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Research Article

Iot System and Convolutional Neural Networks for Anomaly Detection in Fabric Dyeing Machines in A Textile Company.

Ulises Román-Concha[1], Antonio Meléndez[2], Juan Carlos Lazaro[3], Pablo Romero[1], Luzmila Pro[1], Ronald Melgarejo[1], Augusto Cortez[1], Luis Ponce[4], María Elena Ruiz[1]
nromanc@unmsm.edu.pe 12200022@unmsm.edu.pe jlazarog@unia.edu.pe promeron@unmsm.edu.pe lproc@unmsm.edu.pe ronald.melgarejo@unmsm.edu.pe acortezv@unmsm.edu.pe lponcem@unmsm.edu.pe mruizr@unmsm.edu.pe
(1) Professors of the Faculty of Systems and Computer Engineering, UNMSM, Lima-Peru
(2) Graduate of the Faculty of Systems and Computer Engineering, UNMSM, Lima-Peru.
(3) Professor of the Faculty of Engineering and Environmental Sciences, UNIA, Lima-Perú.
(4) Professor of the Faculty of of electronic engineering, UNMSM, Lima-Perú.

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ABSTRACT

In the process of fabric dyeing in textile companies, several problems can occur, mostly due to a kinking in the fabric ropes, which stop and originate losses such as degradé or veteaduras in production. The objective of this article was to develop an IoT system and convolutional neural networks (CNN) for the detection of anomalies in fabric dyeing machines in a textile company. Since traditionally the dyeing machines have a magnet, which takes approximately 2.5 minutes to give a complete rotation. SCRUM methodology was used for the development of the project and supervised learning algorithms were used to detect anomalies in the machines.

As a result, it was decided to place an IP camera in the hatch of each rope and with a supervised algorithm based on convolutional neural networks, an accuracy of 85% was obtained in detecting if there is a rope in "stop or in motion" sending alerts in 2 seconds maximum to the operators through smartwatches connected to the local network via WIFI.

Keywords: Failure detection, CNN, IoT, fabric dyeing, shrinkage, SCRUM

1. INTRODUCCIÓN

The Peruvian market seeks to expand its participation in the global market by applying Industry 4.0 to improve processes and reduce costs. Under this concept of cost reduction, we have a comparative of wastes and a substantial annual increase in the fabric dyeing sector. Performing a Pareto, it is noted that the main increases are due to color problems, such as cracking and degradation, as well as reproducibility problems from the laboratory to the plant. This reveals that there could be potential problems in the fabric dyeing machines, which have an interconnected system that allows the automatic sending of production batches and their parameters to work, but it does not have an efficient alarm system to detect failures, nor does it have a repository where we can observe the exact moment in which the failure occurs.

These machines have a system of alarms for different alerts, such as calls to the operator to load or unload the machine, pour chemicals, etc. But its weak point is that it does not have instantaneous failure detection alarms, so it may take some time to be alerted of some problems; mentioning some examples we have the stopped rope alarm, which is an alarm of the presence of a magnet, which is placed at the beginning of the rope and takes 2.5 minutes to rotate completely, or also to know that there is too much foam in the process, the operator has to be attentive looking through the hatch to see that the foam is above normal levels.

For the above mentioned, we looked for a way to have a real time control of what is happening inside the machine, using the technology that exists today, placing an IP camera in the hatches of each rope that records in real time to visualize what is happening at all times. Then, a program was implemented, using the Python language that allowed access to the frames of these cameras and thus be able to train a Convolutional Neural Network model that detects whether the rope is moving normally or is stopped for some reason. After having an accuracy of more than 85%, we proceeded to take it to production, sending alerts of stops in 2 seconds maximum to the operators through smartwatches connected to the local network via Wifi.

This project involves IoT technologies, convolutional neural networks and artificial vision; and to achieve the proper control of the project, agile methodologies were used as a basis for the possible constant feedback that all iterations would demand.

2. RELATED WORKS

Internet of Things (IoT)

The authors [5] mention that the Internet of Things (Internet of Things) is a type of technology that gives us the possibility of establishing intercommunication between electronic devices and that it is becoming increasingly common to incorporate this technology in our daily lives, so that industry can also take this technology to improve their processes.

