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Modelling of Innovative Approaches for Drowning Prevention: Customized CNNs and Optimization of Binary Chimps for Early Detection

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Abstract

Among the top five global causes of death for children ages one to fourteen is drowning. Drowning is the third most common cause of unintentional mortality, according to data from the World Health Organization (WHO). Existing drowning detection systems including the wearable and camera based approaches have proven to face various limitations such as restricted field view, environmental sensitivity, delayed responses and limited applicability in real world. Moreover, many existing approaches only focus on abnormal motion instead of accurately identifying the drowning behavior which is generally subtle and motionless. These limitations highlight the need for more reliable, feasible and real time drowning system. It is becoming inevitable to design a drowning detection system to protect swimmers, especially kids. This research provides an early drowning detection method based on computer vision and deep learning approach. Using a public available dataset we trained Residual Block 3 and Residual Block 4 of convolutional neural networks (CNNs). The proposed architecture achieved 97.6% accuracy with a training time of 3.9137 seconds after feature optimization, which demonstrated a remarkable performance for both prediction precision and computational capacity.

Keywords: Drowning detection, Binary chimp, Residual block, Data augmentation, Convolutional Neural Networks (CNNs).

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1. Introduction

The drowning ranks third globally among children and young adults aged 1–14 years for unintentional deaths, with children under the age of five being most vulnerable [1]. Worldwide, there are thought to be 236,000 drowning deaths per year [2]. Drowning ranks among the top five causes of death for children between the ages of one and fourteen in 48 out of the 85 nations [3]. Accordingly, the number of drowning deaths will rise as the population grows and more homes and hotels with pools are built. Governments and groups have conducted many inquiries to determine the best course of action for saving lives [4]. Some of these strategies include educating parents about the risks of drowning through child monitoring programs, advocating for the fencing or draining of backyard swimming pools and garden ponds, and stepping up oversight of swimming in lakes, rivers, and beaches to lower the number of incidents. Regretfully, these remedies are deemed inadequate and simplistic [5].

1.1. Major contributions

The major contributions of this article are summarized as follows.

- A customized deep learning architecture based on Residual Block 3 and Residual Block 4 is proposed.
- Features extracted from residual blocks 3 and 4 are fused using a serial-based feature fusion strategy.
- Binary Chimp Optimization (BCO) is applied to reduce feature dimensionality and computational complexity.
- Multiple ML classifiers are evaluated to validate the effectiveness of the proposed hybrid DL framework.
- The proposed framework integrates multilevel feature extraction, fusion, and optimization to improve

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accuracy and generalizability across diverse aquatic environments.

2. Related Work

An intelligent automated monitoring system can be put in place to effectively reduce drowning and ensure swimming pool safety. There are two groups of techniques that fall under the umbrella of automatic drowning detection [6]. The first category's methods center on having swimmers wear sensor equipment that is fastened to them via goggles or a bracelet. These sensors can assess things like heart rate, blood oxygen content, motion, hydraulic pressure, and depth to keep an eye on the behavior of the swimmer [7]. The second category consists of vision-based techniques in which swimmers are observed using overhead or underwater cameras, and incidents of drowning are identified from the camera's output using ML algorithms [8], [70]. However, in the early stages of drowning, drowning victims are extremely silent; therefore, these techniques are not very reliable [9]. Additionally, some researchers categorize normal swimmers and drowners using deep neural networks [10], [47]- [52]. 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. Hence, there aren't many videos of drowning [11].

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 them. Videos that simulate drowning are neither authentic nor reliable since it is difficult for anyone to mimic drowning activity properly [12], [53] – [57]. We can create drowning detection systems with greater intelligence thanks to developments in physical equipment. Drowning detection technologies make swimming pools safer, relieve lifeguard workloads, and increase swimmer comfort [13]. IP cameras are employed as network-edge devices in pool surveillance systems, and videos are uploaded via the network to servers and lifeguards for processing. The swimmers' privacy may be compromised by underwater videos, which must be uploaded to a server for processing and storage [14]. This process uses more network bandwidth and storage space, which may make it impossible for the server to react quickly to drowning incidents.

