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## Artificial intelligence model for the prediction of malignant tumors using a set of medical images from mammography studies

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# Artificial intelligence model for the prediction of malignant tumors using a set of medical images from mammography studies.

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**Abstract.** Currently, the diagnosis of tumors and malignant cells through imaging studies is a great challenge for expert medical personnel, due to the complexity of achieving an early prediction of cancer cells, which would allow to accelerate early medical treatments. Today, technologies have become a fundamental ally for the health sector, specifically the area of artificial intelligence, which has permeated many disciplines, generating important advances. Advances in parallel computing, GPU technology, and deep learning have made real-time image processing easier. The main objective of this research was to generate a deep learning model for the prediction of malignant cells in medical images of diagnosed mammograms. Using the previously trained model based on Faster R-CNN, with the ResNet function extractor. This model works in the Python programming language, using the Tensorflow framework and the OpenCv library. The algorithms were previously trained through the DDSM and MIAS open medical image databases, published on the web. This model not only focuses on recognizing and classifying malignant cells in the image, but also on the location of objects within it, appropriately drawing a bounding box. One of the latent challenges of these models since their inception has been the consumption of computing, but today they have been optimized so much that they allow freezing the pre-trained models by loading them in the memory of the devices, managing to use them in computers without GPUs. As a result, it was found that the Faster R-CNN method with the Resnet101 extractor offers great advantages of precision and speed when it comes to detecting malignant tumors, studies that can serve as a great contribution to the bets of this algorithm in the health sector.

## 1. Introduction

Today there is a great public health problem worldwide, many countries face great challenges due to high mortality rates, the spread of infectious and non-communicable diseases and poor reproductive health. In recent decades, great strides have been made in increasing life expectancy and reducing some of the most common causes of death. As a result, globally, 170 countries have set 17 sustainable development goals in order to have a better planet for future generations, specifically for this research we will be working on objective number three, health and wellness, which aims to decrease the rate of mortality in the countries by 2030 [1].

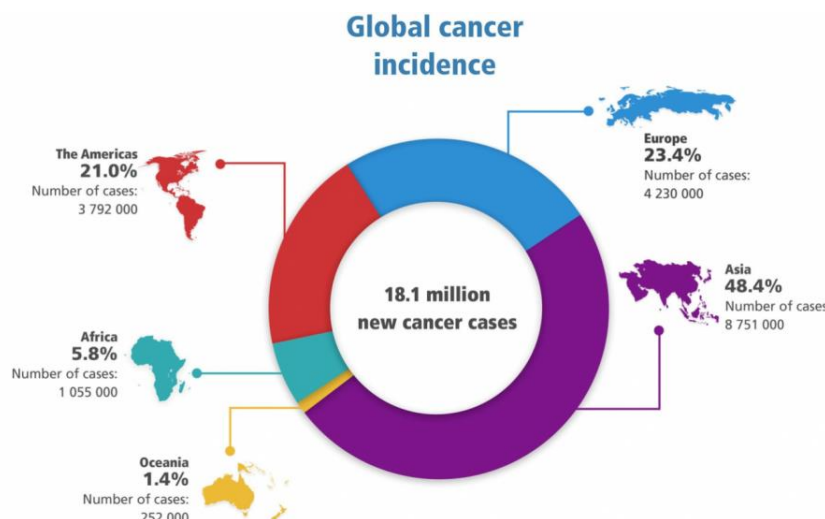
According to the Pan American Health Organization, in the Americas, cancer is the second leading cause of death, the types of cancer most frequently diagnosed among men are: prostate (21.7%), lung (9.5%), colorectal (8%), bladder (4.6%) and stomach (2.9%). Among women, the types of cancer with the highest incidence are: breast (25.2%), lung (8.5%), colorectal (8.2%), thyroid (5.4%) and cervical (3.9%).



The types of cancer with the highest mortality in men are: lung (19.6%), prostate (12.1%), colorectal (9.3%), liver (65) and stomach (5.4%). The cancers that cause more deaths among women are: lung (17.4%), breast (15.1%), colorectal (9.5%) and cervical (5.2%) [2].

