Convert 2D CT scan images into 3D models using Hounsfield Units

Trupti Baraskar[1], Kshitija Supekar[2],Sneh Thorat[3],Kushagra Suryawanshi[4,]Samarjit Sonawane[5]

[1 2 3 4 5] Department of Department of Computer Science and Engineering (CSE),

School of Computer Engineering and Technology (SCET),

Dr. VishwanathKarad MIT World Peace University, Pune, Maharashtra, India

Corresponding Author:

TruptiBaraskar
Department of Computer Science and Engineering, Faculty of Engineering and Technology
Dr. VishwanathKarad MIT World Peace University
411038 Kothrud, Pune, Maharashtra, India

ABSTRACT

Computed tomography scans, which provide accurate information on the internal organs of the human body, are frequently used in medical imaging. The goal of the proposed study is to create a system that uses Hounsfield units to transform scan data into extremely precise 3D models. This method first segments the CT scans, assigns Hounsfield Units values to the segmented regions, and then builds a 3D model using the values of these units. The tool will enable healthcare professionals to visualize and look at anatomical structures in three dimensions by utilizing cutting-edge methods and algorithms. In the 3D models as are generated, this method also efficiently recognizes and represents soft tissues. Two models have been studied for this paper. This proposed work tries to develop 3D models from easy greyscale digital CT scan images of various anatomical structures, and further perform analysis in terms of fracture patterns/fracture anatomy along with soft tissue detection. The primary model is a review of the literature on 3D modelling of x-ray images. To create 3D models from CT scan image, create a machine learning or deep learning model and train it. This model should to be capable of accurately restoring the anatomical structures from the Hounsfield unit values. The process of converting of a CT scan to a 3D model is implemented in the second model. This proposed effort has the potential to revolutionize medical imaging and offer insightful information for surgical planning, therapy, and diagnosis.

1. INTRODUCTION

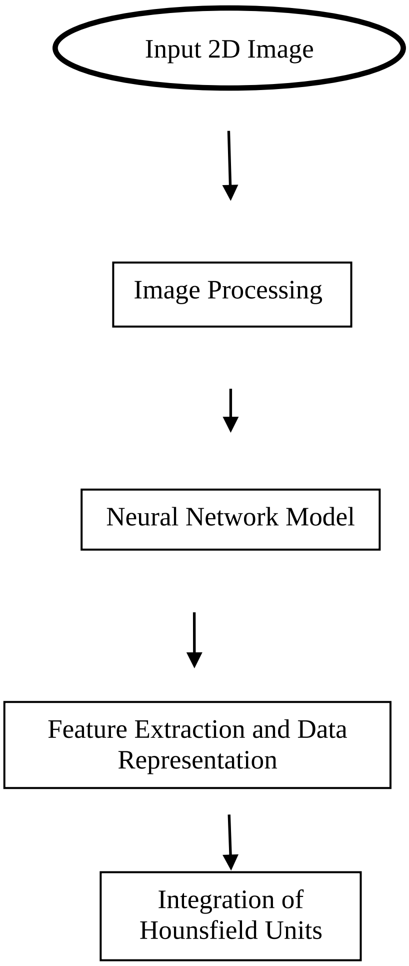
The field of medicine now depends significantly on medical imaging as a tool for treating and diagnosing a wide range of diseases and conditions. Because it creates extremely exact and detailed images of the inner workings of body parts, computed tomography (CT) imaging is a widely used imaging technique. Conventional 2D CT scan images cannot fully reflect the complex nature of anatomical structures, which can make it hard for doctors to observe and understand some aspects of a patient's sickness.The development of complex computer techniques and software has lately made it possible to convert 2D CT scan images into 3D models, offering a more detailed and user-friendly way to study and analyses anatomical details. Recent advances in computer software and algorithms have made it possible to convert 2D CT scan images into 3D models, enabling a more complete and user-friendly method of studying and analyzing anatomical details. This technology, which has the potential to completely change the field of medical imaging, will provide medical professionals with a powerful tool for diagnosing and treating complex medical disorders. The proposed model train a deep neural network to distinguish detailed patterns and attributes in a massive dataset of CT scan images using a combination of supervised and unsupervised learning approaches. Once trained, the network may be used to immediately create high-quality 3D models from 2D CT scan images. Deep learning algorithms have the potential to turn 2D CT scan data into 3D models, revolutionizing medical imaging and providing doctors with a powerful tool for diagnosing and treating complex medical illnesses. By offering a more thorough and convenient means to examine and assess anatomical features, this technology may considerably improve patient outcomes and assist the medical sector. Traditional X-Ray imaging has long been an essential component of medical diagnostics, particularly in the identification of bone fractures. Despite its benefits, there are certain limitations to this technology, particularly when it comes to locating weak transparent external compounds inside the body.

