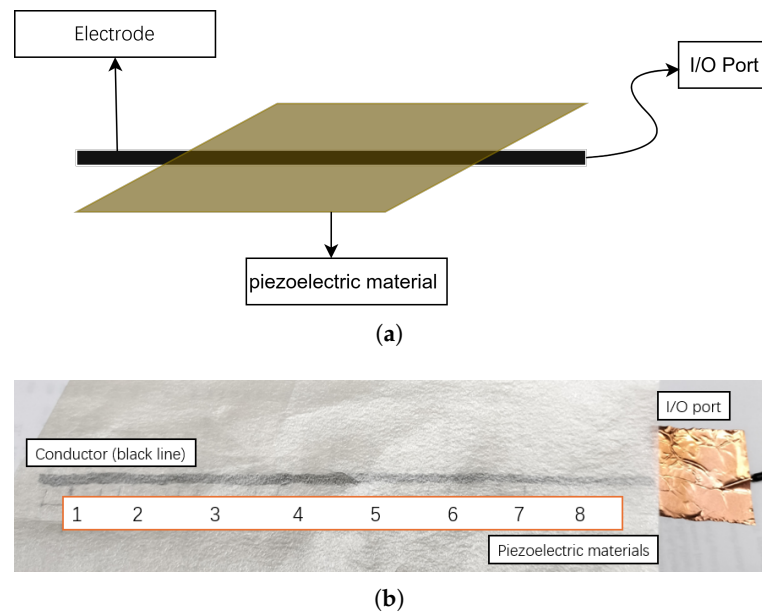


Figure 2. Preliminary testing setup of the piezoelectric material sensor system using Arduino Mega controller and SFCS technology. The configuration shows the piezoelectric material placed on segmented electrodes with 8 distinct sensing locations, each separated by approximately 20 k Ω resistance for force application testing. This structure is referred to as the simplified linear sensor array in this section. (a) Schematic diagram of the test configuration. (b) Preliminary testing setup of the piezoelectric material sensor.

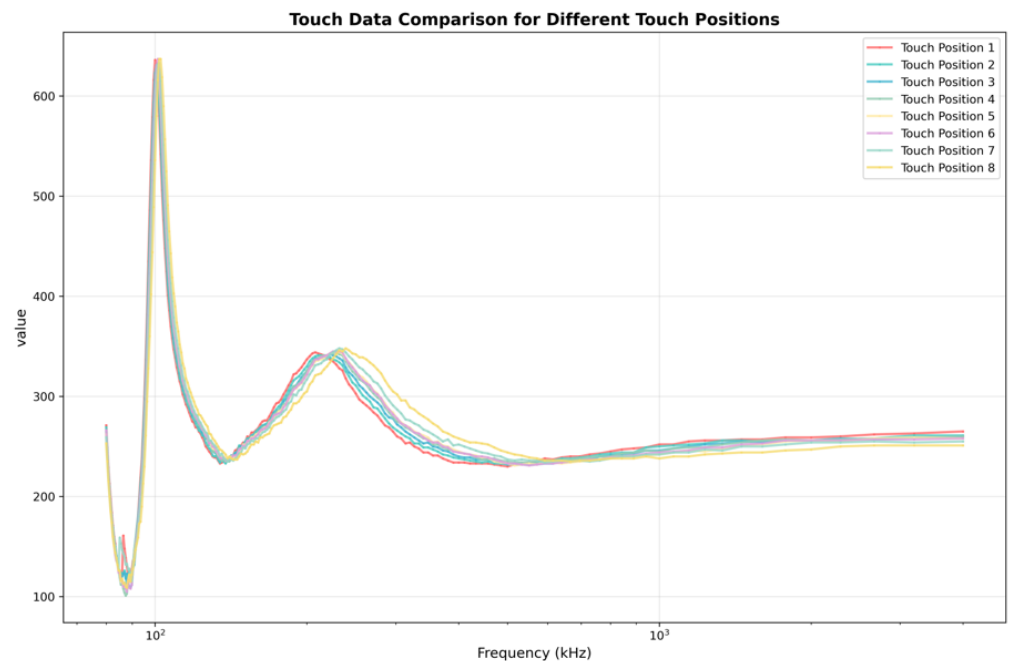


Figure 3. Data curves obtained from testing touch at various sensor points, showing distinct response characteristics for each location. The Y-axis represents the raw digital value (ranging from 0–1023) sampled by the Analog-to-Digital Converter (ADC) via the Arduino Mega analog input pin. This value is proportional to the input voltage.

To validate the feasibility of the SFCS approach with piezoelectric materials, we conducted a controlled experiment using the simplified linear sensor array. During the experiment, force was applied at only one position at a time, with different forces applied at each position. The SFCS results when pressing each position were collected to form a dataset. The resulting data was collected and processed using a simple CNN to test whether

the system could distinguish which position was experiencing the applied pressure. The confusion matrix shown in Figure 4 demonstrates the classification results.

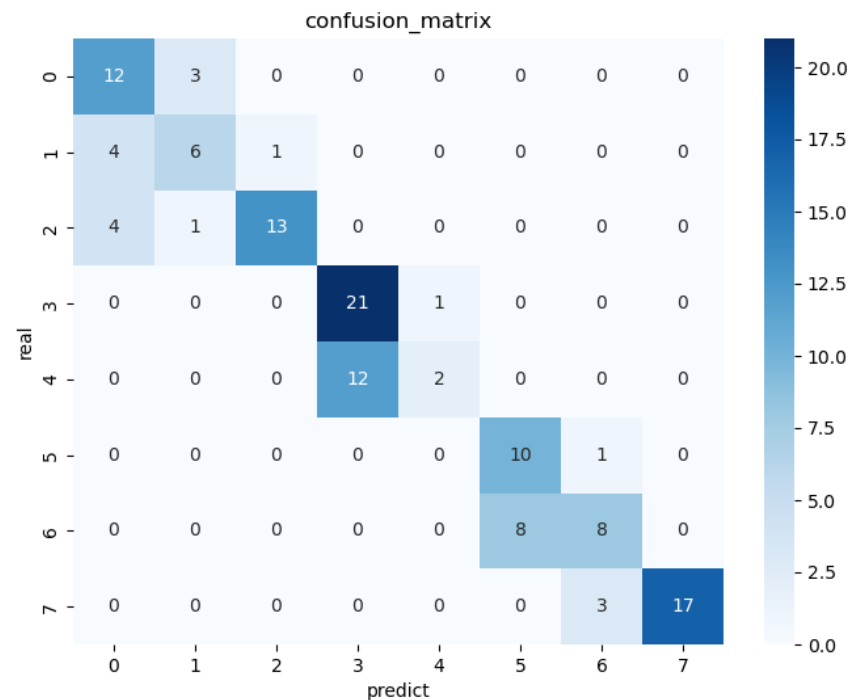


Figure 4. Confusion matrix showing the CNN classification results for distinguishing pressure applied at different positions on the linear sensor array. Labels 0–7 correspond to positions 1–8.

In this preliminary test, the 8 positions were placed in close proximity, with an approximate distance of only 2 cm between adjacent locations. The matrix demonstrates an overall classification accuracy of approximately 70%, defined as the ratio of predicted positions that exactly matched the real positions. A key observation is that the vast majority of misclassifications occur in positions immediately adjacent to the real position. If we account for this proximity and accept a tolerance of ± 1 position (i.e., ± 2 cm) as a successful prediction, the effective accuracy increases to 97%. This result demonstrates that the system's output is strongly correlated with the true position.

