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The Application of Machine Learning Technique to the Detection and Management of Soft Robots

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Abstract: A rapidly developing area of robotics called "soft robotics" provides special benefits including compliance, flexibility, and secure human connection. The detection and control of their complicated and nonlinear dynamics are difficult, nevertheless. Because inherent safety is built into soft robots at the material level, there is interest in using them in practical applications. These manipulative robots use flexible materials that may alter shape and behavior and allow for conformable physical touch. However, the addition of soft and flexible materials to robotic systems brings several obstacles to sensor integration, such as multimodal sensing capable of stretching, the embedding of high-resolution yet large-area sensor arrays, and sensor fusion with a growing amount of data. To address these issues, this research suggests a machine-learning strategy for the detection and management of soft robots. Sampling for force modeling and kinematics The kinematic model and the force model were both learned using data that were collected, and the data were then preprocessed using z-score normalization. Then, we proposed Boosted Central Forced Convolutional Neural Network (BCF-CNN) for data clustering and detection of soft robots. And the results of the experiment demonstrate that our recommended methodology works better than the other available approaches.

Keywords: *Soft robots, management, Boosted Central Forced Convolutional Neural Network (BCF-CNN)*

1. Introduction

Soft robotics is a fast-developing area of robotics that provides distinct benefits over conventional rigid robots. These robots can bend and change their shape to fit their surroundings since they are built of compliant and flexible materials [1]. Soft robots' built-in compliance makes it possible to interact with people safely, use fragile objects, and move through small places [2]. The complicated and nonlinear dynamics of soft robots, however, make it difficult to identify and control them. The inherent unpredictability and uncertainties associated with soft robot behavior make traditional control systems that depend on exact mathematical models and predetermined rules difficult to manage [3]. To accurately identify and manage the states of soft robotics, it is increasingly important to investigate data-driven methodologies, particularly machine learning techniques. The ability of computers to learn from data and make wise judgments has made machine-learning approaches very promising in a variety of fields [4]. Thus Soft robots can perform better, be more versatile, and be safer by using the power of machine learning to adapt and react to changing surroundings.

To overcome the difficulties brought on by the complicated dynamics of soft robotics, this research suggests a Boosted Central Forced Convolutional Neural Network for their detection and administration. Their use in diverse sectors is significantly impacted by the identification and control of soft robot states. Soft robots in healthcare can be used for rehabilitation and safe, pleasant patient aid [5]. Soft robots are capable of navigating difficult terrain and offering help in disaster-stricken regions during search and rescue missions [6]. In human-robot cooperation settings, where their compliance enables intimate and natural engagement with people, soft robots may also be very important.

The rest of the paper is structured as follows: An overview of related research in the area of soft robot management is given in Section 2. The data collecting, preprocessing, and model training procedures are described in full in Section 3 of the proposed machine learning technique. The experimental setup, findings, and performance assessment of the suggested technique are all covered in Section 4. The paper is concluded in Section 5 with a review of the findings and recommendations for further research.

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2. Related works

The study [8] offered cutting-edge Machine Learning (ML) methodologies in soft robotic areas and classifies their use in various soft robotic apps, like soft sensors, soft wearable robots, and soft actuators. Along with the current research area restrictions, a synopsis of the current ML techniques for soft robotics is offered after a study of the tendencies of various ML approaches to various kinds of soft robot apps. The review [9] offered an overview of many such algorithms as well as examples in which they have been used to provide cutting-edge outcomes in practical settings. The numerous basic fields of DRL research in soft robotics are highlighted in summaries. The study [10] described a model-based policy learning approach for closed-loop predictive control of a soft robotic manipulator. A Recurrent Neural Network (RNN) is used to represent the forward dynamic model. Utilizing supervised learning and trajectory optimization, the closed-loop policy is created. The method is initially tested on a cable-driven under-actuated soft manipulator simulation model with piecewise constant tension. The paper [11] analyzed the advantages and difficulties of soft robotics technology and what it can signify for agroforestry and ethical farming. The study described a technique for printing soft pneumatic actuator robots (SPAs) in four dimensions (4D) utilizing nonlinear ML and Finite Element Modelling (FEM). The study demonstrated that a model of the system's discrete state space that has been linearized may be created using the gradients utilized inside a neural network to connect inputs to outputs and system states to system states. To accomplish position control within 2° of the desired joint angle, model predictive control may be constructed using a soft robot with one degree of freedom using the state space representation.