2. LITRATURE REVIEW

This paper [1] employed a deep learning model using an encoder-decoder framework based on convolutional neural networks. After training, in the implementation, the network can input one or more 2D x-ray pictures and produce an array of intensity values that corresponds to a 3D CT image. This implementation's shortcoming is that picture reconstruction requires more power for medical applications. In order to accurately examine a patient's anatomy in orthopedics, this study [2] proposes a machine learning technique that transforms 2D X-ray images into 3D models. The suggested method generates a 3D image utilizing bone extraction and STL conversion with a fair level of accuracy despite the limited dataset availability. The study's results demonstrate that this method produces respectable accuracy and can be improved by utilizing larger datasets and more potent neural networks. In this research [3], a brand-new technique for creating a 3D bone model from two-dimensional X-ray scans of the distal femur is presented. The suggested technique makes use of a template surface mesh model that is modified to take into account the geometry of the bones in orthogonal radiography. For the final deformation of the template, the authors used a Laplacian surface deformation and a Kohonen self-organizing map for 2D-3D correspondence.A useful technique for reconstructing 3D medical X-ray images is provided by the research [4]. The four steps of the procedure include preprocessing, picture improvement, image contour, image reconstruction, and image visualization. The results demonstrate the feasibility of 3D reconstruction of hand geometry X-ray images and highlight the benefits of 3D visualization over 2D visualization. A volumetric tomographic X-ray image of the patient can be created from a single projection view using a deep-learning model that has been trained to map projection radiographs of a patient to the matching 3D anatomy. The authors [5] conclude that their suggested approach, which builds 3D models of the distal femur using biplane radiography, provides good reconstruction accuracy and outstanding computing efficiency. The author [6] proposed a new algorithm to re-configure a 3D template surface mesh model to match the bone shape in orthogonal radiographs. The algorithm is also based on a statistical shaped model. Gaussian filter is used for noise reduction. This research [7] offers a practical method for reconstructing 3D medical X-ray pictures. Preprocessing, picture enhancement, image contour, image reconstruction, and image visualization are the four steps of the method. The outcomes show that hand geometry X-ray pictures may be successfully 3D reconstructed, and they also emphasize the advantages of 3D visualization over 2D visualization. The paper [8] has introduce a network to improve the 3D volume's resolution. A hybrid framework that incorporates two CNN-based networks. The 3D encoder-decoder Generative Adversarial Network, as the first (3D-ED-GAN) and Long-Term Recurrent Convolutional Network is the second (LRCN). This paper [9] clarifies the use of direct linear transformation (DLT) techniques is highlighted in the literature already in existence, which also recognizes the difficulties involved in 3D femur reconstruction from stereo-radiography. In order to achieve correct reconstruction, these techniques rely on the visibility of anatomical landmarks in two images, necessitating edge detection and calibration points. With two main objectives in mind, 3D reconstruction of bones and anomaly identification as well as mimicking bone behavior during orthopedic operations, this paper [10] addresses the issue of 3D bone reconstruction from 2D conventional x-ray projections. Through 3D visualization, parameter evaluation, and shape change analysis, the technique shows the possibility for interactive planning and simulation of orthopedic surgery. A hard X-ray grating interferometer is used in the method described in this paper [11] to create tomographic phase contrast images of centimeter-sized objects. The technique can be applied to a range of fields, including non-destructive testing, medicine, and biology. It is especially well suited for lab-based, low-brilliance X-ray sources. This work [12] discusses the shortcomings of the classical k-means clustering technique, such as its low efficiency due to repeated distance calculations. It proposes a modified k-means algorithm, which avoids repeated distance calculations and improves the speed and accuracy of clustering by storing data in a simple data structure. This article [13] discusses how noise pollution in X-ray images hinders the identification of bone abnormalities in medical applications. It provides a paradigm for X-ray image enhancement based on discrete wavelet transform and histogram matching techniques to improve image visibility. The algorithm's value in qualitatively and mathematically enhancing medical X-ray pictures. The Canny operator and mathematical morphology are combined to create an edge-detection technique for weld image processing in this research [14]. It efficiently removes the pseudo-edges produced by the Canny algorithm and retrieves precise information about the weld edges while minimizing noise interference. The algorithm enhances the Canny operator's performance, making welding seam tracking applications based on vision sensors possible. An improved Canny edge detection method for work piece sorting is presented in this paper [15] in order to address the issues of human threshold setting and Gaussian filtering denoising. The method replaces Gaussian filtering with the Mean Shift algorithm to preserve edges during denoising. In this paper [16], a unique approach for converting 2D X-ray images into 3D models using Hounsfield unit analysis is presented, with potential uses in medical imaging and diagnostic operations. The paper authors [17] discuss cutting-edge image processing methods that improve the detection and segmentation of soft tissue features in CT scans. These methods provide greater visualization as well as potential advantages for treatment planning and diagnostic precision in a variety of medical specialties. The automated method for transforming 2D medical photos to 3D that is suggested in this paper [18] makes use of sophisticated algorithms. With potential applications in medical diagnosis, treatment planning, and research, the technology integrates computer vision techniques with machine learning to create precise and effective reconstruction of three-dimensional structures. This work [19] addresses the significance of precise visualization of anatomical structures by focusing on Hounsfield unit calibration to obtain accurate 3D volume rendering in CT scans. The suggested calibration approach takes scanner settings and patient-specific characteristics into account, which improves volume rendering accuracy. By analysing and contrasting several segmentation algorithms, the authors [20] present a comparative research on cutting-edge methods for soft tissue segmentation in CT scans. The study investigates machine learning and image processing methods, providing insights into the benefits and drawbacks of each strategy for enhanced CT soft tissue segmentation. This paper [21] describes the method for converting 2D images to 3D using deep learning and Hounsfield unit analysis. The authors transform two-dimensional images into three-dimensional models using deep learning algorithms and Hounsfield unit values, with applications in treatment planning and diagnostic imaging. This research [22] suggests a novel technique for converting CT scans into 3D models specifically for the field of orthopedics. The suggested approach has the potential to be advantageous for accurate viewing and study of orthopedic structures, aiding in surgical planning and therapy. Hybrid image processing approaches are presented by the authors [23] to improve the visualization of soft tissue features in CT images. The suggested method improves the visualization of soft tissues by combining several techniques, such as filtering, segmentation, and augmentation, making it easier to comprehend and diagnose medical images. A machine learning method for the automatic detection of soft tissue anomalies in CT scans is presented in the paper [24]. The technology can automatically identify and categories abnormalities by training a model on a dataset, enabling early identification and diagnosis of soft tissue disorders and possibly improving patient outcomes and treatment planning.A machine learning method for the automatic detection of soft tissue anomalies in CT scans is presented in this study [24]. The technology can automatically identify and categories abnormalities by training a model on a dataset, enabling early identification and diagnosis of soft tissue disorders and possibly improving patient outcomes and treatment planning. Adaptive filtering techniques are presented in this study [25] to improve the contrast of soft tissue in CT scans. In order to improve the visualization of soft tissues while maintaining image features, the suggested method modifies filter settings based on local image characteristics, which may help with accurate diagnosis and treatment planning in medical imaging. For dental applications, the authors [26] offer a deep learning-based method for transforming 2D X-ray pictures to 3D models. Convolutional neural networks are used in this technique to learn how to transfer 2D X-ray pictures to their corresponding 3D models, resulting in accurate and effective conversion that has the potential to improve diagnosis. The authors [27] provide a deep learning-based approach for converting 2D X-ray images to 3D models for dental applications. This method converts 2D X-ray images accurately and successfully into their corresponding 3D models, potentially improving diagnosis.

