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RESEARCH ARTICLE

A Novel Pattern Recognition Method for Self-Powered TENG Sensor Embedded to the Robotic Hand

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ABSTRACT This paper presents the development and implementation of a human-like robotic hand integrated with advanced triboelectric nanogenerator (TENG) based tactile sensors for shape and material recognition. Meanwhile, traditional piezo sensors' effectiveness is limited, sensitive to the temperature, and the manufacturing cost is high. TENG sensors offer a self-powered alternative with simplified circuitry, cost-effective fabrication, and enhanced durability. To capitalize on these benefits, we propose a novel machine learning approach that represents time-series data as two-dimensional images processed using a two-dimensional convolutional neural network (2D CNN). This method is compared against the traditional one-dimensional convolutional neural network (1D CNN) method. The research methodology encompasses TENG sensor preparation, noise cancellation, robotic hand design, and control electronics. Experimental results demonstrate that the proposed 2D CNN method significantly improves shape and material recognition accuracy, achieving 98% and 99%, respectively, compared to 94% and 98% with the 1D CNN method. Real-time evaluation further validates the robustness and adaptability of the proposed model in unstructured environments. These findings underscore the potential of integrating TENG sensors with advanced neural network architectures for autonomous dexterous manipulation in various industrial applications, paving the way for future advancements in robotic tactile sensing.

INDEX TERMS Dataset collection, machine learning, robot hand design, signal processing, TENG sensor.

I. INTRODUCTION

The development of advanced tactile sensors is pivotal for enhancing robotic hand capabilities, particularly in terms of shape and material recognition. Among various types of sensors, triboelectric nanogenerators (TENGs) have emerged as a promising alternative to traditional piezoelectric sensors. TENGs offer several advantages, including self-powering capability [1], [2], [3], [4], [5], cost-effective fabrication [6], and enhanced durability [7], [8]. These benefits make TENGs highly suitable for applications in autonomous dexterous manipulation and human-like robotic hands.

While effective, traditional piezoelectric sensors have limitations such as sensitivity to temperature variations and high manufacturing costs. TENG sensors, on the other hand, harness the triboelectric effect to generate electrical signals from mechanical stimuli [1], providing a robust and economical solution for tactile sensing. Integrating TENG sensors into robotic systems can significantly improve their ability to detect and respond to physical interactions with the environment. Wang's pioneering work has laid the foundation for TENG technology, highlighting its potential in various applications [9], [10], [11].

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It has been proven that conventional machine learning algorithms involves signal processing technique and the accuracies, that they achieve in classification tasks using TENG tactile sensors, start from almost 91% [12], [13]. In addition to that, conventional machine learning (ML) methods for signal processing in tactile sensing often involve one-dimensional convolutional neural networks (1D CNNs) [14], [15], [16], [17]. These methods analyze sequential data, capturing temporal patterns within the signal. In addition to that, the recent work done on classification problem involving TENG sensor has demonstrated an 82% accuracy using one-dimensional signal processing technique [18]. However, 1D CNNs may not fully exploit the spatial information embedded in the sensor data, potentially limiting the accuracy and robustness of the recognition system [19], [20], [21]. Futhermore, it has been demonstrated that two-dimensional convolutional neural networks (2D CNNs) outperform 1D CNNs in terms of accuracy [22]. It was also shown that 3D LSTM signal processing model could achieve an accuracy of 94.1-99.2% in classification task that involves a TENG based tactile sensor [23]. However, increasing the dimensionality of the input data may require a larger dataset as well as computational power increment.

To address these limitations, this study proposes a novel approach that transforms time-series data from TENG sensors into 2D images processed using 2D CNNs. This method leverages the spatial hierarchies and patterns present in the data, enabling more accurate and reliable shape and material recognition. The 2D CNNs have shown superior performance in various image processing tasks [24], [25], [26], [27], [28], making them an ideal choice for this application. Pioneers emphasized the advantages of 2D CNNs in processing image-based data [24], which aligns well with the spatial nature of TENG sensor data.

Deep learning methods, such as CNN, have revolutionized various fields, including image recognition and fault diagnosis [24], [25]. The hierarchical structure of 2D CNNs allows them to capture complex patterns and spatial hierarchies in the data, leading to improved performance over traditional methods [29], [30]. For instance, it was demonstrated the effectiveness of 2D CNNs in diagnosing faults in rotating machinery [31], showcasing the potential of these networks in different applications.

The integration of TENG sensors with advanced neural network architectures, particularly 2D CNNs, provides a robust solution for the enhancement of robotic tactile sensing. This study builds on the foundational work of experts in the field to develop a robotic hand with the capacity for accurate shape and material recognition, analogous to that of a human hand. This paper presents the development and implementation of a robotic hand that is capable of replicating the dexterous movements and sensory capabilities of the human hand, and which is integrated with advanced TENG-based tactile sensors. Although previous works have demonstrated the effectiveness of both TENG sensors and CNN-based methods for tactile recognition, few studies have explored transforming signal based sensor data into two-dimensional representations (images) for improved accuracy and robustness. By introducing a novel Image-based pattern recognition method and applying it to TENG sensor data, this study addresses this gap and establishes a new benchmark for tactile sensing in robotic applications. A comparison is presented between the performance of the proposed image recognition method and that of the traditional signal processing method, demonstrating a significant improvement in recognition accuracy. The research methodology encompasses the preparation of TENG sensors, the cancellation of noise, the design of the robotic hand, and the design of control electronics. The experimental results validate the robustness and adaptability of the proposed model in unstructured environments, thereby underscoring the potential of integrating TENG sensors with advanced neural network architectures for a variety of industrial applications.

II. RESEARCH METHODOLOGY

This section will provide a detailed, step-by-step account of the process of developing a TENG sensor, together with a comprehensive description of the methodology involved in the construction of a robotic hand. Subsequently, the paper will present the methodology that employs a well-established machine learning algorithm and offer a comparison with the proposed approach.

A. PREPARATION OF A TENG SENSOR

In order to prepare the TENG sample, Ecoflex® 00-30 was used as a polymer. This was obtained from Smooth-On, Inc., United States. The specific gravity of the material is 1.07 g/cc, and its working time is 45 minutes.

