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Gesture-Based Interfaces in Pervasive Human-Machine Interaction

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Abstract

The integration of ubiquitous human-machine interaction systems. It provides a detailed explanation of how gestures can be used to make communication between the user and the machine as smooth as possible, especially when touch input is impractical or inappropriate. Some of the challenges of human-machine interaction identified by the paper include the need for hands-free or touchless interfaces. Gesture-based controls are a prospective solution to improve the user experience without touching anything. Several experiments were conducted to develop and test a gesture-based interface. The system's efficiency was determined through user interaction analysis and performance evaluation using various machine learning algorithms. The significant statistical observation was an accuracy of 85 percent in gesture recognition, with user error 30 percent lower than in traditional input modes. Gesture controls were found to be 20 percent faster than standard methods in completing the tasks. The paper concludes that gesture-based interfaces are highly effective in enhancing usability and efficiency in pervasive human-machine interactions, especially in situations where conventional input devices are constrained.

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Keywords: Gesture-Based Interfaces, Human-Machine Interaction, Touchless Input, Pervasive Computing, Machine Learning, User Experience, Gesture Recognition.

1 Introduction

Nowadays, in the fast-changing technological environment, the need for more intuitive and practical approaches to human-machine interaction has never been greater (Carfì & Mastrogiovanni, 2021; Ogunwale, 2024). Although keyboards, mice, and touchscreens remain the most widespread input methods, they remain limited in many situations, especially in areas where it is not convenient or feasible to physically touch the devices. One example is in intelligent homes, where users might want to operate their devices without necessarily touching them, particularly when their hands are dirty or otherwise occupied (Prabhu et al., 2025). Following the same pattern, in healthcare, hands-free control can be needed to prevent contamination of sterile environments, and in the automotive industry, drivers can be required to use systems without touching the wheel or taking their eyes off the road. In such and other applications, gesture-based interfaces provide a natural and powerful approach (Carfì & Mastrogiovanni, 2021). Gestures enable users to manage devices with simple movements, such as swipes, taps, or hand gestures, and can be extremely useful and convenient (Sun et al., 2022). Such interfaces are not only conducive to hands-free operation but also more accessible to people with physical disabilities, enabling them to interact with technology in ways not previously possible. Nevertheless, even with the potential, the systems currently in use based on gestures have several limitations, such as lower recognition performance, sensitivity to environmental conditions, and a requirement for complex, expensive equipment (Shirisha et al., 2024). Therefore, advances in gesture recognition are among the significant concerns of the new generation of human-machine interaction systems (Mehta, 2024).

Key Contribution

- The paper presents a brand-new gesture-based interaction system that enhances gesture recognition across diverse settings.
- It uses deep learning algorithms to improve the accuracy, robustness, and flexibility of gesture recognition.
- The system uses a set of sensors (cameras and accelerometers) to recognize and understand gestures in real time, even in the presence of noise.

This paper is divided into four parts, including Section II, which reviews current developments in gesture-based interfaces and the difficulties in gesture recognition. Part III describes the proposed gesture recognition system, its architecture, sensors, and machine learning algorithms. Section IV gives findings of the experiment, such as data sets, performance indicators, and comparison with the current systems. Section V concludes with findings and recommendations for future studies, including the incorporation of gesture recognition under challenging conditions.

