IOSR Journal of Business and Management (IOSR-JBM)
e-ISSN:2278-487X, p-ISSN: 2319-7668. Volume 26, Issue 12. Ser. 13 (December. 2024), PP 55-62
www.iosrjournals.org

Application Of Automation And Computer Vision In Reducing Failures In The Production Process Of Safety Belts

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Resumo:
Product quality is one of the primary criteria considered by customers when choosing an item. Additionally, it is an essential factor for companies to stand out in a highly competitive market. In the Manaus Industrial Hub (PIM), in a machine used for producing safety belts, defect detection is a crucial stage in the production process. To enhance this task, Artificial Intelligence (AI) was implemented, standing out for its high efficiency in analyzing and processing data in industrial environments. The data was captured in image format by a camera, and using Deep Learning (DL) techniques, an intelligent algorithm capable of detecting faults was developed. Due to its autonomous learning capability and ability to identify and characterize defects, this algorithm represents the future of automated inspection. It has already achieved significant success in applications such as object identification and classification, facial recognition, and fault diagnostics. Given this context, the aim of this study is to propose an ideal solution to minimize failures in the production process of safety belts. The proposal seeks to automate the currently manual step using the concept of computer vision with AI, ensuring greater efficiency and reliability in the production process.

***Materials and Methods**: The research, development, and application of AI with the algorithm in the case study were conducted in the R&D laboratory of the company located in the Manaus Industrial Hub (PIM). The project utilized product inputs, a camera equipped with a lens for capturing images, and a computer for data storage and algorithm development.*

***Results**: The application of AI in this environment uses computer vision systems to process image data. For this, a program was developed in Python with the PySimpleGUI library. The trained model was evaluated based on loss and accuracy metrics on the test set, achieving values of 0 and 100%, respectively. During testing, new belts were used, reaching 100% accuracy in the results.*

***Conclusion**: The proposed model showed excellent results. With data processed by AI using Deep Learning (DL) techniques, real-time inspection of the belts was achieved. Additionally, the network achieved perfect accuracy and recall in all tests conducted on the belts, demonstrating the effectiveness of the solution.*

Palavras-chaves: *AI; PIM; Deep Learning; Python; Safety Belts.*

Date of Submission: 15-12-2024 Date of Acceptance: 25-12-2024

I. Introduction

Since the Industrial Revolution, industries have been seeking innovative ways to increase production efficiency, reduce costs, and improve product quality (GAO et al., 2024; CANDRA; SUNARYA; SARASWATI, 2023; MUÑOZ et al., 2019; WALUYA; IQBAL; INDRADEWA, 2019). Currently, "smart machines" and "smart processes" use data to continuously optimize production processes, with minimal or no human intervention (JAN et al., 2023; MEINDL et al., 2021; BENITEZ et al., 2022; KAISER et al., 2022; HWA; CHUAN, 2024).

This transformation is driven by technological advances such as artificial intelligence (AI), machine learning, sensor networks, the Internet of Things (IoT), cloud computing, additive manufacturing, and the availability of large volumes of data that these technologies can exploit (ENKHBAATAR; YAMAZAKI, 2024;

HONG; TAY; ANG, 2023; YANG et al., 2022; RIORDAN et al., 2019). Among these, AI techniques, such as deep learning and computer vision, stand out (PERMANASARI et al., 2022; JAN et al., 2023; BENITEZ; AYALA; FRANK, 2020; AUNG et al., 2024).

Defect detection plays a critical role in the inspection process, as it is essential for deciding whether to accept or reject produced or supplied parts. Furthermore, it enables rework and repair of parts, contributing to reducing material waste (MISHRA; LOURENÇO, 2024; BHATT et al., 2021). Product quality is a determining factor for companies' reputation. Defective products not only lead to raw material waste but also to a significant loss of customers (JING et al., 2022; CANDRA; SUNARYA; SARASWATI, 2023). In this context, process automation reduces defect risks, making production faster, more versatile, and more precise.

The adoption of artificial intelligence techniques, such as deep learning and computer vision, is essential in this scenario. Due to its autonomous learning capability and precision in defect identification and characterization, deep learning is considered the future of automated inspection, with successful applications in areas such as object identification, facial recognition, and fault diagnostics (BHATT et al., 2021; ENKHBAATAR; YAMAZAKI, 2024; HONG; TAY; ANG, 2023; ROŽANEC et al., 2024).

