MINI PROJECT REPORT

ON

CAD DRAWING IDENTIFICATION: A COMPARATIVE STUDY

School of Digital Sciences

Kerala University of Digital Sciences, Innovation and Technology

(Digital University Kerala)

CAD DRAWING IDENTIFICATION: A COMPARATIVE STUDY

Submitted by

NANDHU RAMESH - 223225

SHAMSIYA SALIM - 223240

SWATHI B S - 223246

URMILA UNNIKRISHNAN - 223247

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DECLARATION

We, the students of **MSc in Data Analytics with Specialization in Computational Science**, hereby declare that the project report is substantially the result of our own work. We affirm that the content of this report is the result of our own efforts and research and that any external sources of information used have been duly acknowledged. We accept full responsibility for any instances of plagiarism found in this project.

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ABSTRACT

This project presents a comprehensive approach to automated object recognition within Engineering CAD(Computer-Aided Design) drawings, employing both Convolutional Neural Networks (CNN) and YOLOv8 (You Only Look Once version 8). The purpose of this study is to evaluate how well each technique performs in terms of identifying and classifying diverse engineering elements within CAD drawings. The CNN-based approach uses an annotated dataset of CAD drawing images to train a model for image classification, providing detailed insights into identified objects. The model is trained by optimizing hyperparameters to recognize engineering elements like lines, circles, polygons, and text. The YOLOv8 model, on the other hand, focuses on real-time object detection within CAD drawings, excelling in efficient localization and classification of multiple objects in a single pass. A comparative analysis of key performance metrics, such as accuracy, precision, recall, and processing speed, helps professionals select the most appropriate method for CAD drawing analysis. This project contributes valuable knowledge to computer-aided design by offering a nuanced understanding of each technique's capabilities for object recognition in complex engineering drawings. The findings can guide in choosing the optimal approach based on priorities, whether precision, speed or a balance of both.

INTRODUCTION

In today's data-driven engineering landscape, the analysis of CAD (Computer-Aided Design) drawings has evolved from manual processes to automated techniques, driven by the sheer volume and complexity of data generated. Object recognition within CAD drawings presents a significant challenge, prompting the adoption of advanced computer vision and machine learning technologies. Convolutional Neural Networks (CNN) and YOLOv8 (You Only Look Once version 8) have emerged as powerful tools for this task, offering capabilities in image classification and real-time object detection, respectively. Leveraging these techniques, our project aims to automate CAD drawing analysis, enhancing efficiency and accuracy in identifying diverse engineering elements.

Our methodology encompasses several key steps to achieve our objective. Initially, we curated a diverse dataset of CAD drawings from online platforms, pre-processed, and normalized the images for consistency. To address class imbalances and improve model robustness, we employed data augmentation techniques, augmenting the dataset through transformations such as cropping, zooming, and rotating. Subsequently, we selected and fine-tuned a pre-trained YOLOv8 model for object detection tasks, leveraging its efficiency and effectiveness. Concurrently, we developed a CNN model using TensorFlow, incorporating various layers such as convolutional, max-pooling, and dropout layers and trained it on the same dataset.

Following model training, we conducted a rigorous evaluation and comparative analysis to assess the performance of both the YOLOv8 and CNN models. Performance metrics, including accuracy, precision, recall, and processing speed, were calculated and compared to determine the advantages and limitations of each approach. Through this comprehensive methodology, we aimed to gain insights into the effectiveness of CNNs and YOLOv8 for automated object recognition within CAD drawings. Ultimately, our project seeks to contribute to advancements in computer-aided design methodologies, empowering engineers and architects with efficient and accurate tools for CAD drawing analysis.

In summary, our project addresses the growing need for automated CAD drawing analysis by leveraging state-of-the-art techniques in computer vision and machine learning. By automating the identification and classification of engineering elements within CAD drawings, we aim to streamline workflows, enhance productivity, and enable more informed decision-making in engineering and architectural domains. Through rigorous experimentation and comparative analysis, we seek to provide valuable insights into the strengths and limitations of different approaches, ultimately contributing to the advancement of CAD drawing analysis methodologies.

