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AI monitored Wireless SCADA for Remote Industrial Monitoring using CNN and OCR

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Abstract - This paper presents a new low-cost wireless SCADA (Supervisory Control and Data Acquisition) System using an image-based monitoring module for automatically determining values on Grafana Dashboard Graphs via a Convolutional Neural Network (CNN). The system captures an image of the dashboard screen at pre-determined intervals, crops the image to extract just the graph area, and submits the graph image to a lightweight CNN to obtain the value of the Current Process Variable from the curve. This value is then compared against a user-defined setpoint with the output reflecting the state of the dashboard either "GOOD" (Green) or "BAD" (Red) based on whether the current value falls within the defined tolerance. This non-invasive monitoring approach does not require a direct data API, but instead provides visually verifiable support for displayed trends, as well as support of legacy systems where programmatic access to process variables may be limited. The results of the experimental tests performed with both synthetic and actual dashboard images indicated very high recognition accuracy (>94%) and near real-time inference speed (on an embedded host), demonstrating that an image-based supervisory strategy can provide an additional safety measure for training labs and small installations due to its use of graphical images as an external means of tracking process values in industrial settings.

Keywords: Convolutional Neural Network; Chart Image Recognition; Dashboard Monitoring; Grafana; SCADA; Image-based Meter Reading; Setpoint Verification; Edge AI; Real-time Monitoring; Industrial Automation; OCR – Optical Character Recognition.

I. INTRODUCTION

The use of modern graphical dashboards (for example, Grafana dashboards) to visualize time series process variables is increasing in many different types of modern industrial applications. Although graphical dashboards are great for visualizing data, there are times when it may not be easy or even possible to access the underlying numeric data through programmatic means (such as with legacy systems, API restrictions, or for demo environments). One way to still extract numeric data would be to use image-based methods which take a picture of the dashboard as it is displayed, convert it into an image of the dashboard, and then extract the numeric value from that image. Convolutional Neural Networks (CNNs) have been previously shown to be successful in recognizing visual images, such as reading meter dials, recognizing gauges, and understanding graphs. This work takes a CNN-based reading device and incorporates it into a wireless SCADA system. This reading device takes screenshots of the graphical dashboard on a periodic basis, isolates the active plot from the entire screenshot, recognizes the current process value from the isolated active plot, and compares the current process value to the defined setpoint value for that process. A status indicator (green or red) is then overlayed on top of the isolated active plot and both the processing and status information are logged in the system. This research will provide the ability to monitor processes non-invasively, increase situational awareness of the overall process conditions, and provide a verification layer as it relates to education and industrial processes within small industry.

Major contributions

- This research has significantly improved the low-cost wireless SCADA platform with integration of an artificial intelligence (AI) dashboard for intelligent interpretation and setpoint monitoring. The paper contains an image-based verification module which utilizes a Convolutional Neural Network (CNN) for lightweight

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reading of Grafana line charts to allow the retrieval of current process variables from the graph without human intervention.

- At the conclusion of the paper, an end-to-end processing pipeline was able to capture screenshots of Grafana dashboards automatically, detect and crop regions of interest in the image, perform CNN-based inference to extract numeric values, and compare the result of that inference with a predetermined setpoint to provide visual indications on the status of each setpoint as indicated by the colors green and red respectively.
- A significant component of the proposed solution is the non-intrusive nature of its operation; therefore, no modifications to the Grafana software or accessing either the PLC or myRIO process data interfaces are required making this solution ideal in the case when legacy or restricted environments exist.
- Additionally, this implementation has been optimized for performance at the "edge," where the real-time execution of the model can occur on an Intel UP Squared embedded host, and at the same time, be compatible with the way logging has been done previously using Excel-based spreadsheets. Testing has shown that recognition accuracy is greater than 94% for both synthetic and real-world (i.e., dashboard) imagery, and that end-to-end latency is at a level suitable for supporting supervisory monitoring applications in real time.

