# Intelligent Data Acquisition System for Electrical Voltage Monitoring Using Neural Networks

**Ramos, Josnier[1,*]; Pérez, Maykop[1]; Hernández, Orestes[1]; Silverio, Raimundo[2]**

[1]*Technological University of Havana, Electroenergetic Research and Testing Center, Havana, Cuba*
[2]*Federal University of Campina Grande, Faculty of Electrical Engineering, Campina Grande, Brazil*

**Abstract:** The growing need for efficient monitoring of electrical voltages has led to the development of an intelligent data acquisition system. This work addresses the limitations of existing digital instruments, specifically the METREL MD9225, by implementing a neural network architecture for optical character recognition on its LCD displays. The objective is to facilitate the automatic reading of electrical values using a neural network trained to recognize digits from 0 to 9 and the decimal point. The neural network consists of thirteen layers of neurons. The development team created four Python applications: two to capture images for training the neural network, and two to deploy the system as a desktop and a web application. The Keras library was used to build and train deep learning models, while OpenCV was employed to streamline application development. Database management was handled by sqlite3, highlighting its portability and low resource consumption. The results indicate that the proposed system enhances the capabilities of existing equipment by enabling the reading and communication of electrical measurements, potentially reducing costs by replacing outdated equipment and providing an additional layer of protection against system hacks. Furthermore, the system demonstrated a significant improvement in mitigating arc flash incidents. The system requires a webcam, a laptop, and access to a data network connection.

**Keywords**: Deep neural network, optical character recognition for LCD screen, Python programming language, voltage measurements by automated screen reading

# Sistema Inteligente de Adquisición de Datos para la Monitorización de Tensión Eléctrica Mediante Redes Neuronales

**Resumen:** La creciente necesidad de monitorear eficientemente las tensiones eléctricas ha impulsado el desarrollo de un sistema inteligente de adquisición de datos. Este trabajo aborda las limitaciones de los instrumentos digitales existentes, específicamente el METREL MD9225, mediante la implementación de una arquitectura de red neuronal para el reconocimiento óptico de caracteres en sus pantallas LCD. El objetivo de este trabajo consiste en facilitar la lectura automática de valores eléctricos utilizando una red neuronal entrenada para reconocer los dígitos del 0 al 9 y el punto decimal. La red neuronal está compuesta por trece capas de neuronas. El equipo de desarrollo creó cuatro aplicaciones en Python: dos para capturar imágenes destinadas al entrenamiento de la red neuronal y dos para implementar el sistema como aplicación de escritorio y aplicación web. Se utilizó la biblioteca Keras para construir y entrenar modelos de aprendizaje profundo, y se empleó OpenCV para optimizar el desarrollo de las aplicaciones. La gestión de la base de datos se realizó mediante sqlite3, lo que resalta su portabilidad y bajo consumo de recursos. Los resultados indican que el sistema propuesto mejora las capacidades del equipo existente al permitir la lectura y comunicación de mediciones eléctricas, lo que podría reducir costos al sustituir equipos obsoletos y proporcionar una capa adicional de protección contra ataques al sistema. Además, el sistema mostró una mejora significativa en la mitigación de incidentes por arco eléctrico. El sistema requiere una cámara web, una computadora portátil y acceso a una conexión de red de datos.

**Palabras clave**: Red neuronal profunda, reconocimiento óptico de caracteres para pantalla LCD, lenguaje de programación Python, mediciones de voltaje mediante lectura de pantalla automatizada

## 1. INTRODUCTION

Smart measurements are vital for the efficient and secure operation of electrical infrastructure, particularly in smart electrical grids (Raza et al., 2023). These measurements enhance energy efficiency, reliability, and fault detection. The growth of smart grids has led to a greater density of measurement points, emphasizing the importance of data analysis (Guardarrama et al., 2016). The proper operation of a

*josnier2005@gmail.com
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smart grid requires a large volume of information from generation to consumption (Solís & Jiménez, 2022).

The demand for energy consumption is increasing rapidly, leading to the need for energy measurement in various sectors like; smart farms, hospitals, factories, electric vehicle charging stations, transformers, energy storage systems, and other measurable elements (Živic et al., 2015). This presents new opportunities in smart grids for efficient data utilization, improving the overall functioning of energy infrastructure, and creating new added services. However, there are several challenges to overcome, such as standardizing measurements, regulations for measurement equipment, common protocols among all equipment manufacturers, and electrical protection measures between the measurement and communication equipment (Barai et al., 2015).