Firstly, a rectangle was excised from the carbon cloth with dimensions of 16 mm × 50 mm (Fig. 1a). Secondly, the copper wire was affixed to the carbon cloth along its central axis using a needle. This step was undertaken to enhance the connection between the wire and the carbon cloth, provide insulation for the connected wire, and reinforce the sensor.

Following the cutting and sewing of the carbon cloth, it was positioned within a three-dimensionally printed PLA mould, extended from both extremities and secured by means of plastic plates. This was done in order to apply tension to the carbon cloth, thereby ensuring an even distribution of Ecoflex on both surfaces during the curing process.

In order to prepare the Ecoflex, the two components, designated as A and B, were combined in a 1:1 volumetric ratio. The resulting mixture was then subjected to a vacuum treatment at a temperature of 25°C, with the objective of eliminating any air bubbles that might have formed. (Fig. 1c).

Subsequently, the Ecoflex was poured into the mold containing the carbon cloth and left for curing over a period of four hours (Figure 1). Upon completion of the curing process, any excess carbon cloth was trimmed and the sensor was shaped using a surgical knife to the dimensions of a specific phalanx. Finally, the prepared sample was affixed to the top of the plastic phalanx using super glue.

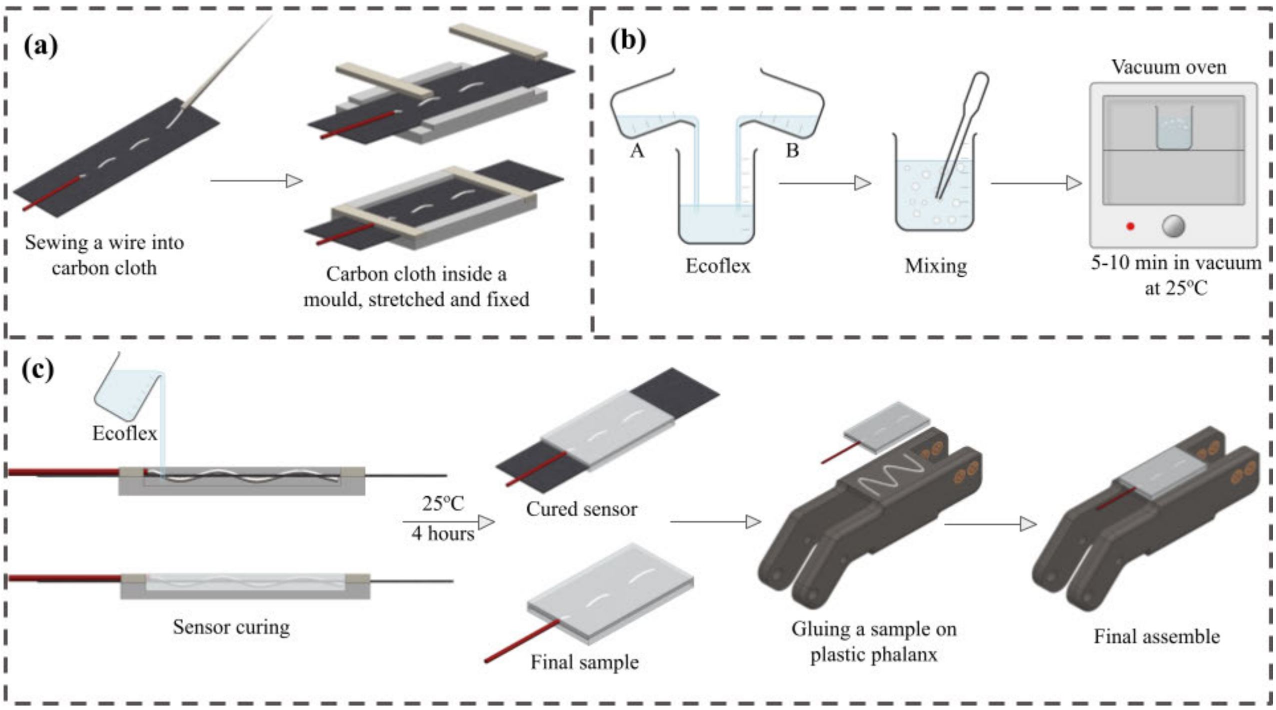

FIGURE 1. TENG sensor preparation.

B. NOISE CANCELLATION

The output voltage readings from the sensors were recorded using an Arduino Mega 2560. In the initial configuration, all 12 sensors were connected to the analog input pins of the Arduino (Fig. 2a). The data obtained through this configuration is illustrated in Graph A of Fig. 2a. Given that the sensor is a single-electrode TENG, it is highly susceptible to external influences, and can generate a considerable amount of noise even in the absence of physical contact with a surface.

In order to circumvent such a phenomenon and to filter the data in a more efficacious manner for the purposes of more efficient machine learning training, a new setup for gathering data was constructed. As illustrated in Fig. 2b, three Arduino Mega 2560 units were employed. Each Arduino was connected to four sensors via its analog input pins, in the following sequence: The aforementioned sensors were designated as A1, A4, A7, and A10. The remaining analog input pins were connected to the ground pin. Additionally, a script was employed to sequentially read all the analog input pins within the void loop, after which the inputs obtained from the sensors were utilized. This resulted in a notable reduction in noise, the prevention of interference between neighboring sensors, and the ability of the sensors to respond when in contact with an object's surface (Fig. 2b).

C. DESIGN AND ASSEMBLY OF ROBOTIC HAND

The robotic hand is anatomically analogous to the human hand, comprising four fingers, with the exception of the thumb. Each finger is composed of three distinct phalanges: a distal phalanx, a middle phalanx, and a proximal phalanx. These phalanges are interconnected by rotational joints (Fig. 3c). The fingers are actuated by a 12 V linear actuator with a load capacity of 200 N. The range of motion of the finger is illustrated in Fig. 3b. The linear actuator exerts a force on the proximal phalanx, and the two link bars facilitate the motion of the entire finger, which is comparable to the trajectory of a human finger. TENG sensors are scaled to the dimensions of each phalanx (Fig. 3a). Sensors are positioned on both the distal and proximal phalanges of each finger. However, the sensors on the middle phalanx of the two middle fingers are of a greater length, due to the fact that these phalanges are 10 mm longer than those on the other two fingers.