The results indicate that using only a single I/O port, the 8 positions can be distinguished due to their varying distances from the I/O interface, which results in different total resistance values. When force is applied at each position, the system generates distinct response patterns that enable successful position identification. This preliminary validation demonstrates the feasibility of combining SFCS with piezoelectric materials for multi-point pressure sensing applications.

Furthermore, to investigate the sensor's ability to discern pressure magnitude, we applied varying levels of force at a single location. The resulting data curves, presented in Figure 5, show a clear distinction between different pressure levels. This demonstrates that the SFCS response is sensitive not only to the location of the touch but also to the applied force, confirming the feasibility of using this method for pressure magnitude estimation.

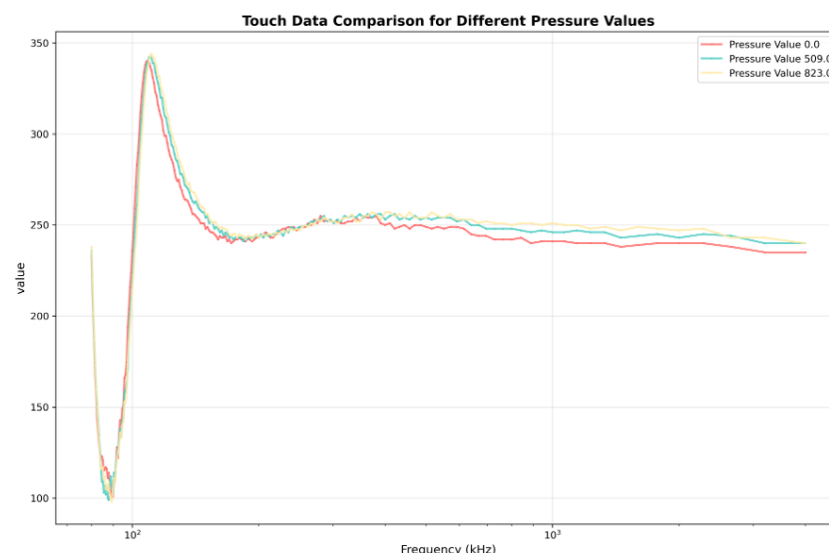


Figure 5. Data curves obtained by applying different pressure magnitudes at the same sensor location, illustrating the system's sensitivity to force variations.

3.4. Hardware Development for the Cyber–Physical–Human System

To achieve multi-point pressure sensing through a single I/O port, we developed a comprehensive hardware system for the Cyber–Physical–Human System (CPHS) integrated into chair cushions and backrests. The system architecture is illustrated in Figure 6.

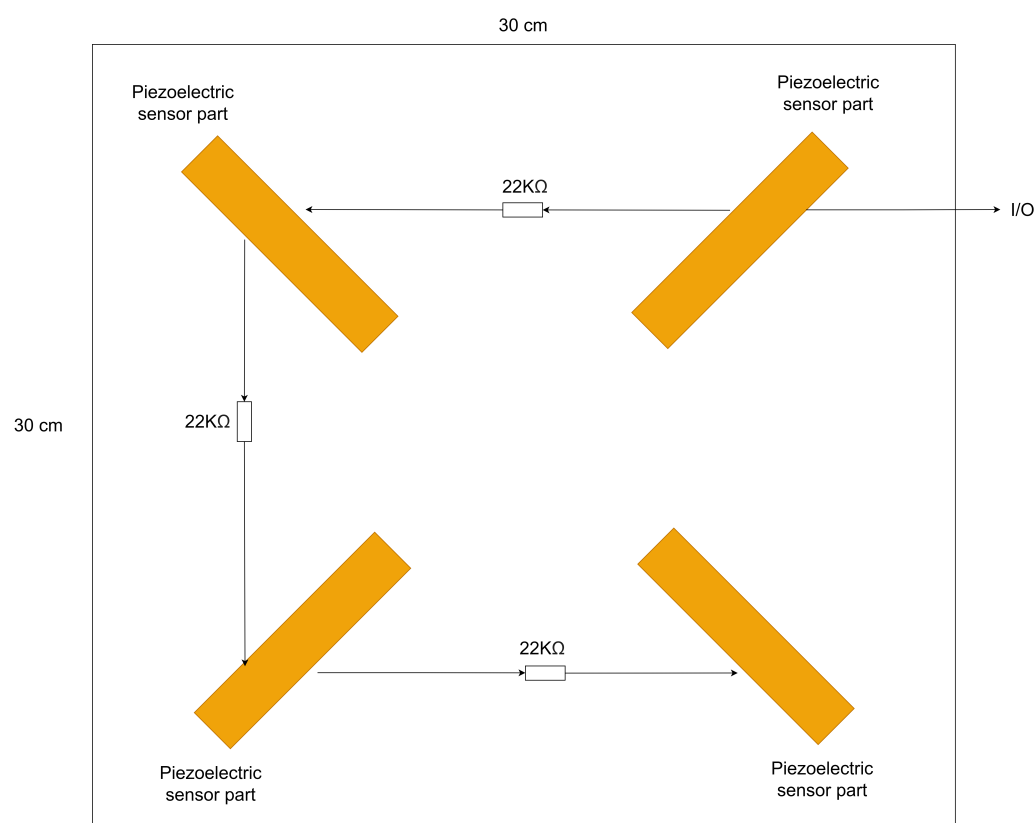


Figure 6. System architecture showing the multi-layer sensor configuration for single I/O multi-point pressure sensing.

The sensor construction follows a layered approach where conductive materials serve as electrodes to detect the electrical characteristics of the piezoelectric material. The piezoelectric layer is positioned above the conductive substrate, with the entire assembly pro-

tected by a cover layer. This configuration enables pressure-induced changes in the piezoelectric material to be detected through impedance variations measured via the underlying electrode array.

For validation and training data generation, we fabricated a reference system using traditional thin-film resistive pressure sensors arranged in an identical spatial configuration. This parallel implementation provides ground truth pressure values at each sensing location, serving as supervised learning targets for our machine learning models.

To be more specific, for each of the four sensing locations, a commercial thin-film resistive pressure sensor (FSR) was placed directly underneath the corresponding area of our piezoelectric sensor assembly, as illustrated in the fabrication sequence in Figure 7. This co-location ensures that any force applied to a sensing point is registered by both systems simultaneously. The data from the FSR array, which provides a direct and calibrated pressure reading, serves as the ground truth for training and validating our machine learning models. In this way, we create a synchronized dataset where each SFCS data sample has a corresponding, validated pressure value from the FSRs.

The complete sensor assembly is shown in the fabrication sequence presented in Figure 7a–e. Figure 7a shows the overall sensor structure, Figure 7b displays the electrode layer configuration, Figure 7c presents the piezoelectric material placement, Figure 7d shows the assembled sensor before covering, and Figure 7e illustrates the final protected sensor assembly.

