Improved Assessment of Offshore Helideck Marking Standards' Compliance using Optimized Machine Learning Principles in the U.S. Gulf of Mexico

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Abstract: There is an unknown number of offshore helidecks in the U.S. Gulf of Mexico that comply with a specific marking standard. This is a direct result from the lack of national regulations enforced. The purpose of this research is to improve the assessment of offshore helideck marking standards' compliance using optimized machine learning principles. Using two different phases and employing the transfer learning approach, an optimized machine learning algorithm is generated to classify offshore helidecks from photographs into CAP 437, HSAC RP 161 or None. Results show that this model can identify marking standards being used with an accuracy of 95.7 percent. Therefore, demonstrating that the machine learning principles used can improve the assessment of offshore helideck marking standards' compliance.

1 INTRODUCTION

Across the world, energy industry workers must be transported to offshore facilities. Originally, this transportation was performed by ship, yet this presented issues such as individuals getting seasick, hazardous transition from the ship to the facility, and wearisome travel times. Now, with the use of helicopters, these legacy issues have been mitigated. Helicopter travel decreases passenger illness, eases transition from the helicopter to the facility, and significantly reduces travel time compared to travel by ship. Due to these benefits, helicopters have been used since 1947 to perform tasks like offshore transportation of personnel, cargo, and parts. To execute offshore helicopter operations, a safe landing area should be guaranteed on these offshore facilities, referred to as helidecks (HSAC ~ Helicopter Safety Advisory Conference - Home, 2016).

A helideck is defined as "a heliport located on a fixed or floating offshore facility such as an exploration and/or production unit used for the exploitation of oil and gas" (International Civil Aviation Organization, 2018).

Many offshore facilities, and their helidecks, were built prior to the introduction of any applicable design standard. Therefore, the underlying design parameters and associated safety aspects for these facilities remain unknown. In the past two decades, design standards and guidance material have been developed and became more readily available; however, compliance with these standards or guidelines for newly built helidecks, as well as the gaps in compliance with those previously built (legacy) helidecks remain an industry concern. This results in a plethora of issues that offshore helicopter pilots must face when attempting to safely land a helicopter on a helideck. For example, the lack of, incorrect, or ambiguous markings force the pilots to adapt and draw their own conclusions as to whether it is safe to land or not during the final stages of landing. To clarify the various interpretations of these markings, standardization of helideck markings is crucial to improve landing safety.

It takes time for a helideck to be inspected and verify compliance with applicable standards or industry guidelines. A trained and competent helideck inspector will need to be transported to the facility by helicopter, leading to significant additional costs. These costs also include travel labor costs of the inspector, offshore room, and board for the inspector, as well as the potential disruption of the daily activities at the facility due to the inspection of the helideck. With the vast number of active helidecks in

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the U.S. Gulf of Mexico, this presents an immense challenge. It will take considerable sum of money and resources to inspect and subsequently improve marking standards' compliance for all helidecks in the U.S. Gulf of Mexico.

1.1 Helidecks in the U.S. Gulf of Mexico

Oversight of platform structures is being handled by the Bureau of Safety and Environmental Enforcement (BSEE) and the U.S. Coast Guard (USCG), where floating facilities and vessels are under the USCG, the fixed-leg facilities on the U.S. Continental Shelf in the Gulf of Mexico are overseen by BSEE. BSEE has a database that maintains the number and details of active and non-active offshore facilities in the U.S Gulf of Mexico, excluding vessels. The number of offshore facilities that are currently active can be derived from this BSEE database. Using the available dataset as of 1/23/2021, a pivot table can be created to identify those facilities that may potentially be non-compliant and in need of inspection to assess if they need to be re-marked to become compliant with current available guidelines. The resulting pivot table shows that there are 1311 facilities that need to be assessed and might be candidates for re-marking.

