



An AI Approach to Diagnosis of Fragility Spinal Fractures in the Elderly Using Pose-Detection Models

Putri Alit Widyastuti Santuary¹, I Ketut Swardika², Dewa Ayu Indah Cahya Dewi³,
and I Gusti Agung Made Yoga Mahaputra⁴

^{1,2,3,4} Electrical Engineering Department, Politeknik Negeri Bali, Bali, Indonesia
putrialit@pnb.ac.id

Abstract. Osteoporotic vertebral compression fractures (VCF) are very common spinal fragility fractures affecting the elderly, with an incidence reaching 700,000 elderly per year, affecting up to 25% of individuals over 70 and 50% over 80 years old. These symptoms typically appear in postmenopausal women and men after their peak bone mass, often due to osteoporosis, where bone quantity decreases as a result of thinning of bone mineral density in the lumbar spine. VCFs can lead to impaired lung function, causing a decrease in forced expiratory volume by up to 9%, and increasing the risk of death due to pulmonary dysfunction. VCF diagnosis can be performed using lateral radiography/X-rays, MRI, or bone scans to assess the severity of the fracture. However, the lengthy and costly VCF diagnosis demands an AI-based approach for VCF diagnosis. This study utilizes pose-detection models, an AI method in computer vision, to determine landmarks on 3D human body structures. Improving existing pose-detection models by adding detailed key points to the spinal structure to suit VCF's diagnosis process. Study progress collecting pose photos of the elderly, reconstructing the spine, and calculating the percentage of deviation from the front, side, and back views of VCF patients in 3D perspective. Results show the BlazePose model successfully points to landmark poses coordinates within maximum mAP (100%). Subject of VCF diagnosis with 10 10-degree inclination of spinal alignment. This study presents an advanced method for utilizing AI as a non-invasive radiography tool for diagnosing the human body structure.

Keywords: AI Diagnosis for Vertebral Compression Fractures, Human Body Structure Diagnosis, Pose Estimation for Healthcare, Spinal Alignment

1 Introduction

Osteoporotic vertebral compression fractures (VCF) are a widespread issue among the elderly, representing a major type of spinal fragility fracture (Al Taha et al., 2024; Alsoof et al., 2022; Shilaskar et al., 2023). These fractures are remarkably common, affecting up to half of individuals over 80 years old, and are a leading cause of back pain (Du et al., 2021; Iwahashi et al., 2022). Beyond pain, VCFs can significantly reduce lung function and increase the risk of death due to pulmonary complications (Xu et al., 2024). The prevalence of VCFs is notable, surpassing hip fractures in geriatric populations in both Indonesia and the US (Sumarwoto et al., 2023), with women disproportionately affected. While diagnostic tools like lateral radiography, x-rays, CT

© The Author(s) 2025

A. A. N. G. Saptika et al. (eds.), *Proceedings of the International Conference on Sustainable Green Tourism Applied Science - Engineering Applied Science 2025 (ICOSTAS-EAS 2025)*, Advances in Engineering Research 280,

https://doi.org/10.2991/978-94-6463-878-3_9

scans, and MRIs exist to assess VCFs. (Basmaji et al., 2022). Artificial intelligence (AI) has been integrated with these, enhancing accuracy and efficiency through image analysis and predictive modeling (Canoni-Meynet et al., 2022). Due to the high cost and lengthy process, it presents considerable hurdles, especially for older patients with mobility issues. As the global elderly population continues to expand, there's an urgent call for the development of efficient and cost-effective VCF diagnostic methods. AI and computer vision are promising avenues for this. Existing research in this area includes the use of such technology for elderly exercise, yoga guidance, fall detection, and repositioning of body or facial posture (Ulya et al., 2024). However, recent research has not covered AI and computer vision for the diagnosis of diseases, such as VCFs or misalignment of human body structures.

This study leverages pose detection models, a type of AI computer vision technique that identifies human body landmarks (e.g., shoulders, hips) via a camera to reconstruct the spine in VCF patients, thereby assisting in the diagnostic process. This paper emphasizes and discusses the diagnosis of VCFs or human body misalignment from an AI perspective, as well as the potential for implementation.