3. 3D MODELLING APPROACH

The basic steps of our proposed 3D model reconstruction approach are shown in figure 1. These steps have different functionality for reconstruction.



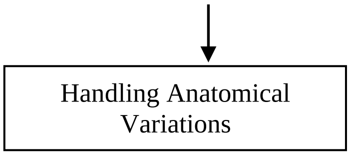


Figure 1. Block Diagram of Proposed 3D Modelling Approach

3.1. Image Preprocessing

CT scan images undergo with preprocessing steps such as normalization, noise reduction, and image enhancement to improve data quality and consistency before inputting them into the model.

3.2 Neural Network Model

The chosen Neural Network Model, such as convolutional neural networks (CNNs) or other 3D volumetric reconstruction methods, is specifically designed to handle CT scan images. It is useful to visualization that extract information from the given portions.

3.3 Feature Extraction and Data Representation

CT scan images undergo from feature extraction and selecting relevant features from Hounsfield unit values.

3.4 Integration of Hounsfield Units

Now Hounsfield units value are integrated into the conversion process. Conversion process use mapping or transformation techniques that convert the values into meaningful data representations. This will be facilitating the generation of 3D models. According to the Hounsfield scale, measuring density, water gets a value of zero Hounsfield units (HU), but tissues which are denser than water have positive values and those that are less dense than water have negative values. Water has a determinate value of 0 HU according to the Hounsfield scale. The calculation of all farther CT values as follows.

$$HU = \frac{1000*(\mu_{tissue} - \mu_{H2O})}{\mu_{H2O}} \quad (1)$$

3.5 Handling Anatomical Variations

This model incorporates adaptive mechanisms or techniques to account for anatomical variations. This include size, shape, and positioning differences across different patients or scan images. To manage anatomical variation, The Marching Cubes Algorithm is employed. This approach offers a quick and simple way to transform volumetric data into polygonal meshes so that it may be successfully shown. These methods allow for the accurate depiction of geometric objects in volumetric data, their change, and their display. To convert volumetric data to polygonal mesh, the steps below must be taken. Figure No. 2 below illustrates the steps that need to be done when attempting to implement the marching cubes algorithm.

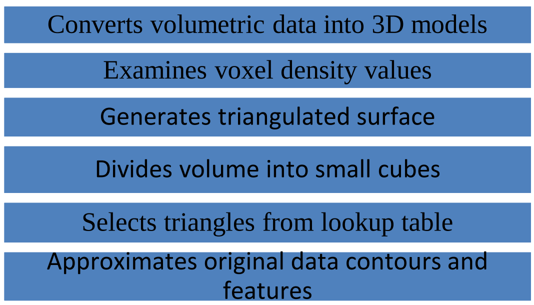


Figure 2. Marching Cudes Algorithm Steps

4. PROPOSED MODEL

In this study, we propose two models. In the first model, x-ray images are hypothetically converting to 3D models. The second model, which we implemented, is CT scan to 3D model.