Campaigns to replace measurement devices, such as electricity meters in households, with intelligent equipment that has communication capabilities to transmit consumption data have resulted in significant infrastructure costs for countries or regions with large coverage areas (Duan et al., 2022; Orlando et al., 2022; Sushma et al., 2023). Devices that acquire and process electrical parameters using sensors typically achieve this, which then transmit the data via a communication network. The measurement systems and communication systems require specific hardware to interface between them. An example of this is the wireless communication of smart energy meters using RJ45 port modems, infrared ports, SigFox, ZigBee links, and any other available means (Suhaimy et al., 2022).

The study titled "Mobile Web Application with Optical Character Recognition for Reading Water Consumption Meters in the Cantón Mocha" presents an innovative solution to automate and improve the process of recording water consumption readings in the Mocha canton, using a mobile application that employs optical character recognition (OCR). This tool enables operators to capture images of the meters and record water consumption accurately and efficiently, while allowing administrators to access user information in real-time through a centralized system. The main advantage of this solution lies in automation and the reduction of human errors, optimizing both administrative management and operational efficiency. However, a potential disadvantage could be the dependence on local technological infrastructure and the adaptation of staff to the new technology. The implications of these results are significant, as they contribute to the modernization of public management systems in rural areas, promoting transparency and efficiency in the management of water resources, and providing a model that could be replicated in other regions (Tibán Chito, 2022).

The Internet of Things (IoT) creates a transformative environment by interconnecting diverse technological components, which enables the processing and control of functionalities through a unified framework. This interconnectedness enhances operational efficiency across various sectors but also introduces vulnerabilities that can be exploited by malicious actors (Gallo & Beatriz, 2023). The proposed forensic action guide for IoT environments addresses these challenges by providing a structured approach to the analysis of digital evidence, which is crucial for understanding and mitigating the risks associated with IoT deployments. One of the primary contributions of this work is the development of a Forensic Action Guide specifically tailored for IoT contexts, synthesizing various methodologies for IoT forensics. This guide serves as a valuable resource for practitioners and researchers, offering a comprehensive framework for investigating incidents involving IoT devices.

The advantages of this approach include improved incident response capabilities and enhanced understanding of the vulnerabilities inherent in IoT systems. By identifying common attack vectors and potential weaknesses, the guide empowers organizations to bolster their security measures and protect against unauthorized access. However, there are also disadvantages to consider; the rapidly evolving nature of IoT technologies means that forensic methodologies must continuously adapt to new threats, which can be resource-intensive. Additionally, the reliance on specific case studies may limit the generalizability of the findings, necessitating further research to validate the guide across diverse IoT applications. Ultimately, the implications of this work extend beyond the immediate context of the case study, laying the groundwork for future research in IoT forensics and contributing to the broader discourse on cybersecurity and digital forensics (Gallo & Beatriz, 2023).

The challenge arises when operational measurement devices cannot communicate, or if it is not compatible with the communication protocols of the deployed data network. Some kinds of electrical measurement nodes, such as power substations or generator groups, replacing or upgrading the measurement equipment with communication and appropriate protocol capabilities can be a significant expense. This can cost thousands of dollars per measurement node, making it a serious economic issue for restructuring the measurements of the electrical network.

Generally, digital equipment used to measure electrical parameters displays readings on a screen for personnel to observe. It is also important to note that data acquisition occurs discretely at regular time intervals. Therefore, it may be feasible to use a video camera to monitor the screen of the digital instrument, optically recognize the displayed values, and transmit or store the measurements of fixed intervals.

The previous solution has the potential to eliminate the need for replacing costly measuring equipment. It also offers the advantage of virtually perfect electrical isolation between the measuring equipment and the intelligent reading system. Regardless of the manufacturer, hardware, or protocols of the measuring equipment, only the availability of measurements on a screen is required for their acquisition, storage, and transmission. This implies that the solution is manufacturer-independent and relatively simple to deploy without interfering with existing electrical systems. It is also not necessary for the systems involved to share the same power supply.

The use of machine learning in smart grids focuses on processing data that is in a database (Jithish et al., 2023; Khan et al., 2023; Zhu et al., 2024). Examples of such analysis include artificial intelligence-based variable prediction techniques for decision-making regarding topics such as estimating electrical demand, wind effects on generation, maintenance determination, expansion of new generation blocks, system control, among other aspects. However, the fundamental use of artificial intelligence as a tool to operate as an interface between measurement systems and their data acquisition towards a database has been significantly lagging behind.

The international community is also concerned with the protection of data and computational systems in smart energy grids. The malicious effects of a cyber-attack can have devastating consequences on the electrical infrastructure (Chen et al., 2022). However, an artificial intelligence data acquisition system through video cameras creates an overwhelming barrier between measurement and communication systems, potentially reducing direct effects on measuring instruments and their internal algorithms, safeguarding a substantial portion of intelligent measurement systems.

