Journal of Computing and Data Technology
https://journal.krrishpub.com/index.php/jcdt/index

A Deep Learning Approach to Early Drowning Detection for Child Safety using ResNet and Flower Pollination Algorithm

Muhammad Aftab Hayat [a,*], Yang Guotian [a], Shams ur Rehman [b]

[a] School of Control and Computer Engineering, North China Electric Power University, Beijing, 102206, China.
[b] Department of Computer Science, HITEC University, Taxila, 47080, Pakistan.

Abstract

Drowning is one of the top five worldwide causes of mortality for kids between the ages of four to fourteen. According to World Health Organization statistics, drowning is the third most common cause of unintentional fatalities. The need to create a drowning detection system to save swimmers especially children is growing. There are several drowning detection systems incorporating distinct technological systems such as wearable sensors, vision based monitoring and AI driven surveillance. Wearable sensors such as heart rate monitoring and accelerometers offer continuous monitoring but these existing systems have their own limitations like intrusiveness and poor visibility. To address these challenges this study offers a deep learning and computer vision-based early drowning detection technique. An overall accuracy of 99.4% has been achieved on our dataset by using pre-trained models including CNN-ResNet50, ResNet18, and Flower Pollination Algorithm. The study contributes to the advancement of intelligent drowning surveillance systems thus abridging the gap in the attainment of more efficient and reliable drowning detection systems.

Keywords: Drowning detection, Deep learning, Computer vision, ResNet, Feature fusion, Flower pollination algorithm, Child safety.

Article information:
DOI: https://doi.org/10.71426/jcdt.v1.i2.pp104-114
Received: *11 Nov. 2025* | Revised: *15 Dec. 2025* | Accepted: *27 Dec. 2025* | Published: *31 Dec. 2025*

Acronyms

1. Introduction

Global public health issues related to drowning are serious [1]. As per the World Health Organization data, there are around 30,0000 annual drowning deaths worldwide [58]. So, most swimming pools have professional lifeguards to prevent drowning incidents; however, lifeguards are not able to remain concentrated for extended periods and are unable to identify drowning victims in time, which can result in deaths from a lack of prompt treatment [2], [36]. To manage swimming pools and rescue drowning victims, efficient and quick drowning-detecting equipment is essential [3]. numerous researchers have previously offered a variety of techniques for detecting drowning cases in swimming pools, drowning detection is still characterized by many challenges [4]. Nowadays, there are two main types of drowning-detecting methods. The first one is founded on wearable sensors [59]–[61], and the second one is vision [5]. In order to detect drowning using the physiological indicators or duration in the water of a swimmer, wearable sensor-based methods fixes various sensors to the body of the swimmer [6]. The use of such devices may at times be a discomfort to the wearers. The vision-based method is used to detect drowning by extracting characteristics mainly of the video of the swimmer to overcome the limitations of wearable devices [7]. The swimmer remains silent in the initial phases of drowning, and a lot of the studies carried out using the vision teach also detect drowning on the basis of position of the swimmer, timing, and speed in the water. In this way, these methods are inaccurate and unstable [8]. Drowning rates can be effectively decreased and swimming pools can be ensured to be safe by installing a sophisticated automated system of monitoring. The areas of automatic drowning detection include two types of methods [6]. The methods employed in the former category involve the use of swimmers wearing sensor devices attached to them either in the form of bracelet or goggles.In order to monitor the swimmer's behavior, these sensors can measure several parameters such as heart rate, blood oxygen content, motion, hydraulic pressure, and depth [7].

*Corresponding author
Email address: aftabsukhera@ncepu.edu.cn, aftabsukhera@gmail.com (Muhammad Aftab Hayat), ygt@ncepu.edu.cn (Yang Guotian), shams.rehman@hitecuni.edu.pk (Shams ur Rehman).

List of acronyms.

Acronym	Description
Acc.	Accuracy
AI	Artificial Intelligence
Aug.	Augmentation
CDF	Cumulative Distribution Function
CNN	Convolutional Neural Network
CV	Cross-Validation
DL	Deep Learning
F1	F1-score
FPA	Flower Pollination Algorithm
FPN	Feature Pyramid Network
HOG	Histogram of Oriented Gradients
IP	Internet Protocol
IoU	Intersection over Union
mAP	mean Average Precision
ML	Machine Learning
Prec.	Precision
Rec.	Recall
ReLU	Rectified Linear Unit
RFID	Radio Frequency Identification
RNN	Recurrent Neural Network
SVM	Support Vector Machine
TNN	Tree-based Neural Network classifier
URPC	Underwater Robot Picking Contest (dataset)
VAD	Video Anomaly Detection
VGG	Visual Geometry Group (CNN family)
WNN	Weighted Neural Network classifier
YOLO	You Only Look Once
WHO	World Health Organization

The second group includes vision-based methods that use cameras overhead or underwater to watch swimmers, and machine learning algorithms to identify drowning episodes from the camera's output. However, these methods are not very reliable because drowning victims are very silent in the early stages of drowning [9]. Furthermore, some studies use deep neural networks to classify swimmers who are normal and swimmers who are down [10]. Drowning, however, is a rather rare emergency disaster. There are not many opportunities for cameras to record drowning incidents. In addition, obtaining the drowning video is challenging and entails privacy concerns. As a result, few videos of drowning exist [11]. Most of these studies extract aspects of drowning behavior and perform supervised classification through the use of simulative drowning behavior. Nevertheless, very few people truly experience drowning due to its complex symptoms. Since it is impossible for anyone to accurately duplicate drowning behavior, videos that simulate drowning are neither authentic nor trustworthy [12]. Advances in physical equipment allow us to construct more intelligent drowning detection systems. Swimming pools become safer with the use of drowning detection devices, which also reduce lifeguard workloads and improve swimmer comfort [13]. In pool surveillance systems, IP cameras are used as network edge devices. Videos are uploaded over the network to servers and lifeguards for processing. Underwater videos, which need to be transferred to a server for processing and storage, may jeopardize the swimmers' privacy [14]. Because of the increased network traffic and storage requirements of this operation, the server might not be able to respond to drowning situations as rapidly.

Additionally, some researchers categorize normal swimmers and downers using deep neural networks [9], [48]. However, drowning is a rather uncommon emergency mishap. Few opportunities exist for video cameras to capture drowning events. Furthermore, the drowning video is difficult to obtain and involves people's privacy [10]. Hence, there aren't many videos of drowning. The majority of these studies use simulative drowning behavior to extract characteristics of drowning behavior and perform supervised classification. Nevertheless, the symptoms of drowning are complicated and very few people experience it. Videos that simulate drowning are neither authentic nor reliable since it is difficult for anyone to mimic drowning activity properly.

More advanced drowning detection systems can be created thanks to technological developments in physical devices. Lifeguard workloads are lessened, swimming pool safety is increased, and swimmers feel more comfortable thanks to drowning detection devices [13]. IP cameras are employed in pool surveillance systems as network edge devices, and footage is uploaded via the network to servers and lifeguards for processing. Underwater films, however, may compromise the privacy of the swimmers [14]. Uploading the movies to the server for processing and storing them may reveal the swimmers' privacy. Additionally, this method demands more network bandwidth and storage capacity that can pose a challenge in responding to drowning cases in a timely manner.

