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DEPARTMENT OF CSE-ARTIFICIAL INTELLIGENCE

A Mini-Project Report On

"SINGLE-VIEW 3D OBJECT RECONSTRUCTION USING DEEP NEURAL NETWORKS"

A report submitted in partial fulfillment of the requirements for the

NEURAL NETWORK AND DEEP LEARNING

Submitted By

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Visvesvaraya Technological University
Belagavi, Karnataka 2025-2026

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DEPARTMENT OF CSE (ARTIFICIAL INTELLIGENCE)

CERTIFICATE

This is to certify that the Mini Project of NEURAL NETWORK AND DEEP LEARNING title "SINGLE-VIEW 3D OBJECT RECONSTRUCTION USING DEEP NEURAL NETWORKS" has been successfully presented by C H BHARGHAVATEJA VARDHAN 3BR22CA011 student of semester B.E for the partial fulfillment of the requirements for the award of Bachelor Degree in CSE(AI) of the BALLARI INSTITUTE OF TECHNOLOGY & MANAGEMENT, BALLARI during the academic year 2025-2026.

It is certified that all corrections and suggestions indicated for internal assessment have been incorporated in the report deposited in the library. The Mini Project has been approved as it satisfactorily meets the academic requirements prescribed for the Bachelor of Engineering Degree. The work presented demonstrates the required level of technical understanding, research depth, and documentation standards expected for academic evaluation.

A handwritten signature in black ink, appearing to read 'Pavan Kumar' and 'Vijay Kumar'.

Signature of Coordinators

Prof. Pavan Kumar

Mr. Vijay Kumar

A handwritten signature in black ink, appearing to read 'Yeresime Suresh'.

Signature of HOD

Dr. Yeresime Suresh

ABSTRACT

This project focuses on reconstructing a three-dimensional (3D) object from a single two-dimensional (2D) image using deep learning techniques. Single-view 3D reconstruction is a challenging task due to the inherent loss of depth information in 2D imagery, but modern neural networks can learn meaningful shape patterns from large datasets. In this work, an encoder–decoder architecture is implemented, where a 2D convolutional neural network extracts visual features from the input image, and a 3D convolutional decoder reconstructs the output as a $32 \times 32 \times 32$ voxel representation. The model is trained on the Pix3D dataset, which contains well-aligned image–model pairs, enabling supervised learning of 3D structure. The system demonstrates strong performance, achieving a stable reduction in loss and an Intersection-over-Union accuracy of approximately 0.90. This project successfully shows that deep learning can infer accurate 3D object geometry from a single image, creating a foundation for more advanced multi-view or higher-resolution reconstruction approaches in the future.

ACKNOWLEDGEMENT

The satisfaction that accompanies the successful completion of project work on the “**SINGLE-VIEW 3D OBJECT RECONSTRUCTION USING DEEP NEURAL NETWORKS**” would be incomplete without the mention of people who made it possible, whose noble gesture, affection, guidance, encouragement and support crowned my efforts with success. It is our privilege to express our gratitude and respect to all those who inspired us in the completion of our mini-project.

I am extremely grateful to my Guide **Mr. Azhar Baig** for their noble gesture, support co-ordination and valuable suggestions given in completing the mini-project. I also thank **Dr. Yeresime Suresh**, H.O.D. Department of CSE(AI), for his co-ordination and valuable suggestions given in completing the mini-project. We also thank Principal, Management and non-teaching staff for their co-ordination and valuable suggestions given to us in completing the Mini project.

Name

USN

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CHAPTER 1

INTRODUCTION

Three-dimensional (3D) object reconstruction plays a crucial role in various modern applications such as robotics, virtual and augmented reality, computer graphics, and autonomous systems. Traditionally, accurate 3D reconstruction requires multiple camera viewpoints, depth sensors, or expensive scanning hardware. However, reconstructing a 3D model from a single two-dimensional (2D) image remains an open and challenging research problem due to the inherent loss of depth information. With the rapid advancement of deep learning, neural networks have shown remarkable capability in learning complex spatial relationships and overcoming the ambiguity present in single-view inputs.

This project focuses on designing and implementing a deep learning model that reconstructs a voxel-based 3D structure from a single RGB image. The system uses an encoder-decoder architecture, where a 2D Convolutional Neural Network (CNN) captures high-level visual features from the input image, and a 3D CNN decoder uses these features to generate a $32 \times 32 \times 32$ voxel representation of the object. The model is trained using the Pix3D dataset, which provides aligned 2D images and 3D CAD models, enabling supervised learning of the mapping between image features and 3D geometry.

The goal of this work is to demonstrate that meaningful 3D object reconstruction can be achieved from a single image using deep neural networks. The project not only highlights the potential of voxel-based reconstruction but also lays the foundation for future improvements such as higher-resolution outputs, multi-view learning, and integration with real-world applications.