The robotic hand is powered by the Arduino Mega 2560 (see Fig. 4). Given that the linear actuators operate at 12 V, DC motor drivers are connected to a 12 V external power supply. Furthermore, the system incorporates an INA 226 current sensor, which facilitates the automation of data collection. The sensor is designed to perform continuous monitoring of the current output from the power supply. Upon contact with an object, the current consumption of the hand will increase. The increase in current is gauged by the INA 226, which then prompts the actuators to halt their movement to prevent the hand from reaching its fullest extent of closure.

D. SENSOR CALIBRATION

To ensure accurate and repeatable voltage measurements, the TENG sensors underwent a calibration procedure prior to

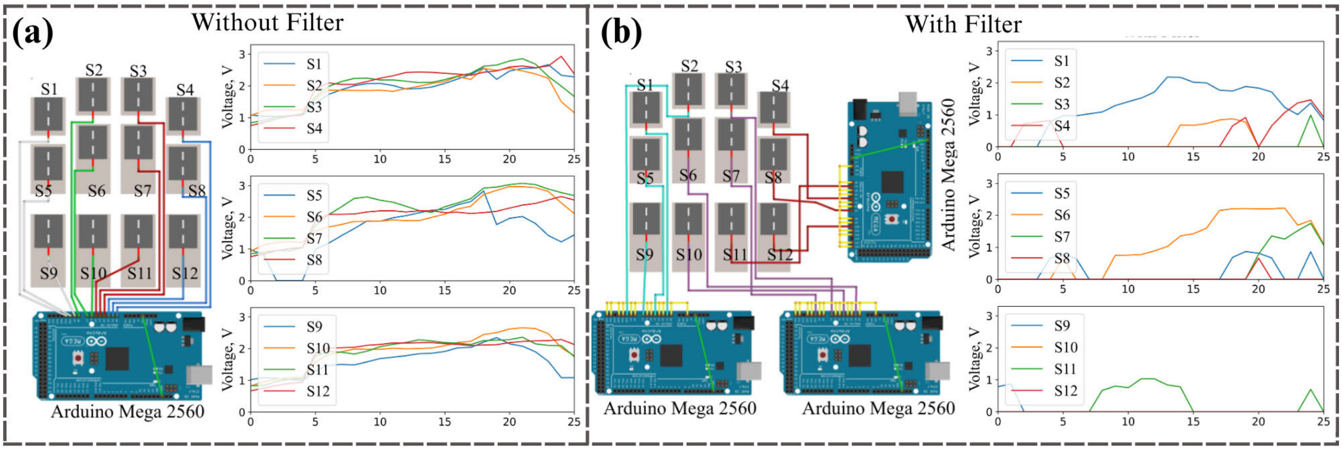

FIGURE 2. Data collection setup without and with noise filtering.

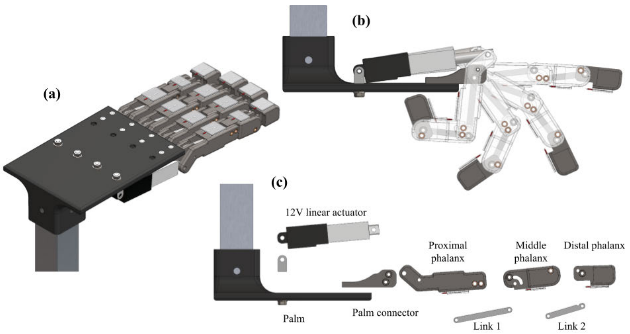

FIGURE 3. CAD design of a robotic hand.

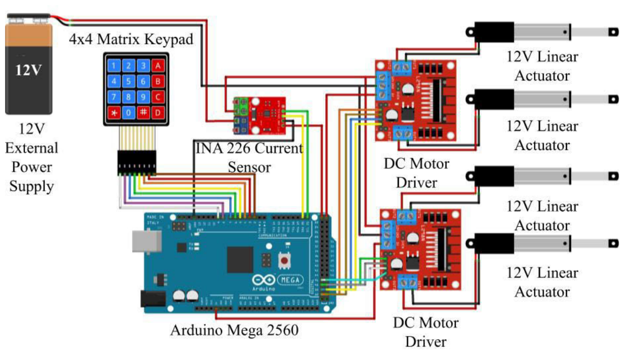

FIGURE 4. Robotic hand electronic schematics.

integration into the robotic hand. First, a series of known forces (ranging from 0.5 N to 5 N) were applied to the sensor surfaces using a laboratory-grade force gauge. The resulting voltage outputs were recorded, averaged, and plotted to establish a force-to-voltage response curve. This reference curve was then used to adjust raw sensor outputs during data collection, mitigating any initial offset or drift. In addition, the calibration involved verifying each TENG unit against a standard reference voltage of 3.3 V to confirm consistency across all twelve sensors. Overall, this calibration routine helped ensure that sensor outputs remained comparable, even when replacing or re-mounting sensors on different phalanges.

III. EXISTING MACHINE LEARNING METHOD: SIGNAL PROCESSING

A. DATA COLLECTION AND PREPROCESSING

Following the fabrication of the robotic hand, the data was obtained from the integrated TENG sensors for subsequent shape and material identification.

In the existing method, data is collected using a TENG sensing device mounted on a robotic hand setup, which gathers voltage readings from the sensors. Approximately 160,000 points of sequential data readings were collected for each shape, with a maximum reading of 3.3 V. It was observed that, even with a noise cancellation setup, the sensors registered contacts when the hand was not in contact with any object. The presence of noise in the sensor data necessitated the establishment of a threshold to differentiate between actual contact and background readings. A threshold of 1.55 V was established, whereby any sensor reading exceeding this value was deemed indicative of contact with an object. The filtering process resulted in a reduction of the dataset to approximately 31,000 sequential points for each shape.

Subsequently, the sequences were divided into smaller segments. Each segment represented a list of 12 consecutive points in sequence. A total of 144 points were obtained by considering 12 such lists as one batch. It should be noted that the aforementioned batches represent a set of one-dimensional signals.

The batches were represented as line plots, which depicted the intensity at each sensor point and were indicative of the normalized voltage readings from the sensors (Fig. 5a). The visualization process facilitated the display of patterns associated with each shape, which is a crucial aspect for the neural network to distinguish between them.

