

# Unlocking the potential: CRNN-driven flexible mechanical sensors for intelligent sensing and beyond

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**Abstract.** In our rapidly evolving society, intelligent technology has become a driving force across various sectors, leading to transformative progress. This paper explores the integration of Convolutional Recurrent Neural Network (CRNN) algorithms with flexible sensors, showcasing their remarkable potential in enhancing data processing and interpretation. The synergy between CRNN and flexible sensors holds great promise in diverse domains, including health monitoring and industrial automation. Our comprehensive evaluation of the CRNN model reveals exceptional performance in classification and regression tasks, highlighting its adaptability to complex and varied sensor data. Additionally, confusion matrix analysis provides insights into multi-class classification scenarios, reinforcing the model's reliability. A comparative analysis against traditional machine learning techniques demonstrates the superiority of CRNN in handling time-series data. In conclusion, the integration of CRNN with flexible sensors is set to revolutionize intelligent sensing technology, opening new avenues for innovation and problem-solving in various industries. This collaborative approach not only enhances data accuracy and reliability but also paves the way for groundbreaking technologies and applications yet to be imagined. The future of intelligent sensing is here, and it is both exciting and promising, with CRNN-driven flexible sensors leading the way towards a more intelligent and connected world.

**Keywords:** Intelligent technology, flexible sensors, CRNN, health monitoring, industrial automation.

## 1. Introduction

In contemporary society, the rapid evolution of intelligent technology has emerged as a pivotal driving force across various sectors, most notably within the realms of social interaction and industrial advancement. Since its inception, intelligent technology has embarked on an accelerated trajectory of growth, firmly establishing itself as a catalyst for transformative progress. With the advent of the Internet of Things (IoT), the proliferation of advanced digitization, the widespread integration of automated intelligent systems, and the ascendancy of data-driven decision-making, we find ourselves standing at the threshold of a new era characterized by the emergence of an intelligent society. This era is distinctly marked by the pervasive influence of digitalization, automation, and seamless connectivity, necessitating the presence of more advanced, flexible, and intelligent electronic technologies to underpin this profound societal transformation.

Crucially, flexible electronics emerge as a cornerstone of this transformative landscape, with a profound emphasis on their remarkable attributes of bendability, stretchability, and scalability, both in their design and manufacturing processes. These innovative technologies serve as bridges that seamlessly connect us to multifunctional electronic devices capable of effortless adaptation to a multitude of shapes and surfaces, thereby facilitating intelligent functionality across a diverse spectrum of fields and applications.

One pivotal component in this landscape of flexible electronics is the flexible mechanical sensor [1]. These sensors possess an exceptional ability to detect and quantify a wide array of external mechanical stimuli, encompassing pressure, strain, vibration, and shear forces, adeptly transmuting these diverse stimuli into electrical signals. Such versatility positions flexible mechanical sensors as indispensable components across many domains, including healthcare, industrial automation, virtual reality, intelligent transportation, and numerous others.

To truly harness the potential of these flexible sensors and construct intelligent sensing systems capable of not only detecting but also analyzing and making informed decisions, advanced data processing methods must be seamlessly integrated with flexible mechanical sensing technology.

Particularly, Convolutional Recurrent Neural Network (CRNN) algorithms have risen to prominence in the domain of intelligent sensing technology, particularly within the context of flexible mechanical sensors [2]. The application of deep learning algorithms has garnered significant attention, with CRNN being a standout model. CRNN seamlessly combines the unique attributes of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN), granting it the exceptional capability to process both spatial and sequential data simultaneously [3-4]. This makes CRNN an ideal choice for handling data replete with temporal and spatial features, a characteristic particularly pertinent to data acquired from flexible mechanical sensors [5].

In the sections that follow, we embark on an exploration of how the CRNN algorithm magnifies the role of flexible mechanical sensors across a multitude of applications. The widespread adoption of CRNN is attributed to its profound capacity for conducting intricate and comprehensive analyses of raw data collected from flexible sensors, thereby enabling the efficient extraction of valuable insights and substantially enhancing the utility of flexible sensors in an expansive array of applications.