According to the World Health Organization [3], each year in the Americas, more than 462,000 women are diagnosed with breast cancer, and almost 100,000 die from this disease, if current trends continue, by 2030, the number of women diagnosed with breast cancer is projected to increase by 34%. Several countries in Latin America and the Caribbean have some of the highest rates of risk of death from breast cancer, highlighting health inequities in the Region. Prevention strategies in developing countries are carried out in very advanced phases, due to the high costs of medical equipment, the absence of trained medical personnel and the scarce resources to acquire these studies.

Despite notable advances in diagnostic technology in recent years, as well as an increase in campaigns aimed at promoting self-examination, many breast cancer patients continue to receive the diagnosis in advanced stages of the disease. Some risk factors for breast cancer are known, however, in most affected women it is not possible to identify specific risk factors [4][5]. Comprehensive cancer control encompasses prevention, early detection, diagnosis and treatment, rehabilitation and palliative care. In Figure 1, we can see the proportion of new cases and deaths from cancer in the Americas.



**Figure 1.** Incidence and mortality from breast cancer in the Americas

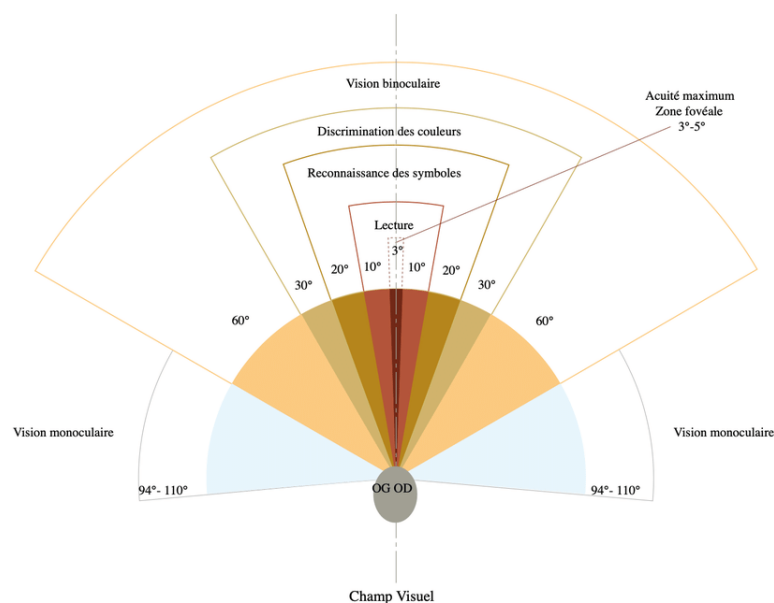
From the national level, according to the Ministry of Health with the support of the National Cancer Institute, the objectives of cancer control have been established, specifically in risk control, early detection, comprehensive treatment, palliative care, epidemiological surveillance, and talent development. human in oncology [6]. Presenting public policy and the 10-year cancer plan as an essential instrument. The number of sick and dead people from this cause has been increasing in recent years; the figures dictate that about 96 people die every day in Colombia from cancer. According to 2010 mortality figures, among women breast cancer was the leading cause of death (2,381), followed by cancer of the cervix (1,892), stomach (1,709), lung (1,606) and colon and rectum (1,456).

Among men, cancer mortality for the same year was led by malignant tumors of the stomach (2,796), followed by those of the prostate (2,431), lung (2,357), colon and rectum (1,261) and leukemias (890) [7].

From the local level, the population of the department of Sucre, like that of Latin America, has a significant incidence of chronic non-communicable diseases, in particular cardiovascular diseases, cancer, diabetes and chronic respiratory diseases. From the departmental administration they propose the initiative to make use of science, technology and innovation, which allow identifying and overcoming the social and environmental determinants related to the appearance of these diseases. Through alliances that include the public and private sectors, as well as NGOs, professional associations, the academic sector and international organizations [8].