1.2 Helideck Design

Offshore helideck safety starts with a safe design. In this section, the available standards and guidance material regarding design will be introduced. Design criteria include the application of markings as visual cues to help the helicopter pilot interpret safety related information.

Currently, there are three prevailing guidance documents available for use in offshore helideck design. These three documents are the International Civil Aviation Organization (ICAO) Doc 9261 Part 1 - Heliport Manual (International Civil Aviation Organization, 2018), United Kingdom Civil Aviation Authority (UK CAA) Publication 437 Standards for offshore helicopter landing areas (CAP 437), and The Code for the Construction and Equipment of Mobile Offshore Drilling Units, 2009 (2009 MODU Code (International Maritime Organization, 2010)).

ICAO Doc 9261 Part 1 is approved by and published under the authority of the Secretary General of the United Nations. Within ICAO, the 191 Member States and several global aviation organizations work together to develop international Standards and Recommended Practices (SARPs). These SARPs are the references countries utilize to develop their national civil aviation regulations, which then become enforceable. This is an important aspect: ICAO SARPs are not legally binding by themselves. Instead, they form the basis of national regulations which have legal status. As such, ICAO Document 9261 provides global guidance regarding the design of offshore helicopter landing areas, including helidecks, and should be used by civil aviation authorities to develop their own regulations.

CAP 437 is a similar standard created by the UK CAA and is a mandatory standard for all the helidecks under their regulatory oversight. CAP 437 has been applied in the North Sea since 1981 and has since undergone several amendments. "CAP 437 presents the criteria required by the CAA in assessing the standards of offshore helicopter landing areas for world-wide use by helicopters registered in the UK" (International Civil Aviation Organization, 2018) . As international vessels and drill ships with helidecks move around the globe, several of those vessels have been in the operating region of the U.S. Gulf of Mexico. As a result, this document has started to influence helideck design guidelines for other platforms and installations in the U.S. Gulf of Mexico. In addition, the CAP 437 design guidelines are considered an equivalent design standard to the design requirements mentioned in the U.S. Code of Federal Regulations for Helideck design by the USCG (Hawkins, 2015).

The 2009 MODU Code is a document that addresses requirements for drilling ships and vessels; it does provide a section regarding helideck design guidelines. It facilitates their international movement and operation, plus it ensures a level of safety for such units and for personnel on board. However, as the MODU code only focuses on ships and vessels, and not all platform facilities, it is outside of the scope of this thesis, so this concludes the introduction and use of the 2009 MODU Code.

Due to the limited number of design criteria specifications in the United States Code of Federal Regulations, the energy industry in the U.S. Gulf of Mexico started developing their own guidance material in the form of Recommended Practices (RPs). In 1978, the Helicopter Safety Advisory Conference (HSAC) was created as a conference composed of over 115 members. This conference creates RPs for the industry in the U.S. Gulf of Mexico. In 2008, they started their process of developing RPs for helideck markings. The RPs were influenced by CAP 437, but not fully identical in every aspect of the document, such as the system of measurement (imperial units versus metric). HSAC decided to combine relevant elements of onshore helideck markings from the Federal Aviation Authority (FAA) Advisory Circulars and from CAP 437. They merged these elements, along with their own innovative ideas, into RP 2008-1 Offshore Helideck Markings in the U.S. Gulf of Mexico. Since 2008, an additional document, RP 2013-1 regarding Helideck Parking Area Markings was developed, and ultimately all helideck marking guidance was absorbed into the HSAC RP 160-series of helideck design guidance between 2016 and 2019.

For a pilot to safely land on the intended helideck, the pilot needs to be able to correctly identify the helideck, know the size and weight capacity of the helideck he is going to land on, and any obstacles he needs to avoid (Bosman, 2021).

To ensure that the pilot safely lands on the helideck of the intended platform, the identification marking on the helideck must be recognizable. Guidance material depicts this identification marking as white lettering in a specific location of the helideck. In HSAC RP 161 (Helicopter Safety Advisory Conference, 2021) and CAP 437 (International Civil Aviation Organization, 2018), the identification marking locations are identical. Both identification markings are white, and while minor differences in size of font may occur, overall, these documents provide similar guidance for pilot recognition.