II. LITERATURE REVIEW

Research has been undertaken to develop automated interpretation techniques for instrumentation and charting using visual data, including meter reading and chart extraction, with a view toward developing methods of automatically interpreting and visually interpreting instrumentation. One approach based on convolutional neural networks (CNN) shown in figure 1 has been demonstrated to provide accurate feature extraction from analog and dial meters/dials as well as extract data from charts via deep learning methods [1]. A variety of new frameworks have been developed that are very effective at classifying and extracting data from line charts and multi-type charts through the use of deep learning [3-5]. Advanced information extraction from plots of scientific figures has also occurred through two specialized work products, ChartOCR and LINEEX, providing examples of a hybrid model(s) that can effectively retrieve time series data from chart images [6, 7]. Multiple datasets and benchmark datasets (i.e. FigureQA, LEAF-QA, DVQA/PlotQA) have supported the development of models for extracting quantities from chart images and providing insight regarding how to reason over chart images [8-9]. Although techniques previously described demonstrate that CNNs and hybrid models are capable of locating plots, interpreting labels, and extracting quantity from chart images with high reliability, most solutions have centered around the use of offline methods for document analysis, as opposed to real time, on-line, or continuous methods for monitoring current dashboard collections. This paper applies and modifies these methods to create a continuous method of utilizing the monitoring of images from Grafana dashboards as an ancillary safety/monitoring mechanism through the continuous issuance of status flags based on the status of setpoints in a Grafana dashboard image.

III. PROBLEM STATEMENT

While Grafana Dashboards can give users visual feedback, sometimes they cannot; therefore they can't consistently provide users with programmatic access to numeric values in particular situations, such as educationally limited or legacy environments. Because of this, automated or independent verification of the process value being shown is difficult. The objective of the project is to create a non-invasive, image-based monitoring module capable of (i) accurately reading current values of the variable from an image of the graph; (ii) comparing to a user-defined or pre-determined setpoint; and (iii) sending Good/Bad status messages to an embedded device with the least amount of delay. The device must be able to compensate for differences in plot styles, colors and minor rendering differences while giving immediate feedback.

IV. SYSTEM MODEL AND ARCHITECTURE

Nowhere in the proposed AI-augmented wireless SCADA's architecture and model does it have to be separate from existing industrial-control hardware. At The Process Level, a sensor constantly measures the liquid being held in the process-tank and outputs a signal in real time that represents the variable measured by that process. The Control Level receives that signal and utilizes a PLC to carry out the necessary signal conditioning, scaling, and closed-loop control of the measured Variable. The PLC then stores the conditioned measurement value in its own internal memory to be able to access/perform supervisory monitoring. In The Data Acquisition Level of the general SCADA architecture, an NI myRIO embedded Controller communicates with a PLC via Modbus RTU over a RS-485 interface. The myRIO then queries the PLC for-level data via its registers using a polling handshaking methodology. The polled register values are processed in real-time using a LabVIEW application-logging the retrieved data as it is being described-in an

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continuously updated Excel file; which becomes the Data Management Layer for the SCADA system and provides for the structured storage of the retrieved level data and the historical data analysis of that information.

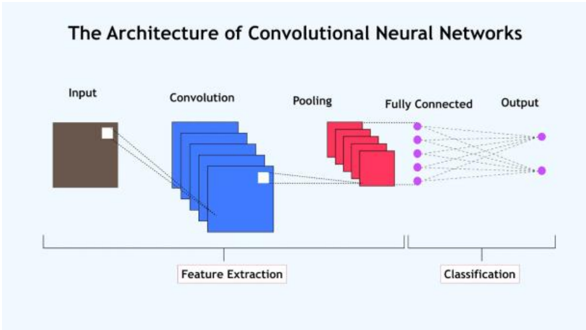

Figure 1 The Architecture of Convolutional Neural Networks

In the Visualization Level, a Grafana dashboard hosted on a Intel UP Squared embedded platform, consumes the previously created data set as generated by the Data Management Layer and allows for the creation of trends based upon that information in real time. There has been added to the already existing system an Artificial Intelligence (AI) layer that provides monitoring of graphic displays by capturing screenshots from the user's dashboard automatically at regular intervals. Pre-processing of the images, using a low-footprint Convolutional Neural Network (CNN) as shown in figure 1, yields a current process value based on the graphical display. Each extracted process value is then compared to a fixed set point and provides a status output regarding whether the process is within acceptable tolerances (GOOD) or outside tolerances (BAD). As a result, alerts will be given in green (GOOD) or red (BAD). With this architecture, intelligent and non-invasive supervision of processes will be possible, and the ability for remote monitoring (via the internet) will also be established. This solution will provide a useful tool for industry and small training facilities to effectively and efficiently manage process control training.