The process of implementing a machine learning-based classifier model in the drowning detection task consists of a number of significant steps [15]. A labelled dataset consisting of the drowning and non-drowning cases is initially gathered to provide variety and to make sure that the dataset is appropriate to the intended deployment scenario. Subsidiary steps of pre-processing data later involve photo or movie resizing, standardization of pixel values, and data augmentation to achieve greater variability. The process also involves feature extraction which involves the elimination of relevant features in the data. It is one method of image-based models that is popular to choose oriented gradients histogram [16]. To classify, the right machine-learning model is selected which can be SVM or randomly-forest. This model is trained and its output is shown when the dataset is separated into a training and a validation set. The model is evaluated based on such evaluation measures as accuracy, precision, recall, and F1 score on a different test set. Depending on the results of the evaluation, fine-tuning may be required, and in this case, it will involve setting the hyper-parameters differently or getting more information [17]. When the training and evaluation are not hindered, the model is sent to the target environment and a monitoring system is established to monitor its persistent performance. At all turns, privacy and ethics should be taken into consideration especially when dealing with sensitive information. Regular updates and retraining with new data improve the strength and performance of this model. Although deep learning techniques might perform state-of-the-art, machine-learning techniques may also prove useful when there is limited data or processing capacity [37]. The effectiveness of the model is subject to the quality of the data, feature extraction method and the suitability of the selected machine-learning model [18].

The computer vision techniques are then applied in order to classify drowning incidents through image processing techniques so as to create improved automated system that is able to detect drowning incidents. The first important step is to have a thoroughly annotated dataset with a set of examples of both drowning and non-drowning situations. Subsequently, the images are or video frames are pre-processed such as normalization to give similar pixel values and scaling to give uniformity [19]. Features extraction and pattern recognition are computer vision techniques that are important in the extraction of important information in the visual input. The edge detecting technique, motion tracking technique, and color analysis technique can be used to obtain relevant features that relate to instances of drowning. After extracting the features, an appropriate classification strategy, which can be a machine learning or deep learning model, is then trained using labeled data [20]. Image-related tasks can be tackled successfully by using CNNs. This has made them commonly used. The measurement of the model performance is through the adjusting of the model and the metrics employed such as accuracy and precision. Once a model shows promise, it can be used in real-world scenarios, such as monitoring live video feeds for signs of danger or integrating with security systems. For the model to function well under a range of environmental conditions, frequent updates and ongoing observation are necessary. Privacy and ethical concerns should be considered extremely seriously when deploying computer vision systems for drowning detection, especially in public locations. The quality of the training data, the robustness of the chosen computer vision algorithms, and the model's ability to adapt to changing conditions all affect how effective this type of system is [21].

Deep neural networks are increasingly being used to tackle business difficulties. Some researchers to detect drowning 16 have used neural networks. However, the majority of these studies first simulate drowning in order to gather drowning sample data because there aren't enough true drowning cases. Next, learning techniques are used to extract the features from the drowning data in order to carry out supervised classification [17]. However, it is challenging to accurately replicate drowning behavior, and the characteristics of simulative drowning behavior are unreal. Drowning is an unusual occurrence. The video anomaly detection (VAD) task and vision-based drowning detection are comparable [18]. The challenge of identifying anomalous events in the absence of films of anomalous events is accomplished by both. We are motivated to employ unsupervised deep learning approaches in drowning detection tasks because most researchers have done so in VAD tasks [22]. The majority of current unsupervised deep learning-based VADs identify anomalies by first predicting or reconstructing frames, and then calculating the reconstruction or prediction error at the pixel level. The method is not suitable to use in pool videos and more likely to be distorted by external noise. In this paper, we therefore combined both a deep convolutional neural network with the Gaussian model. This neural network is stronger and can identify normal and drowning frames on the basis of high-level semantic properties [19].

A feature extraction technique is applied to classify drowning episodes by eliminating the pertinent information displayed in photo or video frame and searching the patterns that can be used to ascertain the presence of drowning incidences [20]. The first important part of this technique is to have a full annotated data set that contains a wide variety of drowning and non-drowning cases. In ensuring uniformity of the input data, the images are first subject to pre-processing methods such as scaling and normalization of the dataset once formed [23]. This is followed by methods of extracting features which are used to identify discriminative data. Such methods may look at color distribution, movement patterns or particular visual indicators of water activity to identify drowning. Observing changes in body posture, movement of limbs, or the movement of the water surface are some of the examples of the critical cues. Training a classification model is based on these extracted features and they are usually utilized with the help of other traditional machine-learning methods [24]. The RF and SVM algorithms are commonly employed in practice because they perform well in classifying jobs. The labeled dataset is trained on the given model, and the results of the model are measured by such metrics as accuracy, precision and recall. The effectiveness of the feature extraction method will determine whether the feature extraction method will be successful or not because it depends on the capability of the chosen features to constitute patterns associated with drowning. This is simpler and easier to read than more complicated deep learning models and is advantageous in situations where the computer resources or data is limited. Periodic evaluation and adjustments to actual performance are largely the factors behind the continued success of the model in drowning detection systems [25].

The most helpful features are to be identified and employed to distinguish between non-drowsing and drowning events in images or in video frames. This is what feature selection-based drowning detection classification attempts to accomplish. The initial one is to collect a large dataset comprised of diverse samples in each scenario to be able to train efficiently. After the preparation of the dataset, some pre-processing tasks such as scaling and normalization are done so that the input data is consistent. Algorithms are then used during the feature selection strategies to determine the most appropriate features that can make a considerable contribution to the classification process. These methods decrease the dimension, improve the readability of the model and constrain the possibility of over-fitting [26]. Typically, it is features like color pattern, movement features, or other visual indicators related to drowning events. Consequently, the information is presented in a more effective and rather concise way. Once the feature selection process has been completed, one then trains a classification model on the filtered feature set. The process of feature selection improves the interpretability and performance of the model especially in situations where the available computational power or data volume might be limited [27]. The real-time efficiency of the model is an advantage to the drowning detection use, and it would be refined in future depending on the actual information. When using feature selection algorithms, ethical considerations that especially relate to privacy should be considered especially when handling sensitive situations or in open areas [28].

In modern implementations, drowning detection is impaired due to a number of factors. Among the main factors that should be of concern is that in different water habitats like swimming pools and other bodies of water the detection systems face different challenges [47]. The provision of datasets, which can be heterogeneous, is limited, it is difficult to train reliable models that will work in various conditions. The processing of information in real time is needed to provide a timely response; however, it can be hard to obtain low latency and high accuracy, particularly in resource-constrained scenarios. Differences in the style of swimming and body formations complicate the differentiation of drowning emergencies and regular aquatic activities. Due to the privacy issues associated with drowning detection devices, special balance between maintaining the safety of people in the community and safeguarding personal privacy rights of individuals must be found when installing such devices in the areas of public use [29]. Poor vision, weather or water conditions are all environmental factors that can affect the efficiency of the detecting systems. Another issue is the interconnection of drowning detection with the current emergency response and surveillance systems, which require the integrated collaboration of various technologies. Such ethical issues as permission, data storage, and algorithmic biases are to be put into focus so that responsible implementation could be introduced. To address these intricate challenges, interdisciplinary cooperation, technological advancements, and a commitment to moral deployment practices are required [30]. Study architect has been summarized as follows.

- Data augmentation has been applied to enhance the training diversity and avoid overfitting.In addition to improve the features' visibility contrast enhancement has been applied on selected features.
- Pre-trained DL models have been fine tuned on the dataset to achieve the efficient and effective results.
- To enhance the classification results and overall performance of the models feature fusion has been applied.
- The Flower Pollination Algorithm has been used to select the best features due to its' efficiency in balancing the exploitation and exploration.
- The optimized features have been used to train the models to improve the overall classification accuracy and performance of the model.