2 Methodology

The initial imperative is a review of the pertinent literature. The author's previous studies focused on deep learning for object detection in botanical and mental health issues (Santiary et al., 2024; Swardika & Santiary, 2024). This study expands to the development of pose detection models. Therefore, the author needs to understand methods for determining landmarks from 3D poses, such as coordinate regression and heatmap approaches. A significant number of recent papers in medical landmark detection utilize CT/MRI imaging with high precision. While heatmaps have become dominant, direct coordinate regression is still being explored, often with sophisticated strategies to improve their performance (Ertl et al., 2025; Jonkers et al., 2025). However, direct applications of pose detection models for health diagnosis, particularly for spinal problems like VCFs, were not found.

2.1 Determine the pose landmarks models

The subsequent phase involves a feasibility study designed to investigate the application of pose detection models for diagnosing spinal structural imperfections in elderly individuals, utilizing landmark data. Concurrently, data acquisition is of paramount importance. This process will entail the systematic collection of photographs, specifically front, side, and back views of elderly subjects, to establish a dedicated dataset. The concluding stage encompasses application and analysis, wherein pose detection models will be deployed on the compiled dataset to ascertain landmark coordinates, reconstruct three-dimensional models, and conduct subsequent analytical procedures to derive conclusive findings. Human pose detection models are commonly based on the COCO pose landmarks dataset, which features 17 key points (cocodataset.org).

BlazePose extended this by incorporating 33 landmarks (https://developers.google.com/pose_model_card.pdf). This study aims to enhance BlazePose for diagnosing vertebral compression fractures (VCFs) by introducing new

symmetrical landmarks (a-b-c) on the thorax, strategically placed between the shoulder (points 11 and 12 for right and left, respectively) and hip (points 23 and 24 for right and left) points to visualize spinal imperfections, this research will capture the positions of landmarks 11, 12, 23, and 24 from front, side, and back photographs of elderly individuals. Each image will include a perpendicular red reference line. By extracting the coordinates for these points, along with the newly added a-b-c landmarks, spinal issues, such as VCFs, can be represented in a 3D plane. Subsequent analysis will then calculate the percentage deviation of these coordinates from established reference values to identify abnormalities. Determining human body landmarks is a complex visual computation.

The following Figure 1 illustrates the process from an elderly person's photo (input) to pose landmarks (output). This involves utilizing the most effective Convolutional Neural Network (CNN) as the backbone network. Detected elderly objects are further processed to extract desired landmarks, utilizing techniques from Spatial Transformer Network (STN) to Feed-Forward Network (FFN), including encode-decode steps for optimal landmark prediction.

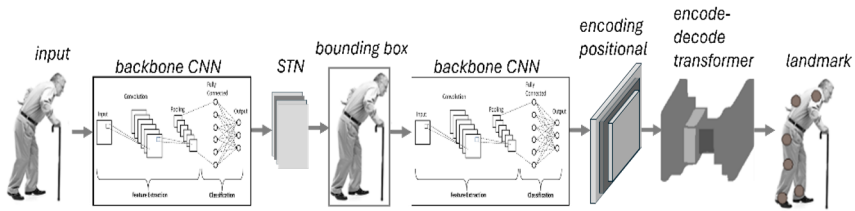


Figure 1. The Model Network for Pose Landmark Determination

2.2 Reconstruction into 3D perspectives

Within the section above, output provides the best landmark positions for 33 joint points (Blaze Pose models); however, it doesn't directly facilitate Vertebral Compression Fracture (VCF) diagnosis, which is our research goal. The next crucial step, as shown in Figure 2, involves reconstructing these pose models into a 3D space from four photographic views. This 3D reconstruction enables analysis of positional shifts from normal alignment, directly leading to the diagnosis of VCF as intended by this research.

