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Smart AI Framework for Real-Time Borewell Child Detection and Rescue Operations

Chiluka Tulasi[1], M.Anusha[2]
[1]MCA Student , Dept of MCA , Ellenki College of Engineering and Technology , Hyderabad
[2]Assistant Professor , Dept of MCA , Ellenki College of Engineering and Technology , Hyderabad

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Abstract— **Borewell accidents involving children remain a serious safety concern, particularly in rural areas where unused borewells are often left uncovered. Delays in locating and rescuing trapped victims can significantly reduce the chances of survival, highlighting the need for an intelligent rescue support system. This research proposes a Smart AI Framework for Real-Time Borewell Child Detection and Rescue Operations that combines wireless monitoring, artificial intelligence, and embedded technologies to improve emergency response. The system uses a Raspberry Pi with a camera module to continuously monitor the child inside the borewell. An enhanced VGG-based model analyzes facial expressions to identify signs of fear or distress, while a VGGish-based audio model detects voice responses to determine whether the child is conscious. A temperature sensor monitors the child's physical condition, and all collected information is transmitted through a wireless network to a web-based interface for real-time observation by rescue teams. The framework enables continuous monitoring of the child's status and supports faster decision-making during rescue operations. By integrating AI-driven monitoring with wireless communication, the proposed system offers a practical, reliable, and efficient approach for improving child safety and assisting rescue personnel during borewell emergencies.**

Keywords— **Borewell Child Rescue, Artificial Intelligence, Wireless Monitoring, Raspberry Pi, Computer Vision, Facial Expression Recognition, Voice Activity Detection, Temperature Monitoring, Real-Time Detection, Emergency Rescue System.**

I. INTRODUCTION

India is an agricultural country where groundwater is one of the primary sources of irrigation, resulting in the construction of thousands of borewells across rural regions. Once these borewells become dry or are no longer useful, many are left open without proper protection, creating a serious risk to public safety. Children playing near these abandoned borewells may accidentally fall into them, leading to life-threatening emergencies that require immediate rescue. Such incidents have repeatedly occurred in different parts of the country and often become challenging because of the narrow and deep structure of borewells [16]. Conventional rescue operations depend largely on manual efforts, which are time-consuming and provide limited information about the trapped child's condition [18]. These recurring accidents emphasize the need for an intelligent rescue support system capable of monitoring the child continuously and assisting rescue teams in making timely and accurate decisions during emergency situations [11].

Traditional borewell rescue methods involve manual monitoring using cameras, ropes, and heavy machinery, making the rescue process slow and highly dependent on human judgment. Rescue personnel often face difficulties in determining whether the trapped child is conscious, frightened, or physically stable because only limited visual information is available from inside the borewell [17]. Continuous observation of the child's emotional and physical condition is essential for planning effective rescue operations, yet existing approaches do not provide automated analysis or real-time decision support. Artificial intelligence has shown remarkable success in recognizing human emotions and behavioural patterns through image and audio analysis, making it suitable for emergency monitoring applications [1]. Deep learning-based emotion recognition techniques can automatically identify signs of fear, stress, or distress, enabling rescue teams to understand the child's condition more accurately and respond appropriately [9].

Recent advancements in deep learning and computer vision have significantly improved the ability of intelligent systems to analyse facial expressions, voice signals, and human behaviour. Convolutional neural networks and VGG-based architectures have demonstrated excellent performance in extracting meaningful visual features for emotion recognition and image classification tasks [10]. Similarly, audio analysis models can evaluate speech responses and determine whether an individual is conscious and capable of communicating during an emergency [6]. Integrating these technologies with embedded hardware allows continuous monitoring inside confined environments such as borewells. Along with facial and audio analysis, monitoring physiological parameters such as body temperature provides additional information about the child's health condition during rescue operations [7]. These intelligent sensing techniques help rescue personnel receive reliable real-time information without relying entirely on manual observation.

The proposed system integrates artificial intelligence, embedded hardware, and wireless communication into a unified rescue monitoring framework. A Raspberry Pi functions as the central processing unit and is connected to a camera, microphone, speaker, and temperature sensor for collecting real-time information from inside the borewell. The captured facial images are analysed using an enhanced VGG-based model to recognize the child's emotional state, while a VGGish-based audio model evaluates voice responses to determine consciousness [11]. Temperature measurements provide additional confirmation of the child's physical condition during rescue operations [7]. All monitoring information is transmitted through a wireless network to a web-based interface, enabling rescue teams to continuously observe the child's condition and make informed decisions without unnecessary delays [16].