At the Manaus Industrial Hub (PIM), a company that manufactures personal protective equipment (PPE) has established a research and development (R&D) laboratory as a key tool for innovation, sustainable development, and support for future research projects (MALIK; MUHAMMAD; WAHEED, 2024; ALAM et al., 2022). A prototype machine was developed for the production of safety belts for working at heights. In this process, the input material is fed via a reel, and the material must be fully inspected. Some reels feature splices that cannot be used and must be discarded to ensure the product's safety and integrity. However, these splices often have colors similar to the belts, complicating manual inspection performed by human operators.

The project was designed to validate a vision system based on artificial intelligence capable of detecting different splice colors. The primary objective was to employ AI and deep learning techniques to develop an intelligent algorithm to inspect the material and accurately identify the splices.

II. Materials And Methods

The research, development, and application of artificial intelligence (AI) with the algorithm developed for the case study were conducted in the Research and Development (R&D) laboratory of the company. This laboratory is equipped with advanced resources that enabled the experiments and validations required. Below is a detailed description of the materials and equipment used, as well as their functionalities and applications in the project's context:

1. **Avell Computer with Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz**

   This computer was used as the central processing unit (CPU) for the development and execution of the project. With a high-performance Intel Core i7 processor, it managed computationally intensive tasks, including executing the AI algorithm and performing initial data processing.

2. **NVIDIA RTX2070 GPU:**

   The graphics processing unit (GPU) was essential for accelerating the calculations needed for training and applying the deep learning model. The RTX2070, with its high-performance architecture, efficiently executed parallel operations and optimized the use of TensorFlow, Cuda, and Cudnn libraries.

3. **Basler acA720-520uc Camera:**

   A high-resolution industrial camera used to capture detailed images of the safety belts. This equipment ensured the collection of high-quality visual data, indispensable for detecting splices using the AI algorithm.

4. **Basler Lens with 4mm Focal Length**

   This lens was coupled to the Basler camera to adjust the field of view and sharpness of the captured images. With a focal length of 4mm, it provided clear and well-defined images, even at short distances, facilitating the analysis of critical details on the belts.

5. **Mechanical Prototype for Camera Support**

   This support was designed to stabilize and appropriately position the Basler camera, ensuring consistency in image capture. It was adjusted to align the camera with the belts under inspection, ensuring data collection precision.

6. **Safety Belts with and Without Splices**

   These materials were used as real samples for training and testing the AI algorithm. Belts with splices represented problematic cases, while those without splices served as quality standards. The diversity of samples was crucial to validating the system's effectiveness in detecting faults.

7. Python 3.10

The Python programming language was chosen for the project's development due to its flexibility and a wide range of libraries for AI and machine learning. It was used to implement the inspection algorithm, integrate devices, and process data.

8. TensorFlow 2.10

TensorFlow is an open-source library for machine learning used for training and executing the deep learning model. Version 2.10 was chosen for its compatibility with the hardware and software versions used in the project.

9. Cuda 11.2

Cuda is a parallel computing platform developed by NVIDIA. This version maximized the GPU RTX2070's potential, accelerating the AI model's training process.

10. Cudnn 8.1

The Cudnn library is fundamental for neural network operations on GPUs. Its integration with TensorFlow and Cuda enabled the efficient execution of operations such as convolution, pooling, and normalization, which are essential for deep learning.

Each of these components played an indispensable role in the development and application of the AI-based solution. The integration between hardware and software was carefully planned to ensure the computer vision system's effectiveness and its ability to detect splices with high precision.

Development

To develop the proof of concept, it was necessary to select a camera and a lens suitable for the inspection system's specifications. The process began with defining fundamental parameters for the application, considering the project's requirements.

Determination of Minimum Dimension to Inspect and Field of View (FOV)

The minimum dimension to inspect was established as 1 millimeter, corresponding to the belt edges that required detailed analysis. Additionally, the field of view (FOV), which is the total area the camera must cover, was set at up to 150 millimeters. These values were critical to ensuring inspection accuracy and the ability to detect minimal imperfections.

Calculation of Required Resolution

To ensure precise inspection, a pixel density of 3 pixels per millimeter was used. The resolution was calculated using the equation:

$$Res = \frac{3 * FOV}{Md} \rightarrow Res = \frac{3 * 150}{1} \rightarrow Res = 450$$

Based on this calculation, the camera's larger axis was defined as 720 pixels, while the smaller axis was 540 pixels, ensuring the proper ratio and required density for meeting the system's requirements.

