Exploring Advance Approaches for Drowning Detection: A Review

Nouf Alharbi
Information System Department, College of Computer Science and Engineering, Taibah University, Madinah 42353, Saudi Arabia
nmoharbi@taibahu.edu.sa (corresponding author)

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ABSTRACT

This research mainly explores the existing drowning detection methodologies, focusing primarily on the roles carried out by Machine Learning (ML) and Deep Learning (DL) algorithms. It directly emphasizes the dominance of ML in the analysis of raw sensor data along with the contribution of DL to computer vision, which also reveals the present gap between advanced vision along detection models. The holistic approaches are mainly advocated, potentially integrating wearable devices, vision-based systems, as well as sensors while also balancing their performance, regional applicability, and cost-effectiveness. The challenges aligned to enabling real-time detection and reduced latency are important for the time-sensitive realm of incidents related to drowning. Future directions necessarily include the exploration of advanced forms of vision models and segmentation techniques for innovative detection algorithms. Integration of wearable devices and sensors with the inclusion of vision-based systems is important for the required adaptability. The upcoming proposal aims to integrate robotics into rescue operations bringing revolution to response times. The study also covers the requirement for a compact combination of ML and DL algorithms and a generalized solution for the equilibrium maintenance between cost-effectiveness, sophistication, and regional applicability.

Keywords-drowning detection; generalizability; ML; DL; cost-effectiveness; computer vision; robotics; IoT

I. INTRODUCTION

Drowning is considered the third most common cause of accidental deaths emerging from injury, directly being associated to about 236,000 deaths per year around the world [1, 2]. The numbers of drowning fatalities also shed light on the demographics that are directly affected by this tragedy. For example, more than half of the deaths from drowning have occurred in individuals under 30 years old [3]. In particular, drowning is the sixth most common cause of death for children aged between 5 to 14 years old [4]. Additionally, it is important to note that more than 90% of the deaths caused by drowning mostly happen in low and middle-income countries. In [5], drowning deaths were grouped according to population percentage. This revealed important differences in the risk levels across America. For example, Saint Vincent, Suriname, and the Grenadines were in Quintile 5, which means they had higher death rates of about 5.06 deaths per 100,000 people. On the other hand, rates have gone down in Jamaica by 0.58 and in Canada by 0.24, respectively. Also, in Quintile 1, the US has reported that a rate of 1.14, i.e. 45% of drowning deaths occur among economically employed people, which shows that the problem has a bigger effect on society as a whole. As it turns out, the economic cost generated from water fatalities/disasters is high: every year, ocean flooding costs $273 million. Australia and Canada have also had to deal with similar financial problems, with the annual cost of drowning injuries amounting to about $85.5 million and $173 million, respectively.

A lot of different risk factors are making people around the world more linked to drowning. Age is one of the biggest risk factors. Children aged between 1 to 14 years old are more likely to get drowned than other children. Within 85 countries, age is one of the five main reasons children die from drowning. Another important factor is gender; men get drowned with twice the rate of women [6]. Having easier access to water is also a danger factor, especially for children who live near open water sources or in low income countries. It turns out that flood events are responsible for almost 75% of deaths by drowning. Low socioeconomic position, being an ethnic minority, travelling by water, and not being able to go to school with safety gear are among other risk factors. For prevention methods to work, individuals need to fully understand these risk factors and take the right steps to deal with them [7]. Many experts have focused on finding ways to prevent drowing incidents. The main goal of the current study is to prevent such incidents in controlled areas like pools and other restricted water spaces [8-12], as well as in open water settings like coastal regions and beaches [13, 14]. The use of technology has been very helpful in keeping an eye on things and making these places safer. Some studies also examine how technology can be employed to deal with situations in remote places and travel emergencies [15].

This review explores the technical fixes that can be deployed to prevent drownings, help with rescues, and detect individuals who are being drowned, focusing on new technologies, especially ML and DL methods. The main reason for carrying out this study is to critically examine whether these technological systems can achieve high levels of accuracy and to find and develop better ways to reduce drownings and raise safety standards.