In the department of Sucre, there are different health entities that have medical equipment to carry out radiological studies, but most of them are digitized, where the image is captured in analog form on a photostimulable phosphor plate (barium halide fluoride activated with europium impurities), compared to the most sophisticated radiology equipment, which comes with digital technology, which have introduced changes in the identification of suspicious images, digital storage to monitor patients, among others. This has allowed the generation of complementary decision-making tools when it comes to expert medical personnel making an accurate assessment.

Cancer is an aggressive disease with a low median survival rate. Treatment is long and very expensive due to its high recurrence and mortality rates. Early diagnosis and prediction of cancer prognosis are essential to improve the patient's survival rate. It exhibits a wide spectrum of behaviors, some are clinically indolent and others are aggressive, requiring prompt treatment. Today, doctors face different obstacles and challenges, such as the existence of less defined tumors, generating little visibility and distinction of cancerous tissues. This leads to false negative diagnoses, erroneous evaluations by medical personnel, when diagnosing a sick person as healthy, consequently, this can worsen the patient's health and delay treatment. Studies show that more experienced radiologists visually scan CT images more systematically [9]. The human field of vision may be short when making these diagnoses, since it only covers the equivalent of a circle of about 2.5 centimeters in diameter with high definition, and also for a defined time [10]. In figure 2, we can detail the width of the human visual field.



**Figure 2.** Structure of the visual field of humans

In figure 2, we detail the visual field of each individual where the objects located in the space can be seen. In which, there are differences in the more defined or less defined surface qualities depending on their distance and the quality of the colors is appreciated; if they are close, they are saturated; if they are far away, they are modulated and not modulated.

In relation to the above, technological advances will be a crucial alternative to develop methodologies that reduce mortality in cancer patients. This disease is difficult to diagnose in the early stages or can easily relapse after treatment. Furthermore, the precise predictions of the disease prognosis with high certainty are very complex. Some cancers are difficult to detect in their early stages due to their vague symptoms and distinctive indications from mammograms and scans [11]. Therefore, it is imperative to develop better predictive models using multi-variable data and high-resolution diagnostic tools in clinical cancer research. Artificial intelligence will be one of the best allies of medical professionals in the diagnosis and treatment of many diseases, such as cancer. Studies have shown that artificial intelligence algorithms have the ability to identify cell by cell and detect if it is a cancer cell or if it is a normal cell. And, through spatial correlation, it is able to make much more reliable predictions [12].

On the other hand, the creation of imaging techniques such as ultrasound, mammography, x-rays, computed tomography (CT), fMRI, magnetic resonance, or nuclear medicine, histology, and histopathology have marked a crucial point in the development of diagnoses of malignant cells in the medical sciences. The images generated by the medical teams of these modalities have two fundamental characteristics, compared to the analog radiography images, these being the spatial resolution (number of pixels per inch or cm) and the density or depth (gray levels that can be represent), who owns the image [13].

Within imaging tests for cancer diagnosis, artificial intelligence finds great utility in the execution of 3 main clinical tasks: (Detection, characterization, and monitoring of tumors).

Detection refers to the location of objects of interest on radiographs, collectively known as computer-assisted detection. The characterization broadly captures the segmentation, determining the shape or volume of the lesion, the histopathological diagnosis, and disease status or molecular profile. Segmentation defines the extent of an abnormality. Monitoring; It allows capturing a large number of discriminating characteristics, to verify the progression or regression of the disease and the monitoring of the appearance of a target or cancer mutations associated with resistance in near real time [14].

Although this technology is still in the testing phase and cannot be widely used at the moment, its implementation gives an idea of what the future may hold for the field of Artificial Intelligence applied to medicine. The researchers caution that these findings must be clinically validated in different types of patients.

The images today play a fundamental role in the process of medical care of patients, imaging studies have transformed modern medicine, to such an extent, from making diagnoses in acute pathologies.

Radiological and histopathological studies, which are part of imaging diagnosis, have become complementary tools that allow early detection of cancer cells in imaging tests, but today these evaluations are still short, due to the fact that medical opinions are highly dependent of specialist expertise.

