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Patient's Airway Monitoring during Cardiopulmonary Resuscitation using Deep Networks

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Highlights

- Providing non-human expert feedback on CPR performance using artificial intelligence.
- Detecting the correct and incorrect position of patient's airway during CPR administration
- Building a dataset consisting of 198 recorded video sequences, each lasting 6-8 seconds, showcasing airway positions
- Employing six cutting-edge deep networks to fine-tune using out CPR dataset.
- Enhancing the effectiveness of emergency response teams long-term effects of CPR using deep transfer learning.

Abstract

Cardiopulmonary resuscitation (CPR) is a crucial life-saving technique commonly administered to individuals experiencing cardiac arrest. Among the important aspects of CPR is ensuring the correct airway position of the patient, which is typically monitored by human tutors or supervisors. This study aims to utilize deep transfer learning for the detection of the patient's correct and incorrect airway position during cardiopulmonary resuscitation. To address the challenge of identifying the airway position, we curated a dataset consisting of 198 recorded video sequences, each lasting 6-8 seconds, showcasing both correct and incorrect airway positions during mouth-to-mouth breathing and breathing with an Ambu Bag. We employed six cutting-edge deep networks, namely DarkNet19, EfficientNetB0, GoogleNet, MobileNet-v2, ResNet50, and NasnetMobile. These networks were initially pre-trained on computer vision data and subsequently fine-tuned using the CPR dataset. The validation of the fine-tuned networks in detecting the patient's correct airway position during mouth-to-mouth breathing achieved impressive results, with the best sensitivity (98.8%), specificity (100%), and F-measure (97.2%). Similarly, the detection of the patient's correct airway position during

breathing with an Ambu Bag exhibited excellent performance, with the best sensitivity (100%), specificity (99.8%), and F-measure (99.7%).

Keywords
Cardiopulmonary resuscitation, CPR, artificial intelligence, deep learning, transfer learning

1. Introduction

1.1 Overview of Cardiopulmonary Resuscitation

Cardiopulmonary resuscitation (CPR) is a crucial life-saving technique administered to individuals experiencing cardiac arrest (1, 2). CPR is applicable in various emergency scenarios, including heart attacks, near drowning incidents, and cases of stopped heartbeat or breathing (2, 3). CPR consists of three fundamental components, conveniently remembered as "CAB": compressions, airway, and breathing. Compressions involve chest compressions that facilitate blood flow to vital organs such as the heart and brain. CPR begins with 30 chest compressions followed by two rescue breaths. The effectiveness of CPR can be measured using well-defined criteria (4).

1.2 Integration of Artificial Intelligence in CPR

The integration of artificial intelligence (AI) approaches, such as machine learning, deep learning, and optimization algorithms, is expanding to enhance and evaluate CPR techniques. For example, Isasi et al. (5) employed a convolutional neural network (CNN) to classify shock and no-shock states using 9-second electrocardiogram (ECG) segments obtained during CPR. Their proposed approach improved shock/no-shock classification accuracy by approximately 1% compared to a baseline handcrafted ECG feature-based random forest classifier. In another study, Isasi et al. (6) utilized quasi-stratified patient-wise nested cross-validation and a support vector machine (SVM) on ECG data during piston-driven CPR to achieve a five-fold reduction in computational demand compared to existing methods.

Ming et al. (7) conducted a retrospective study using a neural network to classify different types of ECG signals corrupted by severe CPR artifact interference, reporting sensitivity and specificity of approximately 99% and 95%, respectively. Sashidhar et al. (8) employed principal component analysis (PCA) and a linear discriminant model to predict pulse presence during CPR using paired ECG segments. Their study achieved an area under the curve (AUC) of 0.84 and 0.89 for predicting pulse presence with and without CPR, respectively. Lalitha et al. (9) utilized the K-means algorithm on CPR biosignals to predict the appropriate degree of compression and decompression required during CPR administration, considering patients of various age ranges.

Mitri et al. (10) proposed CPR Tutor, a real-time multimodal feedback system for CPR training. They incorporated kinematic and electromyographic data into a recurrent neural network (RNN) to assess chest compression during CPR and provided audio feedback based on five performance indicators. Hajeb-M et al. (11) developed a deep CNN-based encoder-decoder approach to suppress CPR artifacts in ECG signals, resulting in improved signal-to-noise ratio (SNR) for shockable and non-shockable rhythms. Despite these promising AI studies related to CPR administration, there has been no AI research conducted to enhance CPR performance by providing automatic feedback on the rescuer's position relative to the patient, which is crucial for effective CPR.