Secondly, the pilot needs to be able to verify the weight limitations and size of the helideck. A helideck is designed for a specific model helicopter, which is the largest helicopter type the helideck is intended to serve. This design helicopter determines the maximum weight and size of the helideck. Once designed for this largest envisioned helicopter to be operating to the helideck, the helideck can safely accept that helicopter type and all smaller and lighter helicopter types. The weight capacity is therefore capped to the maximum allowable take-of mass (MTOM) of the design helicopter, which is available in the rotorcraft flight manual of the design helicopter. The helideck size is determined by the D-value of the design helicopter. The d-value is defined as "The largest overall dimension of the helicopter when rotor(s) are turning, measured from the most forward position of the main rotor-tip-path plane to the most rearward position of the tail rotor-tip-path plane or rearward extension of the helicopter structure" (Helicopter Safety Advisory Conference, 2021). The markings for weight and size between HSAC RP 161 and CAP 437 differ due to separate units of measurements used. CAP 437 documentation and marking standards are fully based on the metric system, whereas HSAC RP 161 is based on the imperial system while also providing some metric system options. CAP 437 (International Civil Aviation Organization, 2018) displays weight markings in metric tons in one specific location on the helideck. Size limitations are displayed on the helideck perimeter line using the applicable D-values. HSAC RP 161 (Helicopter Safety Advisory Conference, 2021) displays the D-value in a location marked inside of the bottom three-tiered box outlined in red preceded by the letter "D".

Finally, the pilot needs to be aware of any obstacles that might surround a helideck. Obstacle related markings are divided into three individual sectors: a 210 degree Obstacle Free Sector (OFS), a 150 degree Limited Obstacle Sector (LOS) and a "No Nose" sector. The OFS is "An area free of all obstacles above helideck level outwards to a distance that will allow for an unobstructed arrival and departure path to/from the helideck for the helicopter(s) it is intended to serve" (Helicopter Safety Advisory Conference, 2021).The opposite side of the chevron marking is the LOS. As opposed to the OFS where n obstacles are allowed, the LOS allows some obstacles to be present, as long as they remain smaller in size than the preset profile. Obstacles in the colored areas shall remain below the associated height profile for the helideck to be considered compliant, providing a safe operating area for helicopters. If an object protrudes from the labeled sections, the helideck is not considered safe to land. The "No Nose" sector is a sector where the location of the helicopter's nose is not allowed to go over to avoid the tail rotor to strike any obstacle or prevent the tail rotor to be maneuvered over a helideck access point.

According to Table 1 (Composed from the BSEE database) there are 1194 facilities that were built before 2008. Resulting in 91.1 percent of the facilities in the U.S. Gulf of Mexico with the potential of being non-compliant to HSAC RP helideck marking guidelines. Additionally, the U.S. Coast Guard did not approve CAP 437 for use within the U.S. Gulf of Mexico until 2015 (Hawkins, 2015). Cross referencing the BSEE database to filter out the number of facilities before 2015 demonstrates that 98.8 percent of helidecks in the U.S. Gulf of Mexico might not follow the CAP 437 guidance materials.

Seeing as a staggering 98.8 percent of helidecks have not yet been verified as compliant with marking standards and therefore cannot be positively confirmed to be safe for landing, it is imperative that arrangements are made to further ensure offshore helideck operations safety. With the use of an image

Table 1: Percentage of helidecks in the Gulf of Mexico.

	Number of Helidecks	Percentage of all
Helidecks in U.S. Gulf of Mexico	1311	100.0%
Helidecks before 2015	1295	98.8%
Helidecks before 2008	1194	91.1%

classification program, this issue of quickly verifying if helideck markings are applied using an available and acceptable standard can be easily resolved with much less hassle and cost.