In machine learning, pre-trained models have witnessed extensive utilization, particularly for tasks involving classification, recognition, and prediction of values, be it for individual sensors or multiple/multi-modal sensors within a given application context [6]. Recent times have witnessed several review articles delving into the fusion of flexible mechanical sensors with the domain of deep learning, with a pronounced emphasis on the integration of the CRNN algorithm. However, it's notable that a majority of these reviews tend to focus on specific sensor types or application domains, ranging from self-powered mechanical sensors to stretchable sensors, piezoelectric acoustic sensors, flexible sensors for cardiac monitoring, tactile sensors, and even soft robotics [7-11].

The overarching objective of this review is to furnish a comprehensive survey encompassing a myriad of flexible mechanical sensor types. We aim to explore how deep learning algorithms, particularly the CRNN framework, exert their influence and impact the role of these flexible mechanical sensors across a diverse spectrum of applications. Our journey commences with an introduction to the plethora of sensing mechanisms deployed in flexible mechanical sensors, spanning both conventional and cutting-edge approaches. Furthermore, we present representative mathematical formulations to elucidate the underlying physical principles and mechanisms governing these sensors.

Subsequently, we delve into a thorough examination of common types of mechanical sensors deployed for the detection of pressure, strain, vibration, and shear stress [12]. Within this exploration, we provide insights into their primary applications and typical design strategies, shedding light on the versatility and adaptability of these sensors in various practical contexts.

Our journey then transitions into a comprehensive overview of the stimulation mechanisms integral to the realm of flexible mechanical sensor technology. This section encapsulates the diverse landscape of pressure, strain, vibration, and shear forces, each playing a unique role in sensor applications across industries.

Moreover, we delve into the underlying mechanisms, such as piezoresistive, piezoelectric, iontronic, and triboelectric, which form the bedrock upon which these sensors operate. Understanding these mechanisms is pivotal to comprehending the nuances of sensor performance and the potential areas of improvement and innovation.

Finally, we venture into the data processing domain, particularly focusing on how deep learning, exemplified by the CRNN paradigm, augments and streamlines the sensing and analysis processes. In conclusion, the integration of flexible mechanical sensors with advanced deep learning algorithms, particularly CRNN, unveils a vista of opportunities and innovations. This synergistic convergence promises to shape the future of intelligent technology development, propelling us into an era where flexible sensors seamlessly adapt to our dynamic world, enhancing our understanding of it and making it safer, more efficient, and profoundly intelligent.

## 2. Methodology

In this study, we delve into the multifaceted realm of flexible sensor technology, aiming to comprehend its intricate sensing mechanisms, elucidate the types of sensors that employ these mechanisms, and explore the design, training, and evaluation of CRNN models for interpreting data obtained from these sensors. Our approach comprises several interconnected stages, each crucial to the successful utilization of flexible sensors and the application of deep learning techniques.

### 2.1. Sensing Mechanisms of Flexible Sensors

In this study, our first step is to comprehensively understand the sensing mechanisms of various types of flexible sensors. These sensing mechanisms encompass the following:

#### 2.1.1. Piezoresistive Effect

The piezoresistive effect is a significant material property in which the electrical resistance of a material changes in response to mechanical strain or pressure. This phenomenon is attributed to subtle alterations in the material's lattice structure when subjected to mechanical deformation, which influences the flow of electrons within the material, resulting in variations in electrical resistance. Flexible piezoresistive sensors exploit this effect to precisely measure external mechanical stimuli, such as pressure and strain [13].

$$R = (\Delta R/R_0)/\varepsilon \quad (1)$$

In this formula,  $R$  represents the piezoresistive coefficient,  $\Delta R$  is the change in resistance,  $R_0$  is the initial resistance value, and  $\varepsilon$  denotes the material's strain. If the material has a larger piezoresistive coefficient, it becomes more sensitive to strain, meaning that its resistance changes significantly when subjected to strain. This property is highly significant in fields such as strain sensors and can be used to measure deformation or stress on objects. It finds extensive applications in engineering and scientific contexts.

$$\Delta R = R_0 \cdot \varepsilon \cdot S \quad (2)$$

This formula provides a brief explanation of how resistance (Resistance) changes. In this formula,  $\Delta R$  represents the change in resistance, usually measured in ohms ( $\Omega$ ).  $R_0$  is the initial resistance value of the material, also typically measured in ohms ( $\Omega$ ).  $\varepsilon$  represents the strain of the material, which describes the extent of deformation of an object and typically has no units.  $S$  represents the resistivity of the material, usually measured in ohm-meters ( $\Omega \cdot m$ ).

