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PROPOSAL OF ENHANCING WATER SAFETY- AN AUTONOMOUS ROBOT FOR DROWNING PREVENTION

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ABSTRACT

This paper presents the development of an advanced image recognition robot, dubbed the "drowning robot," designed to identify individuals at risk of drowning using state-of-the-art hardware and software. The primary aim of the project is to enhance water safety. The system leverages powerful computing platforms, such as the NVIDIA Jetson and Intel NUC, paired with high-resolution cameras and specialized sensors to capture and process real-time video data. By employing image processing technologies like OpenCV and deep learning models such as YOLO (You Only Look Once), the robot can detect human figures and unusual movements in aquatic environments. Operating autonomously, the robot offers a reliable solution for emergency response scenarios and can connect to cloud services for further verification. Key performance metrics, including FLOPS, latency, and frames per second (FPS), are assessed to ensure optimal processing speed for quick detection and action. This cutting-edge technology represents a major advancement in both robotics and safety engineering, with the potential to significantly improve rescue operations during drowning incidents and provide timely alerts to enhance public safety.

Keywords: *Drowning Detection, Robotics, YOLO, OpenCV, Object Detection, Surveillance Technology*

1. INTRODUCTION

Swimming is an essential kind of exercise because it has so many health advantages for people of all ages. It offers a full-body workout that strengthens muscles, increases flexibility, and improves cardiovascular health without putting undue strain on the joints. It also helps people who suffer from long-term illnesses like asthma, arthritis, and heart disease. Moreover, swimming has been linked to better mental health since it releases endorphins, which lower tension and anxiety, and encourages relaxation through rhythmic motions. Drowning is the most serious risk associated with swimming. For children ages 1-4 in the United States, drowning is the most common injury-related death cause, and for those aged 5-14, it is the second most common. Residential pools are the site of most of these incidents [1], but uncontrolled currents and inadequate monitoring also pose a risk in natural water bodies such lakes and rivers. Between 2020 and 2022, the number of unintentional drowning deaths rose, underscoring the necessity of efficient preventative measures including swimming instruction and water safety awareness campaigns. Another risk factor for events involving swimming is substance abuse. The necessity of sober swimming techniques is highlighted by the CDC's report that drugs or alcohol were implicated in 20% of drowning occurrences. The environment might also affect the hazards; for example, swimming in rivers or the ocean can be riskier because of strong currents and waves. Providing access to swimming instruction, raising knowledge of water safety, and putting in place safety precautions like life jackets and round-the-clock monitoring are some of the steps taken to lessen these hazards. Swimming safety can be improved and these occurrences can be considerably decreased by raising awareness of and accessibility to water safety programs [3].

Many times, drowning is misinterpreted as a noisy, thrashing incident. Since victims are unable to call for assistance, it is actually typically silent. Their heads may tilt back, their mouths stay in the water, and their arms may press down to lift their bodies in the "instinctive drowning response," but they do not move or cry out. Both adults and children may struggle silently or with little splashing, making it difficult for untrained witnesses to quickly identify the situation. Due to the peaceful aspect of the incidence, nearly half of kid drownings occur within 25 yards of an adult, who may not be aware of the situation [4]. There are a number of variables that can affect drowning incidents, including age, swimming skill, and alcohol use. Little toddlers are particularly vulnerable since they can drown in as little as one inch of water, which can happen in bathtubs or tiny swimming pools. Drinking alcohol is a major risk factor in adulthood. Rescue operations and results can also be made more difficult by circumstances like rip currents in oceans or hypothermia from exposure to cold water [5]. Since only around 75% of drowning victims survive, the hypoxia that causes them to suffer long-term neurological damage is still a serious public health concern. The length of submersion, the temperature of the water, and the pace at which life support is started all affect the prognosis of drowning victims. Delays in resuscitation or submersion for more than ten minutes can have serious consequences, such as death or irreversible brain damage [5]. The majority of drowning happened during swimming or other leisure activities, with the exception of areas near the ocean or harbor, according to the study [6] [7]. Eighty percent of the instances showed results that were inconclusive about the involvement of drugs or alcohol. Of the 20% who were still proven to have been engaged, 58% involved legal drugs (alcohol was involved in 56% of these cases), 19% involved illegal drugs, 15% involved both legal and illegal substances, and 8% involved no drugs at all. The analysis also included toxicological testing, stomach contents, pulmonary enema, lung and brain weight, and decomposition signs.

