LIFESCAN: Real-Time Survivor Detection Using Non-Contact Vital Sign Monitoring And Deep Learning

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Abstract- *Lifescan offers a non-invasive, efficient, and reliable approach to locating survivors, significantly reducing rescue time and improving the chances of saving lives. This technology has potential applications in disaster management, military operations, and remote healthcare monitoringLifescan: Real-Time Survivor Detection Using Non-Contact Vital Sign Monitoring and Deep Learning is an advanced system designed to enhance search and rescue operations in disaster scenarios. The proposed system utilizes non-contact sensing technologies such as optical cameras, thermal imaging, and radar sensors to detect human vital signs, including heart rate and respiration, without requiring physical contact. These physiological signals are often difficult to capture in challenging environments such as collapsed structures or low-visibility conditions.To address this, the system integrates deep learning algorithms for accurate detection and classificationof human presence based on extracted vital signals. The collected data is processed through signal filtering and feature extraction techniques, and then analyzed using trained neural network models to determine the likelihood of survival. By combining sensor data with intelligent analysis, the system can identify survivors in real time, even if they are unconscious or immobile.Lifescan offers a non-invasive, efficient, and reliable approach to locating survivors, significantly reducing rescue time and improving the chances of saving lives. This technology has potential applications in disaster management, military operations, and remote healthcare monitoringthe proposed system emphasizes robustness and adaptability in dynamic and noisy environments commonly encountered during disaster situations. Advanced preprocessing techniques are employed to minimize interference caused by dust, debris, and environmental disturbances, ensuring reliable signal acquisition. The deep learning models are trained on diverse datasets to improve generalization and accuracy across different scenarios, including varying lighting conditions and partial occlusions. The conductected source can developed.*

I. INTRODUCTION

Natural and man-made disasters such as earthquakes, landslides, and building collapses often result in people being trapped under debris, making search and rescue operations extremely challenging. In such critical situations, the timely detection of survivors is essential to save lives. Traditional rescue methods, which rely on manual searching, trained dogs, or sound-based detection, are often time-consuming, less accurate, and limited by environmental conditions such as low visibility, noise, and restricted access. These limitations highlight the need for advanced technological solutions that can assist rescue teams in locating survivors quickly and efficiently.

In recent years, the development of non-contact vital sign monitoring technologies has opened new possibilities in the field of survivor detection. These techniques use sensors such as cameras, thermal imaging devices, and radar systems to detect physiological signals like heart rate and respiration without any physical contact. Unlike conventional methods, non-contact systems can identify unconscious or immobile individuals by capturing subtle biological signals, even in complex and obstructed environments.

To further enhance detection accuracy, deep learning techniques have been integrated into such systems. Deep learning models, particularly convolutional neural networks (CNNs), are capable of analyzing complex patterns in sensor data and distinguishing between human and non-human signals. By combining non-contact sensing with intelligent data analysis, it becomes possible to develop systems that can automatically detect and classify survivors in real time with high reliability.

The proposed system, LIFESCAN, aims to leverage these advancements by integrating non-contact vital sign monitoring with deep learning algorithms for real-time survivor detection. The system is designed to operate effectively in disaster environments, providing rapid and accurate identification of survivors while minimizing human effort and risk. This approach not only improves the efficiency of rescue operations but also increases the chances of saving lives by enabling faster response times.

Despite the promising capabilities of existing technologies, several challenges still hinder effective survivor detection in real-world scenarios. Environmental factors such as dust, smoke, structural instability, and electromagnetic interference can significantly affect sensor performance and signal quality. Moreover, distinguishing between human vital signals and background noise requires sophisticated processing techniques. Addressing these challenges demands a system that not only captures accurate data but also intelligently filters and interprets it under uncertain and dynamic conditions.