4.1 Proposed Model for X-Ray Images to 3D Model

Below figure 3 shows proposed model for X-Ray Images. In this model, we utilized a prescribed method to deal with and model our dataset. First, we collected a significant dataset of 2D images. following that, we carried out a number of preprocessing methods that improved the data's quality. Some of these techniques include edge detection, K-means clustering, and the discrete wavelet transform (DWT). After preprocessing, we train our model with the preprocessed data. Particularly, the purpose of our method is to create 3D models from the 2D images. Finally, after training, we visualized the generated 3D models to determine their quality and evaluate the performance of our method. This careful technique enabled us to effectively transform 2D images into 3D models, giving useful information and possible uses across a wide range of industries.

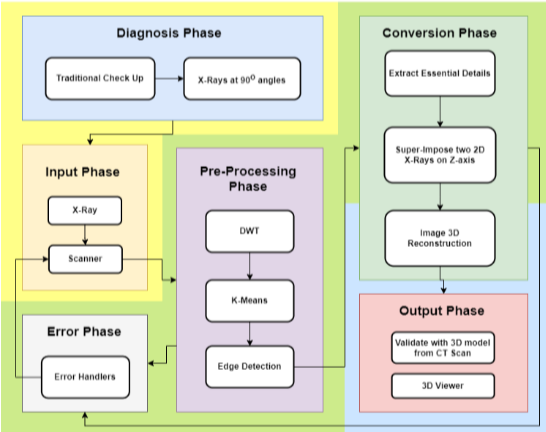


Figure. 3 Proposed Model for X-Ray Images

4.2 Proposed Model for CT Scan Images to 3D Model

Below figure 4 shows proposed model for CT Scan images. In this method, we start by taking a set of DICOM images, which represent in as CT scan slices. Slices of the knee joint of a CT scan had been utilized for our dataset. This dataset has been split into 8 pieces, each of which corresponds to a single CT scan. Each of these portions has 35 slices, while the other sections each have 321 slices. We begin by scanning and organizing all of them. dcm files. The encoded data in the file is where we also get the slice thickness.All slices' Hounsfield Units (HU) are calculated and saved in a numpy stack. A ".np" file is used to hold all pixelated HU values. The slice thickness is then resized and resampled as necessary (ideally to 1mm). The Marching Cubes Algorithm, which is used to extract a polygonal mesh of a surface from a 3D scalar field, is then utilized to generate a mesh. The knee joint bone is thenobtained as our output model by plotting this mesh in 3D using a numpy array.

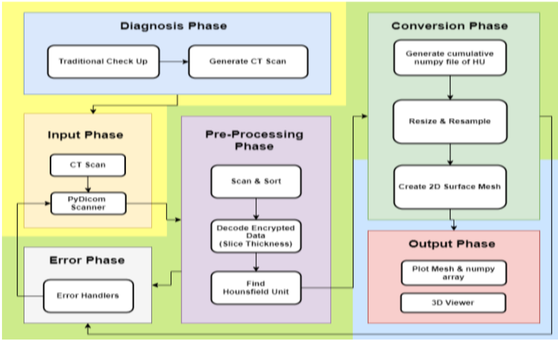


Figure. 4 Proposed Model for CT scans

Proposed model for CT Scan to 3D Model has Following Phases.

4.2.1 Input Phase

A patient gets a routine check-up and a CT scan of the problematic location during this period.

4.2.2 Pre-Processing Phase

The slices are scanned and sorted according to position in this module. The slice thickness as is encoded in these DICOM files can be retrieved by decoding the file. Finally, we determine the pixels' Hounsfield Unit (HU) values.

4.2.3 Conversion Phase

In this case, we're creating a single numpy array to hold the HU values of all the model's slices. This array is stored in a.npy file. The slice thickness is then resized to a standard width and resampled. The numpy array is then used to generate a 2D mesh.

4.2.4 Output phase

Using the FigureFactory module and the plotly library, we plot the mesh and the numpy array. As a result of this, we get a 3D interactive model.

5. RESULT AND ANALYSIS OF PROPOSED MODEL

The second model is applied on available dataset. The dataset consists of up of a set of DICOM images, every one of which represents a CT scan slice. Slices of the knee joint from a CT scan were used to create our dataset. There are 8 folders in this collection, with each component representing a single CT scan. The remaining folders each include 35 slices, whereas the other three have 321 slices each. A slice weights between 80 and 115 KB.The flowchart for the suggested image processing, resizing, and conversion procedure utilizing Hounsfield Units is shown in Figure 5. This flowchart also shows what takes place if the slice thickness is 1. The Marching Cubes Algorithm will then be used to produce the mesh. The CT linear attenuation coefficients are calculated by this algorithm. Each pixel value has a grey scale intensity in order to translate this coefficient into a digital image.