1.3 AI-Enabled Monitoring of Patient's Airway Position

Despite the comprehensive training received by members of official emergency response teams, they may inadvertently misposition themselves or their hands while tending to emergencies. Consequently, these responders often undergo frequent supervised practice sessions to refine their skills. Unfortunately, due to the limited availability of trainers, trainees in emergency response training programs do not always receive one-on-one feedback during their CPR practice sessions in school. Moreover, when these responders practice CPR at home, they lack any form of supervision.

Conversely, individuals who voluntarily undergo first-aid training, including employees of corporate organizations and responsible members of society, typically do not engage in supervised CPR practice after obtaining their training completion certificate. Consequently, their CPR skills may deteriorate over time, prompting the inclusion of expiration dates on first-aid training certificates. These responsible members of corporate organizations or society would greatly benefit from opportunities for periodic supervised CPR practice after their initial training. Therefore, an AI-supervised CPR practice holds several advantages:

- Ensures rescuers maintain proficiency in CPR administration techniques.
- Reduces errors during resuscitation efforts.
- It lowers operating costs and decreases the need for human trainers during practice sessions.
- Enhances overall efficiency in CPR administration.

1.4 Proposed Method

Efficient and optimal airway management by a rescuer depends on several critical factors (4, 12):

- Opening the airway to a past-neutral position using the head-tilt/chin-lift technique.
- Ensuring each breath lasts approximately one second and causes the chest to rise, allowing air to exit before administering the next breath.

Figure 1 and Figure 2 provide illustrative examples of correct and incorrect patient airway positions during CPR, demonstrating both mouth-to-mouth breathing and the use of an Ambu bag.

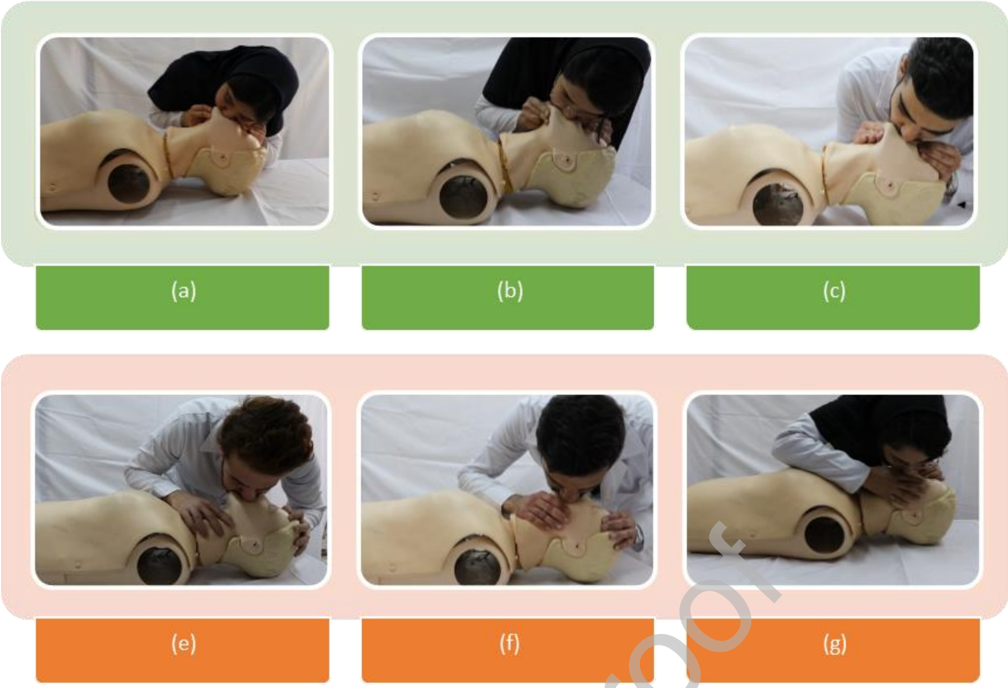

Figure 1. A series of example images depicting the correct (top row) and incorrect (bottom row) positions of patients during mouth-to-mouth breathing.