This research proposes a Smart AI Framework for Real-Time Borewell Child Detection and Rescue Operations to improve the safety and efficiency of emergency rescue missions. The framework continuously analyses the child's facial expressions, voice responses, and body temperature while displaying the collected information through a user-friendly monitoring interface. Real-time updates allow rescue personnel to evaluate the child's condition throughout the rescue process and plan appropriate rescue strategies based on accurate information [1]. The integration of artificial intelligence with wireless monitoring reduces dependence on manual observation and enhances the speed and reliability of emergency response [18]. Overall, the proposed framework demonstrates how modern AI technologies can support rescue operations, improve decision-making, reduce rescue delays, and increase the chances of safely rescuing children trapped inside borewells [16].

II. RELATED WORK

Kosti et al., [2019] [1] proposed a context-aware emotion recognition framework using the EMOTIC dataset to improve the understanding of human emotions in real-world environments. Instead of relying only on facial expressions, their approach also considered surrounding objects, background information, and environmental context to recognize emotional states more accurately. The researchers developed deep learning models capable of extracting visual features from both the individual and the surrounding scene. Their experimental evaluation demonstrated that contextual information significantly improves emotion recognition performance compared to face-only methods. The study highlighted that emotions are influenced by both personal expressions and external situations, making context an essential factor in emotion analysis. This research provides valuable insights for intelligent monitoring systems where understanding a person's emotional condition is important. It also establishes a strong foundation for developing AI-based systems that monitor human emotions in safety-critical applications such as emergency rescue.

Kim and Provost, [2017] [6] introduced the ISLA framework for recognizing emotions from both audio and visual information through temporal segmentation and labeling techniques. Their work focused on understanding how emotions change over time rather than treating them as isolated events. The proposed method analyzed facial movements together with speech signals to improve the overall recognition process. By combining multiple sources of information, the framework achieved better accuracy than systems relying on only one type of input. The authors demonstrated that synchronized audio-visual analysis helps capture emotional changes more effectively in dynamic situations. Their research emphasized the importance of temporal information when developing intelligent emotion recognition systems. This work contributes to the advancement of multimodal artificial intelligence and provides useful concepts for applications that require continuous monitoring of emotional states, including healthcare, human-computer interaction, and emergency response systems.

Li and Deng, [2018] [9] presented a deep learning approach for facial expression recognition using reliable crowdsourced data and locality-preserving learning techniques. Their study addressed the challenge of recognizing facial expressions captured under unconstrained conditions such as different lighting environments, head poses, and facial variations. The proposed framework combined deep feature extraction with improved learning strategies to enhance classification performance across diverse datasets. The authors showed that preserving local feature relationships while learning facial characteristics significantly improved recognition accuracy. Their experimental results demonstrated that the model remained robust even when images contained background noise or pose variations. The study highlighted the importance of high-quality training data and effective feature learning for reliable facial expression analysis. This research serves as a valuable reference for AI-based visual monitoring systems that require accurate emotion recognition under practical real-world conditions.

Girshick, [2015] [10] introduced the Fast R-CNN framework as an improved object detection technique capable of identifying and classifying objects more efficiently than previous approaches. The proposed method reduced computational complexity by processing the entire image through a convolutional neural network before extracting region-based features. This design significantly accelerated training and testing while maintaining high detection accuracy. The framework also introduced an end-to-end learning process that simplified model optimization and improved localization performance. Experimental evaluation demonstrated that Fast R-CNN outperformed earlier object detection methods in both speed and accuracy across multiple benchmark datasets. The study became an important milestone in computer vision research and influenced many later deep learning models. Its efficient feature extraction strategy continues to support applications involving image understanding, object recognition, medical image analysis, and intelligent surveillance systems.

Reshma et al., [2019] [16] developed an Internet of Things (IoT)-based emergency support system that recommends the nearest heart care center during medical emergencies. The proposed framework collected patient information and location details through connected IoT devices and used these data to identify the most suitable healthcare facility. The system aimed to reduce emergency response time by enabling faster communication between patients, hospitals, and healthcare providers. Experimental evaluation demonstrated that integrating IoT with healthcare services improves decision-making and helps deliver timely medical assistance. The authors emphasized that real-time monitoring and automated information sharing can significantly enhance emergency management while reducing delays caused by manual coordination. Their work illustrates the practical benefits of combining intelligent monitoring with wireless communication technologies. This study provides useful guidance for designing AI-enabled emergency response systems that require rapid monitoring and decision support during critical situations.