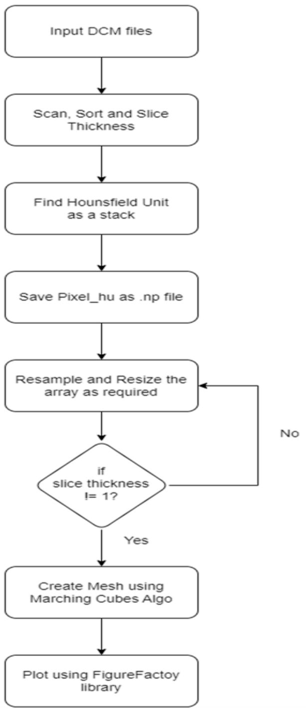
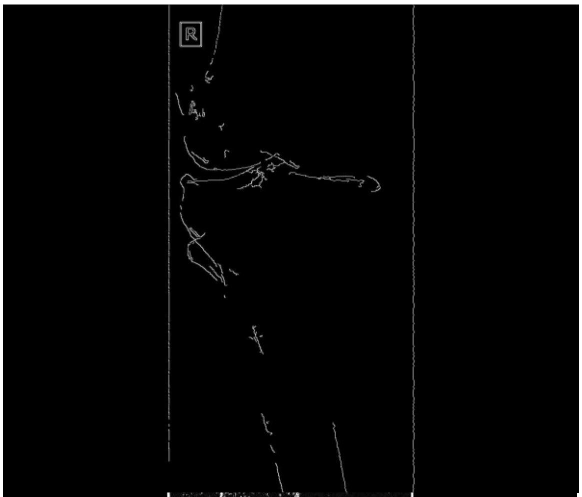


Figure. 5 Flowchart for proposed image processing and conversion process

An X-Ray image of a knee acquired from image right is shown below figure no. 6. Using the Gaussian Filter, K- Means Clustering, and Canny Edge Detection, this image is further processed in order to extract the most important information. The critical and undesired pixels on the X-Ray image were clustered by the K-Means technique. As a result, we were able to work with a clear flat image. Combining computer edge detection with canny edge detection produced excellent results. The precise shape of the knee is depicted in Figure No. 7.The edges of the X-Ray were forced to shatter due to hysteresis thresholding, hence it was discarded. After using the Hysteresis Thresholding function, the results are shown in Figure 8. The following processed image was created by merging effective results from the Gaussian filter, K-Means, and Canny Edge Detection, as well as recoloring a few pixels, the result is shown in figure 9.

Figure. 6 Original X-Ray imageFigure. 7 Result after applying Canny Edge Detection with computer edge strength



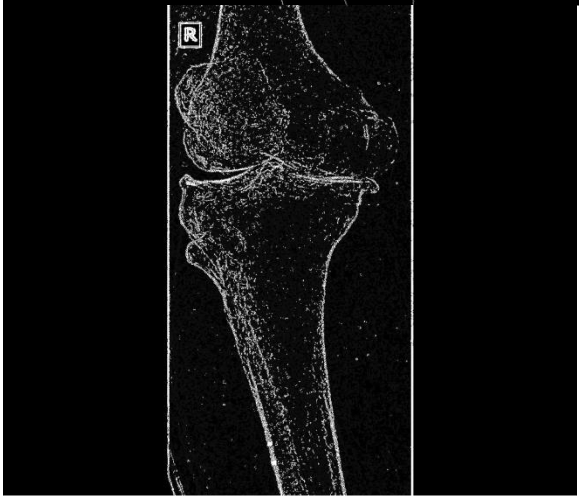
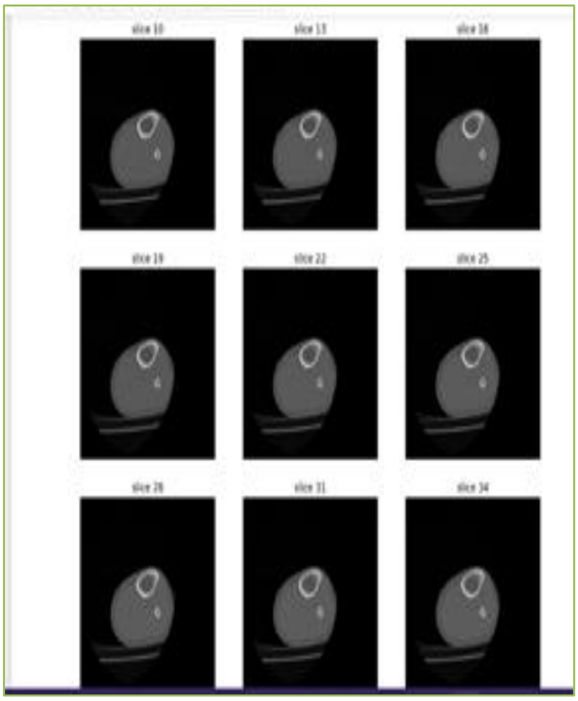


Figure. 8 Result after applying Canny Edge Detection Figure. 9 Preprocessing result after applying Edge Detection, K-means and recolouring pixels with Hysteresis Thresholding

Below figure 10 and 11 show the information about tissue composition (bones, organs, air). It also shown Hounsfield Unit plot and bone detection using available slices. Below figure12 shows the 3D CT scan image reconstruction using proposed method. Figure no. 13 and 14 shows identified 3D view of soft tissue and bone structure. Figure no. 15 shows 3D view of soft tissue for knee joint CT Scan image. Figure no. 16 shows low value of PSNR and SSIM scores in the 3D model.



