Image processing with Artificial Intelligence: coin identifier and counter

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Resumen

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1. Introduction

1.1. Context

Today, Artificial Intelligence (AI) is radically transforming many aspects of our lives, from healthcare to transportation to education. In this context, the need arises to address complex, repetitive and/or automatable problems so that humans can focus on what is necessary. To do this, AI capabilities must be harnessed to deliver innovative and efficient solutions. The university environment is no exception, there are activities that can be automated with artificial intelligence, this is why we decided to lead the project down this path. We decided to implement a solution that would be useful for students, and more specifically for entrepreneurs in the educational field.

1.2. Description of the problem

A very common and often tedious task in our businesses is the accurate identification and counting of coins in various quantities. This problem not only applies to food and snack businesses, but also to jewelry, soft drinks and even collectible figurines. This task consumes entrepreneurs' time and resources that could be invested in other activities, as well as presenting additional challenges when there is high demand and volume, such as miscounting coins or even taking more than one coin at a time.

1.3. Why is it interesting?

The implementation of an AI system capable of identifying and counting coins offers many advantages such as automation and efficiency in cash management. This system could reduce human errors and minimize the risks associated with handling large amounts of cash. In addition, it would provide a scalable and adaptable solution to diverse applications and environments, which could significantly improve productivity, security, accuracy and efficiency in a wide variety of contexts.

2. Problem statement

For the approach of this problem we had to answer different questions that led us to this approach. The questions we posed in a general context for the problem statement were: What activities can be automated with AI? Which people would benefit? In what area would the proposal be applied? Now, we took these questions and modified them in such a way that they would try to answer problems that university students have. What university activities can be automated with AI? What university environments would benefit? In what aspect of university students would the proposal be useful? After having posed these questions, we decided to focus the project on university students' endeavors, where we highlighted the problem of coin identification and counting, which is a problem that resides in any university endeavor.

2.1. Questions of Interest

With respect to questions concerning machine learning, we have the following:

- Is the methodology clear and robust?

- Does the work demonstrate the development of the competencies defined for this course?

3. Theory

To understand which path the project will follow to achieve the solution, we must first adjust the context of the problem to the issues associated with artificial intelligence.

3.1. Type of Problem

In the case of machine learning we have two types of problem, the regression problem and the classification problem [1]. Regression problems seek to predict a continuous numerical value with respect to a set of input variables. These are divided into linear regression, logistic regression, Ridge and Lasso regression, among others. On the other hand, classification problems seek to assign a label or category to an object based on its characteristics. There is binary, multi-class, multi-label and ordinal classification [1]. This is where our problem comes in, since we want to **identify** the coins in an image, so it is a classification problem. Now, which of all the types of sorting problems? The coin identification and counting problem would be a multi-label classification problem, this because in an image there can be more than one coin, and it must not be the same coin, so it is required to pass by parameter more than one label in the same image so that all the coins present can be represented. In other words, the machine learning algorithm must identify and label one or more coins in an image, so it would have to assign multiple classes (labels) to a single data instance (image).

3.2. Categories of Machine Learning

It is also clear to mention that this machine learning algorithm is supervised learning, as the algorithm is given to understand that the data to be learned are labeled in the dataset [7].

Now that we know that the coin identification and counting problem is supervised learning, we must choose which attributes of the data we are going to take for data classification. For coins there are many attributes/features that can be chosen for classification. We choose the most significant characteristics of the coin which are:

1. **coin diameter**: it is relevant because each coin has a different diameter, which can be useful for grading the coin for both new and old.

2. **Thickness of the coin**: it is important in case the image is not totally pointed to the coins, but has some kind of angle, besides it can help us to identify which new coin it is, since new coins change their thickness depending on the price they are worth.

3. **Color of the coin**: it is important because all coins have a unique color, each coin has its own color, no matter if it is new or old, so this characteristic is very relevant when classifying the coin.

4. **Relief and pattern**: this is important, since the figure or symbol on the coin will tell us which coin it is, as well as whether it is new or old. If there are two coins of 100, the relief and pattern will not tell us if it is new or old, which makes it an important characteristic for the classification between the same coins.

3.3. Database

Once the type of problem has been identified, we show the database to be used for this problem. In this case the database was created by ourselves, using a code capable of finding the coins in an image in real time, this method uses **HoughCircles**, which is based on finding circles with the **Hough** transform [2]. This code works, first it asks how many pictures it is going to take, then the name of the folder, then it takes many pictures to the circle it finds in the camera, then that image to a gray scale, makes a crop of the image to only the circle of size 50x50 pixels, then transforms the matrix to a vector, then applies the method **PCA** that eliminates the redundant information of the vector [3], and so it returns us the image and adds it to the folder with the name entered at the beginning. This code returns 18 folders in total.

