Deep Learning Framework for Classification Mechanism of 3D and 2D Sketches

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***Abstract*—The applications of sketches of mechanical mechanisms are valuable representations for engineering design, conceptual modelling, and CAD prototyping. Yet, there are inherent problems in the abstract nature of the sketches, detailing and stylization discrepancies, and variability in drawing style that can be obstructive for automated comprehension. This work details a single deep learning framework for the classification mechanical mechanisms sketches in two and three dimensions consuming visual features derived from pretrained CNN and Transformer models in addition to textual embeddings extracted using BERT. Our system integrates a unique preprocessing pipeline of adaptive augmentation, class-balanced sampling, and fine-grained text-image fusion to address the class imbalance, informational noise, and structural variability in sketches. We perform a number of extensive experiments on a curated dataset consisting of 8,993 sketches to assess the multimodal approach improves classification accuracy, the class imbalances are reduced in particular for infrequent mechanism classes. A MaxViT-based architecture performs the best for the 3D sketches while the RegNet performs the best for the 2D sketches demonstrating the effects of model-dataset alignment. The proposed framework improves the recognition accuracy and also provides interpretable results with Grad-CAM visualizations making it suitable for real-world Engineering use.**

Keywords:-Mechanical mechanism sketches, multimodal deep learning, BERT embeddings, attention mechanism, RegNet, MaxViT

I. Introduction

Mechanical mechanism sketches play a crucial role in engineering design for conveying ideas before detailed CAD models are created [1]. These sketches illustrate component arrangements, motion behavior, and functional intent but are typically rough, abstract, and stylistically inconsistent, making automated interpretation challenging [2]. Hand-drawn imperfections—such as discontinuous lines, variable thickness, missing boundaries, and diverse drawing habits—further complicate recognition. While deep learning models like CNNs and vision transformers can learn abstract visual patterns [3], existing studies mainly target general sketch datasets rather than engineering-specific mechanisms with complex geometric and functional relationships [4].

Classifying 2D and 3D sketches introduces additional complexity: 2D sketches lack depth cues, whereas 3D sketches involve perspective, occlusions, and richer structure, making it difficult for a single model to perform reliably across both forms [5]. To address this, we propose a unified deep learning-based classification framework for 2D and 3D mechanical sketches. The system integrates visual and textual cues, enabling it to capture fine-grained geometric patterns and functional meaning. By employing advanced visual encoders, multimodal fusion, and curated datasets, our framework improves accuracy, robustness, and interpretability, and we analyze the performance of different backbone architectures across sketch types to demonstrate its effectiveness.

II. Literature Survey

Deep learning has greatly advanced the area of automating a range of mechanical engineering problems from fault diagnosis to CAD model retrieval and engineering sketch understanding. Early investigations into this research stream primarily examined CNN-based architectures to recognize mechanical patterns and diagnose faults. Notable examples of some models capable of effectively dealing with imbalanced datasets and generalizing to previously unseen classes are deep feature generating networks which support training based on the proximity of identified classes to provide accurate classification [1], [2]. As sketch datasets became increasingly abstract and structurally complex, a few investigations began utilizing cross-modal retrieval approaches to relate 2D sketches to 3D models. These methods included multi-branch graph convolution networks and attention-based fusion models to improve retrieval performance by learning spatial and structural correspondences from sketches to 3D geometry [3], [4]. Simultaneously, the area of analyzing engineering drawings was developing toward a graph-based representation of drawings where the nodes–edges structure supported robust classification and detected structures or symbols presented in complex CAD diagrams [5], [6].

Various studies have accounted for the issue of sketch noise, distortion, and inconsistency. While various sketch enhancement networks, such as SketchCleanNet, proved improvements in restoring hand-drawn sketch for CAD retrieval systems [7]. Contemporary recognition approaches also employed transformers, relational encoders, and B-rep aware learning paradigms to extract machining features, classify geometries of parts, and facilitate CAD model reuse between industrial systems [8]–[12]. Additionally, object detection approaches, such as YOLO, have also been repurposed to support both mechanical symbol recognition and real-time robotic picking applications, achieving impressive accuracy in challenging imaging conditions [13], [14]. Survey papers frequently highlight continuing challenges, including ambiguous symbol edges, lack of canonical datasets, and the challenge of digitizing legacy engineering schematics [15], [16]. Advancements, though, are beginning to orient towards hybrid physics-learned models, and immersive sketching analysis to support design understanding and modeling fidelity and interpretability [17], [18].