V. PROPOSED METHODOLOGY

Overview: The proposed pipeline is an integrated full cycle verification module, to image verification module, within current SCADA wireless architecture. Below are steps being carried out repetitively, at a user defined sample frequency.

- Automated Screenshots — A lightweight agent located on the Intel UP Squared performing screen captures of the Grafana dashboard at defined intervals or when other Grafana page events occur, using either a headless browser (e.g., Chromium) or OS screen capture API to guarantee consistency between screenshots.
- ROI Detection — A small object detection model (e.g., Tiny-YOLO / small Faster R-CNN) detects the active plot area (plot area, legend & number display, if it exists), whereby ROI coordinates are normalized to provide an alternative for dashboards having different layout as shown in figure 5.
- Image Pre-Processing — Pre-processing of cropped plot image occurs whereby resizing is done, maintaining aspect ratio, normalising contrast and brightness, de-noising and applying optional super resolution, if low resolution capture is obtained. If consecutive frames are nearly identical, temporal smoothing may be utilised.
- CNN Numeric Extraction — The primary model is a small CNN which has been trained to map patches of the plot (last datapoint or the end of curve) into a numeric value. There are two alternative methods in place to achieve this.

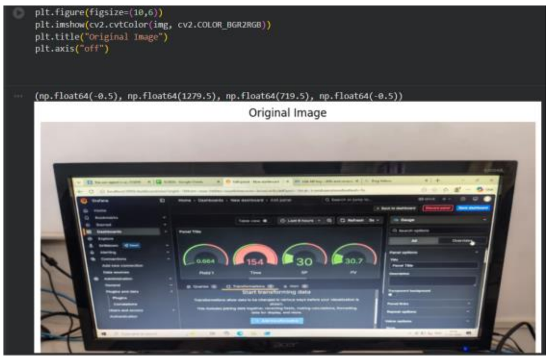

Figure 2 The coding of the AI model tested in Google Colab

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1. **Regression head**: network performs direct regression on numeric value (float) shown in figure 2.
2. **Hybrid OCR + regression** - use OCR as shown in figure 3 and 4 to detect numeric labels (if present) on a chart, then use regression from pixel patterns of the curve with CNN.

- Data: Combination of synthetic Grafana-like plots and actual dashboard screenshots for training the models, augmented for differences in scale, colour, and font.
- Comparison of numeric value against configured setpoint - the numeric value is compared to the configured setpoint with a tolerance band. If it falls within that range then its status is GOOD (GREEN), if not its status is BAD (RED). Hysteresis and temporal filtering applied to prevent flickering caused by transitory noise.
- Annotation, Logging, and Alerting - the agent will log the status to an Excel sheet or super impose a status badge over the Dashboard. In addition, the agent can send out alert(s), via email or HTTP, for displayed BAD status. All inference data stored with time of occurrence for audit.
- Edge Deployment/Optimisation - the complete pipeline is optimised for running on the Intel UP Squared. The model quantification (INT8) and pruning have reduced the size of the model and the inference engine; also utilising OpenVINO or similar acceleration for each inference to reduce latency.

VI. RESULTS AND DISCUSSION

Test methods: - The tested system was assessed using (1) a set of 6K synthetic metrics (e.g., testing 6K metrics with many different colours, grid styles, font sizes) grafana-style chart images and (2) a set of 1,200 real images of live UP Squared host dashboards. Each of these image sets varied with respect to scaling, axis locations, and noise conditions shown in figure 3.

