Identifying Representative Images for Events Description Using Machine Learning

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Abstract: The use of social networks to record events – disasters, demonstrations, parties – has grown a lot and has begun to receive attention in recent years. Existing research focuses primarily on analyzing text-based messages from social media platforms such as Twitter. Images, photos and other media are increasingly used and can provide valuable information to enhance the understanding of an event and can be used as indicators of relevance. This work explores the Twitter social media platform, based on image and text in the case of the demonstrations that took place in Brazil on September 7, 2021, as a result of the Independence celebrations. This work uses machine learning techniques (VGG-16, VGG-19, ResNet50v2 and InceptionResNetv2) for finding relevant Twitter images. The results show that the existence of an image within a social media message can serve as a high probability indicator of relevant content. An extensive experimental evaluation was carried out and demonstrated that high efficiency gains can be obtained compared to state-of-the-art methods.

1 INTRODUCTION

Several events occur every second, are recorded and publicized by newspapers, magazines and other media vehicles and, mainly, by mobile phones of ordinary people. Terrorist acts, natural catastrophes, ceremonies such as weddings, graduation, sporting events, among others, frequently occur around the world. These data, shared on platforms such as Twitter, Facebook and Instagram, are accessible to anyone.

These images can be used as representative of events and, in this way, filtering them is a great challenge. Crucial data, which could really represent the event, may be mixed up with even larger amounts of unimportant data. However, manual selection of representative (useful) images from a large amount of data may be infeasible. Thus, the problem of how to automatically separate representative from non-representative images was identified. In this research, techniques were investigated to identify possible solutions to this problem, considering the lack of labeled images that indicate representativeness.

Existing approaches are based on representations of components that can encode the information needed to describe events, such as people who were part of the event (eg. suspects or victims); objects that appear in the scene (for example, cars or weapons); and the location where the event took place (eg parks, stadiums or buildings).

Consider an event - such as a terrorist attack - that took place at a location with a lot of people with cell phones, such as stadiums or theaters. In minutes, hundreds or even thousands of text messages, images and videos can be shared on social media.

A total of 7,888,374 tweets related to the terrorist attack that occurred during the 2013 Boston Marathon were collected, with the first tweet published less than four minutes after the first explosion. A correct description of the events that make up the event can help in its understanding.

The data obtained for an event E can be divided into two main groups: Representative and Non-Representative. Among the data in the Representative group are those that belong to the event and that, in some way, can help in understanding it. Among the data of the Non-Representative group are those that do not belong to event E, but that may or may not present some similarity with it.

The task of performing this separation into two groups of images, Representative and Non-Representative, can be modeled through neural networks.

This work aimed to analyze different existing techniques for retrieving information that use learning neural networks, seeking to identify representa-

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tive images for an event, based on posts made through mobile phones.

This work collected images from the Wikimedia Commons image base with the keywords - Demonstrations, Manifestations and Acts - and were used to evaluate VGG-16, VGG-19, ResnNet50v2 and InceptionResNetv2 architectures as learning mechanisms. It was observed that the VGG-19 network has obtained the best result. Thus, in an attempt to further improve the results, it was decided to work with a larger base of images and, in this case, the VGG-19 network was tested with images from the GDELT base, for positive results, and Unsplash, for negative results.

2 RELATED WORK

According to Gupta et al. (Gupta et al., 2013), the 2013 Boston Marathon bombing generated 7,888,374 tweets. Of that total, around 29% was false information or rumors, 51% was general comments and opinions, and only 20% contained useful information. Other examples of data that do not belong to the event of interest are shown in Figure 1, where a search for the Notre Dame Cathedral Fire event also retrieves cartoons and memes (Figures 1c and 1d).

To discover representative images, some works compare (Pedronette et al., 2019; Iscen et al., 2019) descriptors, however, currently, many applications use resources extracted from deep networks. These networks, trained for a specific context, try to semantically describe the images (Razavian et al., 2014; Zheng et al., 2017) or locally, through points of interest (Scheirer et al., 2013), obtaining good results in the recovery task.

