Brazilian Banknote Recognition Based on CNN for Blind People

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Abstract: This paper presents an approach based on computer vision techniques for the recognition of Brazilian banknotes. The methods for identifying banknotes, proposed by the Brazilian Central Bank, are unsafe due to intense banknote damage to their original state during daily use. These damages directly affect the recognition ability of the visually impaired. The proposed approach takes into account the second family of the Brazilian currency, the Real (plural Reais), regarding notes of 2, 5, 10, 20, 50 and 100 Reais. Thus, the proposed strategy is composed by two main steps: *i*) Image Pre-Processing; and *ii*) Banknote Classification. In the first step, the images of Brazilian banknotes, acquired by smartphone cameras, are processed to reduce the noise presence and preserve edges, through the bilateral filter. Finally, in the banknote classification step, the feature learning process is performed, representing the main features for banknote image classification. In addition, the Convolutional Neural Network (CNN) is used to classify the note denomination (value). Experiments demonstrated the effectiveness and robustness of the proposed approach, achieving an accuracy of 99.103%, using the proposed dataset with 6365 images of real banknotes in different environments and illumination conditions.

1 INTRODUCTION

The most used payment method worldwide is through banknotes and it still constitutes an essential part in monetary transactions (Joshi et al., 2020). Banknotes recognition is a non-trivial task for visually impaired and blind people. The mentioned difficulty makes people with visual impairment vulnerable to fraud. Moreover, it creates a barrier to daily consumption activities, like purchases and other banking tasks (Sousa et al., 2020).

Studies carried out in 2015 demonstrated that there were an estimated 36 million blind people globally. Meanwhile, moderate and severe vision impairment affected 216.6 million people (Bourne et al., 2017). According to the Brazilian National Health Survey in 2019, 6.978 million Brazilian people have severe vision impairment or blindness (IBGE, 2019).

Banking institutions around the world, responsible for the banknotes manufacture, provide some strategies to facilitate banknote recognition by the visually impaired, such as: different sizes, coded tactile structure, braille markings, irregular edges or tangible features (Joshi et al., 2020)(Ng et al., 2020). However, the tactile analysis represents a considerable difficulty due to intense banknotes turnover, promoting damages in their original state resulting in incorrect identification. Figure 1 presents an example of Brazilian banknote damage, regarding tactile analysis.

Figure 1: Example of Brazilian banknote with damage in tactile marks.

This paper presents an approach to recognizing Brazilian banknotes and assisting people with visual impairment in financial operations. The banknote denomination (value) is represented and classified through the proposed CNN architecture, with a specific learning process for the banknote domain. Experiments in real-world scenarios demonstrate the proposed approach scalability and show that the obtained results are accurate and reliable.

Our main contribution is to provide a robust and

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efficient approach, based on Deep Learning, to classify Brazilian banknotes, assisting the visually impaired in daily monetary transactions. Based on the proposed approach it is possible to embed the learning model into a mobile application to support visually impaired people, in monetary operations. We also highlight the dataset used in this research work, consisting of Brazilian banknotes in different environments and luminosity conditions. Furthermore, it is important to mention the variety of images, including crumpled banknotes and real acquisition scenarios.

This paper is organized as follows. In Section 2 we present the state-of-the-art regarding banknotes recognition. In Section 3 is presented the proposed methodology. We describe the experiments and discuss the obtained results in Section 4. Finally, in Section 5, we provide concluding remarks and discuss paths for future investigation.

2 RELATED WORK

Banknote analysis is a popular research area in Pattern Recognition. It has been the focus of intense investigation to achieve accurate and reliable results, with different approaches reported in the literature (Huang and Gai, 2020)(Tan et al., 2020)(Pham et al., 2019)(Yousry et al., 2018). Several state-of-the-art work perform the banknote image acquisition using different camera settings, with respect to high-resolution (Dittimi et al., 2017), low-resolution (Sousa et al., 2020) and smartphone cameras (Ng et al., 2020). Other research work employ sensors, including contact image sensor (Sanghun Lee et al., 2017) and banknote readers (Tan et al., 2020). In this work, we use smartphone cameras to collect our proposed image dataset.