II. PRELIMINARY STUDY

A. Inclusion and Exclusion Criteria

To guarantee a relevant and purposeful selection of research on this study's subject, inclusion and exclusion criteria have been clearly defined. The requirements for inclusion are papers that were released between 2003 and 2023, mainly in technical areas that help with the detection, rescue, or prevention of drowning. Also, the papers that are chosen must be able to demonstrate significant technical and infrastructure contributions to their respective fields. To be considered for inclusion, papers must focus on how to use data, ensure that data is an important part of the study, and they must provide a thorough analysis of the technical frameworks that were used. Ideally, these technical frameworks should be able to work with a wide range of data types, such as images, videos, sensor data, and more. They may use statistical methods, ML, DL, or other related methodologies for analysis, such as the Internet of Things (IoT), robotics, and web and mobile apps. Different kinds of papers should not be involved in this study. The papers which cannot be entailed are other review papers that evaluate and summarize the existing literature and conference papers that usually focus on both longer and shorter presentations of the research results. These clearly stated inclusion and exclusion criteria are meant to help researchers choose research papers that not only contribute to the study's goals, but also maintain a high level of technical rigor in the areas they choose.

B. Article Selection, Screening, and Quality Assessment

Structured methodological steps were followed to collect studies for review. Endnote X9 [8] was utilized to keep records for the first study and duplicates were removed. Afterwards, Abstrackr [9] and MetaQAT [10] were put into service to search for paper titles and abstracts and to check the overall quality assessments. A thorough quality assessment method was employed on 57 different scientific papers, which was highly based on the MetaQAT [10] framework. For this particular assessment, predefined criteria that were strongly tailored to the study theme were mainly deployed. To certify that the results were reliable, sensitivity analysis was performed to see how different quality score limits affected the outcomes. The overall quality of the study results was improved by the open and thorough method followed. Hence, 29 out of the initial 57 papers were selected.

III. EXPLORATORY DATA ANALYSIS AND DOMAIN MAPPING

Before delving into the detailed review, an initial data analysis was conducted to gain a comprehensive understanding of the research domain through the selected papers. The analysis involved categorizing the papers by the publication year (Figure 1). This approach allowed the authors to discern the temporal evolution of research in the drowning detection domain and identify key contributors to the field. In addition to the study's comprehensive mapping based on categories, data sources, and type-wise distribution, the former sheds light on the focal points within the investigated domain. Out of the 29 selected studies, 21 are dedicated to drowning detection. Additionally, three studies focus on vision-based surveillance systems, while two delve into drowning prevention and early detection. Notably, only one work centers around drowning pattern detection. Turning attention to the landscape of data sources and the types employed in execution, 12 studies collect data from sensors, utilizing numerical data for execution. Another 10 studies derive data from surveillance cameras, while three utilize fixed pool cameras. Furthermore, three studies leverage online image data, and one integrates both camera and sensor data. However, only four studies directly apply images to their algorithms for execution, with 11 studies working with videos—either processing them into images or analyzing video frames. Finally, two works incorporate both video and numerical data. The analysis reveals a distinct pattern in the research activity within the domain under investigation, initially documented in 2012. Despite a steady increase in publications, there was a temporary lull in the intervening years. However, 2023 witnessed a remarkable resurgence, accompanied by a surge in high-impact contributions, featured in IEEE Explore. This in-depth analysis and mapping of the research landscape lay the foundation for further exploration and insight generation within the research domain, emphasizing a significant concentration on drowning detection using varied method designs. The nuanced exploration underscores the domain's heavy reliance on image/video and sensor data, with exclusive contributions primarily driven by these data's sources and types.

