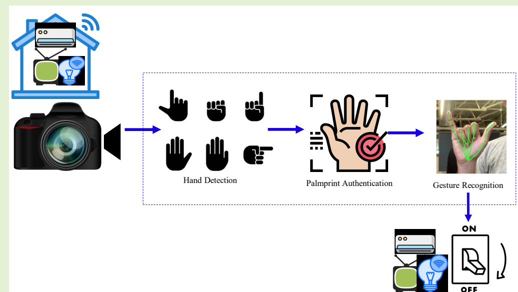
SimplyMime: A Dynamic Gesture Recognition and Authentication System for Smart Remote Control

Sibi C. Sethuraman, *Member, IEEE,* Gaurav Reddy Tadkapally, *Student Member, IEEE,* Athresh Kiran, *Student Member, IEEE,* Saraju P. Mohanty, *Senior Member, IEEE,* and Anitha Subramanian, *Student Member, IEEE*

***Abstract*—The widespread use of consumer electronics in today's society highlights the ever-evolving landscape of technology. With the constant influx of new devices into our households, the accumulation of multiple infrared remote controls, required for their operation not only causes wasteful energy consumption and resource depletion but also a disordered user environment. To tackle these issues, we present SimplyMime, an innovative system that aims to eliminate the need for multiple remote controls in the realm of consumer electronics, while providing users with an intuitive control experience. SimplyMime utilizes a dynamic hand gesture recognition framework that seamlessly integrates Artificial Intelligence with Human-Computer Interaction, allowing users to easily interact with a wide range of electronic devices. The keypoint model used for gesture identification provides a flexible system that can be easily adapted to recognize a variety of hand gestures, even complex ones. Additionally, SimplyMime introduces a novel siamese-based hand palm print authentication system that acts as the security module for our work and ensures that only authorized individuals can control the devices. The system's hand detection is enhanced by a customized Single Shot Multibox Detector (SSD) algorithm, which narrows its anchor boxes and uses a Feature Pyramid Network (FPN) to identify hands across different feature maps, serving as a resource-efficient model. Extensive testing on numerous benchmark datasets has proven the effectiveness of our proposed methodology in detecting and recognizing gestures within motion streams, achieving impressive levels of accuracy.**



***Index Terms*—Smart Remote Control, Object Detection, Gesture Recognition, Hand Gesture Recognition**

I. Introduction

The advent of smart electronics such as televisions, air conditioners, and speakers has become a defining characteristic of modern society, propelling the development of smart cities aimed at optimizing operations with limited resources and maximizing asset utilization to enhance the quality of life. With the increasing availability of inexpensive devices, most households now possess multiple electronic devices, each typically requiring its own remote control for operation and interaction [1]. This proliferation of remote controls, while convenient, leads to resource wastage, increased plastic consumption, and challenges in locating and operating the appropriate remote for a given device [2]. Despite the introduction of remote-control devices in the 1950s and the subsequent development of infrared-based remotes in the 1970s [3], traditional methods of human-computer interaction (HCI) have not been fully adopted because of a lack of seamless functionality.

The prevalence of smart electronics, such as televisions, air conditioners, and speakers, has permeated modern society. This technological phenomenon has propelled the advent of smart cities, aiming to optimize operations with limited resources while maximizing the utilization of available assets to enhance the quality of life. With the proliferation of inexpensive and readily available devices, most households have multiple electronic devices that require remote controls for operation and interaction [1]. As the number of devices increases each year, so does the number of remote controls needed to operate them. This traditional method of interaction, while widespread and commonly used, is not without its flaws.

The limitations of traditional remote controls, such as the requirement for line of sight and precise pointing, hinder the user's freedom of movement and reduce overall comfort. Additionally, traditional remote controls have a limited

S. C. Sethuraman (0000-0001-7778-0453) is with the School of Computer Science and Engineering, VIT-AP University, Andhra Pradesh, India, 522237, Email: chakkaravarthy.sibi@vitap.ac.in

G. R. Tadkapally (0000-0001-6694-9153) is with the Viterbi School of Engineering, University of Southern California, Los Angeles, CA, USA, Email: tadkapal@usc.edu

A. Kiran (0009-0005-3168-4980) is with the Parallel Reality Limited, United Kingdom. Email:athresh.kiran@gmail.com

S. P. Mohanty (0000-0003-2959-6541) is with the Department of Computer Science and Engineering, University of North Texas, TX 76207, USA, Email: saraju.mohanty@unt.edu

A. Subramanian (0009-0007-4708-5848) is with the School of Electronics Engineering, VIT-AP University, Andhra Pradesh, India, 522237. Email: anithachubbu@gmail.com

operational range and are often constrained by infrared or radio frequency technology, which can suffer from interference from other electronic devices. The complexity and number of buttons on these remotes can be confusing and difficult to navigate, particularly for people with disabilities or those with limited dexterity. Moreover, traditional remotes offer limited customization for individual user preferences and are prone to physical damage, wear and tear, and battery replacement issues, which also contribute to environmental concerns due to increased plastic consumption [2]. Although there have been advancements in HCI technology, including alternatives to keyboards and mice and devices utilizing Bluetooth or WiFi communication, a solution that completely eliminates the need for additional devices and provides a more intuitive user experience has yet to be developed [4].

In response to these challenges, we propose SimplyMime, a hand gesture-based control system for consumer electronics that addresses the existing limitations of traditional remote controls. Hand tracking, a natural and intuitive mechanism for identifying hand movements, has been extensively studied and demonstrates significant promise in skeleton-based tracking due to its robustness against various background conditions [5], [6]. SimplyMime offers an efficient and lightweight solution capable of real-time hand tracking, making it suitable for integration into a compact system for any electronic appliance.

A distinctive feature of SimplyMime, setting it apart from extant solutions, is the incorporation of palmprint recognition for user authentication. This advanced biometric security measure substantially enhances the system's utility by ensuring that only authorized users can operate the devices. Unlike conventional remote controls and existing gesture-based systems that may use gestures as passwords, SimplyMime leverages the uniqueness of palmprints. While some systems use sequential hand gestures for biometric authentication, relying on the unique behavioural characteristics and shapes of hand signs, these methods are more vulnerable to environmental variability and require extensive image processing and machine learning algorithms to recognize [7]. SimplyMime's palmprint recognition provides a higher level of security due to the complexity and uniqueness of palm patterns, which are less susceptible to such variability and offer more reliable authentication.

The state-of-the-art hand gesture recognition techniques employed by SimplyMime create an efficient and intuitive control framework for consumer electronics. By obviating the need for multiple controllers, SimplyMime contributes to a more organized and aesthetically pleasing living space while delivering a more immersive and intuitive user experience. Additionally, the palmprint recognition module facilitates user verification and authentication, thus incorporating a crucial security dimension often overlooked in prior solutions. With minimal computational requirements, SimplyMime is highly adaptable and reliable, making it an optimal solution for both residential and commercial applications. A diagrammatic illustration of SimplyMime's workflow is depicted in Figure 1.

Contributions of SimplyMime:

- **User-centric Design**: SimplyMime prioritizes user convenience by offering an effortless control experience, distinguishing it from other technologies in device management.
- SimplyMime offers a one-stop solution for controlling multiple devices, reducing the accumulation of any e-waste.
- The SimplyMime uses a powerful but adaptable paradigm to determine hand movements in hardware with less power consumption. In contrast to mainline approaches with their need for huge sets of training data and powerful computational resources, the minimization of learning was achieved through the keypoint-based identification of gesture, which enables recognizing additional types of gestures, including intricate ones, with only a slight adjustment. This flexibility proves indispensable in the situations when spectrum of possible gestures might be widened or might be changed in future.
- The implementation of a SSD with FPN makes SimplyMime unique as it boosts the hand detection in multiple feature maps. This brings a higher detection rate besides lowering the computational complexity to make it applicable in real-time applications with limited resources.
- SimplyMime enhances security by incorporating user verification and authentication, ensuring authorized access. Also it is dissimilar from a conventional single biometric system, wherein our strategy integrates the effectiveness of the palm print recognition with the flexibility of siamese networks. This leads to improved security and reliability of the access so long as only the correct finger print can unlock the linked devices. The architecture of the proposed siamese network makes it possible to achieve one-shot learning, which simply means that minimum training data are required in order to authenticate users with high level of precision. This is more beneficial where time is of essence especially in situations where the users have to enroll at a certain time or where the system has to quickly accommodate new users.