2. Related work

Research on drowning detection techniques has produced some findings in recent decades. Sensor-based and vision-based drowning detection techniques can be used to broadly categorize drowning detection techniques [20]. These methods include both conventional machine learning algorithms and deep learning models [21], [53] – [56]. This paper presents the relevant work on deep learning-based classification of drowning detection. For example, Chan et al. [5] presented an NVIDIA Jetson Nano-powered Alex Net CNN model. 2333 non-drowning and 1168 drowning images were used to train the algorithm. There were 389 drowning images and 777 non-drowning photos in the testing dataset. Thirty volunteers developed the dataset by striking various positions in the pool. The model's categorization accuracy was 85%. Rashid et al. [7] presented an ascertain the effectiveness of the model's capacity to identify underwater life, researchers examined four iterations of the YOLOv3 detector (they trained the original YOLOv3, Tiny-YOLOv3, YOLOv3-SPP, and TinyYOLOv3-PRN) on two open-source datasets. The outcomes provided strong proof that YOLOv3 is capable of identifying underwater objects with a range of mAP scores between 74.88% and 97.56%. Eng et al. [11] presented and examined various challenges in identifying drowning victims in a wet environment and providing a surveillance system with automatic detection. The authors state that background movements of the reflective zones and water ripples and splashes are the main difficulties in the aquatic environment. Another problematic problem that is mentioned is occlusions when it comes to identifying swimmers. An algorithm that considers each of these problems and recognizes water crises in intricate aquatic environments is their suggested remedy. Alshbatat et al. [31] presented an Arduino Nano board, two Pixy cameras, and a Raspberry Pi as part of an integrated vision-based monitoring system. The swimmers had to wear passive yellow vests, and they used two cameras to measure the positions of the swimmers to detect and track them. Another innovative device is called NEPTUNE, which employs statistical image processing of video sequences to quickly identify drowning fatalities. The variables produced by statistical image processing form the basis for the equations used to identify near-drowning cases. Another system, named VIBE, tracks and detects drowning victims via background extraction. It refreshes the motion area by calculating the frame difference and using the VIBE algorithm, which primarily assesses the swimmers' positions. Handalage et al. [2] presented a three-pronged drowning rescue system: dangerous behavior identification, drowning victim recognition, and drone deployment to victims. The drowning detection component locates drowning victims using a CNN model. The second component is the rescue drone, which is sent to the victim's coordinates. Risky activities, such as running about the pool and drinking, are identified in the third element. The drowning detection system was trained using 5,000 images that showed the stages of drowning, including stage 2, stage 3, and not drowning. The primary sources of the data were the introductions given by the performers and the live video recordings. The backup data source was the Internet. An overhead camera detected swimmers in the pool. Hassan et al. [3] presented a video dataset made up of three aquatic activity behaviours that were recorded with overhead and underwater cameras: swim, drown, and idle. The dataset consisted of 47 videos from above and 44 movies from below, producing 24,729 and 22,010 video frames, respectively. The pre-trained CNN models ResNet50, VGG16, and mobile net were evaluated using this dataset. For these models, the equivalent detection accuracy was 96.85%, 83.25%, and 96.7%. Zhang et al. [32] presented an alert zone's human body area changes at a rate that indicates drowning. Moving objects are extracted from the backdrop using background subtraction. The authors of [33] presented a camera to track swimmers and a finite state machine to assess the features and motions of the swimmers' bodies. The DEWS team creates a module that uses hidden Markov models and data fusion to understand the features of various swimming behaviors. Wong et al. [34] installed a swimming pool monitoring system during off-peak hours to use thermal imaging technology to find moving people and water activity. This system divides the photos into two zones to detect an intruder both inside and outside the swimming pool. Head detection is performed in both regions, while water activity is detected in only the second sector. Li et al. [35] presented a method for locating drowning victims at sea. Using a group of actors, they produced a dataset with 6079 photos. With some adjustments, they used the YOLOv3 algorithm. In summary, the feature extraction network employed the residual module with channel attention mechanism, the feature fusion network (FPN) structure received a bottom-up structure, CIoU was utilized as the loss function, and the anchor boxes produced by the clustering algorithm were handled using a linear transformation technique. The model for human targets identifies four types: sea person, land person, doubtful land person, and land person. The model attained 72.17% accuracy. Fazanes et al. [23] presented a method for locating drowning victims at sea. Using a group of actors, they produced a dataset with 6079 images. With some adjustments, they used the YOLOv3 algorithm. In summary, the feature extraction network employed the residual module with channel attention mechanism, the FPN structure received a bottom-up structure, CIoU was utilized as the loss function, and the anchor boxes produced by the clustering algorithm were handled using a linear transformation technique. The model for human targets identifies four types: sea person, land person, doubtful land person, and land person. The model attained 72.17% accuracy.

Moez et al. [36] proposed a deep learning model that can classify human behaviour. To accomplish this, a spatiotemporal feature-learning three-dimensional convolutional neural network is extended. The spatiotemporal features are then classified using a recurrent neural network. A method for simultaneously learning features and finding commonalities to support individual re-identification is proposed in [37]. To solve the re-identification problem was achieved by altering the layers of a deep convolutional neural network. The author's development of this enables the network to ascertain whether two input images feature the same person. To evaluate YOLOv4 for underwater target detection, Chen et al. [38] used the URPC dataset. The URPC collection has 4757 photos categorized into four target groups: echinus, scallop, holothurian, and starfish. In the detection findings, 73.48% mAP is represented. Hu et al. [39] to recognize uneaten feed pellets in underwater photographs used an improved version of YOLOv4. The high-density, grainy images in the custom dataset were captured from a net cage in the cold-water mass area of the China Yellow Sea. The original YOLOv4 method was improved by adding the Dense-Net shortcut link, changing the PANet network topology, and reducing the number of network layers. The results of training and testing the upgraded YOLOv4 algorithm yielded a mAP score of 92.61% on the test dataset. To detect steel corrosion and concrete cracks, Cha et al. [40] introduced a CNN and Faster R-CNN. The models' mean average precision (mAP), which may reach roughly 90.00%, offers recommendations on which models to employ. However, these studies are designed with adults rather than children in mind because of the major differences between adult and infant drowning postures. While newborns' drowsing positions usually involve resting on one side or upside down in the water with swimming rings attached, without making any violent movements, adults' drowsing positions often involve forceful physical motions as well. To employ waterpower, Xu et al. [41] introduced a YOLOv3 to identify fish underwater. The model was trained and tested on datasets containing murky water, high turbidity, and rapid velocity. Testing yielded a mean average precision value of 54.92% for the model.

Various study gaps have been identified in the above mentioned literature of the drowning detection research and technologies. Most of the existing models generally rely on the traditional CNN based architectures with limited exploration of the advanced networks like vision transformers. Datasets used in these models often lack class diversity and don't truly represent the real world aquatic environment thus effecting the generalization capability. There is limited integration of multi modal data with less focus on the real time deployment, explainability and edge efficiency which are crucial for the life saving applications. Moreover, challenges like complex body movements, occlusion and the use of short video sequence remained unaddressed. Moreover the comparative evaluations are also missing. This study presents generalized drowning detection framework using DL models to enhance the feature extraction, model's performance and overall accuracy.

3. Proposed methodology

This proposed framework as shown in Figure 1 performs drowning detection classification through four main stages: (i) dataset augmentation, (ii) contrast enhancement, (iii) deep feature extraction using pre-trained ResNet50 and ResNet18, and (iv) serial feature fusion followed by FPA based feature selection and final classification. Following the contrast enhancement phase, the contrast-augmented data set was fed into the two pre-trained ResNet50 and ResNet18 models. Techniques of serial-based feature fusion are employed after features from the two pre-trained ResNet50 and ResNet18 models are retrieved and fused. Next, the Flower Pollination Algorithm's optimized features are applied to choose the best features, which are then fed into a machine learning algorithm.