III. Dataset Description

This project used a dataset of 8,993 mechanical mechanism sketches sourced from an open repository of mechanisms [**?**], containing both 2D planar drawings and 3D perspective representations. Each sketch was matched with metadata from a `metadata.jsonl` file, which provided descriptions, mechanism types, and filenames. The raw descriptions were mapped to standardized mechanism labels through a keyword-similarity matching procedure, enabling automatic class generation for both 2D and 3D sketches. During preprocessing, noisy or extremely rare classes—such as “coil spring couplings,” “reverse gear drives with dwell,” and “nonstop regulatable oscillation”—were filtered out to improve dataset consistency. After cleaning, the final structured dataset contained seven valid classes for the 3D sketches and six valid classes for the 2D sketches.

TABLE I
Dataset Distribution of both 2D and 3D Sketches

Mechanism Class	Total	3D Count	2D Count
Transmission w/ Uncompleted Gears	5387	3021	2366
Oval Gear	2005	924	1081
Chain Drive	433	78	355
Spatial Slider Crank	314	313	1
Ratchet Mechanism	298	113	185
Parallelogram Mechanism	249	246	3
One-Way Clutch	218	129	89
Pin Rack Drive	81	19	62

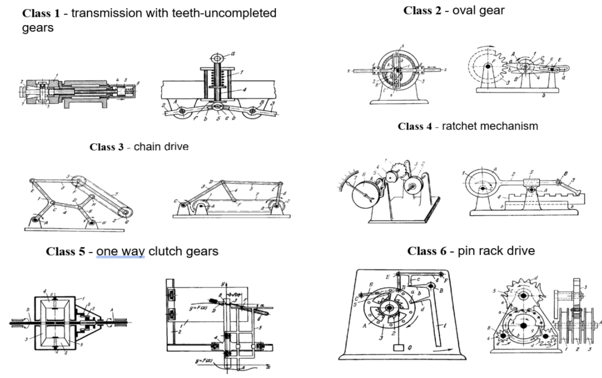

Fig. 1. 2D sketches For Each Class

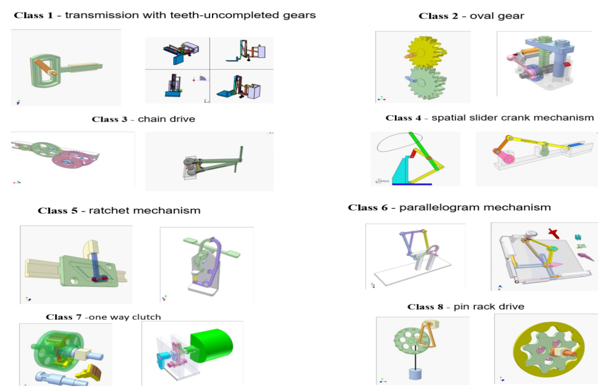

Fig. 2. 3D sketches For Each Class

A. Class Distribution, Filtering Stratified Splits

After labeling the images, the dataset was analyzed for class distribution. The results showed that there was a large class imbalance; one class (”transmission with teeth uncompleted gear”) contained thousands of images while other classes had fewer than 100 images. To obtain meaningful training and proper evaluation data, the classes with very little data were removed from the dataset, and the remaining images were partitioned into 60 percentage training, 20 percentage validation and 20 percentage testing sets, creating two separate sets (2D and 3D) in order to maintain a proper proportional representation level across all of the categories. Since there were still a lot of damaged/fail images left in the dataset and the images were all at different resolutions, Therefore, an additional preprocessing step was taken to clean up the corrupted images, adjust all the images to have the same resolution and convert every image to an RGB format that could be understood by CNN/Transformer architectures. At this point, the original distribution of the data still exhibited a lot skewness due to high numbers of images in some categories (3D) like ”oval gear” and (2D) like ”chain drive”, which also highlighted the need for a controlled augmentation-and-rebalancing approach.

