# Design and development of a robust vision-based tactile sensor

Prasad Rayamane, Ze Ji, and Michael Packianather

***Abstract*— For robots to perform advanced manipulation of objects, touch is a critical source of information, and a high-quality tactile sensor is essential. Image-based optical tactile sensors, and its inheritances, which have soft touch interfaces, can provide high-resolution tactile images of the contact geometry, contact pressure, and slip conditions. However, due to the lack of robustness provided by the current tactile sensors, the ability to grasp hard or sharp objects is minimal. In this work, we propose an image-based optical tactile sensor and overcome the above limitation of poor robustness by introducing a latex layer on the touch interface. We use a combination of silicone elastomer covered with a latex material and an acrylic sheet to support the silicone elastomer. A camera placed at the bottom of the sensor housing captures the deformation of the elastomer surface illuminated by an inner light. To evaluate the performance, we carried out a series of experiments. First, we evaluated the mechanical characteristics of the silicone elastomer with three types of coating, namely latex membrane, metallic coating, and no coating. The proposed latex membrane clearly outperformed the other two in terms of robustness. Second, we carried out the force-displacement experiments quantitatively to further study the sensitivity and robustness. Last, we validated the sensor performance in terms of its spatial resolution by applying the VGG-19 neural network for classifying touch patterns captured by the sensor. Overall, the proposed sensor achieved the desired robustness, sensitivity, and spatial resolution performance.**

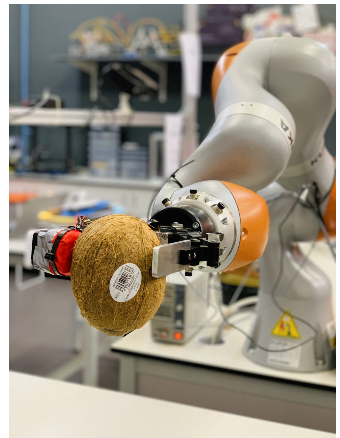

Fig. 1: The proposed robust optical tactile sensor mounted on a gripper, grasping a hard object with a rough surface.

## I. Introduction

For robots to perform advanced manipulation of objects, touch is a critical source of information. Tactile sensors can provide direct information on a system's state, as they can detect the exact forces that a robot applies to touch items. The acquired first-hand information, such as shape, texture, and hardness [1] would provide essential feedback knowledge that allows for smoother and more consistent hand-object interaction patterns and better execution of complex manipulation tasks.

Researchers have developed many different types of tactile sensors for robots in the past decades [2][3]. Tactile sensors can be designed based on various sensing principles, including resistance [4], capacitance [5], piezo-electric [6], optics [7], and magnetics [8]. These sensor arrays usually have limited spatial resolution due to manufacturing constraints. Robots would generally require rich information from tactile sensors to perform manipulation tasks, such as pressure distribution, contact force, location of the contact, as well as slip detection [9]. On the other hand, most existing tactile sensors fall into one of two categories: those that give excellent spatial resolution on a flat surface, such as optical tactile sensors [10], [11], [12], or those that allow sensitivity on substantially curved surfaces but with significantly lower spatial resolution [5], [6], [7]. Although high-resolution tactile sensing is essential for high-fidelity manipulation, the roust sensing surface plays a vital role in sensor durability over the number of grasping. However, less attention is paid to enhancing sensor performance on the sensors' robustness or durability.

A tactile sensor must be robust and compact enough to fit into a robot's finger and deliver a sufficiently rich signal to offer the robot important information about the contact state in order to be effective in robotic manipulation. It is also critical for general-purpose robotic manipulation that the tactile sensor is sensitive on as much of the finger's surface as durable. A robotic finger with a robust sensing surface can make it possible to handle rough and sharp objects and, therefore, should improve the grasping repeatability of the sensor.

Among all tactile sensors, optical sensors based on vision stand out from tactile sensors because they have simple wiring and require simple fabrication processes. Such sensors typically have reasonably high spatial precision in locating contact areas [11]. In addition, the sensing medium for vision-based tactile sensors is typically a deformable body, such as a silicone of rubber, with a camera capturing the deformation of the sensing medium and having the capability to retrieve force information with deep learning algorithms [12]. The contact medium for the sensor was a hollow hemispherical rubber dome with a reflective inside surface. The sensor measures the reflective light from the deformed dome with three receivers in the bottom, measuring

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the three-axis contact force. Furthermore, based on the data collected during the sensing process, it is possible to estimate the object's shape while also analysing the force data by tracking embedded markers [13], [14], [15], [16].

