ISBN: 978-628-95207-8-1. ISSN: 2414-6390. Digital Object Identifier: 10.18687/LACCEI2024.1.1.1543

FOMO Model Based Logo Detection in Embroidery Process

Vanessa Iglesias, Eng.[1], Andrea Pilco, M.Sc.[1], Viviana Moya, PhD[1], and Faruk Abedrabbo, PhD[1]
[1] Faculty of Technical Sciences, International University of Ecuador UIDE, Quito 170411, Ecuador, vaiglesiasza@uide.edu.ec, anpilcoat@uide.edu.ec, vimoyago@uide.edu.ec, anabedrabboha@uide.edu.ec

Abstract*– This paper presents an innovative approach to improve the accuracy and efficiency of the embroidery process by integrating machine vision systems into traditional stitching machines. The problem of maintaining high accuracy in embroidery designs is a well-known challenge, commonly addressed through manual inspection and correction. In this paper, an artificial vision technique, implemented using the Faster Objects, More Objects (FOMO) learning algorithm, which allows machines to recognize patterns and improve accuracy, is proposed. The implementation was performed on the Edge Impulse platform and using the ESP32-CAM camera, successfully recognized and classified the images, achieving a 100% recognition rate for the "First Corporal" logo, 92.3% for the "Second Corporal" logo, and 96.2% for the "Sergeant" logo. The proposed solution has significant implications for the embroidery industry, offering a more accurate and efficient alternative to traditional methods.

Keywords*-- Logo detection, FOMO, MobileNetv2, Embroidery process.

I. INTRODUCTION

Sewing is an activity that has had a significant economic and cultural impact on humanity. Clothing represents the identity of many cultures and regions, and its constant innovation allows us to bring this knowledge to modern times. The textile industry is vital to the economy of countries like India [1] and China [2]. Indian embroidery reflects the country's cultural traditions and showcases the specialized artistry of artisans who create intricate designs with a deep understanding of colors and patterns [1]. To carry out the clothing manufacturing process, it is essential to investigate the types of embroidery. Therefore, some researchers analyze different embroidery patterns and classify them by computer. They use this tool to emphasize the importance of integrating computer embroidery skills to showcase the charm of traditional Chinese culture globally [2].

Textile mechatronics [3], as a specialized application of mechatronics engineering, is an interdisciplinary field of textile engineering that focuses on integrating mechanical systems with other fields, such as electronics and electrical engineering. It involves a combination of mechatronics, robotics [4], computer science, telecommunications, systems control, and product engineering [5]. Many machines fall under this category, including Jacquard, printing, embroidery, knitting, and lace & passementerie stripes.

Sewing machines have been updated with new tools that incorporate artificial intelligence algorithms. This technology improves efficiency and allows for low-cost embroidery [6]. By using AI-based visual inspection systems, it is possible to detect defects with more accuracy and eliminate human limitations such as exhaustion. The fashion industry has seen successful applications of artificial neural networks in predicting changes in garment sizes. These advancements have led to improved productivity and accuracy in decision-making processes such as production planning [7], cut-order planning [8], marker making, sewing automation, and defect inspection [9, 10].

Embroidery technology development seeks to improve efficiency and quality continuously. There are several applications of embroidery technology, such as intelligent garment prototypes, intelligent stitching, classification and detection of manual and computer-created embroidery, and fault detection, among others. An interesting application of embroidery technology is the integration of electronic components into clothes. Conductive threads and embroidery machines are being used to create prototypes for enuresis alarms in children's underwear, as explored in the study [11]. This technology allows improvements in tracking and safety, like parents who can now monitor their children's habits and activities and take proactive measures to address the issue.

Another significant development in embroidery technology is the Needlepaint system presented in [12]. This system integrates image processing, artificial intelligence, and advanced software techniques to enhance the efficiency and quality of embroidery punching. It consists of various modules such as the Contour Processing Module, Stitch Organizing Module, Stitch Optimizing Module, and Data Transforming Module, along with supporting modules for user interface and system management. The system streamlines the embroidery process, making it faster and more efficient, while also improving the quality of the final product. In Ref. [13], focus on the use of augmented reality in embroidery technology. The study involves designing test embroidered images, creating a fabric quilt with embroidered marker images, and developing an augmented reality application to detect and recognize these markers. The research shows that the response time of the augmented reality application is influenced by the brightness levels and contrast levels of the thread colors used in the embroidery markers. This technology opens up new possibilities for designers to create interactive and immersive embroidered designs, bringing a whole new dimension to the art of embroidery.