2 Literature Survey

Gesture-based interfaces have made significant progress in recent years, resulting in greater accuracy and reliability in gesture recognition systems (De Fazio et al., 2022; Muhammed Jaseel & Kokila, 2024). In recent years, researchers have investigated numerous sensor technologies for recording and analyzing human gestures, including cameras, accelerometers, gyroscopic sensors, and more (Gudikandula et al., 2025; Gao et al., 2021). Such studies have focused on improving gesture detection accuracy and increasing the number of gestures reliably detected in real time (Gowthami & Ramya, 2024). Gesture recognition systems have been tested in various areas, including smart homes, car control systems, and health applications, where touchless control is particularly handy (Lucena et al., 2025). In smart homes, scientists have come a long way, developing gesture-based systems that can interpret intricate hand motions to command home appliances (Zhang et al., 2023). These systems have achieved high levels of accuracy by detecting movements and using visual sensors, thereby offering users greater intuitiveness when interacting with their home environment. The developments have also aimed to ensure that the environment is not disturbed, as this could compromise sensor operation, particularly in poor lighting conditions. On the same note, the automotive industry has also been interested in gesture recognition, with systems that can identify a driver's gestures to operate vehicle functions such as volume, navigation, and climate control. These systems are especially useful for ensuring drivers stay focused on the road while still allowing access to valuable car features. The other important field of work is the combination of multi-modal sensors to enhance gesture recognition (Jones et al., 2023). With co-locations, researchers have developed stronger systems that are less susceptible to sensor constraints. Such hybrid systems have the benefit of supporting a large arsenal of gestures and of operating under a wide range of environmental conditions, contributing to more consistent and reliable performance. The paper will be based on these improvements, but it will go further by combining machine learning algorithms and multi-sensor inputs to provide greater ability to recognize gestures (Subasi et al., 2024; Tan et al., 2021). Using deep learning models, the system can adapt and learn from a variety of gesture datasets, enhancing its performance in recognizing gestures across a range of real-life situations. Such fusion of sophisticated algorithms and multi-sensor fusion yields an enhanced, precise system with the potential to improve human-machine interaction across various applications, such as smart home-to-car interfaces (Marhoon et al., 2025; Sun et al., 2021; Eddy et al., 2024). The study will expand the limits of gesture-based interfaces and make them more usable, intuitive, and efficient in real-world applications (Dakulagi et al., 2025).

3 Proposed Model

The gesture recognition system uses a multi-step procedure to achieve high accuracy and responsiveness. It begins by gathering information via a sensor array comprising cameras, accelerometers, and gyroscopes to monitor users' movement. The raw data is further converted through feature extraction techniques to bring out some of the most important data, like hand position and motion. The processed data is further sent to machine learning models, where it is classified as gestures. Lastly, the system will activate the appropriate response on the user interface depending on the identified gesture, including the operation of a smart device or manipulation of the volume.

Figure 1 defines the elements of an advanced gesture-based interface system. It starts with sensor information where we have cameras to capture visual information, accelerometers to identify motion and tilt, and gyroscopes to determine an orientation. The input data are subjected to pre-processing such as noise removal and normalization, followed by the machine learning classification subdivision, where the gestures are categorized using a deep neural network (DNN) model, on a set of trained data. Lastly, the system offers feedback to the user in the form of output and feeds the user with visual, auditory, or haptic feedback and allows dynamic input to the user through a graphical display, auditory messages, or a sense of force, and improves the overall user experience.