3.1. Dataset collection

This study uses a public available drowning detection classification dataset [57]. The dataset contains five classes: drowning, drowning swimming, person out of water, person out of water swimming, and swimming. Since the class sizes are imbalanced, augmentation is applied to obtain sufficient samples for deep learning. Figure 2 illustrates the five classifications that make up this data set of drowning detection classification: drowning, drowning swimming, a person out of the water, the person out of water swimming, and swimming. As shown in Table 1 , there are a limited number of images in each data set that are not enough to

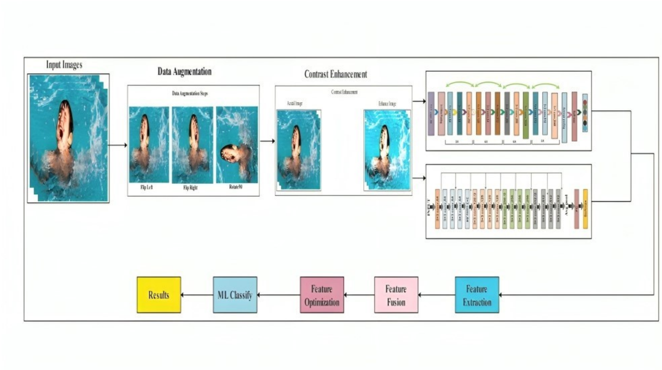

Figure 1: Proposed architecture of drowning detection classification.

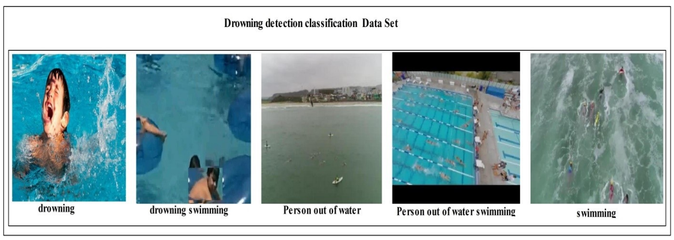

Figure 2: Sample images of the dataset.

train deep learning models. Consequently, these datasets exhibit an imbalance.

3.2. Dataset augmentation

Data augmentation involves making various changes to pre-existing data in order to increase a model's ability to generalize to scenarios that were previously unknown. Figure 3 shows the data augmentation steps. The data augmentation is a technique that is used to alter the input data in order to increase the model's resilience to different conditions [42], [43]. When it comes to drowning detection, for example, different lighting conditions, positions, and viewpoints can be simulated to improve images or video frames that depict persons in the water [44]. Recently, there has been significant research on data augmentation in the field of deep learning [52] – [55]. While the medical field currently uses low-resource data sets, deep-learning neural networks require large amounts of training data [24]. Therefore, data augmentation must be used to increase the diversity of the basic dataset [25].

The data set for drowning detection classification is divided into four classes: swimming (87), the person out of the water (5), drowning (276), a person swimming (25), and swimming (276) [56], [57]. The collection of 472 photos in each class has an average pixel size of 500x500. Furthermore, for training and testing, the data sets were split in half. As such, it is not possible to train the deep learning model with these datasets. As such, used Flip Left, Flip Right, and Rotate 90 for data augmentation, as shown in Figure 3. These procedures are repeated until each data collection has enough number of images for training.

3.3. Contrast enhancement

Contrast enhancement improves visibility in low-quality underwater/overhead imagery [26], [27]. Let the grayscale

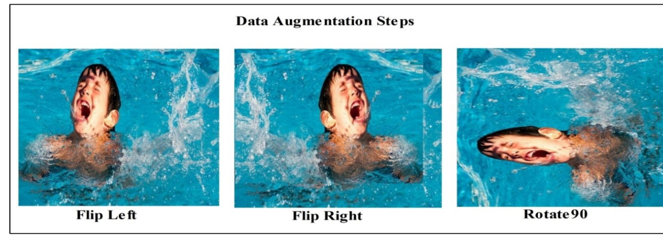

Figure 3: Data augmentation steps.

image be $\lambda(b, y)$. The PDF and CDF are computed as (1) and (2), respectively. Due to the low contrast and poor quality of the images used for the drowning detection classification, Figure 4 depicts the hybrid approach we developed based on the fusion of multiple filtering outputs.

$$t(\lambda_n) = \frac{k_n}{k}, \quad n = 0, 1, \ldots, S-1 \tag{1}$$

$$q(\lambda_n) = \sum_{i=0}^{n} t(\lambda_i) \tag{2}$$

A contrast transformation using the CDF is expressed as (3). The final enhanced output is denoted by $m(b, y)$.

$$m(\lambda_n) = \lambda_0 + \big(\lambda_{g-1} - \lambda_0\big)\, q(\lambda_n) \tag{3}$$

The transformation function utilizing the cumulative distribution function (CDF) is defined as follows (4). Further, the normalized probability distribution is given by (5).

$$m(\lambda_n) = \lambda_0 + \big(\lambda_{g-1} - \lambda_0\big)\, g(\lambda_n) \tag{4}$$

$$\beta = s\big(\lambda(b, y)\big), \quad \forall\, \lambda(b, y) \in \lambda \tag{5}$$

Afterward, a spatial-domain transformation is applied to enhance local contrast, expressed as (6).

$$m(b, y) = m(b, y)\big[a(b, y) - z \times \bar{A}(b, y)\big] + \bar{A}(b, y)\,\varepsilon \tag{6}$$

In (6), the enhanced image is denoted by $m(b, y)$. The mathematical formulation of the contrast-stretching function is defined as (7).

$$m'(b, y) = c \times g_m^{\ell}(b, y) + \mu \tag{7}$$

In (7), g_m represents the global mean value, μ denotes the standard deviation, and c and ℓ are constant parameters assigned manually.

Consequently, the final transformation function is obtained by combining both global and local enhancement terms as (8).

$$m(b, y) = c \times g_m^{\ell}(b, y) + \mu\big[a(b, y) - z \times \bar{A}(b, y)\big] + \bar{A}(b, y)\,\varepsilon \tag{8}$$

The visual result of the contrast-enhanced image is illustrated in Fig. 4.

Table 1: Description of dataset.

Dataset Name	No. of images	No. of classes	Augmented	Training/Testing
5=Drowning detection classification dataset	5c472	Drowning: 300	500	250/250
		Drowning swimming: 306	500	250/250
		Person out of water: 5	500	250/250
		Person out of swimming water: 25	500	250/250
		Swimming: 87	500	250/250

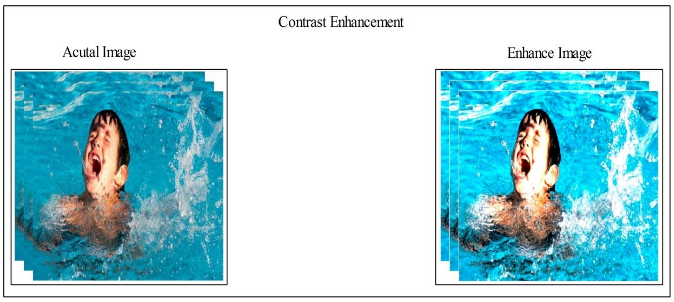

Figure 4: Examples of contrast-enhanced images.

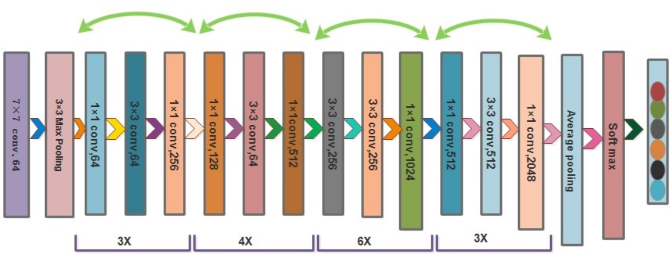

Figure 5: ResNet50 architecture.