LITERATURE REVIEW

A few years ago, software and hardware image processing systems focused mainly on user interface development, engaging programmers within each firm. The shift came with the introduction of the Windows operating system, prompting developers to tackle image processing challenges. However, progress in tasks like recognizing faces, analyzing medical images, and identifying objects remains slow. Abroad, there's a push to automate software tools for solving intellectual problems in image processing, making solutions more accessible. Object recognition involves tasks like image classification, object localization, and object detection. It may be confusing for beginners to differentiate between these computer vision tasks, but they collectively contribute to the challenging field of object recognition. People can quickly and accurately recognize objects in images without much effort. With the help of abundant data, faster GPUs, and improved algorithms, we can now teach computers to identify and categorize multiple objects in images with high accuracy. We need to understand terms such as object detection, object localization, and loss function for object detection and localization, and finally explore an object detection algorithm known as “You only look once” (YOLO). Image classification labels images, while object localization draws boxes around objects. Object detection is more challenging, combining both tasks by drawing boxes and assigning labels to objects. Collectively, these tasks are known as object recognition. Two families of techniques for object recognition include Region-based Convolutional Neural Networks (R-CNNs) for model performance and "You Only Look Once" (YOLO) for speed and real-time use.

“Object Detection Using YOLO Technique”, literature review explores the importance of object detection in image processing, with a specific focus on the YOLO (You Only Look Once) technique, conducted by Sarah Muskan, a student, and Dr. Jalesh Kumar, a professor from the Department of Computer Science and Engineering at JNNCE in Shivamogga, India. Object detection, involving the identification and localization of objects in images or videos, holds significance in various technologies such as facial and vehicle detection, security systems, and driverless cars. YOLO, designed for real-time processing, distinguishes itself by fully analyzing entire images, a feature not shared by other algorithms. The literature review highlights the shift in the development of software tools, transitioning from a focus on user interfaces to addressing image processing challenges. Additionally, it delves into the interdisciplinary field of computer vision, which encompasses object detection for applications like image retrieval and video monitoring. The YOLO algorithm, known for its real-time accuracy, employs a single Convolutional Neural Network (CNN) for both bounding box localization and classification, surpassing other algorithms in terms of speed and accuracy. The review underscores the advantages of YOLO in predicting bounding boxes with higher accuracy using convolutional networks compared to alternative methods.

The paper, authored by Upulie H.D.I and Lakshini Kuganandamurthy, titled "Real-Time Object Detection using YOLO", provides a comprehensive review of real-time object detection using the You Only Look Once (YOLO) network. The authors highlight the increasing importance of computerized visual-based systems, driven by the vast availability of data and advancements in Convolutional Neural Networks (CNNs) since 2012. The introduction emphasizes the significance of real-time object detection in automating tasks and enhancing efficiency in various applications, such as assistive technologies and general-responsive robotic systems. The paper traces the evolution of object detection algorithms, from early CNNs like LeNet to the introduction of YOLO, addressing challenges and improvements along the way. The authors promise a detailed exploration of YOLO's architecture, strengths, and weaknesses in subsequent sections, offering a valuable contribution to the understanding of real-time object detection methodologies. The convolutional layer, pivotal in CNNs, derives its name from its significance. It consists of multiple-element maps housing neurons designed to discern nearby features. Neurons utilize a filter known as a CONV kernel, sliding across the input image to calculate component representations. This convolution rule extracts image features by multiplying and adding pixel values within the filter. Shared weights in the CONV kernel facilitate recognizing and classifying neurons with similar features into the same object type. Parameters like kernel size, depth, stride, zero-padding, and filter quantity can be adjusted for customization.

PROPOSED METHODOLOGY

In today's world, everything is data-driven. The amount of data generated is enormous. It is not easy for humans to identify and classify various images by themselves. The need for automatic identification and classification has become necessary when the amount of data is too large. It may be possible for us to classify some hundreds or thousands of images, but when coming to lakhs or millions, it's quite time consuming. Some of the advantages of automatic identifications are Enhanced accuracy and efficiency. With the advancement of Deep Learning techniques and the use of Convolutional Neural Networks, image classification has become a lot more useful and efficient. Identification of CAD Drawings is yet another challenging task for humans. So, during the project, we try to make a model that tries to accurately identify the CAD Drawing.