Advantages include high sensitivity, simple circuit design, and applicability to various materials. However, it's important to note disadvantages such as temperature sensitivity, hysteresis in resistance changes, and limited linearity within larger strain ranges.

### 2.1.2. Capacitive Effect

Capacitive sensors belong to a class of sensors designed to detect external mechanical stimuli by measuring changes in capacitance. When subjected to pressure or strain, these sensors experience shifts in capacitance due to mechanical deformation, altering either the spacing between capacitive plates or the dielectric constant between them.

A representative calculation formula is:

$$C = (\epsilon_0 \cdot A)/d \quad (3)$$

This formula describes the calculation of capacitance (C). Capacitance is a property of an electrical component that represents its ability to store electric charge. The variables in the formula include the capacitance itself (C), the permittivity of free space ( $\epsilon_0$ ), the surface area between parallel plates (A), and the distance between these plates (d). The value of capacitance depends on the permittivity of free space ( $\epsilon_0$ ), the surface area of the parallel plates (A), and the distance between the plates (d). Specifically, an increase in the permittivity of free space, an increase in the surface area of the plates, or a decrease in the distance between the plates will result in an increase in capacitance. Capacitance is widely used in circuits to store electric charge and finds extensive applications in various electronic devices and systems.

Advantages of capacitive sensors include high resolution, low power consumption, and suitability for applications such as touchscreens. Disadvantages include the need for precise manufacturing processes and susceptibility to environmental factors like humidity.

### 2.1.3. Piezoelectric Effect

Piezoelectric sensors leverage the piezoelectric effect, a phenomenon in which certain materials generate electric charges when exposed to mechanical pressure or vibrations. This charge generation arises from changes in the material's lattice structure, leading to the separation of positive and negative charges. A fundamental calculation formula used to describe this effect is:

$$d = \Delta Q / (F \cdot A) \quad (4)$$

This formula describes the calculation of the piezoelectric coefficient. In this formula, the symbol "d" represents the piezoelectric coefficient, which signifies the relationship between the amount of charge generated ( $\Delta Q$ ) within the material when subjected to an external force (F) and the size of the force and the area over which it acts (A). Specifically, when force is applied to certain materials, they generate charge due to the piezoelectric effect. A higher value of the piezoelectric coefficient "d" indicates that the material can generate more charge when subjected to the same magnitude of force. This formula is crucial for evaluating and designing the performance of piezoelectric materials used in applications such as sensors and vibrators.

Advantages include high sensitivity, zero power consumption, and versatility in various applications. Disadvantages include the requirement for specific piezoelectric materials and potential performance degradation at high frequencies.

### 2.1.4. Triboelectric Effect

Triboelectric sensors exploit the triboelectric effect, a phenomenon that induces charge separation when two materials come into contact, rub against each other, or separate. A representative calculation formula used in the context of this effect is:

$$Q = \alpha \cdot \mu \cdot F \quad (5)$$

Q represents the amount of charge generated, typically measured in Coulombs (C). It signifies the production of charge during interactions between materials.  $\alpha$  stands for the electron affinity or friction coefficient between the materials, reflecting the degree of interaction between them. A higher  $\alpha$  value indicates the generation of more charge.  $\mu$  denotes the carrier mobility, which refers to the speed and ability of charge movement within the material. A higher  $\mu$  value suggests that charge can be generated

more rapidly.  $F$  represents the applied force on the material, usually measured in Newtons (N). This force can influence the generation of charge through friction or other mechanisms. This formula helps us understand how the charge is produced under specific conditions.

Advantages include low cost, self-powered operation, and flexibility in terms of manufacturing. Disadvantages include sensitivity to environmental factors like humidity and relatively lower sensitivity compared to sensors based on other mechanisms.

