Latest in AI/ML application to modeling complex geometry

Prakash "Krish" Krishnaswamy[1], Umesh Mallikarjunaiah[2], Yoshikazu Nakagawa[3]

[1, 2] Xitadel CAE Technologies Pvt. Ltd., India
[3]Honda Motor Co., Ltd, Japan

Abstract- There is rapid convergence of multiple technologies that are creating unprecedented capabilities in every field of technology. The incorporation of new technologies like Artificial Intelligence/Machine Learning (AI/ML) in the CAE process has been quite gradual. Xitadel's XIPA technology is a pioneering effort to leverage the power of ML to transform the CAE model build process and bring this to production level. CAE modeling is a critical path in the overall CAE process. CAE modeling however is very time consuming, particularly because plastic subsystems typically contain multiple complex features and variable thicknesses.

XIPA uses Deep Learning multi-layered Neural Network that automates the recognition of geometry features in the CAD data and automatically applies the appropriate mesh. XIPA can be customized ("ML trained") to expand its recognition capabilities.

The application of XIPA technology to the modeling and assembly of complex plastics components and subsystems like door inner panel, instrument panel, bumper/fascia, etc. achieves modeling productivity gains of 80% or more. Moreover, specifications and organizational best practices for modeling are also captured, facilitating the institutionalization of process and practice in the organization.

Keywords: Machine Learning, Deep Neural Networks, Convolutional Neural Networks, Faster R-CNN, VGG16 Neural Network, XIPA, Machine Learning for Plastics

1 Introduction

Xitadel has been engaged in a lot of modeling effort for several years in the course of its CAE simulation. The CAE modeling tools for sheet metal are effective and quite well streamlined. However, arbitrary shapes encountered in castings and injection molded plastic components pose greater challenge for achieving consistent quality and the excessive modeling time is expended. Around 2015, Xitadel developed Xpress PL, a modeling tool that allowed for meshing algorithms to be applied to "families" of parts; each family consisted of similar although not identical features.

To achieve even higher productivity, Xitadel developed XIPA ("Xitadel Intelligent Process Automation") that leverages the techniques of Machine Learning to automate the classification of data into geometric feature libraries, followed by the application of Feature Specific Mesh (FSM) algorithms to the geometric features. This process enabled higher speed and ease of modeling plastic components.

In this paper, developed AI/ML technology was applied to a plastic part to investigate and validate feature recognition and mesh generation accuracy, and a reduction of manual work during model build process.

2 Technical Details

This section provides brief theory on two architectures used by XIPA AI Module for object detection (Faster R-CNN (Faster Region Convolutional Neural Network) [section 2.1]) and classification (VGG16 (Visual Geometry Group) [section 2.2]:

Figure 2.1 represents XIPA AI module overview

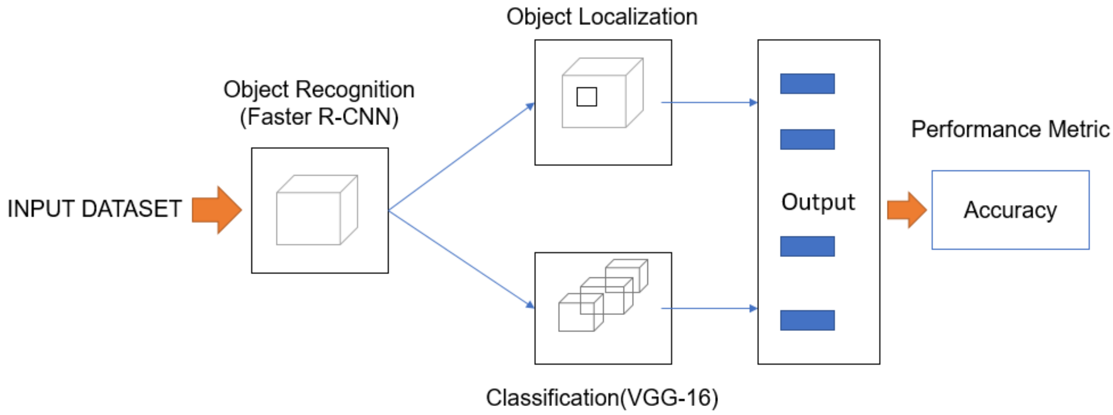

Figure 2.1: XIPA AI module overview

2.1 Faster R-CNN

Faster R-CNN is one of the popular object detection neural network models.This architecture is based on convolutional neural networks and uses “Region Proposal Network (RPN)” replacing the search selection approach for generating regions of interest. This makes Faster R-CNN faster than its predecessor. RPN considers feature maps as an input and generates a set of object proposals, each with an object score as output. A high level overview of the architecture is shown in Figure 2.2 [2].