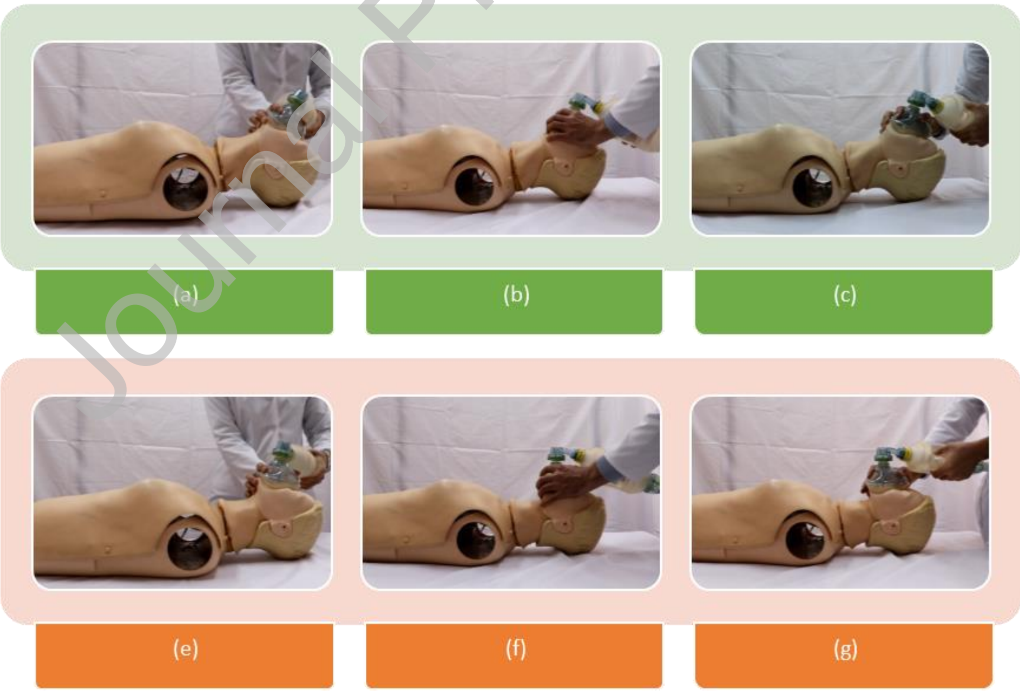

Figure 2. Images showcasing the proper (top row) and improper (bottom row) positions of patients while the rescuer administers breaths using an Ambu Bag.

This paper makes significant contributions to the evaluation of CPR using AI, which can be summarized as follows:

- **Immediate Detection of Correct and Incorrect Airway Position:** The proposed method utilizes deep transfer learning to swiftly identify the accurate and erroneous airway positions of patients during CPR administration.
- **Creation of a Comprehensive Dataset:** To enhance the development of AI methods for CPR performance improvement, the researchers compiled a dataset consisting of 198 CPR videos. Each video is approximately 6-8 seconds in duration and showcases both the correct and incorrect airway positions of the patients.

These contributions demonstrate the paper's valuable insights into utilizing AI techniques to evaluate and enhance CPR practices.

2. Material and Methods

2.1 Dataset

Our objective was to construct an image dataset that encompasses the accurate and erroneous airway positions of patients during both mouth-to-mouth breathing and breathing with an Ambu Bag. To accomplish this, we enlisted the voluntary participation of fifty (50) senior students from an emergency response training school. Each student executed a 6-8 second breathing technique on a manikin, encompassing four distinct scenarios:

- Correct mouth-to-mouth breathing (refer to Figure 3)
- Correct breathing with an Ambu Bag (refer to Figure 4)
- Incorrect mouth-to-mouth breathing (refer to Figure 5)
- Incorrect breathing with an Ambu Bag (refer to Figure 6)

The data collection process yielded a total of 198 recorded video sequences, each lasting 6-8 seconds. We utilized a Canon EOS 80D Digital Camera equipped with an 18-55mm IS STM lens to capture the videos, which were saved in MP4 format. We used all the frames of CPR videos as RGB images for training our deep networks. For further details regarding camera specifications and video recording settings, please refer to Table 1.

To enable the immediate detection of correct and incorrect airway positions, it was crucial to process each frame of the 6-8-second videos independently. Thus, we transformed the recorded videos into image sequences and saved them in TIF format. The provided dataset encompasses a comprehensive collection of 17,579 RGB images.

Table 1. The camera specifications and photography settings

Property	Value	Property	Value
Camera maker	Canon	Dimensions	6000×4000 pixels
Camera model	Canon EOS 80D	Horizontal resolution	72 dpi
F-stop	f/5	Vertical resolution	72 dpi
Exposure time	1/60 sec.	Bit depth	24
ISO speed	ISO-200	Resolution unit	2
Exposure bias	0 step	Color representation	sRGB
Focal length	50mm	Exposure program	Normal
Metering mode	Pattern	EXIF version	0230
Flash mode	Flash, compulsory	White balance	Auto
Frame width	1280	Frame height	720
Data rate	4024kbps	Total bitrate	4292kbps
Frame rate	25 frames/second		

(1) (2) (3) (4) (5)

Figure. Illustration of 5 frames of correct mouth-to-mouth breathing during CPR.

(1) (2) (3) (4) (5)

Figure 3. Illustration of 5 frames of incorrect mouth-to-mouth breathing during CPR.

(1) (2) (3)

Figure 4. Illustration of 3 frames of correct breathing with Ambu Bag during CPR.

(1) (2) (3)

Figure 5. Illustration of 3 frames of incorrect breathing with Ambu Bag during CPR.