In this context, LIFESCAN is designed to provide a comprehensive and efficient solution by integrating advanced sensing technologies with robust deep learning models. The system focuses on delivering real-time analysis, high detection accuracy, and ease of deployment in emergency situations. By incorporating features such as automated signal processing, adaptive learning, and scalable architecture, LIFESCAN aims to support rescue teams with actionable insights. Ultimately, this innovation contributes to the advancement of smart disaster response systems, paving the way for safer and more effective life-saving operations

Another important aspect of modern survivor detection systems is the need for real-time responsiveness and minimal human intervention. In emergency situations, delays in identifying survivors can significantly reduce the chances of successful rescue. Therefore, automated systems like LIFESCAN are designed to continuously monitor the environment and instantly process incoming data to provide rapid results. This reduces dependency on manual efforts and allows rescue personnel to focus on critical decision-making and operational tasks.

Moreover, the integration of such intelligent systems with emerging technologies enhances their overall effectiveness. LIFESCAN can be combined with Internet of Things (IoT) frameworks and wireless communication systems to enable seamless data transmission and remote monitoring. This ensures that rescue teams receive timely updates and accurate information about survivor locations. As technology continues to evolve, such integrated approaches will play a crucial role in building smarter, more resilient disaster management systems capable of saving more lives. Specific Objectives include:

1. **Develop a Non-Contact Sensing System:** To Design and implement a system capable of capturing human vital signs such as heart rate and respiration using sensors like cameras, radar, or thermal devices without physical contact.
2. **Accurately Detect Human Presence In Complex Environments:** To Identify and locate potential survivors in challenging conditions such as debris, low visibility, and obstructed spaces.
3. **Extract And Process Vital Physiological Signals:** To Apply signal processing techniques to filter noise and extract meaningful features from raw sensor data.
4. **Implement Deep Learning Models For Classification:** To Develop and train deep learning algorithms (such as CNNs) to classify detected signals into categories like “alive” or “no vital signs.”
5. **Enable Real-Time Monitoring And Decision-Making:** To Ensure the system processes data quickly and provides instant feedback to assist rescue teams in time-critical situations.
6. **Improve Detection Accuracy And Reliability:** To Enhance system performance by combining multiple sensing techniques and optimizing model accuracy under different environmental conditions.
7. **Design a Scalable And Portable System:** To Create a system that can be integrated with drones, robots, or handheld devices for use in disaster zones.
8. **Reduce Rescue Time And Human Risk:** To Minimize the time required to locate survivors while reducing the exposure of rescue personel to hazardous environments.

Reducing rescue time and minimizing risks to human rescuers is a critical objective of the LIFESCAN system. In disaster environments such as collapsed buildings or hazardous zones, manual search operations can expose rescue personnel to dangers like falling debris, fire, or structural instability. By enabling automated and real-time detection of survivors through non-contact vital sign monitoring, LIFESCAN significantly reduces the need for prolonged physical search efforts. The system quickly identifies potential survivors and pinpoints their location, allowing rescue teams to act more efficiently and strategically. This not only accelerates rescue operations but also enhances the safety of emergency responders by limiting their exposure to life-threatening conditions.

II. SURVEY

A 2022 study by Zhiqiang Gao et al. **investigated** the application of millimeter-wave (mmWave) radar for the instantaneous, touchless monitoring of vital signs. They developed a radar-based system that detects heartbeat and respiration by analyzing Doppler frequency shifts from chest wall motion. The system demonstrated low relative errors (under ~5%) in estimating vital sign parameters, showing feasibility for reliable remote monitoring.

Linas Saikevicius, VidasRaudonis, Gintaras Dervinis & Virginijus Baranauskas (2024) provided a systematic review of non-contact vision-based vital sign monitoring techniques. Their work covers imaging photoplethysmography (iPPG) and related optical methods that use simple cameras to estimate heart and respiratory rates. The review identifies major challenges such as lighting variation and motion artifacts, and highlights preprocessing and dataset needs for more robust performance.

The MRVS technique, introduced by ZhanjunHao et al. (2025), utilizes frequency-modulated continuous wave (FMCW) radar for the remote sensing of physiological signalswave (FMCW) mmWave radar for non-contact vital signs detection. The approach integrates signal enhancement, discrete wavelet decomposition, and adaptive filtering to suppress noise and improve heart rate estimation accuracy under varying conditions such as posture and sensor orientation.

