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A conceptual system proposal for real-time detection of jellyfish density in coastal areas from UAV images

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Anahtar Kelimeler
watershed algorithm,
jellyfish detection,
computer vision,
embedded systems,
edge computing

Abstract: In this study, a system that can be used in unmanned aerial vehicles is proposed in order to be informed early about the jellyfish infestation in coastal areas due to global warming and to take necessary precautions. The main thing in this research is that the dexterity of unmanned systems in the field of monitoring and information gathering was used to detect jellyfish infestations. In this way, an early warning system can be established for situations that may adversely affect important activities such as tourism and hunting in coastal areas. For this, the Watershed Algorithm, which is one of the classical computer vision techniques and is widely used to detect objects that are overlapped or partially obscure, has been preferred. In order to show that this technique can be used in the detection of jellyfish, in this study, firstly, experiments were performed on a CPU-based system, and then the first system was verified in a second GPU-based system. When the results were examined, the Watershed technique showed a success rate of over 92% in detecting jellyfish. In the same tests performed on the GPU-based embedded system used in unmanned aerial vehicles, similar results were obtained with a change of 1%. Thus, it is considered quite appropriate to use the system created as an early warning system for jellyfish detection.

İHA görüntülerinden kıyı bölgelerindeki denizanası yoğunluğunun gerçek zamanlı tespiti için kavramsal bir sistem önerisi

Anahtar Kelimeler:
Havza algoritması,
Deniz anası tespiti,
bilgisayarlı görme,
gömülü sistemler,
uçta hesaplama

Öz: Bu çalışmada, küresel ısınmaya bağlı olarak kıyı bölgelerinde meydana gelen denizanası istilasından erken haberdar olmak ve gerekli önlemleri almak amacıyla insansız hava araçlarında kullanılabilecek bir sistem önerilmiştir. Bu araştırmadaki asıl mesele, insansız sistemlerin izleme ve bilgi toplama alanındaki maharetinin denizanası istilalarını tespit etmek için kullanılmasıdır. Bu sayede kıyı bölgelerinde turizm ve avcılık gibi önemli faaliyetleri olumsuz etkileyebilecek durumlar için erken uyarı sistemi kurulabilecektir. Bunun için klasik bilgisayarlı görme tekniklerinden biri olan ve üst üste binen ya da kısmen belirsiz olan nesnelerin tespitinde yaygın olarak kullanılan Watershed Algoritması tercih edilmiştir. Bu tekniğin denizanası tespitinde kullanılabileceğini göstermek amacıyla bu çalışmada öncelikle CPU tabanlı bir sistem üzerinde deneyler yapılmış ve daha sonra ilk sistem GPU tabanlı ikinci bir sistemde doğrulanmıştır. Sonuçlar incelendiğinde, Watershed tekniği denizanalarını tespit etmede %92'ın üzerinde bir başarı oranı göstermiştir. İnsansız hava araçlarında kullanılan GPU tabanlı gömülü sistem üzerinde yapılan aynı testlerde %1'lik bir değişimle benzer sonuçlar elde edildi. Bu nedenle erken uyarı sistemi olarak oluşturulan sistemin denizanası tespiti için kullanılması oldukça uygun görülmektedir.

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1. Introduction

Along with the 2000s, we have frequently encountered jellyfish invasions and blooms in both visual media and scientific studies [1]. In the last two decades, it has been observed in research that there may be disturbances in the ecological balance that underlie the increasing extent of this situation. Ecologists attribute the reasons for this to two factors: natural and anthropogenic. While factors such as winds, tides, surface currents, water temperature, salinity and turbidity are shown among natural causes, anthropogenic causes are shown as deterioration of water quality, overfishing, displacement and habitat change [2, 3]. It has been proven by research that jellyfish species, which are known to be resistant to harsh environmental conditions, increase in both cases [4]. As a result of the increase in the jellyfish swarm in a region, decreases in fish diversity will be evident with extreme changes in water temperature and oxygen ratio. this will result in significant decreases in the income status of the people in the region. If the region is at the forefront of tourism activity, then it will have negative effects on the socio-economic status of the people living in the region [5, 6, 7].

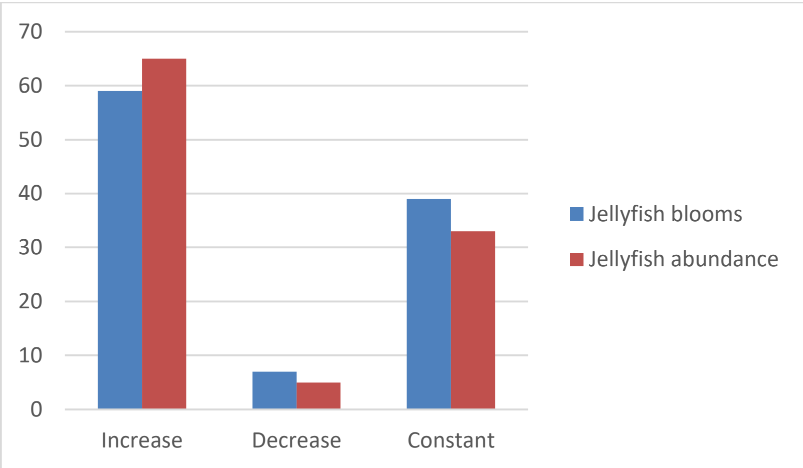


Figure 1. Jellyfish population in the last 10 years in countries (Malta, Italy, Spain, Tunisia)

Figure-1 shows the perception of jellyfish in the last ten years by people living in countries where fishing and tourism are at the forefront, such as Malta, Spain, Italy and Tunisia. Since the study is based on a survey specifically asked to people living in the coastal areas of the country, the results include three statements: increase, decrease and constant. The results clearly show that the density of jellyfish in coastal areas is increasing day by day [8].