TABLE II

3D DATA DISTRIBUTION ACROSS TRAIN, VALIDATION, AND TEST SETS

Class	Train	Validation	Test
chain drive	94	28	21
one way clutch	154	34	32
oval gear	1108	201	210
parallelogram mechanism	296	59	52
pin rack drive	22	10	2
ratchet mechanism	136	10	22
spatial slider crank mechanism	376	17	22
transmission with teeth-uncompleted gears	1812	610	608

TABLE III

2D DATA DISTRIBUTION ACROSS TRAIN, VALIDATION, AND TEST SETS

Class	Train	Validation	Test
chain drive	213	71	71
one way clutch	53	18	18
oval gear	649	216	216
pin rack drive	37	12	13
ratchet mechanism	111	37	37
transmission with teeth-uncompleted gears	1419	474	473

B. *Augmentation Final Balanced Dataset*

A comprehensive augmentation method was employed to balance the distribution and increase the variability within the drawing styles. For the 3D sketch portion, augmentation consisted of the following strategies, Line Thickness Jitter, elastic shear transformation, random flipping, mild contrast alteration, and controlled sampling of minority classes (i.e. using controlled augmentation to provide additional training examples for underrepresented classes). To help balance class representation within the 3D dataset, over-represented classes were down-sampled using methods such as Tomek Link removal; for under-represented classes (i.e. minority class samples) augmented via stronger augmentation techniques. A wider variety of augmentations were used for the 2D sketch dataset; a stronger augmentation pipeline (i.e. augmentations included Random Crop, Random Rotation, Gaussian Blur, Grayscale, Color Jitter, Affine Warp) was employed to ensure that the final model would have a higher degree of generalizability across both the hand-drawn and digital-generated styles. Overall, the balanced dataset for both 2D and 3D datasets resulted in much more evenly distributed class representations; therefore, the potential for overfitting and instability of all models created from this final dataset will be reduced. All baseline, augmented, and multimodal models were built from training on the final balanced dataset.

TABLE IV

COMBINED DATA DISTRIBUTION FOR 3D AND 2D

Class	3D Train Before	3D Train After	2D Train Before	2D Train After
chain drive	47	141	213	639
one way clutch	77	231	53	159
oval gear	554	1108	649	649
parallelogram mechanism	148	296	–	–
ratchet mechanism	68	204	111	333
spatial slider crank mechanism	188	376	–	–
pin rack drive	–	–	37	111
transmission with teeth-uncompleted gears	1812	1500	1419	1000

IV. METHODOLOGY

This methodology outlines the complete workflow used to develop and evaluate deep learning models for classifying mechanical mechanism sketches in both 2D and 3D formats. It covers data preprocessing, augmentation, model architecture design, training strategies, and evaluation procedures, forming a unified pipeline for robust sketch recognition.

A. *Methodology for 3D Sketches*

1) Base Line Model Architecture: To classify 3D sketches, we first load the data, search for restrictively labeled data (i.e., only labeled as 3D sketches), removing non-3D sketches from our dataset, thus the training occurs solely on those samples that represent 3D mechanical devices, i.e., they contain visual clues of perspective variation, depth, and spatial organization. After filtering out all non-3D sketches, we assign numerical labels to each 3D mechanical device category (i.e. label = 1 for a ”Rear View Mirror”) and split the dataset into training, validation, and test sets using stratified sampling to maintain the class distribution as it is found in the original dataset.

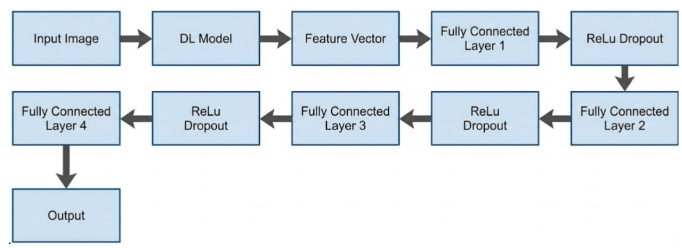

Fig. 3. 3D sketches Base Line Architecture Diagram

We resize the drawings of all sketches, normalize them by removing the mean value and dividing by 255, and then pass them to the backbone of a deep learning (DL) model that was selected due to the ability to retain a large amount of detail, i.e., to use dense reuses of features. The resulting feature maps (or ”feature vectors”) are used in the design of a compact fully connected classifier consisting of 1024 Neu-Metodes $\rightarrow$ 512 Neu-Metodes $\rightarrow$ 256 Neu-Metodes $\rightarrow$ numclasses (the number of 3D mechanical device categories) activated with ReLU and dropout layers for generalization purposes. To avoid a class imbalance in training, class-balanced weights are employed along with Focal Loss (where =2), and we applied the AdamW optimizer along with ReduceLROnPlateau/LR-EarlyStopping training strategies to monitor and optimize our learning. After the completion of model training, we evaluate the best model's performance by measuring accuracy, precision, recall, F1-Score, and by creating confusion matrices to confirm the model consistently demonstrated stability during training while achieving a very strong performance on 3D sketch drawings.