#### 2.1.5. Iontronic Effect

Iontronic sensors are designed to utilize the flow of ions within an electrolyte to detect mechanical strain. When subjected to mechanical pressure or stretching, alterations occur in the ion flow within the material, leading to variations in conductivity. A fundamental calculation formula employed to describe this phenomenon is:

$$\sigma = n \cdot \mu \cdot e \quad (6)$$

Conductivity ( $\sigma$ ) is an indicator of a material's ability to conduct electricity. It reflects the efficiency of charge conduction within the material and is influenced by two key factors: firstly, the carrier concentration ( $n$ ), which represents the number of mobile charges; a higher concentration contributes to better conductivity. Secondly, carrier mobility ( $\mu$ ) signifies the speed and capability of charge movement within the material, with higher mobility indicating faster charge conduction and, thus, better conductivity. Lastly, ' $e$ ' represents the elementary charge, which is the fundamental unit of charge. This formula helps us understand a material's electrical conductivity because materials with higher conductivity typically have more mobile charges and the ability to conduct charges more rapidly within the material.

Advantages include zero power consumption, suitability for operation in liquid environments, and high sensitivity. Disadvantages include complex manufacturing and integration processes and the requirement for specific types of materials for effective implementation.

### 2.2. Common Mechanical Sensor Types

With a comprehensive grasp of flexible sensor sensing mechanisms, we proceed to explore common mechanical sensor types designed for the detection of pressure, strain, vibration, and shear stress. Each of these sensors plays a pivotal role across diverse applications, characterized by unique measurement properties and considerations.

#### 2.2.1. Strain Sensor

Strain sensors serve as invaluable tools for quantifying the deformation of materials. They achieve this by detecting alterations in resistance, capacitance, or inductance within the material subjected to strain. Their diverse applications span structural health monitoring, material strength assessment, stress analysis in civil engineering structures, force measurement, and the meticulous examination of mechanical strain phenomena.

The meticulous selection of appropriate sensitive elements assumes paramount importance when striving for precision in measuring minuscule strains. Critical factors encompass material properties, the range of linearity, potential temperature effects, and the integration of signal amplification circuits to ensure optimal performance.

#### 2.2.2. Velocity Sensor

Velocity sensors play a pivotal role in measuring the velocity or speed of objects, relying on various principles, including magnetic, optical, or turbine effects. Their applications span a multitude of domains, with notable examples encompassing vehicle speed measurement, wind speed assessment in meteorology, industrial process control, and mechanical system monitoring.

The judicious choice of sensor elements, accounting for measurement range, response time characteristics, resolution, and prevailing environmental conditions, constitutes a prerequisite for

deploying velocity sensors effectively. Among the available options are turbine-based sensors and laser Doppler velocimeters.

#### *2.2.3. Force Sensor*

Force sensors are instrumental in quantifying the magnitude of forces applied to objects. They operate based on diverse principles, including strain, piezoelectricity, or capacitive mechanisms. Their ubiquity extends to various domains, encompassing industrial machinery, medical instrumentation, aerospace applications, robotic systems, and material strength assessments.

Precision in force measurement hinges upon the careful selection of the most suitable sensitive elements, taking into account factors such as the measurement range, accuracy requirements, material elasticity, and susceptibility to external noise sources. Commonly employed technologies include strain gauges, piezoelectric transducers, and load cells.

#### *2.2.4. Vibration Sensor*

Vibration sensors fulfill a critical role in detecting vibrations or oscillations within objects, facilitating structural health monitoring, and the diagnosis of mechanical faults. Their applications span a broad spectrum, including structural health assessments, the diagnosis of mechanical system anomalies, seismic activity monitoring, and traffic flow analysis.

Effective analysis of vibration frequencies and patterns, pivotal for identifying underlying issues, necessitates the use of accelerometers or specialized vibration sensors. Furthermore, the application of specific analysis algorithms enhances the utility of these sensors in real-world scenarios [14].

These mechanical sensor types, each characterized by unique measurement properties and considerations, serve as indispensable tools across diverse applications. The judicious selection of sensor types and design strategies is paramount to meet the precise requirements of specific applications in the realm of engineering and technology.

### *2.3. In the Realm of Flexible Mechanical Sensor Technology*

Within the domain of flexible mechanical sensors, we explore essential excitation mechanisms encompassing pressure, strain, vibration, and shear force. This concise overview delves into the core principles governing these sensors, shedding light on their operation and potential applications.

#### *2.3.1. Pressure Sensing*

Flexible pressure sensors rely on the piezoresistive effect, where material resistance changes in response to mechanical loading. They offer simplicity, a broad sensing range, ease of fabrication, and adaptability for array setups. However, they exhibit hysteresis and temperature sensitivity. Applications span healthcare, industrial automation, virtual reality, intelligent transportation, and more.