Table 1. Effect of jellyfish population on different marine activities (results represent positive answers as a percentage)

	Malta	Italy	Spain	Tunisia
Tourism	95.8	100	100	71.4
Ecosystem	25	22.2	60.6	28.6
Fisheries	29.2	55.6	90.9	28.6
Aquaculture	29.2	77.8	90.9	85.7
Human Health	100	74.4	100	50
Fish Health	28.6	100	100	50

Table-1 shows some of the effects that occur as a result of the increase in the jellyfish population in some countries with a Mediterranean coast. This table actually clearly shows how the increase in the jellyfish population negatively affects city life [8]. It is obvious that with the increase in the jellyfish population, life especially related to fishing and tourism has been severely damaged. Therefore, as it is basically the subject of this study, it is extremely important to determine the reasons for the increase in the jellyfish population in terms of solving the problem and reducing the effects of its damages.

Although there are different techniques in the literature for detecting jellyfish, it is seen that current studies are carried out with deep learning. Han et al. proposed a new deep learning model to detect both jellyfish density and jellyfish species in their study using underwater images [9]. Martin et al. recorded the video obtained with the underwater vehicle and processed it simultaneously in real time. With the deep learning model they created in the system they have established, both jellyfish density and jellyfish species have been successfully determined [10]. Mcilwaine and Casado created an early warning system that detects jellyfish density through a deep learning model they created using images obtained by the UAV [11]. They created a dataset of 2141 underwater images of seven jellyfish species and some fish. Using the deep learning model they created from this data set, they determined the density of jellyfish in real time [12]. They created a dataset using different environmental videos from coastal areas. Using this data set, they performed tests with the current YOLO algorithms, JF-YOLO and YOLOv4, and increased the success rate up to 92% with the JF-YOLO deep learning model [13].

In this study, jellyfish densities in the images obtained from unmanned aerial vehicles were determined accurately by a method using the watershed algorithm. Accordingly, a conceptual model of an expert system that can make predictions on the recorded data with the artificial learning model to be created after monitoring the jellyfish population and recording the numerical data obtained in certain periods is proposed. In the study, the idea of using the watershed algorithm in the determination of jellyfish density is originality brought to the literature and the system that is out of the idea is proposed conceptually because the other components of the system are already widely used in the literature. When the current literature is examined, it is observed that the deep learning method is dominant in similar studies. In this, preliminary stages such as creating a special model and obtaining many different images for the training and testing of this model are required. However, in this study, classical computer vision technique was applied to a few images and similar results were obtained. In addition, one of the differences of this study from other studies in the literature is that the experiments are carried out both on a PC and in a separate embedded system and their comparisons are made.

2. Material and Method

In this study, a conceptual system is proposed that detects jellyfish infestations, which has become an important problem in coastal cities, by means of aerial monitoring via UAV and uses the data obtained to solve this problem. However, the system was not entirely implemented in the study, but instead focused on the algorithm used to detect jellyfish, which is the most important situation here. For this, images with different densities of jellyfish taken from an unmanned aerial vehicle were used.

2.1. Monitoring Systems Based on UAV

The use of unmanned aerial vehicles has become widespread in the last decade for activities such as monitoring, data collection and instant intervention [14]. Its capabilities such as being easy to obtain due to the widespread use of its technology [15], being able to stay in the air for a long time with advanced battery systems [16], activating the automatic flight system when necessary [17], and communicating with the ground station in real time [18] contributed to the realization of the process much faster.

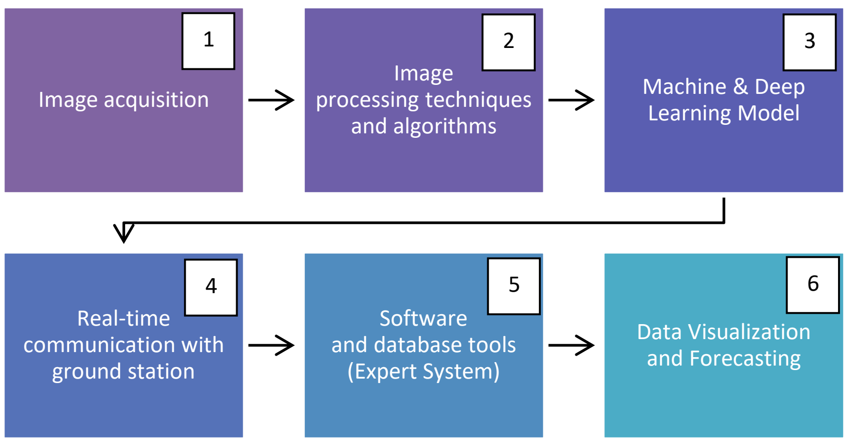


Figure 2. Real-time monitoring system via UAV

The general system diagram used for UAV-based monitoring systems, which is conceptually proposed in this study and is frequently preferred in the literature, is shown in Figure-2. As can be seen in this figure, the process starts with the acquisition of the image with the UAV and as a result of the image processing techniques to be applied to this image, the relevant objects are detected. The third step is completed by transferring the data obtained in the second step to the learning model. Thus, the accuracy of the information obtained from the image processed in the second step is improved. The ground control station, which can be seen as part-4 in Figure-2, is an important part that provides real-time communication with the unmanned aerial vehicle. Through this part, snapshots can be taken from the UAV camera, the environment can be monitored with the camera, or the UAV can be controlled manually. In the next stage, the data transferred from the UAV to the ground station is transferred to the software that acts as the expert system in the general system. The software not only records the data in relation to date and time, but also improves the system's prediction database. In the last stage, the expert system visualizes the existing data and provides a clearer understanding of the current situation. In addition, it presents possible situations for the next years to the users according to the artificial intelligence algorithm. The proposal realized in this study is in the second part of the general system shown in Figure-2. Because, as can be clearly seen in Figure-3, this study starts with the acquisition of the image and ends with the acquisition of the jellyfish density information in the final stage. From the next stages, this information is interpreted and presented to the authorities in different ways.