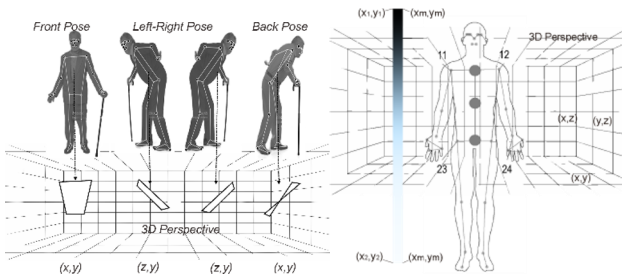


Figure 2. The Methods for the Analysis of 3D Reconstruction Pose Results

2.3 Assisting The Diagnostic Process

The analysis of the detected coordinate results from the pose landmarks above is performed by comparing the slope (m) or degree of inclination from the reference lines (red band perpendicular to base), which were set beforehand during the dataset photo acquisition, in the following equation 1. The slopes that should be analyzed are the slopes of the 11-12 shoulder line, the 23-24 hip line, and the 11-24 backbone line. For each dataset photo, the points of the vertical reference lines (red band) were manually marked (during this research) for the reference line. By mouse pointing ($x_n; y_n$ points that mark as green dots on the photo) provides an average slope (m) result for the perpendicular reference line in degrees (ϕ).

$$m = \tan \phi = 1/n \sum (y_2 - y_1) / (x_2 - x_1) \quad (1)$$

$$\phi = \tan^{-1} m$$

In the same way as above, the degrees of the vertical reference line (ϕ_R), the shoulder line (ϕ_S), the hip line (ϕ_H), and the backbone line (ϕ_B) are obtained. The difference between the degree of the reference line (ϕ_R) and the degree of the backbone line (ϕ_B) indicates the presence of backbone translation.

3 Results and Discussion

3.1 Result

The development of a specialized, low-profile (approximately 5 cm high) 360-degree rotating platform is crucial for efficiently acquiring comprehensive, full-body photographic datasets of elderly individuals (aged 50 and above). This stable platform, designed with elderly safety as its paramount concern, integrates a bearing-equipped rotating ring, a secure standing area, a telescopic camera pod with a smartphone holder, an ultra-wide lens ($0.5\times$ zoom) camera, and a plumb-line-equipped tripod for precise perpendicular referencing. Manual rotation of the camera pod is currently employed during data acquisition. The following Figure 3 is the subject of the VCF who participates in this study.



Figure 3. Front Pose of the Subject of VCF

The dataset collection method is as follows: The elderly subject is positioned on the platform's stand and instructed to remain still. The operator then manually rotates, capturing photos with the telescopic camera pod. The reference line must be visible in

each photo. Photos are taken multiple times over two full rotations. Data collection is performed quickly, as elderly individuals typically cannot stand for extended periods. A total of 12 elderly subjects have had their datasets collected. The dataset collection was performed twice for each subject, resulting in a total of 24 datasets from elderly subjects. For each dataset, 35 photos were taken, covering the entire body from various angles. The detection results for pose landmarks numbers 11, 12, 23, and 24, along with their connecting lines, plus three additional midpoints for these four pose positions, are shown in the following Figure 4. The pose detection results are also plotted in a 3D XYZ plane using world coordinates. The following Figure 4 illustrates the results of pose landmarks and a 3D plot.

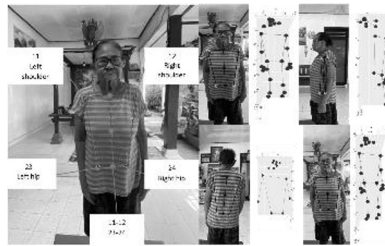


Figure 4. The Results of the Landmarks Pose and the 3D Plot

Diagnosis is carried out by creating a program that directly calculates the difference between the degree of the vertical reference line (ϕR) and the degree of the backbone line (ϕB). This also includes the difference between the horizontal reference line's degree (ϕRH), which is obtained by rotating the vertical reference line by 90 degrees, and the shoulder line's degree (ϕS) and the hip line's degree (ϕH). Next, the average degrees ($^{\circ}$) of inclination from the reference line for each of the 20 elderly subjects are calculated and shown in the following Table 1. In the table, s = shoulder, h = hip, and b = backbone. Since a standard diagnostic degree scale hasn't been established yet, this research uses the following scale (based on subject NNS, an 82-year-old female): With an angle of inclination ≥ 10 degrees, the likelihood of a high spinal problem (H) is indicated. Note: *(anonym)/Age/Sex.