Despite the large amount of data available, recording all possible events (explosions, shootings, floods, fires, etc.) that may be of interest is impractical. This causes this issue to have an open scenario (Garrett,). Furthermore, if two events are considered, even if they are of the same type (like two explosions, for example) there may be very different aspects (such as location, weather or number of people gathered), requiring a large number and variety of training samples of data for the generalization of a model that separates representative from non-representative images.

Work presented in (Starbird et al., 2010) points out that the use of social networks during natural or man-made disasters has increased significantly in recent years and, therefore, there are studies on the relevance and usefulness of the data that can be obtained through these social networks for humanitarian organizations dealing with these disasters. The authors realize, however, that most of these studies are focused on textual content, and so they decided to work on using visual content (i.e., images) to show their value to these humanitarian organizations. Despite their usefulness, they acknowledge that the sheer quantity of images makes them difficult to use effectively, despite how useful such data would be for gaining information and better understanding emergencies.

The authors point out, then, that currently one of the most popular ways to obtain information from images is to use a hybrid model, where human workers classify points of interest within a set of images that are then used to train supervised machine learning models to recognize these points in new images automatically.

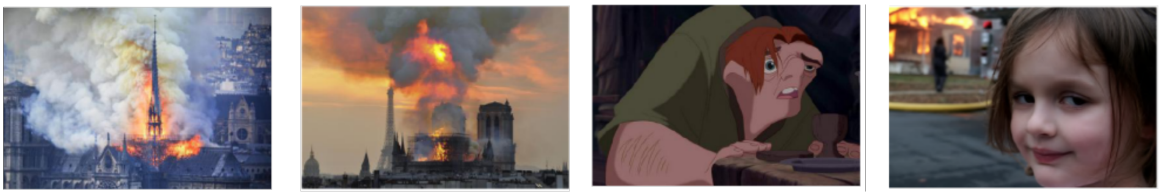
For data collection, the authors used AIDR platform, for classification, the VGG-16 model of convolutional neural network was used as a reference to train on a set of images previously classified by human volunteers, and for the removal of duplicate images was used the Perceptual Hashing (pHash) technique.

The research developed in (Kavanaugh et al., 2012) investigates the use of the Twitter microblogging platform during a critical event for the security of a region, in this case the period of threat of seasonal floods in the Red River Valley in 2009, with the objective of understanding more about chats based on CMC (computer-mediated communication) in the new era of "social networks" and describes characteristics of the relationship between this chat and mass emergency events.

During the study, information was obtained about user behavior in relation to emergency events, how the proximity and severity of the threat change user behavior and how this happens. The study results also provided insight into practical emergency management issues, showing that information obtained through sites such as twitter can complement, but not replace, official sources of information in emergency situations.

The study presented results of an exploratory study conducted between June and December 2010 with government officials in Arlington, Virginia, and the greater National Capitol Region surrounding Washington, D.C., researchers sought to better understand social media use by government officials and other members of society, in addition to seeking to understand the use of social networks specifically to manage crisis situations, whether routine or critical.

The research presented in (Hughes and Palen, 2009) was conducted based on the analysis of local data from social networks and interviews and questionnaires applied to 25 officials from the County of



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

Figure 1: When we consider the Notre Dame Cathedral Fire event that occurred on April 15, 2019, figures (a) and (b) are from the event, but figures (c) and (d), also retrieved in a search for the event, do not belong to the event.

Arlington.

The results of the exploratory study obtained based on interviews, questionnaires and data analysis can be placed in 3 main areas: The local government uses social networks without having notions of cost, benefit, target audience, what it should monitor, how it should respond and what is the effect of using social media to communicate with the public; Among the technical problems found in the study are the ability to: Recognize relevant information accurately and in a timely manner; Alerting government officials to information analyzed from various social media sources and; Visualize current and past states of the obtained information and its analysis.