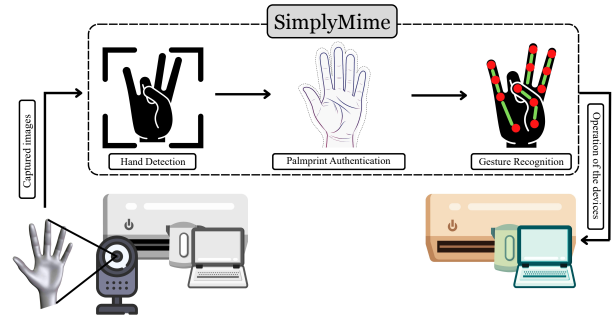


Fig. 1. Diagrammatic representation of the architectural working of SimplyMime

The rest of the paper is organized as follows: Section II discusses the related research. Section III provides the system-level architecture of the proposed approach, SimplyMime. Section IV validates the results and provides a comparative analysis of SimplyMime against the State-of-the-Art solutions. Finally, the paper concludes in Section V.

II. Related Research

Hand gesture recognition technology has been a subject of study for several years, with developments in different fields, including human-computer interaction, gaming, augmented reality, and assistive technology for those with disabilities. The hand, in particular, is used extensively for gesturing compared to other body parts because it is a natural means of human communication and hence the most appropriate tool for HCI [5]. This application area has the potential to revolutionize how we interact with electronic devices in our homes by enabling simple hand gestures to control them.

A. Sensor-based Methods

The majority of existing methods can be categorized as sensor-based systems. Utilizing specialized sensors to capture the movement and orientation of the hand, these methods capture the hand's motion and orientation [14]. These sensors can include accelerometers, gyroscopes, magnetometers, and other types of sensors that measure the hand's movement and position [15], [16]. Sensor-based methods have a number of advantages over other methods such as the ability to capture precise information about the hand's movement and position and the capacity to function in environments with poor lighting or visibility, etc. [17], [18]. Inertial sensors in conjunction with a multilayered perceptron classifier can be employed to recognize hand gestures [19], [20]. Adopting a similar methodology, researchers have developed a finger-worn ring device that captures acceleration data, paired with an LSTM model for the classification of hand gestures [8], [21]–[24]. Likewise, the Inviz device incorporates textile-based flexible capacitive sensor arrays for motion detection [9]. This approach has been utilized to develop systems that cater to individuals with paralysis, paresis, weakness, and restricted range of motion. Other notable developments include the WristCam [25], a wrist-worn camera sensor that estimates and recognizes hand trajectories, as well as the EchoFlex [10], a wearable ultrasonic device that tracks hand movements. The muscle flexor data from the sensors can be used to develop an algorithm that combines image processing and neural networks for gesture recognition. Sensor-based systems offer precise hand movement and position data even in challenging lighting conditions. However, their reliance on additional devices limits their versatility and scalability. Moreover, inaccurate sensor calibration can lead to poor gesture recognition performance.

B. Vision-based Methods

The integration of computer vision and human-computer interaction has enabled the development of innovative systems aimed at addressing sensor-based limitations and providing users with a more immersive and efficient experience [26]. One of the initial approaches in the development of vision-based sensors was the utilization of a coloured glove [11]. This method required the user to wear a coloured glove, which enabled the system to employ a nearest-neighbour approach for tracking hand movements. Several studies that employed the use of the Kinect sensor utilized the colour and image depth data to establish a hand model for the analysis of tracked hand gestures. The hand gesture tracking can be accomplished through the implementation of a Kalman filter [12]. However, it was observed that the gesture recognition accuracy was relatively low. Similar research utilized RGB-D cameras to extract hand location data through the use of in-depth skeleton-joint information from images [27]–[29].

A few works employed neural networks to infer real-time hand landmarks, which were used to analyze the skeletal structure of the hand gesture [13], [30]. Despite these efforts, recognizing gestures from complex backgrounds remains a challenging task.

Vision-based methods for hand gesture recognition face several significant challenges when applied in dynamic and real-world environments. These challenges include background clutter, occlusion, and the need for real-time processing. SimplyMime addresses these challenges through several innovative approaches. The system's hand-tracking model employs advanced architecture based on BlazePalm, which is highly resilient to variable lighting conditions. By utilizing this robust architecture, SimplyMime ensures consistent performance in various environments. Additionally, SimplyMime utilizes a dynamic algorithm to detect gestures on the go, effectively mitigating the issue of background clutter.

III. SimplyMime: The Proposed Smart Remote Control

The proliferation of consumer electronics has resulted in the widespread use of traditional remote controls as the primary means of interaction. However, to effectively replace such a firmly established technology, an alternative solution must not only be robust, precise, and intuitive, but also possess the added benefits of user-friendliness, compatibility with older devices, and scalability [31]. Our proposed work, SimplyMime, addresses the shortcomings of existing solutions while maintaining the immersive experience that traditional remote controls are capable of delivering. The dynamic hand gesture recognition module, represents the most advanced, effective, and ideal replacement for traditional remote controls, providing a unique blend of state-of-the-art performance and efficiency.

The underlying architecture of the system incorporates a hand landmark assignment method, which is utilized to identify and localize key points across the hand, such as fingertips, knuckles, and wrists. These landmarks assigned by the backend model form the basis for the gesture recognition algorithm, which identifies and classifies gestures based on the skeletal structure generated. The system is designed to operate in two distinct modules. The first module, the hand detection model, is responsible for identifying and isolating the human hand within an image. The second module, the gesture recognition model, processes the detected hand to generate a skeletal structure of the gesture and subsequently recognizes it.

A. Hand Detection Model

The foundation of an effective hand gesture identification model is the accurate detection and isolation of the hand from

TABLE I
COMPARISON OF EXISTING HAND GESTURE RECOGNITION MODELS

Research	Methodology Employed	Findings and Outcome	Requirement of additional device	Security Module
TinyDL (2021) [8]	Inertial Sensors	- Utilized a built-in LSTM model leveraging data from a finger-worn ring. - The performance will be impacted by factors such as sensor placement, variations among users, and changes in hand gesture execution over time.	Finger-worn device	None
Inviz (2015) [9]	Textile-based capacitive arrays	- Relies on textile-based capacitive arrays built into clothing. - The production of wearable textile capacitive sensor arrays could increase the cost and complexity of the system.	Wearable textile capacitive sensor Arrays	None
EchoFlex (2017) [10]	Ultrasound Imaging	- Utilizes ultrasound sensors to capture hand movement data, which is then analyzed using ML algorithms. - Susceptible to interference from nearby objects or environments with high acoustic noise	Ultrasonographic Device	None
Wang et al. (2009) [11]	Image Processing	- Employs colour segmentation and a tracking algorithm is applied to estimate the hand pose and motion. - Recognition accuracy would be affected by factors such as lighting conditions,mcolour variations, and occlusions.	Coloured Glove	None
Feng et al. (2014) [12]	Kinect Sensors	- Demonstrates the feasibility of combining various types of sensors for human motion tracking. - Requires a high-performance computing device to achieve real-time performance	Microsoft Kinect Sensor	None
SHREC (2021) [13]	Skeleton-based hand gesture recognition	- Achieved high accuracy in recognizing hand gestures in various real-world scenarios	None	None
SimplyMime (Current Paper)	CNN-based skeletal pose estimation	- Delivers intuitive control without additional devices - Incorporates palmprint authentication to verify and authenticate users	None	Palmprint Authentication

the given image [32]. To achieve this, SimplyMime employs state-of-the-art neural network technology for localizing the coordinates of the palm. While conventional RCNN models have been widely used for object localization, they require significant computational power, making them less suitable for real-time applications [33], [34]. In contrast, the adopted Single-Shot Detector (SSD) algorithm achieves superior real-time performance by eliminating the need for bounding box proposals and subsequent feature re-sampling [35]. This results in a more efficient and effective approach to hand detection, which is a crucial component of an accurate gesture identification system.

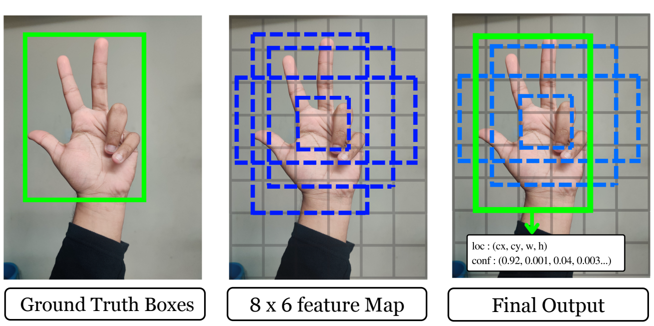


Fig. 2. Visualization of Hand Detection Model in Action

Action Visualisation of the Hand Detection Model is demonstrated using the Figure. 2.