III. DATASET DETAILS

The dataset used in this project consists of facial images, voice responses, and temperature readings collected to monitor the condition of a child trapped inside a borewell. The image data are used to recognize the child's emotional state, while audio recordings help determine whether the child is conscious by analyzing responses to predefined questions. Temperature sensor readings provide additional information about the child's physical condition during the rescue operation. The collected data are organized in a structured format so they can be processed efficiently by artificial intelligence models. Before training, the dataset is carefully examined to remove incomplete or poor-quality samples and to ensure consistency across all data sources. The combination of visual, audio, and sensor information enables the system to perform reliable monitoring and supports rescue teams with accurate real-time updates. This multimodal dataset forms the foundation for developing an intelligent borewell child rescue framework.

To prepare the dataset for model training, several preprocessing techniques are applied to improve data quality and learning performance. Facial images are resized, normalized, and labelled according to different emotional states before being provided to the deep learning model. Audio recordings are converted into feature representations suitable for the VGGish model, allowing efficient voice activity analysis. Temperature readings are filtered to eliminate noise and maintain stable measurements. The complete dataset is shuffled to prevent bias and is divided into 70% training data and 30% testing data to evaluate the performance of the proposed framework on unseen samples. Proper preprocessing ensures that the AI models learn meaningful patterns from multiple data sources, resulting in more accurate emotion recognition, consciousness detection, and health monitoring during real-time borewell rescue operations.

IV. PROPOSED METHODOLOGY

The proposed system follows a structured approach to monitor and assist in real-time borewell child rescue operations using artificial intelligence and wireless technologies. Initially, the facial emotion image dataset is collected and uploaded into the system. The dataset is then preprocessed by reading each image, resizing it to the required dimensions, normalizing pixel values, and removing unnecessary variations that may affect model performance. The processed images are shuffled to ensure balanced learning and are divided into training and testing datasets, allowing the model to learn facial emotion patterns while evaluating its performance on unseen data. These preprocessing steps improve the quality of the input data and help the deep learning model achieve reliable emotion recognition during rescue operations.

After preprocessing, the Enhanced VGG16 model is trained using the prepared facial emotion dataset to identify the emotional condition of the trapped child. The trained model is evaluated using performance metrics such as accuracy, precision, recall, F1-score, and confusion matrix to measure its classification capability. Training history graphs are generated to observe changes in model accuracy and loss over different training epochs. During real-time operation, the webcam continuously captures the child's facial images, and the trained model predicts the detected emotion with a confidence score. Based on the prediction, the system can trigger supportive actions such as playing calming music and displaying the child's emotional status through the monitoring interface, enabling rescue personnel to assess the situation quickly and respond more effectively.

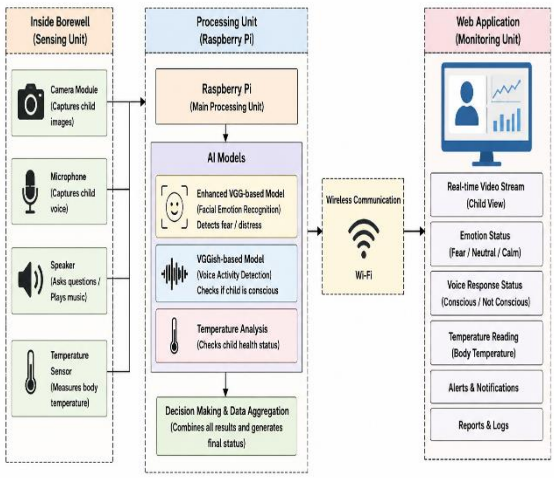

Figure [1]: AI-Based Borewell Child Rescue System

Figure [1] illustrates the overall workflow of the proposed AI-enabled borewell child rescue system. The camera, microphone, speaker, and temperature sensor collect real-time information from inside the borewell and send it to the Raspberry Pi processing unit. The captured data are analyzed using the Enhanced VGG-based emotion recognition model, VGGish voice analysis model, and temperature monitoring module. The processed information is transmitted wirelessly to the web application, where rescue personnel can monitor the child's emotional state, voice response, body temperature, and live status. This enables continuous monitoring and supports faster and more informed rescue decisions.

V. RESULT AND DISCUSSION

The experimental evaluation demonstrates that the proposed Smart AI Framework for Real-Time Borewell Child Detection and Rescue Operations provides an effective solution for monitoring children trapped inside borewells. The system successfully integrates facial emotion recognition, voice activity analysis, and body temperature monitoring to provide continuous updates about the child's condition. After preprocessing the collected image, audio, and sensor data, the Enhanced VGG-based model and the VGGish-based model were trained and tested using separate datasets. The trained models achieved reliable performance in identifying emotional states and determining whether the child was conscious through voice responses. Performance was assessed using evaluation measures such as accuracy, precision, recall, F1-score, and confusion matrix, which indicated consistent and dependable classification results. The training history also showed stable convergence with gradual improvement in accuracy and reduction in loss over successive epochs. The web-based monitoring interface displayed live video, emotional status, voice response, and temperature information, allowing rescue personnel to observe the child's condition in real time. These results confirm that the proposed framework can support faster emergency response and improve the overall efficiency of borewell rescue operations.

