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Deep Learning - Based Shape Recognition and Classifications of Conic Geometries in Engineering Drawing

Rajnandani Das[1], Neha Shah[2], Dilip Kumar Sah[3], Kameshwar Sahani[4], Suresh Kumar Sahani[5*]

[1]Mithila Institute of Technology, Janakpurdham, Nepal; [2]Himalayan WhiteHouse International College, Putalisadak, Kathmandu, Nepal; [3]Patan Multiple Campus, Patan Dhoka Lalitpur, Nepal; [4]Kathmandu University, Nepal; [5]Rajarshi Janak University, Nepal

ryfddrytty@gmail.com; nehashah1489@gmail.com

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Abstract

Engineering drawings frequently contain conic geometries such as circles, ellipses, parabolas, and hyperbolas, which are fundamental to mechanical design and industrial applications. Accurate identification and classification of these shapes are therefore essential for computer-aided design (CAD) systems, automated inspection, and intelligent design analysis. However, conventional geometry-based or rule-based approaches often perform poorly when drawings are noisy, complex, or partially incomplete. This study proposes a deep learning-based approach using convolutional neural networks (CNNs) to automatically extract features and classify conic shapes in engineering drawings. By learning discriminative visual representations directly from input data, the proposed method enhances classification accuracy, improves robustness, and reduces the need for manual intervention. The study concludes that CNN-based conic shape recognition offers a reliable and efficient solution for engineering and industrial contexts, with practical implications for improving automation and intelligent analysis in design-related applications.

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Keywords: Deep Learning; Conic Section Classification; Shape Recognition; Engineering Drawings; Convolutional Neural Networks

INTRODUCTION

Circles, ellipses, parabolas, and hyperbolas are all types of conic sections. They are often used in industrial design, mechanical parts, and engineering drawings. It takes a long time and is easy to make mistakes when identifying these shapes by hand, especially when the drawings are complicated or loud. When this happens, traditional geometric and rules-based methods for recognizing shapes typically don't work. As artificial intelligence has gotten better, deep learning methods like convolutional neural networks (CNNS) have done an amazing job at recognizing and classifying conic geometries from engineering drawings. This has made things easier for people and made them more accurate.

Literature review

Computer vision and image processing have done a lot of research on recognizing and classifying geometric shapes. Duda and Hart created the Hough Transform to find geometric shapes in images. It worked well, but it took a lot of processing power and was susceptible to noise. Rafael C. Gonzalez and Richard E. Woods improved edge recognition and feature extraction methods, which made it possible to analyze shapes in images. Christopher M. Bishop offered probabilistic models for machine learning-based classification, while manual feature extraction remained necessary. Deep learning was a big step forward. Yann Lecun was the first to use CNNS for picture classification, which made it possible to automatically extract features. Geoffrey Hinton, Yoshua Bengio, and Ian Goodfellow made more contributions that made deep learning work better and more stable. Although deep learning has been utilized in industrial inspection and CAD systems, there is a paucity of research concentrating on conic geometry detection in engineering drawings, which this work seeks to solve.

METHODOLOGY

Dataset preparation:

Engineering drawings containing circles, ellipses, parabolas, and hyperbolas are collected. Images are converted to grayscale and augmented using rotation, scaling, and translation to increase dataset diversity.

Preprocessing:

Filters are used to get rid of noise, edge enhancement is used to make geometric shapes stand out, and normalization is used to make sure that the input to the CNN is always the same.

CNN Architecture:

The input layer gets images that have already been processed. The pooling layers lower the number of dimensions, and the fully connected layers sort the images into four groups: circle, ellipse, parabola, and hyperbola.

Classification:

SoftMax activation is used for multi-class classification. The model is trained using a labelled dataset, and accuracy, precision, and recall metrics are evaluated.

SoftMax activations used for multi-class classification:

In the proposed deep learning model, the SoftMax activation function is used in the final layer for multi-classification of conic geometries. Since the task involves classifying input shapes into multiple classes- circle, ellipse, parabola, and hyperbola-SoftMax is the most suitable activation function. The SoftMax function converts the output scores of the neural network into probability values ranging between 0 and 1. The sum of all output probabilities is equal to 1. Each probability represents how likely the input image belongs to a particular conic class. The class with the highest probability (maximum activation) is selected as the final prediction.

