DEFECT DETECTION IN MACHINES USING AR ON ENGINEERING DRAWINGS

Project Reference No.: *47S_BE_1420*

College ***:*** *KLE Dr. M.S Sheshgiri College of Engineering and Technology, Belagavi*
Branch ***:*** *Department of Computer Science & Engineering*
Guide(s) ***:*** *Dr. Manisha Tapale*
Student(S) ***:*** *Ms. Ayesha Mulla*
Ms. Chaitra M. Gunaga
Ms. Shilpa Patil
Mr. M. Sumit Nayak

Keywords:

Orthographic Views, 3D models, Augmented Reality, Crack detection, Convolution Neural Networks (CNN), Machine Learning, ResNet50, Image Analysis.

Introduction:

Cracks in machines can lead to catastrophic failures, causing safety hazards and costly downtime. Timely detection of cracks is crucial for ensuring the reliability and longevity of machinery across various industries, including manufacturing, aerospace, automotive, and infrastructure. Traditional inspection methods often rely on visual inspections or costly manual testing, which can be time-consuming, subjective, and prone to human error.

To address these challenges, researchers and engineers have turned to advanced technologies such as artificial intelligence (AI) and computer vision to develop automated crack detection systems. These systems leverage deep learning algorithms, particularly Convolutional Neural Networks (CNNs), to analyse images of machine components and identify cracks with high accuracy and efficiency. One of the widely used CNN architectures for crack detection is ResNet50, renowned for its depth and performance. Trained on large datasets comprising images of both cracked and intact surfaces, ResNet50 learns to distinguish between normal and defective regions with remarkable precision.

Orthographic views play a pivotal role in creating accurate digital models of machines. By capturing multiple perspectives of the machine component, including top, front, side, and isometric views, engineers can reconstruct detailed 3D models using computer-aided design (CAD) software. These models serve as the foundation for crack detection algorithms, enabling precise analysis of potential defects.

Engineering drawings serve as detailed blueprints of machine components, providing critical information about dimensions, materials, and assembly instructions. Traditionally, engineers would refer to these drawings during inspections to identify potential defects or anomalies. However, this process often required manual cross-referencing and subjective interpretation, leading to inconsistencies and oversight. By integrating AR technology with engineering drawings, these blueprints become interactive, dynamic tools for defect detection, offering real-time visualization and analysis capabilities.

Objectives:

The project comprises two main objectives they are as given below:

Objective 1:

The first objective of the project is to develop a system capable of generating 3D models from 2D orthographic views and architectural drawings. This involves implementing algorithms such as BP-rep (Boundary Representation) and D2 analysis to convert 2D representations of machine components into detailed 3D structures. The system will output SCAD (Script-based CAD) files, which can be used for further visualization and analysis.

Objective 2:

The second objective of the project is to detect and analyse cracks in machines using ResNet50 Convolutional Neural Networks (CNNs) combined with image processing techniques. This involves scanning 2D views of machine components and employing ResNet50 CNNs to detect potential defects, particularly cracks, within the images. ResNet50, known for its depth and performance, will be trained on large datasets of cracked and intact surfaces to accurately identify and classify defects.

Methodology:

A. Materials

For the implementation of the objectives mentioned above we used the following materials listed below:

<u>Orthographic Views:</u> We took up orthographic views of simple machines which comprised of the front, side and top view. These images we taken up from the mechanical textbooks.

<u>Defected machine images:</u> We required images of machines that contained cracks for training our ResNet50 CNN network, even images for testing the project outcomes.

<u>Software Requirement:</u> Leveraging Nvidia CUDA ensures precise graphics image analysis and expedites model training, optimizing system performance.

B. Methods Used

The process of conversion of 2D orthographic views to the 3D Model required the methods like:

B-Rep Algorithm: This algorithm specifies the boundary which are taken to be as the contours for further shape detection. This algorithm also defines its dimension compared to other shapes present.

