

TECHNICAL REPORT



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ABSTRACT:

Identifying the value of electronics components, for this case resistors, from their visuals particularities ,like color bands, is a common yet error-prone job, especially for non-expert or beginners in a fast surrounding conditions.

In this project, we propose a deep learning approach to automatically recognize the value of an electronic resistance from an image, by doing that we will eliminate the need for manual decoding.

Using the Resistor Color Coding v5 dataset from Roboflow, which contains more than 7,000 annotated images of resistors, we trained a YOLO-based object detection model. The trained model (best.pt) is capable of detecting and classifying resistor color bands with high accuracy.

Our implementation demonstrates that combining computer vision with deep learning can provide a reliable, efficient, and user-friendly solution for resistor value recognition.

INTRODUCTION:

One of the most used electronic components is resistor. Their values is identified by understanding the sequence of color bands printed on it, this process is simple in theory but it can be time consuming and can lead to several error in an electronic project, especially for beginners, technicians in training or in a projects where you can not take time to calmly search for your electric components.

Recent advances in deep learning and computer vision have enabled the development of automated recognition systems for tasks previously requiring manual interpretation. In this work, we explore the use of YOLO (You Only Look Once), a state-of-the-art object detection model, to recognize resistor color bands and deduce their electrical value. Our goal is to build a tool that makes resistor identification fast, accurate, and accessible, by combining a robust dataset (Resistor Color Coding v5) with a high-performance deep learning model.



RESEARCH:

Architecture: Our YOLOv8 model has a real-time object detection architecture that combines speed and accuracy. With only 3.2 million parameters, it is a fairly lightweight model, making it quick to train and use even on machines with limited resources.

Types of tasks:

- -Object detection: Automatically identify and locate different electronic components in images.
- -Classification: Assign each detected object to a specific category.

Performance and efficiency: YOLOv8 offers very fast iteration speeds, suitable for systems with limited resources, while maintaining high detection accuracy. Its low memory requirements (compatible with low-capacity GPUs and even CPUs) allow for more flexible training and use.

Applications: YOLOv8 is particularly well suited for projects requiring real-time image processing. For our electronic component recognition project, it automates the detection of resistors in images, facilitating the tracking and analysis of measurements without manual intervention.

DATA ENGINEERING:

For the development of the resistance-reading AI, the main focus was on assembling and preparing the dataset.

Instead of creating our own dataset, we relied on an existing resource: the Resistor Color Coding – v5 dataset available on Roboflow, which contains around 7,000 labeled images of resistors.

This dataset was chosen because it provides a wide variety of resistor images, covering different values and including variations in appearance such as color shades, lighting conditions, and orientations. Its size and diversity ensured that the model had enough examples to train effectively and achieve good generalization.

The dataset was then used directly for supervised training, enabling the AI to learn how to recognize and interpret resistor color codes purely from images, without the need for manually engineered prompts or prior conceptual guidance.

ML TRAINING:

After compiling our dataset, we worked on adapting the pre-trained YOLOv8 model to address our electronic resistance detection issue. This lightweight model, optimized for real-time object detection, allowed us to combine speed and accuracy, even on machines with limited resources. We consulted the technical documentation and conducted several tests to identify the settings best suited to our project, paying particular attention to key parameters such as image size, number of training iterations, and network weight update speed. The goal was to find a good compromise between processing speed and prediction quality, which is essential for smooth integration into an interactive chatbot.

This training stage is based on transfer learning, which allowed us to reuse the knowledge already acquired by YOLOv8 on general datasets, while adapting it to our specific dataset. This reduced the learning time and resources required, while making resistance detection more accurate and efficient.



INTEGRATION:

In order to make the model usable by the entire group, we developed an inference pipeline and a user interface. We integrated the trained model into a simple web application with Gradio, allowing users to upload an image of an electronic component and enter a prompt to obtain a prediction in real time.

QUALITY:

Quality control was carried out continuously throughout the project.

From the earliest stages, coordination and brainstorming enabled us to define clear and achievable objectives.

There were several stages: research, dataset creation, model training, and integration. Regular monitoring ensured that the technical choices made met the defined requirements. We then verified the consistency between the results obtained and the objectives set,

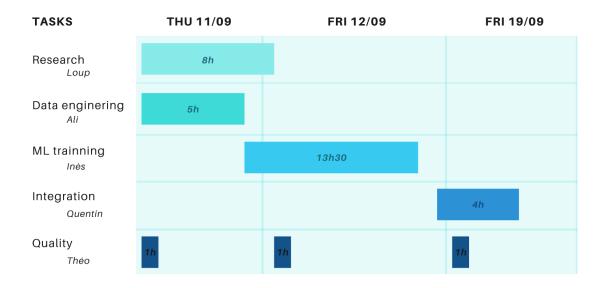
quickly identified bottlenecks or performance gaps,

proposed adjustments to improve the reliability and relevance of the model, and established good communication within the team to maintain smooth progress.

It was thanks to this quality approach that we were able to move forward in a structured manner despite the difficulties encountered, and achieve a functional and effective application. Regular monitoring optimized development time and ensured the overall consistency of the project.

BUDGET & SCHEDULE:

Target: Friday 19/09, 2025



The project was initially estimated at 20 hours of work, corresponding to a budget of 2,000 € (100 €/h). However, the actual workload reached 33.5 hours, for a final budget of 3,350 €.

The main cause of this overrun was the training phase (ML training), which required 13.5 hours due to multiple iterations and parameter adjustments to optimize performance.

Despite this increase (+67.5 % compared to the initial budget), the additional investment allowed us to achieve a functional and efficient application. The time spent on training ensured better accuracy and robustness of the model, which is essential for the reliability of the system.



CONCLUSION

This project demonstrated the feasibility and efficiency of using deep learning techniques for the automated recognition of resistor values from images. By leveraging the YOLOv8 architecture and the Resistor Color Coding v5 dataset, we developed a solution that combines accuracy, speed, and usability. The integration of the trained model into a simple user interface further confirmed the potential for practical applications, making resistor identification more accessible and reducing human error.

Although the project exceeded the initial time and budget estimates, this investment resulted in a more robust and reliable system. The work carried out highlights the relevance of combining computer vision and deep learning to address recurring challenges in electronics.

FUTURE IMPROVMENT:

We have considered grouping other types of electronic components such as AOs to facilitate the search for datasheets, or for coils, capacitors, etc. The possibilities are quite broad and could make work in the field of electronics simpler and faster. We also thought that adding a chatbot could improve our interface and contribute to a better environment for the person using it but we could not make it works as fast as it was without it, this possibility would totally be possible with more time.