The research (Simonyan and Zisserman, 2015) focuses on trying to understand the use of social networks during emergency situations or mass concentration, focusing more specifically on the Twitter site. The research used the Twitter search API during 4 events that took place in the USA between August and September 2008 to obtain data relevant to the investigation, focusing on the textual content of the messages.

The data collected during the study indicate that the platform is used as a support for the dissemination of news. Also, adoption of platform users may be linked to the occurrence of emergency situations and mass convergence.

Finally, they conclude that Twitter and other similar technologies can be used to obtain data for emergency management.

3 MATERIALS

3.1 Hardware

This work was done using the Google Colab environment, a free cloud storage service in which it is possible to write and run Jupyter notebooks with GPU and TPU support.

3.2 Software

As Google Colab uses Jupyter notebooks, the scripts were written in Python. As for the libraries, we used scikit-image (version 0.19.x) that provides tools to perform image pre-processing like background segmentation and Tensorflow (version 2.x) to develop the Neural Networks.

4 PROPOSED METHODOLOGY

Figure 2 summarizes the process developed throughout this work in five main steps:

1. Definition of search keywords
2. Image dataset creation - selection of corresponding images from the Wikimedia Commons base;
3. Training with four distinct architectures: VGG-16, VGG-19, ResNet50v2 and InceptionResNetv2;
4. Performance comparison of different approaches
5. Training VGG-19 with larger image database (GDELT and Unsplash);

Images were collected on the Twitter platform, as it has a large user base in Brazil and allows instant image sharing. We therefore sought to select an event that would generate great movement on the platform and, in this context, the national holiday of September 7, 2021, when Brazil's Independence is celebrated, emerged as the ideal option, since the day would be marked by activities civic events and political demonstrations about the country's situation in relation to the crisis that accompanied the COVID-19 virus pandemic.

A monitoring was carried out of the hashtags present in the trending topics that were related to the national holiday of September 7th and also with the acts that were scheduled for that date. In this way, the hashtags that had the greatest movement in the period of a week around September 7 were selected. Then, tweets, containing images and presenting one of the

Figure 2: Flowchart representing the whole process of representative image identification.

selected hashtags, were collected with the aid of the API tool that Twitter itself provides. A total of 56,937 tweets were collected.

During data collection, it was also defined what would be the keywords based on the events observed on the day. The following words were used: Demonstrations, Manifestations and Acts. Since these would encompass most of the events that took place on that date, such as commemorative acts for the celebration of independence and political demonstrations.

For the training, images were selected, corresponding to the key words, from Wikimedia Commons [1], a portal that has media content curated and classified by the community. These images served as the basis for the generation of a model to classify the images that were collected in the defined period. 1320 positive images and 788 negative images were collected for the defined keywords. These images were pooled into a training dataset and 245 photos were selected from those collected from Twitter to build a test dataset.

To take advantage of the tools available in the Keras library, the concept of transfer learning was used, which consists of taking resources learned in a problem, and taking advantage of them in the solution of another problem that is similar. In the case of deep learning, it consists of using part of a model that has been trained to recognize a wide range of features to accelerate the learning process of the model you want to create.

Four architectures were provisionally separated by their ability to deal with problems similar to those addressed in this work: VGG-16, VGG-19, ResNet50v2 and InceptionResNetv2.

VGG-16 and VGG-19 are part of the architecture family known as VGG Net, being a pre-trained convolutional neural network (or CNN). They are known for their simplicity, being formed by 3x3 convolutional layers stacked in increasing depth. Volume size reduction is handled through maximum pooling. Two interconnected layers are followed by a softmax classifier. The numbers 16 and 19 in the names refer to the number of weight layers in the network. Unlike other sequential network architectures like VGG Net, ResNet relies on micro-architecture modules to build the network. InceptionResNetv2 is a convolutional neural network that is trained on more than a million images from the ImageNet database.

[1]https://commons.wikimedia.org/wiki/Category:Images

4.1 Results

Using each of these architectures, graphs of accuracy and loss were generated for each model, showing the training and validation values and how they behaved during the training duration. Figures 3, 4, 5 and 6 show the accuracy and loss curves for the architectures used.