The authors [1] show us the uses given to the Internet of Things for industrial use, categorizing the papers collected and the most relevant to the research are:

- Applications for anomaly detection with time series: Where it is sought to have real-time data through sensors and LSTM neural networks for anomaly detection, being able to reduce up to 71% of defect detection speed while maintaining accuracy.
- Monitor machine health: The use of IoT sensors that are added to industrial machinery to detect machine problems.
- Sensing applications for IoT sensors: The use of monitoring systems to detect changes in sensor signals caused by unexpected events in the environment.

On the other hand, the author [2] indicates that IoT technologies bring us great benefits such as improving innovation, converting data into information and into ideas and actions, increasing security and scaling differentiated solutions.

The authors [7] show us their investigation of a large-scale manufacturing company, located in Saudi Arabia, which has several types of failures in its machinery that cause loss of productivity and production. These failures are related to mechanical components, which can fail in various parts of the production process and therefore, a research group was created to analyze the data of the manufacturing processes, as well as their failures in order to improve these values. Using real- time data from production reports, as well as interviews with employees, along with statistical analysis, allowed them to conclude that electrical failures are the main cause of failure and that the relationship between the production line and the cause of failure is highly correlated, especially electrical failure with production line 2. This study concludes that the manufacturing industry should focus on future maintenance and eliminating the causes of failure by developing a predictive control system instead of a preventive system.

Convolutional Neural Networks (CNN)

The authors [4], show us the use of CNN networks, creating a system to recognize sign language, using the American system to create the datasets. The identification could be done in 2 ways, the first being a glove that the person wears, which is able to detect hand movements (which was not chosen because it was uncomfortable and could not be used on rainy days), and the second, a method based on computer vision, which recognized the movement. The study concludes that low computational power can be used and 98% accuracy can be obtained using CNN algorithms, rescaling the images to 64 pixels in order to extract pixel values and make the system more robust.

Machine vision

The author [3] tells us that Computer Vision is a field of Artificial Intelligence that uses tools such as Machine Learning and Neural Networks to train systems using digital images or videos, and subsequently make some suggestion based on the results obtained.

The author [6] has developed a housing monitoring system in Guatemala City using IP cameras and convolutional neural networks, demonstrating that this type of technology achieves efficient process optimization.

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3. METHODOLOGY

This article was developed following a standard Agile Methodology (Scrum) for project management, having a variant of the Scrum methodology, adapted to the needs of companies in the textile sector. It was implemented in 5 sprints, which are mentioned below:

- **Sprint 1:** Problem analysis and solution approach: A study of the scope of the problem to be solved was carried out, as well as the best way to solve it, consulting the best sensors to use, compatibility in the work area and the choice of the AI model to use, as well as the computational capacity required for the execution of this model.

Figure 1. *Camera installed on a fabric dyeing machine*

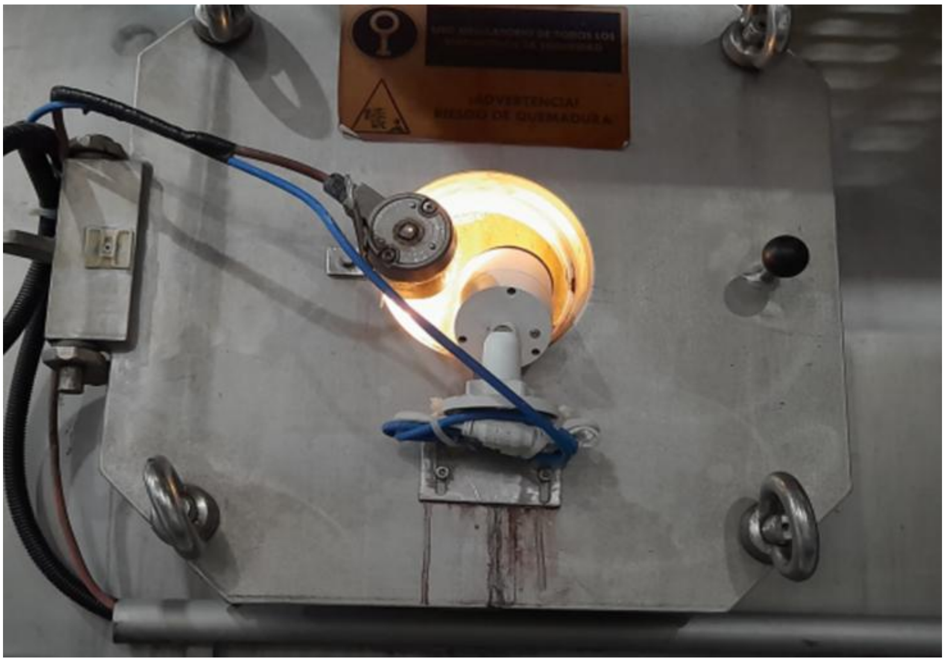

Table 1.