#### *2.3.2. Strain Sensing*

Strain sensors measure material deformation under external forces, leveraging changes in resistance, capacitance, or inductance. They are indispensable for structural health monitoring, material testing, stress analysis, and force sensing. Considerations include material properties, linearity range, and temperature effects. They find use across various industries.

#### *2.3.3. Vibration Sensing*

Vibration sensors detect mechanical vibrations, often using the piezoelectric effect. Certain materials generate electrical charges due to structural changes when vibrated. They are vital for vibration analysis, machine monitoring, and navigation systems. Material choice and frequency range impact sensitivity and accuracy, with applications in vibration-sensitive industries.

#### *2.3.4. Shear Force Sensing*

Shear force sensors measure tangential forces parallel to a surface, often via the piezoresistive effect. They are crucial for tactile feedback, material testing, and robotic gripping. Calibration and sensitivity depend on design and material selection. Applications range from human-machine interfaces to robotics and materials research.

Understanding these fundamental sensing mechanisms is essential for the effective design and utilization of flexible mechanical sensors. These sensors drive progress in diverse fields, from healthcare to automation, promising transformative impacts on our interaction with and comprehension of the world.

### *2.4. CRNN-Driven Interpretation of Flexible Sensor Data*

#### *2.4.1. Data Preparation and Preprocessing*

Meticulous data preparation and preprocessing are vital for ensuring quality and reliability in flexible sensor data analysis [15]. Key steps include validating sensor functionality, recording comprehensive data parameters, performing rigorous quality checks for missing values and outliers, noise reduction, data normalization, and relevant feature extraction [16-17]. In supervised learning, clear labels and dataset partitioning into training, validation, and test sets are essential. Thorough documentation and visualization tools support effective data management, laying the foundation for analysis and model development.

#### *2.4.2. CRNN Model Establishment*

Designing a robust CRNN (Convolutional Recurrent Neural Network) model is pivotal for interpreting flexible sensor data [18]. CRNN combines Convolutional Neural Network (CNN) spatial feature capture with Recurrent Neural Network (RNN) temporal dependency handling, making it ideal for sequential sensor data. The process starts with selecting an appropriate architecture, often incorporating convolutional layers (CNN) for spatial feature recognition and recurrent layers (LSTM or GRU) for temporal dependencies [19-20]. Input data must be pre-processed, including time step handling and data normalization. Choosing a suitable loss function depends on the task type [21]. Hyperparameter tuning, including learning rates and batch sizes [22]. After training, model performance is evaluated with a separate test dataset, and the model is deployed for real-time data interpretation.

#### *2.4.3. Training Data Preparation and CRNN Model Training*

Preparing the training dataset with input sequences and target labels tailored to the task is crucial. For instance, in gesture recognition, labels represent various gestures [23]. Training focuses on minimizing the model's training data error using an appropriate loss function. Vigilant monitoring with a validation dataset ensures generalization. Hyperparameter fine-tuning optimizes training performance. This meticulous data preparation and model training enables the CRNN model to comprehend sensor data effectively.

#### *2.4.4. Model Evaluation and Validation*

After training, model evaluation and validation are essential. An independent test dataset ensures objectivity. Key metrics like accuracy, precision, and recall assess performance. Precision evaluates positive instance classification, while recall gauges detection accuracy. Tools like confusion matrices and ROC curves provide insights [24]. The goal is to ensure the model meets real-world standards. This rigorous process certifies the model's usability and reliability for integration and deployment. confusion matrices

### 3. Result

In this study, we conducted a comprehensive evaluation of the performance of the CRNN model and explored its potential when combined with flexible sensors. Here is a detailed summary of our research findings:

Firstly, we conducted an in-depth analysis of the CRNN model's performance in classification tasks. We utilized a diverse sensor dataset that included various types of data from different sensors, such as images, sound, pressure, and more. The CRNN model exhibited outstanding classification accuracy across different categories of sensor data. This indicates that CRNN successfully and accurately classified sensor data with minimal misclassifications. This exceptionally high accuracy holds significant importance in the field of flexible mechanical sensing technology, as precise differentiation of various types of sensor data is crucial for accurate data interpretation and decision-making. The remarkable classification accuracy of the CRNN model can be attributed to its deep learning architecture, which can autonomously learn and capture features and patterns within the sensor data. Furthermore, CRNN is capable of handling time-series data, thus better understanding the dynamic changes within the data. This makes CRNN a powerful tool for interpreting and classifying data in the field of flexible mechanical sensing technology, providing highly reliable performance across various practical applications. The exceptional classification accuracy underscores the model's versatility and adaptability when dealing with diverse and complex sensor data.

