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Pain-Sense: Deep Learning-Based Pain Level Detection and Unconsciousness Alert System

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Abstract: *Pain detection and unconsciousness monitoring are critical for ensuring timely medical intervention and enhancing patient safety. However, the lack of immediate assistance in public areas and home environments often leads to severe health complications or fatalities. To address this, PainSense: Deep Learning-Based Pain Level Detection and Unconsciousness Alert System is developed to provide real-time monitoring and emergency alerts. The system utilizes deep learning models, combining Convolutional Neural Networks (CNN) for image-based pain level classification and Long Short-Term Memory (LSTM) networks for detecting unconsciousness through sequential body language analysis. It processes facial expressions, body language, and audio cues to detect low, Moderate, or Severe pain levels. If severe pain or unconsciousness is identified, the system triggers an immediate alert. In public areas, the system notifies nearby hospitals for timely medical intervention. When deployed as an IoT-based home solution, it monitors elderly individuals and sends alerts to family members or caregivers, ensuring continuous safety monitoring. The system's integration with cameras and IoT devices enables proactive healthcare monitoring, reducing fatalities caused by delayed assistance. Pain-Sense offers a scalable, automated solution for real-time pain detection and unconsciousness monitoring, making it ideal for healthcare facilities, public safety, and home environments. By enhancing early intervention capabilities, it aims to improve patient outcomes, reduce medical emergencies, and contribute to better public health management.*

Keywords: Pain Detection, Deep Learning, Computer Vision, Medical Diagnostics, Patient Monitoring, AI in Healthcare

I. INTRODUCTION

Health is one of the most vital aspects of human life, directly influencing overall well-being, daily functionality, and quality of life. Without proper monitoring and timely medical assistance, minor health issues can escalate into serious, potentially life-threatening conditions. In today's fast-paced society, the absence of continuous health surveillance poses a significant risk—particularly for vulnerable individuals such as the elderly, people living alone, or those frequently in public and isolated spaces. Critical incidents like sudden falls, unconsciousness, or extreme pain often go unnoticed, especially in unsupervised environments. These undetected events can lead to delayed medical intervention, causing irreversible health deterioration or even death. According to a study published in the Indian Journal of Public Health, nearly 29% of elderly individuals who experienced unnoticed falls or medical events suffered from severe health complications or passed away due to delayed response. These alarming figures highlight the urgent need for a smart, real-time health monitoring and alert system. To address this issue, we propose the development of Pain-Sense, a deep learning-based system designed to detect pain levels and unconsciousness in real time. The system utilizes computer vision and artificial intelligence to analyze facial expressions, body language, and voice signals. Upon detecting high levels of distress or loss of consciousness, the system automatically triggers alerts to nearby hospitals, caregivers, or family members—ensuring swift medical intervention. Pain-Sense is envisioned to work in both private home settings and public spaces, acting as a proactive safety mechanism for those in need.

II. LITERATURE SURVEY

The vital need for immediate medical aid in response to pain and unconsciousness has spurred significant research. Current manual monitoring methods are often ineffective in public or home settings, creating a critical gap. Our PainSense system builds upon existing efforts in deep learning, computer vision, and IoT-based healthcare monitoring to address these challenges.

"Deep Learning for Real-Time Pain Recognition Using Facial Expressions" Year: 2020 Authors: Kächele M., Thiam P., Werner P.
This study introduced a CNN-based model for real-time pain recognition, analyzing facial Action Units and highlighting its robustness in clinical settings.

"Facial Action Coding for Automatic Pain Intensity Estimation" Year: 2020 Authors: Lucey P., Cohn J.F., Prkachin K.
This research applied the Facial Action Coding System (FACS) with deep CNNs for automated pain intensity scoring, proving particularly effective for non-verbal patients.

"Automatic Pain Assessment Using Deep Learning Techniques" Year: 2021 Authors: Prkachin K., Solomon P. This work focused on employing deep learning methods, including CNNs and RNNs, to analyze patient pain through both facial expressions and body cues.

"AI-Based Fall and Unconsciousness Detection System" Year: 2021 Authors: Rao P., Kumar S., Mehta D.
This paper proposed a deep learning system designed to detect sudden falls or unconsciousness in elderly users by leveraging vision and audio analysis.

