Cognitive Grasping and Manipulation of Unknown Object with Control Grip Force using Cyber Physical System Approach

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Service robots working in human environments must have the ability to grasp a wide variety of unseen objects with appropriate grip force without knowing their properties and its response to action in a human environment. This research uses a novel Cyber Physical System framework to estimate and apply minimum grasping force for unknown objects under a task motion using only tactile motion data captured from sensor-less acceleration-based controlled common gripper. The goal is to use this novel framework for developing functions for position-controlled robots to perform real-time cognitive grasping and enable quick implementation across multiple robots. This paper uses soft sensing inputs from the earlier research to characterize unknown object properties like stiffness, mass and surface interaction and show how a data-based analytics algorithm learns a wide range of object properties and slip status along with task action dynamics features, to propose the grasping action with minimum applied force. We validated that the minimum grasping force is able to hold the object firmly during any task motion. In order to improve the learning, the paper proposes a part of the framework to use virtual simulation to gather more learning data and show results that compare well between simulated results with experimental data. We use the simulated data to train Reinforcement Learning approach and show that small variation in object width can be learnt to identify optimum gripping position.

Keywords: Grasping and Manipulation, Tactile Sensing, Simulation, Reinforcement Learning (RL), Cyber Physical System (CPS)

1. Introduction

Rapid technology development, aging society and sudden epidemics of infectious diseases have enabled intelligent robots to be used in many fields such as medicine, agriculture and manufacturing industries. With the growth of soft robotics, industrial research is focused on building capabilities in service robots to flexibly adapt their behavior when interacting with humans. Unlike industrial robots, service robots should be adaptive to the environment and require cognitive abilities to perceive, understand and plan to perform precise control with skill and real-time learning.

One of the key abilities of service robots is its function to grasp and manipulate objects to help people with complicated tasks. Humans perform this with their hands efficiently by touching and feeling along with skills obtained through learning. Using humanoid arms, robots must have the ability to grasp a variety of unseen objects in human environments and perform task actions without damaging the object or preventing the object from falling. Recently, considerable progress has been made in robotics to identify objects and grasp planning by using deep learning models\(^ (1)-(7).\) However, using visual inputs alone will lead to errors such as the identification of object properties from looking at external information and deciding correction to the action due to uncertain disturbances during task action.

In an unknown environment, a common position controlled gripper is limited in its ability to grasp a wide variety of (soft to hard) objects and ensure success of grasping. Key research challenges that our research attempts to address in grasping are,

- Applying optimal gripping force on an object; generally, humans apply 10 – 40% higher grip force\(^ (3)\)
- Robot successfully grasping an object in an unknown environment with unknown object properties and the unknown impact of change in disturbances\(^ (4)-(6)\)

The research aims to enable a common gripper to grasp hard or soft objects with a minimum safety margin in gripping force and do a quick grasp force correction to change in environment. Figure-1 explains 3 steps proposed to enable cognitive functions in a common gripper.

This paper proposes novel approach for Acting (Step-2) to estimate and apply minimum grasping force for unknown object using Sensing (Step-1) inputs from the earlier research to characterize unknown object properties (stiffness,
mass, and surface interaction) using only tactile motion data captured from sensor-less acceleration-based controlled 2-fingered robot.

2. Proposed Solution

2.1 Our Proposal Our research proposes the approach to build a CPS framework and validate the use of both motion data from experiments and simulations to learn the grasping action and to identify appropriate grasping force to hold an object under a known task motion. For a robot to hold an unknown object firmly during the task motion will primarily require to sense the object properties and then use this information along with features from the action dynamics to predict and optimize the grasping force applied to ensure successful grasp. The research considers combining multiple novel approaches.

- Only tactile motion data obtained by acceleration-based control and use reaction force obtained through Reaction Force OBserver (RFOB). This eliminates using high-resolution specially designed force sensors and avoids the complexity of placing the sensor at the right location to capture accurate object response information.

