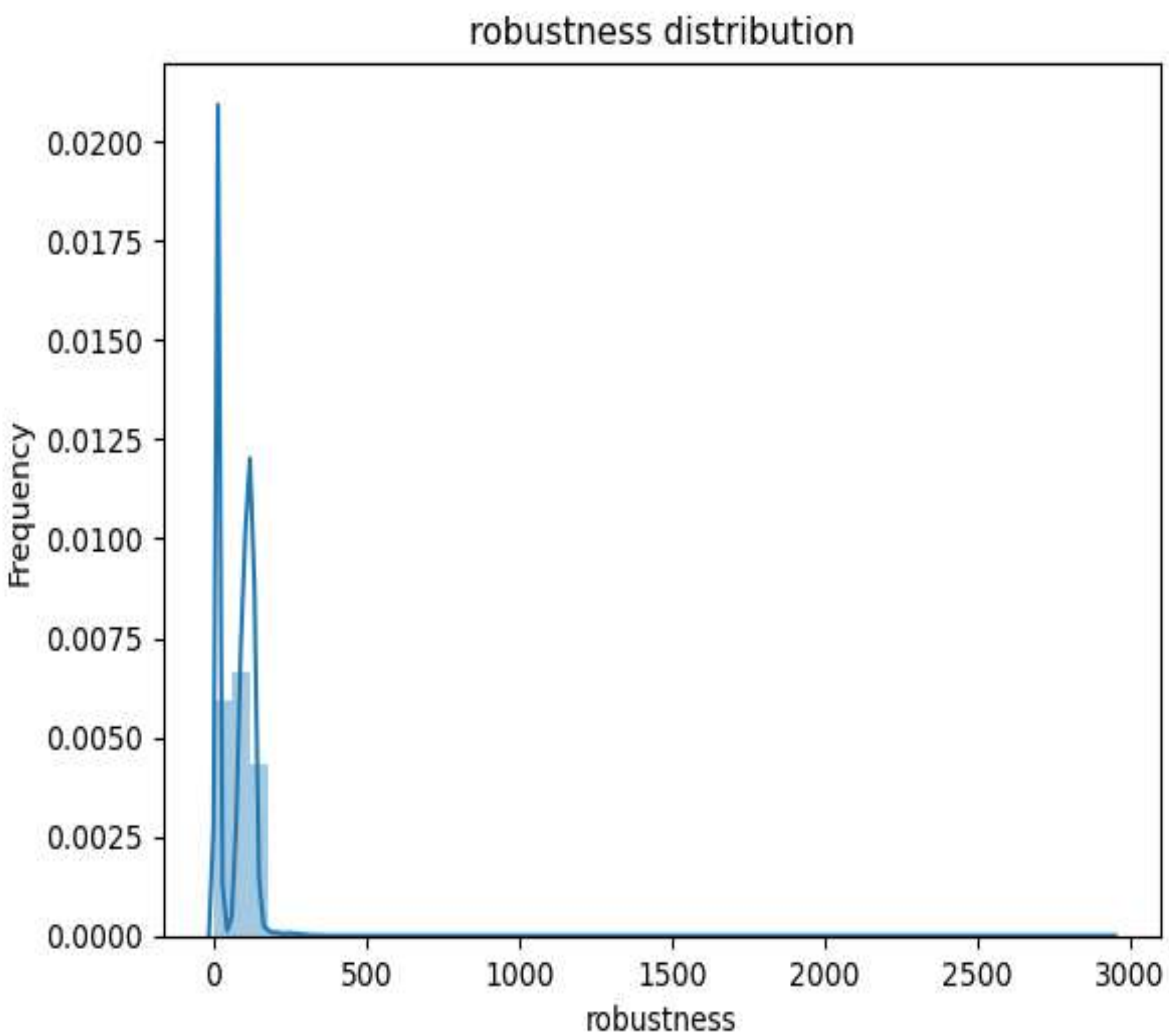
Robotics AI-ML Case Study

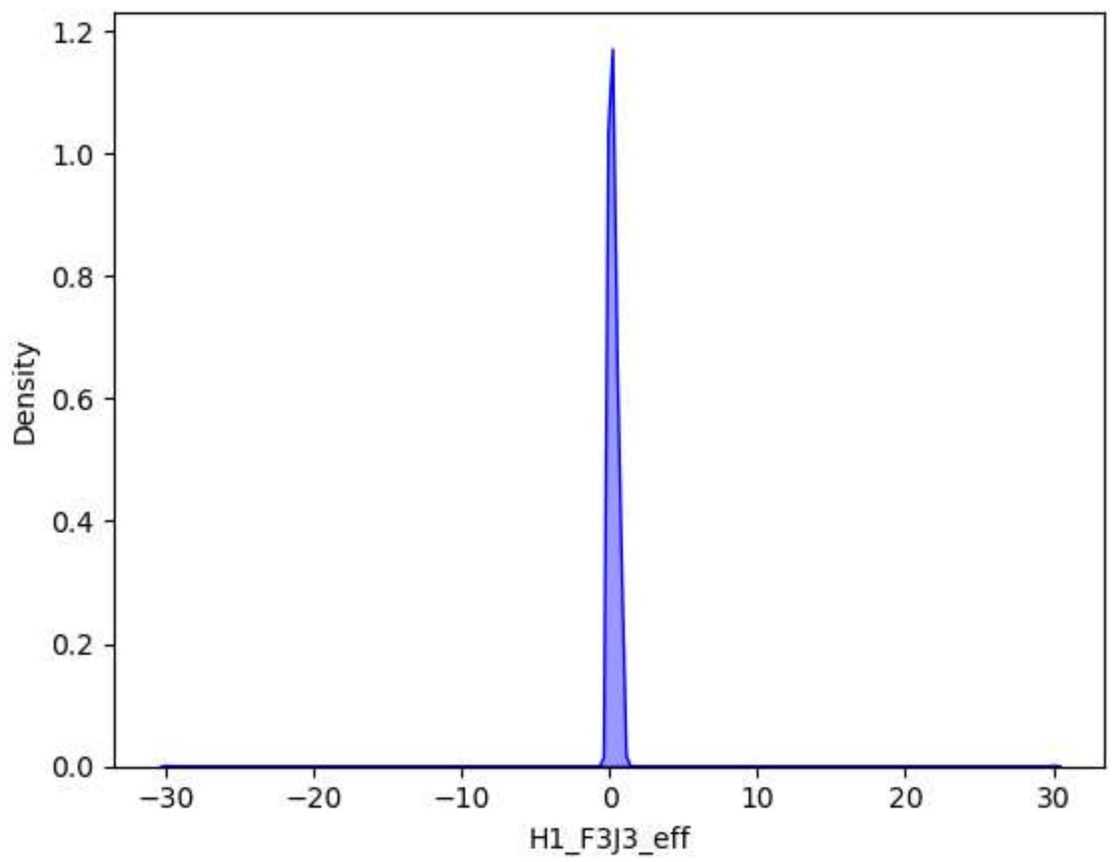
One problem in the Robotics industry that could be solved using data science and Auto-ML is predicting grasp quality. In robotics, grasp quality refers to how well a robot grasps and manipulates an object. By utilizing different data gathered from the joints (position, velocity, effort), Auto-ML models can be trained to predict the quality and stability of a grasp. The goal is to train the robot to grasp objects in a way that ensures that the object does not slip, rotate or fall, and that the robot can manipulate the object with stability and precision.