Especially in the last decade, it can be seen that the use of UAVs has been widely used in many fields such as agriculture, mining, security, forest fire, traffic, maritime and meteorology. Agricultural field is one of the main areas where many applications of unmanned aerial vehicles are seen, and it stands out in terms of the diversity of applications. Some studies are on increasing the yield by observing the agricultural land with UAV, detecting the stress conditions of the plants and taking the necessary precautions [18, 19]. Again in this area, it is seen that the estimation of the yields of the products after the harvesting process from the images obtained from the field is widely used by combining it with deep learning methods [20, 21]. Another application in this area is the classification of vegetation in the field by using images obtained from unmanned aerial systems. Thus, an important step has been taken to prevent possible damage caused by vegetation [22, 23].

The mining industry is an important field of activity for the discovery of underground riches, and applications in which unmanned aerial vehicles are frequently used are encountered in this field too [24]. When we look at mining studies, three important activities are carried out: exploration, exploitation and reclamation [25]. In the literature, monitoring was carried out by using images obtained from UAV in all three activities [26, 27].

The main purpose of this study is to determine the jellyfish densities by processing the images of the coastal areas monitored by an unmanned aerial vehicle in real time and instantaneously. An artificial intelligence computer is integrated into the unmanned aerial vehicle for real-time processing of images. Images obtained at 10 fps are directly transferred to this artificial intelligence computer and processed. As a result, jellyfish density information is obtained as an output from this computer. In order to test the accuracy of the jellyfish density information obtained in real time with the artificial intelligence computer, the images were reanalyzed in the laboratory environment and the obtained results were compared with the artificial intelligence computer.

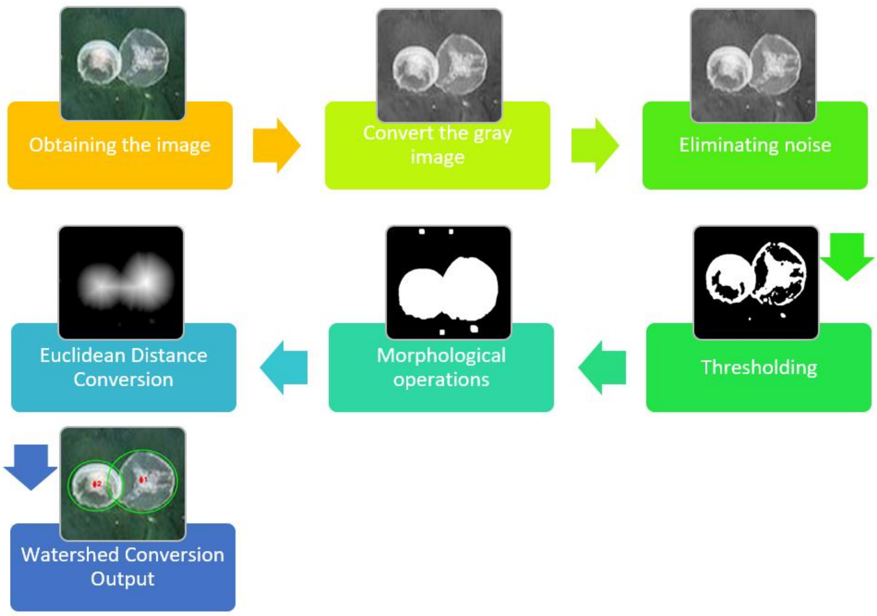


Figure 3. Algorithm steps for detecting jellyfish

Figure-3 shows the algorithm used to subject the images obtained to jellyfish density detection. After performing the Euclidean distance transformation at the end of the classical image processing steps, the algorithm was terminated with the detection of jellyfish with the Watershed segmentation technique.

2.2. Watershed Segmentation Technique

Watershed segmentation based on mathematical morphology is based on the contour structure in grayscale images [28]. As it is known, in an image converted to gray, certain regions have dark tones and certain regions have light tones. The Watershed algorithm considers these dark regions as hills and open regions as valleys. Afterwards, the algorithm performs the process of distinguishing the objects in the image by filling the valleys with water like a basin in the local regions that it has divided into valleys and hills [29]

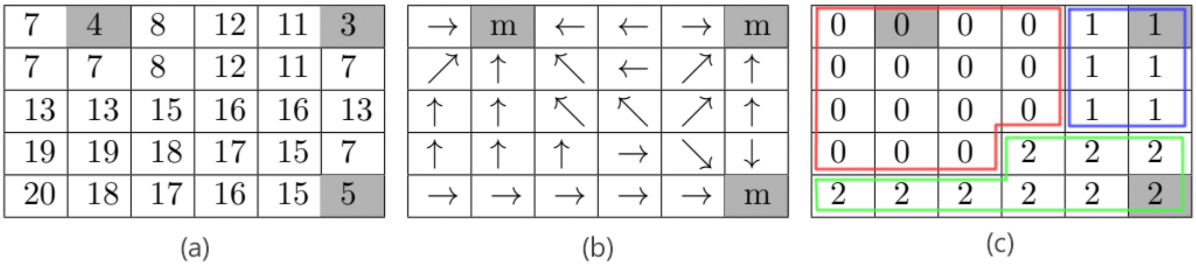


Figure 4. Watershed algorithm based on connected component (a: gray image, b: the connection of each pixel with the smallest value, c: labeling of pixels)

Figure-4 is a very good diagram in terms of describing the operation of the watershed algorithm. Because the algorithm considers these regions as basins based on low and high density pixels and fills them with water. This situation is illustrated in Figure-4b by showing the direction of the pixels towards the lowest pixel. In Figure-4c, the labeling of the pixels was carried out according to the basin structure formed.