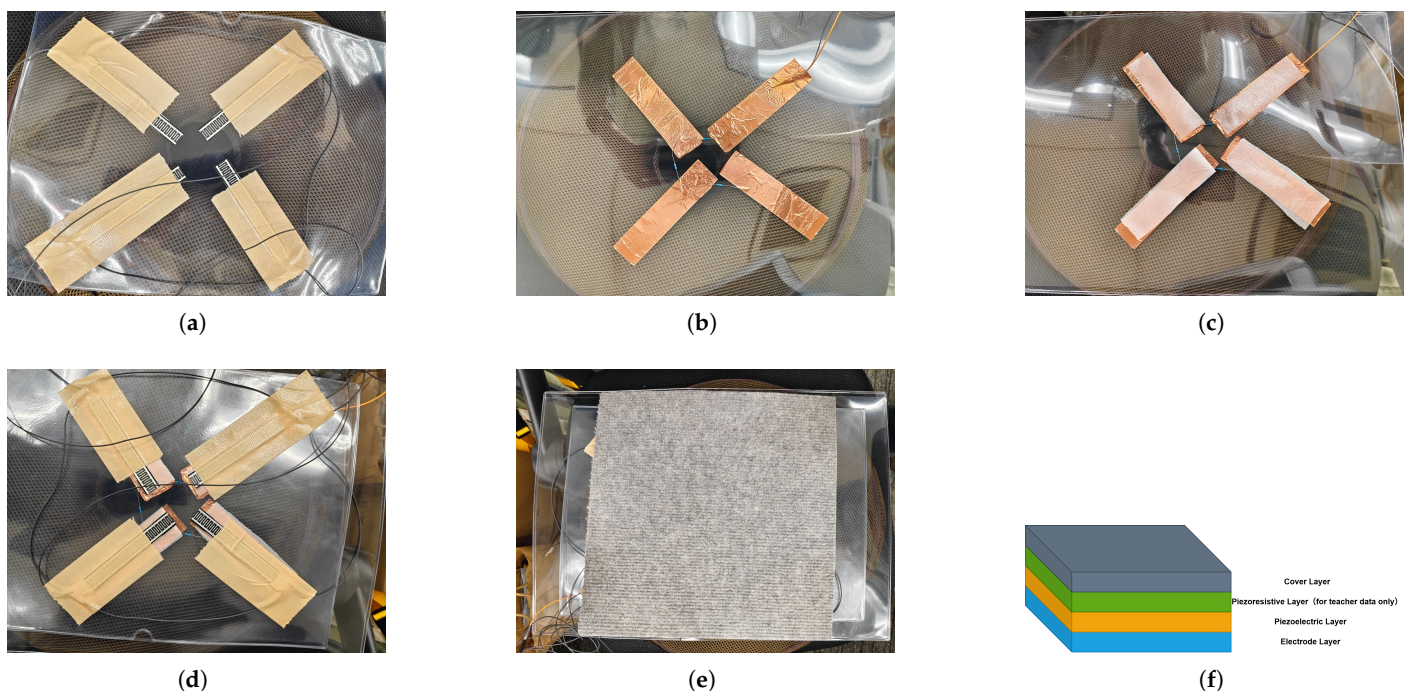


Figure 7. Sensor fabrication sequence showing the complete assembly process from individual components to final protected sensor array for the Cyber-Physical-Human System. (a) Overall pressure sensor structure and assembly. (b) Electrode layer configuration for impedance sensing. (c) Piezoelectric material layer placement. (d) Assembled sensor array before protective covering. (e) Final sensor assembly with protective cover layer. (f) Overall schematic diagram of the sensor.

The data acquisition system operates with a single I/O port collecting SFCS impedance measurements across the frequency spectrum, while the reference resistive sensor array provides corresponding ground truth pressure values at discrete sensing locations. To create a comprehensive training dataset for machine learning applications, we systematically collected pressure data under various loading conditions:

- Single-point loading: Different pressure magnitudes applied to each of the four sensing positions individually
- Dual-point loading: Simultaneous pressure application to two different positions with varying force distributions
- Triple-point loading: Simultaneous pressure application to three sensing locations with varying force distributions
- Quadruple-point loading: Simultaneous pressure application to all four sensing positions with various force distributions

This systematic data collection protocol ensures comprehensive coverage of potential real-world usage scenarios, providing robust training data for machine learning algorithms to accurately decode multi-point pressure information from single I/O measurements. The resulting dataset enables the development of regression and classification models capable of simultaneously estimating both pressure magnitude and spatial distribution across the sensor array.

In summary, using the SFCS technique and piezoelectric material, the system's impedance changes in two ways: its capacitance (C) changes with the force applied to the piezoelectric material, and its resistance (R) changes with the distance of the application point from the I/O port. This makes it possible to detect multi-point pressure values from a single I/O port.

Furthermore, according to our preliminary experiments, if the electrode is made of a conductor with uniform resistivity and the piezoelectric material is placed on top, no additional setup is required for the detection points. This implies that the detection of continuous points, rather than traditional discrete points, is potentially achievable. However, continuous point detection places significant demands on signal filtering and algorithmic complexity. Therefore, the subsequent research in this paper will focus on a discrete-point setup, and the dataset was collected based on this configuration.

4. Methodology

This section details the proposed methodology for touch detection and pressure estimation based on SFCS and piezoelectric materials and apply it for CPHS. We first introduce the processing methods of sensor data. We build a dual-model deep learning architecture, comprising a touch classification model and a multi-modal pressure regression model.

The use of a sophisticated deep learning model is a necessary choice dictated by the inherent complexity of the sensor data. First, the system uses a single I/O port to capture data from four locations, resulting in a multiplexed signal where responses from simultaneous touches interfere with each other. A linear model cannot disentangle these overlapping, non-additive signals. Second, the relationship between the applied pressure and the resulting frequency-dependent impedance profile is highly non-linear due to the physics of the piezoelectric effect and the nature of the SFCS measurement. Our deep learning approach, particularly the use of a CNN, is designed to automatically extract salient features from these complex, non-linear patterns and disentangle the multiplexed signals to estimate pressure at each location.

Furthermore, we chose a data-driven ML approach over a model-based (physics-informed) one. While a physics-based model is powerful for well-defined systems, creating an accurate analytical model for our sensor would be practically difficult due to the extreme complexity of the signal interactions and the difficulty in precisely measuring all relevant physical parameters. The ML approach bypasses these challenges by learning the input-output mapping directly from empirical data, offering a more adaptable solution for this complex sensing paradigm.

The primary objective is to map a multi-variate time series of capacitance readings from four sensors to their corresponding touch states and pressure values. This is decomposed into two distinct tasks:

1. **Multi-Label Touch Classification:** A binary classification task for each of the four sensors to determine the presence of a touch event (touched or not touched).
2. **Multi-Output Pressure Regression:** A regression task to predict the continuous pressure value for each of the four sensors.

To enrich the input representation for the classification task, we augment the raw data sequences (ΔC) with a set of handcrafted statistical features. For each input sequence of length L , we extract four features designed to capture salient local signal characteristics: the maximum value, the position of the maximum value (argmax), the submaximum value, and its corresponding position. The order of each set of raw data sequences is sorted by frequency, and the position of the value refers to the frequency at which the value appears. These features provide the model with explicit, high-level information about the signal's peak dynamics.