3.4. ResNet50 architecture

As shown in Figure 5, it extracts deep semantic features using convolutional layers and residual blocks [28], [29]. A convolution operation can be expressed as (9).

$$\mathrm{Conv}(y, z) = \hat{A}(y * z + s) \tag{9}$$

A residual block outputs (10):

$$\mathbf{o} = \mathcal{F}(\mathbf{x}; \theta) + \mathbf{x} \tag{10}$$

In (10), $\mathcal{F}(\cdot)$ is the residual mapping.

3.5. ResNet18 architecture

ResNet18 is a lightweight residual network with 18 layers, which is shown in Figure 6 [30], [45],[46]. It employs shortcut connections to stabilize gradients and improve optimization.

3.6. Transfer learning

Transfer learning adapts pre-trained weights to the target dataset [49], [50]. Figure 7 and Figure 8 shows the transfer learning pipeline for ResNet50 and ResNet18, respectively. Let the pre-trained model be a_b with parameters θ_b. Fine-tuning minimizes as (11).

$$\min_{\theta} \; \mathcal{L}_t(\theta) + \beta \|\theta - \theta_b\|_2^2 \tag{11}$$

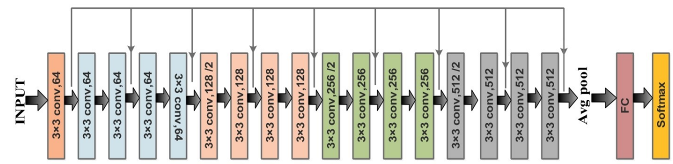

Figure 6: ResNet18 architecture.

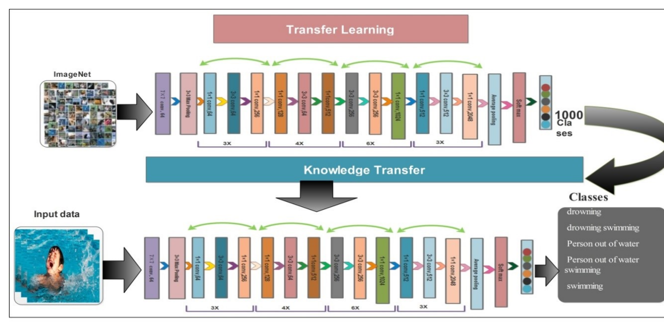

Figure 7: Transfer learning pipeline for ResNet50.

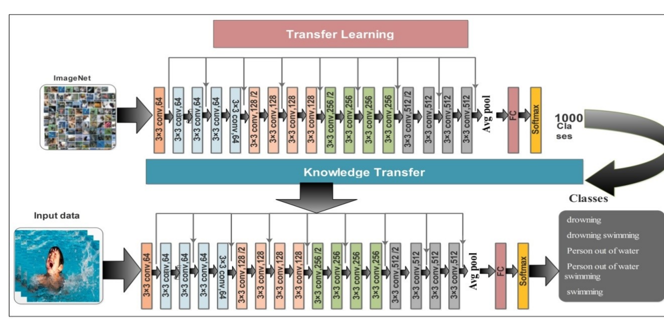

Figure 8: Transfer learning pipeline for ResNet18.

3.7. Serial-based feature fusion

Features from ResNet50 and ResNet18 are concatenated to form a fused descriptor [51], [52] is expressed as (12).

$$\mathbf{u} = \begin{bmatrix} \mathbf{v}_1 \\ \mathbf{v}_2 \end{bmatrix} \tag{12}$$

3.8. Flower Pollination Algorithm for feature selection

FPA selects discriminative features by balancing global and local search [55]. Global pollination is written by (13).

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \vartheta \, L(\lambda) \big(\mathbf{x}_i^{(t)} - \mathbf{g}^*\big) \tag{13}$$

Algorithm 1 Flower Pollination Algorithm for feature selection.

1.2em

Input: Feature matrix $\mathbf{F}$, iterations T, switch probability p
Output: Best feature subset $\mathbf{g}^*$
Initialize population $\{\mathbf{x}_i\}_{i=1}^{n}$ (random feature masks)
Evaluate fitness $f(\mathbf{x}_i)$; set best $\mathbf{g}^* \leftarrow \arg\min f(\mathbf{x}_i)$
for $t = 1$ to T **do**
  for $i = 1$ to n **do**
    if rand $< p$ **then** ▷ Global pollination
      Draw $L(\lambda)$ (Lévy step); update using (13)
    else ▷ Local pollination
      Select $j, k \neq i$; update using (14)
    end if
    Evaluate new solution; update $\mathbf{g}^*$ if improved
  end for
end for
return $\mathbf{g}^*$

Table 2: Feature fusion results on drowning detection dataset.

Classifier	Prec.	Rec.	F1	Acc.	Time (s)
NNN	99.2	99.2	99.2	99.2	113.46
MNN	99.4	99.4	99.4	99.4	178.70
WNN	99.3	99.3	99.3	99.4	211.43
BNN	99.0	99.0	99.0	99.0	244.22
TNN	99.1	99.1	99.1	99.1	309.32

Local pollination is given by (14).

$$\mathbf{x}_i^{(t+1)} = \mathbf{x}_i^{(t)} + \epsilon\big(\mathbf{x}_j^{(t)} - \mathbf{x}_k^{(t)}\big) \tag{14}$$

4. Results and analysis

4.1. Experiment environment

The train/test split was 50:50. The experiments used learning rate 2×10^{-4}, mini-batch size 32, 100 epochs, momentum 0.7223, and SGD optimizer. A 10-fold cross-validation was applied. Performance was reported using Precision, Recall, F1-score, Accuracy, and Time.

4.2. Drowning detection classification dataset results

4.2.1. Performance of proposed feature fusion

Table 2 demonstrates the results of the proposed feature fusion results on drowning detection dataset. The highest accuracy of 99.4% was achieved with MNN classifier and 66.329(s) and the values of precision rate of 99.3, recall rate of 99.4 and F1- Score of 99.4, respectively. The figures of the rest of the classifiers are also estimated, and the most successful MNN is selected. The confusion matrix provided in Figure 9 displays the findings obtained following the fusion of the features.

4.3. Proposed feature optimization results

The optimized feature set (FPA-selected) improved efficiency while maintaining high accuracy. The results are summarized in Table 3, with MNN achieving 99.4% accuracy at 66.329 s. The confusion matrix of the case is shown in Figure 10.

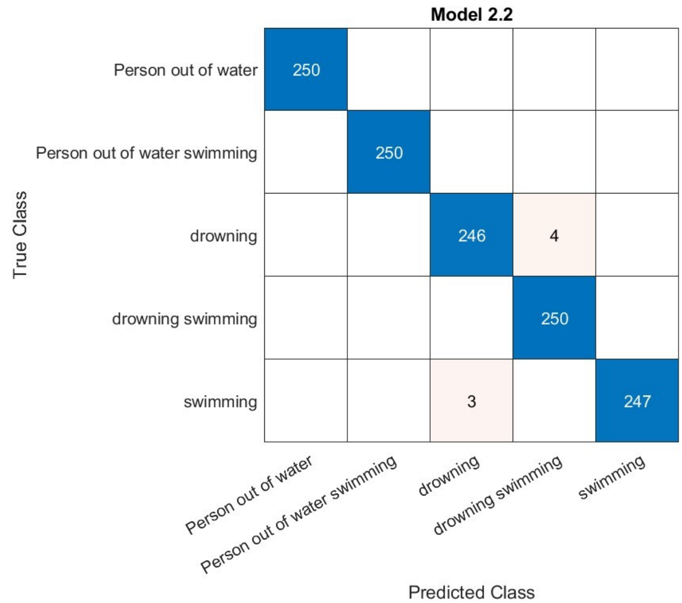

Figure 9: Confusion matrix after feature fusion.

Table 3: Feature optimization results on drowning detection dataset.

