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Implementation Of Smart Gloves for Interactive CPR

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Abstract: The paper outlines the design and implementation of a wearable glove system specifically developed for CPR monitoring and vital sign measurement. This innovative system integrates multiple sensors to track compression rate and depth during CPR while simultaneously measuring critical health indicators such as ECG (electrocardiogram), body temperature, and blood pressure. The system offers real-time feedback through a mobile application, enabling first responders to optimize CPR quality and make data-driven decisions during emergency situations. The goal of the system is to enhance the effectiveness of CPR, ensuring that compression depth and rate align with established guidelines, ultimately improving patient outcomes. This comprehensive monitoring and feedback mechanism assists healthcare providers and emergency medical services (EMS) in delivering high-quality, life-saving care in critical moments.

Keywords: CPR monitoring, ECG(electrocardiogram), Body Temperature, Blood Pressure , EMS(emergency medical services)

I. INTRODUCTION

Cardiopulmonary resuscitation (CPR) is a critical lifesaving intervention for victims of cardiac arrest, but its effectiveness depends on the rescuer's ability to maintain the correct **compression depth** and **rate**. **Real-time monitoring tools** can offer immediate feedback, allowing rescuers to adjust their performance for optimal effectiveness. Moreover, incorporating **vital sign monitoring** into CPR tools can provide a more comprehensive assessment of the patient's condition throughout the resuscitation process.

Recent developments in **wearable healthcare devices** have demonstrated promising potential in automating and enhancing emergency response. For instance, Abraham et al. [4] showcased a wearable system that offers feedback on CPR performance, while Kulkarni and Jadhav [10] investigated wearable technologies for tracking compression quality. Building upon these advancements, this study presents a **smart glove** that integrates both **CPR feedback** and **vital sign monitoring** into a single, unified solution designed to improve the overall quality of CPR.

II. LITERATURE SURVEY

The literature on wearable devices for **Cardiopulmonary Resuscitation (CPR)** and **vital sign monitoring** has seen significant advancements in recent years, focusing on enhancing CPR quality and providing real-time feedback to first responders. Numerous studies have explored the integration of **real-time feedback** systems into CPR to improve compression techniques and overall effectiveness.

S. Seema et al,[9] focuses on techniques that can predict chronic disease by mining the data containing in historical health records using Naïve Bayes, Decision tree, Support Vector Machine (SVM) and Artificial Neural Network (ANN).A comparative study is performed on classifiers to measure the better performance on an accurate rate. From this experiment, SVM gives highest accuracy rate, whereas for diabetes Naïve Bayes gives the highest accuracy.

R. Sharmila et al, [13] proposed to use non- linear classification algorithm for heart disease prediction. It is proposed to use bigdata tools such as Hadoop Distributed File System (HDFS), MapReduce along with SVM for prediction of heart disease with optimized attribute set. This work made an investigation on the use of different data mining techniques for predicting heart diseases.

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It suggests to use HDFS for storing large data in different nodes and executing the prediction algorithm using SVM in more than one node simultaneously using SVM. SVM is used in parallel fashion which yielded better computation time than sequential SVM. Jayami Patel et al, [14] suggested heart disease prediction using data mining and machine learning algorithm. The goal of this study is to extract hidden patterns by applying data mining techniques.

Purushottam et al, [15] proposed an efficient heart disease prediction system using data mining. This system helps medical practitioner to make effective decision making based on the certain parameter. By testing and training phase a certain parameter, it provides 86.3% accuracy in testing phase and 87.3% in training phase. Gomathi et al, [16] suggested multi disease prediction using data mining techniques. Nowadays, data mining plays vital role in predicting multiple disease. By using data mining techniques the number of tests can be reduced. This paper mainly concentrates on predicting the heart disease, diabetes and breast cancer etc., P.Sai Chandrasekhar Reddy et al, [17] proposed Heart disease prediction using ANN algorithm in data mining. Due to increasing expenses of heart disease diagnosis disease, there was a need to develop new system which can predict heart disease. Prediction model is used to predict the condition of the patient after evaluation on the basis of various parameters like heart beat rate, blood pressure, cholesterol etc. The accuracy of the system is proved in java.

In year 2000, research conducted by shusaku Tsumoto says that we as human beings are unable to arrange data if it is huge in size we should use the data mining techniques that are available for finding different patterns from available huge database and can be used again for clinical research and perform various operations on it.

In 2004, Y. p Aslandogan, et. Al worked on three different classifications called k. Nearest neighbour (KNN) rule for this viewpoint to appear as concluding decision.