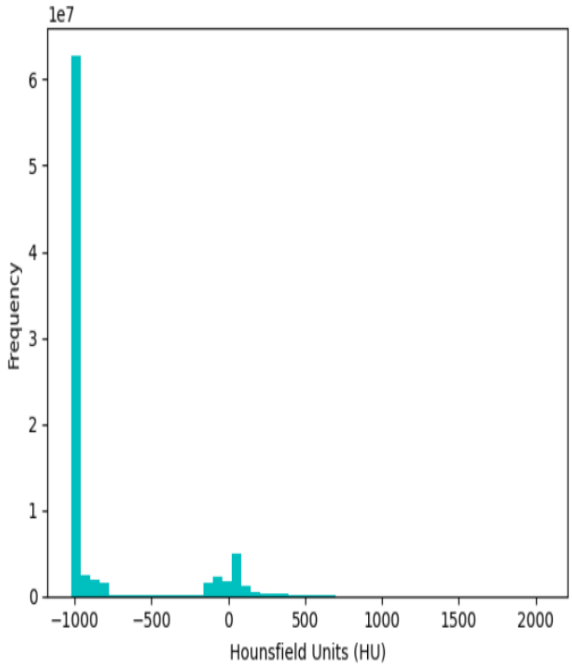
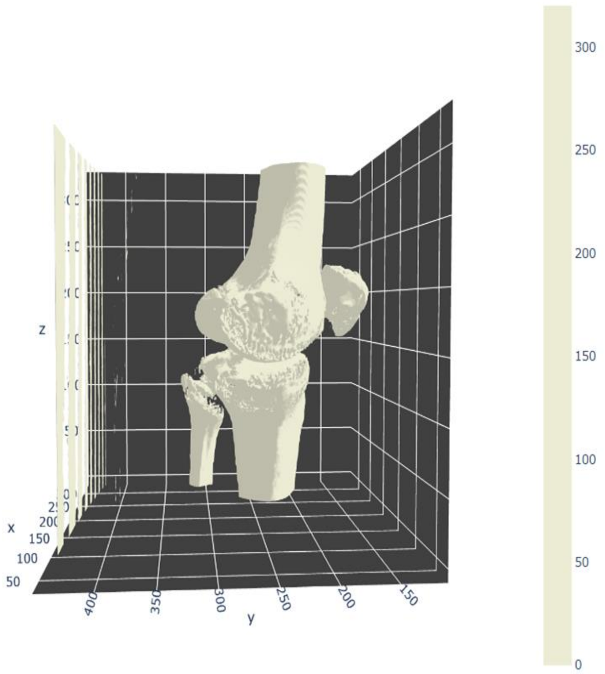
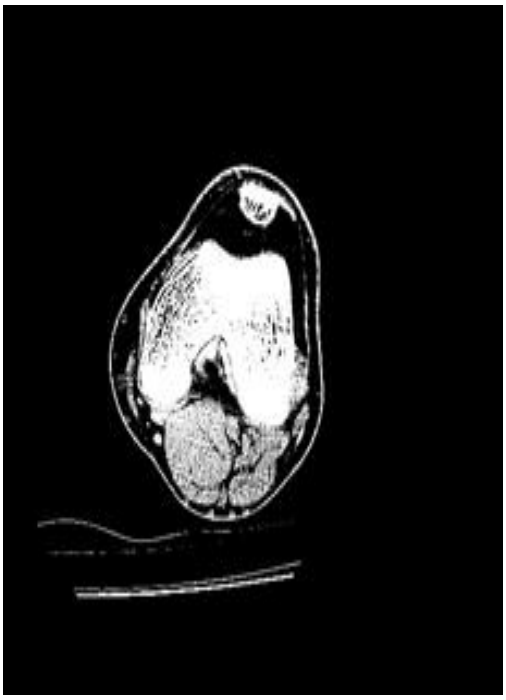


Figure. 10 HU values of slices for used datasetFigure. 11 Bone detected in slices using HU values





- Figure. 12 3D reconstruction of Knee joint from CT-scans Figure. 13 Soft Tissue Identification