There are several research work analyzing distinct currencies, including the US dollar, the Euro and the Brazilian real (Sousa et al., 2020). Other work tackle banknotes from countries such as China (Sun et al., 2018), Hong Kong (Ng et al., 2020), India (Joshi et al., 2020), among many others (Baykal et al., 2018), (Yousry et al., 2018), (Tan et al., 2020) (Kongprasert and chongstitvatana, 2019), (Huang and Gai, 2020), (Pham et al., 2019) and (Dittimi et al., 2017).

In this paper we address banknotes from Brazil, aiming at a robust and effective banknote recognition. Unlike the work mentioned earlier, our image dataset is composed by banknotes in real situations, including crumpled banknotes, blurred and images captured in non-ideal light condition.

Banknote classification techniques typically identify counterfeit (Laavanya and Vijayaraghavan, 2019), soiled (Sanghun Lee et al., 2017), worn (Tan et al., 2020), old (Sun et al., 2018), nationality (Khashman et al., 2018) or denomination (value) (Ng et al., 2020) of banknotes. In some approaches, banknote features are represented through size, color and text (Abburu et al., 2017), Histogram of Oriented Gradients (HOG) (Dittimi et al., 2017), Oriented FAST and Rotated BRIEF (ORB) (Yousry et al., 2018), Discrete Cosine Transformation (DCT) (Tan et al., 2020) and Quaternion Wavelet Transform (QWT) (Huang and Gai, 2020). Different approaches threaten the classification problem using Fuzzy (Tan et al., 2020), Support Vector Machine (SVM) (Kongprasert and chongstitvatana, 2019), Random Forest (Sousa et al., 2020), Neural Networks (Khashman et al., 2018) and Hamming distance (Yousry et al., 2018). In the proposed strategy we address the recognition of banknotes denomination (value) problem. Furthermore, we use a Deep Learning technique to learn better features to depict the banknote characteristics.

State-of-the-art approaches tackle banknote recognition using Deep Learning architectures, including CNN fully trained on their own banknote datasets (Ng et al., 2020)(Huang and Gai, 2020)(Baykal et al., 2018), YOLO-CNN model (Joshi et al., 2020), Alex net tuned through transfer leaning (Laavanya and Vijayaraghavan, 2019), Alex net, VGG-11, VGG-16, Resnet-18 combining (Pham et al., 2019) and DenseNet-121 tuned through transfer leaning (Sun et al., 2018). We also define our feature representation learning and classification process using a CNN architecture. However, our approach tackles images acquired in real scenarios, with different environments and lighting conditions, unlike the mentioned works. Additionally, The proposed approach regards images in distinct capturing settings, varying the positional relation between the camera and the banknote.

The closer work to ours is (Thomas and Meehan, 2021), where the authors created a CNN for banknote recognition, assisting visually impaired people to identify different banknote values. The authors used data augmentation techniques to simulate partial banknote images, resembling those a blind or visually impaired person would take. The created model achieved an average accuracy rate of 94%. The model had some difficult in correctly identifying some banknotes, likely attributed to issues such as poor lighting in the images. Our approach uses varied lighting conditions which may significantly improve the model's sensitivity to illumination conditions.

3 METHODOLOGY

Our problem can be summarized as follows:

Problem (Brazilian Banknote Value Recognition). Let $I = \{i_1, i_2, \ldots, i_n\}$ be a series of images provided by a smartphone camera. Also let $V = \{v_1, v_2, \ldots, v_k\}$ be a series of previously known banknote labels (values). Our main goal is to correctly associate an unknown Brazilian banknote image (i_j) to the correspondent banknote label (v_w), representing its value.

In this paper, we propose an approach for the automatic recognition of Brazilian banknotes, based on visual features and deep learning classification. The proposed approach tackles the recognition problem of banknote denomination (value). An overview of the proposed methodology is shown in Figure 2, whose details will be presented in the next subsections.