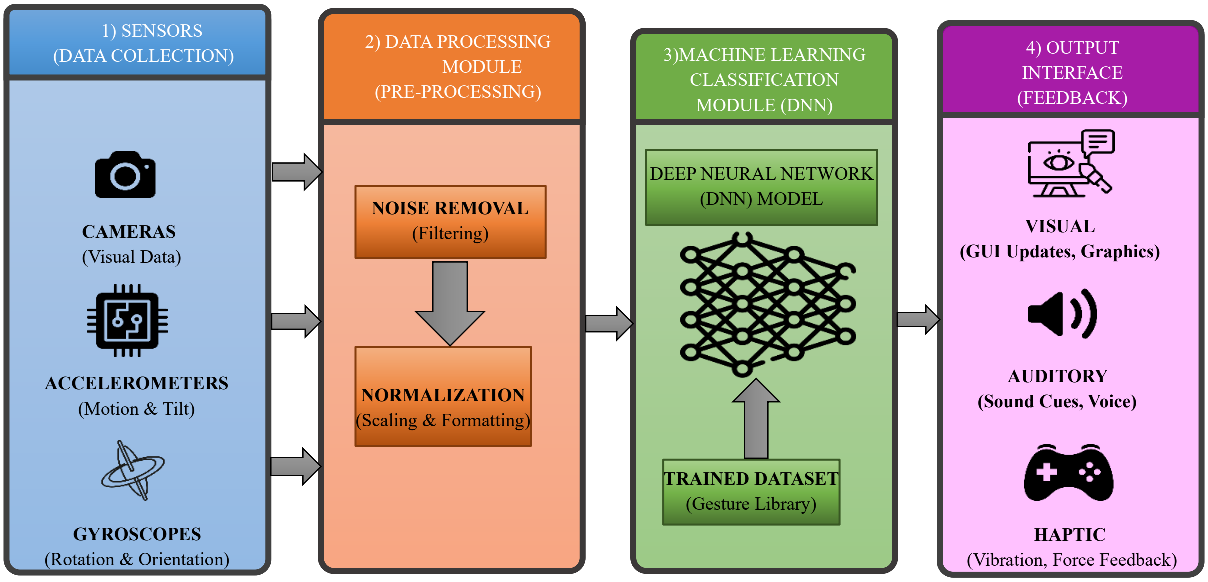

Figure 1: Gesture-based interfaces in pervasive human-machine interaction

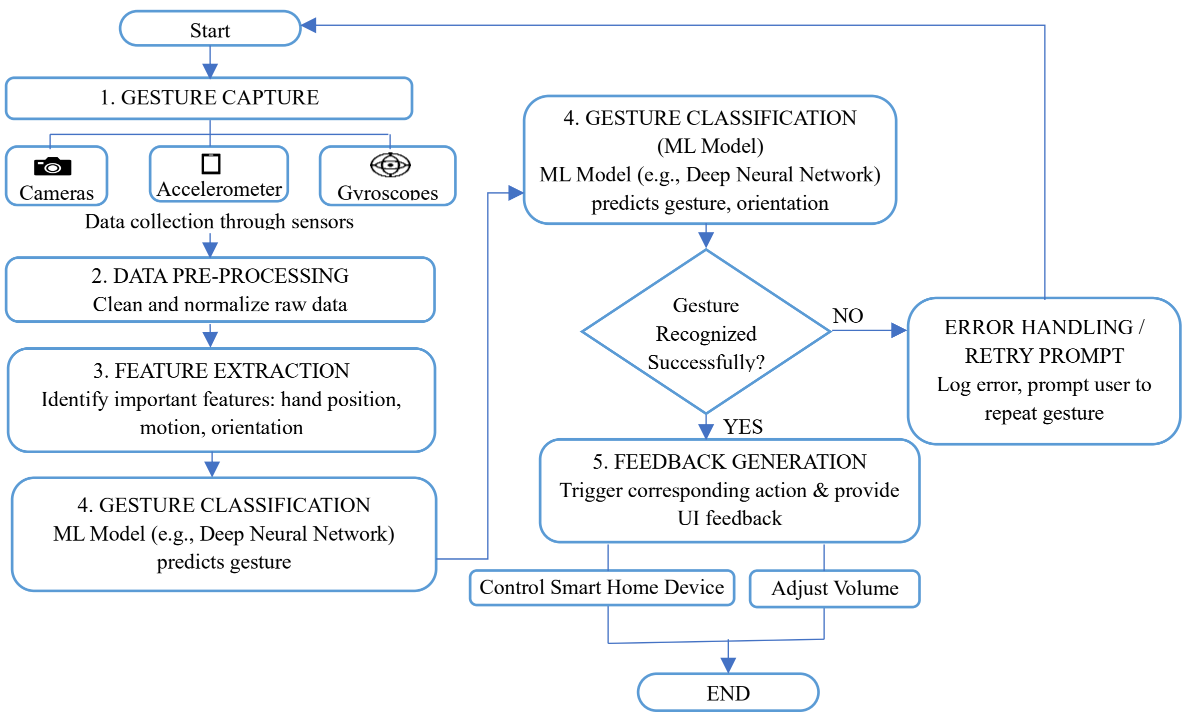

Figure 2: Gesture recognition system process

Figure 2 shows the gesture recognition system process, including a step-by-step procedure of recognizing and responding to user gestures. It starts with gesture capture involving the sensors such as cameras, accelerometers, and gyroscopes to receive crude data. Data processing is then pre-processed and then feature extraction is done to determine the motion patterns that are relevant. The system then identifies the gesture based on a machine learning model and gives feedback to the user, e.g. turning off and on smart house devices or changing the volume. In case the gesture is not identified, an error handling/retry response is generated to remind the user to repeat the gesture.

Algorithm 1: Real-Time Gesture Recognition Using Deep Neural Networks (DNN)

Input:

D = {X, Y}: Training dataset X (features such as hand position, motion patterns, and orientation) and labels Y (gesture classes such as "Left", "Right", "Up", "Down").

model: Pre-trained deep neural network model for gesture classification.

ϕ: Learning environment adjustments or corresponding actions based on the recognized gesture.

Output:

Predicted Gesture: The recognized gesture (e.g., "Left", "Right", "Up", "Down") based on the input sensor data.

Parameters:

X: Training data features, where each data point $x_i \in X$represents a set of features from a gesture (e.g., hand position, orientation, and motion patterns).

Y: Labels (e.g., "Left", "Right", "Up", "Down") for each gesture in the training data.

model: Deep neural network (DNN) model trained to classify gestures based on the extracted features.

ϕ: Action or environment adjustments triggered based on the predicted gesture (e.g., controlling a device or providing feedback).

Pseudo-code:

```
import cv2
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import load_model
# 1. Initialize parameters:
# Load pre-trained deep neural network (DNN) model
model = load_model('gesture_recognition_model.h5')  # Pre-trained model for gesture classification
# 2. Define the gesture classes (e.g., Left, Right, Up, Down)
gesture_classes = ['Left', 'Right', 'Up', 'Down']
