**Work Evaluation Table**

**<Use the same factors you have used in "Work Evaluation Table" to build your own "Proposed and Previous comparison table ">**

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|  | **Work Goal** | **System's Components** | **System's Mechanism** | **Features**  **/Characteristics** | **C**  **o s t** | **Speed** | **S**  **e c u ri ty** | **Performance** | **Advantages** | **Li mit ati ons**  **/Di sad va nta ges** | **Platform** | **Results** |
| Eleftherios Lygouras, Nicholas Santavas,  Anastasios Taitzoglou, Konstantinos  Tarchanidis, Athanasios Mitropoulos, and  Antonios Gasteratos | The goal of the solution is to develop a fully  autonomous UAV system equipped with an  embedded vision system to detect and rescue  open water swimmers in peril without human intervention. | Convolutional Neural Networks (CNN) for image processing and  object detection , Hardware configurations such as the NVIDIA  Jetson X1 for on board image processing , Software configurations  for implementing the embedded vision system ,. Global Navigation  Satellite System (GNSS) techniques for location tracking . | The use of deep The author focused on creating a completely autonomous UAV system with an integrated vision system to identify and assist open water swimmers in danger without human  involvement. | The use of deep learning techniques, specifically the  Tiny YOLO V3 architecture, for real-time human  detection in search and rescue missions using  unmanned aerial vehicles (UAVs). It also incorporates a  combination of global navigation satellite system (GNSS)  techniques and computer vision algorithm. | **-** | **-** | **-** | The performance of the system will be dependent on training and algorithmic specifications. | Development of a fully autonomous UAV system with  an embedded vision system for detecting and rescuing  open water swimmers without human intervention. | **-** | - | improving the  performance of UAV using efficient object  detection and tracking of the target |

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| **Sahana ,**  **Aniket Sengar,**  **Aniruddh Dubey,**  **Umang Agrawal.**  **2021** | The objective of the solution is to develop and  implement advanced technologies, such as  unmanned aerialvehicles (UAVs) and deep  convolutional neural networks, to enhance searchand rescue operations. | Unmanned Aerial Vehicles (UAVs),  Deep Convolutional Neural Networks,  Multispectral Cameras,  Feature Pyramid Networks,  Monte Carlo Tree Search Method. | The drone embedding advanced technologies, such as unmanned aerial vehicles (UAVs) and deep convolutional neural networks, to enhance search and  rescue operations. | The solution involves using UAVs with advanced  vision systems and deep learning algorithms,  such as CNNs and feature pyramids, to  enhance search and rescue operations. It aims to achieve precise human detection and  localization, potentially retraining models. | **-** | **-** | **-** | The validation results show high accuracy in object detection and localization | The automated detection and localization capabilities  of the solution can significantly reduce the time  required to identify and locate individuals in need of  rescue, leading to faster response times and potentially  saving lives. | **-** | **-** | improving the  performance of object detection and localization  using deep neural network |

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| **SUNGTAE MOON**  **JIHUN JEON**  **DOYOON KIM**  **YONGWOO KIM**  **2019** | The goal is to create an unmanned drone  which can fly itself and used for detection of  real time objects such as person’s in larger  areas. | key hardware components used in the system, integration of  these components into the drone, and Yolo algorithm - This  algorithm provides confidence scores for detected humans.  This technology aims to expedite Search and Rescue  operations in natural disasters by swiftly identifying  survivors. | an autonomous drone system designed for real-time object detection. It incorporates the YOLO (You Only Look  Once) algorithm to enable rapid and accurate detection of objects. The hardware components, including the Pixhawk Flight Controller  and a camera, play a crucial role in this setup. | It takes advantage of various sensors, including  GPS and cameras, to gather comprehensive  environmental data. This data informs the  system's core function: generating precise flight  paths for the Unmanned Aerial Vehicle (UAV). | **-** | **-** | **-** | The performance of the system has been evaluated through checking the accuracy in prediction of the model. | The system's use of various sensors, Including  RTK-GPS, ensures centimeter-level precision in  position estimation, enhancing the accuracy of  object detection and tracking. | **-** | **-** | This solution, incorporating YOLO object  detection, addresses a critical real-world  problem, but it encounters challenges due to its  technical complexity and sensitivity to adverse  weather conditions. |