The images provide valuable information for personalized medicine, becoming an important input for non-invasive medical procedures that do not involve instruments that break the skin or physically penetrate the body, which do not affect the integrity of people. These tools have strongly complemented the early detection of breast cancer patients.

The main causes of mortality in patients diagnosed with breast cancer lie in late diagnosis, high examination costs, extensive administrative processes, poor visibility and distinction of cancerous tissues.

Today, the integration of technology and computational methods have optimized early diagnosis, applications involving artificial intelligence technologies in medicine, imply a revolution in the way medical studies are perceived, this technology has left behind traditional prediction methods that are based on patient variables such as age, family history of cancer, or tissue density. However, these factors are weakly correlated with the possibility of developing cancer.

Collaboration between medical pathologists, oncologists, systems, electronic, and biomedical engineers has enabled the improvement of early cancer diagnoses, through the integration of technology and computational methods, in a new area known as digital pathology that optimizes traditional pathology.

The importance of carrying out this research lies in a non-invasive proposal related to a deep learning model for the detection of cancer cells in real time in breast tissues, with the aim of achieving early treatments in patients suffering from this pathology.

## 2. State of the art

A review of the state of the art was made from the international to the national level, of the investigations related to the use of deep learning algorithms for the prediction of malignant cells in mammographic images, finding the following studies:

Authors Scott Mayer McKinney, Marcin Sieniek, and Shravya Shetty of the Department of Surgery and Cancer, Imperial University of London in January 2020, conducted research titled “International Assessment of an Artificial Intelligence (AI) System for Cancer Detection breast”, presenting a proposal as a complementary tool for expert medical personnel in the area, with the aim of making predictions of cancer cells using imaging studies. The authors evaluated the performance of the algorithm in a clinical setting with a representative dataset from the UK and the US They conducted an independent study with six radiologists, to assess the efficiency of the AI system, where it outperformed all expert medical personnel. The area under the receiver operating characteristic curve (AUC-ROC) for the AI system was greater than the AUC-ROC for the average radiologist by an absolute margin of 11.5%. Where they concluded that this technology can have a great impact on the health sector, specifically on the detection of different types of Cancer, which could help mitigate the high mortality rates from this cause [15].

On the other hand, the authors Rui Yana and Fei Ren from the area of Informatics and Technology of the University of Anhui, Hefei of China, in the year 2019, carried out an investigation entitled “classification of histopathological images of breast cancer using a deep neural network hybrid”, generating an artificial intelligence model to support medical personnel in histopathological diagnosis, due to the complexity of this type of study and the dramatic increase in workload, making this task time consuming, as a consequence, Results may be subject to the subjectivity of the pathologist. In this article, they propose a new hybrid recurrent convolutional deep neural network for the classification of histopathological images of breast cancer.

Based on multilevel feature representation of histopathological image patches, the method integrates the advantages of recurrent and convolutional neural networks, and short and long term spatial correlations between feature patches are preserved. The experimental results showed that the technique presented an efficient method in contrast to those of the state of the art with an average precision obtained of 91.3% for the classification task of 4 classes. Model training was performed with a dataset of 3,771 histopathological images of breast cancer, with variability in subclasses spanning different age groups, which provided sufficient diversity of data to alleviate the problem of relatively accurate classification. Low benign images [16].

The authors Andrea Duggento, Manuel Scimeca, Nicoletta Urbano and Elena Bonanno from the department of biomedicine and prevention at the University of Rome in Italy, developed an investigation entitled “a deep neural network of random initialization to discriminate malignant lesions from breast cancer”. In this context, the researchers affirm that the rates of false positives and false negatives when making a cancer diagnosis, commonly achieved by radiologists, are extremely high, and some authors have estimated figures of up to 20% of the total diagnosis or more. Hence, the great importance of computer-assisted diagnosis that has been driven by the introduction of deep learning techniques in general and convolutional neural networks (CNN) in particular. In this article, we propose a design and validation of an ad-hoc CNN architecture specialized in the classification of breast lesions and heuristic exploration on possible combinations of parameters and architecture styles to propose a model selection criterion that can emphasize reducing false negatives while maintaining acceptable accuracy. They achieved regular classification performance in the validation and test set, "Model 1" and "Model 2" achieved an AUC of 0.785 and 0.774, respectively. Demonstrating a moderate classification, demonstrating how an ad-hoc random initialization CNN architecture can provide practical help in the classification and staging of breast cancer [17].