Classifier	Prec.	Rec.	F1	Acc.	Time (s)
NNN	99.1	99.1	99.1	99.1	57.302
MNN	99.3	99.3	99.3	99.4	66.329
WNN	99.3	99.3	99.3	99.4	76.833
BNN	98.8	98.8	98.8	98.9	84.406
TNN	98.9	98.9	98.9	99.0	121.03

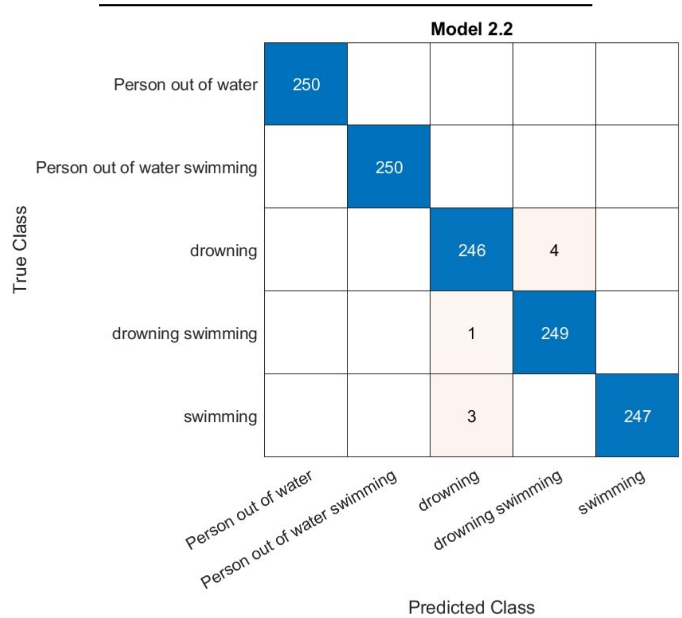

Figure 10: Confusion matrix after feature optimization.

4.4. Comparison study

A comparison with other existing techniques is presented in Table 4, which contrasts the proposed strategy with some of the contemporary approaches. Methodologies provided a multi-fractal and fusion strategy and achieved an accuracy of 85.0%, 85.6%, and 96.7%. The authors of this study employed CNN network-based design. The

Table 4: Comparison with existing techniques.

Study	Method	Accuracy (%)
Chan et al. [5]	AlexNet	85.0
Handalage et al. [2]	YOLO	85.6
Hasan et al. [3]	MobileNet	96.7
Proposed	**ResNet50 + ResNet18 + FPA**	**99.4**

fusion approach and CNN-based architecture were applied. The accuracy of the suggested framework was 99.4% when it came to the drowning detection classification data set. These figures demonstrate the degree of accuracy improvement over the current methods.

5. Conclusion and future scope

5.1. Conclusion

In this work, the dire need for efficient preventive measures is highlighted by the concerning global data that show drowning to be one of the top causes of death for children between the ages of one and fourteen. This work addresses this critical issue by introducing a state-of-the-art drowning detection system that is based on deep learning and computer vision. Applying the Flower Pollination Algorithm and two trained models, ResNet50, and ResNet18, the unprecedented training accuracy of 99.4 was attained. Our proposed solution is placed in the group of effective and reliable methods of early drowning detection due to its great level of accuracy. Efficiency of the system is reflected not only on its greater prediction accuracy but also low cost of processing which is greater than that of other existing procedures. Our drowning identification device is a possible alternative to reduce the tragic consequences of drowning incidents, particularly in the most susceptible population clusters such as children, with the help of innovative technologies such as convolutional neural networks and innovative algorithms. Installation of such systems and further enhancement could be a significant change in the number of accidental drowning cases which are happening across the globe and increased community access to water.

5.2. Future scope

The main aspects of future research are likely to concentrate on the system validation in divers, real world aquatic conditions and utilization of more diverse datasets in order to capture the larger scope of the realistic situations. It might be useful to integrate the real time surveillance architecture and use lightweight models that are optimized to the the edge devices further to make the systems more practical. In addition, the multimodal search of the multimodal methods such as thermal, audio and physiological indicators can enhance the general robustness and early detection.

Declarations and Ethical Statements

Conflict of Interest: The authors declare that there is no conflict of interest.
Funding Statement: The authors declare that no specific funding was received for this research.
Artificial Intelligence usage Statement: During the preparation of this manuscript, the authors utilized ChatGPT solely for language refinement and grammatical corrections. The authors carefully reviewed and revised the generated content and take full responsibility for the accuracy, integrity, and originality of the final manuscript.
Availability of Data and Materials: The data and/or materials that support the findings of this study are available from the corresponding author upon reasonable request.
Publisher's Note: The publisher of this article, Krrish Scientific Publications, remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

References

[1] Shatnawi M, Albreiki F, Alkhoori A, Alhebshi M. Deep learning and vision-based early drowning detection. *Information.* 2023 Jan 16;14(1):52. Available from: `https://doi.org/10.3390/info14010052`

[2] Handalage U, Nikapotha N, Subasinghe C, Prasanga T, Thilakarthna T, Kasthurirathna D. Computer vision enabled drowning detection system. In *2021 International Conference on Advancements in Computing (ICAC)* 3rd 2021 Dec 9 (pp. 240-245). Available from: `https://ieeexplore.ieee.org/document/9671126`

[3] Hasan S, Joy J, Ahsan F, Khambaty H, Agarwal M, Mounsef J.A Water Behavior Dataset for an Image-Based Drowning Solution. In *2021 IEEE green energy and smart systems conference (IGESSC)* 2021 Nov 1 (pp. 1-5). Available from: `https://ieeexplore.ieee.org/document/9618700`

[4] He X, Yuan F, Liu T, Zhu Y. A video system based on convolutional autoencoder for drowning detection.*Neural Computing and Applications.* 2023 Jul;35(21):15791-803. Available from: `https://doi.org/10.1007/s00521-023-08526-9`

[5] Chan YT, Hou TW, Huang YL, Lan WH, Wang PC, Lai CT. Implementation of deep-learning-based edge computing for preventing drowning. *Computing.* 2020;8:13. Available from: `DOI:10.12792/iciae2020.041`.

[6] Bhargavi KN, Suma G. Identifying Drowning Objects in Flood Water and Classifying using Deep Convolution Neural Networks. *I-Manager's Journal on Image Processing.* 2021 Jul 1;8(3). Available from: `https://doi.org/10.26634/jip.8.3.18451`

[7] Rashid AH, Razzak I, Tanveer M, Hobbs M. Reducing rip current drowning: An improved residual based lightweight deep architecture for rip detection. *ISA Transactions.* 2023 Jan 1;132:199-207. Available from: `https://doi.org/10.1016/j.isatra.2022.05.015`.

[8] Zhang J, Zhou Y, Vieira DN, Cao Y, Deng K, Cheng Q, Zhu Y, Zhang J, Qin Z, Ma K, Chen Y. An efficient method for building a database of diatom populations for drowning site inference using a deep learning algorithm. *International Journal of Legal Medicine.* 2021 May;135(3):817-827. Available from: `https://link.springer.com/article/10.1007/s00414-020-02497-5`

[9] Ramos JO, Flores HV, Villena JR, Gonzales JZ, Joseph GM. Development of a detection system for people drowning through aerial images and convolutional neural networks. *Przegląd elektrotechniczny.* 2023;99(2):109-13. Available from: `https://pe.org.pl/articles/2023/2/18.pdf`

[10] Qureshi AH, Zhang X, Ichiji K, Kawasumi Y, Usui A, Funayama M, Homma N. Deep CNN-Based Computer-Aided Diagnosis for Drowning Detection using Post-mortem Lungs CT Images. In *IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* 2021 2021 Dec 9 (pp. 2309-2313). IEEE. Available from: `https://ieeexplore.ieee.org/document/9669644`