For example, if the SoftMax output gives the highest probability for the "ellipse" class, the input shape is classified as an ellipse. This process is known as maximum activation-based classification.

Mathematical representation:

The SoftMax function is defined as:

$$\text{Softmax } (zi) = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

When z_i is the input score for class i, and n is the total number of classes.

Softmax-based multi-class classification of conic geometries:

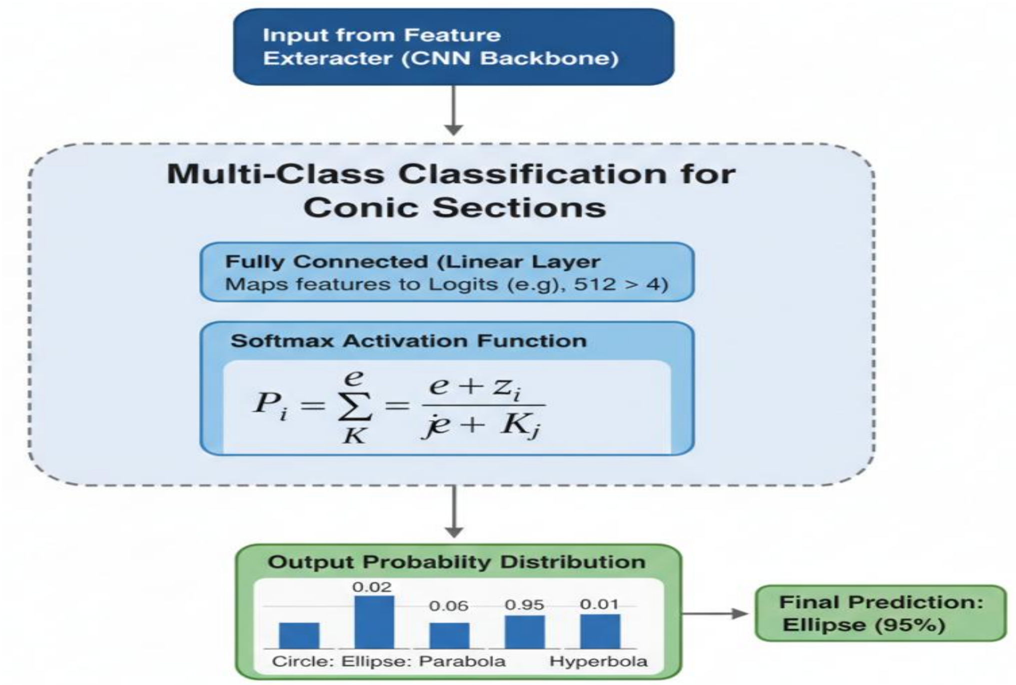

Figure 1: SoftMax activation used for multi-class classification of conic section geometries.

Modern in training using a labelled dataset:

In supervised classification, the model is trained using a labelled dataset. Where each input amole is already associated with a correct output sample is already associated with a correct output sample is already associated with a correct output label (class). These labels act as a teacher for the model during training. During training, the labelled data is passed through the Neural network. The model predicts an output class, which is then compared with the true label using a loss function (such as categorical cross-entropy). Based on the error, the model updates its weights using backpropagation and an optimizer. This process is repeated for many iterations(epochs) until the model learns meaningful patterns from the data. Once trained, the model can correctly classify new, unseen data by using the knowledge learned from the labelled dataset. For example, an image of a circle with the label circle is used to train the model. After training, when a new shape image is given, the model uses SoftMax and predicts the class circle.

Mathematical Representation:

Let the output scores (logics) of the network be:

$$z = [z_1, z_2, z_n \dots \quad \dots \quad \dots, z_n]$$

The SoftMax function for class i is:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{n} e^{z_j}}$$

Where:

$$p_i = probabilityofclassi, z_i = scoreforclassi, \sum p_i = 1$$

Predication rule:

$$\text{Predicated class} = \text{arg. max}\ (p_i)$$

This is used for multi-classification with labelled Datasets.