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|  |  | the recording of facial images during nighttime driving. |  |  |  |  |  |  |  |  |  | to detecting drowsine ss without annoyan ce and interfere nce |
| JAWAD N. YASIN ,  SHERIF A. S. MOHAMED , MOHAMMAD-HASHEM  HAGHBAYAN ,  JUKKA HEIKKONEN1 ,  HANNU TENHUNEN1,  JUHA PLOSILA  .  **2018** | The objective of the solution is to develop  effective collision avoidance systems for  autonomous vehicles, specifically unmanned  aerial vehicles (UAVs). The goal is to enhance the  autonomy and safety of UAVs by integrating  intelligent decision-making . | collision avoidance strategies, sensors used for  collision avoidance in UAVs, and various approaches and techniques  for collision avoidance in different scenariosmethodologies related to radar sensors,  artificial potential fields, particle swarm optimization, and path planning algorithms for UAVs.  . | on obstacle detection using monocular or stereo cameras, with a division of captured images into regions to reduce computational cost. Collision  avoidance control and trajectory control are combined, and an algorithm selects the optimal path based on obstacle classification for safe and efficient drone navigation. | the effective collision avoidance systems for UAVs  incorporates intelligent decision-making capabilities,  obstacle detection algorithms, and path planning  techniques. By analyzing real-time data, UAVs equipped  with this solution can make informed decisions to avoid  potential collisions by assessing the speed, trajectory. | **-** | The system achieves a process speed of 44ms per image, which is faster than YOLO by 18. | **-** | The system achieves an mAP of 86.4 on the testing set, outperforming R-FCN which achieves 67.7. It also shows more than 6% improvement in mAP on the testing set. | The advantages of the system include its speed, accuracy, and robustness. It is faster than YOLO and other object detection algorithms, while outperforming them in accuracy.. | **-** | **-** | The system achieves a process speed of 44ms per image, an mAP of 86.4 on the testing set, and more than 6% improve ment in mAP on the testing set. |

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| **Fadhlan hafeez**  **2018** | The goal of the work is to improve object detection by accelerating the speed while maintaining high accuracy and generalizatio n ability. The paper introduces the You Only Look Once (YOLO)  model as a | You Only Look Once (YOLOv5) deep  learning model for human detection in  search and rescue operations. The model  is trained using data collected during a  simulation of search and rescue  operations, where mannequins were used  to represent human victims. | The YOLO model breaks through the traditional approach of the CNN family and introduces a new way of solving object detection. It achieves high efficiency and speed by processing the entire image at once, rather than using region proposals | YOLO achieves unparalleled speed with a Frame Per Second (FPS) of 155 and a Mean Average Precision (mAP) of 78.6,  surpassing the performance of Faster R-CNN. YOLOv2, an improved version, offers a tradeoff between speed and accuracy. It also has strong generalization ability to | **-** | YOLO  achieves a fast speed with a Frame Per Second (FPS) of 11.7,  surpassin g the performan ce of Faster R- CNN. | **-** | YOLO  achieves a Mean Average Precision (mAP) of 78.6,  surpassing the performance of Faster R- CNN | YOLO offers a simple and highly efficient way of solving object detection. It achieves fast speed and high accuracy, surpassing the performance of Faster R-CNN. It also has strong generalization ability to represent the whole image | **-** | **-** | YOLO  achieves a Frame Per Second (FPS) of  155 and a Mean Average Precisio n (mAP) of 78.6,  surpassi ng the performa nce of Faster  R-CNN |

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|  | solution to this problem. |  |  | represent the whole image. |  |  |  |  |  |  |  |  |