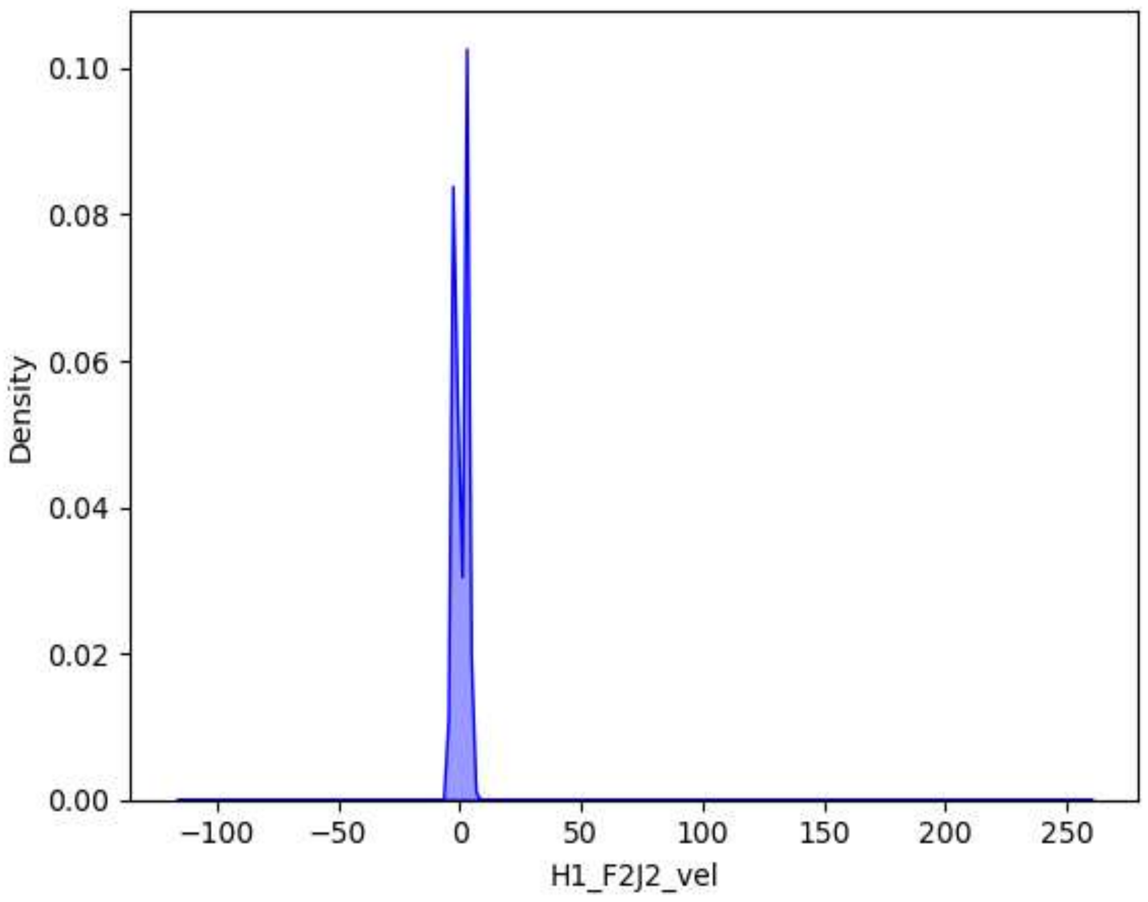
The dataset contains 100,000 observations. The aim of this study is to predict the stability of a grasp (Robustness) and find the factors influencing grasp using Auto-ML.



- The business feature used here is Robustness.
- Robustness is the quality of the grasp experiment
- The distribution plot shows that most of the robustness is from 0 – 300.