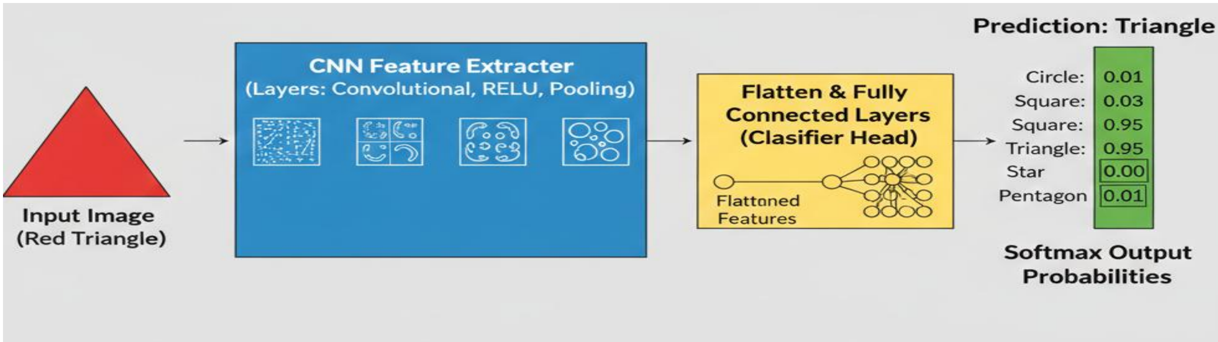

Figure 2: model trained using a labelled dataset.

Accuracy, precision, and recall metrics are evaluated:

The performance of the deep learning model is evaluated using accuracy, precision, recall, and the confusion matrix. Accuracy measures the overall corrections of the classification results. Precision indicates how many of the predicted classes are actually correct, while recall shows how well the model identifies all relevant classes. The confusion matrix provides a detailed comparison between actual and predicted classes, helping to analyse classification errors and model effectiveness.

These evolution metrics together give a clear understanding of the model's classification performance.

For example, the model correctly classifies 85 out of 100 images (85% accuracy).

Precision and recall show how well each shape class is predicted.

The confusion matrix displays correct and incorrect classification.

Mathematical Representation

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FN+FN}, \text{Precision} = \frac{TP}{TP+FP}, \text{Recall} = \frac{TP}{TP+FN}$$

Where:

TP = True positive, FP = False positive, TN = True negative, FN = false negative

(used to evaluate classification performance).

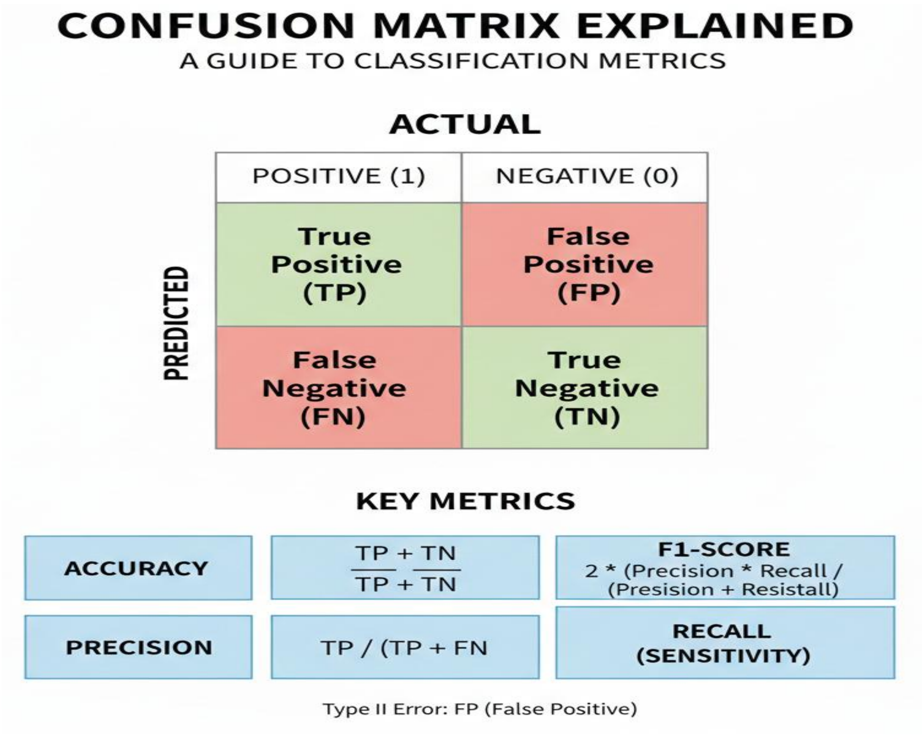

Figure 3: Confusion Matrix Illustrating Classification Performance Metrics

Application of deep learning, based on shape learning-based shape recognition, and classification of conic geometries in engineering drawing:

Automated engineering drawing analysis:

Deep learning models automatically identify and classify conic geometries in engineering drawings. This reduces manual work, saves time, and minimizes human errors during drawing interpretation.