The use of AI in the embroidery industry has been a topic of research in recent years. One such study [14] aimed to develop an automated system to differentiate between

Digital Object Identifier: (only for full papers, inserted by LACCEI).
ISSN, ISBN: (to be inserted by LACCEI).
DO NOT REMOVE

handmade and machine-made embroidery patterns commonly used in African cultures. The system achieved high accuracy in classifying the patterns, providing a reliable tool for embroiderers and users to accurately identify the type of embroidery. Another study [15] focused on developing a system that uses advanced color similarity measurement methods and image entropy theory to automatically identify and extract repetitive patterns in machine embroidery images. These AI-powered systems aim to enhance the accuracy and efficiency of pattern recognition in embroidery designs.

Moreover, AI is not only limited to the embroidery process but also extends to the creation of embroidery designs. In Ref. [16], the researcher aimed to automate the process of creating embroidery designs from regular images, enhancing the efficiency and flexibility of garment design and online display. Similarly, in [17], the Clothing-STGAN model was developed for innovative clothing design, integrating traditional Chinese artistry. The model generates clothing designs that combine historical aesthetics with modern trends, highlighting the impact of AI on creative processes and emphasizing the importance of preserving traditional culture in technological advancements. These studies demonstrate the potential of AI to improve the embroidery industry by making it more efficient and accurate and preserving traditional culture.

In recent years, there has been a growing interest in the use of deep learning and Convolutional Neural Networks (CNN) in the field of embroidery art rendering. In [18], a novel method was proposed that utilized a CNN model to replicate embroidery style as a needle stroke generation problem. This method involved the use of semantic segmentation, color space transfer, and style transfer for transferring embroidery features to content images, resulting in high-quality embroidered images that were like real embroidery images. Similarly, in [19], the focus was on simulating traditional embroidery art using advanced rendering techniques. The study developed 3D embroidery modeling for non-photorealistic rendering (NPR), allowing the application of classic graphical lighting models like the Phong lighting model to embroidery rendering. Additionally, the study also introduced a method that combined stroke-based rendering techniques with the Phong lighting model to create picturesque embroidery-like images with realistic lighting and shading effects. Furthermore, in [20], the emphasis was on enhancing the efficiency and quality of embroidered production through the integration of image processing and AI technologies. By converting traditional sewing machines into computerized embroidery machines, the study aimed to automate the embroidery process and broaden the range of needlework available. This was achieved through the conversion of an old sewing machine into an embroidery machine using hardware components like a 2dplotter, stepper motor, stepper driver, controller, CNC shield, and power supply. The input files were transformed into SVG vector images and machine-readable files compatible with Gcode.

The paper presents a novel approach to using machine learning in the embroidery process. The focus of this paper consists of using a camera and a machine learning algorithm to detect logos and initiate the embroidery process through a sewing machine. When the logo is positioned in front of the camera, the system immediately detects it using the Faster Objects, More Objects (FOMO) model, identifying logos such as "First Corporal," "Second Corporal," and "Sergeant." A computer is also an integral part of the system, storing the G-code associated with each logo. Upon receiving the information, the controller promptly opens the specific code, which is then interpreted by Grbl Controller 3.6.1 software to send signals to motors via Arduino, initiating the embroidery process based on the detected logo.

This article showcases the application of the FOMO model to improve the vision of the embroidery process, leading to time optimization and error prevention. The specific contributions of the research include:

1) Implementation of the detection of "First Corporal," "Second Corporal," and "Sergeant."

2) Achieving an impressive 94.5% accuracy, precision of 92%, and recall of 94% through the model's training, enabling efficient embroidery of the corresponding logos. The system is adaptable for use in any embroidery process with various logos.

This work is organized into several sections to explore the application comprehensively. In Section II, the mechanical and electronic components of the embroidery process are systematically designed. Following this, Section III provides a detailed overview of the artificial intelligent architecture employed in the study. The subsequent section, Section IV, offers an analysis of the results obtained from the FOMO model, showcasing metrics such as accuracy, precision, and recall. Additionally, this section examines the time taken for embroidery for each logo utilizing the provided dataset. Finally, the conclusions are presented in Section V.