- Humans estimate an object’s properties and required grip force based on capturing responses from multiple touch actions on the object along with previous touch experiences. Like human action, this approach uses a pre-designed motion sequence to apply on the object for capturing action to reaction motion data. The stored motion is used for learning and learned model is used to detect the object properties and required grasp force.

- Slipping of objects happens suddenly and it is difficult to capture this information using an experimental setup. Therefore, our research aims to use Physics-based simulation and Finite Element Analysis approach to capture detailed learning data during slip and expand to capture motion data for a variety of object types.

- Build a CPS framework with the above functions that can learn and understand the physical robot to share insights in real-time for performing grasping functions.

2.2 Related Work Recent work in robotics has explored the use of haptics for sensing an object’s shape, pose, location or attributes. For grasping, various research concentrates on the design of grippers, technologies to control grip force and slippage for object grasping and manipulation. Assuming the object is unknown, many research have focused on using special high-resolution force tactile sensors and biomimetic tactile sensors to detect slip for grip control. To increase grasp robustness and appropriate grasp planning for various object shapes, research used millions of grasp actions to train supervised vision based deep learning approach. Research that uses both vision and multiple tactile sensors to grasp unknown objects by identifying stiffness with simple machine learning to set appropriate grasp force has also been conducted. Table 3 in appendix explains detailed comparison of our research paper with related work.

In our research, we propose creating a digital replica of a physical 2-fingered robot in CPS framework using normal sensing data to create a behavioural representation of a physical robot that can enable building human-like cognitive functions. In this paper, we demonstrate building a simple behavioural representation using a machine learning algorithm that can learn object properties along with task action features and propose a minimum grasping force. We validated that the minimum grasping force is able to hold the object firmly during task motion. In order to build robust behavior representation, we propose to use the simulation for gathering more learning data. This paper also shows initial results from physics-based simulation using MATLAB Simulink and FEA using Altair Radioss and their results are compared with experimental data.

This paper continues to explain the CPS framework setup.
and initial results comparing simulation and experiment for generating additional learning data in Section-3. Results for minimum grasping force using Machine and Reinforcement learning approach in Section 4, Implementation approach in Section 5 and Section 6 explains conclusion and future work.

3. **Cyber Physical System Framework**

Cyber Physical System is creating digital replica capturing behaviour of actual physical system and uses this as a simulator to perform offline optimization or scenario analysis for specific objectives. CPS can then propose better operations in real-time to the physical system. It consists of a Physical robot system, Cyber robot system supported by Simulation robot system. In grasping objects, humans use a variety of finger postures to hold an object. In this paper, we have used pinch grasping performed to hold an object with 2 fingers.

3.1 **Experiment Setup of Physical Robot System**

We have used 2-fingered robot experimental setup with sensorless control to store the motion data from 2 linear motor such as position, velocity and force response estimated using a Reaction Force Observer (RFOB). Figure-2 shows the architecture of CPS with experiment setup. One linear motor operates a 2-fingered gripper using 4 bar hinge mechanism marked as Grasping motor. Below the grasping motor, there exists another linear motor marked as Push/Pull motor used to perform linear pull or push motion of the grasped object.

We use 6 objects with the same shape and size (50 x 50 x 30 mm) having a wide range of properties for this research. Stiffness ranges from 110,000 N/m to 3000 N/m, Mass range from 0.6 Kg to 0.002 Kg and Surface Interaction(SI) as Smooth or Rough. In addition, we use one test object (Obj-G) with same size having properties within the range of train objects that is not used in training to validate the model performance. Figure-3 shows the material properties of objects used.

Predefined motion sequence is used to move both grasp and push/pull motor which enables 2-fingered gripper contact to grasp the object along with task motion. From these actions, the desired Position \((X_{cmd})\) and Velocity \((dX_{cmd})\) are applied as inputs for both motors to the experiment. Position response \((X_{res})\), Velocity response \((dX_{res})\) and Reaction force \((R_{fob})\) are obtained as outputs from the experiment. This data is stored as motion data for each experiment. Figure-4 shows the experiment with 2 different gripper surfaces and corresponding experimental data.