Therefore, this improvement in the digitalization of measurements for processing plays a crucial role in eliminating barriers between different manufacturers and in leveraging existing measurement equipment. It significantly reduces infrastructure investment costs by offering a novel and general solution to the problem of electrical measurements in power system infrastructure.

Implementing a computer vision system for reading electricity meters (for example) can offer a viable solution to this challenge. Instead of replacing expensive metering equipment, this approach allows for the digitalization of readings through cameras, eliminating the need for manual intervention and reducing operating costs. For example, in facilities with multiple meters, a camera-based monitoring system could provide accurate readings without the need to dispatch technicians on-site, representing significant savings in time and resources.

This study employs a methodology focused on developing and implementing a computer vision system for reading electricity meters. First, we conducted a comprehensive literature review on optical character recognition (OCR) techniques and their applications in electrical networks. Next, we designed a prototype that uses cameras to capture images of the meters and incorporates image-processing steps—such as segmentation and character recognition—to extract electrical readings. We implemented machine-learning algorithms to enhance the accuracy of the recognition process and conducted tests under various lighting conditions and capture angles. Finally, we evaluated the results in terms of accuracy and efficiency, comparing them with traditional manual reading methods. This comparison validated the viability of the proposed system as an effective solution for the digitalization of electrical measurements.

This paper was structured as follows: Section II reviews prior research on optical character recognition (OCR) prediction and its applications in electrical networks. In this section, we introduce and describe an intelligent system for inferring electrical voltage readings. Section III provides a detailed account of the results obtained through the applications designed for inferring instrument readings from captured images. The results are analyzed in Section IV and possible improvements are suggested. Section V concludes the paper and offers considerations for future work.

## 2. MATERIALS AND METHODS

Advanced measuring devices with digital displays characterize smart meters (Sivadevuni et al., 2023). These devices record the amount of power consumed and the time at which it was consumed, and automatically transmit this information to a meter data management system (MDMS) for processing and storage (Guardarrama et al., 2016; Orlando et al., 2022). To ensure smooth communication between different smart meter vendors and MDMS solution providers, it is essential to follow standardized protocols for data collection, storage, and communication.

A smart grid combines advanced technologies to create a cyber-physical system. It integrates a communication system that manages both power and information flow. The real-time measurement techniques and communication support of the smart grid improve its resilience and forecasting capabilities while protecting it from both internal and external threats.

Smart grid technology uses advanced metering infrastructure (AMI) to collect data from smart meters (Arora et al., 2022; Barai et al., 2015). AMI manages this data through a database called MDMS. Traditionally, AMI uses a centralized MDMS architecture. While the communication architecture of the smart grid is complex, it enables automated control through bidirectional connections for both power and data flow. Communication technology is a critical component of smart meters, and a stable, well-integrated communication architecture requires proper infrastructure. AMI consists of three main components: smart metering devices installed at the user end, a two-way communication path between the user and utility, and an automated software and operations center for data processing.

Figure 1 presents a simplified diagram of the data management system for data acquired from multiple smart energy meters. The key element is the communications subsystem that transmits data from smart energy meters, supporting the entire network.

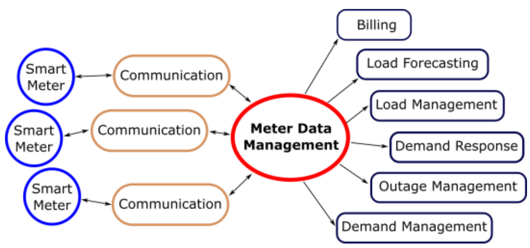


**Figure 1.** Schematic representation of a simplified Meter Data Management System (MDMS). Source: (Barai et al., 2015)

There are two types of communication media: wired and wireless. Wireless media use radio signals, such as Bluetooth, WiFi, and ZigBee. Infrared is another type of wireless media that does not use radio signals (Suhaimy et al., 2022).

*2.1 Neural networks for optical character recognition*

The information contained in text, images, or videos can be valuable for recovery and indexing purposes. However, detecting characters in these images and videos is challenging due to complex backgrounds, varying grayscale values, inconsistent lighting conditions, and differences in character size. To address these challenges, researchers have employed various algorithms, including feature extraction techniques such as texture and region-based methods, as well as machine learning and deep learning approaches.

Optical Character Recognition (OCR) detects characters within text frames and identifies their location in videos (de Oliveira et al., 2023; Srivastava et al., 2022). Natural Language Processing (NLP) is another technique that extracts text in various languages from video frames (de Oliveira et al., 2023). Convolutional Neural Networks (CNN) efficiently recognize text characters from images by selecting the most relevant features (Taye, 2023). Additionally, deep learning algorithms identify textual regions within video frames to aid in text detection.