2.2 Deep Transfer Learning

Researchers worldwide have successfully employed deep learning, a subset of artificial intelligence (AI), in various practical applications (13-21). Particularly, convolutional neural networks (CNNs), a branch of deep learning, have demonstrated their capability to learn high-level features from image data, surpassing traditional machine learning approaches (22-24). CNNs leverage supervised feature learning and hierarchical feature extraction to automatically extract relevant features from images (25).

However, training a CNN to achieve optimal performance necessitates an ample amount of training data. Unfortunately, the scarcity of training data poses a significant challenge, especially in domains like medical imaging and medical technology (13). Constructing a large-scale, well-annotated medical imaging dataset with expert annotations proves to be exceptionally demanding and often unrealistic. Additionally, in the case of rare diseases, the limited number of patients further complicates dataset accumulation.

To address the issue of insufficient training data, transfer learning emerges as a valuable technique in AI. It involves transferring knowledge from a source domain to a target domain, even if the two domains are not necessarily independent or identically distributed. By leveraging knowledge from a source domain with abundant training data, transfer learning enhances AI performance on the target domain with a limited number of training examples. Figure 6 illustrates the process of transfer learning in our proposed method.

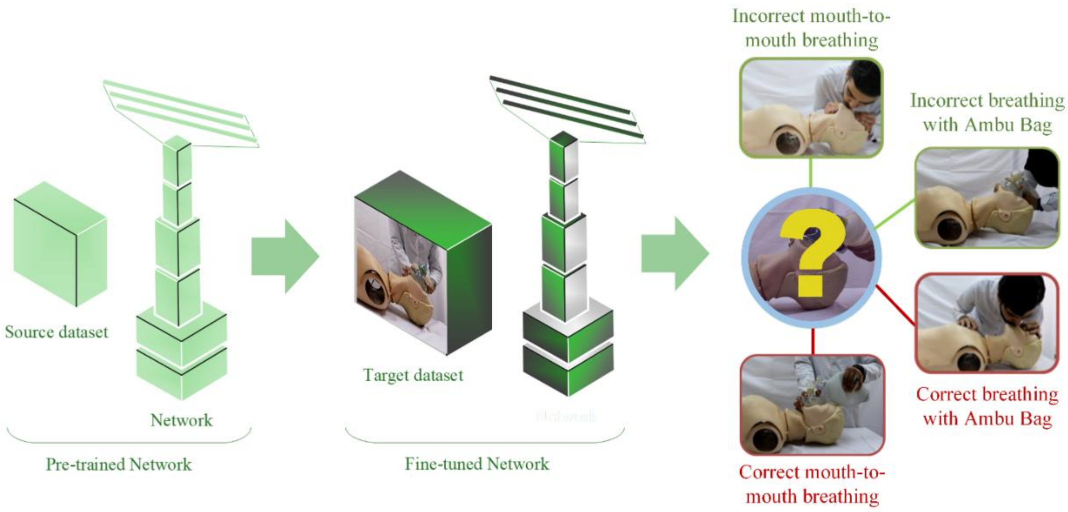

Figure 6. Deep transfer learning is applied for the detection of the patient's correct and incorrect airway position during CPR.

In this study, we employ pre-trained convolutional neural networks (CNNs) and fine-tune them using CPR video data to accurately detect the correct and incorrect positions of rescuers, including their hands and shoulders. We utilize six pre-trained models, namely GoogleNet (26), MobileNet-v2 (27), EfficientNetB0 (28), ResNet50 (29), NASNet-Mobile (30), and DarkNet19 (31).

Table **2** provides a summary of the pre-trained networks utilized in our investigation.

Table 2. Characteristics of pre-trained models.

Networks	Depth	Size (MB)	Number of Parameters (millions)
EfficientNetB0	82	20	5.3
GoogleNet	22	27	7.0
MobileNet-v2	53	13	3.5
ResNet50	50	96	25.6
NASNet-Mobile	*	20	5.3
DarkNet19	19	78	20.8

* The NASNet-Mobile does not consist of a linear sequence of modules.

We used pre-training for our networks on large computer vision datasets comprising over a million labeled images across thousands of classes. In addition, these networks utilize dropout and batch normalization layers, which are effective in reducing overfitting by regularizing the training process. During transfer learning on our airway position images, only a few layers of these models (usually the last few layers) are fine-tuned, while most layers of the network remain frozen. In this way, our deep models leveraged learned features from computer vision data while finetuned on task-specific data. This process encourages model generalizability and reduces the chance of overfitting.