In 2004, Carlos Ordonez, assessed the problematic to recognize and forecast the rule of relationship for the heart disease. A dataset involving medical history of the patients having heart disease with the aspects of risk factors was accessed by him, measurements of narrowed artery and heart perfusion.

In the year 2006, Boleslaw Szymanski, et. Al, operated on a novel experimental to check the aptitude of calculation of scarce kern in SUPANOVA. The author used this technique on a standard Boston housing market dataset for discovering heart disease, measurement of heart activities and prediction of heart disease were found 83.7% correct which were measured with the help of support vector machine and kernel equivalent to it.

III. METHODOLOGY

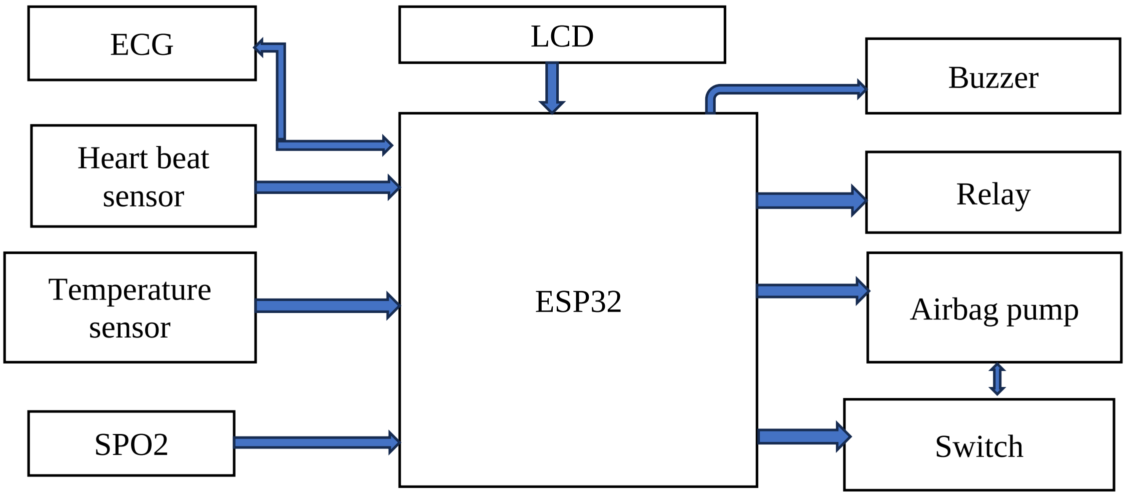

Fig.1. Block Diagram

The methodology for improving smart gloves for interactive CPR involves a multi-step approach integrating cutting-edge technologies in sensors, real-time feedback systems, and wireless connectivity. First, pressure and depth sensors are embedded into the gloves to monitor the force and depth of chest compressions, ensuring they meet recommended guidelines. These sensors provide haptic or auditory feedback to guide the user in adjusting their technique during the process.

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Additionally, ECG sensors are incorporated to monitor the patient's heart rate and rhythm, transmitting this data to wearable devices or mobile apps for continuous monitoring. AI algorithms analyse the compression rate and depth, offering adaptive feedback to optimize CPR performance based on real-time data. Furthermore, the gloves are equipped with environmental and temperature sensors to detect changes in the patient’s condition, offering suggestions for temperature regulation when necessary. Wireless connectivity allows for remote monitoring and collaboration with medical professionals, enabling them to provide guidance during the resuscitation process. The gloves are designed for comfort, using flexible and durable materials to ensure ease of use during prolonged CPR, and are powered by energy-efficient components for long-lasting performance. In addition, the gloves include an educational mode for training, where users receive real-time feedback to refine their technique. Data logging features ensure that CPR performance is recorded, providing valuable insights for future medical assessment.

IV. BACKGROUND AND RELATED WORK

Cardiac arrest is a medical emergency that requires immediate and effective Cardiopulmonary Resuscitation (CPR)to improve survival rates. High quality CPR involves maintaining proper compression depth, rate, and chest recoil, which significantly influence patient outcomes. However, rescuers often struggle to achieve consistent performance due to lack of real-time feedback. Traditional CPR monitoring devices are limited in usability and do not integrate essential health metrics like oxygen levels, ECG, temperature, and blood pressure, crucial for clinical decision during resuscitation.

Advances in wearable technology offer solutions by providing compact, user-friendly devices and health metrics.by leveraging sensors and microcontrollers, wearable devices can provide real-time feedback, improving CPR quality for both professionals and laypersons.