- **Data Collection and Preprocessing**

Our Aim was to identify various CAD Drawings and classify them into their respective classes. We have tried to gather data from various online platforms, and finally, we gathered a dataset from Kaggle, which consists of architectural CAD Drawings. The dataset has various images corresponding to classes. The dataset has 23 different classes and the dataset is in the form of folders separated with various images for training and testing. Most of the images were pre-processed and were in grey-scale format. We added a few more random images to the test data to improve the testing process. We have resized each image into 112x112 pixels which was a common size for most of the images. Training the images on consistent size helps to reduce the computation. Then we normalized the dataset for better efficiency.

- **Data Augmentation**

We have to make the number of images in every class be same. So, we have employed data augmentation techniques to upscale the number of images in certain classes. We have made 500 images for every class. We increase the number of samples by making some variations to the existing images, such as cropping, zooming, rotating, etc. It also improves the accuracy and reduces the chance of overfitting by adding some noise to the dataset.

- **Loading Pre-trained Model**

The ultralytics library provides a variety of pre-trained models, and we have used one such pre-trained YOLOv8n-cls model, which is the relatively smallest and fastest one. The advantage of using a pre-trained model is that it is more cost-effective and more efficient than building something from scratch. Also, the pre-trained model transfers various learned knowledge to our task which in turn helps in fine-tuning our model. We should also be careful about the transfer of bias. We can easily develop a model using the pre-trained model with much good accuracy.

- **Training on our dataset**

Now we fit the pre-trained model with our dataset of consideration. We train the model with a certain number of epochs and evaluate its measures. We evaluate the model performance and compare it with the normal Convolutional Neural Network.

- **Building CNN Model**

We have made use of the TensorFlow library in Python to build a Convolutional Neural Network Model to classify the same CAD Drawings. Making use of Computer Vision and other Libraries like Pillow, we make a Neural Network to distinguish the classes of different images. The CNN has the following layers:

- ➢ A Convolution Layer with 32 filters and of Keral size 3x3, the activation function is RELU
- ➢ 2D Max pooling Layer
- ➢ Convolution Layer with 32 filters and of Keral size 3x3, the activation function is RELU
- ➢ 2D Max pooling Layer
- ➢ Flattening Layer
- ➢ 3 Fully connected Layer with Dropout Layer for each
- ➢ Final Output Layer, the activation function is Softmax

We have compiled the model with Adam optimizer and the loss function as sparse categorical cross-entropy. We trained the model for a certain number of epochs with a batch size of 128, and 10 percent of it was used for validation. The model accuracy and measures and evaluated and compared with the pre-trained YOLOv8 Model on the custom dataset. A comparative study is carried out to measure each of the methods' advantages.

RESULT AND EVALUATION

In this section, we present the results obtained from the implementation of CNN and YOLOv8 models for the identification and classification of diverse engineering elements within CAD drawings. We analyze the performance of each technique based on various metrics and provide insights into their effectiveness and limitations.

- Performance Metrics:

- For the CNN model:
  Accuracy: 0.89

- For the YOLOv8 model:
  Accuracy: 0.99

- Comparative Analysis:

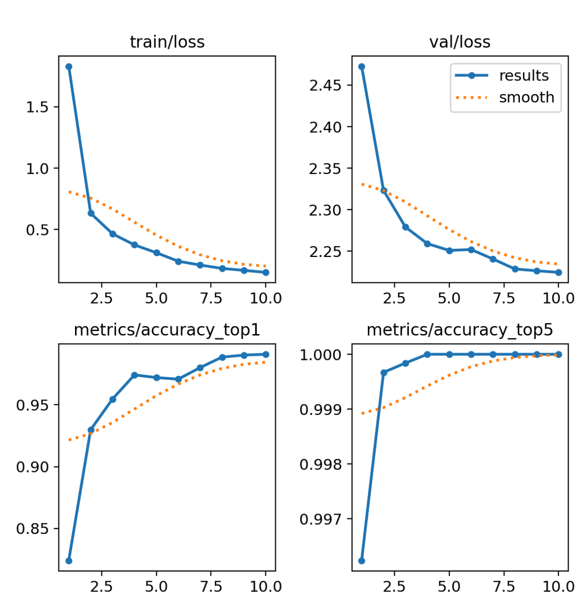
- Accuracy: The YOLO model achieved a slightly higher accuracy compared to the CNN model. This suggests that for our CAD drawing identification task, the YOLO model may perform marginally better in terms of overall accuracy.