Definition of Frames per Second (FPS)

Since the inspection process involves continuous inspection of a moving belt, determining the frames per second (FPS) rate was essential. To ensure consistent and detailed image capture during motion, the highest possible rate, 525 FPS, was chosen. This specification is crucial to avoid data losses or gaps during inspection, enabling continuous and precise monitoring throughout the belt's length.

Lens Definition

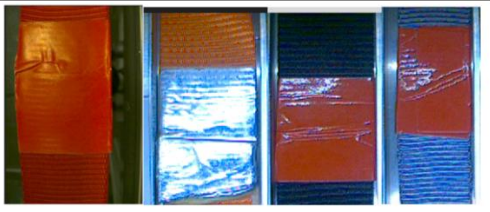
Lens selection considered three main factors: the field of view (FOV), the camera sensor size, and the desired focal length. These parameters were crucial for ensuring the lens met the inspection system's needs. Using a Basler tool, the previously calculated and measured data, such as the 150mm FOV and the Basler acA720-520uc camera sensor size, were inputted. After analysis, the selected lens was the C125-0418-5M model, with a 4mm focal length. This choice ensured the capture of clear and precise images, essential for training and operating the inspection system.

Application

Once the optical setup was defined and acquired, the data collection phase began for neural network training. Thirty-six belts with splices from different models and thirty-six belts without splices were selected, representing diverse samples that reflected possible production scenarios. These belts' images were captured in RGB format using the optical system configured with the chosen camera and lens. Capturing in RGB was essential to preserve color information, as the splices often have tones similar to the belts, complicating detection.

This data was then processed and used to train the neural network model, ensuring that it was able to accurately identify belt splices during the automated inspection process. This step was crucial in validating the system's effectiveness and its ability to operate in real production conditions. Figures 1 and 2 show some of the belts used with and without splices:

Figure 1 - Straps with splices



Source: Author (2024).

Figure 2 - Seamless strapping

Source: Author (2024).

The images captured were RGB with 600x400 pixels, with the following array format: (400,600,3).

Mechanical prototype: Figure 3 shows the mechanical prototype, which was developed entirely in the company's Research and Development (R&D) laboratory, using various materials that ensured the system's functionality and robustness. Each component of the structure was designed and manufactured with precision to meet the requirements of the project.

Main structure: The prototype's main structure was built using 30 mm x 30 mm aluminum profiles, cut to different lengths according to the project's needs. These profiles provided a modular, lightweight, and sturdy base, allowing for future adjustments and modifications if necessary.

Camera support: The camera support was made from 12 mm thick aluminum sheet. This material was chosen for its durability and stability, ensuring that the camera remained fixed and aligned during the tests. The bracket was firmly coupled to the main structure, ensuring precise image capture.

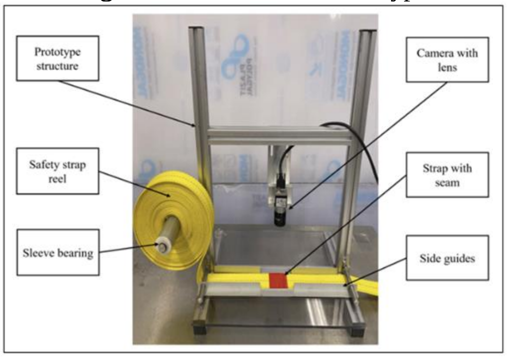
Sliding bearing: To support and allow the inspection coil to slide smoothly, a sliding bearing was made using an aluminum tube with a diameter of 38 mm. This component was designed to reduce friction during the movement of the coil, ensuring that the belt was fed into the system in a stable and uniform manner.

Main Base: The prototype's main base was made from a 10 mm thick polycarbonate sheet. Polycarbonate was chosen for its mechanical strength and transparency, making it easier to see the process and adjust.

Side guides: To ensure the stability of the belt during movement, side guides were added to the structure. These guides ensured that the belt remained aligned throughout the inspection process, reducing deviations, and improving the system's accuracy**.**

Figure 3 shows part of the prototype, assembled and ready for testing. This configuration was essential to validate the performance of the computer vision system and the integration with the artificial intelligence algorithm developed to detect splices in the straps.