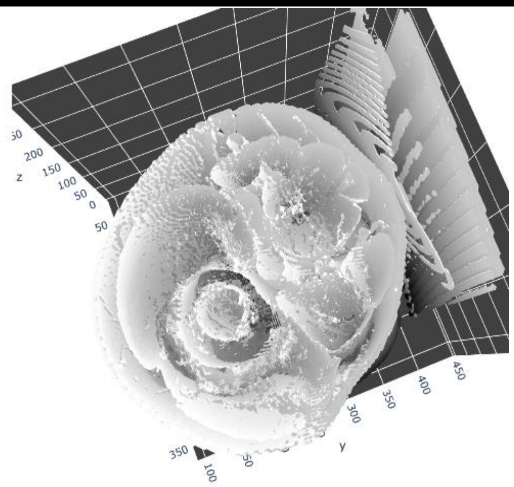
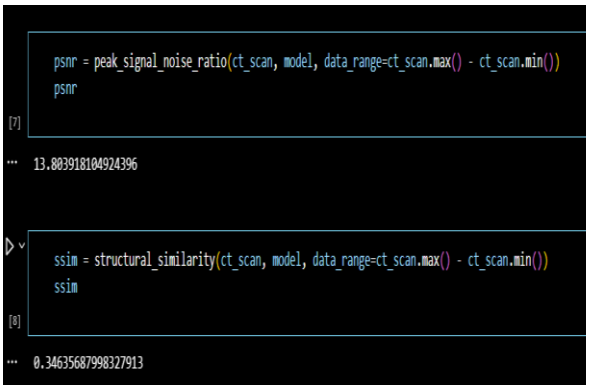


Figure. 14 Bone IdentificationFigure. 15 3D view of Soft Tissue using CT scan



```
psnr = peak_signal_noise_ratio(ct_scan, model, data_range=ct_scan.max() - ct_scan.min())
psnr
[7]
... 13.803918104924396

ssim = structural_similarity(ct_scan, model, data_range=ct_scan.max() - ct_scan.min())
ssim
[8]
... 0.34635687998327913
```

Figure. 16 PSNR and SSIM for CT Scan 3D model

6. CONCLUSION

The conversion of 2D CT scan images to a 3D model using Hounsfield units and the detection of soft tissues based on their Hounsfield unit values are potential techniques for improving medical imaging. Our study's conclusions show that the preprocessing stage resulted in high PSNR and SSIM scores, which show how well the processed images were done. Lower PSNR and SSIM scores in the 3D model produced from the CT scan show that there is scope for improvement in the 3D reconstruction process.Despite this limitation, there is enormous potential for improving the precision and accuracy of medical diagnosis and treatments through the use of Hounsfield units for detecting and classifying soft tissues. Medical experts can gain a more thorough and in-depth grasp of the anatomical structures and disorders within the human body by utilizing this method. Future research and development will be required to optimize the benefits of this novel approach to medical imaging by improving the 3D reconstruction procedure.

ACKNOWLEDGEMENTS

We thank for Dr. VishwanathKarad of the MIT World Peace University for providing us with the chance. We would like to express our gratitude to those authors whose works have contributed to the body of knowledge on this subject and have inspired and guided our research.

REFERENCES

1. *Xiang, Mingren, "Deep Learning-based Reconstruction of Volumetric CT Images of Vertebrae from a Single View X-Ray Image"(2020). Theses and Dissertations. 2629. https://dc.uwm.edu/etd/2629*
2. S. *Dixit, V. G. Pai, V. C. Rodrigues, K. Agnani, and S. R. Priyan, "3D reconstruction of 2d X-ray images," 2019 4th International Conference on Computational Systems and Information Technology for Sustainable Solution (CSITSS), 2019. doi:10.1109/csitss47250.2019.9031045*
3. Y. *Kasten, D. Doktofsky, and I. Kovler, "End-to-end convolutional neural network for 3D reconstruction of kneebones from bi-planar X-ray images," Machine Learning for Medical Image Reconstruction, pp. 123–133, 2020 doi:10.1007/978-3-030-61598-7_12*
4. D. *Buttongkum et al., "3D reconstruction of proximal femoral fracture from biplanar radiographs with fractural representative learning," Scientific Reports, vol. 13, no. 1, 2023. doi:10.1038/s41598-023-27607-2*
5. V. *Karade and B. Ravi, "3D femur model Reconstruction from biplane X-ray images: A novel method based on Laplacian surface deformation," International Journal of Computer Assisted Radiology and Surgery, vol. 10, no. 4, pp473–485, 2014. doi:10.1007/s11548-014-1097-6*
6. L. *Shen, W. Zhao, and L. Xing, "Patient-specific reconstruction of volumetric computed tomography images from a single projection view via Deep Learning," Nature Biomedical Engineering, vol. 3, no. 11, pp. 880–888, 2019. doi:10.1038/s41551-019-0466-4*
7. *Al-Shayea, Qeethara & Al-Ani, Muzhir. (2016). An Efficient Approach to 3D Image Reconstruction. International Journal of Computer Science and Network Security. 16. 35-41.*
8. *W. Wang, Q. Huang, S. You, C. Yang, and U. Neumann, "Shape inpainting using 3D generative adversarial network and recurrent convolutional networks," 2017 IEEE International Conference on Computer Vision (ICCV), 2017. doi:10.1109/iccv.2017.252*
9. B. *Zhang, S. Sun, J. Sun, Z. Chi, and C. Xi, "3D reconstruction method from biplanar radiography using DLT Algorithm:Application to the femur," 2010 First International Conference on Pervasive Computing, Signal Processing andApplications,2010. doi:10.1109/pcspa.2010.68*
10. *L. Caponetti and A. M. Fanelli, "3D bone reconstruction from two X-ray views," [1990] Proceedings of the Twelfth Annual International Conference of the IEEE Engineering in Medicine and*