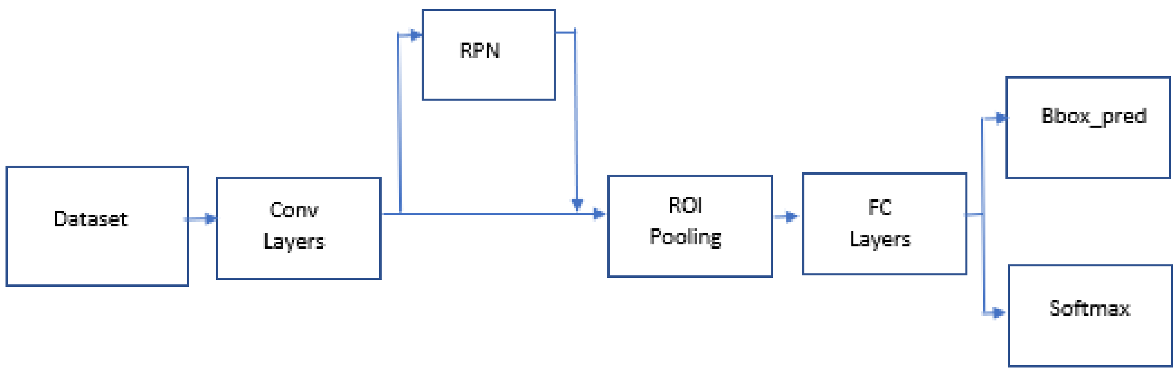

Figure 2.2: Overview of Faster R-CNN Architecture

Figure 2.2 shows process flow of Faster R-CNN architecture which involves the following steps:

1. Input data is fed to the convolutional neural network (commonly known as ConvNet or CNN), where the input is processed, and feature map is obtained.
2. Regional Proposal Network (RPN) is an independent network. In this step, the required object with bounding box is passed for training and it outputs possible proposals for the object.
3. All the proposals from the previous step is passed to ROI (Region of Interest) pooling layer to map it with the original feature map. This will output the highly likely object proposals.
4. Finally, the proposals are passed to fully connected (FC Layers) with softmax activation function and linear regression layers to classify and output the bounding boxes for the objects.

2.2 Visual Geometry Group 16 (VGG16) Neural Network

VGG16 is a convolutional neural network for image recognition. This network takes in a 224X224 pixel RGB image. The convolution layers in VGG16 use a very small receptive field of 3x3. There are also 1x1 size convolution filters that acts as a linear transformation of the input followed by ReLU unit. Spatial resolution is preserved after convolution by using fixed convolution stride of 1 pixel. It has three fully connected layers. All VGG16 hidden layers use ReLU. VGG16 architecture is shown in Figure 2.3 [3]

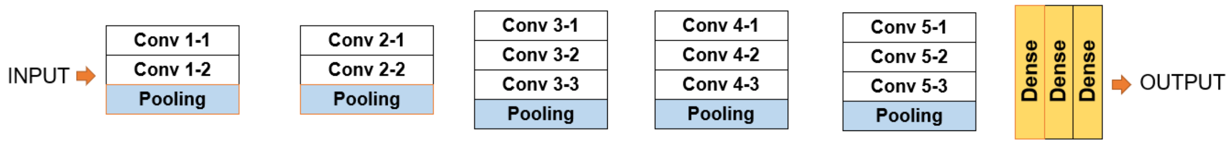

Figure 2.3: VGG16 Architecture

3 XIPA^{TM} Approach for Automating CAE Model Build

This section refers to Xitadel's XIPA (Xitadel Intelligent Process Automation) technology, which leverages the power of machine learning to transform the CAE model build process and bring this to production level. CAE modeling is a critical path in the overall CAE process. CAE modeling however is very time consuming, particularly because plastic subsystems typically contain multiple complex features and variable thicknesses.