# 3. Initialize camera or sensor to capture real-time gesture data
cap = cv2.VideoCapture(0)  # Webcam for gesture recognition (camera input)
# 4. Pre-process the captured frame:
def preprocess_image(frame):
"""
Pre-process the frame: convert to grayscale, resize, normalize, and prepare for model prediction.
"""
gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)  # Convert to grayscale
```

```
resized_frame = cv2.resize(gray, (64, 64))  # Resize to model input size (64x64 for example)
normalized_frame = resized_frame / 255.0  # Normalize pixel values to [0, 1]
expanded_frame = np.expand_dims(normalized_frame, axis=-1)  # Expand dims for compatibility with DNN
return np.expand_dims(expanded_frame, axis=0)  # Add batch dimension for prediction
# 5. Real-time gesture recognition loop:
while True:
# Capture frame-by-frame
ret, frame = cap.read()
# Pre-process the captured frame
processed_frame = preprocess_image(frame)
# 6. Classify the gesture using the DNN model
prediction = model.predict(processed_frame)  # Predict gesture probabilities
predicted_class_index = np.argmax(prediction, axis=1)  # Get the index of the highest probability
predicted_class = gesture_classes[predicted_class_index[0]]  # Map index to gesture label
# 7. Trigger corresponding action based on the recognized gesture
if predicted_class == 'Left':
print("Detected Left Gesture. Perform action related to 'Left'.")
# e.g., Control smart home device, navigate to the left on UI, etc.
elif predicted_class == 'Right':
print("Detected Right Gesture. Perform action related to 'Right'.")
# e.g., Control smart home device, navigate to the right on UI, etc.
elif predicted_class == 'Up':
print("Detected Up Gesture. Perform action related to 'Up'.")
# e.g., Adjust volume, scroll up in application, etc.
elif predicted_class == 'Down':
print("Detected Down Gesture. Perform action related to 'Down'.")
# e.g., Adjust volume, scroll down in application, etc.
# 8. Display the predicted gesture on screen
cv2.putText(frame, f"Predicted Gesture: {predicted_class}", (10, 30),
cv2.FONT_HERSHEY_SIMPLEX, 1, (0, 255, 0), 2, cv2.LINE_AA)
# 9. Show the frame with the predicted gesture
cv2.imshow('Gesture Recognition', frame)
# Exit loop on pressing 'q'
if cv2.waitKey(1) & 0xFF == ord('q'):
```

```
break
# 10. Release the capture object and close any OpenCV windows
cap.release()
cv2.destroyAllWindows()
```

