Computer sciences

UDC 004.8:007.52:004.93

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TRAINING STRATEGIES FOR VISION-BASED AI MODELS IN ROBOT CONTROL APPLICATIONS

Summary. *This work presents a comprehensive guide for training vision-based AI models for robotic control using computer vision, from initial data processing to classification of finger intent states of user actions. An image processing pipeline was developed that combines deterministic ROI extraction (MediaPipe Hands) and CNN-based classifiers. MobileNetV2 is used for efficient real-time output, while ResNet50V2 is used for high-precision feature extraction. To adapt pre-trained models to the custom "Gestures Dataset", a two-phase training strategy was employed, including transfer learning, selective layer freezing and fine-tuning, enabling accurate first-person intention recognition even with a limited dataset. Advanced preprocessing, augmentation techniques and task-specific evaluation metrics were applied to enhance system robustness, accuracy and safety. Moreover, specialized evaluation metrics such as false activation rate and stability were introduced to ensure safe physical interaction. Experimental results demonstrate that the proposed software-hardware model achieves high accuracy and real-time performance (latency ~100 ms), confirming the effectiveness of lightweight computer-vision models in assistive robotics.*

Key words: *vision-based robotic control, training strategies, convolutional neural networks, intent recognition, transfer learning, real-time inference, MobileNetV2, ResNet50V2.*

Introduction. Egocentric vision-based finger interaction intent recognition poses a multifaceted set of challenges that differ from conventional object recognition tasks, encompassing extreme illumination variability, motion-induced blur during rapid movements and frequent self-occlusion [1]. Addressing these complexities necessitates not only the deployment of high-capacity neural architectures, but also a holistic approach that effectively combines robust preprocessing pipelines, state-of-the-art training paradigms and task-specific evaluation metrics designed to ensure operational reliability. Within this context, computer vision represents a practical approach, endowing prosthetic systems with the capability to perceive and accurately interpret user intentions through finger movements [2]. Nevertheless, the real-world implementation of sophisticated CV models on portable, battery-powered platforms requires meticulous optimization to reconcile stringent constraints on latency, computational throughput and energy efficiency, while preserving real-time stability.

The development of a computer-vision software model requires careful selection of the environment and technological tools that ensure efficient data processing, neural-network training and integration with the hardware components of a robotic system. In this work, a vision pipeline combining deterministic preprocessing and CNN-based classifiers was developed. The system utilizes MediaPipe Hands for reliable extraction of regions of interest (ROI) and spatial normalization, while employing MobileNetV2 as a lightweight backbone for efficient real-time inference and ResNet50V2 for high-fidelity feature extraction. This integrative approach ensures an optimal balance between computational efficiency and classification accuracy, which is of paramount

importance in assistive robotic applications where responsiveness and reliability are critical.

To tailor pre-trained backbone models to the custom-developed dataset, state-of-the-art training paradigms (including transfer learning, fine-tuning and selective layer freezing), were systematically employed. These strategies allowed for the effective adaptation of high-level feature representations to domain-specific intention states, thereby enhancing accuracy even under constraints of a limited dataset.

The methodology presented herein provides a rigorous framework for the training and deployment of convolutional neural networks in robotic control applications, demonstrating the capacity for stable, real-time intent recognition in dynamically changing real-world environments. By combining advanced computer-vision architectures with comprehensive data preprocessing, domain-oriented augmentation strategies and task-specific evaluation metrics, the proposed approach ensures reliable prosthetic control. Furthermore, this study highlights the complementary use of different model capacities, leveraging the strengths of lightweight inference models and deep feature extractors to satisfy the operational requirements of assistive robotic systems.

Materials and methods. Convolutional neural networks (CNN) were employed as the primary module for visual processing. The architecture used in this study comprises convolutional blocks with ReLU activation and Batch Normalization, followed by max-pooling for spatial downsampling [3, 4]. The resulting feature tensors are flattened and fed into a compact fully connected classifier optimized for low-latency inference. MediaPipe Hands was used exclusively for deterministic ROI extraction and spatial normalization, not as a trainable model (Figure 1).