II. DESIGN

This initiative seamlessly integrates electronic and mechanical components to establish a cohesive system.

A. *Mechanical Design*

As depicted in Fig. 1, the illustration underscores the smooth integration of mechanical elements into the hardware, resulting in a specialized sewing machine designed for image classification through computer vision.

The overall prototype measures 70x20x50 cm and incorporates aluminium V-Slot profiles and various PETG-printed pieces serving as couplings. The utilized embroidery machine is the HY-203 model, offering the flexibility of straight or zigzag stitches. It is compact and portable and accommodates various fabric types, including cotton, linen, and polyester.

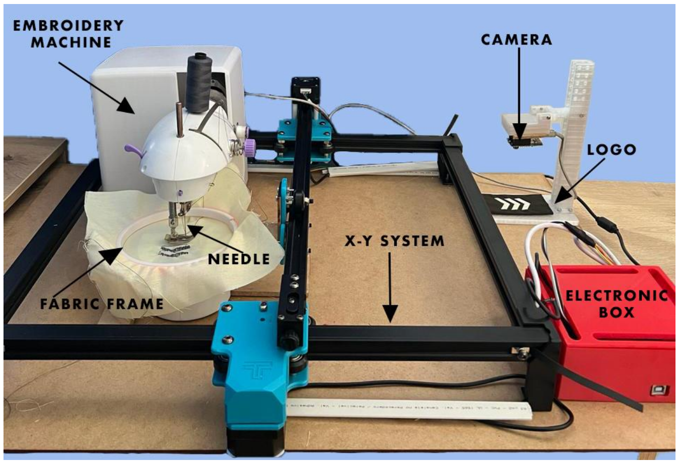

Fig. 1. Hardware components used in the embroidery machine.

B. Electronic Design

At its core, the system features an Arduino with the Microchip ATmega328P, utilizing an 8-bit AVR core as the primary controller. This microcomputer governs all machine operations, managing the program responsible for the movement of Nema 17 stepper motors that control the displacement of the XYZ axes. Additionally, the Arduino oversees the ESP32 camera, as depicted in Fig. 2.

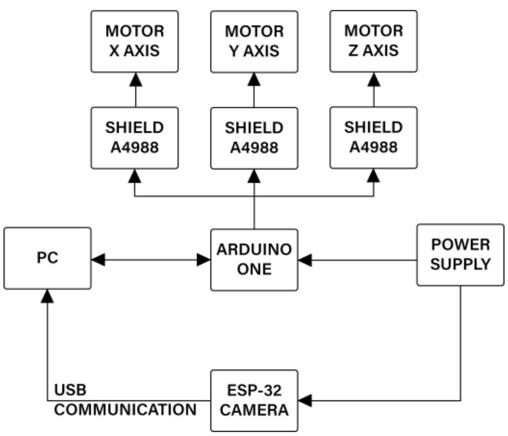

Fig. 2. Electronic configuration of embroidery process.

III. Artificial Intelligence

The forthcoming sections will provide a more detailed exposition of the proposed real-time logo detection system methodology.

A. Faster Objects, More Objects - FOMO

The model used for distinguishing three types of logos is FOMO, which is a novel machine learning algorithm that brings object detection to highly constrained devices, FOMO is characterized by its fully convolutional nature, which simplifies the configuration process, mainly requiring the establishment of the appropriate proportions [21].

The learning algorithm is from the Edge Impulse platform; this algorithm was used for its several advantages: it has a light memory, the execution speed is fast, allows to count objects, find the location of objects in an image, and track multiple objects in real-time using up to 30 times less processing power and memory than YOLOv5 [22].

FOMO model utilizes centroids to signify the position and quantity of objects within each class [23]. This adjustment streamlines the object detection process, rendering the model versatile for a broad spectrum of applications where object size is less critical than their spatial arrangement within the image.

The Edge Impulse platform [24] was utilized to enhance the performance and functionality of the FOMO model. The platform provided a comprehensive set of features, including data acquisition, labeling, data segregation, training, performance evaluation, and model compilation for deployment. Refer to Fig. 3 for an illustration of the methodology.