Zhonghang Yuan et al. (2023) introduced **Nmr-VSM**, a framework that integrates **Ultra-Wideband (UWB) radar** with **deep learning** to ensure resilient, touchless vital sign tracking. Their deep learning-driven framework improves detection in dynamic environments by compensating for motion interference, enabling accurate extraction of vital signals like respiration and heartbeat even when subjects are moving slightly.

Bo Zhang and his research group (2023) introduced **Pi-ViMo**, a specialized mmWave radar system that incorporates **physiological modeling** to achieve non-contact vital sign monitoring. Unlike many earlier methods requiring fixed positions, Pi-ViMo robustly estimates respiratory and heart rates by modeling multiple scattering points and using template matching to separate signals, performing well even with slight bodily movements.

A 2026 review by Marek Ostrysz, ZenonSzczepaniak, and Tadeusz Sondej**evaluated** microwave and radar-based methods for the dynamic, non-contact monitoring of vital signs. Their work emphasizes advances in radar technology that improve performance in real-world conditions, including motion tracking and clutter suppression, making such systems promising for real applications in health monitoring and rescue operations.

A “Deep Learning-Based Heart Rate Estimation” study (2025) utilized FMCW radar and a lightweight convolutional neural network (HRConvNet) to improve heart rate estimation. By integrating non-smooth signal decomposition with deep learning, the method achieved accurate vital sign estimation (\±5 BPM), showcasing how neural networks can enhance radar-based sensing performance.

Arash Shokouhmand, Samuel Eckstrom, Behnood Gholami& Negar Tavassolian (2022) combined RGB-D cameras with FMCW radar for real-time non-contact vital sign monitoring. The camera provided location and depth data while radar captured cardiopulmonary motion, with sensor fusion enabling better subject detection and vital sign extraction under complex scenarios.

Non-Contact Measurement of Respiration and Heartbeat Using W-band Doppler Radar” by Heesoo Kim &JinhoJeong (2020) demonstrated vital sign monitoring with W-band Doppler radar sensors. Their work highlights how radar at specific frequency bands can accurately capture breathing and heartbeat without physical contact, forming a foundation for later non-contact rescue and health monitoring systems.

A 2026 comprehensive review in Measurement & Control (2026) examined non-contact vital sign monitoring across vision, radio, and sensor fusion methods. It discusses datasets, evaluation metrics, and deep learning’s role in improving robustness under noise and movement, providing a broad perspective on the current state of research and future directions for systems like LIFESCAN.

III. PROPOSED SYSTEM

The proposed system, LIFESCAN, is designed to detect survivors in real time using non-contact vital sign monitoring and deep learning. The system primarily relies on sensors such as cameras, thermal imaging devices, and radar to capture physiological signals like heart rate and respiration without physically touching the victim. This approach allows detection of unconscious or immobile individuals in disaster scenarios, such as collapsed buildings or landslides, where traditional manual search methods are slow and risky.

Once the sensor data is collected, it passes through a signal processing module. This module filters out noise caused by environmental disturbances, debris, or movement and extracts meaningful features from the raw signals. Key vital signs, including micro-movements from breathing and heartbeat, are isolated to provide accurate inputs for analysis. This ensures the deep learning algorithms receive high-quality data for precise detection.

The deep learning module serves as the core analytical component. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) analyze the extracted features to identify patterns corresponding to living humans. The system classifies the detected signals into categories such as "Alive" or "No Vital Signs," enabling accurate and fast decision-making. This module also allows the system to adapt to different conditions, such as low light, partial occlusion, or slight subject movement.

Additionally, the system includes an alert and visualization module that provides actionable outputs to rescue teams. Detected survivors are marked on a digital map or video feed, and real-time alerts are sent to connected devices. This enables rapid deployment of rescue resources, reduces human risk, and allows continuous monitoring of multiple victims simultaneously. Overall, LIFESCAN combines advanced sensing and artificial intelligence to create a reliable, non-invasive, and real-timesurvivor detection system.