The work [12] discussed the results of our first research into the use of machine learning to soft robot control. To determine the best open-loop control inputs, they first develop a differentiable model of the quasi-static physics of a soft robot. The study [13] presented the model predictive controller design process and the Koopman-based system identification approach. Using this approach, a pneumatic soft robot arm model and MPC controller were created, and the robot's performance was assessed using a variety of real-world. The article described a textile-based tactile sensor for multipurpose sensing uses in soft robotics and health monitoring. Researchers logically created a tactile sensor with two detecting layers, drawing inspiration from the skin of the fingertip. The research [14] introduced a unique adaptable inductance with multiple uses and a stretchy sensor using LMs that can measure axial stress as well as curvature. By printing a coaxial LM 3D printer, silicone rubber, and LMs were built to produce this sensor. The study [15] described a soft robotic glove that may help people with functional grip disorders carry out everyday tasks. The glove makes use of low-profile, soft fabric-regulated pneumatic actuators that need less pressure than earlier actuator technology.

3. Methods

In this paper, First the kinematic model and the force model were both learned using data that were collected, and the data were then preprocessed using z-score normalization. Then, we proposed Boosted Central Forced Convolutional Neural Network (BCF-CNN) for data clustering and detection of soft robots. And the results of the experiment demonstrate that our recommended methodology works better than the other available approaches. Fig 1 shows the flow of proposed method.

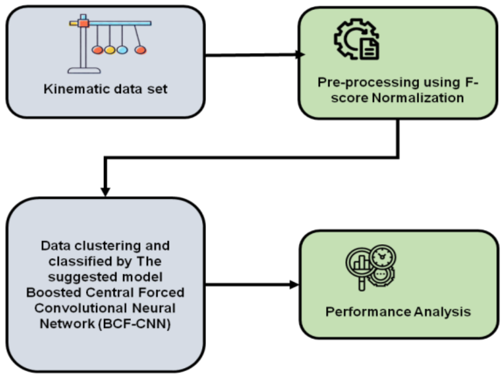

Fig.1. Flow of proposed method

3.1. Data set

Sampling for force modeling and kinematics The kinematic model and the force model were both learned using data that were collected. The kinematic model required the marker data from the motion capture system and the associated sensor data for several kinematic setups. The finger is sometimes required to make contact with two different fixed line connections to do this. The finger could still move in the other way with total freedom even if the external contact was locked in place. Both the finger's tip and a spot near its middle were supposed to be in touch with the contacts. The external touch's duration, location, and timing were all determined at random to avoid biases. Data shuffles were not employed in learning, and sampling was continuous. This is necessary for the temporal information to be preserved. For force modeling, a load cell was connected to the tip's external contact.

3.2. Preprocessing using z-score normalization

We preprocess the data using z-score normalization after data collection. The Z-score normalization uses the data's mean and standard deviation as its starting points. In cases when the lowest and maximum values of the data are unknown, this technique is of great use. This is the formula that is used:

$Y_{new} = \frac{y-\mu}{\sigma} = \frac{y-Mean(Y)}{stdDev(Y)}$ (1)

Y_{new}=The adjusted value obtained after scaling the data

Y = outdated value

μ = Statistics mean

σ = Estimated Standard Deviation

3.3. Boosted Central Forced Convolutional Neural Network (BCF-CNN)

A mini-batch method is often utilized to handle huge training of the data sets in a BCF-CNN. Let $Y = [Y_1, \ldots Y_N]$represents the activating attributes of a batch of N training pictures, where Y_j dimension is R, and let$x = [x_1, \ldots x_N]$, $x_j \in \{-1, 1\}$ represent a vector containing the authentic labels. A strong classifier$(\cdot)$, which is the weighted sum of weak classifiers $Z(\cdot)$, calculates the prediction using the boosting technique as follows:

$$Z(Y_j) = \sum_{i=1}^{R} \alpha_i z(y_{ji}, \lambda_i); z(y_{ji}, \lambda_i) = \frac{l(y_{ji},\lambda_i)}{\sqrt{l(y_{ji},\lambda_i)^2 + \eta^2}} \quad (2)$$

Where $y_{ji} \in x_j$ is the i^{th}activation feature of the j^{th}picture. Each feature is associated with a potentially poor classifier $z(y_{ji}, \lambda_i)$ with a range of results of$(-1,1)$. $\frac{l(.)}{\sqrt{l(.)^2+\eta^2}}$ is used to simulate a $sign(\cdot)$optimization via gradient descent function calculating derivative. In this work, $l(y_{ji}, \lambda_i) \in K$ often employed in AdaBoost, this threshold λ_i is defined as a one-level decision tree (a decision stump).

