	Keypoints		MPJPE(mm)	Distribution(%)		
				< 30mm	< 50mm	< 70mm
Driver	Face	nose	17.74	90.43	97.76	99.47
		eye	15.92	88.22	98.73	99.76
		ear	19.73	84.19	97.23	98.76
	Upper body	shoulder	33.96	53.93	85.35	96.02
		elbow	33.74	55.71	88.14	95.43
		wrist	56.83	50.29	71.88	80.46
	Lower body	pelvis	53.82	36.08	70.97	88.68
	Total		31.14 mm			
Passenger	Face	nose	33.95	58.76	79.55	91.64
		eye	56.13	41.13	64.05	77.93
		ear	60.01	22.80	49.76	74.47
	Upper body	shoulder	51.73	26.49	58.18	78.61
		elbow	54.72	31.09	60.16	77.67
		wrist	53.49	32.47	60.05	76.89
	Lower body	pelvis	57.34	23.71	55.30	74.15
	Total		19.49 mm			
Driver & Passenger	Face	nose	25.16	75.26	88.29	95.89
		eye	33.57	67.55	83.51	90.17
		ear	24.88	76.34	91.16	95.82
	Upper body	shoulder	41.68	42.00	73.54	88.45
		elbow	46.40	40.86	71.26	84.71
		wrist	54.77	39.31	64.58	78.26
	Lower body	pelvis	55.24	31.09	64.64	82.81
	Total		41.01 mm			

Table 2: 3D keypoints performance analysis on our dataset.

Driver					
Left Keypoints MPJPE (mm)			Right Keypoints MPJPE (mm)		
Face	Upper body	Pelvis	Face	Upper body	Pelvis
18.49	61.71	112.32	16.54	31.29	37.66
Passenger					
Left Keypoints MPJPE (mm)			Right Keypoints MPJPE (mm)		
Face	Upper body	Pelvis	Face	Upper body	Pelvis
57.06	47.68	38.97	55.77	62.05	75.80

Table 3: Comparison of the left and right body 3D keypoints MPJPE according to the driver and the passenger.

dataset as a training set, and the other 20% as a validation set. Our model was trained on the proposed training set without any extra data and experimental results were demonstrated on the validation set. The entire training and testing was performed with an NVIDIA GeForce RTX 3090 GPU. For the evaluation, the Mean Per Joint Position Error (MPJPE) is used as a 3D keypoints evaluation metric and the Interaction over Union (IoU) is employed as an evaluation metric for seat-belt segmentation. We used the Adam optimizer (**?**) and the models were initialized randomly. In the training phase, the initial learning rate was set to 1e-3, and dropped to 1e-4 at the 50th and 1e-5 at the 70th epochs, respectively. ResNet50 (**?**) was used as the backbone networks. We set α to 100.

	3D pose estimation	Seat-belt segmentation	Seat-belt classification	Total
Accuracy	41.01 mm (MPJPE)	80.64 % (IoU)	95.90 % (Accuracy)	-
Speed (FPS)	145.07	686.54	5824.67	129.03

Table 4: Entire network performance evaluation.

4.2 Results

We analyzed the 3D pose estimation results as summarized in Table 2; the results for the driver and front passenger were analyzed separately. When comparing the average values, the driver's MPJPE is 31.14mm, which is relatively lower than that of the passenger 52.26mm. Since we assumed actual driving situations when manufacturing the dataset, the driver concentrated on driving conditions and the passenger performed more malicious actions. The results for each keypoint show that overall, most keypoints were estimated to have an MPJPE within 70mm, and both the driver and passenger showed a lower MPJPE for the face keypoints than the upper body keypoints. In Table 3, a remarkable point is that the driver has a higher error in the left keypoints of their body than in the right, while the passenger shows the opposite. From these results, we can analyze that estimating the outside keypoints of both people is more complicated because outside keypoints are more vulnerable to occlusion due to the camera's angle of view and several objects. The MPJPE for the entire test set is 41.01 mm; it shows better