The architectural network of the gesture detection model

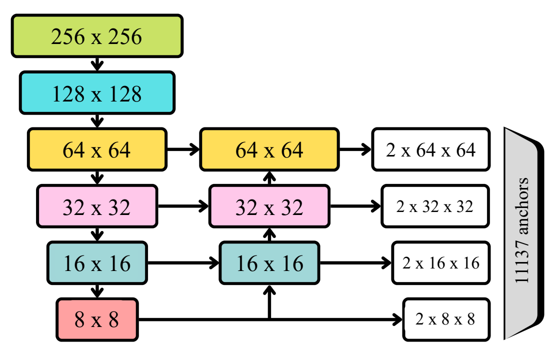


Fig. 3. Comprehensive View: Gesture Recognition Module Architecture

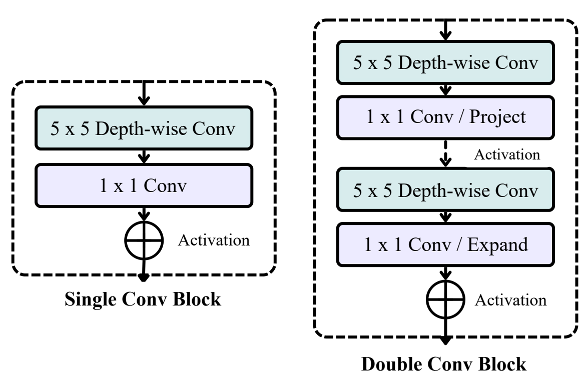


Fig. 4. Inner Structure of the Devised Convolution Blocks

is illustrated in Figure 3. The feature extraction network processes an RGB input image of 224x224 pixels through a series of convolutional layers, referred to as ConvBlocks, which serve as the bottleneck for higher abstraction level layers. The image is passed through 5 single and 6 double ConvBlocks. These ConvBlocks consist of a series of convolutional layers, followed by depth-wise and point-wise convolutional layers. The detailed architecture of our ConvBlocks is depicted in Figure 4. Our model architecture exhibits significant deviations from traditional SSD models, such as MobileNetV2-SSD, tailored to the unique characteristics of hand gesture recognition. Given that hands can be effectively encapsulated within square bounding boxes, we have optimized our model by focusing solely on square aspect ratios, leading to a substantial reduction in the number of anchors by a factor of approximately 3 to 5, thus streamlining the detection process.

Further enhancing the model's performance, we have incorporated a Feature Pyramid Network (FPN) into our architecture. This approach, akin to the multi-scale feature extraction techniques employed in later versions of the YOLO architecture (V3-V5), such as PANet and CSPNet, improves our model's ability to capture details across different scales. This represents a departure from the original Faster R-CNN architecture, which relies on a single-scale feature map extracted from the last layer of a backbone network (VGG or ResNet) for region proposal and object detection.

The model is trained on three datasets: an in-the-wild dataset for diverse conditions, an in-house dataset for consistent hand angles, and a synthetic dataset for various angles and environments. This comprehensive training approach ensures inference speed and accuracy, outperforming MobileNetV2-SSD in both aspects [36].

B. Hand Landmark Detection Model

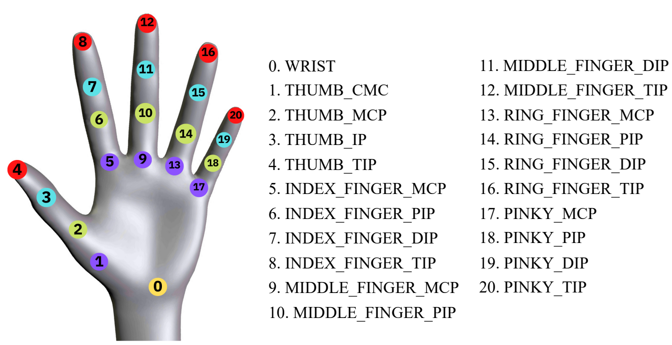


Fig. 5. Key-point Indexes of All Hand Landmarks

The subsequent stage in SimplyMime's pipeline is to extract critical points from the isolated hand region after successful localization in the image. For this purpose, we employ a modified version of the Convolutional Pose Machines (CPM) network, extensively used in human pose estimation [37]. The CPMs generate a confidence map for each key point, represented as a Gaussian centered at the true position. These maps are created based on the input image patch size, with the final location of each key point determined by identifying the peak in the corresponding confidence map. The model constructs a palm skeleton by designating 21 landmarks at various positions throughout the palm.

Dynamic Gesture Detection Algorithm: After extracting the key points from the hand region, they are further analyzed by the gesture detection engine. The 21 important locations extracted indicate different hand regions, as shown in Figure 5. These landmarks serve as the foundation for identifying the gesture the user intends to create. This processed information is then used to control SimplyMime-enabled devices. The proposed algorithm assigns a FingerState value to each digit. An open finger is designated as 1, while a folded finger is denoted as 0. To determine the FingerState, we leverage the Y-axis coordinates of the metacarpophalangeal (MCP) joint and the fingertip. The unique location and alignment of the thumb necessitate calculating its slope to ascertain its FingerState. This approach results in more precise and accurate gesture recognition, enhancing the system's overall performance.

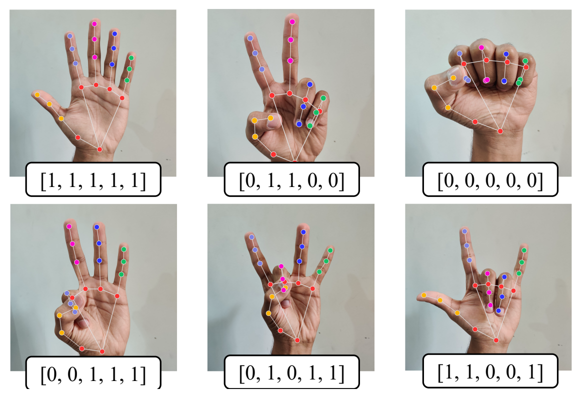


Fig. 6. Working Results and Subsequent Arrays Generated by the Landmark Detection Model

Through the use of a posture array, each gesture can be accurately identified and differentiated. These posture arrays can be designated as trigger functions to control a diverse range of consumer electronics. Additionally, the MCP of the middle finger is employed as the focal point to align and center the camera, ensuring that the palm remains in view. The midpoint between the tips of the thumb and index finger is used to locate the cursor if necessary for a specific device. Figure 6 demonstrates several images and their corresponding posture arrays.

C. Palm Print Authentication Module

Without robust security mechanisms, these systems can be easily compromised, leading to data breaches, unauthorized access to sensitive information, and potential damage to devices. SimplyMime employs PalmPrint identification, utilizing Siamese Network architectures, a common approach used in similarity recognition tasks [38], [39]. Our Siamese Neural Network consists of three identical feature extraction blocks sharing the same weights. This weight sharing enables the network to converge faster compared to training three separate models. The network generates a 4096-dimensional feature vector for each input image, and the similarity between two images is computed using the Euclidean distance between these vectors. The two palms' resemblance is confirmed by calculating the difference between their sets of embeddings using the Euclidean distance function. To verify the legitimacy of the user, a predefined threshold has been established. Access to the system is restricted if the dissimilarity measure exceeds the threshold, ensuring that only authorized individuals have access to the system. This multi-factor approach ensures that only authorized individuals have access to the system, protecting against unauthorized attempts to control consumer electronics.

During the training process, the network is presented with three input images: an anchor image, a positive image, and a negative image, as shown in Figure 7. The anchor and positive images correspond to the palm print of the same individual, while the negative image represents the palm print of a different individual. The network is trained for 100 epochs using the Triplet Loss function, with the Adam optimizer. The XceptionNet [40] serves as the base model, acting as the encoder. Two distances constitute the training process's output, and these are inputted into the triplet loss function [41], [42], denoted by:

$$\begin{aligned} TripleLoss = \sum_{N}^{i} [\|f(x_i^a) - f(x_i^p)\|^2 \\ - \|f(x_i^a) - f(x_i^n)\|^2 + \alpha] \end{aligned} \tag{1}$$

In Equation 1, the function $f(x)$ maps input images to a 4096-dimensional embedding. The anchor, positive, and negative samples are denoted as a, p, and n, respectively. The margin parameter α controls the relative distance between positive and negative pairs to maximize their separation.