Figure 3 - Mechanical Prototype

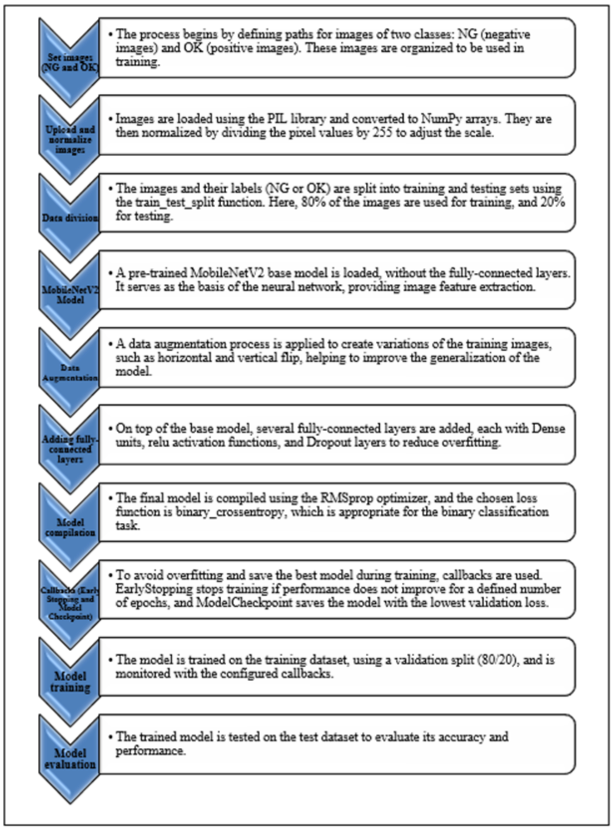


Source: Author (2024).

Architecture: To classify the images, we used a neural network with an architecture based on Mobile Net, known for its lightness and performance. This choice allowed us to take advantage of previous knowledge of the network (transfer learning) and adapt it to our specific problem (fine tuning). At the output of the network, we added a dense layer with a sigmoid activation function, suitable for binary classification problems. The binary cross entropy loss function was chosen to measure the difference between the network's predictions and the actual classes, and the RMSprop optimizer was used to adjust the network's parameters during training. Figure 4 presents a diagram summarizing how the algorithm works, showing step by step how the neural network processes the images and performs the classifications.

Algorithm flowchart: Figure 4 shows the flowchart where each step demonstrates the behavior of the algorithm and its characteristics in its current state.

Figure 4 - Flowchart of the algorithm



Source: Author (2024).

Training: Right from the start of training, it was possible to see that the network had learned the characteristics of the new images. This result is evidenced by the 100% accuracy in the validation set and the loss close to 0, as illustrated in Figure 5.