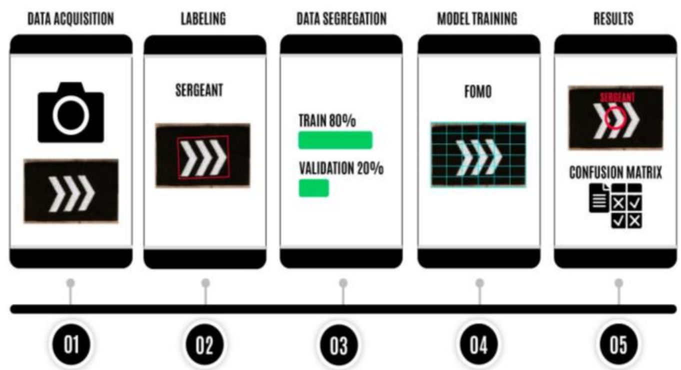

Fig. 3. Flow diagram for the logo detection utilizing FOMO.

B. Technical Specifications

In this study, a proprietary dataset was utilized, corresponding to the military ranks of non-commissioned officers in Quito, Ecuador. The dataset included designations such as "First Corporal," "Second Corporal," and "Sergeant."

1) The own dataset collected for this application has 900 images, 300 for each shape.

2) The images of the dataset have a size 96 x 96 pixels, data required by FOMO to be able to train its network.

3) The dataset images are taken from different positions and distances trying to resemble the view of the robot when focusing on these elements with a 720p WebCam.

4) 80% of the dataset is taken for training, while the remaining 20% is taken for validation.

5) All of the dataset was labeled with Edge Impulse software before training the FOMO.

6) This model's real-time application occurs when the user positions the logo in front of the camera. The system then identifies the corresponding class, triggering a signal to initiate the process on the sewing machine.

Fig. 4 showcases the labeled training images for the "First Corporal" category, as well as for the "Second Corporal" and "Sergeant" classes, respectively.

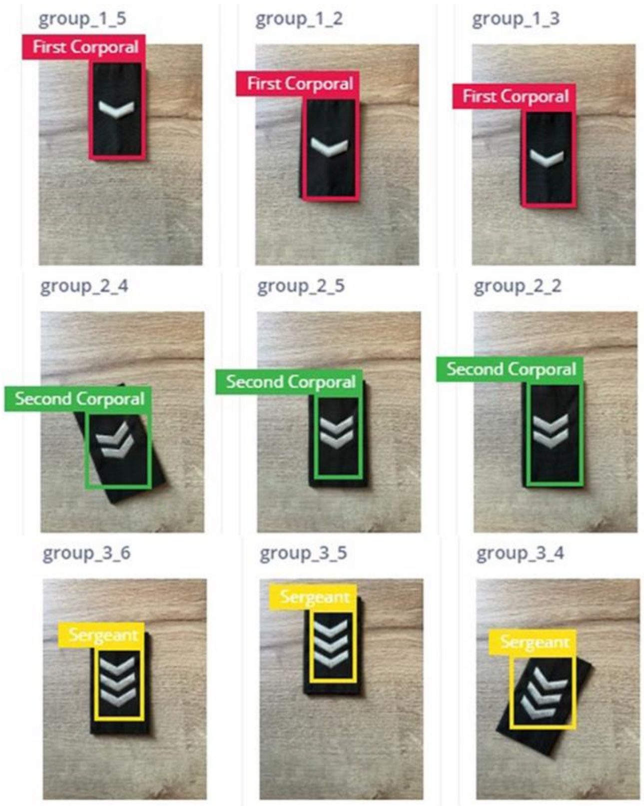

Fig. 4. Labeled dataset for classes "First Corporal," "Second Corporal," and "Sergeant."

C. *Model training*

FOMO has been applied to image classification for three classes corresponding to non-commissioned military ranks. It utilizes convolutional layers to progressively reduce the resolution of the input image, thereby reducing detail but still preserving a degree of locality, it introduces a class-by-region probability map. This modification helps maintain locality within the resulting heat map, visualizing the location of the logos at various resolutions determined by the point at which the network is truncated and thus defining the centroid.