Complex plastic subsytems such as doors, instrument panels, bumper/fascia can be meshed and assembled with connectors at near-batch speeds to reduce modeling time.
XIPA approach overview is shown in Figure 3.1 below:

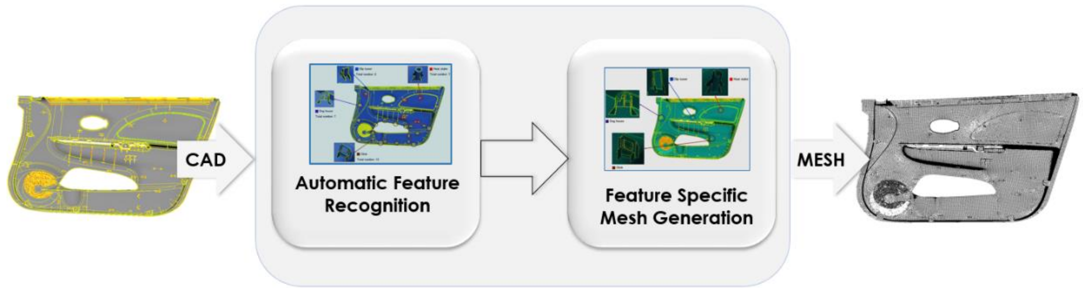

Figure 3.1 : XIPA Approach

Below subsection presents different steps in approach for XIPA.

3.1 Dataset Overview (Theoretical aspects of 3D geometric data)

This section provides overview on representation of CAD data that is provided as input for feature identification.

30 CAD data below were used for XIPA validation. They consist of following plastic features:

- Heat Stake
- Clicks
- Doghouse
- Cups
- Clip Tower
- Locator
- Hole Reinforcement
- Others

Figure 3.2 is an example of the CAD data:

Figure 3.2: Example of CAD data

3.2 Automatic Feature Recognition (AFR)

In this work, Faster R-CNN (section 2.1) with VGG16 (section 2.2) network was used for training for Automatic Feature Recognition. For training of the CAD dataset, 80% of the dataset was utilized for training and remaining 20% was kept aside for testing.

The first step in training was to avoid class imbalance using augmentation techniques to enhance the accuracy of the model. Next, was to identify and localise the features using Faster R-CNN architecture and classify the localised features into their respective feature families using VGG16.

Faster R-CNN architecture was trained on Nvidia GeForce GTX 2080 Ti to accelerate the time required for training the model.

Figure 3.3 shows sample output for identifying the feature and its classification to respective feature families

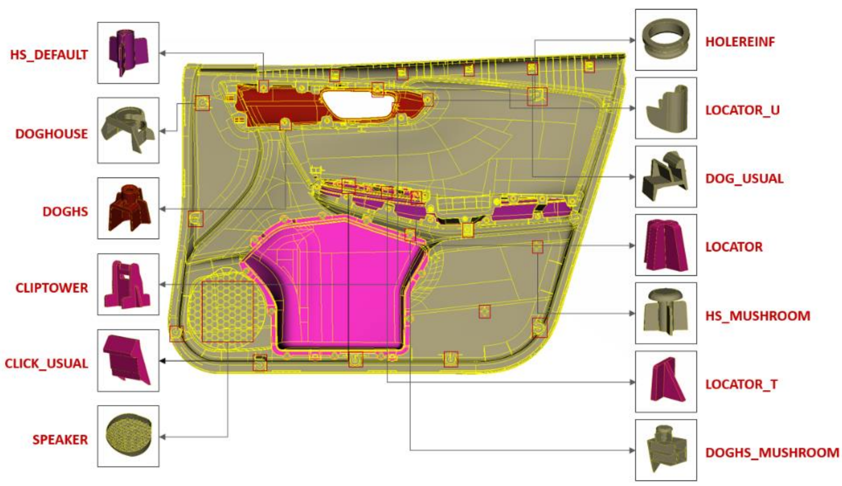

Figure 3.3 : Sample Output on CAD Data

3.3 Feature Specific Meshing (FSM)

This section presents overview on FSM steps in XIPA approach.