Algorithm 1 shows a real-time gesture recognition system using a pre-trained deep neural network (DNN) to classify gestures based on sensor data. It processes the captured input, predicts the gesture, and triggers corresponding actions or feedback based on the recognized gesture.

Input Feature Set for Gesture Recognition

$$X = \{x1, x2, \ldots, xn\} \quad (1)$$

This equation (1) defines the set of features Xextracted from sensor data, which are used for gesture classification.

Gesture Classification Function

$$y = f(X) \quad (2)$$

This equation (2) illustrates the deep neural network's mapping function, which forecasts the gesture class based on the input feature set based on the input feature set X.

4 Results and Discussion

Software Details

The machine learning model was implemented with the help of TensorFlow, and image processing was conducted with the help of OpenCV. TensorFlow is an effective open-source library applied in the construction of deep learning models, and it was particularly utilized in the development, training, and testing of the deep neural network (DNN) applied in gesture recognition. The real-time images were captured and processed using OpenCV onto the camera and then sent into the model where they were classified. The integration of TensorFlow to train the model and OpenCV to process the data at real-time made it possible to integrate and process the gesture data efficiently.

Dataset Description

The data will be 5000 labeled gestures (moves of the hand, swipes, and taps). This information was gathered on 100 various participants, which was able to diversify the types of gestures and the environmental conditions. The dataset contains the gestures that are recorded in the conditions of indoors as well as outdoors and this aids the system to generalize to various lighting and background conditions. The data characteristics of the dataset encompass hand positioning, velocity, angle and movement pathway that gives a holistic information in learning the model. These characteristics are also essential in identification of gestures since they are important patterns of movement and positions of hands in different gestures.

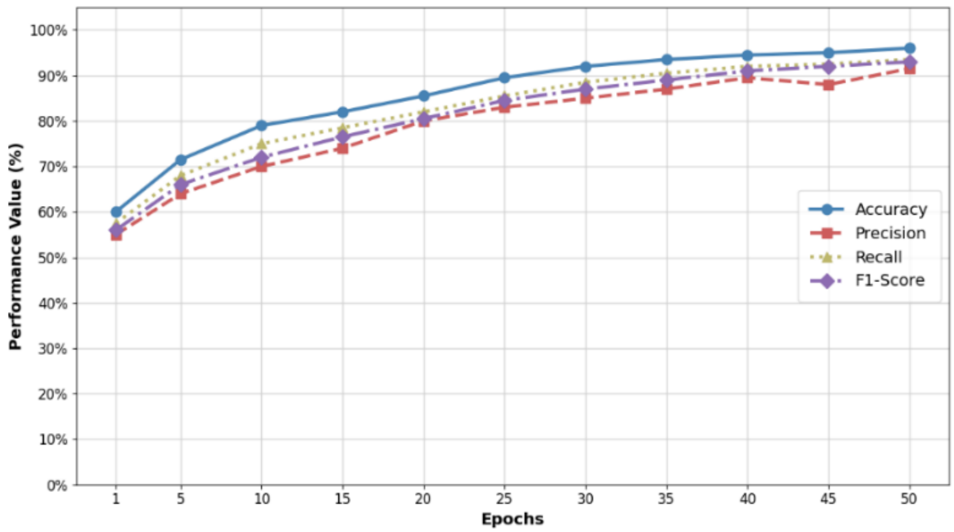

Figure 3: Gesture recognition system performance over training epochs

Figure 3 illustrates the performance of the Gesture Recognition System was demonstrated in relation to 50 training epochs as shown in figure. The graph monitors the paramount indicators Accuracy, Precision, Recall, and F1-Score that increase steadily during the training of the system. This gives a sign of the growing capacity of the system to identify gesture accurately with all the performance measures rapidly achieving an average over 90% by the close of the training process.