After the data was prepared and segmented, the next step on the Edge Impulse platform involved configuring the FOMO algorithm as follows:

1) Accessing FOMO Settings: Navigate to the machine learning section and select FOMO as the model type.

2) Adjusting the Ratio: Set the reduction ratio that FOMO would apply to the images. A 1:2 ratio was selected; each step reduced the resolution of the image by half.

3) Configuring Additional Parameters: The parameters for training the FOMO model were the ones shown in Table I.

4) Model Training: Proceeded to train the model.

5)Validation: The model's performance was validated using the test dataset.

TABLE I
TRAINING PARAMETERS.

Batch Size	32
Learning Rate	0.001
Epochs	60
Number of classes	3

Once the model hyperparameters were defined, including a batch size of 32, 60 epochs, and a learning rate of 0.001, the training process was initiated. Following the configuration, the dataset was partitioned into two subsets: an 80% training set, comprising images with each label, and a 20% validation set.

IV. EXPERIMENTS AND RESULTS

The system incorporates a computer-based interface that shows the message "waiting for an image" until the logo is positioned in front of the camera, acting as the system's input. The distance between the logo and the camera is set at 10 cm. Following this, the FOMO model is applied using the Edge Impulse platform to detect the logo.

Following the successful completion of logo recognition, essential information is transmitted to the computer through the USB connection from ESP32. Preceding this, the computer stores three distinct codes for each logo. When the recognized image aligns with a particular G code, the interface seamlessly triggers the automatic opening of the corresponding file. This streamlined process not only eradicates potential confusion concerning file names but also guarantees precision in the chosen embroidery design. The G-code is formatted in .txt, encompassing crucial parameters such as dimensions and displacements along the x, y and z axes, which were previously stored for reference.

Additionally, the Grbl Controller software is utilized, specifically designed to transmit G code commands to the controller.

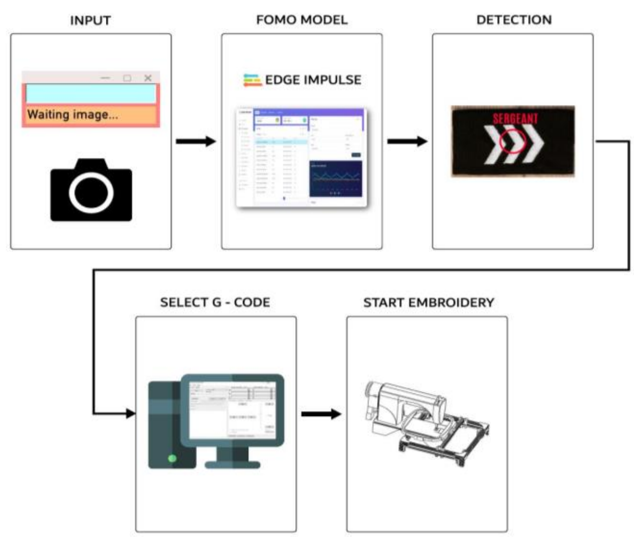

Fig. 5. Testing procedure for the logo detection in embroidery process.

This software plays a pivotal role in receiving and processing the G code information corresponding to the logo.

In essence, the Grbl software interprets the code for the Arduino, initiating motor movements in accordance with the interpreted commands. The testing procedure is illustrated in Fig. 5.

The testing environment utilized a computer with an Intel Core i7-7700HQ processor and an NVIDIA GeForce GTX 1050 Ti boasting 4GB of dedicated graphics memory and 16GB of RAM. The tests conducted were focused on both, logo recognition using the FOMO model and the subsequent embroidery process.

A. Logo Recognition with FOMO

The confusion matrix played a vital role in evaluating the performance of the classification model, providing a detailed view of the correct classification of classes and the extent to which it occurred. This particular confusion matrix was obtained from the Edge Impulse platform.

In Table II, the confusion matrix provided valuable insights into the model's performance, particularly regarding true positives and predicted positives. The results indicated a 100% recognition rate for the "First Corporal" logo, 92.3% for the "Second Corporal" logo, and 96.2% for the "Sergeant" logo. Additionally, there was a 7.7% confusion rate with the background for the "Second Corporal " logo, while the "Sergeant" logo exhibited a 3.8% confusion rate with the background. Upon completing the network training, the subsequent results were obtained, as depicted in Table III.