After the identification and classification of the features from the CAD data into their respective feature/feature families, features like heatstake, doghouse, and cliptowers, etc. which were present in multiple numbers in CAD data were passed as an input to FSM step. In FSM step, specific algorithm for each feature/feature families were applied, the mesh was captured for the features as per stipulated modeling guidelines. The meshed results are shown in Figure 3.4.

XIPA captures the mesh better and faster as per the CAD profile compared to the traditional pre-processor in the following

1. Alignment of the features to the mid profile
2. Mesh flow is oriented normally
3. Consistent capturing of mesh for features like heatstake, doghouse, cliptowers etc. which are present in multiple numbers in CAD data

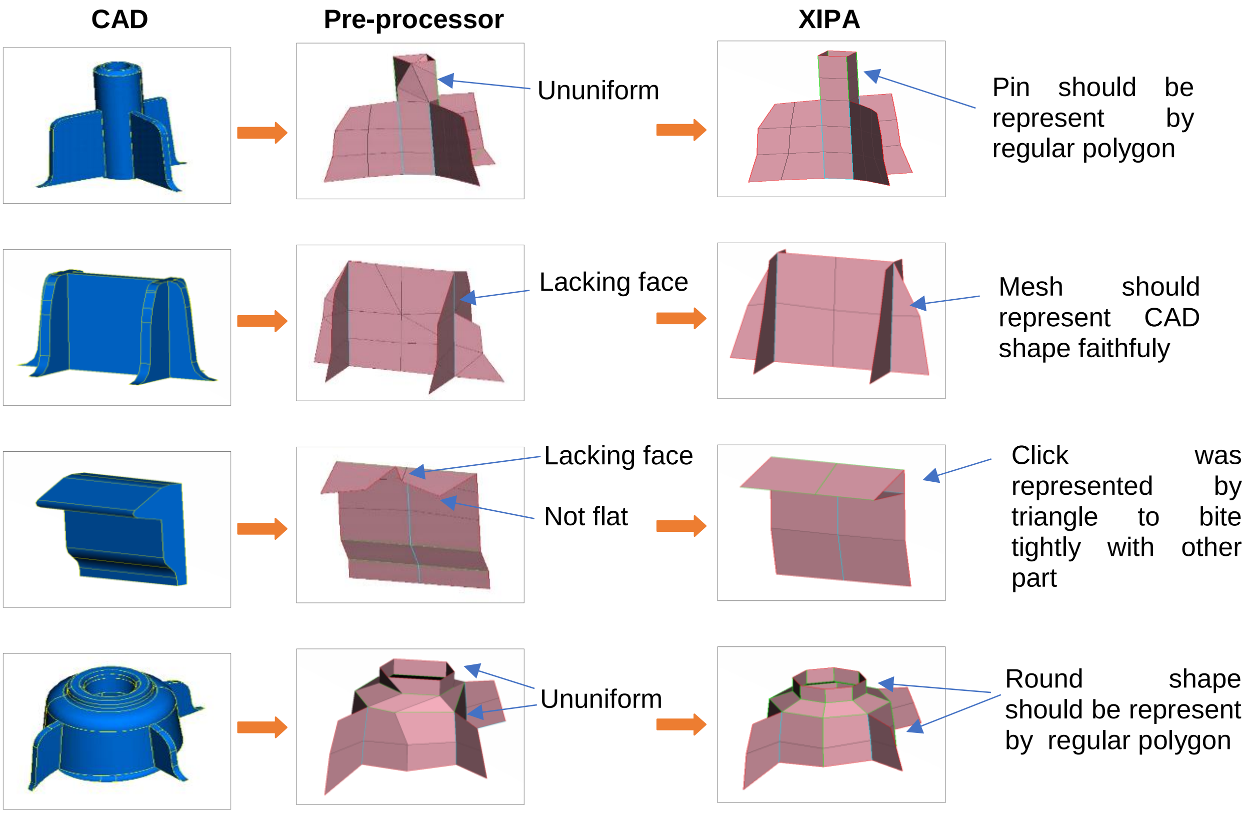

Figure 3.4 : Sample Output of XIPA

3.4 Results of Automatic Feature Recognition

This section presents overview on the results carried out on the training performed on the dataset.The model performance is measured with two curves, accuracy and loss curves. Accuracy curves show the ratio of number of correctly recognized features over total number of features. While the loss value provides details about the model deviation from actual prediction. The model is better if the loss value is smaller.