Optical Character Recognition (OCR) tasks typically consist of two stages. In the first phase, a text detection model identifies bounding boxes around potential text. In the second phase, a text recognition model analyzes these boxes to identify the characters within them. Text recognition requires several pre-processing steps, including Non-Maximal Suppression and perspective transformation.

In the study, the researchers developed a low-cost project to digitize analogue meter readings (Sultana et al., 2022). They employed a deep learning model based on the Single Shot Detector (SSD) MobileNet V2 architecture, in conjunction with the Tesseract optical character recognition (OCR) engine. We trained the model using a dataset of 750 instrument images, allowing us to detect the region of interest that contains the readings of the meter. They used OCR to convert the readings into string data. The researchers applied image-processing techniques with the OpenCV library to improve the quality of the region of interest (ROI). They developed the model using Python and assessed its performance across different meter types, illumination conditions, and backgrounds. The results show that the deep learning model and OCR achieved accuracies of 95% and 93%, respectively.

Another study developed an optical recognition system for analog energy meters that cannot transmit data (Salomon et al., 2020). The researchers used Tesseract with a Convolutional Recurrent Neural Network (CRNN) for the prototype. Their primary goal was to create a custom-trained model using the InceptionResNetV2 training and testing method. The custom model identifies a region of interest (ROI) linked to the power meter readings. They selected InceptionResNetV2 because both the Inception-v4 and ResNetV2 components provide strong single-frame generation performance with the ImageNet validation dataset. Figure 2 illustrates the inference process for the analog energy meter (Salomon et al., 2020). The rectangle in the image highlights the area where the energy consumption numbers are located. The system displays the reading inference at the bottom of the image.


**Figure 2**. Capturing inference results in an energy meter. Source: (Salomon et al., 2020)

A study introduced a pioneering method that combines deep learning and computer vision techniques for pointer meter recognition using Yolov7 and the Hough transform (Zhang et al., 2023). The method employs deep learning tools such as Yolov7, DeepLabv3+, and PGNet: Yolov7 locates the meter, DeepLabv3+ extracts the pointer, and PGNet identifies the model and range of the meter. Additionally, computer vision techniques like Thinning and Hough transforms accurately detect needles and read meter values. By leveraging deep learning for object detection and image segmentation, this method effectively locates instruments and segments pointers directly from images, overcoming challenges such as poor illumination, complex backgrounds, image blur, and diverse meter models. Experimental results show an impressive accuracy rate of 99.8% on the instrument dataset when using Yolov7, with pointer reading accuracy exceeding 95%. The method demonstrates excellent anti-interference, accuracy, and robustness under standard shooting angles but encounters difficulties at larger angles. Figure 3 shows the experimental results of optically detecting the position of the instrument needle and inferring the current intensity.


**Figure 3**. Example of inference from the reading of the ammeter needle. Source: (Zhang et al., 2023)

Other research related to optical character recognition applied to instruments includes studies by Azeem et al. (2020); Hurstet al. (2020); Mo et al. (2020); Zhang et al. (2021); Zhou et al. (2022). These studies emphasize the importance of improving instrument reading methods, reducing the cost of automatic measurement systems, and leveraging the advantages of machine learning over traditional approaches in electrical networks.

*2.2 Smart metering system proposal*

A measurement system for acquiring readings must meet three fundamental requirements: it must be digital, capable of storing information, and able to transmit collected data over a network. Figure 4 illustrates the proposed structure that adheres to these essential principles.

We mounted a video camera on the screen of the measuring instrument to capture images at regular intervals. The system subsequently acquires the necessary image for optical character recognition. Numerous video cameras are available on the market, with a webcam being a cost-effective and practical option, as it connects via USB.

The computer can be a desktop, laptop, or embedded system, such as a Raspberry Pi. This solution requires sufficient RAM and, if possible, a graphics card. Neural network libraries typically rely heavily on graphics cards; however, the CPU can serve smaller applications, although it offers lower performance.

The proposed system offers flexibility by accommodating a broad spectrum of hardware, prioritizing financial constraints over the need for specialized equipment. Users may employ cost-effective hardware when appropriate, while deploying more resource-intensive systems for applications demanding greater computational power, albeit at an elevated expense.

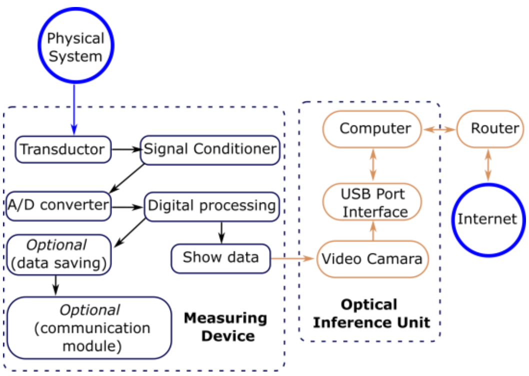


**Figure 4**. Measurement system with proposed optical inference unit

The team implemented the solution in this project using the open-source Keras neural network library, designed for the Python programming language. This library facilitates rapid experimentation with deep learning networks, emphasizing user-friendliness, modularity, and extensibility.