Numerous techniques exist for tracking and identifying instances of drowning, each having pros and cons of their own. Lifeguards provide immediate response and rescue skills, human judgment and expertise, communication and cooperation with authorities, and more [8]. Nevertheless, their efficacy is constrained by their narrow field of vision, susceptibility to human mistake, and physical endurance and fatigue risk [9]. Drones that process video offer an airborne perspective that enables extensive coverage and monitoring. They provide a real-time video stream for situational awareness, facilitating speedy deployment and quick response [10]. However, they have drawbacks such limited battery life, aviation laws, controlled airspace, susceptibility to external factors like wind, and problems with cost and accessibility, especially in low- and middle-income nations [11]. Continuous monitoring and real-time data collecting are supported by image processing technology, which has a high degree of efficacy and accuracy in identifying and classifying drowning episodes. Additionally, it permits the customization of detection levels and the ability to detect underwater [12]. Its limited detection range, requirement for frequent maintenance and calibration, and high implementation costs are some of its drawbacks. Because it requires sophisticated AI methods and infrastructure, it is less accessible and inexpensive in areas with lower incomes. The location and quality of the cameras also affect the technology [13]. Wearable sensors provide cost-effectiveness, real-time data collecting, and ongoing monitoring. They can be readily integrated with AI systems to improve accuracy, and they are widely available and easily adaptable for individual detection [14]. Notwithstanding these advantages, they are susceptible to environmental changes, which could result in false alarms. They also need to be maintained and calibrated, have a restricted communication range underwater, and have limited detecting coverage [15].

This article proposed a moving Artificial Intelligence based device called as drowning robot, which monitors the facial reacting of the swimming person and compared the existing facial reacting of the drowning when he falls in to drowning in the water sources, the device alert the emergency services near to the person. The article has organized in the structure of survey related to latest technology for precaution of drowning accident in the section II, followed by the proposed model in the section III, Technological support for the proposed model in the section IV and finally ends with a conclusion in the section V.

2. LITERATURE SURVEY

. In this section explains the various categories of drowning detection in the water zoon areas like river, pool, Lake Etc. The major area concentration on using hardware devices, Image processing with sensors, Bluetooth, Airbag, latest Model, YOLO, AI, General techniques and computer Vision. Each method is discussed with the innovation techniques and advantages, limitation and any future enhancement etc.

The survey of drowning detection using hardware devices with several innovative methods are discussed. First approach by [16] utilizes a system consisting of a Raspberry Pi running the Raspbian OS, along with a Pixy camera, Arduino Nano, stepper motor, alarm system, and motor driver for detecting drowning incidents. This setup offers real-time calculations to locate and rescue swimmers while alerting staff simultaneously, but it faces challenges due to the complexity of integrating multiple components. Future work aims to optimize embedded systems and sensor integration for improved efficiency. Another method by [17] involves a radar-based system with a two-stage fusion network to enhance feature learning across domains. This method shows strong adaptability to environmental changes and captures micro-Doppler features for precise detection, though it may require specific conditions and involve complex computational processes. The future focus is on improving fusion efficiency and developing robust algorithms suitable for different environments. Additionally, wearable technology like a wristwatch that monitors blood pressure and heartbeat variations through an Arduino Uno microcontroller is proposed by [18,19]. This device is non-invasive, offering real-time safety monitoring and emergency flotation; however, its application is limited to individuals and may not be effective in mass drowning situations. Future advancements aim to enhance wearable technology for remote monitoring capabilities. Lastly, [20] presents a Raspberry Pi-based system integrated with a USB camera and deep learning for activity identification, providing an affordable and accessible setup for real-time monitoring. Despite its potential, it relies heavily on camera quality and environmental factors, highlighting the need for future exploration into advanced camera technologies for better performance in low-light and underwater conditions.