Figure 5 - Overall accuracy

```
Epoch 1/500
2/2 [==============================] - ETA: 0s - loss: 1.8461 - accuracy: 0.5556/usr/local/lib/python3.10/dist-packages/keras/src/engine/
  saving_api.save_model(
2/2 [==============================] - 10s 3s/step - loss: 1.8461 - accuracy: 0.5556 - val_loss: 0.5334 - val_accuracy: 0.7500
Epoch 2/500
2/2 [==============================] - 2s 1s/step - loss: 1.9725 - accuracy: 0.5333 - val_loss: 0.5445 - val_accuracy: 0.7500
Epoch 3/500
2/2 [==============================] - 2s 829ms/step - loss: 1.3598 - accuracy: 0.6000 - val_loss: 0.5490 - val_accuracy: 0.6667
Epoch 4/500
2/2 [==============================] - 2s 844ms/step - loss: 1.6828 - accuracy: 0.4667 - val_loss: 0.5565 - val_accuracy: 0.7500
Epoch 5/500
2/2 [==============================] - 3s 2s/step - loss: 1.6580 - accuracy: 0.5778 - val_loss: 0.5065 - val_accuracy: 0.8333
Epoch 6/500
2/2 [==============================] - 3s 1s/step - loss: 1.4236 - accuracy: 0.6000 - val_loss: 0.4939 - val_accuracy: 0.8333
Epoch 7/500
2/2 [==============================] - 2s 1s/step - loss: 1.5383 - accuracy: 0.5778 - val_loss: 0.4815 - val_accuracy: 0.8333
Epoch 8/500
2/2 [==============================] - 2s 775ms/step - loss: 1.5995 - accuracy: 0.5778 - val_loss: 0.5020 - val_accuracy: 0.8333
Epoch 9/500
2/2 [==============================] - 2s 1s/step - loss: 0.9600 - accuracy: 0.6000 - val_loss: 0.5343 - val_accuracy: 0.8333
Epoch 10/500
2/2 [==============================] - 2s 1s/step - loss: 1.1373 - accuracy: 0.5333 - val_loss: 0.3851 - val_accuracy: 0.9167
Epoch 11/500
2/2 [==============================] - 3s 1s/step - loss: 1.0673 - accuracy: 0.6889 - val_loss: 0.4480 - val_accuracy: 0.8333
Epoch 12/500
2/2 [==============================] - 2s 755ms/step - loss: 1.5332 - accuracy: 0.6222 - val_loss: 0.4941 - val_accuracy: 0.8333
Epoch 13/500
2/2 [==============================] - 2s 739ms/step - loss: 1.3889 - accuracy: 0.6000 - val_loss: 0.4381 - val_accuracy: 1.0000
Epoch 14/500
2/2 [==============================] - 2s 1s/step - loss: 1.0735 - accuracy: 0.6222 - val_loss: 0.4157 - val_accuracy: 0.8333
Epoch 15/500
2/2 [==============================] - 2s 747ms/step - loss: 1.3332 - accuracy: 0.6222 - val_loss: 0.4318 - val_accuracy: 0.9167
Epoch 16/500
2/2 [==============================] - 2s 1s/step - loss: 1.2290 - accuracy: 0.5556 - val_loss: 0.3631 - val_accuracy: 1.0000
Epoch 17/500
2/2 [==============================] - 3s 2s/step - loss: 1.0565 - accuracy: 0.6000 - val_loss: 0.3146 - val_accuracy: 1.0000
Epoch 18/500
2/2 [==============================] - 3s 1s/step - loss: 0.5766 - accuracy: 0.8222 - val_loss: 0.2960 - val_accuracy: 1.0000
Epoch 19/500
2/2 [==============================] - 2s 1s/step - loss: 1.1695 - accuracy: 0.5778 - val_loss: 0.4224 - val_accuracy: 0.6667
Epoch 20/500
2/2 [==============================] - 2s 738ms/step - loss: 1.4380 - accuracy: 0.6444 - val_loss: 0.3864 - val_accuracy: 0.7500
Epoch 21/500
2/2 [==============================] - 2s 715ms/step - loss: 0.9038 - accuracy: 0.6889 - val_loss: 0.3026 - val_accuracy: 0.9167
Epoch 22/500
2/2 [==============================] - 2s 1s/step - loss: 0.9454 - accuracy: 0.6444 - val_loss: 0.2874 - val_accuracy: 1.0000
Epoch 23/500
2/2 [==============================] - 3s 1s/step - loss: 0.7904 - accuracy: 0.6889 - val_loss: 0.3078 - val_accuracy: 1.0000
Epoch 24/500
2/2 [==============================] - 3s 1s/step - loss: 0.7392 - accuracy: 0.7111 - val_loss: 0.3016 - val_accuracy: 1.0000
Epoch 25/500
```

Source: Author (2024).

III. Result

The trained model was evaluated based on the loss and accuracy of the test set, which were 0 and 100% respectively. The test set consisted of 72 images, divided equally into two subsets: 36 images of failed straps (NG) and 36 images of approved straps (OK). The results obtained at the end of training are illustrated in Figure 6.