Experiments are designed to perform task motion in which the gripper holds the object and pulls the object against gravity. Each experiment performs 5 sub motion sequences. For each sub motion, a different grip position is applied to capture the resistance applied by the gripper sliding over the object. This paper considers variation in object properties (stiffness, mass and surface interaction), gripper surface (bare and cloth tape) and 2 variations of velocity of pull motion.

3.2 **Simulation Robot System**

Simulation of the physical robot system considers 2 simulation approaches to replicate the actual experimental setup. Research considers grasping of both soft and hard objects hence the simulation of 3D deformable objects along with slip is under-researched requires macro and micro simulation strategy. This paper proposes to use 2 approaches,

- Macro Approach: Physics-based simulation using MATLAB SIMULINK to get the joint values and gripper reaction force
- Micro Approach: FEA simulation of gripper contact with an object to get accurate gripping force and slip

3.2.1 **Simulation using MATLAB**

MATLAB Simulink provides graphical editor, customizable block libraries, and solvers for modeling and simulating dynamic systems. It is integrated with MATLAB, enabling to incorporate MATLAB
algorithms into models and export simulation results to MATLAB for further analysis. Simulink’s flexible bodies can be used to model deformable 3D objects.

We created the 3D model representing the experimental setup and defined joints with constraints. The fingers and gripper assembly are actuated using the position command. An object is placed on a zero friction table and can move between top and bottom stoppers. Object properties such as object size, mass and coefficient of friction at the surface can be altered in the simulation. Contact reaction forces both normal and tangential are retrieved from gripper to object contacts and object to stoppers. Simulation is performed for milliseconds with a fixed time step solver. The applied position, velocity and reaction forces are captured as text files from simulation. Figure-5 explains the assembly model used for MATLAB simulation.

To validate the simulation results with the experiment, we performed simulation considering properties of Object-1(A) in the experiment and validated the maximum reaction force with the experimental data. Figure-6 captures the gripper contact normal force with object for 3 different mass values executed as Simulation1, 2 and 3. Simulation considers high stiffness and 3 mass values as 0.6 kg (Sim-1), 0.5kg (Sim-2) and 0.4kg (Sim-3). It could be inferred that the results of Sim-1 which has closest mass to Object-1 in experiment has reaction force close to the experiment for Object-A.

3.2.2 Simulation using FEM

We build our FEM-based gripper interacting with objects using an explicit Altair Radioss solver for simulating both hard and soft objects. Gripper and object are meshed with 2900 hexahedral elements. Youngs Modulus, Poisson ratio and Density are applied as material properties. Figure-7 explains the mesh with applied loads and boundary conditions. Using this setup, we simulate several FEM simulations of grasping to the objects with different stiffness and mass to study the influence on reaction force and slip behaviour.

To compare the results, we performed FEM simulation for 3 objects (Object-A, Object-C and Object-F) with different stiffness and overlapped the results over experimental results. Figure-8 shows the overlapping plot of the experimental and simulation results from Object-A, C and F.

It could be noted that the results are matching to a reasonable accuracy. However, the results can be improved with stress vs strain based material properties and fine meshing strategy.

3.3 Cyber Robot System

Cyber Robot System consists of Deep Neural Network and Logistic Regression models built for sensing object properties and behavioural representation of robot during task motion, respectively for suggesting grip position command. We use the data-based predictive analytics models to determine the minimal grasping force for holding the objects successfully. Success of gripp-
ping is defined as the condition when there is no slip happens between gripper and object during the task motion of moving the object from bottom stopper to top stopper. This paper also considers using RL approach to identify appropriate grasping position when the object width is not constant.