Characteristics of the chosen camera

Feature	Value
Brand	Hikvision
Model	DS-2CD2083G0-1
Firmware version	V5.6.2 build 190701
Coding version	V7.3 build 190626
Web version	V4.0.1 build 190506
Add-on version	V3.0.7.16
Number of channels	1
Number of HDDs	0
Alarm output number	0

- **Sprint 2**: Model preparation: The cameras were quoted and installed to the machines, as well as the local connection of these in an independent VLAN so as not to affect the network performance of the other areas. On the programming side, the algorithm that allowed the connection to the cameras was implemented and the model was trained with videos of the four states of the strings to be detected.

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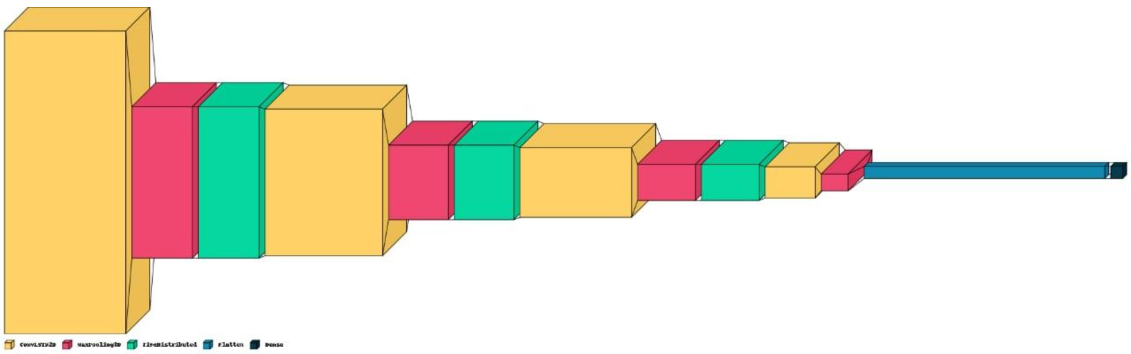
Figure 2. *States detected by the model*

Note. Detection of the camera status by the model (CNN) where 4 states are shown: in motion (normal work), pause (the fabric remains without movement), foam (there is no visualization due to the foam in the machine) and operator (opening to load and unload fabrics to the machine).

Table 2. *Neural network structure*

Layer	Type	Output size
conv_lstm2d	(ConvLSTM2D)	(None, 30, 126, 126, 126, 16)
max_pooling3d	(MaxPooling3D)	(None, 30, 63, 63, 63, 16)
time_distributed	(TimeDistributed)	(None, 30, 63, 63, 63, 16)
conv_lstm2d_1	(ConvLSTM2D)	(None, 30, 61, 61, 61, 32)
max_pooling3d_1	(MaxPooling3D)	(None, 30, 31, 31, 31, 32)
time_distributed_1	(TimeDistributed)	(None, 30, 31, 31, 31, 32)
conv_lstm2d_2	(ConvLSTM2D)	(None, 30, 29, 29, 29, 64)
max_pooling3d_2	(MaxPooling3D)	(None, 30, 15, 15, 15, 64)
time_distributed_2	(TimeDistributed)	(None, 30, 15, 15, 15, 64)
conv_lstm2d_3	(ConvLSTM2D)	(None, 30, 13, 13, 13, 128)
max_pooling3d_3	(MaxPooling3D)	(None, 30, 7, 7, 7, 128)
flatten	(Flatten)	(None, 188160)
dense	(Dense)	(None, 4)

Figure 3. *Graphical structure of the neural network*



Note: In the picture shown, the graphical structure of the neural network can be seen. The yellow color represents the ConvLSTM2D layer, the red color represents the MaxPooling3D layer, the green color represents the TimeDistributed layer, the blue color represents the Flatten layer and the gray color represents the Dense layer.