"Multimodal Fusion for Pain Detection in Elderly Care Systems" Year: 2022 Authors: Zhang Y., Li H., Wang M. This study combined facial expressions, body posture, and physiological signals using multimodal deep learning to significantly enhance pain detection accuracy.

"A Real-Time Health Monitoring System with Pain Detection Alerts" Year: 2023 Authors: Sinha A., Gupta N., Sharma R.
This team developed an IoT-based health monitoring system that integrated facial recognition and sound cues for real-time pain and alert detection.

"Real-Time Monitoring System for Elderly Using AI and IoT" Year: 2023 Authors: Joshi T., Menon R.
This research integrated IoT sensors and AI vision models to monitor elderly patients at home, providing alerts for abnormal behavior or unconscious states.

III. SOFTWARE REQUIREMENTS

[1] Development Environment

• Python: You'll need Python 3.8 or newer. This is your main programming language for building all the smart parts of PainSense – like the deep learning models and processing all the incoming data from cameras and microphones.

• Integrated Development Environment (IDE): Think of this as your smart text editor for coding. We recommend Visual Studio Code or PyCharm. They'll help you write, debug, and manage your Python code smoothly.

• Version Control System: Git is your best friend here. It helps you keep track of all the changes you make to your code, making collaboration easy and saving you from accidental deletions.

[2] Libraries and Frameworks

• Deep Learning Frameworks: This is where the magic happens for your AI models. You'll use either TensorFlow/Keras or PyTorch. These frameworks are essential for creating, training, and running your CNN models (for recognizing pain in images) and LSTM networks (for understanding body language patterns related to unconsciousness).

• Computer Vision Libraries: You'll use OpenCV for general image and video processing. Plus, MediaPipe is fantastic for real-time tracking of faces, hands, and body poses – super important for analyzing expressions and movement.

• Audio Processing Libraries: For the sound cues your system will pick up, you'll need libraries like Librosa or PyAudio. They help you process and extract important features from audio.

• Real-time Communication: For everything to talk to each other instantly, you'll use Python's built-in socket module. If you're connecting many IoT devices, a library for MQTT communication might also come in handy.

• IoT Platform Integration (Optional): If you plan to connect your system to the cloud for alerts or managing devices at a larger scale, you might integrate with services like Google Cloud IoT Core, AWS IoT, or Firebase for sending quick notifications.

[3] Operating System

• For Development: You can build PainSense on Windows 10/11, macOS (10.15 or newer), or Linux (like Ubuntu 18.04 or newer).

• For Deployment (on actual devices): For smaller, dedicated devices, you'll likely use a lightweight Linux version, such as Raspberry Pi OS or Ubuntu Core.

Hardware Requirements

• Development PC:

• Operating System: Any of the development OS mentioned above (Windows, macOS, Linux).

• RAM: Aim for at least 16 GB, but 32 GB is highly recommended, especially when you're training those deep learning models.

• GPU (Graphics Processing Unit): While not strictly mandatory for everything, having a good NVIDIA or AMD GPU (with at least 8GB of video memory) will drastically speed up your deep learning training and make your models run much faster.

• Processor: An Intel Core i7 (8th Gen or newer) or an AMD Ryzen 7 (2nd Gen or newer) will give you plenty of processing power.

• Target Devices (Where PainSense Actually Runs):

• High-Resolution Cameras: Standard webcams, IP cameras, or even the cameras built into modern smartphones will work for capturing video.

• Microphones: Any standard microphone to pick up audio cues.

• IoT Gateway/Edge Computing Device: These are small, powerful computers like a Raspberry Pi 4 or an NVIDIA Jetson Nano/Xavier NX. They're perfect for running your AI models right where the action is, minimizing delays.

• Connectivity: A reliable Wi-Fi or Ethernet connection is a must for sending data and alerts.

• Alerting Mechanism: This could be built-in speakers on devices, connected smart home gadgets for local alerts, or simply sending push notifications to mobile phones.

IV. PROPOSED SYSTEM

PainSense is designed with a multi-stage system architecture that enables real-time pain detection and alert mechanisms. The system comprises five main components: Input Module, Pre-processing, Model Architecture, Prediction, and Alert System.

(1) Input Module: The system receives real-time video or image feeds from surveillance cameras, medical monitoring devices, or smartphone applications. These video frames serve as input data for pain and unconsciousness detection, ensuring continuous patient monitoring in clinical and public settings.