3.4. Exploratory Data Analysis

Exploratory Data Analysis, simply referred to as **EDA**, is the step where you understand the data in detail. You understand each variable individually by calculating frequency counts, visualizing the distributions, etc. Also the relationships between the various combinations of the predictor and response variables by creating scatterplots, correlations, etc. EDA is typically part of every machine learning / predictive modeling project, especially with tabular datasets [4].

As mentioned before, we have a total of 18 folders, these being the same classes we are going to use. Each class represents an option within the coin, i.e. face or stamp. This is the reason why there are so many classes in our database, because we have a class for both the old and the new coin face and a class for the seal. Within each class there are approximately 200 photos, this is because the code that was used captured, in some occasions, data that were not relevant at all, such as background circles, among others. As mentioned before, color is a really important attribute to classify each coin, but it can be a very confusing issue when classifying the same coins but different states. That is, the 100 coin has the same color for both old and new, and it is so for each coin; each has a unique color and "style"for both old and new, so it can become a point of confusion for the model. But it is for this reason that these attributes are not the only ones taken into account for grading coins.

4. Methodology

4.1. CRISP-DM

The methodology is an adaptation of CRISP-DM (CRoss Industry Standard Process for Data Mining)

1. **Business understanding:** Determinate the objective and requirement for the project. Necessary to identify the project goals and define the porject plan.

2. **Data Understanding:** Identify, collect and analyse the DataSet. These activities are necessary to know the quality of the DataSet and made a recognition of the information.

3. **Data preparation:** Using the results from Data Undetstanding to Select and clean the DataSet, create new DataSet derived from the selected Data.

4. **Modeling:** Select modeling techniques, generate a selection of the test set, build the model make the assess.

5. **Evaluation:** Finishing the training process and created a test, es necessary to evaluate results and Review process to generate adjustments.

5. Results

6. Results Analysis

6.1. Metrics

Before analyzing the results, we must know the metrics with which we are going to analyze the data.

It is very important to measure how well the model generalizes over unseen data is what defines adaptive versus non-adaptive machine learning models. By using different metrics for performance evaluation, we should be in a position to improve the overall predictive power of our model before we run it for production on previously unseen data [5] [6].

In this case we chose two metrics that we consider appropriate for the selected problem, which are Accuracy, Precision, Completeness and Specificity. The reasons why these metrics were chosen will now be presented.

- Accuracy: measures how often the classifier is correct. This metric is very useful to evaluate databases with classes of equal size. In our context, this metric measures how many times it is correct that it is a specific coin.

- Precision: measures how often it is correct when it predicts a "YES". This metric allows me to check what the model classified, i.e., if the model classified a 500 coin, measure how many of those coins are actually 500.

- Completeness: measures whether the classifier gets it right when it should get it right. It would be to pass it any coin, and it would get that coin right.
- Specificity: This is the opposite metric to Accuracy, it measures how often the classifier predicts that it does not.

7. Conclusions and Future work

7.1. Conclusion

7.2. Future Work

- Obtain more data
- Data preparation
- Analysis of results
- Recognizing and classifying currencies

8. Bibliographic References

Referencias

[1] 4 tipos de tareas de clasificación en el machine learning - elearning actual. Available at https://elearningactual.com/4-tipos-de-tareas-de-clasificacion-en-el-machine-learning/ (2024/03/14).

[2] Hough circles. Available at http://raerpo2.blogspot.com/2011/02/14-hough-circles-en-python.html (2024/03/15).

[3] Comprende principal component analysis — aprende machine learning). Available at https://www.aprendemachinelearning.com/comprende-principal-component-analysis/ (2024/03/16).

[4] Exploratory data analysis (eda) - how to do eda for machine learning problems using python - mlplus. Available at https://www.machinelearningplus.com/machine-learning/exploratory-data-analysis-eda/ (2024/03/17).

[5] Métricas de evaluación de modelos en el aprendizaje automático. Available at https://www.datasource.ai/es/data-science-articles/metricas-de-evaluacion-de-modelos-en-el-aprendizaje-automatico (2024/03/17).

[6] Métricas y puntuación: cuantificar la calidad de las predicciones — documentación de scikit-learn - 0.24.1. Available at https://qu4nt.github.io/sklearn-doc-es/modules/model_evaluation.html#scoring-parameter (2024/03/18).

[7] Fransico Charte. Qué tipos de problemas podemos resolver con técnicas de aprendizaje automático (machine learning). Available at https://www.campusmvp.es/recursos/post/que-tipos-de-problemas-podemos-resolver-con-tecnicas-de-aprendizaje-automatico-machine-learning.aspx (2024/03/14).