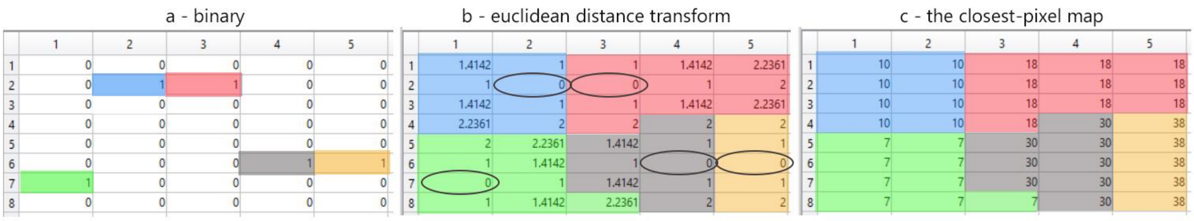


Figure 5. Watershed segmentation based on Euclidean distance transform

Another formation of the Watershed algorithm is the form that segments the binary image with Euclidean distance transform instead of the gray image used in Figure-4, and it is shown in Figure-5. The "a" in this figure represents the binary image and it can be seen that the segmentation transformation actually takes place around the "1s" in this image. In the "b" image, the distance of each pixel to its nearest "0" is calculated. This calculation is known as the Euclidean distance transform. The "c" image is the image where the pixels transform their neighborhood to a map. Thus, the segmentation process is carried out according to these principles, as can be seen here.

2.3. Experimental Installation

As it is known, the topic of artificial intelligence has become the topic of the agenda when artificial neural network algorithms have been instrumental in the emergence of different models over time and these models can be used in many sectors [30]. This situation has led both to the rapid development and diversification of artificial intelligence techniques used. However, this caused algorithms to need more data to work more efficiently. Thus, a large amount of data has emerged that needs to be processed [31]. However, this situation caused the CPU system to become inadequate over time, as it required training a network with thousands of data and required preprocessing of this data over time [32]. To overcome this situation, both academia and industry have focused on multi-core GPUs with sufficient memory resources and parallel processing capability [33].

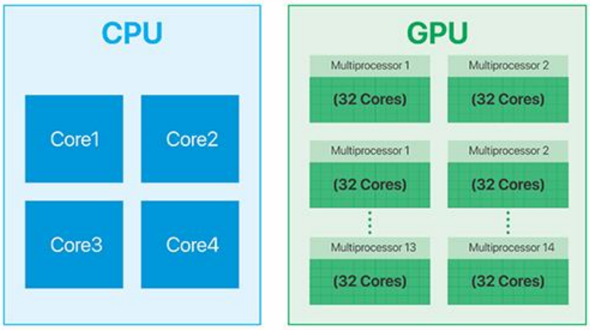


Figure 6. Architecture overview of CPU and GPU.

Figure-6 clearly shows the number of cores that the CPU and GPU architectures have, and even from this figure, the fact that the GPU architecture is multi-core indicates that it has much more performance [34]. This extreme performance of GPUs has over time allowed CPUs to use them as accelerators in big data and then to perform artificial intelligence computing at the edge [35]. Thus, a device with the definition of artificial intelligence computer, whose architecture can be seen in Figure-7, was born [36].

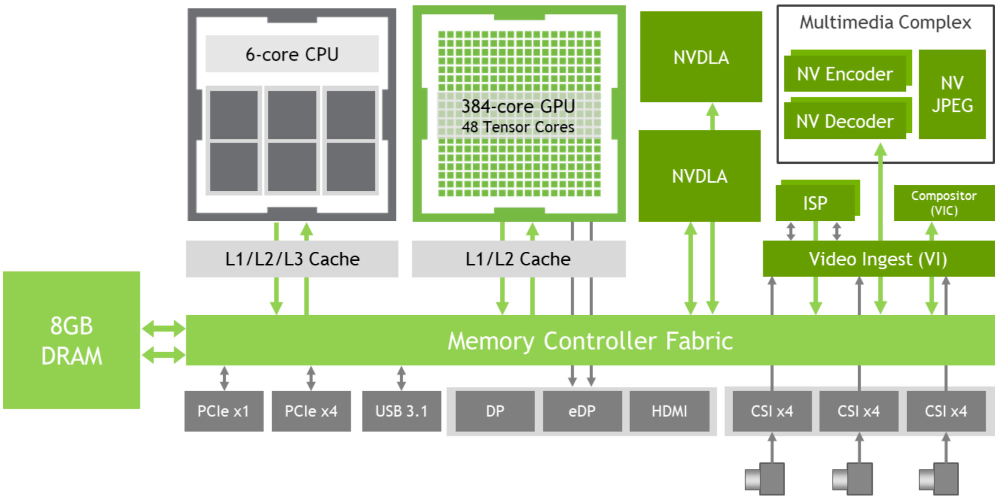


Figure 7. Architecture of the Nvidia Jatson Xavier

As can be seen in Figure-7, the comprehensive block diagram is a highly advanced technology and the device called Jatson can also be used as an embedded system with its portable feature. Not only does the multi-core structure show the sophistication for such a system, but the amount of memory is also very important here. Especially if it is used as an embedded system, the data to be processed in turn should be stored in a temporary memory. Processing data is cached like L1 and L2, and processes are prioritized just like a CPU, allowing the device to perform processes in a much shorter time.

Table 2. Experiment data used in the study (33)

No	Image Resolution	Total Size(MB)	Total Images	Individual Image Size (MB)
1	1024 x 768	216	90	2.4
2	1600 x 900	387	90	4.3
3	1920 x 1080	558	90	6.2
4	2560 x 1440	999	90	11.1

In the literature, the superiority of GPU over CPU has been demonstrated in many studies. In their study where they compared GPU and CPU in terms of efficiency, they performed the test on the images processing. Table-2 contains information about the test data they used in their study, and Figure-8 illustrates the diagram of the data they obtained as a result of the test [37].