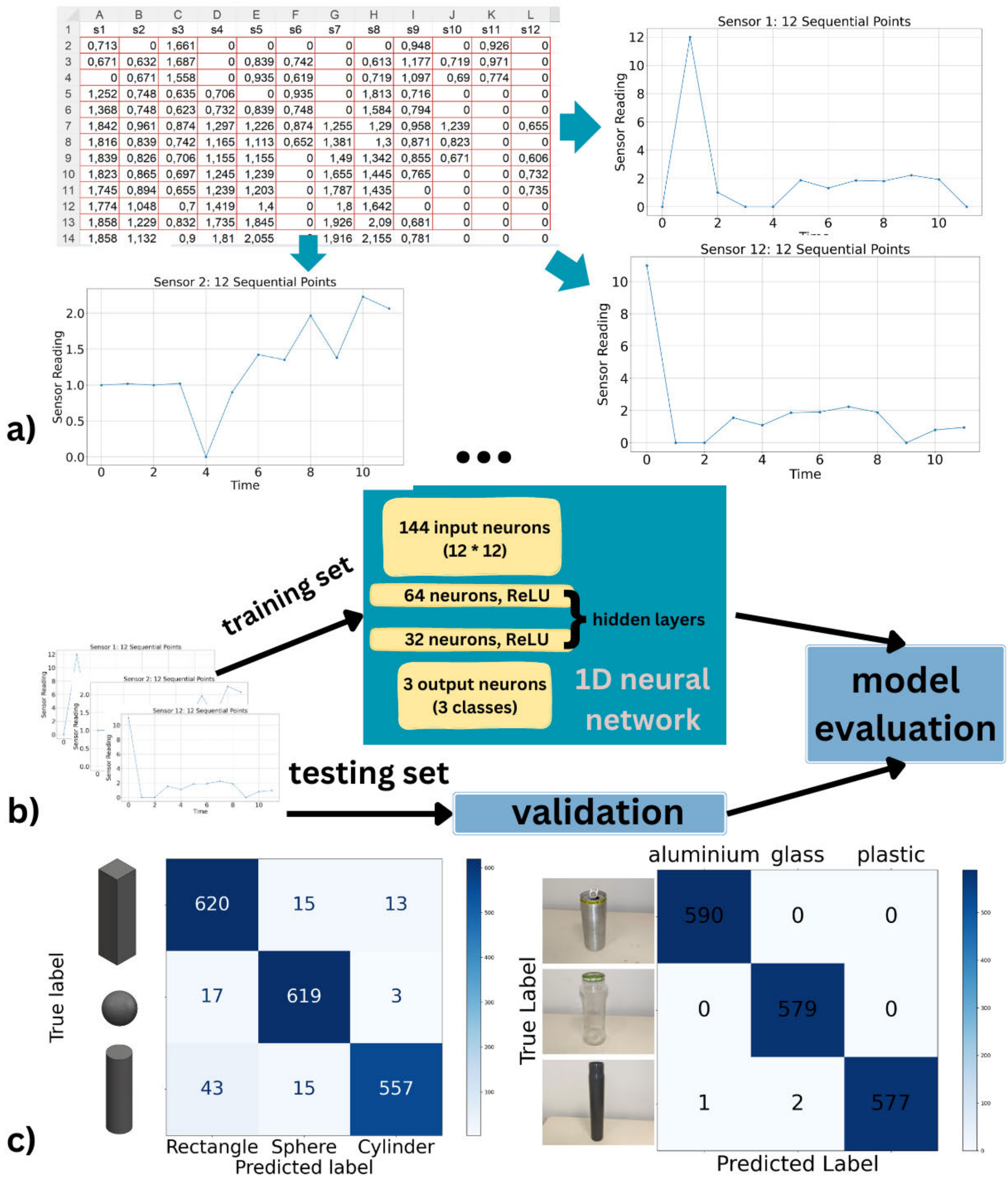

FIGURE 5. (a) Data collection and plotting process. (b) 1D convolutional network architecture. (c) Confusion matrix showing the overall accuracy of the model.

B. MODEL TRAINING AND EVALUATION

The existing method utilized a one-dimensional neural network (1D NN) for the processing of these sequences. The architectural design incorporated layers that processed the sequences, thereby maintaining the temporal relationships inherent within the data. The model was constructed using the Adam optimizer and sparse categorical cross-entropy as the loss function, as illustrated in (Fig. 5b).

The performance of the trained model was evaluated using a confusion matrix (Fig. 5c). To validate the performance of the trained model accuracy scale was used by calculating it as follows:

$$\text{Accuracy} = \frac{\text{TP}_{\text{cylinder}} + \text{TP}_{\text{rectangle}} + \text{TP}_{\text{sphere}}}{\text{Total number of samples}},$$

where TP stands for the true label of specified shape. After substituting the numbers coming from confusion matrix

(Fig. 5c) for both shape and material classification problem, the resulting accuracy is 94% for shape recognition and 99% for material recognition.

IV. PROPOSED MACHINE LEARNING METHOD: IMAGE PROCESSING

A. DATA COLLECTION AND PREPROCESSING

In the proposed method, data is collected in a similar manner using the TENG sensing device on the robotic hand setup. The collected data is subjected to a thresholding process in order to filter out noise. The threshold is set at 1.55 V, with the objective of distinguishing actual contact from background readings. This results in a dataset comprising approximately 31,000 sequential points for each shape (Fig. 6a).

Subsequently, the sequential data is segmented into 12×12 matrices, which represent a snapshot of the sensor data over a brief period of time. The matrices are then visualized as grayscale images and normalized by dividing them by the maximum voltage value (3.3 V), resulting in values between 0 and 1.

The 12×12 matrices were visualized as grayscale images, displaying the intensity at each pixel and indicating the normalized voltage reading from the sensors. This visualization revealed patterns associated with each shape, which were essential for the neural network to distinguish between them. (Fig. 6b).

B. MODEL TRAINING AND EVALUATION

The proposed method utilized a two-dimensional neural network (2D NN) for the processing of the 12×12 images. The proposed method employed a two-dimensional neural network (2D NN) comprising convolutional layers that learned spatial hierarchies and patterns from the input images. These were followed by pooling and dense layers that further refined the learned features for accurate classification (Fig. 6c).