There are various crucial processes involved in developing a machine-learning-based classification model for drowning detection [15]. First, a labeled dataset containing both drowning and non-drowning events is gathered to guarantee diversity and applicability to the intended deployment context. Resizing images or videos, standardizing pixel values, and applying data augmentation methods for increased variability are examples of later data preprocessing tasks. A crucial stage in the process is feature extraction, which involves extracting pertinent features from the data; for example, histogram of oriented gradients (HOG) [16]. One selects a suitable machine learning algorithm, like Random Forests or Support Vector Machines (SVM), for categorization. After dividing the dataset into training and validation sets, the model is trained, and its hyperparameters are adjusted for the best results. On a different test set, evaluation metrics such as accuracy, precision, recall, and F1 score are used to evaluate the model's efficacy. Based on the evaluation results, fine-tuning might be required, which would entail changing the hyperparameters or gathering more data [17]. Ethics and privacy must be taken into account at every stage of the process, especially when working with sensitive data. Consistent updates and retraining with fresh data add to the model's durability and efficacy [18].

The use of computer vision techniques for drowning detection entails utilizing image processing methods to create an automated system that can recognize drowning episodes. Getting a well-annotated dataset with a variety of drowning and non-drowning scenario instances is an important first step. Following that, preprocessing operations are performed on the photos or video frames, such as scaling and normalization to guarantee constant pixel values [19]. After features are extracted, the labeled dataset is used to train an appropriate classification method, which frequently uses machine learning or deep learning models [20], [21], [34]–[37].

In many visual tasks nowadays, deep learning has demonstrated remarkable success. Numerous deep learning-based techniques for visual anomaly detection (VAD) are also proposed by researchers [22]. The VAD challenges share certain similarities with vision-based drowning detection tasks, but they also frequently lack a substantial amount of video data of abnormal events. Moreover, drowning is an unusual occurrence [23]. This encourages the use of convolutional auto-encoders for drowning detection, enabling unsupervised learning with better semantic feature extraction [24]. To the best of our knowledge, this work is the first attempt to apply convolutional auto-encoder technology to the problem of drowning detection [25]. Since outside waterways are often watched using high-altitude cameras or drones, small-target recognition becomes critical [26]. Thus, we present a unique deep learning-based method to improve small object recognition; experimental findings show that the suggested strategy performs better than earlier approaches [27].

In recent years, many researchers have proposed different methods for drowning detection using deep learning [28] – [33]. Li et al. [38] suggested a method for locating victims at sea using a modified YOLOv3 and a dataset of 6079 images, achieving 72.17% accuracy. Chan et al. [39] presented an NVIDIA Jetson Nano-powered AlexNet model trained on 2333 non-drowning and 1168 drowning images with 85% accuracy. Handalage et al. [40] proposed a three-part rescue system including drowning victim detection, risky activity detection, and rescue drone dispatch. Hasan et al. [41] provided a dataset with three aquatic behaviors and reported accuracies of 96.85% (ResNet50), 83.25% (VGG16), and 96.7% (MobileNet). Wearable sensor-based approaches were also explored [42]. Other works focus on anomaly detection through future-frame prediction [43] and small-object swimmer detection using CNN+SVM [44]. Memory-augmented and prototype-based models have been explored for anomaly detection [45], [46].

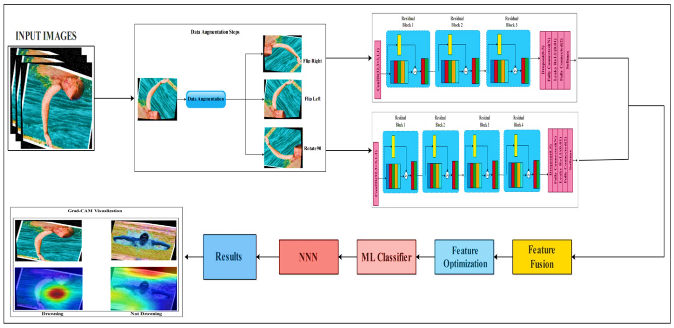

Figure 1: Overall proposed framework for drowning detection classification (augmentation → residual feature extraction → fusion → BCO selection → ML classifier → Grad-CAM).

Table 1: Dataset description (original and augmented).

Dataset	#Images	#Classes	Augmented	Train/Test
Drowning classification	678	2	1000/1000	500/500

2.1. Motivation of the study

Although various approaches have been proposed using CNN architectures, residual models, and handcrafted features, many methods rely on static frame-level analysis, lack multilevel spatiotemporal feature extraction, and use limited fusion/optimization strategies. These limitations affect real-time feasibility, adaptability, and accuracy. To address these gaps, we propose a hybrid DL–optimization framework using Residual Blocks 3 and 4 for multilevel feature extraction, serial feature fusion, and BCO for dimensionality reduction.