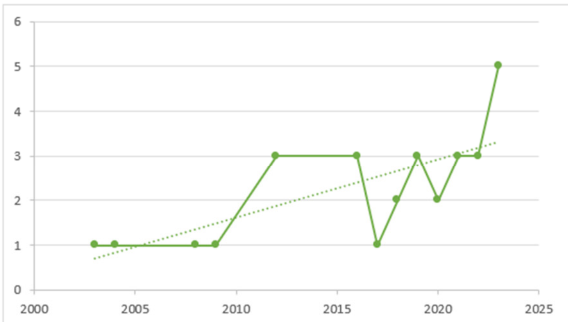

Fig. 1. Year-wise paper count.

IV. DETAILED REVIEW OF THE EXISTING STUDIES

This section meticulously examines studies across three distinct categories, with a particular focus on the utilization of ML and DL approaches. The categories are systematically divided into DL, ML, and other studies for a comprehensive analysis of the diverse research endeavors in the field. Each category undergoes a meticulous review that includes an examination of the study objectives, identification of existing research gaps, exploration of potential areas for improvement, and scrutiny of technical challenges. Additionally, the analysis delves into the utilization of components, data usage, and processing techniques. The exploration performed further proceeds to dissect the methods and algorithms employed, assessing their performance, and culminating in an examination of the applied evaluation matrices.

A. Deep Learning Approaches

In the realm of DL approaches for drowning detection, authors in [16] pioneer the integration of wearable sensors and neural networks to address gaps in early-stage drowning behavior recognition, offering a reliable method even in the absence of real training data. Tackling technical challenges related to wearable headbands and raw data analysis, their groundbreaking automated system showcases the potential for data collection through mimic approaches. Despite this significant achievement, the study underscores the imperative need for future research to enhance system performance, particularly in real-world scenarios. Building upon this foundation, authors in [17] contributed to early drowning detection through a DL-focused study that compared five models for classifying swimming and drowning cases. Their innovative use of transfer learning addresses a critical gap and achieved remarkable success with up to 100% accuracy in models like ResNet50 and ShuffleNet. However, the study acknowledged the necessity of real-life data testing and evaluating real-time execution performance. The exclusion of wearables, vision components, and alarm systems for online data analysis underscores their technical focus, while plans for practical implementation in a surveillance swimming environment demonstrate a commitment to real-world application and potentially life-saving impact in the future.

Transitioning to real-time drowning detection using computer vision and DL techniques, authors in [18] emphasized a dual mission of swiftly detecting drowning incidents and executing timely rescue operations. Despite showcasing an 87% accuracy rate with a custom Convolutional Neural Network (CNN) and a practical approach relying on overhead cameras, concerns arise regarding the absence of an alarm system and possible limitations in accessibility due to high cost. The ongoing evolution of their solution, with plans for more cameras and a web/app-based monitoring platform, suggests a continuous commitment to water safety enhancement. In the pursuit of cost-effective real-time drowning detection, authors in [19] venture into the use of sonar technology, emphasizing affordability and advanced computational algorithms. Overcoming challenges in classifying drowning situations with an impressive 88% accuracy using a Neural Network and overhead cameras, their dedication to robust detection is evident. However, the need for practical testing and addressing obstacles in diverse aquatic conditions remains a crucial aspect for assessing real-world effectiveness and refining the system. Transitioning to underwater drowning detection, authors in [20] present a vision-based system with a hybrid model, effectively addressing challenges in noisy underwater environments. Achieving a remarkable 93.6% AUC score, the study focuses on fixed pool cameras and employs ROC and AUC for evaluation, highlighting the model's success. While opportunities for future refinement, especially in detecting swimmers of varying sizes are acknowledged, the study offers a significant stride in enhancing underwater drowning detection. Considering real-time detection challenges, authors in [21] propose a versatile pipeline adaptable to different domains, addressing variations in lighting, indoor scenes, and pool floor color implementing YOLOv8 and GP-GAN algorithms. Even though demonstrating high detection performance, the limitation of lacking diverse training data suggests a need for future work to enhance the model's robustness under varied real-world conditions. The research contributes valuable insights to flexible detection pipelines.