The architecture comprised the following principal layers:

1) **Convolutional Layers**: These applied convolution filters to the input images while retaining local patterns and features. The model used 32 filters with a 3×3 kernel size, followed by ReLU activation functions to introduce non-linearity.
2) **Pooling Layers**: Max-pooling layers performed down-sampling by decreasing the spatial dimensions of feature maps derived from convolutional layers, preserving crucial information.
3) **Flatten Layers**: The 2D feature maps were flattened to turn them into one-dimensional vectors, preparing them for the following fully connected layers.
4) **Dense Layers**: Integration of features to make a prediction was done by dense layers. The model consisted of a dense layer of 64 neurons, followed by an output layer with three neurons corresponding to the number of classes of shapes or materials.

The model was compiled using the Adam optimizer and categorical cross-entropy as the loss function and the performance of the trained model was evaluated using a confusion matrix6d). The accuracy metric was used in the similar way as it was the case for existing machine learning method by the help of the same formula:

$$\text{Accuracy} = \frac{\text{TP}_{\text{aluminum}} + \text{TP}_{\text{glass}} + \text{TP}_{\text{plastic}}}{\text{Total number of samples}},$$

where TP stands for the true label of specified material and the same formula could be used for shape recognition by replacing the material classes with the shape classes. The proposed method demonstrated an accuracy of 98% in shape recognition and 99% in material recognition.

V. EXPERIMENT AND RESULTS

This section evaluates the performance of the proposed method for shape and material recognition using TENG sensors. Figures 7 and 8 provide detailed visualizations of the experimental results that demonstrate, graphically, our approach to the distinctness of different shapes and materials.

A. SHAPE RECOGNITION

To validate the model, a real-time Python code was constructed to continuously read the output voltages generated by the TENG-integrated robotic hand. Only those entries that satisfied the specified threshold values were retained in the recorded data set. Once the requisite 12 by 12 entries had been obtained, the algorithm proceeded to construct a suitable grayscale image, which was then subjected to analysis by the trained model. Subsequently, the model provided real-time predictions.

Fig. 7 illustrates the recognition patterns for three shapes: a sphere, a cylinder, and a rectangle. The figure illustrates the recorded intensity distributions obtained during the probing of the aforementioned shapes with TENG sensors. It is evident that the distinctive shapes of the objects under examination yield patterns that facilitate enhanced accuracy in shape recognition.

A more detailed examination of the graphical representation in Fig. 7 reveals that the first and second sensors exhibit comparable behavior over time during the grasping process. However, the remaining sensors demonstrate a diversity of output. Moreover, the complete absence of data in the second column, as illustrated in Fig. 7, lends further support to this assertion. In sum, the 12 by 12 images generated by our algorithm offer a comprehensive and perspicacious view of the distinctive patterns exhibited by each shape.

B. MATERIAL IDENTIFICATION

In order to validate the material identification, a similar process was employed to that used for shape recognition. In this instance, the robotic hand was utilized to grasp cylindrical objects comprising aluminum, glass and plastic. To this end, our team undertook training of the various models, utilizing a dataset derived exclusively from the data collected during the holding of materials.

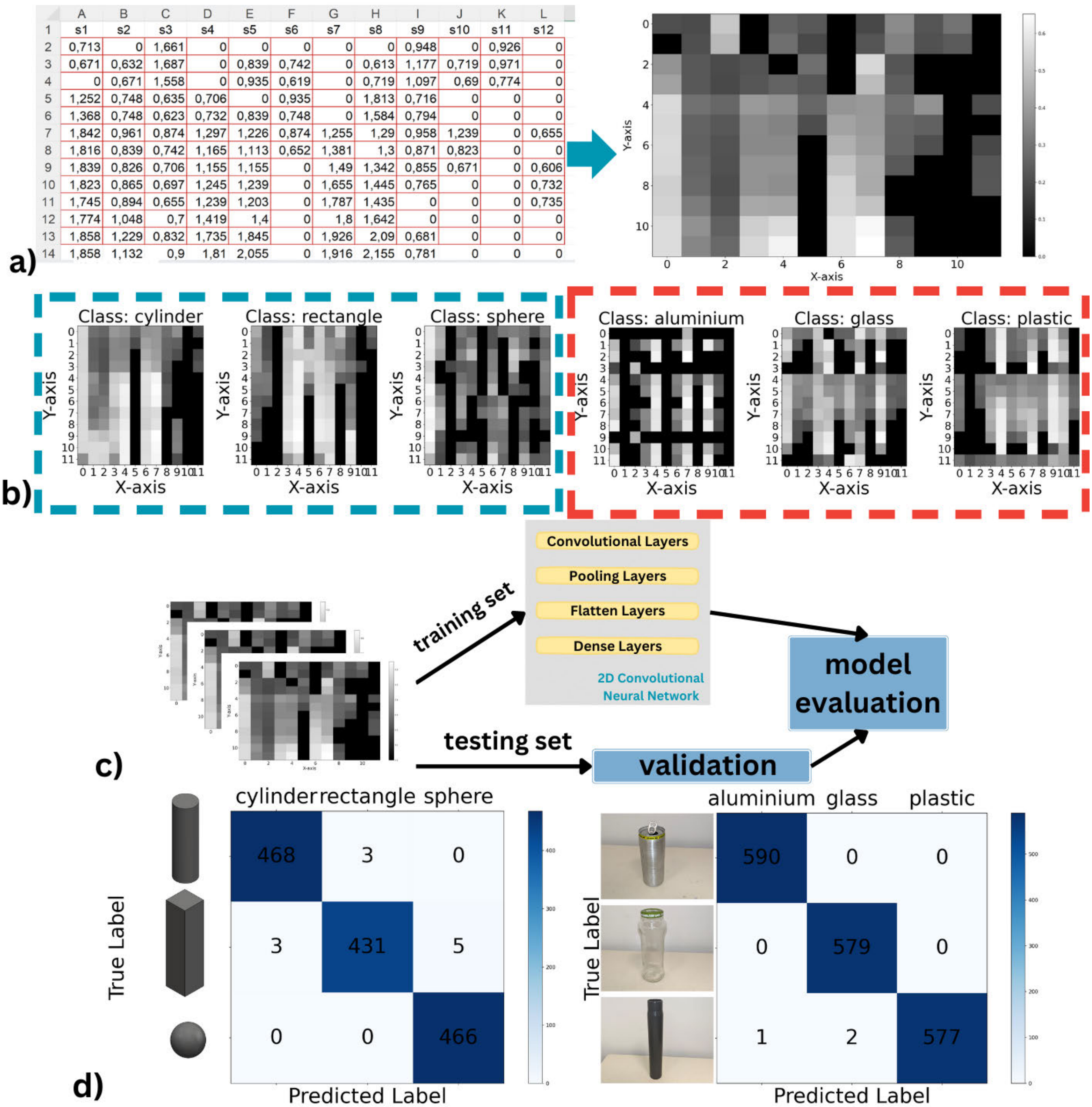

FIGURE 6. **(a) Data collection and thresholding process. (b) Visualization of 12 × 12 matrices for shapes and materials. (c) 2D convolutional network architecture. (d) Confusion matrix showing the overall accuracy of the model.**