3. Modelling of proposed framework

The proposed framework for drowning detection classification is illustrated in Figure 1. Data augmentation is applied to mitigate class imbalance. Then, two customized models (residual block- 3 and 4) extract complementary features that are fused using a serial fusion strategy. The BCO performs feature selection and dimensionality reduction, and the selected features are fed to ML classifiers. Finally, Grad-CAM is used for interpretability.

3.1. Dataset augmentation

An openly accessible dataset is used in this study [76]. The dataset contains two classes (drowning and not drowning). Dataset statistics are reported in Table 1. The data augmentation increases training diversity and improves generalization by applying transformations such as flipping, rotation, translation, and photometric variation [58], [59]. It is especially beneficial for limited datasets and reduces overfitting by exposing the model to plausible input variations [60], [61]. In this work, augmentation operations (e.g., left/right flip and 90° rotation) are applied until sufficient samples per class are produced and which is illustrated in Figure 2 [62], [63].

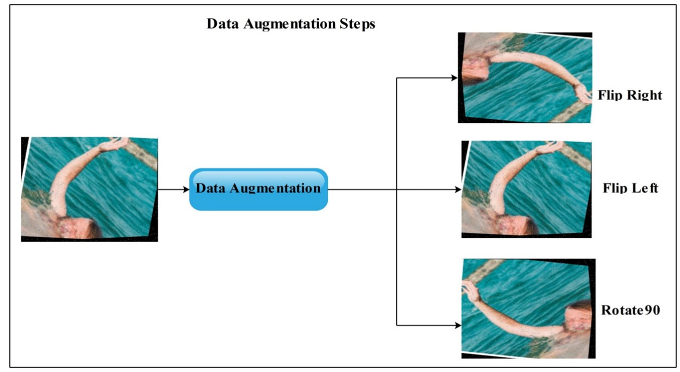

Figure 2: Illustration of augmentation operations applied to generate diverse training samples.

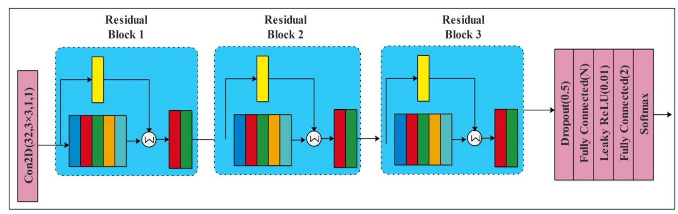

Figure 3: Customized Residual Block 3 architecture used for feature extraction.

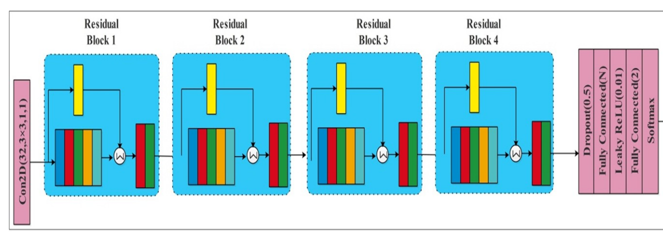

Figure 4: Customized residual block 4 architecture used for deeper feature extraction.

3.2. Architecture of customized residual blocks

Residual blocks mitigate vanishing gradients and enable deeper networks by using skip connections [64] – [66]. The residual block 3 design used in this study is shown in Figure 3. Its operation can be expressed as (1).

$$\mathrm{Out} = \mathrm{Act}\big(\mathrm{BN}(\mathrm{Conv}(\mathbf{n}; x_1)) + \mathrm{Conv}\big(\mathrm{Act}\big(\mathrm{BN}(\mathrm{Conv}(\mathbf{n}; x_2))\big); x_3\big)\big) \tag{1}$$

Residual block 4 extends residual block 3 by increasing representational capacity through an additional residual transformation branch as shown in Figure 4 [67] and which is expressed as (2).

$$\begin{aligned}\mathrm{Out} = \mathrm{Act}\Big(&\mathrm{BN}(\mathrm{Conv}(\mathbf{n}; x_1)) + \mathrm{Conv}\big(\mathrm{Act}(\mathrm{BN}(\mathrm{Conv}(\mathbf{n}; x_2))); x_3\big) \\ &+ \mathrm{Conv}\big(\mathrm{Act}(\mathrm{BN}(\mathrm{Conv}(\mathbf{n}; x_3))); x_4\big)\Big).\end{aligned} \tag{2}$$

3.3. Combined residual blocks 3 and 4: Pseudocode

Algorithm 1 describes the generalized pseudocode for the combined residual blocks.