The main objective of the model was to minimize the loss value & maximize the accuracy value.These values were calculated on both training and testing dataset.

Figure 3.5 shows the accuracy and loss curves. The highest accuracy on the testing dataset was found to be 82%, corresponding to a training accuracy 96%. This results were achieved after training the model for about 350 epochs. The results were also validated with loss curves which showed that loss value was almost reaching to 0.1 on training dataset and 0.2 on the testing dataset. These results were considered to meet required accuracy.

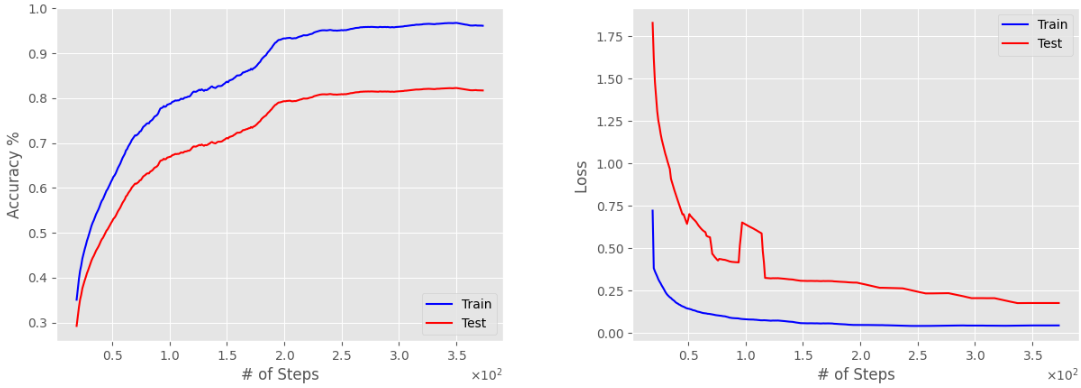

Figure 3.5 : Accuracy & Loss Curve

3.5 Application Result of XIPA (AFR+FSM)

A validation of modeling time was carried out by applying XIPA (AFR+FSM) to an unseen bumper fascia and grille model. The models had 121 pieces of features.

AFR took 12 minutes for recognition. Manual work including the result check and modification took 98 minutes. After that, FSM took 140 minutes for meshing. And finally, a modification to achieve mesh criteria took 533 minutes by hand.

Comparing the manual operation time between a conventional meshing method and XIPA (AFR+FSM), the conventional method took 54 hours and XIPA was 11 hours. Thus, modeling workload was reduced around 80% using XIPA, compared to the conventional one.

If feature recognition and mesh generation accuracy is enhanced in the future, a manual work required can possibly be further reduced.

4 Future Extension of XIPA Technology

XIPA Technology will be extended with Reinforcement Learning. Unlike Deep Learning, reinforcement learning dynamically learns by adjusting actions based on continuous feedback. This will help minimize the manual training effort currently used.

5 Conclusion

- XIPA's Machine Learning techniques are effective in enhancing productivity associated with the modeling of complex plastics parts.
- The testing accuracy on the trained CAD dataset was around 95%, and about 82% for the untrained CAD dataset.
- XIPA saves ~80 % manual modeling work when compared with conventional meshing methods for the complex plastic parts.
- FSM enables fast modeling, consistent with meshing specifications and stipulated modeling guidelines.

6 Literature

[1] https://data-flair.training/blogs/handwritten-character-recognition-neural-network/

[2] https://www.researchgate.net/figure/Faster-RCNN-flow-chart_fig4_335573687

[3] https://www.geeksforgeeks.org/vgg-16-cnn-model/