TABLE II
CONFUSION MATRIX GENERATED BY EDGE IMPULSE.

	Background	First Corporal	Second Corporal	Sergeant
Background	99.9%	0%	0%	0.1%
First Corporal	0%	100%	0%	0%
Second Corporal	7.7%	0%	92.3%	0%
Sergeant	3.8%	0%	0%	96.2%

TABLE III
FOMO MODEL METRICS.

	Accuracy	Precision	Recall	Loss
Value	94.5%	92%	94%	0.1024

B. Embroidery Process

The experimentation included testing cotton fabric using the 94-14 machine needle. This choice was influenced by the 200x190x100 mm dimensions of the sewing machine, and the selection of fabric and needle type was based on the machine's limitations, as it does not support heavy usage. The distance between the needle and the fabric varied, and the time was taken from when the image was recognized until the embroidery process was finished. A total of 10 tests were done for each of the 3 logos. In this way, the system was tested 30 times in different scenarios to validate its robustness and the viability of the results.

The initial logo, identified as the "First Corporal" logo, exhibits an average embroidery time of 6 min, as per Table IV. The optimal distance from the needle to the fabric is 0.54 cm.

TABLE IV
EMBROIDERY DURATION FOR THE "FIRST CORPORAL" LOGO.

N°. Test	Type Fabric	Time (min)	Distance (cm)
1	Cotton	7	0.90
2	Cotton	7	0.80
3	Cotton	7	0.70
4	Cotton	6	0.65
5	Cotton	6	0.60
6	Cotton	6	0.50
7	Cotton	6	0.40
8	Cotton	5	0.35
9	Cotton	5	0.30
10	Cotton	5	0.20
Average		6	0.54

The second logo corresponds to the "Second Corporal" logo, as depicted in Table V. The average embroidery time for this logo is 9 min, and the optimal distance from the needle to the fabric is measured at 0.54 cm.

TABLE V
EMBROIDERY DURATION FOR THE "SECOND CORPORAL" LOGO.

N°. Test	Type Fabric	Time (min)	Distance (cm)
1	Cotton	12	0.90
2	Cotton	12	0.80
3	Cotton	12	0.70
4	Cotton	9	0.65
5	Cotton	9	0.60
6	Cotton	9	0.50
7	Cotton	8	0.40
8	Cotton	7	0.35
9	Cotton	7	0.30
10	Cotton	6	0.20
Average		9	0.54

The third logo corresponds to the "Sergeant" logo, as indicated in Table VI. The average embroidery time for this logo is 14 min, with the needle-to-fabric distance set at 0.54 cm.

TABLE VI
EMBROIDERY DURATION FOR THE "SERGEANT" LOGO.

N°. Test	Type Fabric	Time (min)	Distance (cm)
1	Cotton	17	0.90
2	Cotton	17	0.80
3	Cotton	15	0.70
4	Cotton	15	0.65
5	Cotton	13	0.60
6	Cotton	13	0.50
7	Cotton	11	0.40
8	Cotton	9	0.35
9	Cotton	9	0.30
10	Cotton	9	0.20
Average		14	0.54

Fig. 6. Embroidered logos representing the three classes: "First Corporal," "Second Corporal," and "Sergeant."

In Fig. 6, the final result of the embroidery is observed. The image placed in front of the camera for recognition and the expected generated embroidery are depicted. The finished product exhibits a commendable quality, with stitches falling within an acceptable range. Each embroidered logo corresponds accurately to the photograph captured by the camera.

As seen in the results of this study, the system can detect the desired logo with good precision to carry out the embroidery process. Despite using a home embroidery machine (not industrial) with certain mechanical limitations, the operating times are good, and the results obtained in the embroidery are accurate. However, it was not possible to compare the system presented in this work with the production of industrial embroidery since the mechanical variations and production levels are not comparable.

V. Conclusions

In summary, the research delved into the utilization of the FOMO model for logo detection in embroidery applications. The model exhibited a commendable performance of 94.5%, showcasing its effectiveness in accurately recognizing the three required classes without any issues.