Algorithm 1 Generalized pseudocode for combined residual blocks 3 and 4.

Require: Input images $\mathbf{I}$
Ensure: Output probability $\hat{y}$
$\mathbf{X} \leftarrow \textsc{Conv2D}(\mathbf{I}, 64, 7\times7, \text{stride} = 2)$
$\mathbf{X} \leftarrow \text{BN}(\mathbf{X})$; $\mathbf{X} \leftarrow \textsc{ReLU}(\mathbf{X})$
$\mathbf{X} \leftarrow \textsc{MaxPool}(\mathbf{X}, 3\times3, \text{stride} = 2)$
$\mathbf{S} \leftarrow \mathbf{X}$ ▷ Identity shortcut (RB3)
$\mathbf{X} \leftarrow \textsc{Conv2D}(\mathbf{X}, 64, 3\times3)$; $\mathbf{X} \leftarrow \text{BN}(\mathbf{X})$; $\mathbf{X} \leftarrow \textsc{ReLU}(\mathbf{X})$
$\mathbf{X} \leftarrow \textsc{Conv2D}(\mathbf{X}, 64, 3\times3)$; $\mathbf{X} \leftarrow \text{BN}(\mathbf{X})$
$\mathbf{X} \leftarrow \textsc{Add}(\mathbf{X}, \mathbf{S})$; $\mathbf{X} \leftarrow \textsc{ReLU}(\mathbf{X})$
$\mathbf{S} \leftarrow \textsc{Conv2D}(\mathbf{X}, 128, 1\times1)$ ▷ Projection shortcut (RB4)
$\mathbf{S} \leftarrow \text{BN}(\mathbf{S})$
$\mathbf{X} \leftarrow \textsc{Conv2D}(\mathbf{X}, 128, 3\times3)$; $\mathbf{X} \leftarrow \text{BN}(\mathbf{X})$; $\mathbf{X} \leftarrow \textsc{ReLU}(\mathbf{X})$
$\mathbf{X} \leftarrow \textsc{Conv2D}(\mathbf{X}, 128, 3\times3)$; $\mathbf{X} \leftarrow \text{BN}(\mathbf{X})$
$\mathbf{X} \leftarrow \textsc{Add}(\mathbf{X}, \mathbf{S})$; $\mathbf{X} \leftarrow \textsc{ReLU}(\mathbf{X})$
$\mathbf{X} \leftarrow \text{GAP}(\mathbf{X})$
$\hat{y} \leftarrow \textsc{Dense}(\mathbf{X}, \text{activation} = \texttt{sigmoid})$
return $\hat{y}$

3.4. Serial-based feature fusion

Serial-based feature fusion integrates complementary features in a sequential manner to enhance representation learning [68], [69]. The fusion operation is expressed as:

$$\mathbf{F} = \begin{bmatrix} \mathbf{f}_1 \\ \mathbf{f}_2 \end{bmatrix} \tag{3}$$

In (3), $\mathbf{f}_1$ and $\mathbf{f}_2$ denote features extracted from Residual Blocks 3 and 4, respectively.

3.5. Feature optimization using BCO

Chimp Optimization Algorithm (ChOA) is a swarm-intelligence optimizer that models group hunting behavior [71], [72]. In this work, a binary version is employed for feature selection to reduce dimensionality and improve computational efficiency. The position update is performed using (4)–(13).

$$\mathbf{s}_1(t{+}1) = \mathbf{s}_{\text{att}}(t) - \mathbf{k}_1 \odot \mathbf{u}_{\text{att}}. \tag{4}$$

$$\mathbf{u}_{\text{att}} = \mathbf{b}_1 \odot \mathbf{s}_{\text{att}}(t) - \mathbf{n} \odot \mathbf{s}_{\text{chimp}}(t). \tag{5}$$

$$\mathbf{s}_2(t{+}1) = \mathbf{s}_{\text{bar}}(t) - \mathbf{k}_2 \odot \mathbf{u}_{\text{bar}}. \tag{6}$$

$$\mathbf{u}_{\text{bar}} = \mathbf{b}_2 \odot \mathbf{s}_{\text{bar}}(t) - \mathbf{n} \odot \mathbf{s}_{\text{chimp}}(t). \tag{7}$$

$$\mathbf{s}_3(t{+}1) = \mathbf{s}_{\text{cha}}(t) - \mathbf{k}_3 \odot \mathbf{u}_{\text{cha}}. \tag{8}$$

$$\mathbf{u}_{\text{cha}} = \mathbf{b}_3 \odot \mathbf{s}_{\text{cha}}(t) - \mathbf{n} \odot \mathbf{s}_{\text{chimp}}(t). \tag{9}$$

$$\mathbf{s}_4(t{+}1) = \mathbf{s}_{\text{drv}}(t) - \mathbf{k}_4 \odot \mathbf{u}_{\text{drv}}. \tag{10}$$