3. Validation

3.1 Statistical Metrics

To assess the effectiveness of our proposed method in detecting the patient's correct and incorrect airway position during CPR, we employed a range of evaluation metrics including accuracy, sensitivity, specificity, precision, recall, and F-measure. These metrics are defined as follows (Eqs. a-f, respectively):

$$\text{Accuracy} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}}, \quad \text{(a)}$$

$$\text{Sensitivity} = \frac{\text{TP}}{\text{TP}+\text{FN}}, \quad \text{(b)}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{FP}+\text{TN}}, \quad \text{(c)}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}}, \quad \text{(d)}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}}, \quad \text{(e)}$$

$$\text{F} - \text{measure} = \frac{2\times\text{Precision}\times\text{Reall}}{\text{Precision}+\text{Reall}}, \quad \text{(f)}$$

where TP, TN, FP, and FN denote the true positives, true negatives, false positives, and false negatives, respectively.

3.2 Implementation

Our deep network implementation was carried out using MATLAB 2021b (MathWorks Inc., Natick, MA). The experiments were conducted on a system equipped with an Intel(R) Core(TM) i7-7700HQ CPU 2.81 GHz, 32 GB of RAM, and 8 GB of VRAM. For optimization, we utilized the stochastic gradient descent with momentum (SGDM) algorithm, setting the maximum epoch to 2, the minimum batch size to 30, and an initial learning rate of 0.0001.

We allocated 80% of our data for training and validation purposes, while the remaining 20% was reserved for testing. All findings presented in Section 4 are based on this 20% hold-out test set. To monitor the progress of the training process, we generated visualization graphs. Figure 8 displays the curves depicting the train and validation accuracy versus iteration, as well as the training and validation loss versus iteration, specifically for the GoogleNet network employed in detecting the patient's correct and incorrect airway position during CPR.

It is important to note that all our deep networks were pre-trained on the ImageNet (32) computer vision dataset, providing a strong foundation for our model's performance. Additionally, before feeding the images into our deep models, we resized the original images, which had dimensions of 6000×4000×3 pixels (representing 3 consecutive image frames from a video), to a size of 224×224×3 pixels.

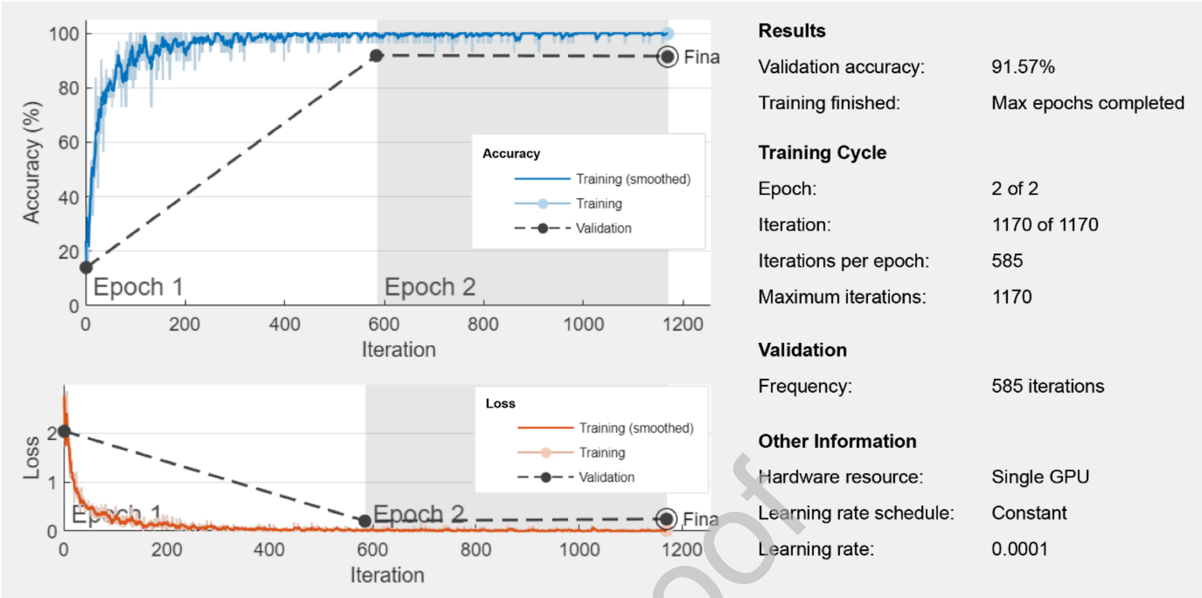

Figure 7. Training and validation curves depicting the accuracy and loss versus iteration for the Google-Mobile network in detecting the patient's correct and incorrect airway position during CPR.

4. Results

We conducted a performance comparison of various pre-trained networks in detecting the patient's correct airway position during CPR. The accuracy achieved by each method is presented in Figure 8 as a bar plot. Notably, the pre-trained GoogleNet exhibited the highest accuracy of 95.8%.