The parameter η in Eq. 2 is used to regulate the gradient of a function $\frac{l(.)}{\sqrt{l(.)^2+\eta^2}}$and can be set according to the allocation of $l(\cdot)$ as $\eta = \frac{\sigma}{v}$, where σ is the mean of $l(\cdot)$ and v is a constant. In this work, η is empirically set to $\frac{\sigma}{2}$. $\alpha_i \geq 0$ is the weight of the i^{th} weak classifier and$\sum_{i=1}^{R} \alpha_i = 1$. When$\alpha_i = 0$, when a neuron is not receiving input, it does not participate in feed-forward or backpropagation.

Overfitting can occur when certain weak classifiers have big weights and traditional boosting approaches only account for the loss of the strong classifier which is used to classify the soft robots. Classification errors made by the strong classifier and the individual classifiers are factored into the loss function, which is defined as the sum of the losses from the strong classifier and the weak classifier:

$$\varepsilon^P = \beta\varepsilon^P_{strong} + (1-\beta)\varepsilon_{weak} \quad (3)$$

Where$\beta \in [0, 1]$ balance both the weak- and strong classifier losses. The strong classifier loss is the metric used to measure how far off a model is from the actual label:

$$\beta\varepsilon^P_{strong} = \frac{1}{N} = \sum_{j=1}^{N} (Z(Y_j) - x_j)^2 \quad (4)$$

The weak-classifier loss is calculated by adding up each weak classifier's loss values.

$$\varepsilon_{weak} = \frac{1}{NM}\sum_{j=1}^{N} \sum_{1\leq i\leq R\ \alpha_i>0} [z(y_{ji}, \lambda_i) - x_j]^2 \quad (5)$$

Where the loss is calculated while excluding inactive neurons due to the condition $\alpha_i > 0$. Backpropagation can be used to iteratively fine-tune the BCF-CNN driven by the loss Defined in Eq. 3. The previously recorded data, such as the weights and thresholds of the activated neurons, is discarded in favor of a fresh set. The trained BCF-CNN may be overfitted because there isn't enough data in each minibatch.

A metaheuristic optimization technique called Central pull Optimization is motivated by the gravitational pull in physics. It was created to address optimization issues by modeling the interactions of celestial bodies subject to gravity.

$$\vec{e}^{\,b}_{i=1} = S\sum_{r=1\ r\neq b}^{M_b} W(N^r_{i-1} - N^b_{i-1})(N^r_{i-1} - N^b_{i-1})^\alpha \frac{(\vec{K}^r_{i=1} - \vec{K}^b_{i=1})}{|\vec{K}^r_{i=1} - \vec{K}^b_{i=1}|^\beta} \quad (6)$$

where M_b = quantity of probes, $b = 1, 2, 3, \ldots, M_b$ name of the probe number, i = calculation time increment, which is the number of iterations used for optimization α, β and S = the BCF-CNN constants, $N^b_{i-1} = V(\vec{K}^b_{i=1})$, value of the probe relative to the objective function b at time step $i-1$ and W is the step function of a single unit that yields $W(y) = 1\ if\ y \geq 0$ and $= 0$ otherwise. W maintains the attractive force of gravity in the BCF-CNN, so larger probes' attractive forces are used merely to shift the probes' position vectors. The position distance $|\vec{K}^r_{i=1} - \vec{K}^b_{i=1}|$between two probes r and b, uses the following equation to derive,

$$|\vec{K}^r_{i=1} - \vec{K}^b_{i=1}| = \sqrt{\sum_{n=1}^{M_t} (K^{r,n}_{i-1} - K^{b,n}_{i-1})^2} \quad (7)$$

The gravitational analogy for a three-dimensional space with four probes was used to clarify the situation. To apply the accelerations calculated at time step i to the probe position vectors, we do the following:

$$\vec{K}^b_i = \vec{K}^b_{i-1} + \frac{1}{2}\vec{e}^{\,b}_{i-1}\Delta d^2 \quad (8)$$

In which Δd = the time step size used here is assumed to be 1. The probes are moved to new positions using Eq. 8, which may be outside the region of possible decisions. How the lost probes are collected and returned can have a significant impact on a CFO's effectiveness. The following equation, proposed by Formato (2007), can be used to fix impractical parts of faulty probes:

$$\text{if}\vec{K}_{i,j}^{b} < y_j^{min} then \vec{K}_{i,j}^{b} = y_j^{min} + L_{rep}\left(\vec{K}_{j-1,j}^{b} - y_j^{min}\right)\text{and,}$$

$$\text{if}\vec{K}_{i,j}^{b} > y_j^{max} then \vec{K}_{i,j}^{b} = y_j^{min} - L_{rep}\left(\vec{K}_{j-1,j}^{b} - \vec{K}_{j-1,j}^{b}\right) \quad (9)$$