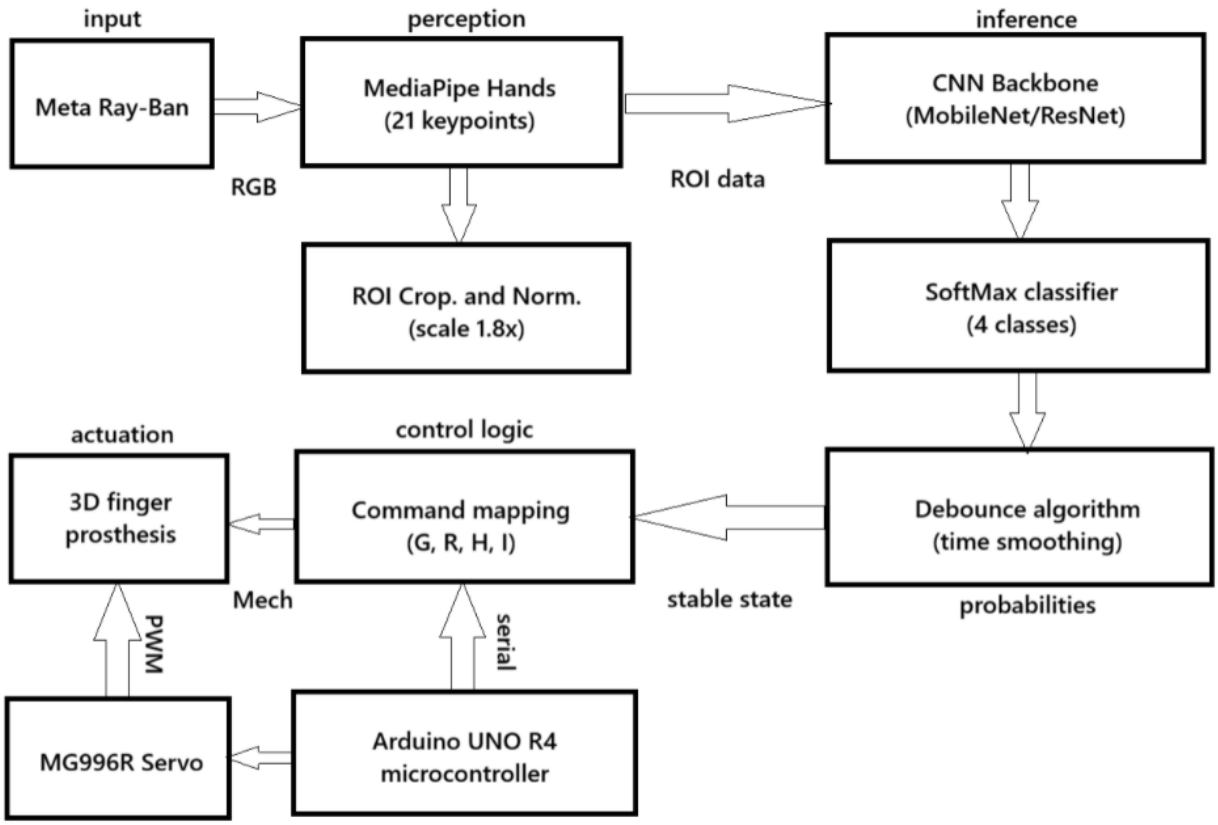


Fig. 1. Architectural block diagram of the proposed vision-based robotic control system

First-person data acquisition was conducted in a naturalistic child-oriented environment to replicate realistic operating conditions. All frames underwent region of interest (ROI) extraction to isolate task-relevant hand regions, followed by class balancing and extensive geometric and photometric augmentation to enhance robustness against illumination changes, background variability and hand-pose diversity.

Model optimization followed a structured two-phase training protocol, described in detail in the following section, as well as in "Analysis of a two-phase training strategy". In Phase 1, early convolutional layers were frozen while higher-level representations were adapted via transfer learning. In Phase 2, selective unfreezing under a reduced learning rate enabled more precise domain alignment. Dropout was applied in the classifier to mitigate overfitting associated with the limited dataset size.

System performance was evaluated through real-time robotic-control experiments. Metrics relevant to real-time intent recognition and control stability were employed, including latency, temporal prediction stability and cross-session consistency.

Theoretical background. Convolutional neural networks rely on a sequence of computational modules designed to progressively transform hand-centered ROI images into increasingly abstract feature representations [5]. Convolutional kernels operate as localized filtering operators that traverse the input image and detect elementary visual cues related to finger position, contact proximity and hand-object interaction. The outputs of these operations form feature maps that encode spatially distributed patterns characteristic of the underlying visual content.