Tests were conducted using cotton fabric and the 94-14 needle. The optimal average times for embroidering logo1 ("First Corporal"), logo2 ("Second Corporal"), and logo3 ("Sergeant") were found to be 6 min, 9 min, and 14 min, respectively, considering a thread tension distance of 0.5 cm. The entire processing model was executed on the ESP-32, chosen as the optimal controller for the task due to its efficiency in handling the model, which is comparatively lightweight compared to other detection algorithms.

The results achieved in detecting and replicating military logos provide a solution to improve productivity metrics inside the embroidery process. The assistance of Computer Vision models based on AI provides a way to increase the quality of the final product by automating the process using motorized autonomous sewing machines that will repeat a design many times without alterations or errors, without being subject to the regular unrest that a human sewer endures after repeating the same pattern a certain number of times. Also, the AI model presented allows for the reduction of human interaction and, therefore, human errors in the process, decreasing the number of wasted materials and the need for human operators to identify a logo and then send the respective commands to the machine. This kind of labor generates discomfort for the human operators. It could be used in other parts of the embroidery process, like quality control, improvement of prime materials, maintenance, and error corrections. Overall, the solution provided by this work can improve production times, resource management, and economic savings.

Further developments in the topic presented here may include more complex designs for the recognition system, allowing it to execute more complex patterns while improving execution time. Another future work derived from this paper could propose alterations to the FOMO algorithm to improve the detection time for a more significant number of designs, presenting a model that not only can detect more symbols but also provide assistance in optimizing the generation of the necessary G Code, in order to make it more efficient and sew the desired pattern using less materials in less time. Additionally, adapting the AI proposed system to an industrial embroidery machine will help to develop a more robust comparison of the process with commercial embroidery systems. Finally, the prototype proposed here can be improved by a higher budget that allows better motors, with smaller steps and, therefore, higher resolution in the design. Also, an overall improvement of the mechatronic design could be proposed to decrease execution times and reproduce symbols at bigger sizes.

References

[1] Guru, Ramratan et al., “A, Embroideries of India Design methods and embroidery processes,” *Asian Textile Journal*, 32 (10): pp. 56-62, 2023.

[2] Zugang Su and Xiaohong Ouyang, "Research on the Application of Computer Embroidery Skills in Modern Chinese Fashion Design," *in Journal of Physics: Conference Series*, vol. 1992, no. 3, pp. 032004, 2021.

[3] Smith, G., “Generative Design for Textiles: Opportunities and Challenges for Entertainment AI,” *Artificial Intelligence and Interactive Digital Entertainment Conference*, 2021, Doi: 10.1609/aiide.v13i1.12925.

[4] Chen, L., Su, Z., He, X., Chen, X. and Dong, L., "The application of robotics and artificial intelligence in embroidery: challenges and benefits", *Assembly Automation*, Vol. 42, No. 6, pp. 851-868, 2022, Doi: https://doi.org/10.1108/AA-07-2022-0183.

[5] Elsayed Ahmed Elnashar, “Applications of Mechatronics Opportunities in Textiles,” *Trends Textile Eng Fashion Technol* TTEFT, 6(3), 000640, 2022, Doi: 10.31031/TTEFT.2022.06.000640.

[6] Abd Jelil, R., “Review of Artificial Intelligence Applications in Garment Manufacturing,” *In: Thomassey, S., Zeng, X. (eds) Artificial Intelligence for Fashion Industry in the Big Data Era*. *Springer Series in Fashion Business*, 2018, Doi: https://doi.org/10.1007/978-981-13-0080-6_6.

[7] Wong WK, Guo Z, and Leung S., “Intelligent multi-objective decision-making model with RFID technology for production planning,” *International Journal of Production Economics*, 147 (Part C), pp. 647–658, 2014, Doi: https://doi.org/10.1016/j.ijpe.2013.05.011.

[8] Xu, Y., Thomassey, S., and Zeng, X., “AI for Apparel Manufacturing in Big Data Era: A Focus on Cutting and Sewing,” *In: Thomassey, S., Zeng, X. (eds) Artificial Intelligence for Fashion Industry in the Big Data Era*. *Springer Series in Fashion Business*, 2018, Doi: https://doi.org/10.1007/978-981-13-0080-6_7.

[9] H.Kulkarni, Anand, “Automated Garment identification and defect detection model based on Texture Features and PNN*,” International Journal of Lastest Trends in Engineering and Technology*, 2012, https://api.semanticscholar.org/CorpusID:201924164.