CHAPTER 2

OBJECTIVES

1. Develop a deep learning model capable of reconstructing a 3D object from a single 2D image:

Design an encoder–decoder architecture that can learn spatial and structural features necessary for 3D reconstruction.

2. To train the model using the Pix3D dataset for supervised 2D-to-3D mapping:

Use paired RGB images and CAD voxel models to teach the network accurate geometric relationships.

3. To generate voxel-based 3D representations of objects:

Produce a $32 \times 32 \times 32$ voxel grid as the output, representing the reconstructed 3D structure.

4. To evaluate the performance of the model using metrics such as Intersection-over-Union (IoU):

Measure reconstruction accuracy and ensure the model reliably captures object shape and structure.

5. To visualize the reconstructed 3D shapes using mesh generation and slicing techniques:

Convert voxel predictions into mesh formats (.ply) for viewing in tools like MeshLab or Blender.

6. To provide a complete end-to-end pipeline for single-view 3D reconstruction:

Include dataset preprocessing, model training, inference, and 3D visualization within a unified system.

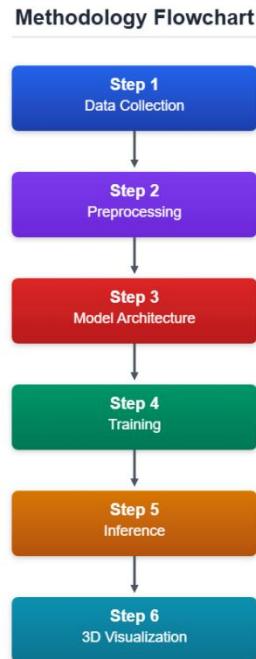
CHAPTER 3

PROBLEM STATEMENT

To develop a deep learning system that reconstructs a 3D object from a single 2D image using an encoder–decoder neural network, enabling accurate 3D shape prediction and visualization for applications in graphics, robotics, and virtual environments.

CHAPTER 4

METHODOLOGY



4.1 Block Diagram of Single-View 3D Object Reconstruction Using Deep Neural Networks

The flowchart shows how the system converts a single 2D image into a 3D model. It begins by collecting paired images and 3D shapes from the Pix3D dataset. These images are resized and the 3D models are turned into voxel grids during preprocessing. The model then uses an encoder–decoder structure, where the encoder learns features from the 2D image and the decoder reconstructs them into a 3D voxel shape. During training, the network learns this mapping using loss functions and accuracy metrics like IoU. Once trained, the model can take any new 2D image and predict its 3D voxel form.

CHAPTER 5

REQUIREMENT ANALYSIS

FUNCTIONAL REQUIREMENTS

- **The system should load and preprocess 2D images and 3D voxel data from the Pix3D dataset.**
- **The model should reconstruct a 3D voxel grid from a single 2D image using an encoder-decoder architecture.**
- **Users should be able to input an image and receive a corresponding 3D voxel or mesh output.**
- **The system should handle invalid or missing inputs with appropriate error messages.**
- **The system should generate visual outputs such as voxel slices and 3D mesh files for reconstructed objects.**

NON-FUNCTIONAL REQUIREMENTS

- **Performance:** The system should provide efficient inference even on CPU-based environments.
- **Accuracy:** The model should maintain high reconstruction accuracy measured through IoU.
- **Scalability:** The system should support larger datasets and allow future upgrades (e.g., higher voxel resolution).
- **Usability:** Outputs should be easy to understand and view using external 3D visualization tools.
- **Maintainability:** Code modules should be simple, clean, and easy to update.