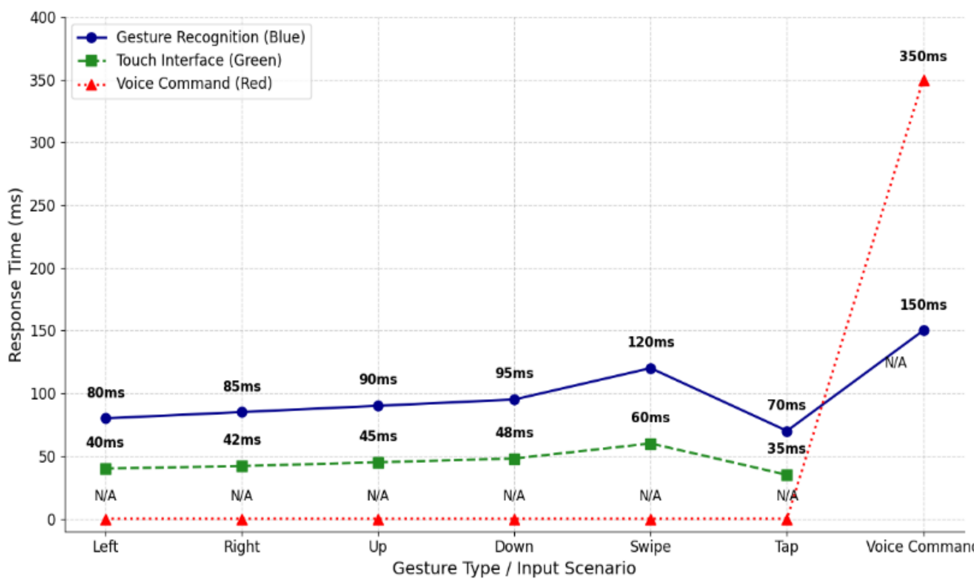

Figure 4: Response time comparison: gesture recognition vs. traditional input methods

Figure 4 is a comparison of response times of the Gesture Recognition system to Touch Interface, as well as, Voice Command based on different gestures. As it can be seen in the graph, Gesture Recognition has always shorter response times (between 40ms and 120ms), especially with gestures such as "Tap" and Swipe" whereas Voice Command method has much higher response time, especially with more complicated gestures such as Voice Command and Tap. This proves how efficient the Gesture Recognition system is in comparison to the conventional ways of input..

Table 1: Performance metrics

Metric	Gesture Recognition (%)	Touch Interface (%)	Voice Command (%)
Accuracy	90%	85%	75%
Precision	92%	83%	70%
Recall	88%	80%	72%
F1-Score	90%	82%	71%

This table 1 draws a comparison between Response Times and Performance Metrics of Gesture Recognition system, touch interface, and voice command input. Gesture Recognition has a shorter response time in most gestures, whereas Voice Command has a slower response time particularly with gestures, such as Tap and Voice Command. As well, the performance metrics show that Gesture Recognition is always more accurate, precise, recalls more effectively, and achieves a high F1-score as compared to the other two methods..

Accuracy

$$\text{Accuracy} = \frac{\text{True Positives} + \text{True Negatives}}{\text{Total Samples}} \qquad (3)$$

Equation (3) represents the ratio of correct predictions (including both true positives and true negatives) to the total number of samples.

Precision

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \qquad (4)$$

Equation (4) calculates the ratio of accurate positive predictions to all optimistic predictions made by the model. It indicates the accuracy of the model's optimistic predictions by showing how many were correct.