Filling a crucial gap in the specialized realm of infant drowning prevention, authors in [22] developed a real-time detection system employing YOLOv5 and Faster R- CNN algorithms with overhead cameras. Demonstrating the effectiveness of their approach, the study reveals YOLOv5's superior performance in detecting infants in small video frames, as proved in [23]. However, the potential issue of false detection in densely packed frames prompts considerations for future work to optimize YOLOv5 for noisy environments [24]. Shifting focus to swimming pool environments, authors in [25] emphasize the construction of a real-time drowning detection system, introducing a pyramid network and a separate detection method (YOLO) to handle complexities. Acknowledging challenges in large pools and noisy environments, the study outlines future work to optimize the model for larger-scale monitoring, displaying dedication to overcoming limitations in existing systems and creating an adaptive model for enhanced drowning detection. Finally, authors in [26] explore the potential of edge computing for drowning prevention, highlighting the importance of data pre-processing and model training for a robust system. Although the research demonstrates the potential of their proposed system, the lack of evidence regarding certain features' implementation and the absence of addressing subject density issues suggest avenues for future work, involving refining the system and tackling additional challenges in drowning prevention scenarios.

B. Machine Learning Approaches

Transitioning to ML approaches in aquatic surveillance, authors in [27] contribute to real-time detection systems in complex aquatic scenes, addressing challenges in outdoor environments with a focus on noise and light reflection. Introducing two novel segmentation approaches, the research utilizes overhead and surveillance cameras alongside an RF transceiver, successfully improving segmentation quality by 20%. While effective in overcoming outdoor complexities, the study acknowledges limitations in handling multi-object occlusion, signaling opportunities for future research in object behavior analysis. In a notable stride to bridge a gap, authors in [28] propose a real-time detection system, for falling and drowning incidents, leveraging smartphone sensors and ML algorithms. With a focus on app-based emergency notifications, their system achieves a remarkable 98% accuracy rate in validation through a 5-fold cross-validation process. Although the conceptual stage of the proposal and limitations related to underwater signal functionality pose challenges, the study reflects a promising direction, necessitating further development.

C. Traditional Approaches

In the dynamic landscape of aquatic surveillance, the quest for effective and cost-efficient vision-based solutions has ignited a cascade of innovative studies. These traditional visions, sensors, and combined approaches stand as pivotal contributors to drowning prevention, providing diverse methodologies to augment detection accuracy and real-time response systems. Authors in [11] conducted two impactful studies in aquatic surveillance, demonstrating a consistent focus on cost-effective solutions and heightened detection accuracy. In their initial work, they introduced the Generalized Reduced Multivariate Polynomials network (GRM), achieving a remarkable 1.85% error rate with overhead cameras. This played a significant role in improved segmentation and classification, especially in swimmer tracking and occlusion handling. Building on this success, their subsequent study dealt with challenges in noisy environments, excelling in monitoring and recognizing swimmer activities utilizing a combination of the Hidden Markov Model (HMM), Support Vector Machine (SVM), and Repeated Measure (RM) [13]. Their approach outperformed existing foreground detection methods, highlighting the real-world applicability of their findings. In contrast, authors in [12] took a distinct approach, addressing the absence of early drowning behavior examination and the high costs associated with underwater cameras. Their proposed system, relying on overhead cameras for vision, HSV color space transformation, and cumulative sum for segmentation, introduced rules for evaluating swimmer conditions and integrating them with finite state machines. While showcasing a unique perspective, the reliance on simulations due to the absence of real-world video data raises questions about the practical implementation of their findings. Authors in [14] contributed to surveillance by using a fixed camera for swimmer detection through background subtraction. The study effectively reduced the impact of noise and shadows, especially in scenarios where moving shadows could be misclassified as moving objects. The proposed approach, utilizing a fixed pool camera, HSV color space transformation, and Gaussian Mixture Model (GMM) with Expectation Maximization (EM) for segmentation, stressed the significance of background subtraction. However, the limited evaluation and the absence of explicit reference to future work are notable considerations.