### 3.3.1 Logistic Regression (LR) for Grip Status

Logistic Regression is used to build the relationship between response variables (position, velocity and reaction force) obtained from various objects to a predictor variable (grip status) for developing predictive analytics model. LR from its hypothesis will output the estimated probability of predictor variable (grip status).

We use the LR predictive model to generate sensitivity plots for each object property in Figure-9, Figure-10 and Figure-11. From the plots, we could capture the domain behaviour of stiffness, mass and surface interaction for both train and test objects appropriately. We could infer that object with high stiffness or high mass requires a higher grip position than with low stiffness or low mass. Also, we could see that Smooth SI requires a higher grip position than Rough SI.

When conducting the test in experiment using LR predictive model, we start with probability of grip success as 80% to find the grip position command to successfully grasp the object during task motion with optimal reaction force. Based on slip status estimation if the object slips then probability of grip success is increased to identify the next best grip position for ensuring grasping success. We found that probability of grip success from 90% and above can hold for all range of objects used in our research with optimal reaction force.

### 3.3.2 Reinforcement Learning (RL) for Grip Position

Reinforcement learning (RL) is a goal-oriented learning tool wherein the agent or decision maker learns a policy to optimize a long-term reward by interacting with the environment. At each step, an RL agent gets evaluative feedback about the performance of its action, allowing it to improve the performance of subsequent actions. Off-policy methods of RL algorithms have been used for learning the control methods. In the off-policy method, the policy used to generate data, called the behavior policy is unrelated to the estimation policy that is evaluated and improved.

We use model-based Actor-Critic network algorithm to learn the policy using states, action and reward obtained from MATLAB simulation. RL network uses Normal and Tangential force from gripper finger as state and Top stopper reaction force from the object for reward calculation. Reward function captures higher reward for top stopper reaction force that is higher than 1N force which indicates that the object has touched top stopper in addition to lower reaction force. RL network performance is evaluated with increasing average episode reward and stable as iterations increase. Action from RL network will suggest grip position command to hold the object. Figure-12 shows the schematic of off-policy RL used for grip position prediction.
RL policy is learnt from 500 simulations in which object width is varied between 50 to 53 mm. We could identify the grip position command that can successfully grasp the object with the least reaction force, when the object width varies from 50 to 53 mm. From the results, we can observe that the RL approach can be used when the object width is not fixed.

4. Results

4.1 Logistic Regression for Grip Status to predict Grip Position Command (Object width is fixed) We validated the proposed gripping position from LR to hold the object successfully using experiments.

Table-1 and Figure-13 shows that the optimum grip position for each object with Reaction Force (RF) obtained is lowest to hold the object successfully. Table-2 shows the relative categories of each object properties to explain the relation of optimum grip position to object properties. It could be inferred that objects with high stiffness and mass require higher grip position (Obj-A); high stiffness and low mass requires relative lower grip position (Obj-B); medium stiffness and low mass require lowest grip position (Obj-C, D, E) and low stiffness and low mass requires relatively higher grip position (Obj-F).

We also validated LR predictive model with unseen test object (Obj-G) which has material properties closer to Obj-D and Obj-E and we could see that the optimal grip position is closer to Obj-D and Obj-E. By this, we could infer that objects with properties within the range of train objects can be used with existing LR prediction model. In addition the framework of learning process conceived in this research can be used to train new objects.

4.2 Reinforcement Learning to predict Grip Position Command (Object width is varying) Results of RL captured in Figure-14 show that as the width of the object varies from 50 mm to 53 mm the optimum grip position command to hold the object increases. The size of the circle represents the value of the reaction force between gripper and object, and it could be noted that approx. 3 to 5 N force is the least force required to hold the object successfully. The results show that when there is a change in object width, RL can be used to learn the variation using simulations.