2) With Attention Layer and Bert Embeddings: When attention layers are added, the 3D pipeline becomes a multimodal refinement architecture. After model extracts the initial feature vector, it is passed through a sequence of fully connected layers and three attention modules that progressively emphasize the most discriminative regions of the sketch—such as gear boundaries, rotational joints, and linkage intersections—while suppressing noise and irrelevant strokes.

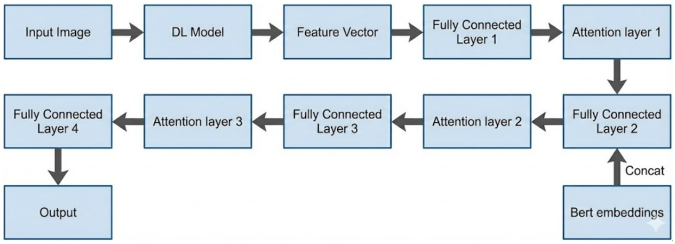

Fig. 4. 3D sketches Architecture With Attention Layer and Bert Embedding Diagram

This hierarchical attention refinement strengthens the model's ability to differentiate visually similar mechanical mechanisms and improves robustness across varying sketch styles. The final attention-enhanced representation is fed into a final fully connected layer for classification, leading to improved accuracy and more interpretable feature focus compared to the baseline.

B. Methadology for 2D sketches

The 2D sketch classification workflow begins by loading the dataset, filtering out everything except the 2D mechanism sketches, and giving a number to each class of mechanism-type. This is then divided into train, validation and test sets, and divided in a stratified way to keep the same ratio of classes in each set. In addition to visual data, BERT-based embeddings also come from descriptive mechanisms. The embeddings enhance the understanding of mechanical function and add to the limited structural information of 2D sketches that do not contain depth information.

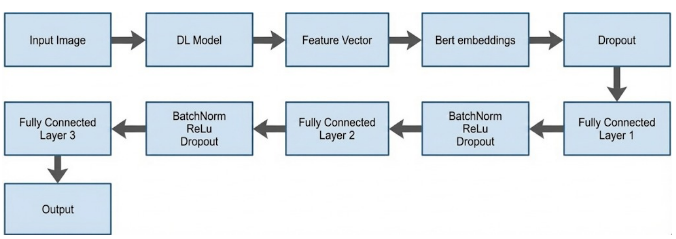

Fig. 5. 2D sketches Base Line Architecture Diagram

The images undergo extensive data augmentation (e.g., random crops, flipping, rotation, affine warping, grayscale, and color jitter). The strong augmentation makes the model more robust to the different ways sketches can be drawn. Model backbone is used to extract the visual features, and either hand-crafted features or BERT embeddings are combined with the extracted image features to create a multimodal representation. The combined representation is then fed to a deep classifier consisting of several batch normalization, ReLU, and Dropout layers. Improved Focal Loss, Mixup augmentation, SGD with Momentum, OneCycleLR, and gradient clipping are among the training techniques used to enhance performance. A final model with strong generalization capabilities and excellent performance across all 2D mechanism categories was generated through a two-step evaluation process using Test-Time Augmentation (TTA)..

TABLE V
HYPERPARAMETERS FOR BOTH 2D AND 3D SKETCHS CLASSIFICATION

Parameter	Value
Batch Size	16
Class Weighting	Enabled
Early Stopping	Patience = 7 epochs
Epochs (Max)	50
Image Size	224×224 (height $\times$ width)
Learning Rate	1×10^{-4} (0.0001)
Loss Function	Focal Loss
Mixed Precision	Enabled(2D)
Optimizer	Adam(3D),SGD(2D)

V. RESULTS

The results section presents a detailed comparison of model performance across both 2D and 3D sketch classification experiments, highlighting the impact of augmentation strategies, architectural choices, and multimodal enhancements. It summarizes how different configurations influence accuracy, stability, and generalization, leading to the identification of the best-performing models for each sketch type.