Where $L_{rep} =$ the positioning factor, a variable that may be set by the user and has a range of 0-0.9, and y_j^{min} and y_j^{max}, the higher and lower bounds of the deciding factors, respectively. Finding the ideal set of constants for BCF-CNN is simpler than for a stochastic metaheuristic since CFO is predictable and devoid of randomness. By comparing the BCF-CNN's parameters to a variety of intricate multi-dimensional test functions, Formato (2009) thoroughly analyzed the CFO's parameters. It was determined that in the majority of situations, setting, and W to be 2 and L_{rep} is 0.5 yields the best performance. But more consideration needs to be given to M_b and L_{rep}. The initial placement of the probes in space, which is based on M_b, specifies how much to start a run with BCF-CNN and is aware of the topology of the decision space, which is another crucial aspect of BCF-CNN. There are a variety of methods that can be used for this, including randomly generating probes or evenly dispersing probes along each axis of the coordinate system. Combining the aforementioned approaches to probe distribution is another tactic that is possible. Understanding both the behavior of the BCF-CNN and the problem at hand analytically is required for a successful and efficient parameter selection.

4. Result and discussion

Soft robots, composed of flexible and deformable materials, offer unique advantages such as adaptability and compliance for tasks in unstructured environments. In this study, we suggested BCF-CNN for the detection and management of soft robots. We compared some of the existing methods such as SVM [16], LSTM [17], and 3D-CNN [18] with our proposed method using several metrics like accuracy, precision, prediction performance, and Motion prediction rate.

Accuracy for soft robot detection and management refers to the overall correctness of the model's predictions and decisions in detecting and managing soft robots. It calculates the percentage of examples that are correctly categorized relative to all of the instances. The Fig 2 and Table 1 show that comparison of accuracy and it depicts that our proposed is higher than other existing methods.

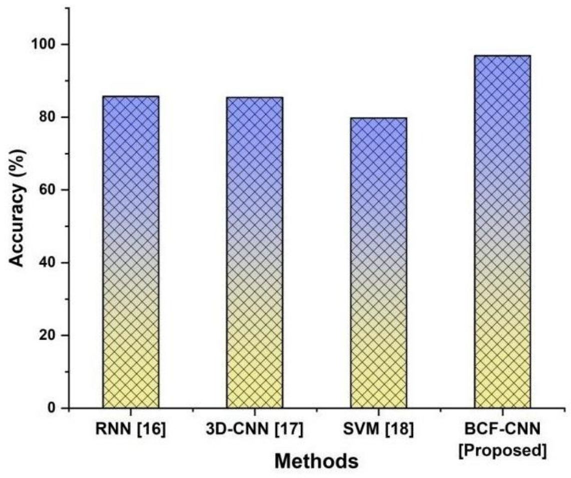

Fig.2. Comparison the accuracy of the conventional and proposed approaches

Table 1. Comparison of accuracy

Methods	*Accuracy (%)*
RNN [16]	85.75
3D-CNN [17]	85.45
SVM [18]	79.78
BCF-CNN [Proposed]	96.92

Soft robot detection precision measures the model's ability to provide accurate, favorable predictions when detecting the presence of a soft robot. It quantifies the proportion of correctly identified soft robots out of all instances classified as soft robots by the model. A high soft robot detection precision implies a low false positive rate, indicating that the model accurately identifies soft robots and minimizes misclassifications of non-soft robot objects as soft robots. The Fig 3 and Table 2 show that comparison of precision and it depicts that our proposed is higher than other existing methods.

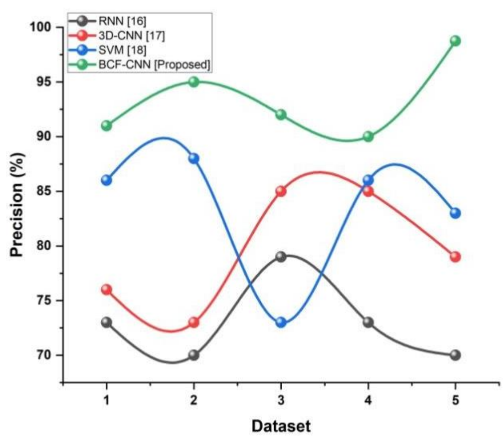

Fig.3. Comparison the precision of the conventional and proposed approaches

Table 2. Comparison of precision

Dataset	***Precision (%)***			
	RNN [16]	*3D-CNN [17]*	*SVM [18]*	*BCF-CNN [Proposed]*
1	73	76	86	91
2	70	73	88	95
3	79	85	73	92
4	73	85	86	90
5	70	79	83	98.75

Fig 4 and Table 3 depicts that comparison of detection performance and it shows the BCF-CNN achieved high accuracy in detecting the presence of soft robots. The BCF-CNN successfully distinguished between soft robots and other objects in the environment, even in complex scenarios with cluttered backgrounds.