One of the biggest impediments to the widespread use of touch sensing in robotic manipulation is the limitation of sensors that meet all the requirements or criteria of resolution, sensitivity, reliability, robustness, portability, and affordability. In this work, we propose introducing a new improved design for the above vision-based optical tactile sensors to meet these objectives better by using a latex membrane surface, providing a versatile composite contact surface based on the proposed optical camera tactile technology. Figure 1 shows the sensor mounted on a Kuka robot grasping an object with a rough surface, where the latex layer increases the mechanical robustness of the sensor.

The rest of this article is structured as follows: Section II introduces related work on an optical-based tactile sensor and a general design strategy. Section III discusses the design and production of customised optical tactile sensors and the mechanical properties of silicone elastomer. Section IV introduces the force-displacement experiments to validate the sensor robustness. In section IV-C, we further validate sensor performance in terms of its spatial resolution, where we use the VGG-19, a Convolutional Neural Network (CNN) to classify touch patterns captured by the sensor. Finally, we summarise the paper's contribution and discuss its potential applications.

## II. Background

Vision-based optical tactile sensors make use of cameras to capture touch information. These cameras are placed at the core of an enclosed shell, pointing to an opaque window made of a soft material. Such characteristics ensure that variations in external illumination do not affect the captured image. Several working principles have been proposed to extract the elastomer deformations from the captured tactile images. There are two main kinds of methods: raw image analysis and marker tracking. One example of marker tracking-based tactile sensors is the TacTip Family of sensors [15] and [17], including the TacTip, TacTip-GR2, TacTip-M2, and TacCylinder. Each TacTip sensor introduces novel manufacturing advancements or surface geometries; however, the same working principle is shared: white pins are imprinted onto a black membrane that can be tracked using computer vision methods. In [18], an optical tactile sensor, FingerVision is proposed to use a transparent membrane with the advantage of gaining proximity sensing. However, the use of the transparent membrane makes the sensor lack the robustness to external illumination variance associated with touch sensing. Therefore, semi-opaque grids of magenta and yellow markers painted on the top and bottom surfaces of a transparent membrane are proposed in [19], in which a mixture of the two colours is used to detect horizontal displacements of the elastomer.

On the other end of the spectrum, the GelSight sensors, originally proposed in [10], use the full resolution of the tactile images captured by the sensor camera rather than just tracking the markers. Due to the soft opaque tactile membrane, the captured images are robust to external light fluctuations and capture information about the surface's geometry structure, unlike most traditional tactile sensors that measure the touch force. Using the high resolution of the captured tactile images, highly accurate geometry reconstructions are created in [20], [21]. The sensor is integrated on a robotic gripper for the task of inserting a USB plug into the port. The sensor measures the surface texture information to determine the orientation of the USB plug toward the grasp closure. Markers were likewise added to the membrane of the GelSight sensor, applying a similar arrangement of techniques investigated in the TacTip sensors. There are some other sensor designs and adaptations for robotic fingers in [22], [23], [24]. In [22], matte aluminium powder is used for improved surface reconstruction, with the LEDs being put close to the elastomer and the elastomer being slightly curved on the top/outside. In [23], a flat and inclined mirror is proposed for a slimmer design. The camera is put on the side of the tactile membrane such that it captures the tactile image reflected in the mirror. In [24], the mechanical characteristics of the DIGIT sensor was tested against elastomer provided by Yuan et al. [11]. In these previous works of camera-based optical tactile sensors, multiple designs and two distinct working principles have been exploited. However, a critical problem is the wear of these vision-based tactile sensors that are susceptible to friction and damage of the soft material [17], [1], [18], [11].

To improve the robustness of the sensor touch surface, researchers investigated using skin like plastic and producing replaceable silicone elastomer by using a 3D printed mould or mechanical characteristics carried out on an abbreviation device against the GelSight elastomer and found that degradation of the gel [18], [17]. The article highlights that the image transfer layers used are thick and robust but would result in loss of spatial resolution in tactile sensing outputs [24]. None of the introduced sensors has the capability of mechanical characterisation of average load with coating and without coating and robust contact surface and the sensor's response to the hard surface being touched. As a result, these sensors are highly constrained in object manipulation tasks. Contacts are only assessed when the manipulated object is within the grasp closure [20], [22], [11].