Furthermore, the authors Zhen Zhang, Yaping Wang and Jiankang Zhang from the Zhengzhou University of China, developed an investigation entitled “comparison of multiple feature extractors in the fastest RCNN architecture for detecting breast tumors” The learning algorithm Deep shows great ability in pattern recognition tasks like object detection and speech recognition. Compared to typical machine learning methods that require manual feature extraction. The deep learning algorithm has more powerful feature learning ability. In this document, the deep learning associated object detection method is applied in the localization and classification of lesions for the detection of medical masses of mammary cells. At the same time, five network function extractors are used, which are ResNet101, V2 start, V3 start, Mobilenet and ResNet V2 start, which were investigated to explore the impact of the model. The dataset from the Digital Mammography Detection Database (DDSM) was used for research, with the objective of determining the performance of the models associated with the five feature extractors and comparing them separately in the detection of mammographic images. with benign and malignant tumors, according to the ROC compensation curves. The simulation results demonstrate that the classification model with the Inception ResNet V2 feature extractor had the best performance, compared to the other four feature extractors [18].

### *2.1 Comparison between deep learning algorithms for object detection*

A state of the art review was performed to validate the performance of the Fast-RCNN, Faster-RCNN, R-FCN and SSD algorithms using different free databases on the web, where MS COCO, IMAGENET and PAS-CAL VOC stand out. with the purpose of reviewing speed and precision parameters of these methods using different image resolutions in different contexts.

It is important to note that technology is constantly evolving, any comparison can quickly become obsolete. An exhaustive review of scientific and academic documents on the performance of different object detection models with the Keras and TensorFlow framework was carried out, where the following studies were found;

In Table 1 the advantages and disadvantages of methods Fast R-CNN, Faster R-CNN, R-FCN, SSD and YOLO for detecting objects in images will be highlighted by various experiments conducted by a variety of authors investigated in Deep Learning area.

**Table 1.** Advantages and disadvantages of some methods for detecting objects in images.

| Method       | Authors                   | Advantage   | Disadvantages  |
|--------------|---------------------------|---|--|
| Fast R-CNN   | (Girshick, 2015) [19]     | The calculation of the characteristics of CNN is done in a single iteration, achieving that the detection of objects is 25 times faster than the RCNN method (it requires 20 seconds on average to analyze an image). | The use of an external candidate region generator creates a bottleneck in the detection process.   |
| Faster R-CNN | (Renet et al., 2015)[20]  | The RPN method allows object detection to be almost real-time, approximately 0.12 seconds per image.  | Despite the efficiency of the algorithm, it is not fast enough to be used in applications that require real time, as would be the autonomous vehicles. |
| R-FCN        | (Dai et al., 2016)[21]    | The test time of R-FCN is much faster than that of R-CNN  | R-FCN has a competitive mAP but lower than that of Faster R-CNN.   |
| Mask R-CNN   | (He et al., 2017)[22]     | The location of the objects is more precise, when making a segmentation of the objects in the images.   | Its execution time is greater than that used by the Faster-RCNN method, therefore, it can not be implemented in applications that require real time.   |
| YOLO         | (Redmon et al., 2015)[23] | The location of objects is very efficient, allowing its use in real-time applications.  | The method has difficulties to correctly detect small objects.   |
| SSD          | (Liu et al., 2016)[24]    | The use of a single network, makes the location of the objects faster than the Fast-RCNN and Faster-RCNN methods.   | The detection accuracy of the objects is lower compared to the Fast-RCNN and Faster-RCNN methods.  |

### 3. Methodology

In recent years, the architecture of the deep networks has been a significant progress for the moment Keras and TensorFlow dominates with different-pre-trained models already included in libraries, among these include VGG16, VGG1, ResNet50, Inception V3, Xception, MobileNet. The VGG and AlexNet 2012 networks follow a typical pattern of classical convolutional networks. MobileNet is a simplified architecture Xception architecture, optimized for mobile applications. The following architectures; ResNet, Inception and Xception have become a reference point for subsequent studies of artificial vision and learning for its versatility Deep.