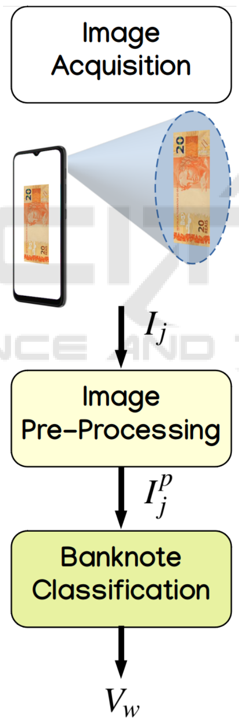


Figure 2: Overview of the proposed approach for Brazilian banknote recognition.

In Figure 2, we present an overview of the proposed approach, highlighting the main steps to achieve the Brazilian banknote classification. To reach this goal, images are acquired by the user and an image pre-processing stage is performed. Different visual aspects are learned in a deep learning procedure, understanding the banknote features for an efficient classification.

3.1 Image Pre-Processing

In this methodology, the images (I) are initially acquired in Red, Green and Blue (RGB) model and later the images are re-scaled to 640x480 pixels. After this, it is needed to process the raw images to highlight the main features to describe the banknote images.

In order to enhance the image quality for the Brazilian banknote recognition, the Bilateral filtering is applied. The Bilateral Filter (BF) is a nonlinear weighted averaging filter, where the weights depend on both the spatial distance and the intensity distance concerning the central pixel. The main feature of the bilateral filter is its ability to preserve edges while doing spatial smoothing. The mentioned nonlinear filter is performed as in the equation below:

$$BF(I)_p = \frac{1}{W_p} \sum_{q \in S} G_{\sigma s}(||p - q||) G_{\sigma r}(|I_p - I_q|) I_q \quad (1)$$

where p is a pixel location, S is the spatial neighborhood of p, q is every neighbor pixel in S, $G_{\sigma s}$ is the spatial domain kernel and $G_{\sigma r}$ is the intensity range kernel. W_p is the normalization factor, as defined below:

$$W_p = \sum_{q \in S} G_{\sigma s}(||p - q||) G_{\sigma r}(|I_p - I_q|) \quad (2)$$

In this stage, every banknote image (I_j) is smoothed, reducing the noise presence, meanwhile the edge quality for the feature representation process is preserved (I_j^p). In this sense, the main features of the banknote images are highlighted, improving the learning step for banknote classification.

3.2 Banknote Classification

From the pre-processed Brazilian banknote images (I_j^p), a feature learning process is applied. For this, a deep learning based approach is used to understand patterns and learn features in different conditions. A CNN architecture is proposed for the feature learning and banknote classification problem.

A CNN is a deep learning architecture strongly used for computer vision applications. CNN models can learn and represent effective features to allow the classification or regression process in real problems. In the banknote classification context, the proposed CNN model, unlike other classical approaches, can learn the features and its representation for the classification stage, even in different scenarios and domains.

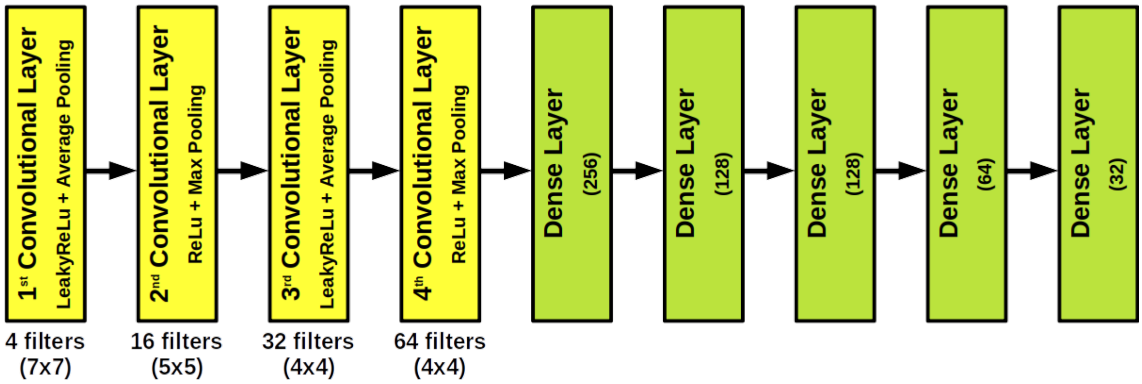


Figure 3: Proposed CNN architecture for Brazilian banknote recognition.