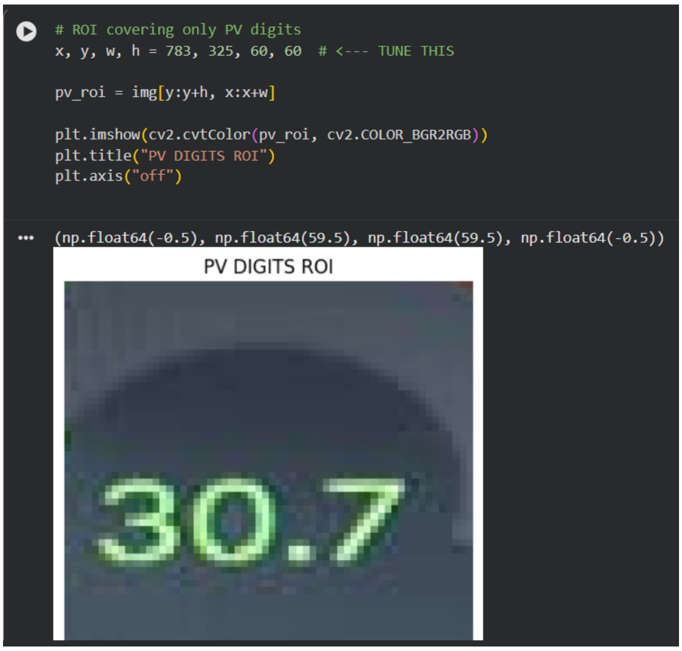

Figure 3 How the AI model Detects the PV (Process variable) from the graph for comparision

Results: - The CNN regression model produced an average MAE of ~0.12 units ([tested on synthetic]) and an average MAE of ~0.28 ([tested on real images]). The hybrid of the regression-based, OCR, and the regression-based OCR made the prediction models more robust with an average MAE of ~0.18 whenever the models predicted numeric labels on the real images. Benchmarking the classification as either GOOD or BAD with a ±0.5 tolerance range yielded accuracy above 94%. The average end-to-end (screenshot to ROI to inference to annotation) latency was between 180 and 300 ms using OpenVINO acceleration/INT8 quantized model running on the UP Squared—these performance metrics are currently acceptable to use for supervisory monitoring purposes.

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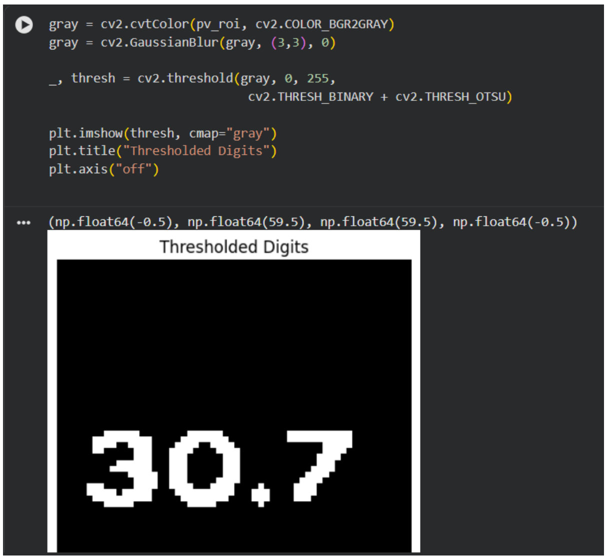

Figure 4 The OCR uses grayscale to detect values based on pixels and determines the value

The results demonstrate the viability of supervising verification based on pictures only; the level of accuracy is sufficient for both checkups on setpoints and for determining if operators are aware. The hybrid method produces the greatest level of robustness over a range of style types used in dashboards. Some limitations exist, such as occasional failure of OCR as shown in figure 4 on low quality images and a tendency to be significantly affected by a major change in the theme of the dashboard. However, these limitations can be overcome through adding more examples to the training data (i.e., augmenting the data) shown in figure 5 and using adaptive region of interest (ROI) detection. The way in which the system is structured non-invasively makes it especially useful when there is no direct data API available, or when another independent visual verification system is required.