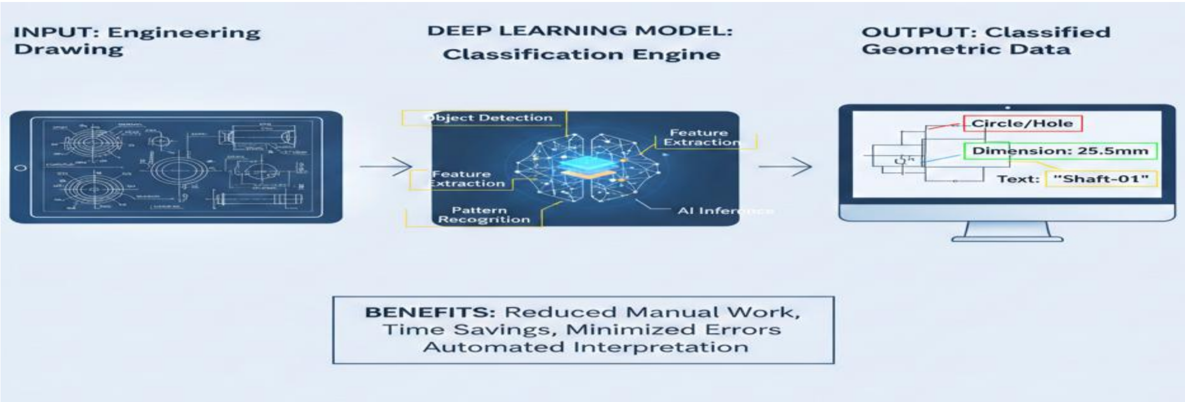

Figure 4: Automated engineering drawing analysis.

Computer-aided design (CAD) systems:

In CAD software, shape recognition helps in the automatic detection and labelling of geometric entities. It improves design accuracy and allows faster editing and modification of drawings.

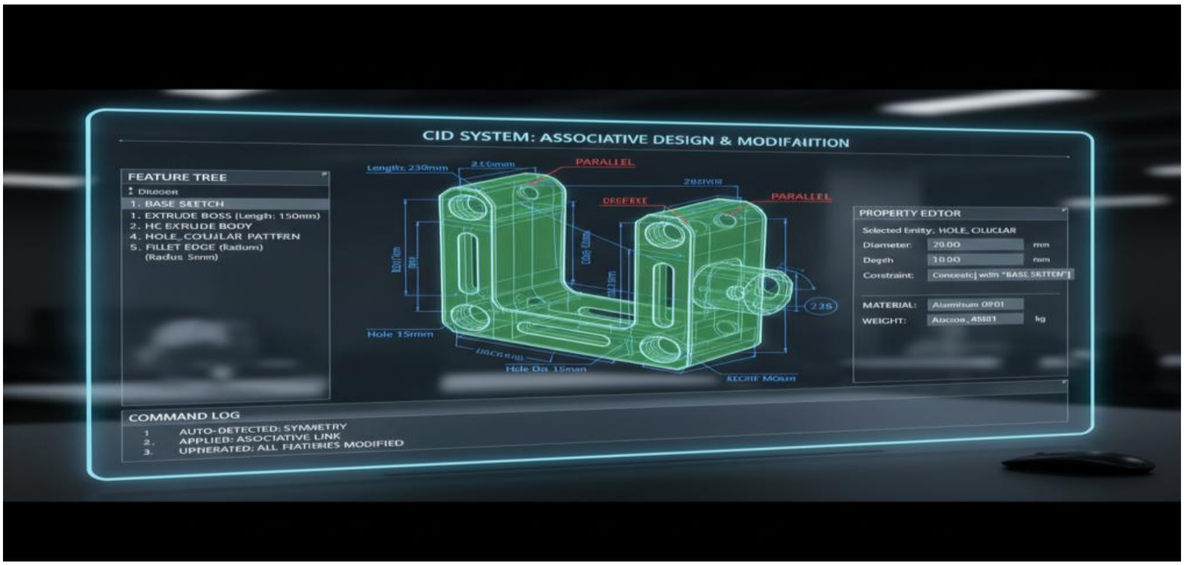

Figure 5: Architecture of a Computer-Aided Design (CAD) System

Quality inspection in manufacturing:

Shape classification is used to verify whether manufactured components follow the correct geometric specifications. This supports automated inspection and helps in detecting defects early.