The next about the survey of drowning detection using image processing and sensors involves several innovative; author of [21] utilizes image processing alongside accelerometers, pulse sensors, pressure sensors, and LASER LDR technology for detecting drowning incidents. This method provides comprehensive data collection from various sensors, enhancing detection accuracy, but faces challenges in sensor calibration and integration, and may not be suitable for all age groups. Future work focuses on exploring additional sensor types and refining image processing algorithms for better accuracy and reliability. Another method by [22] employs pressure sensors, accelerometers, and gyroscopes to assess swimmer behavior and drowning risk, with devices worn on the wrist or chest. This setup enables comprehensive monitoring of swimmer behavior, enhancing safety for different swimming styles, but is limited to individual use and may not be effective for group swimming situations. Future developments include the integration of multiple sensor types for improved group monitoring and distress detection. In [23] introduces the use of ultrasonic sensors in swimming pools to determine the swimmer's state based on a threshold, capable of differentiating between a drowning person and other objects. While this method offers high precision, it has setup complexities and calibration issues, particularly in turbulent water conditions. Future refinement of this technology aims to enhance its detection capabilities in various pool conditions. An embedded system with ultrasonic sensors, as presented by [24], activates alarms upon detecting drowning incidents, with tablets aiding in rescues. This system provides immediate alerts, improving response times, but depends on system setup, reliable power sources, and has a potential for false positives. Future work involves exploring automated response systems and enhancing remote communication between sensors and rescue teams. The authors [25] propose using ultrasonic sensors with receivers and transmitters to determine swimmer positions by analyzing distances with acoustic simulation. This method offers accurate 3D tracking of swimmers, improving monitoring, but may be affected by environmental noise and underwater disturbances, requiring regular calibration. Future research will focus on improving algorithms for position tracking across various aquatic environments. Another method by [26] uses sensor-based classification and movement distance estimation through algorithms inspired by pedestrian dead reckoning (PDR) for swimmer localization. This approach enhances the accuracy of swimmer localization and movement assessment but faces challenges in algorithm implementation and dependency on multiple sensor inputs. Future work involves optimizing PDR algorithms for swimming scenarios and exploring integration with additional sensor technologies. Lastly, in [27] discusses the use of underwater sonar systems combined with deep neural networks for accurate drowning detection, achieving high classification accuracy in short scanning times. This method offers fast and accurate detection in diverse aquatic environments; suitable for real-time use, but its limited testing across various water conditions suggests the need for further validation and optimization. Future efforts include investigating more efficient deep learning techniques and sonar applications in complex scenarios.

Third the study of drowning detection using Bluetooth technology has produced several promising methods. In [28] utilizes wearable Bluetooth tags that send periodic beacon signals. An improved RSSI-based algorithm estimates the swimmer's position and triggers alarms when they are submerged, providing real-time alerts and enhancing swimmer safety. However, this method may face signal disruption issues in deep water or poor conditions and it depends on the battery life of the devices. Future work aims to develop enhanced algorithms to improve accuracy under varying environmental conditions. Another method, proposed by [29], combines cameras with integrated wristbands to recognize drowning postures and monitor pulse signals, promoting self-rescue capabilities. This system allows for quick identification of drowning situations, enabling immediate assistance. However, it relies on the proper positioning and functioning of cameras, and its effectiveness may vary depending on lighting conditions. Future efforts will focus on enhancing algorithms for better recognition across different environments and lighting scenarios.