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Figure 4. *Python code of the neural network model*

```
def build_lstm_model():
  model = Sequential()
  model.add(ConvLSTM2D(filters=16, kernel_size=(3,3), activation='tanh',
            data_format="channels_last", recurrent_dropout=0.2,
            return_sequences=True, input_shape=(SEQUENCE_LENGTH, IMAGE_SIZE, IMAGE_SIZE, 1)))
  model.add(MaxPooling3D(pool_size=(1,2,2), padding='same', data_format='channels_last'))
  model.add(TimeDistributed(Dropout(0.2)))
  model.add(ConvLSTM2D(filters=32, kernel_size=(3,3), activation='tanh',
            data_format="channels_last", recurrent_dropout=0.2,
            return_sequences=True))
  model.add(MaxPooling3D(pool_size=(1,2,2), padding='same', data_format='channels_last'))
  model.add(TimeDistributed(Dropout(0.2)))
  model.add(ConvLSTM2D(filters=64, kernel_size=(3,3), activation='tanh',
            data_format="channels_last", recurrent_dropout=0.2,
            return_sequences=True))
  model.add(MaxPooling3D(pool_size=(1,2,2), padding='same', data_format='channels_last'))
  model.add(TimeDistributed(Dropout(0.2)))
  model.add(ConvLSTM2D(filters=128, kernel_size=(3,3), activation='tanh',
            data_format="channels_last", recurrent_dropout=0.2,
            return_sequences=True))
  model.add(MaxPooling3D(pool_size=(1,2,2), padding='same', data_format='channels_last'))
  model.add(Flatten())
  model.add(Dense(4, activation='softmax'))
  return model
```

- **Sprint 3**: Detection pilot test: The operator alert system was implemented through a Smartwatch and a group of machines operated by the same operator was chosen for the pilot test, while he provided feedback that the detection algorithm was working correctly and alerting in a timely manner.

Figure 5.

Alert of the states detected by the model

(a) (b) (c)

Note. (a) Alert to the operator with the status "Pause", (b) Alert to the operator with the status "Foam" and (c) Alert to the operator with the status "Operator" (Hatch open).º

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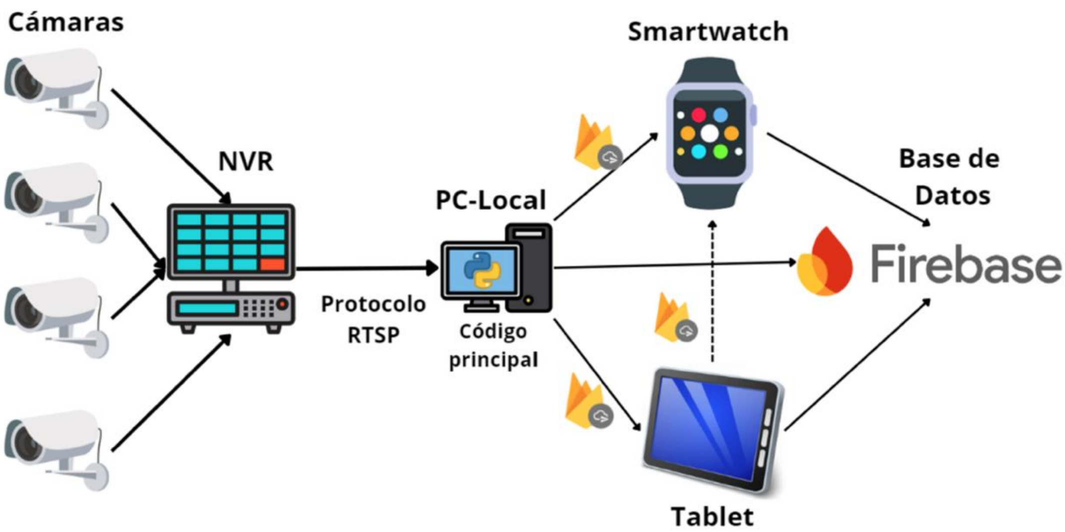
Figure 6. *Architecture used in the implementation of the project*

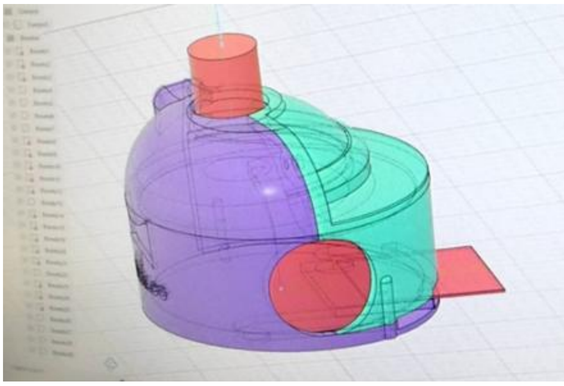


Note: The cameras capture images from the machines and are connected to an NVR, so that they can be accessed through the RTSP protocol from a PC. On the same PC, notifications are sent to the smartwatches and tablets through Firebase, which serves both as a notifier and as a database.