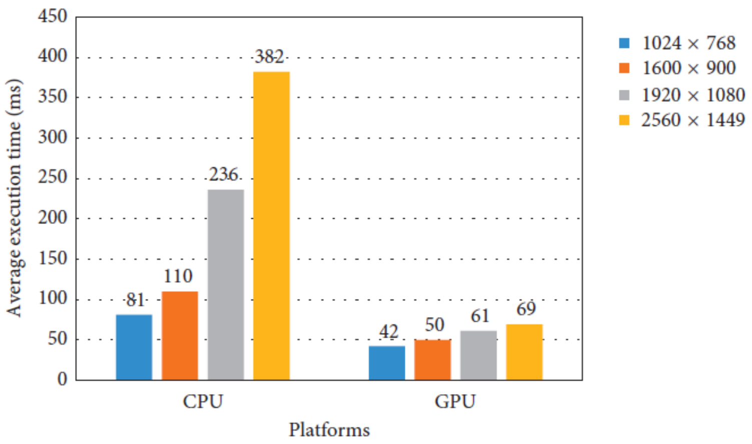


Figure 8. CPU and GPU execution times of different size images (37)

They compared the CPU and GPU in terms of performance by applying three different image processing techniques to images with different pixel sizes in their study. As the results of the study are summarized in Figure-9, the execution time by the CPU increases as the NxM size of the pictures increases. However, this increase is seen very minimal in GPU [38].

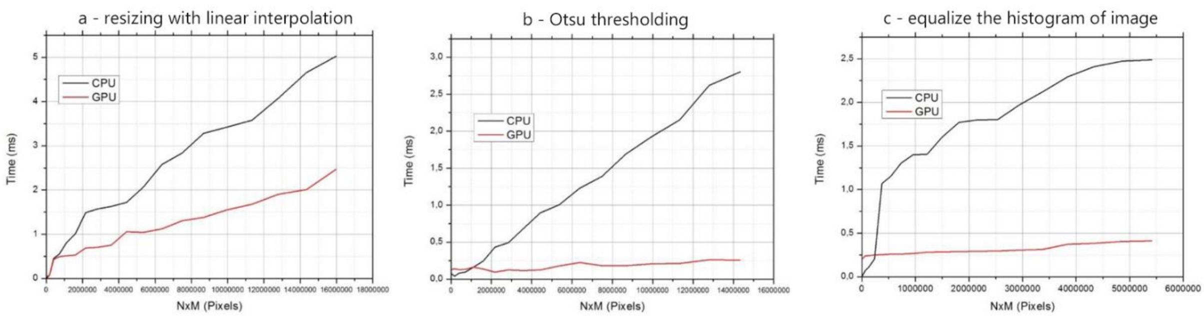


Figure 9. CPU and GPU execution times of different NxM size images

3. Results

In this study, two different systems were used to detect jellyfish through the images obtained: CPU and GPU. While doing this, the aim is to compare the accuracy obtained in the processing performed on the cloud with the CPU with the accuracy of the processing performed on the edge with the GPU and to contribute to the literature in this sense. Therefore, it will be shown that processes can run in real time at the edge by means of an artificial intelligence computer to be mounted on an unmanned aerial vehicle. In this study, the device referred to as artificial intelligence computer is the Jatson Xavier model specially produced by Nvidia company to run artificial intelligence algorithms in a short time with its GPU core structure. The information on the platforms used in the test processes and the results obtained are shown in Table-3.

Table 3. Comparison platform properties

Platform-1: Computer	Platform-2 GPU, Jatson Xavier
○ Intel® Core™ i5-7300HQ6M Cache, up to 3.50 GHz	○ GPU: 384-core NVIDIA Volta™ architecture-based
○ Chipset: Intel® HM175	○ CPU: 6-core Carmel ARM® v8.2
○ Geforce® GTX1050 2GB GDDR5	○ Memory: 4 GB 64-bit LPDDR4; 25.6 gigabytes/second
○ 8 GB DDR4-2400 MHz RAM	○ OS Support: Linux for Tegra®
○ Windows OS	○ Developer Kit Size: 70mm x 45mm

In the experiments, images obtained from unmanned aerial vehicles in different time periods were used. After detecting the jellyfish in the image, the jellyfish density was calculated. Figure 10 shows the images used in the experiments carried out within the scope of this study and the results obtained as a result of processing these images on the CPU and GPU. Five different images were used in the experiments, and the density of jellyfish in each image varies visibly. In fact, it can be said that as the density increases, the correct detection of jellyfish becomes a little more difficult. The same is true for jellyfish, which are deeper in the water than on the surface. However, as seen in Table-4, the accuracy of edge computation, which is the main purpose of the study, is clearly seen in these experiments.

Table 4. Comparison of the results obtained in the experiments

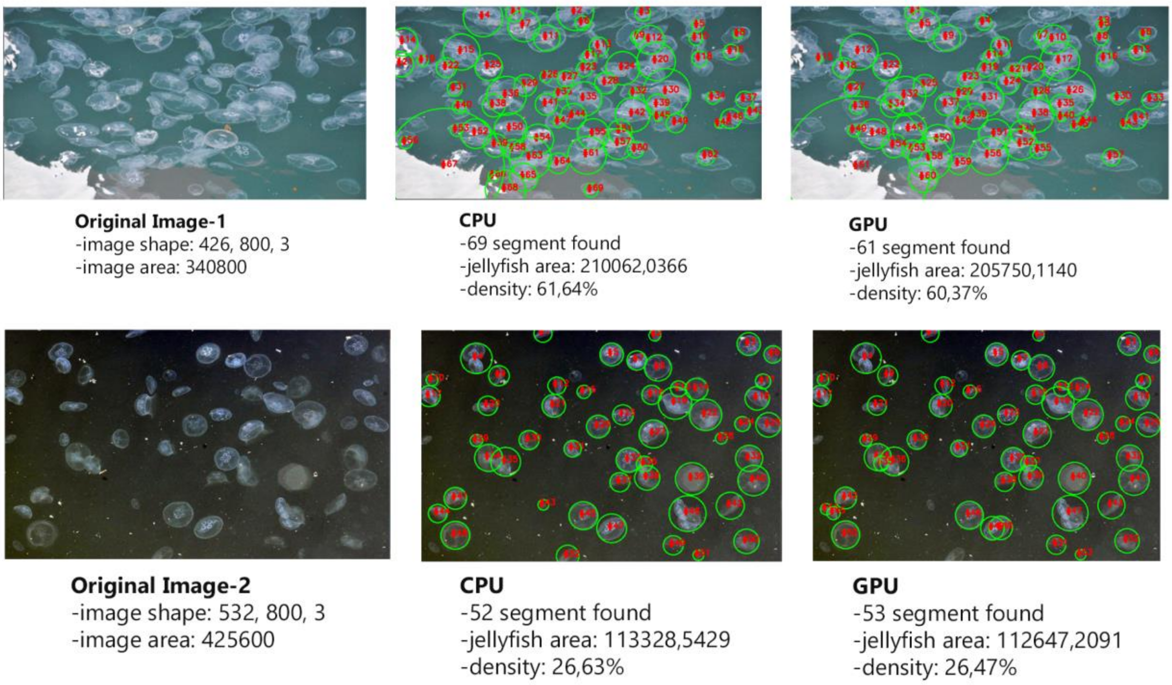
Experiment No	Success Rate	CPU Result	GPU Result	Deviation
1	92%	61,64%	60,37%	1,27%
2	94%	26,63%	26,47%	0,16%
3	95%	23,96%	22,48%	1,48%
4	98%	20,52%	19,38%	1,14%
5	100%	1,93%	1,93%	0%
			Average	**0,81%**