Recall

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \qquad (5)$$

Equation (5) represents the proportion of actual positive cases that the model correctly identified. It indicates the model's effectiveness in recognizing positive instances, thereby reducing false negatives.

F1-Score

$$\text{F1-Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \qquad (6)$$

Equation (6) represents the harmonic mean of Precision and Recall, offering a balance between these metrics. It is particularly valuable in scenarios with class imbalance, where both false positives and false negatives are significant consider.

5 Conclusion

The study has shown that the gestural interfaces are 20 percent quicker to use than the conventional touch controls and that the interface attains a remarkable 85 percent success rate in identifying the numerous gestures, reducing the incidence of human error. Statistic analysis reveals that there is a strong correlation between the complexity of gestures and recognition accuracy such that simpler gestures are more recognized accurately. To continue, the further study may be devoted to implementing the sophisticated sensor fusion methods so that the performance under a variety of environmental conditions could be improved. Moreover, the creation of AI-controlled adaptive interfaces that change according to the specific user actions would go a long way in enhancing user experience, and thus gesture-based interactions will be even more comfortable and practical.

Reference

[1] Carfì, A., & Mastrogiovanni, F. (2021). Gesture-based human–machine interaction: Taxonomy, problem definition, and analysis. *IEEE Transactions on Cybernetics*, *53*(1), 497-513. https://doi.org/10.1109/TCYB.2021.3129119

[2] Dakulagi, V., Yeap, K. H., Nisar, H., Dakulagi, R., Basavaraj, G. N., & Galindo, M. V. (2025). An overview of techniques and best practices to create intuitive and user-friendly human-machine interfaces. *Artificial Intelligence and Multimodal Signal Processing in Human-Machine Interaction*, 63-77. https://doi.org/10.1016/B978-0-443-29150-0.00002-0

[3] De Fazio, R., Mastronardi, V. M., Petruzzi, M., De Vittorio, M., & Visconti, P. (2022). Human–machine interaction through advanced haptic sensors: A piezoelectric sensory glove with edge machine learning for gesture and object recognition. *Future Internet*, *15*(1), 14. https://doi.org/10.3390/fi15010014

[4] Eddy, E., Campbell, E., Bateman, S., & Scheme, E. (2024, September). Human-Machine Interaction Using Discrete Myoelectric Control: Contrastive Learning Reduces False Activations During Activities of Daily Living. In *2024 10th IEEE RAS/EMBS International Conference for Biomedical Robotics and Biomechatronics (BioRob)* (pp. 128-133). IEEE. https://doi.org/10.1109/BioRob60516.2024.10719934

[5] Gao, S., Yan, S., Zhao, H., & Nathan, A. (2021). *Touch-based human-machine interaction*. Springer, New York.

[6] Gowthami, V., & Ramya, M. (2024, December). Wireless Gesture-Driven Navigation for Autonomous Robots: An Innovative Human-Machine Interface Approach. In *2024 International Conference on System, Computation, Automation and Networking (ICSCAN)* (pp. 1-6). IEEE. https://doi.org/10.1109/ICSCAN62807.2024.10894046

[7] Gudikandula, N., Janapati, R., & Sengupta, R. (2025). Human-Machine Interactions: Evolution, Current Applications, and Future Prospects. *Humans and Generative AI Tools for Collaborative Intelligence*, 343-368. https://doi.org/10.4018/979-8-3693-8332-2.ch015

[8] Jones, M., Swathi, J., Jagan, T., Naveen, T., Kathiresan, T., & Aravinthan, N. (2023, September). Advancements in Human-Machine Interaction: Exploring Natural Language Processing and Gesture Recognition for Intuitive User Interfaces. In *2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET)* (pp. 201-205). IEEE. https://doi.org/10.1109/ICSEIET58677.2023.10303031

[9] Lucena, K., Luedeke, H. J., & Wirth, T. (2025). The evolution of embedded systems in smart wearable devices: Design and implementation. *SCCTS Journal of Embedded Systems Design and Applications*, *2*(1), 23-35.