The proposed CNN model is composed by 4 convolutional layers. The first layer is defined with 4 filters, the second layer is defined with 16 filters, the third layer is defined with 32 filters and, at last, the fourth layer is defined with 64 filters. The filters size in the first layer are $(7x7)$, in the second layer are $(5x5)$ and in the third and fourth layers are $(4x4)$.

In the first and third convolutional layers, the LeakyReLu activation function is used, together with the Average Pooling function, regarding a window size of (2x2). In the second and fourth convolutional layers, the ReLu activation function is used, together with the Max Pooling function, regarding window size of $(2x2)$.

After the convolutional layers, 5 fully-connected layers are proposed. The sizes of the fully-connected layers are 256, 128, 128, 64, and 32, respectively for each flatten layer. Between each fully-connected layer are used Dropout layers with rate value of 0.1.

In the training stage, the Stochastic Gradient Descent (SGD) optimization algorithm is used, with learning rate equal to 0.01 and momentum of 0.75. The training procedure was performed for 20 epochs and using a batch size of 20. The CNN model is used for Brazilian banknote classification due to good results achieved in similar scenarios (Thomas and Meehan, 2021). The proposed CNN model is also used due to good feature representation learning, depicting distinct and complementary features for modeling different banknotes and environment conditions, unlike classical approaches.

Figure 3 presents the proposed CNN architecture for the Brazilian banknote value recognition. It also provides details about the deep-learning model, describing the convolutional and dense layers, filters, complementary functions and parameters involved.

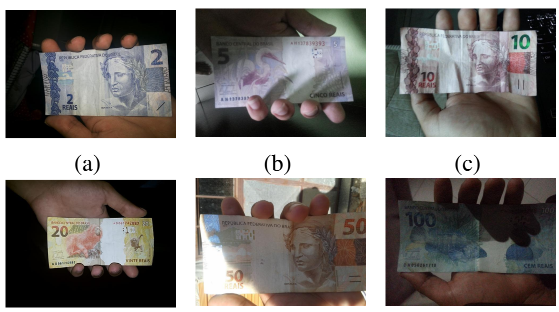
4 EXPERIMENTS

In this section, we evaluate the proposed approach, comparing it with traditional methods. Furthermore, we evaluate the proposed approach regarding simulated noisy and blurry images.

The proposed experimental setup is composed by two low-cost smartphone cameras, with 8.0 megapixels and artificial illumination (flash). For the processing stage a Dell computer, with an Intel Xeon^{TM} Silver 4114 2.20GHz CPU and 128 GB DDR4-2133 main memory, is used to execute the proposed approach.

4.1 Image Acquisition

The image dataset was collected using smartphone cameras, depicting Brazilian banknotes in different real environments and illumination conditions. The proposed dataset is composed by 6 different types of banknotes, regarding notes of 2, 5, 10, 20, 50 and 100 Reais, as can be observed in Figure 4.


(a) (b) (c)

(d) (e) (f)

Figure 4: Different banknote images from the proposed image dataset.

The image dataset consists of 6365 Brazilian banknote images, with variation in natural illumination and artificial illumination (with flash) conditions. Additionally, images from the front and back surface of each banknote were acquired.

For the image acquisition process, the smartphone camera must be positioned keeping a distance of about 10*cm*, between the banknote and the camera device. We suggest a region near the mid-forearm, as reference point, for the correct position of the image acquisition device, as can be seen in Figure 5.

Figure 5: Acquisition process of Brazilian banknote images.