A. 3D Sketches Results

The initial experiments on 3D sketch classification without augmentation showed clear limitations, including unstable accuracies and overfitting caused by heavy class imbalance and stylistic variation, especially in models like MobileNetV, XceptionNet, and GoogLeNet. After introducing a strong baseline augmentation pipeline with geometric transforms, contrast variations, and class-balanced sampling, the overall performance of models such as DenseNet121 and EfficientNet improved noticeably, with DenseNet showing the most consistent accuracy and well-aligned training–validation curves. These augmented results confirmed better generalization, particularly for under-represented classes. The best performance emerged with the attention-enhanced DenseNet, where sequential attention blocks allowed the model to focus more effectively on key mechanical structures such as gear boundaries and linkage joints. Combined with semantic BERT embeddings, this attention-refined architecture achieved the highest accuracy and most stable loss behavior, representing the strongest approach among all 3D classification experiments..

TABLE VI
RESULTS FOR 3D SKETCHES BEFORE AUGMENTATION

Model	Accuracy	Precision	Recall	F1-Score
DenseNet121	0.7183	0.7652	0.7183	0.7315
MobileNetV2	**0.7564**	**0.7983**	**0.7564**	**0.7650**
RegNetY_400MF	0.6275	0.7369	0.6275	0.6581
EfficientNet	0.6584	0.7780	0.6584	0.6921
Xception	0.7214	0.7709	0.7214	0.7326
GoogleNet	0.7183	0.7652	0.7183	0.7315

TABLE VII
RESULTS FOR 3D WITH AUGMENTATION AND BASELINE ARCHITECTURE

Model	Accuracy	Precision	Recall	F1-Score
DenseNet121	0.7518	0.7910	0.7518	0.7636
MobileNetV2	0.6856	0.7597	0.6856	0.7080
RegNetY_400MF	0.7177	0.7527	0.7177	0.7292
EfficientNet	**0.7642**	**0.7981**	**0.7642**	**0.7745**
Xception	0.7735	0.7955	0.7735	0.7800
GoogleNet	0.6960	0.7504	0.6960	0.7110

TABLE VIII
RESULTS FOR 3D AFTER ATTENTION LAYER AND BERT EMBEDDINGS

Model	Accuracy	Precision	Recall	F1-Score
DenseNet121	**0.7963**	**0.8133**	**0.7963**	**0.8000**
MobileNetV2	0.7084	0.7584	0.7084	0.7248
RegNetY_400MF	0.7415	0.7774	0.7415	0.7520
EfficientNet	0.7373	0.7722	0.7373	0.7460
Xception	0.7363	0.7719	0.7363	0.7475
GoogleNet	0.7673	0.7725	0.7673	0.7662

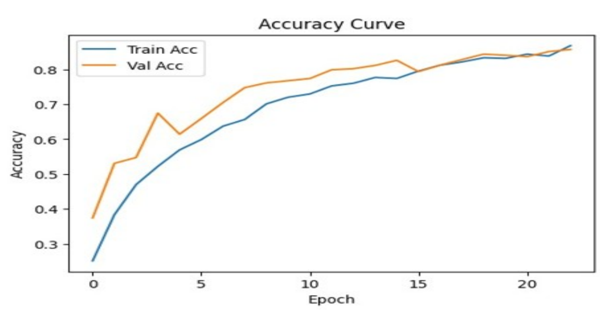

Fig. 6. Accuracy Curve For DenseNet Model(Attention Layer Architecture)

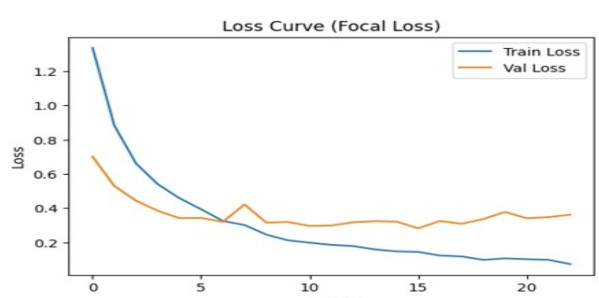

Fig. 7. Loss Curve For DenseNet Model(Attention Layer Architecture)