[11] Eng, Toh, Kam, Wang, Yau. An automatic drowning detection surveillance system for challenging outdoor pool environments. In *Ninth IEEE international conference on computer vision* 2003 Oct 13 (pp. 532-539). IEEE. Available from: `https://ieeexplore.ieee.org/document/1238393`

[12] Cepeda-Pacheco JC, Domingo MC. Deep learning and 5G and beyond for child drowning prevention in swimming pools. *Sensors* 2022 Oct 10;22(19):7684. Available from: `https://doi.org/10.3390/s22197684`

[13] Zeng Y, Zhang X, Kawasumi Y, Usui A, Ichiji K, Funayama M, Homma N. Deep learning-based interpretable computer-aided diagnosis of drowning for forensic radiology. In *60th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)* 2021 Sep 8 (pp. 820-824). Available from: `https://ieeexplore.ieee.org/abstract/document/9555359`

[14] Urruchi C, Cervantes-Chauca D, Huamanchahua D. Proposal of a Swimming Pool Drowning Detection System using Cameras and Raspberry Pi based on Machine Learning. In *2nd International Conference on Robotics, Automation and Artificial Intelligence (RAAI)* 2022 Dec 9 (pp. 178-181). Available from: `https://doi.org/10.1109/RAAI56146.2022.10092956`

[15] Kam AH, Lu W, Yau WY. A video-based drowning detection system. In *European conference on computer vision* 2002 Apr 29 (pp. 297-311) Berlin, Heidelberg: Springer Berlin Heidelberg . Available from: `https://link.springer.com/chapter/10.1007/3-540-47979-1_20`

[16] Zhang FY, Wang LL, Dong WW, Zhang M, Tash D, Li XJ, Du SK, Yuan HM, Zhao R, Guan DW. A preliminary study on early postmortem submersion interval (PMSI) estimation and cause-of-death discrimination based on nontargeted metabolomics and machine learning algorithms. *International Journal of Legal Medicine.* 2022 May;136(3):941-54 . Available from: `https://doi.org/10.1007/s00414-022-02783-4`

[17] Birk A. A survey of underwater human-robot interaction (u-hri). *Current Robotics Reports.* 2022 Dec;3(4):199-211. Available from: `https://doi.org/10.1007/s43154-022-00092-7`

[18] Durairaj M, Subudhi S, Rao VV, Jayanthi J, Suganthi D. AI-driven drowned-detection system for rapid coastal rescue operations. *Spatial Information Research.* 2024 Apr;32(2):143-50. Available from: `https://doi.org/10.1007/s41324-023-00549-7`

[19] Kulhandjian H, Ramachandran N, Kulhandjian M, D'Amours C. Human activity classification in underwater using sonar and deep learning. In *14th International Conference on Underwater Networks & Systems.* 2019 Oct 23 (pp. 1-5). Available from: `https://doi.org/10.1145/3366486.3366509`

[20] Yu W, Xue Y, Knoops R, Yu D, Balmashnova E, Kang X, Falgari P, Zheng D, Liu P, Chen H, Shi H. Automated diatom searching in the digital scanning electron microscopy images of drowning cases using the deep neural networks. *International Journal of Legal Medicine.* 2021 Mar;135(2):497-508. Available from: `https://doi.org/10.1007/s00414-020-02392-z`

[21] Bai B, Chen L, Li X. Improved YOLOv7 Fusion Detection Line for Swimming Pool Drowning Detection. In *IEEE 16th International Conference on Electronic Measurement & Instruments (ICEMI)* 2023 Aug 9 (pp. 129-134). IEEE. Available from: `https://ieeexplore.ieee.org/document/10270676/`

[22] He L, Hou H, Yan Z, Xing G. Demo abstract: An underwater sonar-based drowning detection system. In IEEE *21st ACM/IEEE International Conference on Information Processing in Sensor Networks (IPSN)* 2022 May 4 (pp. 493-494). Available from: `https://ieeexplore.ieee.org/document/9825955`.

[23] Carballo-Fazanes A, Bierens JJLM, Behaviour TIEG to SD. The Visible Behaviour of drowning Persons: A pilot observational study using analytic software and a nominal group technique. *International Journal of Environmental Research and Public Health.* 2020 Sep 22;17(18):6930. Available from: `https://doi.org/10.3390/ijerph17186930`

[24] Wang F, Ai Y, Zhang W. Detection of early dangerous state in deep water of indoor swimming pool based on surveillance video. *Signal, image and video processing.* 2022 Feb;16(1):29-37. Available from: `https://doi.org/10.1007/s11760-021-01953-y`

[25] Zemblys R, Niehorster DC, Komogortsev O, Holmqvist K. Using machine learning to detect events in eye-tracking data. *Behavior Research Methods.* 2017 Feb 23;50(1):160–81. Available from: `https://link.springer.com/article/10.3758/s13428-017-0860-3`

[26] Batislaong JP, Leonin JC, Utto AK, Dadula DP, Banal RG, Dadula CP. Acoustic-Based Classifier for Detecting Abnormal Events in a University Setting. In *6th International Conference on Applied Computational Intelligence in Information Systems (ACIIS).* 2023 Oct 23 (pp. 1-6). Available from: `https://ieeexplore.ieee.org/abstract/document/10367396`

[27] Shoka AA, Dessouky MM, El-Sherbeny AS, El-Sayed A. Fast seizure detection from eeg using machine learning. In *7th International Japan-Africa Conference on Electronics, Communications, and Computations,(JAC-ECC).* 10, no. 21, pp. 7448, 2020. Available from: `https://ieeexplore.ieee.org/abstract/document/9051070`

[28] Harras MS, Saleh S, Battseren B, Hardt W. Vision-based propeller damage inspection using machine learning. *Embedded Selforganising Systems* 2023 Jul 26;10(7):43-7. Available from: `https://doi.org/10.14464/ess.v10i7.604`

[29] Soma AK. Hybrid RNN-GRU-LSTM model for accurate detection of DDOS attacks on IDS dataset. *Journal of Modern Technology.* 2024 May 14;2(1):283–291. Available from: `https://doi.org/10.71426/jmt.v2.i1.pp283-291`

[30] Tao X, Zhang D, Hou W, Ma W, Xu D. Industrial weak scratches inspection based on multifeature fusion network. *IEEE Transactions on Instrumentation and Measurement.* 2020 Sep 21;70:1-4. Available from: `https://doi.org/10.1109/TIM.2020.3025642`

[31] Alshbatat AI, Alhameli S, Almazrouei S, Alhameli S, Almarar W. Automated vision-based surveillance system to detect drowning incidents in swimming pools. *Advances in Science and Engineering Technology International Conferences (ASET).* In 2020 Feb 4 (pp. 1-5). Available from: `https://doi.org/10.1109/ASET48392.2020.9118248`

[32] Zhang C, Li X, Lei F. A novel camera-based drowning detection algorithm. In *Chinese Conference on Image and Graphics Technologies* 2015 Jun 17 (pp. 224-233). Berlin, Heidelberg: Springer Berlin Heidelberg. Available from: `https://link.springer.com/chapter/10.1007/978-3-662-47791-5_26`

[33] Zhang C, Li X, Lei F. A novel Camera-Based drowning Detection Algorithm. In *Communications in computer and information science.* 2015. p. 224–233. Available from: `https://doi.org/10.1007/978-3-662-47791-5_26`

[34] Wong WK, Hui JH, Loo CK, Lim WS. Off-time swimming pool surveillance using thermal imaging system. In *International Conference on Signal and Image Processing Applications (ICSIPA)* 2011 Nov 16 (pp. 366-371). Available from: `https://ieeexplore.ieee.org/document/6144091`

[35] Li D, Yu L, Jin W, Zhang R, Feng J, Fu N. An Improved Detection Method of Human Target at Sea Based on Yolov3. In *IEEE International Conference on Consumer Electronics and Computer Engineering (ICCECE)* 2021 Jan 15 (pp. 100-103). Available from: `https://ieeexplore.ieee.org/document/9342056`