[10] Somayeh Shahrabadi, et al., "Defect detection in the textile industry using image-based machine learning methods: a brief review," *Journal of Physics: Conference Series*, vol. 2224, no. 1, pp. 012010, 2022. Doi: 10.1088/1742-6596/2224/1/012010.

[11] Ugis Briedis, Aleksandrs Valisevskis, and Marianna Grecka, “Development of a Smart Garment Prototype with Enuresis Alarm Using an Embroidery-machine-based Technique for the Integration of Electronic Components,” *Procedia Computer Science*, Volume 104, pp. 369-374, 2017, Doi: https://doi.org/10.1016/j.procs.2017.01.147.

[12] Shifu Chen and Bin Hu, "A new generation of intelligent punching environment for computerized embroidery," *Proceedings Sixth International Conference on Tools with Artificial Intelligence*. TAI 94, New Orleans, LA, USA, pp. 692-695, 1994 Doi: 10.1109/TAI.1994.346424.

[13] Pathak A., Mills I., and Cleary F., "Image Detection and Responsivity Analysis of Embroidered Fabric Markers Using Augmented Reality Technology" *Engineering Proceedings 15*, no.1: 12, 2022, Doi: https://doi.org/10.3390/engproc2022015012.

[14] Jimoh, K.O. et al., “Automated classification of African embroidery patterns using cellular learning automata and support Vector Machines,” *Ghana Journal of Science*, 62(2), pp. 91–101, 2022, Doi:10.4314/gjs.v62i2.9.

[15] Kuo C-FJ. et al., “Automatic machine embroidery image color analysis system, part II: Application of the genetic algorithm in search of a repetitive pattern image,” *Textile Research Journal*, 82(11), pp 1099-1106, 2012, Doi:10.1177/0040517512438130.

[16] Guan, X. et al., “Automatic embroidery texture synthesis for garment design and online display,” *The Visual Computer 37*, pp 2553–2565, 2021, Doi: https://doi.org/10.1007/s00371-021-02216-0.

[17] Qiang Wu, et al. “ClothGAN: generation of fashionable Dunhuang clothes using generative adversarial networks,” *Connection Science*, 33:2, pp. 341-358, 2021, Doi: 10.1080/09540091.2020.1822780.

[18] Qian, W. et al., "CNN-Based Embroidery Style Rendering," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 34, no. 14, 2020, Doi: https://doi.org/10.1142/S0218001420590454.

[19] Cui, D., Sheng, Y., and Zhang, G., “Image-based embroidery modeling and rendering,” *Computer Animation and Virtual Worlds*, 28: e1725, 2017, Doi: 10.1002/cav.1725.

[20] Shariq, Aisha et al., “Image Processing Based Pattern Recognition and Computerized Embroidery Machine,” *Pakistan Journal of Engineering and Technology*, vol 5, pp 68-74, 2022, Doi: https://doi.org/10.51846/vol5iss4pp68-74.

[21] C. Nicolas, B. Naila and R. -C. Amar, "TinyML Smart Sensor for Energy Saving in Internet of Things Precision Agriculture platform," *Thirteenth International Conference on Ubiquitous and Future Networks (ICUFN)*, Barcelona, Spain, pp. 256-259, 2022, Doi: 10.1109/ICUFN55119.2022.9829675.

[22] Picó M., Jorge J., and Micó-Vicent, B., “Práctica de Aprendizaje Profundo en la Asignatura de Tecnología para Sistemas Inteligentes,” *VIII Congreso I+D+i Campus de Alcoi. Creando sinergias: Libro de resúmenes*, Alcoy, Spain, pp. 29-32, 2021.

[23] Da Silva, J. et al., "TinyML-Based Pothole Detection: A Comparative Analysis of YOLO and FOMO Model Performance," *2023 IEEE Latin American Conference on Computational Intelligence (LA-CCI)*, Recife-Pe, Brazil, pp. 1-6, 2023, Doi: 10.1109/LA-CCI58595.2023.10409357.

[24] Edge Impulse, ”Edge Impulse: The leading development platform for machine learning on edge devices,” 2023. [Online]. Available at: https://www.edgeimpulse.com/. [Accessed: January , 2024].