Biology Society. doi:10.1109/iembs.1990.691042

11. *F. Pfeiffer, O. Bunk, C. Kottler, and C. David, "Tomographic reconstruction of threedimensional objects from hard x-ray differential phase contrast projection images," Nuclear Instruments 39 and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, vol. 580, no. 2, pp. 925–928, 2007. doi: 10.1016/j.nima.2007.06.104*
12. S. *Na, L. Xumin and G. Yong, "Research on k-means Clustering Algorithm: An Improved kmeans Clustering Algorithm," 2010 Third International Symposium on Intelligent Information Technology and Security Informatics, Jian, China, 2010, pp. 63-67, doi: 10.1109/IITSI.2010.74.*
13. *T. Sorwar and Z. M. Parvez Sazzad, "Orthopedic X-ray Image Enhancement Based on Wavelet Transform and Histogram Matching,"2017 IEEE International WIE Conference on Electrical and Computer Engineering (WIECON-ECE), Dehradun, India, 2017, pp.188-191, doi: 10.1109/WIECONECE.2017.8468886.*
14. J. *-Y. Lu, H. -P. Pan and Y. -M. Xia, "The weld image edge-detection algorithm combined with Canny operator and mathematical morphology," Proceedings of the 32nd Chinese Control Conference, Xi'an, China, 2013, pp. 4467-4470.*
15. *D. Ji, Y. Liu and C. Wang, "Research on Image Edge Detection Based on Improved Canny Operator," 2022 3rd International Conference on Information Science, Parallel and Distributed Systems (ISPDS), Guangzhou, China, 2022, pp. 229-232, doi:10.1109/ISPDS56360.2022.9874064.*
16. *P Mah, TE Reeves, WD McDavid1 "Deriving Hounsfield units using grey levels in cone beam computed tomograph",Dentomaxillofacial Radiology (2010) 39, 323–335. doi: 10.1259/dmfr/1960330*
17. *Sharma N, Aggarwal LM. "Automated medical image segmentation techniques"* Journal of medical physics / Association of Medical Physicists of India. *2010;35:3–14*
18. *S. Fathima Suhara1 and Dr. M. Safish Mary "Automated 3d Visualization of Brain Tumor using FCPPN Architecture in MR Images", Journal of Tianjin University Science and Technology ISSN (Online): 0493-2137 E-Publication: Online Open AccessVol:54 Issue:04:2021*
19. *Zehra Ese and Waldemar Zylka "Extension of the Stoichiometric Calibration of CT Hounsfield values to Metallic Materials",Current Directions in Biomedical Engineering 2020;6(3): 20203135*
20. *Mohan, G Subashini, "MRI based medical image analysis: Survey on brain tumor grade classification",* Biomed. Signal Process.Control *2018,* 39*, 139–161*
21. *C.J.J. Sheela, G. Suganthi ,"Automatic Brain Tumor Segmentation from MRI using Greedy Snake Model and Fuzzy C-Means Optimization", J. King Saud Univ. - Comput. Inf. Sci. (2019), 10.1016/j.jksuci.2019.04.006*
22. *Green, N., Glatt, V., Tetsworth, K., Wilson, L. J., & Grant, C. A. (2016). A Practical guide to image processing in the creation of 3D models for orthopedics. Techniques in Orthopaedics, 31(3), 153–163.*
23. *Swamy S., Kulkarni P., " Image processing for identifying brain tumor using intelligent system",*Int. J. Innov. Res. Sci. Eng.Technol . *2015*
24. *Varuna Shree N., Kumar T. N. R., "Identification and classification of brain tumor MRI images with feature extraction using DWT and probabilistic neural network", Brain informatics . 2018, doi: 10.1007/s40708-017-0075-5.*

25. *F. Pfeiffer, O. Bunk, C. Kottler, and C. David, "Tomographic reconstruction of three-dimensional objects from hard x-ray differentialphase contrast projection images," Nuclear Instruments and Methods in Physics Research Section A: Accelerators, Spectrometers, Detectors and Associated Equipment, vol. 580, no. 2, pp. 925–928, 2007. doi:10.1016/j.nima.2007.06.104*
26. *Aggarwal R, Sounderajah V, Martin G, Ting DS, Karthikesalingam A, King D, Ashrafian H, Darzi A, " Diagnostic accuracy of deep learning in medical imaging: A systematic review and meta data Analysis", NPJ Digital Medicine, 2021*
27. *Paul S. Calhoun, Brian S. Kuszyk, David G. Heath, Jennifer C. Carley, "Three-dimensional Volume Rendering of Spiral CT Data:*
28. *Theory and Method", RadioGraphics, VOL. 19, NO. 3, 1999*