Table 1. Diagnosis Results for the Subject of VCF

Name of Subject VCF*	Diagnosis results ($^{\circ}$) [s-h-b]			Scale
NNP(1) 57 Female	6.924240169222992	7.150746145746957	6.150746145746957	L/M
KA(1) 55 Female	6.237096414870248	9.05887852601105	9.05887852601105	L/M
KO(2) 53 Female	5.123840129233237	5.824714881738166	6.124714881738166	L/M
NNS(2) 82 Female	10.56476944752226	14.27531304113678	15.57531304113678	H
NWW(1) 79 Female	10.07046278195476	11.17329363657861	11.17329363657861	H
NWR(1) 55 Female	4.423060404355884	8.203514606368026	8.203514606368026	L/M
IWB(2) 57 Male	4.721297362764497	7.655040655235950	7.655040655235950	L/M
NKR(2) 63 Female	10.07046278195476	11.17329363657861	11.17329363657861	H

3.2 Discussion

This study uses recent models of human body pose, the BlazePose (Bazarevsky et al., 2020). The BlazePose model utilizes GHUM (3D human shape modeling pipeline). Instead of directly predicting coordinate regression, BlazePose predicts a heatmap for each landmark. A heatmap is a 2D grayscale image where the intensity of each pixel indicates the probability or confidence that a landmark is located at that pixel (Ertl et al., 2025). This model can infer 33 landmarks in a 3D space and perform background segmentation masking on the entire body within an RGB frame. The first model detects the presence of a human body within an image frame (a bounding box) and then identifies the landmarks within that bounding box. As the results presented above show, these models successfully identify landmark poses, even when using the lite package (size approximately 5.643 kB). The diagnosis of the subject's VCF degrees of deviation shows reasonable results. Even not yet comparable with other results. Since this study is relatively new, a standard diagnostic degree scale hasn't been established.

4 Conclusion

This study presents a method for diagnosing structural shifts in the human body resulting from aging, birth defects, or accidents, particularly when spinal integrity is compromised by bone fragility. This approach utilizes pose detection models to identify landmarks at the shoulder and waist, and then applies geometric principles to estimate the 3D coordinates of the spinal center. Diagnosis involves comparing the slopes of the shoulder, waist, and spinal lines against a reference, with the slope difference quantifying deviation from the normal range. A diagnostic scale is established using subjects with visual bone fragility due to aging as a reference, against which the results of other subjects are compared. Further collaboration with physiologists is recommended to clarify measurement criteria and integrate relevant physiology journal references, enhancing scientific rigor.

Acknowledgment

Thanks to the State Polytechnic of Bali for funding this study, under contract number SP.DIPA-139.03.2.693476/2025 Rev. 03 date 07 March 2025.

References

- Al Taha, K., Lauper, N., Bauer, D. E., Tsoupras, A., Tessitore, E., Biver, E., & Dominguez, D. E. (2024). Multidisciplinary and coordinated management of osteoporotic vertebral compression fractures: Current state of the art. *Journal of Clinical Medicine*, 13(4). <https://doi.org/10.3390/jcm13040930>.
- Alsoof, D., Anderson, G., McDonald, C. L., Basques, B., Kuris, E., & Daniels, A. H. (2022). Diagnosis and management of vertebral compression fracture. *The American Journal of Medicine*, 135(7), 815–821. <https://doi.org/10.1016/j.amjmed.2022.02.035>.