Regarding early drowning detection, authors in [15] present a wireless sensor-based drowning detection system aiming to provide early alerts and enhance parental care. The research addresses the challenge of delayed or false detection in existing systems by developing a low-budget solution. Also, it leverages wireless technology, signal processing, and simulation tools, with a focus on cost-cutting technologies. The evaluation metrics emphasize the system's low budget, high accuracy, and minimal delay. Strengths include its preventive approach, but reliance on simulations and limited real-world testing are noteworthy limitations. Authors in [29] proposed the Early Detection Drowning System (EDDS) using IoT technology. The research aims to fill gaps in compact, web-based drowning prevention solutions. The EDDS combines wearables, sensors, a microprocessor, and an RF transceiver for real-time monitoring. Evaluation metrics emphasize the EDDS system's 94% ROC, particularly focusing on child safety. The lack of testing data diversity and information on the system's response time are acknowledged limitations, requiring future work for comprehensive testing and optimization. Authors in [30] made significant strides in minimizing false alarms and reducing delay times in real-time drowning detection. Their use of overhead and fixed pool cameras, coupled with video and numerical data, resulted in very low delay time for reporting incidents and excelled in reducing false alarms, demonstrating high processing performance. The emphasis on high processing performance, albeit in high-end settings, marked a substantial contribution but the associated high cost posed a substantial limitation. Addressing issues of high cost and limited coverage, authors in [31] introduced a prototype for a sensor-based, low-cost drowning detection system. The employment of wearable wristband sensors for automatic drowning detection showcased portability and positive detection optimization. Despite its valuable contributions, the study acknowledged the need for more comprehensive evaluation criteria, signaling the potential for transformative improvements. In tandem, authors in [32] focused on minimizing misdetection in real-time systems. Their integration of wireless communication modules and water-detection circuits aims to achieve fewer miss-detection but has limitations in distinguishing between diving and drowning, pointing to future improvements. On a different note, authors in [33] introduce a groundbreaking real-time drowning detection system designed for versatility in both pool and sea-level environments. Addressing the lack of such systems, their cost-effective solution involves wearable goggles with integrated sensors. While this work seems promising, the absence of specific evaluation metrics is a worth mentioning limitation, urging the need for rigorous real-world testing. The researchers' commitment to ongoing improvement, evidenced by their plan to integrate GPS tracking, underscores their dedication to enhancing drowning prevention measures.

Authors in [34] tried to enhance water safety with a low-cost, real-time drowning detection system using Radio Frequency Identification (RFID) technology [34]. They addressed shortcomings in vision and sonar-based systems by proposing a wearable wristband with innovative signal transmission methods. The prototype's reliance on RFID technology for accuracy in identifying potential drowning situations signaled a novel direction. Described as a prototype, the research hinted at the potential addition of swimmer tracking, suggesting a commitment to evolving their solution for more comprehensive water safety. Authors in [35] contributed to the field with a focus on developing a low-cost, energy-efficient real-time drowning detection system. The emphasis on precise positioning, efficient identification, and timely alarms for small and medium-sized swimming pools showcased practical applicability. Even though the system's strengths include minimal environmental impact and cost-effectiveness, the lack of live scenario testing raised questions about real-world effectiveness, prompting considerations for future work. Authors in [36] presented an innovative vision-based surveillance system for swimming pools with real-time detection and integrated robotics for rescue operations. While displaying a multifaceted solution, the prototype status and the high-cost nature of the system raised potential financial constraints. The team's dedication to improvement, demonstrated by the addition of an infrared LED, suggested a commitment to refining technology for enhanced swimmer safety. Authors in [20] promoted underwater drowning detection with a vision-based system. Their hybrid model effectively dealt with challenges in noisy underwater environments, achieving a notable 93.6% AUC score. The study, focusing on fixed pool cameras and employing ROC and AUC for evaluation, highlights the model's success, while the limitations in detecting swimmers of varying sizes stressed opportunities for future refinement. Exploring perceptual processing methods for improved detection rates, authors in [37] dealt with a literature gap, emphasizing real-time execution and robust performance under noisy conditions. Utilizing overhead cameras and video data, their perceptual processing method exhibits a significant 63% increase in detection rates. While promising, the study lacks real-life performance measurements, underscoring the need for future work to assess its effectiveness in practical scenarios. Beyond drowning detection, the proposed method holds potential applications in various domains requiring binary classification.