Some conclusions were obtained:

- In all architectures the accuracy rose very quickly but reached a plateau, which may indicate that, under the current conditions of the experiment, increasing the training duration will not give a significant increase in the accuracy of the model;
- The architectures had similar precision and loss numbers, but the VGG-16 and VGG-19 architectures had smaller discrepancies between the training and validation numbers, indicating that we had less overfitting in the models trained with these architectures;
- The ResNet50v2 architecture had a large discrepancy between the training and validation numbers, indicating a high probability that there was overfitting in the model trained with this architecture.

However, despite the numbers presented in the graphs, when asking the trained models to classify images from the test dataset, a relatively high number of false positives was identified, which indicated that the size of the datasets used initially was insufficient to train a model accurate regardless of the architecture used. The Figure 7 shows positive and negative results obtained by tests using the VGG-16 architecture.

Once the performance of the architectures was analyzed, it was decided to continue with the tests and they would be carried out using the VGG-19 architecture, as it is very similar to the VGG-16, the main difference being the number of weight layers. Once the architecture was resolved, larger datasets were used for retraining.

For positive results, the dataset of images of protests provided by the GDELT project[2] was used, based on its Visual Global Knowledge Graph, which is a tool that monitors several media vehicles and categorizes this flow of data and, from it, were collected 30000 images out of the 5 million available.

[2]https://www.gdeltproject.org/

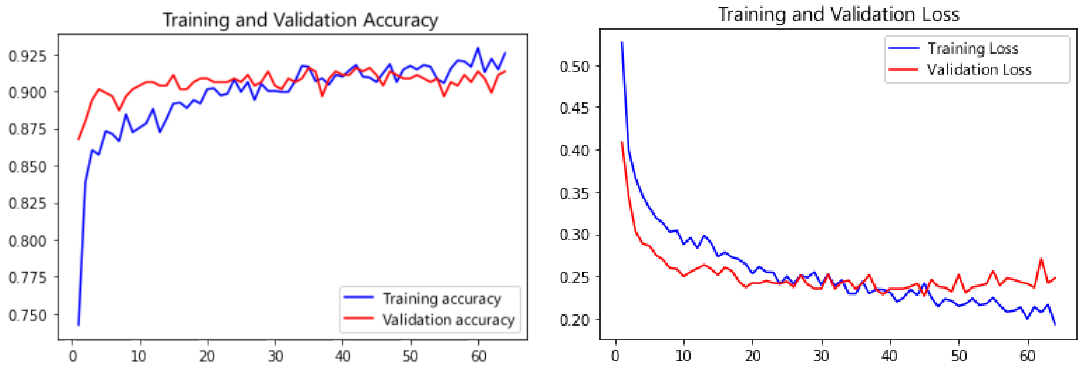


Figure 3: Accuracy and Loss curves based on VGG-16 architecture.

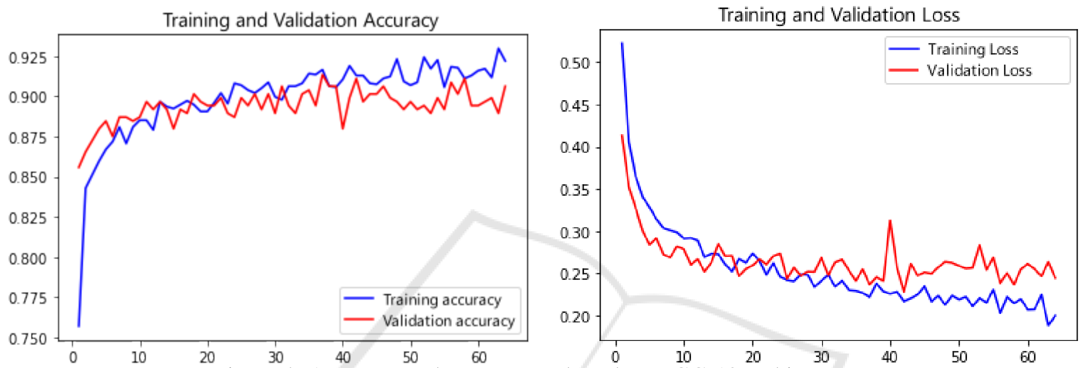


Figure 4: Accuracy and Loss curves based on VGG-19 architecture.

