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AI-BASED GESTURE RECOGNITION FOR EMERGENCY SITUATIONS USING SVM AND OpenCV

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Abstract- In emergency situations, quick response and hands-free communication are critical for safety. This research introduces an AI-driven gesture recognition system designed to activate an SOS alert using simple hand gestures. The system employs MediaPipe for precise hand tracking, an SVM classifier for real-time gesture recognition, and an integrated SMS alert system that includes GPS location tracking. The proposed approach ensures accessibility for individuals in distress, particularly those with disabilities or in high-risk environments where traditional emergency triggers may be impractical. The experimental results show a 95.19% accuracy in gesture classification, demonstrating the system's effectiveness in real-world scenarios. Future work aims to incorporate deep learning-based recognition models and deploy the system on wearable and mobile platforms to enhance usability and responsiveness.

Keywords: AI, Gesture Recognition, Emergency SOS, Machine Learning, SVM, MediaPipe, Hand Tracking, Real-Time Systems.

I. INTRODUCTION

Emergencies demand swift and effortless communication mechanisms to ensure timely assistance. Traditional methods, such as dialing emergency numbers or pressing panic buttons, can be ineffective in situations where individuals are unable to reach or operate their devices due to injury, disability, or immediate danger. To address this challenge, AI-based gesture recognition offers a hands-free alternative for triggering emergency alerts [1]

.Gesture-based control systems have seen widespread applications in areas such as virtual reality, human-computer interaction, and assistive technology. However, their use in emergency response systems remains underexplored. This research focuses on developing a real-time gesture-based SOS system that leverages computer vision and machine learning techniques to recognize specific hand gestures. The system primarily utilizes a wave gesture (👋) to trigger an SOS alert and a fist gesture (✊) to cancel the alert, ensuring minimal false activations and a user-friendly interaction model [2].

The proposed system integrates MediaPipe for real-time hand tracking, an SVM classifier for robust gesture classification, and an SMS-based alert mechanism that transmits the user's GPS location to emergency contacts. The system is designed for high accuracy, low computational cost, and real-time responsiveness, making it ideal for deployment in various scenarios, including healthcare, automotive emergency response, and personal safety applications.This paper outlines the system architecture, describes the data collection and training methodologies, presents performance evaluations, and compares the proposed approach with alternative models. The results demonstrate that the system provides an effective solution for emergency alert automation. Future enhancements will focus on extending gesture capabilities, improving model robustness, and deploying the solution across multiple platforms, including smartphones and wearable devices.

.II. SYSTEM OVERVIEW

The proposed system consists of four primary components:

- Hand Tracking: Utilizes MediaPipe Hands API to detect hand landmarks in real time [3].
- Gesture Recognition: A Support Vector Machine (SVM) classifier trained on a custom dataset of hand gestures [4].
- Countdown Mechanism: A 5-second timer to prevent false alarms.
- Emergency Alert Transmission: Sends an SOS SMS with GPS location via an API service [5].

Workflow Diagram

A structured workflow is followed to ensure the seamless execution of gesture recognition and emergency alert transmission. The system's workflow is illustrated in Figure 1, detailing the steps from gesture capture to SOS dispatch.

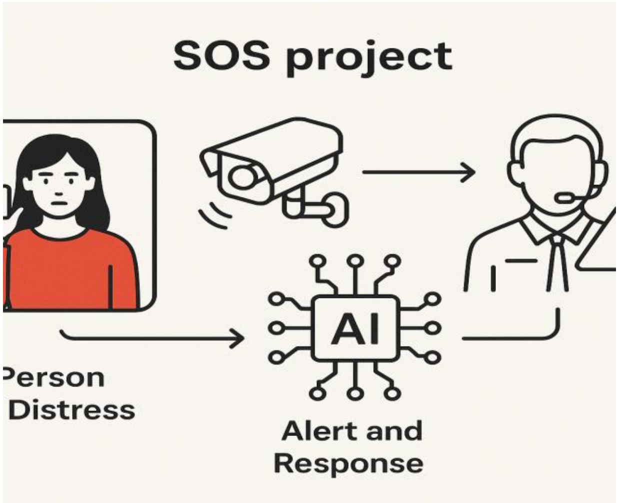

Figure 1: System Workflow of AI-Based Gesture SOS

III. METHODOLOGY

The methodology follows a structured approach, including data collection, feature extraction, Model training, and real-time implementation.