Shifting to beach safety, authors in [38] introduced a low-cost, wearable sensor-based system for sea level environments. Their research introduces a low-cost, wearable sensor-based system designed specifically for sea-level environments. The proposed armband, housing sensors in a compact locket, emphasizes user-friendliness. Although the research presents a promising prototype, it is crucial to mention that it is in the architectural stage, lacking comprehensive testing. The potential extension to monitor international sea levels suggests broader implications for water safety. On the other hand, authors in [39] introduced a sensor-based rescue alert system with a wearable device focus. Leveraging IoT technology, their wristband system aims to detect irregular heart responses as early indicators of possible drowning. Although the study is characterized as architectural and lacking detailed testing, its emphasis on physiological indicators offers a unique approach. The potential for future practical testing and refinement signals a commitment to bringing their innovative concept to fruition. Authors in [40] embarked on a groundbreaking project for drowning prevention, proposing a gantry robot system with early detection capabilities. Their concentration on integrating robotics with surveillance and alarm functionalities intends to minimize response time to emergencies. However, the research is currently in the design and simulation stage, lacking real-life implementation or testing. The suggestion for future improvement through wireless technology indicates a path for enhancing efficiency and adaptability.

V. RESEARCH FINDINGS

A. *Evolution of Different Methodologies*

Through a meticulous examination of the existing literature, this research distills critical insights into a comprehensive framework, as encapsulated in Table I. The latter systematically delineates the evolving landscape of performance methodologies, spotlighting the nuanced impact of advanced technologies in the field of drowning detection.

The analysis yields five distinct research scenarios, each representing a unique stage in the continuum from preliminary to advanced research implications. These scenarios serve as a structured guide for researchers, promoting the understanding and categorization of methodological implications in drowning detection.

The first scenario embraces an exhaustive strategy, incorporating computer vision, IoT sensors, simulation, and real-life data. The implementation of advanced ML or DL algorithms results in remarkably high detection performance. This comprehensive approach ensures adaptability across diverse environments, including pools, beaches, coastal regions, and disaster scenarios. The synergy of technologies enhances the system's capability to effectively identify potential drowning incidents. However, this heightened effectiveness comes at a cost. The extensive integration of technologies and utilization of sophisticated algorithms lead to elevated expenses, making this setup most suitable for situations where optimal performance takes precedence over budgetary constraints.

TABLE I. EVOLUTION OF THE METHODOLOGIES ON DROWNING DETECTION RESEARCH

Computer Vision	IoT & Sensors	Simulation	Real-life data	Use of ML/DL Method	Detection Performance	Area	Cost
Y	Y	Y	Y	Y	High	Pool, beach, coastal, disaster	High
Y	Y	Y	N	Y	Moderate	Pool, beach, coastal, disaster	High
Y	N	Y	Y	Y	Moderate	Pool	Moderate
N	Y	Y	Y	Y	Moderate	Pool, beach, coastal, disaster	Low
N	Y	Y	N	Y	Low	Pool, beach, coastal, disaster	Low

In parallel, the second scenario mirrors comprehensive employed integration strategy, encompassing computer vision, IoT sensors, and simulation, albeit without the inclusion of real-life data. The absence of real-life data impacts the system's ability to effectively detect incidents in real-world scenarios, resulting in a moderate level of detection performance. Despite this limitation, the setup remains adaptable and suitable for deployment in various settings, including pools, beaches, coastal areas, and disaster scenarios. However, the compromise in detection performance is accompanied by a relatively high cost, which may restrict its application in conditions where a balanced trade-off between performance and cost is deemed critical.