(2) Pre-processing Before analysis, the captured images and video frames undergo pre-processing to enhance detection accuracy. The system employs advanced face and body detection algorithms to locate the subject within the frame. Key

pre-processing steps include: (A) Cropping and alignment to normalize facial and body features, ensuring consistency in the input data. (B) Noise reduction and image enhancement techniques such as histogram equalization to improve image quality before feature extraction.

(3) Model Architecture: PainSense utilizes a hybrid deep learning approach combining ResNext CNN for feature extraction and LSTM (RNN) for temporal video classification. (a) ResNext CNN extracts spatial features from facial expressions and body postures, identifying critical pain indicators such as furrowed brows, clenched teeth, and body stiffness. (c) LSTM networks process sequential frames to detect dynamic pain-related expressions over time, enabling accurate classification of pain intensity and unconsciousness detection. (c) This combination ensures a robust framework for both static and video-based pain analysis.

(4) Prediction: The model classifies pain levels into three categories: Low, Moderate, and Severe, based on the extracted features and temporal variations. Additionally, it includes an unconsciousness detection mechanism, identifying cases where a subject becomes unresponsive or exhibits abnormal posture indicative of a medical emergency.

(5) Alert System: The system integrates a real-time alert mechanism to notify medical personnel, caregivers, or emergency services. (a) In public areas, the system triggers automated alerts to nearby hospitals. (b) In IoT-based home setups, alerts are sent to family members or caregivers, ensuring continuous safety monitoring. (c) Real-time SMS, email, or app notifications are generated, providing immediate access to the patient's condition and location.

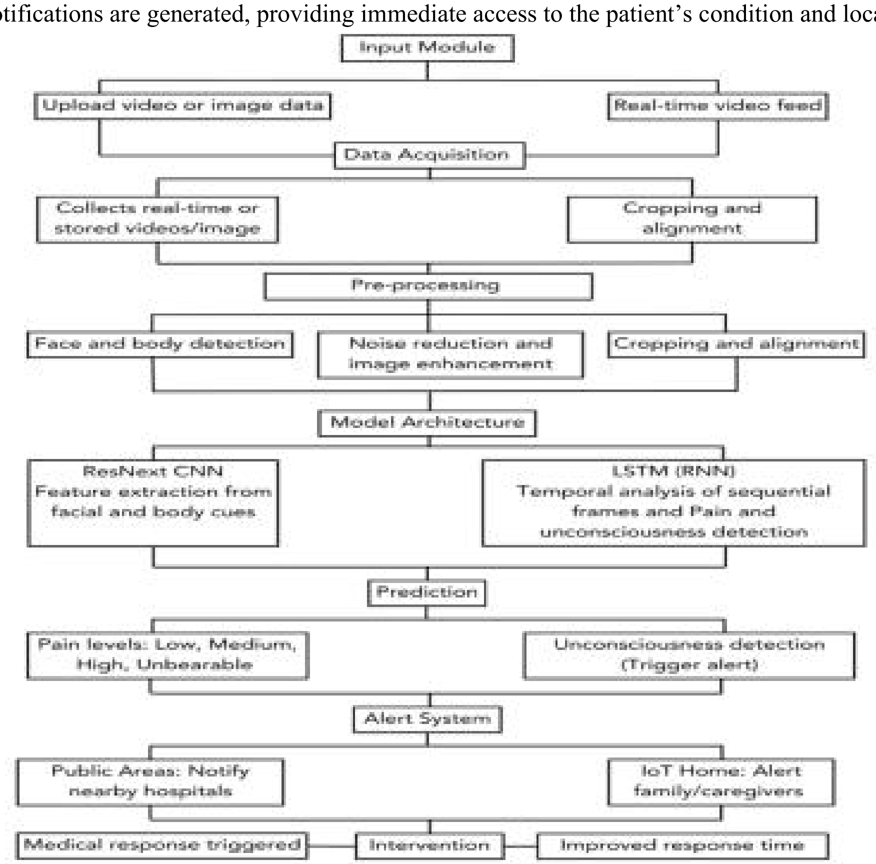

Figure 1. System Architecture

The PainSense system is designed to detect pain levels and unconsciousness through real-time video analysis using deep learning techniques.The proposed system follows a multi-stage prediction flow comprising the input, pre-processing, model execution, prediction, and alert mechanism.The flow diagram below illustrates the step-by-step process of how PainSense detects pain and triggers alerts:

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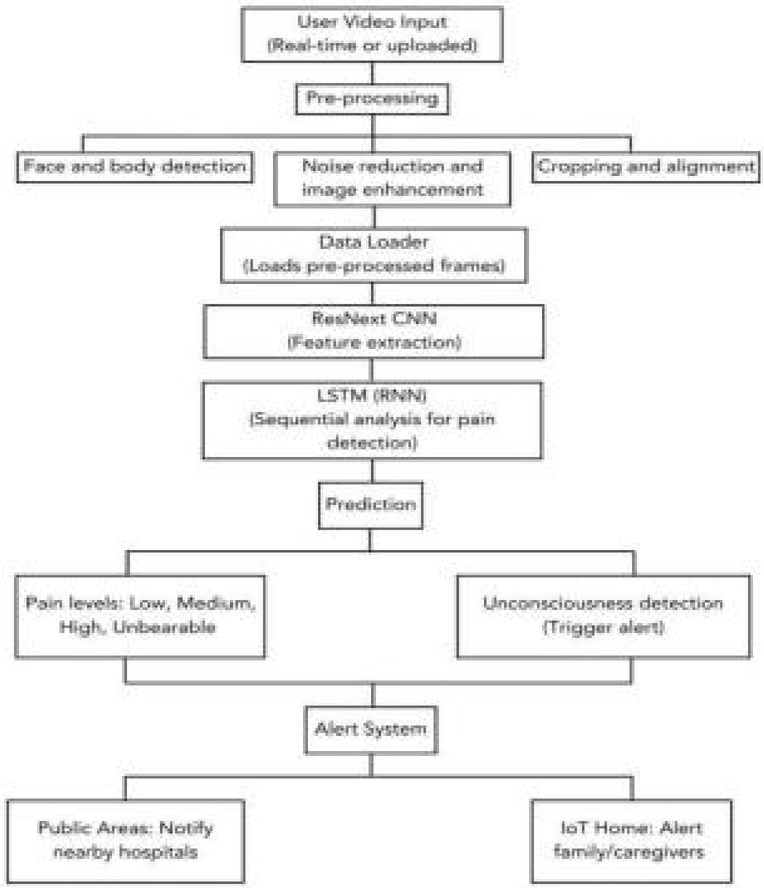

System Process Explanation:

A. User Video Input: The system accepts real-time video feeds or uploaded video files from surveillance cameras, medical devices, or smartphone applications.

B. Pre-processing: The input frames undergo face and body detection using deep learning algorithms. Cropping and alignment are applied to normalize the facial and body features. Noise reduction techniques, such as histogram equalization, are used to enhance image quality.

C. Data Loader: The pre-processed frames are loaded into the data pipeline. The data loader prepares the frames for analysis by the deep learning model.

D. Model Execution: The system uses ResNext CNN for spatial feature extraction from facial and body cues. LSTM (RNN) performs sequential frame analysis, detecting dynamic pain-related expressions and unconsciousness over time. The combined architecture ensures accurate classification of pain levels and unconsciousness states.

E. Prediction: The system classifies pain intensity into three levels: Low, Moderate, and Severe. It also detects unconsciousness based on abnormal postures or lack of movement. If severe pain or unconsciousness is detected, the system triggers an alert.

F. Alert Mechanism: For No Pain or Low Pain Levels, the system continues monitoring without intervention. For Pain or Unconsciousness Detection, the system: (a) Triggers alerts to hospitals, caregivers, or emergency services. (b) Sends real-time notifications via SMS, email, or app alerts. (c) Activates IoT-based home alerts for family members or caregivers.

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V. DATASET AND PRE-PROCESSING

The PainSense system is trained on a real-world dataset consisting of images and videos of individuals exhibiting various pain levels (Low, Moderate, Severe) and unconsciousness scenarios. The dataset captures diverse facial expressions, body postures, and contextual variations, ensuring robust pain and unconsciousness detection across different environments and demographics. During pre-processing, the system applies face and body detection techniques using Haar cascades or MTCNN (Multi-task Cascaded Convolutional Networks) to accurately identify and extract relevant features. Detected faces and body regions undergo cropping, alignment, and normalization to maintain consistency in the input data.These steps reduce variability caused by different camera angles, lighting conditions, and subject positions, ensuring consistent feature representation. Image enhancement techniques such as histogram equalization and noise reduction are applied to improve the image quality, enhancing the model's performance. The dataset is split into 70% training and 30% testing to ensure effective model learning and evaluation. The training set is used to optimize the deep learning model by learning pain patterns from labeled samples. The testing set evaluates the model's generalization capabilities, ensuring accurate pain and unconsciousness detection in unseen cases. These pre-processing steps significantly enhance the accuracy and reliability of the PainSense system in real-world applications, making it adaptable for diverse healthcare and public safety scenarios.