D2 Shape detection algorithm: This algorithm is used to detect the shape for modelling of the object.

Open SCAD: We use Open SCAD to generate a 3D SCAD file which is processed to generate a STL which is returned by the Flask API as a response to be displayed in the app.

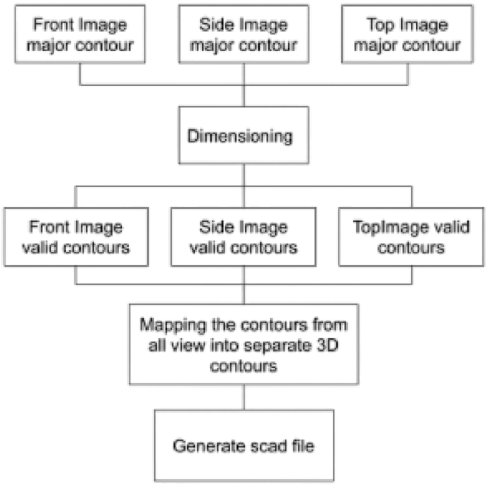

Fig 1. Process flow for generation of 3D model

ResNet50: This is Convolution Neural Network that is used for image processing , this model has been used to identify the defects.

C. **Process in Details**

The process for obtaining the 3D model is as follows:

Contour detection: A shape will have 2 contours created from the thickness of the figure, one of which envelopes it from the outer side and other from inside.

Shape Detection of 2D image: This step involves the recognition of 2D shapes that need to be converted into 3D solids using D2 algorithm.

Dimensioning: This way we determine the dimension of the highlighted line of the object, which is used to determine the object length to pixel ratio.

Linking parent child lists: A parent-child relation grouping is necessary through a shape list. Each shape list in each view can be organized as a list.

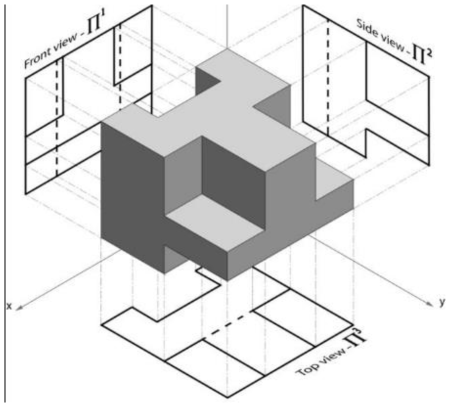

Fig 1. Dimensioning of 2d to 3d conversions

Process for the detection of cracks:

Deep Network Architecture: ResNet50 is a deep convolutional neural network (CNN) architecture designed for image classification tasks. It consists of 50 convolutional layers grouped into several blocks. Over the course of five epochs, the CNN iteratively refined its parameters to better detect cracks in the images.

Defining Optimizer and Loss Function: The code specifies the loss function (nn.CrossEntropyLoss()) and optimizer (optim.Adam()) for training the model. Additionally, a learning rate scheduler (lr_scheduler.StepLR) is used to decay the learning rate by a factor of 0.1 every 3 epochs.