There are many factors that explain the revolution of deep learning, among these factors is highlighted; availability of sets of huge data and quality, parallel computing (GPU) features efficient activation for backpropagation, new architectures, new regularization techniques that allow train more extensive networks with less danger of overshooting, robust optimizers and software platforms with large communities like TensorFlow, Theano, Keras, CNTK, PyTorch, Chainer and Mxnet. All this has allowed solving problems easier. Today the Python programming language has great importance in Machine Learning compared to other languages because of its support for Deep learning framework.



Within this framework include TensorFlow which is a library of open source software for machine learning that allows you to deploy computing in CPU or GPU, developed by Google, using graphs flow data, PyTorch uses Python language and has the support of Facebook, Theano is a Python library that supports mathematical expressions involving tensorers, CNTK are a set of tools developed by Microsoft, open for Deep learning code, Keras is a library of neural networks high level created by Francis Chollet, member of Brain google equipment that lets you choose whether the models that are built will be executed in Theano, TensorFlow or CNTK. Keras and TensorFlow can construct models of three different ways; using a sequential model, a functional API and pre-trained models.

Earlier we talked about the different architectures (MobileNet, Inception, ResNet, among others), now we discuss models for object recognition and Keras TensorFlow; Faster-CCN R, R-FCN, SSD and YOLO. These models are classified based detectors in the region (Faster R-CNN, R-FCN, FPN) and single shot detectors (SSD and YOLO), start from different paths, but they look very similar now fighting for title faster and more accurate detector.

There are different metrics that can improve object detection algorithms based on more accurate positioning, faster speed and more accurate classification; metrics that stand out are: Intersection over Union (IoU), mean average precision (MAP) and rendered frames per second (FPS). Intersection over Union (IoU) It is an indicator that determines how close the predicted picture of the real picture. The average metric average accuracy (MAP) is the product accuracy and recovery detection bounding boxes. It's a good combined measure of how sensitive the network to objects of interest and how well it avoids false alarms. The higher the score the map, the more precise the network, but this has a cost of execution speed. Processed frames per second (FPS) is used to judge how fast is the system.

### 3.1 Datasets

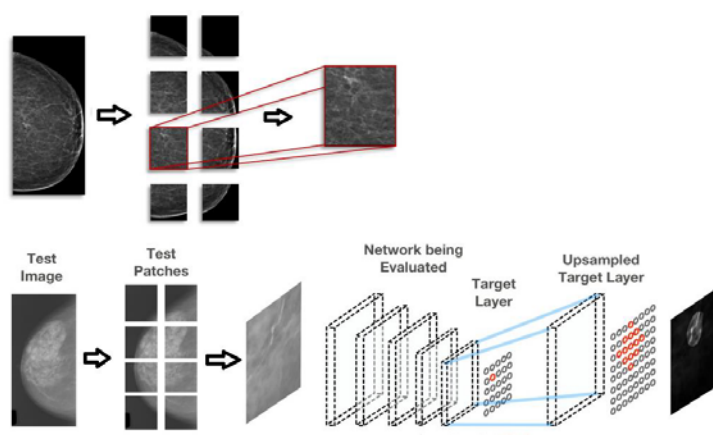
For the training of the selected RCNN and SSD models, free databases of mammography medical images were used, already diagnosed by specialized medical personnel, specifically the digital database for detection mammography (DDSM) and the Society for the Analysis of Mammographic Imaging (MIAS).