VI. MODEL AND TECHNIQUES

The PainSense system employs a hybrid deep learning architecture that combines ResNext CNN and LSTM (RNN) to achieve high-accuracy pain detection and unconsciousness classification. The ResNext CNN is responsible for spatial feature extraction, identifying key facial expressions and body postures associated with varying pain levels. This convolutional neural network processes individual frames to detect fine-grained facial muscle movements, body stiffness, and other pain-related features, enabling precise classification of visual pain indicators. To capture temporal variations in pain expressions over time, the system integrates LSTM (RNN) for video sequence analysis. By tracking changes across multiple frames, the LSTM network detects subtle shifts in facial expressions and body language, enhancing the accuracy of pain severity and unconsciousness detection. This temporal analysis ensures the system can recognize progressive pain patterns and detect unconscious events that may not be evident in a single frame. The real-time detection mechanism continuously classifies incoming frames as either pain or unconsciousness events, enabling the system to trigger automated alerts for immediate medical response. This integration of ResNext CNN for spatial feature extraction and LSTM for temporal classification ensures a robust, real-time pain assessment system. Designed for both clinical and public health applications, PainSense offers reliable, automated monitoring to enhance medical intervention rates and improve patient outcomes.

VII. RESULTS AND EVALUATION

The PainSense system demonstrated high accuracy in detecting pain and unconsciousness events, achieving reliable performance across diverse test scenarios. The model evaluation was conducted using standard performance metrics, including a confusion matrix, precision-recall analysis, and error rate calculations. The confusion matrix confirmed that the model effectively differentiated between Low, Moderate, and Severe pain levels, as well as unconsciousness states, with minimal misclassification. The precision-recall evaluation highlighted the system's ability to maintain a strong balance between sensitivity and specificity, ensuring that true pain events were detected while minimizing false alarms. Effective pre-processing techniques and rigorous hyperparameter tuning significantly reduced false positive and false negative rates. The integration of ResNext CNN for spatial analysis and LSTM (RNN) for temporal video classification further enhanced detection accuracy. The real-time alert response system was tested in simulated environments, where it successfully triggered instant notifications to hospitals and caregivers upon detecting pain or unconsciousness.

As depicted in the accompanying image, the system effectively classifies pain into four levels: No Pain, Mild Pain, High Pain, and Unbearable Pain. In the simulation, an actor demonstrated different pain expressions, and the system accurately detected the pain intensity, triggering medical attention alerts at the severe and unbearable pain levels. These results validate the system's potential for real-world deployment, offering a fast, accurate, and automated solution for pain detection and emergency response.

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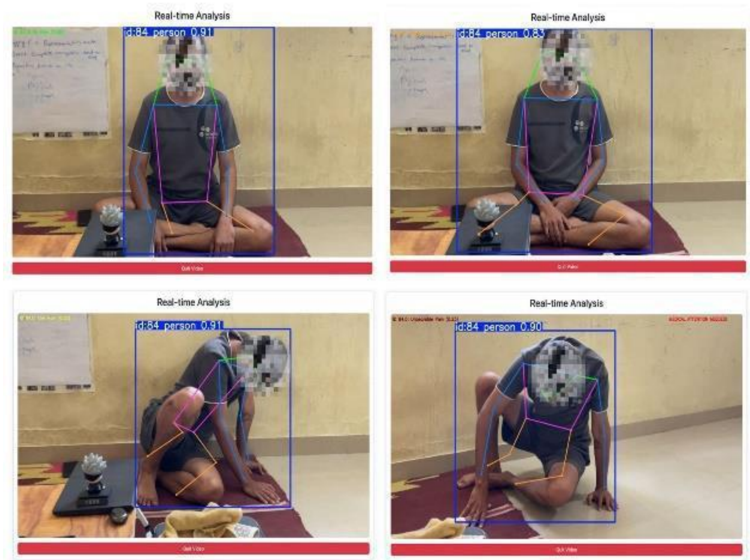