A comparative study by [30-34] of five CNN models (SqueezeNet, GoogLeNet, AlexNet, ShuffleNet, ResNet50) shows that ResNet50 achieved the highest prediction accuracy for drowning detection. While effective, training these models is computationally intensive, leading to future research on reducing requirements while maintaining accuracy. Compares four machine learning models [35-37] (LR, RF, SVM, stacking ensemble) for predicting nonfatal drowning risks, with the stacking ensemble performing best. The complexity and interpretability of these models call for future studies focusing on robustness and explainability. Swimmer detection method [38] using local motion and intensity information from image sequences, leveraging dense optical flows and cyclic graphs for detailed motion analysis. Extracting reliable local motion information in crowded environments remains complex, and future work will improve robustness in dynamic settings. Lastly, combines mean-shift clustering with cascaded reinforcement learning [39] for swimmer detection in an indoor swimming pool, an adaptable approach that may require extensive training for optimal results. Further research will explore integrating clustering with deep learning for enhanced the real time detection.

The application of YOLO (You Only Look Once) models in drowning detection offers various innovative approaches for real-time monitoring and response. In one study, [40] introduces the original YOLO model for object detection, capable of processing images quickly at 45 FPS, allowing for rapid detection and response. However, the model may struggle with small objects or occlusions, and its accuracy can vary based on the training dataset. Future work involves exploring advanced YOLO versions like YOLOv5 to further improve speed and accuracy.[41][42] developed a drowning risk detection system using YOLOv4 combined with the MA_CBAM module to enhance the model's detection capabilities, resulting in improved accuracy and robustness. Despite these advancements, the system's implementation is complex and requires substantial training data for optimal performance. Future efforts will focus on refining the MA_CBAM module for better detection in varied environmental conditions. The studies by [43] [44] utilize Faster R–CNN and YOLOv5 models for rapid drowning detection, particularly for infants. The models achieved high mean Average Precision (mAP) values, with YOLOv5 reaching over 89% accuracy and operating at 75 FPS, providing a good balance between speed and precision. However, Faster R–CNN has a significantly lower processing speed of 6 FPS. Future research aims to develop hybrid models that combine the strengths of different architectures for even better detection performance.

Another approach by [45] uses a swimmer behavior recognition framework based on YOLOv4, analyzing the relationship between the swimming and drowning areas to enhance risk assessment. While this improves the understanding of swimmer behavior, it requires accurate contextual data, and the model's performance may be affected by environmental factors. Future developments will focus on creating context-aware models that adapt to changing swimming conditions.[46][47] Employ YOLOv2 and Tiny-YOLO for swimmer detection in challenging conditions, implemented on low-cost embedded systems, making the approach affordable and efficient for real-time aquatic safety applications. However, the performance is limited by the capabilities of low-cost hardware, and it may decrease in complex scenarios. Future research will explore enhancements in low-cost hardware technology to improve detection capabilities without sacrificing performance.

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The analysis of drowning detection technologies reveals a diverse range of methodologies, including hardware devices, image processing, AI integration, and model-based systems, each employing various technologies such as sensors, cameras, and machine learning algorithms. A strong emphasis on real-time capabilities is evident, enhancing the ability to respond swiftly to drowning incidents, particularly with models like YOLO and advanced sensor technologies. However, many solutions face challenges related to the integration of multiple components, where the complexity of setup and calibration can hinder widespread adoption. Additionally, the effectiveness of these systems often depends on environmental conditions, such as lighting and water clarity, highlighting the need for robustness across varied aquatic settings. Many technologies are limited to individual monitoring, necessitating the development of systems that can effectively monitor groups of swimmers or larger areas. The reliance on machine learning and AI also underscores the importance of optimizing algorithms to improve processing speed and reduce false positives, particularly in dynamic environments. Future directions include enhancing sensor technologies, exploring advanced AI and deep learning models, and expanding datasets to encompass diverse scenarios, all aimed at creating more effective, reliable, and user-friendly solutions to improve swimmer safety in aquatic environments.