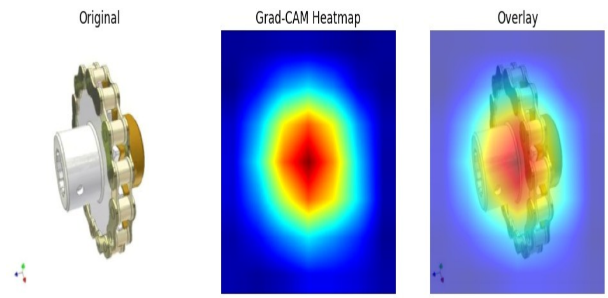

Fig. 8. Grad Cam For DenseNet Model

B. 2D Sketches Results

For the 2D sketch classification task, the initial models trained without augmentation showed strong overfitting and poor generalization, especially for visually similar classes such as chain drives and ratchet mechanisms. Although EfficientNet and DenseNet achieved reasonable accuracy, their validation behavior remained unstable due to the abstract and depthless nature of 2D sketches. After introducing baseline augmentation and class-balancing techniques, overall performance improved, with architectures like XceptionNet and RegNet producing steadier learning curves and handling sketch variability more effectively than the earlier baselines. The most significant gains occurred with the multimodal fusion approach that combined EfficientNet-B3 image features with BERT semantic embeddings, enhanced further by Mixup augmentation, OneCycleLR scheduling, and an improved focal loss. With TTA applied, this multimodal architecture achieved the highest accuracy, minimal overfitting, and the most consistent predictions across all mechanism categories. Among all models tested on 2D data, RegNet delivered the most reliable and stable performance.

TABLE IX
RESULTS FOR 2D BEFORE AUGMENTATION

Model	Accuracy	Precision	Recall	F1-Score
RegNetY_400MF	**0.6594**	**0.6679**	**0.6594**	**0.6111**
DenseNet121	0.6570	0.6811	0.6570	0.6644
Xception	0.6848	0.7035	0.6848	0.6770
MobileNetV2	0.5833	0.6532	0.5833	0.6009
EfficientNetV2	0.6884	0.7269	0.6884	0.7029
GoogleNet	0.6461	0.6299	0.6461	0.6310

TABLE X
RESULTS FOR 2D AFTER AUGMENTATION AND BERT EMBEDDINGS

Model	Accuracy	Precision	Recall	F1-Score
RegNetY_400MF	**0.7343**	**0.7335**	**0.7343**	**0.7278**
DenseNet121	0.7246	0.7323	0.7246	0.7256
Xception	0.7240	0.7225	0.7240	0.7202
MobileNetV2	0.6667	0.6624	0.6667	0.6623
EfficientNetV2S	0.7162	0.7442	0.7162	0.7118
GoogleNet	0.6932	0.7136	0.6932	0.6998

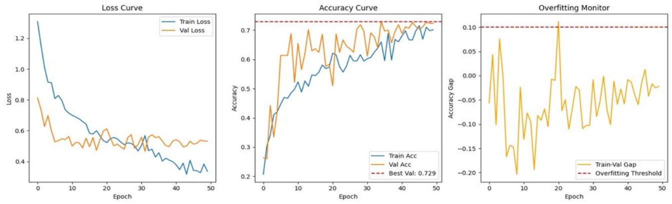

Fig. 9. Accuracy,Loss,Overfitting Plots for RegNet Model(Base Line Model)

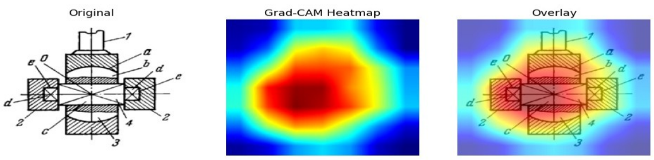

Fig. 10. Grad-Cam Plot for RegNet Model(Base Line Model)

VI. Conclusion and Future Work

Deep learning can accurately identify sketches depicting mechanical mechanisms in both 2D and 3D when using effective preprocessing steps, balanced augmentation techniques, and correctly chosen model architectures. Baseline models that were trained without any augmentation experienced difficulties with class imbalance and variability of sketches; in contrast, with class weights and action augmentation being introduced into models trained on 3D sketches, as a result, models trained on 2D sketches outperformed models that do not make use of augmentation techniques. DenseNet are potential candidates for models capable of accurately classifying 3D sketches, while attention-enhanced DenseNet increases the features' focus and provides additional robustness to the trained model at varying levels of accuracy. The best performing model on 2D sketches uses the fusion of EfficientNet-B3 visual features and BERT embedding with Mixup and OneCycleLR scheduling. RegNet is the most consistent backbone. The models are performing well, but there is still room for additional work in increasing the size of the data set to include more real-life sketches, experimenting with transformer-based and graph-based networks for enhancing the performance of trainable models, using self-supervised learning techniques to reduce the dependency on label information, and extending the current structures to perform part discovery, segmentation, or provide real-time assistance (either through visual or CAD/engineering support) in the development of more comprehensive engineering designs.

VII. References

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