Building on this foundation, convolutional layers automatically learn task-relevant local feature extractors, enabling the model to capture increasingly complex shapes and structural dependencies across layers. Pooling layers complement this process by downsampling the intermediate feature maps, thereby reducing spatial dimensionality while retaining the most salient activations. This contributes to translation and scale invariance and improves computational efficiency.

At later processing stages, fully connected layers integrate the extracted feature hierarchies into compact, mapping visual features to discrete intention states. These layers aggregate global contextual information and serve as the final basis for classification or regression outputs generated by the network.

To enhance generalization, modern architectures incorporate regularization and normalization mechanisms. Dropout randomly suppresses a predefined fraction of neuron activations during training, mitigating feature co-adaptation and reducing overfitting, while leaving inference computations unaffected aside from deterministic rescaling [6]. Batch Normalization normalizes intermediate activations on a per mini-batch basis, followed by a learnable affine

transformation [7]. This technique stabilizes optimization dynamics, enables the use of higher learning rates, accelerates convergence and provides additional regularization.

Together, these architectural components constitute the backbone suitable for real-time intent recognition under limited data conditions. Their combined effect facilitates efficient representation learning, which is particularly critical in scenarios where large, well-balanced, annotated datasets are difficult to obtain or where operational robustness under diverse real-world conditions is required.

Modern training strategies for computer-vision models in robotic control tasks. In contemporary robotic applications, computer-vision models are predominantly trained using approaches that facilitate the efficient reuse of previously acquired knowledge [8]. This is particularly important in scenarios where the collection of large volumes of labeled data demands substantial time and resources. For the development and training of convolutional neural networks, TensorFlow and Keras frameworks were employed, providing a high-level interface for implementing state-of-the-art architectures (MobileNetV2, ResNet50V2) and supporting transfer learning and fine-tuning, thereby reducing training time and enhancing accuracy when working with limited datasets. The effectiveness of modern computer-vision models in robotic applications relies not only on architectural innovations, but also on strategically designed training methodologies. Among these, transfer learning, fine-tuning and layer freezing have emerged as core approaches, enabling pre-trained feature representations to be adapted to new tasks and mitigating the limitations imposed by small or specialized datasets [9]. The adoption of these strategies is particularly critical in robotic control tasks, where obtaining extensive labeled data is often impractical due to the complexity of gesture capture, environmental variability and ethical considerations in human-centered experiments.

Transfer learning is based on using backbone models pre-trained on large-scale datasets such as ImageNet. This allows the model to already possess well-

formed filters for detecting fundamental visual features (edges, textures, shapes) even before training on the target gesture domain.

Fine-tuning refers to the process of adjusting the weights of a pre-trained model using new data. In the context of robotic control, this enables the system to adapt to specific lighting conditions, camera viewpoints and unique user gestures, thereby improving recognition accuracy.

Layer freezing is a technique in which the weights of a portion of the neural network (typically lower layers responsible for general features) are fixed during training. This reduces the number of trainable parameters, prevents catastrophic forgetting of foundational knowledge, and significantly accelerates model convergence [10].

Consequently, modern training strategies provide a robust and adaptive foundation for the development of computer-vision models capable of delivering high-accuracy recognition in real-time and maintaining stable performance across diverse operational scenarios in robotic systems.

A review of CNN architectures adapted to domain-specific constraints. The choice of neural network architecture represents a trade-off between accuracy and computational efficiency, which is critical for real-time systems. ResNet-class architectures (particularly ResNet50V2), owing to their residual connections, mitigate the vanishing-gradient problem and enable training of extremely deep networks [11]. These models provide high classification and detection accuracy in complex environments, which is essential for correctly recognizing a user's movement intentions. However, this accuracy comes at the cost of substantial computational load, which limits the feasibility of using ResNet as a standalone solution.

On the other hand, MobileNetV2 is specifically designed for mobile and embedded systems. Through the use of depthwise separable convolutions and inverted residual blocks, this model achieves acceptable accuracy with a significantly smaller number of parameters and substantially higher inference

speed [12]. This makes MobileNetV2 indispensable in scenarios requiring real-time video-stream processing on constrained computational platforms.

To address the problem of hand localization and the construction of a reliable region of interest (ROI), this study employs the MediaPipe Hands framework. MediaPipe integrates a high-speed Palm Detector with a lightweight regression model capable of estimating 21 anatomically meaningful hand landmarks [13]. Its ability to maintain stable performance on CPU-only hardware and under variable illumination conditions makes it particularly suitable for pediatric prosthetic applications, where the control system must remain robust, minimally intrusive and safe for continuous daily operation.