4.1. Proposed Dual-Model Architecture

We employ a two-stage, dual-model architecture to effectively decouple the classification and regression tasks. The first model identifies which sensors are being touched, and the second model leverages this contextual information to accurately predict the pressure intensity for the corresponding sensors. This sequential approach is designed to improve regression performance, particularly in complex multi-touch scenarios, by explicitly informing the regression model of the active touch pattern.

A critical aspect of this architecture is that both the classification and regression stages are implemented as single, unified models rather than separate models for each of the four sensors. Specifically, we use a single multi-label classification model and a single multi-output regression model. This unified design is necessitated by the fundamental nature of our single I/O port sensor. The SFCS system provides a single, mixed data stream at any given time, which contains the combined, overlapping signals from all four pressure locations. Consequently, it is impossible to isolate the data for an individual sensor prior to processing. Our unified models are designed to decode this complex, multiplexed signal.

While a single pressure measurement might seem like a static event, our rationale for employing a time-dependent model like an LSTM is rooted in the dynamic nature of user interactions. Real-world actions such as sitting down or shifting weight are continuous processes, not instantaneous events. The pressure signal ramps up, fluctuates, and ramps down over time. By processing a sequence of SFCS data rather than a single snapshot, the LSTM can learn these temporal dynamics.

The overall system architecture is illustrated in Figure 8.

4.2. Model Training Hyperparameters

Both the touch classification model and pressure regression model were trained using the Adam optimizer with an initial learning rate of 0.001. A batch size of 32 was used for all training sessions. The dataset was partitioned into 80% for training and 20% for validation. The final test dataset was collected separately and sequentially includes all four scenarios: single-touch, dual-touch, three-point touch, and four-point touch.

For the classification task, the Binary Cross-Entropy (BCE) loss function was employed. For the regression task, the Mean Squared Error (MSE) loss was used. To optimize the training process, a ReduceLROnPlateau learning rate scheduler monitored the validation loss. This scheduler reduced the learning rate by a factor of 0.5 after 5 consecutive epochs of no improvement, with a minimum learning rate of 1×10^{-6} .

To mitigate overfitting, two regularization techniques were applied: dropout and early stopping. Dropout was implemented after each of the two LSTM layers with a rate of 0.3 and after the first dense layer with a rate of 0.4. Early stopping was configured with a patience of 15 epochs, terminating the training process if the validation loss did not show improvement within this window. The maximum number of epochs was set to 200 for the classifier and 150 for the regressor.

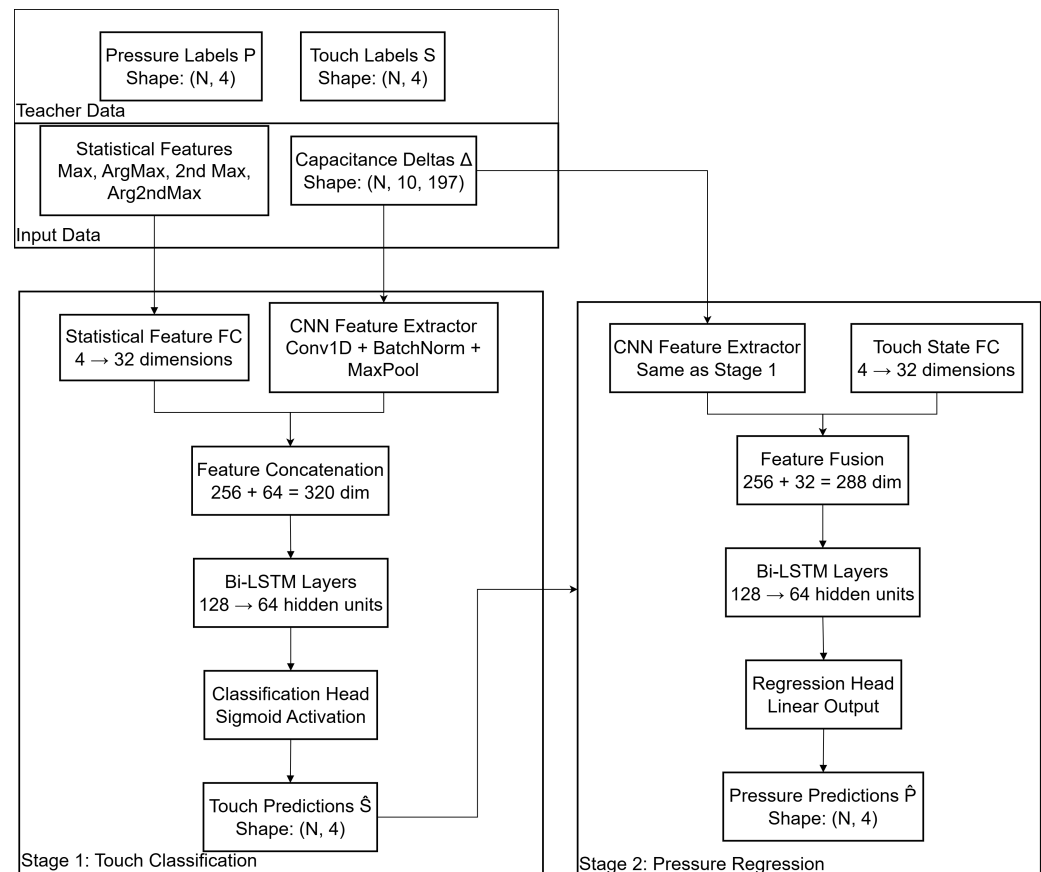


Figure 8. The overall two-stage system architecture. The Touch Classification model first predicts touch states, which are then used as an input to the Pressure Regression model along with the original capacitance data.

4.3. Touch Classification

The touch classification model is a hybrid neural network designed to extract both spatial and temporal features from the input sequences. Its architecture consists of a CNN feature extractor, a feature fusion module, a temporal modeling block, and a classification head.

- **CNN Feature Extractor:** A stack of three 1D convolutional layers is applied to the capacitance delta sequence. The first two layers are followed by batch normalization and max pooling (kernel_size = 2) to learn hierarchical features and reduce dimensionality. The third convolutional layer acts as a final feature refiner. All layers utilize the Rectified Linear Unit (ReLU) activation function. The specific configuration is:
 - Conv1D: 64 filters, kernel size 3.
 - Conv1D: 128 filters, kernel size 3.
 - Conv1D: 256 filters, kernel size 3.
- **Feature Fusion:** The four handcrafted statistical features are processed by a fully connected layer, mapping them from a 4-dimensional to a 64-dimensional space. The

output of this layer is then concatenated with the 256-dimensional output from the CNN block along the feature axis, creating a combined feature representation.

- **Temporal Modeling:** A two-layer unidirectional Long Short-Term Memory (LSTM) network processes the fused feature sequence. The LSTM layers have hidden sizes of 128 and 64, respectively. Dropout with a rate of $p = 0.3$ is applied after each LSTM layer for regularization. The output from the final time step of the second LSTM layer is carried forward, representing a condensed summary of the entire sequence.
- **Classification Head:** The 64-dimensional output from the LSTM is passed through two fully connected layers (with dimensions 128 and 64, ReLU activation, and a dropout of $p = 0.4$) before a final output layer with 4 units. A Sigmoid activation function is applied to the output layer to produce a probability score between 0 and 1 for each of the four sensors.

The detailed architecture is visualized in Figure 9.