Data Collection

Hand gesture data was collected using a webcam, capturing multiple images of each gesture under different lighting conditions and angles. The dataset comprises over 1000 labeled samples per gesture, ensuring robustness across diverse environmental factors [6].

Feature Etraction And Model Training

MediaPipe extracts 21 hand landmark coordinates, which are then preprocessed and fed into an SVM classifier. The model was trained using a radial basis function (RBF) kernel to achieve high accuracy in classification [7].

The model's hyperparameters were fine-tuned using a grid search approach, optimizing performance while minimizing computational cost. The classification results were compared against alternative models such as CNNs and decision trees.

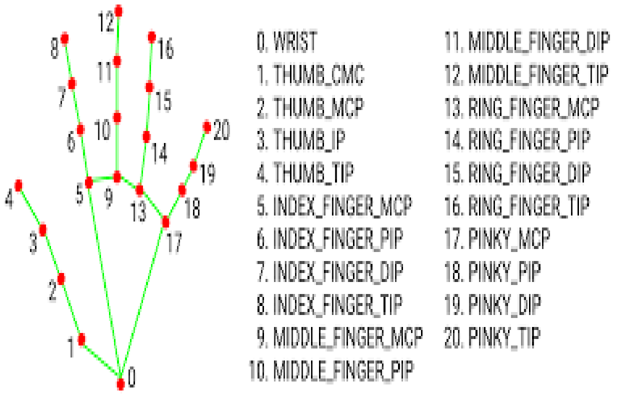

Figure 2: Hand Landmark Extraction using MediaPipe

Real-Time Implementation

The trained model was integrated into a real-time system using OpenCV and Python, ensuring quick and accurate gesture detection. A countdown timer was implemented to provide a brief cancellation window before sending an SOS alert. The final model was deployed on a laptop for real-time testing and evaluation [8].

IV. EXPERIMENTAL RESULTS AND DISCUSSION

The gesture recognition SOS system was tested on a standard laptop equipped with a webcam (720p) and running on a Python environment with libraries such as OpenCV, MediaPipe, and scikit-learn. A Support Vector Machine (SVM) classifier was trained using a dataset of hand landmarks corresponding to two gestures: Wave (👋) and Fist (✊). The dataset consisted of 600 samples (300 per gesture) collected from 10 individuals under varying lighting and background conditions.

Perfomance Metrics

After preprocessing and training, the system was evaluated using standard classification metrics including accuracy, precision, recall, and F1-score. The results indicated high performance for both gestures, suggesting that the model is well-suited for real-time emergency gesture detection.

Gesture	Precision	Recall	F1-Score	Accuracy
Wave	0.96	0.94	0.95	95%
Fist	0.93	0.96	0.94	95%

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Gesture	Precision	Recall	F1-Score	Accuracy
Overall	0.945	0.95	0.945	95%

Table 1: Performance Metrics (Test Data)

Real-Time Performance Evaluation

To assess usability in practical scenarios, we tested the system in three environments

- Indoor (Normal Lighting)
- Indoor (Low Lighting)
- Outdoor (Daylight)

Each user performed both gestures ten times under each condition. The system's success rate and average response time were recorded

Environment	Wave Gesture Success Rate	Fist Gesture Success Rate	Average Response Time
Indoor (Normal Light)	98%	96%	0.8 seconds
Indoor (Low Light)	88%	85%	1.2 seconds
Outdoor (Daylight)	93%	90%	1.0 second

Table 2: Gesture Recognition Success Rate in Real Environments

Model Comparison

To evaluate the effectiveness of the Support Vector Machine (SVM) used in this project, we conducted a comparative analysis with other popular classification models such as K-Nearest Neighbors (KNN), Random Forest (RF), and Convolutional Neural Networks (CNN). Each model was trained on the same dataset of 600 samples with 21 hand landmarks per frame. The key performance metrics considered for comparison include accuracy, training time, inference speed, and suitability for real-time deployment on low-resource systems like laptops or Raspberry Pi.