Figure 1 : Proposed system

3.1.Working

The LIFESCAN system initiates by powering on and activating its core components, including the microcontroller unit (MCU) and various non-contact sensors such as radar, cameras, or thermal imaging devices. Establishing a reliable IoT connection at this stage is crucial for seamless data transmission and remote monitoring. Once initialized, the system continuously measures the distance to potential survivors by capturing reflections of signals in the environment. This real-time distance data helps localize individuals even in challenging scenarios like rubble or low visibility, laying the groundwork for precise detection of vital signs without physical contact.

Following distance measurement, the system acquires raw data that contains subtle physiological movements caused by heartbeat and respiration. This data undergoes preprocessing, where noise filtering techniques remove environmental disturbances such as debris interference or ambient vibrations. Smoothing and segmentation processes further refine the signals to isolate meaningful features. Key parameters like peak detection and breathing rate frequency are extracted, providing vital indicators of human life. These processed features form the input to the system's advanced AI analysis stage, which employs Long Short-Term Memory (LSTM) deep learning models to analyze temporal patterns in the data. The LSTM effectively identifies normal and abnormal breathing patterns, ensuring accurate detection of survivors and their health status, even when slight movements or irregular signals are present.

The final stage of the LIFESCAN workflow focuses on decision-making and alert generation. Based on AI outputs, the system determines whether a survivor has been detected and assesses the urgency of the situation. When a living individual is confirmed, the system promptly triggers multiple alerts including audible buzzers, cloud notifications, SMS messages, and updates to an operational dashboard. This multi-channel alerting ensures that rescue teams receive timely and actionable information, allowing them to prioritize and mobilize resources effectively. By integrating real-time sensing, intelligent analysis, and instant communication, LIFESCAN enhances the speed and safety of search and rescue missions, reducing risks to responders and increasing the chances of saving lives**.**

3.2 LSTM

Developed by Hochreiter and Schmidhuber, **Long Short-Term Memory (LSTM)** networks represent a significant evolution of the standard Recurrent Neural Network (RNN). While conventional RNNs often struggle with information loss over time, LSTMs utilize a specialized **memory cell** to bridge long-term temporal gaps, making them indispensable for complex sequence modeling like speech synthesis and financial forecasting.

The architecture maintains signal integrity through three primary regulatory mechanisms:

- **The Input Gate:** Filters the incoming data stream to update the cell's internal state.
- **The Forget Gate:** Pragmatically prunes obsolete information to prevent memory saturation.

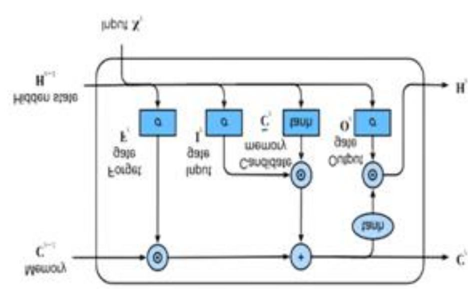

Figure 2 : LSTM

- **The Output Gate:** Determines the specific information to be externalized to the next layer.By balancing this long-term "cell state" with a short-term "hidden state," the network dynamically prioritizes relevant context throughout the sequence.

3.3 How LSTM diffrs from RNN network

Standard RNNs and LSTM networks differ primarily in how they handle memory and information flow over time. A standard RNN is structurally simple, using a single hidden state that is updated at each step, which makes it prone to the vanishing gradient problem where information from the beginning of a long sequence is lost before reaching the end. In contrast, an LSTM (Long Short-Term Memory) network introduces a more complex internal architecture centered around a cell state, which acts as a long-term memory track that allows information to flow through the sequence with minimal interference. This flow is managed by three specialized gates: the forget gate removes irrelevant information, the input gate adds new relevant data, and the output gate determines what part of the internal memory should be visible to the next layer. By using these gating mechanisms to selectively add or delete information, LSTMs can effectively maintain long-term dependencies, making them far superior to standard RNNs for complex tasks like language translation and speech recognition where context from the distant past is crucial**.**