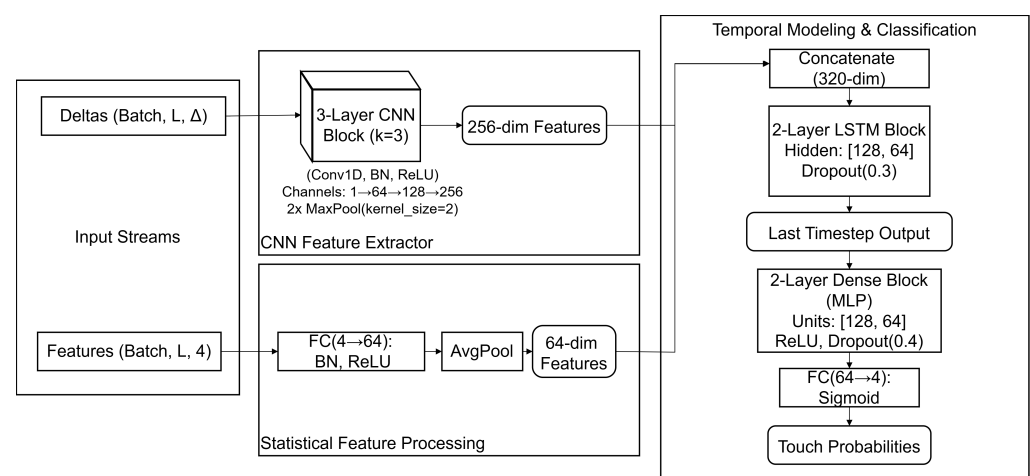


Figure 9. Detailed architecture of the CNN-LSTM model for touch classification.

4.4. Pressure Regression

The pressure regression model integrates the raw capacitance deltas with the predicted touch state information from the classification model described above to generate pressure estimates. This multi-modal approach enables the network to focus its regression capacity on the activated sensors.

- **Capacitance Processing Branch:** This branch uses a CNN architecture similar to the classification model to extract spatio-temporal features from the delta sequences. The key difference is a larger kernel size ($k = 5$) in the first convolutional layer to capture a wider initial receptive field.
- **Touch State Processing Branch:** The binary touch state sequence (predicted by the classification model) is processed by a fully connected layer, mapping the 4-dimensional input to a 32-dimensional feature space. This branch learns a meaningful representation of the multi-touch patterns over time.
- **Feature Fusion:** The outputs from the capacitance branch (256 dimensions) and the touch state branch (32 dimensions) are temporally down-sampled via pooling to match in length and are then concatenated, forming a joint representation of 288 dimensions.
- **Temporal Integration & Regression Head:** The fused sequence is processed by a two-layer LSTM network (hidden sizes 128 and 64) identical to the one in the classification model. The output of the final time step is then passed through a regression head, consisting of two fully connected layers (128 and 64 units with ReLU) and a final linear

output layer that predicts the four continuous pressure values. No activation function is used on the final layer, as is standard for regression tasks.

The architecture is visualized in Figure 10.

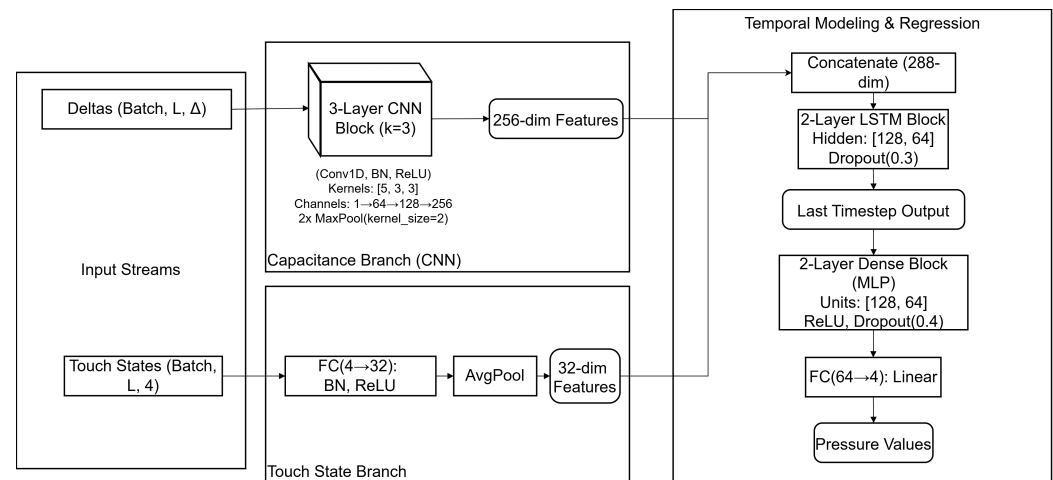


Figure 10. Detailed architecture of the multi-modal CNN-LSTM model for pressure regression. It combines features from the capacitance branch and the touch state branch to predict pressure values.

For both models, we use the Adam optimizer with an initial learning rate of 1×10^{-3} . A learning rate scheduler (ReduceLROnPlateau) is employed to decrease the learning rate by a factor of 0.5 if the validation loss does not improve for 5 consecutive epochs.

4.5. Cyber–Physical–Human System for Elderly Exercises

The pressure sensor studied in this paper will be applied to Cyber–Physical–Human System. The proposed system is designed to assist elderly individuals in performing exercises by providing real-time feedback on their posture and movements. It leverages the pressure sensing capabilities to detect the user’s touch interactions with the system, enabling a more intuitive and engaging exercise experience.

4.5.1. Type of Exercise

For exercise in daily life, reducing the duration of a single session of exercise allows older adults to stick with it better. And High-Intensity Interval Training (HIIT) is a workout method characterized by alternating short, high-intensity phases of exercise with relatively short rest phases to achieve an intensity level at or near maximum heart rate:

- **Seated Back Extension:** is an exercise movement that targets the muscles of the back. The main goal of this movement is to strengthen and stretch the muscle groups of the back, especially the lumbar and upper back muscles. In an application within this system, the elderly user exerts force against the backrest of the recliner. In response, the electric recliner gradually moves into a lying position. The user’s physical ability is then assessed based on the magnitude of the applied force. The seated back extension is shown in Figure 11a.
- **Reverse Pushups:** are an exercise movement that emphasizes the engagement of the back and lumbar muscles and is designed to improve strength in the upper body and core area. In this movement, the individual begins by lying flat on the ground with their legs straight and their arms stretched out on either side of their body, palms facing down. By utilizing the strength of the back and hips, the upper body is lifted off the ground to form an arch, and then slowly lowers the body back to the starting position. This move focuses on strengthening the upper back, lumbar and

core muscles, helping to improve postural stability and strengthen the back muscles while building core strength. In an application within this system, the elderly user exerts force to lift their body off the recliner's seat cushion and holds the position for several seconds. This exercise reduces the pressure detected by the sensors on the seat cushion. After the position is held for the required duration, the recliner returns to a sitting position. The user's physical ability is assessed based on the degree of pressure reduction and the duration of the exercise. The reverse pushups is shown in Figure 11b.