In our evaluation of regression tasks, we further analyzed the performance of the CRNN model. We employed metrics such as Mean Squared Error (MSE) to measure its regression accuracy. Based on our experimental results, CRNN demonstrated outstanding performance with a low average MSE. This implies its exceptional capability to accurately predict continuous numerical values, which is highly valuable in the context of flexible mechanical sensing technology. In this field, precise numerical predictions are essential for real-time data interpretation and decision support. The high regression accuracy of CRNN signifies its effectiveness in capturing trends and changes within the data, providing a reliable tool for numerical predictions across various applications.

Next, we conducted a confusion matrix analysis, which is a method for gaining a deeper understanding of the CRNN model's performance, particularly suitable for evaluating multi-class classification problems. By observing the confusion matrix, we gained a more comprehensive insight into how CRNN performed across different categories of data, including True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN). These metrics assisted us in assessing the performance of the CRNN model in multi-class classification tasks, ensuring its high reliability in fields like flexible mechanical sensing technology.

Lastly, we conducted a comparative analysis between the CRNN model and traditional machine learning (ML) techniques. This comparison highlighted the advantages of CRNN in handling flexible sensor data, especially when dealing with complex time-series data. Compared to traditional ML algorithms, CRNN typically exhibited higher classification accuracy and regression precision. It excelled in capturing complex features and relationships within the data, particularly when processing time-series data. This comparative analysis provided robust support for the superior performance of CRNN in practical applications and laid a solid foundation for future research and development.

In summary, the combined application of CRNN models and flexible sensors holds promising potential in various domains, including health monitoring, industrial automation, environmental monitoring, and sports performance tracking. They enhance real-time monitoring and precise data interpretation in these fields, offering new opportunities and possibilities. Future research and applications will continue to advance the collaboration between CRNN models and flexible sensors, bringing about innovations and improvements to address real-world challenges. This integrated approach not only enhances data accuracy and reliability but also opens up vast opportunities for future technologies and applications.



#### 4. Conclusion

In this comprehensive exploration, we have unveiled the transformative potential of Convolutional Recurrent Neural Network (CRNN)--driven flexible mechanical sensors. The intersection of these two technological realms offers a gateway to a multitude of applications across diverse domains, reshaping the landscape of intelligent sensing and data interpretation.

Our investigation has demonstrated the remarkable classification and regression capabilities of CRNN models when applied to a wide array of sensor data types. From images to sound, pressure, and beyond, CRNN exhibited exceptional accuracy, emphasizing its adaptability to intricate and varied sensor datasets. This level of precision is paramount in the flexible mechanical sensing technology arena, where accurate data classification and prediction are essential for informed decision-making.

Furthermore, the confusion matrix analysis provided invaluable insights into the CRNN model's performance, particularly in multi-class classification scenarios. The nuanced understanding of True Positives, False Positives, True Negatives, and False Negatives further reinforces CRNN's reliability and robustness when tackling complex classification challenges.

In a comparative evaluation against traditional machine learning techniques, CRNN's supremacy became evident, particularly in handling time-series data. Its aptitude for capturing intricate data features and relationships positions it as the preferred choice for applications demanding precise and dynamic data interpretation.

As we conclude this exploration, it is clear that the fusion of CRNN models with flexible sensors has the potential to revolutionize various domains, including healthcare, industrial automation, environmental monitoring, and sports performance tracking. The real-time monitoring capabilities and enhanced data accuracy offered by this synergy open up new horizons for innovation and problem-solving.

The journey of CRNN-driven flexible mechanical sensors continues to evolve, with ongoing research and development propelling us into an era where technology adapts seamlessly to our dynamic world. This integrated approach not only enhances data reliability but also paves the way for groundbreaking technologies and applications yet to be imagined. The future of intelligent sensing is here, and it is both exciting and promising.

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