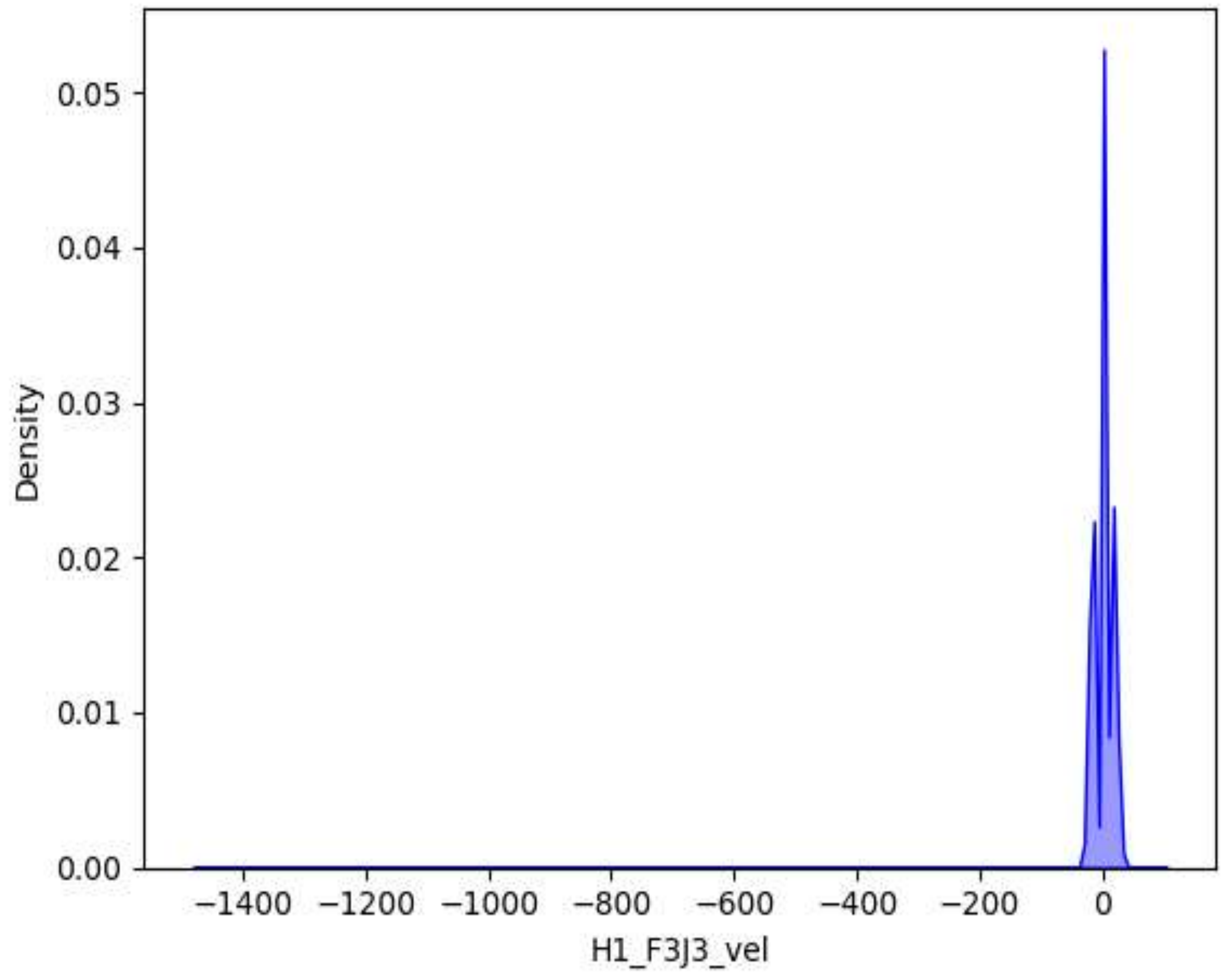
Features Responsible





- **H1_F3J3_eff** : Hand with three Finger with three joins of the effort.
- The three-fingered hand design allows for a wide range of grasping and manipulation tasks, from precision grasping of small objects to robust grasping of larger objects.

- **H1_F2J2_vel** : Hand with two Finger with two joins of the velocity.
- A hand with two fingers and two joints is known as a two-fingered hand or bi-finger hand. The bi-finger hand design allows for fast and precise grasping and manipulation tasks due to its high velocity and low inertia.



- **H1_F3J3_vel** : Hand with three Finger with three joins of the velocity.
- The tri-finger hand design offers a balance of speed, dexterity, and adaptability. The three fingers and three joints allow the hand to perform a wide range of grasping and manipulation tasks with a high level of dexterity and adaptability to objects of varying shapes and sizes.

Auto-ML Methodology Results

Algorithms	Test Accuracy (25 percentile)	Test Accuracy (50 percentile)	Test Accuracy (75 percentile)	Test Accuracy (90 percentile)
Lasso	21	60	61.5	62.1
Random Forest	82.3	85.2	86.4	88
XGBoost	73	76.6	76.8	85.8
MLP	39	39	32.7	35.8
RNN	62.23	58.86	58.37	62.29
Total Features	7	14	21	26
Avg. Accuracy	55.5	63.93	63.15	66.79

- **Based on our observation from the standard ML algorithms, 90th percentile has the best average accuracy.**
- **Random Forest was the best performing algorithm with 88% accuracy in 90 percentile.**

Conclusion

In conclusion, the use of Auto-ML models to predict the robustness of robotic systems can significantly benefit the robotics industry. The design of robotic hands is crucial in determining the overall performance and efficiency of robotic systems. The dataset has 100,000 records with 1 Categorical Features and 29 Numerical Features.

For regression, models were created with algorithms using Auto-ML techniques like Lasso, Random forest, XGBoost, Multilayer Perceptron and Recurrent Neural Network. With these models, performance measurement values were obtained for feature sets of 7, 14, 21 and 26. The Auto-ML algorithms were able to predict the Robustness with an average accuracy between 55% – 67% and helped to identify factors that determine the Robustness. The major factors include H1_F3J3_eff, H1_F2J2_vel and H1_F3J3_vel. The Random forest with 88 % accuracy in 90th percentile where tree showed H1_F3J2_pos (Hand with three Finger with 2 joins of the position) <= 0.19 units and H1_F2J2_eff (Hand with two Finger with two joins of the effort) >= 4.89 units which leads to highest Robustness.

Overall, Auto-ML has the potential to revolutionize the robotics industry by enabling robots to perform tasks that were previously impossible or impractical.