3. PROPOSED WORK

The literature presents various methods and techniques for detecting drowning individuals in water, emphasizing the development of innovative approaches to enhance safety. These include advanced sensor systems, image processing technologies, and artificial intelligence applications designed to identify distress signals in aquatic environments. The analysis of drowning detection technologies highlights various methods, including hardware, image processing, and AI integration, focusing on real-time responsiveness to incidents. Challenges include the complexity of integrating components, dependence on environmental conditions, and limitations in monitoring groups of swimmers. The reliance on machine learning emphasizes the need for optimized algorithms to enhance speed and reduce false positives. Future developments aim to improve sensor technologies, explore advanced AI models, and expand datasets to create more effective and user-friendly solutions for swimmer safety. This section proposes a robot designed to identify the facial reactions of swimmers to determine if someone is drowning. The facial reactions of a drowning person typically include signs of panic and distress, such as wide eyes and an open mouth, indicating attempts to gasp for air. Expressions of fear or struggle may be evident, along with tense or strained facial muscles as the person fights for breath. Additionally, the face may appear pale or show signs of cyanosis due to oxygen deprivation. By analyzing these features, the robot aims to accurately assess drowning situations and enhance safety measures in aquatic environments.

The robot designed for facial recognition in drowning detection operates through several key steps:

1. **Sensor Integration:** Equipped with cameras and sensors, the robot captures real-time images and videos of swimmers in the water.
2. **Image Processing:** Utilizing image processing algorithms, it analyzes these images to detect faces, employing techniques like facial landmark detection to identify features such as eyes and mouth.
3. **Facial Expression Analysis:** The robot uses machine learning models trained on diverse facial expressions to classify emotions, focusing on signs of panic or distress like wide eyes, an open mouth, and tense facial muscles.
4. **Behavioral Context:** Additional data on movement patterns and body language enhances accuracy. For instance, erratic movements or sudden splashes might prompt deeper analysis of facial expressions.
5. **Real-time Monitoring:** The system continuously evaluates swimmers' facial reactions, comparing them to predefined indicators of distress in real time.
6. **Alert Mechanism:** Upon detecting signs consistent with drowning, the robot activates an alert system to notify lifeguards or emergency responders for immediate action.
7. **Learning and Adaptation:** The robot employs ongoing machine learning to refine its recognition capabilities, adapting to various conditions and environments over time.

4. ROBOTIC FRAMEWORK OF THE DROWNING ROBOT

Creating an image recognition robot requires a careful selection of hardware and software components to ensure effective image processing and recognition. On the hardware side, the computing platform should be a powerful unit like the Intel NUC, a mini-PC suitable for handling complex algorithms and heavier computational loads. The camera module should ideally be a 3D/Depth Camera, such as the Intel Real Sense or Microsoft Kinect, for accurate object detection in 3D space, helping with depth and distance analysis. A reliable power supply, either a battery pack or an external adapter, is essential to power the robot's components, including the SBC and camera. For mobility, actuators and motors like a pan-tilt camera mount can be used to move the camera and capture images from different angles. Additionally, sensors such as ultrasonic or IR proximity sensors help detect obstacles, while a Wi-Fi or Bluetooth module facilitates remote control, data transmission, and integration with cloud services all together given.

The software requirements include a Linux-based operating system and programming languages like Python, which is favored for AI development due to its extensive libraries, and C++ for performance-critical modules and integration with robotics frameworks like the Robot Operating System (ROS). Image processing libraries such as OpenCV are crucial for capturing and processing images, while deep learning frameworks like YOLO (You Only Look Once) support real-time object detection and can integrate with OpenCV and other deep learning libraries. ROS, an open-source robotics framework, simplifies robot control and integrates well with image recognition algorithms through packages like cv_bridge (connecting ROS with OpenCV), move base (for navigation), and robot localization. Development tools such as VS Code or PyCharm are used for coding and debugging, and Jupyter Notebook aids in prototyping and testing models. If NVIDIA hardware is being used, the NVIDIA CUDA Toolkit provides GPU acceleration. For optional cloud integration, services like AWS Rekognition, Google Cloud Vision API, or Microsoft Azure Face API offer cloud-based image recognition and analysis capabilities, with MQTT/HTTP protocols used for communication between the robot and cloud services.