2 METHODS

2.1 Marking Standard Comparison

To properly identify helidecks and categorize them accordingly, a comparison needs be made between HSAC RP 161 and CAP 437. Both helidecks are painted green, have a yellow circle (Touch Down/Positioning Marking), an identification name, the letter 'H', and a chevron in a relative location of the 'H'. HSAC RP 161 helidecks have a distinguished three-tiered red box to display the size, dimensions, and weight specifications of the helideck, where CAP 437 helideck size markings are located within the perimeter line and the weight marking is identified in the top left corner. These are the key elements that the machine learning algorithm needs to be able to identify to distinguish between HSAC RP 161 and CAP 437 helidecks. Moreover, a third option will be added for the algorithm to use if the helideck is not able to be classified as either HSAC RP or CAP 437, it will be categorized as None. The third option is the most important option in this regard, as it will show which helidecks are non-compliant to either marking standard or will therefore have to be re-marked using one of the acceptable standards.

2.2 Assessment of Helidecks Utilizing Deep Convolutional Neural Networks

The main goal for the proposed convolutional neural network model is to identify if the helideck is compliant or not based on an image. Since there are limited options in obtaining photographs of offshore helidecks, the use of the guidance material can aid in creating self-developed (artificial) compliant imagery. This will demonstrate to the convolutional neural network how each helideck is supposed to look when following the HSAC RP 161 guidance material, the CAP 437 material, or None at all. Secondly, a convolutional neural network model with initial parameters is needed to provide a base and from there build an optimized model. While the parameters will change within the convolutional neural network through training, certain parameters such as kernel size, pooling size, and the size of the fully connected layer must be set manually. Based on the results of the initial configuration of the model, the accuracy might not be acceptable, therefore layers might need to be added, removed, or modified to adjust the model and increase the desired accuracy.

Convolutional neural networks are like traditional neural networks in that they are both able to optimize their weights by learning. They also end the same way by receiving the outputs of earlier nodes and use loss functions to classify the object (O'Shea & Nash, 2015). Where traditional neural networks and convolutional neural networks differ is that in traditional neural networks, the data is composed of text or numbers, such as a database, whereas convolutional neural networks perform their operations based on imagery and find information within images to recognize patterns.

The proposed framework can be explained using the diagram in Figure 1 below. For each block in the process, a brief explanation is available to explain each specific process and the associated activities that were performed. The process will run in two different phases: phase one being composed of images that were self-developed (artificial) using the guidance materials, and phase two being composed of photographs from offshore facilities in the U.S. Gulf of Mexico. One key difference is the Image Pre-Processing stage, as it is not performed in phase one, while in phase two, each photograph will need to be pre-processed before entering the convolutional neural network.

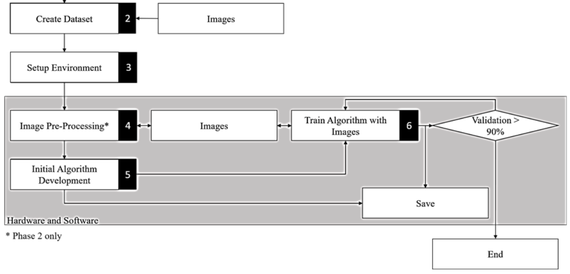

Figure 1: Flowchart of methodology.

2.3 Phase One – Developing the Model using Artificial Images

Using the guidance material, eight individual helideck marking images were made for each document, 8 using HSAC RP 161 and 8 using CAP 437, resulting in 16 distinct images for the machine learning process. These images include helidecks that are round, rectangular, and octagonal. Based on these 16 images, the category None was created manually by copying the images and using a photo editor to change colors and remove key elements. This process resulted in a folder with 23 individual images and were categorized as HSAC, CAP 437 or None.

Before being able to create a dataset, the model will need to distinguish individual images from each other. To achieve this, each image has been verified and classified manually and the filename reflects the classification of the image. The filenames will either start with a prefix CAP 437, HSAC, or None.