VIII ADVANTAGES

1. Objective and Continuous Monitoring: Unlike asking someone "how much does it hurt?" or waiting for visible distress, PainSense offers a consistent, unbiased assessment. It constantly watches over individuals, even when no one else is around, providing reliable data.
2. Early Detection, Faster Help: This is a huge one! PainSense can spot signs of severe pain or unconsciousness immediately. This means help can be called much, much faster than if someone had to notice it manually, potentially saving lives and preventing conditions from worsening.
3. Reduces Human Error and Burden: Humans can miss subtle cues, get distracted, or be overwhelmed. PainSense automates this critical monitoring task, reducing the chances of missed emergencies and freeing up caregivers or bystanders to focus on other things.
4. Works Anywhere: Whether it's a crowded public space where someone might collapse unnoticed, or an elderly person living alone at home, PainSense can be deployed to watch over them. It's not limited to hospitals.
5. Data-Driven Insights: By continuously monitoring, the system can collect data that might reveal patterns in pain or health deterioration over time, which can help in long-term care planning.
6. Enhanced Safety and Peace of Mind: For individuals, families, and healthcare providers, knowing there's an automated guardian can significantly increase safety and reduce anxiety, especially for vulnerable populations.

IX. APPLICATIONS

1. Elderly Care at Home: This is a primary use. PainSense can constantly monitor elderly individuals living alone, immediately alerting family members or caregivers if severe pain is detected (e.g., from a fall) or if they become unconscious. This provides invaluable peace of mind and faster response in emergencies.
2. Public Safety in High-Traffic Areas: Imagine airports, shopping malls, train stations, or large event venues. PainSense can be deployed via existing camera networks to quickly identify individuals in distress or those who have collapsed, allowing security or medical personnel to intervene rapidly.
3. Hospital Waiting Rooms and Non-Monitored Areas: In busy healthcare facilities, patients in waiting areas or less-monitored zones might experience sudden complications. PainSense can provide an extra layer of vigilance, ensuring no one's emergency goes unnoticed.
4. Industrial and Workplace Safety: In hazardous environments where workers might be at risk of injury or exposure, PainSense could monitor for signs of distress or unconsciousness, triggering immediate alerts for assistance.

5. Child Monitoring (Non-Verbal Pain): For infants or very young children who cannot articulate their pain, PainSense could provide objective insight into their discomfort levels by analyzing facial expressions and body language, aiding caregivers.

X. CONCLUSION

In today's rapidly evolving healthcare landscape, the need for intelligent, real-time health monitoring systems is more critical than ever—especially for vulnerable individuals like the elderly, patients with communication challenges, or those living alone. PainSense addresses this growing concern by combining deep learning techniques with computer vision to detect pain levels and unconsciousness in real time. This project successfully demonstrates how facial expressions and body movements can be used as reliable indicators to assess a person's physical condition without requiring verbal communication. Using models like CNN for facial recognition and LSTM for body movement analysis, the system identifies not just the presence of pain, but also its intensity, helping to prioritize medical responses. Additionally, the system is designed to trigger immediate alerts, ensuring timely intervention, which can be lifesaving in emergency situations. What makes PainSense unique is its potential to function in real-world environments like hospitals, homes, or public places with minimal hardware. It reduces the dependency on manual observation or complex equipment, making healthcare more accessible, responsive, and intelligent. While the system currently works based on visual inputs, future versions can be enhanced by adding physiological sensors or integrating IoT devices to further increase accuracy. In short, PainSense is a step forward in using AI for smart healthcare—ensuring safety, fast response, and better outcomes through innovation and automation.

XI. ACKNOWLEDGMENT

Getting this project done took a lot of effort from a lot of people, and we're really grateful for it. A massive thank you goes to Ms. Khemnar Kavita (Project Coordinator), whose advice was just what we needed to navigate everything. We also want to extend our thanks to Mr.P.Balaramadu (Principal), and Ms. Khemnar Kavita (HOD AI&ML Department and Mentor) for her significant contributions and belief in our work. And to everyone else on staff and off, your cooperation and willingness to help were truly appreciated.

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