Over the last decade, there has been substantial studies into camera sensors to predict contact location and force distribution [25]. Researchers used image processing and computer vision techniques to assess the force and movement of markers [26]. Low-level image processing methods and support vector machines are used to examine the distorted materials' patterns [27]. Some investigations detected 3D displacement in tactile skins due to the availability of small circuit technology and high spatial resolution vision systems [28]. Several additional studies attempted to insert numerous camera sensors into the tactile sensor to obtain the greatest possible internal tactile force fields [29].

On the other hand, there has been a surge of interest and enthusiasm for learning-based systems that use deep learning to estimate tactile information [30]. Traditional image processing/computer vision-based and learning-based methods are both used for processing vision-based tactile sensors. In addition, various low-level image manipulation techniques are used in basic image processing/computer vision approaches to improve the images retrieved from the deformation source [31]. Tactile material and object classification is another interest to researchers for processing tactile sensor data [32]. Convolutional Neural Networks (CNN) have been used to produce several cutting-edge results on computer vision challenges and have been effectively used for texture recognition. Cimpoi et al. [33] suggested the FV-CNN architecture, which merged CNN with Fisher Vectors (FV) to extract localised characteristics more effectively. The convolutional layers of FV-CNN are from the VGG model [34], which was pre-trained on ImageNet and employed as filter banks; the FV was utilised to generate the orderless representation. The CNN models created for computer vision were also successful in processing tactile information: [35], [1] employed the CNNs on GelSight data to estimate material hardness or fabric qualities, whereas the networks were pre-trained on standard images.

To address the gap of poor durability and robustness, we propose an improved tactile sensor design in terms of the robustness/repeatability of silicone elastomer by introducing a latex layer on top of the silicone to better manipulate hard surface objects without damaging the internal sensing part. Robustness is the key of the tactile sensor for the piratical application, such as manipulating rough/sharp surface objects. However, none of the cited works above provides the force-displacement experiment to validate the sensor robustness. We further validate the sensor performance using the VGG-19, by fine-tuning the pre-trained CNN, to classify images captured by the sensor to validate the performance in terms of spatial resolution.

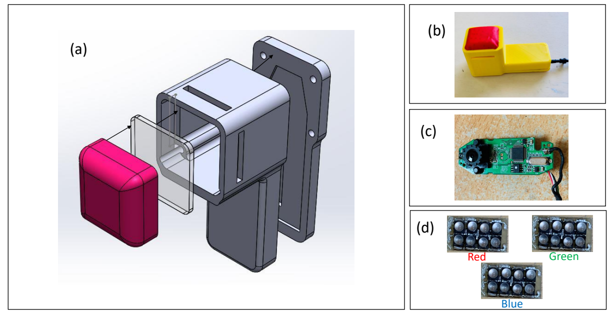


Fig. 2: The exploded view of the proposed optical tactile sensor. (a) Exploded view optical tactile sensor, (b) Assembled sensor, (c) USB web camera, (d) 3 LEDs for illumination.

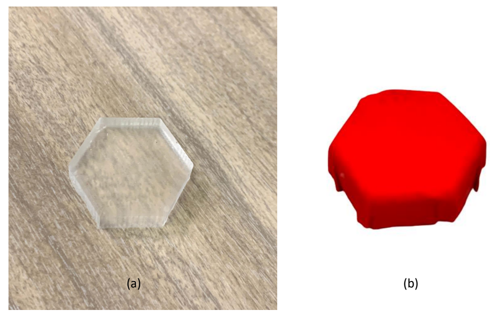


Fig. 3: Silicone elastomer (a) without coating (b) with coating

## III. Design and fabrication of optical tactile sensor

This section summarises the design of the proposed tactile sensor and the procedure of fabrication in detail.As shown in Figure 2, the key components of the sensors include the elastomer, the acrylic sheet, latex membrane, a camera, LEDs for illumination, and so on.