The third scenario adopts a cost-effective approach pursued by limiting the integration to computer vision. The simulated and real-life data are then trained using ML or DL algorithms to maintain a moderate level of detection performance. This setup is primarily designed for pool environments, where the full range of technologies may not be necessary. The moderate cost associated with this scenario makes it an attractive option for settings where achieving a balance between performance and budget constraints is paramount. It is particularly popular in modern pool settings equipped with various rescue measures, providing an effective yet economical solution.

Transitioning to the fourth scenario, a more constrained approach is observed, where integration includes IoT sensors, simulation, and real-life data. However, the detection component relies on ML algorithms, leading to compromised detection performance. Despite this limitation, the setup remains versatile and suitable for deployment in various scenarios, including pools, beaches, coastal areas, and disaster situations. The key advantage lies in the lower cost combined with reduced technological complexity. This setup is particularly popular in both developed and underdeveloped countries, offering a cost-effective and versatile solution, adaptable for detection, observation, and rescue measures.

In the final scenario, the research adopts a minimalist approach, utilizing only IoT sensors, with simulated data used for training ML algorithms. While this minimalist setup results in notably low detection performance, it proves suitable for scenarios where budget constraints take precedence over performance requirements. Primarily applicable for minimal security purposes in professional swimming settings, the very low cost associated with this setup positions it as a cost-effective solution for scenarios with limited resource availability. This minimalist approach, while sacrificing some level of performance, offers a viable solution for specific use cases where budget considerations are paramount.

The examination of the five scenarios reveals a substantial correlation between the cost of drowning detection setups and the chosen methodology. Specifically, setups utilizing computer vision are observed to incur higher costs compared to those reliant on sensor-based approaches. Furthermore, the efficacy of the methodology is intricately tied to the type of data employed. Models trained on a combination of real and simulated data consistently outperform those trained solely on simulated data, underscoring the significance of dataset diversity for model accuracy. This observation highlights the adaptability of drowning detection setups across various budgetary constraints and other pertinent scenarios.

B. Comparative Analysis on ML and DL Approaches

Given that the core focus of this research is on detection methodologies, it becomes evident that both ML and DL play integral roles in these settings (Table II). The research systematically categorizes and identifies the most frequently utilized DL and ML algorithms within the domain. Notably, the evaluation metrics associated with these algorithms are presented, shedding light on their performance in live or simulation scenarios. This comprehensive analysis provides a nuanced understanding of the overall effectiveness of these models in the context of drowning detection.

The initial section of Table II scrutinizes the application of computer vision techniques for recognition and detection purposes. Referenced studies, such as [16-24], predominantly leverage DL algorithms like YOLO, Faster R-CNN, SqueezeNet, GoogleNet, AlezNet, ShuffleMet, and ResNet50. Remarkably, this approach excludes traditional ML methods. The evaluation metrics span a comprehensive set, encompassing True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN), accuracy, precision, recall, specificity, F-1 score, confusion metrics, and false acceptance rate. Varying degrees of success are observed across studies, with 5 out of 9 examining the methodology in live scenarios and 4 out of 9 in simulated scenarios. Reported accuracy ranges between 85% and 100%, with the lowest detection delay recorded at 1.5 s. Shifting focus, the subsequent section of the table delves into drowning detection through the analysis of sensor data, as evident in studies [25, 26]. In contrast to the computer vision approach, this method opts for ML algorithms such as Linear Regression (LR), Bayesian Network (BN), and Logistic Model Trees (LMT), omitting the use of DL. Evaluation metrics include Matthews Correlation Coefficient (MCC), Error Rate, and Mean Average Precision (MAP). Explored in 1 out of 2 studies in both live and simulated scenarios, this approach reveals a noteworthy 20% enhancement in the false acceptance rate. This underscores the effectiveness of sensor data analysis in refining the precision of drowning detection systems.