CHAPTER 6 DESIGN

FLOW CHART

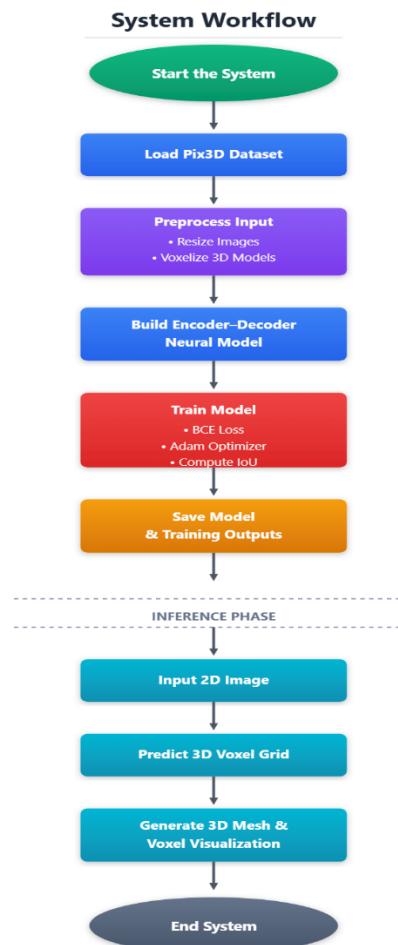


Fig 6.1 Flow Chart

USE CASE DIAGRAM

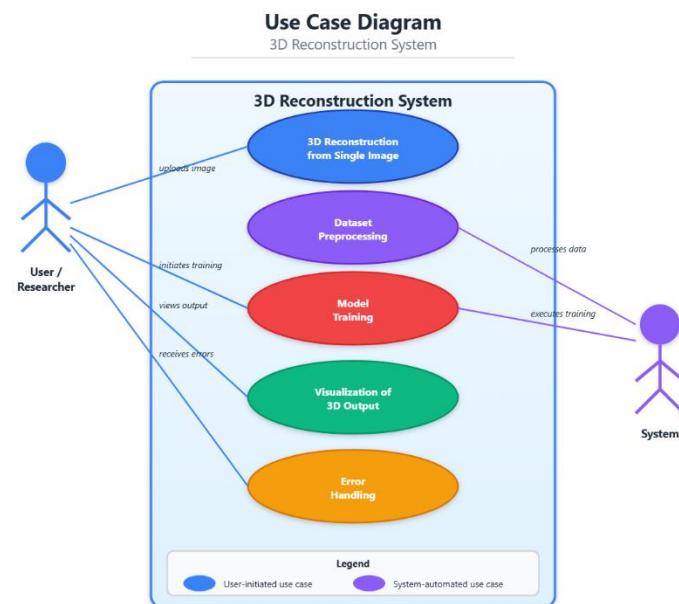


Fig 6.2 Use Case Diagram

SEQUENCE DIAGRAM

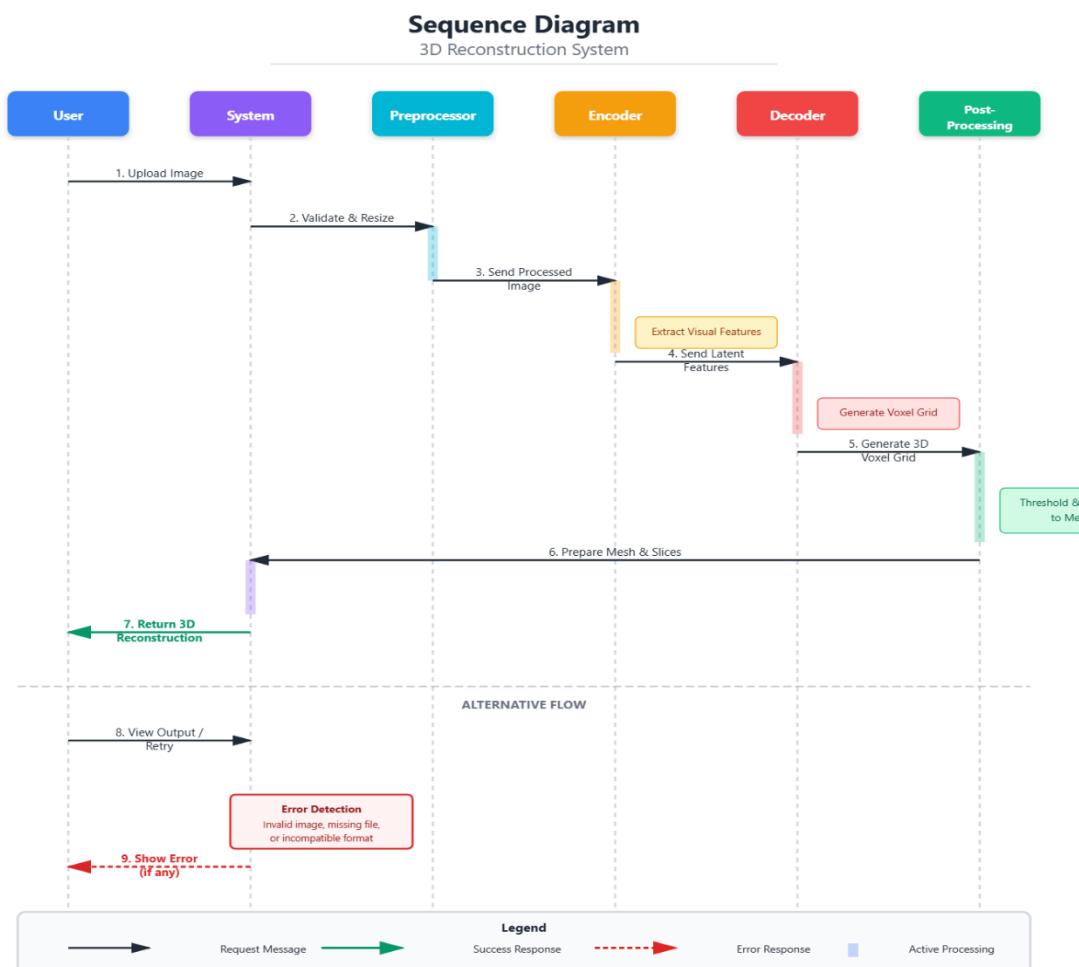


Fig 6.3 Sequence Diagram

CHAPTER 7

IMPLEMENTATION

Phase 1: Data Preparation

- Collect paired 2D images and 3D models from the Pix3D dataset.
- Resize all images to 128×128 and convert 3D CAD models into $32 \times 32 \times 32$ voxel grids.
- Normalize image pixel values and structure the dataset for training and validation.

Phase 2: Model Development

- Build an encoder–decoder deep learning model using 2D CNNs for feature extraction and 3D CNNs for voxel reconstruction.
- Compile the model with Adam optimizer and Binary Cross-Entropy loss.
- Train the model on the preprocessed dataset and evaluate it using Intersection-over-Union (IoU).

Phase 3: Deployment and Testing

- Save trained model weights and sample reconstruction outputs.
- Use the model to generate a 3D voxel grid from a new 2D image.
- Visualize the predicted 3D structure through voxel slices and mesh (.ply) files.

CHAPTER 10 RESULT AND DISCUSSION

CHAPTER 8

RESULTS AND DISCUSSION

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To support symlinks on Windows, you either need to activate Developer Mode or to run Python as an administrator. In order to activate developer mode, see this article: https://docs.microsoft.com/en-us/windows/apps/get-started/enable-your-device-for-development
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For better performance, install the package with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
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To support symlinks on Windows, you either need to Follow link \(ctrl + click\) here or to run Python as an administrator. In order to activate developer mode, see this article: https://docs.microsoft.com/en-us/windows/apps/get-started/enable-your-device-for-development
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For better performance, install the package with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
Xet Storage is enabled for this repo, but the 'hf_xet' package is not installed. Falling back to regular HTTP download.
For better performance, install the package with: `pip install huggingface_hub[hf_xet]` or `pip install hf_xet`
