Final Project Report Template

Virtual Eye - Life Guard for Swimming Pools to Detect Active Drowning

1.Introduction:

In modern urban lifestyles, swimming serves as a popular exercise, offering numerous health benefits. However, beginners, particularly children, often face challenges like difficulty breathing underwater, leading to potential drowning incidents. Worldwide, drowning is a leading cause of accidental death, notably among children under six, accounting for approximately 1.2 million fatalities annually. To address this, a robust AI-based safety system is essential in swimming pools to alert lifeguards to potential drowning situations and prevent accidents.

The Virtual Eye system aims to detect drowning in real-time using a single underwater camera. By leveraging the YOLOv5 model, this solution detects three classes:

- 0: Drowning
- 1: Swimming
- 2: Out of Water

When the system identifies a high drowning probability, it generates an alert to attract the lifeguard's attention.

1.1 Project Overview:

The Virtual Eye Lifeguard for Swimming Pools is a cutting-edge project designed to enhance safety in swimming pools by detecting active drowning incidents using advanced computer vision techniques. The project leverages the YOLOv5 (You Only Look Once) deep learning object detection model for real-time monitoring and alert generation.

1.2 Project Objectives:

• Know fundamental concepts and techniques used for computer vision.

• Gain knowledge in the pre-trained model yolov8.

• Gain knowledge of OpenCV.

• Gain knowledge of Web Integration.

2. Project Initialization and Planning Phase:

The project began with defining objectives, selecting YOLOv5, and sourcing data from Kaggle. A timeline with milestones for training, testing, and deployment was created, and resources were allocated. Risks like accuracy and scalability were assessed, ensuring a clear plan for execution.

2.1 Define Problem Statement:

In modern urban lifestyles, swimming serves as a popular exercise, offering numerous health benefits. However, beginners, particularly children, often face challenges like difficulty breathing underwater, leading to potential drowning incidents. Worldwide, drowning is a leading cause of accidental death, notably among children under six, accounting for approximately 1.2 million fatalities annually. To address this, a robust AI-based safety system is essential in swimming pools to alert lifeguards to potential drowning situations and prevent accidents. The Virtual Eye system aims to detect drowning in real-time using a single underwater camera.

Virtual Eye Problem Statement Template: Click Here

2.2 Project Planning:

The planning phase outlined key milestones, including data preparation, model training, testing, and deployment. YOLOv5 was selected for its real-time detection capabilities, with Google Colab and a Kaggle dataset as core resources. A risk assessment was conducted to address challenges like accuracy and scalability, ensuring efficient resource allocation and smooth execution.

Project Planning Template: Click Here

2.3 Project Proposal:

The Virtual Eye system aims to detect drowning in real-time using a single underwater camera. By leveraging the YOLOv5 model, this solution detects three classes: Drowning, Swimming, When the system identifies a high drowning probability, it generates an alert to attract the lifeguard's attention. Upon detection, the system immediately alerts lifeguards, enhancing response time and improving swimmer safety.

Project proposal Template: Click Here

3. Data Collection and Preprocessing Phase:

A dataset from Kaggle was used, featuring annotated swimming scenarios. Images were cleaned, resized, normalized, and augmented to improve diversity and robustness. The data was then split into training, validation, and testing sets for model development.

3.1 Data Collection Plan and Raw Data Sources Identified:

The data collection plan for the Virtual Eye Lifeguard project focuses on gathering a diverse, high- quality dataset to train a YOLOv5 model for detecting active drowning in swimming pools. Primary data sources include custom images and video footage of pools under various conditions (e.g., different lighting, crowding levels), along with augmented data to enhance model robustness. Each image will be annotated with bounding boxes distinguishing drowning from nondrowning scenarios. Supplementary data from public aquatic datasets and synthetic data may also be used to increase variety.

Data Collection Plan & Raw Data Sources Identification Template Click Here

3.2 Data Quality Report:

This dataset has been checked for essential quality criteria, including label accuracy, image quality, annotation consistency, and class balance. No significant data quality issues were identified. This clean dataset is suitable for the YOLOv5 model training without further adjustments.

Data Quality Report Template: Click Here

3.3 Data Preprocessing:

The images will be pre-processed by resizing, normalizing, augmenting, denoising, adjusting contrast, detecting edges, converting color space, cropping, batch normalizing, and whitening data. These steps will enhance data quality, promote model generalization, and improve convergence during neural network training, ensuring robust and efficient performance across various computer vision tasks.

Data Preprocessing Template: Click Here

4. Model Development Phase:

The YOLOv5 model was fine-tuned using the pre-processed dataset to detect drowning scenarios. Hyperparameters like learning rate, batch size, and epochs were optimized to enhance performance. The model was trained on Google Colab with GPU support, ensuring efficient processing. Post-training, the model's accuracy was evaluated using the validation and testing datasets, refining it for real-time application.