The OpenCV computer vision library is widely recognized in robotics and machine learning (Ariza & Pearce, 2022; Selami et al., 2023). It offers several advantages, including multiplatform support, a BSD license, comprehensive documentation, and a large global community. In this work, the team uses OpenCV to capture video camera images.

To train the neural network, a collection of images captured from the instrument screen is essential. A Python-based program captures and sequences these images from the LCD screen. The team stores the resulting data with labels identifying the corresponding measurements, thereby facilitating their use in the neural network training process.

The team reviewed each image for duplicates, capturing errors, and the correct incorporation of the identifying label. This process is slow, meticulous, and crucial for ensuring data quality. An auxiliary automatic program ensures that each image has consistent width and height in pixels. The input data consists of 140x150 pixel images in PNG format. The quality of the neural network's classification depends on the correct selection of the training data.

The hardware has the following technical specifications:

- Digital camera: Maximum resolution of 1080p/30 fps, 3 megapixels, autofocus, glass lens, diagonal field of view (dFoV) of 78°, USB connection and maximum consumption of 500 mA.
- Computer: Gateway brand, model NE57007B, Intel Core i5-3337U, 4 GB RAM and 1 TB hard drive.
- Clamp Meter: Model MD9225 with the capacity to measure up to 600 volts in alternating current, with a 4000 count resolution, 3-3/4 digit LCD display with backlight, true RMS (root mean square) sensing and accuracy of 1.0% + 4d. It has other functions but they are not of interest in this article.

The intelligent measurement system consists of four independent computer programs developed in Python for the Windows 8.1 64-bit platform. Each program has a specific function, as outlined below:

1) Script “acquisition_images_auto_v1.py”: As the name suggests, it is responsible for capturing frames at regular intervals of the instrument's LCD screen and saving the information in the “saves” folder in the same directory as the script.
2) Script “training_v1.py”: It is responsible for reading the images from a “samples” directory, using 90% of the images for training the neural network and the remaining 10% of the images as a check on the operation of the inference. It stores the configuration and adjustment of the parameters of the trained neural network on disk.
3) “ElecEye_GUI_V1”: Fundamental application for the deployment of electrical parameter measurement nodes for capturing frames by the digital camera, processing them with the neural network and storing the measurements in a *sqlite3* database. The visual interface is built using the *Tkinter* library that comes by default in the Python installation.
4) Script "service_server.py": It creates an independent process that transmits each acquisition made from the neural network inference via the *http* protocol. The service works by automatically refreshing the measurement information in the destination web browser at five-second intervals.

The four programs fall into two distinct groups. The first group is responsible for obtaining data and training the artificial neural network model, while the second group focuses on applying the model. Figure 5 illustrates the processes carried out by the capture and training group of the artificial neural network.

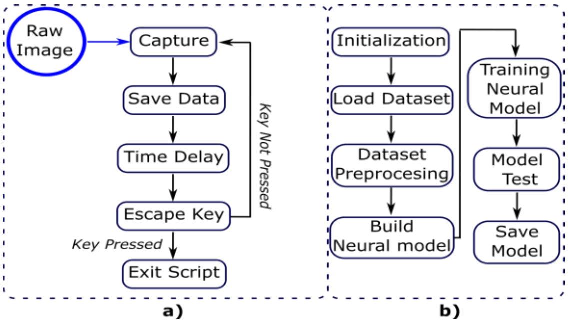


**Figure 5**. Procedures to obtain the datasets and train the neural network model: a) Algorithm of the "acquisition_images_auto_v1.py" script. b) Algorithm for training the script "training_v1.py"

In Figure 5 a), the algorithm captures and saves images from the measuring instrument screen at regular intervals. In Figure 5 b), the labeled dataset is loaded and used to train the model. A manual review and labeling process, as mentioned earlier, occurs between storing the images and creating the training dataset.

The two programs used to apply the neural network have distinct operating procedures, as shown in Figure 6. The block responsible for preprocessing the dataframes converts the colors to grayscale, resizes the image, and normalizes the color scale from 0 to 1. The database manager selected for the applications is SQLite3, a lightweight, Python-integrated solution that is easy to deploy.

Pressing "Control + C" or closing the runtime console stops the HTML protocol service. The server runs the Flask library, a minimalist framework that allows for the rapid deployment of web solutions. Both the "index.html" template and the corresponding Python script are stored in the same folder as the database. The desktop application and the web application share the same SQLite3 database.