4.2 Brazilian Banknote Classification Assessment

This experiment evaluates the accuracy of the proposed approach for the Brazilian banknote classification. Different approaches are implemented and evaluated to address this classification problem. The approaches used for comparison are: *i*) Local Binary Pattern (LBP) and Ada Boosting (AB) classifier; *ii*) LBP and Random Forest (RF) classifier; *iii*) HOG and AB classifier; and *iv*) HOG and RF classifier. The comparison techniques were used due to good results obtained in related approaches for banknotes recognition (Dittimi et al., 2017), (Sousa et al., 2020) and overall banknotes analysis (Ayalew Tessfaw et al., 2018) and (Thomas and Meehan, 2021).

The setting parameters for the AB classifier were the number of estimators equals to 100. For the RF classifier the setting parameters were the number of estimators equal to 30 and the max depth equal to 30. The parameters tuning for the proposed approach was performed by varying a set of parameters to maximize accuracy, during the training and testing stages. Different scenarios changing the number of convolutional layers, the number of filters, the size of filters, the number of fully-connected layers, the size of the fully-connected layers and the learning rate were experimented.

The training stage of the classification model was performed from a set of input images and the testing stage uses another set of input images since the cross-validation 5-fold protocol is applied. The dataset used for the training process is composed of 6365 images of Brazilian banknotes, acquired manually by a visually impaired human operator.

The achieved results show that the proposed CNN model outperforms the other traditional techniques, as we can observe in Table 1. The combination of the LBP descriptor (depicting texture features) with the RF classifier (banknote value recognition), obtained the best results among the traditional techniques.

Table 1: Results for Brazilian banknote classification. This experiment presents the accuracy for CNN (proposed), HOG and LBP descriptors. Additionally, were used the Random Forest (RF) and Ada Boosting (AB) for the classification problem.

Method	Accuracy
LBP + AB	48.672 ± 1.226
LBP + RF	81.257 ± 1.301
HOG + AB	61.461 ± 0.670
HOG + RF	78.020 ± 0.985
Our method	**99.103 ± 0.326**

The proposed approach achieved accurate results, in the Brazilian banknote classification process, due to the learning of different filters during the value recognition process. The CNN process allows the learning of patterns in different contexts and regarding different features. Thereby, some banknote conditions can be better represented and classified using the convolutional learning process.

4.3 Brazilian Banknote Evaluation: Noise Analysis

This experiment evaluates the robustness of the proposed approach for Brazilian banknote classification in the presence of noise. Two different types of noise are added in banknote images, Salt and Pepper and Gaussian noises. All the traditional techniques used in the experiment described in the previous subsection and the proposed CNN model are evaluated. In this experiment the added noise simulates possible problems in the image acquisition process in real-world situations and different types of smartphone cameras.

For this assessment, the classification model training is performed from a set of images without noise and the testing stage uses another set of images with added noise. Figure 6 represents Brazilian banknote image examples. Figure 6 represents a Brazilian banknote without noise. Figure 6 represents a Brazilian

(a) (b) (c)

Figure 6: Examples of Brazilian banknote images. In Figure 6 a banknote image is presented without the presence of noise. Figure 6 presents a banknote image with Salt and Pepper noise, with 0.02 noise density. Figure 6 presents a banknote image with Gaussian noise, with 0.02 noise density.

Table 2: Results for robustness evaluation of Brazilian banknotes classification, in the presence of noise. In this experiment, all the considered methods are evaluated for Salt and Pepper noise.

	Salt and Pepper		
Noise density	**0.005**	**0.01**	**0.02**
LBP+AB	44.446 ± 1.775	41.147 ± 0.988	36.009 ± 1.208
LBP+RF	65.750 ± 1.688	51.155 ± 1.242	36.434 ± 1.924
HOG+AB	46.771 ± 1.388	35.570 ± 1.836	27.133 ± 1.812
HOG+RF	63.378 ± 1.751	49.568 ± 1.018	35.617 ± 1.827
Our method	**98.879 ± 0.291**	**98.975 ± 0.517**	**98.911 ± 0.747**

Table 3: Results for robustness evaluation of Brazilian banknote classification, in the presence of noise. In this experiment, all the considered methods are evaluated for Gaussian noise.