The selection of a 224x224 pixel input resolution is a deliberate choice as it strikes a balance between computational efficiency and the level of detail necessary for accurate hand gesture recognition and palm print authentication. Our hand gesture detection employs the BlazePalm [43] model as a feature extractor, while palm print authentication is facilitated by the XceptionNet model [40]. Both models are pre-trained and belong to established convolutional neural network architectures, which are typically optimized for this specific input size (224 x 224 pixels). This alignment with standard input dimensions allows for leveraging the inherent advantages of these well-established models, thereby enhancing the overall performance and reliability of our system.

IV. Experimental Results

We conducted extensive testing on three benchmark datasets. The first dataset assessed the model's ability to accurately detect gestures in images, resulting in an impressive 96.16%. accuracy [44]. The second dataset [45] was utilized to evaluate the model's detection rate, yielding an accuracy of 87.37%. Further, we evaluated the proposed Siamese network-based palmprint authentication system using the CASIA dataset [46], resulting in an accuracy rate of over 90%. Benchmark datasets utilized are shown in Figure. 8.

TABLE II
Results of proposed Hand Gesture Recognition Model on the HANDS dataset [44]

Gesture name	Total frames	Accurately predicted frames	Accuracy %
Collab	750	670	89.33
TimeOut	750	686	91.46
XSign	750	704	93.86
Eight_VRF	750	708	94.40
Seven_VRF	750	714	95.20
Eight_VRF	750	718	95.73
Horiz_HRF	750	727	96.93
Span_VRF	750	728	97.06
Six_VRF	750	732	97.60
Five_VRF	750	733	97.73
Four_VRF	750	736	98.13
Three_VRF	750	738	98.40
Two_VRF	750	739	98.53
One_VRF	750	741	98.80
Punch_VRF	750	742	98.93
Total	**11250**	**10816**	**96.16%**

A. HANDS Dataset

The HANDS dataset comprises a substantial corpus of samples collected from 5 diverse participants, consisting of 3 male and 2 female individuals [44]. The participants were instructed to perform 16 pre-defined gestures, including 12 single-handed gestures performed with both arms and 4 double-handed gestures. Each gesture was captured in 150 RGB frames, resulting in a total of 11,250 images across all participants. Additionally, the gestures were captured from varying distances, resulting in a diverse range of depths and variations in hand poses. This dataset was specifically chosen to evaluate SimplyMime's gesture detection capabilities due to its comprehensive range of gestures and the inclusion of varied hand poses and distances, which are critical for assessing the robustness and accuracy of gesture recognition models. The dataset's extensive variety and depth make it particularly suited for testing the resilience of SimplyMime's architecture in real-world scenarios. Upon evaluation of the dataset, our proposed model achieved an overall accuracy of 96.16%. These performances are further highlighted in Figure 9 and Table II, illustrating the gesture-specific results.

To evaluate the effectiveness of the SimplyMime system, we conducted a comparative analysis against other notable models- Generative Adversarial Networks for hand gesture detection [47], MobileNetV2 architecture [48] as shown in Table III.

B. FreiHand Dataset

The FreiHand dataset is a benchmark dataset specifically designed to evaluate the performance of hand detection and hand pose estimation models [45]. The dataset contains over 32,560 frames of synchronized RGB and depth data, captured using Microsoft Kinect v2 sensors, collected from 32 participants. The participants were asked to perform a variety of actions, including American Sign Language signs, counting, and moving their fingers to their kinematic limits. They also interacted with various objects such as workshop tools (e.g., drills, wrenches, screwdrivers) and kitchen supplies (e.g., chopsticks, cutlery, bottles). These diverse actions and object interactions ensure that the dataset comprehensively captures

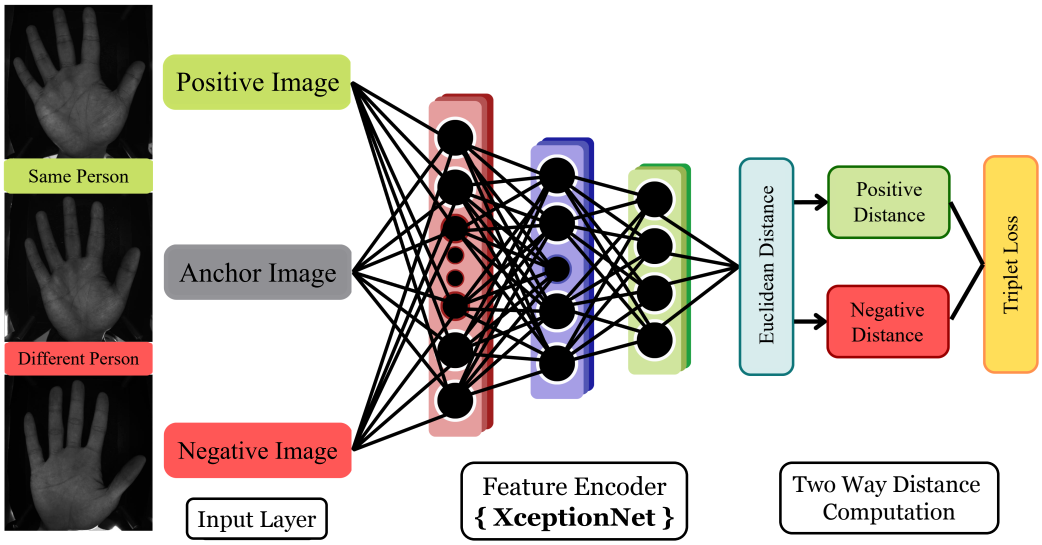
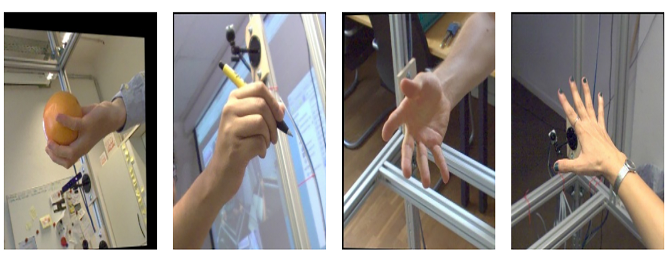
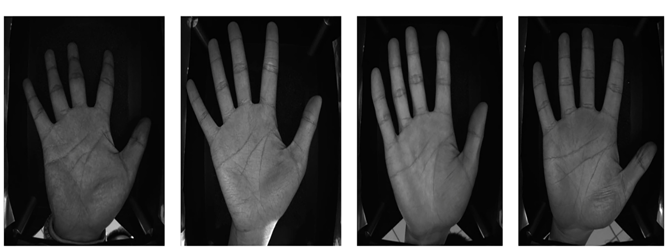


Fig. 7. Siamese Network-based Authentication model Operational Pipeline

(a) [HANDS Dataset [44]]



(b) [FreiHand Dataset [45]]



(c) [CASIA Dataset [46]]

Fig. 8. Benchmark Datasets Utilized in SimplyMime Experimentation

TABLE III
COMPARISON OF SIMPLYMIME WITH THE EXISTING SOLUTION

Research	Approach	Accuracy
Kim et al. (2017) [49]	CNN	90%
Dang et al. (2018) [50]	CNN with Parallel Convolution	91.28%
Nunez et al. (2018) [51]	CNN+LSTM	95.7%
Sagayam et al. (2019) [52]	HMM + SSA	90.74%
Chung et al. (2019) [53]	Deep CNN	95.61%
Sharma et al. (2020) [54]	KNN+ORB	95.81%
Tasmere et al. (2021) [55]	CNN	94.61%
Dang et al. (2022) [48]	MobileNetV2	94%
Feng et al. (2022) [47]	GANs	96%
Xiong et al. (2023) [56]	Deep CNN	85.75%
Leelakittisin et al. (2023) [57]	GLF-CNN	88.34%
SimplyMime	CNN based Skeletal Pose Estimation	96%

different types of grasps and hand movements, making it ideal for testing the robustness of hand detection models.