*3.1.1 DDSM - Digital Database for Screening Mammography.* The Database (DDSM) is a resource for use by the mammographic imaging research community. Primary support for this project was a grant from the U.S. Army Medical and Materiel Research Command Breast Cancer Research Program. The DDSM project is a collaborative effort involving colleagues at Massachusetts General Hospital (D. Kopans, R. Moore), the University of South Florida (K. Bowyer), and Sandia National Laboratories (P. Kegelmeyer). The primary purpose of the database is to facilitate sound research in the development of computer algorithms to aid in detection. Secondary purposes of the database may include the development of algorithms to aid in diagnosis and the development of teaching or training aids. The database contains approximately 2,500 studies. Each study includes two images of each breast, along with some associated information about the patient and the diagnosed pathology [25].

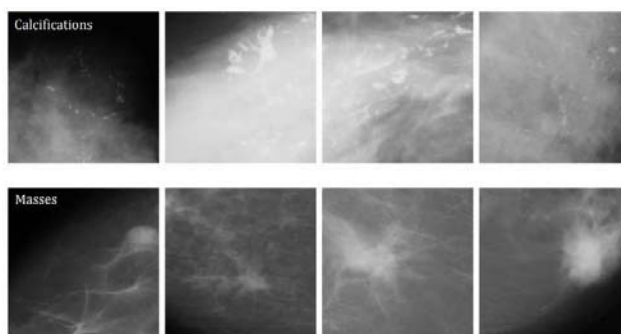
*3.1.2 Mammographic Image Analysis Society (MIAS).* It is an organization of UK research groups interested in understanding mammograms and has generated a database of digital mammograms. Images taken from the UK's National Breast Detection Program have been digitized to a 50 micron pixel edge with a Joyce-Loebl scanning microdensitometer, a linear device in the 0-3.2 optical density range and representing each pixel with an 8-bit word. The database contains 322 digitized images. All images are diagnosed by expert medical personnel, with all locations of any abnormalities that may be present. All images have a dimension of 1024x1024 [26].

#### 4. Results

For the development of this research, the deep learning method Faster-RCNN was used with the ResNet50 architecture, supported under the TensorFlow framework, the Python programming language and the OpenCV library. This model was trained on a Linux server with 32 cores and 93 GB RAM, where 10,000 medical images of mammograms diagnosed with malignant and binary tumors from the DDSM and MIAS databases were used, with different resolutions. The cross-validation technique was 85% of the images for training and 15% for validation. Deep convolutional neural networks were successfully applied to localize calcifications and masses on mammography images using the BI-RADS criteria. During the training there was a problem with the images with high resolutions, to solve this problem, smaller patches of the main images were formed, with the objective of improving the detection of the algorithms and increasing the data. As can be seen in figure 3 and 4.



**Figure 3.** Evaluation of neural networks in image patches [27].



**Figure 4.** Examples of highest scoring patches for malignancy [27].

For the following investigation, the following block diagram was used to detect malignant tumors in mammography images.

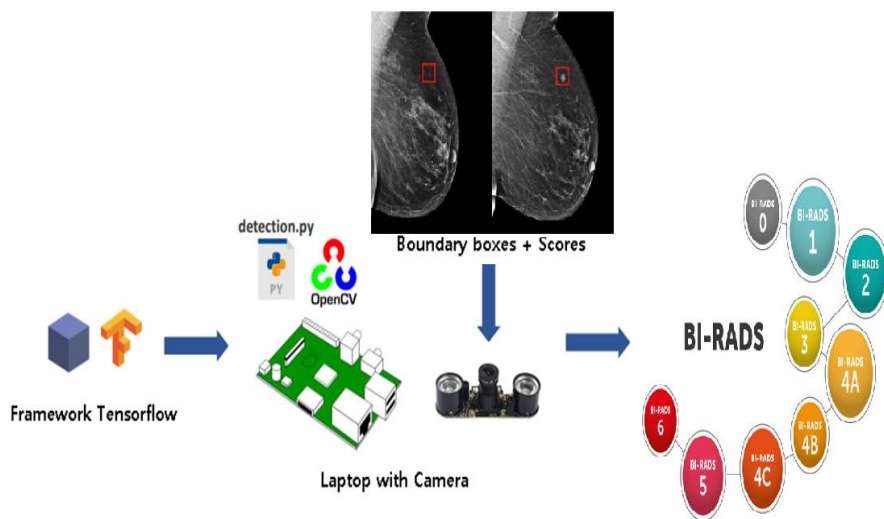


Figure 5. Block diagram of the system

The trained algorithm is capable of detecting masses and classifications in order to verify the probability of detecting a malignant or benign tumor, as we can see in Figures 6-8.