[36] Rostami-Moez M, Kangavari M, Teimori G, Afshari M, Khah ME. Cultural adaptation for country diversity: A systematic review of injury prevention interventions caused by domestic accidents in children under five years old. *Medical Journal of the Islamic Republic of Iran.*2019 Nov 20;33:124. Available from: `https://pmc.ncbi.nlm.nih.gov/articles/PMC7137865/`

[37] Chen Y, Zhu X, Gong S. Person re-identification by deep learning multi-scale representations. In *Proceedings of the IEEE International Conference on Computer Vision (ICCV) Workshops*; Oct 2017. Available from: `https://openaccess.thecvf.com/content_ICCV_2017_workshops/html/Chen_Person_Re-Identification_by_ICCV_2017_paper.html`

[38] Chen H, Yuan H, Qin H, Mu X. Underwater Drowning People Detection Based On Bottleneck Transformer And Feature Pyra-

mid Network. In *IEEE International Conference on Unmanned Systems (ICUS)* 2022 Oct 28 (pp. 1145-1150). IEEE Available from: https://ieeexplore.ieee.org/document/9986998

[39] Hu X, Liu Y, Zhao Z, Liu J, Yang X, Sun C, Chen S, Li B, Zhou C. Real-time detection of uneaten feed pellets in underwater images for aquaculture using an improved YOLO-V4 network. *Computers and Electronics in Agriculture*. 2021 Jun 1;185:106135. Available from: https://doi.org/10.1016/j.compag.2021.106135

[40] Cha YJ, Choi W, Büyüköztürk O. Deep learning-based crack damage detection using convolutional neural networks. *Computer-Aided Civil and Infrastructure Engineering* 2017 May;32(5):361-78. Available from: https://doi.org/10.1111/mice.12263

[41] Xu W, Matzner S. Underwater fish detection using deep learning for water power applications. In *International conference on computational science and computational intelligence (CSCI)* 2018 Dec 12 (pp. 313-318). Available from: https://ieeexplore.ieee.org/document/8947884

[42] Chen J, Tam D, Raffel C, Bansal M, Yang D. An Empirical survey of data augmentation for Limited data learning in NLP. *Transactions of the Association for Computational Linguistics*. 2023 Jan 1;11:191–211. Available from:https://doi.org/10.1162/tacl_a_00542

[43] Alomar K, Aysel HI, Cai X. Data Augmentation in Classification and Segmentation: A Survey and New Strategies. *Journal of Imaging* 2023 Feb 17;9(2):46. Available from: https://doi.org/10.3390/jimaging9020046

[44] Huang H, Feng Y, Shi C, Xu L, Yu J, Yang S. Free-bloom: zero-shot text-to-video generator with LLM director and LDM animator. In *Advances in Neural Information Processing Systems*. Vol. 36. Curran Associates, Inc.; 2023. p. 26135–26158. Available from: https://proceedings.neurips.cc/paper_files/paper/2023/file/52f050499cf82fa8efb588e263f6f3a7-Paper-Conference.pdf

[45] Fang J, Xu Y, Zhao Y, Yan Y, Liu J, Liu J. Weighing features of lung and heart regions for thoracic disease classification. *BMC Medical Imaging*.2021 Jun 10;21(1):99. Available from: https://doi.org/10.1186/s12880-021-00627-y

[46] Han M, Du S, Ge Y, Zhang D, Chi Y, Long H, Yang J, Yang Y, Xin J, Chen T, Zheng N. With or without human interference for precise age estimation based on machine learning?. *International Journal of Legal Medicine*. 2022 May;136(3):821-31. Available from: https://doi.org/10.1007/s00414-022-02796-z

[47] Cohen J, Rosenfeld E, Kolter Z. Certified adversarial robustness via randomized smoothing. In *international conference on machine learning* 2019 May 24 (pp. 1310-1320). PMLR. Available from: https://proceedings.mlr.press/v97/cohen19c.html

[48] Shi Z, Liao Z, Tabata H. Enhancing performance of convolutional neural network-based epileptic electroencephalogram diagnosis by asymmetric stochastic resonance. *IEEE Journal of Biomedical and Health Informatics*. 2023 Jun 2;27(9):4228-39. Available from: https://doi.org/10.1109/JBHI.2023.3282251

[49] Huo G, Wu Z, Li J. Underwater object classification in sidescan sonar images using deep transfer learning and semisynthetic training data. *IEEE access*. 2020 Mar 6;8:47407-18.. Available from: https://doi.org/10.1109/ACCESS.2020.2978880

[50] Shoeibi A, Khodatars M, Jafari M, Ghassemi N, Sadeghi D, Moridian P, Khadem A, Alizadehsani R, Hussain S, Zare A, Sani ZA. Automated detection and forecasting of covid-19 using deep learning techniques: A review. *Neurocomputing*. 2024 Apr 7;577:127317. Available from: https://doi.org/10.1016/j.neucom.2024.127317

[51] Alqahtani A, Alsubai S, Sha M, Peter V, Almadhor AS, Abbas S. Falling and Drowning Detection Framework using smartphone sensors. *Computational Intelligence and Neuroscience*. 2022 Aug 12;2022:1–12. Available from: https://doi.org/10.1155/2022/6468870

[52] Liu T, He X, He L, Yuan F. A video drowning detection device based on underwater computer vision. 2*IET Image Processing* 2023 May;17(6):1905-18. Available from: https://doi.org/10.1049/ipr2.12765

[53] Pandiyan N, Narayan S. A survey on deep learning models embed Bio-Inspired algorithms in cardiac disease classification. *The Open Biomedical Engineering Journal*. 2022 Dec 27;17(1). Available from: https://doi.org/10.2174/18741207-v16-e221227-2022-ht27-3589-14

[54] Kiliç Ş, Askerzade I, Kaya Y. Using ResNet Transfer Deep Learning Methods in Person Identification According to Physical Actions. *IEEE Access*. 2020 Nov 26;8:220364-73. Available from: https://doi.org/10.1109/ACCESS.2020.3040649

[55] Dhal P, Azad C. Hybrid momentum accelerated bat algorithm with GWO based optimization approach for spam classification. *Multimedia Tools and Applications*. 2024 Mar;83(9):26929-69. Available from: https://link.springer.com/article/10.1007/s11042-023-16448-w

[56] [Online Available]: Drowning detection classification dataset. Available from: https://universe.roboflow.com/team-burraq/drowning-detect-wiqs0/dataset/3/download

[57] [Online Available]: Available from: https://universe.roboflow.com/team-burraq/drowning-detect-wiqs0/dataset/3/

[58] [Online Available]: Drowning. Available from: https://www.who.int/news-room/fact-sheets/detail/drowning

[59] Kara RV. SmartBio: An AI-Enabled Smart Medical Device for Early Cancer Detection using Variational Autoencoders and Multimodal Sensor Integration. *Journal of Modern Technology*. 2025 Jun 28;2(1):292–301. Available from: https://doi.org/10.71426/jmt.v2.i1.pp292-301

[60] Elango PFM, Dhanabalan SS, Robel MR, Elango SP, Walia S, Sriram S, et al. Dry electrode geometry optimization for wearable ECG devices. *Applied Physics Reviews*. 2023 Oct 30;10(4). Available from: https://doi.org/10.1063/5.0152554

[61] Yang M, Dhanabalan SS, Robel MR, Thekkekara LV, Mahasivam S, Rahman MA, et al. Miniaturized Optical Glucose Sensor Using 1600–1700 nm Near-Infrared Light. *Advanced Sensor Research*. 2024 Mar 15;4(3). Available from: https://doi.org/10.1002/adsr.202300160