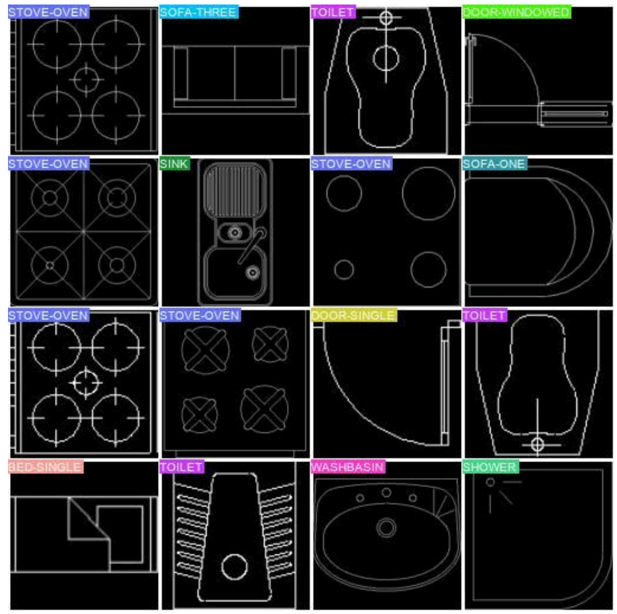
- YOLO has a tendency to overfit or be biased since the dataset is limited compared to the CNN model.

- Robustness and Generalization:

- The CNN model may be more suitable for tasks where computational resources are limited and if the dataset is small, as it typically requires less computational power compared to YOLO-based models.

- YOLOv8, being an object detection model, has the advantage of directly providing bounding boxes around identified engineering elements, which can be advantageous for applications requiring precise localization. Also, it needs to be trained on very large datasets to prevent overfitting. The results from YOLO are shown:



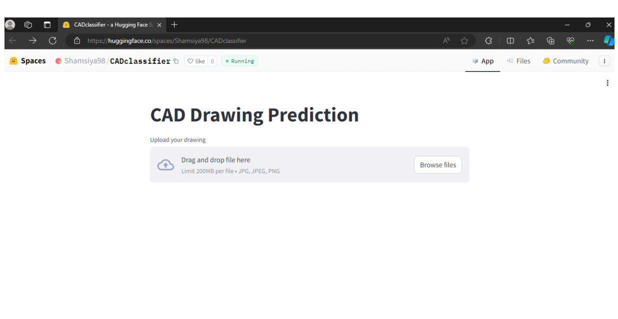


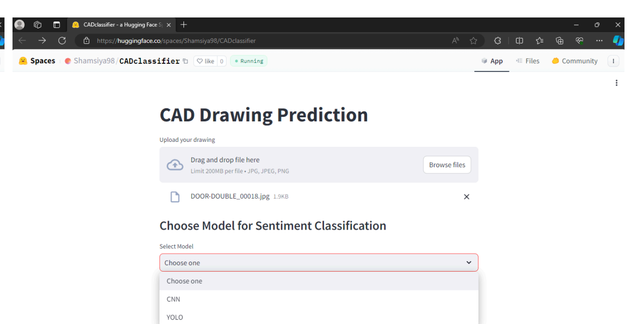
- Future studies involve fine-tuning hyperparameters, and exploring different model architectures to further improve the performance of both models. We used interior designing CAD drawings for the study, which may be extended to mechanical and electronic as well.