### A. *Fabrication of the sensor silicone elastomer*

The sensing elastomer is made of two parts: A transparent silicone elastomer base and the latex membrane. The silicone elastomer sheet can be made from different kinds of silicone, as long as it is transparent and has good deformability. The latex membrane is essential for increased robustness and flexibility for handling a slightly sharp object without damaging the sensing material. The membrane must be uniform, thin, smooth, firm, and light-blocking for good signal quality. The thickness of the membrane will influence the resolution sensor. If the membrane is not uniform or smooth, the tactile images will contain noise from the irregularities on the surface. Finally, we must attach the elastomer to the sensor to the supporting plate to reduce residue force during the contact.

The silicone elastomer is the central part of the sensor. Fabricating the sensing silicone elastomer requires two parts: making the transparent elastomer base and adding the latex membrane top as shown in Figure 3, where Figure 3 (a) shows the elastomer block without coating and (b) is with the coating. The transparent elastomer base is the central sensing part of the sensor. We chose a commercialised polymer to make the silicone elastomer in the fluid phase. For the elastomer base, the elastomer we use is the SMOOTH-ON® silicone product, Solaris, which is a low-viscosity, clear and colourless liquid platinum-cured silicone rubber compound (Part A and Part B). It comes in two liquid parts after dispensing the required amount of Part A and B into the mixing container (1A:1B by volume or weight), mixed thoroughly for 3 minutes. For getting transparent silicone elastomer, vacuum degassing is necessary to help to eliminate any entrapped air while mixing. For getting transparent silicone elastomer, vacuum degassing is necessary to help to eliminate any entrapped air while mixing. Vacuum degassing before pouring, subject to 14.21 psi in the suitable vacuum chamber for 2–3 minutes or until mixture rises, breaks, and falls. We pour this mixture in a single spot at the lowest point of the mould, which is made by a 3d printed

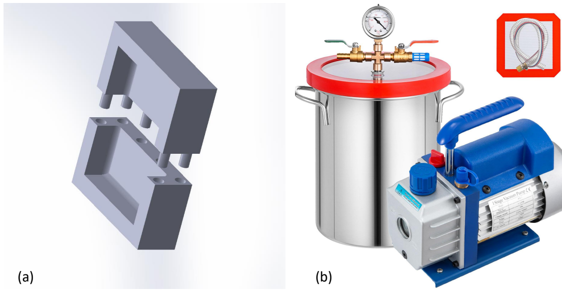


Fig. 4: Silicone Elastomer (a) Mould cavity, (b) Vacuum pump with vacuum chamber

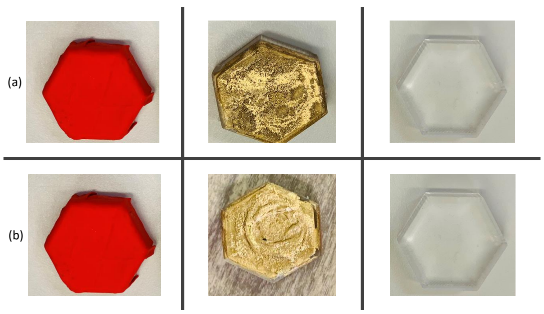


Fig. 5: Normal Load testing sample (a) Prepared silicone sample. (b) silicone sample after testing.

hexagonal container, and it solidifies within 24 hours at room temperature (see Figure 4). The hardness of the elastomer can be changed by adjusting the mixture portion of parts A and B. Then, we put latex on top with the help of glue. The main component of our tactile sensor, including the acrylic sheet and outer support structure, is 3D printed with non-transparent material, which holds the camera and the acrylic guiding plate and provides the mounting structure to the robot gripper. Then, a laser cutter cuts the transparent acrylic plates.

### B. Camera and lighting system

Around the silicone, there is provision for the LED arrays at three points in three colours, Red, Green, and Blue, respectively. The LEDs (Osram Opto® Semiconductor LEDs SMD, Sunnyvale, CA, USA) are manually soldered into the compact array, as shown in Figure 2 (d), and glued to the top side of the support just in front of the silicone mould. The embedded camera is a USB webcam (C310 from Logitech®) placed horizontally at the bottom and parallel to the silicone elastomer. The camera can capture images at 30hz with a resolution of $1920 \times 1080$. The camera cover is removed, and only the central part of its circuit is used, as shown in Figure 2 (c).