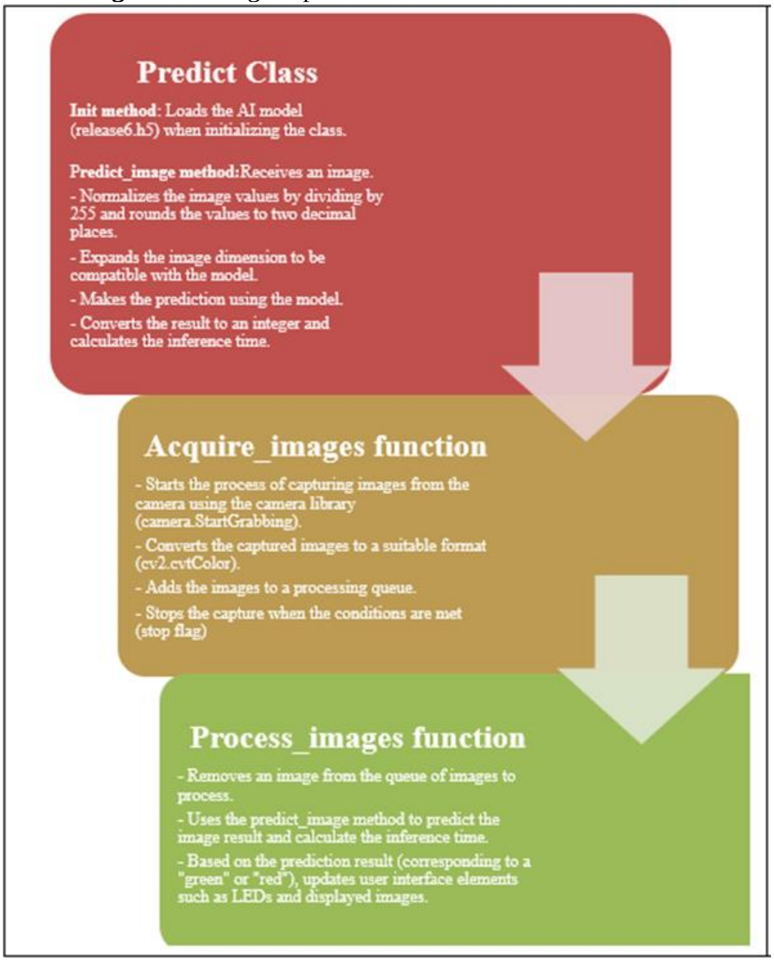
Figure 6 - Test set evaluation

```
Epoch 496/500
2/2 [==============================] - 3s 1s/step - loss: 5.7445e-04 - accuracy: 1.0000 - val_loss: 6.8893e-06 - val_accuracy: 1.0000
Epoch 497/500
2/2 [==============================] - 2s 771ms/step - loss: 0.0011 - accuracy: 1.0000 - val_loss: 6.7346e-06 - val_accuracy: 1.0000
Epoch 498/500
2/2 [==============================] - 2s 1s/step - loss: 0.0677 - accuracy: 0.9778 - val_loss: 5.8569e-06 - val_accuracy: 1.0000
Epoch 499/500
2/2 [==============================] - 2s 1s/step - loss: 2.3246e-05 - accuracy: 1.0000 - val_loss: 5.8483e-06 - val_accuracy: 1.0000
Epoch 500/500
2/2 [==============================] - 2s 1s/step - loss: 0.0050 - accuracy: 1.0000 - val_loss: 3.5513e-06 - val_accuracy: 1.0000
1/1 [==============================] - 0s 430ms/step - loss: 7.8643e-08 - accuracy: 1.0000
[7.864286288850053e-08, 1.0]
```

Source: Author (2024).

To test the neural network with real-time images, new straps were used that had not been used before in other processes, in which the neural network showed 100% accuracy. To make this evaluation possible, a Python program was developed using the PySimpleGUI library. Figure 7 shows the algorithm's capture and inference classes.

Figure 7 - Image capture and classification classes



Source: Author (2024).

Figures 8 and 9 show the interface of the program responsible for inspecting lanes with and without seams. It can be seen that when a splice is identified, the interface LED lights up red; otherwise, the LED remains green. The total capture and inference (inspection) time is less than 100 milliseconds, demonstrating the system's efficiency.

Figure 8 - Network deployment, strap approved **Figure 9 -** Deployed from the net, failed strap

Source: Author (2024).

IV. Conclusion

The research demonstrated that the application of artificial intelligence, especially deep learning, is an effective and viable solution for automating the inspection of safety straps in industrial environments. The proposed system, based on computer vision, proved to be highly accurate in identifying splices, overcoming the limitations of manual inspection, which is often hampered by the similarity of colors between splices and straps.

The implementation of the MobileNet architecture, combined with transfer learning and fine-tuning techniques, enabled the development of a lightweight and efficient model, in line with the project's needs. Validated in a controlled environment with real samples of safety straps with and without splices, the system achieved a high hit rate, proving its effectiveness and potential for integration into production lines. This automation promises to increase process reliability and reduce waste.

The results obtained highlight the importance of integrating hardware and software components, such as high-resolution industrial cameras, lenses adjusted to the project specifications, and optimized algorithms developed in Python with TensorFlow. In addition, the use of high-performance GPUs, such as the NVIDIA RTX2070, ensured agility in both the training and execution of the model.

The study reaffirms the role of artificial intelligence in Industry 4.0, demonstrating its potential to transform production processes and improve product quality. As future work, we suggest expanding the system to identify other types of defects and carrying out tests in real production conditions in order to validate its scalability and robustness on a large scale.

V. Acknowledgements

To the Postgraduate Program in Engineering, Process, Systems and Environmental Management of the Galileo Institute of Technology and Education of the Amazon (PPG.EGPSA/ITEGAM), and FPFtech for supporting the research project.

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