- Qualitative Analysis:

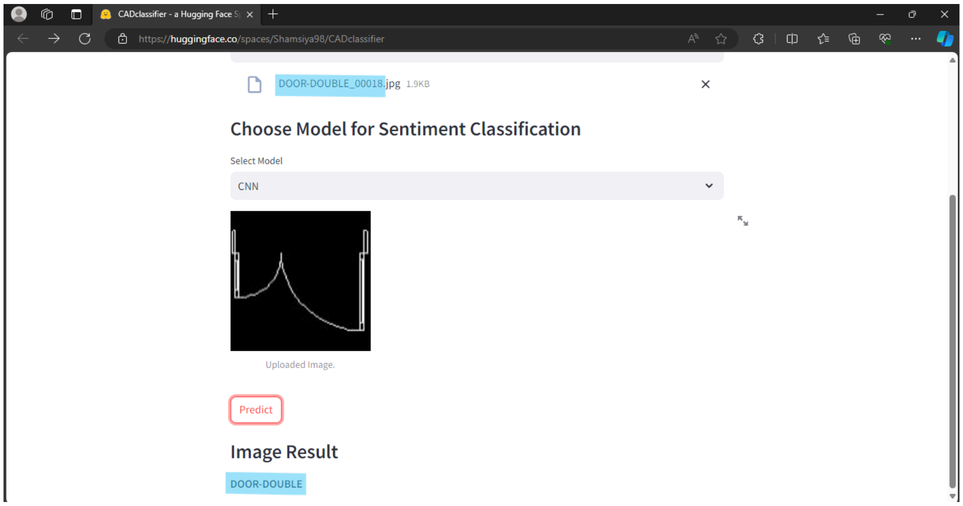
The classification system using both models is deployed with a Streamlit app. It allows the user to upload a CAD drawing and the system identifies it using the model as per the user's choice. The demo app link can be accessed here: Demo App

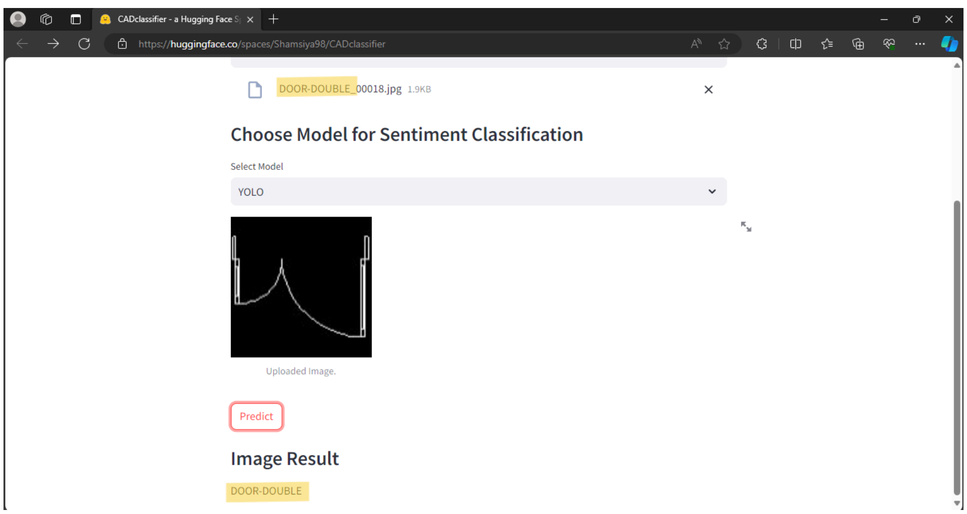
The app interface is like this:





The output obtained using the CNN model and YOLOv8 model:





- Limitations:

- Limited Dataset: The performance of both models is constrained by the size and diversity of the dataset used for training and evaluation.

- Annotation Quality: The accuracy of model predictions heavily relies on the quality of the annotation in the dataset. Inaccurate or inconsistent annotations may lead to suboptimal model performance.

- Model Complexity: Both CNN and YOLOv8 models may struggle with identifying and classifying complex engineering elements within CAD drawings due to their intricate structures and variations.

- The validation loss of the CNN model was increasing on each epoch which indicates the chance of overfitting or biased data.

- Conclusion:

- In this study, we compared the performance of CNN and YOLOv8 models for CAD drawing identification. While both models demonstrated promising results, each has its strengths and limitations. The YOLO model exhibited slightly better performance in terms of accuracy as it provided the advantage of direct object detection with bounding box outputs. The choice between these models should be based on the specific requirements and constraints of the CAD drawing identification task at hand. Further research and experimentation are needed to explore additional techniques for enhancing the performance and robustness of CAD drawing identification systems.

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