Building upon this foundation, a composite modelling strategy is adopted. ResNet50V2 is utilized to obtain high discriminative accuracy in visually complex scenarios, benefiting from deep residual learning and enhanced representational capacity. MobileNetV2, in contrast, serves as an efficient backbone for real-time inference on resource-constrained platforms due to its use of depth wise separable convolutions and inverted residual structures, which substantially reduce computational overhead without disproportionate losses in recognition performance. MediaPipe Hands provides reliable ROI extraction and landmark localization, enabling the downstream models to operate on anatomically relevant and spatially consistent input regions.

Collectively, this hybrid configuration offers a well-calibrated balance between accuracy, computational efficiency and operational robustness. Such a balance is essential for the development of a prosthetic-control system intended not only for controlled experimental environments but also for real-world deployment, where stability, responsiveness and user safety are equally critical performance attributes.

Preprocessing techniques, data balancing approaches and robotics-oriented augmentation pipelines. Prior to the commencement of model training, a bespoke and meticulously curated dataset was established, constituting the

foundational corpus for the subsequent development and optimization of the robotic control mechanism. Data acquisition utilized pre-recorded egocentric video streams captured via Meta Ray-Ban smart photo-video glasses in a prototypical domestic environment. The dataset encapsulated four discrete classes of finger intention states, reflecting the functional states critical for prosthetic operation: "Idle", "Intent Grasp", "Hold" and "Intent Release".