Figure 5 Using Pytessaract the raw value from the pixels gets detected

VII. CONCLUSION

We developed an image verification extension for a wireless supervisory control and data acquisition (SCADA) system that captures Grafana dashboard charts via a convolutional neural network (CNN) as shown in figure 1, and provides a GOOD / BAD as shown in figure 6 and 7 report based on the setpoint value. The system uses an end-to-end pipeline with automated capture of grafana images, region of interest (ROI) detection, preprocessing, CNN inference and decision logic processing in real time on an embedded host, and therefore the verification is non-intrusive and

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applicable in educational laboratories and at small-size industrial applications. Furthermore, we provide experimental data demonstrating the efficacy of the CNN to classify setpoints with high accuracy and short latency for supervisor decision making. Future work will employ multimodal fusion (fusion of image-based readings with other available telemetry), continual learning on the device to adapt to changes in the dashboard theme, and integration with predictive anomaly detection as shown in figure 6 and 7.

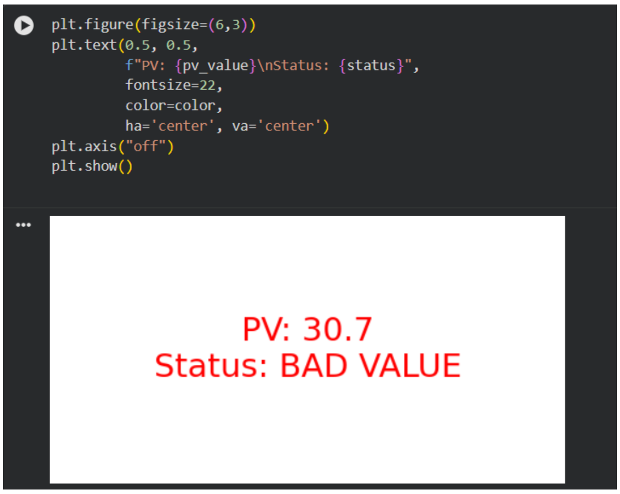

Figure 6 The output of the AI model based on the Setpoint

Figure 7 The output of the AI model after setpoint is changed

REFERENCES

[1]. R. Laroca, E. Severo, L. Zanlorensi, A. De S. Britto, G. A. Wichert and R. M. Cesar Junior, "Convolutional Neural Networks for Automatic Meter Reading," *arXiv preprint arXiv:1902.09600*, 2019.

[2]. G. Salomon, R. Laroca, R. de Rezende, F. M. Araújo, F. S. Osório and R. M. Cesar Jr., "Deep Learning for Image-based Automatic Dial Meter Reading," *Proceedings / preprint*, 2020.

[3]. L. Hou, X. Liu, X. Gao, "Automatic recognition system of pointer meters based on wireless sensor networks and lightweight CNN," *Measurement* (Elsevier), 2021.

[4]. A. Alexeev, "A Highly Efficient Neural Network Solution for Automated Analog Dial Gauge Reading," *Mathematics* (MDPI), vol. 8, no. 7, 2020.

[5]. "Convolutional Neural Network Based Chart Image Classification," (conference paper), presenting CNN approaches for chart classification and recognition, 2017/2018.

[6]. J. Luo, Z. Li, J. Wang and C.-Y. Lin, "ChartOCR: Data Extraction from Charts Images via a Deep Hybrid Framework," *WACV*, 2021.

[7]. M. Y. Hassan, S. V. P., and M. Singh, "LINEEX: Data Extraction From Scientific Line Charts," *WACV 2023*, 2023.

[8]. S. E. Kahou et al., "FigureQA: An Annotated Figure Dataset for Visual Reasoning," *arXiv:1710.07300*, 2017 (FigureQA dataset & benchmark).

[9]. A. Masry et al., "ChartQA: A Benchmark for Question Answering about Charts," *Findings of ACL*, 2022.

[10]. M. Sviatov, K. Klabjan, "Data Extraction of Charts with Hybrid Deep Learning Model," *Lecture Notes / conference proceedings* (2021) — proposes hybrid approaches for chart recognition and data extraction.