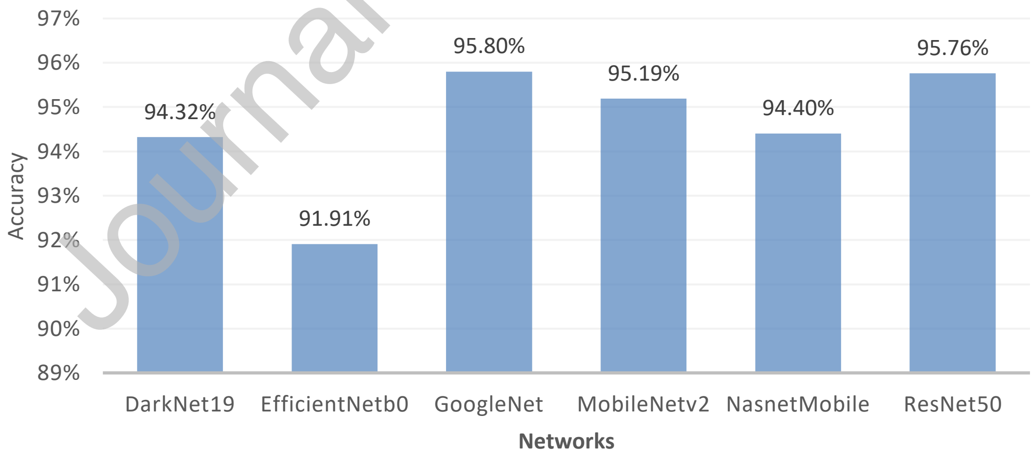

Figure 8. Accuracy comparison of fine-tuned networks for detecting patient's correct airway position during cardiopulmonary resuscitation.

To provide a more comprehensive evaluation, Table 3 presents the quantitative performance of different networks in terms of TP (true positive), FP (false positive), TN (true negative), FN (false negative), sensitivity, specificity, and F-measure for detecting the patient's correct airway position during CPR administration. The analysis in Table 3 focuses on four cases: (i) correct mouth-to-mouth breathing, (ii) correct breathing with Ambu Bag, (iii) incorrect mouth-to-mouth breathing, and (iv) incorrect breathing with Ambu Bag. The results in Table 3 highlight that the ResNet50 achieved the highest sensitivity of 98.8%, while the GoogleNet demonstrated 100% specificity and precision, and an F-measure of 94.9%. Additionally, ResNet50 achieved a recall of 98.8%. Notably, the NasnetMobile network performed exceptionally well in detecting the positive class of 'correct breathing with Ambu Bag' with 100% sensitivity, 99.8% specificity, 99.4% precision, 100% recall, and 99.7% F-measure.

For better visualization and comparison, Figure 8 and Figure 9 depict the performance results in terms of sensitivity, specificity, and F-measure. These figures provide a clearer understanding of the performance variations among the different networks evaluated.

Table 3. Quantitative comparison in terms of true positive (TP), false positive (FP), true negative (TN), false negative (FN), sensitivity, specificity, and F-measure in detecting rescuers' correct position during CPR administration. The positive classes are denoted by (i) correct mouth-to-mouth breathing, (ii) correct breathing with Ambu Bag, (iii) incorrect mouth-to-mouth breathing, and (iv) incorrect breathing with Ambu Bag.

	Positive Class	TP	FP	TN	FN	Sensitivity	Specificity	Precision	Recall	F-measure
DarkNet19	(i)	1324	73	3882	147	0.900	0.982	0.948	0.900	0.923
	(ii)	1613	88	3725	0	1.000	0.977	0.948	1.000	0.973
	(iii)	708	147	4498	73	0.907	0.968	0.828	0.907	0.866
	(iv)	1473	0	3865	88	0.944	1.000	1.000	0.944	0.971
EfficientNetb0	(i)	1187	14	3941	284	0.807	0.996	0.988	0.807	0.888
	(ii)	1613	122	3691	0	1.000	0.968	0.930	1.000	0.964
	(iii)	730	266	4379	51	0.935	0.943	0.733	0.935	0.822
	(iv)	1457	37	3828	104	0.933	0.990	0.975	0.933	0.954
GoogleNet	(i)	1327	0	3955	144	0.902	1.000	1.000	0.902	0.949
	(ii)	1613	84	3729	0	1.000	0.978	0.951	1.000	0.975
	(iii)	781	142	4503	0	1.000	0.969	0.846	1.000	0.917
	(iv)	1477	2	3863	84	0.946	0.999	0.999	0.946	0.972
MobileNetv2	(i)	1341	47	3908	130	0.912	0.988	0.966	0.912	0.938
	(ii)	1613	80	3733	0	1.000	0.979	0.953	1.000	0.976
	(iii)	730	130	4515	51	0.935	0.972	0.849	0.935	0.890
	(iv)	1481	4	3861	80	0.949	0.999	0.997	0.949	0.972
NasnetMobile	(i)	1365	95	3860	106	0.928	0.976	0.935	0.928	0.931
	(ii)	1613	9	3804	0	1.000	0.998	0.994	1.000	0.997
	(iii)	678	80	4565	103	0.868	0.983	0.894	0.868	0.881
	(iv)	1466	120	3745	95	0.939	0.969	0.924	0.939	0.932
ResNet50	(i)	1454	66	3889	17	0.988	0.983	0.957	0.988	0.972
	(ii)	1613	147	3666	0	1.000	0.961	0.916	1.000	0.956
	(iii)	715	17	4628	66	0.915	0.996	0.977	0.915	0.945
	(iv)	1414	0	3865	147	0.906	1.000	1.000	0.906	0.951