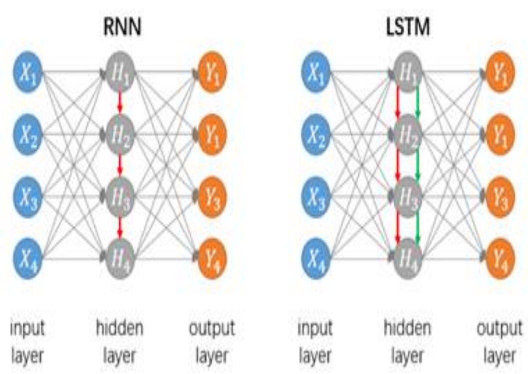

Figure 3 : RNN vs LSTM

the standard LSTM is the most common, several variants have been developed to improve computational efficiency or performance for specific data types.

1. Vanilla LSTM (Standard)
2. Peephole LSTM
3. Gated Recurrent Unit (GRU)
4. Bi-directional LSTM (Bi-LSTM)
5. Stacked LSTM (Deep LSTM)
6. ConvLSTM (Convolutional LSTM)

Vanilla LSTM (Standard)

It consists of a cell state and three gates (input, forget, and output). It uses sigmoid activation functions for the gates and tanh for the cell state and output.

Peephole LSTM

In a standard LSTM, gates only receive the previous hidden state () and the current input (). In a **Peephole LSTM**, the cell state () is also fed directly into the gate layers.

Gated Recurrent Unit (GRU)

It merges the forget and input gates into a single **update gate** and combines the cell state and hidden state. It is computationally "lighter" because it has fewer parameters.

Bi-directional LSTM (Bi-LSTM)

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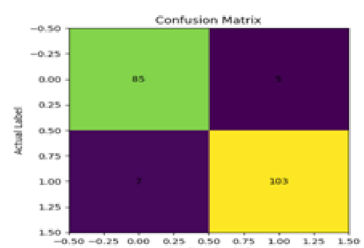
Stacked LSTM (Deep LSTM)

The hidden state output of the first LSTM layer is used as the input for the second LSTM layer, and so on. This allows the model to learn higher-level abstractions of the data.

ConvLSTM (Convolutional LSTM)

Instead of using simple matrix multiplication for the gate transitions, it uses **convolutional layers**. This allows the network to capture spatial features along with temporal ones.



IV. RESULTS AND DISCUSSION

The performance analysis of the proposed LifeScan system evaluates the ability of the model to accurately detect human respiration signals in disaster environments. The system uses an ultrasonic sensing module to capture subtle chest movements caused by breathing and processes the collected time-series data using a Long Short-Term Memory (LSTM) deep learning model. The collected signals are preprocessed to remove environmental noise before being analyzed by the model. The evaluation is carried out using standard classification metrics to measure the reliability and accuracy of the proposed detection system.

Confusion Matrix Analysis

A confusion matrix is used to analyze the classification performance of the model by comparing predicted results with the actual observations. It helps to understand how well the system identifies survivors and avoids incorrect detections.

The confusion matrix contains four important components:

- **True Positive (TP):** The system correctly detects a survivor when a survivor is actually present.
- **True Negative (TN):** The system correctly identifies that no survivor is present in the monitored area.
- **False Positive (FP):** The system incorrectly detects a survivor when none is present.
- **False Negative (FN):** The system fails to detect a survivor when a survivor is actually present.

The confusion matrix results show that the proposed LifeScan system produces a high number of correct predictions, indicating reliable detection of respiration signals. The number of false predictions is relatively low, which demonstrates that the system can effectively distinguish human breathing patterns from environmental disturbances.

Accuracy Analysis

Accuracy is one of the most commonly used performance metrics for evaluating machine learning models. It measures the overall correctness of the prediction model by calculating the ratio of correctly predicted observations to the total number of predictions.

The proposed LifeScan system achieves a high accuracy value, indicating that the system can correctly identify survivor respiration signals in most cases.