Additionally, while YOLO is often regarded as faster than SSD, its grid-based method can struggle with the detection of small objects. Particularly, YOLO models even with the integration of FPN, may not extract features as effectively as SSD for small objects. This is because SSD specifically leverages multiple feature maps from different levels of the network to make predictions, capturing more detailed information. A detailed performance analysis, depicted in Figure 11, compares the inference speed and performance of our model with that of Faster R-CNN and YOLO, demonstrating the tailored efficacy of our architecture for hand gesture recognition.

Table IV presents a comparative analysis of the performance metrics for Raspberry Pi 4, Jetson Nano, and Arduino Portenta H7 across different configurations. It highlights the latency, RAM usage, flash memory consumption, and accuracy for both quantized (int8) and unoptimized (float32) models. The results indicate varying performance characteristics depending

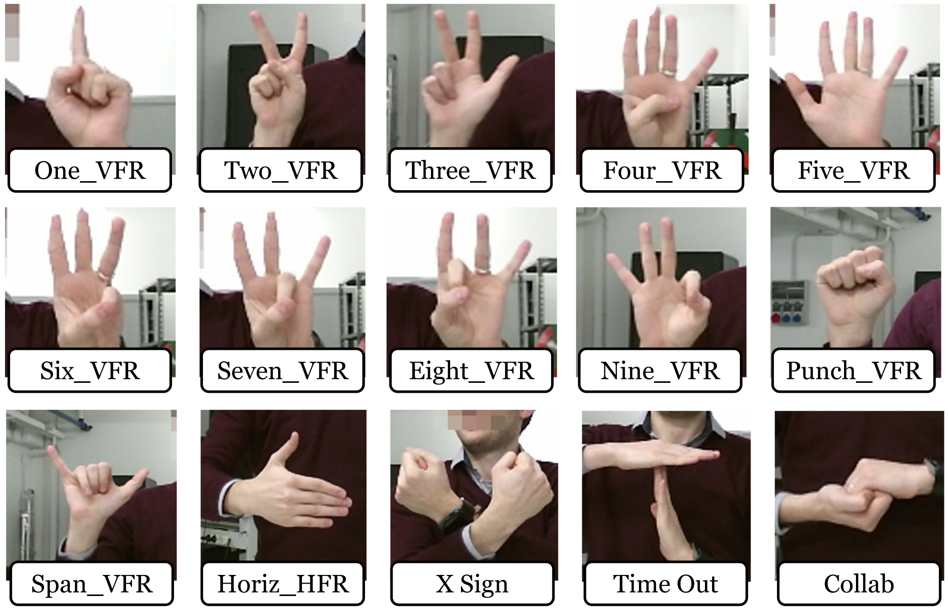


Fig. 9. Results of Various Gestures Classified and Labeled

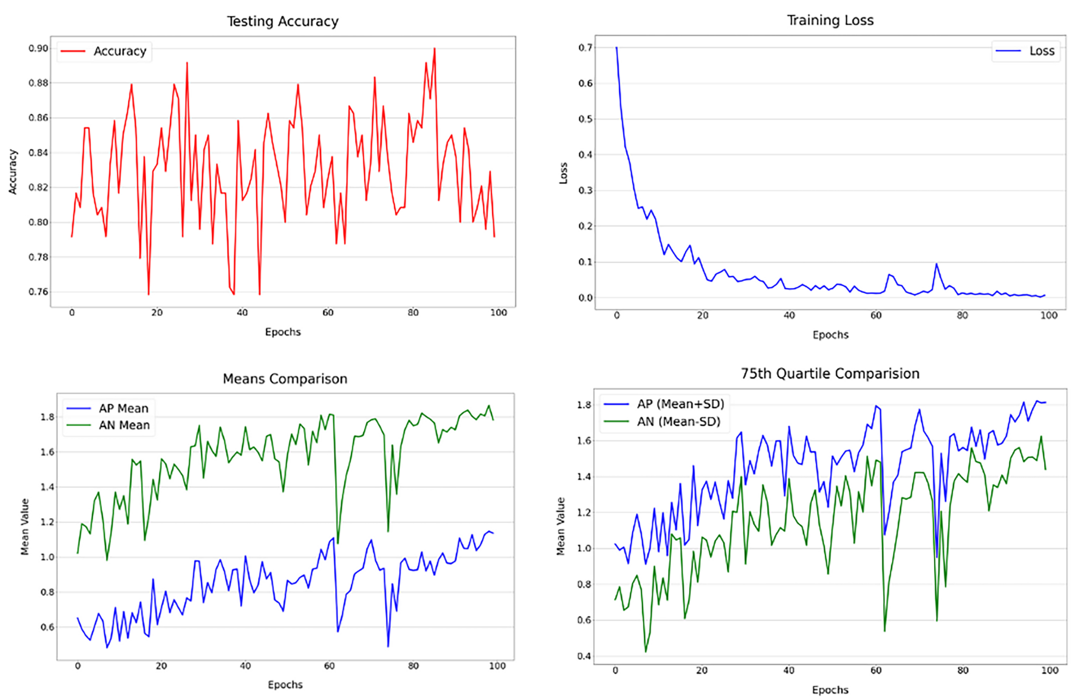


Fig. 10. Performance Measures of the Proposed Palmprint Authentication Model

on the hardware and model optimizations, with each device showcasing unique strengths in specific configurations.

In addition to evaluating the performance of the proposed model, we assessed the accuracy of our palmprint identification component using the CASIA Palmprint Image Database (CASIA-Palmprint) [46]. This dataset comprises 5,502 palmprint images captured from 312 subjects, providing a diverse and comprehensive collection of palmprints under various lighting conditions. For our experiments, we utilized a subset of the data, focusing on images taken in the lowest wavelength sample and white light, resulting in a dataset with 12,000 samples in total. This subset was chosen to rigorously test the model's performance under different lighting conditions, crucial for real-world applicability.

We pre-processed the dataset leveraging a custom data loader that generated test triplets from the CASIA dataset, where a triplet consists of an anchor image, a positive image, and a negative image. During training, the model was presented with these triplets, using the triplet loss function to optimize the embedding space, ensuring that similar images

TABLE IV
DEVICE PERFORMANCE COMPARISON OF SIMPLYMIME ON VARIOUS DEVICES [RASPBERRY PI 4, JETSON NANO, AND ARDUINO PORTENTA H7

Device	Configuration	Latency (per frame)	Latency (model)	RAM	Flash	Accuracy
Raspberry Pi 4 (RAM – 8GB, Processor Family – CortexA)	Quantized (int8)	1 ms	3 ms	412K	229.3K	94.90%
	Unoptimized (float32)	1 ms	8 ms	1.4M	310.9K	94.90%
Jetson Nano (RAM – 4GB, Processor Family – CortexA)	Quantized (int8)	1 ms	9 ms	1.1M	229.3K	94.90%
	Unoptimized (float32)	1 ms	4 ms	1.1M	310.9K	94.90%
Arduino Portenta H7 (RAM – 440KB, Processor Family – CortexM7)	Quantized (int8)	1 ms	71 ms	1.1M	229.3K	94.90%
	Unoptimized (float32)	1 ms	115 ms	1.1M	310.9K	94.90%

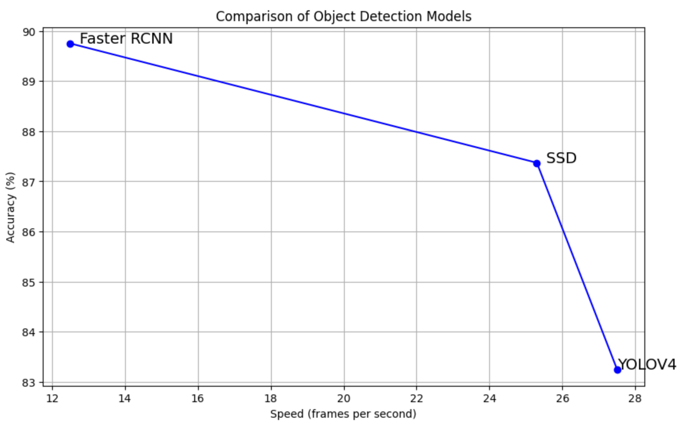


Fig. 11. Comparative Analysis of Object Detection Models

TABLE V
MODEL'S PERFORMANCE ON VARIOUS DATASETS

Evaluation Metric	FrieHand [45]	SHREC'17 (14 Gesture) [58]
Total images	32560	280000
Truly detected images	28448	221536
Falsely detected images	4112	58464
Accuracy	87.37%	79.12%
Error	12.62%	20.87%

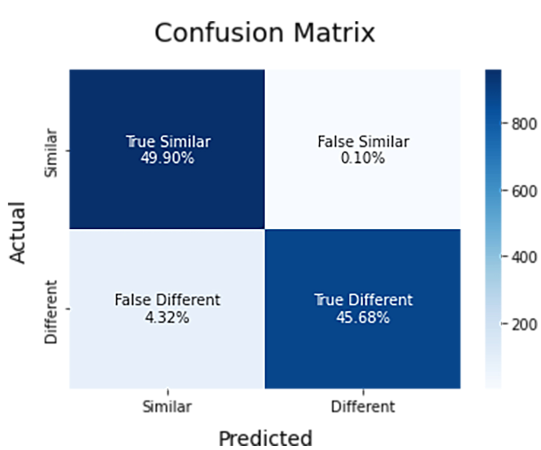


Fig. 12. Confusion Matrix Generated by the Siamese Networks

are closer together while dissimilar images are further apart.