5. Discussion

The proper positioning of a patient's airway during CPR plays a vital role in enhancing the effectiveness of resuscitation efforts. The integration of AI-based feedback systems into CPR training can greatly enhance the performance of both professional emergency response teams and lay first aid providers worldwide. With the widespread availability of mobile phone technology, real-time evaluation of CPR performance through live recording has become feasible. Incorporating our proposed approach into recording devices or mobile applications can serve as a valuable training tool for rescuers. Providing immediate feedback during CPR training, whether conducted in a training center or at home, can help prevent injuries such as broken ribs or sternum fractures resulting from improper CPR techniques. Such injuries are particularly critical for vulnerable populations like children and seniors (33).

While our proposed approach holds significant promise for CPR training, its practical application in real-life emergencies may be limited, as time constraints during high-pressure situations may not allow for the setup of video cameras to guide rescuers. However, retraining and implementing our technique in rescuers' body-mounted cameras could potentially address this limitation. Despite these considerations, our proposed method shows great potential for enhancing CPR performance.

It is worth noting that the selection of deep learning models is a critical aspect of our study, and we believe that our chosen models align well with the objectives of our research, which focuses on detecting correct and incorrect positioning in CPR. Moreover, these models have demonstrated efficacy in various computer vision tasks, showcasing their ability to capture complex features and patterns, making them reliable choices for our medical imaging application. In addition, leveraging pre-trained models provides a significant advantage, especially when dealing with limited medical imaging data. The models have been trained on large and diverse datasets, enabling them to learn generalized features that are transferable to our specific task. Finally, the use of models available in the MATLAB library enhances the accessibility and reproducibility of our research. Researchers and practitioners can readily access and implement our methodology using the same set of models, ensuring consistency and comparability of results across different studies.

One limitation of our approach is the relatively small size of our CPR dataset. Additionally, all videos were recorded under uniform conditions, featuring rescuers wearing standardized attire and performing CPR on a manikin with a consistent color. Therefore, further evaluation and analysis of the proposed method on diverse and variable datasets are necessary to validate its efficacy in real-life scenarios. We further envision developing a deep learning-based system for detecting the pose during the use of an Ambo Bag as well as capturing the CPR performer's position during mouth-to-mouth resuscitation. In addition, we plan to produce more CPR data from varied environments (i.e., surroundings of a CPR administration) and patient demographics.

We also aim to include considerations for user interface design, real-time feedback mechanisms, and the model's adaptability to different CPR training settings. Additionally, we will explore potential collaborations with CPR training organizations to ensure alignment with existing practices and address any practical challenges associated with integrating AI into traditional training methodologies.

Finally, we acknowledge the importance of a comparative analysis with existing non-AI CPR training methods to further elucidate the advantages and potential drawbacks of our AI-based approach. We recognize that such a comparative study is indeed valuable for a comprehensive evaluation of our proposed methodology. Therefore, we plan to extend our analysis in the future by incorporating a comparative study with conventional non-AI CPR training methods. This additional work will involve obtaining data from traditional CPR training sessions, utilizing expert assessments, and comparing the outcomes with those derived from our AI-based approach. By conducting this comparative analysis, we aim to provide a more thorough understanding of the strengths and limitations of our proposed method in comparison to established non-AI CPR training practices.