Sensitivity (Recall) Analysis

Sensitivity measures the ability of the system to correctly detect actual survivors. A higher sensitivity value indicates that the system successfully detects most of the respiration signals present in the monitored environment.

Sensitivity = TP / (TP + FN)

High sensitivity ensures that trapped victims are less likely to be missed during rescue operations.

Specificity Analysis

Specificity measures the ability of the system to correctly identify cases where no survivor is present. This helps reduce false alarms caused by environmental noise or movement of debris.

Specificity = TN / (TN + FP)

A high specificity value indicates that the system effectively distinguishes human respiration signals from other environmental signals.

Precision Analysis

Precision measures the proportion of correctly detected survivors among all predicted survivor detections. It indicates how reliable the positive predictions made by the system are.

Precision = TP / (TP + FP)

High precision indicates that the system generates fewer false alerts while detecting survivors.

V. RESULTS

The project was successfully implemented to detect human respiration using a non-contact sensing approach. The ultrasonic sensor captured chest displacement signals caused by breathing, and the collected data was processed using an LSTM-based deep learning model. The experimental results showed that the system could accurately identify respiration patterns and detect the presence of survivors in real time. The confusion matrix analysis indicated a high number of correct classifications, demonstrating that the model effectively distinguishes between respiration signals and environmental noise.

Additionally, the alert mechanism successfully generated notifications when human breathing was detected, enabling rapid response from rescue teams.

VI. DISCUSSION

The experimental results demonstrate that the project provides an effective solution for survivor detection in disaster environments. The use of non-contact sensing technology allows monitoring of vital signs without requiring physical contact, which is highly beneficial in rescue scenarios where victims may be trapped or inaccessible. The LSTM deep learning model improves detection accuracy by learning the temporal patterns of respiration signals. Furthermore, the integration of IoT communication and alert systems supports real-time monitoring and quick decision-making by rescue teams. Overall, the system offers a reliable, portable, and efficient approach for improving the speed and effectiveness of disaster rescue operations.

VII. CONCLUSION

In conclusion, this project presents the design and development of project, an intelligent system developed to assist disaster rescue operations by detecting human respiration without physical contact. The system integrates ultrasonic sensing technology, IoT-enabled processing, and deep learning techniques to monitor subtle chest movements caused by breathing. The collected sensor data is preprocessed to remove environmental noise and disturbances, and the processed time-series data is analyzed using a Long Short-Term Memory (LSTM) neural network algorithm, which is capable of learning temporal patterns in respiration signals. The use of the LSTM algorithm improves the accuracy and reliability of survivor detection by identifying sequential breathing characteristics over time. In addition, the system utilizes IoT communication protocols to transmit detection results and generate automated alerts when human respiration is detected. The confusion matrix evaluation and performance analysis demonstrate that the proposed system achieves high accuracy in distinguishing between human breathing signals and environmental noise. By combining IoT sensing, data preprocessing techniques, and LSTM-based deep learning algorithms, the project provides a portable, low-cost, and real-time solution for locating survivors in disaster environments. This project demonstrates the practical application of artificial intelligence and IoT technologies to improve the efficiency and speed of search and rescue operations, ultimately increasing the chances of saving human lives.

VIII. FUTURE ENHANCEMENT

Integration of Advanced Sensing Technologies

The system can be enhanced by integrating advanced sensing technologies such as radar sensors or thermal imaging cameras. These sensors can detect human presence and vital signs even through debris or obstacles, improving the accuracy and reliability of survivor detection in complex disaster environments.

Enhanced Deep Learning Models

Future improvements can include the use of advanced deep learning models such as CNN-LSTM hybrid networks or transformer-based architectures. These models can analyze respiration signals more effectively and improve the overall accuracy and robustness of the detection system.

Mobile and Cloud-Based Monitoring System

A dedicated mobile application and cloud-based monitoring platform can be developed to allow rescue teams to monitor detection results in real time. This enhancement would enable instant alerts, remote monitoring, and faster coordination during disaster rescue operations.

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