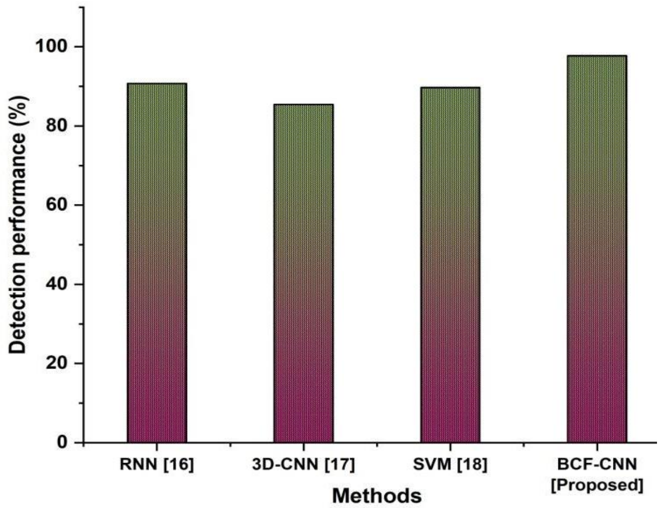

Fig.4. Analyzing the soft robots detection performance of the conventional and proposed approaches

Table 3. Comparison of detection performance

Methods	***Detection performance (%)***
RNN [16]	90.75
3D-CNN [17]	85.45
SVM [18]	89.72
BCF-CNN [Proposed]	97.75

The Fig 5 and Table 4 depict that comparison of detection performance and it shows the BCF-CNN demonstrated the ability to predict the future motion of soft robots based on their current state. This prediction capability enabled more accurate and responsive control, facilitating tasks that require precise manipulation.

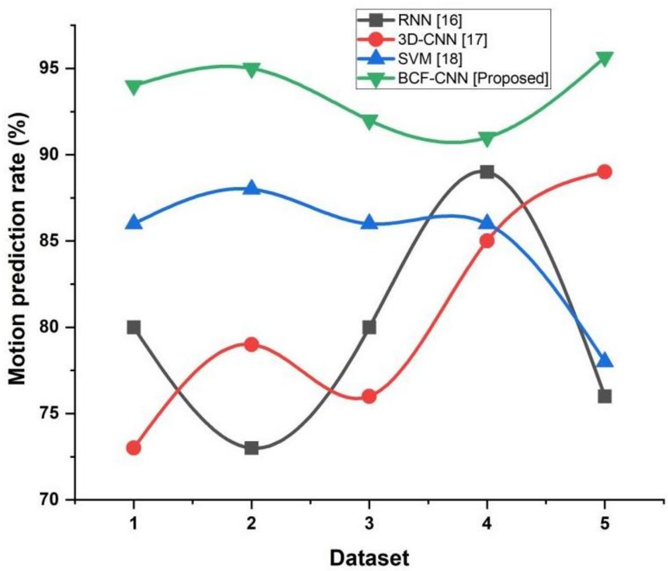

Fig 5. Analyzing the soft robots motion prediction rate of the conventional and proposed approaches

Table 4. Comparison of motion prediction rate

Dataset	***Motion prediction rate (%)***			
	RNN [16]	3D-CNN [17]	SVM [18]	BCF-CNN [Proposed]
1	80	73	86	94
2	73	79	88	95
3	80	76	86	92
4	89	85	86	91
5	76	89	78	95.65

5. Conclusion

The application of machine learning techniques to the detection and management of soft robots has shown promising results [19]. The trained BCF-CNN demonstrated high accuracy in detecting soft robots, detecting performance, and predicting their motion. These findings pave the way for improved soft robot performance and expanded applications in various domains, including healthcare, manufacturing, and exploration. Future research should focus on addressing challenges and further enhancing the abilities of machine learning-based soft robot management systems. Future research in the application of machine learning techniques to the detection and management of soft robots should focus on expanding datasets, enabling online learning and adaptation, incorporating sensor fusion, exploring reinforcement learning for control, enhancing human-robot interaction, ensuring robustness and safety, and addressing practical deployment challenges.

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