Fig. 8 illustrates the recognition patterns for a range of materials, including aluminum, glass and plastic. The subfigures demonstrate the varying intensity distributions of the interaction between the TENG sensors and the aforementioned materials.

The investigation of the graphical representation of the online entries from the sensors yielded comparable results to those observed in shape recognition with regard to the first and second sensors. Furthermore, the observed behavior is consistent across all three materials. However, as was the case with the shape recognition process, the remaining sensor outputs provide unique patterns, and the final grayscale images are distinct for each class. The replication of analogous outcomes pertaining to both material and shape real-time recognition serves to reinforce the consistency of this research endeavor.

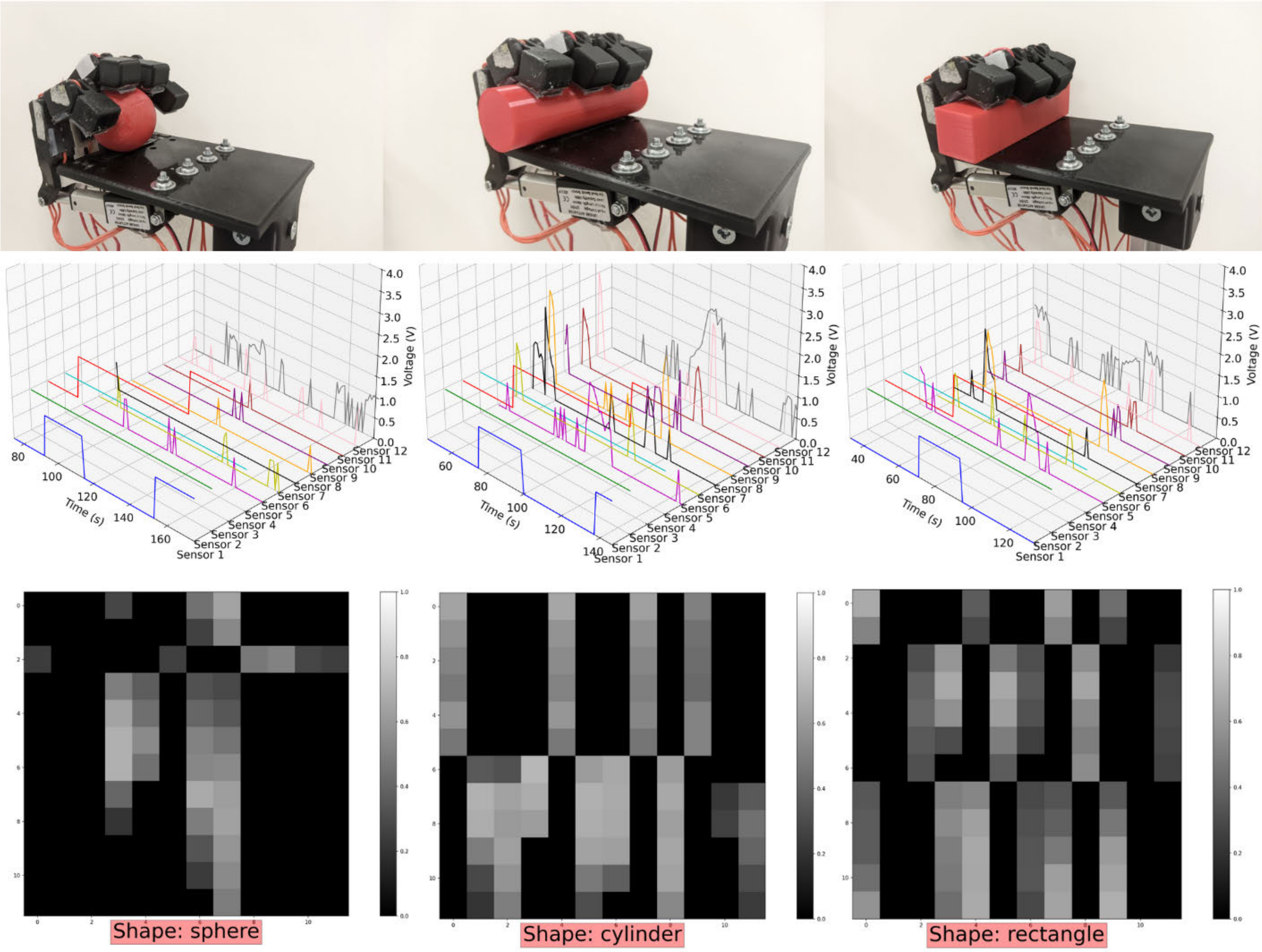

FIGURE 7. Real-time prediction on the shape of the object.

C. OVERVIEW

In general, the proposed method displays greater efficacy than the existing 1D NN method. The proposed method, which employs 12×12 image inputs and a 2D neural network architecture, exhibits enhanced accuracy in both shape and material recognition. The enhanced visualization and preprocessing steps ensure that the neural network is able to effectively learn and generalize from the data, thereby improving its recognition capabilities.

While the experiments presented here primarily focused on controlled laboratory conditions, preliminary trials in a dynamic environment—such as grasping objects moving on a conveyor belt—indicated that the proposed 2D CNN approach maintains robust recognition performance. Future investigations will expand on these tests to include variable lighting, temperature fluctuations, and a broader range of object geometries to ensure consistent, reliable performance under real-world operating conditions.