The versions of libraries operated in the study are given in Table 5. As can be seen from the table, the libraries whose current versions are given have been tested on CPU and GPU simultaneously.

Table 5. Versions of libraries used in the experiments

Feature	Version	Feature	Version
imutils	0.5.4	opencv	4.5.1
matplotlib	3.7.0	scipy	1.9.1
numpy	1.24.2	skimage	0.0

Figure-10 shows the data obtained by processing the images obtained from unmanned aerial vehicles at different times from the coastal regions as a result of experiments. In the first experiment, the proposed technique was able to detect jellyfish with 92% and calculated the density as 60% in CPU and GPU environments. In the second experiment, the number of jellyfish decreased slightly and the detection rate increased to 94%. The density ratio obtained in both CPU and GPU devices is seen as 26%. In the third experiment, the jellyfish detection success of the technique was 95% and the density was 23%. Since the fourth experiment was an image with much less jellyfish, the detection success was 98% and the density ratio was 20%. In the fifth and final experiment, a single jellyfish was seen and was successfully detected. The density of jellyfish in the image was obtained as 1%.



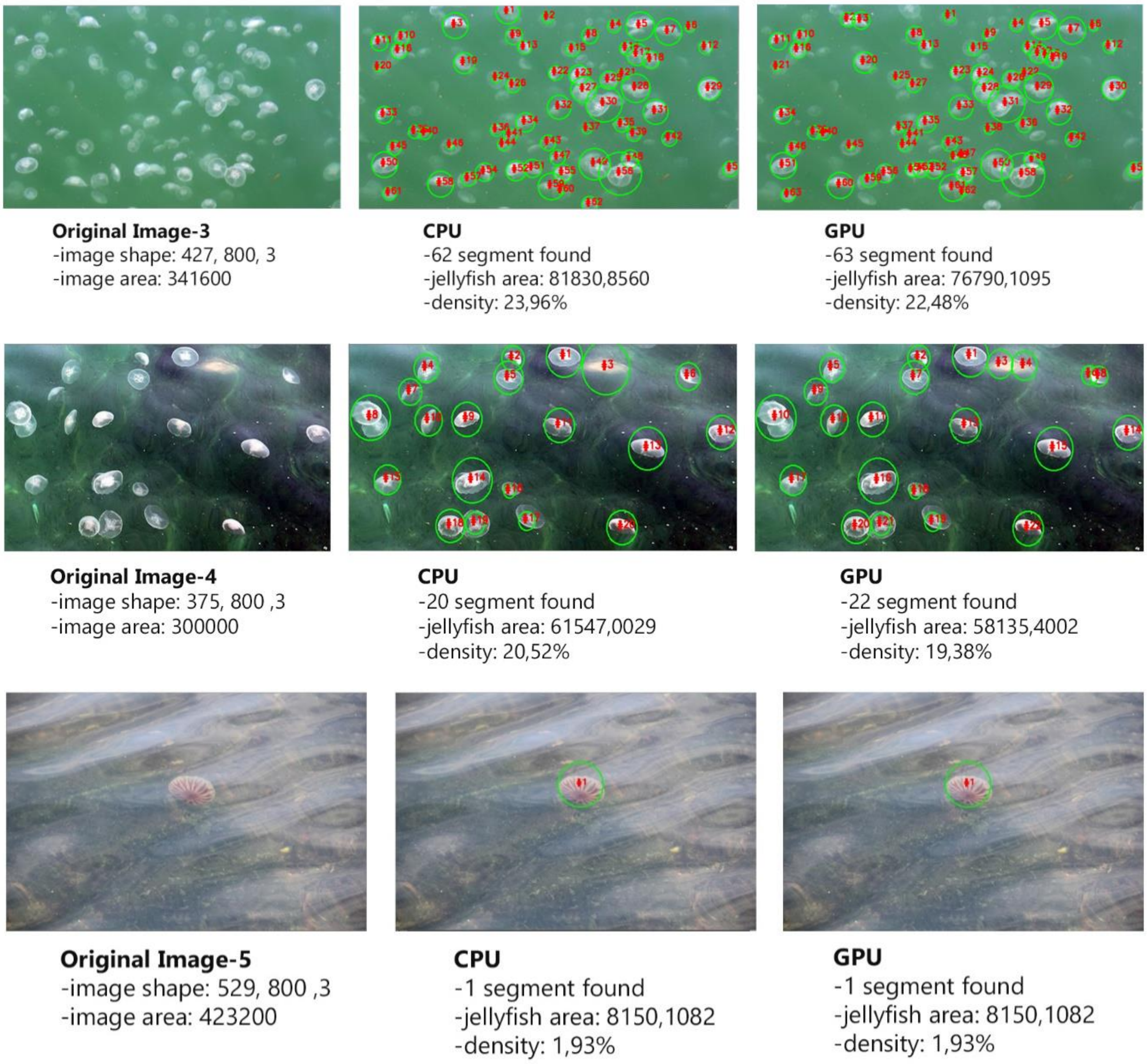


Figure 10. Images used in the experiments and their outputs

Recently, similar studies are generally carried out with deep learning method. However, in order to use deep learning methods, a model must first be created, and then the model must be trained with a lot of data. Therefore, when the deep learning method is desired to be used, the preprocessing stage of the study can be quite laborious. In this study, a similar project was carried out by directly applying a computer vision technique without the need for any preliminary preparation. Therefore, the prominent feature of this study is seen as simplicity. Table-6 shows the data comparing the Watershed Algorithm proposed in this study with the deep learning method used in current studies in the literature. As it is clearly seen in this table, the method proposed in this study showed similar success with the current techniques in the literature in detecting jellyfish density. In addition, while other studies were carried out with PC, the experiments in this study were carried out on the Jatson embedded artificial intelligence device, which is widely used in both PC and unmanned aerial vehicles [39].

Table 6. Summary table comparing some studies from the literature

Ref.	Device	Method	Images used	Details	Accuracy (Avg.)
[9]	PC	Deep Learning	Underwater images	Density Detection and classification	95%
[10]	PC	Deep Learning	Underwater videos	Density Detection and classification	95%
[11]	PC	Deep Learning	UAV images	Density Detection	90%
[12]	PC	Deep Learning (YOLOV3)	Underwater images	Density Detection	91%
[13]	PC	Deep Learning (JF-YOLO)	Different environment videos	Density Detection	92%

This Paper	PC, Jatson	Watershed Algorithm	UAV images	Density Detection	95%

4. Discussion and Conclusion