## IV. Experimental Setup

### A. Mechanical characteristics of coating materials

To evaluate the mechanical characteristics of the silicone elastomer, we first evaluate the performance of the silicone elastomer with three coating conditions, namely latex membrane, metallic coating, and no coating, as shown in Figure 5(a). We used a ZwickRoell® material testing machine to apply a uniform load on the silicone elastomer to perform this test. The force-displacement characteristic plot (Figure 6) was constructed to analyze the effect of force on the silicone elastomer, i.e., the surface deformation of the material.

Figure 6 shows that, with the increase of the force, the pure silicone was easily deformed, losing its linearity in terms of elastic deformation, i.e. pure silicone is elastically deformed and regains its shape without damage on the surface. On the other hand, the force with the latex membrane (the red curve) can reach higher than with pure silicone above for more travel distance. Also, the silicone with metallic coating is also deformed with improved maximum force applied, but unfortunately cannot regain its shape, due to the damage on the surface, as shown in Figure 5 (b). Therefore, we consider that the latex membrane-based coating is more preferred considering both its optimal elastic deformation stability and its durability on the surface, which has no damage on the surface.

The force-displacement curves for spherical indentations are quantified in nonlinear large-deformation indentations, and the relationship between applied force and displacement are as follows [36][37]:

$$\delta - \delta_{contact} = \frac{a^2}{R} - \sqrt{\frac{2\pi\left(1-\nu^2\right)a\Delta\gamma}{E}} \tag{1}$$

$$F = \frac{4Ea^3}{3\left(1-\nu^2\right)R} - 2\sqrt{\frac{2\pi E\Delta\gamma a^3}{1-\nu^2}} \tag{2}$$

where $\Delta\gamma = -\frac{2F_{adh}}{3\pi R}$, $\delta$ the probe displacement, $\delta_{contact}$ denotes the displacement at the contact point in loading stage, $a$ the contact radius between the probe and the underlaying sample, $R$ the probe radius, $F$ the applied indentation force, $\Delta\gamma$ is the corresponding adhesion energy density, $F_{\mathrm{adh}}$ is the pull-off force, $E$ and $\nu$ denote the Young's modulus and Poisson's ratio of the soft silicone material, respectively. In the current data analysis, we plot the silicone deformation over the force, indicating the silicone elastomer's mechanical strength, as illustrated in Figure 6.

### B. Robustness validation of sensor surface

In this section, we introduce another further force-displacement experiment to quantitatively validate the sensor's surface robustness. We exert force in the normal direction of the sensor surface, as shown in Figure 7, where we push the modified optical tactile sensor with the help of an indenter.

There are two phases of this experiment, namely data collection and validation of sensor robustness. The Kuka robot arm end effector mounted with the indenter is pushed against the sensor up to 10mm in distance and 50N in force. The Kuka iiwa robot is used because it provides intrinsic force feedback directly, making it convenient to measure

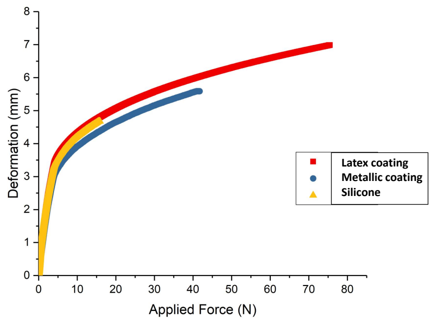


Fig. 6: Force displacement characteristic different silicone material.

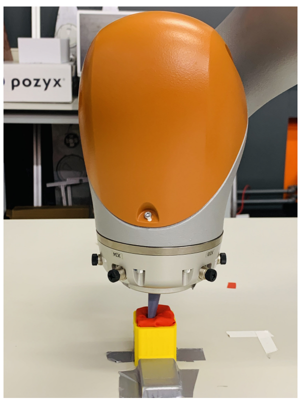


Fig. 7: Validation of robustness of sensor surface on Kuka robot arm

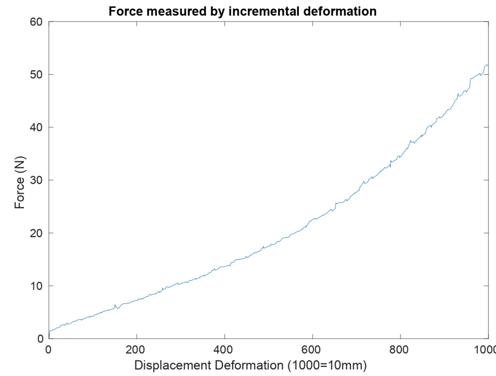


Fig. 8: Force measured by incremental deformation.

the performance. The robot gradually increases the travel distance at a predefined contact point on the sensor surface, and simultaneously measure the force. In this experiment, the end effector travel 10mm perpendicular to the sensor's surface, as shown in Figure 8. The sensor testing makes it possible to sustain 50N force at 10mm deformation at a single location, as shown in Figure 8.