	Gaussian		
Noise density	**0.005**	**0.01**	**0.02**
LBP+AB	18.350 ± 0.825	17.753 ± 1.638	18.130 ± 0.939
LBP+RF	18.068 ± 0.917	18.382 ± 0.810	18.209 ± 0.756
HOG+AB	29.411 ± 0.616	24.195 ± 0.999	21.430 ± 0.480
HOG+RF	31.767 ± 0.686	25.232 ± 1.104	21.728 ± 1.313
Our method	**98.783 ± 0.314**	**98.255 ± 0.527**	**98.015 ± 0.313**

banknote with Salt and Pepper noise, with 0.02 noise density. Figure 6 represents a Brazilian banknote with Gaussian noise, with 0.02 noise density.

The achieved results in this experiment show that the proposed CNN model presents better performance even in the presence of noise, as we can observe in Table 2 and Table 3. Table 2 shows the Brazilian banknote classification results for Salt and Pepper noise, using the accuracy and standard deviation measures. Table 3 shows the Brazilian banknote classification results for Gaussian noise, also using the accuracy and standard deviation measures. The results show that the proposed CNN model outperforms the other classification approaches even in the presence of noise, demonstrating the robustness of our approach.

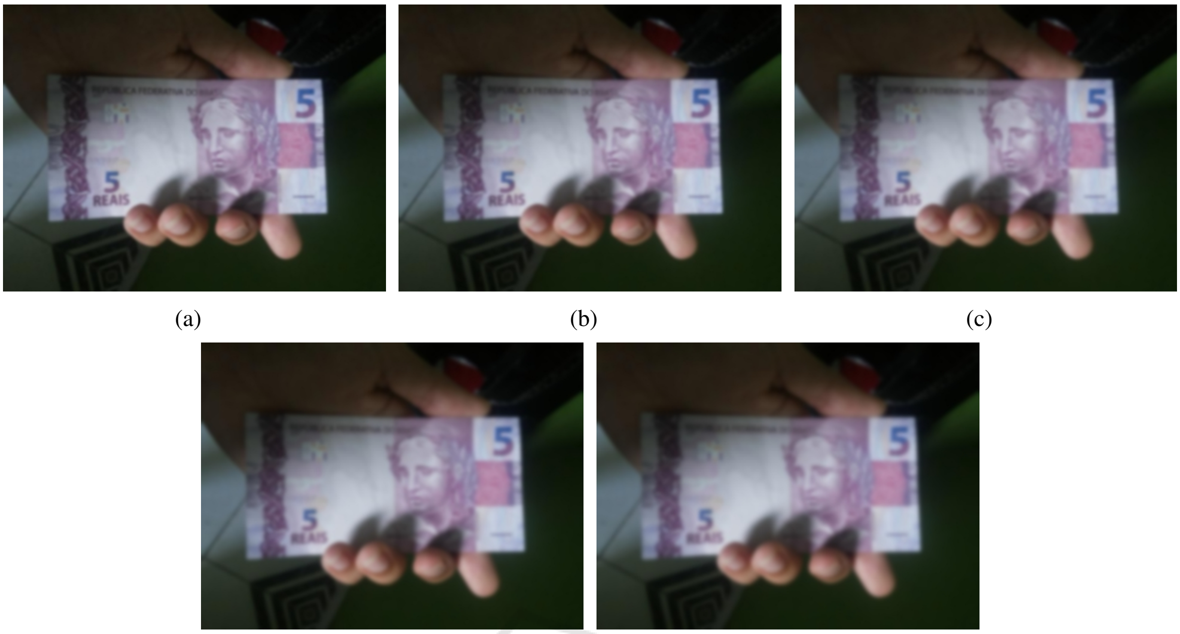
4.4 Brazilian Banknote Evaluation: Blurring Analysis

This experiment evaluates the robustness of the proposed approach for Brazilian banknote classification with blurred images. For this, the Gaussian blurring technique is used to generate different blurring degrees for banknote images. In this experiment, Gaussian filters were used with size 13x13, 15x15, 17x17, 19x19 and 21x21, simulating a blur effect in the image capturing process.