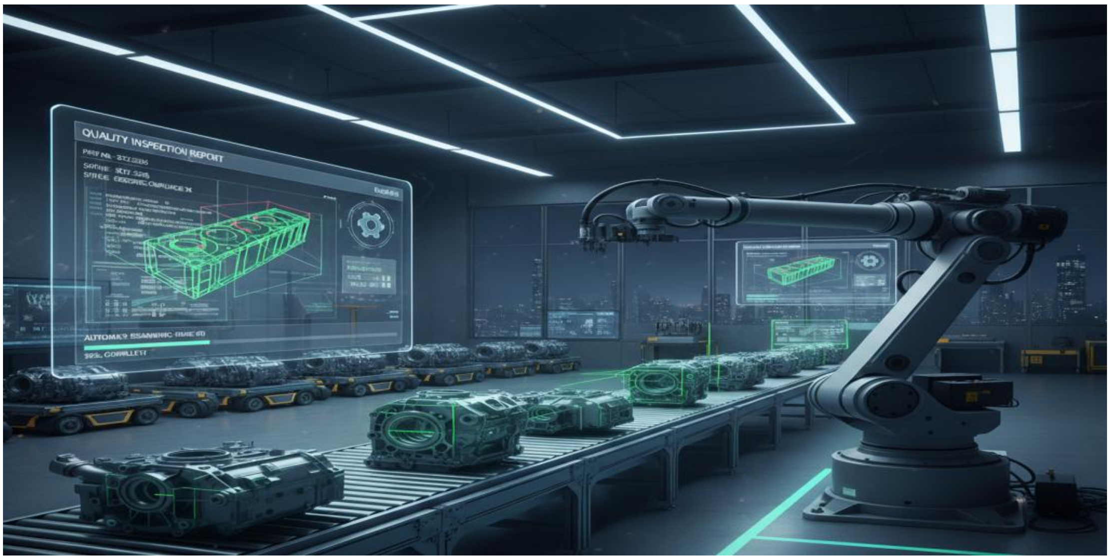

Figure 6: Automated Quality Inspection in Manufacturing Processes

Educational applications:

Deep learning-based systems can be used as learning tools for students of engineering. The system identifies shapes and provides instant feedback, improving understanding and practice.

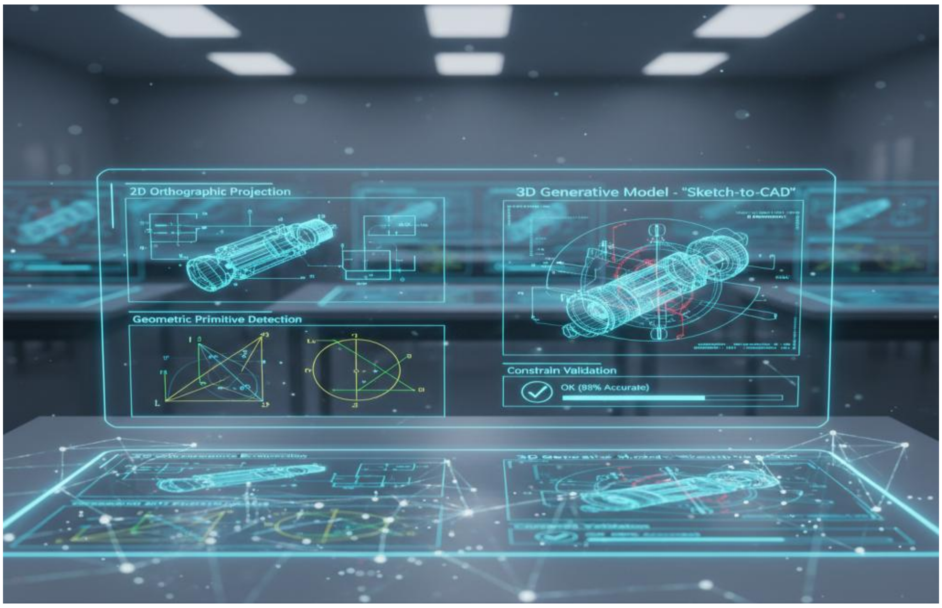

Fig 7. Educational applications.