Table 2: Feature fusion results on drowning detection classification dataset

Classifier	**Precision**	**Recall**	**F1**	**Acc.**	**Time (s)**
NNN	97.9	97.9	97.9	97.9	11.971
MNN	97.9	97.9	97.9	97.9	9.1934
WNN	97.5	97.5	97.5	97.5	13.437
BNN	97.7	97.1	97.4	97.1	9.1136
TNN	97.2	97.2	97.2	97.2	8.8681

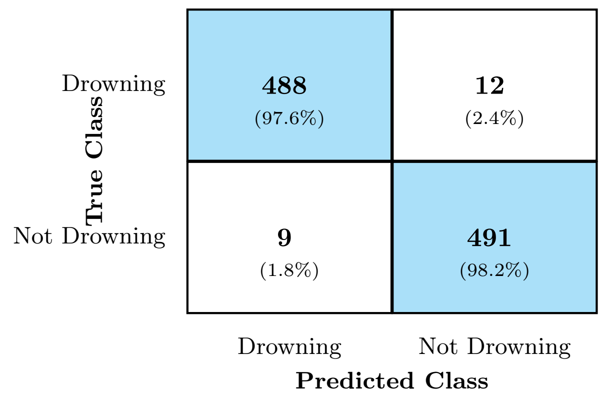

Figure 5: Confusion matrix of NNN classifier after BCO-based feature selection (488, 12, 9, 491).

$$\mathbf{u}_{\text{drv}} = \mathbf{b}_4 \odot \mathbf{s}_{\text{drv}}(t) - \mathbf{n} \odot \mathbf{s}_{\text{chimp}}(t). \tag{11}$$

$$\mathbf{s}_{\text{chimp}}(t{+}1) = \frac{\mathbf{s}_1(t{+}1) + \mathbf{s}_2(t{+}1) + \mathbf{s}_3(t{+}1) + \mathbf{s}_4(t{+}1)}{4}. \tag{12}$$

$$\mathbf{s}_{chimp}(t{+}1) = \frac{\mathbf{s}_1 + \mathbf{s}_2 + \mathbf{s}_3 + \mathbf{s}_4}{4}. \tag{13}$$

4. Experimental Results and Analysis

The training/testing ratio is fixed at 50:50. Hyperparameters include learning rate 0.0002, mini-batch size 32, epochs 100, momentum 0.7223, and SGD optimizer. A 10-fold cross-validation is used. Metrics include accuracy, precision, recall, F1-score, and computational time.

Table 2 reports results for feature fusion. The highest accuracy (97.9%) is achieved by NNN with time 11.971 s and its corresponding confusion matrix is shown in Figure 5, and further the time comparison is shown in Figure 7.

Table 3 reports the results after selecting the BCO feature. The best accuracy (96.8%) is achieved by WNN with time 3.9137 s and its corresponding confusion matrix is shown in Figure 6. Table 4 compares the proposed approach with representative existing methods.

Grad-CAM highlights discriminative regions used by CNNs for classification, improving interpretability [73] – [75]. The Grad-CAM visualization for the proposed framework is shown in Figure 8.

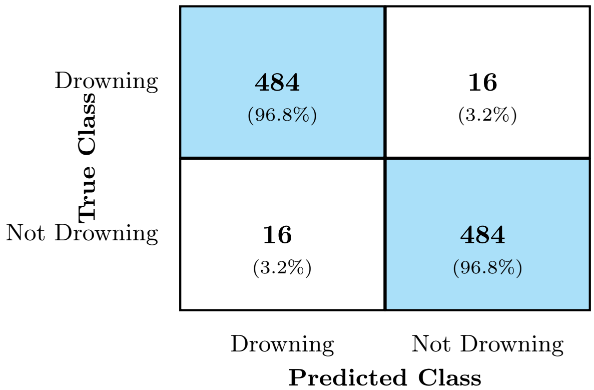

Figure 6: Confusion matrix of WNN classifier after BCO-based feature selection (484, 16, 16, 484).