All the traditional techniques used in the experiments described in the previous subsections and our proposed CNN model are evaluated. For this assessment, the classification model training is performed with a set of images without blur and the testing stage uses another set of images with added blur. Figure 7 shows examples of blurred images of Brazilian banknotes. Figures 7, 7, 7, 7 and 7 represent a Brazilian banknote with 13x13, 15x15, 17x17, 19x19 and 21x21 filter sizes, respectively.

The achieved results in this experiment show that the proposed CNN model presents better performance even when the banknote image is blurred, as we can observe in Table 4. Table 4 shows the Brazilian banknote blurred image classification results, using the accuracy and standard deviation measures.

In Figure 8, it is also possible to verify the performance of the proposed approach regarding the blurring problem in image capturing process, highlighting



(a) (b) (c) (d) (e)

Figure 7: Examples of blurred images of Brazilian banknotes. Figures 7, 7, 7, 7 and 7 present blurring effects, with Gaussian filters with sizes $13x13$, $15x15$, $17x17$, $19x19$ and $21x21$, respectively.

Table 4: Results for robustness evaluation of Brazilian banknote classification, in out of focus images. In this experiment, all the considered methods are evaluated using low-pass Gaussian filter.

	Lowpass Gaussian Filter				
Kernel size	**13**	**15**	**17**	**19**	**21**
LBP+AB	15.727 ±1.215	15.727 ±1.440	16.041 ±1.690	16.057 ±1.757	15.837 ±1.541
LBP+RF	16.292 ±0.790	16.386 ±0.714	16.057 ±0.819	16.119 ±1.063	16.182 ±1.165
HOG+AB	62.577 ±1.228	60.644 ±1.164	59.230 ±0.749	59.199 ±1.351	58.445 ±1.354
HOG+RF	76.198 ±1.093	74.863 ±0.749	74.187 ±0.756	73.260 ±0.844	72.333 ±0.904
Our method	**99.055 ± 0.211**	**98.767 ± 0.212**	**98.895 ± 0.484**	**98.639 ± 0.444**	**98.687 ± 0.767**

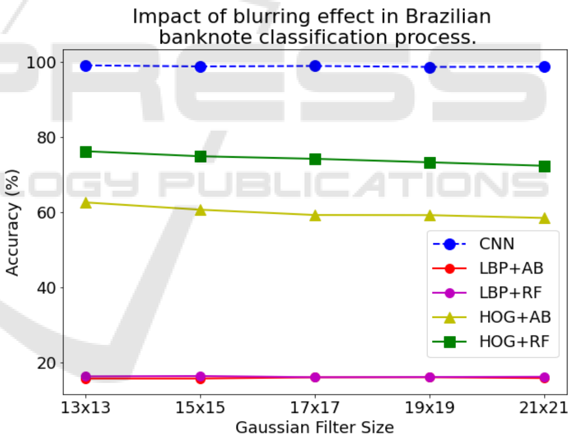


Figure 8: Evaluation of Brazilian banknote classification methods under blurring impact.

the high accuracy of our method. Results show that the proposed CNN model outperforms the other classification approaches even in blurred banknote images, demonstrating the robustness of the proposed approach in real image capturing conditions.

5 CONCLUSION

In this paper we addressed the problem of Brazilian banknote classification, recognizing the note denomination (value), for visually impaired people. Unlike other state-of-the-art approaches, our method achieves high accuracy with images of banknotes in a real-world scenario, reproducing the manual banknote image acquisition through smartphone cameras.

Experiments involving different classification techniques have shown that the obtained Brazilian banknote classification results are reliable and accurate, considering the image dataset used. Additionally, the proposed approach presents robustness, even in presence of noise, blurring and defocusing during image acquisition. It also demonstrates the feasibility for real applications, once the experiments were carried out in real-world scenarios.

As future work, we intend to combine different classification methods to improve the current classification accuracy. We also plan to concentrate efforts on extending the banknote classification process to tackle banknotes from other countries. Furthermore, we intend to address deformed image banknotes, reproducing crumpled banknotes.

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