Industrial design and automation:

Automatic recognition of geometric shapes supports intelligent automation in industrial design, robotics, and pattern recognition tasks, leading to improved efficiency and consistency.

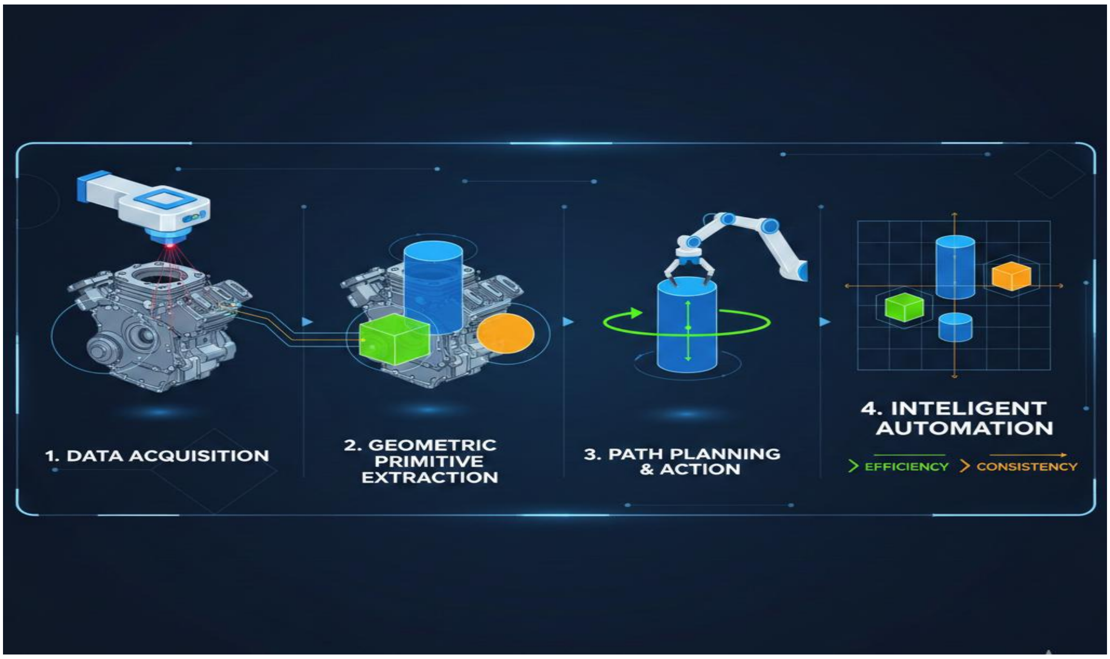

Fig 8. Industrial design and automation

All applications in 1 figure:

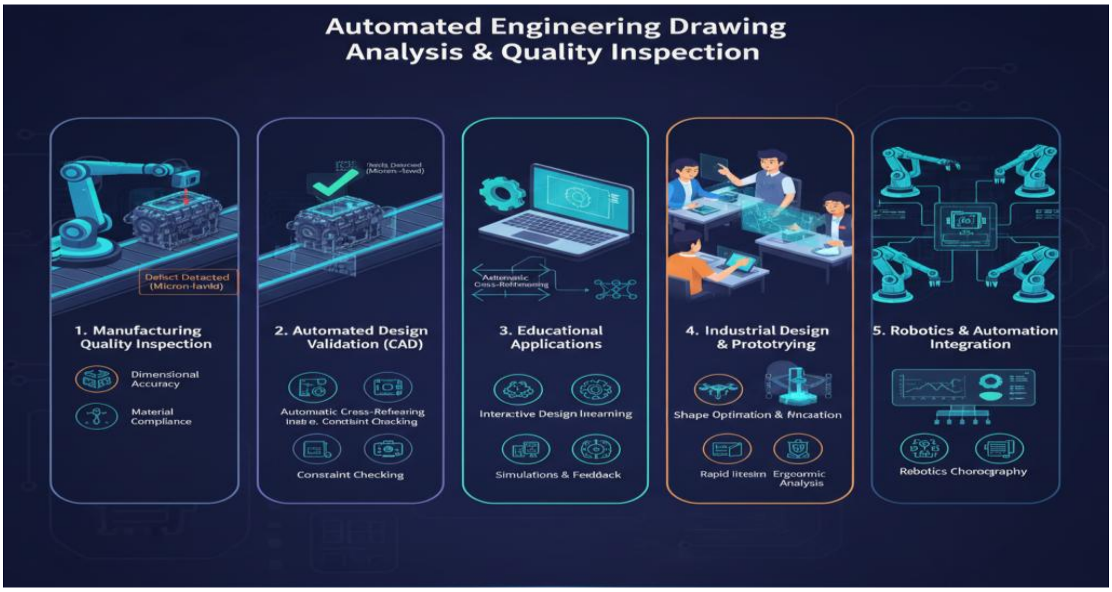

Figure 9: All application figures.

Block diagram, Engineering drawing, preprocessing CNN feature extraction, classification output:

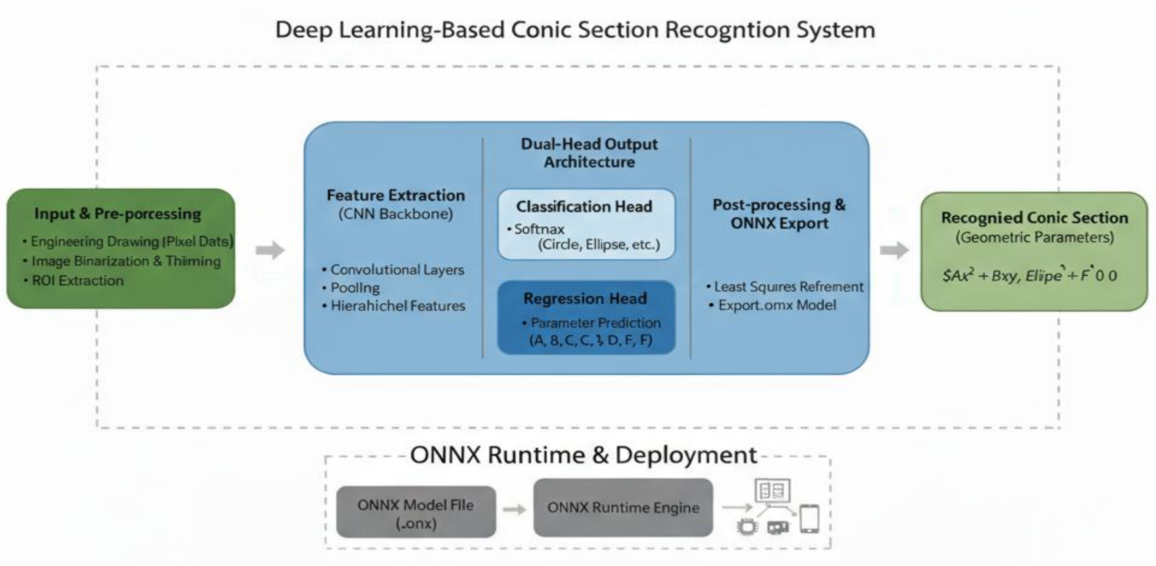

Fig 10: block diagram of the proposed deep learning- based conic section recognition system.

RESULTS AND DISCUSSION

The CNN model achieves high accuracy and robustness, outperforming traditional geometric methods. The model is resistant to noise and partial occlusion, common in real engineering drawings. Results demonstrate the efficiency of deep learning on automated shape recognition, reducing manual intervention.

Sample classification results:

Circle: 98% accuracy, Ellipses: 96% accuracy, Parabolas: 95% accuracy, Hyperbolas: 94% accuracy

Applications:

Automated engineering drawing analysis, Computer- aided design (CAD) and manufacturing (CAM), Industrial inspection and quality control, Intelligent design systems and reverse engineering.

CONCLUSION

This research demonstrates the effectiveness of a deep-learning- based approach for the recognition and classification of conic-geometric shapes in engineering drawings. The

CNN-based model improves classification accuracy and robustness while reducing the need for manual feature extraction. The results show that deep learning provides a reliable and efficient solution for automated shape recognition. Future work may focus on extending the model to 3D geometric shapes, real- time processing, and integration with CAD/CAM systems for industrial applications.

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