In Convolutional Neural Networks, more available data provides better overall results. The number of 23 images currently available is not enough to properly train a convolutional neural network. Data augmentation was used to automatically generate more images for the network to use during learning. The data augmentation consisted of taking a single image and altering saturation, brightness, or rotation to generate additional images that have different properties. Tensorflow has an ImageDataGenerator function that can adjust the mentioned property values and save the newly generated image to a different location (Abadi, et al., 2015). Additionally, this function can perform functions such as flipping the image orientation, shifting horizontally and vertically, adjusting zoom levels to make it appear closer or further away, and shearing the image to make the helideck appear angled (Abadi, et al., 2015). The augmented image was sheared, mirrored horizontally, zoomed out, and has an increased brightness. Repeating this step for each image 100 times will result in over 4,343 images as a dataset for the neural network learning.

Just as important as the algorithm itself, the environment used to train the algorithm needs to be taken into consideration. While the model can be exported and be reused in other hardware, the training process requires a more robust setting. For this training process a desktop computer with a ZOTAC GeForce® GTX 1070 Ti Mini graphics card was used to train the model.

The graphics card aids in accelerating the neural network training process by using the Tensorflow library. This library will use the CUDA cores to allow parallel processing (Abadi, et al., 2015). The software used in this process was Microsoft Visual Studio Code with the Python extension provided by Microsoft. Libraries within Python 3.8.7 mainly consist of Tensorflow 2.4.1 and keras 2.4.3, while sklearn was used for metrics (Pedregosa, et al., 2011).

A base convolutional neural network model is first created to start the process of finding an optimized model. The base model is manually constructed to increase productivity and a gradient descent optimizer is selected. Based on the resulting graphs of accuracy and loss, manual modifications are made to add and adjust layers and create a model that demonstrates the desired learning curve, as well as a desired loss function curve.

This initial model will also define the compiler used for future fine-tuning, and will be chosen between SGD, AdaDelta, RMSprop, and Adam. The chosen optimizer will be based on the graphs generated after each training session and by the performance of the model.

During the training, the model will be modified until it has a validation accuracy above 90 percent This number was chosen as this program is meant to be an aid to the pilot, so in case it does misidentify, the pilot will still be able to personally verify the helideck. In this process, the computer uses a loop to modify the number of convolutions per layer and the number of nodes per dense layers to find a model that has an accuracy above 90 percent.

The accuracy of the predictions is dependent on the training and testing data. There are no universal rules regarding the identification of proper ratios between training and testing data to obtain a certain percentage in accuracy. Also, as the size of the training data increases, the accuracy of the model will likewise increase (Medar, Rajpurohit, & Rashmi, 2017). Focusing on the model, rather than the number of images it is training and testing on, will give the program the chance to obtain accuracies of 90 percent or higher. The training and testing ratio will be set at 75 percent training and 25 percent testing. Using this ratio, the model will have enough images to learn and adapt to the ratio to get accuracies above 90 percent. In case the optimization process is not able to obtain 90 percent, the training and testing ratio will be modified and then the process will have to be restarted to find the proper model.

2.4 Phase Two - Developing the Model using Real Images

Phase two of the process is similar to phase one, except that instead of self-developed images actual photographs are used. The photographs need to be pre-processed before entering the neural network. Additionally, the previously optimized model in phase one is now being used as the initial model to start phase 2. In other words, the model used in phase 2 benefits from the transfer learning approach. Most of the photographs obtained had a broad range of resolutions. Some images were as large as 4252 by 2838 pixels compared to other images which were as small as 640 by 480 pixels in resolution. In addition, some images included the entire facility and not just the helideck. Therefore, some images needed to be resized and cropped to focus on the helideck in order to be usable in the convolutional neural network. The image preparation was performed through a process of segmentation, in which certain features are filtered out of the image depending on the users' specifications.