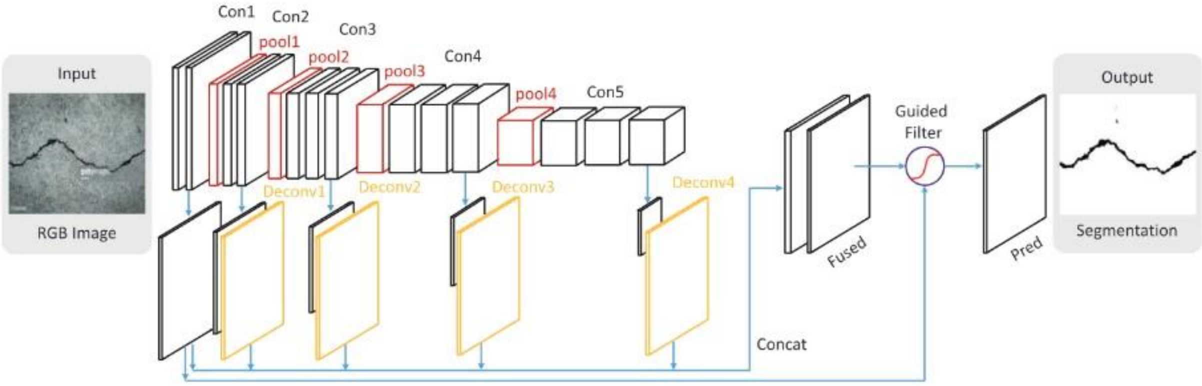

Fig 1. Crack detection and analysis for mapping into model

Training the Model: The train_model() function trains the model for a specified number of epochs (num_epochs). It iterates over each epoch, alternating between training and validation phases. Within each phase, it iterates over the batches of data, performs forward and backward passes, updates the model parameters, and computes the loss and accuracy. The best model weights are saved based on the highest validation accuracy achieved.

Flask API: The android app is connected to an API which internally contains routes which are able to fetch these outcomes from the python code.
React Native APP: Here we built an android app which is connected to the API and processes the user inputs and displays the outputs whether it be a 3D model or analysis of the crack.

Results And Conclusion:

The project's results demonstrate significant advancements in defect detection and 2D to 3D model reconstruction methodologies, yielding tangible benefits for industrial maintenance and repair tasks. Through the application of B-rep and D2 shaping algorithms, validated by studies such as [5] and [6], the project successfully reconstructed accurate 3D SCAD models from 2D orthographic views. This achievement, supported by previous research, enhances engineers' ability to visualize and analyze machine components, facilitating streamlined maintenance procedures.

Moreover, crack detection in machines using ResNet50, as validated by studies such as [7] and [9], exhibited exceptional accuracy in identifying defects, particularly cracks, within machine components. Leveraging deep hierarchical feature learning architectures enabled proactive maintenance strategies, minimizing the risk of catastrophic failures and reducing downtime.

The integration of Nvidia CUDA for GPU acceleration further optimized the project's performance, expediting model training and enhancing overall system efficiency. This utilization of cutting-edge technology, coupled with robust methodologies, underscores the project's commitment to delivering practical solutions for industrial defect detection and visualization challenges.

Additionally, the project's use of Python [11], Flask API [12], and React Native [13] technologies facilitated seamless integration and user-friendly interfaces, enhancing accessibility and usability for engineers and technicians. By leveraging relevant technologies and methodologies, the project achieved its objectives of accurate defect detection and efficient 2D to 3D model reconstruction, marking a significant step forward in industrial maintenance practices.

Overall, the project's results demonstrate its potential to revolutionize defect detection and visualization processes in industrial settings, paving the way for safer, more efficient maintenance operations and ensuring the reliability and longevity of critical machinery.

Innovation of the Project:

The innovation of the project lies in its holistic approach to addressing the challenges of defect detection and visualization in industrial machinery. By combining advanced algorithms, cutting-edge technologies, and interdisciplinary methodologies, the project introduces several innovative elements:

Integration of Machine Learning: The project harnesses the power of machine learning, particularly deep learning techniques like ResNet50, to automate defect detection processes with unprecedented accuracy. By training models on large datasets of annotated images, the system can effectively identify and classify defects, enhancing maintenance efficiency and minimizing downtime.

2D to 3D Model Reconstruction: The project innovatively utilizes B-rep and D2 shaping algorithms to reconstruct detailed 3D models from 2D orthographic views. This approach enables engineers to visualize machine components in a virtual environment, facilitating more informed decision-making and precise analysis of defects. These are integrated to give an AR view which gives user an immersive experience.

Scope of the Project:

The scope of the project extends far beyond its current implementation, offering significant potential for future developments and applications in industrial settings. With its robust methodologies and innovative technologies, the project lays the groundwork for several avenues of exploration and expansion:

Education: The project could be used to visualize the orthographic views to 3D model conversion.