- **Sprint 4**: Implementation on all machines: The algorithm was implemented on all remaining machines, moving the execution from one developer's PC to another with a higher level of processing, as well as optimizing the algorithm initially proposed to reduce the computational cost.

- **Sprint 5:** Validation of the project's success: We constantly checked that the preventive and corrective maintenance performed on the machines were not affected by the cameras installed, optimizing the supports with new ones made with a 3D printer and that the metrics obtained did not decrease. We also controlled the shrinkage metrics and the correlation with the use of the system.

Figure 7. *3D design of the camera attachment piece*



Note. IP camera protector and holder (3D printing of parts) material used was ePLA + HS.

4. RESULTS AND DISCUSIÓN

Implementation Results

- A system was implemented using the Internet of Things, composed of IP cameras installed in the fabric dyeing machines, a convolutional neural network model and smart watches distributed to the operators. All data were collected and sent to a PC to be processed in real time.

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- Regarding the accuracy of the convolutional neural network, it was trained using historical videos taken from the same camera recordings in normal situations (working) and with anomalies presented, which were previously labeled.

Table 3.

Metrics of the confusion matrices of the detected states.

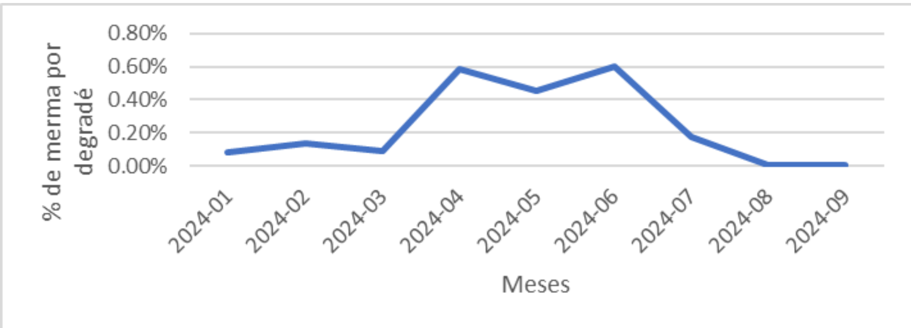
Metrics/status	Foam	Trader	Movement	Pause
Correctness	98.2%	92.5%	89.1%	88.8%
Accuracy	91.3%	80.9%	90.4%	77.2%
Sensitivity	98.9%	76%	77.2%	89.4%

- The model was able to detect rope stoppages to the operators and they were able to evaluate what caused them, obtaining rope breaks, slipping of the rollers and unhooking of ropes as the main causes.
- The average response time, including status detection and sending to the smart watch was approximately 3 seconds after the anomaly occurred.

Discussion

- The results obtained have shown us that the model is efficient and reliable with respect to the detection of anomalies that occur in the fabric dyeing machines, being a crucial control point for the adaptation of the use in production by depending entirely on the physical response of the operators for the success of the project.
- Some limitations have been identified such as dirty hatches, which are fogged by the use of the machine and cause the efficiency percentage of the model to be reduced. In addition, events have been identified with the "Stop" status of the rope, which last between 3-5 seconds, in which the event is detected, but when the operator arrives at the machine he finds it already working, believing that it is a false positive and sending these cases for review with the plant management and the maintenance team.
- The implementation of the system reduced the shrinkage attributed to degradation from 0.6% to 0.01%. This included reestablishing the process in a controlled manner, in addition to having a better response time to the customer due to fewer outages and/or replacements.

Figure 8. *Monthly evolution of the percentage of degradation*



5. CONCLUSIONS

1. The implementation of this project demonstrates that an Internet of Things system has made it possible to reduce the amount of waste due to degradation caused by the time a rope remained without movement.
2. Having innovative tools, associated with AI, allows us to reassure customers that the company is constantly seeking to reduce costs and improve the quality of products and processes.

3. A system with a high level of precision allows us to give operators greater peace of mind by providing them with precise and direct alerts.
4. We can exploit information from machine failures to analyze trends or correlations.
5. Low-cost tools can fulfill functions that are offered in industrial and high-cost solutions.
6. Older machines can be adapted to new technologies, becoming efficiently controlled in a manner similar to state-of-the-art machines.

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