TABLE II. COMPARATIVE ANALYSIS OF DL AND ML APPROACHES IN DROWNING DETECTION

Purpose of use	**Use of DL**	**Use of ML**	**Evaluation metrics**	**Examined in live scenario**	**Examined in simulation scenario**	**Overall performance**
Computer Vision (recognition, detection) [16-24]	YOLO Faster R-CNN, SqueezeNet, GoogleNet, AlezNet, ShffleMet, ResNet50	N	TP, TN, FB, FN, Accuracy, Precision, Recall, Specificity, F-1 Score, confusion matrix, ralse acceptance rate	5 out of 9 studies	4 out of 9 studies	Accuracy 85% - 100%, lowest detection delay 1.5 s
Sensor data analysis [25, 26]	N	LR, BN, LMT, (regression)	MCC, Error rate, MAP	1 out of 2 studies	1 out of 2 studies	20% result improvement in false acceptance rate

While certain prior research has demonstrated significant achievements in the realms of detection and recognition, a closer examination of the detailed Table III reveals a worth mentioning trend. It becomes apparent that experiments yielding favorable results are primarily those that have not been scrutinized in live scenarios. In contrast, research conducted in live scenarios has yet to achieve an accuracy surpassing 88%. This observation implies a substantial opportunity for improvement in the effectiveness of detection methodologies, particularly in real-world scenarios.

VI. CONCLUSION

It is concluded that the drowning spotting methods of Machine Learning (ML) algorithms are best for examining raw sensor data, whereas Deep Learning (DL) algorithms are the best for computer vision techniques. However, there is still a limitation of knowledge when it comes to studying advanced vision, segmentation, and detection models. It is recommended for future studies to find the appropriate mix between performance, and cost-effectiveness. The loopholes in advanced vision models and real-time response clearly showed how crucial it is to not only understand complex technologies, but also allow researchers to find out the appropriate ways to save time and effort.

TABLE III. EXTRACTED INFORMATION OF RESULT ANALYSIS AND EVALUATION MATRICES FROM THE SELECTED STUDIES

Paper ID	**Evaluation Metrics**	**Algorithms**	**Accuracy**	**Error rate**	**Examined in live scenario**	**Examined in simulation Scenario**	**Maximum detection delay**
[16]	Confusion matrix, Accuracy	N	100%	N	N	N	N
[17]	TP, TN, FP, FN, Accuracy, Precision, Recall, Specificity, MCC	SqueezNet, GoogleNet, AlexNet, ShuffleNet, ResNet50	100%	Y	N	N	N
[25]	False acceptance rate	MoG, HSV	20% improvement	N	N	N	N
[18]	TP, TN, FP, FN, Accuracy	N	85.60 %	Y	Y	N	Y
[26]	TP, TN, FP, FN, Accuracy, Precision, Recall, F1-score, Confusion matrix	LMT, BN, LR	98%	Y	Y	N	N
[19]	Accuracy, Error	DNN	88%	Y	Y	N	1.5 s
[20]	ROC, AUC	APN, MNA, Hf-VAD, sRNN-AE, YOLOv5-DDN (Gaussian)	N	Y	Y	N	N
[21]	MAP		N	Y	N	N	N
[22]	Precision, Recall, MAP, FPS	YOLOv5, Faster R-CNN	N	Y	Y	N	N
[23]	N	YOLO	N	N	Y	N	N
[24]	Accuracy, Loss	N	99%	Y	N	N	N

With the help of the current study, theoretical advances are turned into useful, real-world solutions that meet a variety of needs and help effective, user-friendly, and widely applicable drowning detection systems come into being. The researchers can make custom solutions that strongly work in a variety of circumstances by eagerly looking into sub-parts of vision-based technologies that have not been investigated yet.

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