In this study, a conceptual system that can be used by an unmanned aerial vehicle and performs computation at the edge is proposed for the detection of jellyfish density, which is one of the most important problems of coastal regions. Therefore, in the study, the accuracy of the algorithm (Watershed) that can be used in this device, together with the device that performs computation only at the edge, is revealed, not the system as a whole. Because the design and implementation of an unmanned aerial vehicle system has been mentioned many times in the literature. The issue here is the way computer vision and artificial intelligence calculations are performed throughout the system. In the study, an artificial intelligence computer with a GPU was used for these calculations, and the Watershed Algorithm was used to detect jellyfish. Images obtained by unmanned aerial vehicles at different times of the day were processed, and the Watershed algorithm was run first on the PC and then on the GPU, which is used as a computing device at the edge. As a result of the experiments, the rate of correctly detecting jellyfish with both devices was over 90%, which clearly demonstrates the success of the algorithm. The variation in the ratio of the CPU and GPU in terms of jellyfish density detection is about 1%. Therefore, this value clearly shows that the Watershed Algorithm can be used in unmanned aerial vehicles with a computational device at the edge. In the future, this work could perform the data collection phase in expert systems such as jellyfish early warning. The collected data can be easily transferred to information systems automatically via a special wireless connection method when the unmanned aerial vehicle arrives at the center. In this way, data can be visualized and in-depth analysis can be performed.

References

[1] Vandendriessche, S., Vansteenbrugge, L., Derweduwen, J., Maelfait, H., & Hostens, K. (2016). Jellyfish jelly press and jelly perception. Journal of Coastal Conservation, 20(2), 117-125.

[2] Baliarsingh, S. K., Lotliker, A. A., Srichandan, S., Samanta, A., Kumar, N., & Nair, T. B. (2020). A review of jellyfish aggregations, focusing on India's coastal waters. Ecological Processes, 9, 1-9.

[3] Quiñones, J., Mianzan, H., P. S., Robinson, K. L., Adams, G. D., & Marcelo Acha, E. (2015). Climate-driven population size fluctuations of jellyfish (Chrysaora plocamia) off Peru. Marine biology, 162, 2339-2350.

[4] Richardson, A., Bakun, A., Hays, G., & Gibbons, M. (2009). The jellyfish joyride: causes, consequences and management responses to a more gelatinous future. Trends in ecology & evolution, 312-322.

[5] Sweetman, A., & Chapman, A. (2011). First observations of jelly-falls at the seafloor in a deep-sea fjord. Deep Sea Research Part I: Oceanographic Research Papers, 1206-1211.

[6] Ghermandi, A., Galil, B., Gowdy, J., & Nunes, P. (2015). Jellyfish outbreak impacts on recreation in the Mediterranean Sea: welfare estimates from a socioeconomic pilot survey in Israel. Ecosystem services, 140-147.

[7] Sahu, B., Baliarsingh, S., Samanta, A., Srichandan, S., & Singh, S. (2020). Mass beach stranding of blue button jellies (Porpita porpita, Linnaeus, 1758) along Odisha coast during summer season. Indian J Geo-Mar Sci, 49, 1093-1096.

[8] Bosch-Belmar, M., Azzurro, E., Pulis, K., Milisenda, G., Fuentes, V., Yahia, O. K., . . . Piraino, S. (2017). Jellyfish blooms perception in Mediterranean finfish aquaculture. Marine Policy, 76, 1-7.

[9] Han, Y., Chang, Q., Ding, S., Gao, M., Zhang, B., & Li, S. (2022). Research on multiple jellyfish classification and detection based on deep learning. Multimedia Tools and Applications, 1-16.

[10] Martin-Abadal, M., Ruiz-Frau, A., Hinz, H., & Gonzalez-Cid, Y. (2020). Jellytoring: real-time jellyfish monitoring based on deep learning object detection. Sensors, 20(6), 1708.

[11] Mcilwaine, B., & Casado, M. R. (2021). JellyNet: The convolutional neural network jellyfish bloom detector. International Journal of Applied Earth Observation and Geoinformation, 97, 102279.