The similarities in HSAC RP 161 and CAP 437 work in the favor of segmentation in such a way that the computer can focus on the helideck being green to find it in the image. For this process to work, each image is converted into a three-dimensional array, this is done because each image is composed of values for red, green, and blue, and range from zero to 255. Unfortunately, there is a drawback, as each pixel in an image has a green value to create its color. This results in it being more difficult for the computer to find the green helideck. To remedy this, hue, saturation, and value (also known as intensity) are used to give more control over which green to look for. Applying a range of green values, contrast values, and intensity values, the computer can filter the image based on the range provided. This is also known as thresholding.

Within python, using the OpenCV (commonly called cv2) library, the use of masks can help segment the helideck from the rest of the image (Bradski, 2000). To develop this mask, a custom tool was created to find the ranges of hue, saturation, and intensity of the green helideck. The tool provides a graphical interface where color (HSV) values can be adjusted at will, filtering the color of the resulting image. Once the values are identified, they can then be used in the findContours function built into the cv2 library. This function will locate a rectangle around the helideck and create the image that will later be used in the neural network (Bradski, 2000).

Moreover, a total of 56 photographs of helidecks or offshore platforms with helidecks were collected, and these underwent the same data augmentation process as mentioned under phase one to generate additional photographs for the dataset. The same parameters for data augmentation were used as in phase one. This resulted in 4,873 photographs that the neural network can use.

3 RESULTS

3.1 Results of Phase One

The initial model starts off with a single 200-by-200 pixel image. This image was then convoluted with 32 filters in the convolutional layer. Following this, the ReLU activation layer was used to remove the negative values that may appear and adjust them to zero. After activation, a dropout rate of 50 percent was applied; meaning that out of the 32 nodes, 16 were randomly selected to be passed onto the next layer. The next layer is the fully connected layer, in which the 16 nodes are then condensed into one single vector. At the end of the network, the dense layer will further narrow the results down to three choices. The softmax activation layer will then use these three choices to return a probability vector.

Using this model, different optimization algorithms were used to find the optimum. Adam and RMSProp show the most potential. Adam, however, showed a more stable curve, and was therefore chosen to be used for the rest of the development. Using the Adam compiler and step five of the methodology, a more complex network was created. This model was able to reach an accuracy of 98.1 percent. Both the confusion matrix and classification report are shown below in Table 2 and Table 3. These show the model tends to classify some helidecks that were None as HSAC RP 161 helidecks. As seen in Figure 2, the model was able to learn the data at a steady rate, and both accuracy and loss remained close together throughout the entire training process.

Table 2: Confusion matrix of final theoretical model.

	Precision	Recall	F1-score	Support
CAP 437	0.98	0.97	0.98	427
HSAC	0.99	0.95	0.97	603
None	0.91	0.98	0.95	189

Table 3: Classification report of the final theoretical model.

		Actual		
		CAP 437	HSAC	None
Predicted	CAP 437	200	0	2
	HSAC	0	183	14
	None	0	4	683

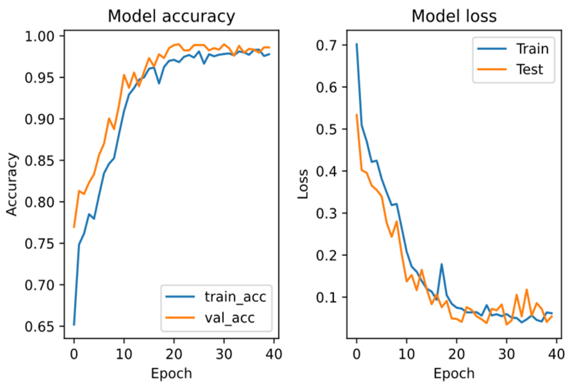

Figure 2: Accuracy and loss of the phase one model.