It is important to note that Figures 5 and 6 do not include small auxiliary functions and mathematical operations. This simplification is intentional to maintain a clear outline of how the program operates.

These processes, implemented in Python, use the numpy, matplotlib, Keras, and os libraries. The model training process is resource-intensive and, depending on the provided dataset, can take several minutes. The Keras library simplifies the implementation of machine learning solutions (Pineda et al., 2023).

*2.3 Neural network layers*

The deployed solution comprises 13 layers of different types. The input layer has a shape of 140x150 to accommodate the images. The output layer is a CTCLayer, commonly used for sequence prediction tasks. The hidden layers include Conv2D, MaxPooling2D, Reshape, Dense, Dropout, and Bidirectional layers.

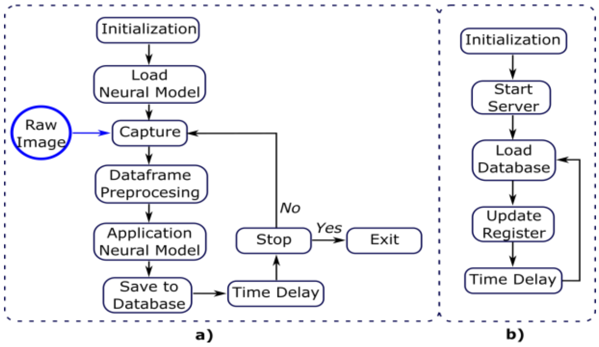


**Figure 6**. Procedures to apply the artificial neural network model: a) Algorithm of the desktop application. b) Algorithm for server the script "service_server.py"

A convolution layer (Conv2D) is a fundamental component that applies a convolution operation to the input, generating a feature map that summarizes the presence of detected features (Singh et al., 2023). This layer performs a dot product between two matrices: a matrix of learnable parameters, known as a kernel, and a portion of the input, called the receptive field. The kernel is smaller spatially than the image but extends across all the channels (e.g., RGB) in the input. During the forward pass, the kernel slides across the image, generating an activation map that represents the response of each receptive region. The convolution layer helps reduce the spatial dimensions of the input while extracting meaningful features, thereby aiding the processing in subsequent layers.

The MaxPooling2D layer down samples the input by selecting the maximum value within a specified window for each channel, reducing the spatial dimensions (height and width). Common applications of the MaxPooling2D layer in deep learning include reducing spatial dimensions, extracting important features, and helping to avoid overfitting.

The Reshape layer, as its name implies, reshapes the input data into the specified shape. This transformation ensures compatibility between different layers of the neural network, enabling effective data flow and processing for tasks like pattern recognition, natural language processing, and computer vision. The Reshape layer is essential for adapting data to the appropriate dimensions required by subsequent layers in the network.

The Dense layer, also known as a fully connected layer, creates connections between every neuron in one layer and every neuron in the next. This connectivity enables the network to learn complex patterns by combining signals from all neurons in the previous layer. The ReLU activation function introduces non-linearities, which are essential for tasks such as classification or regression within the network.

The Dropout layer applies dropout during training by randomly setting a fraction of the input units to 0, using a specified rate. The units that are not set to zero are scaled by a factor to maintain the overall sum. This regularization technique helps improve the generalization of the model by reducing overfitting. Randomly deactivating neurons encourages the network to learn more robust features, reduces inter-neuronal dependence, and improves the ability of the model to generalize to new data.

A Bidirectional layer in a neural network allows information to flow in both forward and backward directions, enabling the model to access both past and future context simultaneously. This technique is particularly useful in tasks like handwriting recognition, speech recognition, sentiment analysis, and natural language processing, where understanding context from both directions enhances data interpretation.

The number of layers in a neural network directly influences its ability to extract features and address complex tasks like optical character recognition (OCR). The architecture of the network plays a vital role in achieving optimal performance in OCR tasks. Hidden layers are responsible for detecting patterns such as edges, contours, and shapes within text, allowing the network to identify characters effectively. A deeper network, with more hidden layers, increases the ability to abstract and recognize complex typographies and styles. However, an excessive number of layers may lead to diminishing returns, negatively affecting performance due to overfitting and increased computational complexity.

Table 1 shows the layer distribution of the artificial neural network model. The information presented in the table is extracted using the *keras.Model()* class and the *model.summary()* method, which provides an overview of the model architecture, including its layers and parameters. The neural network model, based on an example from (Nain, s. f.), was used as a template and starting point for the development of the applications.