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CHAPTER 9

CONCLUSION

This project successfully demonstrates how deep learning can be used to reconstruct three-dimensional objects from a single two-dimensional image. By utilizing an encoder–decoder architecture with 2D and 3D convolutional neural networks, the system is able to learn meaningful spatial features and generate accurate $32 \times 32 \times 32$ voxel representations of objects. Training on the Pix3D dataset enabled the model to achieve strong reconstruction performance, supported by consistent improvements in loss and Intersection-over-Union (IoU).

The results show that even with limited input information, neural networks can infer complex 3D structure and produce visualizable outputs such as voxel slices and mesh models. This work establishes a solid foundation for future enhancements, including higher-resolution outputs, multi-view learning, and real-time 3D reconstruction applications.

CHAPTER 10

REFERENCES

- [1] Choy, C., Xu, D., Gwak, J., Chen, K., & Savarese, S. (2016). *3D-R2N2: A Unified Approach for Single and Multi-view 3D Object Reconstruction*. European Conference on Computer Vision (ECCV).
- [2] Sun, X., Wu, J., Zhang, X., Zhang, Z., Zhang, C., Xue, T., Tenenbaum, J., & Freeman, W. (2018). *Pix3D: Dataset and Methods for Single-Image 3D Shape Modeling*. IEEE Conference on Computer Vision and Pattern Recognition (CVPR).
- [3] Wu, J., Zhang, C., Xue, T., Freeman, B., & Tenenbaum, J. (2016). *Learning a Probabilistic Latent Space of Object Shapes via 3D Generative-Adversarial Modeling*. Advances in Neural Information Processing Systems (NeurIPS).
- [4] Tatarchenko, M., Dosovitskiy, A., & Brox, T. (2017). *Octree Generating Networks: Efficient Convolutional Architectures for High-Resolution 3D Outputs*. IEEE International Conference on Computer Vision (ICCV).
- [5] Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.
- [6] Ji, S., Xu, W., Yang, M., & Yu, K. (2013). *3D Convolutional Neural Networks for Human Action Recognition*. IEEE Transactions on Pattern Analysis and Machine Intelligence.
- [7] Kingma, D. P., & Ba, J. (2014). *Adam: A Method for Stochastic Optimization*. International Conference on Learning Representations (ICLR).
- [8] Paszke, A. et al. (2019). *PyTorch: An Imperative Style, High-Performance Deep Learning Library*. Advances in Neural Information Processing Systems (NeurIPS)