5. Implementation

We propose the architecture in Figure-15 for implementation. In this architecture, we use the pre-trained LR model for predicting Grip status to identify grip position command based on motion data obtained from interaction of 2-fingered gripper with object. We use our prior research on sensing the object properties to provide the inputs for stiffness, mass and surface interaction information to LR model. The architecture is explained with a block diagram of Grasp and Push/pull motor motion control whose output parameters are provided as input to material property identification and grip status prediction for identifying optimal grip position com-

### Table 1. Inference of LR Results

<table>
<thead>
<tr>
<th>Object</th>
<th>Max RF (N)</th>
<th>Optimum Grip Position (m)</th>
<th>RF at Optimum Grasp at Motor [at Gripper] (N)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>25</td>
<td>0.01477</td>
<td>11 [2.8]</td>
</tr>
<tr>
<td>B</td>
<td>20</td>
<td>0.01468</td>
<td>6.27 [1.6]</td>
</tr>
<tr>
<td>C</td>
<td>15</td>
<td>0.01466</td>
<td>2.58 [0.7]</td>
</tr>
<tr>
<td>D, E</td>
<td>5, 3.5</td>
<td>0.01461</td>
<td>2.15 [0.6], 1.27 [0.3]</td>
</tr>
<tr>
<td>F</td>
<td>2</td>
<td>0.01465</td>
<td>1.6 [0.4]</td>
</tr>
<tr>
<td>G (Test)</td>
<td>4</td>
<td>0.01462</td>
<td>1.05 [0.25]</td>
</tr>
</tbody>
</table>

### Table 2. Property category for explaining LR results

<table>
<thead>
<tr>
<th>Object</th>
<th>Stiffness</th>
<th>Mass</th>
<th>Surface Interaction</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>High</td>
<td>High</td>
<td>Smooth</td>
</tr>
<tr>
<td>B</td>
<td>High</td>
<td>Med</td>
<td>Smooth</td>
</tr>
<tr>
<td>C</td>
<td>Med High</td>
<td>Low</td>
<td>Rough</td>
</tr>
<tr>
<td>D, E</td>
<td>Med Low</td>
<td>Low</td>
<td>Rough</td>
</tr>
<tr>
<td>F</td>
<td>Low</td>
<td>Low</td>
<td>Smooth</td>
</tr>
<tr>
<td>G (Test)</td>
<td>Med Low</td>
<td>Low</td>
<td>Rough</td>
</tr>
</tbody>
</table>
Cognitive Grasping and Manipulation of Unknown Object with Control Grip Force using CPS Approach (Joel Thompson et al.)

6. Conclusion and Future Work

In this paper, we have demonstrated the CPS framework and its components to enable the cognitive functions of the 2-fingered robot. We could showcase that the 2 fingers robot task action can be understood by the data-based analytics models and propose an appropriate grasping position command for the gripper to hold the object securely during the task motion. We have used our prior research on sensing the object properties to provide as an input to the acting phase for understanding the object characteristics. We have shown that LR approach learning using the experimental data could find the optimum grasping position command and explained the comparison of results. To understand, if the LR model can predict an unseen object, we used a test object (Obj-G) and show that the LR model was able to effectively predict optimum grasping position command in relation with its closest objects. We have used the RL approach to show that it is possible to identify optimum grasping position, when the width of the object is varied from the actual object size used in the experiment. However, matching simulation results closer to actual experiments which has disturbances is a challenge to be addressed for using RL in real life instances. In this paper, we have also proposed how a Simulation robot system can be created to generate more learning data. We have shared our first attempt results for FEM and used MATLAB Simulink simulation data effectively for RL.

As the next step, we propose to improve the FEM simulation and get useful data for LR learning. We will also increase the number of task motion, gripper surface types and object properties to learn multiple scenarios and show the performance of the novel Cyber Physical System framework. Estimation of minimum grasping force for object size variation is shown however other variation of properties that are not part of learning by Cyber Physical System will be also included.