The proposed model's training metrics are depicted in Figure 10. When trained, the model weights and biases were adjusted to better discriminate between the three inputs. Figure 12 illustrates the confusion matrix acquired from the test set of the data.

Our evaluation of the SimplyMime model on these benchmark datasets validates its strong performance in hand gesture recognition and palmprint identification. The HANDS dataset was selected for its comprehensive gesture variety and diverse participant demographics, providing a thorough test of gesture recognition capabilities. The FreiHand dataset was chosen for its challenging conditions that mimic real-world scenarios, ensuring robustness in various environments. The CASIA dataset was employed to rigorously test the palmprint authentication system under different lighting conditions. These datasets collectively demonstrate SimplyMime's efficacy, outperformance of existing solutions, and enhanced practicality and usability in real-world scenarios. This innovative combination of hand gesture recognition and palmprint identification represents a significant advancement in human-computer interaction.

C. Evaluation of SimplyMime Usability

We performed Usability Testing (UT) of SimplyMime with the help of 44 engineering students, faculty, staffs from VIT-AP University . The participants were asked to use SimplyMime while at the same time completing a comprehensively oriented questionnaire. Some of these self-developed questions consist of perceived easy interface, satisfied the 'easier to operate than the original remote control' condition, and satisfaction with the system. Some of the following responses indicated that a significant population of users regarded SimplyMime to be highly usable, or more preferable to conventional remote controls. In addition, the responses obtained showed high satisfaction with the technology with variations in the perceived ease of the technology.

Figure. 13 shows the detailing responses of the participants from VIT-AP University who tested SimplyMime's usability. The graphs encompass data about the age of the participants, the participants' generalized willingness towards using SimplyMime, the willingness to employ SimplyMime ahead of the standard remote control, and the satisfaction of the SimplyMime technology. This clear overview allows

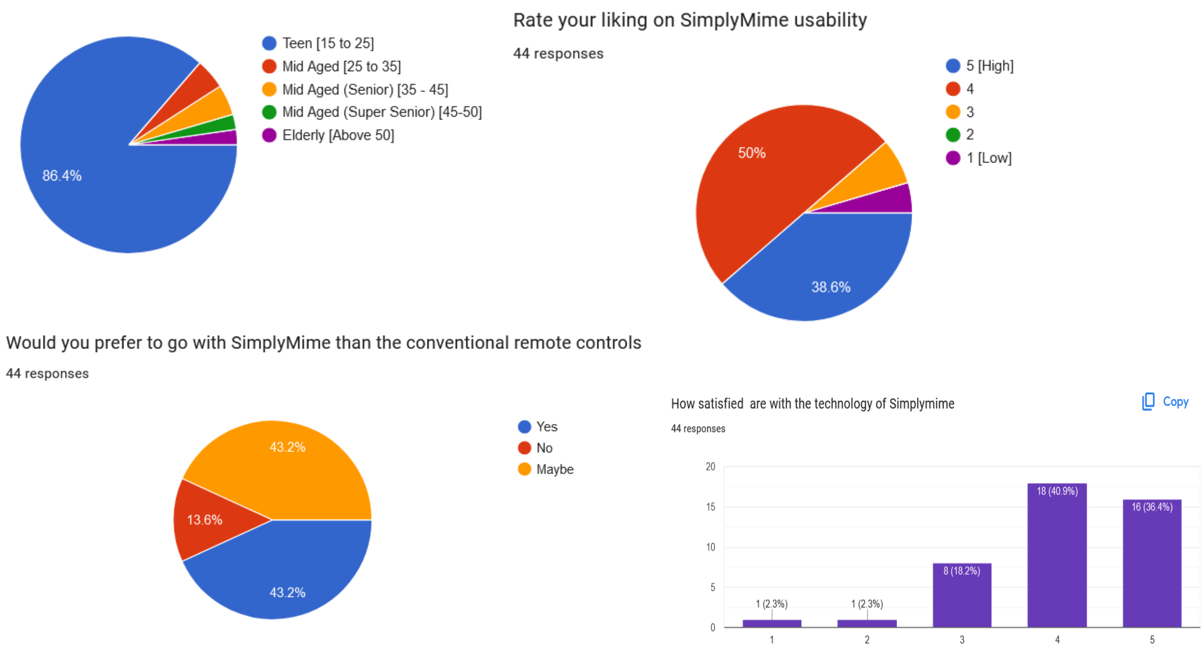


Fig. 13. Usability Testing and User Feedback of SimplyMime

identifying how people from various age groups can further assess the usability and efficiency of SimplyMime.

V. Conclusion and Future Enhancement

In this paper, we present SimplyMime, a novel hand gesture-based control system that aims to provide an immersive, efficient, and secure user experience. Eliminating the need for multiple remote controls, the system leverages advanced hand gesture recognition techniques, to create a sophisticated architecture that can recognize a wide range of hand gestures with high accuracy. Additionally, SimplyMime incorporates a palmprint authentication module, which enhances the security of the system by ensuring that only authorized users can access the device. Through thorough testing and evaluation, SimplyMime achieved accuracy levels of 96.16% for hand detection, 87.37% for gesture recognition, and 90% for palmprint authentication. These results serve as a testament to the effectiveness and efficiency of SimplyMime. Overall, SimplyMime offers significant advantages over traditional remote control systems, making it an excellent alternative for users looking for a more intuitive and efficient way of controlling their consumer electronics.

Despite the impressive performance of SimplyMime, there is still scope for further enhancements. Future improvements to the accuracy and dependability of the system could come from adding more sensors, like proximity and depth sensors, to increase the system's robustness. Subsequent developments will also try to lower the processing power needed while raising the model's accuracy.

Acknowledgments

A different version of this work is archived as [59]. A real-time video of the experimentation process, where we conducted our experiments in real-time, along with experimental images and the circuit diagram used in our study, can be found in [60].

References

[1] Z. Ming, Y. Zhang, X. Sun, X. Zeng, and J. Li, "Comparative life cycle assessment of smartphone and tablet production: A focus on critical raw materials and energy consumption," *Journal of Cleaner Production*, vol. 373, p. 134092, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0959652623016939

[2] T. Issa and P. Isaias, "Usability and Human–Computer Interaction (HCI)," in *Sustainable Design: HCI, Usability and Environmental Concerns*. Springer, 2022, pp. 23–40.

[3] M. Oudah, A. Al-Naji, and J. Chahl, "Hand Gesture Recognition Based on Computer Vision: A Review of Techniques," *J. Imag.*, vol. 6, no. 8, p. 73, Aug. 2020.

[4] A. D. Lotz, *Portals: A Treatise on Internet-Distributed Television*. Maize Books, 2017. [Online]. Available: https://www.fulcrum.org/concern/monographs/44558d29t

[5] C. S. Tang and S. Zhou, "Research advances in environmentally and socially sustainable operations," *European Journal of Operational Research*, vol. 287, no. 1, pp. 1–16, 2020. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0377221719309605

[6] X. Hou, W. Li, Y. Han, A. Wang, Y. Yang, L. Liu, and Y. Tian, "A novel mobile robot navigation method based on hand-drawn paths," *IEEE Sensors J.*, vol. 20, no. 19, pp. 11 660–11 673, 2020.