Although the proposed model demonstrates adaptability in real-time scenarios, certain challenges arose during the initial deployment. For example, object-material mismatches occurred when the robotic hand first attempted to grasp objects outside the training distribution or when environmental factors—such as slight variations in lighting or the presence of surface contaminants—affected sensor readings. In these cases, the model might have initially misclassified a material or shape due to insufficient prior exposure to similar conditions. However, repeated interactions allowed the model to gather additional sensor data, thereby refining its internal representations. Through these iterative encounters, the model improved its predictions in subsequent attempts, effectively ''learning on the fly.'' By incorporating incremental learning strategies or dynamic threshold adjustments, future work could further expedite the model's adaptation to new conditions, ensuring that real-time performance remains robust, accurate, and responsive to a wide range of operational scenarios.

A key component of our approach is its capacity to generalize to new shapes and materials that were not explicitly included in the training dataset. To evaluate this,

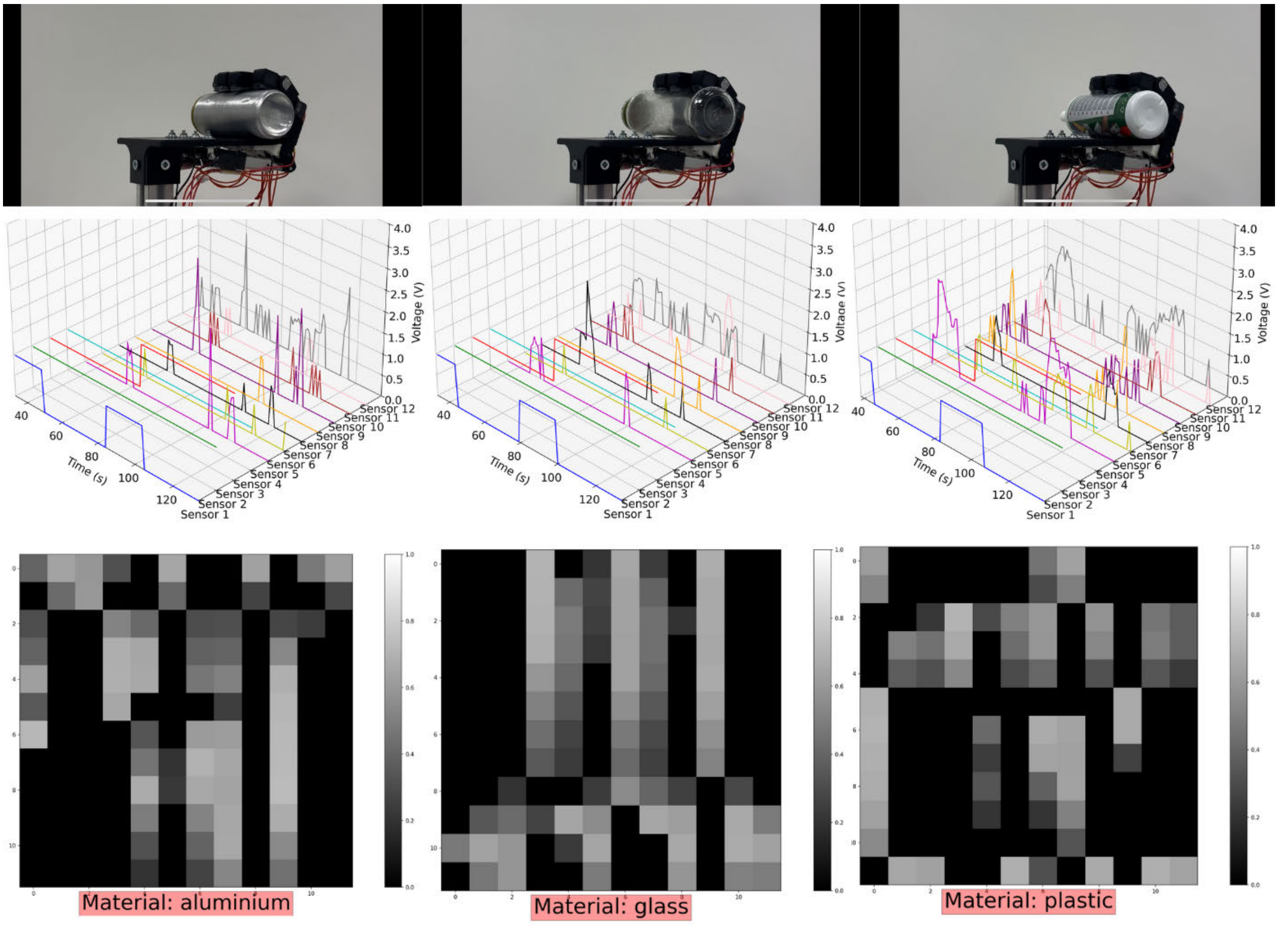

FIGURE 8. **Real-time prediction on the material of the object.**

we conducted hold-out experiments in which the model was tested on novel objects—e.g., an elongated prism shape or a composite rubber material—that the model had never encountered. Despite these variations, the recognition rate remained above 90%, suggesting that the spatial features learned by the 2D CNN are sufficiently robust to handle modest deviations in shape or material composition. Additionally, we explored incorporating a simple transfer learning scheme, wherein the final classification layer was retrained for new object classes using a limited set of new data samples. Preliminary results showed an improvement in recognition speed of adaptation, implying that more advanced fine-tuning or dynamic thresholding strategies could further enhance the model's performance in highly variable environments.

It should be noted that the reliability of material identification is contingent upon the quality and scope of the training dataset. In the event that the majority of the materials within the dataset are cylindrical in shape, the input of shape, which is likely to be that of a rectangle, may be misclassified by the model. This reveals a limitation of the current model, namely the necessity for a diversified dataset to enhance the model's robustness and relevance in practical applications. Furthermore, an object-material mismatch occurs during the initial grasp in real-time evaluation. This demonstrates that the model is capable of learning and adapting to new situations as it interacts with its surroundings in real time, correctly identifying both the object and the material in subsequent iterations.