To the best knowledge of the authors no other research works have performed such a test. Since every application has a different type of load required, for this reason, we exert a 50N load with 10mm deformation to test the behaviour of the membrane. We conducted this experiment to investigate how the sensor membrane responds to strain, motion, and pressure. For this reason, we applied 50N force to check the robustness sensor. This test was conducted to check the robustness of the sensor. On the other hand, when the object is touched and pressed against the sensor with a relatively high force (higher than 30N), it gives imprints to where the object touches, but it regains its original shape after some time.

### C. *Evaluating spatial resolution on a grasping system*

Despite the improved robustness with the introduced latex membrane surface, it is also important to make sure the sensor is performing equally well on perceiving high-resolution texture information. Since we are evaluating different objects, including many objects with rough surfaces, it is difficult to directly compare the sensor with existing sensors, such as Gelsight. Therefore, in our work, we carry out texture classification experiments using a state-of-the-art deep learning algorithm and aim to demonstrate that our proposed sensor's performance is not sacrificed in terms of its spatial resolution for object perception.

In our work, we mounted the sensor on one fingertip of a ROBOTIQ® gripper 2F-140, as shown in Figure 1. This gripper has two articulated fingers with two joints on each one of them. The gripper is connected using a serial communication protocol to a PC and controlled with Python. The gripper's position, velocity and force can be controlled. Different objects produce different shapes during contact.

As said above, we validate sensor performance in terms of its spatial resolution using a classification task via a Neural Network (NN), a VGG-19 in particular to classify images captured by the sensor. We used Keras to implement our system.

**Data collection:** Nine rough and slightly sharp objects are used for data collection, as shown in Figure 9. We included objects of different sizes, shapes and materials. An object is pressed against the sensor surface by a human hand during the data collection process, and then the forces are applied to objects to generate target images for a certain period. The labelling of specific data is determined by object category. The dataset comprises nine classes, and every class has 2000 samples. In our work, the relatively small size of the dataset is first manually collected, and further data augmentation is performed. The total dataset contains 3636 images in each class. After that, we split the data for training and testing. All the experimentation is done in Python 3.7.2, Keras 2.4.0 and Tensorflow 2.4.1. We used (Intel Core i5-8400 CPU @ 2.8Ghz) with a Nvidia RTX 2080 GPU.

**Result:** The training history is plotted in Figure 10. Our classification accuracy on the testing dataset rises by over 93%. The validation curve aligns with the training curve