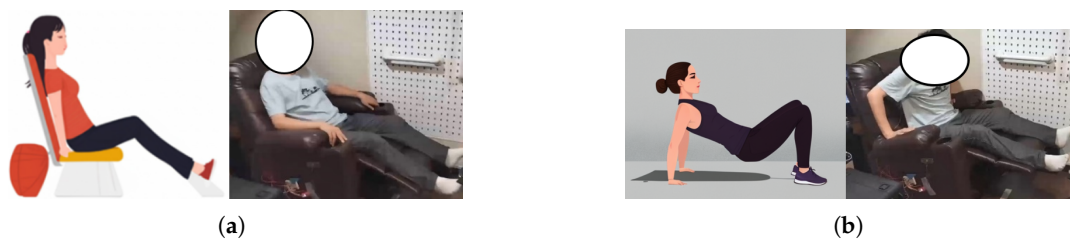


Figure 11. Two typical HIIT exercises for elderly exercises. (a) Seated Back Extension. (b) Reverse Pushups.

4.5.2. Exercise Equipment

Exercise equipment uses existing electric recliners, shown in Figure 12a. The pressure sensors studied in this paper are located on the seat and backrest of the electric recliner to detect pressure in these areas. The IMU sensor, located on the backrest, is used to monitor the status of the electric recliner. The recliner chair with sensors is shown in Figure 12b.

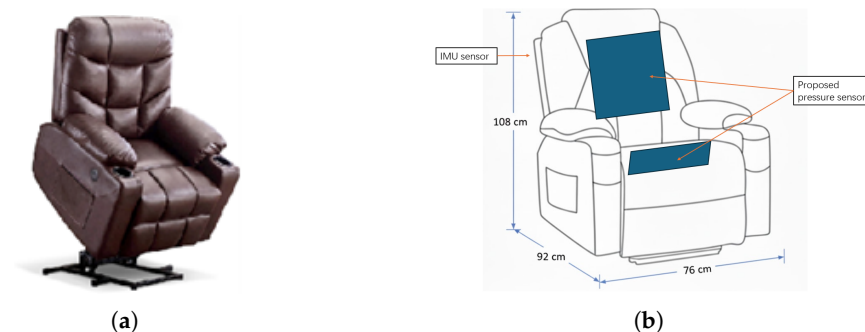


Figure 12. The electric recliner chair and its integration with pressure sensing and IMU monitoring systems for elderly exercise applications. (a) Electric recliner chair. (b) Sensor location diagram.

5. Experiment and Results

The thin-film resistive pressure sensor used to generate the ground truth data was the RP-L-110 thin-film force-sensing resistor (FSR), paired with a 33 k Ω voltage divider resistor for the readings. The sensor has an off-state resistance of greater than 10 M Ω and an active pressure sensing range from 20 g to 10 kg. It is highly responsive, with a trigger force of less than 20 g and an activation time of less than 0.01 s. The sensor is rated for both static and dynamic force applications (up to 10 Hz).

Although this FSR exhibits an approximately linear force-to-resistance response, we used its raw sensor data directly as the ground truth for our comparison. This approach was chosen to avoid introducing potential conversion errors that might arise from a non-ideal resistance-to-force calibration, thereby ensuring a more direct and reliable baseline.

The collected dataset contains:

- The SFCS results, with each sample consisting of readings obtained at 197 distinct frequencies.
- The corresponding frequencies used for the SFCS sweep.
- The four numerical values from the thin-film resistive pressure sensors.

The total size of the training and validation sets is 7440 samples, with an additional 1118 samples reserved for the test set.

To evaluate the system's foundational capability to detect the presence or absence of pressure at each individual sensing location, we first formulated the problem as a binary classification task. The objective was to determine the presence (Class 1) or absence (Class 0) of pressure at each of the four sensing locations independently. A Convolutional Neural Network (CNN) was trained on the high-dimensional SFCS dataset to learn the distinct frequency-domain signatures corresponding to 'Pressed' and 'Not Pressed' states for each sensor.

Furthermore, we chose a data-driven machine learning approach over a model-based (physics-informed) one. While a physics-based model is powerful for well-defined systems, creating an accurate analytical model for our novel sensor would be practically infeasible due to the extreme complexity of the signal interactions and the difficulty in precisely measuring all relevant physical parameters. The ML approach bypasses these challenges by learning the input-output mapping directly from empirical data, offering a adaptable solution for this complex sensing paradigm.

The qualitative performance of the classifier is summarized in the confusion matrices shown in Figure 13. Each matrix corresponds to one of the four sensor locations and illustrates the model's accuracy in distinguishing between the 'Pressed' and 'Not Pressed' states. The confusion matrices demonstrate that the system can determine whether pressure is being applied at a specific point on the array, even when using data from a single I/O channel.

Figure 14 illustrates the capability of touch from single-touch to four-point-touch. The curves demonstrate the model's distinct output responses for different combinations of concurrent pressure applications, such as single-point versus two-point presses. This shows that the model has learned to decode the complex, overlapping signals generated when multiple points are active, successfully distinguishing complex touch patterns. Overall, these results confirm the system's foundational capability to spatially localize both single and multiple pressure points, which is crucial for the subsequent task of pressure magnitude estimation.

A detailed quantitative breakdown of this task is provided in Table 1. These metrics confirm the strong performance visualized in the confusion matrices. Sensors 1, 2, and 4 achieved high accuracy (0.935, 0.938, and 0.962, respectively) and F1-Scores for the 'Touch' class. Sensor 4, for instance, reached a balanced F1-Score of 0.941. However, Sensor 3 exhibited notably lower performance, with an accuracy of 0.865 and, more significantly, a recall of only 0.706 for the 'Touch' class.

Table 1. Touch Classification Performance Metrics.

Sensor	Accuracy	Precision (Touch)	Recall (Touch)	F1-Score (Touch)	Macro Avg Precision	Macro Avg F1-Score
Sensor 1	0.935	0.829	0.977	0.897	0.909	0.925
Sensor 2	0.938	0.971	0.850	0.906	0.947	0.930
Sensor 3	0.865	0.831	0.706	0.764	0.854	0.834
Sensor 4	0.962	0.948	0.935	0.941	0.958	0.957