[7] S. Fong, Y. Zhuang, I. Fister, and I. Fister, "A biometric authentication model using hand gesture images," *BioMedical Engineering OnLine*, vol. 12, no. 1, p. 111, Oct. 2013. [Online]. Available: https://doi.org/10.1186/1475-925X-12-111

[8] B. Coffen and M. Mahmud, "TinyDL: Edge Computing and Deep Learning Based Real-time Hand Gesture Recognition Using Wearable Sensor," in *Proc. Intl. Conf. e-health Net. App. Ser.*, Mar. 2021, pp. 1–6.

[9] G. Singh, A. Nelson, R. Robucci, C. Patel, and N. Banerjee, "Inviz: Low-power personalized gesture recognition using wearable textile capacitive sensor arrays," in *Proc. Intl. Conf. Perv. Comp. Comm.*, Mar. 2015, pp. 198–206.

[10] J. McIntosh, A. Marzo, M. Fraser, and C. Phillips, "EchoFlex: Hand Gesture Recognition using Ultrasound Imaging," in *Proc. CHI Conf. Hum. Fac. Comp. Sys.*, 2017, pp. 1923–1934.

[11] R. Y. Wang and J. Popović, "Real-time hand-tracking with a color glove," *ACM Trans. Graphics*, vol. 28, no. 3, pp. 63:1–63:8, Jul. 2009.

[12] S. Feng and R. Murray-Smith, “Fusing Kinect sensor and inertial sensors with multi-rate Kalman filter,” in *Proc. IET. Conf. Data Fus. Tar. Track. Alg. App.*, 2014, pp. 1–8.

[13] A. Caputo, A. Giachetti, S. Soso, D. Pintani, A. D’Eusanio, S. Pini, G. Borghi, A. Simoni, R. Vezzani, R. Cucchiara, A. Ranieri, F. Giannini, K. Lupinetti, M. Monti, M. Maghoumi, J. J. LaViola Jr, M.-Q. Le, H.-D. Nguyen, and M.-T. Tran, “SHREC 2021: Skeleton-based hand gesture recognition in the wild,” *Comp. Grap.*, vol. 99, pp. 201–211, Oct. 2021.

[14] S. Yao, L. Vargas, X. Hu, and Y. Zhu, “A novel finger kinematic tracking method based on skin-like wearable strain sensors,” *IEEE Sensors J.*, vol. 18, no. 7, pp. 3010–3015, 2018.

[15] L. Guo, Z. Lu, and L. Yao, “Human-Machine Interaction Sensing Technology Based on Hand Gesture Recognition: A Review,” *IEEE Trans. Hum. Mac. Sys.*, vol. 51, no. 4, pp. 300–309, Aug. 2021.

[16] N. Mohamed, M. B. Mustafa, and N. Jomhari, “A review of the hand gesture recognition system: Current progress and future directions,” *IEEE Access*, vol. 9, pp. 157 422–157 436, 2021.

[17] L. Guo, Z. Lu, and L. Yao, “Human-machine interaction sensing technology based on hand gesture recognition: A review,” *IEEE Trans. Hum. Mac. Sys.*, vol. 51, no. 4, pp. 300–309, 2021.

[18] Y. Xue, Z. Ju, K. Xiang, J. Chen, and H. Liu, “Multimodal human hand motion sensing and analysis—a review,” *IEEE Trans.Cogni. Develop. Sys.*, vol. 11, no. 2, pp. 162–175, 2018.

[19] K. Teachasrisaksakul, L. Wu, G.-Z. Yang, and B. Lo, “Hand Gesture Recognition with Inertial Sensors,” in *Proc. Intl. Conf. Engg. Med. Bio. Soc.*, 2018, pp. 3517–3520.

[20] J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A survey,” *Patt. Recog. Let.*, vol. 119, pp. 3–11, 2019.

[21] K. Nguyen-Trong, H. N. Vu, N. N. Trung, and C. Pham, “Gesture Recognition Using Wearable Sensors With Bi-Long Short-Term Memory Convolutional Neural Networks,” *IEEE Sensors J.*, vol. 21, no. 13, pp. 15 065–15 079, Jul. 2021.

[22] G. Yuan, X. Liu, Q. Yan, S. Qiao, Z. Wang, and L. Yuan, “Hand Gesture Recognition Using Deep Feature Fusion Network Based on Wearable Sensors,” *IEEE Sensors J.*, vol. 21, no. 1, pp. 539–547, Jan. 2021.

[23] X. Zhang, Z. Yang, T. Chen, D. Chen, and M.-C. Huang, “Cooperative sensing and wearable computing for sequential hand gesture recognition,” *IEEE Sensors J.*, vol. 19, no. 14, pp. 5775–5783, 2019.

[24] L. Gan, Y. Liu, Y. Li, R. Zhang, L. Huang, and C. Shi, “Gesture recognition system using 24 ghz fmcw radar sensor realized on real-time edge computing platform,” *IEEE Sensors J.*, vol. 22, no. 9, pp. 8904–8914, 2022.

[25] F. Chen, H. Lv, Z. Pang, J. Zhang, Y. Hou, Y. Gu, H. Yang, and G. Yang, “WristCam: A Wearable Sensor for Hand Trajectory Gesture Recognition and Intelligent Human–Robot Interaction,” *IEEE Sensors J.*, vol. 19, no. 19, pp. 8441–8451, Oct. 2019.

[26] A.-M. Yang, J.-M. Zhi, K. Yang, J.-H. Wang, and T. Xue, “Computer vision technology based on sensor data and hybrid deep learning for security detection of blast furnace bearing,” *IEEE Sensors J.*, vol. 21, no. 22, pp. 24 982–24 992, 2021.

[27] J. Xu, H. Wang, J. Zhang, and L. Cai, “Robust Hand Gesture Recognition Based on RGB-D Data for Natural Human–Computer Interaction,” *IEEE Access*, vol. 10, pp. 54 549–54 562, 2022.

[28] D.-S. Tran, N.-H. Ho, H.-J. Yang, S.-H. Kim, and G. S. Lee, “Real-time virtual mouse system using RGB-D images and fingertip detection,” *Mult. Tools. App.*, vol. 80, no. 7, pp. 10 473–10 490, Mar. 2021.

[29] C.-C. Sun, Y.-H. Wang, and M.-H. Sheu, “Fast motion object detection algorithm using complementary depth image on an rgb-d camera,” *IEEE Sensors J.*, vol. 17, no. 17, pp. 5728–5734, 2017.

[30] S. Shin and W.-Y. Kim, “Skeleton-Based Dynamic Hand Gesture Recognition Using a Part-Based GRU-RNN for Gesture-Based Interface,” *IEEE Access*, vol. 8, pp. 50 236–50 243, 2020.

[31] P. Cao, Z. Wang, R. Gao, P. Li, R. Wang, and L. Li, “A comprehensive survey on hand gesture recognition with a comparative study on hand segmentation and feature extraction techniques,” *IEEE Transactions on Human-Machine Systems*, vol. 12, pp. 779–794, 2021. [Online]. Available: https://ieeexplore.ieee.org/document/9481557

[32] E. Fujiwara, M. dos Santos Rodrigues, M. K. Gomes, Y. T. Wu, and C. K. Suzuki, “Identification of hand gestures using the inertial measurement unit of a smartphone: a proof-of-concept study,” *IEEE Sensors J.*, vol. 21, no. 12, pp. 13 916–13 923, 2021.

[33] S. Sonkar, P. Kumar, R. C. George, T. Yuvaraj, D. Philip, and A. Ghosh, “Real-time object detection and recognition using fixed-wing lale vtol uav,” *IEEE Sensors J.*, vol. 22, no. 21, pp. 20 738–20 747, 2022.

[34] Y. Wu, F. Liu, L. Wan, and Z. Wang, “Intelligent fault diagnostic model for industrial equipment based on multimodal knowledge graph,” *IEEE Sensors J.*, 2023.

[35] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, “SSD: Single Shot MultiBox Detector,” in *Computer Vision – ECCV 2016*. Springer International Publishing, 2016, pp. 21–37.

[36] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, M. Andreetto, and H. Adam, “MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications,” Apr. 2017, arXiv:1704.04861 [cs]. [Online]. Available: http://arxiv.org/abs/1704.04861

[37] S.-E. Wei, V. Ramakrishna, T. Kanade, and Y. Sheikh, “Convolutional Pose Machines,” Apr. 2016, arXiv:1602.00134 [cs].