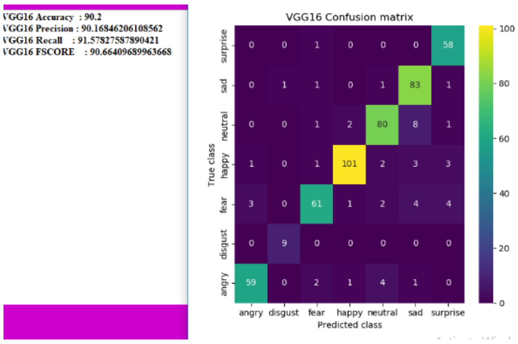

Figure [2]: VGG16 Model Performance

Figure [2] shows the performance of the Enhanced VGG16 model for facial emotion recognition. It displays the evaluation metrics, including accuracy, precision, recall, and F1-score, along with the confusion matrix. The confusion matrix compares the predicted emotions with the actual emotion classes, where higher diagonal values indicate correct classifications. The results demonstrate that the model performs effectively in recognizing different emotional states and can support real-time borewell child monitoring.

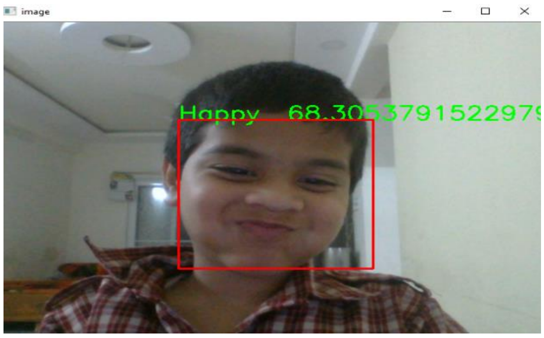

Figure [3]: Real-Time Emotion Detection

Figure [3] shows the real-time emotion detection process using the Enhanced VGG16 model. The webcam captures the child's facial image, detects the face, and predicts the corresponding emotional state along with a confidence score. The detected emotion is displayed on the screen, enabling continuous monitoring of the child's condition during borewell rescue operations.

DISCUSSION

The findings of this study demonstrate that combining artificial intelligence with embedded monitoring devices can significantly improve the effectiveness of borewell child rescue operations. The Enhanced VGG model accurately recognized facial emotions, while the VGGish model successfully analyzed voice responses to determine the child's level of consciousness. Integrating these models with temperature sensing provided a comprehensive understanding of the child's physical and emotional condition throughout the rescue process. Proper preprocessing of images and audio signals played an important role in improving prediction accuracy and reducing classification errors. The use of performance metrics and confusion matrices verified the reliability of the proposed models, while the training history confirmed stable learning behaviour. The web application further enhanced the system by providing rescue teams with continuous real-time monitoring and easy access to critical information. This intelligent framework reduces dependence on manual observation and supports quicker decision-making during emergency situations. Overall, the proposed system demonstrates that AI-based monitoring can enhance rescue planning, improve communication between monitoring units and rescue teams, reduce response time, and increase the possibility of saving lives during borewell rescue missions.

VI. CONCLUSION

The proposed Smart AI Framework for Real-Time Borewell Child Detection and Rescue Operations demonstrates an effective approach for improving the safety and monitoring of children trapped inside borewells. By integrating artificial intelligence with embedded hardware and wireless communication, the system provides continuous monitoring of the child's emotional state, voice response, and body temperature throughout the rescue process. The Enhanced VGG model accurately recognizes facial emotions, while the VGGish-based voice analysis helps determine whether the child is conscious and responsive. Temperature sensing further supports the assessment of the child's physical condition, enabling rescue teams to obtain real-time information without relying solely on manual observation. The web-based monitoring interface allows emergency personnel to access live updates and make faster, more informed rescue decisions. Experimental results indicate that the proposed framework performs reliably in recognizing emotions and monitoring the child's condition, making it a practical solution for emergency rescue applications. Overall, this intelligent system reduces rescue delays, enhances situational awareness, and supports more efficient rescue planning. Future improvements may include integrating additional health sensors, advanced communication technologies, and autonomous rescue mechanisms to further strengthen the effectiveness of borewell rescue operations.

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