**Table 1.** Artificial neural network model

| Layer | Output Shape | Connected to |
|---|---|---|
| image (InputLayer) | [(None, 140, 150, 1)] | [] |
| Conv1 (Conv2D) | (None, 140, 150, 32) | ['image[0][0]'] |
| pool1 (MaxPooling2D) | (None, 70, 75, 32) | ['Conv1[0][0]'] |
| Conv2 (Conv2D) | (None, 70, 75, 64) | ['pool1[0][0]'] |
| pool2 (MaxPooling2D) | (None, 35, 37, 64) | ['Conv2[0][0]'] |
| reshape (Reshape) | (None, 35, 2368) | ['pool2[0][0]'] |
| dense1 (Dense) | (None, 35, 64) | ['reshape[0][0]'] |
| dropout (Dropout) | (None, 35, 64) | ['dense1[0][0]'] |
| bidirectional (Bidirectional) | (None, 35, 256) | ['dropout[0][0]'] |
| Bidirectional_1 (Bidirectional) | (None, 35, 128) | ['bidirectional[0][0]'] |
| label (InputLayer) | [(None, None)] | [] |
| dense2 (Dense) | (None, 35, 13) | ['bidirectional_1[0][0]'] |
| ctc_loss (CTCLayer) | (None, 35, 13) | ['label[0][0]','dense2[0][0]'] |

During neural network inference, a trained deep neural network (DNN) applies the features it learned during training to predict outcomes for new, unseen data. The DNN leverages its acquired capabilities to analyze and make predictions based on these features. Techniques like pruning, by removing unnecessary weights, and quantization, which reduces the precision of weights, optimize models for inference by decreasing computational, memory, and energy usage (Afro et al., 2023; Parente Mesquita et al., 2015).

## 3. RESULTS

The dataset used to train the neural network initially consisted of 5318 raw images. After removing duplicates and conducting a thorough selection process, the final dataset comprised 374 labeled images. This smaller, focused dataset only required the digits 0–9 and the dot character, offering a significant advantage over models trained on the entire Latin alphabet or varied letter formats. Additionally, the numbers on the screen have well-defined shapes, which further simplifies the task for the neural network.

Figure 7 shows the application performing inference, capturing data, and storing it in the local database. The visual application consists of five sections. The first section is the control panel, where users configure the operational parameters of the application, such as the camera selection, time interval between frame captures, database name, remote reference unit (RTU) name, measurement type, and activation of two control buttons.

The "Help" section provides access to online resources for learning how to use the program. Adjacent to it, the “Last Screen” section displays the captured image from the LCD screen. The “Inference from Reading” section displays the inference results, while the 'Video Streaming' section shows the live camera feed.

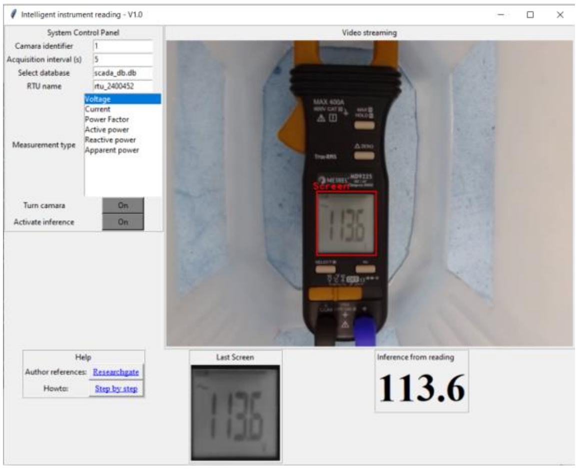


**Figure 7**. Capture of the visual application for identification of the instrument readings

The program allows users to select from various types of fundamental electrical measurements, including power. Additionally, it is possible to add other types of measurements, such as energy, if required.

At the same time, the measurement transmission service runs via HTML. Figure 8 shows how the service information is displayed in the browser.

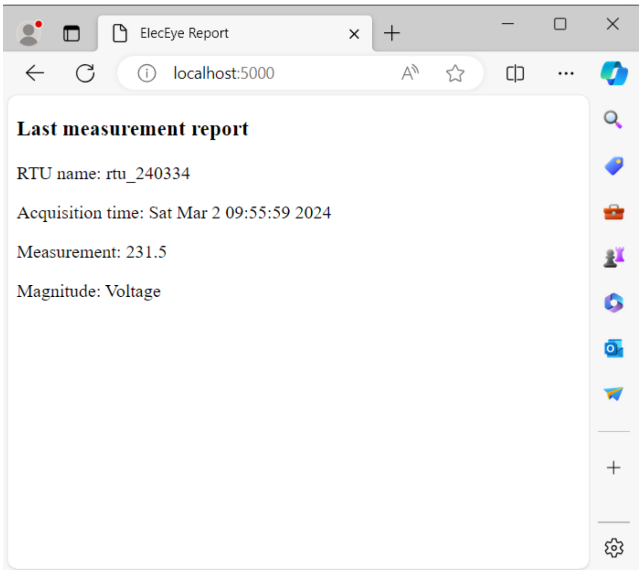


**Figure 8**. Capture of the self-updatable reading transmission service via HTML protocol

Currently, the system operates as an open platform without user management or access controls, providing data directly from a measurement node. While there are no explicit security measures in place, the system inherently resists unauthorized access due to the limitations of its frame acquisition process, which physically prevents external tampering.