The results demonstrate a clear advantage of the two-dimensional image based convolutional neural network over the one-dimensional signal based approach, as highlighted in Table 1. While the 1D CNN achieved satisfactory performance with a mean cross-validation accuracy of 98.18% and a test accuracy of 98.29%, the 2D CNN significantly outperformed it with a mean cross-validation accuracy of 99.79% and a test accuracy of 99.83%. Additionally, the 2D CNN exhibited superior robustness to noisy data, higher precision, recall, and F1-scores compared to the 1D CNN's 98% across these metrics. The preprocessing steps, including the formation of 12×12 matrices and normalization, proved critical for leveraging the strengths of image-based data and 2D CNN architectures, ensuring enhanced recognition of shapes and materials. These findings emphasize the efficacy of the proposed methodology in tactile sensing applications and provide a strong basis for

TABLE 1. Comparison of evaluation metrics for 1D and 2D CNN models.

Metric	Signal based	Image based
K-Fold Acc (Fold 1)	0.9858	0.9964
K-Fold Acc (Fold 2)	0.9836	0.9986
K-Fold Acc (Fold 3)	0.9758	0.9993
K-Fold Acc (Fold 4)	0.9850	1.0000
K-Fold Acc (Fold 5)	0.9786	0.9950
Mean K-Fold Acc	0.9818	0.9979
Test Accuracy	0.9829	0.9983
Test Loss	0.0641	0.0161
Multi-Class ROC-AUC	0.9985	0.9998
Inference Time (ms/sample)	40.6897	40.4603
Noisy Data Accuracy	0.9704	0.9960
Noisy Data Loss	0.0874	0.0229
Precision	0.98	1.00
Recall	0.98	1.00
F1-Score	0.98	1.00
Training Accuracy	0.9780	0.9982
Validation Accuracy	0.9808	0.9964

further advancements in integrating TENG sensors with sophisticated neural network architectures.

To contextualize our findings, we compared our approach against several recent state-of-the-art tactile sensing models. For instance, Issabek et al. [18] utilized a 1D CNN for TENG-based flatfoot classification and reported accuracies around 82%, especially under varying load forces. Another notable study by Zhao et al. [23] integrated similar TENG based sensors with an LSTM-based model, achieving 95% accuracy in classification problem. In contrast, our 2D CNN framework consistently reached 98–99% accuracy under similar conditions, highlighting the benefit of converting time-series signals into 2D representations. Additionally, while these prior works often required complex signal preprocessing or larger datasets, our image-based approach remained relatively simple and still offered robust performance. This suggests that incorporating spatial features from TENG data—combined with a well-designed 2D CNN—can outperform purely sequential models, making it a compelling alternative for tactile sensing applications.

D. EXTENDED REAL-WORLD TESTING

Although our primary experiments were conducted under controlled laboratory conditions, additional trials were performed to assess real-world performance. Specifically, the robotic hand was tested in an industrial-like setting where ambient temperature fluctuated between 20°C and 35°C, and intermittent lighting changes were introduced. Furthermore, the sensors were exposed to minor surface contaminants such as dust and moisture on the objects. Despite these varying conditions, the proposed 2D CNN model maintained a high recognition accuracy (above 95% for both shape and material), demonstrating robustness against moderate environmental shifts. Occasional misclassifications arose when contaminants significantly altered the surface texture or when the ambient temperature was excessively high, but these were limited to less than 3% of total trials, indicating strong real-world adaptability.

VI. CONCLUSION

This work presents the development of a robotic hand integrated with triboelectric nanogenerator (TENG) sensors for the recognition of shape and material. We put forth a novel machine learning-based methodology to augment the efficacy of such systems. The research methodology employed a comprehensive approach to sensor preparation, noise cancellation, robotic hand design, and control electronics.

The primary objective was to develop a two-dimensional convolutional neural network that could process 12×12 image inputs based on TENG sensor data. The proposed method was evaluated against the existing one-dimensional neural network approach. As a result of this procedure, there was a notable enhancement in the accuracy of shape and material recognition. The proposed model exhibited an accuracy rate of 98% for shape recognition and 99% for material recognition, which represents a significant improvement over the existing method, which achieved an accuracy rate of 94% for shape recognition and 98% for material recognition.

The experimental results demonstrate that the proposed two-dimensional convolutional neural network (CNN) method exhibits superior performance compared to existing methods. In order to facilitate effective learning from the neural network, it is crucial to consider the formation of visualisations and the preprocessing of data for the cancellation of noise and the formation of 12×12 matrices. The efficacy of the proposed approach was demonstrated through the utilisation of confusion matrices and accuracy metrics.

Furthermore, real-time evaluation substantiated the robustness and adaptability of the proposed model, demonstrating its capacity to accurately identify shapes and materials even in an unstructured environment. This has implications for a number of potential applications in a variety of industrial contexts where reliable robotic and adaptive manipulation is required.

A promising avenue for further research lies in the development of smart tactile gloves, where the TENG sensors and the proposed pattern recognition approach could be leveraged for fine-grained haptic feedback in virtual reality, telemedicine, or rehabilitation. By integrating an array of TENG sensors across a glove's surface, the enhanced 2D CNN-based recognition pipeline would enable precise detection and classification of tactile interactions, potentially aiding in tasks such as sign language interpretation or delicate surgical procedures.

Additionally, robotic grippers for waste management present another compelling real-world application. Embedding TENG sensors in the gripper's contact pads, combined with the image-based pattern recognition architecture, would allow the system to accurately discern different types of recyclable materials (e.g., paper, plastic, metal) based on material-specific interaction signatures. Such an intelligent waste-sorting solution could reduce manual labor, increase recycling rates, and improve overall sustainability.

The robust performance observed in our experiments indicates that the 2D CNN method, once refined with more extensive datasets and tested under variable environmental conditions, can serve as a versatile tactile sensing platform. Looking ahead, coupling this self-powered TENG infrastructure with advanced robotics and machine learning frameworks could pave the way for autonomous, low-energy solutions in next-generation human–machine interfaces, industrial automation, and wearable sensing devices.

Our findings provide comprehensive insight into the potential approach for autonomous dexterous manipulation with the assistance of advanced machine learning technologies, facilitated by the integration of tactile-sensing technologies. The results provide a rationale for further research and development in this area, establishing a foundation for future robotic systems.

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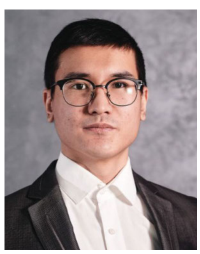

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