3.2 Results of Phase Two

In phase two, images are cropped and resized to the resolution of 200 by 200 pixels in the pre-processing stage. The same model and compiler from the previous phase were used for this phase as well, with the model being re-trained using the pre-processed photographs rather than the manually created images used in phase one. The model was able to train up to an accuracy of 95.7 percent. This is lower than phase one, but it is to be expected due to the noise presented in the photographs. The same confusion matrix, classification report and performance graphs were generated to evaluate the model and are shown in Table 4 and Table 5 as well as Figure 3.

Table 4: Confusion matrix from phase two model.

		Actual		
		CAP437	HSAC	None
Predicted	CAP437	407	7	13
	HSAC	16	551	36
	None	4	1	184

Table 5: Classification report from phase two model.

	Precision	Recall	F1-score	Support
CAP 437	1.00	1.00	1.00	202
HSAC	0.98	0.94	0.96	197
None	0.98	1.00	0.99	687

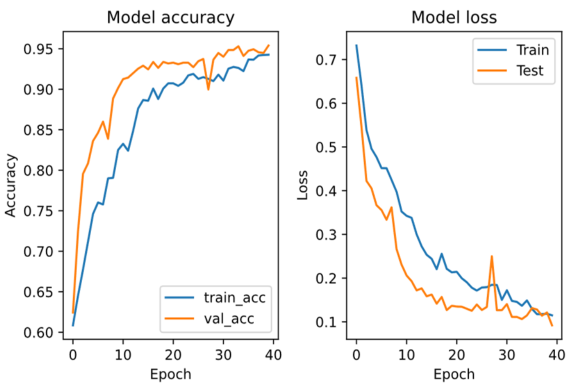

Figure 3: Accuracy and Loss curves of phase two model.

4 DISCUSSION

4.1 Conclusions

According to the literature review, the standardization of offshore helideck marking is an important aspect for the safety of offshore helicopter occupants. With standardized markings in place, the pilot will be able to identify the correct helideck, know its weight and size limitations, and be able to find obstacle sector markings crucial for landing safely such as the OFS, LOS, and “No Nose” sectors. To ensure that acceptable marking standards are complied with, assessments of each individual offshore helideck must be completed. Unfortunately, to do this requires many resources due to the number of applicable helidecks, manpower needed to perform the inspections, and costs associated with offshore travel for the inspectors and their hourly rate as subject matter experts. In-person assessment of individual helidecks will also require many years to complete. Using machine learning, this task can be accelerated and simplified with the use of convolutional neural networks, where images are used to classify a helideck into three different categories of helideck marking standards: HSAC RP 161, CAP 437, or None. These standards depict safety related markings in specific locations on a helideck where the pilots can obtain information quickly. Images were generated based on the marking requirements in HSAC RP 161, CAP 437, and None, and photographs were pre-processed to focus on the helideck rather than the entire platform.

Using the literature review results, and the flowchart depicting the methodology, two models were created in separate phases. Phase one to classify manually constructed images, and phase two to classify actual helideck photographs using the transfer learning approach. The objective of each phase was to create a theoretical model that had an accuracy above 90 percent. The first phase resulted in a model classification success rate of 98.1 percent, while phase two had a success rate only slightly decreased at 95.7 percent. These results show that optimized machine learning principles can be used to improve the assessment of compliance of offshore helideck marking standards in the U.S. Gulf of Mexico.

4.2 Future Work

There is potential in this model to possibly be integrated into a helicopter, where a camera and artificial intelligence can assist the pilot in identifying hazards, obstacles, and destination information in real-time. This model can also be adjusted to possibly include other marking standards or recommended practices, thereby furthering its reach to outside of the U.S. Gulf of Mexico.

This model could provide a base understanding to add additional features such as obstacle detection around the helidecks to improve safety even more or initiate another research to use infrared and/or radar imagery in real time to augment pilot vision and situational awareness.

Moreover, this model is not limited by the offshore applications. It can also be used for onshore applications such as hospital and rooftop heliports.

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