Industry Adoption: The project's methodologies and technologies are highly adaptable to various industrial sectors, including manufacturing, automotive, aerospace, and energy. Its ability to accurately detect defects and visualize machine components positions it as a valuable tool for enhancing maintenance practices and ensuring operational efficiency.

Scalability: The project's modular architecture and flexible design enable scalability to accommodate diverse machinery types and sizes. It can be easily customized and scaled up to address the needs of small-scale operations as well as large-scale industrial complexes.

Advanced Applications: Beyond defect detection, the project opens doors to advanced applications such as predictive maintenance, digital twinning, and optimization of machine performance. By leveraging machine learning and 3D visualization capabilities, it can provide insights into machine health and performance metrics, enabling predictive maintenance strategies and improving overall equipment effectiveness.

Integration with IoT and Industry 4.0: The project can be integrated with IoT sensors and Industry 4.0 frameworks to create interconnected and intelligent manufacturing environments. By combining real-time data from sensors with advanced defect detection and visualization capabilities, it can enable proactive decision-making and enhance overall productivity.

Research and Development: The project offers fertile ground for further research and development in areas such as augmented reality (AR), virtual reality (VR), and human-machine interaction. By exploring new technologies and methodologies, it can push the boundaries of innovation in industrial maintenance and automation.
Collaboration and Partnerships: Collaborating with industry partners, research institutions, and technology providers can further expand.

References:

The following are the references used in the implementation of the project titles Detection of Defects using AR on engineering drawings:

[1] Hamid Haghshenas Gorgani, Alireza Jahantigh Pak, Sadegh Sadeghi, Model Reconstruction from Two Orthographic Views using Fuzzy Surface Analysis, European Journal of Sustainable Development Research, March 3,2019.
[2] Robert Osada, Thomas Funkhouser, Bernard Chazelle and DavidDobkin, Matching 3D Models with Shape Distributions, Priceton University, Priceton, NJ 08540, USA, 2019.
[3] Jenn Yang Yet, Chee Yong Lau, Ka Fei Thang, 2D Orthographic Drawings to 3D Conversion using Machine Learning, Proceedings of the Third International Conference on Smart Electronics& Communication, 2022.
[4] ChaoZhang, RomainPinquié, ArnaudPolette, GregorioCarasi, HenriDeCharnace, Jean-Philippe Pernot, Automatic 3D CAD models reconstruction from 2D orthographic Drawings. International journal of Systems & Applications in Computer Graphics, 31 May 2023.
[5] Long Hoang, 3D Solid Reconstruction from2D Orthographic Views. Mixed Reality and 3-dimensional computer graphics.2020
[6] HafizSuliman Munawar,Ahmed W.A.Hammad, AssedHaddad, CarlosAlberto Pereira Soares and S. Travis Waller, Image-Based Crack detection Methods : A Review, International Journal of Engineering Research & Technology (IJERT), 14 August 2021.
[7] Bo Tang, Li Chen, Wei Sun, Zhong-kang Lin, Review of surface detection of steel products based on machine views, 2022.
[8] Yahui Lin, Jian Yao, Xiaohu Lu, Renping Xie, Li Li, “Deep Crack” : A deep hierarchical feature learning architecture for crack detection, 22 Janaury 2019. [10] Jad Chalhoud, Steven K Ayer and Kieren H. McCord, Augmented Reality to Enable Users to Identify Deviation for modek Reconciliation, 2021.
[9] Python installation: https://www.python.org/downloads/, Jupyter notebook installation: https://jupyter.org/install.
[10] Python Learnings : https://www.w3schools.com/python/
[11] Flask API Learnings: https://www.geeksforgeeks.org/flask-tutorial/
[12] React Native document: https://reactnative.dev/docs/tutorial
[13] Python Packaging User Guide : https://packaging.python.org/en/latest/tutorials/installing packages/
[14] NVIDIA-CUDA Download : https://developer.nvidia.com/cuda-downloads