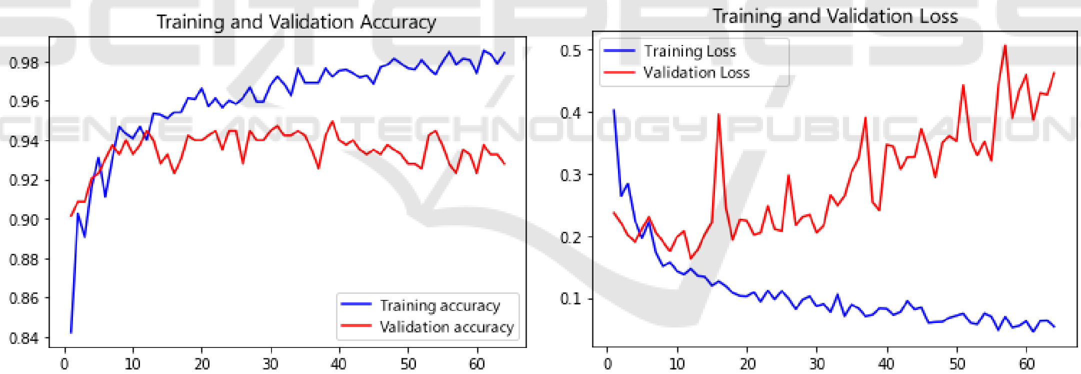


Figure 5: Accuracy and Loss curves based on Resnet50v2 architecture.

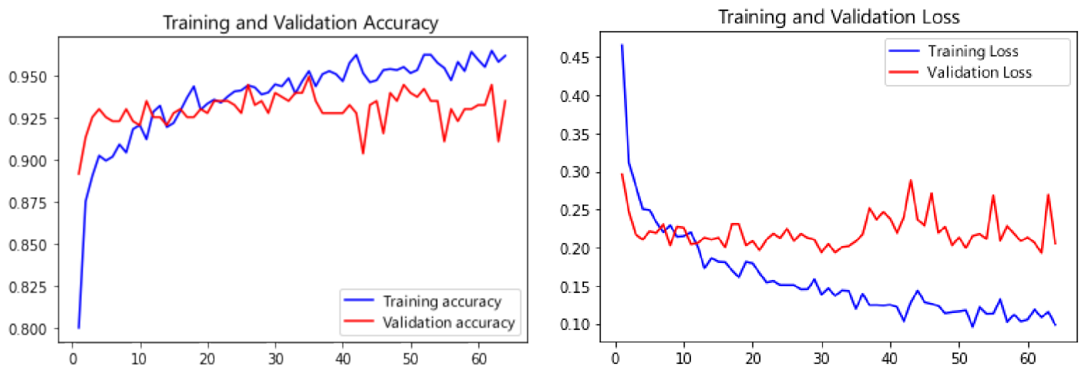
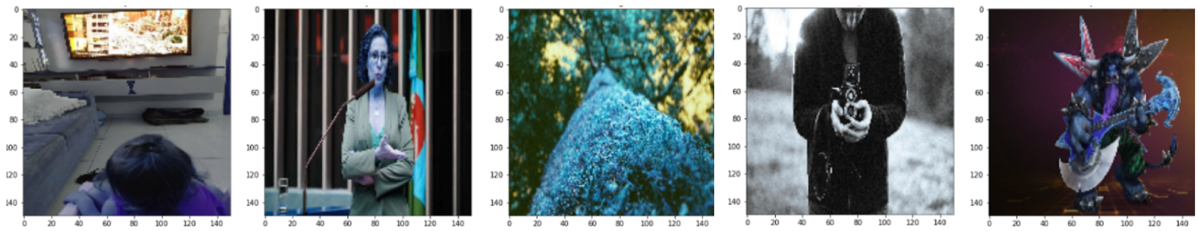
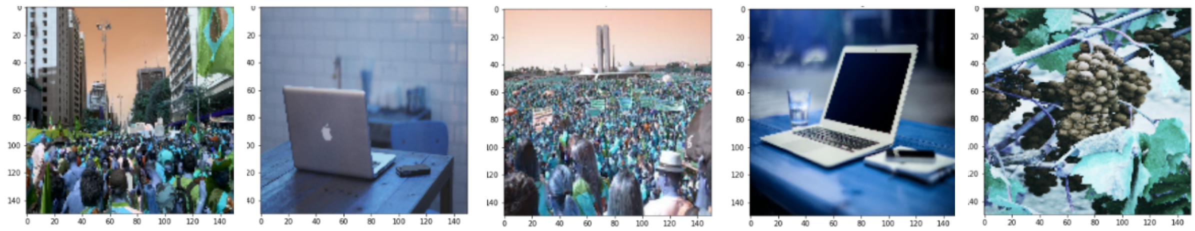