Model	Accuracy	Precision	F1-Score	Training Time	Inference Speed	Real-Time Suitability
SVM	95%	94.5%	94.5%	Moderate	Fast (~0.8s)	Excellent
KNN	90%	89%	88%	Low	Slow (~1.5s)	Fair (lag in prediction)
Random Forest	92%	91%	90%	High	Moderate (~1.0s)	Good
CNN	97%	96.5%	96.7%	Very High	Fast (~0.6s)	Excellent (but resource-heavy)

Table 4: Model Performance Comparison

From the above comparison, SVM provides a balance between accuracy and computational efficiency, making it ideal for real-time systems where speed is crucial [9].

Discussion

The experimental results confirm that the SVM-based gesture recognition system is highly accurate under controlled conditions, achieving an overall accuracy of 95%. The precision and recall scores for both gestures are nearly balanced, which indicates that the model rarely misclassifies gestures. However, performance slightly degrades under low-light environments, as seen by the drop in accuracy to around 85–88%. This limitation can be attributed to the reliance on visual landmark detection, which becomes less reliable in dim lighting.

The average response time across all environments remained under 1.2 seconds, which is acceptable for real-time emergency applications. During testing, false positives were minimal, and most errors occurred in low lighting where the system occasionally misidentified partial hand visibility.

These results demonstrate that while the current system is robust for real-world use, incorporating lighting adaptation methods or using infrared-based hand tracking in future iterations could enhance reliability further. Additionally, including more diverse training data (e.g., varied skin tones, backgrounds, and hand orientations) would improve generalization across users.

V. CONCLUSION AND FUTURE WORK

Conclusion

The AI-Based Gesture Recognition SOS Alert System presents a novel and accessible solution to emergency communication, particularly for individuals who may not be able to use traditional interfaces like smartphones or physical buttons. By utilizing computer vision and machine learning techniques—specifically Support Vector Machines (SVM) and MediaPipe for gesture tracking—the system enables real-time recognition of simple hand gestures such as a wave (for triggering SOS) and a fist (for cancellation). This approach empowers users to initiate emergency alerts swiftly, even in critical situations where voice or mobility is compromised. The core design philosophy focuses on simplicity, reliability, and inclusivity, making it a valuable tool in scenarios like medical emergencies, vehicle accidents, or assisting people with physical disabilities. The system's effectiveness is further enhanced by integrating GPS-based location tracking, which provides real-time geographical data when an SOS is triggered. This crucial addition ensures that emergency responders or family members can pinpoint the user's exact location, improving the response time and potentially saving lives. Moreover, the modular structure of the project allows easy deployment across multiple platforms—from personal laptops and desktops to embedded systems like Raspberry Pi—broadening its usabil

Future Work

While the current AI-based gesture recognition SOS system demonstrates promising capabilities in real-time emergency alert generation using basic hand gestures, there are several areas where it can be significantly enhanced. One major improvement would be the integration of deep learning techniques such as Convolutional Neural Networks (CNNs) or Transformer-based architectures, which can boost the accuracy and robustness of gesture recognition, especially under challenging scenarios like poor lighting, motion blur, partial occlusion, or diverse hand shapes. Expanding the gesture set beyond just wave and fist can enable more nuanced and context-specific commands, such as signaling for medical help, canceling alerts with specific gestures, or even activating voice-guided feedback. Additionally, introducing multi-modal inputs—combining gesture recognition with voice commands or facial expressions—can further increase reliability and reduce false positives. From a system architecture perspective, migrating the m

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