[12] Gao, M., Bai, Y., Li, Z., Li, S., Zhang, B., & Chang, Q. (2021). Real-time jellyfish classification and detection based on improved YOLOV3 algorithm. Sensors, 21(23), 8160.

[13] Zhang, W., Rui, F., Xiao, C., Li, H., & Li, Y. (2023). JF-YOLO: the jellyfish bloom detector based on deep learning. Multimedia Tools and Applications, 1-21.

[14] Gomez, C., & Purdie, H. (2016). UAV-based photogrammetry and geocomputing for hazards and disaster risk monitoring–a review. Geoenvironmental Disasters, 3, 1-11.

[15] Ke, Y., Wang, K., & Chen, B. (2018). Design and implementation of a hybrid UAV with model-based flight capabilities. IEEE/ASME Transactions on Mechatronics, 23, 1114-1125.

[16] Campion, M., Ranganathan, P., & Faruque, S. (2018). UAV swarm communication and control architectures: a review. Journal of Unmanned Vehicle Systems, 7, 93-106.

[17] Gnemmi, P., Changey, S., Wey, P., Roussel, E., Rey, C., Boutayeb, M., & Lozano, R. (2017). Flight phases with tests of a projectile-drone hybrid system. EEE Transactions on Control Systems Technology, 26, 2091-2105.

[18] Zhou, J., Mou, H., Zhou, J., Ali, M. L., Ye, H., Chen, P., & Nguyen, H. T. (2021). Qualification of soybean responses to flooding stress using UAV-based imagery and deep learning. Plant Phenomics, 1-13. doi:10.34133/2021/9892570

[19] Zhou, J., Zhou, J., Ye, H., Ali, M. L., Nguyen, H. T., & Chen, P. (2020). Classification of soybean leaf wilting due to drought stress using UAV-based imagery. Computers and Electronics in Agriculture, 175, 1-9.

[20] Feng, L., Zhang, Z., Ma, Y., Du, Q., Williams, P., Drewry, J., & Luck, B. (2020). Alfalfa yield prediction using UAV-based hyperspectral imagery and ensemble learning. Remote Sensing, 12, 1-24.

[21] Nevavuori, P., Narra, N., Linna, P., & Lipping, T. (2020). Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. Remote Sensing, 12, 1-18.

[22] Zhao, F., Wu, X., & Wang, S. (2020). Object-oriented vegetation classification method based on UAV and satellite image fusion. Procedia Computer Science, 174, 609-615.

[23] Feng, Q., Liu, J., & Gong, J. (2015). UAV remote sensing for urban vegetation mapping using random forest and texture analysis. Remote sensing, 7, 1074-1094.

[24] Park, S., & Choi, Y. (2020). Applications of unmanned aerial vehicles in mining from exploration to reclamation: A review. Minerals, 10, 663.

[25] Johansen, K., Erskine, P. D., & McCabe, M. F. (2019). Using Unmanned Aerial Vehicles to assess the rehabilitation performance of open cut coal mines. Journal of cleaner production, 209, 819-833.

[26] Li, H., Savkin, A. V., & Vucetic, B. (2020). Autonomous area exploration and mapping in underground mine environments by unmanned aerial vehicles. Robotica, 38, 442-456.

[27] Lee, S., & Choi, Y. (2016). Reviews of unmanned aerial vehicle (drone) technology trends and its applications in the mining industry. Geosystem Engineering, 19, 197-204.

[28] Zhang, H., Tang, Z., Xie, Y., Gao, X., & Chen, Q. (2019). A watershed segmentation algorithm based on an optimal marker for bubble size measurement. Measurement, 138, 182-193.

[29] Zhou, J., & Yang, M. (2022). Bone Region Segmentation in Medical Images Based on Improved Watershed Algorithm. Computational Intelligence and Neuroscience. doi:10.1155/2022/3975853.

[30] Shi, Y., Yang, K., Jiang, T., Zhang, J., & Letaief, K. B. (2020). Communication-efficient edge AI: Algorithms and systems. IEEE Communications Surveys & Tutorials, 22, 2167-2191.

[31] Georgis, G., Lentaris, G., & Reisis, D. (2019). Acceleration techniques and evaluation on multi-core CPU, GPU and FPGA for image processing and super-resolution. Journal of real-time image processing, 1207-1234.

[32] Raschka, S., Patterson, J., & Nolet, C. (2020). Machine learning in python: Main developments and technology trends in data science, machine learning, and artificial intelligence. Information, 11.

[33] Dereli, S. (2021). Micro-sized parallel system design proposal for the solution of robotics based engineering problem. Microsystem Technologies, 27, 4217-4226.

[34] Kalaiselvi, T., Sriramakrishnan, P., & Somasundaram, K. (2017). Survey of using GPU CUDA programming model in medical image analysis. Informatics in Medicine Unlocked, 9, 133-144.

[35] HajiRassouliha, A., Taberner, A. J., Nash, M. P., & Nielsen, P. M. (2018). Suitability of recent hardware accelerators (DSPs, FPGAs, and GPUs) for computer vision and image processing algorithms. Signal Processing: Image Communication, 68, 101-119.

[36] Rausch, T., Rashed, A., & Dustdar, S. (2021). Optimized container scheduling for data-intensive serverless edge computing. Future Generation Computer Systems, 114, 259-271.

[37] Naz, N., Haseeb Malik, A., Khurshid, A. B., Aziz, F., Alouffi, B., Uddin, M. I., & AlGhamdi, A. (2020). Efficient processing of image processing applications on CPU/GPU. Mathematical Problems in Engineering, 1-14.

[38] Hangün, B., & Eyecioğlu, Ö. (2017). Performance comparison between OpenCV built in CPU and GPU functions on image processing operations. International Journal of Engineering Science and Application, 1, 34-41.

[39] Fan, B., Li, Y., Zhang, R., & Fu, Q. (2020). Review on the technological development and application of UAV systems. Chinese Journal of Electronics, 29, 199-207.