- Ulya, A. R. A., Yuniarno, E. M., Muhtadin, & Purnomo, M. H. (2024). Elderly exercise activity classification based on pose estimation using CNN-LSTM. *2024 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 698–703. <https://doi.org/10.1109/ISITIA63062.2024.10667962>.
- Basmaji, T., Yaghi, M., Zia, H., Qamhie, L., Abueida, D., Abueida, M., & Ghazal, M. (2022). Posture detection framework using the internet of wearable things. *2022 2nd International Conference on Computing and Machine Intelligence (ICMI)*, 1–5. <https://doi.org/10.1109/ICMI55296.2022.9873656>.
- Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., & Grundmann, M. (2020). *BlazePose: On-device real-time body pose tracking*. <https://doi.org/10.48550/arXiv.2006.10204>.
- Canoni-Meynet, L., Verdot, P., Danner, A., Calame, P., & Aubry, S. (2022). Added value of an artificial intelligence solution for fracture detection in the radiologist's daily trauma emergencies workflow. *Diagnostic and Interventional Imaging*, 103(12), 594–600. <https://doi.org/10.1016/j.diii.2022.06.004>.
- Du, M., Fan, J., Huang, Y., & Cao, M. (2021). Mosaicking of mountain tunnel images guided by laser rangefinder. *Automation in Construction*, 127, 103708. <https://doi.org/10.1016/j.autcon.2021.103708>.
- Ertl, A., Xiao, S., Denner, S., Peretzke, R., Zimmerer, D., Neher, P., Isensee, F., & Maier-Hein, K. (2025). *Landmark: A Self-configuring method for 3D medical landmark detection*. <https://doi.org/10.48550/arXiv.2504.06742>.
- Iwahashi, S., Hashida, R., Matsuse, H., Higashi, E., Bekki, M., Iwanaga, S., Hara, K., Higuchi, T., Hirakawa, Y., Kubota, A., Imagawa, H., Muta, Y., Minamitani, K., Yoshida, T., Yokosuka, K., Yamada, K., Sato, K., & Shiba, N. (2022). The impact of sarcopenia on low back pain and quality of life in patients with osteoporosis. *BMC Musculoskeletal Disorders*, 23(1), 142. <https://doi.org/10.1186/s12891-022-05086-2>.
- Jonkers, J., Duchateau, L., Wallendael, G. V., & Hoecke, S. V. (2025). Landmarker: A toolkit for anatomical landmark localization in 2D/3D images. *SoftwareX*, 30, 102165. <https://doi.org/10.1016/j.softx.2025.102165>.
- Santiary, P. A. W., Swardika, I. K., Dewi, D. A. I. C., & Sugirianta, I. B. K. (2024). Intra-class deep learning object detection on embedded computer system. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 13(1), <https://doi.org/10.11591/ijai.v13.i1.pp430-439>.
- Shilaskar, S., Ghosh, P., Bhatlawande, S., & Chandolikor, N. (2023). An expert system for posture detection of elderly people. *AIP Conference Proceedings*, 2851(1), 040003. <https://doi.org/10.1063/5.0179290>.
- Sumarwoto, T., Hartanto, D., & Utomo, P. (2023). Managing fractures in geriatrics: Current approaches and update. *JKKI: Jurnal Kedokteran dan Kesehatan Indonesia*, 69–81. <https://doi.org/10.20885/JKKI.Vol14.Iss1.art11>.
- Swardika, I. K., & Santiary, P. A. W. (2024). Detection of vague object signatures on deep learning surveillance devices. *IAES International Journal of Artificial Intelligence (IJ-AI)*, 13(3), Article 3. <https://doi.org/10.11591/ijai.v13.i3.pp3262-3272>.
- Xu, Y., Li, D., Zhang, Q., & Tong, L. (2024). Efficacy of lumbar and abdominal muscle rehabilitation training on the degree of osteoporosis, pain, and anxiety in elderly patients with osteoporotic vertebral compression fracture after PKP and compliance analysis. *Frontiers in Medicine*, 11. <https://doi.org/10.3389/fmed.2024.1364497>.

Open Access This chapter is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International License (<http://creativecommons.org/licenses/by-nc/4.0/>), which permits any noncommercial use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons license and indicate if changes were made.

The images or other third party material in this chapter are included in the chapter's Creative Commons license, unless indicated otherwise in a credit line to the material. If material is not included in the chapter's Creative Commons license and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder.