The webcam is positioned 20.5 cm away from the screen, providing excellent electrical insulation due to air serving as the dielectric material. This distance significantly reduces the risk of electrical arcs from energized components between the measurement hardware and the intelligent neural network system.

The computer's CPU handles the operations with the Keras library, as no GPU is available for neural network calculations. While specialized hardware could improve system performance and capabilities, it is not present in this setup.

## 4. DISCUSSION

Assessing the performance of an artificial neural network involves evaluating its generalization ability to produce accurate results with previously unseen data. It is crucial to fine-tune parameters to prevent the network from learning unnecessary details or noise from the training set. The evaluation focuses on ensuring the network performs optimally, avoids overfitting, and maintains accuracy when generalizing to new data.

With the artificial neural network running continuously, both the inference results and the corresponding captured images were stored. Using these data, the error rate of the inference on previously unseen data was calculated. Table 2 presents the results.

**Table 2.** Successes of the artificial neural network

| | Frequency | Percent |
|---|---|---|
| Success | 242 | 94.4 |
| Error | 14 | 5.6 |

The research team conducted a series of tests to identify the sources of error in the inference of the neural network. The primary factor contributing to errors is the illumination of the instrument screen. When personnel stand between the luminaire and the camera, their shadow often reduces the network's accuracy by affecting the LCD screen. One potential solution is to collect additional samples under varying lighting conditions to account for these variations. Another option is to apply filters or techniques that enhance the contrast between the numbers and the LCD screen background.

This study acknowledges the functioning of the neural network, but highlights significant potential to improve its inference capabilities. Future research could focus on further training the model to better identify instrument readings, particularly under challenging conditions such as varying lighting or obstructions.

## 5. CONCLUSIONS

This article has achieved its objectives. First, it identified an appropriate neural network structure for optical character recognition, tailored specifically to recognize integers from zero to nine and the decimal separator "dot" on LCD screens of the METREL MD9225 digital instrument. Second, a reduced and specialized dataset effectively trained the neural network. Finally, the development of a multiplatform application for Microsoft Windows and GNU/Linux enabled the deployment of an intelligent data acquisition system to monitor electrical voltage at a specific node. These accomplishments underscore the successful realization of the set objectives and highlight the contributions made in this work.

Improving the neural network's accuracy requires analyzing and identifying appropriate solutions. This includes implementing a user management and a permission system to protect the data of the node.

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## BIOGRAPHIES

**Josnier, Ramos**, born in 1982 in Cuba, earned his electrical engineering degree from the Instituto Superior Politécnico José Antonio Echeverría (CUJAE) in 2006. He successfully obtain his MSc. degree in 2010 and has since been actively engaged in teaching various subjects, including simulation, analog and digital electronics, microcontrollers, and power electronics. His areas of interest include embedded systems, electronics, power transformer testing, and open-source software applications. Currently, he is pursuing his doctorate.

**Maykop, Pérez,** graduated in Electrical Engineering from the Instituto Superior Politécnico José Antonio Echeverría (CUJAE) in 2006. In 2010, he earned a Master's degree in Electrical Engineering. He was the position of auxiliary professor the head of the teaching department at the Faculty of Electrical Engineering of the José Antonio Echeverría Technological University of Havana, CUJAE. PhD Student Doctorate in Engineering with a mention in Electrical Engineering, Universidad de Concepción, Chile.

**Orestes, Hernández,** was born in Havana, Cuba, on September 4, 1958. He graduated in Electrical Engineering from the Technological University of Havana in 1981. His professional experience encompasses roles such as Researcher, Head of Department, and Director of the Investigations and Electroenergetical Tests Center (CIPEL) at the Technological University of Havana. His research interests are power transformer design, diagnostics, and other areas related to high voltage systems. Additionally, he serves as the head of the research center at the Faculty of Electrical Engineering of the José Antonio Echeverría Technological University of Havana, CUJAE.

**Raimundo, Silverio,** obtained his degree in Electrical Engineering from the Federal University of Maranhão in 1979, followed by a master's degree from the Federal University of Paraíba in 1982 and a Ph.D. from the Institut National Polytechnique de Lorraine, France, in 1988. After completing postdoctoral research in Paris, France, he served as a professor at various institutions, including the Federal University of Maranhão and the Ecole Nationale Supérieure des Télécommunications. Currently a full professor at the Federal University of Campina Grande, his professional expertise spans electronic instrumentation, metrology, biomedical instrumentation, and microelectronics.