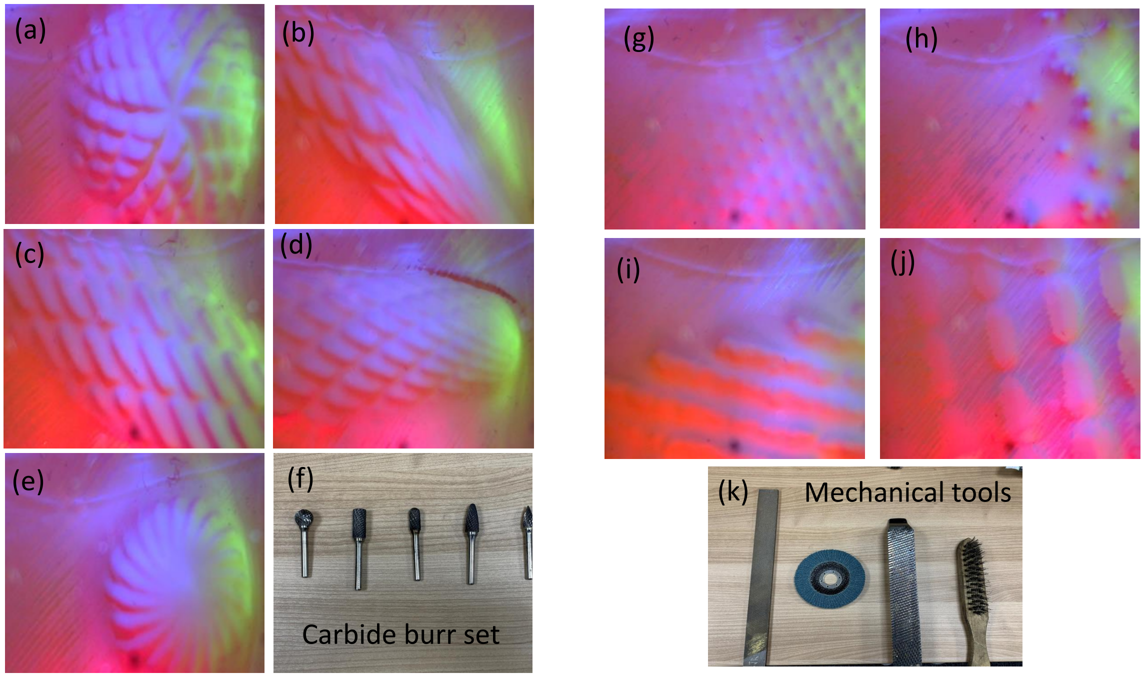


Fig. 9: Example of modified sensor dataset. Carbide Burr Set JESTUOUS 1/4 Inch Shank Diameter Double Cut Edge Rotary files Metal Grinding Polishing Carving Tool for die Grinder. (a) SD Ball shape, (b) SF-3 Tree radius at end, (c) SA-3 Cylindrical shape, (d) SF-3 Tree radius at end, (e) SC3 Cylindrical radius at end, (f) Carbide burr set, (g) Roughfile, (h) Wirebrush, (i) Grindingwheel (j) Woodenbrush, (k) Mechanicaltool set

closely. Specifically, the difference between training and validation loss is nearly equal, indicating no strong sign of overfitting. Furthermore, training and validation losses are minimised, as shown in Figure 10.

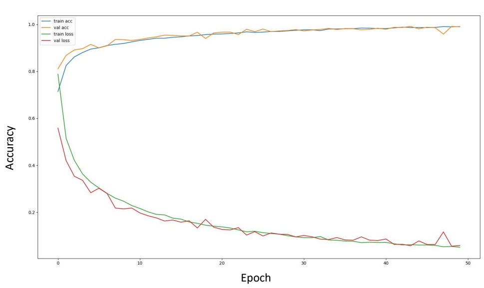


Fig. 10: The CNN network model training process

## V. Conclusions and Future Work

In this work, we present a modified optical tactile sensor. We introduced a latex layer on top of the silicone elastomer to improve the mechanical robustness of the sensor. To evaluate the performance, we carried out a series of experiments. First, we evaluated the mechanical characteristics of the silicone elastomer with three types of coating, namely latex membrane, metallic coating, and no coating. The proposed latex membrane clearly outperformed the other two in terms of robustness. Second, we carried out the force-displacement experiments quantitatively to further study the sensitivity and robustness. Lastly, we validated the sensor performance in terms of its spatial resolution by applying the VGG-19 neural network for classifying touch patterns captured by the sensor. Overall, the proposed sensor achieved the desired robustness, sensitivity, and spatial resolution performance.

The sensor output images of tactile imprints encode the object's shape and pattern at contact, as shown in Figure 9. For example, contact patterns in the pixel space could be used for classification. These quantities, as well as the sensor's calibrated image output, can be used directly in model-based or learning-based approaches to robot grasping and manipulation. For example, this information could be used to track object pose, inform a data-driven classifier to predict grasp stability, or as real-time observations in a closed-loop grasp policy.

We anticipate that our modified optical tactile sensor is suitable for hard surface object manipulation. These facilitate the use of the sensor in various applications, especially in the scenario where visual feedback is lacking and where access is limited or difficult to handle rough/sharp surface objects. We are especially interested in contact texture information for classification. In future, this information can be used for hand dexterity and reactivity, such as picking a mechanical tool for functional grasp and using it. Ultimately, grasping tasks can be performed with robust sensing integrated in the control loop.

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