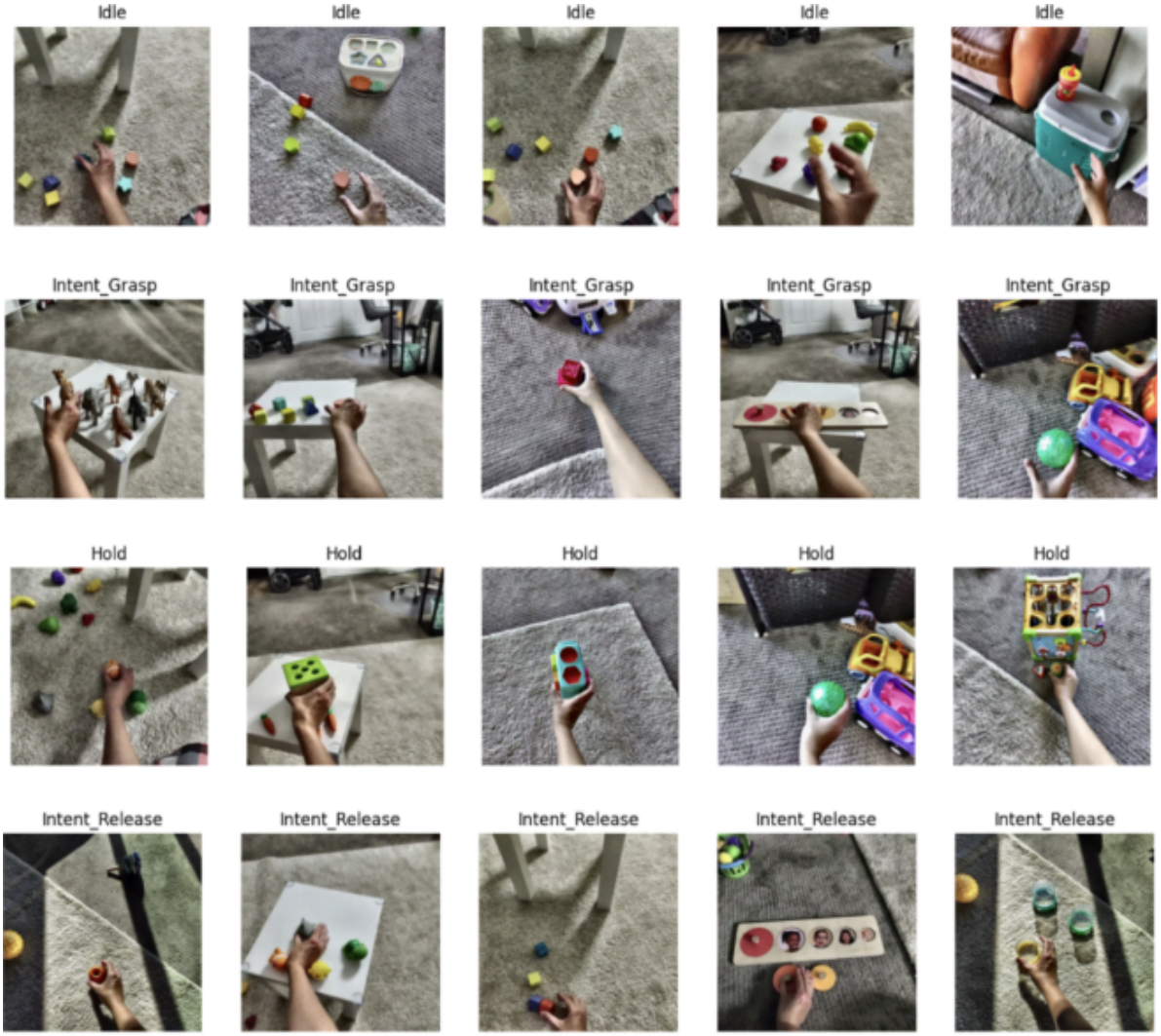


Fig. 2. Representative samples from the custom "Gestures Dataset" captured from a first-person perspective

To facilitate automated data preparation, a dedicated Python-based processing pipeline was implemented. This system parsed the continuous video streams into individual frames, which were subsequently subjected to rigorous quality control to exclude frames exhibiting blurring, underexposure or

duplication. Crucially, a deterministic ROI extraction was performed using MediaPipe Hands. This step isolated the hand area from the background clutter prior to resizing, ensuring that the classifier input was spatially normalized and focused exclusively on relevant anatomical features.

All extracted ROI were resized to standardized dimensions to conform with the input requirements of the selected CNN architectures. This preprocessing and filtration procedure produced a high-quality dataset, fully prepared for the subsequent model training phase. The resulting dataset comprised 1200 images, evenly distributed across the four classes, with 300 images per class, thus mitigating class imbalance effects that typically bias network training toward overrepresented categories. Such imbalance is particularly consequential in the current context, as the "Idle" state predominates temporally. Without corrective measures, this could result in false-positive activations and degraded recognition performance for temporally brief, but functionally essential classes, specifically "Intent Grasp" and "Intent Release".

To ensure representativeness and reproducibility, the dataset was stratified into training and validation subsets using an 80/20 split, and random number generators within Python, NumPy and TensorFlow were fixed to guarantee consistent experimental outcomes. To enhance model robustness and generalization, a comprehensive data augmentation pipeline was employed [14].

Geometric augmentations: rotations, translations and scaling transformations to simulate spatial variability (excluding horizontal flips to preserve hand laterality semantics).

Photometric augmentations: modifications to brightness and contrast, along with stochastic Gaussian blurring to replicate variable lighting conditions.

Cutout technique: random occlusion of image regions to promote invariance to partial visibility [15].

MixUp augmentation: linear interpolation between pairs of images and their corresponding labels, applied conservatively to ensure the semantic integrity

of the intention states while improving generalization and reducing overfitting [16].

This multi-tiered approach to dataset curation, ROI-based preprocessing and augmentation provides a rigorously controlled foundation for training vision-based AI models capable of reliable intention recognition in dynamic robotic applications.

An analysis of a two-phase training strategy. The training process was conducted in two distinct stages. In the first stage (Stage 1), the entire feature extraction backbone was frozen and only the upper classifier layers were trained. This approach enabled rapid adaptation of the model to the specific characteristics of the newly curated dataset. Specifically, all layers of the backbone network remained frozen, while the classifier was composed of a GlobalAveragePooling layer, GlobalMaxPooling layer (concatenated), a Dense layer with 256 neurons incorporating L2 regularization and Dropout (0.3) and a final Softmax output layer [17].

Convolutional layers within the backbone automatically extract local features - such as contours, textures and shapes through the application of learned filters to the input image. Subsequently, subsampling operations (pooling layers) are applied. Pooling layers reduce the spatial dimensionality of feature maps while retaining the most informative elements, thereby enhancing invariance to translations and scaling. This procedure reduces computational cost and increases the network's robustness to noise, spatial shifts and scale variations.