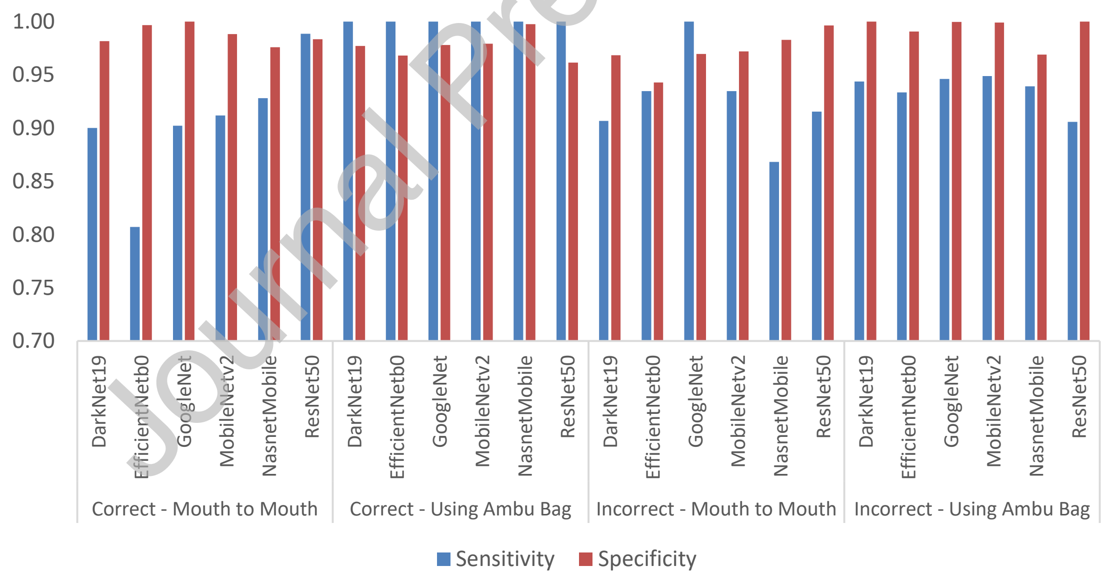

Figure 9. Sensitivity comparison of fine-tuned networks in detecting the patient's correct airway position during breathing.

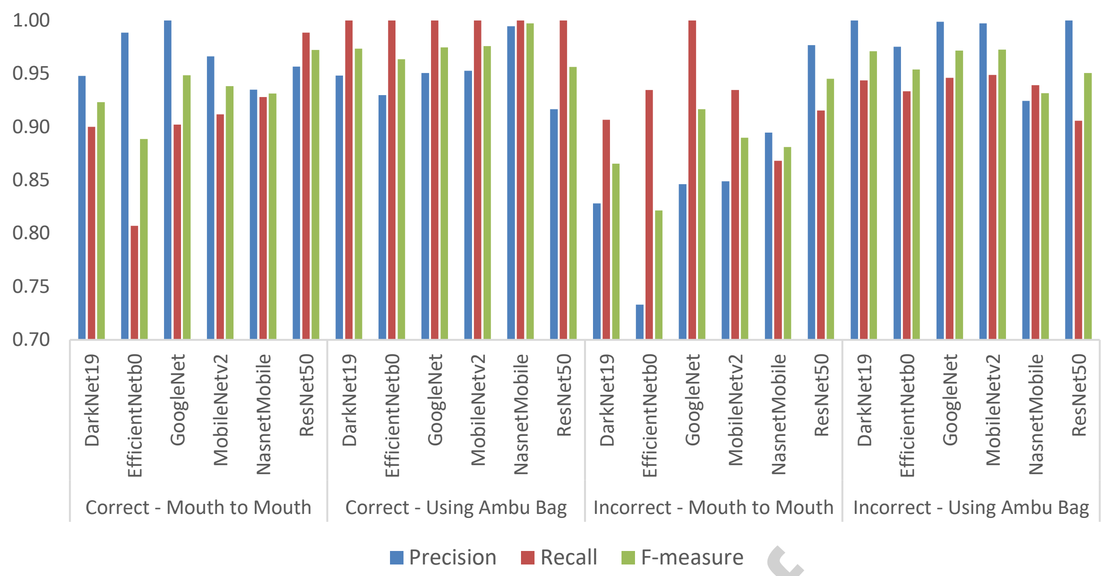

Figure 10. Comparison of F-Measure for fine-tuned networks in detecting the patient's correct airway position during breathing.

6. Conclusion

This paper introduced a deep transfer learning approach for accurately detecting the correct and incorrect positions of patients during CPR. By leveraging pre-trained deep models from ImageNet, we addressed the challenge of limited training data, which can hinder optimal training. We curated a comprehensive CPR dataset consisting of both video and image data to support AI-based CPR performance improvement. Our evaluation showcased the effectiveness of the proposed method, achieving excellent results in detecting the correct and incorrect positions of patients during CPR administration. Specifically, the best performance was observed with a sensitivity of 98.8% (ResNet50), specificity of 100% (GoogleNet), and F-measure of 97.2% (ResNet50) when detecting 'correct mouth-to-mouth breathing'. Furthermore, NasNetMobile demonstrated outstanding results with 100% sensitivity, 99.8% specificity, and 99.7% F-measure when detecting 'correct breathing with Ambu Bag'. As a future direction, we aim to expand our dataset size and make it publicly available to foster AI research for further CPR performance enhancement.

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Ethical approval: Not required

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