Figure 6: Accuracy and Loss curves based on InceptionResNetv2 architecture.



(a) positive (b) positive (c) negative (d) negative (e) positive



(f) positive (g) negative (h) positive (i) negative (j) positive

Figure 7: Results obtained from testing the model created with the VGG-16 architecture.

For negative results, the open dataset provided by the Unsplash[3] website was used, which maintains a curation of images available through a free license and, in this way, the 25,000 images available in the lite version of the dataset were obtained. With the architecture and the larger dataset, a new wave of training of the model was performed, initially in 32 periods and, at the end of the training and validation, accuracy and loss graphs were obtained, as shown in Figure 8:

By observing these graphs, it is possible to verify that increasing the number of samples contributed a lot to increase the accuracy, reaching values of 0.9755 of training accuracy and 0.9830 of validation accuracy in its last training season. The graph shows that the accuracy during training became more stable and with validation results compatible with training and even above them.

To corroborate these results (shown in Figure 8), Figure 9 shows that the model had excellent results in image classification, presenting only 1 false positive (second figure from the left of the first row), a considerable advance in relation to the initial tests with smaller datasets. To test whether the model could be further refined, further training of the model was performed. When training the model, with the same architecture, but with more epochs (32 to 64), we obtained the following results in precision and loss, shown in Figure 10.

Although validation and training values were close, the accuracy of the model shown in the graphs dropped slightly, in this example reaching 0.9762 of training accuracy and 0.9570 of validation accuracy in its last training epoch. Subsequent tests showed that, even increasing the number of epochs, the precision value continued to vary very close to the values obtained in training with fewer epochs, and this information is reinforced by the results of the model classifying test images continuing to perform similarly to the model trained in 32 epochs, as Figure 11 shows.

In order to improve the comparison, we can also see in Table 1 the direct comparison between the models.

This low variation leads to the conclusion that, after choosing an adequate architecture and performing refinement on the model's training variables, what had the most impact on the final efficiency of the trained model was the size of the dataset on which it was trained.

4.2 Conclusions

The results of this research show that there are several machine learning techniques capable of serving as a basis for the development of a prototype for identifying representative images. For this work, images related to the events of the Brazilian holiday of September 7, 2021 were used.

During model training, it was possible to identify that the architectures of the VGG family performed better.

In addition, it was possible to verify the need for a suitable dataset for training, which is large enough for the model to obtain the characteristics of the event that one wants to recognize.