Several studied have highlighted the importance of integrating real-time feedback system into CPR training an application:

Field	Role Description	Key Responsibilities
Biomedical Engineering	Develops sensor integration and ensures accurate measurement of physiological parameters.	Design and calibration of SPO2, ECG ,and temperature sensors for real-time monitoring
Electronics Engineering	Designs the microcontroller system and intel -grates hardware components	Develop and implement ESP32based con -trol systems hardware soft -ware interfacing, and circuit design.
Mechanical Engineering	Design mechanical components for user comfort and automation	Develop air pump mechanism for automated compressions and ensure ergonomic glove design.
Project Management	Coordinates interdisciplinary efforts and ensure project milestone are met.	Oversee timelines, resource allocation, inter-team communication, and objectives.
Quality Assurance	Tests and validate system is intuitive for end-users.	Conduct extensive performance teste, ensure compliance with healthcare standards, and document
Data Science	Analyzes sensor data and optimizes algorithms for accuracy and reliability	Process raw data from sensors, implement machine learning algorithms for better CPR monitoring, and refine feedback models.

TABLE 1. Interdisciplinary team roles.

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V. DESIGN PROCESS

A. BRAINSTORMING AND REQUIREMENT ANALYSIS

The design process began with brainstorming sessions involving interdisciplinary team members. These sessions aimed to identify critical challenges in performing high-quality CPR, such as maintaining correct compression depth, rate, and full chest recoil. Input from clinical experts and feedback from prior studies (e.g., Change al., 2019, and Grief et al., 2021) guided the conceptualization of a wearable smart glove system. Key requirements included:

Integration of sensor to monitor CPR metrics. User comfort and wearability. Automation of chest compressions in emergencies.

B. COMPONENT SELECTION AND PROTOTYPING

1.Microcontroller: The ESP32 was chosen for its compact design, processing capabilities, and support for wireless communication.

2.Sensors: SPO2 for blood oxygen and pressure monitoring.
ECG and heartbeat sensors for cardiac activity.
A temperature sensor for real-time body heat assessment.

3. Feedback Mechanisms: A buzzer and an LCD display were integrated for immediate user feedback and data visualization.

C. FABRICATION OF THE SMART GLOVES

The glove was designed with lightweight and Flexible materials to ensure usability during prolonged use. Sensors were embedded in strategic locations on the glove to maximize data accuracy without compromising user comfort. The system included a wrist strap to prevent displacement during use.

D. SOFTWARE DEVELOPMENT

Custom software was developed using the Arduino IDE. The ESP32 was programmed to collect sensor data, analyse CPR metrics, and provide feedback. A Telegram-based alert system was integrated to notify emergency contacts during critical scenarios.

E. TESTING AND VALIDATION

The prototype was tested on CPR manikins to validate its performance indicators, such as compression depth accuracy and response time, were evaluated. Usability feedback from testers was used to refine the glove's design and functionality. This design process ensured a user-friendly and effective smart glove system capable of enhancing CPR quality and monitoring.

VI. RESULTS

This smart glove prototype integrates flexible taxable txtile-besed resistive pressure sensors and an inertial measurement unit (IMU) to monitor CPR performance. The glove is made of elastic polyamide and cotton fabric for comfort and adaptability, with strategically placed sensors on the palm for accurate data collection.

A wrist strap ensures proper fit and sensors stability during use. Data form the sensors is processed by an Arduino Uno, providing real-time analysis of compression depth, rate, and chest recoil. The design emphasizes wearability, durability, and ease of use, making it suitable for both performance and laypersons during CPR training and assessment.

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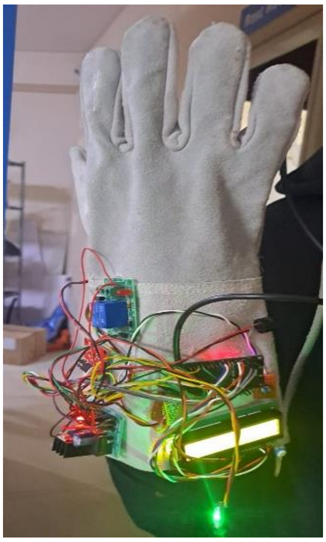

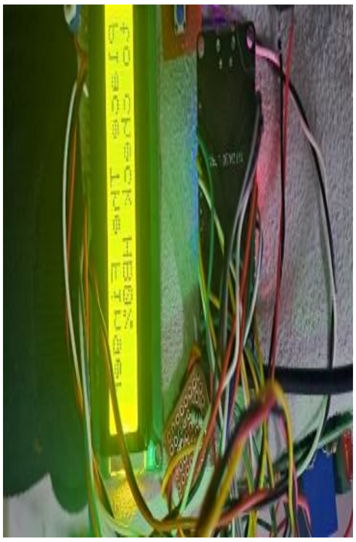

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