# Guided By Touch: Teaching Robots How to Feel

## How can imitation learning using tactile data enhance the dexterity of soft robotic systems in performing human like manipulation tasks?

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## Background:

**Research Problem:**

- The lack of dexterity in current robotic technology, essential for performing manipulation tasks.

**Aim:**

- Navigate a ball through a maze using a robotic arm (Fig. 1) GelSight sensor (Fig. 2), using imitation learning
- Unlike prior work, this method and model do not rely on any vision input

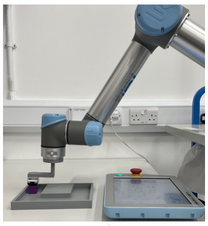


Figure 1: Task Setup

**The imitation learning algorithm used:**

- Long Short-Term Memory (LSTM)
  - Great for predicting sequential tactile interactions by capturing long-term temporal relationships.
  - LSTM models selectively store, discard, and retrieve data [2].

This allows the model to learn a general navigation strategy rather than memorising fixed trajectories.

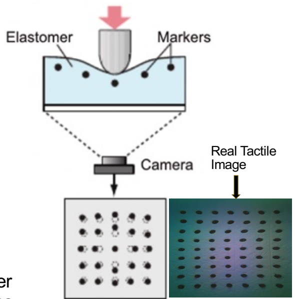



Figure 2: Diagram of GelSight Sensor Adapted from [1]

## Method:

**Data Collection**:

- Cube movement direction (↑ ↓ → ←) is manually updated during exploration
- Cube-wall collision manually updated
- Robot state sampled at 10 Hz
- 40 demonstrations per maze

These interactions help the policy learn directional adjustment from tactile data

Design 1 Design 2 Design 3

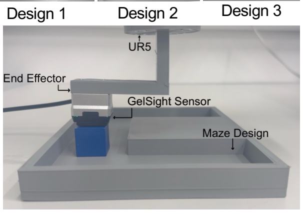
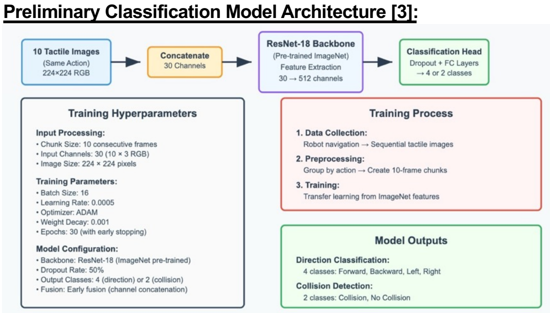
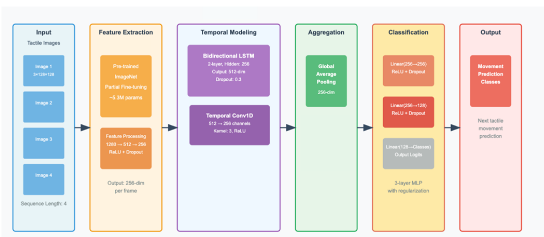



Figure 2: Experimental setup

**Preliminary Classification Model Architecture [3]:**




**TCN-BiLSTM Direction Prediction Model Architecture:**




## Results:

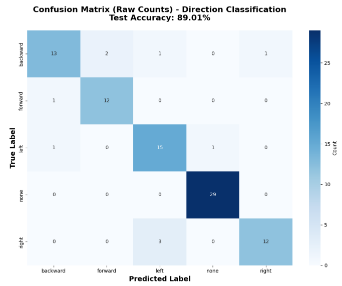



Figure 3: Preliminary confusion matrix in direction classification

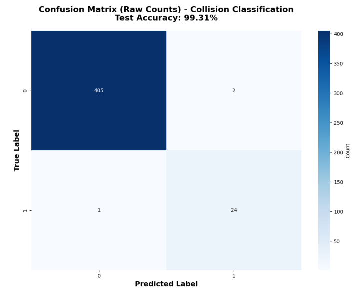



Figure 5: Preliminary confusion matrix in collision classification

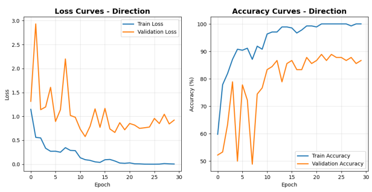



Figure 4: Direction classification model learning results

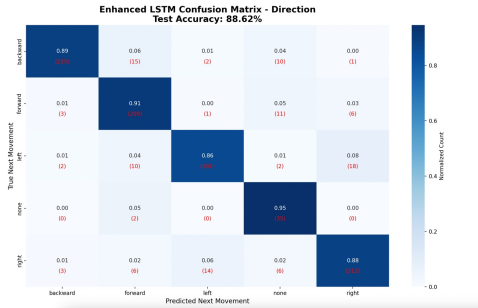



Figure 6: TCN-BiLSTM confusion matrix for predicted next movement

## Analysis:

**Classification accuracy for preliminary results:**

**Direction:** 89% test accuracy (Fig. 3)

- Classifying zero motion was the most accurate followed by forward and leftward motion (100%, 92% and 88% respectively).
- Generalisation gap, in Fig. 4, between the training and test accuracy may be indicative of overfitting [4]

**Collision:** 99% test accuracy (Fig. 5)

- Superior accuracy in identifying no collision versus collision (100% and 96% accuracy respectively)
- The difference in accuracy may be due to the significantly smaller number of collision samples

**Direction prediction accuracy for final results:**

**Highest class accuracy:**

- "None" (no movement) due to simple tactile frames.

**Forward motion:**

- Highest directional prediction accuracy: 91%
- Strong alignment between classification and prediction performance.

**Backward and rightward motions:**

- Classification and prediction performance remain consistent.

**Leftward motion:**

- Despite high classification accuracy, it had the lowest prediction accuracy (86%),

## Discussion:

**Limitations:**

- Collision labelling is subjective
  - Noisy labels reduce model accuracy
- Subconscious visual input limits the learnability of the data
- Unintentional biases in the maze geometry
- Narrower mazes require more precision (post-collision correction), preventing generalisation
- The classification model is trained on pre-trained weights,
  - Not suitable for subtle feature detection
  - Accuracy fluctuations during training caused by sensitivity to model parameters [5]
- Action chunking transformer (ACT) network prevents compounding errors that can arise in stepwise models like LSTM [6]

**Improvements:**

- Automatic collision labelling to eliminate subjectivity
- Replace the GelSight sensor with a 3D tactile finger for realistic manipulation demonstrations [7]
- Train classification model from scratch
- Implement ACT for long-horizon planning for complex manipulation tasks
  - Replacing the cube with a sphere requires learning to regain contact with shape during navigation
  - Introduce more complex maze designs that require sophisticated maze-solving strategies [8]

## Conclusion:

In summary:

- The LSTM-based model demonstrated strong theoretical performance in tactile classification and prediction
- Its real-world deployment on the UR5 revealed limited generalisation

This highlights a clear gap between offline accuracy and embodied performance. Underscoring the need for:

- Enhanced data quality
- More robust modelling
- Richer tactile sensing

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Scan the QR code for a video demonstration of data collection:

Scan the QR code for the References:

In collaboration with Luchen Li and under the supervision of Dr. Thuruthel in the Department of Computer Science