[38] T. Müller, G. Pérez-Torró, and M. Franco-Salvador, “Few-Shot Learning with Siamese Networks and Label Tuning,” Apr. 2022, arXiv:2203.14655 [cs]. [Online]. Available: http://arxiv.org/abs/2203.14655

[39] H. Xiang, X. Zhu, W. Shi, W. Fan, P. Chen, and S. Bao, “Delightlcd: A deep and lightweight network for loop closure detection in lidar slam,” *IEEE Sensors J.*, vol. 22, no. 21, pp. 20 761–20 772, 2022.

[40] F. Chollet, “Xception: Deep Learning with Depthwise Separable Convolutions,” Apr. 2017, arXiv:1610.02357 [cs] version: 3. [Online]. Available: http://arxiv.org/abs/1610.02357

[41] E. Hoffer and N. Ailon, “Deep metric learning using Triplet network,” Dec. 2018, arXiv:1412.6622 [cs, stat]. [Online]. Available: http://arxiv.org/abs/1412.6622

[42] H. Xiao, K. Peng, X. Huang, A. Roitberg, H. Li, Z. Wang, and R. Stiefelhagen, “Towards privacy-supporting fall detection via deep unsupervised rgb2depth adaptation,” *IEEE Sensors J.*, 2023.

[43] “MediaPipe Hands: On-device Real-time Hand Tracking — arxiv.org,” https://arxiv.org/abs/2006.10214, [Accessed 10-03-2024].

[44] C. Nuzzi, S. Pasinetti, R. Pagani, G. Coffetti, and G. Sansoni, “HANDS: an RGB-D dataset of static hand-gestures for human-robot interaction,” *Data in Brief*, vol. 3, p. 106791, Apr. 2021.

[45] C. Zimmermann, D. Ceylan, J. Yang, B. Russell, M. Argus, and T. Brox, “FreiHAND: A Dataset for Markerless Capture of Hand Pose and Shape from Single RGB Images,” Sep. 2019, arXiv:1909.04349 [cs].

[46] Z. Sun, T. Tan, Y. Wang, and S. Li, “Ordinal palmprint represention for personal identification [represention read representation],” in *Intl. Conf. Comp. Vis. Patt. Recog.*, 2005, pp. 279–284.

[47] J. Feng, P. Ji, and F. Ma, “Gesture Position Detection Based on Generative Adversarial Networks,” in *Proc. Intl. Conf. Rob. Cont. Engg.* Association for Computing Machinery, 2022, pp. 39–44.

[48] T. L. Dang, S. D. Tran, T. H. Nguyen, S. Kim, and N. Monet, “An improved hand gesture recognition system using keypoints and hand bounding boxes,” *Array*, vol. 16, p. 100251, 2022.

[49] S. Y. Kim, H. G. Han, J. W. Kim, S. Lee, and T. W. Kim, “A hand gesture recognition sensor using reflected impulses,” *IEEE Sensors J.*, vol. 17, no. 10, pp. 2975–2976, 2017.

[50] G. Devineau, F. Moutarde, W. Xi, and J. Yang, “Deep learning for hand gesture recognition on skeletal data,” in *Proc. Intl. Conf. Auto. Face. Ges. Recog.* IEEE, 2018, pp. 106–113.

[51] J. C. Nunez, R. Cabido, J. J. Pantrigo, A. S. Montemayor, and J. F. Velez, “Convolutional neural networks and long short-term memory for skeleton-based human activity and hand gesture recognition,” *Patt. Recog.*, vol. 76, pp. 80–94, 2018.

[52] K. M. Sagayam and D. J. Hemanth, “A probabilistic model for state sequence analysis in hidden markov model for hand gesture recognition,” *Comp. Intell.*, vol. 35, no. 1, pp. 59–81, 2019.

[53] H.-Y. Chung, Y.-L. Chung, and W.-F. Tsai, “An efficient hand gesture recognition system based on deep cnn,” in *Proc. Intl. Conf. Ind. Techn.* IEEE, 2019, pp. 853–858.

[54] A. Sharma, A. Mittal, S. Singh, and V. Awatramani, “Hand gesture recognition using image processing and feature extraction techniques,” *Proc. Comp. Sci.*, vol. 173, pp. 181–190, 2020.

[55] D. Tasmere, B. Ahmed, and S. R. Das, “Real time hand gesture recognition in depth image using cnn,” *Intl. J. of Comp. Appli.*, vol. 174, no. 16, pp. 28–32, 2021.

[56] B. Xiong, W. Chen, Y. Niu, Z. Gan, G. Mao, and Y. Xu, “A global and local feature fused cnn architecture for the semg-based hand gesture recognition,” *Comp. Bio. Med.*, vol. 166, p. 107497, 2023.

[57] B. Leelakittisin, M. Trakulruangroj, S. Sangnark, T. Wilaiprasitporn, and T. Sudhawiyangkul, “Enhanced lightweight cnn using joint classification with averaging probability for semg-based subject-independent hand gesture recognition,” *IEEE Sensors J.*, 2023.

[58] J.-P. V. J. G. B. L. S. D. F. Quentin De Smedt, Hazem Wannous, "Shrec'17 track: 3d hand gesture recognition using a depth and skeletal dataset," in *Euro. Work. 3D obj. ret.*, 2017.
[59] S. C. Sethuraman, G. R. Tadkapally, A. Kiran, S. P. Mohanty, and A. Subramanian, "Simplymime: A control at our fingertips," 2023. [Online]. Available: https://arxiv.org/abs/2304.11377
[60] ——, "Simplymime - realtime experimentation video, youtube link, circuit diagram & source code," Mar. 2024. [Online]. Available: https://github.com/sibichakkaravarthy/SimplyMime

Sibi C. Sethuraman (M'18) received his Ph.D. from Anna University in the year 2018. He is an Associate Professor in the School of Computer Science and Engineering at Vellore Institute of Technology – Andhra Pradesh (VIT-AP) University. Further, he is the coordinator for the Artificial Intelligence and Robotics (AIR) Center at VIT-AP. He is an active reviewer in many reputed journals including IEEE, Springer, and Elsevier. He is a recipient of the DST fellowship.

Gaurav Reddy Tadkapally (S'19) is a Master of Science student at University of Southern California (USC) specializing in the applications of Artificial Intelligence in Consumer Electronics and Embedded Hardware. As a member of the Artificial Intelligence and Robotics Center at VIT-AP, Gaurav has developed innovative technologies such as iDrone, an IoT-powered drone for wildfire detection, and MagicEye, an intelligent wearable for visually impaired individuals.

Athresh Kiran (M'22) received a bachelor's degree in Computer Science & Engg. from the VIT-AP University, India, in 2021. He is currently working in Parallel Reality Limited, UK. His research interests include reality platforms, Metaverse, IT, and full-stack development.

Saraju P. Mohanty (Senior Member, IEEE) received the bachelor's degree (Honors) in electrical engineering from the Orissa University of Agriculture and Technology, Bhubaneswar, in 1995, the master's degree in Systems Science and Automation from the Indian Institute of Science, Bengaluru, in 1999, and the Ph.D. degree in Computer Science and Engineering from the University of South Florida, Tampa, in 2003. He is a Professor with the University of North Texas. His research is in "Smart Electronic Systems" which has been funded by National Science Foundations (NSF), Semiconductor Research Corporation (SRC), U.S. Air Force, IUSSTF, and Mission Innovation. He has authored 500 research articles, 5 books, and invented 10 granted/pending patents. His Google Scholar h-index is 57 and i10-index is 243 with 13,000 citations. He is a recipient of 19 best paper awards, Fulbright Specialist Award in 2021, IEEE Consumer Electronics Society Outstanding Service Award in 2020, the IEEE-CS-TCVLSI Distinguished Leadership Award in 2018, and the PROSE Award for Best Textbook in Physical Sciences and Mathematics category in 2016. He has delivered 24 keynotes and served on 14 panels at various International Conferences. He has been the Editor-in-Chief of the IEEE Consumer Electronics Magazine during 2016-2021 and currently serves on the editorial board of 8 journals/transactions. He has mentored 3 post-doctoral researchers, and supervised 15 Ph.D. dissertations, 27 M.S. theses, and 27 undergraduate senior-projects.

Anitha Subramanian (M'22) received the bachelor's degree in Electronics & Communication Engg. from Anna University, India, in 2017, a master's degree in Power Electronics from Anna University University in 2019, and she is currently pursuing her Ph.D. degree in Electronics Engineering from VIT-AP University.