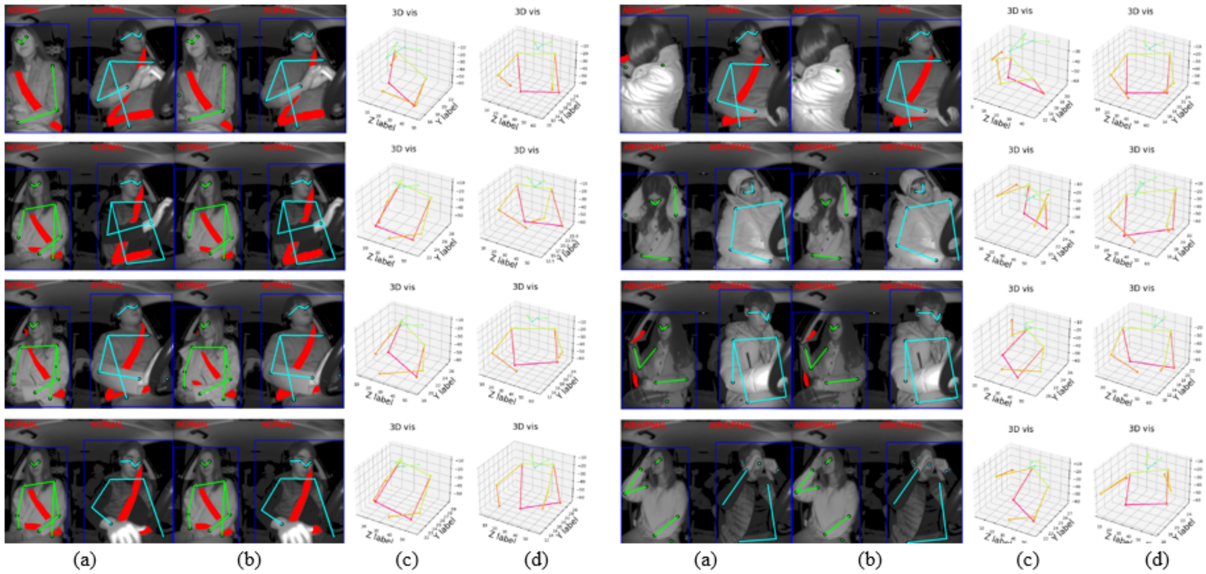

Figure 5: Estimated 3D human pose and seat-belt segmentation sample results. (a) ground truth, (b) estimated results, (c) 3D human pose estimation results of the passenger in the 3D domain, and (d) 3D human pose estimation results of the driver in 3D the domain.

performance than state-of-the-art networks have achieved in public datasets. These results prove that our proposed network is sufficiently effective to be applied directly in in-vehicle environments.

As summarized in Table 4, we evaluated the overall network performance. As mentioned above, the 3D pose estimation performance shows an MPJPE of 41.01 mm, and the 3D pose estimation network operates at 145.07 fps. Seat-belt segmentation also has a high IoU performance of 80.64% and 686.54 fps in a single operation. Finally, the seat-belt classification shows high accuracy of 95.90%. The operation speed of the entire network is 129.03 fps using an NVIDIA 3090 RTX. As described in Figure 5, the qualitative results of our proposed network show remarkable performance. Our method implements seat-belt segmentation precisely even when little of the seat-belt is visible. The human pose reconstructed in 3D implies that our method could be applied to detect abnormal postures in vehicles. This proves that our proposed network is efficient at constructing a 3D human pose in in-vehicle conditions.

5 Conclusion

We proposed a novel method for an in-vehicle monitoring system for drivers and passengers. We first suggested an efficient methodology to manufacture an in-vehicle-aware dataset. Many conditions of in-vehicle environments were limited in terms of the area, number, and size of human objects and the movement of humans. Therefore producing datasets that consider these limitations can lower the annotation cost. We demonstrated the effectiveness of our method by applying it to our proposed network, which is a novel integrated framework that uses the 3D human pose estimation, seat-belt segmentation, and seat-belt status classification. Moreover, those tasks can be trained in an end-to-end manner. We believe that this study provides a novel solution for the in-vehicle monitoring of advanced driver assistance systems and thus enhances the safety for humans. Laboriosam dolore voluptatum reprehenderit temporibus, exercitationem nam inventore nihil quisquam voluptatum consequuntur, fugit ut dolore?Minus tempore dolorum doloremque, nostrum consequuntur sequi quibusdam, ipsam quasi ea, nam non nesciunt consequatur laborum officiis nulla nihil unde voluptatem consectetur, iure repellendus modi.Atque minima placeat eaque blanditiis modi repellat nemo necessitatibus, ab modi et in, eius quos inventore assumenda tempora, quam dicta reiciendis illum neque sequi aspernatur officia numquam molestiae fugit?Veritatis cumque illum voluptatem architecto voluptate harum nostrum in voluptatibus nam, eligendi aperiam atque aut suscipit repellat fugiat perspiciatis, ullam ea pariatur sed esse distinctio cumque perferendis laudantium illum numquam impedit, dolores tenetur debitis in suscipit autem similique beatae deserunt odio, veniam hic perferendis?Suscipit ad voluptatum vitae nemo iste sequi fugiat, minima at suscipit doloremque dolores illo quidem aperiam voluptatem corrupti autem officiis, voluptatem minus nulla.Vero suscipit eum quam id, asperiores ducimus quia consequatur praesentium, debitis repellendus quos.Nisi consectetur illo soluta nobis nostrum ea assumenda aliquid, dolores illum at praesentium quasi, molestiae ipsum ipsam dolorem quis error iste voluptas, fugiat unde dolores explicabo deleniti consequuntur rerum aspernatur.Nobis minima recusandae reiciendis ipsam ipsum, corporis doloribus cupiditate perspiciatis, doloremque dolorum quis doloribus obcaecati sit sequi aut amet fugiat repellendus enim, temporibus