In the second stage (Stage 2), the upper convolutional blocks were selectively unfrozen of the backbone, allowing fine-tuning of high-level feature representations specifically for intention recognition within a first-person perspective. Once all feature maps are extracted, they are transformed into a flattened vector, facilitating the transition from multidimensional spatial representations to a classical fully connected neural network architecture. The fully connected layers integrate previously extracted features to generate high-

level abstractions that serve as the basis for classification. These final layers implement the decision-making process for classification or regression tasks, with the ultimate layer typically realized as a Softmax classifier. The primary objective was to adapt high-level feature representations to the specific patterns of hand gestures. This stage facilitated an improvement in the Macro-F1 metric and enhanced the discriminability between visually or semantically similar classes, thereby increasing the overall classification robustness and precision.

Thus, the convolutional neural network implements a sequential processing pipeline: from local feature extraction to the construction of high-level abstractions and the decision-making process regarding the assignment of an image to a specific class. This hierarchical processing capability underpins the fundamental role of CNN in computer vision systems, including robotic prosthetics, where high accuracy and robustness in real-time operation are critically required.

Evaluation metrics tailored to robotic systems. To ensure operational reliability in vision-based prosthetic control, the evaluation framework must go beyond generic performance indicators and address specific failure modes associated with intention recognition. For a robotic hand, the cost of error varies significantly between state transitions: a false positive in "Intent Grasp" can lead to an unintended clamping force, while a false negative in "Intent Release" causes the prosthesis to retain an object against the user`s will. Consequently, the following metrics were tailored to assess specific aspects of the interaction:

Precision: precision quantifies the system`s resistance to spurious activations. It is particularly critical for distinguishing static states ("Idle", "Hold") from active transitions. Low precision implies that the model frequently hallucinates an "Intent Grasp" or "Intent Release" when the user is actually static, leading to erratic prototype behavior.

Recall: measures the system`s sensitivity to genuine user commands. High recall is essential for the "Intent Grasp" and "Intent Release" classes to ensure

responsiveness. A low recall score here would mean the user physically attempts to perform an action, but the system fails to register the intention, resulting in a non-responsive prosthesis and user frustration [18].

F1-Score: this metric provides a balanced view of the trade-off between safety (Precision) and responsiveness (Recall). It is used to evaluate the consistency of the model for each specific intention state, ensuring that neither false activations nor missed commands dominate the error profile.

Macro-F1 Score: given that the "Idle" and "Hold" states are naturally more stable and may predominate in duration compared to the brief, dynamic "Intent" transitions, standard accuracy can be misleading. Macro-F1 is employed as the primary success metric because it treats all classes equally in the calculation, preventing the high performance on static states from masking poor performance on critical, short-lived transition states. It ensures that the system is optimized for dynamic control, not just for maintaining a static pose.

While raw model output provides per-frame class probabilities, direct mapping of these predictions to motor commands can result in flickering due to sensor noise or transitional ambiguity. To mitigate this, specific post-processing algorithms were implemented to ensure smooth actuation.

Temporal probability smoothing: to reduce high-frequency noise in the prediction confidence, a moving average filter is applied to the output probabilities over a sliding window of the last 5 frames. This prevents isolated outliers from affecting the decision logic.

Debounce logic: a state transition is only registered if the new class is consistently detected for a predefined number of consecutive frames. This hysteresis mechanism prevents rapid oscillation between classes (oscillating between "Intent Grasp" and "Hold" during the onset of a movement), ensuring that motor commands are issued only when the user`s intention is stable and unambiguous.

Results. The experimental evaluation of the developed system demonstrated robust model performance. The control mechanism exhibited stability, precision and consistency in mapping intention states to actions, facilitating intuitive control and adaptive response to user commands. Crucially, the system maintained high operational reliability, minimizing the risk of unintended actuations - a key factor for safe usage in assistive applications. Furthermore, the prosthetic system operated with an observed latency of approximately 100 ms, falling well within acceptable bounds for real-time interaction.

The use of a hybrid, mutually complementary architecture MediaPipe with one of the CNN (MobileNet or ResNet), a two-stage training pipeline (transfer learning followed by fine-tuning), a custom dataset ("Gestures Dataset"), a structured class taxonomy ("Idle", "Intent Grasp", "Hold", "Intent Release"), as well as additional evaluation metrics (false-activation rate, temporal stability, Macro-F1 Score and inter-session consistency) collectively ensured a seamless and reliable integration of all prosthetic control components.