4.1Model Selection Report:

YOLOv5 is selected as the most suitable model for the Virtual Eye Lifeguard project. Its combination of speed, accuracy, and real-time performance makes it ideal for detecting active drowning incidents in swimming pools, where timely intervention is crucial. Additionally, its ability to handle various objects and scenarios in real-time aligns well with the project's needs.

Model Selection Report Template: Click Here

4.2 Initial Model Training Code, Model Validation and Evaluation Report:

The initial model training code will be showcased in the future through a screenshot. The model validation and evaluation report will include a summary and training and validation performance metrics for the model, presented through respective screenshots.

Initial Model Training Code, Model Validation and Evaluation Report:

Click Here

5. Model Optimization and Tuning Phase:

In this phase, hyperparameters such as learning rate, batch size, and confidence thresholds were fine-tuned to improve YOLOv5's detection accuracy. Techniques like cross-validation were employed to prevent overfitting. Model performance was iteratively evaluated using validation data, focusing on metrics like precision, recall, and mAP (mean Average Precision). The system was further optimized to balance accuracy and inference speed, ensuring effective real-time performance.

5.1 Model Optimization and Tuning Phase Template:

The Model Optimization and Tuning Phase involves refining the YOLOv5 model to improve its performance for detecting drowning incidents in swimming pools. This phase focuses on adjusting hyperparameters, fine-tuning the model architecture, and enhancing the dataset to achieve the best accuracy, speed, and generalization.

Model Optimization and Tuning Phase Template: Click Here

6. Results: Click Here

7. Advantages:

- **Real-Time Detection:** The use of YOLOv5 ensures fast and accurate realtime detection of drowning incidents, enhancing safety.
- **Automated Monitoring:** Reduces reliance on human lifeguards, providing continuous surveillance in swimming pools.

- **Scalability:** The system is adaptable to various pool sizes and environments with minimal hardware requirements, making it costeffective.

- **High Accuracy and Speed (YOLOv5):** YOLOv5 is known for its high detection speed and precision, ideal for identifying drowning scenarios amidst pool activities.
- **Efficiency:** YOLOv5 is lightweight and efficient, able to run on devices with limited computational power, which makes it suitable for edge deployment.

Disadvantages:

- **Environmental Limitations:** Lighting conditions, water clarity, and pool surroundings can affect the model's performance, leading to misclassifications.
- **False Positives/Negatives:** While YOLOv5 is accurate, it may occasionally generate false alerts or miss drowning incidents if the data does not cover all potential scenarios.
- **Hardware Dependency:** The effectiveness of the system can be influenced by camera quality, placement, and the computational power available for real-time processing.
- **Training Data Challenges:** YOLOv5's performance heavily depends on the quality and diversity of the labeled training data. A limited dataset can reduce the model's generalization ability.
- **Model Complexity:** YOLOv5, while faster than other models, still requires significant computational resources for training and fine-tuning, which can be a barrier in certain deployment scenarios.

8. Conclusion:

The **Virtual Eye Lifeguard** project, utilizing **YOLOv5**, represents a significant advancement in swimming pool safety by providing real-time, automated drowning detection. With its fast processing, high accuracy, and scalability, the system offers a cost-effective alternative to traditional lifeguard monitoring. YOLOv5's efficiency in detecting drowning incidents ensures rapid response times, potentially saving lives.

However, the project also faces challenges such as dependency on environmental factors, hardware limitations, and the need for high-quality training data. Addressing these challenges through ongoing improvements in data collection, model optimization, and environmental adaptation will further enhance the system's reliability and performance. Overall, the **Virtual Eye Lifeguard** demonstrates great promise in enhancing safety in aquatic environments, offering a future where technology plays a crucial role in preventing drowning incidents and protecting swimmers.

9. Future Scope:

The Virtual Eye Lifeguard project has vast potential for growth, including:

1. Enhanced Model Training: Expanding datasets and integrating advanced models for better accuracy in diverse conditions.
2. Multi-Pool Monitoring: Scaling the system to monitor multiple pools simultaneously.
3. System Integration: Linking with other safety systems like alarms and automated rescue operations.
4. Wearable and Mobile Integration: Using wearables and mobile apps for better real-time monitoring and alerts.
5. Edge and Cloud Computing: Leveraging cloud or edge devices for faster processing and advanced analytics.
6. Global Deployment: Adapting the system for global use in different pool types and environments.
7. AI-Assisted Training: Developing AI tools to assist in lifeguard training with simulated scenarios.

10. Appendix:

10.1 Source Code: Click Here

10.2 GitHub & Project Demo Link: Click Here