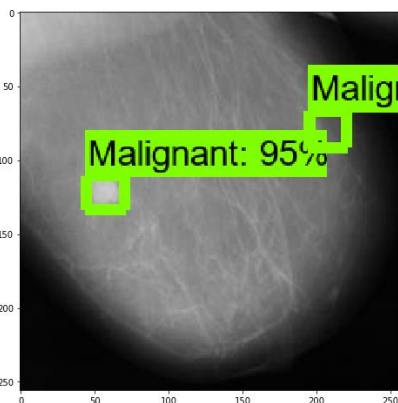


Figure 6. Detection of malignant tumors with the Faster-RCNN model and the Resnet50 extractor.

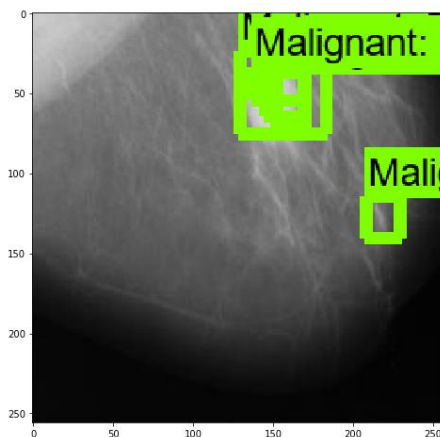
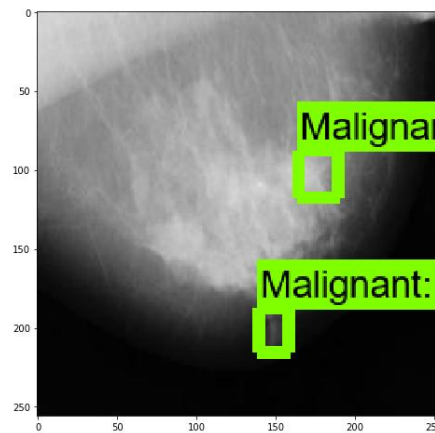


Figure 7. Detection of malignant tumors with the Faster-RCNN model and the Resnet50 extractor.



**Figure 8.** Detection of malignant tumors with the Faster-RCNN model and the Resnet50 extractor.

In figures 6,7 and 8 we can see the effectiveness of the Faster-RCNN model with the Resnet50 extractor, at the time of detecting malignant tumors, for this case images already previously diagnosed in the DDSM and MIAS databases were used. It is important to highlight that the more diagnosed images used to train the model, the better the algorithm's behavior.

## 5. Conclusion

We can conclude that the Faster-RCNN algorithm with the Resnet50 feature extractor is a good predictor of tumors in mammography images, but its functionality depends on the quantity and quality of the images with which the algorithm is trained, which shows us the great importance of this type of research, to complement the medical diagnoses of breast cancer, which has a high incidence and deaths worldwide.

It is important to highlight from this research that, depending on the type of application, a faster, slower or more precise model should be selected. In addition, combinations can be made between feature extractors and other parameters mentioned above, which will allow better performance depending on the application.

The difference between the detectors is narrowing. Single shot detectors use more complex designs to increase their accuracy, and region-based detectors speed up operations to be faster. There are many challenges to be overcome in object detection methods, deep learning will have a more prospective future in a wide range of applications in the field of medicine.

As future work, it is proposed to train other models and architectures using boxes and masks not only to locate the tumor within the mammogram, but also to create a mask with its shape. In this way, the tumor size can be estimated more precisely and taken into account in the decision-making task.

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