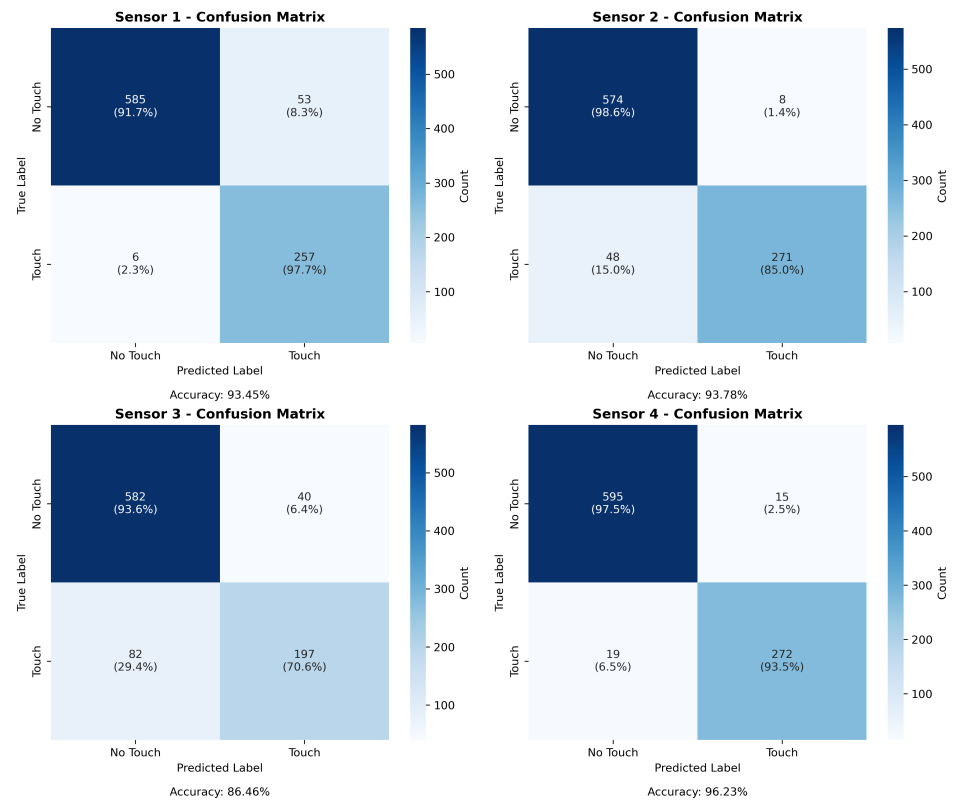


Figure 13. Confusion matrices for the binary classification of pressure application at each of the four sensor positions. Each matrix shows the model's performance in detecting the presence ('Pressed') or absence ('Not Pressed') of force at a specific location.

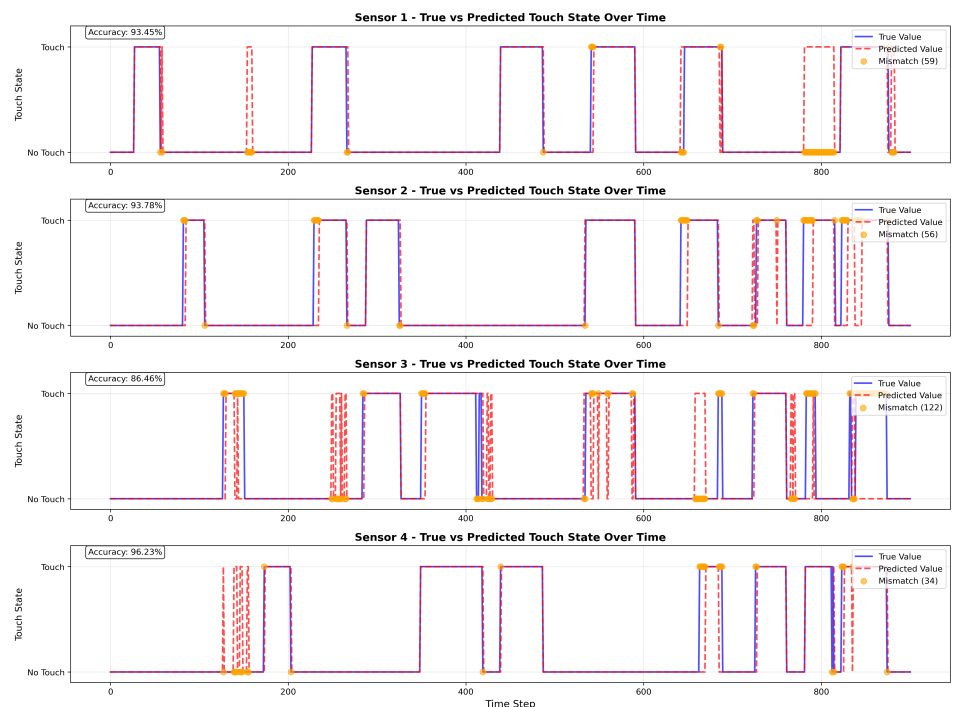


Figure 14. Comparison curves demonstrating the system's performance in detecting simultaneous pressure applications at multiple sensor locations.

This discrepancy warrants a deeper investigation. We hypothesize that the primary cause for Sensor 3's weaker performance is heightened signal ambiguity inherent in our single-channel, multiplexed architecture. In this system, the model must de-multiplex a

mixed signal based on unique frequency-domain signatures determined by the interplay of location-dependent resistance and pressure-dependent apparent capacitance. The lower recall for Sensor 3 suggests that its signal signature is less distinct and more susceptible to being masked or confused with signals from other sensors, particularly in multi-touch scenarios. For example, a moderate pressure on Sensor 3 might generate a signature that is partially obscured by a strong, concurrent pressure on an adjacent sensor, leading the model to miss the event. This specific challenge highlights the complexity of decoding entangled signals from a single I/O port and suggests that the physical layout of the electrode trace relative to Sensor 3 may create a less favorable signal-to-noise ratio or greater feature overlap. Despite this variation, the overall results confirm the system's foundational capability to spatially localize pressure, which is crucial for the subsequent, more complex task of pressure magnitude estimation.

Building on the successful classification of touch presence and location, the second task was to evaluate the system's ability to estimate the magnitude of the applied pressure. This moves the problem from classification to a more challenging multi-output regression task.

The performance for quantitative pressure magnitude estimation is presented in Figure 15. This figure plots the relationship between the pressure values predicted by the model (from the SFCS data) and the actual ground truth values (from the co-located resistive sensors). The plots show a clear positive correlation across the sensors, indicating that as the actual pressure increases, the model's predicted pressure value increases accordingly.

The quantitative metrics for this regression task are summarized in Table 2. The R^2 (R-squared) and Correlation values quantify the linear relationship shown in Figure 15. Sensors 1, 2, and 4 again show strong results, with R^2 values of 0.715, 0.778, and 0.806, respectively. The correlation coefficients for these sensors are also high (0.855 to 0.899), confirming a strong linear relationship between the predicted and actual values. Similar to the classification task, Sensor 3 had the weakest performance, with an R^2 of 0.437. This suggests that while the model can detect the presence of a touch at Sensor 3 with reasonable accuracy, it struggles to accurately predict its magnitude. This is a clear area for future improvement, potentially through more targeted feature engineering or a larger training dataset for that specific location.

Table 2. Pressure Regression Performance Metrics.

Sensor	R^2	Correlation
Sensor 1	0.715	0.855
Sensor 2	0.778	0.887
Sensor 3	0.437	0.694
Sensor 4	0.806	0.899

To demonstrate the practical application of our CPHS, we integrated the sensorized chair into the two previously described exercise routines: the Seated Back Extension and Reverse Pushups. The system was used to monitor the user's interaction with the chair in real-time during these activities. The sensor array successfully captured the dynamic pressure changes corresponding to the user's movements. This demonstrates the system's capability to provide the necessary data for real-time feedback and performance analysis, validating its potential as an effective tool for guided, in-home exercise for the elderly.