In future work, it is possible to evaluate how much an annotated dataset can impact the need to have a large dataset for training. In view of the observations,

[3] https://unsplash.com/

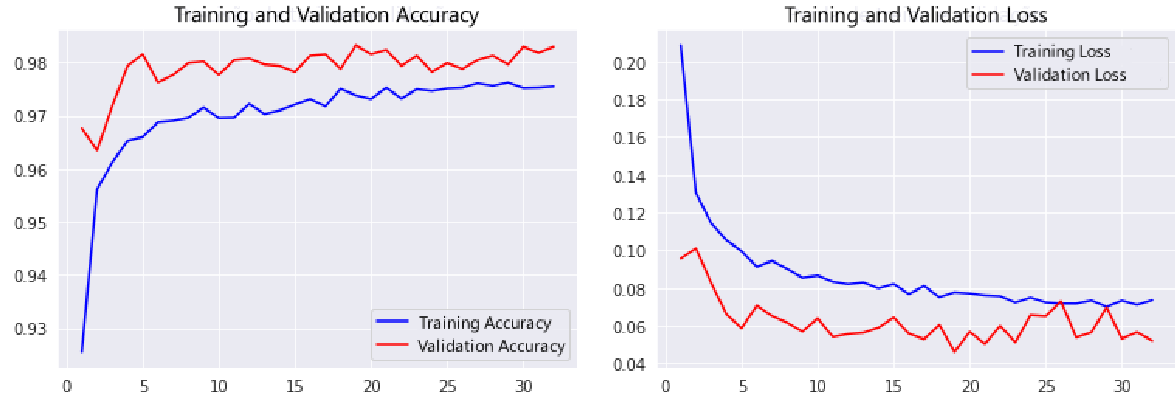
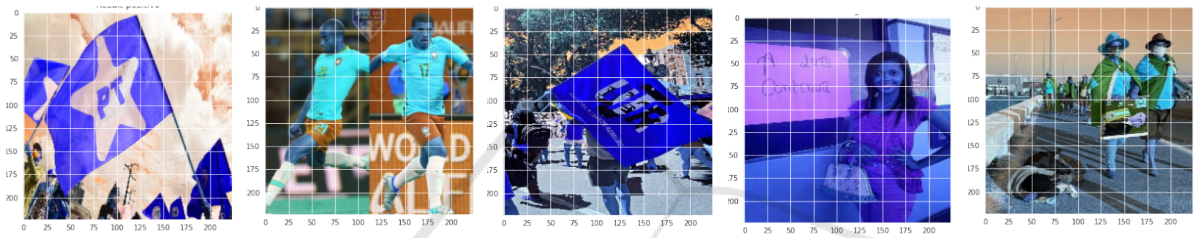
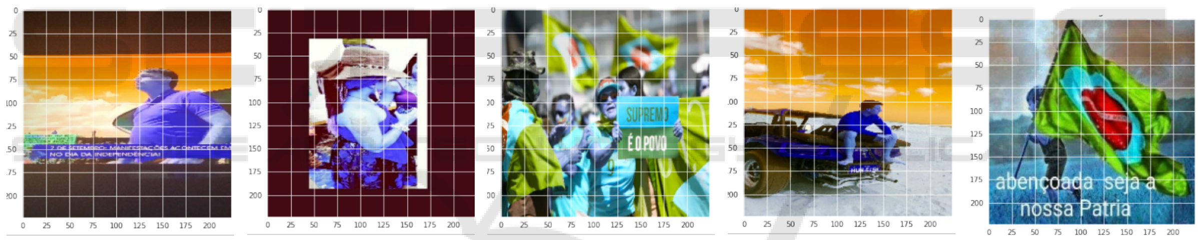


Figure 8: Accuracy and loss curves of the model based on the VGG-19 architecture with larger datasets and training in 32 epochs.



(a) positive (b) positive (c) positive (d) negative (e) positive



(f) negative (g) negative (h) positive (i) negative (j) negative

Figure 9: Example of classification of images obtained from the model created with the VGG-19 architecture with expanded datasets and training in 32 epochs.