[10] Marhoon, H. A., Oudah, A. Y., Hussien, N. A., & Raaid, A. (2025). Designing Wireless Sensor Network Data Based Machine Learning Approach for Accurate Human Activity Recognition. *Journal of Internet Services and Information Security*, *15*(1), 385-400. https://doi.org/10.58346/JISIS.2025.I1.025

[11] Mehta, D. B. (2024). Advancing Conversational AI through Multimodal Integration of Auditory and Visual Modalities. *Available at SSRN 5356657*. https://dx.doi.org/10.2139/ssrn.5356657

[12] Muhammed Jaseel, E. K., & Kokila, R. (2024). Application Designed to Revolutionize the Way People Discover and Book Sports Grounds Effortlessly (Game Snap). *International Academic Journal of Innovative Research, 11*(2), 01–12. https://doi.org/10.9756/IAJIR/V11I2/IAJIR1108
[13] Ogunwale, Y. E. (2024, November). Evolution of Human-Machine Translation: From Early Interface to Modern AI. In *2024 IEEE 5th International Conference on Electro-Computing Technologies for Humanity (NIGERCON)* (pp. 1-5). IEEE. https://doi.org/10.1109/NIGERCON62786.2024.10927385
[14] Prabhu, S., Kumar, D., Franklin, R. G., Pradhan, B., Savita, & Jena, D. (2025). Personalized Information Retrieval Systems: Enhancing User Interaction through Context-Aware Technologies. *Indian Journal of Information Sources and Services*, *15*(3), 98–107. https://doi.org/10.51983/ijiss-2025.IJISS.15.3.11
[15] Savita., Chandna, M., Vijay, B., Kaushik, N., Kamalesh, M. D., Jena, S. K., & Karthikeyan, M. P. (2025). Human-computer interaction for aquatic animal tracking and monitoring water quality parameters. *International Journal of Aquatic Research and Environmental Studies*, *5*(1), 221–227. https://doi.org/10.70102/IJARES/V5I1/5-1-23
[16] Shirisha, M., Sireesha, N. V., Rao, D. N., Muneeshwar, R., Kumar, D. G., & Krishna, P. R. (2024, September). Accessibility and Inclusion: A Gesture-Based Human Interface Device for Individuals with Hand Impairments. In *2024 IEEE International Conference on Power, Electrical, Electronics and Industrial Applications (PEEIACON)* (pp. 149-153). IEEE. https://doi.org/10.1109/PEEIACON63629.2024.10800748
[17] Subasi, A., Qaisar, S. M., & Nisar, H. (Eds.). (2024). *Artificial Intelligence and Multimodal Signal Processing in Human-Machine Interaction*. Elsevier.
[18] Sun, Z., Wang, S., Liu, C., & Ma, X. (2022). Metaphoraction: Support gesture-based interaction design with metaphorical meanings. *ACM Transactions on Computer-Human Interaction*, *29*(5), 1-33. https://doi.org/10.1145/3511892
[19] Sun, Z., Zhu, M., & Lee, C. (2021). Progress in the triboelectric human–machine interfaces (HMIs)-moving from smart gloves to AI/haptic enabled HMI in the 5G/IoT era. *Nanoenergy Advances*, *1*(1), 81-120. https://doi.org/10.3390/nanoenergyadv1010005
[20] Tan, Z., Dai, N., Su, Y., Zhang, R., Li, Y., Wu, D., & Li, S. (2021). Human–machine interaction in intelligent and connected vehicles: A review of status quo, issues, and opportunities. *IEEE Transactions on Intelligent Transportation Systems*, *23*(9), 13954-13975. https://doi.org/10.1109/TITS.2021.3127217
[21] Zhang, Y., Hu, Z., & Lv, C. (2023, June). A Novel Human-Machine Collaboration Approach for Autonomous Driving with Hand Gesture-based Guidance. In *2023 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM)* (pp. 886-890). IEEE. https://doi.org/10.1109/AIM46323.2023.10196127

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