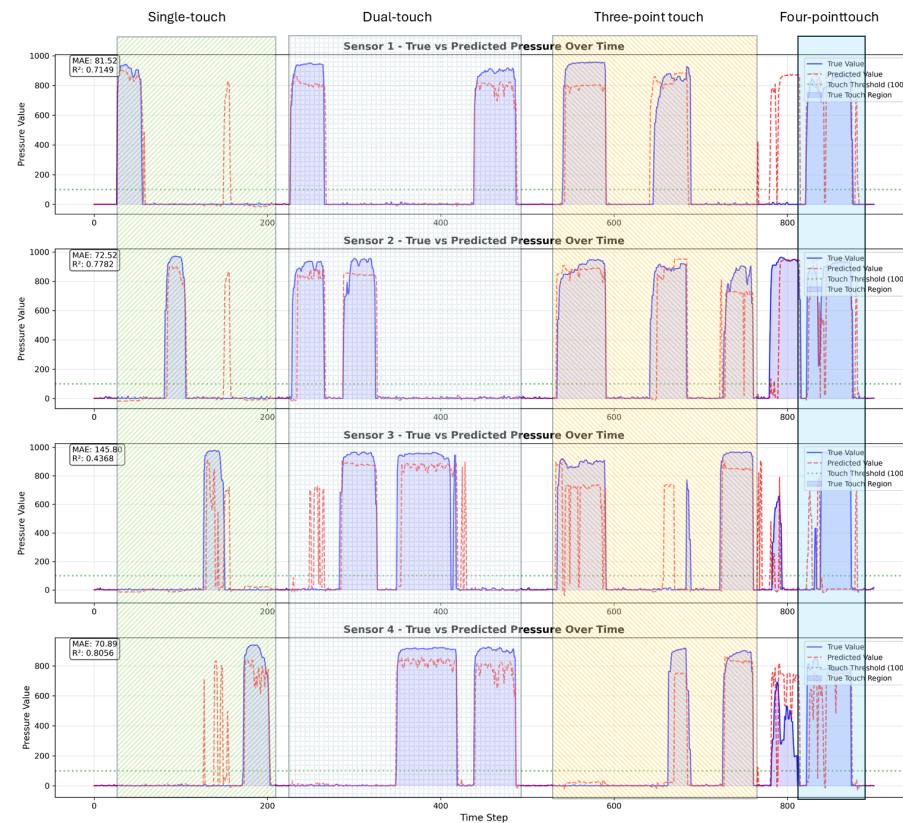


Figure 15. Pressure magnitude estimation results showing the correlation between measured and actual pressure values.

6. Conclusions

We demonstrate that a hybrid piezoelectric-swept-frequency capacitive sensing (SFCS) approach is a viable method for creating low-cost, flexible, and easily integrated multi-point pressure sensors. We developed a novel pressure sensor that can be used to develop a new generation of smart interactive furniture for elderly care and rehabilitation in CPHS. Our results demonstrate the effectiveness of this system. The classification model accurately identifies the presence and location of pressure, including multiple simultaneous touches. The regression model successfully estimates the magnitude of applied pressure and correlates well with ground truth data.

6.1. Summary of Research and Core Contributions

Existing pressure sensors typically employ rigid designs, require complex wiring, and suffer from durability issues.

To address these issues, we introduce a novel sensor system. Our approach combines flexible piezoelectric materials with swept-frequency capacitive sensing (SFCS). This design enables a flexible multi-point pressure sensor array operating through a single input/output (I/O) port. To interpret the complex sensor signals, we use a CNN-LSTM model for classification and regression. Ultimately, the proposed sensor is implemented in a CPHS system, using a reclining chair to enable elderly people to exercise in their daily lives.

6.2. Research Limitations

One limitation is that our dataset was collected in a controlled laboratory environment. Real home environments introduce more complex factors, including signal noise, temperature and humidity variations, and more diverse user interaction patterns. This study focused on discrete point measurements, not continuous point measurements. The SFCS cir-

cuit directly references Colin Honigman et al. [23], but there is still room for improvement in filtering and other related work.

The quantitative results of our models, such as a multi-label classification accuracy of 86% and R^2 scores for regression ranging from 0.4 to 0.8, may appear modest when evaluated against benchmarks in more established sensing domains.

The core difficulty stems from the fundamental design of our sensor: decoding four simultaneous, dynamic pressure values from a single, multiplexed data stream generated by a single I/O port. This architecture introduces a high degree of signal ambiguity, where the signals from all four locations are inherently mixed and overlapping. The model must learn to de-multiplex these entangled signals, a task where the signature of a light touch on one sensor can be easily masked by a heavy touch on another. This ambiguity is the primary cause of errors, especially in multi-touch scenarios as seen in our sequential tests.

From an application-oriented perspective, particularly for our target CPHS for elderly exercise, high-precision quantitative pressure values are not always required. The system's ability to reliably detect the presence of a touch, its general location, and its approximate magnitude (e.g., low, medium, high) is often sufficient to guide the interactive exercises. Our system successfully achieves this level of qualitative performance.

In conclusion, while we acknowledge the limitations in the quantitative performance, our work successfully demonstrates a feasible and novel pathway to achieving something previously impractical: multi-point, static pressure sensing with a single I/O port using a flexible, durable, and low-cost sensor. Crucially, static pressure measurement can be performed using piezoelectric sensors without the need for sampling and holding circuits. This study establishes the viability of this new sensing paradigm.

6.3. Future Work

We suggest that future work could focus on enhancing raw data accuracy through filtering, as well as further optimizing the model to improve output performance, thereby making the method more robust and comprehensive.

Based on our findings, we will explore the potential of continuous pressure sensing. Our preliminary results suggest this is feasible. Future work will focus on developing more advanced algorithms to move from discrete point detection to mapping continuous pressure distributions.

Finally, this sensing technology could be applied to other fields. Potential areas include smart mattresses for sleep quality monitoring, wearable devices for rehabilitation, or smart car seats for posture detection.

6.4. Final Conclusion

In summary, piezoelectric materials are traditionally used for dynamic pressure measurement due to their charge leakage, and the combination of SFCS technology and piezoelectric materials has been less studied. In this paper, a pressure sensing system combining SFCS technology and piezoelectric materials was successfully developed and verified. By combining a unique hardware approach with an intelligent decoding algorithm, a single I/O port can measure pressure at four locations. This approach, when applied to CPHS, enables a power recliner to help elderly people exercise in their daily lives. Our work opens up new possibilities for creating low-cost and accessible cyber–physical–human systems.

Author Contributions: Conceptualization, Q.S., C.Z.S. and N.K.; data curation, Q.S. and T.O.; formal analysis, Q.S.; investigation, Q.S.; methodology, Q.S. and C.Z.S.; project administration, N.K.; resources, Q.S. and C.Z.S.; software, Q.S. and T.O.; supervision, C.Z.S. and T.O.; validation, Q.S., C.Z.S. and T.O.; visualization, Q.S.; writing—original draft, Q.S. and N.K.; writing—review and editing, Q.S. and T.O. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethics Committee of Tokyo Metropolitan University Hino Campus (R7-014) on [26 May 2025].

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The data that support the findings of this study are openly available on GitHub at <https://github.com/sqwgithub/Piezoelectric-Sensor-with-SFCS> (accessed on 20 October 2025).

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CPHS	Cyber–Physical–Human System
SFCS	Swept Frequency Capacitive Sensing
CNN	Convolutional Neural Network
I/O	Input/Output
CPS	Cyber-Physical Systems
AAL	Ambient Assisted Living
ECG	Electrocardiogram
PZT	Lead Zirconate Titanate
PVDF	Polyvinylidene Fluoride
FDM	Frequency Division Multiplexing
LC	Inductor-Capacitor
PWM	Pulse-Width Modulation
ReLU	Rectified Linear Unit
LSTM	Long Short-Term Memory
BCE	Binary Cross-Entropy
MSE	Mean Squared Error
HIIT	High-Intensity Interval Training
IMU	Inertial Measurement Unit

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