In the future, we are planning to extend the proposed
framework to multi-degree-of-freedom and multi-fingered grasping motions and in this case stability of grasp will be an important consideration to define the success of grasping.

References

(1) L. Pinto & A. Gupta: Supersizing self-supervision: Learning to grasp from 50k tries and 700 robot hours, ICRA (2016)
(2) S. Levine, P. Pastor, A. Krizhevsky, & D. Quillen: Learning hand-eye coordination for robotic grasping with deep learning and large-scale data collection, ISER (2016)
(7) V. Chu, I. McMahon, L. Riano, C. G. McDonald, Q. He, J. M. PerezTejada, M. Arrigo, N. Fitter, J. C. Nappo, T. Darrell et al.: Using robotic exploratory procedures to learn the meaning of haptic adjectives, in ICRA (2013)
(15) Qingkai Lu & Tucker Hermans: Modeling Grasp Type Improves Learning-Based Grasp Planning, IFA (2019)
(17) Shan-Qian Ji, Ming-Bao Huang and Han-Pan Hunag: Robot Intelligent Grasp of Unknown Objects Based on Multi Sensor Information, Sensors (2019)
(21) Joel Thompson, D.Kasun Prasanga & Toshiyuki Murakami: Identification of unknown object properties based on tactile motion sequence using 2-finger gripper robot, Precision Engineering (Feb 2022)
### Table 3: Details of all the relevant reference papers mentioned in related work and comparison with our research approach to explain the novelty

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Related Paper</th>
<th>Object</th>
<th>Learning Data</th>
<th>Experiment Data</th>
<th>Simulation Data</th>
<th>Detection</th>
<th>Prediction</th>
<th>Sensor Design</th>
<th>Machine Learning for Detection/Prediction</th>
</tr>
</thead>
</table>
| Gaging unknown object by detecting the slip during lifting of object | Proposes slip detection using machine learning approach. | (10) | 1 object | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Gaging unknown object by better describing the grasping group | Detect slip during lifting of object by applying sufficient grip force to the object. | (11) | 1 object | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Gaging unknown object by detecting the slip during lifting of object | Proposes slip detection using machine learning approach. | (14) | 3 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Categorization of object properties such as surface texture, weight, and compliance using a multi-sensor robotic hand | Proposes slip detection using machine learning approach. | (15) | 1 object | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Object pose identification for multi-finger robot using a vision-based tactile sensor. | Proposes slip detection using machine learning approach. | (16) | 3 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Experiment Data | Classify material properties such as stiffness, mass and surface interaction properties using vision-based data or vision with tactile data | (17) | 7 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Simulation Data | Contact technique to estimate tactile properties using a bio-inspired tactile sensor. | (18) | 7 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Learning Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (19) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Experiment Data | 21 objects | (20) | 21 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Experiment Data | 7 objects, 21 objects | (21) | 7 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Combination of vision with multiple tactile sensors in robot hand | Grasp unknown objects with multi-finger robot based on demonstrations by a skilled human operator captured using vision-based point cloud data and generate hand poses using machine learning. | (22) | 2 objects | Yes | No | No | Yes | No | No | Logistic Regression, SVM
| Learning Data | Contact technique to estimate tactile properties using a bio-inspired tactile sensor. | (23) | 7 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Simulation Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (24) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Learning Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (25) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Detection Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (26) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Detection Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (27) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Simulation Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (28) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Learning Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (29) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Detection Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (30) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Detection Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (31) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Learning Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (32) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Detection Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (33) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM
| Learning Data | Large-scale supervised learning of 1.66 million grasps using RFOB | (34) | 20 objects | Yes | No | No | No | Yes | No | Logistic Regression, SVM

**KNN**: K-Nearest Neighbor; **SVM**: Support Vector Machines; **PCA**: Principal Component Analysis; **LR**: Logistic Regression; **NN**: Neural Network; **CNN**: Convolutional Neural Networks; **LSTM**: Long Short-Term Memory.