Table 3: Feature optimization-(BCO) results on drowning detection classification dataset.

Classifier	Precision	Recall	F1	Acc.	Time (s)
NNN	96.3	96.3	96.3	96.3	4.028
MNN	95.7	95.7	95.7	95.7	3.0174
WNN	96.8	96.8	96.8	96.8	3.9137
BNN	96.3	96.3	96.3	96.3	2.8941
TNN	96.0	96.0	96.0	96.0	2.9428

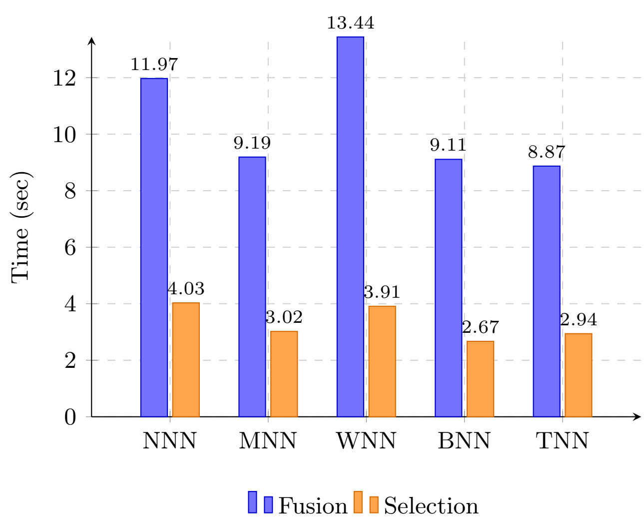

Figure 7: Time comparison for feature fusion and BCO-based feature selection across different classifiers

Table 4: Comparison with existing drowning detection methods.

Study	Method	Accuracy (%)
Chan et al. [39]	AlexNet	85.0
Handalage et al. [40]	YOLO-based system	85.6
Hasan et al. [41]	MobileNet	96.7
Proposed	RB3+RB4 + Fusion + BCO	**97.9**

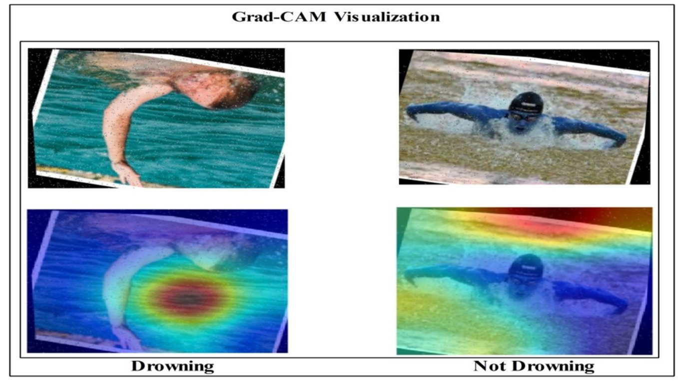

Figure 8: Grad-CAM visualization of the proposed drowning detection framework.

5. Conclusion

A deep learning-based method for early drowning detection has been presented in this paper. Using publicly available dataset, we trained two customized-CNN. Residual blocks 3 and 4 were combined into one model to achieve optimal performance. Binary Chimp Optimization was employed for feature selection, and 97.9% accuracy was achived, respectively. Residual block 3 was the best model out of them all because it had the highest testing and validation accuracy. The system performed remarkably well in terms of training time and prediction accuracy compared to other methods. The outcomes of the experiments demonstrated that the suggested models could identify drowning incidents in swimming pools with a high degree of certainty. The recommended technique can be used in a range of pools and environments, such as fitness centers, hotels, villas, and schools. This technique can be put in place and linked with either an automated drowning rescue system or an alert system. There are substantial practical implication of this proposed framework. This framework can effectively play role in early and accurate detection of drowning subjects quickly, thus significantly reducing the response time and saving lives. Real time implementation of this life saving system with existing surveillance infrastructure can enhance the safety monitoring both in public and private pool environments. Presented DL model is trained on a single data set. However, the efficiency and reliability of the model can be significantly be validated by training it on more diverse and large dataset. In this context future research should explore the collection of more comprehensive dataset from diverse real world and swimming environments including the variations in day light, crowd density and weather conditions. Briefly this study lays the foundation of a scalable and reliable drowning detection system for the real world implementation.

Declarations and Ethical Statements

Conflict of Interest: The authors declare that there is no conflict of interest.

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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.

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