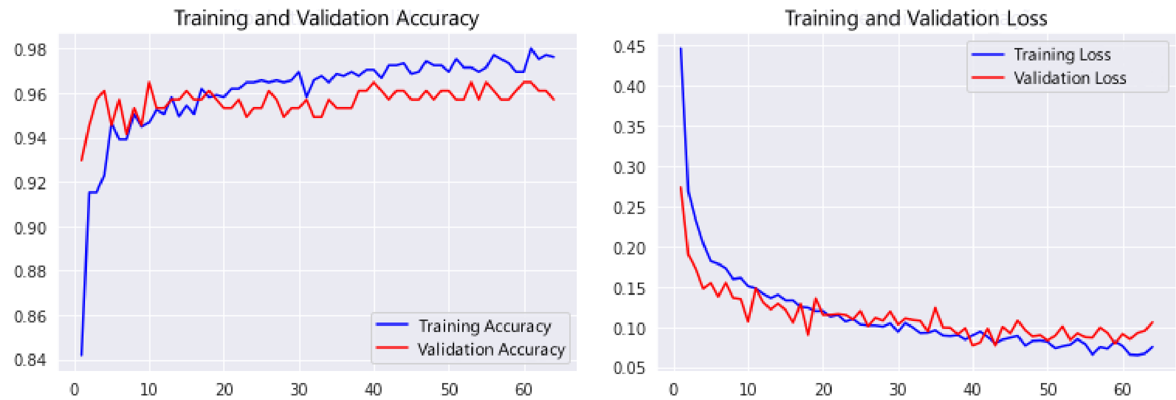
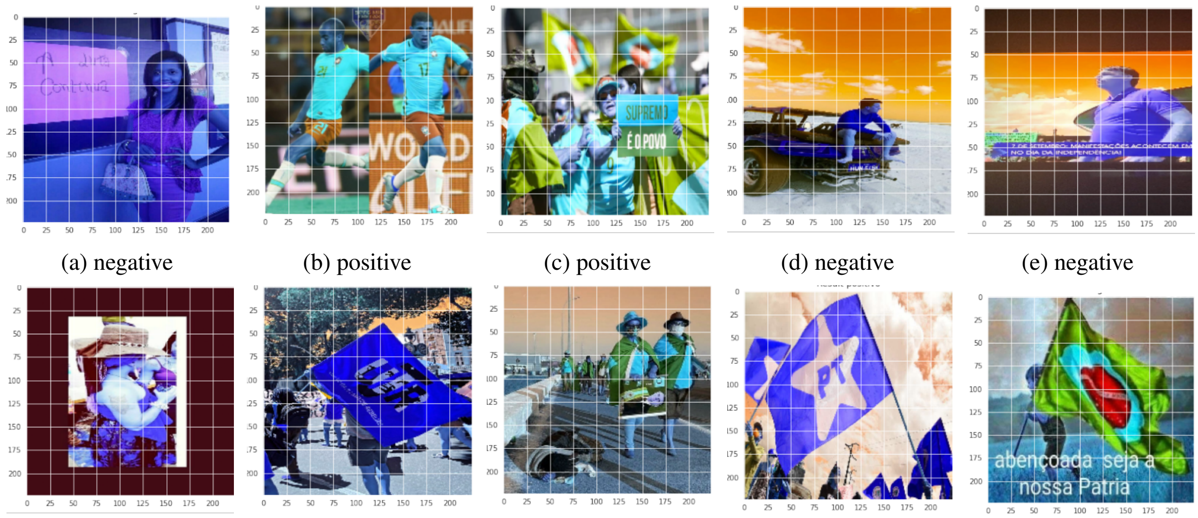


Figure 10: Accuracy and loss curves of the model based on the VGG-19 architecture with larger datasets and training in 64 epochs.



(a) negative (b) positive (c) positive (d) negative (e) negative

(f) negative (g) positive (h) positive (i) positive (j) negative

Figure 11: Example of classification of images obtained from the model created with the VGG-19 architecture with expanded datasets and training in 64 epochs.

Table 1: Comparison between precision and loss values between models trained with different amounts of epochs.

	VGG-19 (32 epochs)	VGG-19 (64 epochs)
training accuracy (max)	0.9761	0.9800
validation accuracy (max.)	0.9833	0.9648
loss of training (min.)	0.0700	0.0649
validation loss (min.)	0.0461	0.0769

the results obtained show that the solution presented here is viable and presented good results.

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