The operation sequence of the image recognition robot begins with its initialization, where the operating system boots up, and all hardware components, including the camera, proximity sensors, and motors, are tested for functionality. Once the system is ready, the robot activates its camera and enters surveillance mode, scanning the water surface and adjusting the pan-tilt mechanism for maximum coverage while monitoring its surroundings using proximity sensors to avoid obstacles. The captured video frames are processed in real-time using OpenCV, and the YOLO deep learning model analyzes the frames to detect human-like shapes and distress signals. If abnormal movements, such as flailing arms, are detected, the robot verifies the situation by analyzing depth information and, if necessary, sends the flagged frames to a cloud service like AWS Rekognition for further confirmation. Upon confirmation of a drowning incident, the robot sends an alert to rescue personnel or triggers an emergency response while continuing to track the individual and providing updates. If no drowning is detected, the robot resumes its normal surveillance mode, scanning for other potential incidents, and may initiate a safe shutdown if low power or system errors are identified.

4.1 SPECIFICATIONS AND PERFORMANCE CONSIDERATIONS

This combination of hardware and software forms a comprehensive setup for an image recognition robot, providing flexibility and capability for a variety of applications such as object detection, facial recognition, and navigation. To make the Specifications and Performance Considerations the four parameters are considered like Processing Speed which ensure the hardware has sufficient processing power (CPU/GPU) for the chosen algorithms. Latency used for real-time processing; a GPU-accelerated platform (like NVIDIA Jetson) may be necessary. Third is Accuracy used in Image recognition models need to be well-trained with datasets relevant to the robot's intended environment and tasks, and finally Scalability that Consider modular software architecture, such as ROS nodes, to facilitate future upgrades and additional functionalities.

Measure Frame Processing Time (FPS)

To compute the processing speed of a robot performing image recognition tasks, you must evaluate several key factors, including the hardware specifications, algorithm performance, and the time required to complete specific operations. Processing speed is often measured in Frames per Second (FPS), which indicates how many frames the robot can process within a second. To determine FPS, the image recognition algorithm is run, and the time taken to process a set number of frames is recorded.

FPS = (Total Frames Processed) / (Time Taken). ----Eq (1)

Additionally, latency per frame, which is the time it takes to process a single frame, is another crucial metric and is calculated by measuring the time difference between the start and end of the processing for each frame. The algorithm execution time is also broken down into different stages, such

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as pre-processing, inference, and post-processing, to understand the total time needed per frame.

Latency per frame = (End Time - Start Time) ------ Eq (2)

Hardware performance, particularly CPU and GPU capabilities, is benchmarked using tools like NVIDIA Nsight for GPUs or sysbench for CPUs to determine their processing power. For GPU-accelerated image recognition tasks, the number of CUDA cores or Tensor cores available plays a significant role in handling parallel processing efficiently. Processing speed can also be measured in terms of FLOPS (Floating Point Operations per Second), which indicates the raw power of the system's CPU or GPU. Combining these metrics, such as FPS, latency, and FLOPS, provides a comprehensive evaluation of the robot's processing speed, ensuring it can perform image recognition efficiently and respond to events, such as detecting a drowning person, in real time.

5. CONCLUSION

In conclusion, the development of an image recognition robot designed to identify people who are drowning is a prime example of how state-of-the-art hardware and software may be successfully integrated to enhance water safety. Through the utilization of robust computing platforms such as the NVIDIA Jetson or Intel NUC, in conjunction with sophisticated sensors and high-resolution cameras, the robot can efficiently capture and process real-time video data. It is possible to precisely identify human forms and irregular movements in the water by combining image processing frameworks like OpenCV with deep learning models like YOLO. This system is a dependable option for emergency reaction situations since it may operate independently and establish connections with cloud-based services for additional verification. Metrics such as Frames per Second (FPS), latency, and FLOPS are used to evaluate processing speed and make sure the robot meets the necessary performance standards for prompt detection and action. In the end, this ground-breaking technology represents a huge advancement in robotics and safety engineering and has the potential to save lives by providing timely alerts and supporting rescue attempts in drowning events.

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