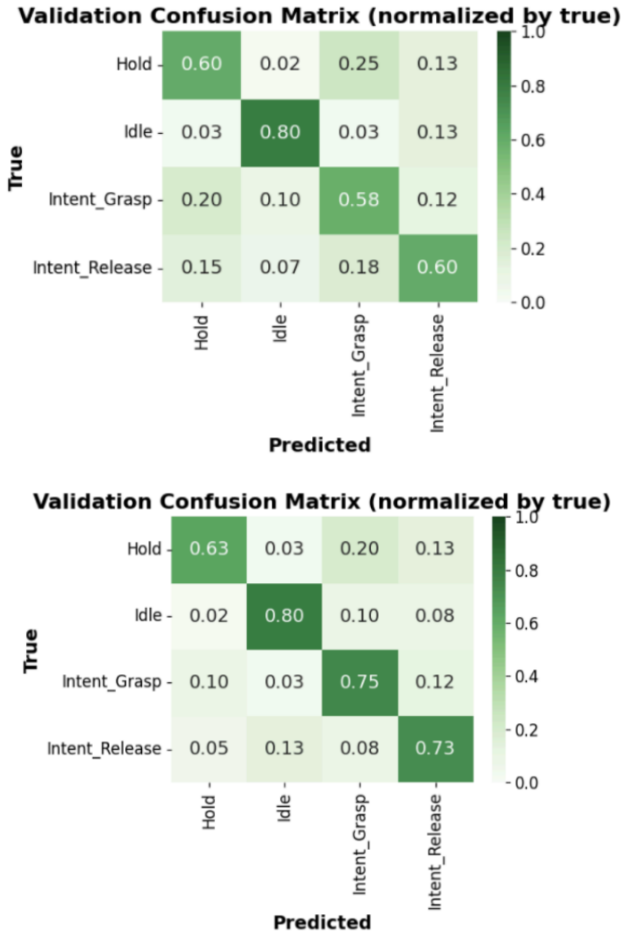


Fig. 3. Normalized confusion matrices evaluated on the validation set

(Left) MobileNetV2 shows higher misclassification rates between "Hold" and "Intent Grasp" states. (Right) ResNet50V2 demonstrates superior class separability, particularly for dynamic transition states, confirming its suitability for high-precision control tasks despite higher computational cost.

Furthermore, augmentation strategies, class balancing and the implemented debounce logic significantly enhanced the model's robustness to lighting variability, partial occlusion and natural movement diversity. Final experiments conducted during toy-manipulation tasks demonstrated the system's reliability, stability and highly predictable behaviour in dynamic environments, confirming its suitability for pediatric assistive robotic applications.

Table 1

Comparative performance analysis of the implemented neural architectures.

Parameter	MobileNetV2 (Lightweight)	ResNet50V2 (High-Fidelity)
Model architecture	Inverted residuals	Residual connections
Input resolution	224×224	256×256
Validation accuracy	64.6%	72.9%
Macro-F1 score	0.646	0.729
System latency	< 100 ms	~150-200 ms
Deployment target	Embedded / MCU	PC / Cloud

*The analysis highlights the trade-off between recognition precision (ResNet50V2) and real-time inference capability (MobileNetV2) required for the robotic control loop

Conclusions. In summary, the results of this study underscore that the integration of lightweight and deep neural models enables simultaneous optimization of computational efficiency and recognition accuracy, which is critical for real-time prosthetic control. The use of specialized data preprocessing, augmentation techniques and task-specific evaluation metrics significantly enhances the model's capability, interpretability and robustness. The two-phase training strategy demonstrated its effectiveness in adapting high-level feature representations to complex, domain-specific hand gestures. Experimental outcomes confirm the practical applicability of hybrid CNN architectures in human-centered robotic systems, ensuring reliable, safe and responsive prosthetic operation. The methodology validates the feasibility of deploying hybrid CNN models for real-time robotic control in dynamic and unstructured environments. High precision and recall for functionally critical gesture classes ("Intent Grasp" and "Intent Release") guarantee safe and natural prosthesis operation. The implementation of the two-phase training strategy freezing the backbone followed by selective fine-tuning proved essential for adapting deep learning models to the custom-developed "Gestures Dataset". This approach enabled the system to learn

domain-specific features from a first-person perspective without overfitting, despite the limited dataset size.

Finally, the proposed system effectively mitigates challenges associated with variable lighting and dynamic environments through a robust preprocessing pipeline and temporal stabilization logic. Combined with a balanced dataset and optimized inference speed suitable for resource-constrained hardware, this work establishes a solid foundation for the next generation of intelligent pediatric prostheses with vision-based control, ensuring both safety and intuitive usability.

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